Corporate Loan Spreads and Economic Activity*

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Abstract

We use secondary corporate loan market prices to construct a novel loan market-based credit spread. This measure has additional predictive power across macroeconomic outcomes beyond existing bond credit spreads as well as other commonly used predictors in both the U.S. and Europe. Consistent with theoretical predictions, our evidence highlights the *joint* role of financial intermediary and borrower balance sheet frictions. In particular, loan market borrowers are compositionally different from bond market borrowers, which helps explain the differential predictive power of loan over bond spreads. Exploiting industry specific loan spreads and alternative weighting schemes further improves our business cycle forecasts.

JEL classification: E23, E44, G20
Keywords: Credit spreads, Secondary loan market, Bonds, Credit supply, Business cycle

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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 financial accelerator type mechanisms or credit channel theories (e.g. Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997). These theories focus on the role of financial frictions—reflected in credit spreads—in affecting investment and output decisions of firms. Hence, credit spreads can act as signals, i.e., leading indicators of real economic activity.

The existing empirical literature generally relies on credit spreads derived from the corporate bond market likely because corporate loan prices, until recently, have not been available. Hence, an implicit assumption in most studies is that the same set of frictions are reflected across corporate bond *and* loan 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 macroeconomic 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 individual loans to U.S. non-financial firms over the November 1999 to March 2020 period. By using secondary market loan prices instead of the spread of new issuances in the primary market, we reduce the impact of sample selection driven by variation in borrower access to the loan market. 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), opening up the possibility that loan spreads convey additional useful information.

Our main finding is that loan spreads contain information about the future business cycle above and beyond other commonly used credit spread indicators. To motivate this result, Figure 1 Panel A, shows the development of our loan 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 deterioration in the health of the macroeconomy.

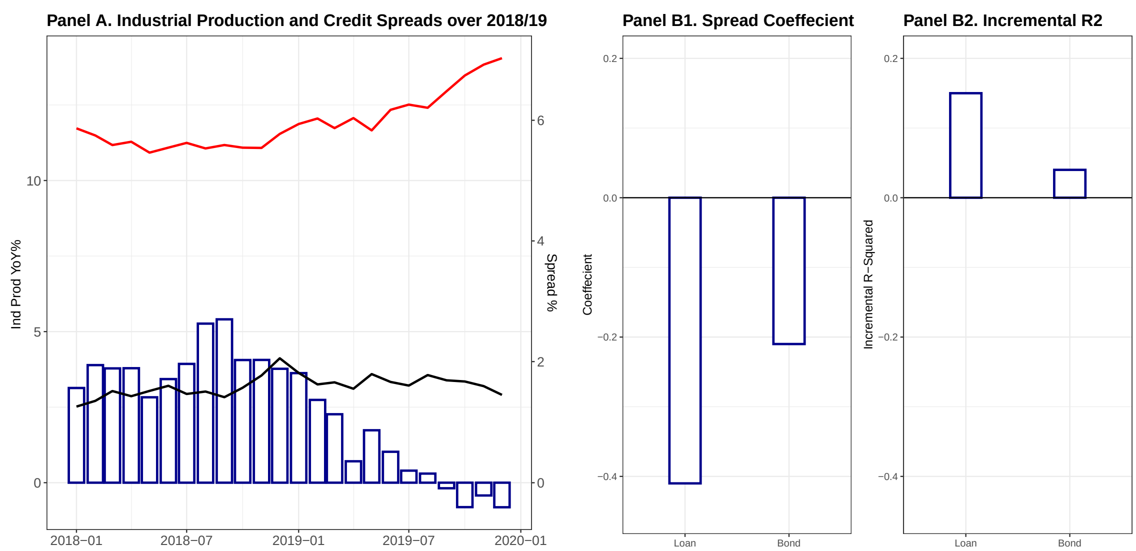

Figure 1: **Motivating evidence and main results**
Panel A plots the loan spread (red), bond spread (black) and YoY% in U.S. industrial production from January 2018 to December 2019 (blue bars). See Section 2 for details on the construction of the credit spread measures and underlying data sources. Panel B compares the coefficients and incremental R^2 of using the loan spread versus the bond spread 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 2 for underlying regressions, and Section 4 for a full discussion of the model.

We rigorously scrutinize this effect by means of predictive regressions over the entire 20-year sample period. Figure 1 Panel B summarizes our main result. 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 spread measure. In Panel B1, the standardized coefficient 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 subsequent 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 a 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 result using different economic aggregates, forecast horizons, and in out-of-sample tests.

We provide a series of robustness tests. First, we compare our loan spread measure to a wide 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 a high-yield bond spread 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 that are rated have a BB or B rating). Second, we run a horse race against the equity market, which is potentially the more informationally sensitive instrument. Third, we control for supply-demand conditions in secondary markets using a measure of loan market liquidity. 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) of loans vis-à-vis bonds could affect our results. We regress loan spreads on a set of loan level characteristics to extract a loan spread orthogonal to these characteristics. Fifth, we drop the financial crisis period (2007:Q4 – 2009:Q2) and the predictive effect of the loan spread drops by approximately half, but remains significant. The bond spread, in contrast, becomes economically small and insignificant, consistent with the interpretation that bond 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 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 spreads appear to have predictive power above and beyond other credit spread measures, we next examine potential explanations for why this might be the case. We explore two potential, non-mutually exclusive, channels: the additional predictive power of the loan market could be driven either by bank or borrower balance sheet frictions.

The first channel is based on the idea that loan market borrowers may have limited funding alternatives and hence are particularly sensitive to shocks to the balance sheets of financial intermediaries (e.g. Kiyotaki and Moore, 1997; Gertler and Kiyotaki, 2010; He and Krishnamurthy, 2013). We provide several pieces of evidence to test this hypothesis.

First, 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 as a measure of credit standards.[1] We use banks' undrawn C&I loan commitments as an alternative measure. In addition, we use bank profitability as well as loan loss provisions as proxies for bank health. Overall, our evidence suggests that loan spreads are more strongly correlated with both changes in credit standards in the loan market as well as bank health compared to bond spreads. This supports the view that loan spreads better reflect bank balance sheet frictions compared to other credit spread measures.

Second, we follow Gilchrist and Zakrajšek (2012) and decompose the loan spread into

[1] We use equivalent information from the European Central Bank's (ECB) Bank lending survey (BLS) for Germany, France, and Spain.

two components: i) a predicted spread that captures changes in the expected default risk of a borrower, and ii) an "Excess Loan Premium" (ELP), which captures the part of the spread not explained by expected default risk [i.e., the loan market equivalent of the "Excess Bond Premium" (EBP)]. Credit spreads adjusted for borrower fundamentals have frequently been used to proxy for supply-side frictions in the financial intermediary sector. We find evidence that both the excess bond and loan premia have predictive power for macroeconomic outcomes. The relative contribution of the ELP to the prediction model is larger compared to the EBP over our sample period, consistent with loan spreads reflecting changes in the risk bearing capacity of financial intermediaries.

However, it is the *predicted* component of the loan spread in particular that accounts for most of its explanatory power. Approximately two-thirds of the incremental R^2 relates to the predicted loan spread component compared to the ELP. The predicted bond spread, in contrast, is usually small and insignificant. This evidence highlights the role of borrower fundamentals in understanding the additional predictive power of loan spreads, i.e., intermediary frictions alone do not seem to fully explain the differential predictive power of loan versus bond spreads.

Motivated by the spread decomposition, we explore a second channel, which is based on the idea that loan market borrowers may be particularly sensitive to financial frictions that emanate from their own balance sheet (e.g. Bernanke and Gertler, 1989; Bernanke *et al.*, 1999). Several additional 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-à-vis bond markets.

First, we find the loan market is populated with firms that have limited access to alternative funding sources. For example, more than 70% of borrowers in the bond market have a credit rating of BBB or higher, while the majority of rated loan market borrowers 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. Further, loan market borrowers are, on average, significantly smaller and younger compared to bond market issuers. Thus, there is a limited overlap between bond and loan borrowers.

We then show that, within the loan market, the spread of smaller, younger, and private firms drives a substantial portion of the loan spread's predictive power. Small, young, and private firms are more likely to be financially constrained (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 more affected when credit market conditions tighten because of a lack of alternative funding sources, which eventually feeds into the real economy.[2] 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 19% of small borrowers also have a bond outstanding, compared to 70% for larger borrowers. As a result, the predictive power of a loan spread comprised of large and old firms—i.e., the segment with the largest loan-bond market overlap—is close to that of the bond spread. Similarly, we find that when we split loans according to loan level ratings, we find it is the loans with lower or no rating that contribute more to the predictive power of loan spreads for macroeconomic outcomes. Taken together this suggests that the characteristics of loan market borrowers can help explain the differential predictive power of the loan spread.

In summary, our evidence highlights the *joint* role of financial intermediary and borrower balance sheet frictions in understanding macroeconomic developments (Rampini and Viswanathan, 2019). Specifically, we find evidence that frictions on the side of financial intermediaries matter. However, borrower-specific risk seems to be the key driver of the differential predictive power of the loan vis-à-vis the bond spread. This emphasizes the importance of the borrower balance-sheet channel and is consistent with substantial differences in the composition of borrowers in the loan and the bond market. We also briefly discuss al-

[2] Cloyne *et al.* (2020), for instance, provide evidence that younger firms' investment behaviour 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.

ternative channels that highlight the role of e.g. uncertainty or investor sentiment. However, evidence suggests these channels are unlikely to explain the *differential* predictive power of loan vis-à-vis bond spreads.

In the last part of the paper, we show that there is important information at a less aggregated level (e.g., at an industry level) that can be useful when predicting macroeconomic outcomes. 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 Analysis (BEA) sector definitions. 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 heterogeneity 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 spread, we also find at the sectorial level that loan spreads have greater predictive power in industries with firms that are more dependent on external finance (Rajan and Zingales, 1998).

We can use this information to alter the way in which we aggregate loan-level spreads. Until now, the literature 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 research that examines the ability 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, 2020; López-Salido *et al.*, 2017; Philippon, 2009; Mueller, 2009), composite financial cycle indices (Borio *et al.*, 2020), and mutual fund flows (Ben-Rephael *et al.*, 2020).[3] 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 the existing empirical literature has focused mostly on supply-side frictions in understanding the predictive power of credit spreads, our results highlight the *joint* role of financial intermediary and borrower balance sheet constraints for understanding macroeconomic developments (Rampini and Viswanathan, 2019).

Our discussion thereby also relates to a strand of 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 opportunities 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 fluctuations. 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

[3] 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.*, 2020; Giroud and Müller, 2018).

macroeconomic outcomes.[4]

Our paper proceeds as follows. In Section 2, we provide details on the construction of the loan spread measure. Section 3 describes the differences in borrower composition between the bond and loan market. We present the baseline results in Section 4 and provide robustness tests as well as evidence from Europe. We explore the mechanisms in Section 5. Section 6 introduces alternative weighting schemes. Section 7 concludes.

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 the observation of 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

[4] 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 (2020) show that traders can use information from secondary loan market prices to generate positive alpha suggesting that information in loan spreads suggesting that information is incorporated earlier in the loan market as compared to the equity market.

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 50% of borrowers are private firms.

Data: Our analysis utilizes a novel dataset comprised 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",[5] and investors trade through dealer desks at large underwriting banks. The LSTA receives bid and ask quotes, every day, from over 35 dealers that represent the loan trading desks of virtually all major commercial and investment banks.[6] These dealers and their quoted loan prices represent over 80% of the secondary market trading in syndicated loans. Furthermore, it has been established that loan price quotes provide an accurate representation of secondary loan market prices for large corporate loans (Berndt and Gupta, 2009).[7]

We exclude credit lines and special loan types (around 1,703 loans), i.e., restrict our sample to term loans.[8] 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 LPC's 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

[5] 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.

[6] Investors usually trade through the dealer desks at large loan issuing banks. There is little public information about dealers who provide quotes that are collected by LSTA. However, we know the identities of the dealer banks for all loans in 2009. In Section C.2 of the Online Appendix we show that the top 25 dealers account for more than 90% of all quotes. We rank 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.

[7] We choose to focus our analysis on secondary market credit spreads instead of a primary market spread, e.g., the all-in-spread-drawn. Primary market loan spreads may simply reflect the endogenous changes to the composition of issuers over time. For example, during an economic downturn only the highest rated borrowers may be able to access the loan market.

[8] 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).

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 observations. On average, our sample is comprised of around 1,219 outstanding loans per month (min ∼330; maximum ∼2,293).[9]

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 Loan Identification Number (LIN), if available, or else a combination of the borrower name, dates, and 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. Section A of the Online Appendix contains a full list of the variables used and their sources.

Methodology: To examine the predictive power of loan 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 (obtained from Bloomberg) 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

[9] Section C.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 81 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.

quarterly.[10] 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 in 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 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 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:

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

Figure 3 plots our estimated loan spread as well as the bond spread measure by Gilchrist and Zakrajšek (2012) over time.[11] The loan spread and bond spread follow a similar pattern over time, with sharp movements around the 2001 recession, the 2008/2009 financial crisis,

[10] 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.

[11] 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.

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 to 0.45, or 0.23 excluding the 2008-09 crisis period (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 has an unconditional mean an order of magnitude higher than the bond spread. This is consistent with the syndicated loan market containing a wider universe of borrowers, in particular including more lower credit quality borrowers such as private firms who cannot access public bond markets.[12] A full summary of descriptive statistics for all variables is available in Section B of the Online Appendix.

3 Differences in borrower composition between loan and bond market

Before we turn to the analysis of whether loan spreads contain information about the future business cycle, it is useful to first understand how firms that borrow in the loan market compare with firms that are active in other markets, such as the bond market. Compositional differences between markets may help to understand potential differences in the predictive power of loan spreads relative to other measures, such as bond spreads, that have been used in the literature.

The sample of loan market borrowers comprises of all borrowers with loans traded on the secondary market at any point during our sample period that enter the calculation of our loan spread measure, as described in the previous section (3,713 unique borrowers). To construct a sample of bond market issuers we replicate the Gilchrist and Zakrajšek (2012)

[12] However, Schwert (2020) provides evidence that primary market loan spreads are higher than bond spreads also in a sample of loans matched with bond spreads from the same firm on the same date and accounting for other differences between loan and bond contracts.

bond spread measure using TRACE data.[13] This sample comprises of 2,917 unique issuers.

Table 1, Panel A, splits the sample into public and private firms. Public firms are defined as firms that can be linked to the Compustat database; the remaining firms are classified as private.[14] The overwhelming fraction of bond issuers are public firms (67%). In contrast, only about half of all loan market borrowers are public. This gives a first indication that the loan market is comprised of a wider universe of borrowers, including a larger share of firms that cannot/do not access public markets.

