Corporate Loan Spreads and Economic Activity*

Anthony Saunders
Stern School of Business, New York University

Alessandro Spina
Copenhagen Business School

Sascha Steffen
Frankfurt School of Finance & Management

Daniel Streitz
Copenhagen Business School
Danish Finance Institute

October 16, 2020

Abstract

We study the predictive power of loan versus bond spreads for business cycle fluctuations. Using a novel credit spread measure derived from the secondary loan market, we show that loan market-based credit spreads have additional predictive power for macroeconomic outcomes (such as employment and industrial production) compared to bond spreads as well as other credit spreads and equity returns, both in the U.S. and Europe. Differences in the composition of firms borrowing in loan or bond markets are important in understanding the differential predictive power of both credit spreads. Industry specific loan spreads predict different industry cycles and can be used to construct alternative weighting schemes which further improve the predictive power of loan spreads.

JEL classification: E23, E44, G20

Keywords: Secondary loan market, Bonds, Credit supply, Real economic activity

*Corresponding author: Sascha Steffen, Frankfurt School of Finance & Management, Adickesallee 32-34. 60322 Frankfurt, Germany. E-mail: s.steffen@fs.de. We thank Ed Altman, Yakov Amihud, Giovanni Dell'Ariccia, Tobias Berg, Nina Boyarchenko, Jennifer Carpenter, Itay Goldstein, Arpit Guptda, Kose John, Toomas Laaritz, Yuearan Ma, Emanuel Moench, Holger Mueller, Cecilia Palatore, Carolin Pflueger, Martin Oehmke, Moritz Schularick, Marti Subrahmanyam, Olivier Wang and seminar participants at Bundesbank, Cass Business School, Frankfurt School, IMF, NYU, Science Po, WU Vienna and participants at the Bonn Macro Workshop, the Danish Finance Institute Annual Conference, the Mannheim Banking Workshop, the 2019 Santiago Finance Workshop, the Villanova Webinar in Financial Intermediation, and the Regulating Financial Markets conference for many helpful suggestions. Spina and Streitz gratefully acknowledge support from the Center for Financial Frictions (FRIC), grant no. DNRF102. Streitz gratefully acknowledges support from the Danish Finance Institute (DFI).

1 Introduction

Credit spreads are widely used to forecast the business cycle (see, among others, Bernanke, 1990; Friedman and Kuttner, 1992, 1993a; Gertler and Lown, 1999; Gilchrist and Zakrajšek, 2012; López-Salido *et al.*, 2017). This is typically motivated by theories that focus on the role of financial market frictions in propagating and amplifying shocks to the economy (e.g. Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997). For example, a weakening of financial intermediaries' balance sheets can lead to a credit supply contraction, reflected in credit spreads, followed by a reduction in economic activity. Hence, credit spreads can act as signals that may lead real economic activity.

While theory focuses on the central role of intermediaries, specifically banks, the empirical literature generally relies on credit spread information from the corporate bond market likely because corporate loan prices have, until recently, not been available. Hence, an implicit assumption in most studies is that frictions are reflected across corporate debt markets. For example, López-Salido *et al.* (2017) argue that "*we have in mind that the pricing of credit risk in the bond market is [...] linked to the pricing of credit risk in the banking system. Although the former is easier for us to measure empirically, we suspect that the latter may be as or more important in terms of economic impact*" (p. 1398).

We introduce a novel *loan* market-based credit spread to predict economic outcomes. Over the last 30 years, a liquid secondary market for syndicated corporate loans has developed (the annual trading volume reached $742 billion in 2019), enabling us to construct a novel bottom-up credit spread measure based on granular data from secondary market pricing information for about 9,100 individual loans to U.S. non-financial firms over the December 1999 to March 2020 period. Importantly, this market mainly comprises of firms that do not have access to public debt or equity markets and for which financial frictions are an important driver of the cost of external finance (Bernanke and Gertler, 1989; Holmström and Tirole, 1997).

Our main finding is that loan spreads contain information about the future business cycle above and beyond other credit spread indicators. To motivate this result, Figure 1 Panel A, shows the development of our loan market credit spread measure as well as a corporate bond market credit spread measure over the 2018 to 2019 period. The figure highlights that during the 2019 "late-cycle phase", the loan spread was gradually increasing at the same time as growth in industrial production had begun to cool off. The bond spread, in contrast, was not yet signalling any deteriotation in the health of the macroeconomy.

We rigorously scrutinize this effect by means of predictive regressions over the entire 20-year sample period. Figure 1 Panel B summarizes our main results. The details, data description, and formal statistical analysis are all left to the main text. The figure documents the predictive power of our monthly loan spread measure for three-month ahead industrial production in the U.S., benchmarked against a bond credit spread measure. In Panel B1, the standardized coeffecient implies that a one standard deviation (SD) increase in the loan spread is associated with a 0.410 SD decrease in industrial production over the subsquent three months, whereas the economic magnitude of the bond spread coefficient is half of this effect. This result prevails if loan and bond spreads are jointly included in the model. Panel B2 highlights that the loan spread measure yields a sizable improvement in the in-sample fit, with an R^2 increase of about +15 percentage points (p.p.) relative to a baseline prediction model (with no credit spreads). Later sections give the same results using different economic aggregates and time horizons.

We provide a series of robustness tests. First, we compare our loan market measure to a large range of alternative credit spread measures that have been used in the literature, such as commercial paper – bill spreads, Baa-Aaa credit spreads, or high-yield corporate bond spreads. Benchmarking our loan spread measure against high-yield bond spreads suggests that the superior predictive power of the loan market cannot solely be attributed to the fact that loans traded in the secondary market are of higher credit risk than bonds (the majority of loan market borrowers who are rated have a BB or B rating). Second, we control for supply-demand conditions in secondary markets using measures of loan market liquidity. Third, we run a horse race against predictors from the equity market, which are potentially

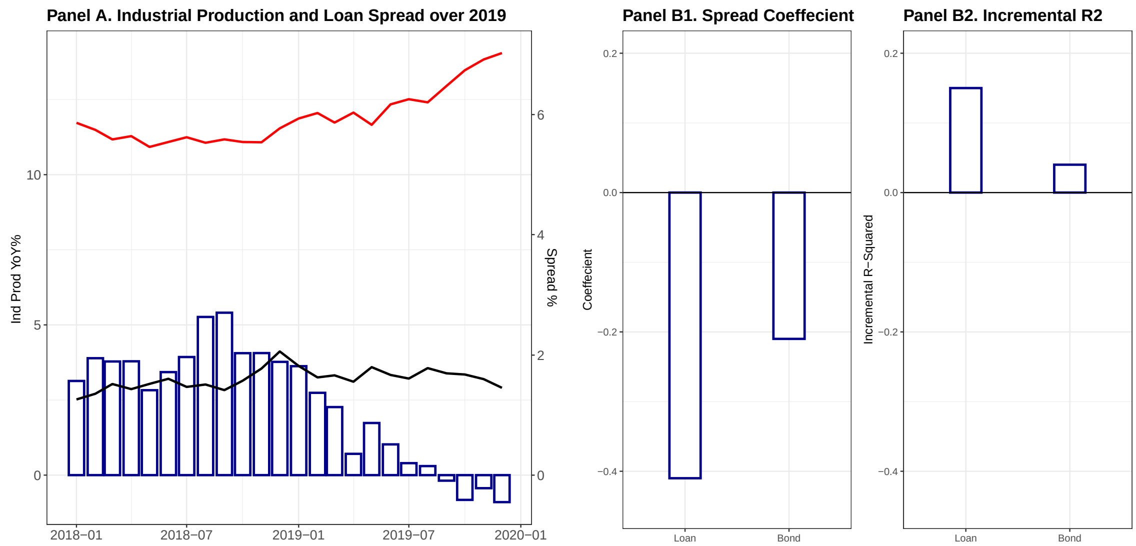

Figure 1: **Motivating evidence and main results**
Panel A plots the loan spread (red), bond spread (black) and YoY% in U.S. industrial production from January 2019 to December 2019 (blue bars). See Section 2 for details on the construction of the credit spread measures and underlying data sources. Panel B compares the coeffecients and incremental R^2 of using loan spreads versus bond spreads to forecast three-month ahead changes in industrial production over the December 1999 to March 2020 period. Incremental R^2 is the change in adjusted R^2 that results from adding the respective credit spread measure to a baseline prediction model that includes the term spread, the federal funds rate, and lagged industrial production. See Table 1 for underlying regressions, and Section 3 for a full discussion of the model.

more informationally sensitive instruments. Fourth, we take into account that loan and bond contracts are structured differently. That is, differences in non-price loan terms (maturity, collateral or covenants) and callability of loans vis-a-vis bonds could affect our results. We regress loans spreads on a set of loan level characteristics to extract a loan spread orthogonal to these characteristics. Fifth, when we drop the financial crisis period (2007:Q4 – 2009:Q2), the predictive effect of the loan spread drops by approximately half, but remains significant. The bond market credit spread, in contrast, becomes economically small and insignificant. This is consistent with the interpretation that credit spreads in particular are good predictors of "tail events" (Adrian *et al.*, 2019). In all tests our main result remains unchanged.

A further potential objection to our result is that the sample period covers the 1999 to 2020 period and is thus relatively short to be making strong claims regarding the predictive power of loan spreads for the business cycle. We collect loan and bond spreads as well as economic outcome data for Germany, France, and Spain (some of Europe's largest economies for which we have sufficient secondary loan market data coverage) and run the same set of tests as we did for the U.S. We again find that loan spreads provide additional information to forecast manufacturing and consumption good production as well as the unemployment rate compared to other credit spread measures. Overall, outside the U.S. and in arguably more bank-dependent countries (which exhibit differential cycles over the last 20 years), we document the same patterns.

After having documented that loan market credit spreads appear to have predictive power above and beyond other credit spread measures, we next examine potential channels for why this might be the case. One important feature of the loan market is that they are populated with firms that may have limited access to alternative funding sources and exhibit a higher sensitivity to bank loan supply frictions. For example, more than 80% of borrowers in the bond market have a credit rating of BBB or higher, while the majority of loan market borrowers who are rated have a BB or B rating, while others are private firms with no public rating. Of our entire sample, only 57% are loans to publicly traded firms. Thus, there is a limited overlap between bond and loan borrowers. Consequently, a repricing of risks by banks in the loan market might have implications for the overall economy that are not perfectly reflected by investors in bonds.

Several pieces of evidence support the conjecture that the more robust predictive power of loan over other credit spreads reflects the differential type of firms in the loan vis-a-vis bond and equity markets. First, we show that within the loan market, it is the spread of smaller, younger, and private firms which drives a substantial portion of the loan spread's predictive power. Small, young, and private firms are more likely to be financially constraint (Hadlock and Pierce, 2010), face more severe informational frictions that may add to the costs of external finance (Gertler and Gilchrist, 1994), and are more likely to borrow using collateral (Lian and Ma, 2020), i.e., are more dependent on bank financing. That is, these borrowers are presumably most affected when credit market conditions tighten because of a lack of alternative funding sources, which eventually feeds into the real economy.[1] In particular among the group of small, young, and private firms the overlap between the loan and bond market is limited. For instance, in our loan sample only 16% of smaller and younger borrowers also have a bond outstanding, compared to 39% for larger and older borrowers.

Second, we provide evidence consistent with the conjecture that loan market spreads better reflect credit supply conditions in the primary market than bond market spreads. To that end, we use information from the Federal Reserve's quarterly Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS) on changes in credit conditions for commercial and industrial (C&I) loans at U.S. banks and alternatively a measure of bank undrawn commitments. We use equivalent information from the European Central Bank's (ECB) Bank lending survey (BLS) for Germany, France, and Spain (i.e., the European countries for which we are able to construct our loan market credit spread). Our evidence suggests that loan spreads are more strongly correlated with changes in credit standards compared to bond spreads, both for the U.S. as well as for European countries. This supports the view that loan spreads better reflect credit supply conditions in the primary loan market compared to other credit spread measures.

Third, we construct loan and bond spreads on an industry rather than an economy-wide level classifying U.S. firms into industries using the Bureau of Economic Analaysis (BEA) sector definition. We show that industry-specific loan spreads have significant forecasting power for industry-level production and employment, controlling for any economy-wide factors through time fixed effects. More importantly, we look at the predictive power of loan spreads across industries and find a large degree of hetrogeneity in the ability of industry level spreads to predict industry-level macro variables. Consistent with our finding at the economy-wide level that smaller, younger, and private firms account for most of the predictive power of the loan market credit spread, we also find at the sectorial level that loan

[1] Cloyne *et al.* (2020), for instance, provide evidence that younger firms' investment behavior responds more strongly to changes in market interest rates compared to older firms. Begenau and Salomao (2019) also explore the financing patterns of small and large firms over the business cycle and find smaller firms financing policy is procyclical due to financial constraints. Pflueger *et al.* (2020) show that a measure for the price of volatile firms, which exhibit a behavior similar to private firms, is related to future macroeconomic activity.

spreads have greater predictive power in industries with firms that are more dependent on external finance (Rajan and Zingales, 1998). Overall, compositional differences between firms who borrow in the loan versus bond market are important to understand the differential predictive power of loan and bond spreads.

In a final set of tests,we investigate whether we can further improve the predictive power of loan spreads by alterting the way how we aggregate individual loan spreads. Until now, the literature (including our paper) has used a simple average to construct aggregate spreads. We show that an aggregate loan spread that puts more weight on industries in which the loan spread has a higher predictive power increases the in-sample fit by an additional +3 p.p. relative to the baseline (i.e., unweighted) loan spread measure. That is, industries in which loan spreads have a higher predictive power also contribute more to the aggregate forecasting power of loan spreads. A similar improvement can be obtained by assigning more weight to industries that comprise of firms that are more sensitive to external financing frictions.

Related Literature: There exists a long history of studies that examine the power of financial market prices to predict macroeconomic outcomes and financial crises. Previous research has focused on stock and bond markets (Harvey, 1989), commercial paper spreads (Bernanke, 1990; Friedman and Kuttner, 1993b), the slope of the yield curve (Estrella and Hardouvelis, 1991), high yield bonds (Gertler and Lown, 1999), corporate bond credit spreads (Gilchrist and Zakrajšek, 2012; Krishnamurthy and Muir, 2017; López-Salido *et al.*, 2017; Philippon, 2009), and composite financial cycle indices (Borio *et al.*, 2020). We introduce a novel credit spread measure derived from the syndicated loan market and explore if loan market based credit spreads can offer additional information for understanding business cycles fluctuations. While we focus on credit spreads, there is also a related broad empirical literature on the implications of credit quantities, i.e., aggregate amount of credit within the banking system, for credit cycles using cross-country level (Schularick and Tyler, 2012; Jordà *et al.*, 2013), bank level data (Baron and Xiong, 2017), and data for large (Ivashina and Scharfstein, 2010; Chodorow-Reich, 2014) and small firms (Greenstone *et al.*, 2017; Giroud and Müller, 2018).

