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 considerable predictive power for economic activity across macroeconomic outcomes in both the U.S. and Europe and captures unique information not contained in public market credit spreads. Loan-market borrowers are compositionally different and particularly sensitive to supply-side frictions as well as financial frictions that emanate from their own balance sheets. This evidence highlights the *joint* role of financial intermediary and borrower balance-sheet frictions in understanding macroeconomic developments and enriches our understanding of which type of financial frictions matter for the economy.

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

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1 Introduction

Fluctuations in credit-market conditions are large, cyclical, and they drive business cycles. Firms that depend on external funding can become financially constrained when credit conditions tighten. This is particularly severe for firms reliant on intermediated credit via bank loans, such as small and private firms (Holmström and Tirole, 1997; Diamond and Rajan, 2005; Chodorow-Reich, 2014). Firms with access to alternative funding sources, such as public bond markets, on the other hand, are less sensitive to frictions in credit markets (Greenstone *et al.*, 2020a; Chava and Purnanandam, 2011).

Figure 1 highlights the cyclicality of corporate bond and loan-market issuances. Strikingly, year-on-year growth rates in the loan and bond market are *negatively* correlated in recessions, as firms with access to public bond markets can substitute from loans to bonds when bank credit-market conditions deteriorate (Adrian *et al.*, 2012; Becker and Ivanshina, 2014; Crouzet, 2018, 2021).[1] This implies that bond and loan markets are not subject to the same frictions over time; each market is therefore likely to encode unique information.

In this paper, we forecast business-cycle fluctuations using the information content of bond and loan-market credit spreads. The literature has documented that credit spreads contain useful information for forecasting macroeconomic fluctuations (see, among others, Friedman and Kuttner, 1993; Estrella and Hardouvelis, 1991; Gertler and Lown, 1999; Gilchrist and Zakrajšek, 2012; López-Salido *et al.*, 2017; Mueller, 2009). This is typically motivated by theories of intermediary and borrower financial frictions, which affect investment and output decisions of firms (see, e.g., Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997).

Existing evidence, however, generally relies on spreads derived from public-credit markets and hence captures frictions that affect the least-constrained firms in the economy. Generalizing this evidence to other firms requires the assumption that the same frictions pertain to both bond and loan markets (e.g., López-Salido *et al.*, 2017). This is put into question

[1] There is a large literature on the determinants of corporate debt structures. See, e.g., Bolton and Scharfstein (1996), Diamond (1991), and Rajan (1992) for seminal theoretical contributions and Colla *et al.* (2013) and Rauh and Sufi (2010) for empirical evidence documenting a large debt structure heterogeneity in the cross-section of firms. Crouzet (2018) studies the aggregate implications of corporate debt choices.

by the evidence that firms with access to both markets actively substitute private for public debt when loan-market conditions deteriorate. Further, spreads derived exclusively from firms with access to public debt exclude the part of the economy that is most sensitive to financial frictions–both in the intermediary sector and emanating from firms' own balance sheets.

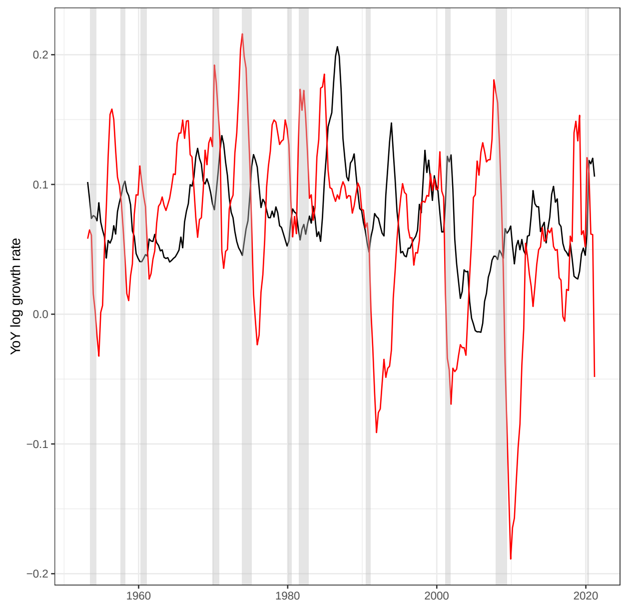

Figure 1: **Loan and bond market cyclicality**
This figure plots the year-on-year growth rate in outstanding corporate loans (red) and corporate bonds (black). Data comes from the U.S. Flow of Funds dataset. The sample period is 1953-2020. Grey bars are NBER recessions.

A key contribution of this paper is to introduce a novel *loan*-market-based credit spread that captures these frictions. 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.

Our first main finding is that the loan spread has substantial predictive power for the business cycle above and beyond that of other commonly used credit-spread indicators.

Using predictive regressions over the entire 20-year sample period, we find that our loan-spread measure sizably improves the in-sample fit of business-cycle prediction models, i.e., it adds information that is not contained in credit spreads derived from public debt markets and other commonly used indicators. This holds across a host of different macroeconomic outcome variables and different prediction horizons. The result also extends to out-of-sample forecasting models.

We provide a series of additional robustness tests, including i) accounting for supply-demand conditions in secondary markets, ii) accounting for information contained in equity markets, iii) controlling for indicators of macroeconomic uncertainty, iv) accounting for differences in terms across bond and loan contracts, and v) excluding the financial crisis period (2007:Q4 – 2009:Q2). In all tests, our main result remains unchanged.

While the time series might be short to study the predictive power of loan spreads for the business cycle, we extend our analysis to examine both across-country variation and across-industry variation within country. We analyze non-U.S.–arguably more bank dependent–countries such as Germany, France and Spain (which exhibit different business cycles over the last 20 years), and document the same basic patterns. We then construct credit spreads on a U.S. industry rather than an economy-wide level, as industries also display distinctive economic cycles. We also show that industry-specific loan spreads have significant forecasting power for industry-level developments, controlling for industry and time fixed effects.

What explains the strong predictive power of loan spreads? Our previous discussion suggests that bond and loan-market credit spreads likely account for the different frictions prevalent in each market. These frictions can originate either on intermediary or borrower balance sheets.

The first explanation is supported by a strand of literature arguing that credit spreads predict economic developments as they contain informative about frictions in the intermediary sector, i.e., shocks to intermediary balance sheets that may propagate to the real economy (e.g., Kiyotaki and Moore, 1997; Gertler and Kiyotaki, 2010; He and Krishnamurthy, 2013). Credit spreads of firms with bond-market access, however, might only capture frictions affecting the least-constrained firms in the economy.[2] Loan-market borrowers, on the other hand, have limited funding alternatives and are particularly sensitive to supply-side frictions. Hence, loan spreads could more accurately proxy for intermediary constraints.

Alternatively, loan-market borrowers might also be particularly sensitive to financial frictions that emanate from their own balance sheet (e.g., Bernanke and Gertler, 1989; Bernanke *et al.*, 1999; Holmström and Tirole, 1997). While the recent literature concludes that intermediary frictions account for the largest part of the predictive power of credit spreads (e.g., Gilchrist and Zakrajšek, 2012), this evidence is derived from bond-market firms. Firms that are active in loan markets, such as smaller and private firms, more closely resemble "low net-worth firms" in models that explain aggregate movements with borrower balance-sheet constraints. In other words, by focussing only on bond-market credit spreads we might underestimate the role of borrower balance-sheet frictions in explaining economic developments.

To isolate these channels, we start by examining the potential link between loan-market credit spreads and intermediary frictions. We use several indicators for loan-market conditions and bank health, including the Fed's quarterly Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS) on changes in credit conditions for commercial and industrial (C&I) loans, banks' undrawn C&I loan commitments, aggregate banking sector profitability, and loan loss provisions. Overall, our evidence suggests that loan spreads, when compared with public-credit-market spreads, are more strongly correlated with changes in credit standards and bank health. This supports the view that loan spreads, in comparison with other credit-spread measures, contain additional information about bank balance-sheet frictions.

Next, we follow Gilchrist and Zakrajšek (2012) and decompose the loan spread into two components: a predicted spread that captures changes in expected default risk of borrowers and an excess component, which captures the part of the spread not explained by expected default risk. Credit spreads adjusted for borrower fundamentals have frequently been used to proxy for supply-side frictions in the financial intermediary sector (e.g., Philippon, 2009).

[2] Consistent with this argument, Adrian *et al.* (2019) provide evidence that bond spreads in particular are good predictors of "tail events."

We find evidence that both the predicted and the excess spread have forecasting power for macroeconomic outcomes. However, in contrast to evidence from the bond market, it is the *predicted* component of the loan spread that accounts for most of its explanatory power. Approximately half to two-thirds of the additional R^2 gained by including the loan spread in the forecasting model can be attributed to variation in borrower fundamentals. That is, intermediary frictions alone do not appear to explain the incremental predictive power of loan spreads.

We then turn to the potential role of borrower balance-sheet frictions. We document that 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. Even though our secondary loan-market dataset is limited to somewhat larger (syndicated) loans, only 57% of loans in the sample are from publicly traded firms. Further, loan-market borrowers are, on average, significantly smaller and younger compared to bond-market borrowers. Thus, there is a limited overlap between bond- and loan-market borrowers.

Next, we show that the spread of relatively smaller, younger, and private firms drives a substantial portion of the loan spread's predictive power. These borrowers are more affected when credit market conditions tighten because of a lack of alternative funding sources, which eventually feeds into the real economy. Larger firms with access to both markets, in contrast, can substitute between private and public debt, i.e., they can respond to frictions that do not affect markets to the same degree (Crouzet, 2018).[3]

In particular, among the group of smaller, younger, and private firms, the overlap between the loan and bond market is limited. For instance, in our loan sample only 19% of smaller borrowers also have a bond outstanding, compared to 70% for larger borrowers. As a result,

[3] Smaller, younger, and private firms are generally more volatile and more sensitive to changes in economic conditions (e.g. Davis *et al.*, 2006; Pflueger *et al.*, 2020; Cloyne *et al.*, 2020; Begenau and Salomao, 2019). Despite their potentially smaller role in driving aggregate movements (e.g. Gabaix, 2011; Crouzet and Mehrotra, 2020), their market prices can be important signals for future economic development (Holmström and Tirole, 1997; Pflueger *et al.*, 2020).

the predictive power of a loan spread comprised of larger and older firms–i.e., the segment with the largest loan-bond market overlap–is close to that of public bond spreads. Similarly, 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.

Overall, these results suggest that bond and loan spreads each encode unique information and that differences across markets are important for understanding which types of financial frictions affect business cycles. Our results indicate that relying only on credit spreads from public markets can underestimate the role of borrower balance-sheet frictions. In fact, our findings highlight the *joint* role of financial intermediary and borrower balance-sheet frictions in understanding macroeconomic developments (Rampini and Viswanathan, 2019).

Related Literature: This paper introduces a novel measure of credit spreads derived directly from traded corporate loans. There is a long tradition of using financial market prices–credit spreads in particular–to predict business cycles.[4] While the existing empirical literature generally relies on measures derived from public capital markets, we introduce a novel measure based on private market credit spreads and show that this measure encodes unique information about future economic developments.[5]

The second main focus of this paper is on understanding why loan-market spreads contain additional information. We thereby contribute to the debate on what *type* of financial frictions matter for aggregate business cycle movements. Financial frictions can emanate from borrower balance sheets (e.g., Bernanke and Gertler, 1989; Bernanke *et al.*, 1999; Holmström and Tirole, 1997), from shocks to intermediaries (e.g., Kiyotaki and Moore, 1997; Gertler and

[4] Previous research has focused on stock and bond markets (Harvey, 1989), commercial paper spreads (Bernanke, 1990; Friedman and Kuttner, 1993), 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). While we focus on credit spreads, there is also a related broad empirical literature on the implications of credit quantities for credit cycles using cross-country-level data (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.*, 2020b; Giroud and Müller, 2018).

[5] Another strand of literature examines secondary loan markets in an asset-pricing and corporate-finance context (see, among others, Addoum and Murfin, 2020; Altman *et al.*, 2010).