In the following, we compare characteristics of loan and bond market borrowers in more detail. Note that this discussion is based upon the sample of *public* firms for which data is available in Compustat. Therefore, given the larger fraction of private firms in the loan market, this comparison likely understates the differences in characteristics between loan and bond market borrowers.

Loan market borrowers are younger than bond market borrowers, on average.[15] Table 1, Panel B, reports that while 29% of loan market borrowers have an age <= 5 years, only 19% of bond market issuers fall in this age bucket. In contrast, 42% of bond market issuers are older than 20 years, compared to only 27% of borrowers in the loan market. These differences in the firm age distribution are also visualized in the top row of Figure 4.

Panel B further reports the fraction of loan (bond) market borrowers that are also active bond (loan) issuers by age group. While around 58% of "old" firms (age > 20 years) are also bond issuers, only 33% of "young" firms (age <= 5 years) are also active in the bond market. This indicates that the market overlap is larger for more mature firms. Conditional

[13] While we use the bond spread measure directly provided by Favara *et al.* (2016) in most of our analysis, the correlation with the bond spread measure calculated using TRACE data is very high (0.96). We rely on this measure in sub-sample analyses—see details in the next sections.

[14] Note that the number of unique "parent firms" in the public firm sample—identified by firms' Compustat Global Company Keys (GVKEY)—is somewhat lower than the number of loan market borrowers / bond market issuers. This is because some borrower IDs (issuer IDs) in the LSTA (TRACE) database are assigned to the same GVKEY. Given that this aggregation of firms to the parent level is only feasible for the set of public firms, we report the base private/public split using borrower/issuer IDs and then proceed reporting statistics at the parent firm, i.e., GVKEY, level in Panels B and C.

[15] Note that age or size information is not available for all firms in the Compustat database, hence the total number of firms in Panels B and C does not add up the to the total number of public firms reported in Panel A.

on being active in the bond market, it is in particular "young" firms that simultaneously are also loan market borrowers (42% of firms aged <= 5 years).

Panel C paints a similar picture, grouping firms by size. The typical loan market borrower is smaller than the typical bond market borrower and the pattern is even more striking compared to the evidence based on firm age. Only 16% of loan market borrowers have total assets > $6billion and 67% are in the smallest size category (<= $2billion). In contrast, about 37% of all bond issuers have total assets > $6billion. These differences are visualized in the middle row of Figure 4.

Focusing on the overlap between the markets, Panel C shows that in particular larger loan market issuers are likely to be also active in the bond market—around 2/3 of loan market borrowers with total assets > $6billion are also active bond issuers. Among the small loan market borrowers (<= $2billion), which account for 61% of all loan market firms, only 19% also are active in the bond market.

Overall, this discussion highlights that the overlap between the loan and the bond market is limited, in particular for the set of smaller, younger firms. This implies that the loan market is comprised of a wider universe of borrowers, including a larger fraction of firms that are not active in the bond market. This also highlights that simply conditioning on borrowers with both loans and bonds outstanding would exclude a large fraction of firms active in the loan market that may contribute to the predictive power of loan market credit spreads. We will return to this discussion when analyzing in detail if compositional differences can explain potential differences in predictive power of loan versus bond spread measures.

4 Loan spreads and economic activity

4.1 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 Gilchrist and Zakrajšek

(2012) 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, and ΔS_t is the change in spread from $t-1$ to t.[16] 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.[17] The regressions are estimated by ordinary least squares (OLS), with one lag of the dependent variable, i.e., economic activity from $t-2$ to $t-1$.[18] Due to the low level of persistence in the dependent variable (and ΔS_t), we use heteroskedasticity and autocorrelation corrected Newey-West standard errors with a four period lag structure. Alternatively, Hansen-Hodrick standard errors return very similar results. The sample period covers the November 1999 to March 2020 period.

Table 2 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, at the bottom of each panel we report the incremental increase in adjusted R^2 relative to a baseline model that uses only

[16] 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 (2020) for diagnosing financial crises. The forecasting power of spread changes can arise for two reasons. First, because 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.

[17] 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].

[18] 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 persistence. However, including additional lags up to 6 periods, or allowing for an optimal lag length selection based on the AIC leads to very similar results.

the term spread, the real federal funds rate, and the lagged dependent variable. Panel A of Table 2 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 the loan spread being associated with a 0.74% decrease in industrial production over the next 3 months, compared to an unconditional mean of 0.23% growth in industrial production.[19]

In column (2) we benchmark this result against a commonly used credit spread measure from the corporate *bond* market, the GZ spread (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 in-sample fit due to the bond spread is modest with a 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 are almost unchanged compared to a 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 for 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 2.

To examine dynamics, we extend our prediction model to consider longer forecast horizons in a local projections framework (Jordà, 2005). Figure 5 plots the coefficient 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 spread models are estimated in separate regressions.

[19] See Section B of the Online Appendix for a full list of the unconditional moments for each variable.

Focusing on industrial production (top-left panel), the predictive power of the loan spread 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 stronger predictive power compared to the bond spread.

4.2 Other credit spread and equity market measures

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. The bottom row of Figure 4 highlights that more than 70% 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). Thus a cleaner evaluation of the loan spread's additional predictive power might be to compare it to a bond spread conditional on a set of riskier borrowers.

To that end, Table 3, Panel A, columns (2) and (3) use the Baa-Aaa credit spread and a high-yield credit spread.[20] The Baa-Aaa credit spread measures the spread between Aaa rated corporate bonds and Baa rated corporate 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 spread has 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

[20] 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.

baseline corporate bond spread is -0.198 and the incremental R^2 is +3.5 p.p. [Table 2 column (2)]. For both spreads, however, the economic magnitude and contribution to in-sample fit remains significantly below that of the loan spread [reported again in Table 3, Panel A, column (1), as benchmark]. Section D.1 of the Online Appendix repeats Table 2 but keeps the loan spread in each column and the loan spread retains its significant predictive power.

We provide additional tests in Section D.2 of the Online Appendix. In particular, we use bond level pricing data from TRACE to create bottom-up bond 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 (4) in Table 3, Panel A, 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.

Finally, 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 3, Panel A, column (5) 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 spread [Table 3, Panel A, column (1)].

4.3 Robustness

This section further discusses the robustness of our main result. First, we control for supply-demand conditions in the secondary market by using a measure of loan market liquidity (plotted in Section C.1 of the Online Appendix). In particular, in Table 3, Panel B, column (2) we include the contemporaneous median bid-ask spread as an additional control. Our main result remains unchanged. Second, loan and bond contracts might be different with respect to non-price contract terms. We regress loan spreads on various contract terms and take the residual spread (see Section D.6 of the Online Appendix for details). Column (3) in Table 3, Panel B, uses this "residual loan spread" and finds very little difference in predictive power relative to the baseline loan spread. Third, results may be exclusively driven by the large changes in credit spreads during the 2008-09 financial crisis. Table 3, Panel B, columns (4) and (5) show that the predictive power of the bond spread becomes economically small and insignificant when excluding the financial crisis. 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).[21]

4.4 Evidence from European countries

A time series of secondary market loan prices has only been available for about 20 years, which is shorter than that of bonds and other debt instruments that often have a longer data history. While we cannot extend the time-series backwards, we can perform similar predictability tests using European data, i.e., exploit the fact that different countries have different business cycles. We focus on three of Europe's largest economies, Germany, France,

[21] We conduct a series of additional tests, which are relegated to—and discussed in more detail in—the Online Appendix Section D, including: i) The baseline forecasting regression assumes that increases and decreases of spreads have the same relationship with future economic activity. We test for potential asymmetric impacts (Stein, 2014) and find that both increases and decreases in loan spreads are correlated with future economic developments, with the effect of spread increases being somewhat stronger compared to decreases. ii) We test the predictive ability of loan and bond spreads on pseudo out-of-sample data and continue to find a higher predictive power for loan versus bond spreads.

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.[22] For the aggregate bond spread, we use the spread provided by Mojon and Gilchrist (2016).

Section E.2 of the Online Appendix plots 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 are substantially lower compared to the U.S. bond spread. This is consistent with the interpretation that only the highest quality European firms can access public debt markets and that European markets are more 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 and report the results in Table 4. Our dependent macroeconomic variables are the monthly unemployment rate, manufacturing goods production, and consumption goods production.

We start with the three-month ahead forecasts of macroeconomic outcomes in Germany in Panel A of Table 4. 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. The explanatory power increases by +11.1 p.p. above the baseline model. Decomposing this R^2 increase into a part that is due to the inclusion of the loan spread and a part that is due to the inclusion of the bond spread, we find the 86%

[22] We adjust the methodology by using equivalent EU variables. The term spread, i.e., the difference between 10-year Euro area 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.

of the increase in in-sample fit comes from the loan spread.

We find consistent results for an index of unemployment rate [column (2)] and an index of construction activity [column (3)] and 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.

5 Exploring the mechanism

What are the mechanisms that explain the higher predictive power of loan spreads vis-à-vis other commonly used measures? In the next step, we investigate both frictions on bank balance-sheets (Section 5.1) as well as borrower balance-sheets (Section 5.2) as potential channels.

5.1 Bank balance-sheet constraints

The first hypothesis is based on the idea that loan market borrowers may have limited funding alternatives and hence are particularly sensitive to shocks to the balance sheets of financial intermediaries. A deterioration in the health of intermediaries (e.g. Holmström and Tirole, 1997), frictions in raising new capital (e.g. He and Krishnamurthy, 2013; Gertler and Kiyotaki, 2010) or fluctuations in collateral value (e.g. Kiyotaki and Moore, 1997), can impede the capacity and/or willingness of intermediaries to provide credit to the economy which is reflected in credit spreads. We find several pieces of evidence that support the hypothesis that intermediary frictions are related to the differential predictive power of the loan spread.

5.1.1 Financial conditions

We first examine to what extent loan and bond spreads are associated with a tightening of financial conditions using two commonly used measures in the literature, i) the Federal

Reserve Loan Officer survey and ii) commercial banks' unused credit lines.

In Panel A of Table 5, we regress a measure of aggregate bank lending standards on our loan spread and benchmark the effect against the bond spread. The dependent variable in columns (1) to (3) 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). Specifically, it is defined as the percentage who respond "lending tightened", less the percentage who responded that "lending eased", i.e., a net percentage. A higher SLOOS measure signals a tightening of lending standards and thus supply-side frictions of financial intermediaries. The survey is conducted quarterly and reflects the credit conditions in the previous quarter.

In column (1) [column (2)], we regress the SLOOS indicator on the change in loan (bond) spread also over the previous quarter—i.e., we focus on the contemporaneous relationship between credit conditions and spreads. 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 economically small and insignificant. In the Online Appendix Section E.1, 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.

We use banks' unused commitments as a second measure of financial conditions. The dependent variable in columns (4) to (6) of Table 5 are 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 (4) [column (5)] we regress the change in the undrawn commitments over the previous quarter on the change in loan (bond) spread over the same quarter—i.e., a measure of the contemporaneous relationship. We include both spreads in column (6). 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. Overall, the results of both tests are consistent with loan spreads reflecting a reduction in credit supply in the primary loan market.

Table 5, columns (7) to (9) documents a link between the loan spread and the profitability of the financial corporate sector as measured by its return on assets (aggregated ROA across all U.S. banks using data from the SNL financial database). Again, results indicate a stronger link between the profitability of the financial sector and the loan spread compared to the bond spread. Consistent results are obtained using loan loss reserves (as a fraction of gross loans) as a proxy for the condition of the financial intermediary sector [columns (10) to (12)].

Overall, the results indicate a stronger link between the health of the financial intermediary sector and corporate loan spreads compared to bond market credit spread. This evidence is consistent with loan spreads better approximating balance sheet frictions of financial intermediaries, which manifest in credit supply contractions, and hence affecting real economic development.

5.1.2 Credit spread decomposition

As a second test to better gauge the differential importance of the bank and borrower balance-sheet channel, we follow Gilchrist and Zakrajšek (2012) and decompose the loan spread into two components: i) a component that captures changes in default risk based on the fundamentals of the borrower (or differences in contractual terms), i.e., the "predicted spread", and ii) a residual component that captures the price of risk above a default risk premium, i.e., the "excess loan premium" (ELP). A detailed description of the methodology used to decompose the loan spread is provided in Online Appendix Section D.6. The decomposition of the bond spread—used as a benchmark—is available from the Federal Reserve website.

The idea behind the decomposition is that the residual part of the spread, i.e., the part that cannot be explained by borrower default risk, plausibly captures frictions in the financial intermediary sector that are reflected in credit spreads. The predicted component of the spread, in contrast, captures spread variations due to changes in balance sheet conditions of borrowers, i.e., economic fundamentals (Philippon, 2009). This decomposition is therefore helpful in assessing the relative importance of bank and borrower balance sheet constraints in explaining the predictive power of loan spreads for economic developments.

We run forecasting regression (2) using decomposed spreads and report the results in Table 6. For all macroeconomic outcomes, i.e., industrial production (Panel A), unemployment rate (Panel B), and payroll employment (Panel C), we find that both the predicted spread, $\hat{S}_t^{Loan}$, and the ELP_t have significant predictive power. Interestingly, the economic magnitude is higher for the predicted component as compared to the ELP_t, suggesting that borrower balance sheets might be relatively more important in understanding the predictive power of the loan spread—a hypothesis we explore in more detail in Section 5.2. Consistently, the incremental contribution of the predicted spread to the R^2 is also higher compared to the ELP_t (e.g., 67% in Panel A of Table 6).

The importance of the predicted bond spread, $\hat{S}_t^{Bond}$, versus the excess bond premium (EBP_t) is less clear [column (2)]. For example, $\hat{S}_t^{Bond}$ and the EBP_t have similar predictive power for the 3-month ahead industrial production, no predictive power for the unemployment rate, and only the EBP_t appears to predict payroll employment (77% of the incremental R^2). Overall, however, results indicate that the EBP_t, if anything, has more predictive power relative to the predicted bond spread, which is consistent with the results reported by Gilchrist and Zakrajšek (2012) over a longer time period.

Finally, we run a horse race between all credit spread components and report the results in column (3). We find that—similar to the baseline results reported in Table 2—the $\hat{S}_t^{Bond}$ and EBP_t do not appear to add much predictive power to the forecasting model. Again, the coefficients become small and are also statistically not distinguishable from zero. Overall, while the ELP_t has some predictive power, the predicted spread, i.e., our measure of the deterioration of a borrower's balance sheet, appears to have the larger contribution to the model. We explore borrower balance sheet effects in the next section in more detail.

