Corporate Loan Spreads and Economic Activity*

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September 5, 2022

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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We thank Klaus Adam, Ed Altman, Yakov Amihud, Giovanni Dell'Ariccia, Tobias Berg, Nina Boyarchenko, Jennifer Carpenter, Filippo De Marco, Itay Goldstein, Arpit Gupta, Kose John, Toomas Laaritz, Yuearan Ma, Juan F. Martinez, Atif Mian, Emanuel Moench, Holger Mueller, Martin Oehmke, Cecilia Palatore, Carolin Pflueger, Tarun Ramadori, Adriano Rampini, Immo Schott, Or Shachar, Juliana Salomao, Immo Schott, Moritz Schularick, Marti Subrahmanyam, Elu von Thadden, Marliese Uhrig-Homburg, Olivier Wang, Michael Weber and seminar participants at ABFER 8th Annual Conference, Bundesbank, Cass Business School, Corporate Restructuring and Insolvency Seminar, Fed Board, Frankfurt School, IMF, IWH, IWH-FIN-FIRE Workshop, LawFin, Miami Business School, NYU, OCC, Science Po, UTS, Warwick Business School, WU Vienna, 33rd Australasian Finance and Banking Conference, Bonn Macro Workshop, Central Bank of Ireland, Danish Finance Institute Annual Conference, 2021 Financial Intermediation Research Society Conference (FIRS), ifo Conference on Macroeconomics and Survey Data, Mannheim Banking Workshop, Regulating Financial Markets 2019, 2019 Santiago Finance Workshop, SFS Cavalcade North America 2021, Villanova Webinar in Financial Intermediation, Virtual Finance Seminar, and the World Finance and Banking Symposium Conference for many helpful suggestions. Spina and Streitz gratefully acknowledge support from the Center for Financial Frictions (FRIC), grant no. DNRF102. Streitz gratefully acknowledges support from the Danish Finance Institute (DFI). Steffen gratefully acknowledges support from the German Science Foundation (DFG), grant number STE 1836/4-1.

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.

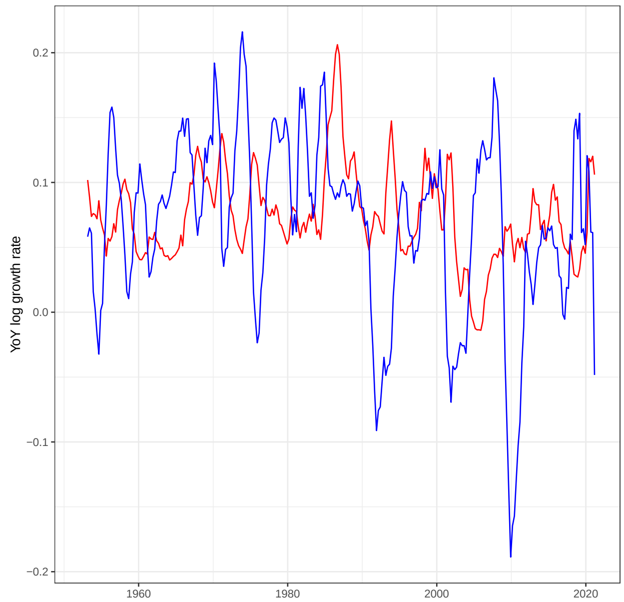

Figure 1: **Loan and bond market cyclicality**
This figure plots the year-on-year growth rate in outstanding corporate loans (red) and corporate bonds (black). Data comes from the U.S. Flow of Funds dataset. The sample period is 1953-2020. Grey bars are NBER recessions.

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, ∼70% of non-financial firms in Compustat N.A. issued a syndicated loan 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 representation of prices in this market (Berndt and Gupta, 2009).[8]

[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 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 underwriter market share in the primary loan market and find a correlation of 0.87.

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

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 mostly 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 pricing data with information about the underlying loans from Dealscan. This includes information on maturity and scheduled interest payments, i.e., key inputs for the credit spread calculation. The databases are merged using the Loan Identification Number (LIN), if available, or else a combination of the borrower name, dates, and loan characteristics. Online Appendix B 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 (Berg *et al.*, 2016, 2017). We assume that interest is paid quarterly and the principal is repaid at the end of the term.[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.

[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 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.

[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.

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. Specifically, the loan spread is defined as:

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

Figure 4 plots our 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 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 C for additional descriptive statistics.

[12] The commercial paper-bill spread is from the Federal Reserve H.15 report and is defined as three-month treasury-bill minus 30-day AA non-financial commercial paper. The (Moody's) Baa-Aaa credit spread 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).

[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).

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 the Compustat database, i.e., firms with publicly sold securities (equity and/or debt) that must file periodic reports with the Securities & Exchange Commission (SEC). The remaining firms are classified as private.[15] The vast majority of bond issuers are public (90%).[16] 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 loan market and bond market firms in more detail. This discussion is based on *public* firms for which data is available in Compustat. Given the larger share of private firms in the loan market, this comparison *understates* differences between loan markets and bond markets. Results are reported in Table 1.

We measure firm size by total assets. Borrowers are significantly smaller than bond

[14] While we mostly use the bond spread provided by Favara *et al.* (2016) in our analyses, the correlation with the TRACE measure is high (0.96).

[15] The number of unique "parent firms" in the public firm sample—identified by firms' Compustat GVKEYs—is lower than the number of loan market borrowers or bond market issuers. This is because some 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 versus public split using borrower/issuer IDs and then proceed by reporting statistics at the parent level in Panels B and C.

[16] The remaining 10% of issuers that cannot be linked to Compustat include, e.g., firms with private placements and other issuers with limited disclosure requirements.

issuers (Panel B).[17] The median firm size is \$1.45 billion in the loan market compared to \$21.3 billion in the bond market. Only 16% of loan market borrowers have total assets > \$6 billion and 61% are in the smallest size bucket (<= \$2 billion). In contrast, 33% of bond issuers have assets > \$6 billion.

We next look at the market overlap, i.e., the fraction of loan market firms that are also active bond issuers by size bucket. Larger borrowers are particularly likely to be bond issuers also—around two-thirds of borrowers with assets > \$6 billion are also active in the bond market. Among the small borrowers (<= \$2 billion), which account for 61% of all loan market firms, only 28% are also bond issuers.

This statistic weights all issuers equally, however, when constructing aggregate credit spreads we use instrument-month data and larger firms (that tend to issue debt more frequently) might account for a disproportionate share of observations. Figure 3 shows the issuer size distribution at the instrument-month level. At this level the differences between the bond and loan market are even more striking. While large bond issuers (assets > \$10 billion) account for 29% of all issuers, they amount to 79% of all bond-month observations. In fact, >55% of observations are by very large issuers with assets > \$20 billion. The distribution in the loan market, in contrast, is highly left-skewed. While almost 40% (67%) of loan-month observations are by borrowers with assets < \$2 billion (< \$6 billion), less than 11% (16%) of bond-month observations are in this category.

Finally, Panel C of Table 1 paints a similar picture, grouping firms by age. Firm age is defined as the number of years with non-missing total assets in Compustat. Borrowers are younger than bond issuers. The median firm age is 11 years in the loan market compared to 15 years in the bond market. 29% of borrowers are <= 5 years, compared to only 19% of bond issuers. In contrast, 40% of bond issuers are > 20 years, compared to only 27% of borrowers.

Focussing on the market overlap, around 65% of older borrowers (> 20 years) are also

[17] 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.

bond issuers, compared to only 46% of younger borrowers (<= 5 years). Conditional on being active in the bond market, mainly younger firms also borrow in the loan 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 might contain information about economic developments.

4 Loan spreads and economic activity

4.1 Empirical setup

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 $t+h$.[18] 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.[19]

We follow López-Salido *et al.* (2017) and use spread changes rather than levels in the 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

[18] 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.

[19] 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].

arise for two reasons. First, because the asset side of bank balance sheets are sensitive to credit spreads, changes in spreads are correlated with bank losses. Second, because spread increases 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-spreads.

Regressions are estimated by OLS, with one lag of the dependent variable.[20] Due to the low level of persistence in the dependent variables (and ΔS_t), we use Newey-West standard 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 D wherein we also provide results using alternative timing conventions with very similar results.

4.2 Baseline results

Table 2, Panel A, 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).[21] Except for the paper-bill spread, which has little variation during the sample period, all credit spreads have significant predictive

[20] 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.

[21] 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.

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 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 relative to other credit spreads. The model with the second largest increase in in-sample fit (the Baa-Aaa spread) 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.[22]

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 (Panel B). These include employment-related measures and inventory and order measures. 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 significantly adds to the predictive power of the models. The incremental R^2 ranges from +6 to +16 p.p. and this effect comes almost entirely from the loan spread, not the

[22] 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 G, we create bottom-up bond spread measures for different rating categories and document similar results. We further examine the predictive power of different risk segments *within* the loan market and find that the predictive power is highest amongst the lower rated loans.

inclusion of the bond-spread PC (the incremental R^2 of a model that includes just the loan but not the bond-spread PC is virtually identical to the incremental R^2 of the model that includes both spreads, see Panel B). 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).[23]

Table 3 presents further robustness tests, such as including other financial market predictors and accounting for contractual differences between bonds and loans. We focus on industrial production for brevity. Results using other macroeconomic outcomes are similar (Online Appendix D).

Loan contracts might be different with respect to non-price terms compared to bonds. We regress loan spreads on contract terms and take the residual spread, which is by definition orthogonal (see Online Appendix D for details). Panel A, column (1), shows that this "residual loan spread" has very similar predictive power relative to the baseline spread. Next, we control for liquidity in the secondary market using the median bid-ask spread. Our main result again remains unchanged, cf. 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. To capture this, we include the VIX in the model in column (4). While the VIX does have predictive power, the forecasting coefficient on the loan spread remains large and significant.[24]

Results may be driven by the 2008-09 financial crisis. Columns (5) and (6) show that

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

[24] In the Online Appendix G, we report results adding additional proxies for uncertainty, 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). Our main result remains unchanged.