Our paper also relates to the literature on the role of financial frictions in the generation, propagation and amplification of shocks through the economy as discussed in Bernanke and Gertler (1989), Gertler and Gilchrist (1994) and Holmström and Tirole (1997). A loan market credit spread may better capture these financial frictions.

Finally, we contribute to the strand literature which highlights the importance of smaller, younger, and private firms in the economy. Asker *et al.* (2015) show that private firms invest more than public firms holding firm size, industry, and investment oppurtunities constant. Davis *et al.* (2006) highlight that private firms show a greater volatility and dispersion of growth rates than public firms. Pflueger *et al.* (2020) introduce a measure of risk perceptions based on the price of volatile firms, which behave similar to private firms, and provide evidence that the measure helps understand macroeconomic flucuations. Cloyne *et al.* (2020) provide evidence that younger firms' investment behavior responds more strongly to changes in market interest rates compared to older firms. Begenau and Salomao (2019) also explore the financing patterns of small and large firms over the business cycle and find smaller firms financing policy is procyclical due to financial constraints. We add to this literature and show that loan spreads may be a more accurate measure of the cost of credit for more constrained, private firms, which may be especially prescient in forecasting macro outcomes.[2]

Our paper proceeds as follows. In Section 2, we provide details on the construction of the loan spread measure. We present the baseline results in Section 3 and provide robustness tests as well as evidence from Europe. We explore the mechanisms in Section 4. Section 5 shows results from industry-level tests, We introduce a new weighting scheme in Section 6. Section 7 concludes.

[2] Our paper also relates to the literature studying secondary loan markets. Altman *et al.* (2010) and Gande and Saunders (2012) argue that banks still have an advantage as information provider even when previous loans of borrowers have been traded on the secondary loan market. Drucker and Puri (2009) document better access to credit and lower cost of debt for firms with traded loans. Consistent with the forecasting power of loan spreads documented in this paper, Addoum and Murfin (2019) show that traders can use infromation from secondary loan market prices to generate positive alpha.

2 Constructing the loan credit spread measure

Over the last two decades, the U.S. secondary market for corporate loans has developed into an active and liquid dealer-driven market, where loans are traded much like other debt securities that trade in over-the-counter (OTC) markets. This allows observing daily price quotes for private claims, i.e., claims that are not public securities under U.S. securities law and hence can be traded by institutions such as banks legally in possession of material non-public information (Taylor and Sansone, 2006).

A nascent secondary market emerged in the 1980's but it was not until the founding of the Loan Syndication and Trading Association (LSTA) in 1995, which standardized loan market contracts and procedures, that the market began to flourish (Thomas and Wang, 2004). In 2019 the annual secondary market trading volume reached 742 billion USD (see Figure 2).

The majority of loans traded in the secondary market are syndicated corporate loans, i.e., loans that are issued to a borrower jointly by multiple financial institutions under one lending contract. The syndicated loan market is one of the most important sources of private debt for corporations. For example, about 69% of non-financial firms in the Compustat North America database are active syndicated loan issuers during the 1999 to 2020 period and the annual primary market issuance volume in the U.S. exceeded that of public debt and equity as early as 2005 (Sufi, 2007). Both public and (larger) private firms rely on syndicated loans. Of our entire sample, described in detail below, about 40% are loans to private firms.

Data: Our analysis utilises a novel dataset comprising of daily secondary market quotes for corporate loans that trade in the OTC market, which we obtain from the LSTA. Our sample spans the December 1999 to March 2020 period and contains 13,221 loans issued by U.S. non-financial firms. Loan sales are usually structured as "assignments",[3] and investors trade through dealer desks at the large underwriting banks. The LSTA receives bid and ask

[3] In an assignment, the buyer becomes a direct signatory to the loan. Assignments make trading easier as the loan ownership is assigned, or 'transferred', from seller to buyer. In contrast, in a participation agreement the lender retains official ownership of the loan.

quotes, every day, from over 35 dealers that represent the loan trading desks of virtually all major commercial and investment banks.[4] These dealers and their quoted loan prices represent over 80% of the secondary market trading in syndicated loans. Therefore, these loan price quotes provide an adequate representation of the secondary loan market for large corporate loans (Berndt and Gupta, 2009).

We exclude credit lines and special loan types (around 1,703 loans), i.e., restrict our sample to term loans.[5] Term loans are fully funded at origination and are typically repaid mostly at maturity, i.e., have a cashflow structure similar to bonds. Further, we require that loans can be linked to the DealScan database and restrict the sample to loans with a remaining maturity of at least one year, resulting in a final sample of around 9,095 term loans.

As we use monthly measures of economic activity in our forecasting regressions, we rely on monthly mid quotes. That is, for each loan-month we take the average mid quote across all trading days in the month. This results in about 302,223 loan-month obervations. On average, our sample comprises around 1,219 outstanding loans per month (min ∼330; maximum ∼2,293).[6]

We complement the LSTA pricing data with information about the structure of the underlying loans from the DealScan database. The databases are merged using the LIN, if feasable, or else a combination of the borrower name, dates, and available loan characteristics. DealScan contains information on maturity and scheduled interest payments as of origination, which are key inputs used to determine our credit spread measure, as described below. Table

[4] Investors usually trade through the dealer desks at large loan issuing banks. There is little public information about the dealers who provide the quotes that are collected by LSTA. However, we know the identities of the dealer banks for all loans in 2009. In Table A.5 of the Online Appendix we show that the top 25 dealers account for more than 90% of all quotes. We rank the dealers according to their market share in the secondary loan market and as loan underwriter in the primary loan market and find a correlation of 0.87.

[5] The vast majority of loans that are traded in the secondary market are term loans, as (non-bank) institutional investors typically dislike the uncertain cash flow structure of credit lines (Gatev and Strahan, 2009, 2006).

[6] Figure A.1 in the Online Appendix provides information on liquidity in the secondary loan market over time. The median bid-ask spread in the 1999 to 2020 period was 97 basis points (bps). For comparison, Feldhütter and Poulsen (2018) report an average bid-ask spread for the U.S. bond market of 34 bps over the 2002 to 2015 period. This suggests that while the secondary loan market has become an increasingly liquid market, it is still somewhat less liquid than the bond market.

A.1 of the Online Appendix contains a full list of the variables used and their sources.

Methodology: To examine the predictive power of loan credit spreads, we use a bottom-up methodology similar to Gilchrist and Zakrajšek (2012). In contrast to bonds, loans do not carry a fixed coupon but are floating rate debt instruments based on an interest rate, typically the three-month LIBOR, plus a fixed spread. Therefore, to construct the sequence of future cash flows for each term loan, we use the three-month LIBOR forward curve and the spread obtained from DealScan to estimate projected cash flows. In particular, we add the three-month forward LIBOR rate for the respective period to the term loan's fixed all-in-spread-drawn (AISD). The AISD comprises of the spread over the benchmark rate and the facility fee, and has been shown to be an adequate measure for the pricing of term loans (Berg *et al.*, 2016, 2017). We assume that cash flows are paid quarterly.[7] Let $P_{it}[k]$ be the price of loan k issued by firm i in period t promising a series of cash flows $C(S)$. Using this information we calculate the implied yield to maturity, $y_{it}[k]$, for each loan and each period.

To avoid a "duration mismatch" in the calculation of the spread, for each term loan we construct a synthetic risk-free security that has exactly the same cash payment profile as the loan. Let $P^f_{it}[k]$ be the "risk-free equivalent price" of loan k. $P^f_{it}[k]$ is defined as the sum of the projected cash flows discounted using the continuously compounded zero-coupon Treasury yields from Gürkaynak *et al.* (2007). From this price we extract a synthetic risk-free equivalent yield to maturity, $y^f_{it}[k]$. The loan spread $S_{it}[k]$ is defined as the difference between the loan's implied yield to maturity and its risk-free equivalent yield to maturity. To ensure the results are not driven by outliers, all loan-month observations with loan spreads below five bps and above 3,500 bps as well as observations with a remaining maturity below 12 months are excluded.

We take a monthly arithmetic average of all secondary market loan spreads, to create a loan spread index S^{Loan}_t. Whilst a variety of alternative weighting mechanisms could be adopted, we stick to the method used by Gilchrist and Zakrajšek (2012) to minimize any

[7] We use the same interest period for all loans, as information on the loan-specific interest period is often missing in the DealScan database. However, in a sub-sample of term loans to U.S. non-financial firms for which the interest period is reported in DealScan, interest is paid on a quarterly basis for over 70% of loans.

chance of data mining and to ensure comparability to the existing literature. We discuss alternative weighting schemes in later sections. Specifically, the loan spread is defined as:

$$S_t^{Loan} = \frac{1}{N_t} \sum_i \sum_k S_{it}[k], \tag{1}$$

Figure 4 plots our estimated loan spread as well as the bond credit spread measure by Gilchrist and Zakrajšek (2012) over time.[8] The loan spread and bond spread follow a similar pattern over time, with sharp movements around the 2001 recession, the 2008/2009 financial crisis, and at the beginning of the COVID-19 pandemic. The correlation between the loan spread and bond spread is high but not perfect (0.76 over the entire sample period and 0.65 when excluding the 2008-09 crisis period). In our empirical tests we use spread changes, which substantially reduces this correlation (details are provided in the following section). Further, the loan spread is significantly more volatility with a standard deviation (SD) of 2.4% (versus 1.0% for the bond spread) and an order of magnitude higher than the bond spread. This is consistent with the syndicated loan market containing a wider universe of borrowers and especially including more lower credit quality borrowers such as private firms who cannot access public bond markets.[9]

3 Loan spreads and economic activity

3.1 Baseline results

In this section we start out by examining whether loan spreads contain information that is useful for predicting aggregate economic variables. We build on López-Salido *et al.* (2017)

[8] The bond spread measure is provided by Favara *et al.* (2016), which is an updated version (i.e., available also for more recent periods) of the bond spread measure by Gilchrist and Zakrajšek (2012). See https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/files/ebp_csv.csv for details.

[9] A full summary of descriptive statistics for all variables is available in Table A2 of the Online Appendix.

and run forecasting regressions of the following form:

$$\Delta y_{t+h} = \alpha + \beta \Delta y_{t-1} + \gamma \Delta S_t + \lambda TS + \phi RFF + \epsilon_{t+h}, \tag{2}$$

where h is the forecast horizon and Δy is the log growth rate for a measure of economic activity from $t-1$ to $t+h$. S is a credit spread index, and ΔS_t is the change in spread from $t-1$ to t.[10] In most tests we use the loan spread measure as defined in the previous section. In some tests we benchmark the loan spread results against predictive regressions utilizing other credit spread measures, such as a bond spread. We further include the term spread, which is defined as the slope of the Treasury yield curve (i.e., the difference between the ten-year constant-maturity Treasury yield and the three-month constant-maturity Treasury yield), and the real effective federal funds rate.[11] The regressions are estimated by ordinary least squares (OLS), with one lag, i.e., economic activity from $t-2$ to $t-1$.[12] Standard errors are heteroskedasticity and autocorrelation corrected Newey-West standard errors with a four period lag structure. The sample period covers the December 1999 to March 2020 period.

Table 1 shows the results using a forecast horizon of three months (h=3). To gauge the contribution of the loan spread to the in-sample fit of the model, we report at the bottom of each panel the incremental increase in adjusted R^2 relative to a baseline model that uses only the term spread, the real federal funds rate, and the lagged dependent variable. Panel A of

[10] We follow López-Salido *et al.* (2017) and use changes rather than levels in our predictive regressions. This can also be motivated by the framework provided by Krishnamurthy and Muir (2017) for diagnosing financial crisis. The forecasting power of spread changes can arise for two reasons. First, becasue the asset side of bank balance sheets are sensitive to credit spreads, changes in spreads will be correlated with bank losses. Second, increases in credit spreads reflect an increase in the cost of credit which impacts investment decisions. Finally, first differencing accounts for non-stationary of the credit spread time series.

[11] Aggregate macroeconomic data, i.e., monthly (non-farm private) payroll employment [NPPTTL], unemployment rate [UNRATE], and (manufacturing) industrial production [IPMAN], are obtained from the Federal Reserve's FRED website. The term spread data comes from the ten-year Treasury constant maturity minus three-month Treasury constant maturity data series [T10Y3MM] available via FRED. The real effective federal funds rate is estimated using data from the Fed's H.15 release [FEDFUNDS] and realised inflation as measured by the core consumer price index less food and energy [CPILFESL].

[12] In all specifications we hold the lag structure fixed to facilitate the comparison of R^2 across models. An AR(1) process, i.e., a one period lag structure, captures most of the peristence. However, including additional lags up to 6 periods, or allowing for an optimal lag length selection based on the AIC leads to very similiar results.

Table 1 reports the results using industrial production as the dependent variable. Column (1) shows that a model including the loan spread can explain 31.3% of the variation in changes in industrial production. This represents a sizable R^2 increase of 15 percentage points (p.p.) relative to the baseline model. The loan spread coefficient indicates that a one SD increase in loan spread is associated with a decrease in three-month ahead industrial production by 0.410 SD. In economic terms this equates to a 45bps increase in loan spreads being associated with a 0.74% decrease in industrial producion over the next 3 months, compared to an unconditional mean of 0.23% growth in industrial production.[13]

In column (2) we benchmark this result against a commonly used credit spread indicator from the corporate *bond* market (Gilchrist and Zakrajšek, 2012). The economic magnitude of the bond spread coefficient is half that of the loan spread coefficient in Column (1). In particular, a one SD increase in bond spread is associated with a decrease in industrial production by 0.198 SD. Also the improvement in-sample fit due to the bond spread is modest with an R^2 increase of 3.5 p.p. from the baseline.