Kiyotaki, 2010; He and Krishnamurthy, 2013), or both (Rampini and Viswanathan, 2019). Understanding the type of frictions that matter for the aggregate economy is important for evaluating the importance of different strands of economic theory as well as for policy responses to credit-market frictions. In particular since the 2008-2009 financial crisis, most empirical evidence points to a prominent role of intermediary frictions (Chodorow-Reich, 2014; He and Krishnamurthy, 2013; Brunnermeier *et al.*, 2012). This evidence, however, relies on credit spreads derived from public bond markets. Hence, an implicit assumption is that bond markets alone provide an accurate measurement of the type of financial frictions that might affect economic activity. Using a novel dataset on loan-market prices, our findings highlight the *joint* role of financial intermediary and borrower balance-sheet frictions in understanding macroeconomic developments.

Our discussion thereby relates to a strand of literature that examines firms' debt capital structure across the business cycle. Crouzet (2018) imbeds firms' debt capital structure choices in a model to study the transmission of financial shocks. Firms trade off the flexibility of loans with the lower cost of public debt. In response to shocks that affect markets differentially, firms with access to both markets switch between instruments. Adrian *et al.* (2012), Becker and Ivanshina (2014), and Crouzet (2021) empirically examine debt issuance behaviour of firms with access to both loan and bond markets and document that firms substitute between debt types depending on aggregate market conditions. Hence, debt capital structure adjustments of such firms can be an indication of the relative frictions across debt markets. We add to this literature by examining the information content in loan-market prices for a sample of firms with access to public debt markets as well as firms that exclusively depend on intermediated credit. Our evidence indicates that there is unique information encoded in credit spreads of firms without bond-market access that is relevant for understanding aggregate developments and the nature of financial frictions.

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 like debt securities. 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 1980s but it was not until the founding of the Loan Syndication and Trading Association (LSTA) in 1995, which standardized loan 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 (Figure 2).

The majority of loans traded in the secondary market are syndicated loans, i.e., loans issued to a borrower jointly by multiple financial institutions under one contract. The syndicated loan market is one of the most important sources of private debt for corporations. For example, ∼69% of non-financial firms in Compustat N.A. were 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. About 50% of borrowers in our sample are private firms.

Data: We use a novel dataset from the LSTA comprised of daily secondary market quotes for corporate loans spanning December 1999 to March 2020. Loan sales are usually structured as assignments,[6] and investors trade through dealer desks at underwriting banks. The LSTA receives daily bid and ask quotes from over 35 dealers that represent over 80% of the secondary market trading.[7] It has been shown that price quotes provide an accurate

[6] In assignments the buyer becomes a loan signatory. This facilitates trading as ownership is transferred from seller to buyer. In contrast, in participation agreements the lender retains official ownership.

[7] There is little public information about dealers who provide quotes collected by the LSTA. However, the data identifies dealer banks for a subsample of loans in 2009. In Online Appendix Section A we show that the top 25 dealers account for about 90% of all quotes. We rank dealers by their market share in the secondary loan market and market share as loan underwriter in the primary loan market and find a correlation of 0.87.

representation of prices in this market (Berndt and Gupta, 2009).[8]

The sample contains 13,221 loans to U.S. non-financial firms. We exclude credit lines and special loan types (1,703 loans), i.e., we restrict our sample to term loans.[9] Term loans are fully funded at origination and typically repaid at maturity, i.e., the cash-flow structure is similar to bonds. We require that loans can be linked to LPC's Dealscan and remove loans with a remaining maturity of less than one year, resulting in a final sample of 9,095 loans. As we use monthly measures of economic activity, we calculate mid quotes for each loan-month. The final sample contains 302,223 loan-month observations.[10]

We complement the LSTA pricing data with information about the structure of the underlying loans from Dealscan. 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. Section Section B of the Online Appendix contains a full list of the variables used and their sources.

Methodology: We use a bottom-up methodology similar to Gilchrist and Zakrajšek (2012). In contrast to bonds, loans are floating-rate instruments based on an interest rate, typically the three-month LIBOR, plus a fixed spread. To construct the sequence of projected cash flows for each loan we use the three-month LIBOR forward curve (from Bloomberg) and the spread (from Dealscan). We add the forward LIBOR for the respective period to the loan's all-in-spread-drawn (AISD). The AISD comprises the spread over the benchmark rate and the facility fee, and has been shown to be an adequate pricing measure for term loans

[8] We focus on secondary market spreads because primary market spreads may reflect endogenous changes to the issuer composition over time (e.g., in a recession, only high-quality firms may be able to access the market).

[9] The vast majority of loans 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).

[10] Online Appendix Section A provides information on market liquidity. The median bid-ask spread in the 1999 to 2020 period was 81 bps. For comparison, Feldhütter and Poulsen (2018) report an average bid-ask spread of 34 bps for the U.S. bond market over the 2002-2015 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.

(Berg *et al.*, 2016, 2017). We assume that cash flows are paid quarterly.[11] 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, for each loan we construct a synthetic risk-free loan with the same cash-flow profile. Let $P_{it}^{f}[k]$ be the risk-free equivalent price of loan k, where $P_{it}^{f}[k]$ is the sum of the projected cash flows, discounted using zero-coupon Treasury yields from Gürkaynak *et al.* (2007). Using $P_{it}^{f}[k]$ we extract the risk-free equivalent yield to maturity, $y_{it}^{f}[k]$. The loan spread $S_{it}[k]$ is defined as $y_{it}[k] - y_{it}^{f}[k]$. We exclude observations with a spread below 5 bps, above 3,500 bps, or with a remaining maturity below 12 months.

We take a monthly arithmetic average of all loan spreads to create the aggregate loan spread following 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:

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

Figure 3 plots our loan spread and other commonly used credit spread measures.[12] While the commercial paper-bill spread is essentially flat over our sample period, the loan spread and the other credit spreads follow similar patterns over time, with sharp movements around the 2001 recession, the 2008-2009 financial crisis, and the beginning of the COVID-19 pandemic. The correlation between loan and GZ spread (Baa-Aaa spread) is 0.76 (0.80) over the entire sample period and 0.65 (0.68) excluding the 2008-2009 crisis. We use spread changes in our tests, which substantially reduces the correlation between loan and GZ spread (Baa-Aaa spread) to 0.45 (0.64) (or 0.21 (0.41) excluding the financial crisis). The loan spread

[11] We use the same interest period for all loans, as information on the loan-specific interest period is often missing in Dealscan. However, in a subsample 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.

[12] The commercial paper-bill spread is from the Federal Reserve H.15 report and is defined as 3-Month Treasury-Bill minus 30-Day AA Non-financial Commercial Paper. The Baa-Aaa credit spread (constructed by Moody's) is from Federal Reserve's FRED website. The GZ spread is provided by Favara *et al.* (2016) and is an updated version (available also for more recent periods) of the measure by Gilchrist and Zakrajšek (2012). See https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/files/ebp_csv.csv for details.

is significantly more volatile, with a standard deviation (SD) of 2.4% (vs. 1.0% for the GZ and 0.43% for the Baa-Aaa spread) and has an unconditional mean an order of magnitude higher than the bond spreads. This is consistent with loan markets containing a broader set of borrowers, including more lower-credit-quality borrowers such as private firms who cannot access public bond markets.[13] See Online Appendix Section C for detailed descriptive statistics.

3 Borrower composition in loan and bond markets

Before we examine whether loan spreads contain information about the future business cycle, it is useful to understand how firms that borrow in loan markets compare with firms that are active in public-credit markets. Compositional differences between markets may help to understand differences in information content of loan and other credit-spread measures.

Our sample of (secondary) loan-market borrowers comprises 3,713 unique firms. To construct a benchmark sample of bond-market issuers we reconstruct the Gilchrist and Zakrajšek (2012) measure using bond-pricing data from TRACE.[14] This sample comprises 2,917 firms. Table 1, Panel A, splits the samples into public and private firms. Public firms are defined as firms that can be linked to Compustat and the remaining firms are classified as private.[15] The majority of bond issuers are public (67%). In contrast, about half of all loan market borrowers are private. This gives a first indication that loan markets cover a broader set of borrowers, including a larger share of firms that cannot/do not access public markets.

Next, we compare characteristics of loan- and bond-market borrowers in more detail. This discussion is based on *public* firms for which data is available in Compustat. Given the larger

[13] However, Schwert (2020) documents that primary market loan spreads are also higher than bond spreads in a sample of loans matched with bonds from the same firm (and accounting for other differences).

[14] While we mostly use the bond spread provided by Favara *et al.* (2016), the correlation with the TRACE measure is high (0.96). This measure is used in subsample analyses–see details in later sections.

[15] The number of unique "parent firms" in the public firm sample–identified by firms' Compustat IDs (GVKEY)–is lower than the number of loan(bond)-market issuers. This is because borrower IDs (issuer IDs) in the LSTA (TRACE) database can be assigned to the same GVKEY. Given that this aggregation to the parent level is only feasible for public firms, we report the private/public split using borrower/issuer IDs and then proceed by reporting statistics at the parent (GVKEY) level in Panels B and C.

share of private firms in the loan market, this comparison understates differences between loan- and bond-market borrowers. All statistics are reported in Table 1 and visualized in Figure 4.

Loan-market borrowers are younger than bond-market borrowers, on average.[16] Panel B, reports that while 29% of loan market borrowers have an age <= 5 years, only 19% of bond market borrowers fall in this age category. In contrast, 42% of bond market-borrowers are older than 20 years, compared to only 27% of borrowers in the loan market. 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 > 20years) are also bond issuers, only 33% of "young" firms (age <= 5years) are also active in the bond market. This indicates that the market overlap is larger for more mature firms. Conditional on being active in the bond market, "young" firms in particular are more likely to also be loan-market borrowers (42% of firms <= 5years).

Panel C paints a similar picture, grouping firms by size. Loan-market borrowers are smaller than bond-market borrowers. Only 16% of loan-market firms have assets > \$6 billion and 67% are in the smallest size category (<= \$2 billion). In contrast, about 37% of bond issuers have assets > \$6 billion. Focussing on the market overlap, larger loan-market issuers are particularly likely to also be active in the bond market–around two-thirds of borrowers with assets > \$6 billion are also active bond issuers. Among the small loan-market borrowers (<= \$2 billion), which account for 61% of all loan-market firms, only 19% also are active in the bond market.

Overall, the overlap between loan and bond markets is limited, particularly for smaller, younger, and private firms. The loan market comprises a broader set of borrowers, including firms not active in the bond market. This highlights that conditioning on borrowers with access to both public and private credit markets would exclude a large fraction of firms active in the loan market that may be particularly sensitive to financial frictions.

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

4 Loan spreads and economic activity

4.1 Baseline results

We first examine *if* loan spreads contain information that is useful for predicting aggregate developments. We analyze channels through which the loan markets' predictive power can arise in later sections. We start by running standard forecasting regressions:

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

where h is the forecast horizon and Δy is the log growth rate for a measure of economic activity from $t-1$ to $t+h$.[17] ΔS_t is the change in a credit-spread measure from $t-1$ to t. TS is the term spread and RFF is the real effective federal funds rate.[18]

We follow López-Salido *et al.* (2017) and use credit-spread changes rather than levels in our predictive regressions. This is 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, because increases in credit spreads reflect an increase in the cost of credit, which impacts investment decisions. Finally, first differencing accounts for non-stationary present in the time series of credit-spread.

Regressions are estimated by OLS, with one lag of the dependent variable.[19] Due to the low level of persistence in the dependent variable (and ΔS_t), we use Newey-West standard

[17] Including monthly (non-farm private) payroll employment [NPPTTL], unemployment rate [UNRATE], industrial production [INDPRO], total industrial capacity utilization [TCU], new orders for capital goods (ex. defence) [NEWORDER] and total business inventories [BUSINV]. Data is obtained from FRED.

[18] The term spread, defined as the difference between the ten-year Treasury yield and the three-month Treasury yield, is available from FRED [T10Y3MM]. The real effective federal funds rate is estimated using data from the Fed's H.15 release [FEDFUNDS] and realized inflation as measured by the core consumer price index less food and energy [CPILFESL].