5.2 Borrower balance-sheet constraints

The second hypothesis is based on the idea that loan market borrowers may be particularly sensitive to financial frictions that emanate from their own balance sheet. These frictions manifest themselves in a wedge between the cost of external funds and the opportunity cost of internal funds, labelled the "external finance premium" (e.g. Bernanke and Gertler, 1989). A deterioration in the health of borrower balance sheets is further amplified via a "financial accelerator" effect (e.g. Bernanke *et al.*, 1999), which is subsequently reflected in the borrower's cost of credit. Several pieces of evidence support the conjecture that the differential predictive power of the loan spread reflects compositional differences in borrower exposure to financial frictions.

5.2.1 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 contractions. For example, Figure 4 highlights that more than 70% 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 half of the borrowers are publicly traded firms. Thus, there is a limited overlap between bond and loan borrowers. Consequently, a repricing of risk 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 predictive 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 constrained (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 7 performs the same aggregate forecasting regression as Table 2 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 database (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 (coefficient 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 7 reports results using a loan spread measure constructed from private firms, defined as firms that cannot be linked to Compustat.[23] The results indicate that the predictive power of a loan spread constructed from private firms is stronger even compared to small and young firms with a coefficient of -0.420 and an incremental R^2 of +15.7 p.p.

In Table 7 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 stronger for small and young versus old and large firms. The coefficient 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 baseline bond spread measure [coefficient of -0.210 versus -0.19 and incremental R^2 of +3.7 p.p. versus +3.5 p.p., cf. Table 2, column (2)].

[23] 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.

The predictive power of small and young firms is close to that of private firms [coefficient of -0.390 versus -0.420 and incremental R^2 of +14.7 p.p. versus +15.7 p.p., cf. Table 2, column (2)].

The results documented in Panel C indicate that restricting attention to borrowers with the largest overlap between the loan and the bond market—i.e., large and old firms—attenuates the predicitve power of loan vis-à-vis bond spreads. That is, it is precisely the set of *non-overlapping* borrowers that explains the largest part of the additional predictive power of loan spreads.

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 financial frictions. Importantly, among the group of small, young, and private firms in particular, the overlap between the loan and bond market is limited, as discussed in Section 3.

5.2.2 Effect by ratings

An alternative way to examine the role of financial frictions on the borrower side is to look at loan spreads conditional on rating groups. 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 8 performs the same aggregate forecasting regression as Table 2, 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 three-month ahead macroeconomic outcomes. This is consistent with the safest borrowers being least exposed to bank loan supply contractions.

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, shows a very similar pattern to loans rated B or below. Comparing to the baseline results in Table 2, 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 financial frictions to matter the most.

5.3 Discussion and alternative explanations

The evidence presented so far in this section indicates that frictions on both the side of financial intermediaries and borrower fundamentals matter for understanding the predictive power of credit spreads. Specifically, the evidence suggests that borrower-specific risks are a key driver of the differential predictive power of the loan vis-à-vis the bond spread. This emphasizes the importance of the borrower balance sheet channel and is in line with the substantial differences in the composition of borrowers in the loan and the bond market. Overall, our evidence is consistent with models that highlight that financial intermediary and firm balance sheet constraints *jointly* determine economic activity, see e.g. Rampini and Viswanathan (2019).

Beyond financial friction-based explanations, the literature has explored other potential channels that could explain the loan spread's differential predictive power. In this section, we provide a brief discussion.

An alternative channel highlights the role of uncertainty in driving borrower demand for credit. In the seminal work of Bloom (2009) and Baker *et al.* (2016) uncertainty affects firm incentives to invest and hire via a real options channel. Alternatively, uncertainty can affect borrower demand for credit by affecting the cost of capital (Pflueger *et al.*, 2020). Hence, an increase in credit spreads may in fact be capturing an uncertainty-induced increase in the marginal cost of new finance, which impacts future economic activity. This may be better captured by loan compared to bond market credit spreads, as the loan market comprises of smaller more volatile firms.

We examine this hypothesis by including proxies for uncertainty in the prediction model. The proxies include the VIX, Price of Volatile Stocks (PVS) index of Pflueger *et al.* (2020), the Economic Policy Uncertainty (EPU) index of Baker *et al.* (2016), the financial uncertainty index of Jurado *et al.* (2015), and the newspaper-based index of Bybee *et al.* (2020). Results are reported in Table 9. While uncertainty proxies do contain predictive power for future economic conditions, consistent with the channels discussed above, the forecasting coefficient on the loan spread remains large and statistically significant in all specifications. This indicates that uncertainty does not (fully) explain the additional predictive power of the loan spread.

An alternative behavioural channel highlights the role of investor sentiment/beliefs. Greenwood and Hanson (2013) and López-Salido *et al.* (2017), examine the role of investor sentiment in shaping economic outcomes. Specifically, they find narrow credit spreads typically proceed economic downturns, a sign that credit risk is not being appropriately priced. This behaviour can be motivated by models based on "extrapolative/diagnostic expectations". Bordalo *et al.* (2018), for example, argue that investors under-price risk in good times creating a credit boom. At some point this boom begins to sour as the malinvestment is realized, leading credit spreads to overreact in the opposite direction.

Consequently, investor sentiment appear to be important to understand credit spreads. Our focus, in contrast, is on the relative predictive power of loan vis-à-vis bond spreads. Our tests suggest that borrower fundamentals—and not the excess loan spread—account for the largest part of the predictive power of the loan spread. López-Salido *et al.* (2017), however, argue that investor sentiment is more likely to be captured by the excess credit spread. In other words, investor sentiment unlikely explains the *relative* predictive power of loan versus bond market credit spreads. A more detailed examination of the role that sentiment plays *within* the loan market is an interesting avenue for future research.

6 Industry-level evidence and aggregation

In this section, we extend the basic bottom-up credit spread calculation framework along two important dimensions. First, we aggregate credit spreads at a more granular level—the industry level—instead of creating one aggregate economy-level time series using loan-level spreads. Second, we explore alternative weighting schemes. That is, we examine if forecasting power can be improved by deviating from the assumption that credit spreads are aggregated using equal weights. Both exercises can shed further light on the sources of the predictive power of loan market credit spreads.

6.1 Across industry heterogeneity

In this section, we show there is additional information to be captured by going beyond aggregate spreads and looking at the cross-sectional heterogeneity in spreads. Bottom-up credit spread measures allow 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 further our understanding as to why loan spreads are informative.

6.1.1 Industry-level forecasting

Constructing industry-level credit spreads: 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 definitions, excluding financial and government owned firms. Industry-level loan spreads, S_{bt}^{Loan}, 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.[24]

Figure 6 plots industry loan spreads over time. Loan spreads are not perfectly correlated across industries. For example, while the "Construction" and "Transportation" sectors 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 fuelled by collapsing oil and metal prices, which is reflected in a spread increase that even surpassed the 2008-09 level. Figure 6 also highlights the heterogeneous impact of COVID-19 across industries, with exposed industries such as "Mining" and "Retail Trade" experiencing larger spikes in spreads as the crisis unfolded.

Baseline industry-level 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.[25] The baseline results are reported in Table 10.

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 now include the loan spread level and not the change in 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 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

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

[25] 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-seasonalized macroeconomic data is any underlying time trend and residual component.

common time trends that affect 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 remains similar.[26] We find consistent results in Panels B and C using alternative industry specific economic outcomes as dependent variables.

6.1.2 Differences in external finance dependence across industry

Table 10 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 Sections 3 and Section 5.2, the loan market comprises of firms that may have limited access to alternative funding sources and exhibit a higher sensitivity to bank loan supply contractions. 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 7 summarizes the results of separate OLS regressions for each industry, where industry-level employment growth is regressed on the industry-level loan spread. The blue bars indicate the regression coefficient and highlight the heterogeneity in correlations. Loan spreads in "Manufacturing", "Wholesale trade", "Construction", and "Mining" seem to be relatively more associated with future growth in employment than other

[26] 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.

industries.

The bottom panel of Figure 7 summarizes the external finance dependence (hereafter EFD) of each industry. We define a sector's dependence on external finance following Rajan and Zingales (1998). EFD is defined as the ratio of total capital expenditures minus current cash flow to total capital expenditure.[27] The correlation between the top and bottom panel is 0.50. Table 11 mirrors the specification in column (3) of Table 10 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 result indicates 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 continuous *EFD* measure for a given industry, with similar 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 consistent results using industry establishments and gross output as dependent variables (untabulated).

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

6.2 Alternative weighting schemes

Finally, we explore if alternative weighting schemes in the creation of the aggregate loan spread time series can be used to improve forecasting. So far, 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

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

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 12 reports aggregate level regressions using the three-month ahead industrial production as the dependent variable. That is, the table mirrors Table 2, 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 7 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 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 11 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 being comprised 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. That is, we use a statistical approach 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)].[28] 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, results untabulated).

Overall, this section highlights the usefulness of bottom-up credit spread measures in uncovering cross-sectional heterogeneity. Further, deviating from simple arithmetic averaging when constructing aggregate measures from microdata can help improve aggregate forecasting results—an area that deserves more attention in future research.

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 used in previous literature. Importantly, the predictive power of our loan spread measure is consistent with existing the-

[28] Results are similar if LASSO or Ridge regressions are used to choose optimal weights. Note the R^2 using a machine learning approach in column (5) is slightly below the R^2 using alternative aggregation schemes. This is due to the regularization penalty added to the least squares estimation to prevent model overfitting.

ories on the role of financial frictions in amplifying business cycles. Compositional differences between firms borrowing in the loan vis-à-vis the bond market explain part of the predictive power of loan over bond spreads. We show how the forecasting power can be enhanced even further through different aggregation methods.

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 with respect to 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 the loan spread (and of other 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 covers the last 20 years (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 additional 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 were 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 a time 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.

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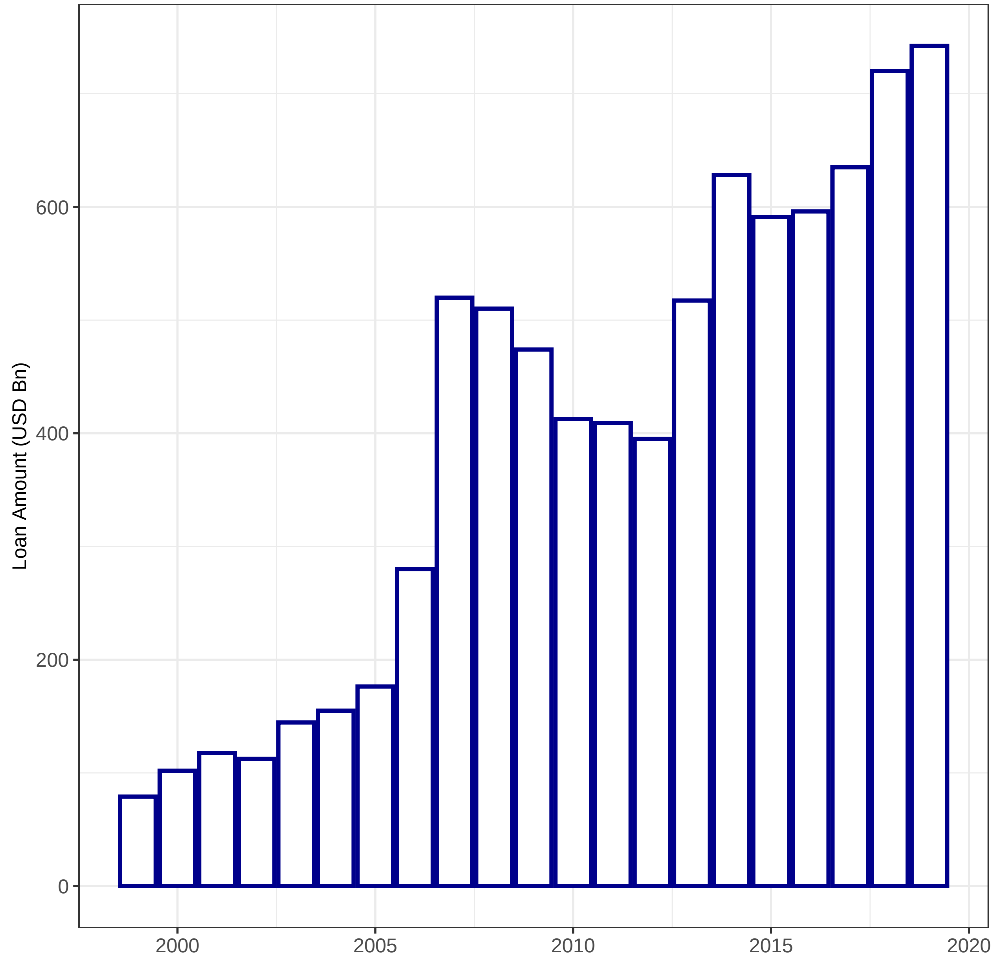

Figure 2: **Secondary loan market trading volume**
This figure plots the development of total loan volume traded in the secondary U.S. syndicated loan market over the 1999 to 2019 period. Source: LSTA.