When we combine both spreads in one model in column (3), we find that the loan spread coefficient and incremental R^2 is almost unchanged compared to the model with the loan spread only. In other words, while both bond and loan spreads have predictive power for industrial production, the loan spread has additional forecasting power. A variance inflation factor of below 1.5 of both loan and bond spreads suggests that the correlation between both spreads is not affecting our results. The results remain consistent when we look at the unemployment rate in Panel B and payroll employment in Panel C of Table 1.

To examine dynamics, we extend our prediction model to consider longer forecast horizons in a local projections framework (Jordà, 2005). Figure 5 plots the coeffecient and 95% confidence intervals on the loan spread and bond spread at various forecasting horizons (one to 12 months ahead) using each of our dependent variables. The loan and bond credit spread models are estimated in separate regressions.

Focusing on industrial production (top-left panel), the predictive power of the loan spread

[13] See Table A.2/A.3 of the Online Appendix for a full list of the unconditional moments for each variable.

peaks around h=3, i.e., the loan spread today is most correlated with the growth in industrial production three months from now, and then dissipates slowly. The bond spread, in contrast, shows the largest predictive power at a horizon of about eight months and then the effect levels out. However, even at longer forecasting horizons the loan spread shows a stonger predictive power compared to the bond spread.

3.2 Robustness

Alternative credit spread indicators: One potential explanation for why the loan spread possesses additional predictive power relative to other credit spread measures is that the secondary loan market is populated by a set of riskier borrowers than the bond market. Figure 3 highlights that more than 80% of borrowers in the bond market have a credit rating of BBB or higher, while the majority of loan market borrowers who are rated have a BB or B rating, while others are private firms with no public rating. Firms with higher credit risk may be more exposed to financial frictions and face a higher external finance premium. Hence, their credit spread may be particularly suitable for forecasting economic developments (Gertler and Lown, 1999; Mueller, 2009). A cleaner evaluation of the loan spread's additional predictive power might thus be to compare it to a corporate bond spread conditional on a set of riskier borrowers.

To that end, Table 2 columns (1) and (2) use the Baa-Aaa credit spread and a high-yield credit spread.[14] The Baa-Aaa credit spread measures the spread between Aaa rated corporate bonds and Baa rated corpoate bonds and has been used among others by Gertler and Lown (1999). The high yield corporate bond spread measures the spread between high yield corporate bonds and AAA rated bonds. The results indicate that the high-yield corporate bond spreads have a somewhat larger predictive power compared to the baseline bond spread. The coefficient on the Baa-Aaa spread (high-yield spread) is -0.277 (-0.248) and the incremental R^2 is +8 p.p. (+6 p.p.). For comparison, the coefficient on the baseline

[14] Baa-Aaa credit spread [BAA_AAA] is obtained from Federal Reserve's FRED website. The spread is constructed by Moody's and is based on bonds with 20 years to maturity and above. The high yield index [BAMLH0A0HYM2EY] also comes from FRED is based on the ICE Bofa US high yield effective index.

corporate bond spread is -0.198 and the incremental R^2 is +3.5 p.p. [Table 1 column (2)]. For both spreads, however, the economic magnitude and contribution to in-sample fit remains significantly below that of the loan spread [Table 1 column (1)].

We provide additional tests in Online Appendix Table A.6. In particular, we use bond level pricing data from TRACE to create bottom-up corporate bond credit spreads (Gilchrist and Zakrajšek, 2012) for different rating categories: (i) A or higher, (ii) BBB, and (iii) below BBB. We find a monotonic increase in the size of the coefficient as we condition on a risker set of borrowers in the bond market. However, a bottom-up measure comprised of non-investment grade bonds does not match the predictive power of the loan spread. A one SD higher non-investment grade bond spread is associated with only a 0.222 SD decrease in industrial production three months ahead and an incremental R^2 of 4.9%. Overall, the results indicate that while credit risk can explain some of the improvement in predictive power between loan and bond credit spreads, it cannot account for the entire difference.

Column (3) in Table 2 uses the commercial paper - bill spread to forecast three-month ahead industrial production (see, among others, Friedman and Kuttner, 1993b, 1998; Estrella and Mishkin, 1998). Commercial paper are unsecured, short-term debt instruments issued by high credit quality corporations. During our sample period it shows no predictive power and adds little to the model's R^2.

Equity returns: Informationally sensitive securities like equity may contain signals about the development of the economy as well (see e.g. Greenwood *et al.*, 2020; López-Salido *et al.*, 2017). In Table 2 column (4) we use the monthly return of the S&P 500 index to forecast industrial production. A one SD higher equity market return is associated with a 0.216 SD increase in industrial production three months ahead and the incremental R^2 of including the equity market return in the prediction model is +4.1 p.p. Again, this is well below the effect we document for the loan market credit spread in Table 1.

Loan market liquidity: We control for supply-demand conditions in secondary markets by using a measure of loan market liquidity as plotted in Figure A.1 of the Online Appendix. In particular, in Table 2 column (5) we include the contemperaneous median bid-ask spread as an additional control. Our main result remains unchanged.

Non-price terms: Loan and bond contracts might be different with respect to e.g. non-price contract terms (such as maturity, collateral and covenants and other characteristics such as size, age, amount). To control for the impact of contract terms on loan spreads we regress loan spreads on various characteristics, such as loan age, loan size, (log) loan amount, the loan's initial all-in-drawn spread, remaining time to maturity, as well as indicators for secured loans, senior loans, and financial covenants. We then take the residual loan spread. See Section D.2 and Table A.7 of the Online Appendix for details. Column (8) in Table 2 uses this 'residual loan spread' and finds very little difference in predictive power relative to the baseline loan spread [Table 1 column (1)].

Ex financial crisis: One criticism may be that the results are driven by the large changes in spreads during the 2008-09 financial crisises. Table 2 columns (6) and (7) shows the results when we exclude the financial crisis period (2007:Q4 – 2009:Q2). The predictive power of the bond spread becomes economically small and insignificant. The predictive effect of the loan spread drops by approximately half, but remains significant. That is, aggregate loan and, particularly, bond spreads perform weaker outside of financial crisis periods consistent with the interpretation that credit spreads perform better as predictors of "tail events" (Adrian *et al.*, 2019).

Asymmetric reactions We also consider the asymmetric impact of loan and bond spreads. In particular, the baseline aggregate forecasting regression presented in Table 1 assumes that increases and decreases of spreads have the same relationship with future economic activity. In Table A.8 of the Online Appendix we test for potential asymmetric impacts. The results suggests both increases and decreases in loan spreads are significantly correlated with future economic developments. However, the effect of spread increases is somewhat stronger than the effect of spread decreases. For the bond spread we only find an effect for spread increases. This suggest that bond spreads primarily capture deteriorations in economic conditions, while loan spreads capture both improving as well as deteriorating conditions.

Out of sample prediction: We further test the predictive ability of loan and bond spreads on pseudo out-of-sample data. To do this we use a standard expanding rolling window RMSE test. We first run the aggregate forecasting regressions on an initial training window (initially 150 observations) and use the resulting coefficients to predict the 151st macroeconomic variable. We then repeat this exercise including the next observation and so forth. We then compute the RMSE of the predictions against the realized macroeconomic outcome.

Table A.9 of the Online Appendix reports the RMSE for different model specifications across each of our macroeconomic variables. Column (1) examines a baseline model with no credit spreads (only control variables). Column (2) examines a model with only the loan spread. Column (3) uses only the bond spread and Column (4) uses a model with both loan and bond spreads. Across all panels it is the model with the loan spread that performs best with the lowest RMSE of out of sample predictions, compared to specifications including only the bond spread. A Diebold-Mariano test of the difference in forecasting power (between Column 2 and 3) confirms that the loan spread is superior at forecasting out of sample for industrial production and payroll employment.

Excess Loan Premium: Following the path of Gilchrist and Zakrajšek (2012), we decompose the loan spread into two components: a component that captures changes in default risk based on the fundamentals of a firm and a residual component that captures the price of risk demanded above a default risk premium, which we call the "excess loan premium" (ELP). We first regress the natural logarithm of the loan spread of loan k on a firm's distance-to-default (DD) as a measure for default risk and a vector of loan-level variables ($Z_{(i,t)}[k]$) such as loan type, loan maturity etc.

$$ln\ S_{i,t}[k] = \beta DD_{i,t} + \beta DD_{i,t}^2 + \gamma^{'} Z_{i,t}[k] + \epsilon_{it}[k] \tag{3}$$

We thus obtain a predicted component of the loan spread $\hat{S}_{it}[k]$ reflecting the fundamental default risk of firm i. The excess loan premium (ELP) is then defined as the residual, i.e., in the same way as the excess bond premium (EBP) in Gilchrist and Zakrajšek (2012). Panel A of Table A.7 in the Online Appendix summarise these results. The question then becomes how much of the predictive power of the loan spread is driven by the predicted component and how much by the excess loan premium? Panel B of Table A.7 in the Online Appendix uses the 3 month ahead change in industrial production as the dependent variable, and on the right hand side both the predicted and excess loan spread are included along with the usual controls. We find both components of the loan spread are statistically significant at the 3month horizon. Interestingly, it is the predicted component that contributes around two thirds of the incremental adjusted R^2, suggesting the loan spread is atleast partly capturing the default risk of loan market borrowers.

3.3 Evidence from European countries

A potential objection to our result is that our sample period covers the 2000 to March 2020 period and our time-series is thus relatively short to make strong claims regarding the predictive power of loan spreads for the business cycle. To address this issue, we perform similar tests using European data. We focus on three of Europe's largest economies, Germany, France, and Spain, as we have sufficient loan market data available to perform meaningful tests. We construct the European loan spread following the methodology described in Section 2.[15] For the aggregate bond spread, we use the spread provided by Mojon and Gilchrist (2016).

Figure 6 shows aggregate bond and loan spreads for Germany, France, and Spain. Similar to the U.S., loan spreads are higher in levels compared to bond spreads consistent with different types of firms issuing debt instruments in both markets. Aggregate bond spreads also decrease following the 2008-2009 financial crisis, but remain elevated during the sovereign debt crisis (but at a lower level compared to 2008-2009). Interestingly, absolute bond spreads in and out of crises is substantially lower compared to U.S. bond spreads. This is consistent with the interpretation that only the highest quality European firms can access public debt

[15] We adjust the methodology by using equivalent EU variables. The term spread, i.e., the difference between 10-year Euro government bond (i.e. a GDP weighted average all Euro area government bonds, Source: OECD's MEI) and three-month EURIBOR (Source: ECB), and the real EONIA, i.e., the overnight rate (Source: ECB) minus realised inflation EURIBOR forward curves to calculate loan cashflows and a different risk free rate.

markets and that European markets are more universal bank debt dominated. Aggregate loan spreads increase during the financial crisis up to about 15%, a level comparable to the U.S. spread. Similar to the U.S., loan spreads remain higher after both crises periods compared to the period before 2008.

We run similar aggregate forecasting models as in the U.S. setting using a term spread (defined as the 10-year benchmark Euroarea government bond minus the three-month EURIBOR rate) and the real EONIA (defined as EONIA minus HCIP inflation over the previous 12 months) and report the results in Table 3. Our dependent macro variables are the monthly unemployment rate, manufacturing goods production, and consumption goods production.

We start with the three-month ahead forecasts of macro outcomes in Germany in Panel A of Table 3. In our baseline model (not shown), we include only the term spread, real EONIA, and lag of the dependent variable to match the set up of previous tables. In column (1) we look at the predictive power of the aggregate bond spread and loan spread for the manufacturing production index. Again the loan spread remains positive and significant even controlling for the bond spread across all three countries. The explanatory power increases by +11.1 p.p. above the baseline model. We find consistent results for an index of unemployment rate [column (2)] and an index of construction activity [column (3)].

The results extend to France and Spain. Overall, our evidence from the European market is consistent with the U.S. evidence. Loan spreads have more predictive power for macroeconomic outcomes compared to bond spreads.

4 Exploring the mechanism

In the previous section, we showed that loan spreads have predictive power beyond other commonly used measures. This results holds for a host of different macroeconomic outcome variables, additional controls, different time horizons, and for different countries. In this section we explore potential mechanisms that might explain this result. A testable hypothesis is that the loan market is populated with firms that have limited access to alternative funding sources and are more exposed to bank loan supply frictions. Hence, this set of firms may be particulary sensitive to financial market frictions, which makes them an important channel for amplifying credit supply shocks.

We attempt to explore this hypothesis by (i) analyzing which set of firms account for most of the predictive power of loan spreads and (ii) examining the link between loan spreads and credit supply conditions in the economy.

4.1 Effect by firm size, age, and listing

One important feature of the loan market is that it is populated with firms that may have limited access to alternative funding sources and exhibit a higher sensitivity to bank loan supply frictions. For example, Figure 3 highlights that more than 80% of borrowers in the bond market have a credit rating of BBB or higher, while the majority of loan market borrowers who are rated have a BB or B rating, while others are private firms with no public rating. Of our entire sample, only 57% are loans to publicly traded firms. Thus, there is a limited overlap between bond and loan borrowers. Consequently, a repricing of risks by banks in the loan market might have implications for the overall economy that are not perfectly reflected by investors in bonds.

In this section we examine which types of borrowers account for most of the predicitve power of loan spreads. As suggested above, the loan market may comprise of firm's which are more reliant on external financing but do not have access to public debt or equity markets. This is specifically the case for small, young, and private firms, which are more likely to be financially constraint (Hadlock and Pierce, 2010), face more severe informational frictions that may add to the costs of external finance (Gertler and Gilchrist, 1994), and are more likely to borrow using collateral (Lian and Ma, 2020), i.e., are more dependent on bank financing. That is, these borrowers are presumably most affected when credit market conditions tighten because of a lack of alternative funding sources, which eventually feeds into the real economy.

Table 4 performs the same aggregate forecasting regression as Table 1 for the U.S. economy, but includes loan spreads that are conditional on the size of the borrower, as measured by total assets (Panel A), or the age of the borrower, as measured by length of time the firm has financial information available in the Compustat North America dabase (Panel B). Panel A, column (1) [column (2)] shows the aggregate loan spread for small (large) borrowers, i.e., total assets <= (>) median. The results are significantly stronger for small firms compared to large firms (coefficent of -0.380 versus -0.260 and incremental R^2 of +13.7 p.p. versus +6.7 p.p.). Panel B provides consistent, albeit weaker, results splitting the firm sample by firm age.

