Essays in Financial Markets and Beliefs

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ALESSANDRO SPINA

ESSAYS IN FINANCIAL MARKETS AND BELIEFS

CBS

Essays in Financial Markets and Beliefs

Alessandro Spina

A thesis presented for the degree of
Doctor of Philosophy

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Secondary supervisor: Daniel Streitz
CBS PhD School
Copenhagen Business School

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Abstract

This thesis represents the final product of my PhD studies at the Department of Finance and the Center for Financial Frictions (FRIC) at Copenhagen Business School. The thesis consists of three chapters. The chapters are self-contained and can be read independently.

The first chapter, “Corporate Loan Spreads and Economic Activity,” documents a novel predictive measure of economic activity. We construct a loan spread measure based on the credit spreads of syndicated corporate loans. Credit spreads from syndicated loans capture information about borrower fundamentals and financial frictions not available in alternative credit spreads derived from the corporate bond market.

The second chapter, “Market Segmentation and Cross-predictability,” examines how information diffuses across equity and syndicated loan markets. I test whether asset prices in one industry predict asset prices in an economically related industry. I expand these tests beyond the equity market, for the first time, and find evidence of slow information diffusion in the syndicated loan market, in contrast to the equity market.

The third chapter, “Heterogenous Expectation Formation,” studies how agents form expectations. I use forecasts from macroeconomic surveys to explore the pattern of overreaction and underreaction in forecast revisions. I find that patterns in expectation formation are related to the experience of the analyst making the forecast. These findings show that heterogeneity amongst respondents cannot be ignored when studying expectation formation.

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In the process of writing this thesis, I have been fortunate to benefit from the support of many people. Among this long list, are some who deserve a special mention.

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Alessandro Spina
Copenhagen, April 2024

Introduction and Summaries

This thesis examines the information in asset prices and how macroeconomic expectations are formed. Chapter 1 finds there is unique information contained in the loan spreads of syndicated loans. This information can improve forecasts of economic conditions. Chapter 2 studies how information can be slow to spread within an asset class. I show information takes time to diffuse within the syndicated loan market. Finally, in Chapter 3 I expand my focus to study how agents form expectations of macroeconomic variables.

All three chapters document new empirical facts that deepen our understanding of financial markets and belief formation. Chapter 1 introduces a new asset class for macroeconomic forecasting and reveals it contains useful information above and beyond existing predictors. Chapter 2 finds that the information contained within loan spreads can take time to diffuse across the loan market, in contrast to equity markets. Chapter 3 shows that heterogeneity amongst respondents cannot be ignored when studying expectation formation. The next pages provide summaries of the individual papers in English and Danish. These summaries clarify the individual papers' contribution.

Summaries in English

Corporate Loan Spreads and Economic Activity

In the paper, "**Corporate Loan Spreads and Economic Activity**" we use secondary loan-market prices to construct a novel loan-market based credit spread. We find this measure has considerable predictive power for a range of macroeconomic variables. For example, a 1 standard deviation increase in the loan market credit spread is associated with a 0.40 standard deviation decrease in industrial production over the subsequent 3 months. This is an economically significant improvement relative to existing predictors of economic activity. This finding is robust across time, country, and controlling for a range of known macroeconomic predictors.

We argue that the predictive power of the loan spread works through two channels: a fundamental channel and a friction-based channel. According to the first channel, firms borrowing in the syndicated loan market exhibit different characteristics than firms borrowing in the corporate bond market. Thus, loan spreads capture fundamental information about a class of borrowers, which until now was simply not available through other financial securities. According to the second channel, these different borrowers are exposed to greater financial frictions on either the borrower or intermediary side. We find evidence that both channels can explain this additional predictive power. Overall, while our results highlight that different channels are important in understanding the additional predictive power of the loan spread (such as borrower fundamentals as well as investor demand or behavioural stories), we document that financial frictions are a first order determinant of the predictive power of the loan vis-a-vis other credit market spreads. In particular, intermediary frictions are an important driver of syndicated loan spreads.

Market Segmentation and Cross-predictability

In my second paper, "**Market Segmentation and Cross-predictability**" I examine the hypothesis that information diffuses slowly across financial markets by testing for cross predictability in asset prices. Cross-predictability has been documented between the returns of economically connected firms by Cohen and Frazzini (2008), and related industries by Menzly and Ozbas (2010). However, over the last two decades, an active secondary market has developed, where U.S. corporate syndicated loans are traded like securities. The availability of granular data on loan prices now allows the study of cross-predictability in the loan market. The study of information dynamics in credit markets is particularly interesting because it is not clear *a priori* what to expect. Institutional dominance in credit markets may encourage information dissemination, yet the inherent illiquidity and opacity of credit markets might impede such information diffusion.

First, I test the ability of industry-specific loan spreads to predict loan spreads in economically related industries. Over the full sample period I find no evidence of cross predictability. However, focusing on the post-2010 period, I find a 100bps increase in the loan spread of upstream industries is associated with a 32bps increase in the loan spread of downstream industries in the following month. A potential explanation for the emergence of cross-predictability is industry specialization by loan market investors, i.e. Collateralised Loan Obligation (CLO) managers. If CLO managers specialize along industry lines, an informative signal arising in one industry is received first by CLO managers specializing in that industry, leading to cross-predictability in loan spreads. I find evidence that CLO managers do specialize within industries. Second, I reexamine cross-predictability in equity returns. Employing the Menzly and Ozbas (2010) sample period from 1962 to 2005, I replicate the original finding of cross-predictability. However, extending the analysis to an out of sample period from 2005 to 2022, reveals equity returns in upstream industries no longer predict equity returns in downstream industries. A potential explanation for the disappearance of cross-predictability is post-publication awareness of the trade, combined with the rise of industry mutual funds/ETFs. In summary, this paper investigates the ability of loan spreads to predict loan spreads in other industries and finds that predictability depends on the period investigated. I then test if a similar time dependence can be found in equity markets, and I find that this is indeed the case. I hypothesize and deliver some preliminary evidence that the change in loan predictability is due to the emergence of institutional investors, while the change in equity markets is due to improvements in market liquidity.

Heterogenous Expectation Formation

In my third paper "**Heterogenous Expectation Formation**" I use forecasts from the Wall Street Journal Economic survey to study how respondents form expectations of macroeconomic variables. Existing empirical studies of expectations have typically assumed that forecasts from any given firm are coming from the same individual. I show that the individual providing forecasts on behalf of a firm does regularly change and those changes matter, as "new" respondents tend to form their expectations differently than more experienced respondents. To test the expectation formation process I use the method popularized by Coibion and Gordonichenko (2015), in which they compare the correlation between forecast revisions and subsequent forecast errors from macroeconomic surveys. Under the full information rational expectations (FIRE) model, forecast revisions should not predict future forecast errors. When the correlation is positive, upward revisions predict higher realizations compared to the forecast, implying the forecaster underreacted to new information. When the correlation is negative, upward revisions predict lower realizations compared to the forecast, implying the forecaster overreacted to new information. With this method, I document three main results.

First, I find that individual forecasters show a mix of underreaction and overreaction to news. These findings support the notion that respondents are not fully rational in how they form expectations. However, these findings are in contrast to the overreaction documented by Bordalo *et al.* (2020). Second, I find the extent of underreaction or overreaction is influenced by the relative experience of the respondent. When I split the sample in two, based on the respondent's experience, I find that "less-experienced" respondents (under 12-months) tend to react in line with the predictions of FIRE models. It is the more experienced respondents (over 12-months), that show a strong tendency to underreact to information. This pattern of underreaction suggests experienced respondents are less efficient at updating their forecasts. Third, I study how survey respondents vary their joint forecasts of Federal Funds Rate, Consumer Price Inflation, Gross Domestic Product and Unemployment, to understand which variables respondents believe are important, i.e., I back out respondent's subjective Federal Reserve reaction function. I find that the type of organization forecasters belong to, and their level of forecasting experience, affect their perceptions of the Fed reaction function. Together, these findings show that heterogeneity amongst respondents cannot be ignored when studying expectation formation.

Resuméer på dansk

Kreditspænd på erhvervslån og økonomisk aktivitet

I kapitlet "**Kreditspænd på erhvervslån og økonomisk aktivitet**" bruger vi priser på lån i sekundærmarkeder til at konstruere et nyt lånemarkedsbaseret kreditspænd. Vi finder, at dette mål i betydelig grad kan foudsige en række makroøkonomiske variable. For eksempel er en stigning på 1 standardafvigelse i lånemarkedets kreditspænd forbundet med et fald i standardafvigelsen på 0,40 i industriproduktionen over de efterfølgende 3 måneder. Dette giver en økonomisk signifikant forbedring i forhold til eksisterende forudsigelser for økonomisk aktivitet. Forbedringen er robust på tværs af tid, land og efter at have kontrolleret for en række kendte makroøkonomiske prediktorer.

Vi argumenterer for, at lånespændets evne til at forudsige økonomisk aktivitet virker gennem to kanaler: en fundamental kanal og en friktionsbaseret kanal. Ifølge den første kanal er virksomheder, der låner på det syndikerede lånemarked, forskellige fra firmaer, der låner på markedet for virksomhedsobligationer. Lånespænd fanger således grundlæggende information om en klasse af låntagere, som indtil nu ikke kunne aflæses gennem handlede aktiver. Ifølge den anden kanal er disse forskellige låntagere udsat for større økonomiske friktioner på enten låntager- eller formidlingssiden. Vi finder indikationer på, at begge kanaler kan forklare denne yderligere forudsigelsesevne. Selvom vores resultater fremhæver, at forskellige kanaler er vigtige for at forstå lånespændet forklaringskraft (såsom låntagers egenskaber såvel som investorernes efterspørgsel og adfærdsøkonomiske forklaringer), dokumenterer vi, at finansielle friktioner i formidling af lånene er afgørende for forudsigelseskraften af syndikerede lån i forhold til andre kreditmarkedsspænd.

Markedssegmentering og krydsforudsigelighed

I mit andet kapitel "**Markedssegmentering og krydsforudsigelighed**" undersøger jeg hypotesen om, at information flyder med forsinkelse på tværs af finansielle markeder ved at teste for en type aktivpris' evne til at forudsiger udviklingen i lignende aktiver for andre virksomheder eller i en anden aktivklasse. Denne type prediktion er blevet dokumenteret mellem afkast fra økonomisk forbundne virksomheder af Cohen and Frazzini (2008) og industrier af Menzly and Ozbas (2010). Men i løbet af de sidste to årtier er der opstået et aktivt sekundært marked for amerikanske virksomhedssyndikerede lån, som handles som værdipapirer. Data fra disse markeder kan bruges til at undersøge sopredning af information gennem priser i lånemarkedet. Dette er særligt interessant, fordi det ikke er klart *a priori*, hvad man kan forvente. Institutionel dominans på kreditmarkederne kan fremme informationsspredning, mens kreditmarkedernes iboende illikviditet og uigennemsigtighed kan hæmme spredningen.

Først tester jeg branchespecifikke lånespænds evne til at forudsige lånespænd i økonomisk relaterede brancher. I hele observationsperioden finder jeg ingen tegn på forudsigelighed. Men med fokus på perioden efter 2010 finder jeg en stigning på 100bps i lånespændet for upstream-industrier er forbundet med en 32bps-stigning i lånespændet for downstream-industrier i den følgende måned. En potentiel forklaring på denne forudsigelighed er branchespecialisering af lånemarkedsinvestorer, særligt Collateralised Loan Obligation (CLO)-forvaltere. Hvis CLO-managere specialiserer sig langs branchelinjer, modtages et informativt signal, der opstår i én branche, først af CLO-managere med speciale i den pågældende branche, hvilket fører til påvirkning af lånespænd i samme branche. Jeg finder dokumentation for, at CLO-managere faktisk specialiserer sig inden for brancher. Dernæst genbesøger jeg brancherelaterede forudsigelser af aktieafkast. Ved at bruge Menzly and Ozbas (2010)-observationsperioden fra 1962 til 2005, replikerer jeg det oprindelige resultat, som tyder på samme type forudsigelighed, som dokumenteret ovenfor. Udvidelse af analysen til en periode uden for stikprøven fra 2005 til 2022 afslører dog, at aktieafkast i upstream-industrier ikke længere forudsiger aktieafkast i downstream-industrier. En potentiel forklaring på denne forsvinden af forudsigelighed kan være, at markedet er blevet opmærksomme på det empiriske resultat efter publikationen af Menzly and Ozbas (2010), men en anden mulighed er stigningen i antallet af investeringsfonde og ETF'er. Sammenfattende undersøger dette papir lånespændets evne til at forudsige lånespænd i andre brancher og finder, at forudsigeligheden afhænger af den undersøgte periode. Jeg tester så, om der kan findes en lignende tidsafhængighed på aktiemarkederne, og jeg finder, at det faktisk er tilfældet. Jeg leverer nogle indikationer på, at ændringen i lånets forudsigelighed skyldes fremkomsten af institutionelle investorer, mens ændringen på aktiemarkederne skyldes forbedringer i markedslikviditeten.

Heterogen Forventningsdannelse

I mit tredje kapitel "**Heterogen Forventningsdannelse**" bruger jeg prognoser fra Wall Street Journal Economic Survey til at studere, hvordan survey-respondenterne danner forventninger til makroøkonomiske variable. Eksisterende empiriske undersøgelser af forventninger har typisk antaget, at prognoser fra en given virksomhed kommer fra det samme individ. Jeg viser, at der jævnligt er ændringer i hvilken analytiker, der leverer prognoser på vegne af en virksomheden, og disse ændringer har betydning, da "nye" respondenter har en tendens til at danne deres forventninger anderledes end mere erfarne respondenter. For at undersøge forventningsdannelsesprocessen bruger jeg metoden, som blev gjort almindelig kendt af Coibion and Gordonichenko (2015), hvor forfatterne sammenligner sammenhængen mellem prognoseændringer og efterfølgende prognosefejl fra makroøkonomiske undersøgelser. I henhold til modellen for fuld-information rationelle forventninger (FIRE) bør prognoserevisioner ikke forudsige fremtidige prognosefejl. Når korrelationen er positiv, forudsiger opjusteringer højere realiseringer sammenlignet med prognosen, hvilket betyder, at analytikeren under-reagerede på ny information. Når korrelationen er negativ, forudsiger opjusteringer lavere realiseringer sammenlignet med prognosen, hvilket betyder, at analytikeren overreagerede på ny information. Med denne metode dokumenterer jeg tre hovedresultater.

For det første finder jeg, at individuelle analytikere viser en blanding af underreaktion og overreaktion på nyheder. Disse resultater understøtter forestillingen om, at respondenterne ikke er fuldt ud rationelle i deres forventningsdannelse. Disse resultater står i modsætning til overreaktionen dokumenteret af Bordalo *et al.* (2020). For det andet finder jeg, at omfanget af underreaktion eller overreaktion er påvirket af respondentens relative erfaring. Når jeg opdeler stikprøven i to, baseret på respondentens erfaring, finder jeg ud af, at "mindre erfarne" respondenter (under 12 måneder) har en tendens til at reagere i overensstemmelse med FIRE-modellernes forudsigelser. Det er de erfarne respondenter (over 12 måneder), der viser en stærk tendens til at underreagere på information. Dette mønster af underreaktion tyder på, at erfarne respondenter er mindre effektive til at opdatere deres prognoser. For det tredje studerer jeg, hvordan respondenterne i undersøgelsen varierer deres fælles prognoser for Federal Funds rente, forbrugerprisinflation, bruttonationalprodukt og arbejdsløshed for at forstå, hvilke variable respondenterne mener er vigtige, dvs. udleder respondentens subjektive Federal Reserve reaktionsfunktion. Jeg finder, at den type organisation, som analytikerne tilhører, og deres erfaring, påvirker deres opfattelse af Feds reaktionsfunktion. Tilsammen viser disse resultater, at heterogenitet blandt respondenterne ikke kan ignoreres, når man studerer forventningsdannelse.

Contents

Chapter 1

Corporate Loan Spreads and Economic Activity

with Anthony Saunders, Sascha Steffen and Daniel Streitz [1]

Abstract

We investigate the predictive power of loan spreads for forecasting business cycles, specifically focusing on more constrained, intermediary-reliant firms. We introduce a novel loan-market-based credit spread constructed using secondary corporate loan-market prices over the 1999 to 2023 period. Loan spreads significantly enhance the prediction of macroeconomic outcomes, outperforming other credit-spread indicators. The paper also explores the underlying mechanisms, differentiating between borrower fundamentals and financial frictions, with evidence suggesting that supply-side frictions are a decisive factor in loan spreads' forecasting ability.

[1] We thank Viral Acharya, Klaus Adam, Ed Altman, Yakov Amihud, Giovanni Dell'Ariccia, Tobias Berg, Nina Boyarchenko, Jennifer Carpenter, Dominic Cucic, 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, Egon Zakrajšek and seminar participants at 2022 American Finance Association Annual Meeting (AFA), 2022 Swiss Winter Conference on Financial Intermediation, 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.

1.1 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 poses a particularly acute challenge for businesses reliant on intermediary credit in the form of bank loans, especially smaller and privately-held firms (Holmström and Tirole, 1997; Diamond and Rajan, 2005; Chodorow-Reich, 2014). A sharp increase in loan credit spreads, for example, might have a significant impact on their business decisions. On the other hand, firms with access to alternative funding channels, such as public bond markets, are less sensitive to disruptions in credit markets. (Greenstone *et al.*, 2020; Chava and Purnanandam, 2011). In other words, loan spreads could hold valuable insights for future (*aggregate*) economic developments as they more effectively capture the constraints faced by a substantial portion of borrowers in the economy.[2]

In this paper, we introduce corporate loan spreads into macroeconomic business-cycle forecasts. The prior literature has documented that credit spreads more broadly 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 financial frictions, which affect both 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 therefore captures frictions that (if at all) affect the least-constrained firms in the economy.

A key contribution of this paper is to introduce a novel loan-market-based credit spread that captures frictions faced by bank-dependent firms. Over the last 30 years, a liquid secondary market for syndicated corporate loans has developed (the annual trading volume reached $824 billion in 2022), 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 2023 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

[2] Consistently, another literature studying loan quantities finds that 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; Becker and Benmelech, 2021; Crouzet, 2018, 2021).

market.

We first document a limited overlap between borrowers in the loan vis-a-vis the bond market. For example, we show that (i) over three-quarters of bond issuers are public, while half of the loan market borrowers are private; (ii) the median bond issuer is about 3 times larger than the median loan market borrower; and (iii) the median bond issuer is 4 years older compared to loan market borrowers. In other words, information from loan spreads with respect to (aggregate) economic developments might be very different compared to information obtained from bond spreads. Importantly, we show that firms that only issue loans also matter for aggregate economic activity in the U.S. as they account for about 75% of all firms in Compustat and about 40% of total assets. This is a lower-bound estimate as many secondary loan market firms are private.

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.[3] Using predictive regressions over the entire 23-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 other indicators. We demonstrate the predictive power across a variety of different macroeconomic outcome variables such as employment, inventory, and order-related measures.