[19] 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 six periods, or allowing for an optimal lag length selection based on the AIC leads to very similar results.

errors with a four-period lag structure. Hansen-Hodrick standard errors return very similar results. The timing conventions we adopt are standard (e.g., Gilchrist and Zakrajšek, 2012). Macroeconomic data is often released with a lag; hence growth rates are defined starting in $t-1$. Likewise, the lagged dependent variable is measured over $t-2$ to $t-1$ to prevent any lag overlap. A full discussion is provided in Online Appendix Section D wherein we also provide results using alternative timing conventions with very similar results.

Table 2 shows the results for industrial production over a forecast horizon of three months (h=3). Dynamic effects are examined in the next sub-section. In column (1), we report a baseline model with only TS, RFF, and the lagged dependent variable. This model can explain 19% of the variation in changes in three-month-ahead industrial production. To gauge the contribution of other predictors to the in-sample fit, we report the incremental increase in adjusted R^2 relative to this baseline at the bottom of each panel.

Columns (2) to (5) include credit spreads that have been used in the prior literature, including i) the paper-bill spread (Friedman and Kuttner, 1993, 1998; Estrella and Mishkin, 1998), ii) the Baa-Aaa spread (e.g., Gertler and Lown, 1999), iii) a high-yield spread, iv) and the GZ spread (Gilchrist and Zakrajšek, 2012).[20] Except for the paper-bill spread, which has little variation during the sample period, all credit spreads have significant predictive power and add between +4 percentage points (p.p.) and +7.3 p.p. to the in-sample fit.

Column (6) adds our loan spread in the prediction model. This model can explain 33.5% of the variation in changes in industrial production. This is a sizeable R^2 increase of about 15 p.p. relative to the baseline. The coefficient indicates that a one standard-deviation (SD) increase in loan spread is associated with a decrease in industrial production by 0.405 SD, i.e., a 45 bps spread increase corresponds with a 0.72% decline in production (unconditional mean: 0.15%). The loan market's predictive power is sizeable also when compared to bond spreads. The bond-spread model that yields the largest in-sample fit increase [Baa-Aaa spread; column (3)] has an incremental R^2 of +7.3 p.p. This is only half of the loan spread's incremental R^2 of +14.6 p.p.

[20] The high-yield index [BAMLH0A0HYM2EY] is obtained from FRED and based on the ICE Bofa US high yield effective index. See footnote 12 for details on the other credit spread measures.

Note that the results in column (3) and (4) indicate that a bond spread measure based on non-investment grade rated firms, which may be more comparable to the typical loan market firm, does not yield the same predictive power as that of the loan spread. In Online Appendix Section D.3, we create bottom-up bond spread measures for different rating categories and document similar results. We examine the predictive power of different risk segements *within* the loan market in Section 5.2.2.

Next, we benchmark the loan spread more explicitly against other credit spreads. Given the high correlation across bond spreads, we take the first principal component (PC) of the spreads used in columns (2) to (5). Column (7) shows that this first PC has significant predictive power on its own. When we combine the bond-spread PC and the loan spread in one model, the loan-spread coefficient and incremental R^2 remain almost unchanged. In other words, while both bond and loan spreads have predictive power, the loan spread has additional forecasting power. A formal likelihood ratio (LR) test confirms that adding the loan spread yields a statistically significant improvement in model fit relative to column (7). A variance inflation factor of below 1.5 for both loan spreads and for the first PC of the bond spreads suggests that the correlation between both spreads is not affecting our results.

Similar results are obtained when looking at other measures for macroeconomic development in Panel A of Table 3. These include employment-related measures (payroll employment, unemployment), and inventory and order measures (industrial capacity utilization, new orders capital goods, business inventory). For brevity we only report specifications that jointly include the loan spread and the bond-spread PC (and the base variables). Across all outcomes, we find that the loan spread adds to the predictive power of the model above and beyond bond market information. The incremental R^2 ranges from +2 p.p. to +13 p.p. and this effect comes almost entirely from the loan spread, not the inclusion of the bond-spread PC. In untabulated analyses we find that the contribution of the loan spread varies from 76% to 95% across outcome measures. We further report LR tests that confirm that including the loan spread yields a statistically significant improvement in model fit (relative to the same model without the loan spread).[21]

4.2 Dynamics

We have focused on three-month-ahead predictions so far. To examine dynamics we use a local projections framework (Jordà, 2005). Figure 5 plots the coefficient and 95% confidence intervals on the loan spread at various forecasting horizons (1 to 12 months ahead) using each of our dependent variables.

For most variables, the predictive power of the loan spread peaks around h=3, i.e., the loan spread today is most correlated with economic development one quarter from now. However, even at longer forecasting horizons the loan spread retains predictive power, i.e., the results do not hinge on the specific forecast horizon. In addition to the forecasting coefficient, the figure shows the models' incremental R^2 over the 1 to 12 month horizon (black line). While the magnitudes vary across outcomes, the loan spread consistently adds significantly to the models' in-sample fit, including over different forecasting horizons. This confirms that the loan spread's additional predictive power is not specific to the three-month horizon. Online Appendix Section D.5 provides similar results, dynamically benchmarking loan spreads against bond spreads.

4.3 Out-of-sample prediction

Next, we provide indicative evidence that the loan spread's predictive power extends to out-of-sample forecasts. Out-of-sample performance is measured via an expanding window. Specifically, we start with 60 months of data and forecast the dependent variable one step ahead, i.e., over the next three-months. We then compare the forecast to the actual growth rate and calculate the forecast error. We repeat this procedure rolling forward one month at a time. This yields a vector of forecast errors across different training/testing windows that

[21] The effects is somewhat weaker for employment measures. This may be a function of the persistent nature of these variables, which is not well suited to prediction with fast-moving financial-market-based indicators.

can be used for root mean squared error (RMSE) comparisons across models.

Table 4 summarizes the results. In each panel (i.e., for each outcome) we compare three models: "Baseline" uses only TS, RFF, and a one-period lag of the dependent variable as predictors (mirroring the baseline in-sample model). "Baseline + $\Delta S_t^{Bond\ PC}$" adds the bond-spread PC. "Baseline + ΔS_t^{Loan}" adds our loan-spread measure (but no bond spreads) to the baseline. Column (1) reports the base RMSE and column (2) the normalized RMSE to facilitate comparisons across models with different outcome variables.

Consistently across all macro variables, the model with the loan spread returns the lowest RMSE. Column (3) reports a t-test for the difference in the mean RMSE between the model that uses the bond-spread PC and the loan spread model. Despite the relatively short sample period, for four out of the six dependent variables the RMSE is statistically lower for the loan-spread model compared to the bond-spread model at the 10% significance level or lower. Again, the evidence is consistent but somewhat weaker for the more-persistent employment measures. Overall, the results indicate that the loan spread adds predictive power above and beyond other credit-spread measures, in and out-of-sample.

4.4 Robustness

This section discusses further robustness tests. We focus on industrial production in our main tests for brevity. Similar conclusions are obtained for other macroeconomic outcomes (see Online Appendix Section D.2).

Loan contracts might be different with respect to non-price terms compared to bonds. We regress loan spreads on various contract terms and take the residual spread, which is by definition orthogonal to loan contract terms (see Online Appendix Section D.4 for details). Table 3, Panel B, column (1) uses this "residual loan spread" and finds very little difference in predictive power relative to the baseline loan spread.

Next we control for supply-demand conditions in the secondary market using the median bid-ask spread as a measure of loan-market liquidity (plotted in Online Appendix Section

A.2). Our main result remains unchanged [column (2)].

Equity markets may also contain signals about economic development (see, e.g., Greenwood *et al.*, 2020; López-Salido *et al.*, 2017). In column (3), we include the monthly return of the S&P 500 index. While the equity market return does have predictive power, the forecasting coefficients on the loan spread remain largely unchanged.

Uncertainty can affect firm incentives to invest and hire via a real options channel (Bloom, 2009; Baker *et al.*, 2016) or borrower demand for credit by affecting the cost of capital. Hence, credit spreads may capture an uncertainty-induced change in the marginal cost of new finance, which impacts future economic activity. In column (4) we include the VIX in the model. While the VIX does have predictive power, the forecasting coefficient on the loan spread remains large and significant.

Finally, results may be driven by the 2008-2009 financial crisis. Columns (5) and (6) show that the predictive power of bond spreads becomes small and insignificant when excluding the crisis. The loan-spread coefficient drops by half, but remains significant. That is, loan and, particularly, bond spreads perform weaker outside of financial crisis periods. This is consistent with bond spreads capturing frictions affecting the least-constrained firms in the economy and hence mainly serving as predictors of "tail events" (Adrian *et al.*, 2019). Loan spreads, in contrast, retain predictive power also outside of crisis periods.

4.5 Evidence from European countries

A time series of secondary market loan prices has only been available for about 20 years, which is a relatively short period for macroeconomic predictions. We therefore exploit the fact that different countries have different business cycles. We focus on three of Europe's largest economies: Germany, France, and Spain, for which we have sufficient loan-market data (coverage is too limited in other countries) and construct European loan spreads following the methodology described in Section 2 (see Online Appendix Section E for details). We focus on manufacturing production and unemployment as outcome variables.

We start with three-month-ahead forecasts for Germany in Panel A of Table 5. The baseline model, column (1), includes the term spread, real EONIA, and one lag of the dependent variable. This model can explain 14.1% of the variation in changes to the manufacturing index. In columns (2) and (3) we add a high-yield bond spread (ICE BofA Euro High Yield Index OAS from FRED) and the Mojon and Gilchrist (2016) spread, respectively. These predictors have an incremental R^2 of +6.5 to +2.9 p.p. relative to column (1).

We add the loan spread in column (4), which provides a sizeable increase in R^2 of +12.2 p.p. The coefficient and incremental R^2 hardly change when the loan-spread and bond-spread PC are jointly included [column (5)]. We find consistent results for unemployment [column (6)] and the results extend to France and Spain (Panels B and C). Overall, our evidence from Europe is consistent with the U.S. evidence. Loan spreads have significant predictive power for macroeconomic outcomes, above and beyond commonly used measures.

5 Exploring the mechanism

Our results so far provide robust evidence that loan-market credit spreads contain unique information. What are the mechanisms that explain this predictive power, in particular, relative to 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. Firms with access to alternative funding sources, such as public bond markets, are generally less sensitive to such frictions (Greenstone *et al.*, 2020a; Chava and Purnanandam, 2011). That is, credit spreads of firms with bond-market access might only capture frictions affecting the least-constrained firms in the economy, while loan-market credit could capture intermediary constraints more broadly.

5.1.1 Financial conditions

We first examine to what extent loan spreads are associated with a tightening of financial conditions using two commonly used measures in the literature, i) The Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS) and ii) commercial banks' unused credit lines.

In Panel A of Table 6, we regress a measure of bank lending standards on the loan spread and benchmark the effect against other measures. The dependent variable is the change in bank lending standards obtained from the 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.

We also regress the indicator on the change in credit spreads over the previous quarter, i.e., we focus on the contemporaneous relationship between credit conditions and spreads. Similar to the baseline forecasting results, the paper-bill spread is uncorrelated with the SLOOS. The loan spread, in contrast, has a high correlation with the SLOOS. A one-SD increase in loan spread is associated with a 0.44% increase in the net percentage indicating tighter lending conditions and the model's R^2 is 18.2%. The bond PC (cf. Section 4.1) is also correlated with the SLOOS, albeit significantly weaker (R^2 of 8.5%). Including both spreads in the model shows consistent results. The loan spread retains its economic and statistical significance, while the bond spreads become economically small and insignificant.

In Online Appendix Section E.2, we extend these results to Europe using the ECB's Bank Lending Survey and find a similar pattern.

Next, we use banks' unused commitments (as % of total assets) as a second measure of financial conditions in Panel B. Banks might curtail their exposure at the beginning of an economic downturn primarily by reducing undrawn commitments (Bassett *et al.*, 2014). We regress the change in undrawn commitments over the previous quarter on the change in credit spreads over the same quarter, i.e., we examine the contemporaneous relationship. An increase in both loan and bond spreads is associated with a decrease in banks' unused commitments; however, the effect is again significantly stronger for the loan spread.