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.

Finally, Panel B includes all the controls described above simultaneously in a "kitchen-sink" specification. Importantly, the loan spread's predictive power remains large and significant despite the inclusion of all controls jointly. This further suggests that there is additional information in loan spreads not captured by other asset prices.

In Online Appendix D we also consider out of sample performance and find across all macro variables, the model with the loan spread consistently returns the lowest RMSE. Although with a small sample period the corresponding out of sample window is short. A t-test for the difference in the mean RMSE between the model that uses the bond-spread PC and the loan spread model, still finds a statistically significant difference at the 10% significane level or lower for four out of six variables.

4.3 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 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 incremental R^2 over the 1 to 12 month horizon. 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 D provides similar results, dynamically benchmarking loan spreads against bond spreads.

4.4 Evidence across industries and countries

Secondary market loan prices have only been available for about 20 years, which is a relatively short period for macroeconomic predictions. We therefore measure loan spreads in the cross-section of industries and countries, i.e., exploit the fact that industries and countries can have different economic cycles, for robustness.

Evidence from other countries: We start by extending our results across 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). We focus on manufacturing production as outcome variable. We report a baseline model, which includes only the country-specific loan spread and then add the country-specific bond spread from Mojon and Gilchrist (2016). Starting with Germany, we find that the loan spread adds 12.2 p.p. R^2 to a baseline model without credit spreads (see Table 4, Panel B, column 1). The addition of the bond spread in Column 2 adds only 0.07 p.p. to the R^2. In Columns 3 and 4 we find similar results for France. The Spanish loan spread is significant only when included separately. Online Appendix E shows that the results are robust to including additional controls.

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. 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.[25]

The results are reported in Panel A. Column 1 starts with a model that includes the industry and aggregate loan spread in a pooled regression.[26] Column 2 adds time fixed effects that absorb any common time trends. 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. Column 3 includes 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.[27] In Columns 4 and 5 we use establishments and output as outcome variables and find similar results.

Overall, our evidence from across U.S. industries and across Europe is consistent with the aggregate U.S. evidence. Loan spreads have significant predictive power for macroeconomic outcomes, above and beyond other credit spread measures.

5 Mechanisms

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 layout potential channels and their predictions (Section 5.1) and investigate the empirical evidence for each channel

[25] 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.

[26] 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.

[27] In untabulated robustness tests, we 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. We further find that the predictive power of the industry loan spread is largest in industries that are most dependent on external finance (Online Appendix E).

(Section 5.2). We discuss alternative channels in Section 5.3. It should be noted that all mechanisms discussed below likely have some empirical relevance, i.e., they are complementary rather than mutually exclusive (López-Salido *et al.*, 2017).

5.1 The role of financial frictions: Theoretical background

In this section, we discuss different theories that suggest that credit spreads are leading indicators for economic development. We classify those theories into two categories: theories without market frictions and theories that, in turn, highlight the importance of financial frictions. We further derive implications for the *relative* predictive power of loan vis-a-vis bond spreads. While we focus on the role of financial frictions as the main mechanism, as explained below, we discuss the potential role of other channels, such as behavioural theories and investor demand-driven explanations, in Section 5.3.

Theories without market frictions: Credit spreads can reflect economic developments even in a frictionless market because prices contain forward looking information about firm fundamentals. While all financial asset prices should reflect investors' expectations, credit markets might be particularly informative about fundamentals. Philippon (2009) provides evidence that a q measure inferred from bond prices explains aggregate investment dynamics better than a q measure based on equity markets. One possible explanation is that the bond market is less prone to mispricing compared to the equity market.[28]

This channel implies that both loan and bond spreads can have predictive power for economic developments because they reflect information on investors' expectations about firm default. However, for this channel to explain the *relative* predictive power of loan versus bond spreads, the fact that asset prices are inherently forward looking is not sufficient. Loan spreads should only contain additional information if i) loan markets reflect fundamental information more accurately compared to bond markets, or ii) there is additional fundamental information in loan markets not available in bond markets that has relevance for aggregate

[28] Alternatively, equity markets might particularly reflect information on intangible capital and not on the existing stock of physical capital—the main determinant of q.

movements of economic variables.

Given that the bond market is large and liquid compared to the (secondary) loan market, it seems unlikely that it is more subject to mispricing compared to the loan market. Hence, it is unlikely that loan spreads reflect the *same* information more accurately than bond spreads. It is, however, possible that different fundamental information is reflected in loan spreads that is not available in bond spreads. As documented in Section 3, the overlap between the loan and the bond market is limited, i.e., loan spreads might comprise information about fundamentals for a different set of firms.[29] This argument implies that the additional predictive power of loan spreads should come from firms for which no bond market information is available.

Theories based on financial frictions: There is a large literature that departs from the perfect market assumption and introduces financial frictions to study aggregate fluctuations. One source of financial frictions is the balance sheet of the borrower. Seminal contributions include Bernanke and Gertler (1989), Holmström and Tirole (1997), and Kiyotaki and Moore (1997), among others. In these models, firms face agency costs creating a wedge between the cost of external funds and the opportunity cost of internal funds, often labelled "external finance premium." If a firm's net worth becomes impaired due to a shock to the health of their balance sheets, these frictions in the debt market forces it to reduce borrowing and investment. This can lead to amplification effects as the resulting reduction in aggregate demand puts further pressure on firm net worth leading to additional reductions in investment.

A related strand of the literature emphasizes the role of financial intermediaries and their balance sheets (see, among others, He and Krishnamurthy, 2013; Adrian *et al.*, 2010a,b). A deterioration in the health of intermediaries can impede their effective risk-bearing capacity and lead to credit supply contractions. Firms depending on external financing from intermediaries are forced to cut back on investment, affecting the aggregate economic development.

[29] However, while a large fraction of firms the economy do not have access to bond markets, evidence indicates that it is generally the fundamentals of large (bond market) firms that drive the business cycle (Crouzet and Mehrotra, 2020; Gabaix, 2011). This would speak against a fundamentals-based explanation for the additional predictive power of loan spreads.

Loan markets are populated with firms that have limited access to alternative funding sources. It is therefore natural to conjecture that financial frictions help explain the predictive power of loan spreads. Models that highlight the role of borrower balance sheet frictions and intermediary frictions share similar empirical predictions: As highlighted in Holmström and Tirole (1997) both shocks to aggregate firm capital and intermediary capital will particularly affect low net worth firms. That is, both types of frictions are more severe for firms reliant on intermediated credit via bank loans, such as small and private firms (Diamond and Rajan, 2005; Chodorow-Reich, 2014), compared to firms with access to alternative funding sources, such as public bond markets (Greenstone *et al.*, 2020a; Chava and Purnanandam, 2011).

Note that the empirical predictions resulting from models based financial frictions are also similar to the predictions resulting from models without frictions (discussed above). Both channels would imply that the additional predictive power should arise from firms active in the loan market that do not have access to public markets. However, conditional on observing a firm only in the loan market, financial frictions are particularly relevant for the most constrained firms (e.g., small, young, and private firms). In contrast, if loan spreads are informative only because they capture fundamental information for a set of firms that is not observable in the bond market, the predicitive power should come, if anything, from the largest loan market firms, i.e., the firms that contribute the most to aggregate movements (Crouzet and Mehrotra, 2020; Gabaix, 2011). Thus, exploring the predictive power in the cross-section of firms within the loan market suggests a way of assessing the role of frictions versus non-frictions explanations.

Further note that is empirically challenging to differentiate between frictions emanating from the intermediary side or the borrower side. Gilchrist and Zakrajšek (2012) suggest to decompose credit spreads into two components: a fundamental component and a residual that captures the price of risk above a default risk premium. This residual, i.e., the part of the spread that cannot be explained by borrower fundamentals, has been shown to correlate with indicators for the health of the financial intermediary sector. This decomposition can therefore be helpful in assessing the relative importance of bank vis-a-vis borrower constraints in explaining the predictive power of loan spreads.

Empirical predictions: To summarize, we are going to test the following empirical predictions in the next section:

1. The predictive power of the loan spread should be higher for firms that are not observed in the bond market, such as private firms with limited access to public debt or equity markets. This prediction is common to both theories with and without financial frictions.

2. If the friction-based channel is *not* at work, the predictive power of the loan spread should (if anything) be higher for larger (and older) loan market firms, which contribute most to aggregate economic movements.

3. If the friction-based channel, however, is at work, the predictive power of the loan spread should be highest for loan market firms that are most exposed to financial frictions, such as smaller and younger firms.

4. If financial intermediary frictions and not borrower balance sheet frictions explain the predictive power of the loan spread, the part of the loan spread that is orthogonal to borrower fundamentals should account for most of the loan spread's predictive power.

5.2 The role of financial frictions: Empirical evidence

In this section we test the empirical predictions outlined in the previous section.

5.2.1 Friction vs. non-frictions-based channels

In a first test, we focus on private firms, which account for about half of our loan sample, and construct an aggregate loan spread for private firms, only (S_t^{Loan} *Private*). We estimate models similar to Table 2, column 8 (baseline prediction model with both loan spread and bond spread PC), and report the results in Panel A of Table 5. Consistent with the first empirical prediction, we find that the private firm loan spread has large predictive power. Focussing on industrial production over the 3-month-horizon, the incremental R^2 is about 17 p.p., which is even somewhat larger than the incremental R^2 of the baseline loan spread, comprising both public and private firms (15.4 p.p., cf. Table 2, column 8). In other words, most of the predictive power of the loan spread is coming from firms without access to public capital markets, consistent with both theories with and without frictions.