We provide a series of robustness tests, thereby accounting for the liquidity of secondary markets, the information content in equity prices, as well as a range of indicators of macroeconomic uncertainty. We also adjust our loan spread to account for contractual differences of bonds vis-a-vis loans. Moreover, we show that our results persist outside of the global financial crisis (2007:Q4 – 2009:Q2). While we mainly focus on three-months ahead predictions, we use a local projection framework and document the predictive power of the loan spread over a one to twelve-months horizon, also dynamically benchmarking our loan against bond spreads. Finally, we show that the results also extend to out-of-sample forecasting models. Overall, our baseline results as well as robustness and extensions are consistent with the view that loan spreads contain important and unique information about future economic developments.

In the next step, we empirically investigate the mechanisms, and, specifically, the poten-

[3] Including Gilchrist and Zakrajšek (2012)'s bond spread, CP-bill spread, BAA-AAA spread, HY-AAA spread, Term Spread, and Federal Funds Rate.

tial role of borrower fundamentals and financial frictions to understand the predictive power of the loan spread. Credit spreads can signal economic trends even in frictionless markets by reflecting forward looking information about company fundamentals.[4] That is, an increase in credit spreads can signal an increase in borrower default probability and thus a deterioration in real economic activity.

There is a large literature that departs from the perfect market assumption and introduces financial frictions to study aggregate fluctuations. Financial frictions—specifically on the side of financial intermediaries—can affect real activity. A deterioration of intermediary balance-sheets can limit risk-bearing ability, thereby causing credit supply reductions (see, among others, Adrian *et al.*, 2010a,b; He and Krishnamurthy, 2013). Firms reliant on intermediated credit, especially those facing high switching costs, may have to cut investment, impacting overall economic development (Chodorow-Reich, 2014). Loan market borrowers frequently lack alternative funding sources and are thus particularly prone to this type of friction.

We first provide cross-sectional evidence to better understand the origins of the loan spread's additional predictive power. A loan spread constructed exclusively from firms that *only* issue loans has up to 70% higher predictive power compared to a loan spread constructed using firms that also actively issue bonds. This evidence indicates that the additional predictive power of the loan spread mainly comes from the non-overlapping segment of the bond market and loan market. While this test is a natural starting point, it does not allow to directly differentiate between a fundamentals- or friction-based channel.

To empirically distinguish between these mechanisms, we perform two sets of analyses: First, we decompose the loan spread into a component that reflects borrower fundamentals and a component that, as we show, reflects supply-side frictions, which we term the "Excess Loan Premium" (ELP). This is analogous in methodology and name as the "Excess Bond Premium" (EBP) in Gilchrist and Zakrajšek (2012).[5] In a series of tests, we show that the ELP is more correlated with measures of credit supply conditions (specifically for small firms) as well as bank balance-sheet strength compared to the EBP. Our predictive regressions show that the ELP has significantly more predictive power compared to the fundamental component. Overall, the evidence suggests that supply-side frictions play a key role for the predictive power of the loan spread.

[4] They are often more informative than equity securities. For instance, (Philippon, 2009) documents that a bond-based q measure better predicts investment dynamics than equity-based measures.

[5] We discuss in detail under which assumptions this is a valid exercise in subsection 1.5.2.

Second, we provide two tests at the loan level to show that supply side frictions on the side of financial intermediaries (causally) impact loan spreads. The identifying assumption in both tests is that the shock adversely impacts intermediaries but is orthogonal to firm fundamental risk. In the first test, we use the Lehman Brothers collapse as shock to those banks that co-syndicated credit lines with Lehman. These banks had to honor commitments for loans Lehman was no longer able to provide, which adversely affected their ability to supply loans (Chodorow-Reich, 2014; Ivashina and Scharfstein, 2010). We show in a difference-in-difference setting that loan spreads of firms with large exposure to banks affected by the Lehman bankruptcy increased more after the collapse relative to spreads of other firms controlling for year-month and firm fixed effects. The effect is economically sizeable.

We then use the oil price decline during the 2014 to 2016 period as a shock to the supply of credit by Collateralized Loan Obligations (CLOs), the largest group of non-bank institutional investors in the market.[6] CLOs were differentially exposed to the oil price decline. As some of them were close to breaching covenants, they were forced to also offload loans to firms who were *not* exposed to the oil shock (Kundu, 2022). We exploit this variation in a difference-in-difference framework similar to the Lehman shock and find that loan spreads of non-oil and gas firms that were only indirectly affected to the oil price shock through their investor base, significantly increased in the months following the shock. This effect is mostly driven by an increase in the ELP and not the fundamental component of the spread.

In our last subsection, we discuss behavioral explanations as an alternative channel. The literature suggests that investors' expectations about future economic growth, overly influenced by the current economy, can lead to undue optimism (see, e.g., Bordalo *et al.*, 2018; Greenwood and Hanson, 2013; Greenwood *et al.*, 2019; López-Salido *et al.*, 2017). This results in narrower credit spreads and excessive credit extension. However, since future news often fails to meet these optimistic expectations, a reversal in sentiment occurs. This phenomenon explains why low credit spreads, despite solid fundamentals, often signal future spread increases and economic downturns. While tests for these theories are complicated given our relative short sample period, we use the high-yield loan share following Greenwood and Hanson (2013) as a proxy for market sentiment. Including contemporaneous sentiment measures does not affect our loan spread's predictive power.

[6] Post the global financial crisis, approximately 86% of loans from leveraged firms were held by institutional investors. Notably, almost 96% of this portion is accounted for by CLOs along with mutual or hedge funds.

Overall, we find evidence that supply-side factors are of first-order importance for understanding the loan spread's large additional predictive power. Micro evidence documents that there is a causal effect of supply-side factors on loan spreads. Aggregate credit spread decomposition exercises show that the variation above and beyond borrower fundamentals is an economically important channel that can explain a large part of the loan market's additional predictive power.

1.2 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 2022, the annual secondary market trading volume reached $824 billion USD (Figure 1.1).

Most 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 the Compustat database 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 2023. Loan sales are usually structured as assignments,[7] 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

[7] 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.

secondary market trading.[8] It has been shown that price quotes provide an accurate representation of prices in this market (Addoum and Murfin, 2020; Berndt and Gupta, 2009).

The sample contains 14,874 loans to U.S. non-financial firms. We exclude credit lines and special loan types (4,830 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 10,044 loans. As we use monthly measures of economic activity, we calculate mid quotes for each loan-month. The final sample contains 348,335 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

[8] 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.1 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.

[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). About 90% of loans in our secondary market dataset are institutional term loans (term loan B). Only around 10% are term loan A. A loan spread constructed exclusively based on term loan B behaves very similar compared to our baseline loan spread measure; see Online Appendix D.1 for details.

[10] Online Appendix A.2 provides information on market liquidity. The median bid-ask spread in the 1999 to 2023 period was 87 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.

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.

To avoid a duration mismatch, for each loan we construct a synthetic risk-free loan with the same cash-flow profile. Let $P^f_{it}[k]$ be the risk-free equivalent price of loan k, where $P^f_{it}[k]$ is the sum of the projected cash flows, discounted using zero-coupon Treasury yields from Gürkaynak *et al.* (2007). Using $P^f_{it}[k]$ we extract the risk-free equivalent yield to maturity, $y^f_{it}[k]$. The loan spread $S_{it}[k]$ is defined as $y_{it}[k] - y^f_{it}[k]$. 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 an aggregate 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:

$$S^{Loan}_t = \frac{1}{N_t} \sum_i \sum_k S_{it}[k], \tag{1.1}$$

Figure 1.2 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 0.74 (0.80) over the entire sample period and 0.60 (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 0.47 (0.67) (or 0.32 (0.53) excluding the financial crisis). The loan spread is significantly more volatile, with a standard deviation (SD) of 2.25% (vs. 1.0% for the GZ and 0.41% for the Baa-Aaa spread) and has an unconditional mean an order of magnitude

[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. For robustness, we further re-calculated the yield to maturity for all loans assuming semi-annual payments (the second most common payment frequency). The correlation with our baseline loan spread is 96% (Online Appendix D.2). Further note that loans are typically prepayable at par, i.e., the contractual maturity might be different from the de facto life of the loan. On average, loans stop trading in the secondary market 58% of the way to their expected maturity. Given that the typical maturity is 5 years, this implies an effective life of only 3 years for most loans. For robustness, we re-constructed our loan spread assuming 3 years to maturity for all loans and find very similar results (Online Appendix D.3).

[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 obtained from FRED. 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).

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.

1.3 Borrower composition in loan and bond markets

Loan versus bond market firms: 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 3,773 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 1.1, 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 (76%).[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 even *understates* differences between loan

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

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

[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 issuers that cannot be linked to Compustat include, e.g., firms with private placements and other issuers with limited disclosure requirements.

markets and bond markets. Results are reported in Table 1.1, Panels B and C.

We measure firm size by total assets. Borrowers are significantly smaller than bond issuers (Panel B).[17] The median firm size is \$1.38 billion in the loan market compared to \$3.69 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, 37% of bond issuers have assets > \$6 billion.

We next investigate 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 20% are also bond issuers.[18]

Panel C of Table 1.1 shows consistent results grouping firms by age, which is defined as the number of years with non-missing total assets in Compustat. Borrowers are significantly younger than bond issuers.

These statistics weight 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 1.3 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 27% of all issuers (Table 1.1, Panel B), they amount to 73% of all bond-month observations. In fact, >57% 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 37% (67%) of loan-month observations are by borrowers with assets < \$2 billion (< \$6 billion), less than 5% (17%) of bond-month observations are in this category.

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

[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.

[18] This is consistent with Rauh and Sufi (2010), who document a negative correlation between firm size and the share of bank debt in the capital structure for a random sample of rated public firms.

in the loan market that might contain information about economic developments.

Aggregate importance of (non-)bond market firms: How important are firms that are not active in the bond market for aggregate quantities? Figure 1.4 shows the fraction of total assets and other metrics (sales, PP&E, Capex, employment) accounted for by non-bond issuing firms using the universe of (non-financial) Compustat firms. A non-bond issuing firm is defined as a firm that has *never* issued a corporate bond according to the Mergent Fixed Income Securities Database (FISD) database. These firms account for about 75% of all firms in Compustat and for about 35-40% of total assets, sales, PP&E, Capex, and employment. That is, while non-bond issuing firms have a disproportionately smaller share in aggregate quantities, they do matter for aggregate economic activity.[19] Of the non-bond issuing firms most are active in the loan market—about 50% can be identified in the DealScan database.

Note that this is a lower bound for the importance of loan market firms. This figure only considers the universe of Compustat firms, i.e., excludes private firms, which account for about half of our loan spread sample. For instance, Asker *et al.* (2015) document that, as of 2010, only 0.06% of all U.S. firms were listed (and even among firms with 500 or more employees 86.4% were privately held). They estimate that private U.S. firms account for over half of aggregate investment, sales, and profits and almost two-thirds of aggregate employment. Timely information on such firms is hard to come by. Loan market credit spreads give us, for the first time, daily information on the performance of (larger) private firms, which we document to be useful in macroeconomic prediction models.

1.4 Loan spreads and economic activity

1.4.1 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

[19] A related literature on network economics examines the role of large firms for aggregate movements. Carvalho and Grassi (2019) show that large firm dynamics account for about one-third of aggregate fluctuations. See also di Giovanni *et al.* (2014) for related evidence and Carvalho and Tahbaz-Salehi (2019) for an overview. While this literature confirms the important role of large firms, a sizable fraction of aggregate fluctuations is driven by other factors.

arise in later sections. We start by running standard forecasting regressions:

$$\Delta y_{t+h} = \alpha + \beta \Delta y_{t-1} + \gamma \Delta S_t + \lambda TS + \phi RFF + \epsilon_{t+h}, \tag{1.2}$$

where h is the forecast horizon and Δy is the log growth rate for a measure of economic activity from $t-1$ to $t+h$.[20] 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.[21]

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 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.[22] 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.[23]

[20] Including the monthly ISM Manufacturing and Non-Manufacturing employment index, 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 and ISM.

[21] 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].

[22] 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.

[23] A full discussion is provided in Online Appendix D.4 wherein we also provide results using alternative timing conventions.

1.4.2 Baseline results

Table 1.2, 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. To gauge the contribution of predictors to the in-sample fit of the model, we report the incremental increase in adjusted R^2 relative to a baseline model that includes only TS, RFF, and the lagged dependent variable.[24]

Columns 1 to 4 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).[25] Except for the paper-bill spread, which has little variation during the sample period, all credit spreads have significant predictive power and add between +8.2 percentage points (p.p.) and +9.8 p.p. to the in-sample fit.

Column 5 adds our loan spread in the prediction model. This model has a sizeable R^2 increase of about 15 p.p. relative to the baseline. The coefficient indicates that a one SD increase in the loan spread is associated with a decrease in industrial production by 0.397 SD, i.e., a 46 bps spread increase corresponds with a 1.02% decline in production (unconditional mean: 0.17%). 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 +9.8 p.p. This is less than two-thirds of the loan spread's incremental R^2 of +15.1 p.p.

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 1 to 4. Column 6 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 in column 7, 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

[24] The R^2 of the baseline model is low. This is mainly due to the large and unanticipated effects of the COVID-19 pandemic. See Online Appendix D.5 for details and results excluding the COVID-19 pandemic period.

[25] 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.

loan spread yields a statistically significant improvement in model fit relative to column 6.[26] 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 +4.5 to +19.5 p.p. and this effect comes almost entirely from the loan spread, not the 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 similar 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).[27]

Table 1.3 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 most tests for brevity. Results using other macroeconomic outcomes are similar (Online Appendix D.7).

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.8 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, see column 2.[28]

Equity markets may also contain signals about economic development (see, e.g., Green-

[26] This also holds when comparing the loan spread model with the individual bond spread models (columns 1 to 4) (untabulated).

[27] In Online Appendix D.6, we confirm that the loan spread's predictive power extends beyond the six variables used in the main paper. We use all variables related to real activity, i.e., the categories "output," "labor," "housing," and "consumption/orders," contained in the FRED-MD database. The results show that the loan spread is a significant predictor across a wide range of variables (the only the exception being of some of the labor variables, which tend to be sticky with limited variation outside of large crisis periods).

[28] In Online Appendix D.9 we examine if loan or bond market predictability differs across maturity. There is little variation in predictive power across maturity buckets suggesting that the additional predictive power of the loan spread is not explained by the average loan versus bond maturity difference.

wood *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.[29]

The results in Table 1.2, Panel A, column 2 and 3, use aggregate bond spread measures based on non-investment grade rated firms, which may be more comparable to the typical loan market firm. For robustness we additionally create *bottom-up* bond spread measures for different rating categories. Table 1.3, column 5 includes a bottom-up bond spread constructed exclusively using non-investment grade rated bonds.[30] Column 6 additionally includes spreads for bonds rated "AAA to A" and bonds rated BBB. While non-investment grade rated bonds indeed seem to have stronger forecasting power compared to investment grade rated bonds, the predictive power of the loan spread remains unchanged.[31]

Panel B reports results excluding the 2008-09 global financial crisis (GFC). The loan spread continues to have significant predictive power. Only the employment results are somewhat more mixed. While the non-manufacturing employment effect (ISM-NONMAN) remains statistically and economically significant, the effect is (borderline) insignificant for manufacturing employment (ISM-MAN). In untabulated results we find that the loan spread does not have significant predictive power for alternative employment measures such as payroll employment and the unemployment rate when removing the GFC period. This is because labor market variables (in particular realized measures such as [un-]employment rates) are sticky with limited variation outside of large crisis periods and are thus less suitable for prediction on a month-by-month basis.[32]

[29] In Online Appendix D.10, we report results adding additional proxies for uncertainty, including the Economic Policy Uncertainty (EPU) index of Baker *et al.* (2016) and the financial uncertainty index of Jurado *et al.* (2015). Our main result remains unchanged. In Online Appendix D.11 we orthogonalize the loan spread with respect to the three macro shocks used by Boons *et al.* (2023). Again, results remain unchanged.

[30] Sample sizes are too small to create robust spreads separately for BB, B, and CCC rated bonds.

[31] In Online Appendix D.12, we examine the predictive power of different risk segments *within* the loan market and find that the predictive power is higher amongst the lower rated loans.

[32] In Online Appendix D.13 we 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. The results show that the predictive power of the loan spread extends to other countries and that industry-specific loan spreads contain information that is not captured by other aggregate economic factors.

Panel C 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.[33,34]

1.4.3 Dynamics

We have focused on three-month-ahead predictions so far. To examine dynamics we use a local projections framework (Jordà, 2005). Figure 1.5 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= 1 to h=3, i.e., the loan spread today is most correlated with economic development one month to one quarter from now. However, the loan spread retains predictive power even at longer horizons, i.e., the results do not hinge on the specific forecast horizon (the exception being the employment measures for which the forecasting power is largest in the short to medium term and then declines for longer forecasting horizons). 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.16 provides similar results, dynamically benchmarking loan spreads against bond spreads.

[33] We compare the predictive power of credit spreads across models instead of starting with a "kitchen-sink" approach to avoid that our results are plagued by multicollinearity issues. An alternative to cross-model comparisons is to orthogonalize the loan spread w.r.t. to other credit spreads and use the residual component in the predictions. Results using orthogonalized spreads are similar (Online Appendix D.14).

[34] In Online Appendix D.15 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% significance level or lower for most of our outcome variables.

1.5 Understanding the loan spread's predictive power

In this section, we discuss and test different mechanisms that suggest that credit spreads are leading indicators for economic development. We classify theories into two categories: theories with and without market frictions. While we focus on the role of financial frictions as the main mechanisms in Sections 1.5.1 and 1.5.2, we discuss the potential role of other channels, such as behavioral theories, in Section 1.5.3.

1.5.1 Theoretical background

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), for example, provides evidence that a q measure inferred from bond prices explains aggregate investment dynamics better than a q measure based on equity markets. He argues that a possible explanation is that bond markets (and, by extension, credit markets more broadly) are less prone to mispricing compared to equity markets. For example, equity prices often appear too volatile given their fundamentals (see, e.g., Shiller, 1981; Campbell *et al.*, 1997).

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, i.e., firms that cannot switch lenders without incurring costs, e.g., due to adverse selection or non-transferable relationship-specific information (e.g., Chodorow-Reich, 2014), are forced to cut back on investments, affecting the aggregate economic development.

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. As highlighted in Holmström and Tirole (1997) shocks to aggregate firm capital or intermediary capital will particularly affect low net worth firms. That is, financial frictions are more severe for firms reliant on intermediated credit via bank loans, such as small and private firms, compared to firms with access to alternative funding sources, such as public bond markets (Greenstone *et al.*, 2020; Chava and Purnanandam, 2011).

In the following sections, we empirically examine the potential role of borrower fundamentals and financial frictions in understanding the additional predictive power of the loan spread. Frictions on the side of the borrower are, in theory, closely linked to the balance sheet strength of the firm (e.g., Bernanke and Gertler, 1989; Holmström and Tirole, 1997). Any variation that plausibly affects net worth (and thus borrower frictions) also impacts fundamentals, i.e., the two concepts are closely linked. Our empirical analyses thus aims at distinguishing between borrower factors (fundamentals or balance sheet frictions) and supply-side, i.e., intermediary, frictions. Results indicate that intermediary frictions play a key role in understanding the loans spreads additional predictive power.