Panel C documents a link between the credit spreads and the profitability of the financial sector as measured by its return on assets (ROA across all U.S. banks). Again, results indicate a stronger link between financial sector ROA and the loan spread compared to other credit spreads. 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 (Panel D).

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

5.1.2 Credit spread decomposition

To further gauge the relative importance of the bank and borrower balance-sheet channel, we decompose the loan spread into two components (Gilchrist and Zakrajšek, 2012): i) a component that captures changes in default risk based on the fundamentals of the borrower ("predicted spread"), and ii) a residual that captures the price of risk above a default risk premium, i.e., the "excess loan premium" (ELP). A detailed description of the methodology is provided in Online Appendix Section F.

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

We run forecasting regression (2) using decomposed spreads and report the results in Table 7. For all macroeconomic outcomes, we find that both the predicted spread, $\hat{S}^{Loan}$, and the ELP have significant predictive power at the 3-month (Panel A) and 12-month horizon (Panel B). Interestingly, however, for four out of the six macroeconomic variables (IP, INV, UE, TCU) most of the forecasting power comes from the *predicted* part of the loan spread (55-74%). Also, for PEMP and NEW, the predicted component still accounts for 35-43% of the predictive power. This is in contrast to evidence from the bond market, where the residual component tends to account for most of the predictive power (Gilchrist and Zakrajšek, 2012). This suggests 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 the next section.

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.

While the recent literature concludes that intermediary frictions account for the largest part of the predictive power of credit spreads, this evidence is derived from bond-market firms. Firms that are active in loan markets, such as smaller and private firms, more closely resemble "low net-worth firms" in models that explain aggregate movements with borrower balance-sheet constraints. In other words, by focussing only on bond-market credit spreads we might underestimate the role of borrower balance-sheet frictions in explaining economic developments. We test this conjecture by exploring whether it is the more-constrained firms, active in loan but not bond markets, that account for the loan spread's additional predictive power.

5.2.1 Effect by firm size, age, and listing

Loan markets are populated with firms that may have limited access to alternative funding sources. For example, Figure 4 highlights that more than 70% of firms 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 and 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. 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. These borrowers are most affected when credit conditions tighten.

Table 8 uses loan spreads conditional on the size of the borrower (measured by total assets) or the age of the borrower (number of years with total assets in Compustat) in aggregate forecasting regressions. Panel A focuses on the 3-month-ahead horizon, Panel B the 12-month-horizon. We double-sort firms by median age and size categories (Hadlock and Pierce, 2010). Results using single sorts (untabulated) show very similar results.

The results indicate that a loan spread constructed using young and small firms has significantly more predictive power than a spread based on old and large firms. Focussing on industrial production over the 3-month-horizon, the incremental R^2 is about twice as large for the young and small spread compared to the old and large spread (13 p.p. versus 6.4 p.p.). Interestingly, the predictive power of large and old firms is close to that of the base bond-spread measure [coefficient of -0.266 versus -0.253, cf. Table 2, column (7)]. This is consistent with the overlap between loan and bond markets being largest in this segment, cf. Section 3. That is, conditioning on a similar set of firms yields a similar predictive power. Consistent results are obtained for the other outcome variables as well as for the 12-month horizon (Panel B).

In addition to the size and age splits, Table 8 reports results using a loan-spread measure constructed from private firms.[22] The results indicate that the predictive power of a loan spread constructed from private firms, which are presumably the most-constrained firms, is stronger even compared to small and young firms across all variables [e.g., incremental R^2 of 15.2 p.p. versus 13 p.p. in Panel A, column (1)].

Overall, the results indicate that restricting attention to borrowers with the largest overlap between loan and bond markets–i.e., large and old firms–attenuates the predictive power of loan relative to 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. The predictive power of the loan spread is stronger for younger, smaller, and private borrowers who are more exposed to financial frictions. Among this group of firms, the overlap between the loan and the bond market is limited (Section 3).

5.2.2 Effect by credit rating

Credit ratings are a possible alternative measure of borrower financial frictions. The spread of riskier firms may be an even-better proxy for the external finance premium and hence particularly suitable for prediction (Gertler and Lown, 1999; Mueller, 2009). Table 9 sorts loans into four groups, BBB, BB, B and below, and unrated. Loan ratings are sourced from Dealscan and Leveraged Commentary and Data (LCD). The top row of Panel A (Panel B)

[22] Private firms are firms that cannot be linked to Compustat, and hence, a size or age split cannot be performed.

highlights that a loan spread derived from the highest-rated loans, BBB, has no predictive power for 3-month (12-month)-ahead macroeconomic outcomes. This is consistent with the safest borrowers facing the least balance sheet constraints and being less exposed to financial frictions.

As we condition on a riskier set of loans, the loan spread increases in its predictive power. The spread of unrated loans shows a very similar pattern to loans rated B or below. Comparing to the baseline results in Table 2, it appears that most of the predictive power of the loan spread is coming from loans rated B or below and loans with no available rating. This is consistent with the previous section as these borrowers, most likely private firms, are the type of firms for which we would expect financial frictions to matter the most.

In summary, we find that frictions on financial intermediary and borrower balance sheets matter for understanding the predictive power of credit spreads. Specifically, we show that frictions arising from the borrower side are a key driver of the differential predictive power of the loan spread relative to the bond spread. Our evidence is therefore consistent with models highlighting that financial intermediary and firm balance sheet constraints *jointly* determine economic activity, see e.g., Rampini and Viswanathan (2019). Importantly, studies focussing only on bond-market credit spreads can thus underestimate the role of borrower balance-sheet frictions in explaining economic developments.

While we focus on financial frictions to understand the differential predictive power of bond and loan spreads, there are other possible explanations. One alternative channel highlights the role of uncertainty in driving borrower demand for credit (Bloom, 2009; Baker *et al.*, 2016).[23] Another alternative channel highlights the role of investor sentiment/beliefs (Greenwood and Hanson, 2013; López-Salido *et al.*, 2017; Bordalo *et al.*, 2018).[24] Overall, while these alternative channels are clearly meaningful, financial frictions appear to be the

[23] In the Online Appendix Section G, we report results using alternative proxies for uncertainty and risk aversion, including the 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). While these proxies do contain predictive power, the forecasting coefficient on the loan spread remains large and statistically significant in all specifications.

[24] Our evidence suggests that borrower fundamentals account for the largest part of the predictive power of the loan spread but not excess loan spreads, which likely capture investor sentiment (López-Salido *et al.*, 2017).

economically more meaningful driver of the differential predictive power of the loan spread when compared to bond spreads documented in this paper. These are promising areas for future research.

6 Industry heterogeneity and weighting schemes

In this final section, we analyze cross-sectional heterogeneity in the predictive power of spreads as well as alternative methods to aggregate loan-level spreads. Starting with loan-level spreads allows us to aggregate spreads not only at the economy-wide but also at less-aggregated levels, such as the industry level. This has several advantages. 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 using fixed effects. Third, studying in which industries credit spreads have more predictive power can improve our understanding as to why loan spreads are informative.

6.1 Industry-level forecasting

Industry-level 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 spreads, S_{bt}^{Loan}, are constructed following Section 2, but loan spreads are aggregated using an arithmetic average across all firms in a BEA sector b. Overall, we construct spreads for 11 BEA sectors.[25]

Figure 6 plots industry loan spreads over time. Spreads are not perfectly correlated across industries. For example, while "Construction" and "Transportation" experienced a significant spread increase during the 2008-2009 crisis, this increase is less pronounced for more-stable sectors such as "Education and health care" and "Utilities". Further, some industries experienced idiosyncratic crisis periods. The "Mining" sector (which includes

[25] "Agriculture, forestry, fishing, and hunting" and "Other services, except government" are excluded due to an insufficient number of observations. We further exclude industry-months with less than five loans.

oil and gas), 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 2008-2009 level. There is also a 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.

Forecasting results: To assess the relationship between industry-specific spreads and industry-specific macroeconomic outcomes, we use quarterly employment and establishment figures from the Bureau of Labour Statistic's (BLS). In addition, we use quarterly industry gross output from the BEA. [26] The baseline results are reported in Table 10.

We start with a model that includes the industry and aggregate loan spread in a pooled regression.[27] Both spread measures have predictive power. Next, we include time fixed effects, which absorbs any 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, or overall regulatory changes. Interestingly, industry-specific loan spreads remain highly statistically and economically significant. That is, there is significant information contained in loan spreads that is not captured by other aggregate economic factors. Finally, we 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.[28] Results are consistent across all outcome variables, albeit weaker for gross output, which is only available since Q1 2005.

External finance dependence: The predictive power of loan spreads may vary across industries. Our results so far indicate that the loan market comprises firms that have limited access to alternative funding sources and that exhibit a higher sensitivity to financial fric-

[26] The BEA data is only available from Q1 2005 to 2019 Q4. The underlying macroeconomic data obtained from both BEA and BLS is not seasonally adjusted. 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.

[27] In contrast to the aggregate forecasting regressions, we include the loan-spread level. 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.

[28] 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.

tions. Hence, loan spreads may have more predictive power in industries that comprise firms more dependent on external finance.

Table 10, column (4) interacts loan spreads with indicators for the sector's dependence on external finance, defined following Rajan and Zingales (1998).[29] The most external-finance-dependent industries have the strongest relationship with loan spreads. This is consistent with our finding that more external-(bank)-finance-dependent firms, such as smaller, younger, and private firms, account for most of the predictive power of the loan spread.

6.2 Alternative weighting schemes

Finally, we explore if alternative weighting schemes to construct an aggregate loan spread can be used to improve forecasting. So far, a simple arithmetic average of all loan spreads available each month is used to create an aggregate measure, following Gilchrist and Zakrajšek (2012). However, firms or industries may differ in their importance and spreads may have a differential information content across sectors, as implied by the previous section. This may or may not be reflected in the number of loans outstanding across industries.

Table 11 reports aggregate-level regressions (model 2) using spreads constructed using alternative weighting schemes. The top row of Panel A and B reports the baseline aggregate loan spread, constructed as a simple arithmetic average across all individual loan-month observations, for comparison.

The second row uses a spread constructed by weighting each industry loan spread by that industry's contribution to GDP. Interestingly, a GDP-weighted loan spread performs similarly to the baseline. This implies that assigning a higher weight to industries that account for a larger share of aggregate economic outcome does not improve the prediction. This relates to the evidence presented in Section 5.2. While large firms (sectors) may account for a sizeable fraction of aggregate movements, their credit spread may not contain the most-useful information relating to future economic development.

[29] Note that the base *EFD* effect is absorbed by the industry fixed effects.

Next, we put more weight on industries in which the loan spread has a higher predictive power (cf. Section 6.1). This weighting scheme results in an improvement in coefficients relative to the baseline. 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.

Finally, we construct a spread using the industry's external finance dependence (EFD) as weights. That is, more weight is put on industries exposed to external financing frictions. This approach yields similar results as in row (3), which is a reflection of the evidence reported in Table 10 that the loan spread performs better in industries with a higher EFD. 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.

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

Fluctuations in credit-market conditions are large, cyclical, and they drive business cycles. Borrowers with access to alternative funding sources such as bond markets might be less affected by tightening conditions as compared to borrowers that have to rely on bank financing. Consequently, spreads derived from bond and loan markets might capture the distinctive frictions these different types of borrowers are facing. In this paper, we use the information content in loan and bond prices and assess their ability to forecast business-cycle movements.

Our paper has three main results. First, we document that loan spreads have higher predictive power relative to bond and other capital-market spreads in forecasting business-cycle movements. Second, we show that frictions originating on borrower balance sheets are driving most of the incremental predictive power of the loan spread, but that intermediary frictions also matter. Third, we show (on the methodological side) that credit spread construction matters, particularly how bottom-up (i.e., micro-level) spreads are aggregated to the macro-level.

Looking forward, the results presented in this paper have important implications for the literature on bond and loan spreads in macro, corporate finance or asset-pricing settings. Understanding the type of frictions that matter for the aggregate economy is important for evaluating the importance of different strands of economic theory. Our results highlight that focusing only on public market credit spreads would underestimate the role of borrower balance sheet frictions in any comparison of theories. In addition, 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). The forecasting power of the loan spread might also be interesting for other applications and on different aggregation levels, e.g., at industry or even firm-level.