The large predictive power of the private firm loan spread becomes even more apparent, when compared to a loan spread constructed using public firms that are also observed in the bond market. Specifically, we next examine variation across different types of firms in more detail. As documented in Section 3, mainly larger and older loan market borrowers are often also bond issuers.[30] Few smaller and younger borrowers are observed in the bond market. Further, smaller and younger firms tend to be more constrained and exposed to financial frictions (Diamond and Rajan, 2005; Chodorow-Reich, 2014). Following the classifications and definitions outlined in Section 3, we split firms by their size and age. Specifically, we double-sort firms by median age and size categories (Hadlock and Pierce, 2010) to classify them as "large and old" or "small and young." Note that we focus on double-sorts for brevity. Results are very similar if we split firms only by their size (Online Appendix E). We run separate models using a loan spread comprised of old and large firms (S_t^{Loan} *Old/Large*) as well as a spread comprised of young and small firms (S_t^{Loan} *Young/Small*) and report the results in Panel B.

Comparing the specification using S_t^{Loan} *Private* and S_t^{Loan} *Old/Large* shows that the incremental R^2 is twice as large using $S_t^{Loan} Private$. That is, a loan spread of private firms with limited access to public debt or equity markets has a significantly larger predictive power compared to a spread comprised of public firms that are often active in both markets (73% of large and old loan market firms are also active bond issuers). Interestingly, the coefficient of S_t^{Loan} *Old/Large* is close to that of the baseline bond-spread measure (coefficient of -0.189 versus -0.207, cf. Table 2, column 5). Intuitively, conditioning on a similar set of firms yields

[30] Recall that private firms are firms that cannot be linked to financial variables in Compustat, i.e., this test is performed for firms with available financial information, only.

a similar predictive power.

We further find that loan spreads of small and young public firms have significantly larger predictive power compared to large and old firms (incremental R^2 of 14 versus 8 p.p.). In fact, the predictive power is similar in magnitude to the private firm loan spread. We find consistent results using the other outcome variables (column 2 to 6), as well as different forecasting horizons (Online Appendix E).

To summarize, a loan spread based on private firms has the largest predictive power. However, even within the set of public firms a loan spread constructed using young and small firms has significantly more predictive power than a spread based on old and large firms. That is, our observations are consistent with the predictions of the financial friction channel (prediction 3): more constrained firms, i.e., small, private, and young firms, should be most sensitive to both borrower and intermediary frictions.

However, an alternative explanation could still be that private, small, and young firms are less likely to have access to public bond markets and therefore additional information about this set of firms is only available in loan prices and not bond prices, even absent of financial market friction (prediction 2).

To separate the no-frictions explanations from the frictions explanation more cleanly, we next examine the cross-section of firms only observed in the loan market. That is, we exclude firms for which fundamental information can also be observed in bond prices. As discussed in Section 5.1, conditional on observing a firm only in the loan market, financial frictions are particularly relevant for the most constrained firms (prediction 2). In contrast, if loan spreads are informative only because they capture fundamental information for a set of firms that is not observable in the bond market, the predicitive power should come from the largest loan market firms, i.e., the firms that contribute the most to aggregate movements (prediction 3).

The results reported in Table 5, Panel C, indicate that the incremental R^2 is again about twice as large for the small and young loan market only borrowers, compared to the spread from old and large loan market only borrowers (14 p.p. versus 8 p.p.). In fact, the results are very similar to the size-age split using all public firms, reported in Panel B. This is consistent with the idea that the loan spread's additional predictive power is unlikely to be explained by the no-frictions story, i.e., financial frictions experienced by the borrowers likely play a role in driving the additional predictive power of the loan market.[31]

Overall, the results so far 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. This holds true even within the set of firms that are only observed in the loan market and is consistent with a frictions-based explanation for the additional predictive power of loan spreads.

5.2.2 Types of frictions: bank vs. borrower balance-sheets

As noted above it is empirically challenging to differentiate between frictions emanating from the intermediary side or the borrower side. To further gauge the relative importance of the bank and borrower financial frictions channel, we decompose the loan spread into two components following 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). This decomposition can be helpful in assessing the relative importance of bank and borrower constraints in explaining the predictive power of loan spreads. A detailed description of the methodology is provided in Online Appendix 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

[31] Online Appendix G we split bond market firms by size. Unlike the loan market, within the bond market we find little difference in predicitive power across size groups.

financial intermediary sector (prediction 4). Gilchrist and Zakrajšek (2012), for instance, present evidence that the "excess bond premium" (EBP) correlates with the health of the financial sector. We find that also the ELP is a strong indicator for financial sector conditions (Online Appendix E). The predicted component, in contrast, captures spread variations due to changes in borrower conditions, such as changes in net worth. That is, it captures fundamental information about firm default or information about financial frictions emanating from borrower balance sheets.

In Table 6, Panel A, we run baseline forecasting regressions using decomposed spreads. Two key results emerge: First, the ELP contributes significantly to the predictive power of the loan spread across all regressions. The forecasting power that comes from the ELP relative to the *predicted* part of the loan spread ranges between 43-83% for five out of the six outcome variables. For UE the ELP accounts for only about one-third of the forecasting power. This evidence is consistent with the idea that the loan spread, in part, has additional predictive power because it captures frictions in the intermediary sector.

Second, while a large fraction of the forecasting power is coming from the ELP, also the predicted spread has forecasting power. It is highly statistically significant for all six macroeconomic outcomes and for three out of the six regressions the predicted spread accounts for over 50% of the additional predictive power. This suggests that borrower balance sheets might also be important in understanding the predictive power of the loan spread.

Next, we again split the sample into "large and old" and "small and young" firms to better understand the sources of financial frictions. Table 6, Panel C, shows results for large and old borrowers. While the ELP and predicted spread *jointly* have predictive power also for large and old firms (see Table 5), the individual components are mostly statistically insignificant. This again highlights that, after controlling for the information contained in the bond market (S_t^{BondPC}), the predictive power of the loan market is attenuated in the market segment where the overlap between the bond and the loan market is the largest. Interestingly, for four out of the six macroeconomic variables a very large fraction of the incremental forecasting power of loan spreads is coming from the predicted part of the spread, not the ELP. That is, for the set of firms that is less subject to (and hence less informative about) financial frictions most of the loan market's predictive power arises because loan spread do contain additional information about the fundamentals of larger loan market firms.

In Table 6, Panel B, we condition on the smaller and younger borrowers within the loan market. Here, the opposite result emerges. Both the predicted spread and the ELP are highly statistically significant in all forecasting regressions, however, a large fraction of the predictive power is coming from the ELP (between 50-80% for five out of the six macroeconomic variables). That is, for the set of firms that is most subject to financial frictions, it is the "non-fundamental" part of the loan spread that contributes most to the predictive power. This is consistent with the conjecture that smaller loan market firms are highly exposed to (and hence contain information about) frictions in the financial sector, which are informative about macroeconomic developments.

However, it should be noted that this does not imply that frictions emanating from borrower balance sheets do not contribute to the loan market's predictive power. In fact, the predicted part of the "small and young spread" is highly statistically significant in all forecasting regressions and does account for a sizable share of the loan market's predictive power. Given the fact that smaller and younger firms contribute less to aggregate fluctuations, it is highly plausible that the predicted part of the spread for small and young firms captures changes in net worth that correlate with frictions emanating from the borrower side.

In summary, we find evidence that suggests that it is unlikely that the loan spread's relative predictive power can be explained by a no-frictions channel alone. Private, small, and young firms, i.e., firms that are plausibly most exposed to financial frictions, contribute most to the predictive power of the loan market. In particular frictions on financial intermediary balance sheets captured in the spread of smaller and younger loan market firms seem to contribute to the relative predictive power of the loan spread. However, also the conditions of borrower balance sheets of smaller and younger firms matter. Overall, our evidence is consistent with models highlighting that financial intermediary and firm balance sheet constraints *jointly* determine economic activity, see e.g., Rampini and Viswanathan (2019).

5.3 Other potential channels

This section discusses the potential of other channels, such as investor demand and behavioral theories, in understanding the additional predictive power of loan spreads.

Investor demand: Investor demand can be an important factor in explaining asset price dynamics (see, e.g., Koijen and Yogo, 2019), i.e., loan and bond prices might contain information about shocks to investors rather than to borrowers or dealer banks. Changes in investor demand can affect funding conditions for firms and thus have real effects, i.e., can be informative about economic developments (see, among others, Ben-Rephael *et al.*, 2020; Kubitza, 2021). If the composition of investors in the loan market and in the bond market is different, loan prices could be informative because they reflect additional information about demand conditions on the investor side.

The largest investor group in the secondary loan market are collateralized loan obligations (CLOs) and loan market mutual funds (Irani *et al.*, 2021). Insurance companies and debt funds are among the largest investors in the bond market (Koijen and Yogo, 2019). While this suggests that the investor base in the loan market and in the bond market is different, CLOs obtain their funding from other institutional investors that tend to be active in the bond market as well, e.g., insurance companies, (pension, hedge, or debt) funds, and banks (see, e.g., Liu and Schmidt-Eisenlohr, 2019). That is, there is an overlap in the ultimate investor base between bond and loan markets. This overlap, however, is far from complete giving rise to the possibility that (part of) the loan market's predictive power arises because loan spreads contain information about investor demand.