1.5.2 Empirical evidence

Cross-sectional evidence

We start by examining the predictive power of loan spreads in the cross-section of firms. As documented in Section 1.3, the overlap between loan and bond markets is limited. It is thus plausible that the additional predictive power of the loan vis-a-vis the bond market in particular comes from firms that are not already observed in the bond market, such as private and bank-dependent firms. While such cross-sectional tests do not discriminate between theories with and without market frictions, they are a natural starting point to better understand where the predictive power of the loan spread is coming from.

In a first test, we compare the predictive power of a loan spread constructed exclusively from public firms with a loan spread constructed using private firms (non-Compustat firms). We report the results in Panel A of Table 1.24. The standardized coefficients and incremental R^2 are higher for the private firm loan spread compared to the public firm loan spread. For most macroeconomic variables, however, the difference is economically small.

The vast majority (75%) of Compustat firms are non-bond issuing firms (see Section 1.3). Panel B therefore compares a loan spread comprised of firms that also issue bonds with "loan-only firms" (non-bond issuers, i.e., firms exclusively contained in our loan spread). The predictive power (standardized coefficients and incremental R^2) of loan-only firms is substantially higher (10-70%) compared to a loan spread constructed from bond-issuing firms. For all outcome variables, the spread of loan-only firms a yields a statistically significant improvement in model fit relative to the same model with a loan spread constructed based on bond-issuing firms (see LR tests reported at the bottom of the Panel).

This evidence indicates that the additional predictive power of the loan spread mainly comes from the non-overlapping segment of the bond market and loan market. This is consistent with loan markets comprising information about firm fundamentals not contained in bond spreads.[35] Alternatively, loan-only firms might be more exposed to financial frictions, i.e., the loan spread might comprise additional information about investor constraints in credit market. We explore the role of frictions with a specific emphasis on isolating supply-side constraints in more detail next.

Credit spread decomposition

To gauge the relative importance of financial frictions and borrower fundamentals, we start with a decomposition of the loan spread following Gilchrist and Zakrajšek (2012). The aim is to isolate the effect of borrower fundamentals on credit spreads using models similar to:

$$S_{i,l,t} = \alpha_0 + \alpha_1 DD_{i,t} + \lambda' \mathbf{Z}_{i,l,t} + \nu_{i,l,t}, \tag{1.3}$$

[35] An alternative explanation for the additional predictive power of the loan spread is that loan markets price the same fundamental information more accurately compared to bond markets. Given that the secondary loan market is still less developed and less liquid compared to the bond market this is unlikely. Further, the evidence reported in Table 1.24 suggests that firms that are not active in the bond market contribute most to the predictive power of the loan spread. This is consistent with loan spreads containing additional information and not with the same information being priced more accurately.

where S is the spread of loan l in month t issued by firm i. DD is the distance-to-default for issuer i using an option-implied default-risk indicator based on Merton (1974). $\boldsymbol{Z}$ is a set of instrument-specific controls including contract terms and credit rating information. ν is the residual. A detailed description of the methodology is provided in Online Appendix D.17.

The spread predicted by the model ($\widehat{S}_{i,l,t}$) captures changes in default risk based on the fundamentals of the borrower. The residual (ν) captures the price of risk above a default risk premium. We label the residual the "excess loan premium" (ELP). A common interpretation of the credit spread residual is that it captures supply-side constraints. That is, the residual reflects that for the same underlying borrower risk, intermediaries demand a different compensation depending on the constraints they currently face.[36]

The key assumption under which the residual is a good proxy for supply factors is that model (1.3) correctly captures variation in borrower fundamentals.[37] In our baseline estimation, we use firm-specific distance-to-default (DtD) when available. Else, for private firms, we use industry DtD (including higher order moments and within industry DtD volatility). For robustness, we run spread decompositions based exclusively on firms with available DtD (see below) or use (industry) CDS spreads (see Online Appendix D.17).

To support the prediction that the excess premium captures intermediary frictions, Gilchrist and Zakrajšek (2012) present evidence that the "excess bond premium" (EBP) correlates with the health of the financial sector. Similar in spirit, we examine the relationship between the ELP (and the EBP for comparison)[38] and proxies for financial market conditions. These include indicators for overall credit conditions (FSLOSS) and credit conditions for small firms (NFIB)[39] as well as measures for primary market activity in the syndicated loan market (the total number and amount of monthly term loan issuances). Finally, we use the aggregate banking sector non-performing loans ratio and capitalization (equity ratio) as commonly used measures of the health of the banking sector. We plot these measures alongside the ELP (and the bond EBP) in Figure 1.6.

We find that, while the correlation of the ELP and EBP with the FSLOOS is about

[36] The concept of risk-bearing capacity of the financial sector is also similar in spirit to the intermediary asset pricing literature; see, e.g., Adrian *et al.* (2014).

[37] This assumption is not specific to our setup but is also inherent in Gilchrist and Zakrajšek (2012) and all follow-up work on the bond market using similar decompositions.

[38] We obtain the decomposition of the bond spread from Favara *et al.* (2016).

[39] The National Foundation of Independent Business Inc. (NFIB) index measures credit conditions for small firms and has been released quarterly since 1973.

the same (0.67 vs. 0.69), the ELP is substantially more correlated with credit conditions of smaller firms (0.39 vs. 0.25). This is consistent with intermediary frictions more adversely impacting the credit availability of smaller firms that are dependent on bank-loan financing. Also, the correlation between the ELP and primary market conditions in the syndicated loan market is substantially stronger compared to the EBP (0.54 versus 0.21 for number of loans being issued and 0.58 versus 0.25 for loan amount). Finally, the correlation between loan spreads and the health of the financial system is higher compared to the correlation with bond market spreads (0.46 versus 0.26 for bank capitalization and 0.2 versus 0.01 for bank NPL). This suggests that the balance-sheet strength of banks matters more in the loan market, while other intermediaries might be more important in the bond market.

In Table 1.5, Panel A, we run baseline forecasting regressions using decomposed loan spreads (controlling for the bond spread PC). Results indicate that it is mostly the ELP that contributes to the loan spreads predictive power. While the ELP is highly statistically significant in all models, the predicted spread is only significant for TCU and INV (but with smaller economic magnitudes compared to the ELP). This evidence is consistent with the idea that supply-side factors above and beyond borrower fundamentals explain a large part of the additional predictive power of the loan spread.

One potential concern is that we have to rely on industry-level DtD for private firms. This can introduce noise in the loan spread decomposition and hence there might be fundamental information that is still captured in the residual. For robustness, we hence restrict our loan sample to firms for which firm-specific DtD is available. While this reduces the sample, it makes the prediction more accurate. Results are reported in Table 1.5, Panel B. If anything, the relative importance of the predicted spread is further reduced in this estimation.[40]

Overall, the strong correlation between the ELP and aggregate credit supply conditions as well as the evidence that it is mainly the ELP and not the predicted spread is consistent with the conjecture that supply-side factors above and beyond borrower fundamentals explain a large part of the additional predictive power of the loan spread.

[40] In Online Appendix D.17, we run an alternative prediction model based on firm-level (or industry-level) CDS spreads instead of DtD, for robustness. CDS spreads are timely measure of firm-specific default risk that is not based on balance sheet information (as is the case with the Merton (1974) and Bharath and Shumway (2008) method). Results are very similar.

Loan-level evidence

While the aggregate evidence presented so far strongly suggests that supply-side frictions explain (a large part of) the loan spread's additional predictive power, this evidence is not causal. Causality is difficult to establish using aggregate measures. However, at the firm level we can exploit plausible exogenous shocks to intermediaries that are unrelated to borrower fundamentals to more cleanly highlight that supply-side frictions are reflected in loan spreads above and beyond borrower fundamentals.

Lehman Brothers collapse: In the first exercise, we examine the heterogenous impact of the collapse of Lehman Brothers in 2008 on bank-dependent firms. The setup closely follows Chodorow-Reich (2014) and Ivashina and Scharfstein (2010). The key idea is to find a shock to bank health that is orthogonal to the fundamentals of the bank's borrowers. Ivashina and Scharfstein (2010) propose to use the (pre-2008) exposure to Lehman, defined as the fraction of a bank b's credit line (CL) portfolio where Lehman had a lead role:[41]

$$\text{Bank Lehman Exp}_b = \frac{\sum \text{CL commitment co-syndicated with Lehman (USD)}_b}{\sum \text{CL commitment (USD)}_b} \tag{1.4}$$

The idea of this instrument is that following the disappearance of Lehman the remaining syndicate members had to honor outstanding (drawn and undrawn) credit line commitments. Given that firms ran on their credit lines as a precautionary measure during the financial crisis, this led to a draining of liquidity from banks with large outstanding credit line commitments, and particularly so for banks that had to honor commitments Lehman could no longer provide. Consistent with this idea, Ivashina and Scharfstein (2010) and Chodorow-Reich (2014) show that this measure correlates negatively with new lending for the affected banks with negative consequences for their borrowers. Using this identification strategy we estimate the following difference-in-differences (DID) regression model at the loan level:

$$S_{i,l,t} = \alpha_i + \alpha_t + \beta\,(\text{Firm Lehman Exp}_i \times \text{Post}_t) + \epsilon_{i,l,t}, \tag{1.5}$$

where S is the credit spread in month t of loan l issued by firm i. α_l and α_t is a set of issuer and year-month fixed effects, respectively. *Firm Lehman Exp* is the Lehman exposure

[41] Following Chodorow-Reich (2014) we exclude very small banks, i.e., banks with less than 100 loans over the sample period. Consistent with Ivashina and Scharfstein (2010), we use all credit lines that are outstanding through Q4 2008 for the construction of the measure.

of firm i's relationship banks. Specifically, we follow Chodorow-Reich (2014), and calculate the weighted average Lehman exposure over the members of the borrower's last precrisis syndicate (the last loan obtained with a start date before September 2008). *Post* is an indicator variable for the months after the Lehman collapse. The time period is the +/− 6 month window around the Lehman collapse in September 2008. The sample excludes all borrowers with a direct exposure to (i.e., any lending from) Lehman Brothers.

The key idea of this setting is that the *indirect* Lehman exposure of firm i is a plausibly exogenous shock to the constraints of firm i's relationship lenders that is orthogonal to the firm's fundamentals.[42] As shown by Ivashina and Scharfstein (2010) and Chodorow-Reich (2014) the exposure measure negatively correlates with credit supply to affected firms. Such credit supply frictions—unrelated to borrower demand and fundamentals—should be reflected in the credit spreads of the firm's outstanding loans, if credit supply frictions are priced (i.e., the market anticipates that the borrower's ability to roll-over their debt or obtain new external financing is reduced).

Table 1.6, Panel A, reports the results. Controlling for year-month and issuer fixed effects, secondary market loan spreads increase significantly more post the Lehman collapse for loans by borrowers that have a larger indirect Lehman exposure through their relationship banks. To facilitate the economic interpretation of the results, in column 2 we use an indicator variable equal to one for borrowers with a high indirect Lehman exposure (top 25% of the distribution). Spreads increase by 1.9 percentage points (p.p.) more after the Lehman collapse for borrowers with a high indirect Lehman exposure relative to borrowers with a low Lehman exposure. This is a sizable effect compared to the average aggregate loan spread of 6.75 percent (see Figure 1.2), and highlights that supply-side factors can significantly affect loan spreads.

CLO oil and gas exposure: The identification strategy above focusses on the role of lenders that are active in the primary (and secondary) loan market. In the secondary loan market, however, there is an increasing involvement of non-bank investors, in particular col-

[42] There are two assumptions underlying this identification strategy. First, borrowers from banks with a large Lehman co-syndication exposure were not different from borrowers from banks with a smaller Lehman exposure. See Chodorow-Reich (2014) for a detailed discussion on the plausibility and evidence on this assumption. Second, the identification strategy requires that bank-borrower relationships are sticky. If this were not the case then firms paired with a high-Lehman-exposure-bank could costlessly switch to a bank with low Lehman exposure. There is a large literature supporting this assumption, including direct evidence for the syndicated loan market provided by Chodorow-Reich (2014).

lateralized loan obligations (CLOs), and frictions to this group of lenders can be reflected in loan spreads as well (and contain information about credit conditions and economic development going forward).[43] We therefore, as a second exercise, utilize a shock that heterogeneously affected CLOs but not borrower fundamentals.

Specifically, we follow Kundu (2022) and exploit shocks to the Oil and Gas (O&G) industry. From 2014 there was a rapid and sustained decrease in the global price of oil, which particularly impacted O&G firms. CLOs, as holders of a range of loans in their portfolios, were heterogeneously exposed to this industry shock, depending on how many O&G loans they held at the time. CLOs more exposed were more likely to be pushed closer to breaching covenants, and were forced to also sell *non-O&G loans*, putting price and funding pressure on non-O&G firms, as documented by Kundu (2022).[44]

We compare loan spreads of *non*-O&G firms held in US CLOs that differ solely in the extent to which their investor base was exposed to the shock. The idea is similar to the Lehman shock discussed above: a shock to the constraints of a firm's investor base (orthogonal to firm fundamentals and loan demand) can affect credit conditions for firms, e.g., because firms have a harder time getting new credit or renegotiating or rolling over their existing debt as, e.g., documented by Giannetti and Meisenzahl (2023). Consistently, Fleckenstein (2024) documents that frictions in the CLO sector can have real consequences for CLO-dependent borrowers.

Specifically, we compare loan spreads of non-O&G firms before versus after the O&G price plunge in September 2014 across firms with heterogeneous *indirect* O&G exposure that solely arises through their investor base in a DiD framework. Similar to the Lehman setup, firms with a direct exposure, i.e., firms in the oil and gas sector, are excluded from the analysis. This industry shock represents a quasi-exogenous shock to firms coming from supply side frictions. If loan spreads reflected *only* fundamentals, loan spreads of non-O&G firms should not be influenced by the constraints of CLO managers that hold the firm's loans. As in Kundu (2022) a firm's exposure to the shock is constructed as the weighted

[43] Fleckenstein *et al.* (2021), for instance, document that non-bank lending is significantly more cyclical than bank lending.

[44] Giannetti and Meisenzahl (2023) use a similar identification strategy and exploit exogenous variation in secondary loan market participants' constraints arising from shocks to parts of these intermediaries' portfolios in industries that are unrelated to a specific firm/loan. They find that borrowers that are indirectly exposed to shocks in unrelated industries through a common loan market investor base have a harder time renegotiating their loans, which can have negative effects on performance.

average O&G exposure across the CLOs that hold the firm's loans (before the shock, i.e., as of June 2014). We estimate the following DiD specification:

$$S_{i,l,t} = \alpha_i + \alpha_t + \beta \left(\text{O\&G Exp}_i \times \text{Post}_t\right) + \epsilon_{i,j,t}, \tag{1.6}$$

where S is the credit spread in month t of loan l issued by firm i. *O&G Exp* is the exposure of firm i's lenders (CLOs) to the oil and gas industry before the shock occurs. *Post* is an indicator variable for the months after the drop in oil price. The sample period is 2013-2015.

Results are reported in Table 1.6, Panel B. Column 3 reports the average loan spread change before versus after the oil price drop for the set of *directly* affected O&G firms. For this set of firms, the oil price movement was a fundamental shock and we only report this evidence as a baseline test to document that oil and gas firms were indeed substantially affected. Loan spreads for oil and gas firms increased by 6.4 p.p., highlighting the very large economic magnitude of the shock for the directly affected firms.

Columns 4 and 5 report the main results, focusing on the set of non-O&G firms that differ in their (indirect) exposure to the shock due to differences in their investor bases. Controlling for year-month and issuer fixed effects, secondary market loan spreads increase significantly more post the oil price plunge for loans by borrowers that have a larger *indirect* oil and gas exposure through their investor base. To facilitate the economic interpretation of the results, in column 5 we use an indicator variable equal to one for borrowers with a high indirect oil and gas exposure (top 25% of the distribution). Loan spreads increase by 0.66 p.p. more after the oil shock for borrowers with a high indirect oil and gas exposure relative to borrowers with a low exposure. As expected, this effect is much smaller compared to the direct effect on the O&G firms themselves (column 3). The effect is also smaller compared to the Lehman setting. This is plausible given that the Lehman collapse was arguably a larger shock. However, a 66 basis point spread increase still constitutes an increase of ∼10%

relative to the average aggregate loan spread (6.75 percent).[45]

Credit spread decomposition: Finally, we separately examine effects on the ELP and the predicted loan spread at the loan level. Table 1.7, Panel A, columns 1 and 2, report the results for the Lehman experiment. These columns mirror column 1 in Table 1.6 but use the loan-level ELP and predicted spread as dependent variables. We find that the largest spread increase is for the ELP and not for the predicted spread (coefficients of 1.84 versus 0.39). This again confirms that the indirect Lehman exposure indeed is a shock that is mostly reflected in movements in the spread component that is orthogonal to borrower fundamentals, i.e., highlights that the ELP plausibly captures supply-side frictions.

Table 1.7, Panel B, columns 3 and 4 show the corresponding results for the CLO oil and gas exposure experiment (these columns mirror column 4 in Table 1.6). Similar to the Lehman setting, the largest spread increase is for the ELP and not for the predicted spread.

Overall, we find clear evidence that supply-side frictions (that can affect the funding conditions and outcomes of borrowers) are priced in secondary loan market above and beyond borrower fundamentals. While the micro-evidence is useful to establish causality, i.e., we can identify settings with exogenous shocks to investors that are plausibly unrelated to borrowers, this evidence does not allow for a time-series decomposition of credit spreads into a fundamental and financial frictions part. This evidence should thus be viewed as *complementary* to the credit spread decomposition and other aggregate evidence discussed above. The joint evidence, however, paints a clear picture that supports the conjecture that the loan spread's additional predictive power (in part) comes from information about supply-side financial frictions that specifically affect bank-dependent firms.

[45] Consistent with CLO frictions being quickly reflected in secondary market loan spreads, we find that the loan spread predicts institutional investor demand in the primary market. Figure 1.7 shows the dynamic relationship between the loan spread and *Time-on-market* using impulse response functions in the spirit of Ben-Rephael *et al.* (2020). *Time-on-market* is constructed following Ivashina and Sun (2011) and 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. Results indicated that a shock to the loan spread predicts a widening of the Time-on-market measure up to 5 months ahead. There is no evidence that primary market institutional demand predicts the loan spread.

1.5.3 Alternative channel: Behavioral Explanations

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 additional predictive power of loan spreads *relative* to other credit spreads, loan market investors need to be more susceptible to (different) biases compared to bond investors. Investors in the loan market are, if anything, equally professional, large-scale institutional 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).[46]

Table 1.8, Panel A, adds the HY Loan Share as an additional control. 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 in some of the models. An increase in the share of high yield credit signals a short-run increase in economic activity (reverting in the future). Table 1.8 Panel B reveals similar results for the HY Bond share. Finally, Panel C shows that adding the additional controls

[46] 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.

to the "kitchen sink" leaves the results unchanged.