Even though our time series covers the last 20 years, we believe that the additional predictive power of the loan spread over that of the bond spread will likely grow in the years ahead. The development of both spreads has already substantially diverged in recent years. Moreover, monetary policy interventions that were introduced during the COVID-19 pandemic have directly targeted corporate bonds with bond spreads declining below pre-COVID-19 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 bond markets remain targeted by monetary policy. We look forward to future research in these promising areas.

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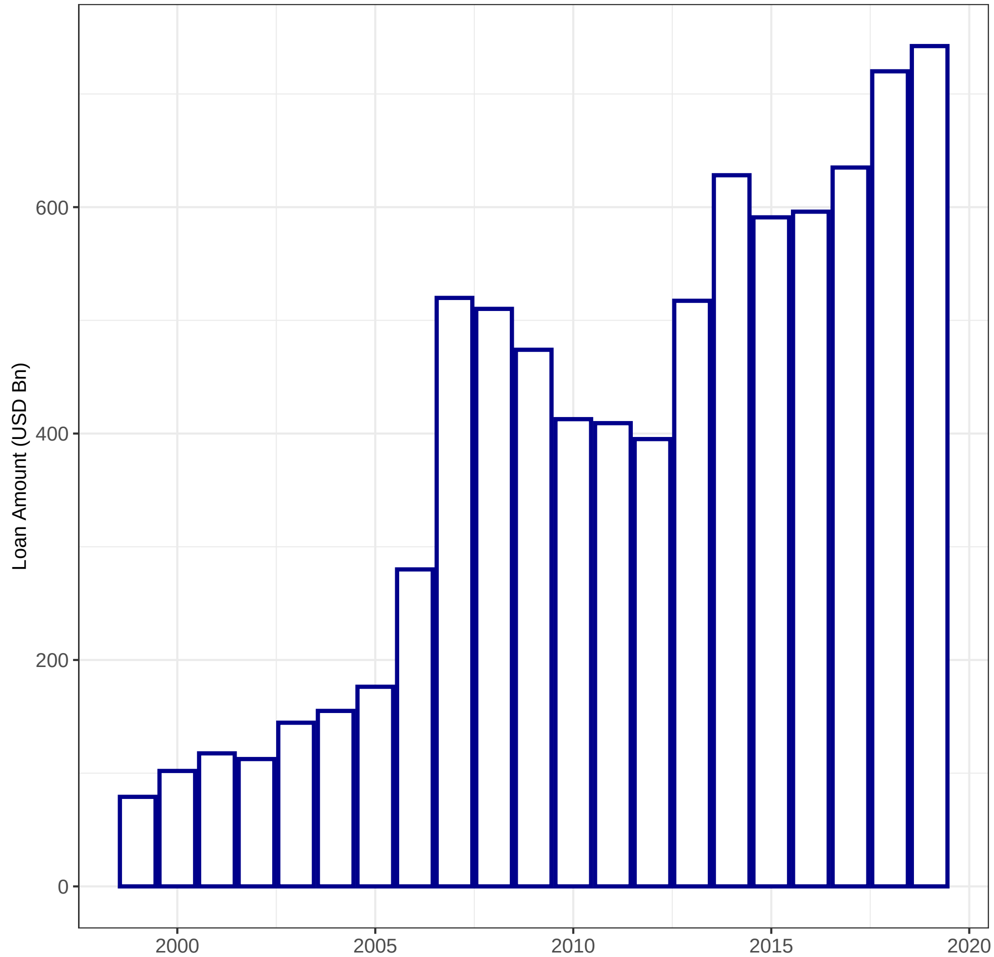

Figure 2: **Secondary loan market trading volume**
This figure plots the development of total loan volume traded in the secondary U.S. syndicated loan market over the 1999 to 2019 period. Source: LSTA.

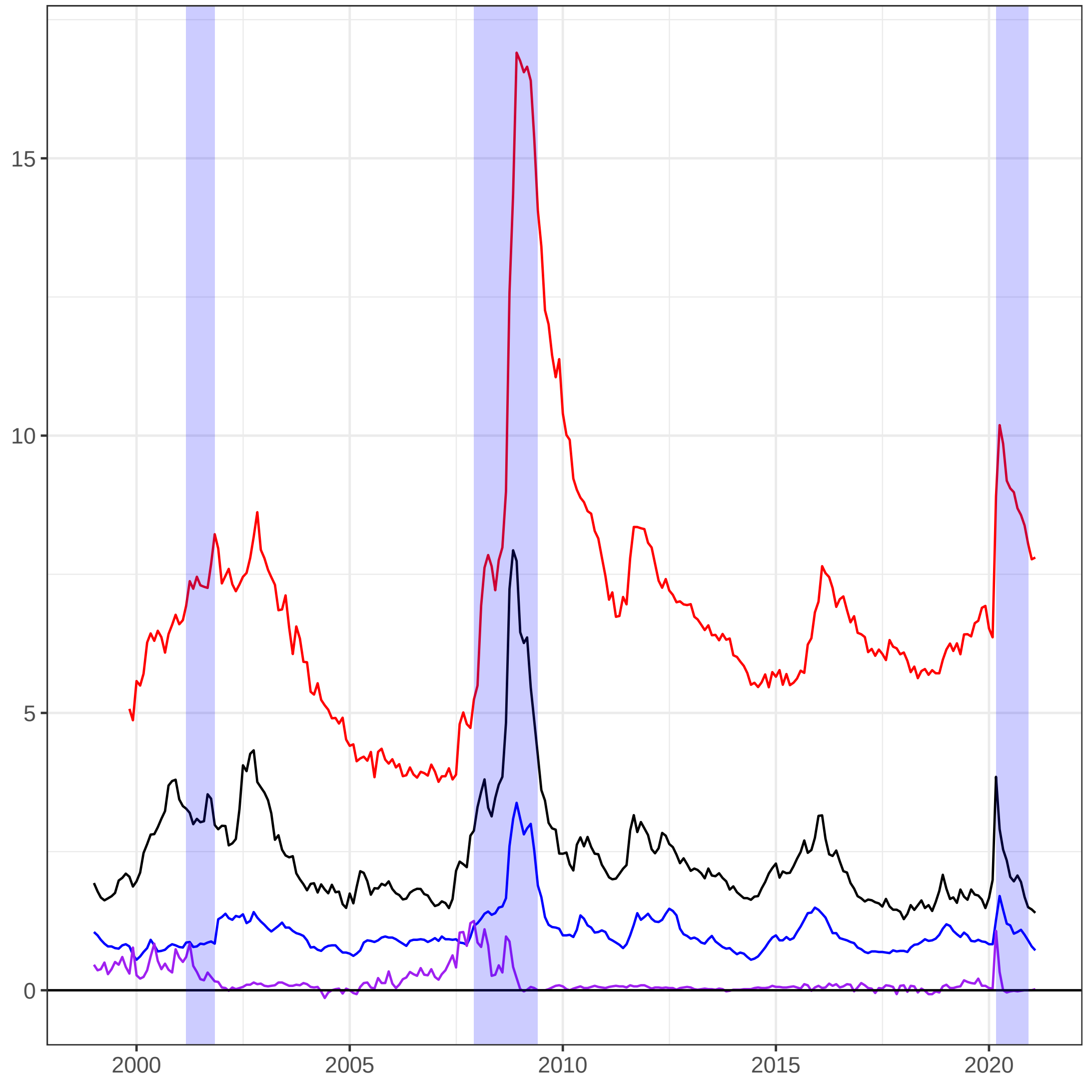

Figure 3: **Corporate credit spreads**
This figure plots monthly credit spread measures over time. Depicted are: (i) the loan spread (red line), defined as the average credit spread of syndicated loans issued by non-financial firms that are traded in the secondary market, (ii) the bond spread (black line), defined following Gilchrist and Zakrajšek (2012) as the average credit spread on senior unsecured bonds issued by non-financial firms, (iii) the Baa-Aaa spread (blue line), defined as the spread between Baa and Aaa corporate bond yields as constructed by Moodys, (iv) the commercial paper - bill spread (purple line), defined as the spread between 3month U.S. T-bills and 30-day AA Non-financial commercial paper. Bars indicate NBER recessions. The sample period is 1999:11 to 2021:01.

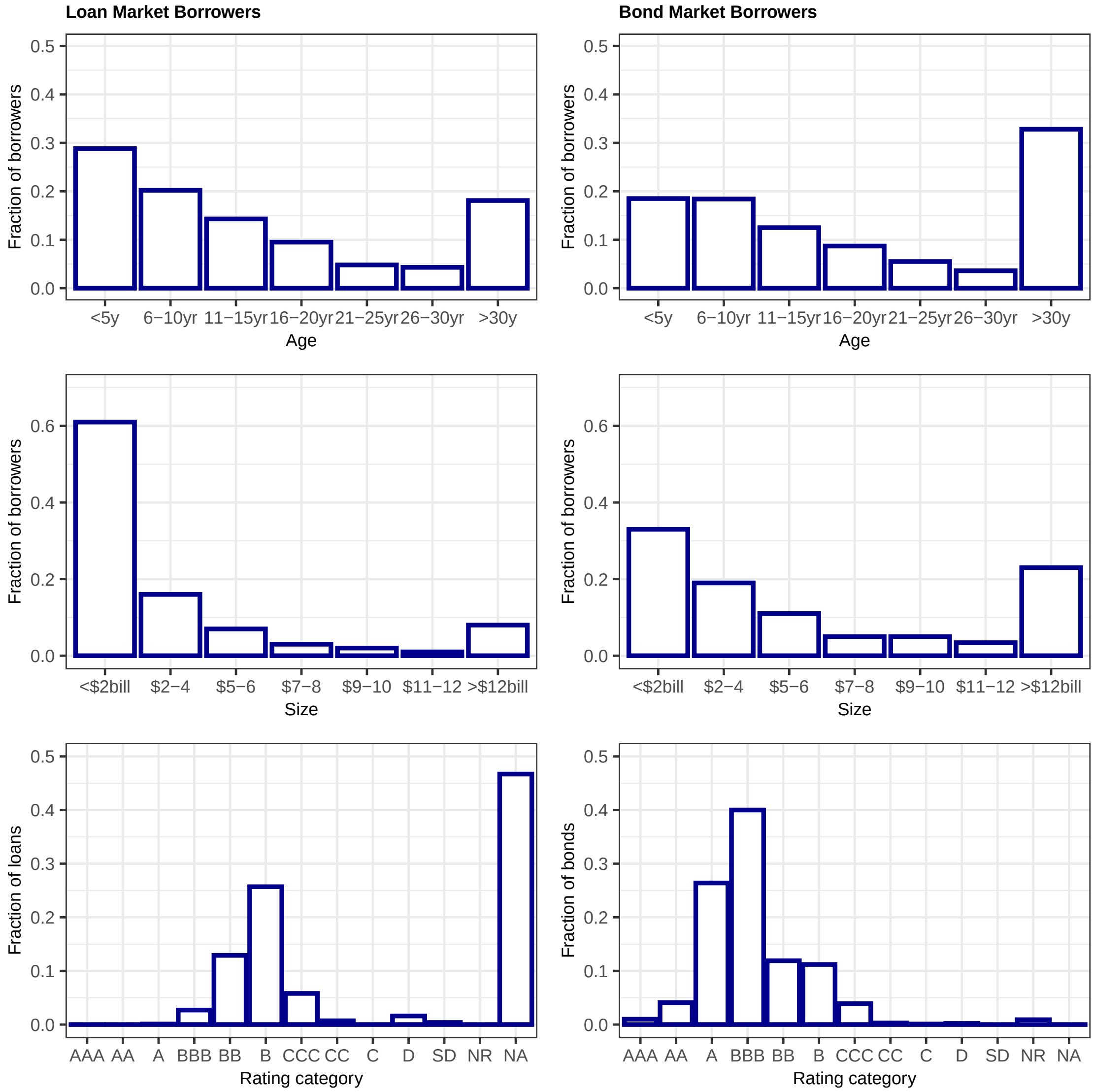

Figure 4: **Borrower characteristics**
This figure plots the characteristics of loan- and bond-market borrowers. The top row plots the distribution of age (number of years firm data exists in the Compustat North America database). The middle row plots the distribution of size (Total Assets in the Compustat 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.