We construct proxies for demand by large loan market investors, such as CLOs. First, we use a measure based on the USD value of monthly new CLO issuance from S&P/LCD's CLO Global Databank. Second, we use Ivashina and Sun (2011)'s *Time-on-market* measure, which is defined as the average time in days between syndication launch date (start of the book building process) for loan tranches marketed to institutional investors and the date at which the borrower gains access to funds (completion date). In a "hot" market this measure is low reflecting a quick turnaround time due to high institutional loan demand. We include these measures into our predictive regressions to test if investor demand explains (part of) the predictive power of the loan spread. Table 7, Panel A, adds the USD value of new CLO issuance and Panel B adds the Time-on-market measure to the baseline model (cf. Table 2, Panel B). Panel C adds both measures to the "kitchen sink" model (cf. Table 3, Panel B).

Focusing on industrial production as an outcome variable, the results show that the predictive power of the loan spread is hardly affected by the inclusion of investor demand proxies. The coefficient on the loan spread is virtually unchanged compared to the baseline model. This indicates that the predictive power of the loan spread is largely orthogonal to contemporaneous investor demand conditions. This conclusions extends to the other macroeconomic outcome variables as well as to the "kitchen sink" model shown in Panel C. Interestingly, while the demand proxies do not affect the loan spread's predictive power, both proxies have independent predictive power of their own. For example, adding the Time-on-market measure increases the incremental R^2 of the model by about 4 p.p. (incremental R^2 of 19.8 p.p. in Table 7, Panel B, columnn 1, versus 15.4 p.p. in Table 2, Panel B, column 1).

The evidence so far focuses on the contemporaneous relationship between loan spread and investor demand conditions. We follow Ben-Rephael *et al.* (2020) and also examine the dynamic relationship using impulse response functions based on a monthly VAR (vector autoregression) with the number of lags of each variable chosen by AIC. Figure 6 shows that a shock to the loan spread predicts a significant widening of the Time-on-market measure and a decrease in CLO issuance up to 5 months ahead. In contrast, while a negative shock to investor demand tends to go along with an increase in spreads in the following months, none of the estimates are statistically significant and the error bars are wide. That is, evidence suggests that, if anything, the loan spread moves contemporaneously with or before changes in primary market investor demand conditions.

Behavioral theories: Finally, there is a literature that highlights the role of extrapolative beliefs (see, e.g., Bordalo *et al.*, 2018; Greenwood and Hanson, 2013; Greenwood *et al.*, 2019; López-Salido *et al.*, 2017). If expectations about future economic development are overly influenced by the current state of the economy, investors become overly optimistic in response to positive news. This leads to narrower credit spreads and an (over-) extension of credit. Given that future news will, on average, be negative compared to optimistic expectations, an endogenous reversal of sentiment occurs. The predictive power of credit spreads arises because a period of (too) low credit spreads will, controlling for fundamentals, predict a future rise of spreads and a contraction in economic activity.

To explain the *relative* predictive power of loan spreads versus bond spreads, loan market investors need to be more susceptible to (different) biases compared to bond market investors. As noted above, there is an overlap in the investor base between both markets and loan market investors are, if anything, equally professional, large-scale investors compared to bond market investors, making it less likely that they should be *more* susceptible to biases.

Testing behavioral theories is complicated by our relatively short sample period, as a sentiment reversal is typically evaluated against a longer time period of buoyant market conditions (e.g., bond spreads tend to fall alongside credit growth in years leading up to a financial crisis; Krishnamurthy and Muir, 2020). We can, however, define contemporaneous sentiment proxies, such as a "High Yield (HY) Loan Share" measure. This proxy is defined analogous to Greenwood and Hanson (2013)'s "HY Bond Share" measure. The idea is that large changes in the pricing of credit risk disproportionately affects the debt issuance behavior of low credit-quality firms, i.e., a deterioration in the average issuer quality can signal buoyant market conditions (which revert in the future).[32]

Table 8, Panel A, adds the HY Loan Share as an additional control. Again, the loan spread's predictive power is hardly affected suggesting that loan spreads are largely orthogonal to *contemporaneous* sentiment. Interestingly, the HY Loan Share itself has additional predictive power. An increase in the share of high yield credit signals a short-run increase in economic activity (reverting in the future). Table 8 Panel B reveals similar results for the HY Bond share. Finally, Panel C shows that adding the additional controls to the "kitchen sink" leaves the results unchanged.

[32] Given that almost all loans traded in the secondary loan market are in the high-yield space, we define the HY loan share as the fraction of C and B rated loans to total loan issuance.

We again examine the dynamic relationship in a VAR model. Thinking about the dynamic relationship between credit market conditions and spreads is closer in spirit to López-Salido *et al.* (2017), who provide evidence that an increase in HY bond share correlates with higher bond spreads two years ahead (i.e., buoyant market conditions precede sentiment reversals). Figure 6 reveals that a shock to the loan spread predicts a decrease in the HY loan share, i.e., a decrease in issuance by riskier borrowers that gradually reverses over the next two years. Consistent with the arguments in López-Salido *et al.* (2017) an increase in HY issuance is associated with an initial drop in spreads that reverses over time. This effect, however, is not significant and the error bars are large.

Overall, our evidence presented in this paper is most consistent with financial frictions being a meaningful driver of the differential predictive power of the loan spread when compared to bond spreads. While alternative channels such as investor demand and behavioral theories are clearly meaningful, evidence suggest that they unlikely fully explain the loan market's additional predictive power. However, with more data becoming available, questions such as exploring the potential role of behavioral biases in secondary loan markets in more detail are clearly promising areas for future research.

6 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.

References

Addoum, J. M. and Murfin, J. R. (2020). Equity price discovery with informed private debt. *Review of Financial Studies*, **33** (8), 3766–3803.

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

—, Colla, P. and Shin, H. S. (2012). Which financial frictions? parsing the evidence from the financial crisis of 2007 to 2009. *NBER Macroeconomics Annual*, **27**, 159–214.

—, Moench, E. and Shin, H. S. (2010a). Financial intermediation, asset prices, and macroeconomic dynamics. *Federal Reserve Bank of New York Staff Report 422.*

—, — and — (2010b). Macro risk premium and intermediary balance sheet quantities. *IMF Economic Review 58*, **58** (1), 179–207.

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

Baker, S., Bloom, N. and Davis, S. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, **131**, 1593–1636.

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

Becker, B. and Ivanshina, V. (2014). Cyclicality of credit supply: Firm level evidence. *Journal of Monetary Economics*, **62**, 76–93.

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

Ben-Rephael, A., Choi, J. and Goldstein, I. (2020). Mutual fund flows and fluctuations in credit and business cycles. *Journal Financial Economics.*

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

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

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

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

—, — and Gilchrist, S. (1999). *The Financial Accelerator in a Quantitative Business Cycle Framework*, Amsterdam: North-Holland, chap. 21, pp. 1341–1393.

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

Bloom, N. (2009). The impact of uncertainty shocks. *Econemetrica*, **77**, 623–685.

Bolton, P. and Scharfstein, D. (1996). Optimal debt structure and the number of creditors. *Journal of Political Economy*, **104**, 1–25.

Bordalo, P., Gennaioli, N. and Shleifer, A. (2018). Diagnostic expectations and credit cycles. *Journal of Finance*, (1), 199–227.

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

Brunnermeier, M. K., Eisenbach, T. M. and Sannikov, Y. (2012). Macroeconomics with financial frictions: A survey. (18102).

Bybee, L., Kelly, B. T., Manela, A. and Xiu, D. (2020). The structure of economic news. *NBER Working Paper*.

Chava, S. and Purnanandam, A. (2011). The effect of banking crisis on bank-dependent borrowers. *Journal of Financial Economics*, **99** (1), 116–135.

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

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

Colla, P., Ippolito, F. and Li, K. (2013). Debt specialization. *Journal of Finance*, **68**, 2117–2141.

Crouzet, N. (2018). Aggregate implications of corporate debt choices. *Review of Economic Studies*, **85**, 1635–1682.

— (2021). Credit disintermediation and monetary policy. *IMF Economic Review*, **69**, 23–89.

— and Mehrotra, N. (2020). Small and large firms over the business cycle. *American Economic Review*, **110** (11).

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

Diamond, D. W. (1991). Monitoring and reputation: The choice between bank loans and directly placed debt. *Journal of Political Economy*, **99**, 689–721.

— and Rajan, R. G. (2005). Liquidity risk, liquidity creation, and financial fragility: a theory of banking. *Journal of Political Economy*, **109**, 287–327.

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

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

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

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

Friedman, B. M. and Kuttner, K. N. (1993). *Why Does the Paper-Bill Spread Predict Real Economic Activity?*, University of Chicago Press, pp. 213–254.

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

Gabaix, X. (2011). The granular origins of aggregate fluctuations. *Econemetrica*, **79** (3).

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

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

Gertler, M. and Kiyotaki, N. (2010). Financial intermediation and credit policy in business cycle analysis. *Handbook of Macroeconomics.*

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

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

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

Greenstone, M., Mas, A. and Nguyen, H.-L. (2020a). Do credit market shocks affect the real economy? quasi-experimental evidence from the great recession and "normal" economic times. *American Economic Journal: Economic Policy*, **12** (1), 200–225.

—, — and — (2020b). Do credit market shocks affect the real economy? Quasi-experimental evidence from the great recession and "normal" economic times. *American Economic Journal: Economic Policy*, **12** (1), 200–225.

Greenwood, R. and Hanson, S. G. (2013). Issuer quality and corporate bond returns. *Review of Financial Studies*, **26**, 1438 – 1525.

—, — and Jin, L. J. (2019). Reflexivity in credit markets. *NBER Working Paper No. 25747.*

—, —, Shleifer, A. and Sørensen, J. A. (2020). Predictable financial crises. *NBER Working Paper No. 27396.*

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

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

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

He, Z. and Krishnamurthy, A. (2013). Intermediary asset pricing. *American Economic Review*, **103** (2), 732–770.