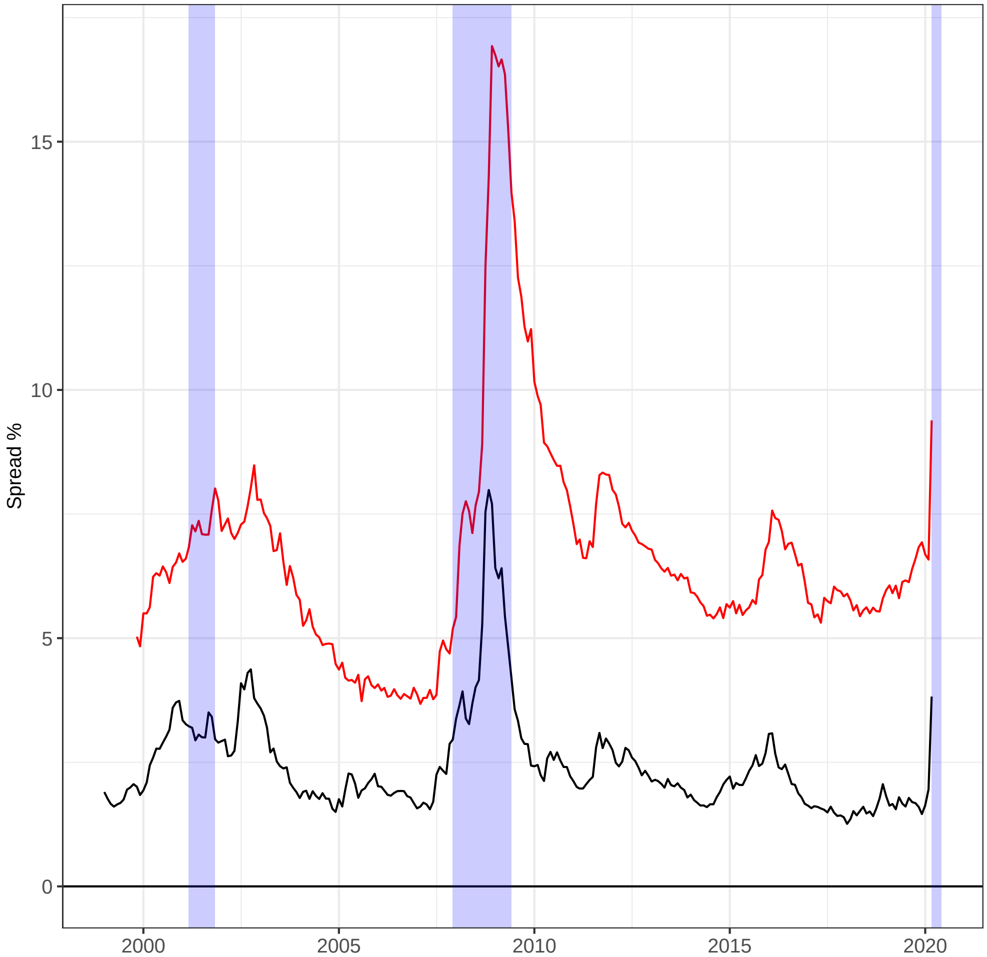

Figure 3: **Corporate credit spreads**
This figure plots monthly credit spread measures over time. Depicted are: (i) the loan spread (red line), defined as the average credit spread of syndicated loans issued by non-financial firms that are traded in the secondary market, (ii) the bond spread (black 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.

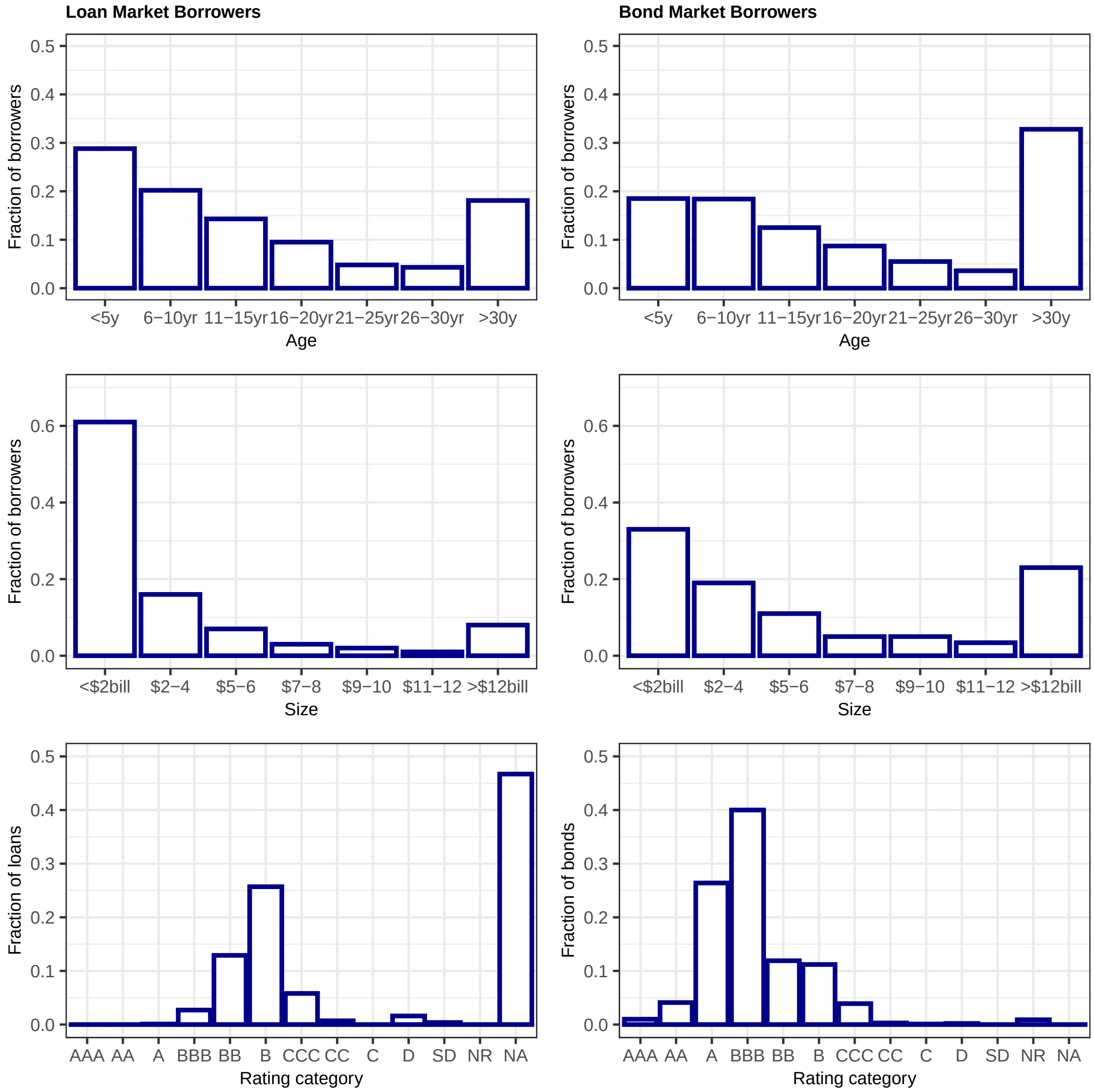

Figure 4: **Borrower characteristics**

This figure plots the characteristics of loan and bond market borrowers. The top row plots the distribution of age (number of years firm data exists in the Compustat North America database). The middle row plots the distribution of size (Total Assets in the Compustat North America database). The bottom row plots the security level rating distribution. Loan level ratings come from Standard & Poor's Leveraged Commentary & Data (S&P LCD) and Refinitiv's Loanconnector. Bond level ratings come from TRACE.

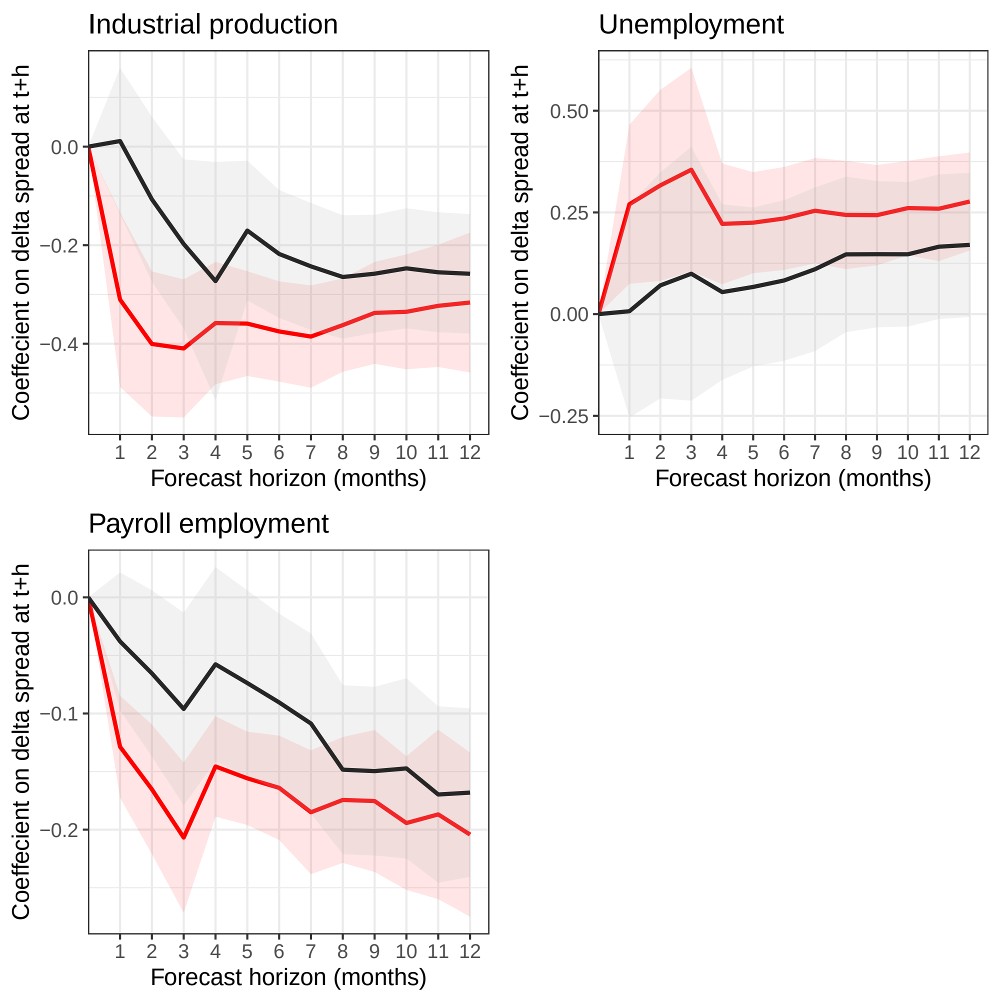

Figure 5: **Local Projections**

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. In the top right panel, the 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 coefficient, at each forecast horizon, for the loan spread is in red. The black line is the coefficient on the bond spread. Shaded areas indicate 95% confidence intervals. The sample period is 1999:11 to 2020:03.

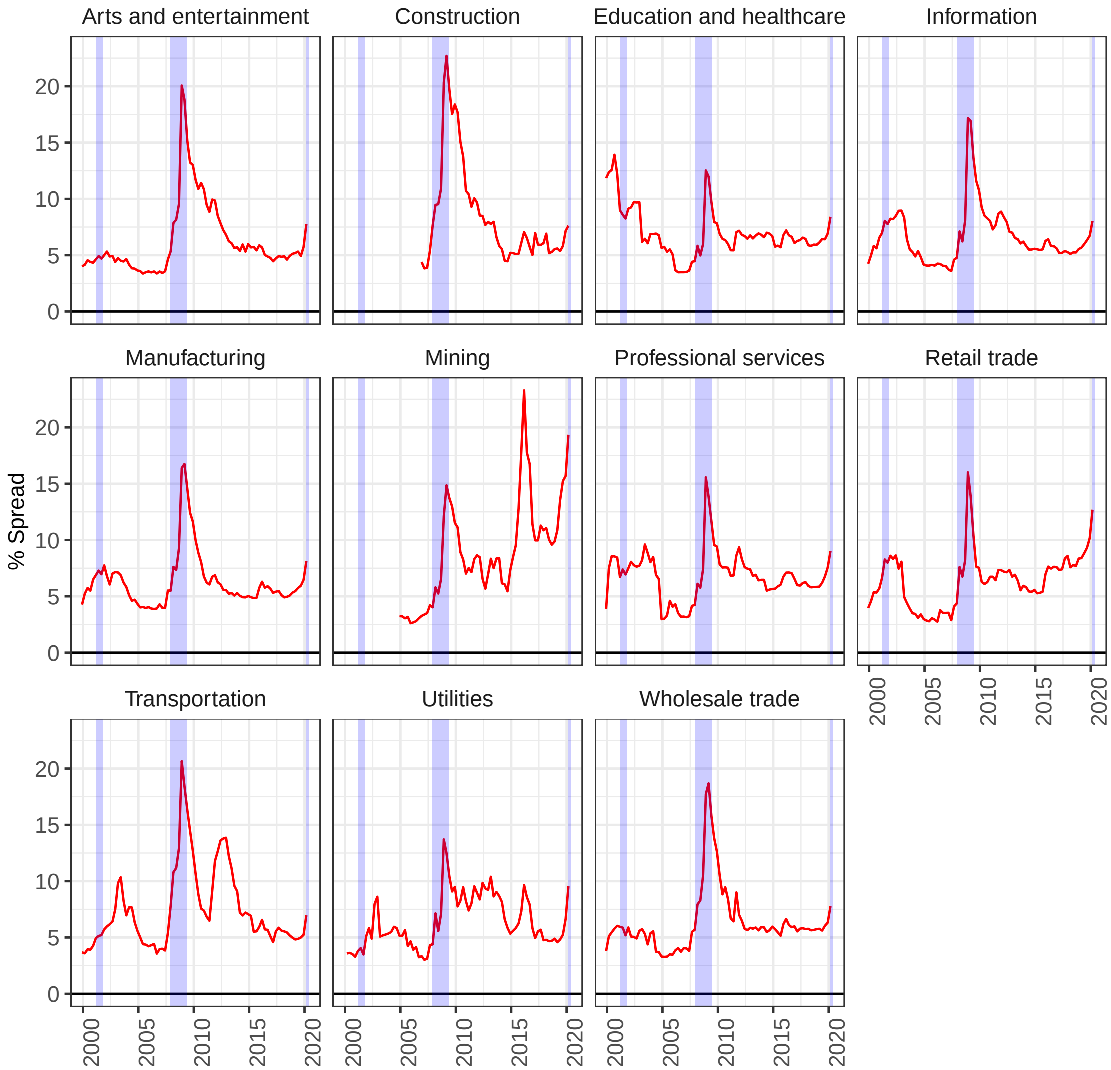

Figure 6: **Industry loan spreads**
This figure plots monthly loan spread measures over time for 11 non-financial sectors. Firms are classified into sectors following the BEA sector definition. The sample period is 1999:11 to 2020:03 (except for "Construction" and "Mining" due to limited data availability in the early sample period). Bars indicate NBER recessions.