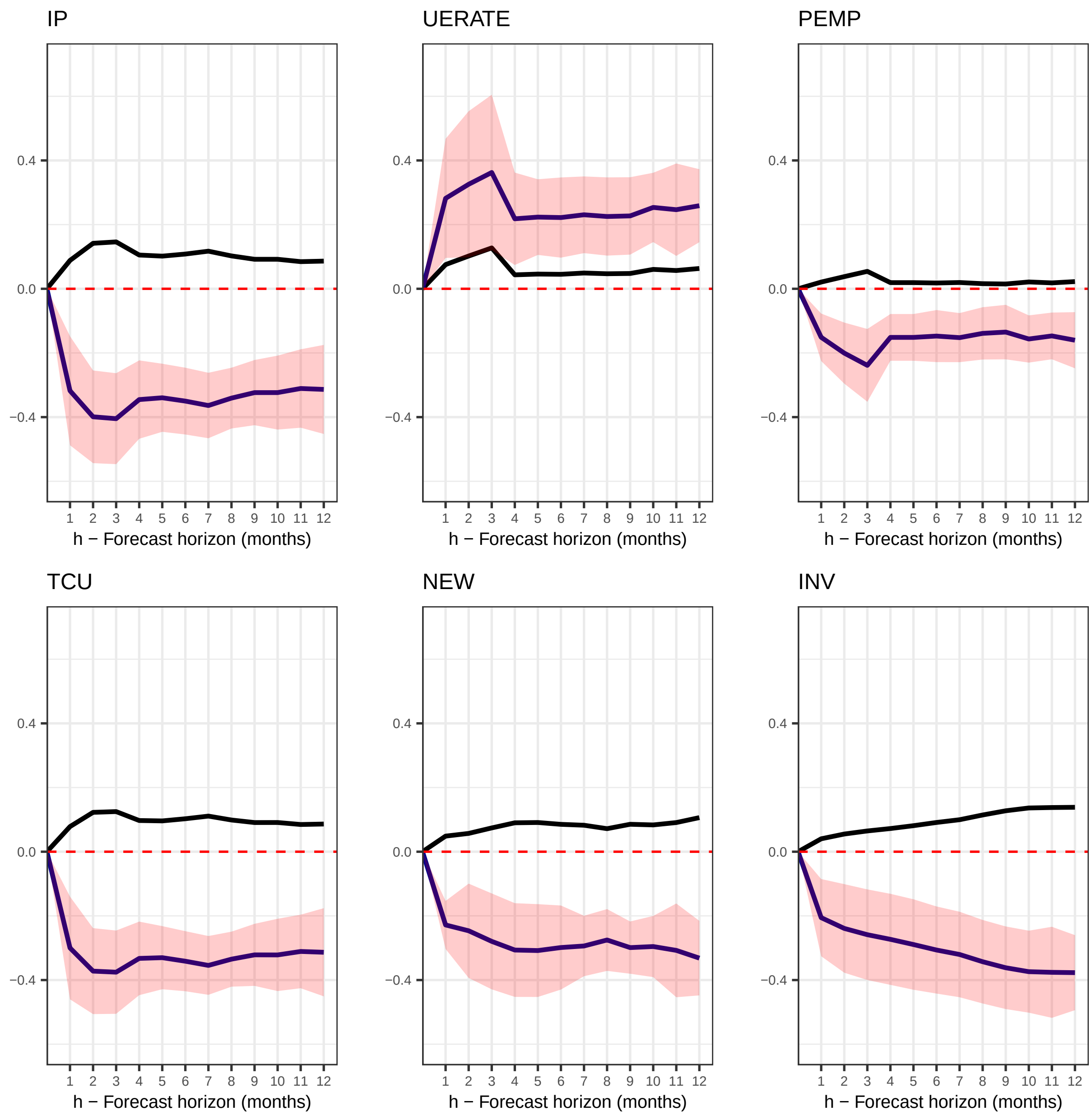

Figure 5: **Local Projections and Incremental R-squared**
This figure plots the impulse response function using a Jordà (2005) local projections framework (blue line) and the incremental adjusted R^2 (black line). In each figure, the dependent variable is the h-month ahead growth in the macro variable. The x-axis indicates the forecast horizon (in months). The coefficient, at each forecast horizon, for the loan spread is in blue. Shaded areas indicate 95% confidence intervals. The black line is the incremental adjusted R^2 at each forecast horizon, defined as the difference between a model with the loan spread and a baseline model with no credit spreads. The sample period is 1999:11 to 2020:03.

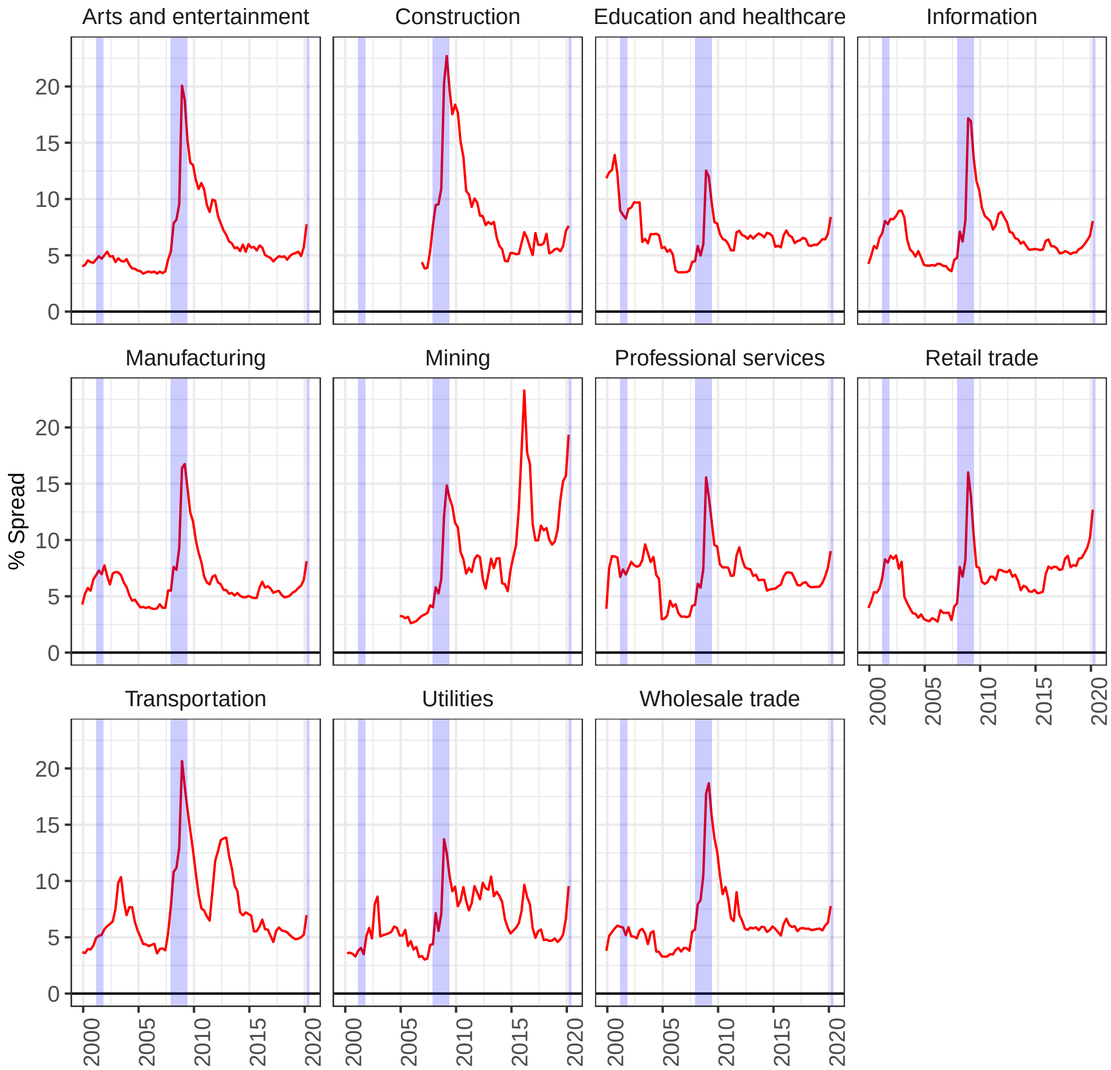

Figure 6: **Industry loan spreads**
This figure plots monthly loan-spread measures over time for 11 non-financial sectors. Firms are classified into sectors following the BEA sector definition. The sample period is 1999:11 to 2020:03 (except for "Construction" and "Mining" due to limited data availability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

Table 1: **Borrower composition loan and bond market**

This table compares the characteristics 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 time-series 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 and other indicators 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, (IP) i.e., growth from $t-1$ to $t+3$. Each specification includes a one-period lag of the dependent variable, i.e., growth from $t-2$ to $t-1$ (not shown), 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 with no credit spreads (i.e column 1). LR Test(χ^2) tests the significance of the inclusion of ΔS_t^{Loan} in column 8 versus column 7. 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 = 3m							
	IP	IP	IP	IP	IP	IP	IP	IP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta S_t^{CP\text{-}Bill}$		0.081						
		(0.919)						
$\Delta S_t^{Baa\text{-}Aaa}$			-0.276					
			(-3.860)					
$\Delta S_t^{HY\text{-}AAA}$				-0.252				
				(-3.520)				
ΔS_t^{Bond}					-0.207			
					(-2.650)			
ΔS_t^{Loan}						-0.405		-0.356
						(-5.600)		(-4.590)
$\Delta S_t^{Bond\ PC}$							-0.253	-0.115
							(-3.540)	(-1.690)
Term Spread	0.179	0.182	0.174	0.180	0.182	0.132	0.180	0.139
	(1.720)	(1.750)	(1.900)	(2.010)	(1.980)	(1.630)	(2.020)	(1.760)
FFR	0.076	0.071	0.085	0.104	0.104	0.084	0.105	0.096
	(0.918)	(0.866)	(1.040)	(1.270)	(1.240)	(1.010)	(1.280)	(1.160)
Adjusted R^2	0.189	0.192	0.262	0.249	0.228	0.335	0.249	0.343
Incremental R^2	-	+0.03	+0.073	+0.060	+0.039	+0.146	+0.06	+0.154
LR Test(χ^2)	-	-	-	-	-	-	-	33.26
Observations	241	241	241	241	241	241	241	241

Table 3: **Robustness**

This table relates credit spread measures and other indicators 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 variables in Panel A are the three-month ahead percentage change in industrial production, i.e., the growth from $t-1$ to $t+3$ (IP) [column 1], non-farm payroll employment (PEMP)[column 2], unemployment rate (UE)[column 3], total industrial capacity utilization (TCU)[column 4], new orders for capital goods (ex. defence) (NEW)[column 5] and total business inventories (INV)[column 6]. The dependent variable in Panel B is the three-month ahead percentage change in industrial production, (IP). Each specification includes a one-period lag of the dependent variable , i.e., growth from $t-2$ to $t-1$(not shown), the term spread, i.e., the difference between 10-year and three-month U.S. Treasury, the real FFR, i.e., the effective federal funds rate minus realized inflation, and the first principal component extracted from $\Delta S_t^{Baa\text{-}Aaa}$, $\Delta S_t^{HY\text{-}AAA}$, and ΔS_t^{Bond}. 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 with no credit spreads. In Panel A, LR Test(χ^2) tests the significance of the inclusion of ΔS_t^{Loan} relative to a model without it. In Panel B column 1, LR Test(χ^2) tests the significance of the inclusion of *Residual* ΔS_t^{Loan}, and column 6 tests the significance of the inclusion of $\Delta S_t^{Bond\ PC}$. 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 = 3m					
Panel A.	IP	PEMP	UE	TCU	NEW	INV
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}	-0.356	-0.177	0.314	-0.329	-0.227	-0.191
	(-4.590)	(-3.380)	(3.060)	(-3.670)	(-4.510)	(-3.090)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.343	0.664	0.183	0.235	0.224	0.599
Incremental R^2	+0.154	+0.054	+0.023	+0.133	+0.071	+0.067
LR Test(χ^2)	33.26	35.14	33.01	30.21	15.98	23.68
Observations	241	241	241	241	241	241
Panel B.	IP	IP	IP	IP	IP	IP
	(1)	(2)	(3)	(4)	(5)	(6)
	Terms	Liq	Equity	VIX	Ex. 08-09	Ex. 08-09
ΔS_t^{Loan}		-0.358	-0.378	-0.264	-0.148	
		(-5.150)	(-5.370)	(-4.400)	(-1.980)	
$\Delta S_t^{Bond\ PC}$						0.063
						(0.756)
Residual ΔS_t^{Loan}	-0.389					
	(-5.413)					
Bid-Ask		-0.311				
		(-2.920)				
Δ S&P500			0.152			
			(2.990)			
ΔVIX				-0.351		
				(-3.110)		
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.325	0.401	0.354	0.407	0.107	0.091
Incremental R^2	+0.136	+0.212	+0.165	+0.218	+0.016	+0.000
LR Test(χ)	45.310	41.986	23.841	20.062	10.087	2.830
Observations	241	241	241	241	225	225

