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Market Sentiment, Financial Fragility, and Economic Activity
The Role of Corporate Securities Issuance

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Abstract

Using new quarterly U.S. data for the past 120 years, I show that sudden reversals in equity and credit market sentiment approximated by several measures of corporate securities issuance are highly predictive of banking crises and recessions. Deviations in equity issuance from historical averages also help to explain economic activity over the business cycle. Crises and recessions often occur independently of domestic leverage, making the credit-to-GDP gap a deficient early-warning indicator historically. The fact that equity issuance reversals predict banking crises without elevated private credit levels, suggests that changes in investor sentiment can trigger financial crises even in the absence of underlying banking fragility.

JEL classification: E32, G01, G32, G41, N11, N12.

Keywords: Corporate securities issuance, market sentiment, financial fragility, banking crises, recessions.

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I. Introduction

Banking crises tend to occur after credit booms go bust (Schularick & Taylor, 2012). The business cycle, too, is fundamentally at the mercy of the ebb and flow of private credit (Gilchrist & Zakrajšek, 2012). What, however, drives these credit booms? Several well-known propositions have been made including technological shocks (Minsky's (1986) displacement), credit supply shocks (Mian et al., 2017), financial deregulation (Favara & Imbs, 2015), "irrational exuberance" (Shiller, 2016), or "new era" thinking (Reinhart & Rogoff, 2009). Many of these propositions involve—implicitly or explicitly—a radical shift in agents' expectations about future income and profit opportunities towards the better. As the behavioral finance literature shows, this shift in sentiment can be so forceful that it pushes investors' expectations beyond numbers that can be justified by fundamentals. In this case, the result is an upward spiral of increased borrowing and booming asset prices feeding off each other through rising collateral values. Whether we look at economic activity or financial fragility, investors sentiment plays a pivotal role. It is thus all the more surprising that while a substantial number of empirical studies have looked into the role of market sentiment for economic activity (Greenwood & Hanson, 2013; López-Salido et al., 2017; Milani, 2017), its impact on financial fragility, and the assessment of its predictive power for banking crises, has largely been neglected. This study seeks to fill this void.

I present new quarterly data spanning 120 years of securities issuance in the United States as a proxy for investor sentiment in corporate debt and equity markets to assess its usefulness in explaining economic activity and financial fragility. Specifically, I investigate how sudden shifts in sentiment can be used for the prediction of banking crises and recessions ahead of time. Previous assessments of this question were constrained by historical data availability only at annual frequency (Philippon, 2015; López-Salido et al., 2017; Krishnamurthy & Muir, 2017) or by small sample sizes due to the availability of higher frequency data only well after World War II (Gilchrist & Zakrajšek, 2012; Mian et al., 2017).

Assuming "limits to arbitrage" (Shleifer & Vishny, 1997), I approximate investor sentiment with issuance activity in corporate debt and equity markets and find that sudden reversals in market sentiment are highly predictive of impending banking crises over an average time horizon of six months and of future recessions up to two years ahead of time. Issuance activity outperforms the private credit-to-GDP gap in its capacity to predict banking fragility in and out of sample. Deviations in equity issuance from historical averages also help to explain economic activity over the business cycle. Crises and recessions often occur independently of domestic leverage, making the credit-to-GDP gap a deficient early-warning indicator in historical application. The fact that equity issuance reversals predict banking crises without elevated private credit levels, suggests that changes in investor sentiment can trigger financial crises even in the absence of underlying banking fragility. A recently proposed triggers-plus-vulnerabilities interpretation of the credit cycle by López-Salido et al. (2017) seems less likely to hold in light of my findings, as financial fragility measures based on credit aggregates perform poorly in predicting the economy's susceptibility to shocks, putting a much stronger focus on the strength of triggers than on the vulnerabilities induced by private sector leverage. Novel quarterly data on bank lending further supports the interpretation that not the built-up of private credit is responsible for financial fragility and bank distress, but its sudden retraction.

The remainder of this paper is structure as follows. Section II briefly reviews the literature on market sentiment, presents the data, and explains how I approximate sentiment through several different measures of corporate securities issuance. Section III discusses the relationship between financial fragility and the credit cycle, computes a historically consistent credit-to-GDP gap, and predicts banking crises using the data and methodology introduced before. Section IV applies my market sentiment proxies to the business cycle and assesses their ability to predict recessions. The conclusion in section V summarizes the main contributions, discusses avenues for further research, and outlines policy advice.

II. Market Sentiment and securities issuance

Recently, several studies have revisited the impact of credit and equity market sentiment on macroeconomic performance from empirical (Baker & Wurgler, 2007; Greenwood & Hanson, 2013; López-Salido et al., 2017) and theoretical viewpoints (Shleifer & Vishny, 2010; Greenwood et al., 2016; Bordalo et al., 2018). While the ability of the Treasury yield curve—i.e. the 10-year-to-3-months term spread in U.S. government bonds—to predict recessions ahead of time is well-known (Estrella & Mishkin, 1998), this study looks at issuance activity in corporate securities markets—i.e. corporate bonds and stocks—to proxy investor sentiment and explain macroeconomic performance. In particular, I explore the informational content of several measures of gross equity and debt issuance to forecast future stock returns and the future term spread, respectively, as proxies for investors' sentiment in equity and credit markets and their ability to predict banking crises, economic growth, and recessions.

In their seminal study on sentiment in the stock market, Baker & Wurgler (2007) define "investor sentiment, [...] broadly, [...as] a belief about future cash flows and investment risks that is not justified by the facts at hand" (p. 129), and lay out two now well-established assumptions of the behavioral finance literature: First, market participants are subject to sentiment (De Long et al., 1990); and second, betting against sentiment—i.e. forcing asset prices back to their fair values justified by fundamentals—is costly and risky, inducing "limits to arbitrage" (Shleifer & Vishny, 1997). Managers of corporations may exploit this deviation from rationality by issuing stocks when prices are high relative to fundamentals due to buoyant sentiment and by repurchasing stocks when prices are low. On a market-wide scale this means that sentiment can be well proxied by the variation in aggregate stock issuance. In the following, I adopt this line of reasoning and extend it to the market of corporate debt securities, as well, assuming that corporations issue new debt when prices are high—i.e. when payable interest rates are low—in comparison to what would be justified by the companies' fundamentals.

Approximating sentiment

This study follows large parts of the literature in assuming that corporate securities issuance activity is a suitable proxy for market sentiment. This assumptions has widely been accepted for both stock (Baker & Wurgler, 2000) and bond markets (Greenwood & Hanson, 2013), and has been used successfully to predict economic activity (López-Salido et al., 2017) and recessions (Estrella & Mishkin, 1998).[1] The link between corporate securities issuance and banking crises, however, has largely been neglected. This study seeks to step into this breach. The intuition behind using corporate securities issuance to proxy investor sentiment when assessing financial fragility is that, first, elevated issuance activity soaks up liquidity that will be unavailable to market participants in case cash flows fall short, thereby increasing the risk of bankruptcies, and second, that it allows economic agents to over-extend their funding beyond what would be attainable in a more sober market environment. These excess means will then engage in investment as well as in speculation, driving sentiment up even higher, reinforcing the destabilizing mechanism. A more encompassing review of the theoretical literature on the link between sentiment and banking crises and economic activity, respectively, is discussed at the end of this section. First, I introduce my issuance measures and explain the methodology for approximating sentiment using these measures.

To the best of my knowledge, this paper is the first to present quarterly data on debt and equity issuance in the United States for the past 120 years. An influential study by Baker & Wurgler (2000), which argues that high ratios of equity-to-debt issuance—interpreted as a sentiment proxy—predict low stock market returns, uses annual data beginning in 1927 only. Based on my data, I present three variables which I use to compute my sentiment proxies for credit and equity markets:[2]

[1] Derrien & Kecskés (2009) cautions against the use of equity issuance as a proxy for invest sentiment and argues that, when controlled for accurately measured fundamentals, the effect of investor sentiment on the issuance of corporate stocks is relatively small. Their findings, however, are based on firm-level regressions, and the authors do not control for times of elevated *aggregate* sentiment that may temporarily overrule the otherwise fundamentals-based valuation of corporate equity.

[2] In Figure A.9 in the appendix, I discuss a fourth measure of issuance activity: the equity issuance-to-price

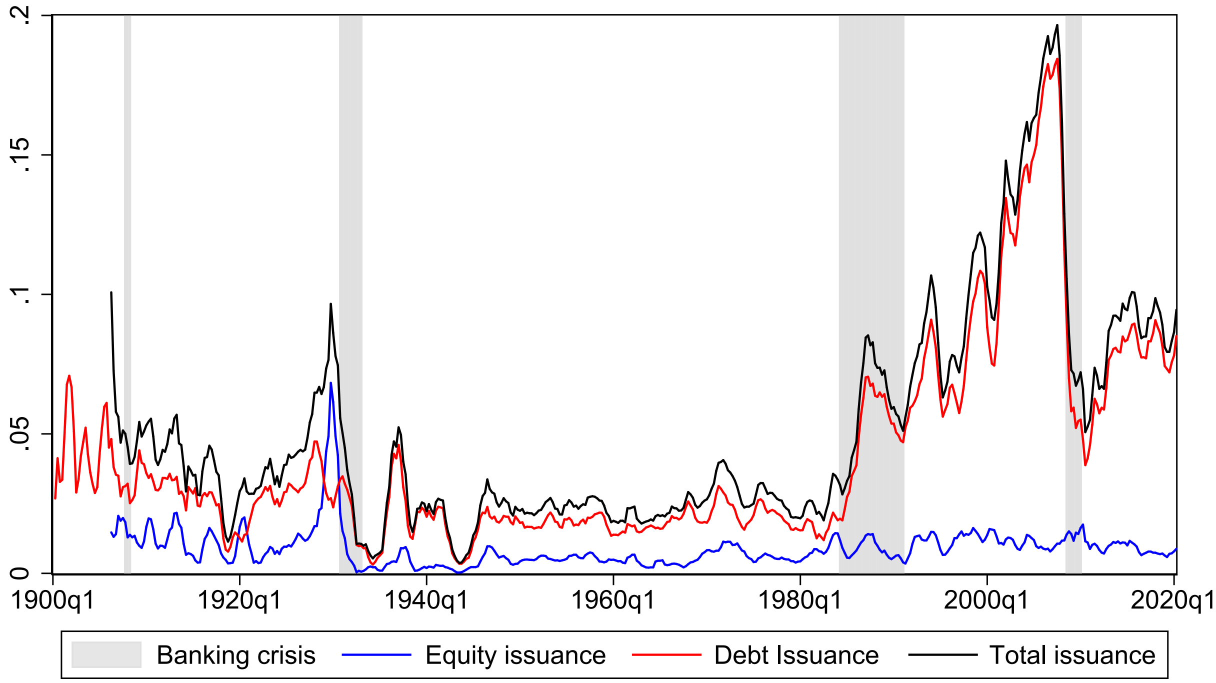
$$
\begin{aligned}
\text{Issuance-to-GDP ratio} &= \frac{\text{equity issuance} + \text{debt issuance}}{\text{GDP}} &= \frac{E+D}{GDP} \\
\text{Equity share} &= \frac{\text{equity issuance}}{\text{equity issuance} + \text{debt issuance}} &= \frac{E}{E+D} \\
\text{High yield share} &= \frac{\text{high yield debt issuance}}{\text{debt issuance}} &= \frac{HY}{E+D}
\end{aligned}
$$

where equity issuance E refers to the gross amount of corporate stocks issued within one quarter and debt issuance D is the gross amount of corporate bonds issued over the same period. HY is the gross issuance volume of high yield bonds. GDP is the nominal gross domestic product at the end of the respective quarter. When gross issuance is negative for equities in the source data (only buybacks) the number is set to zero. All figures are in million U.S. Dollars and in current prices. The construction of the figures and their sources are explained in detail in Table A.7 in the appendix. Figure 1 plots data for companies' gross equity and debt issuance relative to GDP with periods of banking crisis shaded in grey, while Figure 2 displays the equity and high yield share.

As can be seen from Figure 1, total securities issuance in relation to GDP accelerates before periods of banking crises and drops sharply very shortly—i.e. one to several quarters—before the onset of the crises. I employ data and narrative evidence from Baron & Dieckelmann (2021) to determine the beginning and end of banking crisis periods in the United States. A beginning is dated to the quarter of a panic event, such as bank runs or large failures, at which the banking crisis becomes systemic: The drop in copper prices that triggered bank runs and the failure of Knickerbocker Trust in October 1907, the Great Depression's first wave of bank failures in October 1930, the run on Continental Illinois National Bank in May 1984, and the collapse of Lehman Brothers in September 2008. In comparison to its historical average, the issuance of corporate debt securities explodes in the mid-1980s: a trend that arguably can be attributed to the deregulation at the time. Except

ratio. This measure is highly illustrative of the ability of issuance activity to predict banking crises but does not add informational content to the three measures and their respective application in computing the sentiment proxies. I discuss the reason for the measure's exclusion in more detail in the appendix.

Figure 1: Corporate securities issuance relative to GDP, 1900–2020

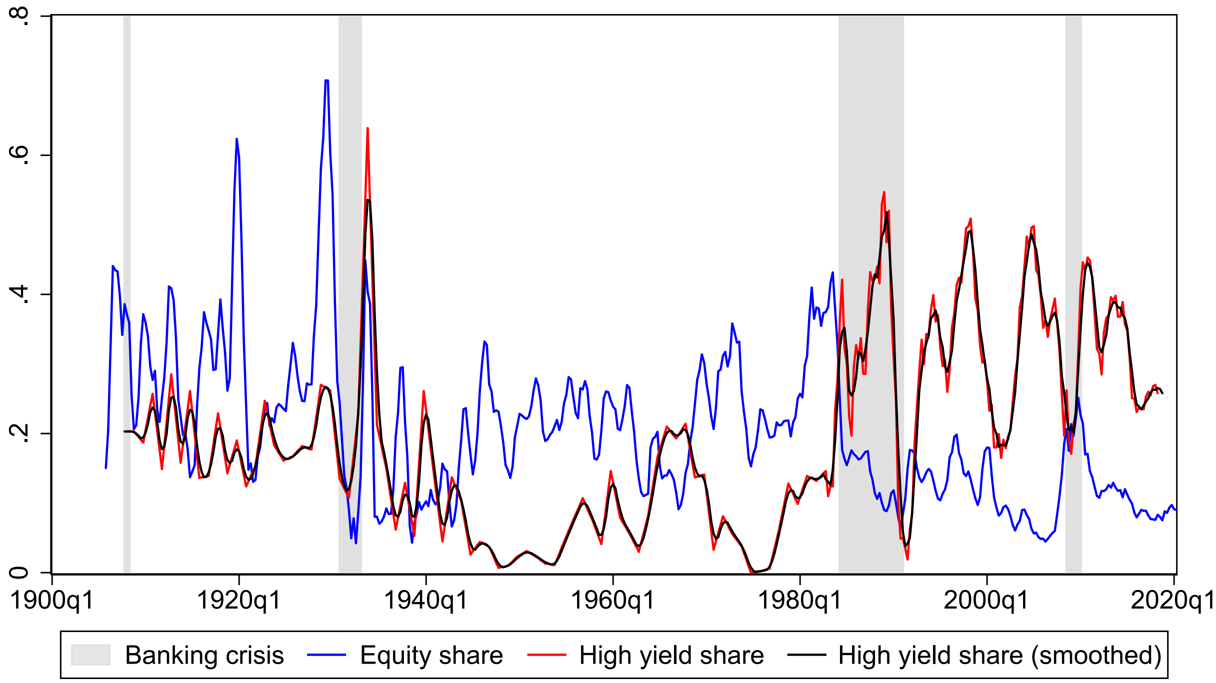


Notes: The lines represent annualized four-quarter averages of gross corporate securities issuance in relation to nominal GDP. Shaded areas in grey represent periods of banking crises according to Baron & Dieckelmann (2021).

for the years preceding the Great Depression, equity issuance remains largely constant in relation to the size of the economy albeit exhibiting oscillating behavior (Covas & Den Haan, 2011; Baron, 2020). Equity and debt issuance flattens out almost entirely in the aftermath of the Great Depression.