In addition to the size and age splits, Table 4 reports results using a loan spread measure constructed based on private firms, defined as firms that cannot be linked to Compustat.[16] The results indicate that the predictive power of a loan spread constructed based on private firms is stronger even compared to small and young firms with a coefficent of -0.420 and an incremental R^2 of +15.7 p.p.

In Table 4 Panel C for those loan market borrowers for which we do have age and size information available, we double sort firms by age and size buckets. Again the effect is stonger for small and young versus old and large firms. The coefficent for the former group is -0.390 and the incremental R^2 +14.7 p.p. compared to a coefficient of -0.210 and an incremental R^2 of +3.7 p.p. for the latter group. Interestingly, the predictive power of large and old firms is close to that of the bond spread measure [coefficent of -0.210 versus -0.19 and incremental R^2 of +3.7 p.p. versus +3.5 p.p., cf. Table 1, colum (2)] The predictive power of small and young firms is close to that of private firms [coefficent of -0.390 versus -0.420 and incremental R^2 of +14.7 p.p. versus +15.7 p.p., cf. Table 1, colum (2)]

Taken together, the results suggest that the predictive power of the loan spread is stronger for younger, smaller, and private borrowers who are more exposed to increases in the exteneral finance premium. Importantly, in particular among the group of small, young, and private firms the overlap between the loan and bond market is limited. We match borrowers

[16] Hence, a size or age split cannot be performed for these firms. We report the private firm result throughout Panels A-C, i.e., in all three panels, to facilitate a comparison with the other spread measures.

in the loan market with borrowers in the bond market each year using company names in Mergent. Only 16% of smaller and younger borrowers in our loan sample also have a bond outstanding, compared to 39% for larger and older borrowers. This suggests that compositional differences may explain (part of) the difference in predictive power of loan versus bond markets.

4.2 Effect by ratings

An alternative way to examine the role of financial frictions is to look at loan spreads conditional on ratings group. Credit ratings are an alternative proxy that may capture the riskiness of borrowers and their exposure to financial frictions. Loan level ratings are sourced from Dealscan and Leveraged Commentary and Data (LCD). Table 5 performs the same aggregate forecasting regression as Table 1, but sorts loans into four groups, BBB, BB, B and below and a group for which no rating can be found. Column (1) highlights that a loan spread derived from the highest rated loans, BBB, has no predictive power for 3 month ahead macroeconomic outcomes. This is consistent with the safest borrowers being least exposed to bank loan supply frictions.

Column (2) and (3) show that as we condition on a riskier set of loans, the loan spread increases in its predictive power. Column (4), which includes loans for which no loan rating could be identified, show a very similar pattern to loans rated B or below. Comparing to the baseline results in Table 1, it appears most of the predictive power of the loan spread is coming from loans rated B or below and loans with no available rating. These borrowers, most likely private firms, are the type of firms for which we would expect bank supply frictions to matter the most.

4.3 Credit supply

Higher loan spreads could reflect a general tightening of lending standards or a reduction in loan supply by banks because of deteriorating bank balance sheets, which leads to an increase in loan spreads and a subsequent reduction in economic activity. In this section we examine whether loan spreads are associated with a tightening of financial conditions.

In Table 6 we regress a measure of aggregate bank lending standards on our loan spread and benchmark the effect against a bond spread. The dependent variable in Panel A.1 is the aggregated measure for changing bank lending standards obtained from the Senior Loan Officer Opinion Survey on Bank Lending Practices administered from the Board of Governors of the Federal Reserve System (SLOOS). Specfically it is defined as the percentage who respond ”lending tightened”, less the percentage who responded that ”lending eased”. The survey is conducted quarterly and reflects the credit conditions in the previous quarter i.e a net percentage. A higher SLOOS measure signals a tightening of lending standards.

In column (1) [column (2)] we regress the SLOOS indicator on the change in loan (bond) spread also over the previous quarter. The loan spread has a higher correlation with the SLOOS indicator compared to the bond spread and a substantially higher R^2. A one SD increase in loan spread over the quarter is associated with a 0.43% increase in the net percentage indicating tighter lending conditions. Including both spreads in the same model shows consistent results [column (3)]. In line with our prior results, the loan spread retains its economic and statistical significance while the bond spread becomes small and insignificant.

The dependent variable in Panle A.2 is banks' unused commitments (as % of total assets) as a measure of bank credit supply. Banks might curtail their exposure at the beginning of an economic downturn primarily by reducing the amount of undrawn commitments (Bassett *et al.*, 2014). In column (1) [column (2)] we regress the change in the undrawn commitments on the change in loan (bond) spread over the previous quarter. We include both spreads in column (3). An increase in both loan and bond spreads decreases banks' unused commitments in the quarter ahead, but the R^2 is higher in the loan spread regression and the coefficient of the loan spread is higher both individually and collectively when the bond spread is included.

In Panel B of Table 6, we extend these results to Europe using the European Central Bank's (ECB)' equivalent Bank Lending Survey (BLS). We see a similar pattern across all three European countries, where the loan spread is more highly correlated with bank lending standards than the bond spread.

Overall, these tests consistently show that loan spreads derived from secondary market prices reflect supply effects in the primary loan market. These results are consistent with the interpretation that the pricing of credit risk in the loan market is closely linked to the supply of credit in the banking system.

5 Industry-level forecasting

In this section we show there is additional information to be captured by going beyond aggreagate spreads and looking at the cross-sectional heterogeneity in spreads. Bottom-up credit spread measures create the ability to aggregate spreads not only at the economy-wide but also at less aggregated levels, such as the industry level. There are several reasons for studying the predictive power of credit spreads at disaggregated levels. First, it allows for more nuanced tests as to the predictive power of credit spreads and economic aggregates. Second, in cross sectional tests it is easier to shut down potential confounding factors that may affect real outcomes but are correlated with credit spreads. Hence, one can isolate the credit spread specific forecasting power more cleanly, as will become clear below. Third, by exploiting variation in the cross section, we are able to study in which industries loan credit spreads have greater predictive power. This can speak to potential mechanisms as to why loan spreads are informative.

5.1 Baseline results

Industry credit spread: To construct a loan spread measure at the industry level, we classify U.S. firms into industries using the Bureau of Economic Analysis (BEA) sector definition, excluding financial and government owned firms. Industry level loan spreads, S^{Loan}_{bt}, are constructed following Section 2, but instead of aggregating across all firms in the economy we now aggregate loan spreads using an arithmetic average across all firms in a BEA sector b. We exclude industry-months with less than 5 loans. Overall, we construct spreads for 11 distinct BEA sectors.[17]

Figure 7 plots the industry loan spreads over time. Loan spreads are not perfectly correlated across industries. For example, while the sectors "Construction" and "Transportation" experienced a significant spread increase during the 2008-09 crisis, this increase is less pronounced for more stable sectors such as "Education and health care" and "Utilities". Further, some industries experienced industry-specific crisis periods. The "Mining" sector (which includes volatile oil and gas companies), for instance, experienced a wave of defaults in 2015 fueled by collapsing oil and metal prices, which is reflected in a spread increase that even surpassed the 2008-09 level. Figure 7 also highlights the heterogenous impact of COVID-19 across industries, with exposed industries such as "Mining" and "Retail Trade" experiencing larger spikes in spreads as the crises unfolded.

Industry forecasting results: To assess the relationship between industry specific spreads and industry specific macroeconomic variables, we use quarterly total employment and total establishment figures from the Bureau of Labour Statistic's (BLS) Quarterly Census of Employment and Wages (QCEW). In addition we use quarterly industry gross output from the BEA's industry accounts. This data is only available from Q1 2005 to 2019 Q4 [18]. The baseline results are reported in Table 7.

The first column in Panel A starts with a model that includes the industry loan spread in a pooled regression. Note that in contrast to the aggregate forecasting regressions, we include the loan spread level and not the change in the spread. This is because by later including industry fixed effects we effectively run a demeaned regression, i.e., we capture spread deviations from the industry mean. The dependent variable is the one quarter ahead change in industry employment. Controlling for the aggregate loan spread, a one SD increase

[17] The sectors "Agriculture, forestry, fishing, and hunting" and "Other services, except government" are excluded due to an insufficent number of observations.

[18] The underlying macroeconomic data obtained from the BEA and BLS is not seasonally adjusted. To ensure that any monthly seasonal variation does not interfere with our analysis, we use a seasonal trend decomposition to remove any predictable monthly seasonal variation from the raw data. What remains in the de-seasonalised macroeconomic data is any underlying time trend and residual component.

in industry loan spreads is associated with a decrease in employment by 0.13 SD. The incremental R^2 is +8.6 p.p.

In column (2), we include time fixed effects, which absorbs any common time trends that affects all industries. In particular, this captures variables such as aggregate credit spreads but also the stance of monetary policy, aggregate business cycle fluctuations (such as the overall effect of the 2008-09 crisis), or overall regulatory changes. Interestingly, industry specific loan spreads remain highly statistically and economically significant. In fact, the coefficient remains hardly changed relative to column (1), indicating that omitted aggregate variables do not bias the coefficient to a significant extent. This shows that there is significant information contained in loan spreads that are not captured by other aggregate economic factors. In column (3), we further include industry fixed effects to absorb any time-invariant unobserved cross-industry differences. Again the statistical significance and economic magnitude of industry loan spreads remain virtually unchanged.[19] We find consistent results in Panels B and C using alternative industry specific economic outcomes as dependent variables.

5.2 Across industry heterogeneity

Table 7 reveals that industry level loan spreads have predictive power for industry-specific outcomes, above and beyond aggregate level information. The predictive power, however, may vary across industries. As discussed in Section 4, the loan market comprises of firms that may have limited access to alternative funding sources and exhibit a higher sensitivity to bank loan supply frictions. Hence, loan spreads may have predictive power in particular in industries that comprise of firms that are more dependent on external finance.

The top panel of Figure 8 summarises the results of seperate OLS regressions for each industry, where industry-level employment growth is regressed on the industry-level loan spread. The blue bars indicate the regression coeffecient and highlight the heterogeneity

[19] In untabulated robustness tests, we also include industry-level bond spread measures, constructed using bond price data from TRACE, in the model. Controlling for the industry-specific bond spread has little impact on magnitude or significance of the industry loan spread coefficient.

in correlations. Loan spreads in "Manufacturing", "Wholesale trade", "Construction", and "Mining" seem to be relativly more associated with future growth in employment than other industries.

The bottom panel of Figure 8 summarises the external finance dependence of each industry. We define a sector's dependence on external finance following Rajan and Zingales (1998). External dependence is defined as the ratio of total capital expenditures minus current cash flow to total capital expenditure.[20] The correlation between the top and bottom panel is 0.50. Table 8 mirrors the specificaion in column (3) of Table 7 but interacts loan spreads with indicator variables for the sector's dependence on external finance. Note that the base *EFD* effect is absorbed by the industry fixed effects. Column (1) interacts loan spreads with a dummy variable equal to one for the five industries most reliant on external funding. The results indicate that industries more reliant on external funding indeed show a significantly stronger relationship between total employed and industry loan spread. Alternatively, Column (2) interacts loan spreads with the actual *EFD* for a given industry, with similiar results. Finally, Column (3) includes dummy variables for the top three industries with the largest *EFD*, middle four and bottom four and we see industries with less reliance on external finance have a weaker relationship with loan spreads. We find consitent results using industry establishments and gross output as dependent variables.

Overall, these results are consistent with our finding at the economy-wide level that presumably more external (bank) finance dependent firms, such as smaller and younger firms, account for most of the predictive power of the loan market credit spread. That is, compositional difference across loan and bond markets contribute to the differential predictive power.

[20] Specifically, the measure is calculated using firm-level data from Compustat on capital expenditures (CAPX) and free cash flow (OANCF). The industry-level external finance dependence is based on the median firm within each industry over the 2000-2019 period.

6 Weighting schemes using industry-level information

Finally, we explore if the heterogeneity in forecasting power across industries can be exploited to improve forecasting results at the aggregate level. In constructing the aggregate loan spread a simple arithmetic average of all loan spreads available each month is used, following Gilchrist and Zakrajšek (2012). This method puts an equal weight on all loan-month observations. For instance, at an industry level this implies that a higher weight is assigned to industries with a greater number of loans outstanding. However, industries may differ in their aggregate importance and loan spreads may have a differential information content across industries, as implied by the tests in the previous section. This may or may not be reflected in the number of loans outstanding across industries. In this section we explore alternative weighting schemes to construct an aggregate loan spread.

One can envisage a number of alternative weighting schemes that instead put a higher weight on the spreads from some industries relative to others, for example based on that industry's predictive power. Table 9 reports aggregate level regressions using the three-month ahead industrial production as the dependent variable. That is, the table mirrors Table 1, Panel A. Column (1) reports the baseline aggregate loan spread, constructed as a simple arithmetic average across all individual loan-month observations, for comparison. In columns (2) to (5) we use aggregate loan spreads employing alternative weighting schemes.

Column (2) uses a loan spread constructed by weighting each industry loan spread by that industry's contribution to GDP in the respective year. Interestingly, a GDP weighted loan spread performs similarly to the arithmetic average in column (1). This implies that assigning a higher weight to industries that account for a larger share of aggregate economic outcome does not improve the prediction.

In column (3), we take the loan spread coefficients from the top panel of Figure 8 as weights (rescaled to sum to one). That is, this aggregate spread puts more weight on industries in which the loan spread has a higher predictive power. This weighting scheme results in a sizable improvement in adjusted R^2 of +3 p.p. That is, industries in which the loan spread has a higher predictive power also contribute more to the aggregate forecasting power of the loan spread.

In column (4), the loan spread is constructed using the industry's external finance dependence (EFD) as weights, as defined in the previous section. That is, in the construction of the spread more weight is put on industries that comprise of firms that are more sensitive to external financing frictions. This approach yields similar results as in column (3). This is a reflection of the evidence reported in Table 7 that the predictive power of the loan spread is larger in industries that are more externally finance dependent. That is, both the weighting scheme employed in column (3) and column (4) put a larger weight on high EFD industries. Again, these results are consistent with the conjecture that (part of) the predictive power of the loan spread can be explained by loan markets comprising of firms that are particularly sensitive to financial frictions.

Finally, in column (5) we weight industries using optimal weights chosen by an elastic net regression.[21] That is, we use a statistical appraoch to improve the in-sample fit of the model. As expected, this results in an improvement in R^2 relative to the baseline loan spread [cf. column (1)]. More interestingly, the data mining approach does not improve upon the economically motivated weighting schemes in column (3) and (4). Specifically, the elastic net approach also places a larger weight on high EFD sectors, consistent with the conjecture that the predictive power of the loan market credit spread is driven by a better coverage of firms that are more sensitive to external financing frictions. These results are robust to using other macro outcomes (payroll employment and unemployment).