Table 4: **Out-of-sample**

This table computes the out of sample performance of each forecasting regression. The unit of observation 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 (IP) i.e., the growth from $t-1$ to $t+3$. Panel B uses non-farm payroll employment (PEMP), Panel C uses the unemployment rate (UE), Panel D uses total industrial capacity utilization (TCI), Panel E uses new orders for capital goods (ex. defence) (NEW) and Panel F uses total business inventories (INV). Column (1) calculates the out of sample RMSE via cross validation using a rolling window and a one step ahead horizon. Within each panel we compare three models: "Baseline" contains only 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. "Baseline + PC Bond spreads" adds the first principal component extracted from $\Delta S_t^{Baa\text{-}Aaa}$, $\Delta S_t^{HY\text{-}AAA}$, and ΔS_t^{Bond}, and "Baseline + S_t^{Loan}" uses S_t^{Loan}. Normalized CV RMSE, scales the CV RMSE by the standard deviation of the dependent variable in order to compare across panels. Column (3) is a t-test of a difference in the mean RMSE between "Baseline + PC Bond spreads" and "Baseline + S_t^{Loan}"

	OOS horizon: h = 3 month		
	CV RMSE	Normalized CV RMSE	$T-stat(p-value)$
	(1)	(2)	(3)
Panel A. IP			
Baseline	0.0125	0.7033	-
Baseline + $\Delta S_t^{Bond\ PC}$	0.0125	0.7027	-
Baseline + ΔS_t^{Loan}	0.0113	0.6359	$-2.836(0.005)$
Panel B. PEMP			
Baseline	0.00325	0.4808	-
Baseline + $\Delta S_t^{Bond\ PC}$	0.00328	0.4843	-
Baseline + ΔS_t^{Loan}	0.00315	0.4660	$-1.115(0.266)$
Panel C. UE			
Baseline	0.3181	0.7524	-
Baseline + $\Delta S_t^{Bond\ PC}$	0.3182	0.7528	-
Baseline +ΔS_t^{Loan}	0.3014	0.7130	$-1.583(0.115)$
Panel D. TCU			
Baseline	0.9751	0.6807	-
Baseline + $\Delta S_t^{Bond\ PC}$	0.9775	0.6823	-
Baseline + ΔS_t^{Loan}	0.9009	0.6289	$-2.482(0.014)$
Panel E. NEW			
Baseline	0.1036	0.7878	-
Baseline + $\Delta S_t^{Bond\ PC}$	0.1031	0.7839	-
Baseline +ΔS_t^{Loan}	0.0985	0.7493	$-1.733(0.085)$
Panel F. INV			
Baseline	0.0098	0.5158	-
Baseline + $\Delta S_t^{Bond\ PC}$	0.0097	0.5142	-
Baseline +ΔS_t^{Loan}	0.0092	0.4838	$-1.652(0.100)$

Table 5: **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 (Panel A), 2004:04 to 2020:03 for France (Panel B), and 2004:05 to 2020:03 for Spain (Panel C). The dependent variable in column (1)-(5) 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 (6) is the three-month ahead change in the unemployment rate. Each specification includes (not shown) 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 with no credit spreads. 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.

	MAN	MAN	MAN	MAN	MAN	UE
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Germany						
$\Delta S_t^{HY\,Bond}$		-0.280				
		(-1.861)				
ΔS_t^{Bond}			-0.187			
			(-1.659)			
ΔS_t^{Loan}				-0.379	-0.316	0.153
				(-2.455)	(-2.423)	(2.470)
$\Delta S_t^{Bond\ PC}$					-0.128	0.0004
					(-1.802)	(0.006)
Adjusted R^2	0.141	0.207	0.171	0.263	0.271	0.415
Incremental R^2	-	+0.065	+0.029	+0.122	+0.129	+0.016
Contribution from ΔS_t^{Loan}	-	-	-	-	0.704	0.890
Observations	227	227	227	227	227	227
Panel B. France						
$\Delta S_t^{HY\,Bond}$		-0.241				
		(-1.661)				
ΔS_t^{Bond}			-0.138			
			(-0.937)			
ΔS_t^{Loan}				-0.338	-0.289	0.263
				(-2.167)	(-2.170)	(2.232)
$\Delta S_t^{Bond\ PC}$					-0.102	0.065
					(-1.080)	(0.727)
Adjusted R^2	0.097	0.143	0.110	0.192	0.195	0.217
Incremental R^2	-	+0.046	+0.013	+0.095	+0.098	+0.070
Contribution from ΔS_t^{Loan}	-	-	-	-	0.730	0.775
Observations	188	188	188	188	188	188
Panel C. Spain						
$\Delta S_t^{HY\,Bond}$		-0.292				
		(-1.935)				
ΔS_t^{Bond}			-0.188			
			(-1.184)			
ΔS_t^{Loan}				-0.238	-0.122	0.103
				(-1.972)	(-1.145)	(2.268)
$\Delta S_t^{Bond\ PC}$					-0.224	0.085
					(-1.398)	(1.173)
Adjusted R^2	0.132	0.180	0.153	0.180	0.207	0.712
Incremental R^2	-	+0.069	+0.030	+0.048	+0.075	+0.021
Contribution from ΔS_t^{Loan}	-	-	-	-	0.371	0.553
Observations	187	187	187	187	187	187
Controls (all panels):						
Term Spread	✓	✓	✓	✓	✓	✓
EONIA	✓	✓	✓	✓	✓	✓

Table 6: **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. The dependent variable in Panel A 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 Panel B 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 Panel C is the aggregate return on assets (ROA) across all U.S. banks from SNL. The dependent variable in Panel D 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.

	(1)	(2)	(3)	(4)
Panel A. FSLOSS				
$\Delta S_t^{CP-Bill}$	-0.015			
	(-0.108)			
ΔS_t^{Loan}		0.439		0.464
		(3.758)		(4.904)
$\Delta S_t^{Bond\ PC}$			0.310	-0.034
			(2.218)	(-0.239)
Adjusted R^2	-0.012	0.182	0.085	0.172
Observations	81	81	81	81
Panel B. Unsued Commitments				
$\Delta S_t^{CP-Bill}$	-0.057			
	(-0.284)			
ΔS_t^{Loan}		-0.343		-0.309
		(-2.443)		(-1.712)
$\Delta S_t^{Bond\ PC}$			-0.288	-0.043
			(-1.638)	(-0.167)
Adjusted R^2	-0.010	0.106	0.071	0.095
Observations	81	81	81	81
Panel C. Bank ROA				
$\Delta S_t^{CP-Bill}$	0.062			
	(0.364)			
ΔS_t^{Loan}		-0.432		-0.470
		(-2.189)		(-1.812)
$\Delta S_t^{Bond\ PC}$			-0.324	0.049
			(-1.449)	(0.241)
Adjusted R^2	-0.009	0.176	0.094	0.166
Observations	81	81	81	81
Panel D. Bank LLP				
$\Delta S_t^{CP-Bill}$	0.260			
	(0.791)			
ΔS_t^{Loan}		0.446		0.288
		(2.329)		(1.737)
$\Delta S_t^{Bond\ PC}$			0.427	0.199
			(1.752)	(0.563)
Adjusted R^2	0.056	0.188	0.172	0.193
Observations	81	81	81	81

Table 7: **Credit-Spread Decomposition**

This table relates the decomposed loan spread measure 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. Panel A uses a 3-month ahead forecasting horizon, Panel B uses a 12-month ahead forecasting horizon. The dependent variable used are the three-month ahead percentage change in industrial production, i.e., the growth from $t-1$ to $t+3$ (IP)[column 1], non-farm payroll employment (PEMP)[column 2], unemployment rate (UE)[column 3], total industrial capacity utilization (TCU)[column 4], new orders for capital goods (ex. defence) (NEW)[column 5] and total business inventories (INV)[column 6]. Each specification includes a one period lag of the dependent variable , i.e., growth from $t-2$ to $t-1$(not shown), 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 with no credit spreads. 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 four-period lag structure, are reported in parentheses.

Panel A.	Forecast horizon: h = 3 month					
	IP	PEMP	UE	TCU	NEW	INV
	(1)	(2)	(3)	(4)	(5)	(6)
ΔELP_t	-0.265	-0.194	0.218	-0.236	-0.240	-0.187
	(-4.682)	(-3.784)	(2.392)	(-4.516)	(-3.869)	(-2.876)
$\Delta\hat{S}_t^{Loan}$	-0.373	-0.150	0.345	-0.361	-0.179	-0.205
	(-5.009)	(-3.043)	(3.324)	(-5.324)	(-2.197)	(-3.576)
Controls:						
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.355	0.668	0.302	0.397	0.140	0.576
Incremental R^2	+0.166	+0.051	+0.144	+0.147	+0.074	+0.066
Contribution from $\Delta\hat{S}_t^{Loan}$	0.676	0.355	0.728	0.716	0.338	0.545
Observations	241	241	241	241	241	241
Panel B.	Forecast horizon: h = 12 month					
	IP	PEMP	UE	TCU	NEW	INV
	(1)	(2)	(3)	(4)	(5)	(6)
ΔELP_t	-0.208	-0.135	0.181	-0.191	-0.262	-0.250
	(-3.165)	(-2.705)	(3.376)	(-2.854)	(-4.824)	(-4.849)
$\Delta\hat{S}_t^{Loan}$	-0.279	-0.098	0.205	-0.305	-0.232	-0.331
	(-4.140)	(-2.400)	(3.628)	(-4.281)	(-3.723)	(-5.568)
Controls:						
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.255	0.356	0.224	0.364	0.220	0.363
Incremental R^2	+0.093	+0.020	+0.061	+0.101	+0.104	+0.149
Contribution from $\Delta\hat{S}_t^{Loan}$	0.652	0.324	0.561	0.736	0.423	0.647
Observations	241	241	241	241	241	241

Table 8: **Impact of financial constraints**

This table relates loan spreads conditional on firm characteristics 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. Panel A uses a 3-month ahead forecasting horizon, Panel B uses a 12-month ahead forecasting horizon. The dependent variable used are the three-month ahead percentage change in industrial production, i.e., the growth from $t-1$ to $t+3$ (IP)[column 1], non-farm payroll employment (PEMP)[column 2], unemployment rate (UE)[column 3], total industrial capacity utilization (TCU)[column 4], new orders for capital goods (ex. defence) (NEW)[column 5] and total business inventories (INV)[column 6]. Each specification includes a one-period lag of the dependent variable , i.e., growth from $t-2$ to $t-1$(not shown), 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 with no credit spreads. 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.