In Figure 2 we observe that the equity share has a tendency to shoot up before periods of bank distress within a range of several years to a few quarters prior. The picture for the high yield share looks somewhat different: An increase in the relative issuance of high yield bonds followed by a subsequent reversal tend to precede banking crises. The timing, however, is much less precise than with the equity share or the total issuance-to-GDP ratio, and thus maybe hold less predictive power. Parallel to the volume of debt issuance, in the 1980s, a structural break occurs after which the high yield share seems to follow a cyclical pattern closely related to the business cycle and mirrored in the findings of Greenwood & Hanson (2013), who show that the credit quality of corporate debt issuers deteriorates—

Figure 2: Equity and high yield bond shares, 1900–2020



Notes: Equity share refers to the ratio of the volumes of issued shares over corporate bonds per quarter. High yield share refers to ratio of bonds categorized as high yield by rating agencies over the total volume of corporate bonds issued. Data from 1980 is quarterly and presented as a four-quarter moving average, whereas previous data is annual. A centered four-quarter moving average is used to smooth the full series. Shaded areas in grey represent periods of banking crises according to Baron & Dieckelmann (2021).

i.e. the high yield share increases—during credit booms, pointing towards overheating as a recurring feature of the credit cycle. The sharp uptake of the high yield share and equity share in the wake of the Great Depression should be interpreted with great caution, as they coincide with virtually no issuance of new corporate securities in absolute terms, as shown above.

The stylized facts presented here motivate my investigation of the usefulness of corporate securities as proxies for investor sentiment and as early-warning indicators of banking sector distress. Methodologically, I follow the approach of López-Salido et al. (2017) and use a two-step regression to compute forecasts of future credit spreads and equity returns, respectively, as proxies of sentiment. First, I regress credit spreads or equity returns on their lagged values and on a combination of the corporate securities issuance measures presented above. Then, in the following sections, I use the fitted values—alongside credit aggregate measures—to explain and predict the incidence of recessions and banking crises. For out-of-sample predictions, I estimate the first-step regression on a recursive basis, ensuring that fitted values only incorporate information that was available at the time of the fitted value. Following Greenwood & Hanson (2013) and López-Salido et al. (2017), I interpret the fitted values of the first-step regression as fluctuations in investor sentiment in corporate debt and equity markets.

Now, why exactly do I believe that this methodology captures market sentiment? I follow López-Salido et al.'s (2017) line of argument and hypothesize that when *expected* (i.e. forecasted) returns of corporate bonds are unusually low—or in the case of equity returns, unusually high—in comparison to historical averages, then this is a sign of elevated sentiment. Following the assumption that there are "limits to arbitrage", these buoyant expectations then would be reflected in elevated issuance activity as managers seek to profit from the abnormally high prices that exalted investors are willing to pay. I, thus, regress future returns on credit or equity on the indicators of issuance activity presented above and on an auto-regressive factor. In the following, I discuss the estimations of the respective market sentiment proxies in detail.

Stock market sentiment

To derive an indicator of investor sentiment in the stock market, I forecast future quarterly stock returns r^e with lagged values of historical stock returns and of the issuance measures presented above—namely, the total corporate securities issuance-to-GDP $\frac{E+D}{GDP}$, the equity share $\frac{E}{E+D}$, and, additionally, the interaction of the two former variables, the equity-issuance-to-GDP ratio $\frac{E}{GDP}$.[3] I include the last four quarters as lagged values for each of these variables to capture sudden changes.[4] Although I am estimating a stock market sentiment proxy, the

[3] Note that $\dfrac{E+D}{GDP} \times \dfrac{E}{E+D} = \dfrac{E}{GDP}$.

[4] I choose four lags as the result of a trade-off consideration between a sufficiently long horizon to observe the unfolding of reversals in issuance activity and a sufficiently low number of coefficients to not over-

inclusion of the *total* issuance activity is deliberate as I want to disentangle the predictive effect of issuance in equity markets from aggregate investor sentiment. I estimate a simple ordinary least squares (OLS) regression model of the form

$$r^e = \beta_0 + \sum_{i=1}^{4} \beta_1^i r_{t-i}^e + \sum_{i=1}^{4} \beta_2^i (\frac{E+D}{GDP})_{t-i} + \sum_{i=1}^{4} \beta_3^i (\frac{E}{E+D})_{t-i} + \sum_{i=1}^{4} \beta_4^i (\frac{E}{GDP})_{t-i} + \epsilon \qquad (1)$$

where I interpret the estimated forecast of the future growth rate of the equity index as equity sentiment $s^e = \widehat{r^e}$. Table 1 displays the estimation results.

I generally find that the addition of corporate securities issuance measures improves the performance of an otherwise auto-regressive process with four lags (model one). Baker & Wurgler's (2000) finding that a higher equity share forecasts lower stock returns is confirmed in models three, four, and six at high significance. Interestingly, the total issuance-to-GDP ratio becomes a negative predictor of future stock returns even when I include the equity issuance-to-GDP ratio in model six, increasing the adjusted R^2 by 0.017. This lets me conclude that aggregate sentiment adds to the predictability of future stock returns on top of sentiment in the equity market. In summary, the sum of the lagged coefficients of each variable tend to be negative, indicating that elevated issuance activity and a higher equity share, representing buoyant sentiment, are typically followed by lower future stock returns.

Relying on a large literature that has established that stock returns predict investment (Morck et al., 1990), I conclude that periods of buoyant sentiment and above-average issuance activity are followed by lower stock returns, and thus, in response, by lower investment, inducing a decline in economic activity. Further, the fact that a higher equity share is predictive of lower stock returns can be interpreted such that managers acting upon inside knowledge make use of the still optimistic market environment to raise additional equity in anticipation of an economic slowdown or a deterioration of their business activity in the future. Markets will react to these developments with a lag, and when stock prices ultimately

identify the model. The choice of four lags is also informed by the inspection of the styled facts above, showing that reversals in issuance activity tend to occur only shortly before periods of banking crises and unravel over very short time spans of a few quarters.

Table 1: Estimating the stock market sentiment proxy

	(1) r^e	(2) r^e	(3) r^e	(4) r^e	(5) r^e	(6) r^e
L.r^e	0.025	0.022	0.000	−0.008	0.013	0.009
	(0.046)	(0.047)	(0.046)	(0.048)	(0.047)	(0.048)
L2.r^e	0.045	0.038	0.030	0.022	0.036	0.015
	(0.046)	(0.047)	(0.046)	(0.049)	(0.048)	(0.049)
L3.r^e	0.123***	0.109**	0.126***	0.115**	0.104**	0.092*
	(0.046)	(0.047)	(0.046)	(0.049)	(0.048)	(0.049)
L4.r^e	−0.115**	−0.113**	−0.100**	−0.091*	−0.093**	−0.063
	(0.046)	(0.047)	(0.046)	(0.047)	(0.046)	(0.047)
L.(E+D)/GDP		0.023		−0.266		2.190
		(1.202)		(1.209)		(1.605)
L2.(E+D)/GDP		0.896		0.766		−3.797**
		(1.361)		(1.357)		(1.903)
L3.(E+D)/GDP		0.275		0.020		2.859
		(1.368)		(1.369)		(1.907)
L4.(E+D)/GDP		−1.552		−1.654		−2.051
		(1.197)		(1.205)		(1.598)
L.E/(E+D)			−0.016	−0.026		0.073
			(0.048)	(0.049)		(0.071)
L2.E/(E+D)			−0.076	−0.070		−0.248***
			(0.055)	(0.056)		(0.078)
L3.E/(E+D)			0.020	0.014		0.130*
			(0.054)	(0.055)		(0.077)
L4.E/(E+D)			−0.083*	−0.105**		−0.110
			(0.047)	(0.048)		(0.069)
L.E/GDP					−5.183	−10.508*
					(3.387)	(5.493)
L2.E/GDP					5.270	20.146***
					(3.707)	(6.182)
L3.E/GDP					−3.508	−12.108*
					(3.717)	(6.164)
L4.E/GDP					−6.753**	−0.214
					(3.389)	(5.448)
Constant	0.012***	0.017**	0.044***	0.065***	0.035***	0.060***
	(0.005)	(0.008)	(0.010)	(0.014)	(0.007)	(0.017)
Observations	477	477	477	477	477	477
R^2	0.030	0.035	0.061	0.074	0.068	0.098
Adjusted R^2	0.022	0.019	0.045	0.050	0.052	0.067

Notes: *, **, *** indicate significance at the 10%, 5%, and 1% confidence level, respectively. $(E+D)/GDP$ symbolizes total issuance-to-GDP ratio, with E referring to equity issuance and D to debt issuance, respectively. Consequently, $E/(E+D)$ signifies the equity share. E/GDP is the equity issuance-to-debt ratio and simultaneously the interaction term between the total issuance-to-GDP ratio and the equity share. L stands for a one-quarter lag, while L followed by a number refers to a variable lagged by n quarters.

fall, investment decisions will be postponed on an aggregate level, initiating or exacerbating the economic slowdown.

Credit market sentiment

To derive a sentiment proxy for credit markets, I regress the absolute future difference in the corporate term spread—defined as the difference between the yield of BAA-rated corporate bonds with 10-year maturity and the yield of three-month commercial paper—between two consecutive quarters ΔCTS on lagged values of the level of the term spread, of the total issuance-to-GDP ratio $\frac{E+D}{GDP}$, of the equity share $\frac{E}{E+D}$, of the high yield share $\frac{HY}{D}$, and of the debt issuance-to-GDP ratio $\frac{D}{GDP}$.[5] For each variable I use four quarters of lagged values and estimate a simple OLS regression model of the form

$$\begin{aligned}\Delta CTS = \beta_0 + \sum_{i=1}^{4} \beta_1^i CTS_{t-i} + \sum_{i=1}^{4} \beta_2^i (\frac{E+D}{GDP})_{t-i} + \sum_{i=1}^{4} \beta_3^i (\frac{E}{E+D})_{t-i} \\ + \sum_{i=1}^{4} \beta_4^i (\frac{HY}{D})_{t-i} + \sum_{i=1}^{4} \beta_5^i (\frac{D}{GDP})_{t-i} + \epsilon\end{aligned} \tag{2}$$

where I interpret the estimated forecast of the future corporate term spread as credit sentiment $s^c = \widehat{\Delta CTS}$. I choose the corporate *term* spread over the *credit* spread because the former is known to have better predictive capabilities in terms of economic activity (Stock & Watson, 2003). The estimation results are displayed in Table 2.

I find that future changes in the term spread are well predicted by lagged values of the term spread with a adjusted R^2 of 0.154 in model one.[6] The addition of the high yield or equity share adds no or even slightly reduces predictive power, while the inclusion of total issuance in model two increases the adjusted R^2 by 0.012. While all four lagged values of the term spread are significant, only the positive coefficient of the fourth lag of the total issuance-to-GDP ratio is significant, as well. Aggregate issuance activity clearly forecasts

[5] Note that the debt issuance-to-GDP ratio is the interaction term between the total-issuance-to-GDP ratio and the equity share with an inverse sign.

[6] While this number seems relatively small, it is well in line with similar results in (López-Salido et al., 2017). Considering how many macroeconomic and global factors influence the U.S. term spread (for which I do not control), the fact that I am able to explain around 16% of the variation in the future term spread by autoregressive factors alone is actually quite astonishing.