Overall, this section highlights the usefulness of bottom-up credit spread measures in uncovering cross-sectional heterogeneity. Further, deviating from simple arithmetic averaging when construcing aggregate measures from microdata can help improve aggregate forecasting results.

[21] Results are similar if LASSO or Ridge regressions are used to choose optimal weights.

7 Conclusion

We introduce a novel measure of credit spreads based on the prices of traded syndicated corporate loans. We document extensive evidence that this new measure outperforms corporate bond spreads as well as other existing credit spread measures and equity returns used in the previous literature. Importantly, the predictive power of our loan spread measure is consistent with existing theories on the role of financial frictions in amplifying business cycles. Compositional differences between firms borrowing in the loan vis-a-vis the bond market explain the predictive power of loan over bond spreads. We show how the forecasting power can be even enhanced further through different aggregation mechanisms.

This is the first paper to use secondary loan market prices to construct a bottom-up measure of loan spreads to forecast business cycles. We only scratch the surface w.r.t many issues that we raise in our paper. For example, we provide a very simple way to aggregate the loan spread measure. We clearly need more research on how to improve the forecasting power of our loan spread (and of all bottom-up measures, such as the bond spread). Moreover, the forecasting power of the loan spread might be interesting for other applications and on different aggregation levels, e.g., the industry- or even the firm-level.

Even though our time-series is not long (due to data availability) we are able to provide very consistent evidence as to its predictive power across different specifications as well as cross-country evidence. We believe that the addtional predictive power of the loan over the bond spread will likely grow in the years ahead. The development of both spreads has already substantially diverged during the 2018 to 2019 period. Moreover, monetary policy interventions that have been introduced in March 2020 at an early stage of the COVID-19 pandemic have directly targeted corporate bonds with bond spreads declining below pre-COVID levels at times when the economy was far from recovering (while loan spreads remain elevated). In other words, the information content of bond spreads might be severely impaired if targeted by monetary policy. We look forward to future research in these promising areas.

References

Addoum, J. M. and Murfin, J. R. (2019). Hidden in plain sight: Equity price discovery with informed private debt. *Review of Financial Studies, forthcoming*.

Adrian, T., Boyarchenko, N. and Giannone, D. (2019). Vulnerable growth. *American Economic Review*, **109** (4), 1263–1289.

Altman, E., Gande, A. and Saunders, A. (2010). Bank debt versus bond debt: Evidence from secondary loan prices,. *Journal of Money, Credit and Banking*, **42**, 755–767.

Asker, Farre-Mensa and Ljungqvist (2015). Corporate investment and stock market listing: A puzzle? *Review of Financial Studies*, **28** (2), 342–390.

Baron, M. and Xiong, W. (2017). Credit expansion and neglegted crash risk. *Quarterly Journal of Economics*, **132** (2), 713–764.

Bassett, W. F., Chosak, M. B., Driscoll, J. C. and Zakrajšek, E. (2014). Changes in bank lending standards and the macroeconomy. *Journal of Monetary Economics*, **62**, 23–40.

Begenau, J. and Salomao, J. (2019). Firm financing over the busines cycle. *Review of Financial Studies*, **32** (4), 1235–1274.

Berg, T., Saunders, A. and Steffen, S. (2016). The Total Costs of Corporate Borrowing in the Loan Market: Don't Ignore the Fees. *Journal of Finance*, **71** (3), 1357–1392.

—, —, — and Streitz, D. (2017). Mind the gap: The difference between u.s. and european loan rates. *Review of Financial Studies*, **30** (3), 948–987.

Bernanke, B. S. (1990). On the predictive power of interest rates and interes rate spreads. *New England Economic Review*, pp. 51–68.

— and Gertler, M. (1989). Agency costs, net worth, and business fluctuations. *American Economic Review*, **79** (1), 14–31.

Berndt, A. and Gupta, A. (2009). Moral hazard and adverse selection in the originate-to-distribute model of bank credit. *Journal of Monetary Economics*, **56** (5), 725–743.

Borio, C., Drehmann, M. and Xia, D. (2020). Predicting recessions: financial cycle versus term spread. *BIS Working Papers*, (818), 1–27.

Chodorow-Reich, G. (2014). The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis. *Quarterly Journal of Economics*, **129** (1), 1–59.

Cloyne, J., Ferreira, C., Froemel, M. and Surico, P. (2020). Monetary policy, corporate finance and investment. *Working Paper, University of California Davis*.

Davis, Haltiwanger, Jarmin and Miranda (2006). Volatility and dispersion in business growth rates: Publicly traded versus privately held firms. *NBER Macroeconomics Annual*, **21**, 107–179.

Drucker, S. and Puri, M. (2009). On loan sales, loan contracting, and lending relationships. *Review of Financial Studies*, **22** (7), 2835–2872.

Estrella, A. and Hardouvelis, G. (1991). The term structure as a predictor of real economic activity. *The Journal of Finance*, **46** (2), 555 – 576.

— and Mishkin, F. S. (1998). Predicting u.s. recessions: Financial variables as leading indicators. *Review of Economics and Statistics*, **80** (1), 45–61.

Favara, G., Gilchrist, S., Lewis, K. F. and Zakrajšek, E. (2016). Updating the recession risk and the excess bond premium. *FEDS Notes. Washington: Board of Governors of the Federal Reserve System.*

Feldhütter, P. and Poulsen, T. K. (2018). What determines bid-ask spreads in over-the-countermarkets? *Working Paper, Copenhagen Business School.*

Friedman, B. M. and Kuttner, K. N. (1992). Money, income, prices and interest rates. *American Economic Review*, **82**, 472–492.

— and — (1993a). Economic activity and the short-term credit markets: An analysis of prices and quantities. *Brookings Papers on Economic Activity*, **24**, 192–283.

— and — (1993b). *Why Does the Paper-Bill Spread Predict Real Economic Activity?*, University of Chicago Press, pp. 213–254.

— and — (1998). Indicator properties of the paper-bill spread: Lessons from recent experience. *Review of Economics and Statistics*, **80** (1), 34–44.

Gande, A. and Saunders, A. (2012). Are banks still special when there is a secondary market for loans? *Journal of Finance*, **67** (5), 1649–1684.

Gatev, E. and Strahan, P. E. (2006). Banks' advantage in hedging liquidity risk: Theory and evidence from the commercial paper market. *Journal of Finance*, **61** (2), 867–892.

— and — (2009). Liquidity risk and syndicate structure. *Journal of Financial Economics*, **93**, 490–504.

Gertler, M. and Gilchrist, S. (1994). Monetary policy, business cycles, and the behavior of small manufacturing firms. *Quarterly Journal of Economics*, **109** (2), 309–340.

— and Lown, C. S. (1999). The information in the high yield bond spread for the business cycle: Evidence and some implications. *Oxford Review of Economic Policy*, **15** (3), 132–150.

Gilchrist, S. and Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American Economic Review*, **102** (4), 1692–1720.

Giroud, X. and Müller, H. (2018). Firm leverage and regional business cycles. *Working Paper, New York University.*

Greenstone, M., Mas, A. and Nguyen, H.-L. (2017). Do credit market shocks affect the real economy? quasi-experimental evidence from the great recession and 'normal' economic times. *Working Paper, University of Chicago.*

Greenwood, R., Hanson, S. G., Shleifer, A. and Sørensen, J. A. (2020). Predictable financial crises. *NBER Working Paper No. 27396*.

Gürkaynak, R. S., Sack, B. and Wright, J. H. (2007). The u.s. treasury yield curve: 1961 to the present. *Journal of Monetary Economics*, **54** (8), 2291–2304.

Hadlock, C. J. and Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *Review of Financial Studies*, **23** (5), 1909–1940.

Harvey, C. (1989). Forecasts of economic growth from the bond and stock markets. *Financial Analysts Journal*, **45** (5), 38 – 45.

Holmström, B. and Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector. *Quarterly Journal of Economics*, **112** (3), 663–691.

Ivashina, V. and Scharfstein, D. (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics*, **97**, 319–338.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, **95** (1), 161–182.

Jordà, Ò., Schularick, M. and Tyler, A. M. (2013). When credit bites back. *Journal of Money, Credit and Banking*, **45** (s2).

Kiyotaki, N. and Moore, J. (1997). Credit cycles. *Journal of Political Economy*, **105** (2), 211–248.

Krishnamurthy, A. and Muir, T. (2017). How credit cycles across financial crisis.

Lian, C. and Ma, Y. (2020). Anatomy of corporate borrowing constraints. *Working Paper, University of Chicago*.

López-Salido, D., Stein, J. C. and Zakrajšek, E. (2017). Credit-market sentiment and the business cycle. *Quarterly Journal of Economics*, **132** (3), 1373–1426.

Mojon, B. and Gilchrist, S. (2016). Credit risk in the euro area. *The Economic Journal*, (2), 118–158.

Mueller, P. (2009). Credit spreads and real activity. *Working Paper, London School of Economics*.

Pflueger, C., Siriwardane, E. and Sunderam, A. (2020). Financial market risk perceptions and the macroeconomy. *Quarterly Journal of Economics*, **135** (3), 1443 – 1491.

Philippon, T. (2009). The bond market's q. *Quarterly Journal of Economics*, **124** (3), 1011–1056.

Rajan, R. G. and Zingales, L. (1998). Financial dependence and growth. *American Economic Review*, **88** (3), 559–586.

Schularick, M. and Tyler, A. M. (2012). Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. *American Economic Review*, **102** (2), 1029–1061.

Sufi, A. (2007). Information asymmetry and financing arrangements: Evidence from syndicated loans. *Journal of Finance*, **62** (2), 629–668.

Taylor, A. and Sansone, A. (2006). *The Handbook of Loan Syndications and Trading.* McGraw-Hill and the Loan Syndications and Trading Association (LSTA).

Thomas, H. and Wang, Z. (2004). The integration of bank syndicated loan and junk bond markets. *Journal of Banking & Finance*, **28** (2), 299–329.

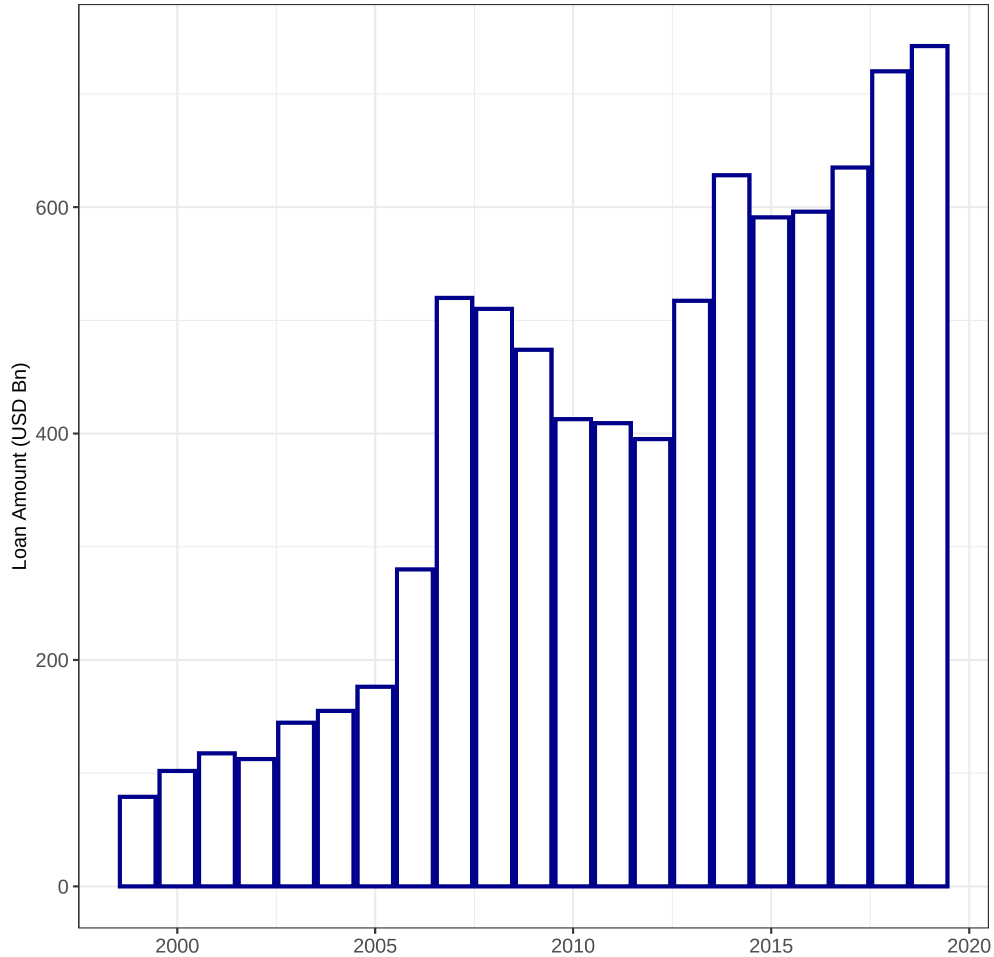

Figure 2: **Secondary loan market trading volume**
This figure plots the development of total loan volume traded in the secondary U.S. syndicated loan market over the 1999 to 2019 period. Source: LSTA.