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

Irani, R. M., Iyer, R., Meisenzahl, R. R. and Peydró, J.-L. (2021). The rise of shadow banking: Evidence from capital regulation. *Review of Financial Studies*, **34** (5), 2181–2235.

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

— and Sun, Z. (2011). Institutional demand pressure and the cost of corporate loans. *Journal Financial Economics*, **99**, 500–522.

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

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

Jurado, K., Ludvigson, S. C. and Ng, S. (2015). Measuring uncertainty. *American Economic Review*, **105**, 1177–1216.

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

Koijen, R. S. J. and Yogo, M. (2019). A demand system approach to asset pricing. *Journal of Political Economy*, **127** (4), 1475–1515.

Krishnamurthy, A. and Muir, T. (2020). How credit cycles across financial crisis. *NBER Working Paper No. 23850.*

Kubitza, C. (2021). Investor-driven corporate finance: Evidence from insurance markets. *Working Paper, Bonn University.*

Liu, E. and Schmidt-Eisenlohr, T. (2019). Who owns u.s. clo securities? *FEDS Notes.*

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

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

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

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

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

Rajan, R. G. (1992). Insiders and outsiders: The choice between informed and arm's-length debt. *Journal of Finance*, **47**, 1367–1400.

Rampini, A. A. and Viswanathan, S. (2019). Financial intermediary capital. *Review of Economic Studies*, **86**, 413–455.

Rauh, J. D. and Sufi, A. (2010). Capital structure and debt structure. *Review of Financial Studies*, **23**, 4242–4280.

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

Schwert, M. (2020). Does borrowing from banks cost more than borrowing from the market? *Journal of Finance*, **75** (2), 905–947.

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

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

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

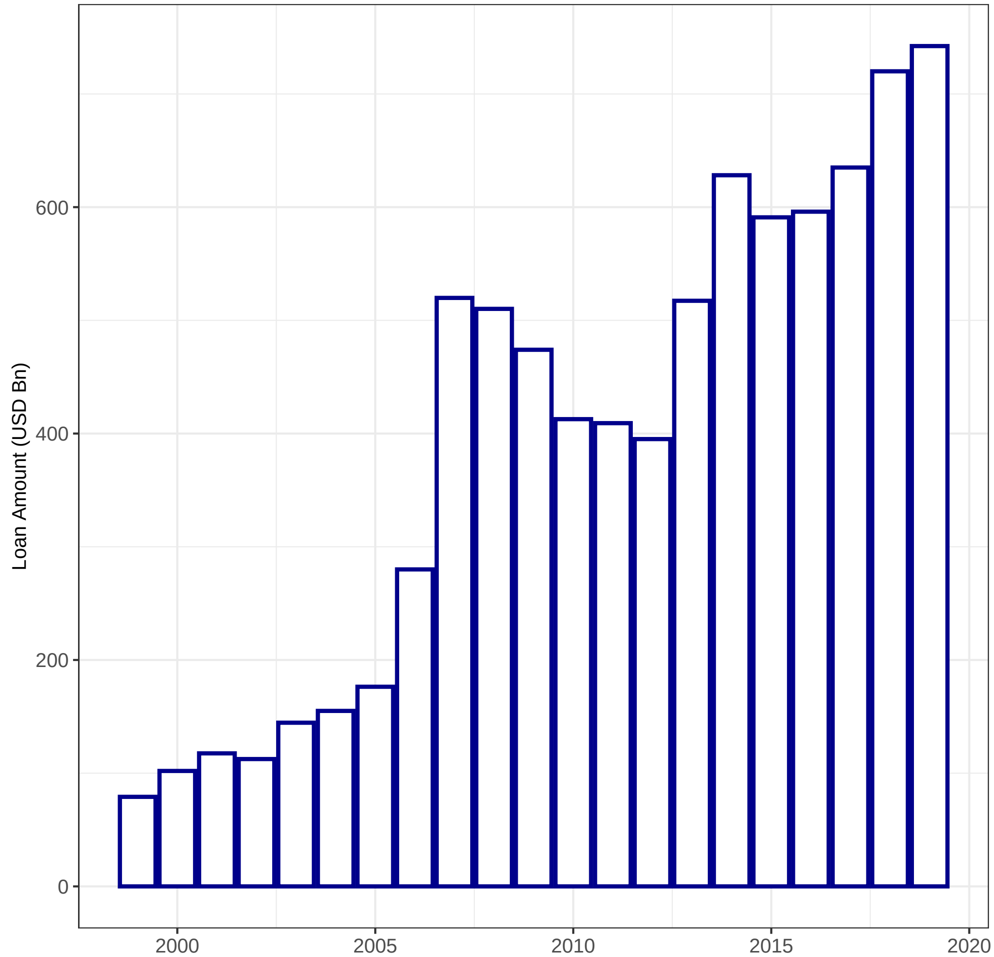

Figure 2: **Secondary loan market trading volume**
This figure plots the development of total loan volume traded in the secondary U.S. syndicated loan market over the 1999 to 2019 period. Source: LSTA.

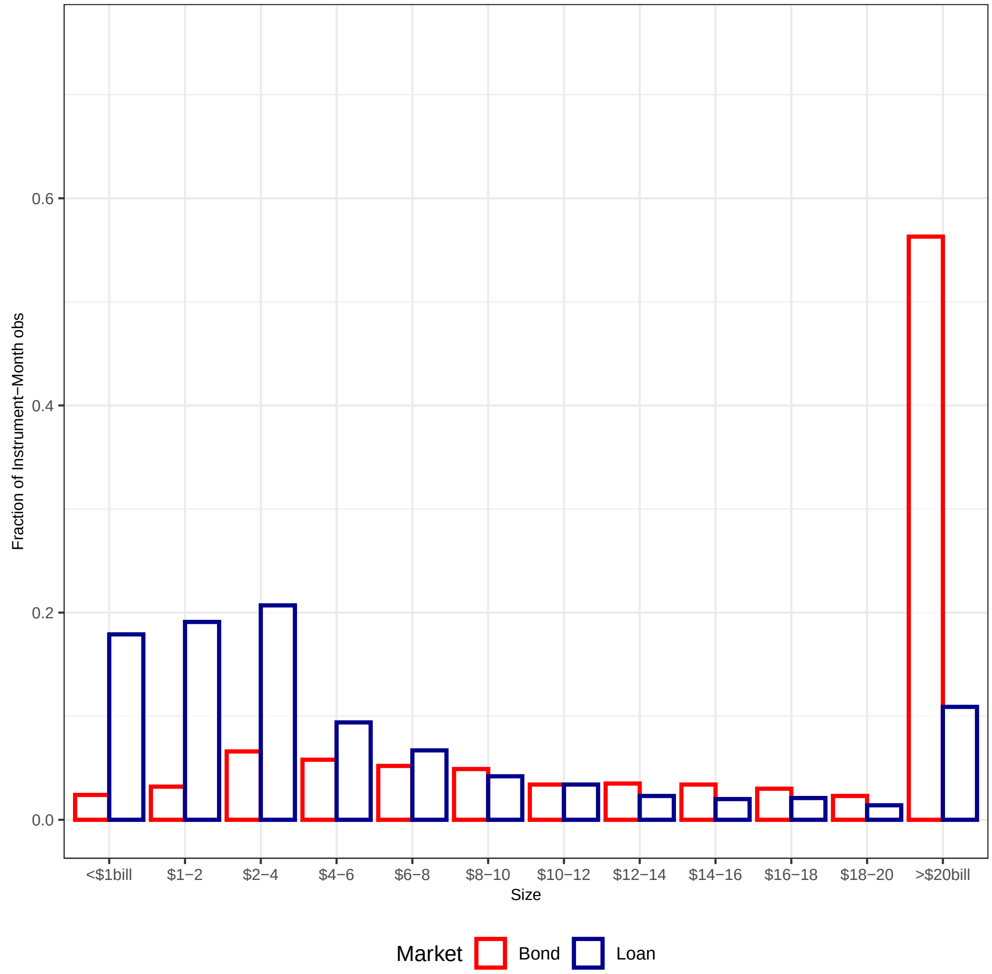

Figure 3: **Borrower size across loan and bond market**
This figure plots the distribution of borrower size across the loan and bond market. Source: Dealscan/Mergent/COMPUSTAT.