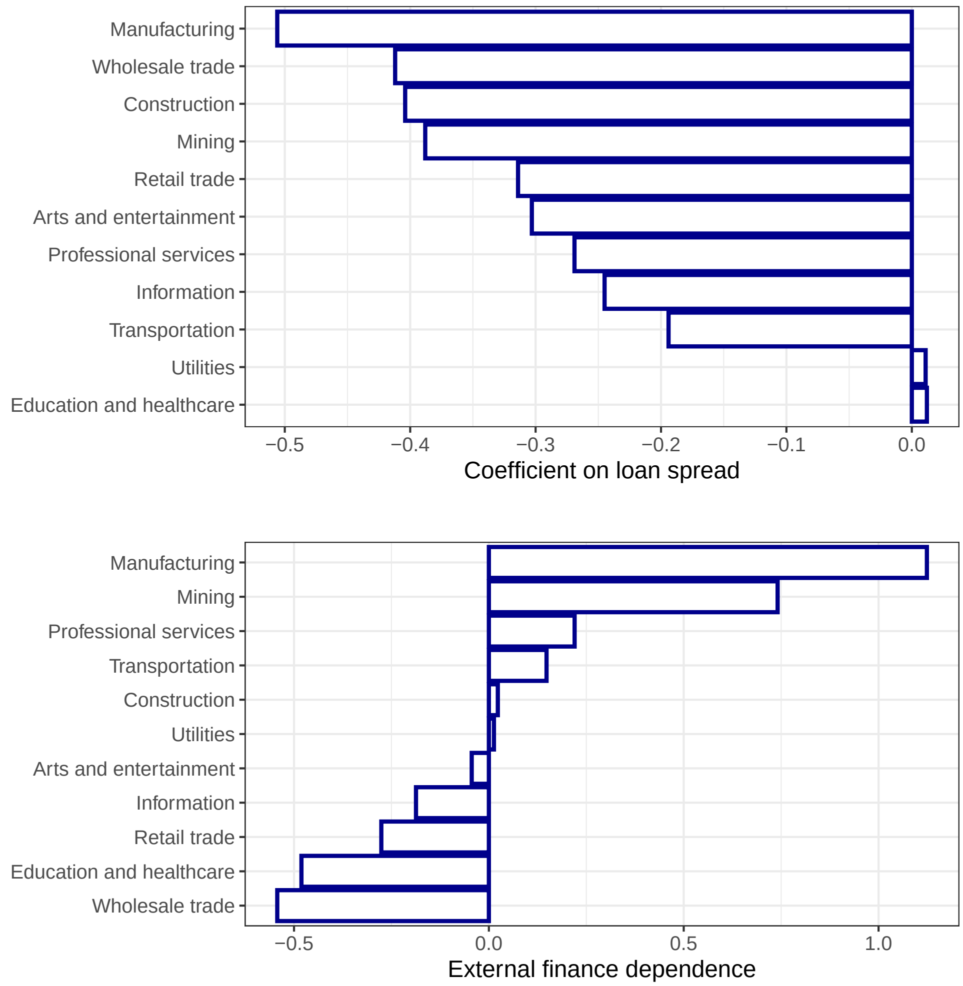

Figure 7: **Industry heterogeneity**
The top panel plots regression coefficients using separate OLS regressions of industry level employment growth on the industry level loan spread. The bottom panel plots the Rajan and Zingales (1998) measure of external finance dependence for each industry over the 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: **Borrower composition loan and bond market**

This table compares the characterisitics of borrowers in the loan and bond market. Panel A defines "All borrowers" as the number of unique borrowers that can be identified in our loan and bond data. Private borrowers are firms that cannot be linked to the Compustat North America database. Public borrowers are firms that can be linked to the Compustat North America database. Panel B and C cover only "Public borrowers", where a borrower is identified by a GVKEY. Borrower age is defined by taking the age of the firm when it first appears in the loan or bond data. Age is calculated as the number of years a firm has data available in the Compustat North America database. Firm size is defined by taking the timeseries average of a firm's Total Assets (Compustat item AT) over the sample period. The sample period is 1999:11 to 2020:03.

	Loan market		Bond market	
	(%)	(n)	(%)	(n)
Panel A. Public vs. private:				
All borrowers	100%	3,713	100%	2,917
thereof:				
Private	50%	1,854	33%	981
Public (i.e., w/ Compustat link)	50%	1,859	67%	1,936
Unique parents (Compustat "GVKEYs")		1,685		1,530
Panel B. Age distribution (public firms only):				
<=5yr	29%	335	19%	265
>5yr & <=10yr	20%	235	18%	264
>10yr & <=20yr	24%	278	21%	304
>20yr	27%	317	42%	599
thereof: also a bond issuer			also a loan issuer	
<=5yr	33%	110	42%	110
>5yr & <=10yr	44%	103	39%	103
>10yr & <=20yr	44%	121	40%	121
>20yr	58%	184	31%	184
Panel C. Size distribution (public firms only):				
<= $2bill	61%	939	33%	495
>2 & <=6 $bill	23%	357	30%	444
>6 & <=10 $bill	6%	87	10%	150
> $10bill	10%	166	27%	403
thereof: also a bond issuer			also a loan issuer	
<= $2bill	19%	178	36%	178
>2 & <=6 $bill	48%	173	39%	173
>6 & <=10 $bill	66%	57	38%	57
> $10bill	70%	117	29%	117

Table 2: **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 1999:11 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 four period lag structure, are reported in parentheses and $***$, $**$, $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	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 3: **Other measures and robustness**

This table relates different credit spread measures and additional controls to future economic outcomes for the U.S. economy. The unit of observation is the monthly level t. The sample period is 1999:11 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 focuses on alternative credit spreads. Column (1) uses the loan spread as a baseline comparision. Column (2) uses the Baa-Aaa corporate bond spread. Column (3) uses the corporate high yield minus AAA spread. Column (4) uses the Commercial paper - three-month Treasury bill spread. Column (5) uses the S&P500 monthly return from $t-1$ to t. Panel B focuses on additional robustness checks. Column (1) uses the loan spread as a baseline comparision. Column (2) controls for the median bid-ask spread in the loan market at time t. Column (3) 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. Column (4-5) contain the loan and bond spread removing the 2008-09 crisis period. 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 four period lag structure, are reported in parentheses and $***$, $**$, $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	Forecast horizon: h = 3 months				
	Baseline	Other credit spreads			Equity market
	(1)	(2)	(3)	(4)	(5)
Panel A. Other measures					
ΔS_t^{Loan}	-0.410^{***}				
	(-5.727)				
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)
Adjusted R^2	0.313	0.237	0.222	0.166	0.204
Incremental R^2	+0.150	+0.077	+0.062	+0.006	+0.041
Observations	241	241	241	241	241
	Baseline	Loan mkt liquidity	Contract terms	Ex 2008-09 crisis	
	(1)	(2)	(3)	(4)	(5)
Panel B. Robustness					
ΔS_t^{Loan}	-0.410^{***}	-0.360^{***}		-0.207^{***}	
	(-5.727)	(-5.337)		(-3.047)	
ΔS_t^{Bond}					-0.058
					(-0.720)
Loan bid-ask spread		-0.328^{***}			
		(-3.141)			
Residual ΔS_t^{Loan}			-0.405^{***}		
			(-5.646)		
Adjusted R^2	0.313	0.386	0.318	0.150	0.115
Incremental R^2	+0.150	+0.226	+0.120	+0.034	+0.001
Observations	241	241	241	241	241

Table 4: **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., 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., 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 four period lag structure, are reported in parentheses and $***$, $**$, $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	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 5: **Credit conditions and bank health**

This table relates proxies for credit supply conditions and bank health to loan spreads in the U.S. The unit of observation is the quarterly level t. The sample period is 1999:11 to 2020:03 for the U.S. The dependent variable in Column (1)-(3) is 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. The dependent variable in Column (4)-(6) is the bank level ratio of total unused commitments/total assets (Commit) from FDIC Call Reports and constructs an aggregate ratio as a weighted average across banks each quarter. The dependent variable in Column (7)-(9) is the aggregate return on assets (ROA) across all U.S. banks from SNL. The dependent variable in Column (10)-(12) is loan loss reserves/gross loans (LLP) from SNL. In all specifications we regress the proxy over $t-1$ to t on the change in credit spread over the same period, i.e., spreads and credit conditions are measured contemporaneously. 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 and $***$, $**$, $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	SLOSS (1)	SLOSS (2)	SLOSS (3)	Commit (4)	Commit (5)	Commit (6)
ΔS_t^{Loan}	0.430***		0.418***	−0.351**		−0.287**
	(3.810)		(5.176)	(−2.435)		(−2.166)
ΔS_t^{Bond}		0.290*	0.019		−0.306*	−0.223
		(1.879)	(0.118)		(−1.922)	(−1.512)
Adjusted R^2	0.174	0.073	0.164	0.112	0.082	0.148
Observations	81	81	81	81	81	81
	ROA (7)	ROA (8)	ROA (9)	LLP (10)	LLP (11)	LLP (12)
ΔS_t^{Loan}	−0.430**		−0.492**	0.465**		0.304**
	(−2.163)		(−2.118)	(2.203)		(2.454)
ΔS_t^{Bond}		−0.282	0.084		0.442	0.216
		(−1.234)	(0.286)		(1.604)	(0.613)
Adjusted R^2	0.174	0.068	0.167	0.206	0.185	0.217
Observations	81	81	81	81	81	81

Table 6: **Credit spread decomposition**

This table compares the predicted loan spread and excess loan premium to the predicted bond spread and excess bond premium. 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, i.e., growth from $t-1$ to $t+3$. The dependent variable in Panel C is the three-month ahead percentage change in payroll employment, i.e., growth from $t-1$ to $t+3$. 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. $\hat{S}_t^{Loan}$ is constructed using distance-to-default, contract terms and fixed effects, i.e., Column 4 of Table A.10 in the Online Appendix. ELP_t is constructed as the actual loan spread minus $\hat{S}_t^{Loan}$. 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 and $***$, $**$, $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	Forecast horizon: h = 3 months		
	(1)	(2)	(3)
Panel A. Industrial Production			
$\Delta\hat{S}_t^{Loan}$	−0.376***		−0.401***
	(−5.084)		(−3.143)
ΔELP_t	−0.268***		−0.276***
	(−4.720)		(−4.149)
$\Delta\hat{S}_t^{Bond}$		−0.191**	0.038
		(−2.027)	(0.320)
ΔEBP_t		−0.182**	0.043
		(−2.116)	(0.303)
Adjusted R^2	0.332	0.196	0.328
Incremental R^2	+0.169	+0.030	0.165
Contribution from ΔS_t	0.67	0.69	
Observations	241	241	241
Panel B. Unemployment Rate			
$\Delta\hat{S}_t^{Loan}$	0.347***		0.458***
	(3.319)		(3.146)
ΔELP_t	0.213**		0.248***
	(2.324)		(2.642)
$\Delta\hat{S}_t^{Bond}$		0.083	−0.179
		(0.546)	(−1.306)
ΔEBP_t		0.101	−0.179
		(0.641)	(−1.404)
Adjusted R^2	0.293	0.152	0.311
Incremental R^2	+0.143	+0.002	+0.161
Contribution from ΔS_t	0.74	0.38	
Observations	241	241	241
Panel C. Payroll Employment			
$\Delta\hat{S}_t^{Loan}$	−0.169***		−0.189***
	(-6.153)		(−3.720)
ΔELP_t	−0.147***		−0.154***
	(-4.743)		(−4.037)
$\Delta\hat{S}_t^{Bond}$		−0.068	0.025
		(−1.464)	(0.485)
ΔEBP_t		−0.106***	−0.012
		(−2.616)	(−0.284)
Adjusted R^2	0.841	0.806	0.841
Incremental R^2	+0.043	+0.008	+0.043
Contribution from ΔS_t	0.57	0.23	
Observations	241	241	241

Table 7: **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 1999:11 to 2020:03. The dependent variable is the three-month ahead percentage change in industrial production, i.e., 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 four period lag structure, are reported in parentheses and $***$, $**$, $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	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 8: **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 1999:11 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 four period lag structure, are reported in parentheses and $***$, $**$, $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	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 and below]			−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 9: **Alternative explanations: uncertainty**

This table relates credit spread measures to (future) economic outcomes controlling for common proxies for uncertainty. The unit of observation in Column (1),(2),(4)-(6) is the monthly level t, Column (3) is the quarterly level. The sample period is 1999:12 to 2020:03, except Col (6) which is only available up untill 2017. The dependent variable is the 3 month ahead change in industrial production payroll employment (h=3), i.e, growth from $t-1$ to $t+3$. Column (1) uses the aggregate loan spread as a baseline comparison. Column (2) adds the VIX (level) at time t as a control. Column (3) adds the Price of Volatile Stocks (PVS) measure of (Pflueger *et al.*, 2020)). Column (4) adds the Economic Policy Uncertainty (EPU) index of (Baker *et al.*, 2016). Column (5) adds the Financial Uncertainty index (3m ahead) of (Jurado *et al.*, 2015). Column (6) adds the newspaper based index of (Bybee *et al.*, 2020). Each specification includes (not reported) one period lag of the dependent variable, i.e, growth from $t-2$ to $t-1$, the term spread, i.e, difference between 10year and 3month US treasury, and the real FFR, i.e, effective federal funds rate minus realised inflation. Reported OLS coeffecients are standardised. t-statistics, based on heteroskedasticity and autocorrelation corrected Newey-West standard errors with a 4 period lag structure, are reported in parentheses and $***$, $**$, $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	Forecast horizon: 3 months					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}	-0.410^{***}	-0.261^{***}	-0.442^{***}	-0.389^{***}	-0.325^{***}	-0.243^{***}
	(-5.727)	(-4.468)	(-4.963)	(-5.450)	(-5.271)	(-3.001)
VIX		-0.367^{***}				
		(-3.329)				
PVS Index			0.267^{**}			
			(2.404)			
EPU Index				-0.109		
				(-1.633)		
FU Index					-0.399^{***}	
					(-3.311)	
'Recession' Index						-0.514^{***}
						(-4.408)
Adjusted R^2	0.313	0.393	0.386	0.320	0.432	0.518
Incremental R^2	+0.150	+0.230	+0.223	+0.157	+0.269	+0.355
Observations	241	241	76	241	241	211

Table 10: **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 1999:11 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). Coefficients are standardized. Standard errors are clustered by industry. t-statistics are reported in parentheses and $***$, $**$, $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	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 11: **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 1999:11 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 five industries with the 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). Coefficients are standardized. Standard errors are clustered by industry. t-statistics are reported in parentheses and $***$, $**$, $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	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 12: **Alternative weighting schemes**

This table relates alternative 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 1999:11 to 2020:03. The dependent variable is the three-month ahead change in industrial production, i.e., growth from $t-1$ to $t+3$. Column (1) reports the baseline aggregate loan spread results for comparison [cf. Table 2 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 7 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). OOS RMSE uses a training period from 1999:12 to 2012:05 and expanding rolling window to calculate RMSE between the predictions (1 period ahead) and the realized macro outcome from 2012:06 to 2020:03. 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 and $***$, $**$, $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	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
OOS RMSE	0.0132	0.0118	0.0115	0.0117	0.0115
Observations	241	241	241	241	241

Internet Appendix: Corporate Loan Spreads and Economic Activity

A Variable definitions

This section outlines the key variables used in the main paper and their construction. Table A.1 describes each variable. Column(1) indicates the country for which the data applies and the name of the variable used throughout the paper. Column(2) provides a brief description and the source of the data. Column (3) indicates the data frequency.