Next, we 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 1.8 indicates that a shock to the loan spread predicts a decrease in the HY loan share that gradually reverses. The effect, however, is not significant and the error bars are large. 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. Again, however, the effect is only borderline significant over the short run 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 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.

1.6 Conclusion

The evidence presented in this paper underscores the significant role that loan spreads play in predicting aggregate economic developments. The novel loan-market-based credit spread introduced here captures the constraints of bank-dependent firms more accurately than traditional public credit market measures. Our findings suggest that private and smaller firms, which are typically more sensitive to credit conditions, are important to forecast economic fluctuations. The robust predictive power of loan spreads, validated through various robustness checks and across different macroeconomic variables, challenges the conventional reliance on public credit market spreads for economic forecasting. This shift in perspective has important implications for investors, policymakers, and researchers, emphasizing the need to pay closer attention to the loan market for early economic signals.

Moreover, the distinction between borrower fundamentals and supply-side frictions, as reflected in the Excess Loan Premium, enhances our understanding of credit markets' dynamics. Our empirical tests—particularly the significant impact of events like the Lehman Brothers collapse and oil price shocks—point to the sensitivity of the loan market to intermediary health. This sensitivity, and the subsequent reaction of loan spreads, provide a more nuanced and immediate reflection of economic health than previously considered. These insights contribute to a more comprehensive framework for economic prediction and suggest potential avenues for mitigating risks associated with financial frictions.

Looking ahead, our results 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 intermediary balance sheet frictions. 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 the industry or even the firm-level.

Even though our time series only covers the last two decades, 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 remained 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.

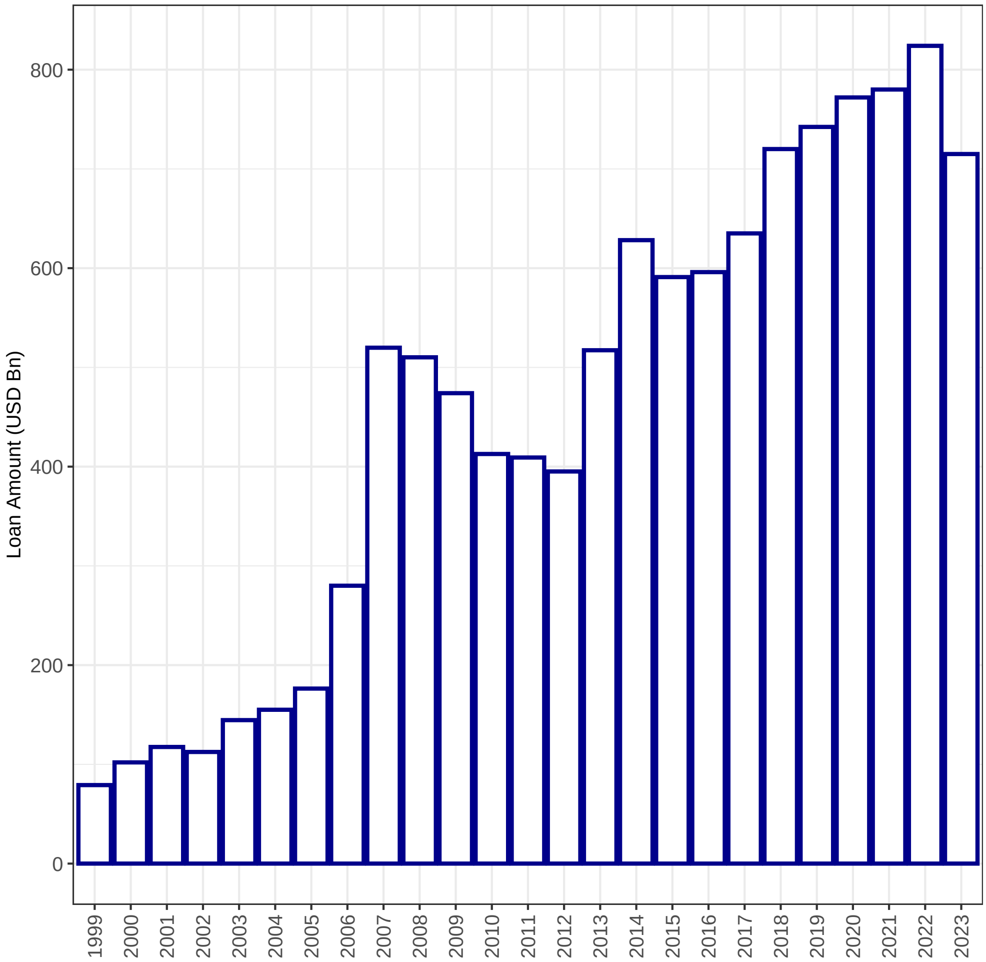


Figure 1.1: **Secondary loan market trading volume**
This figure plots the development of total loan volume traded in the secondary U.S. syndicated loan market over the 1999 to 2023 period. Source: LSTA.

Figure 1.2: **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, and (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 2023:03.

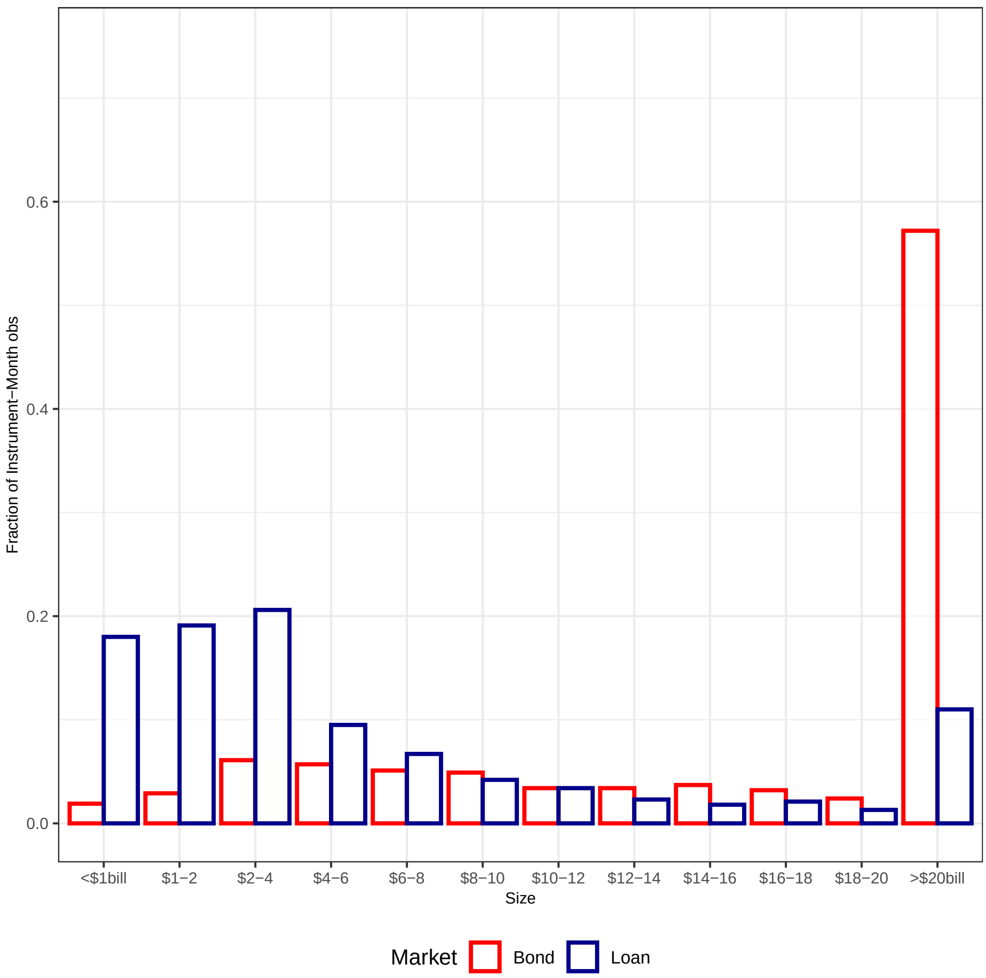


Figure 1.3: **Firm size across loan and bond market**
This figure plots the instrument-month distribution by borrower/issuer size across the loan and bond market. Source: Dealscan/Mergent/Compustat. The sample period is 1999:11 to 2023:03.

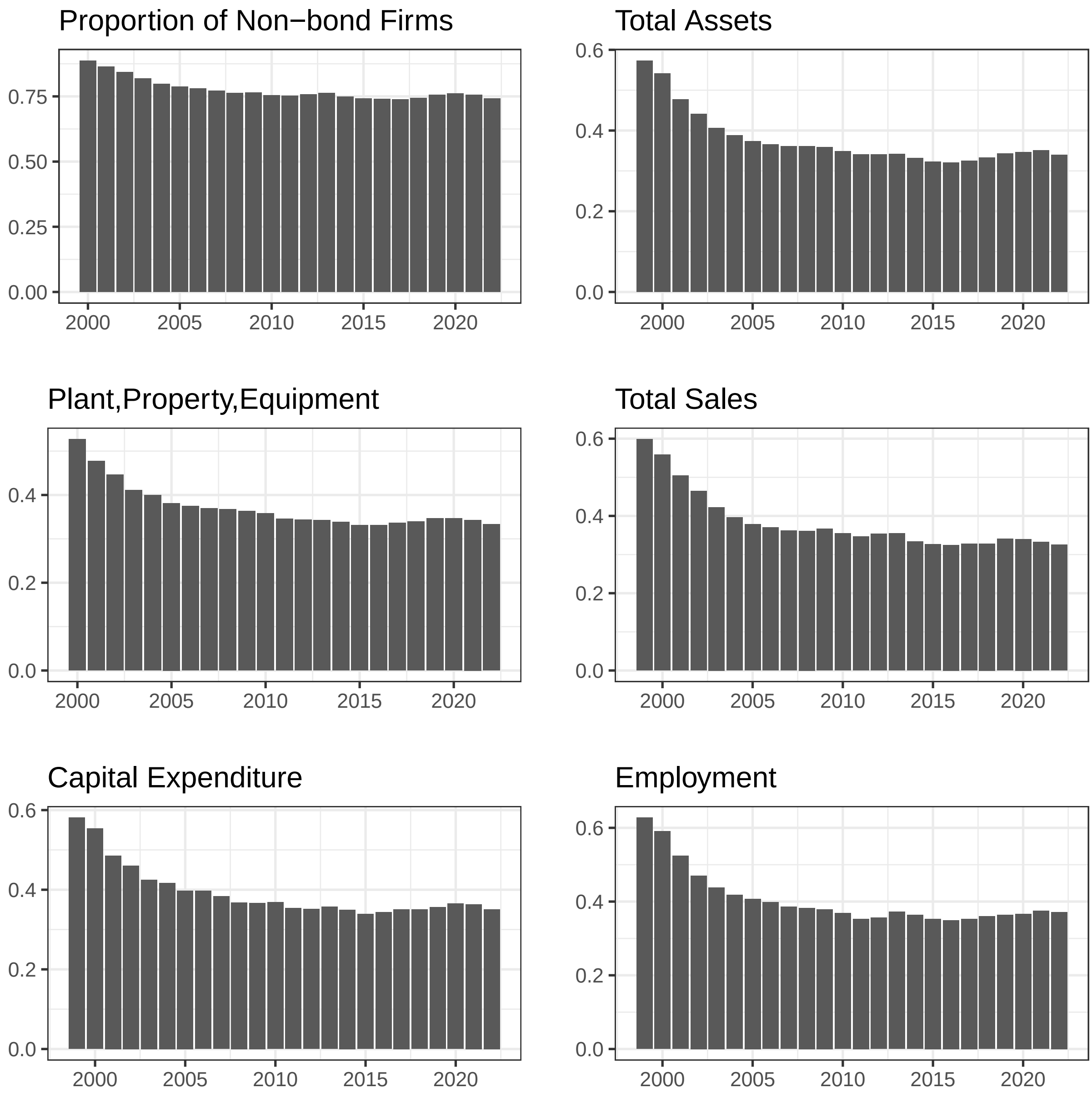


Figure 1.4: **Share of non-bond issuers in aggregate quantities**
This figure plots the share of non-bond issuers in aggregate quantities using data from Compustat North America. The sample comprises the universe of (non-financial) Compustat firms. Bond issuers (non-bond issuers) are defined as firms that have ever (never) issued a corporate bond.

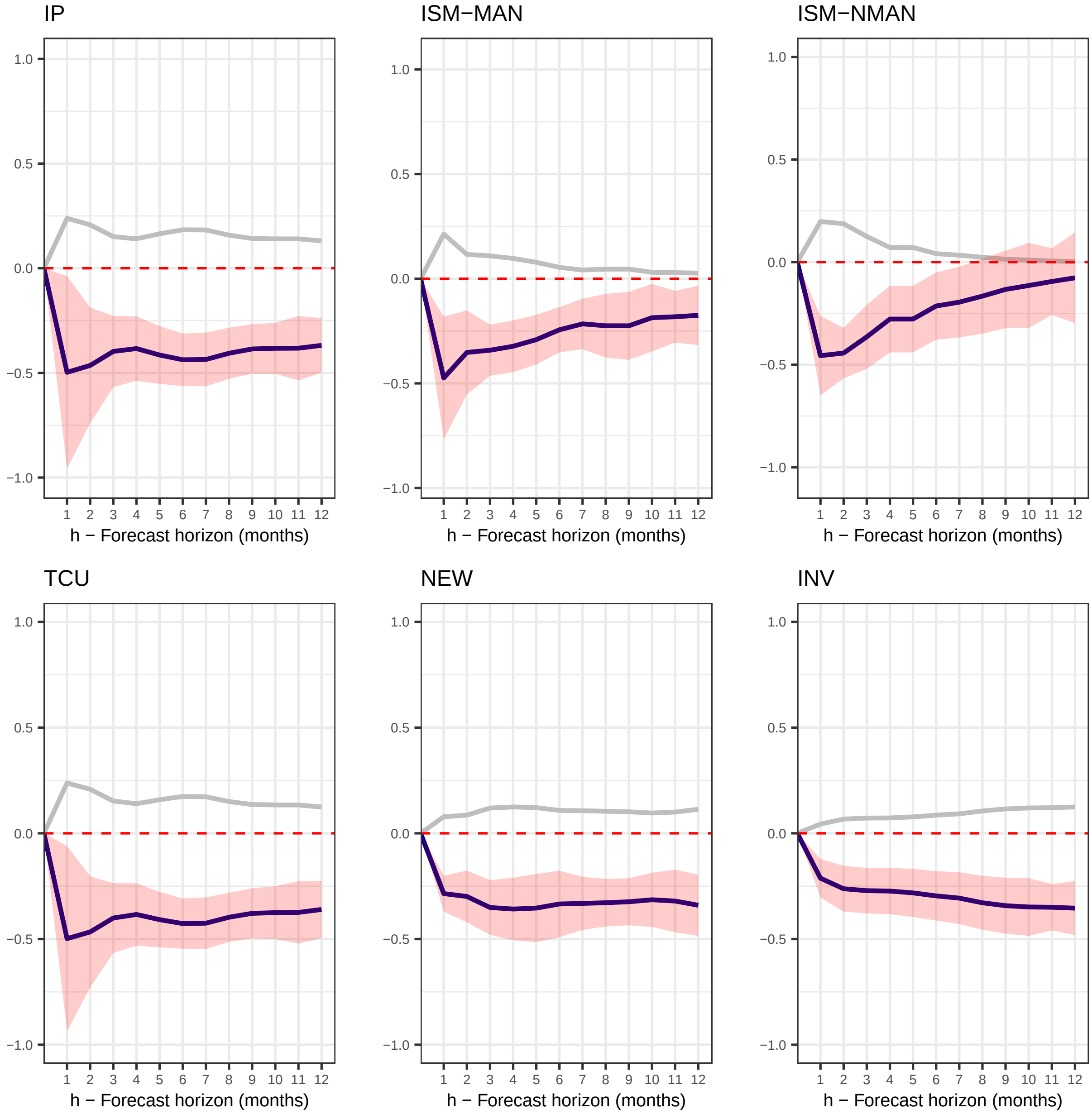


Figure 1.5: **Local projections and incremental R-squared**
This figure plots the impulse response function using a Jordà (2005) local projections framework (blue line) and the incremental adjusted R^2 (grey line). In each figure, the dependent variable is the h-month ahead growth in the macro variable. 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 2023:03.

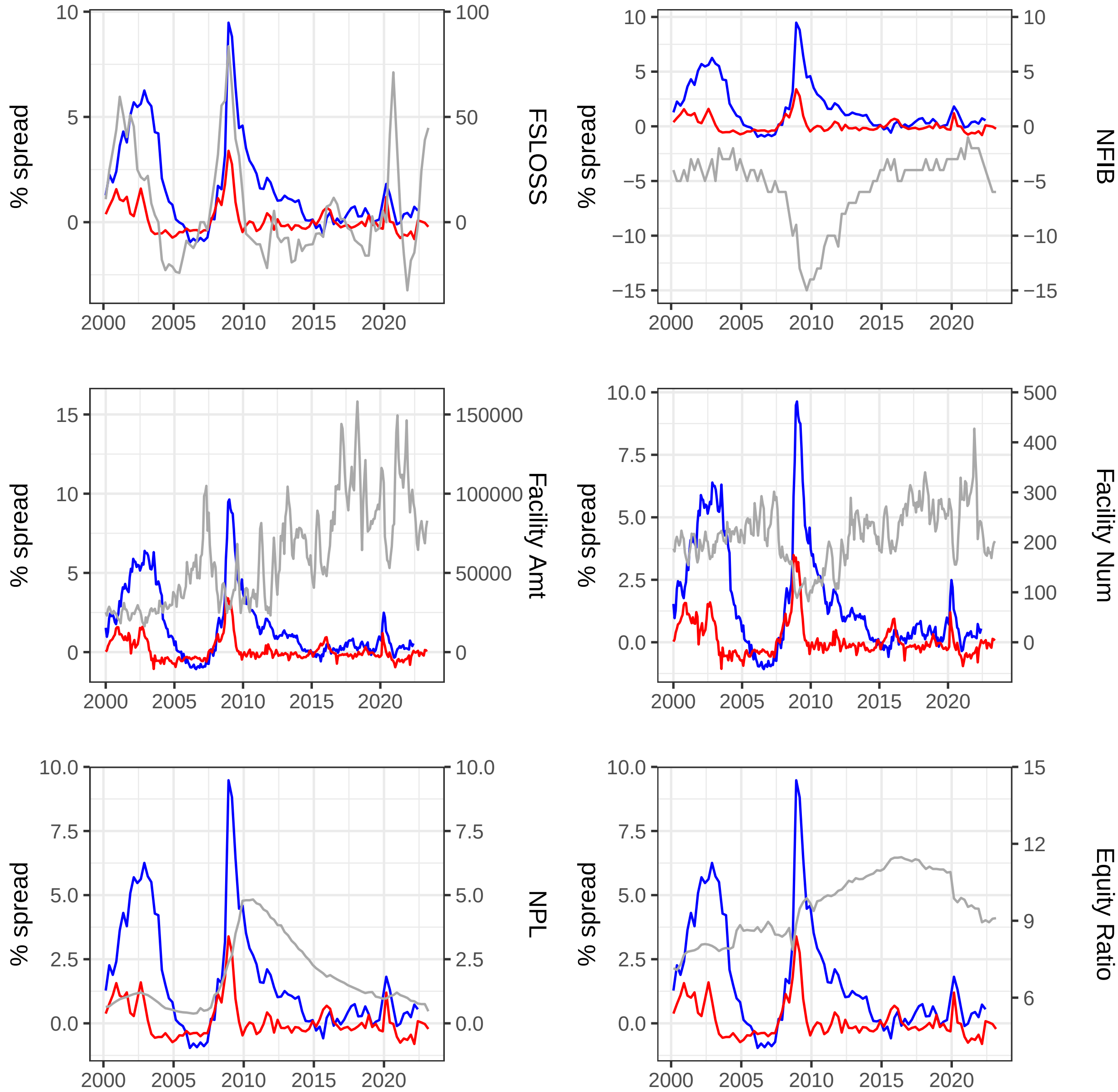


Figure 1.6: **Loan spread and credit supply conditions**
This figure plots the ELP, EBP and various measures of financial conditions. The top-left figure compares the ELP/EBP to the Fed Senior Loan Officer Survey of financial conditions (FSLOSS). The top-right figure compares the ELP/EBP to the Small Business Association survey of credit availability (NFIB). The middle-left figure compares the ELP/EBP to the amount of new term loans recorded in Dealscan (Facility Amt). The middle-right figure compares the ELP/EBP to the number of new term loan recorded in Dealscan (Facility Num). The bottom-left figure compares the ELP/EBP to the non-preforming loan ratio for the US banking sector (NPL). The bottom-right figure compares the ELP/EBP to average bank equity ratio for the US banking sector (Equity Ratio). The sample period is 1999:11 to 2022:06.