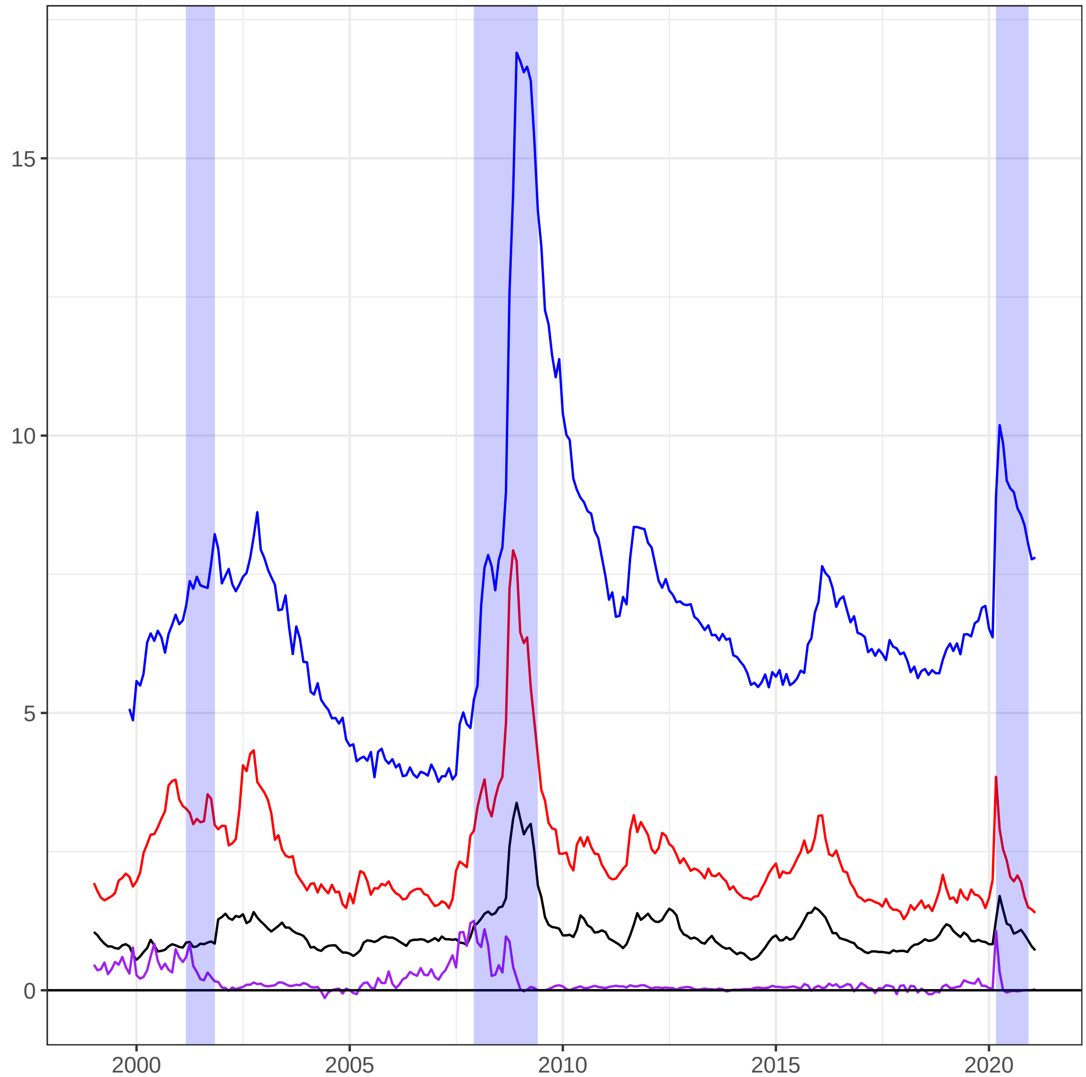

Figure 4: **Corporate credit spreads**
This figure plots monthly credit spread measures over time. Depicted are: (i) the loan spread (blue line), defined as the average credit spread of syndicated loans issued by non-financial firms that are traded in the secondary market, (ii) the bond spread (red line), 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 (black 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.

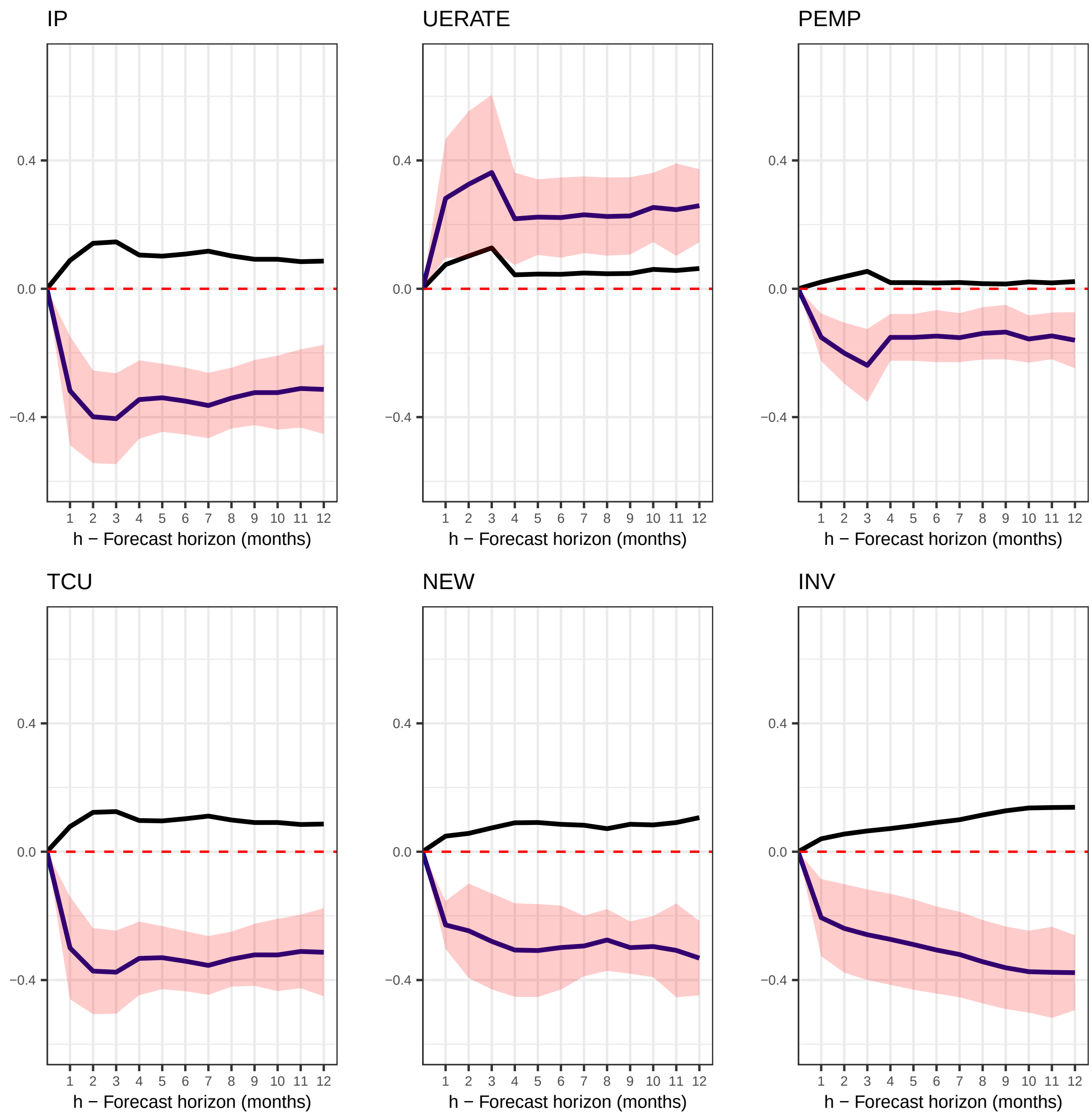

Figure 5: **Local Projections and Incremental R-squared**
This figure plots the impulse response function using a Jordà (2005) local projections framework (blue line) and the incremental adjusted R^2 (black line). In each figure, the dependent variable is the h-month ahead growth in the macro variable. 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.

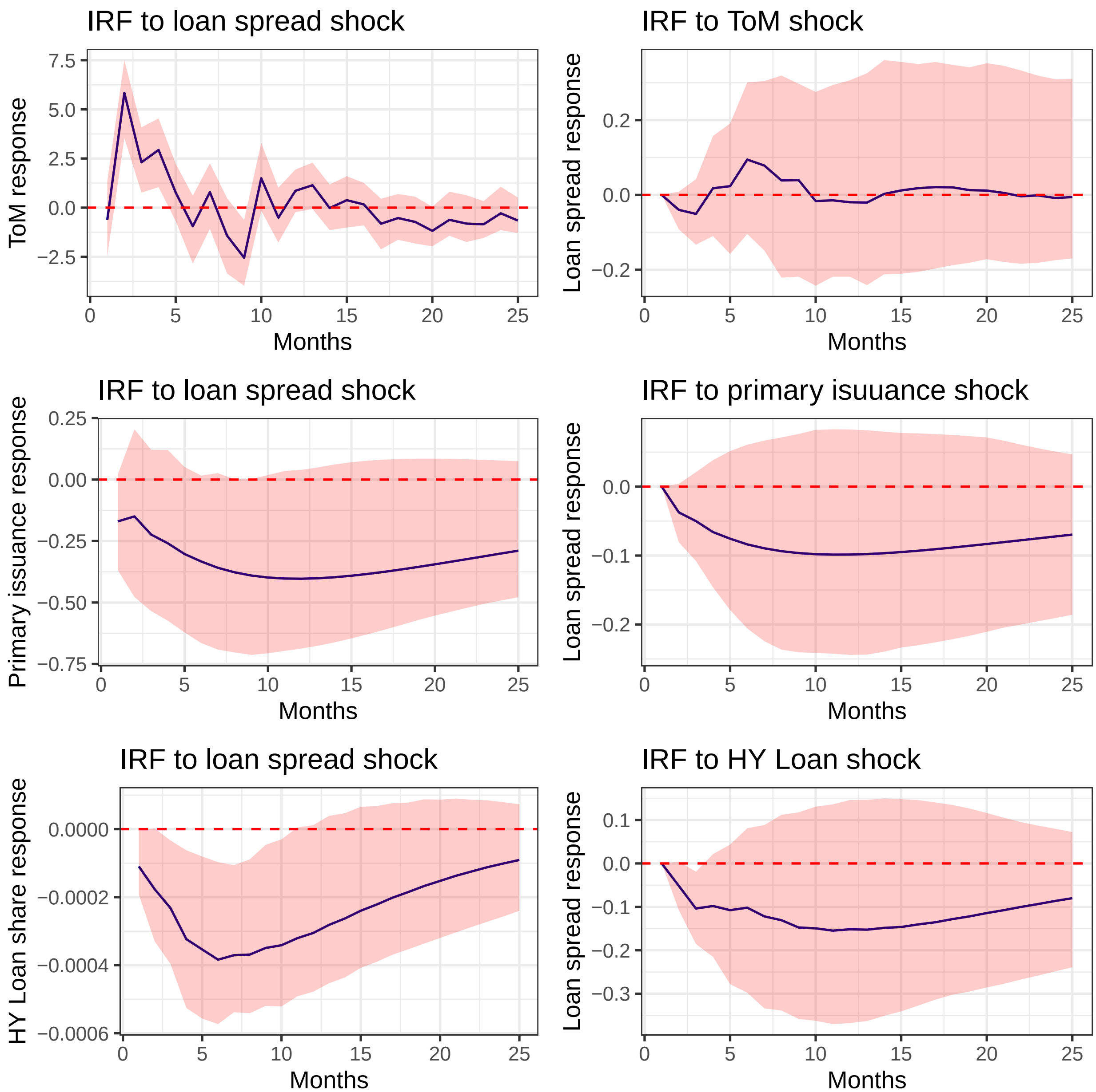

Figure 6: **IRF**
This figure plots the impulse response function of CLO Primary Issuance, Time on Market, and HY Loan Share to shocks to the loan spread. The sample period is 2001:01 to 2020:01.