Table 2: Estimating the corporate credit market sentiment proxy

	(1) ΔCTS	(2) ΔCTS	(3) ΔCTS	(4) ΔCTS	(5) ΔCTS	(6) ΔCTS	(7) ΔCTS
L.CTS	0.195***	0.185***	0.182***	0.186***	0.174***	0.176***	0.172***
	(0.045)	(0.045)	(0.045)	(0.047)	(0.045)	(0.046)	(0.048)
L2.CTS	−0.506***	−0.485***	−0.503***	−0.495***	−0.485***	−0.490***	−0.491***
	(0.068)	(0.068)	(0.068)	(0.071)	(0.069)	(0.069)	(0.072)
L3.CTS	0.490***	0.476***	0.506***	0.486***	0.492***	0.495***	0.489***
	(0.068)	(0.068)	(0.069)	(0.071)	(0.069)	(0.069)	(0.073)
L4.CTS	−0.256***	−0.256***	−0.270***	−0.261***	−0.267***	−0.269***	−0.262***
	(0.045)	(0.045)	(0.046)	(0.048)	(0.046)	(0.046)	(0.050)
L.(E+D)/GDP		−0.066			−0.078	−0.265	−0.234
		(0.073)			(0.074)	(0.288)	(0.302)
L2.(E+D)/GDP		−0.086			−0.094	0.166	0.074
		(0.085)			(0.086)	(0.312)	(0.331)
L3.(E+D)/GDP		−0.010			0.001	−0.258	−0.163
		(0.085)			(0.086)	(0.312)	(0.331)
L4.(E+D)/GDP		0.201***			0.201***	0.631**	0.649**
		(0.073)			(0.074)	(0.285)	(0.300)
L.E/(E+D)			−0.005		−0.005	−0.003	−0.002
			(0.003)		(0.003)	(0.005)	(0.005)
L2.E/(E+D)			0.001		−0.000	−0.003	−0.005
			(0.004)		(0.004)	(0.005)	(0.005)
L3.E/(E+D)			0.001		0.001	0.005	0.003
			(0.003)		(0.003)	(0.005)	(0.005)
L4.E/(E+D)			−0.000		0.000	−0.005	−0.004
			(0.003)		(0.003)	(0.004)	(0.005)
L.HY/D				−0.008			−0.007
				(0.011)			(0.011)
L2.HY/D				−0.002			−0.002
				(0.017)			(0.018)
L3.HY/D				0.015			0.012
				(0.017)			(0.018)
L4.HY/D				−0.003			−0.003
				(0.011)			(0.011)
L.D/GDP						0.247	0.138
						(0.345)	(0.369)
L2.D/GDP						−0.344	−0.152
						(0.386)	(0.422)
L3.D/GDP						0.356	0.199
						(0.387)	(0.422)
L4.D/GDP						−0.538	−0.514
						(0.344)	(0.369)
Constant	0.002***	0.002***	0.003***	0.002***	0.002**	0.003**	0.003**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	472	472	472	433	472	472	433
R^2	0.161	0.180	0.166	0.170	0.186	0.193	0.200
Adjusted R^2	0.154	0.166	0.152	0.154	0.165	0.164	0.161

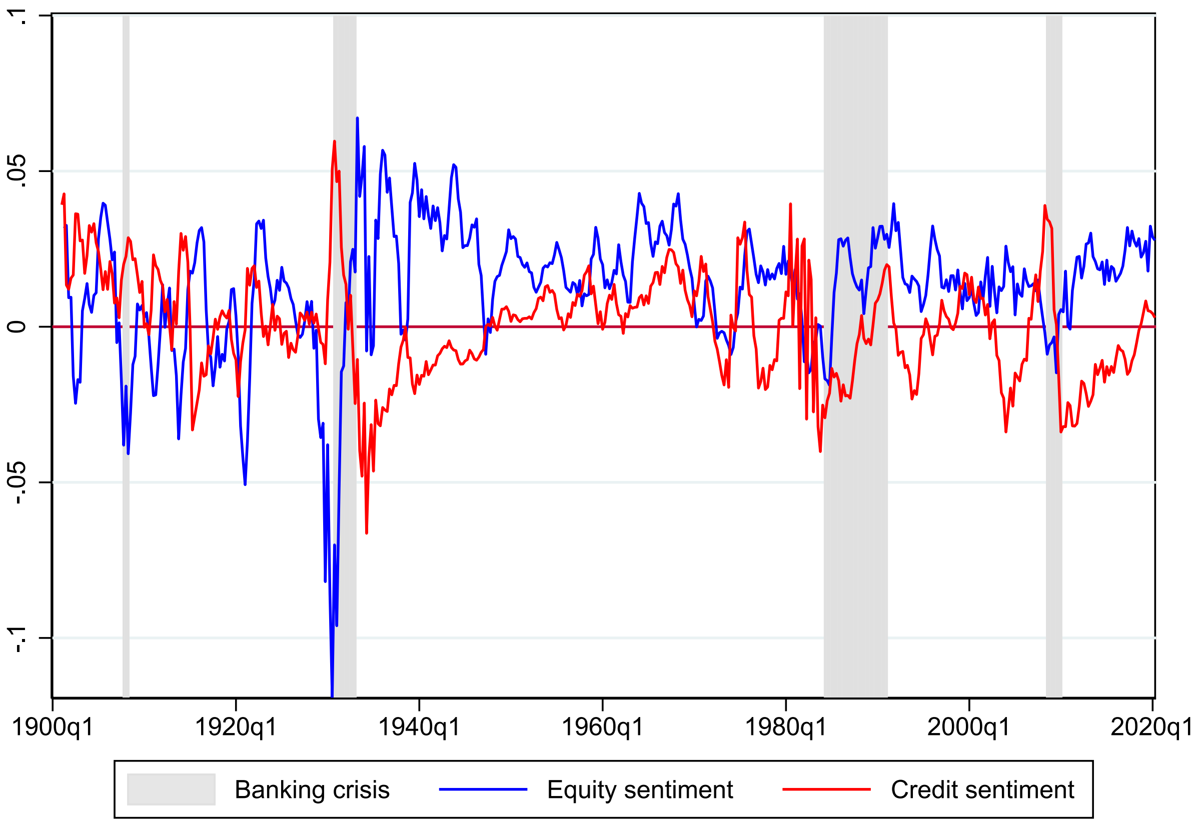
Notes: *, **, *** indicate significance at the 10%, 5%, and 1% confidence level, respectively. Δ is the difference operator and CTS stands for the credit term spread. L symbolizes a one-quarter lag, while L followed by a number refers to a variable lagged by n quarters.

a positive change in the term spread, indicating that elevated market sentiment tends to be followed by economic downturns, as rising spreads typically occur during or prior to recessions. In contrast to Greenwood & Hanson (2013) who find that the high yield share is a good proxy for credit sentiment which soars during credit booms, I find that the high yield share performs poorly in my setting, adding virtually no predictive power in comparison to the other issuance measures. I explain this with the fact that I investigate a much longer time horizon and use data of higher frequency than Greenwood & Hanson (2013) which brings to light that the predictive ability of a deterioration of issuer quality—i.e. a rising high yield share—for future bond returns and for credit market overheating is a phenomenon that only occurs since the 1980s. This is nicely visible from Figure 2 in the previous section.

Intuitively, the link between the term spread and market sentiment is captured by the fact that decreasing term spreads represent a deterioration in investors' perception of interest rate risk. The lower the term spread, the more aggressively is long term credit priced in comparison to short term credit of comparable issuer quality. The increasing price of long term credit relative to short term credit—i.e. the relatively declining financing costs—caused by investors' overly optimistic risk perception is then exploited by managers through increased corporate bond issuance. This is why, I assume that buoyant credit sentiment can be approximated by elevated issuance activity. The results in Table 2 show that this increased issuance activity will then lead to rising term spreads, lending itself well to Arif & Lee's (2014) finding that periods of over-investment caused by overly favorable market conditions are typically followed by a slowdown in economic activity.

The adjusted R^2 of the full model for forecasting term spreads is more than double than that of the respective full model for the forecasts of stock returns in Table 1. However, the inclusion of corporate securities issuance measures had a much bigger impact on predictive ability in forecasting future stock returns than in predicting changes in the future term spread, indicating that the approximation of sentiment through issuance activity might be slightly more relevant for equity markets than for credit markets. Figure 3 shows the es-

Figure 3: Sentiment proxies for equity and credit markets, in-sample, 1901–2020



Notes: Sentiment proxies refer to in-sample predictions of future growth in stock prices or the absolute future change in the corporate term spread, respectively. Positive values for the equity sentiment proxy and negative values for the credit sentiment proxy, respectively, indicate buoyant sentiment, while the reverse signals overly pessimistic sentiment. Shaded areas in grey represent periods of banking crises according to Baron & Dieckelmann (2021).

timated forecasts on the basis of model six from Table 1 and of model six from Table 2, respectively, which I interpret as proxies for market sentiment in equity and credit markets.[7]

Credit sentiment—proxied by the forecasted absolute change in the term spread—shows a clear pattern of cyclicality. This stylized fact has recently received considerable attention with studies investigating the role of sentiment in driving the business cycle and, more

[7] I choose model six over model seven from Table 2 and, thus, exclude the high yield share from the ultimate credit sentiment proxy estimation for several reasons. First, my high yield share data starts only in 1908 and the estimation would exclude the important panic of 1907. Second, the inclusion of the high yield share actually decreases the adjusted R^2 relative to model 6 and, thus, does not add predictive power to the estimation. And third, I achieve consistency through the exclusion as both ultimate sentiment proxies are estimated using the autoregressive factor, the total issuance-to-GDP ratio, the equity share, and the (inverse) interaction of the latter two.

concretely, focusing on the role of credit sentiment as a driver of a potential credit cycle at business cycle wavelengths (e.g. López-Salido et al., 2017). Equity sentiment—proxied by the forecasted percentage change in equity prices—deteriorates sharply shortly before episodes of banking crises, while credit sentiment improves during banking crises but has a tendency to collapse shortly before their outbreak. Note that, as the credit sentiment proxy captures investors' forecast of the future change in the term spread, a positive value is associated with the expectation of widening spreads and, thus, with a shift towards pessimistic sentiment. The reverse applies to the equity sentiment proxy where a positive value refers to the expectation of positive future stock returns on the basis of issuance activity and, thus, indicates buoyant sentiment. I interpret these pronounced swings before periods of bank distress as a sign that the sharp reversal of sentiment has a triggering effect. Bordalo et al. (2018) come to a similar conclusion and write "that crises occur when good news stops coming, so that excess optimism reverts" (p. 223). Not all sharp reversals are followed by banking crises, however. In section III, I investigate under which conditions these sudden shifts in sentiment are followed by the outbreak of banking crises.

Theoretical background

In the following, I briefly discuss the link between market sentiment and banking crises and economic activity, respectively. I begin with reviewing the literature on sentiment, banking crises, and financial fragility, and its relation to the credit cycle. I then move on to theoretical explanations of the relationship between sentiment and economic activity and recessions.

Theorists of banking crises have long stressed the importance of sentiment in their formation: "Animal spirits" (Keynes), "irrational exuberance" (Greenspan, Shiller), and "euphoria" (Minsky) all refer to buoyant collective emotional states during periods of persistent deviation from asset price valuations and volumes of external finance justifiable by fundamentals or desirable from the perspective of a social planner. Market participants buy assets based on overly confident beliefs about future profits, while corporations leverage up by discounting over-optimistic forecasts of future cash flows. When the toxic combination of rising asset prices and ballooning private debt reaches its apex, the ”Minsky moment” sets in and euphoria turns into panic. The sharp reversal in sentiment triggers a cascade of fire sales in a scramble for cash where not fundamentals or rational expectations of future profits take the helm, but the sheer fear of ending up the hindmost who the devil takes.

Attempting to flesh out the narrative above, several studies have investigated the link between sentiment and banking crises from a theoretical perspective. Shleifer & Vishny (2010) propose a formal three-period model in which banks make, securitize, distribute, and trade loans, and are influenced by investor sentiment. During good times—i.e. when prices for securitized assets are high—banks extend their balance sheets and borrow short-term to engage in the very profitable business of securitizing loans. This over-leveraging leaves them with little means in bad times which increases the risk of them having to liquidate their portfolios. Bank profits and real investments become highly cyclical and swings in investor sentiment are transmitted through the banking system to the real economy. Greenwood et al. (2016) present a model of credit market sentiment in which investors extrapolate past defaults in the bond market. A feedback loop between sentiment and market outcomes arises endogenously and several well-documented features of credit-driven boom-bust cycles can be explained. Ultimately, elevated sentiment covers up the deterioration of fundamentals before crises and, thus, artificially prolongs credit booms, creating an environment of "calm before the storm" that is consistent with historical narratives. Bordalo et al. (2018) develop a model of credit cycles in which expectations form by overweighting "future outcomes that become more likely in light of new data" (p. 199) and credit spreads turn out to be overly volatile and their reversals to be predictable. As a result, "crises occur when good news stops coming, so that excess optimism [i.e. buoyant sentiment] reverts" (p. 223).

Empirically, market sentiment and banking crises have also received fresh attention recently, using both narrative and quantitative approaches. Reinhart & Rogoff (2009) famously argue that banking crises tend to be preceded by "new era"-thinking according to which over-optimistic expectations of future incomes are seemingly justified, because "this time is different". Greenwood & Hanson (2013) find that credit market sentiment can be well approximated by a combination of bond credit spreads relative to their historical means and of the high yield share of bond issuance. The so-measured deterioration in issuer quality induced by investors' elevated sentiment can be a better predictor of credit overheating and subsequent economic decline than rapid credit growth. López-Salido et al. (2017) find that buoyant credit market sentiment is followed by a decline in economic activity two to three years later, and by a change in the composition of external finance: An increasing equity share in the issuance of corporate securities points towards the role of negative credit supply shocks. The authors do not, however, narrow down their analyses of periods of declining economic activity to those of financial recessions or banking crises. Baker & Wurgler (2000) show that the equity share in total corporate securities issuance is a strong predictor of lower future stock market returns. The authors rule out efficient market explanations, and thus López-Salido et al. (2017) use the equity share as a proxy for stock market sentiment but find that it has no predictive ability for economic growth. They come to a similar conclusion when using Shiller's (2000) cyclically adjusted price-earnings ratio as a proxy for stock market sentiment. Regarding banking crises, however, Shiller (2016) provides a popular narrative of sentiment-driven asset price bubbles that have a tendency to end in major bank distress focusing on technological, economic, political, and cultural factors inducing over-optimism.

Much more well-established is the literature on investor sentiment and economic activity according to which periods of buoyant sentiment lead to a predictable decline in economic output in the near future. The observation of mean-reverting sentiment as a major driving force behind fluctuations in the real economy is consistent with the business cycle literature.

Arif & Lee (2014) find that corporate investment peaks during periods of high sentiment which is followed both by lower equity returns and lower economic growth, lending itself to an interpretation of over- and under-investment during booms and busts, respectively. The authors employ several proxies of investor sentiment—household surveys, fund flow data, and a composite sentiment index—and find their results to be robust to the choice of sentiment approximation. Milani (2017) finds that above 40% of business cycle fluctuations are driven by psychological factors in markets, and particularly by sentiment related to future investment expectations. Using annual U.S. data going back to 1929, López-Salido et al. (2017) report that elevated credit market sentiment is associated with a decline in economic activity after two to three years. Investors sentiment is suspect to a predictable mean reversion which induces a widening of credit spreads that, in turn, are associated with economic contractions.

Into a similar vain fits the long-established literature around the prediction of recessions using bond spreads, and particularly the difference between the yield of 3-month U.S. Treasury bills and the yield of 10-year U.S. Treasury bonds.[8] Narrow *credit* spreads—i.e. the difference between yields of different quality (as represented by rating classes) but equal maturity—in comparison to their historical averages reflect elevated sentiment and precede economic recessions (López-Salido et al., 2017). Assuming that the risk of default stays constant over time, as approximated by the restriction to one specific credit rating level (e.g. BAA), the time-variation in spreads of corporate debt then represent changes in investor sentiment. Intuitively, aggressively priced corporate credit reflects expectations of an overly low risk of default. In turn, this increases lending activity and firms' leverage making the aggregate economy more susceptible to adverse shocks and increasing economic and financial fragility. Better suited for the prediction of recessions are, however, *term* spreads—i.e. the difference between yields of different maturity but equal quality—turning negative, as a vast literature has shown (Estrella & Mishkin, 1998). Very narrow or even negative term spreads mean that short-term yields start to exceed longer-term yields for the same debtor, indicating that market participants are increasingly willing to pay a premium for a more long-term fixed investment to weather an anticipated economic slowdown and the associated rise in economic uncertainty.