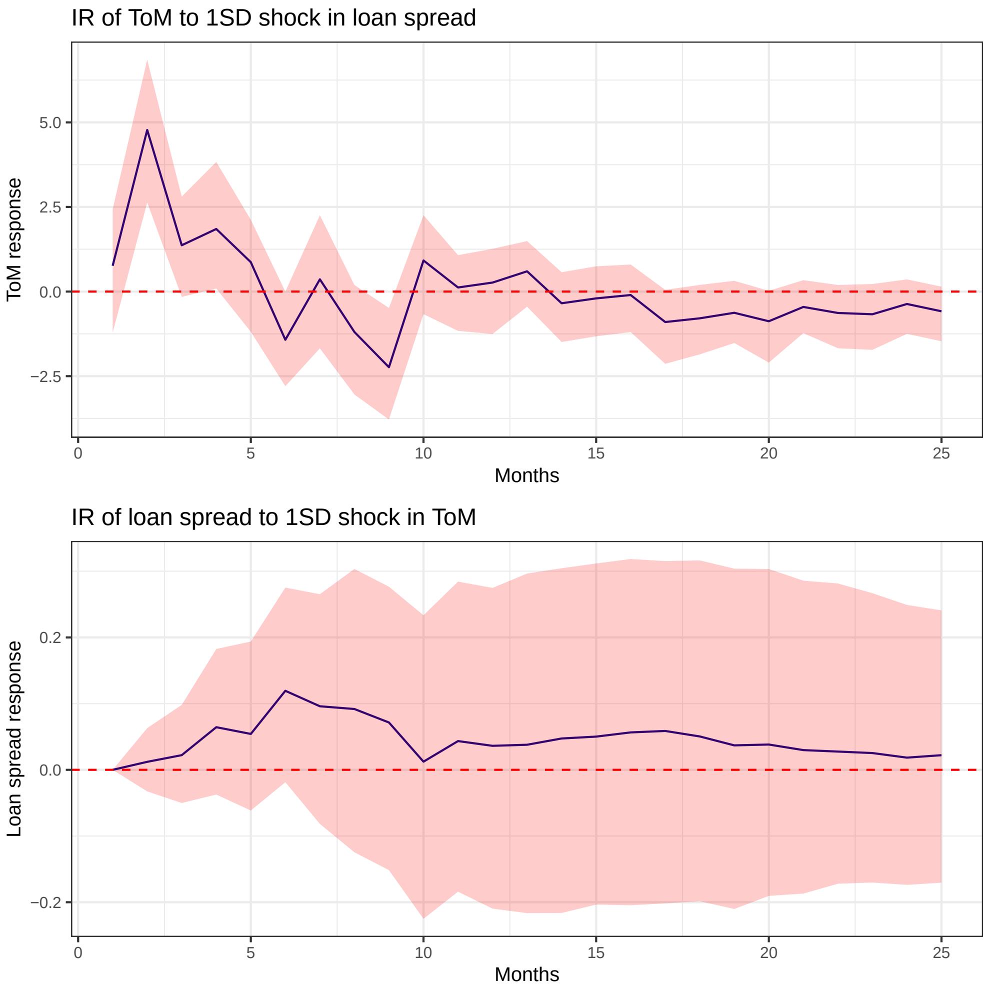
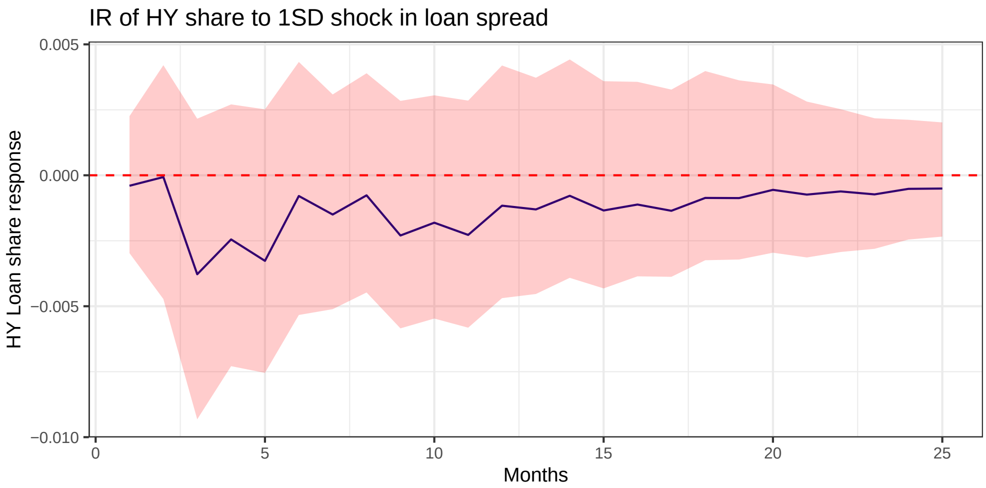


Figure 1.7: **Impulse response of loan spread and time on market**
This figure plots the impulse response function of the loan spread and Time on Market. Time on Market is measured as the average time between syndication launch date and completion date for new institutional loan tranches issued in the primary market in period t (Ivashina and Sun, 2011). The figure plots the cumulative response of one variable to a one standard deviation shock in the other. The sample period is 2001:01 to 2023:03.



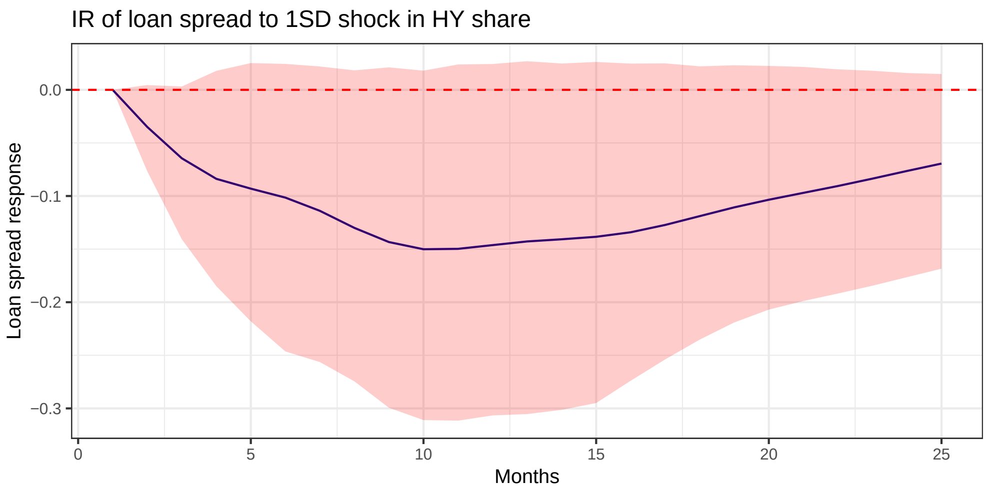


Figure 1.8: **Impulse response of loan spread and HY loan share**
This figure plots the impulse response function of the loan spread and the HY Loan Share. HY Loan Share measures the proportion of all new loans issued in period t that are rated B or below. The figure plots the cumulative response of one variable to a one standard deviation shock in the other. The sample period is 2001:01 to 2023:03.

Table 1.1: **Borrower/issuer composition in the 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/issuers" as the number of unique borrowers/issuers that can be identified in our loan and bond data sourced from the LSTA and TRACE, respectively. Private borrowers/issuers are firms that cannot be linked to the Compustat database. Public borrowers/issuers 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/issuers", where a borrower/issuer is identified by a GVKEY. Firm Age is defined by taking the time-series average of a firm's age. 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 2023:03.

	Loan market		Bond market	
	(%)	(n)	(%)	(n)
Panel A. Public versus private:				
All borrowers/issuers	100%	3,773	100%	2,917
thereof:				
Private	46%	1,743	24%	712
Public	54%	2,030	76%	2,205
Unique parents ("GVKEYs")		1,776		1,610
Panel B. Size distribution:				
<= $2bill	61%	974	33%	516
>2 & <=6 $bill	23%	362	30%	475
>6 & <=10 $bill	6%	93	10%	155
> $10bill	10%	168	27%	424
Market overlap:	thereof: also a bond issuer		thereof: also a loan borrower	
<= $2bill	20%	190	37%	190
>2 & <=6 $bill	52%	188	40%	188
>6 & <=10 $bill	65%	60	39%	60
> $10bill	76%	127	30%	127
Panel C. Age distribution:				
<=5yr	32%	540	12%	188
>5yr & <=10yr	28%	472	24%	372
>10yr & <=20yr	27%	450	33%	520
>20yr	14%	235	31%	495
Market overlap:	thereof: also a bond issuer		thereof: also a loan borrower	
<=5yr	10%	52	28%	52
>5yr & <=10yr	31%	145	39%	145
>10yr & <=20yr	46%	208	40%	208
>20yr	58%	160	32%	160

Table 1.2: **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 2023:03. The dependent variable in Panel A is the three-month ahead percentage change in industrial production (IP), i.e., growth from $t-1$ to $t+3$. The dependent variables in Panel B are the three-month ahead percentage change in industrial production (IP) [column 1], total industrial capacity utilization (TCU) [column 2], new orders for capital goods (ex. defense) (NEW) [column 3], total business inventories (INV) [column 4], and ISM (Non-) Manufacturing index (IS-MAN and ISM-NONMAN) [columns 5 and 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. $S_t^{CP\text{-}Bill}$ is defined as the spread between three-month U.S. T-bills and 30-day AA Non-financial commercial paper. $S_t^{Baa\text{-}Aaa}$ is defined as the spread between Baa and Aaa corporate bond yields as constructed by Moodys. $S_t^{HY\text{-}AAA}$ is the ICE Bofa US high yield effective index. S_t^{Bond} is defined following Gilchrist and Zakrajšek (2012) as the average credit spread on senior unsecured bonds issued by non-financial firms. S_t^{Loan} is defined as the average credit spread of syndicated loans issued by non-financial firms that are traded in the secondary market (see Section 1.2 for details). $S_t^{Bond\ PC}$ is the first principal component (PC) of the spreads used in Panel A, columns 1 to 4. 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 (see Section 3.4 for details). LR Test(χ^2) tests the significance of the inclusion of ΔS_t^{Loan} in a bond spread model (i.e., baseline prediction model including $\Delta S_t^{Bond\ PC}$). "Incremental R^2 (w/o $\Delta S_t^{Bond\ PC}$)" reports the incremental R^2 of a model that includes the loan spread but no bond spread. Reported OLS coefficients are standardized. t-statistics, based on heteroskedasticity and autocorrelation corrected Newey-West standard errors with a four-period lag structure, are reported in parentheses.

	Forecast horizon: h = 3m						
Panel A.	IP	IP	IP	IP	IP	IP	IP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta S_t^{CP\text{-}Bill}$	-0.077						
	(-0.817)						
$\Delta S_t^{Baa\text{-}Aaa}$		-0.317					
		(-3.026)					
$\Delta S_t^{HY\text{-}AAA}$			-0.298				
			(-2.800)				
ΔS_t^{Bond}				-0.292			
				(-2.729)			
ΔS_t^{Loan}					-0.397		-0.323
					(-4.585)		(-3.414)
$\Delta S_t^{Bond\ PC}$						-0.307	-0.167
						(-2.857)	(-1.635)
Term Spread	0.106	0.097	0.099	0.100	0.066	0.098	0.068
	(0.863)	(0.850)	(0.892)	(0.896)	(0.590)	(0.891)	(0.617)
FFR	-0.005	-0.016	0.004	0.008	-0.014	0.005	-0.005
	(-0.058)	(-0.200)	(0.049)	(0.103)	(-0.182)	(0.063)	(-0.069)
Adjusted R^2	0.005	0.100	0.089	0.085	0.154	0.094	0.173
Incremental R^2	+0.002	+0.098	+0.086	+0.082	+0.151	+0.091	+0.171
LR Test(χ^2)	-	-	-	-	-	-	26.8
Observations	281	281	281	281	281	281	281

Panel B.	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}	-0.323	-0.326	-0.224	-0.156	-0.241	-0.234
	(-3.414)	(-3.602)	(-2.980)	(-3.027)	(-3.470)	(-3.187)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.173	0.208	0.174	0.602	0.244	0.231
Incremental R^2 (w/o $\Delta S_t^{Bond\ PC}$)	+0.151	+0.153	+0.073	+0.038	+0.125	+0.109
Incremental R^2	+0.171	+0.173	+0.082	+0.045	+0.195	+0.151
LR Test(χ^2)	26.8	28.3	13.3	13.2	16.9	15.2
Observations	281	281	281	281	281	281

Table 1.3: **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 2023:03 (except for Panel A, columns 5 and 6 in which the sample period is 2002:06 to 2022:12 due to limited data availability for some of the control variables). *Residual* S_t^{Loan} is the residual from a regression of the loan spread on loan contract terms (see Online Appendix D.8 for details). *Bid-Ask* is the median bid-ask spread in the secondary loan market. *S&P500* is the monthly return of the S&P 500 index. *VIX* is a measure of the stock market's expectation of volatility based on S&P 500 index options. S_t^{Bond-A} is a bottom-up bond spread measure based on bonds rated AAA to A-, $S_t^{Bond-BBB}$ is a bottom-up bond spread measure based on bonds rated BBB+ to BBB-, and $S_t^{Bond-HY}$ is a bottom-up bond spread measure based on bonds rated BB+ and below. All other variables and statistics are defined in Table 1.2. Panel B excludes the 2008-09 global financial crisis period (i.e., 2007:12 to 2009:03). Reported OLS coefficients are standardized. t-statistics, based on heteroskedasticity and autocorrelation corrected Newey-West standard errors with a four-period lag structure, are reported in parentheses.

	Forecast horizon: h = 3m					
Panel A.	IP	IP	IP	IP	IP	IP
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}		-0.363	-0.357	-0.327	-0.399	-0.415
		(-3.861)	(-4.458)	(-2.900)	(-4.685)	(-4.327)
Residual ΔS_t^{Loan}	-0.393					
	(-4.401)					
Bid-Ask		-0.170				
		(-1.434)				
ΔS&P500			0.188			
			(2.333)			
ΔVIX				-0.150		
				(-1.304)		
ΔS_t^{Bond-A}						0.031
						(0.748)
$\Delta S_t^{Bond-BBB}$						0.026
						(0.747)
$\Delta S_t^{Bond-HY}$					-0.080	-0.082
					(-2.032)	(-2.084)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.150	0.174	0.184	0.166	0.161	0.155
Incremental R^2	+0.148	+0.171	+0.182	+0.164	+0.159	+0.153
LR Test(χ)	46.1	15.8	20.1	26.5	40.7	37.9
Observations	281	281	281	281	246	246
Panel B.	*Excluding the 2008-09 global financial crisis period*					
	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}	-0.256	-0.275	-0.091	-0.147	-0.225	-0.268
	(-2.144)	(-2.548)	(-1.920)	(-1.755)	(-2.503)	(-2.919)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.112	0.159	0.140	0.533	0.126	0.173
Incremental R^2	+0.110	+0.123	+0.047	-0.023	+0.077	+0.093
Observations	265	265	265	265	265	265
Panel C.	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}	-0.304	-0.305	-0.254	-0.128	-0.331	-0.307
	(-2.847)	(-2.874)	(-3.789)	(-1.903)	(-3.687)	(-3.255)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Bid-Ask	✓	✓	✓	✓	✓	✓
ΔSP&500	✓	✓	✓	✓	✓	✓
ΔVIX	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.212	0.237	0.187	0.616	0.292	0.266
Incremental R^2	+0.210	+0.201	+0.094	+0.059	+0.244	+0.186
Observations	281	281	281	281	281	281

Table 1.4: **Cross-sectional comparison**

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 2023:03. S_t^{Loan} *Public* (*Private*) is a loan spread constructed exclusively based on public (private) firms, i.e., firms that can (cannot) be linked to the Compustat database. S_t^{Loan} *Bond* (*No-Bond*) is a loan spread constructed exclusively based on firms that are (not) active issuers in the corporate bond market. All other variables and statistics are defined in Table 2. 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	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Private vs. Public:						
ΔS_t^{Loan} Private	-0.306	-0.316	-0.196	-0.142	-0.214	-0.201
	(-3.217)	(-3.549)	(-2.587)	(-2.555)	(-3.302)	(-2.834)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.169	0.207	0.166	0.599	0.236	0.222
Incremental R^2	+0.166	+0.172	+0.074	+0.043	+0.187	+0.142
LR Test(χ^2)	12.4	15.1	1.67	3.95	0.83	2.25
Observations	281	281	281	281	281	281
ΔS_t^{Loan} Public	-0.229	-0.225	-0.189	-0.118	-0.217	-0.190
	(-1.979)	(-2.057)	(-2.366)	(-2.250)	(-2.494)	(-2.001)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.131	0.163	0.161	0.594	0.234	0.216
Incremental R^2	+0.129	+0.128	+0.069	+0.037	+0.185	+0.136
Observations	281	281	281	281	281	281
Panel B. Bond vs. No-Bond:						
ΔS_t^{Loan} No-Bond	-0.323	-0.326	-0.223	-0.156	-0.239	-0.233
	(-3.386)	(-3.576)	(-2.958)	(-3.019)	(-3.435)	(-3.143)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.174	0.209	0.174	0.602	0.243	0.231
Incremental R^2	+0.171	+0.173	+0.082	+0.045	+0.195	+0.151
LR Test(χ^2)	16.3	19.0	11.6	8.82	8.83	4.53
Observations	281	281	281	281	281	281
ΔS_t^{Loan} Bond	-0.200	-0.185	-0.076	-0.085	-0.158	-0.186
	(-3.486)	(-3.463)	(-1.022)	(-2.366)	(-2.168)	(-3.918)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.124	0.153	0.139	0.589	0.219	0.219
Incremental R^2	+0.122	+0.118	+0.047	+0.032	+0.171	+0.139
Observations	281	281	281	281	281	281