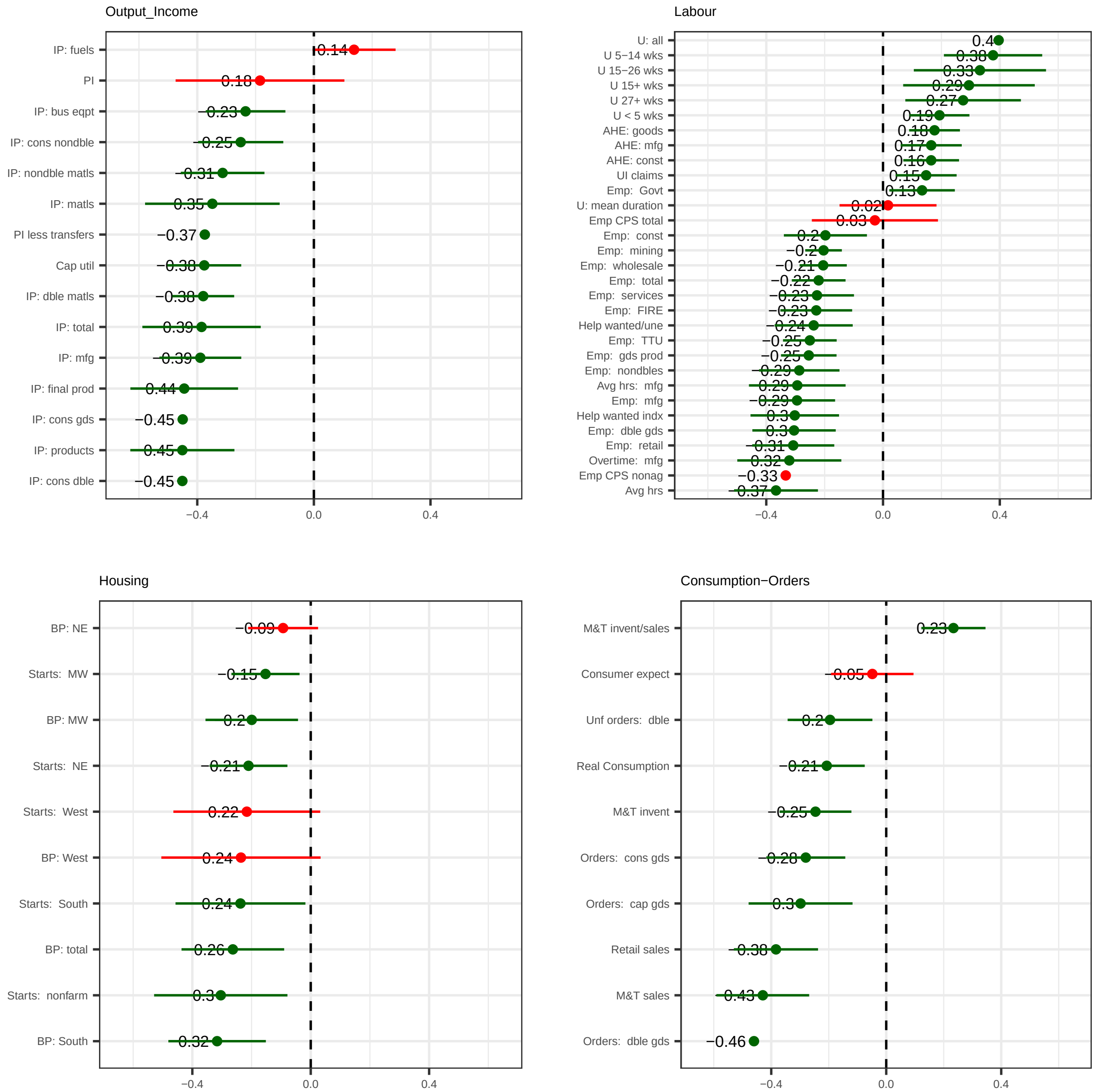

Figure 7: **Baseline Regression - FRED-MD**
This figure plots the coefficient on the loan spread across 126 variables in the FRED-MD dataset. Variables are grouped by theme... The sample period is 2001:01 to 2020:01. The sample period is 2001:01 to 2020:01

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

This table compares the characteristics of borrowers in the loan market and issuers in the bond market. Panel A defines "All borrowers" as the number of unique borrowers that can be identified in our loan and bond data sourced from the LSTA and TRACE, respectively. Private borrowers are firms that cannot be linked to the Compustat database. Public borrowers are firms that can be linked to the Compustat database, i.e., firms with publicly sold securities (equity and/or debt) that must file periodic reports with the Securities & Exchange Commission (SEC). 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 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 versus private:				
All borrowers	100%	3,713	100%	2,762
thereof:				
Private	51%	1,923	11%	310
Public	49%	1,854	89%	2452
Unique parents ("GVKEYs")		1,685		1,782
Panel B. Size distribution:				
<= $2bill	61%	939	38%	659
>2 & <=6 $bill	23%	357	28%	493
>6 & <=10 $bill	6%	87	9%	160
> $10bill	10%	166	24%	421
Market overlap:	thereof: also a bond issuer		thereof: also a loan issuer	
<= $2bill	28%	266	40%	266
>2 & <=6 $bill	57%	202	41%	202
>6 & <=10 $bill	69%	60	38%	60
> $10bill	72%	120	29%	120
Panel C. Age distribution:				
<=5yr	29%	335	19%	299
>5yr & <=10yr	20%	235	18%	291
>10yr & <=20yr	24%	278	23%	371
>20yr	27%	317	40%	636
Market overlap:	thereof: also a bond issuer		thereof: also a loan issuer	
<=5yr	46%	155	52%	155
>5yr & <=10yr	51%	119	41%	119
>10yr & <=20yr	51%	142	38%	142
>20yr	65%	206	32%	206

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							
Panel A.	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	+0.060	+0.154
LR Test(χ^2)	-	-	-	-	-	-	-	33.26
Observations	241	241	241	241	241	241	241	241

Panel B.	IP	PEMP	UE	TCU	NEW	INV
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}	-0.356	-0.251	0.356	-0.328	-0.266	-0.230
	(-4.590)	(-3.626)	(3.016)	(-4.651)	(-3.687)	(-3.598)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.343	0.671	0.283	0.383	0.138	0.577
Incremental R^2 (w/o $\Delta S_t^{Bond\ PC}$)	+0.146	+0.054	+0.127	+0.125	+0.074	+0.065
Incremental R^2	+0.154	+0.054	+0.125	+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

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	IP	IP	IP	IP	IP
	(1)	(2)	(3)	(4)	(5) Ex. 08-09	(6) Ex. 08-09
ΔS_t^{Loan}		-0.358	-0.378	-0.264	-0.201	
		(-5.153)	(-5.374)	(-4.404)	(-2.905)	
$\Delta S_t^{Bond\ PC}$						-0.104
						(-1.447)
Residual ΔS_t^{Loan}	-0.389					
	(-5.413)					
Bid-Ask		-0.311				
		(-2.922)				
Δ S&P500			0.152			
			(2.990)			
ΔVIX				-0.351		
				(-3.109)		
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.325	0.401	0.354	0.407	0.199	0.180
Incremental R^2	+0.136	+0.212	+0.165	+0.219	+0.010	-0.009
LR Test(χ)	45.310	41.986	23.841	20.062	10.087	2.830
Observations	241	241	241	241	225	225

Panel B.	IP	PEMP	UE	TCU	NEW	INV
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}	-0.271	-0.164	0.150	-0.237	-0.236	-0.137
	(-4.375)	(-3.500)	(2.955)	(-4.269)	(-4.180)	(-2.299)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Bid-Ask	✓	✓	✓	✓	✓	✓
SP500	✓	✓	✓	✓	✓	✓
VIX	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.425	0.731	0.589	0.449	0.141	0.624
Incremental R^2	+0.236	+0.114	+0.431	+0.199	+0.075	+0.114
Observations	241	241	241	241	241	241

Table 4: **Robustness across industry and countries**

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				
Panel A. Across Industry	EMP	EMP	EMP	EST	OUT
	(1)	(2)	(3)	(4)	(5)
S_{bt}^{Loan}	−0.182	−0.231	−0.233	−0.301	−0.185
	(−1.885)	(−1.965)	(−1.949)	(−3.036)	(−2.826)
S_{t}^{Loan}	−0.330				
	(−3.267)				
Year × qtr fixed effects	No	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes	Yes
Overall R^2	0.338	0.474	0.474	0.491	0.532
Within R^2	-	0.091	0.091	0.221	0.073
Incremental R^2	+0.161	+0.296	+0.296	+0.252	+0.421
Observations	803	803	803	803	611