[8] For an introduction to the use of the yield curve as a recession predictor in practice, see https://www.newyorkfed.org/research/capital_markets/ycfaq.html.

III. Financial fragility and the credit cycle

The idea that the economy can fluctuate between a state of financial stability and fragility dates back to Minsky (1986) and Kindleberger & Aliber (2015), but can also be found in earlier works of Schumpeter (1934), Fisher (1933) and even before in the writings of John Stuart Mill, Knut Wicksell, and Adam Smith (Kindleberger & Aliber, 2015, p. 16). No uniform definition of financial fragility exists in the literature but it is usually roughly referred to as an economy's state in which relatively small and otherwise less important shocks can have large and potentially disastrous macroeconomic effects by being able to trigger banking crises or deep recessions. What all discussions—old or new—of financial fragility have in common, however, is the focus on (private) credit.

Does credit have an effect on macroeconomic outcomes? And if yes, is it positive or negative? As one of the core themes of macroeconomics, this question has received vast attention both historically and recently. While the positive post-World War II experience led economist to investigate the so-called finance-growth nexus, confirming that credit was good for growth (Levine, 2005; Ang, 2008), the Global Financial Crisis of 2008 reignited an older debate that looked into the opposite direction and found that excessive credit growth and leverage is and always has been associated with deep recessions and banking crises (Schularick & Taylor, 2012; Baron & Xiong, 2017). López-Salido et al. (2017) recently introduced a distinction of the respective literature into two strands: theories of financial frictions that explain why economies exhibit financial vulnerabilities (Bernanke & Gertler, 1989; Kiyotaki & Moore, 1997; Eggertsson & Krugman, 2012), and behavioral theories emphasizing market sentiment and expectations which give rise to sudden reversals of overoptimism, thereby functioning as recession or crisis triggers (Minsky, 1986; Greenwood et al., 2016). These two strands play out over different time horizons. The former covers a medium-term time span that could be related either to the frequency of the business cycle but also to longer waves of credit cycles of 15 to 30 years as has been shown in the financial cycle literature (Drehmann et al., 2012; Borio, 2014; Strohsal et al., 2019).[9] The latter strand takes on a more short-term perspective with investors' sentiment changing rapidly over the course of months, weeks, or even days. Covas & Den Haan (2011, 2012) provide evidence for cyclicality in equity and credit markets that revolves around the business cycle.

The credit-to-GDP gap

Financial fragility is commonly approximated by high domestic leverage. In particular, it has been common practice since the Global Financial Crisis to look at private credit aggregates—such as outstanding bank loans, household debt, or total credit to the private non-financial sector. Especially, the so-called credit-to-GDP gap has risen to a position of great prominence during the implementation of the Basel III regulatory framework in the aftermath of the crisis. It is defined as the difference between the ratio of credit to the private non-financial sector to GDP and the ratio's long-term trend (Drehmann & Tsatsaronis, 2014). The Basel Committee on Banking Supervision (2010) precisely defines this long-term trend as the trend component of the private credit-to-GDP ratio extracted by an one-sided HP filter (Hodrick & Prescott, 1997) with a smoothing parameter of $\lambda = 400,000$. The resulting gap informs the built-up of countercyclical capital buffers according to which national banks must ramp up their capital reserve in response to increasing leverage in the domestic economy. The idea is to have high capital ratios in boom times, so that eventual bank losses in the downturn are first met by writing down the capital buffers.

The Bank for International Settlements (BIS) publishes credit-to-GDP gaps according to the above definition and collects private credit and GDP data for more than 40 countries at quarterly frequency. The BIS' definition of the private non-financial sector consists of households, non-profit organizations, and private and public non-financial businesses as debtors.

[9] There is a remarkable amount of disagreement and ambiguity on the time horizon of the credit cycle. However, two main camps emerge from the literature: one that sees the credit cycle revolving around the business cycle as presented by the view of López-Salido et al. (2017), and one that sees the credit cycle playing out over time horizons of up to 30 years, as best presented by the financial cycle-view of the BIS (Drehmann et al., 2012; Borio, 2014). Future research should explicitly address these ambiguities.

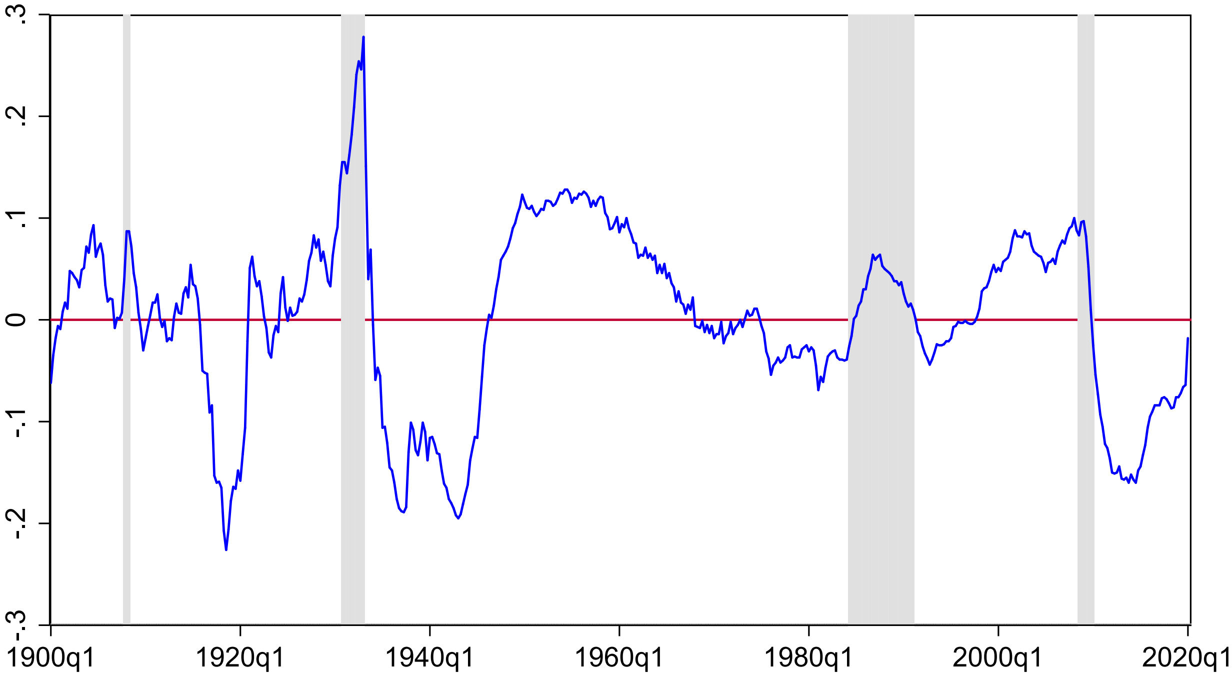
It considers bank loans and debt securities but not equities, investment fund shares, insurance and pension schemes, financial derivatives, trade credit, and other accounts payable or receivable. (Dembiermont et al., 2013, p. 67).

For this study, I reconstruct the BIS' private credit series as best as possible using my new consistent time series of credit components available at quarterly frequency from 1900–2020: outstanding corporate debt securities, commercial paper, bank loans, and—in the post-WWII era—various types of asset-backed securities. A consistent time series for non-bank, non-securitized lending can unfortunately not be constructed and is thus omitted from the private credit series I present in this paper. Figure A.10 in the appendix plots the BIS' estimation of the credit-to-GDP gap in comparison to the one that is based on my historical data. I mirror the construction of the gap with my own data one-to-one. As can be seen from the graph, the two data series yield very similar results with two peaks in the late 1980s and around 2008.

Figure 4 displays the estimation of the credit-to-GDP gap using my data over the whole time horizon. While the raw series begins in 1900, I backward extrapolate the private credit series to the first quarter of 1890 using growth rates of total loans by national banks and railroad bonds outstanding which are available at quarterly frequency before 1900. This allows the gap to start at the first quarter of 1900 using the proxy data for the first ten years. From the graph, we observe that the forward-looking gap estimate exhibits five pronounced peak periods—around 1905, in 1931, in the 1950s, in the late 1980s, and in 2008—and three marked troughs—after WWI, during the Great Depression, and after the Global Financial Crisis. As is indicated by shaded areas in the graph, four out of these five peaks coincide with periods of banking crises according to the definition of Baron & Dieckelmann (2021). The troughs occur either in the aftermath of the two most severe banking crises—the Great Depression and the Global Financial Crisis—or during times of war.

What drives peaks and troughs over the medium-term credit cycle? Sharp uptakes in economic growth like during the war economies of world wars I and II drive down the

Figure 4: Private credit-to-GDP gap, 1900–2019



Notes: The blue line depicts the credit-to-GDP gap based on my historically consistent series for total credit to the private non-financial sector divided by GDP. The gap is computed as the deviation from the series' medium-term trend using a one-sided HP-filter with a smoothing parameter of $\lambda = 400,000$. Shaded areas in grey represent periods of banking crises according to Baron & Dieckelmann (2021).

credit-to-GDP ratio abruptly and thus create an acute deviation from trend, causing the credit-to-GDP gap to fall. Additionally, sharp credit contractions caused by major banking crises cause the ratio's numerator to collapse and put the ratio on a below-trend trajectory. From the 1930s to the first half of the 1940s, both of these phenomena occur successively, causing the HP filter to produce a far-below-trend gap estimate. The healthy economic development after World War II characterized by stable and sustainable growth in credit and GDP then induces a sharp reversal of the gap estimation into above-trend territory which causes a false warning in the 1950s and 1960s if we interpret the credit-to-GDP as an indicator of financial fragility. Sudden and substantial movements in the credit-to-GDP ratio can induce spurious movements in the gap estimation that have no informational content for the degree of financial fragility.

The ongoing global economic crisis caused by the Covid-19 pandemic may have a similar effect: A rapid contraction of GDP with a simultaneous large-scale extension of private credit to bridge the adverse economic effects of lock-downs will ramp up the credit-to-GDP ratio suddenly and move the gap estimate most likely onto an above-trend trajectory. Naturally, the Covid-19 crisis poses a threat to financial stability and, thus, a shooting up of the credit-to-GDP gap could be seen as a desirable signal to inform a policy maker of heightened financial fragility—I will argue, however, that this is a false signal as it does exactly not represent the gradual built-up of fragility brought about by an over-extension of credit that the gap was designed to capture, but rather is caused by a sudden change in economic conditions that should be reflected by indicators of López-Salido et al.'s (2017) second strand of the credit cycle literature that captures market sentiment and sudden changes in expectations, as I explained in the previous section.

Thus, the historical record not only shows that, first, large crisis events can distort the informational content of the credit-to-GDP gap as an indicator of financial fragility, but also that, second, we may be on the verge of receiving yet another such distorted signal due to extraordinary consequences of the Covid-19 pandemic. Third, we have seen that the ability of the credit-to-GDP gap to measure financial fragility works well in hindsight but may depend significantly on at what point in time the estimation commences.[10] Last, it is not immediately visible form the stylized facts whether the credit-to-GDP can be useful for the correct timing of crisis events. While its recent popularity is explained by the fact the it would have worked well before the collapse of Lehman Brothers in 2008, the picture is less clear with regard to the Great Depression or the Savings and Loan crisis of the 1980s. In the following, I turn to securities issuance-based proxies of credit and equity market sentiment to investigate the possibility of more precise and timely warning signals of imminent crises.

[10] This phenomenon is known to the financial cycle literature as the "starting-point bias" (Geršl & Seidler, 2012; Drehmann & Tsatsaronis, 2014). The BIS' credit-to-GDP gap does not indicate any above-trend leverage prior to the 1980s as the data coverage starts only in 1952. Using longer data starting in 1900, however, induces a spurious positive value throughout the post-WWII era, as I have shown previously.

Predicting banking crises

Considering the limited usefulness of the de-trended credit aggregate to predict periods of bank distress, I question its ability to proxy financial fragility. If fragility is defined as a state of high susceptibility to external shocks we would expect sudden reversals in market sentiment during periods of high domestic leverage in comparison to historical averages to function as crisis triggers. This is the triggers-plus-vulnerabilities hypothesis of López-Salido et al. (2017). In the following, I test this hypothesis by regressing pre-crisis periods on the credit and equity sentiment proxies s^e and s^e, on the credit-to-GDP gap c, and on interaction terms of the former two with the latter.[11] A pre-crisis period is defined as the four quarters prior to the starting quarter of a banking crisis. Since this independent variable is coded as a dummy variable, I use a logistic regression function of the form

$$logit(\pi^p) = \ln \frac{\pi^p}{1-\pi^p} = \beta_0 + \beta_1 s^e + \beta_2 s^c + \beta_3 c + \beta_4 (s^e \times c) + \beta_5 (s^c \times c) + \epsilon \qquad (3)$$

where π^p is interpreted as the probability of an impending banking crisis within the next four quarters. Table 3 presents the estimation results.

The general take-away from the regression results in Table 3 is that sentiment proxies clearly outperform the credit aggregate in explaining periods of financial fragility, as defined by four consecutive pre-crisis quarters.[12] With a pseudo R^2 of 0.02, the credit-to-GDP gap is a very weak predictor of fragility in comparison to equity sentiment (pseudo $\mathrm{R}^2 = 0.173$) and credit sentiment (pseudo $\mathrm{R}^2 = 0.051$). Although the coefficient is positive and significant, indicating that excessive leverage is indeed followed by bank distress, the low coefficient of determination indicates that many other periods of high leverage are not followed by crises. As expected, a deterioration in both equity and credit sentiment is predictive of bank

[11] Recall that the sentiment proxies are estimated forecasts of future stock returns or term spreads, respectively, on the basis of measures of past securities issuance activity.

[12] These results are robust with regard to longer pre-crisis horizons and other credit aggregate measures, such as a credit gap computed from bank loans instead of from total credit or conventional credit-to-GDP ratios.