Table 1.5: **Credit spread decomposition**

This table relates the decomposed loan spread measure to future economic outcomes for the U.S. economy. The unit of observation is the monthly level t. The sample period is 1999:11 to 2022:06. Credit spreads are decomposed into a part that captures changes in default risk based on the fundamentals of the firm ("predicted spread;" $\hat{S}_t^{Loan}$) and a residual ("excess premium;" ELP_t). Panel A uses a credit spread decomposition based on distance-to-default (as well as other firm-level and loan-level controls). Firm-specific distance-to-default (DtD) is used in the prediction, when available. For private firms, industry DtD (including higher order moments and within industry DtD volatility) is used. Panel B uses a credit spread decomposition relying only on firms for which DtD is available, for robustness. See Section 1.5.2 and Online Appendix D.17 for details. All other variables and statistics are defined in Table 1.2. 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	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
ΔELP_t	-0.251	-0.254	-0.191	-0.113	-0.248	-0.213
	(-2.892)	(-3.104)	(-2.523)	(-2.118)	(-3.501)	(-3.215)
$\Delta \hat{S}_t^{Loan}$	-0.157	-0.185	-0.037	-0.098	-0.028	-0.023
	(-1.590)	(-1.902)	(-0.565)	(-1.944)	(-0.294)	(-0.307)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta Bond_t^{PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.159	0.201	0.175	0.603	0.254	0.234
Observations	272	272	272	272	272	272
Panel B.	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
ΔELP_t	-0.211	-0.203	-0.157	-0.108	-0.228	-0.157
	(-2.527)	(-2.457)	(-2.515)	(-2.147)	(-2.917)	(-2.100)
$\Delta \hat{S}_t^{Loan}$	-0.110	-0.120	-0.083	-0.042	-0.018	-0.004
	(-1.317)	(-1.467)	(-1.337)	(-0.903)	(-0.272)	(-0.070)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta Bond_t^{PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.134	0.168	0.167	0.597	0.244	0.214
Observations	272	272	272	272	272	272

Table 1.6: **Loan spreads and financial frictions − baseline**

Panel A of this table examines loan spreads around the 2008 Lehman Brothers collapse. The dependent variable is the spread of loan l by borrower i in month t. The sample period is the 12-month period around the Lehman Brothers collapse, i.e., March 2008 to February 2009. *Post* is an indicator variable equal to one for months after the Lehman collapse. Lehman Exposure is defined following Chodorow-Reich (2014) as the the fraction of the bank's syndication portfolio where Lehman Brothers had a lead role in the loan deal. For each borrower, the bank-level measure is averaged over the members of the firm's last precrisis loan syndicate (*Exposure*). *High Exposure* is an indicator variable for borrowers with a Lehman Exposure in the top 25% of the distribution. Panel B of this table examines loan spreads around the 2014 oil price drop. The dependent variable is the spread of loan l by borrower i in month t. The sample period is 2013 to 2015. *Post* is an indicator variable equal to one for months after the oil price plunge in September 2014. *Exposure* is defined following Kundu (2022) as the exposure of firm i's investor base (CLOs) to the oil and gas industry before the oil price drop (as of June 2014). See main text for details. *High Exposure* is an indicator variable for firms with an oil and gas exposure (via their investor base) in the top 25% of the distribution. In column 3 the sample is restricted to firms in the oil and gas sector. In columns 4 and 5 the sample is restricted to firms *not* in the oil and gas sector. The regressions include issuer and year-month fixed effects, when indicated. t-statistics, based on robust standard errors, clustered at the loan level, are in parentheses.

	Panel A. Lehman Exposure		**Panel B. CLO Oil&Gas Exposure**		
Sample:			Oil&Gas Firms	Non-Oil&Gas Firms	
Variable:	Spread	Spread	Spread	Spread	Spread
	(1)	(2)	(3)	(4)	(5)
$\text{Exposure}_i \times \text{Post}_t$	2.547			0.351	
	(2.04)			(2.68)	
$\text{High Exposure}_i \times \text{Post}_t$		0.019			0.007
		(2.10)			(2.28)
Post_t	(omitted)	(omitted)	0.064	(omitted)	(omitted)
			(5.84)		
Issuer FE	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	No	Yes	Yes
Observations	4,725	4,725	2,559	50,754	50,754
Adj R^2	0.69	0.69	0.53	0.643	0.643

Table 1.7: **Loan spreads and financial frictions – ELP versus predicted spread**

This table mirrors Table 1.6 Panels A and B but uses the ELP or the predicted spread of loan l by borrower i in month t as dependent variable (see Section 1.5.2 for details). All other variables are defined in Table 1.6. In Panel B the sample is restricted to firms *not* in the oil and gas sector. The regressions include issuer and year-month fixed effects, when indicated. t-statistics, based on robust standard errors, clustered at the loan level, are in parentheses.

	Panel A. Lehman Exposure		**Panel B. CLO Oil&Gas Exposure**	
Sample:			Non-Oil&Gas Firms	
Variable:	ELP	$\widehat{\text{Spread}}$	ELP	$\widehat{\text{Spread}}$
	(1)	(2)	(3)	(4)
$\text{Exposure}_i \times \text{Post}_t$	1.838	0.392	0.251	0.099
	(2.69)	(3.32)	(2.00)	(1.91)
Issuer FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Observations	3,031	3,031	50,754	50,754
Adj R^2	0.72	0.77	0.57	0.68

Table 1.8: **Sentiment**

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 2023:03. *HY Loan Share* measures the proportion of all new loans issued in period t that are rated B or below. *HY Bond Share* is defined following Greenwood and Hanson (2013) as the share of bonds issued in period t that have a high-yield rating. All other variables and statistics are defined in Table 1.2. 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	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}	-0.386	-0.389	-0.271	-0.199	-0.365	-0.343
	(-4.205)	(-4.384)	(-3.660)	(-3.081)	(-4.489)	(-5.179)
$HY\ Loan\ Share_t$	0.105	0.113	0.003	0.071	-0.021	0.059
	(1.804)	(2.021)	(0.044)	(1.492)	(-0.361)	(1.014)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.166	0.204	0.168	0.597	0.168	0.189
Incremental R^2	+0.164	+0.169	+0.076	+0.040	+0.120	+0.110
Observations	281	281	281	281	281	281
Panel B.						
ΔS_t^{Loan}	-0.375	-0.375	-0.250	-0.189	-0.382	-0.346
	(-4.137)	(-4.306)	(-3.199)	(-2.878)	(-4.857)	(-5.578)
$HY\ Bond\ Share_t$	0.106	0.130	0.122	0.093	-0.101	-0.001
	(0.989)	(1.253)	(1.941)	(1.344)	(-1.002)	(-0.010)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.164	0.204	0.179	0.598	0.175	0.186
Incremental R^2	+0.161	+0.168	+0.087	+0.041	+0.127	+0.106
Observations	281	281	281	281	281	281
Panel C.						
ΔS_t^{Loan}	-0.343	-0.340	-0.271	-0.145	-0.392	-0.343
	(-3.397)	(-3.342)	(-3.457)	(-2.159)	(-4.218)	(-4.018)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Bid-Ask	✓	✓	✓	✓	✓	✓
ΔSP&500	✓	✓	✓	✓	✓	✓
ΔVIX	✓	✓	✓	✓	✓	✓
HY Loan Share	✓	✓	✓	✓	✓	✓
HY Bond Share	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.205	0.237	0.198	0.616	0.268	0.261
Incremental R^2	+0.202	+0.202	+0.106	+0.059	+0.220	+0.182
Observations	281	281	281	281	281	281

1.7 Online Appendix

1.7.1 Additional institutional background

Loan market dealers

Table 1.9 shows the loan market lead arranger (underwriter) market share in the primary market for the top 10 dealers in the secondary market for 2009.[47] The five largest dealer banks are Credit Suisse, Bank of America, Barclays, Citigroup, and JP Morgan which together account for 36.8% of quotes in the secondary loan market in 2009. The top 10 (25) dealers account for 58.4% (about 90%) of all quotes. These banks are also the largest underwriters in the primary loan market.

Table 1.9: **Top 10 dealers in the secondary loan market in 2009**

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

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

Loan market liquidity

Figure 1.9 plots the median bid-ask spread (scaled by the mid-quote) over the 1999-2023 period as well as the interquartile range (grey area). The median bid-ask spread in the 1999 to 2023 period is 87 bps. For comparison, Feldhütter and Poulsen (2018) report an average bid-ask spread for the U.S. bond market of 34 bps over the 2002 to 2015 period.

[47] 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.

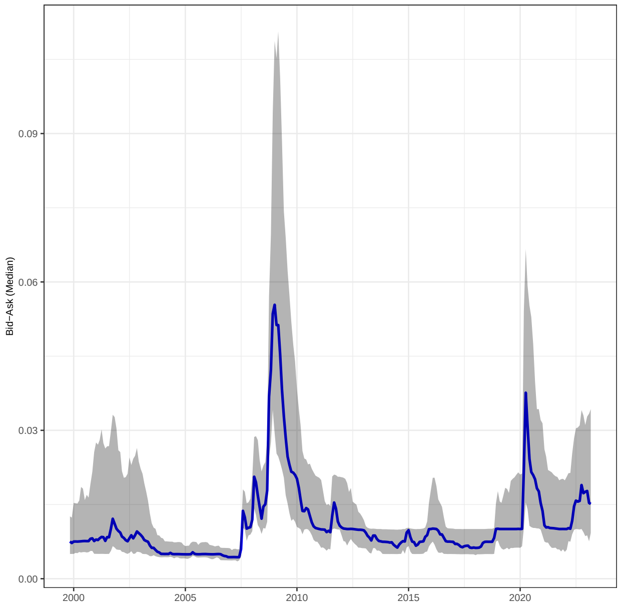


Figure 1.9: **U.S. secondary loan market liquidity**
This figure plots the median bid-ask spread (scaled by the mid quote) over the 1999:11 to 2023:03 period as well as the interquartile range. The sample is restricted to term loans issued by U.S. firms. Source: LSTA.

1.7.2 Variable definitions

This section outlines the key variables used in the main paper and their construction. Table 1.10 describes each variable. Column (1) indicates the country for which the data applies and the name of the variable used throughout the paper. Column (2) provides a brief description and the source of the data. Column (3) indicates the data frequency.

Table 1.10: **Description of variables**

Economic Variables	Description	Frequency
USA - Industrial production	Total industrial production index (FRED)	M
USA - Total capacity utilization	Total capacity utilization (FRED)	M
USA - New orders	New orders for capital goods (ex. defense) (FRED)	M
USA - Business inventory	Total business inventories (FRED)	M
USA - ISM Manufacturing	ISM Manufacturing Employment Diffusion Index (ISM)	M
USA - ISM Non-Manufacturing	ISM Non-Manufacturing Employment Diffusion Index (ISM)	M
USA - FSLOSS	Fed senior loan officer survey (Federal Reserve)	Q
USA - NFIB	Credit conditions survey for small firms (NFIB)	Q
USA - NPL	Non performing Loans % - US banks (SNL)	Q
USA - Equity ratio	Equity ratio % - US banks (SNL)	Q
USA - Facility Amt	Total amount ($Millions) of new term loan facilities issued (Dealscan)	M
USA - Facility Num	Total number of new term loan facilities issued (Dealscan)	M
USA - S&P500	S&P500 monthly return (CRSP)	M
USA - Bid-ask spread	Median loan bid-ask spread (Authors)	M
USA - VIX	VIX (monthly average)	M
USA - CLO Primary Issuance	Primary issuance new CLO	M
USA - Time on market	Time from syndication to completion (Authors)	M
USA - HY Loan share	Proportion of B and below new issuance (Authors)	M
USA - HY Bond share	Proportion of HY new issuance (Authors)	M
Interest rates		
USA - Real federal funds rate	Avg effective federal funds rate minus core PCE index (FRED)	M
USA - Baa-Aaa spread	10year Baa minus 10year Aaa corporate bond spread (FRED)	M
USA - Commercial spread	Paper/bill spread: 1 month A1/P1 commercial paper minus 3m UST (FRED)	M
USA - HY-AAA spread	High Yield minus AAA yield (FRED)	M
USA - $\Delta S_t^{Bond\ PC}$	First PC extracted from $\Delta S_t^{Baa\text{-}Aaa}$, $\Delta S_t^{CP\text{-}Bill}$, $\Delta S_t^{HY\text{-}AAA}$, and ΔS_t^{Bond}	M
USA - ΔS_t^{Loan}	Monthly aggregate loan spread constructed from loan market (Authors)	M
USA - ΔS_t^{Bond}	Monthly aggregate bond spread Gilchrist and Zakrajšek (2012)	M

1.7.3 Descriptive statistics

Table 1.11 summarizes basic descriptive statistics for the main macro outcomes and credit spreads used in the paper for the U.S. sample.

Table 1.11: **Summary Statistics**

This table summarizes key descriptive statistics for each credit spread and macroeconomic outcome variables used in the forecasting regressions for the U.S. The unit of observation is the monthly level t. The sample period is 1999:11 to 2023:03.

Variable	Mean	SD	Min	Median	Max
Credit spreads:					
$\Delta CP - billspread$ (bps)	-0.04	14.69	-74.0	0.0	104.0
$\Delta Baa - Aaaspread$ (bps)	0.14	12.27	-63.0	-1.0	94.0
$\Delta HY - aaaspread$ (bps)	-0.04	69.31	-324.0	-4.0	455.0
ΔS_t^{Bond} (bps)	-0.19	29.80	-129.09	-2.86	238.81
ΔS_t^{Loan} (bps)	1.04	46.50	-125.0	-4.37	361.51
$\Delta S_t^{Bond\ PC}$ (bps)	-0.02	74.16	-323.91	-4.66	521.70
Macro outcomes:					
Δy_{t+3} Industrial production (%)	0.17	2.58	-18.59	0.58	12.53
Δy_{t+3} ISM Manufacturing (Index)	-0.05	5.03	-17.90	-0.10	18.10
Δy_{t+3} ISM Non-Manufacturing (Index)	-0.01	4.23	-25.90	0.00	18.30
Δy_{t+3} Total Capacity Utilization (%)	-0.04	1.97	-13.25	0.19	8.87
Δy_{t+3} New orders (%)	0.36	10.43	-59.16	0.21	56.08
Δy_{t+3} Total business inventory (%)	0.86	1.70	-5.05	1.05	6.04

Table 1.12 provides a comparison of the instrument level characteristics in the bond and loan market. Loan market data is a combination of LSTA data for secondary market quotes complemented with information about the underlying loans from the Dealscan database. Bond market data is a combination of monthly TRACE data for prices combined with Mergent FISD for information about the underlying bond.

Table 1.12: **Bond and loan market comparison**

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

Panel A. Bond Market Characteristics

Variable	Mean	SD	Min	Median	Max	N
Total No. of Bonds	-	-	-	-	-	14939
No. Bonds per month	4434	1613	214	4885	6378	
No. Bonds per firm/month	3.6	4.4	1.0	2.0	86.0	
Offering Amount ($mill)	618.3	593	0.0	500.0	15000	
Maturity at issue (years)	11.6	8.7	0.52	9.8	41	
Term to Maturity (years)	9.7	8.7	0.0	6.4	30.0	
Duration (years)	6.0	4.1	0.0	5.0	19.2	
Coupon (%)	5.5	2.1	0.4	5.5	18.0	
Secured (%)	9.0	-	-	-	-	
Bond Spread (bps)	511	437.5	13.6	260.2	3495.6	

Panel B. Loan Market Characteristics

Variable	Mean	SD	Min	Median	Max	N
Total No. of Loans	-	-	-	-	-	10044
No. Loans per month	1240	528.5	329	1409	2114.0	
No. Loans per firm/month	1.5	0.85	1.0	1.0	15.0	
Facility Amount ($mill)	501.8	736.5	1.0	290.0	24000.0	
Maturity at issue (years)	6.2	1.3	0.7	6.5	12.2	
Term to Maturity (years)	4.1	1.9	0.0	4.3	11.8	
All In Spread Drawn (bps)	428.4	201.2	12.8	400.0	1600.0	
Secured (%)	89	-	-	-	-	
Senior (%)	95	-	-	-	-	
Loan Spread (bps)	600	458.7	5.3	460.2	3500.0	

1.7.4 Additional results

Term loan B spread

The overwhelming part of term loans in our secondary market dataset are institutional term loans (term loan B). Only around 10% are term loan A. The table below compares our baseline results with results using a loan spread that is exclusively constructed based on institutional term loans. Consistent with the fact that term loan B make up for the largest part of the sample, results are virtually identical if we use a “term loan B only” spread instead of our baseline loan spread measure.

Table 1.13: **Term loan B spread**

Panel A mirrors Table 2, Panel B, in the main manuscript. Panel B reports the same specification but uses a loan spread that is exclusively constructed based on institutional "Term B" loans.

	Forecast horizon: h = 3m					
Panel A.	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}	-0.323	-0.326	-0.224	-0.156	-0.241	-0.234
	(-3.414)	(-3.602)	(-2.980)	(-3.027)	(-3.470)	(-3.187)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.173	0.208	0.174	0.602	0.244	0.231
Incremental R^2	+0.171	+0.173	+0.082	+0.045	+0.195	+0.151
Observations	281	281	281	281	281	281
Panel B.	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta S_t^{Loan,\ \text{Term loan B}}$	-0.330	-0.333	-0.220	-0.166	-0.236	-0.239
	(-3.414)	(-3.592)	(-2.836)	(-3.297)	(-3.278)	(-3.148)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.178	0.213	0.174	0.605	0.243	0.234
Incremental R^2	+0.176	+0.178	+0.082	+0.048	+0.194	+0.154
Observations	281	281	281	281	281	281

Payment frequency

Throughout the paper we assume that cash flows are paid quarterly as we do not have information on the payment frequency for most loans (payment frequency is available in DealScan for less than 15% of our loan sample). Hence, using loan-specific frequencies is not possible. However, for the small subset of loans for which information on payment frequency is available, the vast majority of loans have a quarterly payment schedule. This is consistent with, e.g., Beyhaghi and Ehsani (2017) who also assume loans have a quarterly payment schedule.