Panel A.	Forecast horizon: h = 3 months					
	IP	PEMP	UE	TCU	NEW	INV
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}[Young + Small Firms]	-0.375	-0.185	0.291	-0.340	-0.275	-0.253
	(-4.115)	(-2.282)	(-0.584)	(-3.908)	(-3.063)	(-3.019)
Adjusted R^2	0.320	0.650	0.240	0.357	0.139	0.573
Incremental R^2	+0.131	+0.032	+0.082	+0.107	+0.072	+0.062
ΔS_t^{Loan}[Old + Large Firms]	-0.266	-0.151	0.222	-0.237	-0.238	-0.197
	(-3.463)	(-2.143)	(1.450)	(-3.275)	(-2.796)	(-2.176)
Adjusted R^2	0.254	0.639	0.204	0.300	0.120	0.548
Incremental R^2	+0.064	+0.021	+0.046	+0.050	+0.053	+0.037
ΔS_t^{Loan}[Private]	-0.415	-0.231	0.373	-0.391	-0.289	-0.264
	(-5.340)	(-3.632)	(3.110)	(-5.663)	(-3.762)	(-3.678)
Adjusted R^2	0.341	0.668	0.292	0.384	0.145	0.577
Incremental R^2	+0.152	+0.050	+0.133	+0.134	+0.078	+0.066
Panel B.	Forecast horizon: h = 12 months					
	IP	PEMP	UE	TCU	NEW	INV
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}[Young + Small Firms]	-0.299	-0.160	0.241	-0.294	-0.315	-0.360
	(-5.731)	(-3.133)	(-2.992)	(-5.546)	(-7.161)	(-4.843)
Adjusted R^2	0.244	0.360	0.218	0.343	0.213	0.341
Incremental R^2	+0.081	+0.023	+0.055	+0.080	+0.097	+0.127
ΔS_t^{Loan}[Old + Large Firms]	-0.211	-0.095	0.156	-0.207	-0.244	-0.281
	(-3.244)	(-1.770)	(1.741)	(-3.266)	(-3.976)	(-3.184)
Adjusted R^2	0.201	0.343	0.184	0.302	0.173	0.290
Incremental R^2	+0.039	+0.006	+0.021	+0.037	+0.056	+0.076
ΔS_t^{Loan}[Private]	-0.315	-0.168	0.262	-0.318	-0.350	-0.398
	(-4.440)	(-3.660)	(4.276)	(-4.528)	(-5.458)	(-6.134)
Adjusted R^2	0.248	0.361	0.228	0.351	0.234	0.367
Incremental R^2	+0.086	+0.024	+0.064	+0.087	+0.117	+0.153
Controls (all panels):						
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
Observations	241	241	241	241	241	241

Table 9: **Impact of loan rating**

This table relates loan spreads conditional on loan ratings 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. Panel A uses a 3-month ahead forecasting horizon, Panel B uses a 12-month ahead forecasting horizon. The dependent variable used are the three-month ahead percentage change in industrial production(IP), i.e., the growth from $t-1$ to $t+3$ (IP)[column 1], non-farm payroll employment (PEMP)[column 2], unemployment rate (UE)[column 3], total industrial capacity utilization (TCU)[column 4], new orders for capital goods (ex. defence) (NEW)[column 5] and total business inventories (INV)[column 6]. Each specification includes a one-period lag of the dependent variable , i.e., growth from $t-2$ to $t-1$(not shown), 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 with no credit spreads. 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.

Panel A.	Forecast horizon: h = 3 months					
	IP	PEMP	UE	TCU	NEW	INV
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}[BBB]	-0.101	-0.099	0.095	-0.088	-0.164	-0.131
	(-1.532)	(-1.512)	(0.670)	(-1.477)	(-2.049)	(-1.710)
Adjusted R^2	0.195	0.626	0.164	0.254	0.089	0.526
Incremental R^2	+0.006	+0.008	+0.005	+0.004	+0.023	+0.015
ΔS_t^{Loan}[BB]	-0.260	-0.197	0.231	-0.236	-0.231	-0.193
	(-3.600)	(-3.836)	(1.453)	(-3.579)	(-2.911)	(-2.169)
Adjusted R^2	0.251	0.655	0.209	0.301	0.116	0.546
Incremental R^2	+0.062	+0.037	+0.050	+0.051	+0.049	+0.035
ΔS_t^{Loan}[B and below]	-0.422	-0.232	0.343	-0.392	-0.299	-0.267
	(-5.311)	(-3.275)	(2.397)	(-5.443)	(-3.953)	(-3.530)
Adjusted R^2	0.345	0.669	0.270	0.384	0.151	0.579
Incremental R^2	+0.156	+0.051	+0.111	+0.134	+0.084	+0.068
ΔS_t^{Loan}[Not Available]	-0.410	-0.245	0.404	-0.381	-0.289	-0.246
	(-3.972)	(-3.464)	(3.066)	(-4.074)	(-3.169)	(-2.889)
Adjusted R^2	0.336	0.674	0.316	0.376	0.146	0.568
Incremental R^2	+0.147	+0.056	+0.158	+0.127	+0.080	+0.057
Panel B.	Forecast horizon: h = 12 months					
	IP	PEMP	UE	TCU	NEW	INV
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}[BBB]	-0.112	-0.057	0.080	-0.113	-0.159	-0.168
	(-1.723)	(-0.964)	(0.886)	(-1.839)	(-2.309)	(-1.872)
Adjusted R^2	0.171	0.337	0.166	0.273	0.138	0.239
Incremental R^2	+0.008	+0.0005	+0.002	+0.009	+0.021	+0.025
ΔS_t^{Loan}[BB]	-0.224	-0.133	0.185	-0.227	-0.264	-0.282
	(-3.906)	(-3.338)	(2.361)	(-3.906)	(-5.794)	(-3.758)
Adjusted R^2	0.207	0.352	0.194	0.310	0.184	0.290
Incremental R^2	+0.045	+0.015	+0.031	+0.046	+0.067	+0.076
ΔS_t^{Loan}[B and below]	-0.333	-0.170	0.260	-0.335	-0.351	-0.403
	(-4.648)	(-3.640)	(4.124)	(-4.696)	(-5.597)	(-6.865)
Adjusted R^2	0.258	0.362	0.226	0.361	0.235	0.372
Incremental R^2	+0.095	+0.025	+0.062	+0.097	+0.118	+0.157
ΔS_t^{Loan}[Not Available]	-0.263	-0.137	0.246	-0.265	-0.313	-0.363
	(-3.855)	(-2.592)	(3.356)	(-4.023)	(-5.394)	(-4.246)
Adjusted R^2	0.221	0.352	0.220	0.323	0.211	0.340
Incremental R^2	+0.058	+0.015	+0.056	+0.059	+0.093	+0.126
Controls (all panels):						
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
Observations	241	241	241	241	241	241

Table 10: **Baseline industry forecasting results**

This table relates industry credit spread measures to future industry outcomes for the U.S. economy. 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. The dependent variable in Panel C is the one-quarter-ahead percentage change in gross output for industry b. 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 (not shown) 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 with no credit spread or fixed effects. Coefficients are standardized. Standard errors are clustered by industry. t-statistics are reported in parentheses.

	Forecast horizon: h = 3 months			
	(1)	(2)	(3)	(4)
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)			
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)
Year × quarter fixed effects	No	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes
Adjusted R^2	0.452	0.558	0.590	0.606
Incremental R^2	+0.086	+0.192	+0.224	+0.240
Observations	803	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)			
S_{bt}^{Loan} x Top 3 EFD				−0.605
				(−4.727)
S_{bt}^{Loan} x Middle 4 EFD				−0.363
				(−2.903)
S_{bt}^{Loan} x Bottom 4 EFD				−0.309
				(−2.641)
Year × quarter fixed effects	No	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes
Adjusted R^2	0.196	0.294	0.395	0.413
Incremental R^2	+0.063	+0.151	+0.252	+0.280
Observations	803	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)			
S_{bt}^{Loan} x Top 3 EFD				−0.127
				(−3.726)
S_{bt}^{Loan} x Middle 4 EFD				−0.084
				(−1.128)
S_{bt}^{Loan} x Bottom 4 EFD				0.119
				(1.532)
Year × quarter fixed effects	No	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes
Adjusted R^2	0.183	0.379	0.387	0.390
Incremental R^2	+0.082	+0.233	+0.241	+0.289
Observations	611	611	611	611

Table 11: **Alternative weighting schemes**

This table relates alternative loan 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. Panel A uses a 3-month ahead forecasting horizon, Panel B uses a 12-month ahead forecasting horizon. The dependent variable used are the three-month ahead percentage change in industrial production, i.e., the growth from $t-1$ to $t+3$ (IP)[column 1], non-farm payroll employment (PEMP)[column 2], unemployment rate (UE)[column 3], total industrial capacity utilization (TCU)[column 4], new orders for capital goods (ex. defence) (NEW)[column 5] and total business inventories (INV)[column 6]. Each specification includes a one-period lag of the dependent variable , i.e., growth from $t-2$ to $t-1$(not shown), 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 with no credit spreads. 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.

Panel A.	Forecast horizon: h = 3 months					
	IP	PEMP	UE	TCU	NEW	INV
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}	-0.405	-0.239	0.362	-0.376	-0.280	-0.259
	(-5.600)	(-4.124)	(2.932)	(-5.671)	(-3.664)	(-3.591)
Adjusted R^2	0.335	0.672	0.286	0.375	0.140	0.575
Incremental R^2	+0.146	+0.054	+0.127	+0.125	+0.074	+0.064
ΔS_t^{Loan}[GDP]	-0.393	-0.222	0.350	-0.363	-0.262	-0.257
	(-4.941)	(-3.420)	(2.676)	(-4.965)	(-3.051)	(-3.447)
Adjusted R^2	0.328	0.664	0.276	0.369	0.131	0.574
Incremental R^2	+0.139	+0.046	+0.117	+0.118	+0.064	+0.063
ΔS_t^{Loan}[Industry]	-0.439	-0.231	0.382	-0.403	-0.267	-0.265
	(-5.944)	(-3.433)	(3.060)	(-5.786)	(-3.045)	(-3.445)
Adjusted R^2	0.363	0.668	0.299	0.396	0.133	0.578
Incremental R^2	+0.173	+0.050	+0.140	+0.146	+0.067	+0.067
ΔS_t^{Loan}[EFD]	-0.431	-0.209	0.379	-0.401	-0.257	-0.273
	(-4.488)	(-2.536)	(2.724)	(-4.556)	(-2.470)	(-3.322)
Adjusted R^2	0.353	0.658	0.296	0.391	0.128	0.582
Incremental R^2	+0.164	+0.041	+0.138	+0.141	+0.062	+0.071
Panel B.	Forecast horizon: h = 12 months					
	IP	PEMP	UE	TCU	NEW	INV
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}	-0.314	-0.160	0.259	-0.313	-0.332	-0.377
	(-4.430)	(-3.590)	(4.463)	(-4.470)	(-5.595)	(-6.318)
Adjusted R^2	0.248	0.359	0.227	0.350	0.223	0.352
Incremental R^2	+0.086	+0.022	+0.063	+0.086	+0.106	+0.138
ΔS_t^{Loan}[GDP]	-0.305	-0.159	0.251	-0.303	-0.324	-0.357
	(-4.486)	(-3.564)	(4.098)	(-4.522)	(-5.616)	(-5.269)
Adjusted R^2	0.244	0.359	0.222	0.345	0.218	0.337
Incremental R^2	+0.082	+0.021	+0.059	+0.081	+0.101	+0.123
ΔS_t^{Loan}[Industry]	-0.336	-0.177	0.280	-0.327	-0.334	-0.380
	(-4.732)	(-3.857)	(5.077)	(-4.661)	(-5.523)	(-5.888)
Adjusted R^2	0.262	0.364	0.237	0.359	0.224	0.353
Incremental R^2	+0.100	+0.028	+0.074	+0.095	+0.107	+0.140
ΔS_t^{Loan}[EFD]	-0.341	-0.176	0.296	-0.337	-0.321	-0.386
	(-5.518)	(-3.263)	(4.501)	(-5.527)	(-5.348)	(-4.626)
Adjusted R^2	0.263	0.364	0.247	0.363	0.215	0.358
Incremental R^2	+0.101	+0.027	+0.083	+0.099	+0.098	+0.143
Controls (all panels):						
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
Observations	241	241	241	241	241	241