Table 3: Financial fragility and market sentiment

	(1) Pre-crisis	(2) Pre-crisis	(3) Pre-crisis	(4) Pre-crisis	(5) Pre-crisis	(6) Pre-crisis
Equity sentiment s^e	-26.94^{***}			-25.76^{***}	-25.34^{***}	-24.82^{***}
	(5.13)			(5.43)	(5.62)	(6.08)
Credit sentiment s^c		222.79^{**}		146.38^{*}	137.20	130.64
		(92.91)		(88.85)	(88.20)	(79.80)
Credit−to−GDP gap c			5.10^{**}		2.47	0.85
			(2.36)		(2.46)	(2.00)
$s^e \times c$						14.20
						(47.68)
$s^c \times c$						2716.19^{**}
						(1084.05)
Constant	-3.43^{***}	-3.56^{***}	-3.47^{***}	-3.53^{***}	-3.56^{***}	-3.82^{***}
	(0.29)	(0.31)	(0.27)	(0.32)	(0.33)	(0.37)
Observations	477	473	481	472	471	471
Pseudo R^2	0.173	0.051	0.020	0.195	0.198	0.234

Notes: *, **, *** indicate significance at the 10%, 5%, and 1% confidence level, respectively. The table shows estimations for logistic regressions of pre-crisis periods, which refer to the four quarters prior to the start of banking crisis events. Positive equity sentiment values represent buoyancy while positive credit sentiment values indicate pessimism.

distress. [13] Thus, it is no wonder that taking sentiment proxies and the credit aggregate together in model five only marginally increases the predictive ability of model four which includes sentiment measures only. The coefficient of the credit gap becomes insignificant, too. Interacting both sentiment proxies with the credit aggregate in model six, however, yields an interesting result: While the contribution to predictive ability of equity sentiment remains largely unchanged, and importantly remains significant only independently of the credit-to-GDP gap, credit sentiment becomes highly significant when interacted with the credit gap. This means that equity sentiment is a predictor of bank distress irrespective of credit aggregates—a result that goes along nicely with recent findings by Baron et al. (2021) who show that substantial bank equity declines are predictive of banking crises. Contrarily, a deterioration of credit sentiment is predictive of bank distress *only if* it is accompanied

[13] Recall that a positive value for the *equity* sentiment proxy indicates buoyancy while a positive value for the *credit* sentiment proxy—as it refers to an expected widening of term spreads—represents a shift towards pessimism.

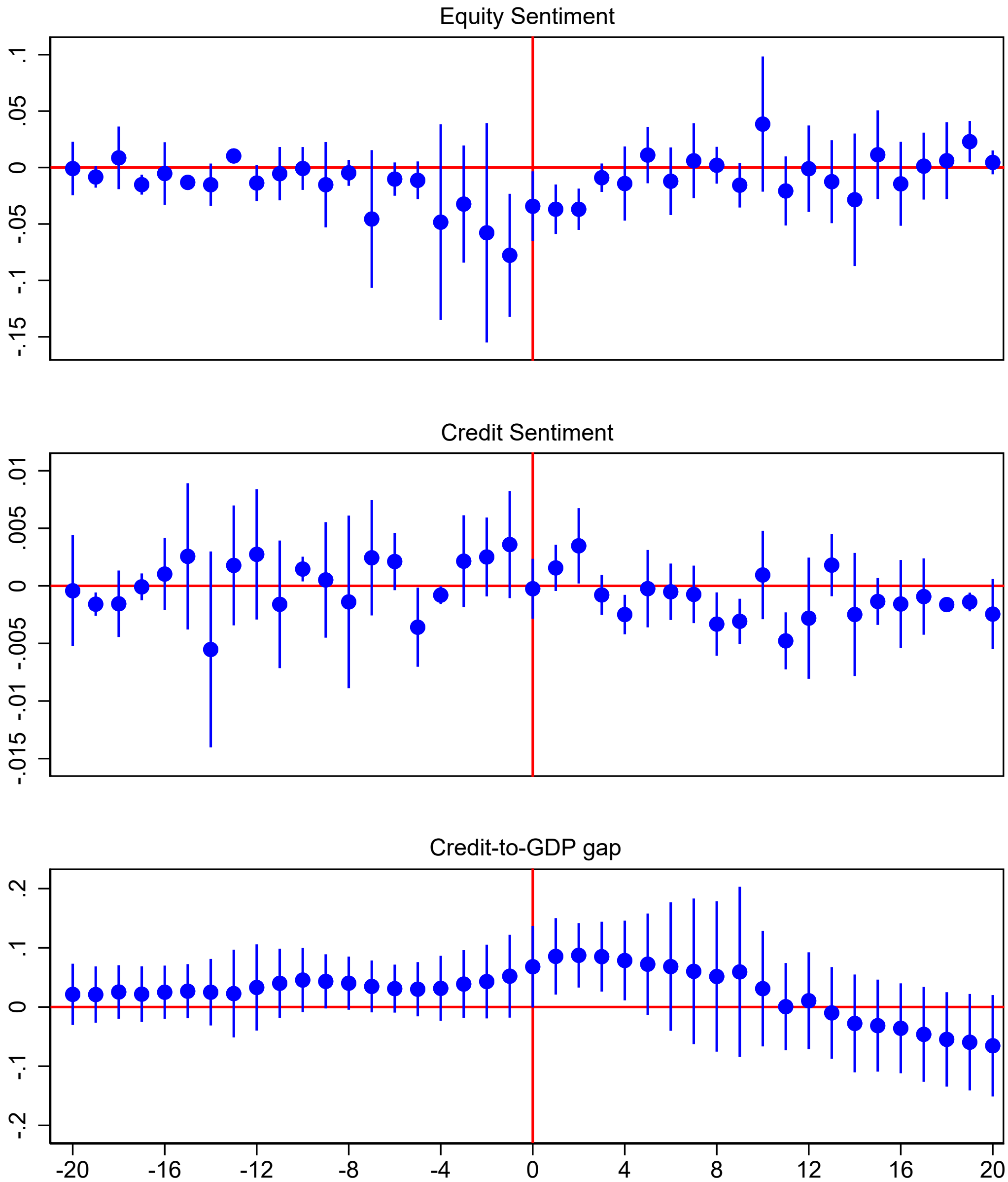
by high leverage, returning some credibility to López-Salido et al.'s (2017) trigger-plus-vulnerabilities hypothesis.

Next, I take on a slightly longer-term perspective and investigate how sentiment and the credit aggregate evolve twenty quarters before and after crisis periods. The idea is, first, to shed some light on the question whether sentiment builds up alongside credit and could thus be a potential driver of credit booms, and, second, to investigate the horizon over which reversals of sentiment prior to crises play out. For this, I regress the sentiment proxies and the credit-to-GDP gap on twenty lags, twenty leads, and the contemporaneous value of the banking crisis starting date dummy. I include the constant in the regressions but exclude it from the graphs and plot the coefficient estimates and their confidence intervals as event studies in Figure 5.[14]

The first plot in Figure 5 shows the average development of the equity sentiment proxy 5 years before and after the start of banking crises. It is immediately visible that around four quarters before the start of a crisis equity sentiment declines drastically to below zero, even though only the estimate for the last quarter before the beginning of the crisis is significant at the 95% level. This is matched by a deterioration of credit sentiment three quarters prior, as indicated by a borderline significant and positive surge in the foretasted corporate term spread. The credit-to-GDP gap, being the credit-based proxy for financial fragility, shows no interesting behavior with the exception that its value is slightly above zero on average but not significantly. The forward-looking credit gap estimate is only significantly different from zero and positive four quarters into to the crisis which I attribute mainly to a stronger decline in GDP than in total credit occurring during the crises in the sample. The observed behavior of the credit gap is fundamentally different from what we would expect from the perspective of a vulnerabilities-interpretation of the credit cycle according to which fragility builds up a gradually to very high levels prior to crises, as proxied by high domestic leverage in comparison to its historical trend.

[14] I use a robust estimation method for the standard errors to achieve variance over time in the event studies.

Figure 5: Event studies around banking crises



Notes: Depicted are coefficient estimates from regressing the variables on 20 leads and lags of the banking crisis start dummy. Vertical bars represent 95% confidence intervals. Positive equity sentiment values represent buoyancy while positive credit sentiment values indicate pessimism.

Along the same lines fits the observation that buoyant market sentiment does not seem to be persistently sustained in the medium-term run-up to banking crises. Neither equity nor credit sentiment follow statistically significant non-zero trajectories prior to crises. Since neither the credit gap consistently surges prior to crises, nor buoyant sentiment is sustained over a sufficiently long time horizon, I can rule out the hypothesis that market sentiment is a driver of credit booms that end in banking crises. Furthermore, equity sentiment has a tendency to quickly return to (around) the value of zero after five to ten quarters, displaying mean-reverting behavior which is in line with the literature (De Long et al., 1990; López-Salido et al., 2017). The key message from Table 3 is mirrored in these findings, namely that it's not the excessive built-up of credit on potentially irrational grounds that predict banking crises, but instead the sudden reversal of such buoyant sentiment. The fact that equity issuance reversals predict banking crises without elevated private credit levels, suggests that changes in investor sentiment can trigger financial crises even in the absence of underlying banking fragility. I thus give much more weight to the triggers-aspect of López-Salido et al.'s (2017) interpretation of the credit cycle than to the vulnerabilities-side. I interpret the evidence in such a way that it is not the built-up of leverage that causes banking crises, it is the moment when external finance stops coming which causes the system to fold.

In light of this interpretation, I argue for revisiting the definition of financial fragility as a state of susceptibility to shocks and the use of credit aggregates as its main measure. The results presented above show that banking crises unfold irrespective of a long-term built-up of leverage—and thus, potentially independently of the state of financial fragility, as it is currently defined. Naturally, this interpretation has several important caveats. First, it rests on the approximation of market sentiment through measures of corporate securities issuance. It remains an open question whether other proxies confirm the important role of sentiment in a banking crises setting. Second, all results are obviously limited to the United States. Having a rather market-based financial system is certainly an important factor in explaining why corporate securities issuance is such a well-functioning predictor. Third, due to the lack of quarterly data prior to World War II, credit by financial intermediaries other than banks is excluded from the analysis. As a final exercise, I test the discovered predictive capabilities of the sudden sentiment proxy reversals in a pseudo-real-time setting and move the analysis out of sample.

Out-of-sample analysis

To test the usefulness of this section's findings for policy makers, I move the analysis from an ex post to an ex ante perspective and assess the predictive capabilities of my corporate securities issuance measures for banking crises out-of-sample. Importantly, this means that the previously estimated sentiment proxies cannot be used for this exercise since the respective fitted values are estimated over the entire sample size and time horizon. Instead, I estimate the sentiment proxies recursively using only observations that were available at each point in time. The credit-to-GDP gap is already a forward-looking measure and can thus be kept. Otherwise, I use the same logistic regression model (3) as in the previous subsection and estimate this model through the first quarter of 2005 such that the pre-crisis observations of the subsequent Subprime Crisis are excluded from the model estimation. I then compute predicted values out-of-sample for the second quarter of 2005 through the second quarter of 2009. The start of the banking crisis is dated to when it became systemic after the collapse of Lehman Brothers in the third quarter of 2008 in accordance with Baron & Dieckelmann (2021). Model estimation results are presented in Table 4.

From Table 4 we can confirm that the recursively estimated sentiment proxies behave very similarly to their full-sample counterparts. Significance levels and coefficient signs are comparable to those presented in Table 3. Since the proxies themselves represent forecasts of future equity returns or corporate term spreads, respectively, it is not surprising that their predictive ability for banking crises does not change in an ex ante scenario. A second and very important finding is that, with a pseudo R^2 of 0.001, the credit-to-GDP gap is totally unrelated to banking crises when the Subprime crisis is removed from the sample. This adds to the poor performance previously reported in Table 3: The de-trended credit aggregate alone is a poor predictor of banking crises and, thus, by definition also a poor proxy for financial fragility. When adding the interaction terms in model six, an even more striking finding comes to light: An above-trend value of the credit-to-GDP gap significantly

Table 4: Model estimation for out-of-sample exercise, 1900–2005q1

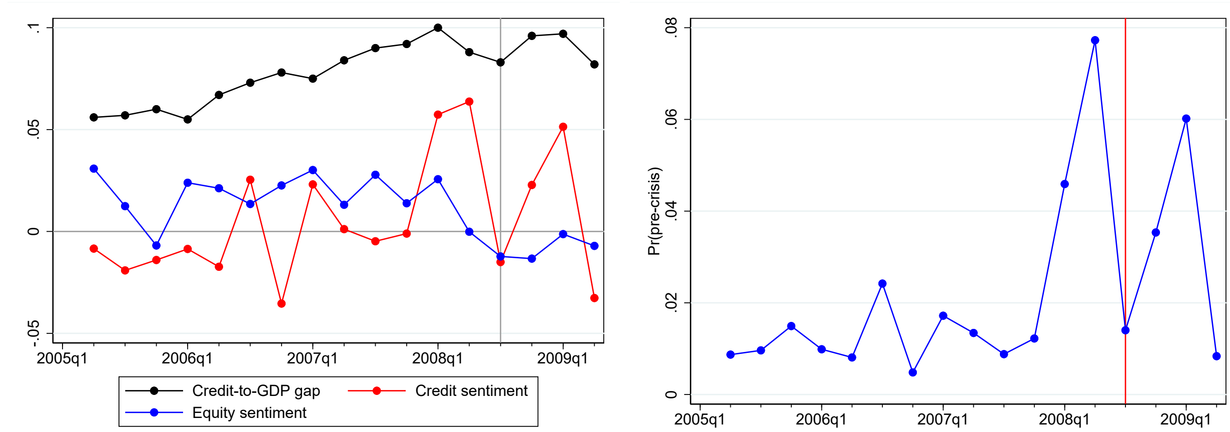
	(1) Pre-crisis	(2) Pre-crisis	(3) Pre-crisis	(4) Pre-crisis	(5) Pre-crisis	(6) Pre-crisis
Recursive equity sentiment s_R^e	-21.32^{***}			-20.48^{***}	-21.21^{***}	-19.90^{***}
	(4.73)			(5.31)	(5.19)	(5.61)
Recursive credit sentiment s_R^c		170.47^{*}		118.49	128.99	138.80
		(97.86)		(97.11)	(87.85)	(94.13)
Credit−to−GDP gap c			1.25		-2.79	-3.72^{*}
			(2.53)		(2.24)	(1.90)
$s_R^e \times c$						29.38
						(37.91)
$s_R^c \times c$						1328.08^{*}
						(815.35)
Constant	-3.73^{***}	-3.57^{***}	-3.55^{***}	-3.71^{***}	-3.72^{***}	-3.78^{***}
	(0.40)	(0.34)	(0.30)	(0.38)	(0.38)	(0.36)
Observations	397	392	421	392	392	392
Pseudo R^2	0.219	0.042	0.001	0.237	0.242	0.257

Notes: *, **, *** indicate significance at the 10%, 5%, and 1% confidence level, respectively. The table shows estimations for logistic regressions of pre-crisis periods, which refer to the four quarters prior to the start of banking crisis events. Positive equity sentiment values represent buoyancy while positive credit sentiment values indicate pessimism.

reduces financial fragility when it is not associated with buoyant sentiment in credit markets. Recalling the insignificance of the standalone credit gap coefficient in model six of the full-sample exercise in Table 3, I conclude that if aggregate leverage is not accompanied by buoyant sentiment it also does not induce financial fragility. This stands in opposition to López-Salido et al.'s (2017) triggers-plus-vulnerabilities interpretation of the credit cycle, as my findings suggest that credit booms themselves are irrelevant for financial fragility if they are not accompanied by buoyant sentiment. It is thus not leverage itself that induces fragility, but it is the deterioration in sentiment from a formerly over-optimistic market environment that induces crises: Again, it is not credit that causes crises, it is when credit stops coming that turmoil breaks loose.