Table A.1: **Description of variables**

Economic Variables	Description	Frequency
USA - Unemployment rate	Unemployment rate (FRED)	M
USA - Payroll employment	Total private non-farm payroll employment (FRED)	M
USA - Industrial production	Total industrial production index (FRED)	M
USA - Industry output	Gross output by industry (Bureau of Economic Analysis)	Q
USA - Industry employment	Employment level by industry (Bureau of Labour Statistics)	Q
USA - Industry establishments	Count of establishments by industry (Bureau of Labour Statistics)	Q
USA - FSLOSS	Fed senior loan officer survey (Federal Reserve)	Q
USA - Bank commitments	Bank unused commitments (FDIC Call Reports)	Q
USA - ROA	Return on assets - US banks (SNL)	Q
USA - LLP	Loan loss provisions - US banks (SNL)	Q
USA - S&P500	S&P500 monthly return (CRSP)	M
USA - Loan bid-ask spread	Median bid-ask spread (Authors)	M
USA - EFD	External finance dependence Rajan and Zingales (1998) (Authors)	M
USA - VIX	VIX (monthly average)	M
USA - PVS	Price of Volatile Stocks index Pflueger *et al.* (2020)	Q
USA - EPU	Economic Policy Uncertainty (EPU) index (Baker *et al.*, 2016)	M
USA - FU	Financial Uncertainty index (3m ahead) of (Jurado *et al.*, 2015)	M
USA - Recession Index	Newspaper based index of (Bybee *et al.*, 2020)	M
Europe - EONIA	EONIA minus HCIP inflation previous 12months (ECB)	M
Europe - Unemployment rate	Unemployment rate (Eurostat)	M
Europe - Manufacturing index	Manufacturing production index (Eurostat)	M
Europe - Construction index	Construction production index (Eurostat)	M
Interest rates		
USA - Real federal funds rate	Avg effective federal funds rate minus core PCE index (FRED)	M
USA - Baa-Aaa spread	10year Baa minus 10year Aaa corporate bond spread (FRED)	M
USA - Commercial spread	Paper/bill spread: 1 month A1/P1 commercial paper minus 3m UST (FRED)	M
USA - HY-AAA spread	High Yield minus AAA yield (FRED)	M
USA - ΔS_t^{Loan}	Monthly aggregate loan spread constructed from loan market (Authors)	M
USA - ΔS_t^{Bond}	Monthly aggregate bond spread Gilchrist and Zakrajšek (2012)	M
USA - S_{bt}^{Loan}	Monthly industry loan spread (Authors)	M
Europe - Term spread	10yr Euro area government bond minus 3m EURIBOR (FRED and Eurostat)	M
Europe - ΔS_t^{Loan}	Monthly aggregate loan spread constructed from loan market (Authors)	M
Europe - ΔS_t^{Bond}	Monthly aggregate bond spread constructed by Mojon and Gilchrist (2016)	M

B Descriptive statistics

Tables A.2 and A.3 summarize basic descriptive statistics for the dependent and independent variables used in each table of the main paper in order to interpret the standardized coefficients reported.

Table A.2: **Summary Statistics**

This table shows summary statistics for independent and dependent variables in each table of the main paper. See the table descriptions in the main paper for more details.

Variable	Mean	SD	Min	Median	Max
Table 2:					
Δy_{t+3} Industrial production (%)	0.23	1.79	-7.72	0.65	3.28
Δy_{t+3} Unemployment rate (pp)	0.00	0.42	-0.80	-0.10	1.90
Δy_{t+3} Payroll employment (%)	0.27	0.68	-2.67	0.51	0.98
ΔS_t^{Loan} (bps)	0.79	44.52	-129.11	-3.78	357.18
ΔS_t^{Bond} (bps)	-0.23	28.51	-129.49	-2.53	226.86
Table 3:					
$\Delta Baa - aaaspread$ (bps)	-0.52	69.08	-324.0	-4.0	455.0
$\Delta HY - aaaspread$ (bps)	0.03	12.19	-63.0	-1.0	94.0
$\Delta CP - billspread$ (bps)	-0.09	12.92	-55.0	0.0	65.0
$\Delta S\&P500return$ (%)	0.44	4.19	-16.94	0.94	10.77
Loan bid-ask spread (%)	1.01	0.80	0.43	0.81	5.53
Residual ΔS_t^{Loan} (bps)	0.43	44.33	-132.63	-4.19	356.24
Table 4:					
Δy_{t+3} Unemployment rate Germany (pp)	-0.09	0.29	-0.70	-0.10	0.50
Δy_{t+3} Manufacturing index Germany (index points)	0.36	3.02	-17.4	0.90	6.80
Δy_{t+3} Construction index Germany (index points)	0.05	4.67	-13.70	0.20	19.40
ΔS_t^{Loan} Germany (bps)	1.10	38.64	-152.7	-0.17	320.2
ΔS_t^{Bond} Germany (bps)	0.28	17.50	-40.0	-1.00	163.40
Δy_{t+3} Unemployment rate France (pp)	-0.02	0.28	-0.70	0.00	1.00
Δy_{t+3} Manufacturing index France (index points)	-0.27	3.11	-20.30	0.25	5.10
Δy_{t+3} Construction index France (index points)	-0.44	4.39	-42.10	-0.40	9.80
ΔS_t^{Loan} France (bps)	1.56	38.23	-110.80	-1.07	256.10
ΔS_t^{Bond} France (bps)	0.89	21.59	-62.6	-1.59	151.60
Δy_{t+3} Unemployment Rate Spain (pp)	0.06	0.97	-1.10	-0.20	3.90
Δy_{t+3} Manufacturing Index Spain (index points)	-0.53	3.49	-18.60	0.20	4.30
Δy_{t+3} Construction Index Spain (index points)	-1.50	8.52	-64.50	-0.80	39.60
ΔS_t^{Loan} Spain (bps)	3.08	66.43	-489.60	-0.51	370.00
ΔS_t^{Bond} Spain (bps)	0.63	28.24	-72.3	-2.38	163.80

Table A.3: **Summary Statistics**

This table shows summary statistics for independent and dependent variables in each table of the main paper. See the table descriptions in the main paper for more details.

Variable	Mean	SD	Min	Median	Max
Table 5:					
FSLOSS (%)	5.63	24.15	-24.10	-3.80	83.60
Commitments	0.00	0.02	-0.06	0.00	0.06
ROA (%)	0.90	0.51	-1.56	1.00	1.44
LLP (%)	1.19	0.79	1.11	1.66	4.16
ΔS_t^{Loan} (bps)	4.80	114.48	-268.00	-9.46	782.83
ΔS_t^{Bond} (bps)	2.33	55.84	-220.24	-5.17	218.85
Table 6:					
$\Delta \hat{S}_t^{Loan}$ (bps)	0.87	28.28	-79.81	-0.24	174.35
ΔELP_t (bps)	-0.20	37.10	-141.26	-1.73	194.28
$\Delta \hat{S}_t^{Bond}$ (bps)	-0.04	24.39	-96.65	-0.11	99.56
ΔEBP_t (bps)	-0.18	24.48	-122.99	0.83	149.93
Table 7:					
ΔS_t^{Loan}[Small firms] (bps)	0.93	46	-142	-1.1	310
ΔS_t^{Loan}[Large firms] (bps)	-1.50	50	190	-2.3	394
ΔS_t^{Loan}[Young firms] (bps)	-0.23	48	-159	-0.66	378
ΔS_t^{Loan}[Old firms] (bps)	0.22	47	-180	-1.24	331
ΔS_t^{Loan}[Small & young firms] (bps)	0.52	48	-162	-1.67	305
ΔS_t^{Loan}[Large & old firms] (bps)	-0.08	54	-369	-0.82	319
ΔS_t^{Loan}[Private firms] (bps)	1.2	48	-117	-4.5	352
Table 8:					
ΔS_t^{Loan}[BBB] (bps)	-0.48	33	-131	-0.34	224
ΔS_t^{Loan}[BB] (bps)	-0.37	41	-133	-2.78	370
ΔS_t^{Loan}[B and below] (bps)	1.45	52	-158	-0.97	395
ΔS_t^{Loan}[Not available] (bps)	0.77	42	-101	-2.51	386
Table 9:					
VIX	19.51	8.16	10.12	17.42	62.64
PVS Index	-0.29	0.34	-1.72	0.26	0.25
EPU Index	125.54	48.48	44.74	114.76	284.14
FU Index	0.94	0.15	0.72	0.91	1.43
Recession Index	0.006	0.003	0.003	0.006	0.017
Table 10:					
Δy_{t+3} Industry employment (%)	0.23	2.24	-13.28	0.55	7.20
Δy_{t+3} Industry establishments (%)	0.50	1.36	-13.19	0.51	5.41
Δy_{t+3} Industry gross output (%)	1.93	5.98	-37.70	2.30	32.55
S_{bt}^{Loan} (bps)	688.68	308.65	261.00	599.67	2328.82
S_t^{Loan} (bps)	583.75	192.18	352.23	553.60	1466.37
Table 12:					
ΔS_{bt}^{Loan}[GDP] (bps)	1.19	42.30	-125.98	-2.02	323.89
ΔS_{bt}^{Loan}[Industry] (bps)	1.94	37.19	-119.96	-1.31	260.16
ΔS_{bt}^{Loan}[EFD] (bps)	2.79	42.75	-122.38	0.07	270.06
ΔS_{bt}^{Loan}[Elastic Net] (bps)	2.52	43.09	-120.86	0.38	291.65

Table A.4 provides a comparison of the bond and loan market. Loan market data is a combination of LSTA data for secondary market quotes complemented with information about the underlying loans from the Dealscan database. Bond market data is a combination of monthly TRACE data for prices combined with Mergent FISD for information about the underlying bond.

The loan and bond market differ in many dimensions. Bonds exhibit a longer maturity at issuance (11.6 years) and term to maturity (8.2 years) than loans (6.0 and 4.6 years, respectively). On average, bond issues tend to be of larger size ($537million v $454million) than loans. The vast majority of loans are structured as senior and secured, whereas only 9% of bonds are secured.

Table A.4: **Bond and loan market comparison**

This table shows summary statistics for the bond and loan market. Loan market data comes from LSTA and Dealscan. Bond market data comes from TRACE and Mergent FISD.

Panel A. Bond Market Characteristics

Variable	Mean	SD	Min	Median	Max
No. Bonds per month	4297.2	906.2	2980.0	4010.0	5817.0
No. Bonds per firm/month	5.4	10.3	1.0	2.0	138.0
Offering Amount ($mill)	536.9	544.3	0.0	400.0	15000.0
Maturity at issue (years)	11.6	8.4	0.5	9.8	50.0
Term to Maturity (years)	8.2	7.7	0.0	5.6	30.0
Duration (years)	6.0	4.1	0.0	5.0	19.2
Coupon (%)	6.2	2.5	0.4	6.2	18.0
Secured (%)	9.0	-	-	-	-
Bond Spread (bps)	405.1	437.5	13.6	260.2	3495.6

Panel B. Loan Market Characteristics

Variable	Mean	SD	Min	Median	Max
No. Loans per month	1183.2	530.3	443.0	977.0	2125.0
No. Loans per firm/month	2.7	2.5	1.0	2.0	31.0
Facility Amount ($mill)	454.4	666.6	1.0	250.0	24000.0
Maturity at issue (years)	6.0	1.4	0.1	6.0	27.0
Term to Maturity (years)	4.6	1.7	0.0	4.6	26.6
Facility Amount ($mill)	454.4	666.6	1.0	250.0	24000.0
All In Spread Drawn (bps)	401.5	194.4	12.5	350.0	1600.0
Secured (%)	92	-	-	-	-
Senior (%)	99	-	-	-	-
Loan Spread (bps)	577.8	429.0	12.7	448.6	3477.0

C Additional institutitional background

C.1 Loan market liquidity

Figure A.8 plots the median bid-ask spread (scaled by the mid-quote) over the 1999-2020 period as well as the interquartile range in grey. The median bid-ask spread in the pre-2008-2009 crisis period was 68 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 the secondary loan market is still somewhat less liquid than the bond market.

Section 4.3 finds the inclusions of the median bid-ask spread as an additional control, has very little impact on the main result.

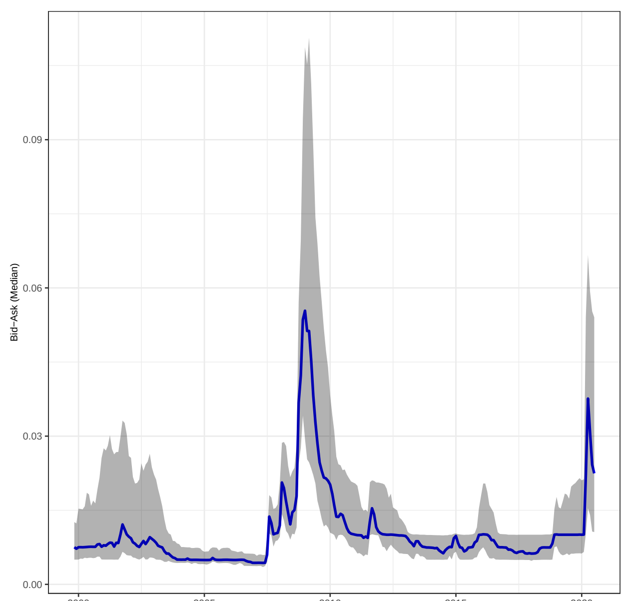

Figure A.8: **U.S. secondary loan market liquidity**
This figure plots the median bid-ask spread (scaled by the mid quote) over the 1999:11 to 2020:03 period as well as the interquartile range. The sample is restricted to term loans issued by U.S. firms. Source: LSTA.