For robustness, we re-calculate the yield to maturity for all loans assuming semi-annual payments (the second most common payment frequency according to DealScan). The correlation between a loan spread assuming semi-annual payments and our baseline loan spread is 95%. Table 1.14 below compares our baseline results (assuming quarterly payments) in Panel A, to a loan spread that assumes semi-annual payments in Panel B.

Table 1.14: **Payment frequency**

Panel A mirrors Table 2, Panel B, in the main manuscript. Panel B reports the same specification but uses a loan spread that assumes semi-annual payments when calculating the yield to maturity.

	Forecast horizon: h = 3m					
Panel A.	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}	-0.323	-0.326	-0.224	-0.156	-0.241	-0.234
	(-3.414)	(-3.602)	(-2.980)	(-3.027)	(-3.470)	(-3.187)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.173	0.208	0.174	0.602	0.244	0.231
Incremental R^2	+0.171	+0.173	+0.082	+0.045	+0.195	+0.151
Observations	281	281	281	281	281	281
Panel B.	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta S_t^{Loan,\text{semi-annual}}$	-0.383	-0.378	-0.246	-0.201	-0.238	-0.220
	(-4.988)	(-5.064)	(-3.488)	(-3.390)	(-3.648)	(-3.576)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.204	0.234	0.182	0.612	0.242	0.224
Incremental R^2	+0.201	+0.198	+0.089	+0.056	+0.193	+0.145
Observations	281	281	281	281	281	281

Prepayment of loans

Given that loans are typically prepayable at par, it is not possible to know the future payment profile of a loan at a given time. To test the sensitivity of our results to the maturity profile of loans, we reconstruct the loan spread assuming alternative maturities.

We first start by checking the average prepayment time of our loans. We define the last month in which we see a price for the loan as a proxy for the prepayment date. That is, for each loan (that contractually matures before the end of our sample period) we calculate (Last Date At Which Loan Price Is Observed - Issuance Date)/(Maturity Date - Issuance Date). This "fraction of loan's lifespan" measures the ratio of effective loan lifespan, to the expected loan lifespan. Figure 1.10 plots the distribution of this measure across all loans. On average, the typical loan only makes it 54% of the way to it's expected maturity. Given the typical loan maturity is 5.8 years, this implies an "effective" maturity of 3 years.

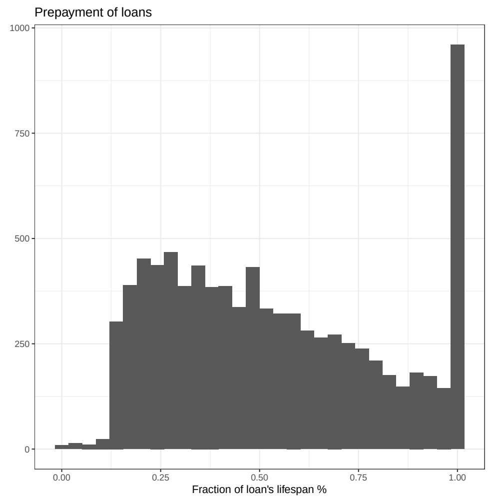


Figure 1.10: **Prepayment of loans**

Table 1.15 reports our baseline findings in Panel A (which are reported in Table 2, Panel B in the manuscript), and in Panel B we reconstruct the loan spread assuming the loan does not make it to stated maturity, but only 3 years. The results confirm that assuming a different maturity profile does not lead to different results.

Table 1.15: **Assuming 3yr maturity**

Panel A reproduces Table 2, Panel B, in the main manuscript for comparison. Panel B reports the same specification but using a loan spread assuming only 3 years to maturity.

	Forecast horizon: h = 3m					
Panel A.	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}	-0.323	-0.326	-0.224	-0.156	-0.241	-0.234
	(-3.414)	(-3.602)	(-2.980)	(-3.027)	(-3.470)	(-3.187)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.173	0.208	0.174	0.602	0.244	0.231
Incremental R^2	+0.171	+0.173	+0.082	+0.045	+0.195	+0.151
Observations	281	281	281	281	281	281

Panel B.	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta S_t^{Loan-3yrMat}$	-0.331	-0.346	-0.202	-0.191	-0.228	-0.265
	(-3.080)	(-3.257)	(-2.457)	(-3.074)	(-2.324)	(-2.767)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.164	0.204	0.161	0.607	0.233	0.235
Incremental R^2	+0.161	+0.168	+0.069	+0.050	+0.184	+0.155
Observations	281	281	281	281	281	281

Alternative timing conventions

Most forecasting regressions in the paper (unless indicated) adopt the same timing conventions as commonly adopted in the macro forecasting literature (including Gilchrist and Zakrajšek, 2012) in defining growth rates and lags of macro-outcomes. Fig 1.11 summarizes visually the timings adopted for the baseline forecasting regressions. This setup is chosen in recognition of the fact that in period t, macro-outcomes are often not available due to reporting lags, whereas financial market variables are more readily available. In this section we consider the impact of alternative timing conventions on our main results.

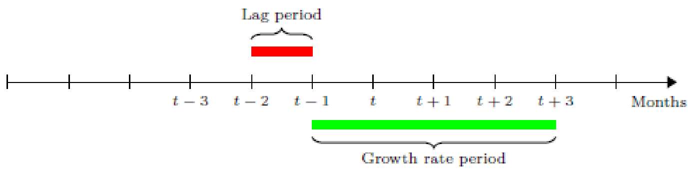


Figure 1.11: **Baseline timing conventions**
This figure summarizes the timing conventions used throughout the paper.

The first alternative timing convention we try, defines the growth rate as the growth from t to $t+3$, as summarized in Fig 1.12. Table **??**, Panel A summarizes the results of the forecasting regression using this alternative timing convention. Overall, the key results remain unchanged, with similar forecasting coefficients across all macro-outcomes. In some cases (e.g. IP and TCU) incremental R^2 is improved under the alternative definition.

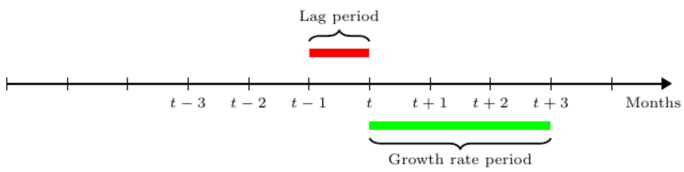


Figure 1.12: **Alternative timing conventions - A**
This figure summarizes an alternative timing convention used in Table **??**. It defines the growth rate as the growth from t to $t+3$

The second alternative timing convention we try, adopts the same growth rate at Panel A, but uses a lagged dependent variable with a matching period, i.e., the lagged growth rate from $t-3$ to t, as summarized in Fig 1.13. Table **??**, Panel B summarizes the results of the forecasting regression using this alternative timing convention. Once again, the baseline results remain unchanged, even strengthening for some variables.

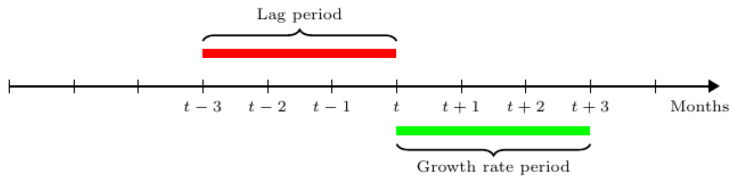


Figure 1.13: **Alternative timing conventions - B**
This figure summarizes an alternative timing convention used Table **??**. It defines the lagged growth rate from $t-3$ to t.

Table 1.16: **Alternative timing**

Panel A mirrors Table 2, Panel B, in the main manuscript but adopts the timing conventions depicted in Figure D.3. Panel B mirrors Table 2, Panel B, in the main manuscript but adopts the timing conventions depicted in Figure D.4.

	Forecast horizon: h = 3m					
Panel A.	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}	-0.320	-0.294	-0.242	-0.112	-0.162	-0.186
	(-4.865)	(-4.827)	(-3.553)	(-1.962)	(-2.686)	(-3.957)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.375	0.405	0.172	0.562	0.192	0.194
Incremental R^2	+0.221	+0.192	+0.078	+0.022	+0.126	+0.066
Observations	241	241	241	241	241	241
Panel B.	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}	-0.261	-0.234	-0.268	-0.197	-0.236	-0.352
	(-3.666)	(-3.665)	(-3.739)	(-3.786)	(-2.538)	(-6.350)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.463	0.499	0.153	0.600	0.203	0.216
Incremental R^2	+0.136	+0.113	+0.095	+0.062	0.137	+0.088
Observations	241	241	241	241	241	241

Pre-COVID period

Throughout the paper we use the sample period 1999:11 to 2023:03. In Table 1.17 we limit the sample period up untill Covid i.e 1999:11 to 2020:01. The coefficients and adjusted R-squared in Table 1.17 are slightly reduced compared to the main sample reported in Table 2, Panel B. This is consistent given the large macroeconomic shock in the dependent variables around March 2020. Figure 1.14 as an example, highlights the volaility introduced by extending the sample period past 2020.

Table 1.17: **Pre-COVID sample**

Panel A mirrors Table 2, Panel B, in the main manuscript. Panel B reports the same specification but uses a sample period ending in January 2020.

	Forecast horizon: h = 3m					
Panel A.	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}	-0.356	-0.327	-0.242	-0.112	-0.278	-0.304
	(-4.528)	(-4.598)	(-3.553)	(-1.962)	(-5.383)	(-7.362)
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	+0.154	+0.245	+ 0.03	-0.022	+0.083	+0.139
Observations	241	241	241	241	241	241

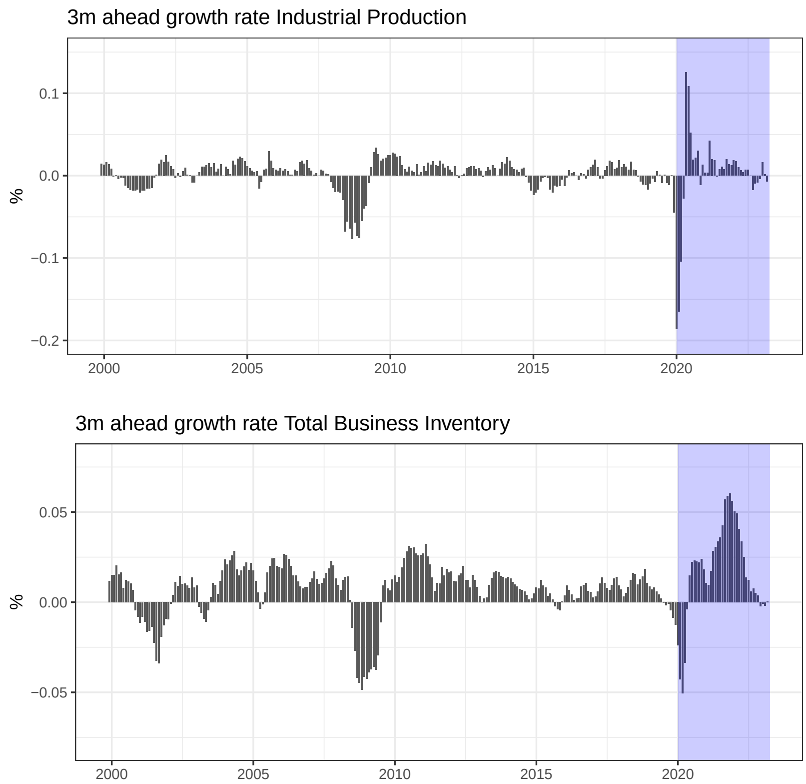


Figure 1.14: **Dependent variable across the sample period**

Alternative variables

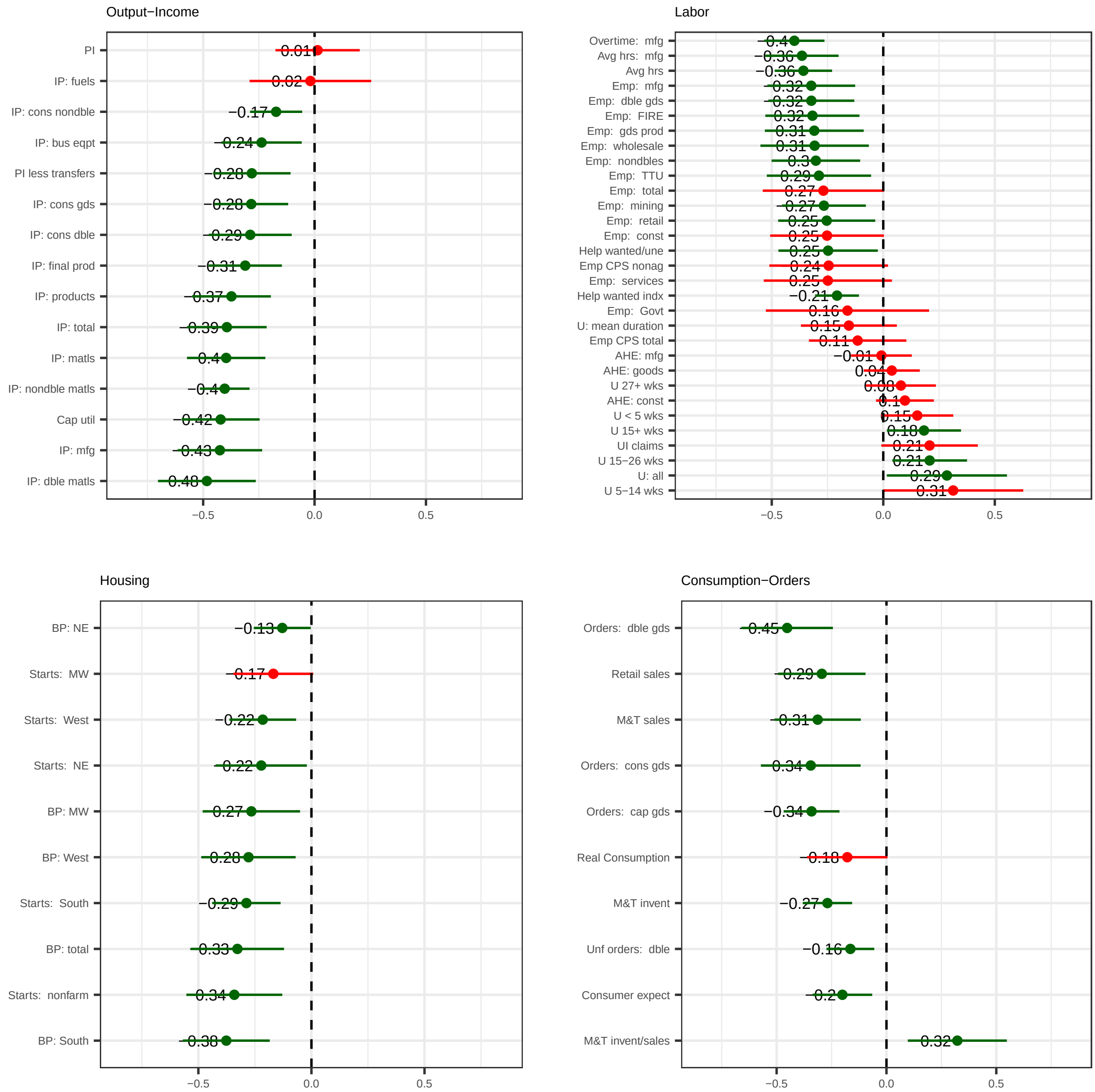


Figure 1.15: **Other macroeconomic indicators**
This figure plots the coefficient on the loan spread across a range of macroeconomic variables from the FRED-MD dataset. The specification is the same as our baseline loan spread forecasting model (Table 2, Panel A, column 7). Variables colored green are statically significant at the 5% level. Variables are grouped by theme (Output-Income, Labor, Housing, and Consumption-Orders). The sample period is 1999:11 to 2023:03.

Robustness tests for all macroeconomic outcomes

Table 1.18: **Robustness**

This table mirrors Table 3, Panel A, in the main manuscript but each panel shows robustness test for each of the six macro variables considered.

	Forecast horizon: h = 3m					
Panel A.	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
Residual ΔS_t^{Loan}	-0.393	-0.390	-0.286	-0.194	-0.364	-0.359
	(-4.401)	(-4.442)	(-3.794)	(-2.931)	(-4.494)	(-5.756)
Adjusted R^2	0.150	0.180	0.169	0.592	0.173	0.200
Incremental R^2	+0.148	+0.145	+0.076	+0.035	+0.125	+0.120
Panel B.						
ΔS_t^{Loan}	-0.363	-0.374	-0.282	-0.180	-0.430	-0.386
	(-3.861)	(-4.049)	(-3.983)	(-2.773)	(-4.780)	(-5.146)
Bid-Ask	-0.170	-0.138	0.016	-0.144	0.281	0.196
	(-1.434)	(-1.122)	(0.190)	(-2.078)	(2.665)	(2.525)
Adjusted R^2	0.174	0.200	0.162	0.606	0.240	0.220
Incremental R^2	+0.171	+0.165	+0.070	+0.049	+0.192	+0.140
Panel C.						
ΔS_t^{Loan}	-0.357	-0.360	-0.237	-0.175	-0.325	-0.289
	(-4.458)	(-4.634)	(-3.432)	(-3.043)	(-4.497)	(-4.533)
Δ S&P500	0.188	0.193	0.175	0.113	0.199	0.219
	(2.333)	(2.502)	(3.387)	(2.370)	(3.094)	(3.878)
Adjusted R^2	0.184	0.221	0.191	0.606	0.208	0.232
Incremental R^2	+0.182	+0.185	+0.099	+0.049	+0.159	+0.152
Panel D.						
ΔS_t^{Loan}	-0.327	-0.331	-0.282	-0.140	-0.445	-0.395
	(-2.900)	(-2.931)	(-3.819)	(-1.879)	(-4.010)	(-3.965)
ΔVIX	-0.150	-0.149	0.007	-0.140	0.170	0.110
	(-1.304)	(-1.292)	(0.076)	(-2.048)	(1.338)	(1.129)
Adjusted R^2	0.166	0.201	0.162	0.606	0.192	0.195
Incremental R^2	+0.164	+0.166	+0.070	+0.049	+0.143	+0.115
Panel E. Ex. 08-09						
ΔS_t^{Loan}	-0.256	-0.275	-0.091	-0.147	-0.225	-0.268
	(-2.144)	(-2.548)	(-1.920)	(-1.755)	(-2.503)	(-2.919)
Adjusted R^2	0.112	0.159	0.140	0.533	0.126	0.173
Incremental R^2	+0.110	+0.123	+0.047	-0.023	+0.077	+0.093
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
Observations	281	281	281	281	281	281

Impact of loan contract terms

Loan and bond contracts might be different with respect to, e.g., non-price contract terms (such as maturity, collateral and covenants and other characteristics such as size, age, and amount). To control for the impact of contract terms on loan spreads we orthogonalize loan spreads with respect to various characteristics, such as loan age, loan size, (log) loan amount, the loan's initial all-in-drawn spread, remaining time to maturity, as well as indicators for secured loans, senior loans, and financial covenants. We run the following regression

$$\begin{aligned} ln\ S_{it}[k] &= \alpha_b + \beta_1\ ln(Age) + \beta_2\ ln(Size) + \beta_3\ ln(Amt) + \beta_4\ ln(AISD) \\ &+ \beta_5\ Secured(0/1) + \beta_6\ Senior(0/1) + \beta_7\ Covenants(0/1) + \epsilon_{it}[k]. \end{aligned} \quad (1.7)$$

Column 5 of Table 1.27 (in the ELP section below) summarizes the result of this regression. We take the residual and use it in place of our loan spread in Column (1), Panel A Table 3 of the main paper. We find that this "residual loan spread", which controls for contract terms, has very little difference in predictive power relative to the baseline loan spread in Table 2 of the main paper.