In the following, I use model six from Table 4 to compute fitted values out of sample and derive forward-looking banking crises probabilities. The input variables are plotted in the left plot of Figure 6, and the out-of-sample predictions are displayed on the right-hand side.

Figure 6: Out-of-sample prediction for the 2008 Subprime Crisis



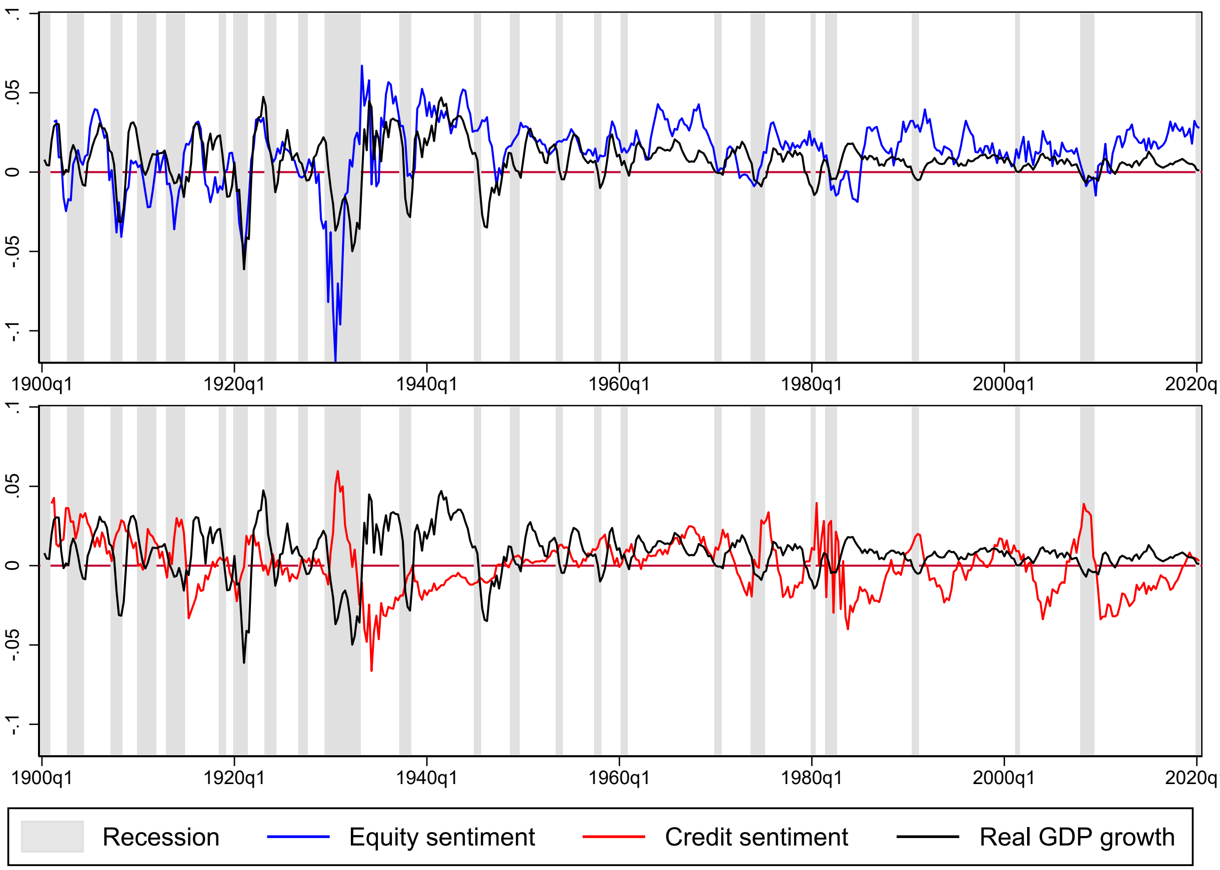
Notes: Recursively predicted and forward-looking probabilties of impending banking crisis from 2005 to the beginning of 2009. The start of the banking crisis is dated to the collapse of Lehman Brothers in the third quarter of 2008, as indicated by the vertical line. Positive equity sentiment values represent buoyancy while positive credit sentiment values indicate pessimism.

The credit-to-GDP gap is at elevated levels during the run-up to the Subprime crisis. The forward-looking proxy for equity sentiment is optimistic up until the beginning of 2008 and then deteriorates into pessimistic territory in the second quarter of 2008. Credit sentiment moves from buoyancy in 2005 and 2006, into a neutral zone in 2007, and ultimately reverses rapidly in the first and second quarter of 2008. The reversal of sentiment is mirrored in the out-of-sample predictions. In the six months before the collapse of Lehman Brothers, the model exhibits a drastic surge in the predicted probability of banking crisis within the next four quarters. In line with results from the events studies in Figure 5, sudden reversals in sentiment contain significant predictive information of impending banking crises, and a respective sentiment-based model trained with 100 years of historical data up until 2005 would have issued a warning signal half a year ahead of time.

IV. Economic activity and recessions

The second major field of analysis of this study is the role of market sentiment proxied by corporate securities issuance in explaining real economic activity. In particular, I test its ability to predict future real GDP growth and recessions. I start out by plotting real GDP growth against my sentiment proxies in Figure 7 to inspect the sentiment dynamics over the business cycle.

Figure 7: Sentiment and the business cycle, 1900–2020



Notes: The sentiment proxies refer to in-sample predictions on the basis of model estimations (1) and (2). Shaded areas in grey represent periods of recessions according to the National Bureau of Economic Research. Positive equity sentiment values represent buoyancy while positive credit sentiment values indicate pessimism.

In a first inspection of Figure 7, we observe that an expected decline in stock prices—as indicated by a negative value of the equity sentiment proxy—is associated with economic slowdowns. Particularly, recessions seem to follow after periods of declining equity sentiment, even though the forecasted return may not be negative. An expected widening of credit spreads—as indicated by a positive value of the credit sentiment proxy—tends to coincide with declining economic activity and recessions. After the end of recessions, credit sentiment takes on rather low values indicating the expectation of a lower term spread in the future. Further, recessions tend to occur after long periods of buoyant credit sentiment which is in line with one of the main findings of López-Salido et al. (2017). From these stylized facts, both equity and credit sentiment seem to exhibit pro-cyclical behavior.

In a simple vector auto-regressive (VAR) model, I analyze this observation in more detail: I regress real GDP growth, nominal total credit growth,[15] equity sentiment, and credit sentiment individually on lags of each of the other variables. Formally,

$$Y_t = c + \sum_{i=1}^{p} \boldsymbol{A}_i Y_{t-i} + e_t \tag{4}$$

where c is a k-dimensional vector of constants and Y_t is a four-dimensional vector of time series—namely real GDP growth, total credit growth, the equity sentiment proxy, and the credit sentiment proxy. $\boldsymbol{A}_i$ are $k \times k$ matrices of coefficients, e_t is the error term vector, and p is called the order of the VAR and corresponds to the number of lags included for each variable and is set according to a majority of standard information criteria to $p = 7$.[16]

The estimation of model (4) is displayed in the appendix in Table A.8. After estimating the VAR model, I use Wald tests to check for Granger causality between economic growth, credit growth, and the respective market sentiment proxies. Specifically, I test for each of the four variables, first, the null hypothesis that the estimated coefficients of the lagged values of *each* explanatory variable are jointly zero and, second, an alternative null hypothesis that estimated coefficients of the lagged values of *all* explanatory variables are jointly zero. If a null hypothesis cannot be rejected at a certain confidence level, this is equivalent to saying that Granger causality cannot be rejected. It is important to highlight that Granger causality of course does not imply actual causation but rather showcases the usefulness of lagged values of a certain variable (or of all variables jointly) for predicting one of the four variables specified in the VAR model. The Wald test results are shown below in Table 5.

[15] The results hold when using real credit growth instead.

[16] The order of the model fits well with the general time horizon of up to two years over which asset prices generally have been found to be predictive of economic activity (Stock & Watson, 2003).

Table 5: Wald tests for Granger causality

	χ^2	df	p
Δ(GDP/CPI)			
Δ(total credit)	13.162	7	0.068
Equity sentiment	27.785	7	0.0002
Credit sentiment	7.210	7	0.407
ALL	52.597	21	0.0002
Δ(total credit)			
Δ(GDP/CPI)	22.003	7	0.003
Equity sentiment	10.441	7	0.165
Credit sentiment	1.088	7	0.993
ALL	33.898	21	0.037
Equity sentiment			
Δ(GDP/CPI)	30.081	7	0.00009
Δ(total credit)	13.581	7	0.0592
Credit sentiment	48.173	7	3.29×10^{-8}
ALL	99.544	21	3.47×10^{-12}
Credit sentiment			
Δ(GDP/CPI)	21.650	7	0.003
Δ(total credit)	11.537	7	0.117
Equity sentiment	41.757	7	5.79×10^{-7}
ALL	101.878	21	1.34×10^{-12}

Notes: χ^2 refers to the test statistic, *df* denotes degrees of freedom, and p is the p-value indicating statistical significance. Δ is the one-quarter growth operator. The respective recipient variables of Granger causality are printed in *italics*. ALL refers to a test of Granger causality originating from the lagged values of all remaining variables jointly.

The results in Table 5 reveal some interesting facts: At 99% confidence, equity sentiment and economic activity exhibit strong bidirectional Granger causality, implying that while equity sentiment contains predictive information for economic growth, the reverse holds true as well. This in line with findings of Stock & Watson (2003). Summing over the estimated coefficients in Table A.8 clearly yields a positive value and, thus, shows that buoyant sentiment in stock markets is predictive of future economic activity and vice versa. Interestingly, this does not hold for credit sentiment. The forecast of future corporate term spreads is not predictive of Real GDP at any reasonable confidence level ($p = 0.407$). The reverse direction, however, is. The immediate conclusion from this finding is that credit sentiment—as proxied by corporate securities issuance—cannot be a driver of economic activity and, thus, cannot lead the business cycle. One potential channel through which credit sentiment could drive the business cycle is the credit cycle (López-Salido et al., 2017). When we examine the Granger causality properties of nominal credit growth, we observe that credit sentiment holds virtually no predictive information for the credit aggregate ($p = 0.993$). While total credit alone Granger-causes real GDP at about 93% confidence, no role for sentiment can be found in this context. While this does not speak directly against a business-cycle interpretation of the credit cycle, as suggested by López-Salido et al. (2017), it rules out, however, the interpretation that the driving force behind a credit-based business cycle is market sentiment. In summary, I find that equity sentiment performs well in forecasting economic activity while this cannot be said for credit sentiment. In the following subsection, I investigate whether sudden changes in either sentiment proxy are helpful in predicting economic decline, i.e. recessions.

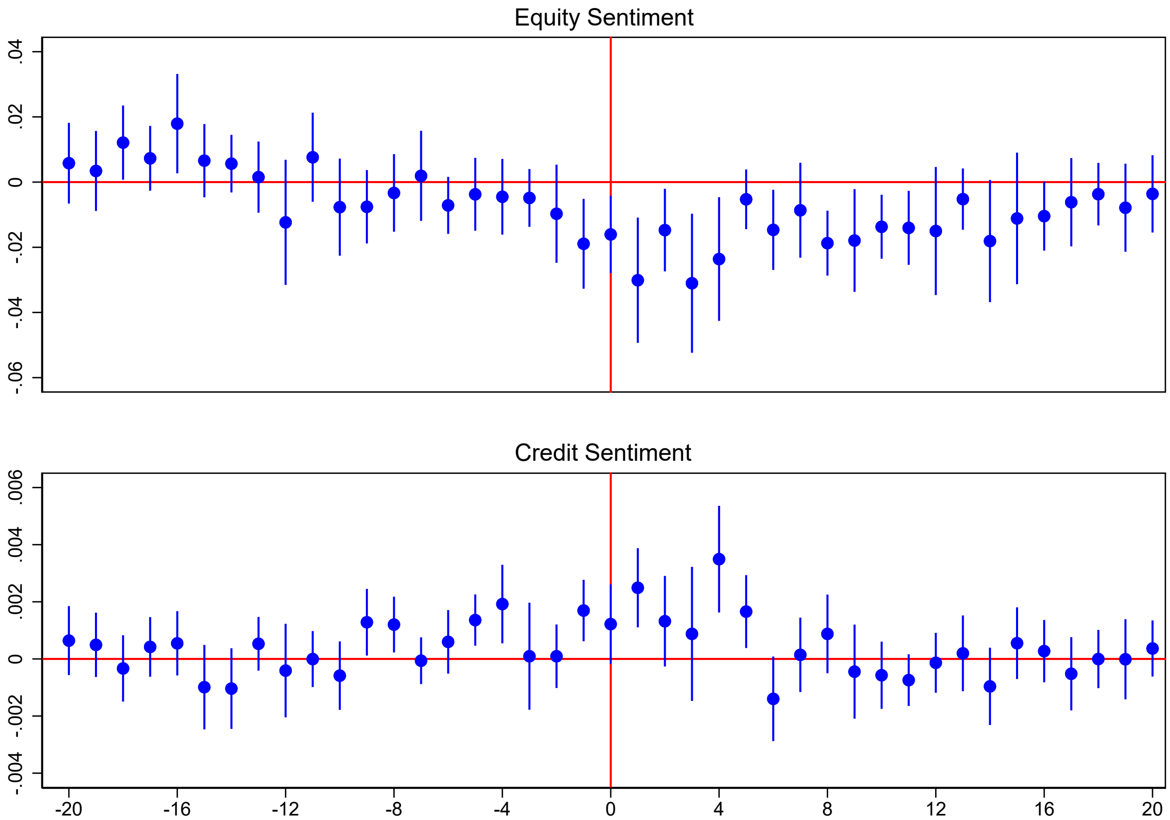
Predicting recessions

To better understand how sentiment dynamics evolve around recessions, I again compute event studies and regress both sentiment proxies on twenty lags, twenty leads, and the contemporaneous value of the recession starting date dummy. Recessions are dated according to the National Bureau of Economic Research.[17] Event studies are depicted in Figure 8.