As might be expected, bid-ask spreads surged during the 2008-2009 period, reaching a median of 500bps in 2009. Following the crisis period the bid-ask spreads fell and stabilized again at a level higher than prior to the crisis. A similar phenomenon can be observed in the bond market. However, Dick-Nielsen and Rossi (2019) provide evidence that liquidity provision has become more expensive after the financial crisis and link this fact to a more stringent regulatory environment, which disincentivized dealers from taking on large inventories in the post-Volcker rule world.[29]

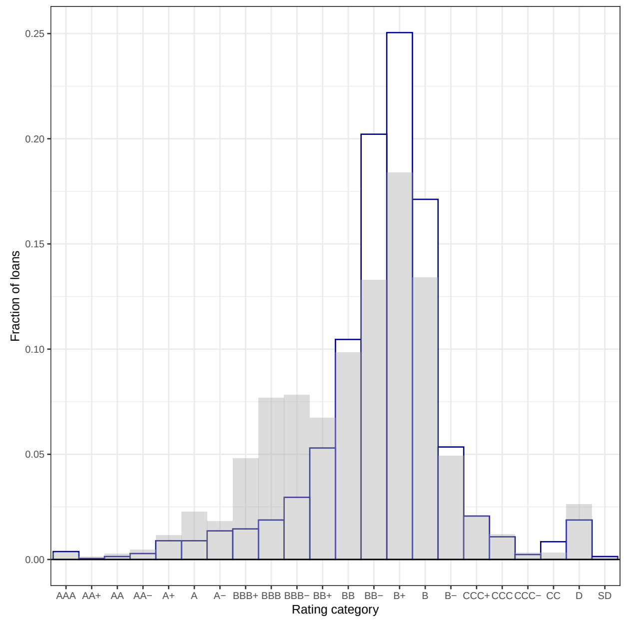

Figure A.9: **Rating distribution of traded and non-traded loans**
This figure plots the security level rating distribution across the loan market for loans that are traded (grey bars) and loans that are not traded (white bars). Loan level ratings come from Dealscan.

Figure A.9 shows the distribution of rating categories across the loan market for loans which are traded (grey bars) and not traded (white bars) over the 1999 to 2020 period. While the rating distribution is similar (particularly for the very low-risk and very high-risk loans), the distribution of traded (non-traded) loans has a larger mass in the BB to B (BBB) rating categories, indicating that a significant portion of traded loans is below investment grade.

C.2 Loan market dealers

Table A.5 shows the lead arranger (underwriter) market share in the primary market for the top 10 dealers in the secondary market for 2009. The five largest dealer banks are Credit

[29] Although the Volcker-rule restrictions on secondary market positions by banks was part of the Dodd-Frank Act of 2011, it has only really become operational at the regulatory level post 2015.

Suisse, Bank of America, Barclays, Citigroup, and JP Morgan with a combined market share of 35%. These banks are also the largest underwriters in the primary loan market.

Table A.5: **Top 10 dealers in the secondary loan market in 2009**

This table shows the lead arranger (underwriter) market share in the primary syndicated loan market as well as the dealer market share in the secondary market for syndicated loans for the top 10 dealers in 2009.

Name	Dealer Market Share	Underwriter Market Share
Credit Suisse	9.0%	6.6%
Bank of America	8.3%	12.3%
Barclays	7.7%	7.7%
Citigroup	6.0%	7.3%
JP Morgan	5.8%	12.4%
Morgan Stanley	5.7%	6.4%
Deutsche Bank	5.2%	5.1%
BNP Paribas	3.9%	2.9%
Wells Fargo	3.5%	3.2%
Royal Bank of Canada	3.3%	1.8%

D Aggregate forcasting results

D.1 Other measures and robustness

Table A.6 replicates Table 3, Panel A of the main paper but includes the loan spread in each column.

Table A.6: **Other measures and robustness**

This table relates different credit spread measures and additional controls 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 focuses on alternative credit spreads. Column (1) uses the loan spread as a baseline comparision. Column (2) uses the Baa-Aaa corporate bond spread. Column (3) uses the corporate high yield minus AAA spread. Column (4) uses the Commercial paper - three-month Treasury bill spread. Column (5) uses the S&P500 monthly return from $t-1$ to t. Panel B focuses on additional robustness checks. Column (1) uses the loan spread as a baseline comparision. Column (2) controls for the median bid-ask spread in the loan market at time t. Column (3) 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. Column (4-5) contain the loan and bond spread removing the 2009-09 crisis period. 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				
	Baseline	Other credit spreads			Equity market
	(1)	(2)	(3)	(4)	(5)
Panel A. Other measures					
ΔS_t^{Loan}	−0.410***	−0.380***	−0.364***	−0.407***	−0.382***
	(−5.727)	(−3.757)	(−4.968)	(−6.040)	(−5.459)
Δ Baa-Aaa spread		−0.044			
		(−0.567)			
Δ HY-Aaa spread			−0.117*		
			(−1.901)		
Δ CP-bill spread				0.069	
				(0.939)	
S&P500 return					0.148***
					(2.858)
Adjusted R^2	0.313	0.312	0.323	0.315	0.331
Incremental R^2	+0.150	+0.149	+0.160	+0.152	+0.168
Observations	241	241	241	241	241

D.2 Conditional on bond rating groups

As discussed in Section 3 of the main paper, the loan market is populated by a set of riskier borrowers than the bond market. Hence, the superior predictive power of the loan spread could reflect credit risk. A cleaner evaluation of the loan spread's additional predictive power would be to compare the loan spread to a bond spread conditional on a set of riskier borrowers.

Table A.7: **Aggregate forecasting results by bond ratings**

This table relates credit spread measures to (future) economic outcomes. 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 3 month ahead change in industrial production payroll employment (h=3) i.e growth from $t-1$ to $t+3$. The dependent variable in Panel B is the 3 month ahead change in unemployment rate. The dependent variable in Panel C is the 3 month ahead change in non-farm payroll employment. Col (1) uses a loan spread calculated from all firms and time periods. Col(2)-(4) uses alternative versions of the bond spread for different ratings classes. The ratings are bond level ratings available throught TRACE. Each specification includes (not reported) one period lag of the dependent variable i.e growth from $t-2$ to $t-1$, the term spread i.e difference between 10year and 3month US treasury, and the real FFR i.e effective federal funds rate minus realised inflation. Reported OLS coeffecients are standardised. t-statistics, based on heteroskedasticity and autocorrelation corrected Newey-West standard errors with a 4 period lag structure, are reported in parentheses and $***$, $**$, $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	Forecast horizon: 3 months			
	(1)	(2)	(3)	(4)
Panel A. Industrial Production				
ΔS_t^{Loan}	-0.410^{***}			
	(-5.727)			
$\Delta S_t^{Bond-A's}$		-0.144		
		(-1.417)		
$\Delta S_t^{Bond-BBB}$			-0.212^{***}	
			(-3.127)	
$\Delta S_t^{Bond-HY}$				-0.222^{**}
				(-2.322)
Adjusted R^2	0.313	0.184	0.207	0.212
Incremental R^2	+0.150	+0.021	+0.044	+0.049
Observations	241	206	206	206
Panel B. Unemployment				
ΔS_t^{Loan}	0.355^{***}			
	(2.808)			
$\Delta S_t^{Bond-A's}$		0.068		
		(0.439)		
$\Delta S_t^{Bond-BBB}$			0.157	
			(1.006)	
$\Delta S_t^{Bond-HY}$				0.180
				(1.244)
Adjusted R^2	0.272	0.154	0.174	0.182
Incremental R^2	+0.122	+0.004	+0.024	+0.032
Observations	241	206	206	206
Panel C. Payroll Employment				
ΔS_t^{Loan}	-0.207^{***}			
	(-6.332)			
$\Delta S_t^{Bond-A's}$		-0.051		
		(-1.151)		
$\Delta S_t^{Bond-BBB}$			-0.098^{**}	
			(-2.304)	
$\Delta S_t^{Bond-HY}$				-0.097^{**}
				(-2.235)
Adjusted R^2	0.839	0.832	0.839	0.845
Incremental R^2	+0.041	+0.034	+0.041	+0.041
Observations	241	206	206	206

Table A.7 performs the same aggregate forecasting regression as Table 2 in the main paper, but instead includes a bond spread conditional on bond level rating. We use bond level pricing data from TRACE to create bottom-up corporate bond credit spreads following the methodology of Gilchrist and Zakrajšek (2012). This gives us the ability to create bond spreads aggregated for different rating categories. Column (1) shows the baseline loan spread results for comparison, Column (2) shows results using a bond spread comprised of A-rated bonds, Column(3) uses BBB-rated bonds, and Column (4) uses below investment grade-rated bonds.

Firstly, we see a monotonic increase in the bond coefficient size as we condition on a risker set of borrowers in the bond market. Secondly, we see that even a bond spread conditional on being non-investment grade does not match the predictive power of the loan spread. A one standard deviation increase in loan spreads is associated with a decrease in industrial production by about 0.410 standard deviations, whereas a one standard deviation increase in bond spread conditional on non-investment grade bonds, is associated with a decrease in industrial production by only 0.222 standard deviations. A similar conclusion can be drawn from comparing the incremental R^2. This highlights that the riskiness of the underlying borrowers is not solely responsible for the wedge between the loan and bond market predictability.

D.3 Conditional on increases versus decreases

As discussed in Section 4.3 of the main paper, we also consider potential asymmetries in the impact of the loan and bond spread. The baseline aggregate forecasting regressions presented in Table 2 of the main paper assume that an increase and a decrease of the loan spread has the same relationship with future economic activity. In Table A.8 we test for potential asymmetric impacts. The results suggests that 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. Consistent with Stein (2014), 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.

Table A.8: **Baseline forecasting results conditional on increases versus decreases**

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 (h=3), i.e., growth from $t-1$ to $t+3$. Column(1) interacts the loan spread with a dummy for increases and decreases in the loan spread. Column(2) interacts the bond spread with a dummy for increases and decreases in the bond spread. Each specification includes (not reported) 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 realised 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 coeffecients are standardised. t-statistics, based on heteroskedasticity and autocorrelation corrected Newey-West standard errors with a 4 period lag structure, are reported in parentheses and $***$, $**$, $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	Forecast horizon: h = 3 months	
	(1)	(2)
Panel A. Industrial Production		
ΔS_t^{Loan} x Increase	-0.487^{***}	
	(-6.043)	
ΔS_t^{Loan} x Decrease	-0.225^{*}	
	(-1.756)	
ΔS_t^{Bond} x Increase		-0.294^{***}
		(-3.748)
ΔS_t^{Bond} x Decrease		-0.040
		(-0.253)
t-stat (ΔS_t^{Loan} x Increase = ΔS_t^{Loan} x Decrease)	(-1.62)	(-1.52)
Adjusted R^2	0.317	0.207
Incremental R^2	+0.154	+0.044
Observations	241	241

D.4 Out of sample evaluation

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 root mean square error (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 repeat this exercise including the next observation and so forth. We compute the RMSE of the predictions against the realized macroeconomic outcome.

Table A.9 reports the RMSE across of variety of model specifications. 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, i.e. that has the lowest RMSE. 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, consistent with in sample results reported in the main paper.

Table A.9: **Aggregate forecasting results - out of sample forecast**

This table reports the RMSE of an out of sample regression of credit spread measures to (future) economic outcomes. The unit of observation in Panels A, B, and C is the monthly level t. The training period is 1999:12 to 2012:05 or 150 observations. We use an expanding rolling window to calculate RMSE error between the predictions (1 period ahead) and realized macro outcome. The dependent variable in Panel A is the 3 month ahead change in industrial production (h=3), i.e, growth from $t-1$ to $t+3$. Panel B is the 3 month ahead change in industrial production unemployment (h=3), i.e, growth from $t-1$ to $t+3$. Panel C is the 3 month ahead change in payroll employment (h=3), i.e, growth from $t-1$ to $t+3$. Column (1) uses a baseline model with no credit spreads. Column (2) includes the loan spread. Column (3) includes the bond spread. Column (4) includes both loan and bond spread. Each specification includes (not reported) one period lag of the dependent variable, i.e, growth from $t-2$ to $t-1$, the term spread i.e difference between 10year and 3month US treasury, and the real FFR, i.e, effective federal funds rate minus realised inflation. The Diebold-Mariano (DM) Test null hypothesis is that the two models have the same forecast accuracy. $***$, $**$, $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	(1) (Baseline)	(2) (ΔS_t^{Loan})	(3) (ΔS_t^{Bond})	(4) (Both)
Panel A. Industrial Production				
RMSE	0.0132	0.0118	0.0131	0.0118
DM Test p-value (Col(2) = Col(3))			(0.03**)	
Observations	91	91	91	91
Panel B. Unemployment Rate				
RMSE	0.3271	0.3242	0.3287	0.3248
DM Test p-value (Col(2) = Col(3))			(0.50)	
Observations	91	91	91	91
Panel C. Payroll Employment				
RMSE	0.0018	0.0019	0.0019	0.0019
DM Test p-value (Col(2) = Col(3))			(0.01**)	
Observations	91	91	91	91

D.5 Controlling for loan level contract 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, and 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 run the following regression

$$\begin{aligned} ln\ S_{it}[k] &= \alpha_b + \beta_1\ ln(Age) + \beta_2\ ln(Size) + \beta_3\ ln(Amt) + \beta_4\ ln(AISD) \\ &+ \beta_5\ Secured(0/1) + \beta_6\ Senior(0/1) + \beta_7\ Covenants(0/1) + \epsilon_{it}[k]. \end{aligned} \quad (3)$$

Column 5, Panel A of Table A.10 summarizes the result of this regression. We then take the residual and Column (3), Panel B Table 3 of the main paper uses this "residual loan spread" and finds very little difference in predictive power relative to the baseline loan spread in Table 2.

D.6 Excess loan premium

We follow Gilchrist and Zakrajšek (2012) and decompose the loan spread into two components: a component that captures changes in default risk based on the fundamentals of a firm or differences in contractual terms and a residual component that captures the price of risk above a default risk premium. We implement the "naive distance to default" approach described in Bharath and Shumway (2008). We start with an estimate of σ_E using the previous years daily returns. From this σ_D is approximated as $\sigma_D = 0.05 + 0.25(\sigma_E)$. We next calculate a value of $\sigma_V = \sigma_E[E/(D+E)] + \sigma_D[D/(D+E)]$. μ is taken to be the stock return over the previous year. The implied distance-to-default over the next one year horizon from this procedure is then calculated as:

$$DD = (ln((E+D)/D) + \left(\mu_V - 0.5\sigma_V^2\right) / (\sigma_V)\,. \tag{4}$$

Decomposition: To isolate the portion of the loan spread driven by variation in the expected default of the firm or contractual terms, we regress the natural logarithm of the loan spread of loan k on the average distance-to-default across all firms in the industry in the respective month ($\overline{DD}_{bt}$). We do not use the firm-specific DD as this measure cannot be calculated for private firms, which comprise about 40% of our sample.[30] We further include a squared term ($\overline{DD}^2_{bt}$) to capture a possible non-linear effect of DD on loan spreads, as well as the volatility of DD across firms in the industry (σDD_{bt}). We run the following regression

$$ln\ S_{it}[k] = \alpha_b + \beta_1\ \overline{DD}_{bt} + \beta_2\ \overline{DD}^2_{bt} + \beta_3\ \sigma DD^2_{bt} + \gamma^{'} Z_{it}[k] + \epsilon_{it}[k]. \tag{5}$$

[30] Further, DD can also only be calculated for a subset of public firms with sufficient coverage in CRSP and Compustat. Overall, we are able to calculate DD for about one-third of the firms in our sample.