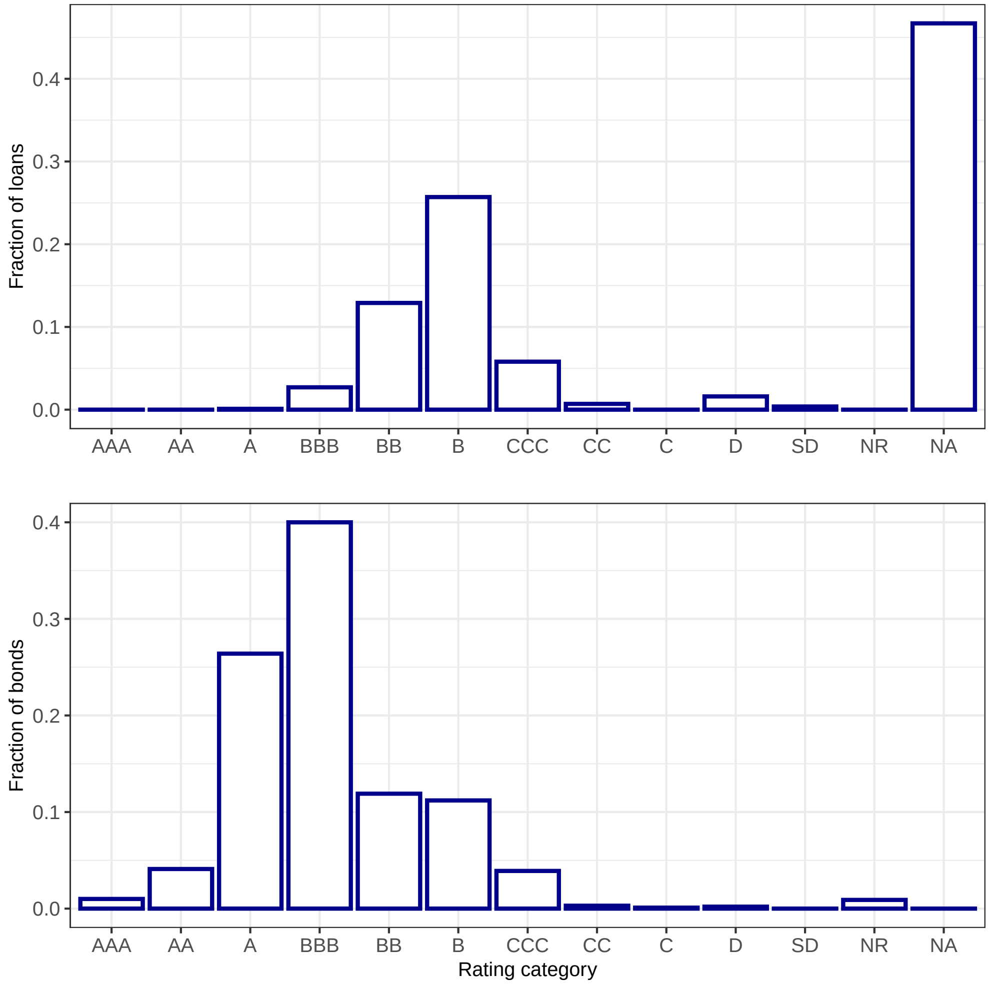

Figure 3: **Rating Distribution**
This figure plots the security level rating distribution across the loan market (top panel) and the bond market (bottom panel). Loan level ratings come from Standard & Poor's Leveraged Commentary & Data (S&P LCD) and Dealscan. Bond level ratings come frome TRACE.

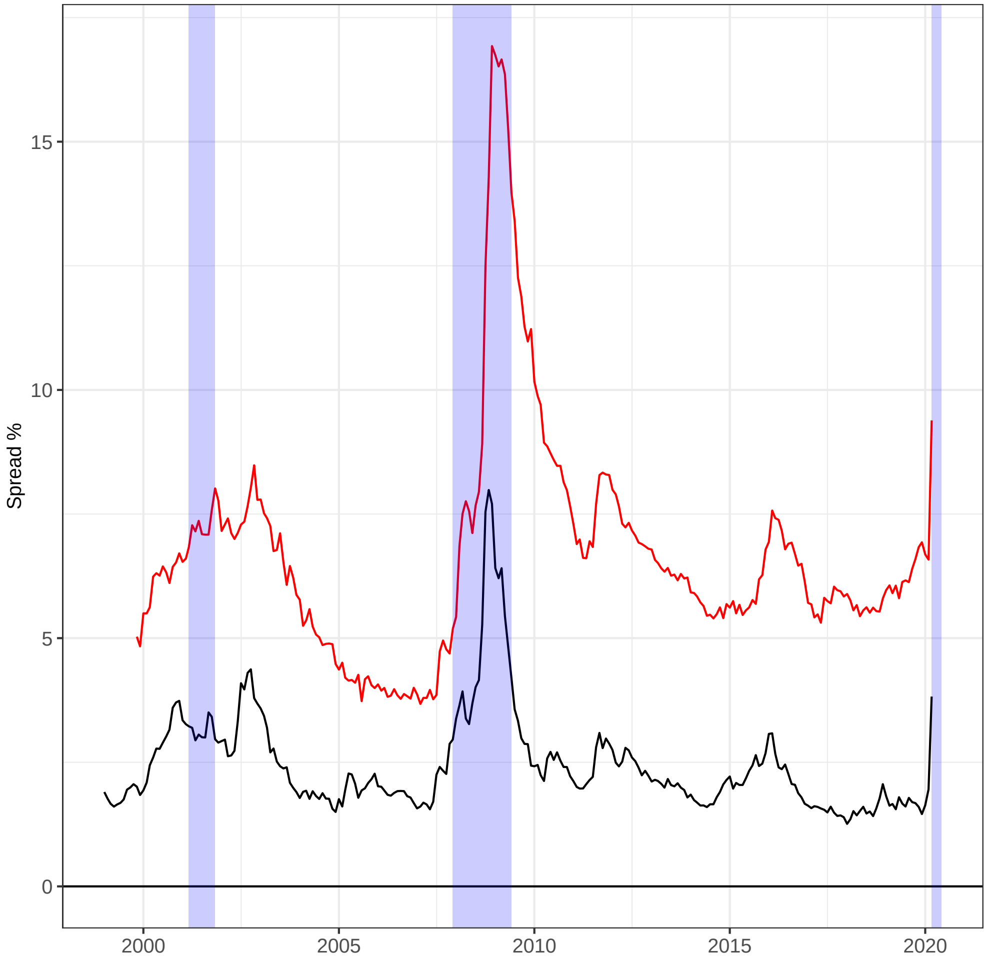

Figure 4: **Corporate credit spreads**
This figure plots monthly credit spread measures over time. Depicted are: (i) the loan spread (red line), defined as the average credit spread of syndicated loans issued by non-financial firms that are traded in the secondary market, and (ii) the bond spread (black line), defined following Gilchrist and Zakrajšek (2012) as the average credit spread on senior unsecured bonds issued by non-financial firms. Bars indicate NBER recessions. The sample period is 1999:11 to 2020:03.

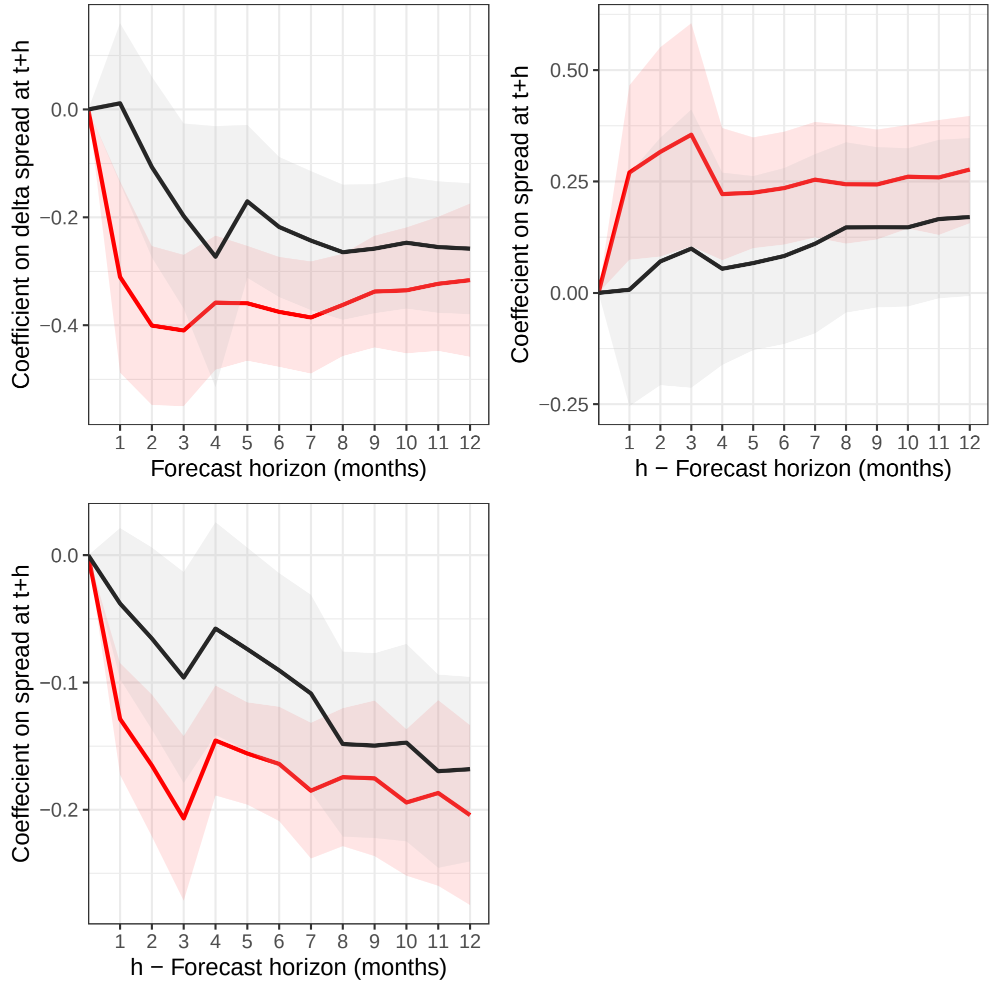

Figure 5: **Local Projections**
This figure plots the impulse response function using a Jordà (2005) local projections framework. In the top left panel the dependent variable is the h-month ahead growth in industrial production. The top right panel dependent variable is the h-month ahead change in unemployment rate. In the bottom left panel the dependent variable is the h-month ahead growth in payroll employment. The x-axis indicates the forecast horizon (in months). The coeffecient, at each forecast horizon, for the loan spread is in red. The black line is the bond spread. Shaded areas indicate 95% confidence intervals. The sample period is 1999:11 to 2020:03.

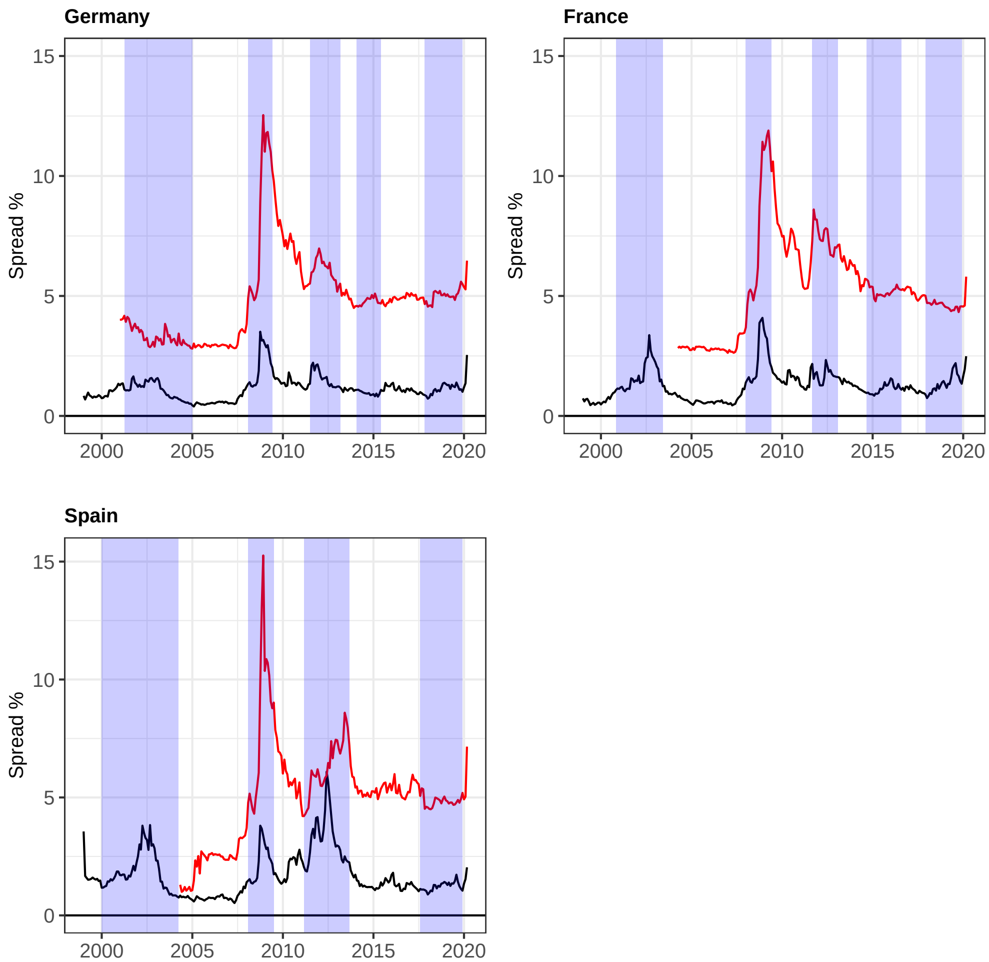

Figure 6: **European country loan and bond spreads**
This figure plots monthly loan (red lines) and bond (black lines) spread measures over time for Germany (top left), France (top right) and Spain (bottom left). Observations based on less than five loans are excluded. Bars indicate OECD recessions. The sample period for the loan spread is 2001:01 to 2020:03 for Germany, 2004:04 to 2020:03 for France, and 2004:05 to 2020:03 for Spain. The sample period for the bond spread is 1999:11 to 2020:03.