The main take-away from both plots in Figure 8 is that both sentiment proxies signal future recessions by diverging from zero at 95% confidence ahead of time. Equity sentiment starts deteriorating two to three quarters prior to a crisis, although only the quarter directly prior to the business cycle peak is statistically significant. This explains why López-Salido et al. (2017) do not find that their equity sentiment proxies predict economic downturns: They use annual data and are unable to detect the historically persistent effect at higher

[17] The NBER dates recessions such that they start at the peak of a business cycle and end at the trough. My recession starting dummy thus corresponds to the quarter at which the business cycle is at its peak. See https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions, accessed on November 11, 2020.

Figure 8: Event studies around recessions



Notes: Depicted are coefficient estimates from regressing the variables on 20 leads and lags of the recession start dummy. Vertical bars represent 95% confidence intervals. Recessions are dated according to the National Bureau of Economic Research. Positive equity sentiment values represent buoyancy while positive credit sentiment values indicate pessimism.

frequencies. The picture is different for credit sentiment, however: Here, we observe that a statistically significant deterioration of sentiment occurs up to nine quarters ahead of the beginning of a recession. My credit sentiment proxy seems to be particularly useful in predicting recessions over a horizon of nine to four quarters ahead of business cycle peaks. I can thus confirm López-Salido et al.'s (2017) finding that elevated credit sentiment two years prior is associated with economic decline. It is, however, not buoyant sentiment that predicts the recession but rather the rapid and significant deterioration of sentiment starting up to two years prior that heralds the beginning of the downturn.

Before I go deeper into analyzing how sentiment is connected to recessions and how this relationship can be exploited for their prediction, I can already establish that, while credit sentiment performs poorly in forecasting GDP growth, it excels at predicting recessions. There is preliminary evidence that equity sentiment is useful in predicting both, but on rather short notice. Further, and similar to what I discussed previously with regard to banking crises, it seems that particularly the reversal of sentiment is the defining characteristic that contains the predictive information. Next, I set up a logistic regression model similar to model (3) in the previous section to test the in-sample performance and the forecasting horizon of the two sentiment proxies in predicting recessions. The model takes the form

$$logit(\pi^p) = \ln \frac{\pi^p}{1-\pi^p} = \beta_0 + \sum_{i=0}^{j} \beta_1^j s_{t-i}^e + \sum_{i=0}^{j} \beta_2^j s_{t-i}^c + \epsilon \tag{5}$$

where π^p is interpreted as the probability of recession, and j is the number of included lags, which I set to four and eight, respectively. Estimation results are displayed in Table 6.

The results confirm the key findings of the event studies. Equity sentiment deteriorates with statistical significance one to two quarters before the business cycle peaks, indicating that reversals in equity issuance activity signal recessions two to three quarters ahead of time.[18] Credit sentiment is predictive of downturns, too, but at a longer time horizon: As model specifications three to six show, a sudden deterioration of sentiment—indicated by a relatively large and positive coefficient estimate—four to five quarters before the peak of the business cycle significantly increases the probability of an impending recession. Thus, corporate debt issuance activity contains predictive information of impending downturns up to two years ahead of time, which is in line with what López-Salido et al. (2017) find using their own credit sentiment proxy.

The fact that I use higher frequency data, however, reveals an important distinction from what is already known about sentiment and recessions. The estimation results in Table 6 do not allow for an interpretation where recessions occur after long periods of buoyant equity and credit sentiment. Instead, the only statistically significant feature that produces

[18] Note that at time t, the sentiment proxies contain historical data only, as equations (1) and (2) include one to four lags but no contemporaneous values of the corporate securities issuance measures.

Table 6: Recessions and market sentiment

	(1) RS	(2) RS	(3) RS	(4) RS	(5) RS	(6) RS
Equity sentiment	−7.28	−8.67			−6.36	−8.70
	(5.86)	(6.09)			(6.41)	(6.96)
L.Equity sentiment	−11.55*	−11.55			−13.07**	−15.82**
	(6.82)	(7.67)			(6.48)	(7.25)
L2.Equity sentiment	−5.32	−5.97			−7.46	−17.10*
	(7.11)	(8.69)			(7.98)	(9.37)
L3.Equity sentiment	10.38**	11.54*			13.58**	10.08
	(4.58)	(6.04)			(5.55)	(7.99)
L4.Equity sentiment	8.65	9.98			11.49*	20.90*
	(7.22)	(8.48)			(7.04)	(11.23)
L5.Equity sentiment		3.76				16.82**
		(8.09)				(8.32)
L6.Equity sentiment		−3.48				−3.90
		(7.71)				(9.40)
L7.Equity sentiment		6.99				0.48
		(10.25)				(11.44)
L8.Equity sentiment		−2.52				−3.97
		(8.17)				(8.25)
Credit sentiment			31.08	40.71	0.65	−13.26
			(63.75)	(69.37)	(62.51)	(68.93)
L.Credit sentiment			63.77	18.17	6.72	−64.92
			(55.87)	(54.98)	(63.39)	(64.00)
L2.Credit sentiment			−39.79	−114.95**	−22.12	−108.76*
			(50.30)	(48.60)	(52.98)	(61.97)
L3.Credit sentiment			−47.68	−103.91	5.99	30.30
			(79.29)	(92.52)	(77.44)	(110.09)
L4.Credit sentiment			106.30*	121.88*	165.34**	294.96***
			(64.92)	(67.33)	(68.69)	(81.05)
L5.Credit sentiment				89.26		192.56**
				(63.49)		(89.94)
L6.Credit sentiment				54.16		33.22
				(68.91)		(78.61)
L7.Credit sentiment				−31.95		−147.57*
				(48.89)		(78.49)
L8.Credit sentiment				15.82		−81.42
				(68.37)		(91.85)
Constant	−3.00***	−3.14***	−3.05***	−3.13***	−3.12***	−3.30***
	(0.24)	(0.31)	(0.23)	(0.24)	(0.28)	(0.34)
Observations	473	469	465	457	464	456
Pseudo R^2	0.026	0.035	0.025	0.043	0.054	0.098

Notes: *, **, *** indicate significance at the 10%, 5%, and 1% confidence level, respectively. The table shows estimations for logistic regressions of quarters that mark the beginning of a recession RS, according to the NBER's methodology. Positive equity sentiment values represent buoyancy while positive credit sentiment values indicate pessimism.

the proxies' predictive power are the sudden reversals of sentiment that play out over a time horizon of a few quarters. It is thus—similar to what I find with regard to financial fragility—not periods of overly optimistic market sentiment that drive the business cycle but it is its sudden reversal that induces the end of the boom. In line with Bordalo et al. (2018) it is when "good news stop coming" that economies slow down. This proposition further lends itself very well to the commonly accepted observation that there is little regularity to the business cycle (which is why business *cycle* is such a notorious misnomer). Notwithstanding the well-established role of rational expectations and exogenous shocks for the business cycle, my results show that shifts in market participants' irrationally formed expectations—that is, investors decisions disconnected from fundamentals—also play a significant role in perturbing economic activity and in inducing downturns.

My analysis shows that equity market sentiment has predictive power for both economic activity and economic downturns. I, thus, suggest that investors sentiment in equity markets is indeed a potential driver of the business cycle. This, however, does not hold for credit sentiment. Credit sentiment is only predictive of recessions but not of economic growth, and I thus rule out the hypothesis that a *sentiment-driven* credit cycle is a major driver of the business cycle. Not the quantity of credit determines economic activity, but the sudden absence of credit will send the economy down the drain. Policy makers would do well in looking at issuance activity in corporate securities markets to complement their tools for growth and recession forecasts.

V. Conclusion

This study investigates the role of corporate securities issuance in approximating investor sentiment in credit and equity markets and the role of sentiment in explaining economic activity and financial fragility. In particular, I contribute to the existing literature in four distinct ways.

First, I present new historical U.S. data at quarterly frequency from 1900–2020 on the gross issuance of equities and corporate debt securities, and a historically consistent estimate of total private credit mainly based on quarterly data of outstanding corporate debt and total bank loans. Second, I use several measures of corporate securities issuance to forecast future equity returns and corporate term spreads, respectively. Following López-Salido et al. (2017), I interpret these forecasts as sentiment proxies and investigate their role in explaining and predicting financial fragility, banking crises, economic activity, and recessions at quarterly frequency. Third, I provide a historical assessment of credit aggregates—and particularly of the one-sided credit-to-GDP gap—and their role in proxying financial fragility as well as their ability to predict banking crises in real time. Fourth, I present policy makers with a complement to their tool box for predicting recessions and banking crises by proposing to harness the informational content in higher-frequency data on corporate securities issuance whereby sudden reversals of issuance activity signal a sudden drop in investors sentiment that is highly predictive of impending recessions and banking crises several quarters ahead of time.

The main finding of this paper is that in the United States from 1900–2020 sudden reversals in equity and credit market sentiment proxied by corporate securities issuance are highly predictive of impending banking crises over an average time horizon of six months and of future recessions up to two years ahead of time. Issuance activity outperforms the private credit-to-GDP gap in its capacity to predict banking fragility in and out of sample. Deviations in equity issuance from historical averages also help to explain economic activity over the business cycle. Crises and recessions often occur independently of domestic leverage, making the credit-to-GDP gap a deficient early-warning indicator in historical application. I do not find convincing evidence that credit market sentiment is a driver of the business cycle or that it induces the built-up of financial fragility in the form of above-trend private credit levels. The fact that equity issuance reversals predict banking crises without elevated private credit levels, suggests that changes in investor sentiment can trigger financial crises even in the absence of underlying banking fragility. A recently proposed triggers-plus-vulnerabilities interpretation of the credit cycle by López-Salido et al. (2017) seems less likely to hold in light of my findings, as financial fragility measures based on credit aggregates perform poorly in predicting the economy's susceptibility to shocks, putting a much stronger focus on the strength of triggers than on the vulnerabilities induced by private sector leverage. In my sample, periods of sustained buoyant sentiment only rarely precede crises and recessions. The evidence rather points towards short moments of drastic reversal in issuance activity—and thus, in sentiment—that serve as triggers. Novel quarterly data on bank lending further supports the interpretation that not the built-up of private credit is responsible for financial fragility and bank distress, but its sudden retraction. In line with Bordalo et al. (2018), I conclude that it is "when good news stop coming" that the economy falters.

My findings are highly relevant for policy makers concerned with the prediction of recessions and banking crises. First, my results should be seen as a reason for caution in the application of the credit-to-GDP gap when determining the counter-cyclical capital buffers under the Basel accords. Its prominence rests mainly on its strong predictive performance prior to the Global Financial Crisis, but my historical assessments casts doubt on its general applicability and usefulness. Second, policy makers should add the surveillance of gross issuance activity in corporate securities markets at high frequencies to their macro-prudential tool set. The informational content in sudden reversals of issuance activity is predictive of crises and recessions several quarters ahead of time.

As an avenue for further research, the predictive ability of corporate securities issuance should further be investigated by expanding this analysis to more countries at similar time spans and frequencies. Finding the necessary data for this undertaking is certainly no easy endeavor but will shed light on the important question whether this study's findings hold in less market-centered and more bank-focused financial systems, as well.

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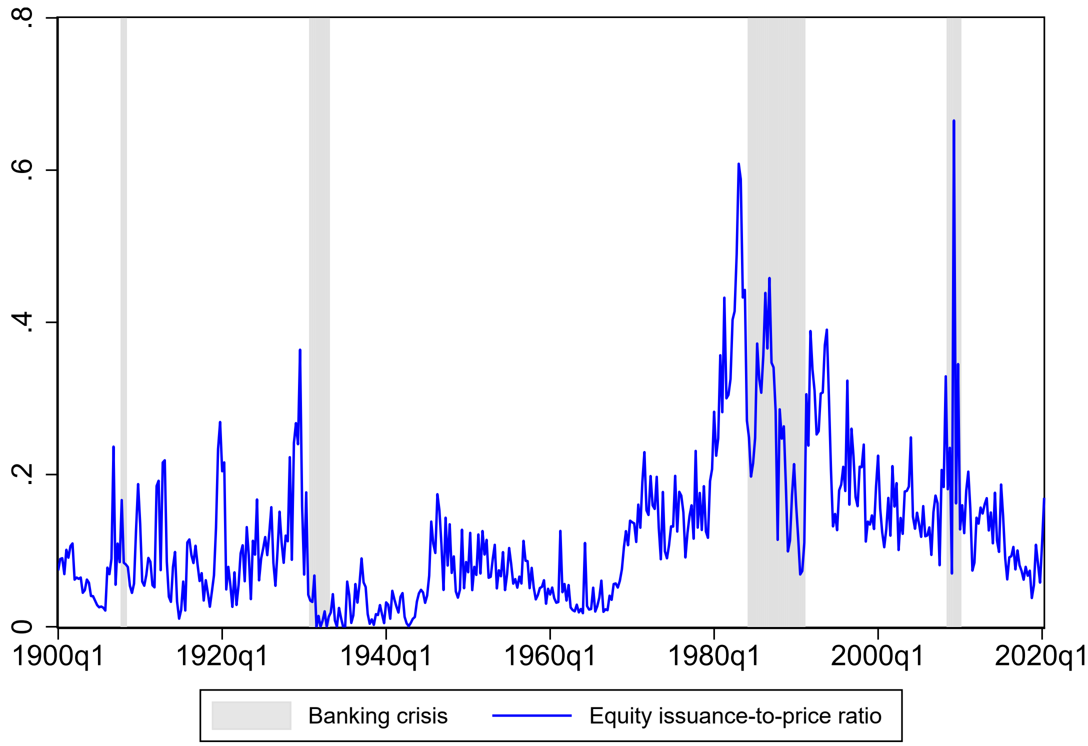
Appendix