Panel B. Across Country	Germany		France		Spain	
	MAN	MAN	MAN	MAN	MAN	MAN
	(1)	(2)	(3)	(4)	(5)	(6)
S_{t}^{Loan}	−0.379	−0.316	−0.338	−0.289	−0.238	−0.122
	(−2.455)	(−2.423)	(−2.167)	(−2.170)	(−1.972)	(−1.145)
S_{t}^{Bond}		−0.128		−0.102		−0.224
		(−1.802)		(−1.080)		(−1.398)
EU Term Spread	✓	✓	✓	✓	✓	✓
EONIA	✓	✓	✓	✓	✓	✓
Adj R^2	0.263	0.271	0.192	0.195	0.180	0.207
Incremental R^2	+0.122	+0.129	+0.095	+0.098	+0.048	+0.075
Observations	227	227	188	188	187	187

Table 5: **Friction vs. non-frictions-based channels**

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	PEMP	UE	TCU	NEW	INV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:Firms NOT in COMPUSTAT						
ΔS_t^{Loan} Private	-0.367	-0.232	0.359	-0.346	-0.272	-0.235
	(-5.016)	(-3.318)	(3.300)	(-5.342)	(-3.980)	(-4.011)
Adjusted R^2	0.355	0.666	0.290	0.397	0.144	0.581
Incremental R^2	+0.166	+0.048	+0.132	+0.147	+0.078	+0.071
Panel B: Firms in COMPUSTAT						
ΔS_t^{Loan} Small/Young	-0.324	-0.188	0.271	-0.289	-0.261	-0.223
	(-3.449)	(-2.072)	(1.882)	(-3.270)	(-2.987)	(-2.997)
Adjusted R^2	0.330	0.649	0.239	0.367	0.136	0.575
Incremental R^2	+0.141	+0.031	+0.080	+0.117	+0.070	+0.065
ΔS_t^{Loan} Old/Large	-0.189	-0.148	0.187	-0.161	-0.219	-0.155
	(-2.667)	(-2.004)	(1.483)	(-2.418)	(-3.048)	(-2.098)
Adjusted R^2	0.274	0.637	0.206	0.321	0.118	0.553
Incremental R^2	+ 0.085	+0.020	+0.048	+0.071	+0.051	+0.043
Panel C: Firms NO bond access						
ΔS_t^{Loan} Small/Young	-0.327	-0.192	0.278	-0.292	-0.271	-0.223
	(-3.665)	(-2.132)	(1.931)	(-3.482)	(-3.186)	(-3.232)
Adjusted R^2	0.333	0.651	0.243	0.370	0.142	0.576
Incremental R^2	+0.144	+0.033	+0.085	+0.120	+0.075	+0.066
ΔS_t^{Loan} Old/Large	-0.181	-0.148	0.178	-0.157	-0.188	-0.145
	(-3.337)	(-2.184)	(1.521)	(-3.021)	(-3.032)	(-1.996)
Adjusted R^2	0.272	0.638	0.204	0.320	0.108	0.551
Incremental R^2	+0.083	+0.020	+0.045	+0.070	+0.042	+0.041
Controls in Panel A-C:						
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Observations	241	241	241	241	241	241

Table 6: **Credit-Spread Decomposition - Split by Size**

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.

	Forecast horizon: h = 3 month					
	IP	PEMP	UE	TCU	NEW	INV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. *Baseline*						
ΔELP_t	-0.260	-0.197	0.227	-0.232	-0.236	-0.182
	(-4.491)	(-3.667)	(2.497)	(-4.342)	(-3.858)	(-2.962)
$\Delta\hat{S}_t^{Loan}$	-0.345	-0.175	0.409	-0.339	-0.152	-0.172
	(-3.054)	(-2.295)	(2.752)	(-3.367)	(-1.664)	(-2.330)
Adjusted R^2	0.353	0.668	0.305	0.395	0.138	0.576
Incremental R^2	+0.164	+0.050	+0.147	+0.145	+0.071	+0.065
Contribution from $\Delta\hat{S}_t^{Loan}$	0.510	0.295	0.678	0.568	0.169	0.322
Observations	241	241	241	241	241	241
Panel B. *Small/Young Firms*						
ΔELP_t	-0.267	-0.156	0.199	-0.227	-0.272	-0.174
	(-3.443)	(-2.220)	(1.703)	(-3.142)	(-3.067)	(-2.271)
$\Delta\hat{S}_t^{Loan}$	-0.303	-0.165	0.320	-0.298	-0.191	-0.144
	(-2.366)	(-1.754)	(1.924)	(-2.507)	(-2.003)	(-2.130)
Adjusted R^2	0.348	0.654	0.264	0.385	0.160	0.569
Incremental R^2	+0.159	+0.036	+0.106	+0.135	+0.093	+0.059
Contribution from $\Delta\hat{S}_t^{Loan}$	0.440	0.411	0.647	0.526	0.211	0.281
Observations	241	241	241	241	241	241
Panel C. *Large/Old Firms*						
ΔELP_t	-0.079	-0.098	0.070	-0.058	-0.168	-0.108
	(-1.588)	(-1.865)	(0.696)	(-1.272)	(-2.904)	(-1.671)
$\Delta\hat{S}_t^{Loan}$	-0.227	-0.109	0.254	-0.234	-0.063	-0.072
	(-1.572)	(-1.199)	(1.464)	(-1.715)	(-0.577)	(-0.923)
Adjusted R^2	0.280	0.634	0.218	0.334	0.104	0.545
Incremental R^2	+0.091	+0.017	+0.060	+0.084	+0.038	+0.035
Contribution from $\Delta\hat{S}_t^{Loan}$	0.864	0.444	0.912	0.931	0.069	0.212
Observations	241	241	241	241	241	241
Controls in Panel A-C:						
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓

Table 7: **Investor Demand Proxies**

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}	-0.347	-0.240	0.333	-0.319	-0.264	-0.222
	(-4.609)	(-3.463)	(2.889)	(-4.559)	(-3.860)	(-3.594)
CLO Primary Issuance	0.225	0.101	-0.284	0.237	0.070	0.117
	(2.358)	(1.973)	(-3.242)	(2.558)	(0.588)	(1.820)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.371	0.689	0.341	0.401	0.131	0.601
Incremental R^2	+0.182	+0.072	+0.183	+0.151	+0.065	+0.090
Observations	228	228	228	228	228	228
Panel B.						
ΔS_t^{Loan}	-0.331	-0.234	0.318	-0.309	-0.246	-0.294
	(-4.621)	(-3.060)	(2.496)	(-4.609)	(-4.151)	(-4.234)
Time on Market	-0.259	-0.157	0.342	-0.270	-0.087	-0.023
	(-2.599)	(-2.779)	(3.783)	(-2.745)	(-0.915)	(-0.365)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.387	0.653	0.351	0.414	0.151	0.550
Incremental R^2	+0.198	+0.035	+0.193	+0.164	+0.085	+0.039
Observations	213	213	213	213	213	213
Panel C.						
ΔS_t^{Loan}	-0.313	-0.141	0.153	-0.302	-0.225	-0.147
	(-5.007)	(-2.693)	(2.908)	(-5.467)	(-3.983)	(-2.103)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Bid-Ask	✓	✓	✓	✓	✓	✓
SP500	✓	✓	✓	✓	✓	✓
VIX	✓	✓	✓	✓	✓	✓
CLO Iss	✓	✓	✓	✓	✓	✓
ToM	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.416	0.732	0.610	0.438	0.157	0.641
Incremental R^2	+0.227	+0.115	+0.452	+0.188	+0.091	+0.130
Observations	213	213	213	213	213	213

Table 8: **Behavioural Proxies**

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}	-0.335	-0.240	0.333	-0.306	-0.249	-0.218
	(-4.319)	(-3.488)	(2.868)	(-4.280)	(-3.606)	(-3.381)
HY Loan Share	0.209	0.090	-0.176	0.251	0.111	0.104
	(3.387)	(1.830)	(-2.397)	(4.467)	(1.718)	(2.300)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.381	0.677	0.308	0.438	0.145	0.585
Incremental R^2	+0.192	+0.060	+0.150	+0.188	+0.079	+0.074
Observations	241	241	241	241	241	241
Panel B.						
ΔS_t^{Loan}	-0.336	-0.235	0.313	-0.310	-0.251	-0.217
	(-4.000)	(-3.120)	(2.398)	(-4.018)	(-3.315)	(-3.051)
HY Bond Share	0.251	0.145	-0.315	0.245	0.092	0.120
	(3.279)	(2.715)	(-4.028)	(3.282)	(1.008)	(1.781)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.390	0.686	0.360	0.427	0.141	0.585
Incremental R^2	+0.201	+0.068	+0.202	+0.177	+0.075	+0.075
Observations	241	241	241	241	241	241
Panel C.						
ΔS_t^{Loan}	-0.285	-0.159	0.144	-0.257	-0.243	-0.134
	(-4.219)	(-3.214)	(2.655)	(-4.128)	(-4.043)	(-2.162)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Bid-Ask	✓	✓	✓	✓	✓	✓
SP500	✓	✓	✓	✓	✓	✓
VIX	✓	✓	✓	✓	✓	✓
HY Loan Share	✓	✓	✓	✓	✓	✓
HY Bond Share	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.447	0.740	0.617	0.478	0.142	0.628
Incremental R^2	+0.258	+0.122	+0.458	+0.228	+0.076	+0.118
Observations	241	241	241	241	241	241