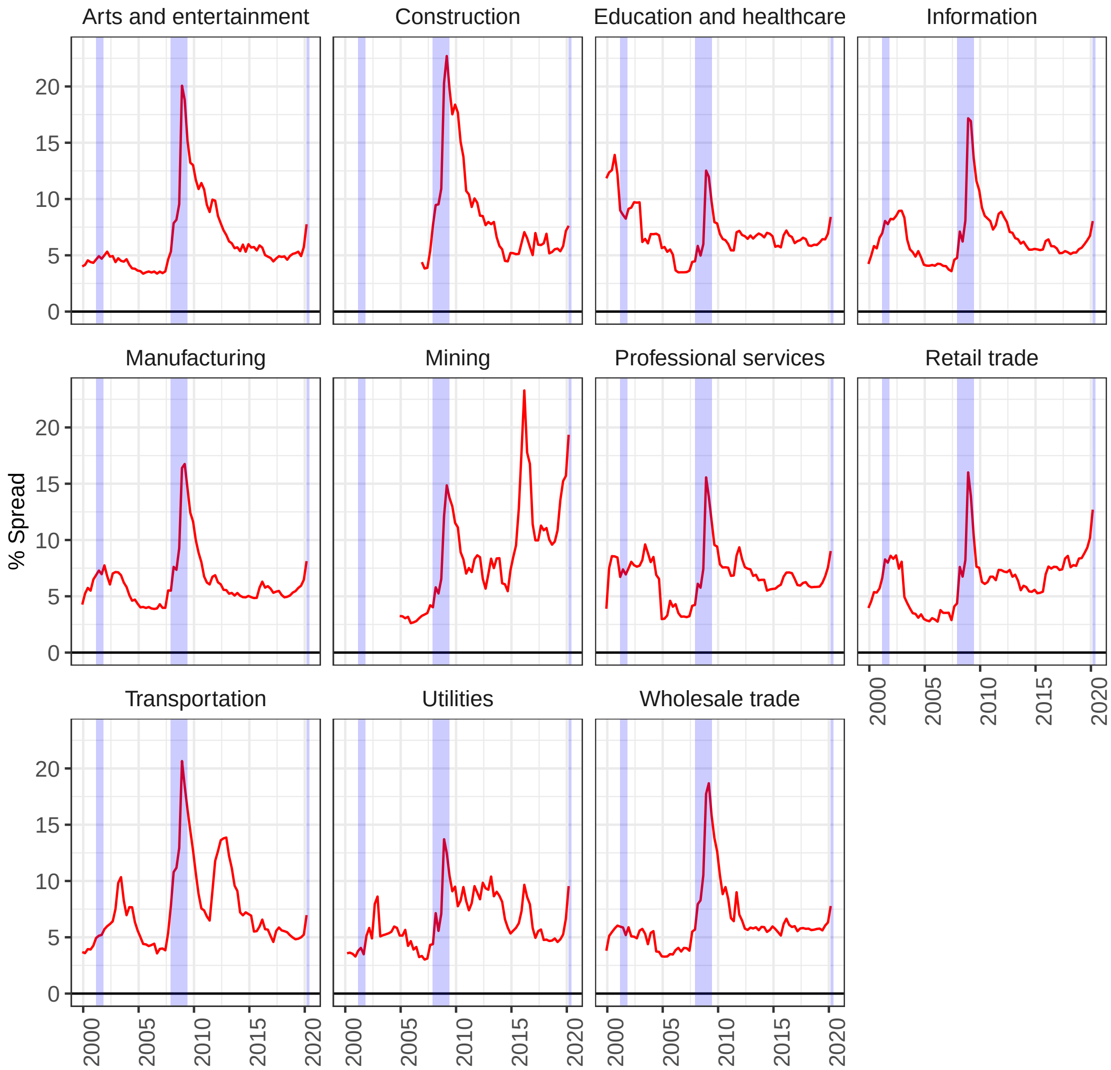

Figure 7: **Industry loan spreads**

This figure plots monthly loan spread measures over time for 11 non-financial sectors. Firms are classified into sectors following the BEA sector definition. The sample period is 1999:11 to 2020:03 (except for "Construction" and "Mining" due to limited data availablity in the early sample period). Bars indicate NBER recessions.

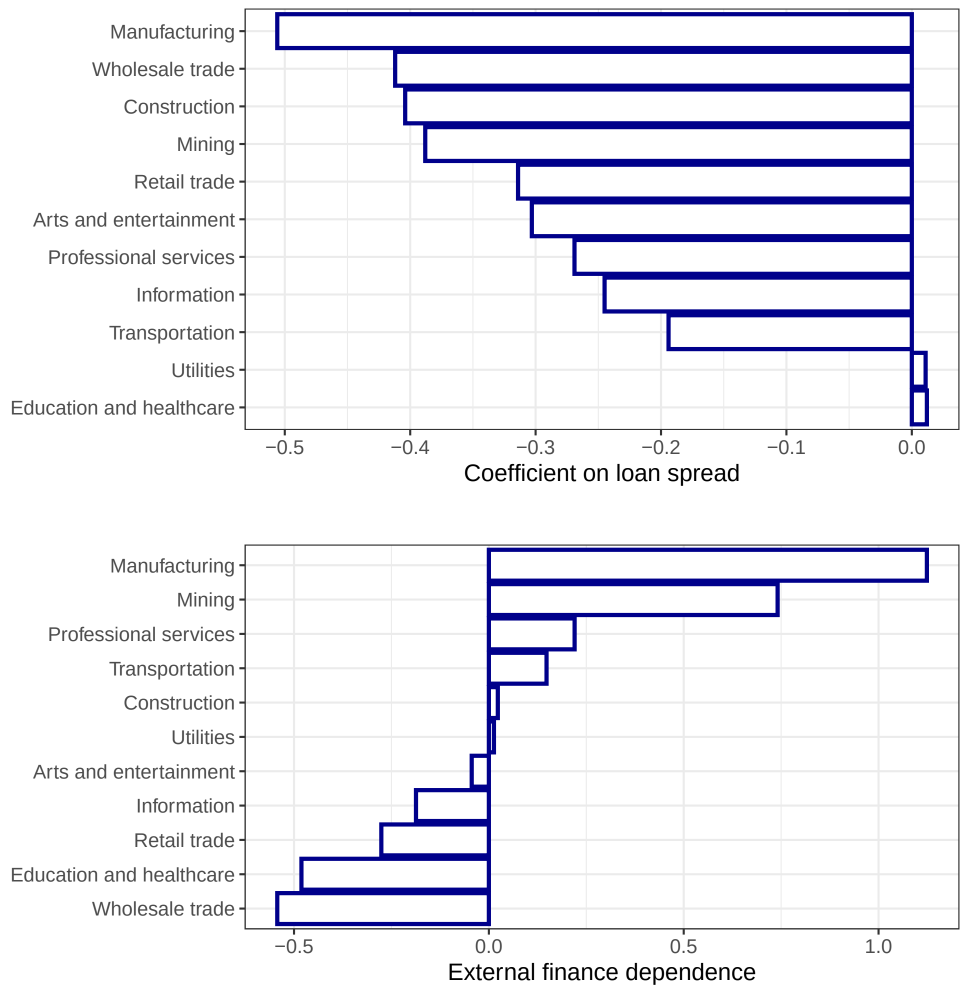

Figure 8: **Industry heterogeneity**
The top panel plots regression coefficients using seperate OLS regressions of industry level employment growth on the industry level loan spread. The bottom panel plots the Rajan and Zingales (1998) measure of external finance dependence for each industry over the 1999-2020 sample period. External dependence is defined as the ratio of total capital expenditures minus current cash flow to total capital expenditure.

Table 1: **Baseline forecasting results**

This table relates credit spread measures to future economic outcomes for the U.S. economy. The unit of observation in Panels A, B, and C is the monthly level t. The sample period is 1999:12 to 2020:03. The dependent variable in Panel A is the three-month ahead percentage change in industrial production, i.e., growth from $t-1$ to $t+3$. The dependent variable in Panel B is the three-month ahead change in unemployment rate. The dependent variable in Panel C is the three-month ahead percentage change in non-farm payroll employment. Each specification includes (not reported) a one period lag of the dependent variable, i.e., growth from $t-2$ to $t-1$, the term spread, i.e., the difference between 10-year and three-month U.S. treasury and the real FFR, i.e., the effective federal funds rate minus realized inflation. Incremental R^2 refers to the difference between the adjusted R^2 in the respective column and the adjusted R^2 of a baseline forecasting model, i.e., a model that only includes a one period lag of the dependent variable, the term spread, and the real FFR (but no credit spread). Reported OLS coefficients are standardized. t-statistics, based on heteroskedasticity and autocorrelation corrected Newey-West standard errors with a 4 period lag structure, are reported in parentheses.

	Forecast horizon: h = 3 months		
	(1)	(2)	(3)
Panel A. Industrial Production			
ΔS_t^{Loan}	-0.410		-0.396
	(-5.727)		(-3.831)
ΔS_t^{Bond}		-0.198	-0.030
		(-2.257)	(-0.267)
Adjusted R^2	0.313	0.198	0.311
Incremental R^2	+0.150	+0.035	+0.148
Observations	241	241	241
Panel B. Unemployment Rate			
ΔS_t^{Loan}	0.355		0.392
	(2.808)		(2.943)
ΔS_t^{Bond}		0.099	-0.081
		(0.623)	(-0.812)
Adjusted R^2	0.272	0.156	0.274
Incremental R^2	+0.122	+0.006	+0.124
Observations	241	241	241
Panel C. Payroll Employment			
ΔS_t^{Loan}	-0.207		-0.207
	(-6.332)		(-4.080)
ΔS_t^{Bond}		-0.096	0.004
		(-2.273)	(0.009)
Adjusted R^2	0.839	0.806	0.838
Incremental R^2	+0.041	+0.008	+0.040
Observations	241	241	241

Table 2: **Robustness**

This table relates different credit spread measures and equity returns to future economic outcomes for the U.S. economy. The unit of observation is the monthly level t. The sample period is 1999:12 to 2020:03. The dependent variable is the three-month ahead percentage change in industrial production, i.e., the growth from $t-1$ to $t+3$. Column (1) uses the Baa-Aaa corporate bond spread. Column (2) uses the corporate high yield minus AAA spread. Column (3) uses the Commercial paper - three-month Treasury bill spread. Column (4) uses the S&P500 monthly return from $t-1$ to t. Column (5) controls for the median bid-ask spread in the loan market at time t. Column (6-7) contain the loan and bond spread removing the 2009-09 crisis period. Column (8) uses a residual loan spread from a regression of the loan spread on loan contract terms such as size, age, amount, AISD, and indicators for secured, senior, and financial covenants. Each specification includes (not reported) a one period lag of the dependent variable, i.e., growth from $t-2$ to $t-1$, the term spread, i.e., the difference between 10-year and three-month U.S. treasury and the real FFR, i.e., the effective federal funds rate minus realized inflation. Incremental R^2 refers to the difference between the adjusted R^2 in the respective column and the adjusted R^2 of a baseline forecasting model, i.e., a model that only includes a one period lag of the dependent variable, the term spread, and the real FFR (but no credit spread or equity market return). Reported OLS coefficients are standardized. t-statistics, based on heteroskedasticity and autocorrelation corrected Newey-West standard errors with a four period lag structure, are reported in parentheses.

	Forecast horizon: h = 3 months							
	Other credit spreads			Equity market	Loan mkt liquidity	Ex 2008-09 crisis		Contract terms
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔS_t^{Loan}					-0.360	-0.207		
					(-5.337)	(-3.047)		
ΔS_t^{Bond}							-0.058	
							(-0.720)	
Δ Baa-Aaa spread	-0.277							
	(-3.918)							
Δ HY-Aaa spread		-0.248						
		(-4.013)						
Δ CP-bill spread			0.080					
			(0.898)					
S&P500 return				0.216				
				(2.921)				
Loan bid-ask spread					-0.328			
					(-3.141)			
Residual ΔS_t^{Loan}								-0.405
								(-5.646)
Adjusted R^2	0.237	0.222	0.166	0.204	0.386	0.150	0.115	0.318
Incremental R^2	+0.077	+0.062	+0.006	+0.041	+0.226	+0.034	+0.001	+0.120
Observations	241	241	241	241	241	225	225	241

Table 3: **Evidence from European countries**

This table relates credit spread measures to future economic outcomes across European countries. The unit of observation is the monthly level t. The sample period is 2001:01 to 2020:03 for Germany, 2004:04 to 2020:03 for France, and 2004:05 to 2020:03 for Spain. The dependent variable in column (1) is the three-month ahead percentage change in manufacturing production index, i.e., the growth from $t-1$ to $t+3$. The dependent variable in column (2) is the three-month ahead change in the unemployment rate. The dependent variable in column (3) is the three-month ahead percentage change in the construction index. Each specification includes (not reported) a one period lag of the dependent variable, i.e., the growth from $t-2$ to $t-1$, the term spread, i.e., the difference between 10-year Euro government bond (a GDP weighted average of all Euro area government bonds) and three-month EURIBOR, and the real EONIA, i.e., the overnight rate minus realized inflation. Incremental R^2 refers to the difference between the adjusted R^2 in the respective column and the adjusted R^2 of a baseline forecasting model, i.e., a model that only includes a one period lag of the dependent variable, the term spread, and real EONIA (but no credit spread). Contribution from ΔS_t^{Loan} measures the proportion of the increase in adjusted R^2 in the respective column that results from the inclusion ΔS_t^{Loan} as opposed to ΔS_t^{Bond}. Reported OLS coefficients are standardized. t-statistics, based on heteroskedasticity and autocorrelation corrected Newey-West standard errors with a 4 period lag structure, are reported in parentheses.

	Forecast horizon: h = 3 months		
	Manufacturing Index (1)	U/E (2)	Construction Index (3)
Panel A. Germany			
ΔS_t^{Loan}	-0.360	0.160	-0.093
	(-2.300)	(2.600)	(-1.300)
ΔS_t^{Bond}	-0.048	-0.0019	0.029
	(-0.690)	(-0.350)	(0.600)
Adjusted R^2	0.260	0.410	0.090
Incremental R^2	+0.111	+0.029	-0.031
% Contribution from ΔS_t^{Loan}	0.86	0.95	0.94
Observations	227	227	227
Panel B. France			
ΔS_t^{Loan}	-0.34	0.290	-0.068
	(-2.100)	(2.200)	(-1.200)
ΔS_t^{Bond}	-0.009	-0.002	0.010
	(-0.100)	(-0.019)	(0.140)
Adjusted R^2	0.190	0.210	0.082
Incremental R^2	+0.071	+0.035	-0.044
% Contribution from ΔS_t^{Loan}	0.91	0.92	0.96
Observations	188	188	188
Panel C. Spain			
ΔS_t^{Loan}	-0.200	0.130	-0.057
	(-1.900)	(2.800)	(-0.910)
ΔS_t^{Bond}	-0.130	0.052	-0.160
	(-1.000)	(0.830)	(-1.800)
Adjusted R^2	0.190	0.710	0.140
Incremental R^2	+0.058	+0.102	+0.051
% Contribution from ΔS_t^{Loan}	0.62	0.78	0.19
Observations	186	186	186

Table 4: **Impact of financial constraints**

This table relates credit spread measures to future economic outcomes for the U.S. economy. The unit of observation is the monthly level t. The sample period is 1999:12 to 2020:03. The dependent variable is the three-month ahead percentage change in industrial production, i.e., the growth from $t-1$ to $t+3$. Panel A reports results using loan spreads constructed separately for firms with total assets below and above the median level. Panel B reports results using loan spreads constructed separately for firms with age below and above the median level. In Panel C, firms are double sorted by age and size buckets, i.e., loan spreads are constructed separately for "young and small firms" (below median total assets *and* below median age) and "old and large firms" (above median total assets *and* above median age). Each panel includes a group of "private firms", defined as firms that cannot be matched to the Compustat North America database. Each specification includes (not reported) a one period lag of the dependent variable, i.e., growth from $t-2$ to $t-1$, the term spread, i.e., the difference between 10-year and three-month U.S. treasury and the real FFR, i.e., the effective federal funds rate minus realized inflation. Incremental R^2 refers to the difference between the adjusted R^2 in the respective column and the adjusted R^2 of a baseline forecasting model, i.e., a model that only includes a one period lag of the dependent variable, the term spread, and the real FFR (but no credit spread). Reported OLS coefficients are standardized. t-statistics, based on heteroskedasticity and autocorrelation corrected Newey-West standard errors with a 4 period lag structure, are reported in parentheses.