Figure A.9: Additional measure: equity-issuance-to-price ratio, 1900–2020

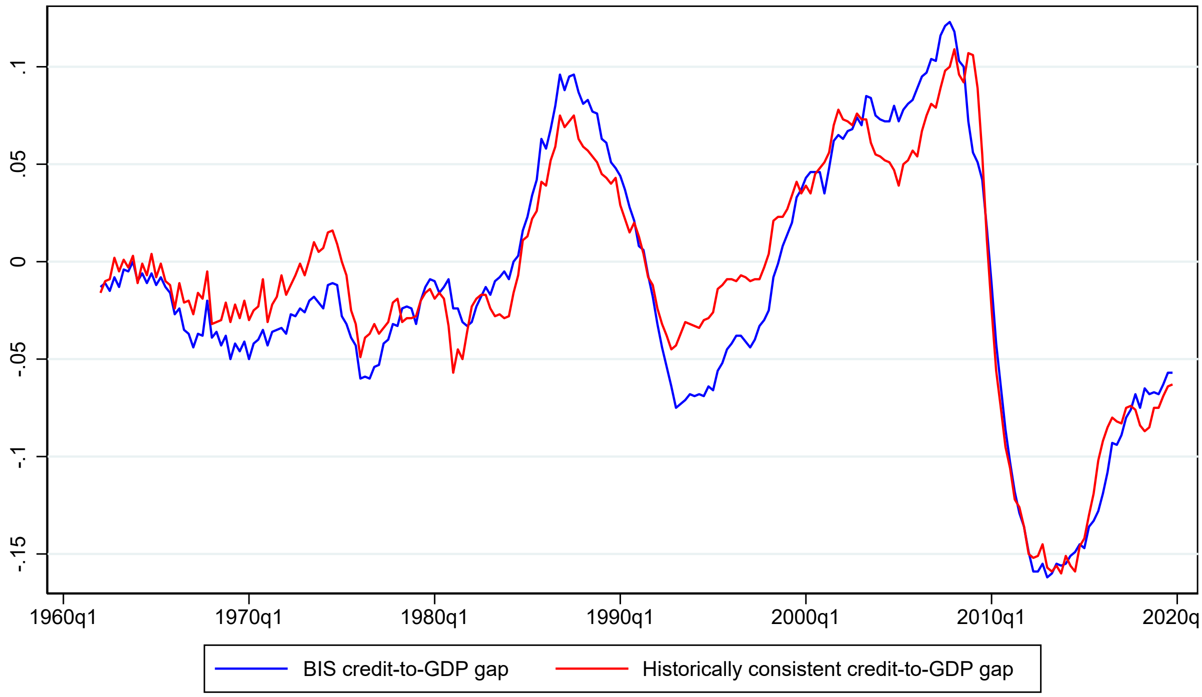


Notes: This measure is defined as $\frac{\text{equity issuance}}{\text{equity index level}}$, the division of gross equity issuance per quarter by the accumulated quarterly returns of the Dow Jones Industrial Average since the first quarter of 1900 at the end of the same quarter. Due to the unit mismatch between nominator (millions of U.S. dollars) and denominator (index points), the resulting ratio is not interpretable in levels but only in growth rates. Shaded areas in grey represent periods of banking crises according to Baron & Dieckelmann (2021).

The equity issuance-to-price ratio can be interpreted as managers' anticipation of future capital needs. I interpret sudden increases in gross equity issuance in comparison to the equity price level as managers making use of a buoyant investment environment to raise new capital expectation of impending commercial hardship. Managers exploit informational asymmetries in the equity market to raise capital while investors are not aware of the expected decline in profits to which they would of course react by selling stocks, resulting in falling prices. From the graph, it is visible that the ratio tends to shoot up shortly before periods of bank distress—like in 1907, in the 1930s, or in the 1980s—or of general financial instability—like at the outbreak of World War I in 1914 or in the early 1920s. To the most recent banking crisis, however, managers reacted too late, indicating that the downturn was unexpected by managers and investors alike.

For the purpose of estimating the sentiment proxies, I exclude the equity-issuance-to-price ratio as it adds virtually no new informational content to the regression: variation from equity issuance and lagged stock returns is already captured by other variables. The ratio is depicted here to underline the usefulness of issuance data for crisis prediction.

Figure A.10: Credit-to-GDP gap comparison, 1952–2019



Notes: The red line represents the forward-looking gap estimate with my historically consistent total credit series. The blue line is the official credit-to-GDP gap estimate based on more complete data as published by the BIS.

The BIS' private credit data for the United States starts in the first quarter of 1952 and the trend is estimated for the first time after 10 years of continuous data coverage such that the first estimation is for the first quarter of 1962. The HP filter is applied one-sidedly which means that it is re-estimated recursively with every successive quarter to include only data which are available up to the point in time of the estimation and to prevent a look-ahead bias.

Table A.7: Data construction and sources

Variable	Construction and Sources
Total credit	Sum of total bank loans, non-financial corporate bonds outstanding, non-financial commercial paper outstanding, and municipal bonds backed by corporations outstanding.
Bank loans	From 1945q4: Until 1951q4 interpolated from annual data on the basis of quarterly growth rates from "all bank data" and if not available from national bank data. Afterwards quarterly data directly from source. Source: Loans, all private depository institutions, from Z.1 financial accounts from the Federal Reserve available at https://fred.stlouisfed.org/series/BOGZ1FL704023005Q. Historical all bank data and national bank data from various Annual Reports of the Comptroller of the Currency, available at https://fraser.stlouisfed.org/title/annual-report-comptroller-currency-56, and various Fed Bulletins available at https://fraser.stlouisfed.org/title/federal-reserve-bulletin-62. From 1900q1 to 1945q3: Backward extended on the basis of total loans from all bank data (source see above). When all bank data was not available, resorting to Fed member bank data, and when that was not available, resorting to national bank data. Source for Fed member bank data: Board of Governors (1943, pp. 72–75, Table No. 18).
Corporate bonds	1900q1 to 1943q4: Hickman (1953, pp. 308–309, appendix A, Table A-13) available at https://fred.stlouisfed.org/series/M10083USM311NNBR. From 1944q1: Until 1951q4 interpolated from annual data, afterwards quarterly data. From Z.1 Financial accounts from the Federal Reserve available at https://fred.stlouisfed.org/series/CBLBSNNCB.
Commercial paper	From 1945q4: Until 1951q4 interpolated from annual data, afterwards quarterly data. From Z.1 Financial accounts from the Federal Reserve available at https://fred.stlouisfed.org/series/CPLBSNNCB. In 1945, commercial paper outstanding was less than 0.25% of total credit, it thus excluded for prior dates due to little importance and lack of reliable data.
Municipal bonds	Municipal bonds backed by corporations. From 1952q1: Quarterly data from Z.1 Financial accounts from the Federal Reserve. Available at https://fred.stlouisfed.org/series/MSLBSNNCB. Zero prior to 1971.
Gross domestic product	From 1947q1: Quarterly data from the U.S. Bureau of Economic Analysis available at https://fred.stlouisfed.org/series/GDP. Before: Backward extended on the basis of quarterly growth rates of gross national product data by Gordon (1986, appendix B) until 1890q1. Available at https://www.nber.org/research/data/tables-american-business-cycle.
Consumer price index	From 1913q1: Consumer Price Index for All Urban Consumers: All Items in U.S. City Average as reported by the U.S. Bureau of Labor Statistics. Available at https://fred.stlouisfed.org/series/CPIAUCNS. Before: Backward extension on the basis of quarterly growth rates of GNP deflator data by Gordon (1986, appendix B) until 1900q1.
Credit-to-GDP gap	One-sided HP-filter applied to total credit series divided by GDP series with smoothing parameter $\lambda = 400,000$ and first data point in 1900q1 based on further backward extended data from 1890q1. Backward extension on the basis of quarterly growth rates of interpolated annual data on railroad bonds outstanding from Hickman (1953, p. 252) and quarterly national bank loans from various annual reports of the Comptroller of the Currency available at https://fraser.stlouisfed.org/title/annual-report-comptroller-currency-56.

Table A.7: Data construction and sources *(continued)*

Variable	Construction and Sources
Corporate term spread	From 1984q1: BAA corporate bond yield as reported by Moody's and made available at https://fred.stlouisfed.org/series/BAA minus 3 month-commercial paper rate as reported by the Board of Governors of the Federal Reserve System before August 1997 under https://fred.stlouisfed.org/series/CP3M and afterwards the non-financial 3-month AA commercial paper rate available at https://fred.stlouisfed.org/series/CPN3M. From 1900q1 to 1983q4: corporate bond yield minus commercial paper rate as reported by Gordon (1986, appendix B).
Stock prices	From 1900q1: From daily closing price data of the Dow Jones Industrial Average by Samuel H. Williamson, available at https://www.measuringworth.com/datasets/DJA/.
Total issuance	Sum of equity and debt issuance.
Equity issuance	From 1900q1 to 1905q4: Interpolated from annual data on new listings of equity at NYSE from Warshow (1924, p. 27), thus an underestimation of total equity issuance. From 1906q1 to 1918q4: Corporate Issues, Stocks, Including Refunds, U.S., Canadian, and Foreign from the NBER Macrohistory database, available at https://fred.stlouisfed.org/series/M10029M144NNBR. The data description leads one to believe this must be an overestimate of the actual equity issuance activity. The data is however consistent with the annual series reported from 1910 in Carter et al. (2006, series Cj837) which is why I assume its accuracy. From 1919q1 to 1926q3: New securities issues, for new capital, domestic, preferred and common reported by Board of Governors (1943, p. 487). From 1926q4 to 2008q1: Baker & Wurgler (2000), updated in September 2008. From 2008q2: Financial and non-financial stock issues, U.S. corporations reported by the Federal Reserve in Table 1.46, available at https://www.federalreserve.gov/data/corpsecure/current.htm.
Debt Issuance	From 1900q1 to 1926q3: U.S. bond offerings, par value, all industries reported by Hickman (1953, pp. 324–325, appendix A, table A-15). Available under code m10071 at https://www.nber.org/research/data/nber-macrohistory-x-savings-and-investment. From 1926q4 to 2008q1: Baker & Wurgler (2000), updated in September 2008. From 2008q2: bonds, sold in the United States, U.S. corporations reported by the Federal Reserve in Table 1.46, available at https://www.federalreserve.gov/data/corpsecure/current.htm.
High yield share	From 1908q1 to 1943q4: Annual averages computed from Hickman (1958, p. 179, Table 34, classes X and above) used as quarterly averages and then four-quarter moving average applied for smoothing. From 1944q1 to 1982q4: Annual averages from Greenwood & Hanson (2013), method as before. From 1983q1 to 2015q4: Quarterly averages from Greenwood & Hanson (2013), smoothing as before. From 2016q1 to 2018q2: Quarterly averages from https://www.hbs.edu/behavioral-finance-and-financial-stability/data/Pages/sentiment.aspx, smoothing as before.
Recession	Quarter of business cycle peak based on NBER dating methodology. Source: https://fred.stlouisfed.org/series/USREC.
Banking crisis	First quarter of a banking crisis according to Baron & Dieckelmann (2021).

Table A.8: VAR model estimation: Market sentiment, credit, and economic activity

	Δ(GDP/CPI)		Δ(total credit)		Equity sentiment		Credit sentiment	
L.Δ(GDP/CPI)	0.275***	(0.048)	0.196***	(0.055)	−0.036	(0.057)	−0.019***	(0.005)
L2.Δ(GDP/CPI)	−0.082*	(0.049)	−0.090	(0.057)	0.201***	(0.059)	−0.004	(0.006)
L3.Δ(GDP/CPI)	0.130***	(0.050)	−0.063	(0.057)	−0.120**	(0.059)	0.001	(0.006)
L4.Δ(GDP/CPI)	0.085*	(0.050)	−0.130**	(0.057)	−0.164***	(0.059)	0.002	(0.006)
L5.Δ(GDP/CPI)	−0.136***	(0.050)	−0.044	(0.057)	−0.093	(0.060)	0.011**	(0.006)
L6.Δ(GDP/CPI)	0.018	(0.050)	0.019	(0.058)	−0.042	(0.060)	0.003	(0.006)
L7.Δ(GDP/CPI)	−0.047	(0.048)	0.059	(0.056)	0.106*	(0.058)	0.008	(0.005)
L.Δ(total credit)	−0.001	(0.041)	0.150***	(0.047)	−0.078	(0.049)	−0.001	(0.005)
L2.Δ(total credit)	−0.030	(0.041)	0.057	(0.048)	−0.111**	(0.050)	0.007	(0.005)
L3.Δ(total credit)	−0.034	(0.041)	0.150***	(0.048)	0.061	(0.049)	0.004	(0.005)
L4.Δ(total credit)	−0.044	(0.042)	0.040	(0.048)	−0.060	(0.050)	0.007	(0.005)
L5.Δ(total credit)	0.052	(0.041)	0.128***	(0.047)	0.061	(0.049)	0.003	(0.005)
L6.Δ(total credit)	−0.103**	(0.042)	0.008	(0.048)	−0.007	(0.050)	0.001	(0.005)
L7.Δ(total credit)	0.088**	(0.041)	0.064	(0.047)	−0.024	(0.049)	0.003	(0.005)
L.Equity sentiment	0.117***	(0.040)	0.008	(0.046)	−0.053	(0.047)	−0.026***	(0.004)
L2.Equity sentiment	0.044	(0.041)	−0.018	(0.047)	0.376***	(0.049)	−0.002	(0.005)
L3.Equity sentiment	0.073*	(0.043)	0.091*	(0.049)	0.501***	(0.051)	0.016***	(0.005)
L4.Equity sentiment	−0.013	(0.046)	0.047	(0.053)	−0.024	(0.055)	0.006	(0.005)
L5.Equity sentiment	−0.042	(0.042)	0.034	(0.049)	−0.030	(0.050)	−0.004	(0.005)
L6.Equity sentiment	0.028	(0.039)	−0.005	(0.045)	−0.089*	(0.047)	−0.008*	(0.004)
L7.Equity sentiment	0.048	(0.038)	0.035	(0.043)	0.044	(0.045)	0.005	(0.004)
L.Credit sentiment	0.061	(0.395)	−0.064	(0.456)	−0.573	(0.474)	−0.259***	(0.045)
L2.Credit sentiment	0.106	(0.404)	−0.296	(0.466)	2.591***	(0.484)	−0.007	(0.046)
L3.Credit sentiment	0.968**	(0.410)	−0.369	(0.472)	1.853***	(0.490)	0.532***	(0.046)
L4.Credit sentiment	0.105	(0.437)	−0.066	(0.504)	1.012*	(0.523)	0.444***	(0.050)
L5.Credit sentiment	−0.484	(0.402)	0.246	(0.463)	−1.667***	(0.481)	0.127***	(0.046)
L6.Credit sentiment	−0.540	(0.405)	0.392	(0.467)	−1.668***	(0.485)	−0.107**	(0.046)
L7.Credit sentiment	−0.373	(0.397)	0.115	(0.457)	−1.513***	(0.475)	−0.274***	(0.045)
Constant	0.003*	(0.002)	0.004**	(0.002)	0.007***	(0.002)	−0.000	(0.000)
Observations	457		457		457		457	

Notes: *, **, *** indicate significance at the 10%, 5%, and 1% confidence level, respectively. Standard errors are printed to the right of the coefficient estimates in parentheses.

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