Table A.10: **Decomposing the loan spread**

This table shows the results of the loan spread decomposition based on Gilchrist and Zakrajšek (2012). Panel A regresses the loan spread on loan level characteristics. The dependent variable is the loan spread for facility i at time t. $\overline{DD}_{bt}$ is the average distance-to-default across all firms in the industry in the respective month based on Bharath and Shumway (2008). $\overline{DD}_{bt}^2$ is the distance to default squared. σDD_{bt} is the volatility of DD_{bt} across firms in the same industry. $AISD$ is the all-in-spread-drawn measured in basis points. *Age* is measured as the time elapsed since the loan is first reported in Dealscan. *Amount* is measured as the par amount of the loan at issuance. *Covenants* is a dummy variable that equals 1 if the loan contract includes covenants. *Secured* is a dummy variable that equals 1 if the loan is secured by collateral. *Senior* is a dummy variable that equals 1 if the loan is senior. t-statistics, based on time and loan clustered standard errors, are reported in parentheses. Panel B relates the predicted spread and residual spread from Panel A to future economic outcomes. The dependent variable in Panel B is the three-month ahead percentage change in industrial production, i.e., growth from $t-1$ to $t+3$. Contribution from $\Delta\hat{S}_t^{Loan}$ measures the proportion of the increase in adjusted R^2 in the respective column that results from the inclusion $\Delta\hat{S}_t^{Loan}$ as opposed to ΔELP_t. 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.

Panel A. Decomposing loan spreads	(1)	(2)	(3)	(4)	(5)
$\overline{DD}_{bt}$	−0.320***	−0.403***	−0.403***	−0.429***	
	(−20.420)	(−28.050)	(−28.080)	(−36.620)	
$\overline{DD}_{bt}^2$	0.021***	0.025***	0.025***	0.027***	
	(15.680)	(21.470)	(21.460)	(28.190)	
σDD_{bt}	−0.022**	0.0004	0.001	−0.023***	
	(−2.275)	(0.056)	(0.091)	(−3.501)	
Ln(AISD)		0.741***	0.743***	0.670***	0.684***
		(39.550)	(35.870)	(30.710)	(32.120)
Ln(Age)		0.074***	0.074***	0.066***	0.040***
		(30.810)	(30.860)	(29.680)	(13.700)
Ln(Amount)		−0.077***	−0.076***	−0.055***	−0.093***
		(−11.900)	(−11.670)	(−8.896)	(−13.460)
Secured(0/1)			−0.042*	−0.011	0.083***
			(−1.750)	(−0.441)	(3.152)
Covenants(0/1)			−0.003	0.009	0.034***
			(−0.208)	(0.750)	(2.478)
Senior(0/1)			0.119*	0.115	0.028
			(1.787)	(1.111)	(0.512)
Loan type fixed effects	No	No	No	Yes	No
Industry fixed effects	No	No	No	Yes	No
Rating fixed effects	No	No	No	Yes	No
Adjusted R^2	0.080	0.401	0.401	0.465	0.314
Observations	288,072	288,072	288,072	288,072	288,072

Panel B. Aggregate Forecasting regression				
$\Delta\hat{S}_t^{Loan}$	−0.300***			
	(−4.259)			
ΔELP_t	−0.253***			
	(−4.068)			
$\Delta\hat{S}_t^{Loan}$		−0.345***		
		(−4.454)		
ΔELP_t		−0.283***		
		(−4.924)		
$\Delta\hat{S}_t^{Loan}$			−0.346***	
			(−4.458)	
ΔELP_t			−0.283***	
			(−4.924)	
$\Delta\hat{S}_t^{Loan}$				−0.376***
				(−5.084)
ΔELP_t				−0.268***
				(−4.720)
Adjusted R^2	0.333	0.331	0.331	0.332
Incremental R^2	+0.170	+0.168	+0.168	+0.169
Contribution from $\Delta\hat{S}_t^{Loan}$	0.56	0.59	0.60	0.67
Observations	241	241	241	241

The top panel of Table A.10 shows the results of these regressions. Column (1) begins by including only the DD regressors. As expected, a higher DD reduces loan spreads and the positive coefficient on $\overline{DD}^2_{bt}$ is consistent with a non-linear effect. Column (2) then adds a vector of loan-level control variables ($Z_{(it)}[k]$), including the (log) loan amount, the (log) age of the issue and (log) AISD. Column (3) further includes a dummy variable indicating whether the loan includes financial covenants, is a secured loan, and is senior. The signs of the coefficients are as expected: larger loans or those that include covenants have lower loan spreads. Loans that are secured have a higher AISD and have been on the market longer have higher spreads. These loan terms, which are designed to address firms' default risk, have considerable explanatory power for spreads increasing the adjusted R^2 to about 40%. The coefficients remain similar across these specifications, but the explanatory power somewhat improves. Column (4) further includes fixed effects for loan type, borrower industry and loan rating category, the main results remain unchanged. We then calculate the predicted loan spread as

$$\hat{S}^{Loan}_{bt} = \exp\left[\hat{\beta}_1\ \overline{DD}_{bt} + \hat{\beta}_2\ \overline{DD}^2_{bt} + \hat{\beta}_3\ \sigma DD^2_{bt} + \hat{\gamma}'\, Z_{it}[k] + \frac{\hat{\sigma^2}}{2}\right] \tag{6}$$

The predicted component of the loan spread $\hat{S}_{it}[k]$ reflects the fundamental default risk of firm i. We also aggregate the predicted component across all firms and obtain an aggregate time series $\hat{S}^{Loan}_t$. The residual loan spread, in the spirit of Gilchrist and Zakrajšek (2012)'s *excess bond premium*, is then defined as the difference ($Residual\ Loan\ Spread_t = S^{Loan}_t - \hat{S}^{Loan}_t$), i.e., the part of the loan spread that cannot be explained by default risk or contract terms.

Panel B of Table A.10 then uses the "predicted" and "residual" components of the loan spread in an aggregate forecasting regression to mimic Panel A of Table 2 in the main paper. The dependent variable here is the three-month ahead growth in industrial production. We find both components of the loan spread are statistically significant at the three-month horizon. Interestingly, it is the predicted component that contributes around two thirds of the incremental adjusted R^2, suggesting that the predictive power of the loan spread is at least partly driven by borrower fundamentals.

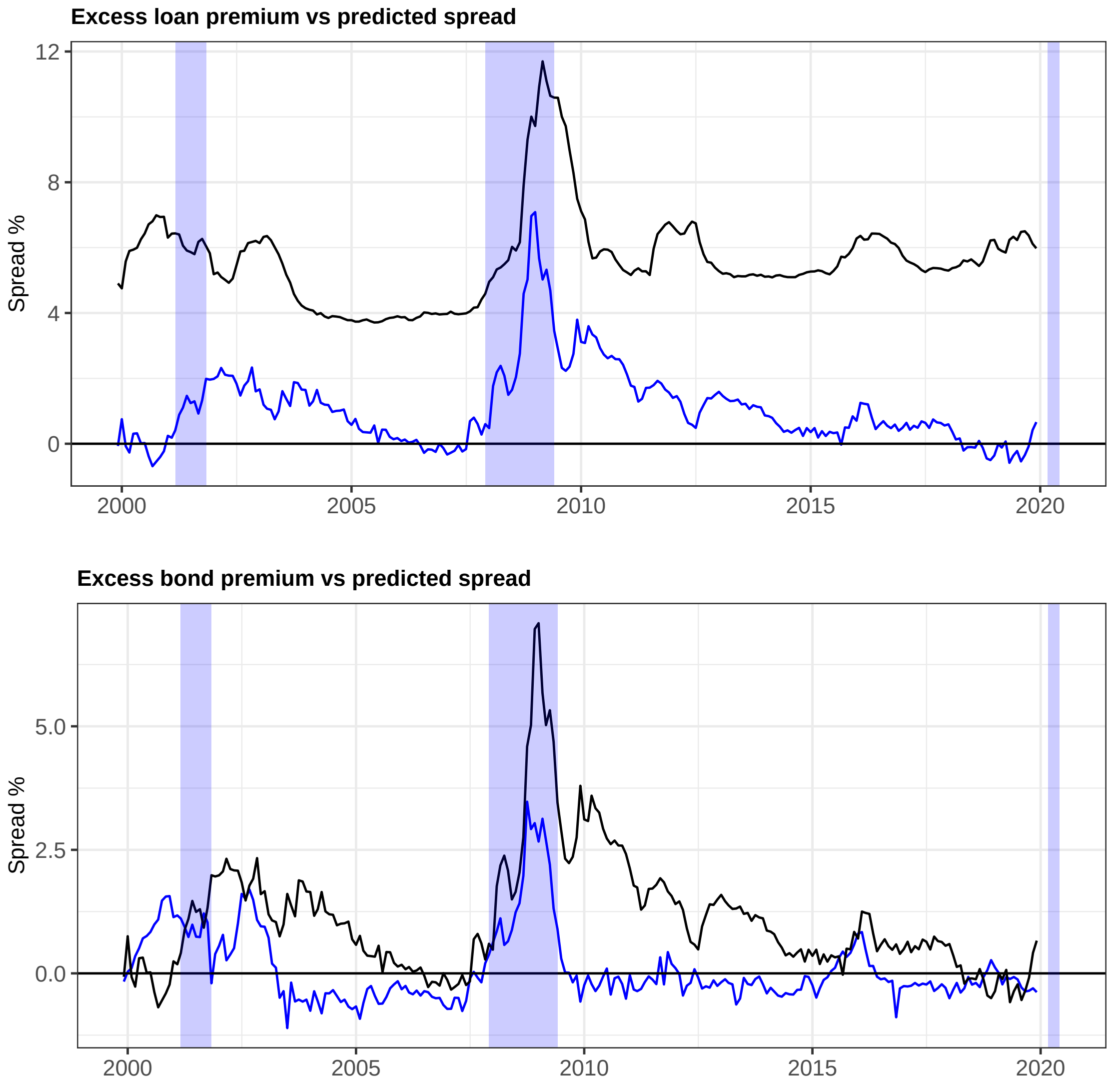

Figure A.10: **Excess loan/bond premium**
This figure plots monthly decomposed credit spreads defined following Gilchrist and Zakrajšek (2012). The top panel depicts the: (i) the excess loan spread (blue line), (ii) the predicted loan spread (black line). The bottom panel depicts the: (i) the excess bond spread (blue line), (ii) the predicted bond spread (black line). Bars indicate NBER recessions. The sample period is 1999:11 to 2019:12.

E Europe

E.1 Credit conditions

Table A.11: **Credit conditions europe**

This table relates credit supply conditions to credit spreads in 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. The dependent variables in Panel A 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, i.e., spreads and credit conditions are measured contemporaneously. 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.

Panel A. Credit conditions	(1)	(2)	(3)
Panel A1. 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 A2. 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 A3. 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

E.2 Aggregate spreads

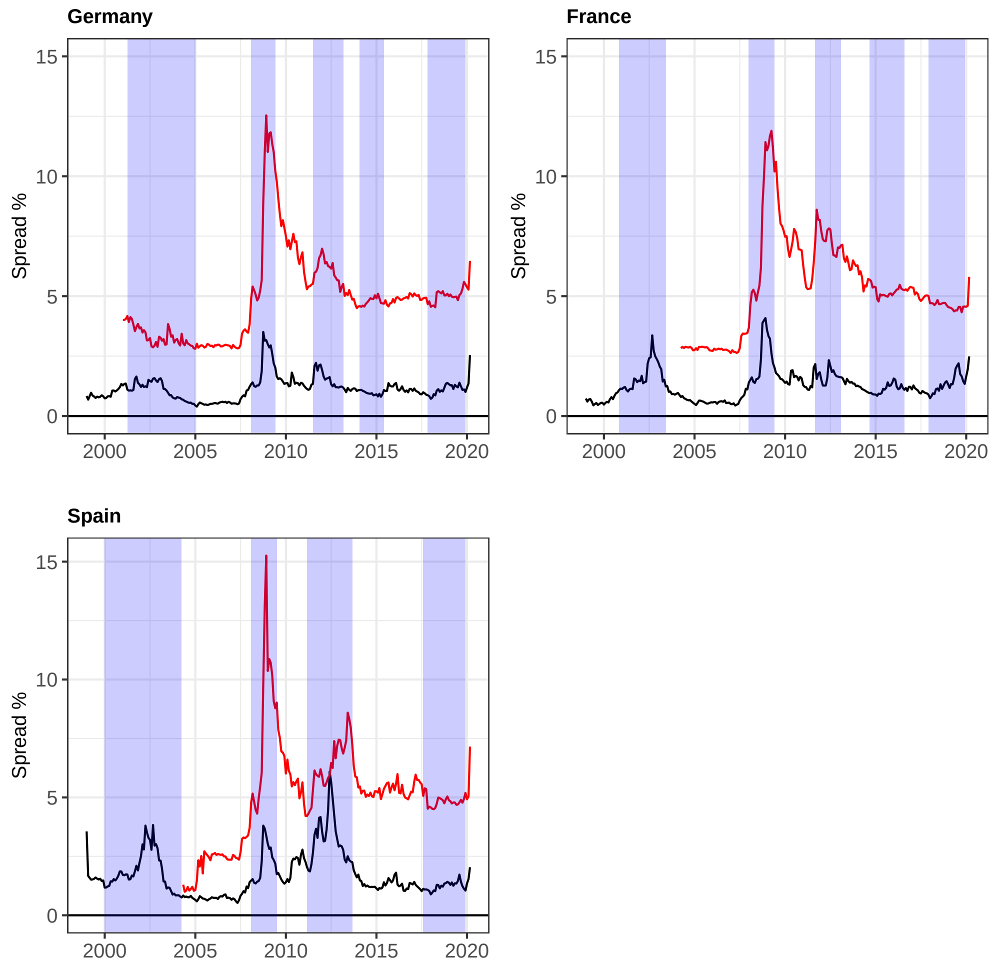

Figure A.11: **European country loan and bond spreads**
This figure plots monthly loan (red lines) and bond (black lines) spread measures over time for Germany (top left), France (top right) and Spain (bottom left). Observations based on less than five loans are excluded. Bars indicate OECD downturns. 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.