	Forecast horizon: h = 3 months		
	(1)	(2)	(3)
Panel A. By Size			
ΔS_t^{Loan} [Small firms]	−0.380		
	(−4.20)		
ΔS_t^{Loan} [Large firms]		−0.260	
		(−3.400)	
ΔS_t^{Loan} [Private firms]			−0.420
			(−5.500)
Adjusted R^2	0.300	0.230	0.320
Incremental R^2	+0.137	+0.067	+0.157
Observations	241	241	241
Panel B. By Age			
ΔS_t^{Loan} [Young firms]	−0.340		
	(−4.500)		
ΔS_t^{Loan} [Old firms]		−0.290	
		(−2.800)	
ΔS_t^{Loan} [Private firms]			−0.420
			(−5.500)
Adjusted R^2	0.270	0.240	0.320
Incremental R^2	+0.107	+0.077	+0.157
Observations	241	241	241
Panel C. By Size and Age			
ΔS_t^{Loan} [Small & young firms]	−0.390		
	(−4.500)		
ΔS_t^{Loan} [Large & old firms]		−0.210	
		(−1.800)	
ΔS_t^{Loan} [Private firms]			−0.420
			(−5.500)
Adjusted R^2	0.310	0.200	0.320
Incremental R^2	+0.147	+0.037	+0.157
Observations	241	241	241

Table 5: **Impact of loan rating**

This table relates credit spread measures conditional on loan ratings to future economic outcomes for the U.S. economy. The unit of observation in Panels A, B, and C is the monthly level t. The sample period is 1999:12 to 2020:03. Each panel reports results using loan spreads conditional on a loan level rating of BBB in Column (1), BB in Column (2), B and below in Column (3), and loans without available rating information in Column (4). The dependent variable in Panel A is the three-month ahead percentage change in industrial production, i.e., growth from $t-1$ to $t+3$. The dependent variable in Panel B is the three-month ahead change in unemployment rate. The dependent variable in Panel C is the three-month ahead percentage change in non-farm payroll employment. Each specification includes (not reported) a one period lag of the dependent variable, i.e., growth from $t-2$ to $t-1$, the term spread, i.e., the difference between 10-year and three-month U.S. treasury and the real FFR, i.e., the effective federal funds rate minus realized inflation. Incremental R^2 refers to the difference between the adjusted R^2 in the respective column and the adjusted R^2 of a baseline forecasting model, i.e., a model that only includes a one period lag of the dependent variable, the term spread, and the real FFR (but no credit spread). Reported OLS coefficients are standardized. t-statistics, based on heteroskedasticity and autocorrelation corrected Newey-West standard errors with a 4 period lag structure, are reported in parentheses.

	Forecast horizon: h = 3 months			
	(1)	(2)	(3)	(4)
Panel A. Industrial Production				
ΔS_t^{Loan}[BBB]	-0.105			
	(-1.557)			
ΔS_t^{Loan}[BB]		-0.260		
		(-3.538)		
ΔS_t^{Loan}[B and below]			-0.425	
			(-5.425)	
ΔS_t^{Loan}[Not Available]				-0.415
				(-4.040)
Adjusted R^2	0.170	0.226	0.322	0.315
Incremental R^2	+0.007	+0.063	+0.159	+0.152
Observations	241	241	241	241
Panel B. Unemployment Rate				
ΔS_t^{Loan}[BBB]	0.093			
	(0.654)			
ΔS_t^{Loan}[BB]		0.228		
		(1.424)		
ΔS_t^{Loan}[B and below]			0.341	
			(2.374)	
ΔS_t^{Loan}[Not Available]				0.401
				(3.019)
Adjusted R^2	0.155	0.199	0.260	0.305
Incremental R^2	+0.005	+0.049	+0.110	+0.155
Observations	241	241	241	241
Panel C. Payroll employment				
ΔS_t^{Loan}[BBB]	-0.089			
	(-1.793)			
ΔS_t^{Loan}[BBB/BB]		-0.174		
		(-5.742)		
ΔS_t^{Loan}[B/CCC/CC]			-0.221	
			(-6.578)	
ΔS_t^{Loan}[Not Available]				-0.199
				(-3.902)
Adjusted R^2	0.805	0.828	0.845	0.834
Incremental R^2	+0.007	+0.030	+0.047	+0.036
Observations	241	241	241	241

Table 6: **Credit Conditions**

This table relates credit supply conditions to credit spreads in the U.S. and Europe. The unit of observation is the quarterly level t. The sample period is 1999:11 to 2020:03 for the U.S., 2001:01 to 2020:03 for Germany, 2004:04 to 2020:03 for France, and 2004:05 to 2020:03 for Spain. Panel A focuses on U.S. data. Panel A1 uses as a dependent variable the Federal Reserve's Senior Loan Officer Survey, and is defined as the percentage of loan officers who respond that "lending tightened" less the percentage of loan officers who responded that "lending eased" over the previous quarter. For panel A2 we use the bank level ratio of total unused commitments/total assets and construct an aggregate ratio as a weighted average across banks each quarter. Specifically, the dependent variable is then the change in the aggregate ratio from the previous quarter. Panel B focuses on European data. The dependent variables in Panel B come from the European Central Banks' Banking Lending Survey and are defined in a similar way as the Federal Reserve's Senior Loan Officer Survey, i.e., are measures for country-specific credit supply conditions based on loan officer survey data. In all specifications we regress the credit conditions over $t-1$ to t on the change in credit spread over the same period. t-statistics are reported in parentheses. Coefficients are standardized.

Panel A. U.S.	(1)	(2)	(3)
Panel A1. Credit supply conditions			
ΔS_t^{Loan}	0.430		0.418
	(3.810)		(5.176)
ΔS_t^{Bond}		0.290	0.019
		(1.879)	(0.118)
Adjusted R^2	0.171	0.073	0.164
Observations	81	81	81
Panel A2. Banks' unused commitments			
ΔS_t^{Loan}	-0.351		-0.287
	(-2.435)		(-2.166)
ΔS_t^{Bond}		-0.306	-0.223
		(-1.922)	(-1.512)
Adjusted R^2	0.112	0.082	0.148
Observations	81	81	81

Panel B. Credit supply conditions in Europe			
Panel B1. Germany			
ΔS_t^{Loan}	0.376		0.458
	(3.748)		(3.214)
ΔS_t^{Bond}		0.159	-0.130
		(1.182)	(-1.031)
Adjusted R^2	0.128	0.011	0.126
Observations	70	70	70
Panel B2. France			
ΔS_t^{Loan}	0.480		0.417
	(3.545)		(3.533)
ΔS_t^{Bond}		0.329	0.140
		(1.436)	(0.778)
Adjusted R^2	0.218	0.094	0.221
Observations	64	64	64
Panel B3. Spain			
ΔS_t^{Loan}	0.370		0.357
	(2.018)		(1.951)
ΔS_t^{Bond}		0.176	0.031
		(1.008)	(0.352)
Adjusted R^2	0.122	0.015	0.109
Observations	63	63	63

Table 7: **Baseline industry forecasting results**

This table relates industry credit spread measures to future industry outcomes. The unit of observation is the industry-quarter level bt. The sample period is 1999:12 to 2019:12. The dependent variable in Panel A is the one quarter ahead percentage change in employment for industry b, i.e., the growth from $t-1$ to $t+1$. The dependent variable in Panel B is the one quarter ahead percentage change in establishments for industry b, i.e., the growth from $t-1$ to $t+1$. The dependent variable in Panel C is the one quarter ahead percentage change in gross output for industry b, i.e., the growth from $t-1$ to $t+1$. Each specification includes (not reported) a one period lag of the dependent variable, i.e., the growth from $t-2$ to $t-1$. The model reported in column (1) further includes the aggregate loan spread, term spread, i.e., the difference between 10-year and three-month U.S. treasury and the real FFR, i.e., the effective federal funds rate minus realized inflation. Year × quarter and industry fixed effects are included when indicated. Incremental R^2 refers to the difference between the adjusted R^2 in the respective column and the adjusted R^2 of a baseline forecasting model, i.e., a model that only includes a one period lag of the dependent variable, the term spread, and the real FFR (but no credit spread or fixed effects). Standard errors are clustered by industry. t-statistics are reported in parentheses. Coefficients are standardized.

	Forecast horizon: h = 3 months		
	(1)	(2)	(3)
Panel A. Industry total employed			
S_{bt}^{Loan}	−0.130	−0.171	−0.292
	(−3.491)	(−3.534)	(−4.609)
S_{t}^{Loan}	−0.239		
	(−3.818)		
Year × quarter fixed effects	No	Yes	Yes
Industry fixed effects	No	No	Yes
Adjusted R^2	0.452	0.558	0.590
Incremental R^2	+0.086	+0.192	+0.224
Observations	803	803	803
Panel B. Industry total establishments			
S_{bt}^{Loan}	−0.321	−0.304	−0.413
	(−3.373)	(−2.713)	(−2.834)
S_{t}^{Loan}	0.056		
	(0.746)		
Year × quarter fixed effects	No	Yes	Yes
Industry fixed effects	No	No	Yes
Adjusted R^2	0.196	0.294	0.395
Incremental R^2	+0.063	+0.151	+0.252
Observations	803	803	803
Panel C. Industry gross output			
S_{bt}^{Loan}	−0.003	−0.071	−0.099
	(−0.039)	(−1.075)	(−1.542)
S_{t}^{Loan}	−0.330		
	(−3.553)		
Year × quarter fixed effects	No	Yes	Yes
Industry fixed effects	No	No	Yes
Adjusted R^2	0.183	0.379	0.387
Incremental R^2	+0.082	+0.233	+0.241
Observations	611	611	611

Table 8: **Industry heterogeneity**

This table relates industry credit spread measures to future industry outcomes. The unit of observation is the industry-quarter level bt. The sample period is 1999:12 to 2019:12. The dependent variable is the one quarter ahead change in employment for industry b, i.e., the growth from $t-1$ to $t+1$. Column (1) interacts the industry loan spread with a dummy for the industries with the five largest external finance dependent (EFD) ratios. Column (2) interacts the industry loan spread with the continuous EDF value of the industry. Column (3) simultaneosuly interacts the loan spread with a dummy for the industries with the three largest external finance dependent (EFD) ratios, middle four and bottom four. Each specification includes (not reported) a one period lag of the dependent variable, i.e., the growth from $t-2$ to $t-1$, the term spread, i.e., the difference between 10-year and three-month U.S. treasury, and the real FFR, i.e., the effective federal funds rate minus realized inflation. EFD is defined following Rajan and Zingales (1998). Standard errors are clustered by industry. t-statistics are reported in parentheses. Coefficients are standardized.

	Forecast horizon: h = 3 months		
	(1)	(2)	(3)
S_{bt}^{Loan} x Top 5 EFD	-0.311		
	(-4.527)		
S_{bt}^{Loan} x Continuous EFD		-0.319	
		(-2.698)	
S_{bt}^{Loan} x Top 3 EFD			-0.519
			(-5.408)
S_{bt}^{Loan} x Middle 4 EFD			-0.269
			(-2.754)
S_{bt}^{Loan} x Bottom 4 EFD			-0.139
			(-1.606)
Industry fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Adjusted R^2	0.271	0.268	0.269
Observations	803	803	803

Table 9: **Alternative Weighting Schemes**

This table relates credit spread measures to future economic outcomes for the U.S. economy. The unit of observation is the monthly level t. The sample period is 1999:12 to 2020:03. The dependent variable is the three-month ahead change in industrial production, i.e., the growth from $t-1$ to $t+3$. Column (1) reports the baseline aggregate loan spread results for comparison [cf. Table 1 Column (1)]. In Columns (2) - (5) an aggregate loan spread is constructed as a weighted average across industry loan spreads using different weighting schemes. Specifically, Column (2) GDP-weights each industry-level loan spread. Column (3) weights each industry by its correlation between loan spread and industry employment [cf. Figure 8 Top panel]. Column (4) weights each industry according to its external finance dependence. Column (5) weights each industry by coefficients from an Elastic net regression. Each specification includes (not reported) a one period lag of the dependent variable, i.e., the growth from $t-2$ to $t-1$, the term spread, i.e., the difference between 10-year and three-month U.S. treasury and the real FFR, i.e., the effective federal funds rate minus realized inflation. Incremental R^2 refers to the difference between the adjusted R^2 in the respective column and the adjusted R^2 of a baseline forecasting model, i.e., a model that only includes a one period lag of the dependent variable, the term spread, and the real FFR (but no credit spread). Reported OLS coefficients are standardized. t-statistics, based on heteroskedasticity and autocorrelation corrected Newey-West standard errors with a 4 period lag structure, are reported in parentheses.

	Forecast horizon: h = 3 months				
	(1)	(2)	(3)	(4)	(5)
ΔS_t^{Loan} [Base]	-0.410				
	(-5.727)				
ΔS_t^{Loan} [GDP]		-0.396			
		(-5.006)			
ΔS_t^{Loan} [Industry]			-0.445		
			(-6.236)		
ΔS_t^{Loan} [EFD]				-0.443	
				(-4.805)	
ΔS_t^{Loan} [Elastic Net]					-0.449
					(-5.162)
Adjusted R^2	0.313	0.305	0.343	0.337	0.339
Incremental R^2	+0.150	+0.142	+0.180	+0.174	+0.176
Observations	241	241	241	241	241