Effects by maturity

Loans have shorter maturities (6 years) compared to bonds (11.6 years), on average. To examine if predictability varies by maturity we construct spreads for different maturity buckets. Table 1.19, Panel A, below reports results for loan spreads by maturity quartile. (The table only reports results using industrial production as dependent variable, for brevity. Results using the other indicators for economic development are similar.) The predictive power is overall slightly lower for the loan spread across all maturity buckets compared to the baseline estimate. This is because the subsamples are somewhat noisier due to the reduced number of observations.

However, there is little variation in predictive power across maturity buckets. Panel B performs the same exercise for the bond market with similar conclusions.

Table 1.19: **Effects by maturity**

Panel A of this table mirrors Table 2, Panel A, column 7, in the main manuscript. Columns 2 to 5 use the same specification but loan spreads are calculated separately for each loan maturity quartile. Table B of this table performs the same exercise for the bond spread (here, Table 2, Panel A, column 4, in the main manuscript is the baseline). Disaggregated bond spreads are only available from 2002 onwards, hence the shorter sample.

	Forecast horizon: h = 3m				
Panel A.	IP	IP	IP	IP	IP
	Baseline	Mat. Q1	Mat. Q2	Mat. Q3	Mat. Q4
	(1)	(2)	(3)	(4)	(5)
ΔS_t^{Loan}	-0.323	-0.277	-0.296	-0.297	-0.303
	(-3.414)	(-3.298)	(-2.836)	(-3.513)	(-2.828)
Term Spread	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓
Adjusted R^2	0.173	0.150	0.163	0.165	0.170
Incremental R^2	+0.171	+0.147	+0.161	+0.162	+0.167
Observations	281	281	281	281	281
Panel B.	IP	IP	IP	IP	IP
	Baseline	Mat. Q1	Mat. Q2	Mat. Q3	Mat. Q4
	(1)	(2)	(3)	(4)	(5)
ΔS_t^{Bond}	-0.292	-0.087	-0.091	-0.190	-0.047
	(-2.729)	(-1.662)	(-1.378)	(-1.986)	(-1.141)
Term Spread	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓
Adjusted R^2	0.085	-0.001	-0.0004	0.028	-0.006
Incremental R^2	+0.082	-0.004	-0.003	+0.025	-0.009
Observations	281	246	246	246	246

Economic uncertainty

Figure 1.16 below shows the correlation between changes in the loan spread and various uncertainty proxies. The correlation is positive, in particular between the loan spread and the VIX. Table 1.20, Panel B, reports a kitchen sink specification with all the uncertainty proxies simultaneously. The results show that even when we add in all the uncertainty proxies jointly the loan spread remains significant.

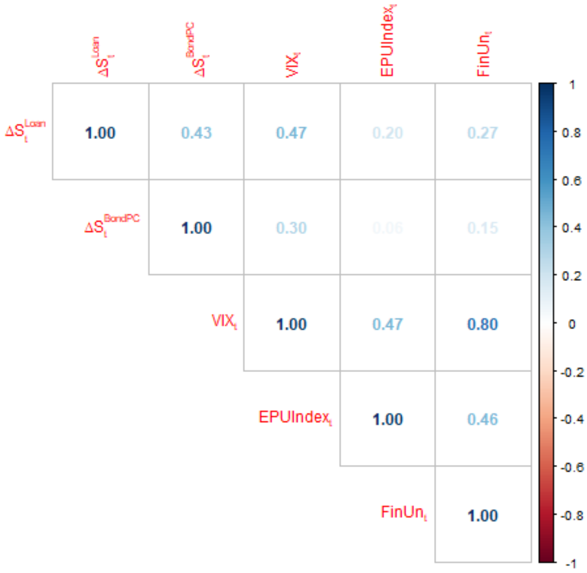


Figure 1.16: **Correlation across credit spreads and uncertainty proxies**
The figure shows the cross correlations across the loan/bond spead and each proxy for uncertainty. VIX_t is the VIX (level) at time t, $EPUIndex_t$ is the Economic Policy Uncertainty (EPU) index of Baker *et al.* (2016), and $FinUn_t$ is the Financial Uncertainty index (3m ahead) of Jurado *et al.* (2015).

Table 1.20: **Uncertainity proxies**

Panel A of this table mirrors Table 3, Panel A, column 4, in the main paper (but reports results for all six dependent variables). Panel B shows the same specification but includes additional uncertainty proxies in the model. VIX_t is the VIX (level) at time t, $EPUIndex_t$ is the Economic Policy Uncertainty (EPU) index of (Baker *et al.*, 2016), and $FinUn_t$ is the Financial Uncertainty index (3m ahead) of (Jurado *et al.*, 2015).

	Forecast horizon: h = 3m					
Panel A.	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}	-0.327	-0.331	-0.282	-0.140	-0.445	-0.395
	(-2.900)	(-2.931)	(-3.819)	(-1.879)	(-4.010)	(-3.965)
VIX	-0.150	-0.149	0.007	-0.140	0.170	0.110
	(-1.304)	(-1.292)	(0.076)	(-2.048)	(1.338)	(1.129)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.166	0.201	0.162	0.606	0.192	0.195
LR Test(χ^2)	25.9	27.6	19.2	10.4	31.5	37.5
Observations	281	281	281	281	281	281
Panel B.						
ΔS_t^{Loan}	-0.395	-0.395	-0.321	-0.168	-0.492	-0.432
	(-3.553)	(-3.708)	(-4.524)	(-2.087)	(-4.258)	(-4.462)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
VIX_t	✓	✓	✓	✓	✓	✓
$EPUIndex_t$	✓	✓	✓	✓	✓	✓
$FinUn_t$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.254	0.304	0.196	0.614	0.239	0.238
Incremental R^2	+0.251	+0.269	+0.104	+0.057	+0.190	+0.159
Observations	281	281	281	281	281	281

Macro Shocks

In Table 1.21 below, we use the shocks used by Boons, Ottonello and Valkanov (2023) in our baseline regression. As per your suggestion, we orthogonalize the loan spread w.r.t. each shock and use the residual. Note that, due to data availability, the sample size is smaller in Panel B and C (compared to A). Specifically, Boons *et al.* (2023) utilize three shocks; the oil supply shock from Baumeister and Hamilton (2019), the investment specific technology (IST) news shock from Zeev and Khan (2015), and the military spending shock from Ramey (2011). The oil shock is a monthly variable, with updated data available from the author's website, thus Panel A matches our sample period. The IST shock is a quarterly variable, with no updated data available. The effective sample period is 1999Q4:2012Q2. The defense spending shock is also a quarterly variable, with no updated data available. The effective sample period is 1999Q4:2015Q2. Because of the different frequencies and sample periods, we report separate results for each shock. Despite these limitations, Table 1.21 confirms that the coefficient on the (residualized) loan spread is largely unaffected, relative to the baseline results reported in Table 2 in the paper.

Table 1.21: **Boons, Ottonello, and Valkanov (2023) Shocks**

	Forecast horizon: h = 3m					
Panel A. Oil Shock	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta S_t^{Loanresid}$	-0.289	-0.292	-0.239	-0.161	-0.310	-0.282
	(-2.864)	(-3.048)	(-2.674)	(-2.645)	(-3.211)	(-4.151)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.087	0.123	0.160	0.576	0.137	0.149
Observations	280	280	280	280	280	280
Panel B. IST News	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta S_t^{Loanresid}$	-0.469	-0.469	-0.527	-0.216	-0.417	-0.395
	(-3.911)	(-3.327)	(-3.931)	(-2.971)	(-3.779)	(-2.932)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.500	0.529	0.221	0.628	0.205	0.381
Observations	49	49	49	49	49	49
Panel C. Defense Spending News	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta S_t^{Loanresid}$	-0.369	-0.315	-0.308	0.011	-0.337	-0.551
	(-3.440)	(-3.218)	(-3.988)	(0.285)	(-2.750)	(-5.591)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
$\Delta S_t^{Bond\ PC}$	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.430	0.492	0.284	0.661	0.144	0.247
Observations	57	57	57	57	57	57

Effects by rating category

Table 1.22: **Robustness – bond spreads by rating category**

	Forecast horizon: h = 3m				
Panel A.	IP	IP	IP	IP	IP
	(1)	(2)	(3)	(4)	(5)
ΔS_t^{Loan}	-0.397	-0.422	-0.418	-0.399	-0.415
	(-4.585)	(-4.540)	(-4.337)	(-4.685)	(-4.327)
$\Delta S_t^{Bond-A's}$		0.045			0.031
		(0.985)			(0.748)
$\Delta S_t^{Bond-BBB's}$			0.011		0.026
			(0.294)		(0.747)
$\Delta S_t^{Bond-HY's}$				-0.080	-0.082
				(-2.032)	(-2.084)
Term Spread	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓
Adjusted R^2	0.154	0.156	0.155	0.161	0.155
Observations	281	246	246	246	246
Panel B.	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)
ΔS_t^{Loan}	-0.425	-0.288	-0.233	-0.385	-0.318
	(-4.446)	(-3.279)	(-3.461)	(-4.224)	(-4.205)
$\Delta S_t^{Bond-A's}$	0.034	0.015	0.044	0.021	0.026
	(0.756)	(0.415)	(1.124)	(0.536)	(0.503)
$\Delta S_t^{Bond-BBB's}$	0.029	-0.016	-0.004	-0.027	-0.056
	(0.851)	(-0.348)	(-0.078)	(-0.473)	(-1.294)
$\Delta S_t^{Bond-HY's}$	-0.082	0.031	-0.052	-0.002	-0.059
	(-2.063)	(0.626)	(-1.523)	(-0.042)	(-1.499)
Term Spread	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓
Adjusted R^2	0.174	0.173	0.598	0.153	0.184
Observations	246	246	246	246	246

Table 1.23: **Impact of loan rating**

This table mirrors Table 2, Panel B, in the main manuscript but creates a loan spread for different rating categories.

	Forecast horizon: h = 3 months					
	IP	TCU	NEW	INV	ISM-MAN	ISM-NMAN
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}[BBB]	-0.090	-0.087	-0.132	-0.096	-0.020	-0.073
	(-1.518)	(-1.571)	(-2.191)	(-2.873)	(-0.187)	(-0.776)
Adjusted R^2	0.110	0.131	0.168	0.576	0.217	0.219
Incremental R^2	+0.107	+0.095	+0.076	+0.019	+0.169	+0.139
ΔS_t^{Loan}[BB]	-0.153	-0.149	-0.179	-0.096	-0.192	-0.170
	(-1.608)	(-1.589)	(-2.937)	(-1.885)	(-2.275)	(-2.432)
Adjusted R^2	0.110	0.143	0.161	0.591	0.228	0.213
Incremental R^2	+0.108	+0.107	+0.069	+0.034	+0.180	+0.133
ΔS_t^{Loan}[B and below]	-0.285	-0.284	-0.197	-0.123	-0.223	-0.218
	(-2.695)	(-2.718)	(-2.415)	(-2.048)	(-2.675)	(-2.935)
Adjusted R^2	0.157	0.189	0.167	0.595	0.238	0.227
Incremental R^2	+0.154	+0.154	+0.074	+0.038	+0.190	+0.147
ΔS_t^{Loan}[Not Available]	-0.298	-0.301	-0.179	-0.138	-0.201	-0.208
	(-3.169)	(-3.368)	(-2.242)	(-2.732)	(-2.966)	(-2.874)
Adjusted R^2	0.163	0.198	0.160	0.598	0.231	0.223
Incremental R^2	+0.161	+0.162	+0.068	+0.041	+0.182	+0.143
Controls:						
ΔS_t^{BondPC}	✓	✓	✓	✓	✓	✓
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
Observations	281	281	281	281	281	281

Europe and Industry level

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). Finally, we report "kitchen-sink" models that additionally include the country-specific stock market index, the European "VIX" (VSTOXX), and the loan market bid-ask spread (similar to Table **??**, Panel B). Starting with Germany, we find that the loan spread adds 7.7 p.p. R^2 to a baseline model without credit spreads (see Table 1.24, Panel A, column 1). The addition of the bond spread in column 2 adds only 2.7 p.p. to the R^2. In column 3 we report the "kitchen-sink" model; the loan spread retains its predictive power. In columns 4 to 9 we find similar results for France and Spain.

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 1.2, 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 Labor Statistic's (BLS). In addition, we use quarterly industry gross output from the BEA.[48]

The results are reported in Panel B. Column 1 starts with a model that includes the industry and aggregate loan spread in a pooled regression.[49] Column 2 adds time fixed

[48] 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.

[49] 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.

effects that absorb any common time trends. 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. In column 4, 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 the predictive power of the industry loan-spread. In columns 5 to 8 we use establishments and output as outcome variables and find similar results.[50]

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.

[50] In Online Appendix D.16 we explore if the predictive power of loan spreads varies across industries. We find that loan spreads have more predictive power in industries that comprise firms more dependent on external finance.

Table 1.24: **Robustness across industries and countries**

Panel A of this table relates credit spread measures to future economic outcomes across European countries. The unit of observation is the monthly level t. The sample period is 2002:03 to 2022:03 for Germany (columns 1 to 3), 2002:03 to 2022:09 for France (columns 4 to 6), and 2002:03 to 2023:03 for Spain (columns 7 to 9). The dependent variable is the three-month ahead percentage change in the country's manufacturing production index, i.e., growth from $t-1$ to $t+3$. Each specification includes (not shown) a one-period lag of the dependent variable, i.e., growth from $t-2$ to $t-1$, the term spread, i.e., the difference between 10-year Euro government bond (a GDP-weighted average of all Euro area government bonds) and three-month EURIBOR, and the real EONIA, i.e., the overnight rate minus realized inflation. Further included are the country-specific stock market index, the European "VIX" (VSTOXX), and the (country-specific) median bid-ask spread in the secondary loan market, 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 spreads. S_t^{Loan} is our country-specific loan spread measure (see section 2 of the main paper for details). S_t^{Bond} is the country-specific bond spread from Mojon and Gilchrist (2016). Panel B of 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 2021:12. The dependent variable in columns 1 to 4 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 columns 5 and 6 is the one-quarter-ahead percentage change in establishments. The dependent variable in columns 7 and 8 is the one-quarter-ahead percentage change in gross output. Each specification includes (not reported) a one-period lag of the dependent variable, i.e., the growth from $t-2$ to $t-1$. The model reported in column (1) further includes the aggregate loan spread, term spread, and the real FFR (not shown). S_{bt}^{Loan} (S_{bt}^{Bond}) is an industry-specific loan (bond) spread measure (see section **??** for details). 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.

Panel A Across country	Germany MAN	Germany MAN	Germany MAN	France MAN	France MAN	France MAN	Spain MAN	Spain MAN	Spain MAN
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔS_t^{Loan}	-0.293	-0.230	-0.185	-0.155	-0.118	-0.121	-0.219	-0.194	-0.174
	(-2.226)	(-1.827)	(-1.575)	(-1.518)	(-1.627)	(-1.775)	(-1.730)	(-1.704)	(-1.525)
ΔS_t^{Bond}		-0.189	-0.136		-0.211	-0.162		-0.155	-0.108
		(-2.669)	(-1.947)		(-1.898)	(-1.516)		(-1.502)	(-1.011)
EU Term Spread	✓	✓	✓	✓	✓	✓	✓	✓	✓
EONIA	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bid-Ask			✓			✓			✓
ΔStock Index			✓			✓			✓
ΔVIX			✓			✓			✓
Adj R^2	0.139	0.167	0.193	0.062	0.099	0.105	0.059	0.078	0.081
Incremental R^2	+0.077	+0.104	+0.131	+0.014	+0.051	+0.056	+0.040	+0.059	+0.062
Observations	247	247	247	221	221	221	220	220	220

Panel B. Across industry	EMP	EMP	EMP	EMP	EST	EST	OUT	OUT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
S_{bt}^{Loan}	−0.174	−0.132	−0.133	−0.135	−0.108	−0.111	−0.248	−0.210
	(−2.244)	(−2.180)	(−2.183)	(−2.187)	(−1.160)	(−1.090)	(−2.724)	(−2.734)
S_t^{Loan}	−0.267							
	(−2.737)							
S_{bt}^{Bond}				−0.057		−0.104		−0.085
				(−2.449)		(−2.120)		(−2.081)
Year × qtr fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Overall R^2	0.167	0.502	0.503	0.534	0.403	0.416	0.513	0.517
Within R^2	-	0.049	0.048	0.081	0.115	0.130	0.044	0.053
Incremental R^2	+0.156	+0.491	+0.492	+0.523	+0.320	+0.333	+0.510	+0.514
Observations	1,001	1,001	1,001	880	1,001	880	744	744

Orthogonalized spread

The correlation between the loan and bond spreads is high (0.74), albeit weaker in changes (0.48) which we use in the predictive regressions. We therefore carefully establish the loan spread's predictive power first by comparing the predictive power across models that include different spreads instead of a joint forecasting model including all information (which might be plagued by multicollinearity issues). Further, when including loan and bond spreads jointly, we generally only use the first principal component across all bond spreads, as the different bond spreads are also highly correlated with each other.

An alternative approach is to orthogonalize the loan spread and use the residual component in the predictions. Table 1.25 below, shows the results using 3-month ahead industrial production as dependent variable (results are similar for the other measures of economic development). Results using orthogonalized spreads are similar compared to the results obtained by the cross-model comparisons reported in the paper. For instance, adding the loan spread orthogonalized w.r.t. Gilchrist and Zakrajšek (2012)'s bond spread increases the model's R^2 by approximately 8 p.p. (Table 1.25, column 3). This is approximately equivalent to comparing the incremental R^2 of a model that just adds the loan spread to the baseline (Table 1.25, column 1) and a model that just adds the bond spread (Table 1.25, column 2). Here, the loan versus bond incremental R^2 difference amounts to 15.1 p.p. – 8.2 p.p. = 6.9 p.p.

Column 4 reports results that additionally include the bid-ask spread, the S&P 500 return, and the VIX in the model (i.e., the additional controls from Table 3, Panel B). While these factors add to the explanatory power of the model, the orthogonalized loan spread remains highly statistically and economically significant. Similar results can be obtained when orthogonalizing w.r.t. the Baa-Aaa spread (columns 5-6).

Table 1.25: **Orthogonalized loan spread**

This table mirrors Table 2, Panel A, in the main manuscript. Column 1 (2) re-reports column 6 (5) from Table 2, Panel A, in the main manuscript, for comparison. In columns 3-4 (5-6) we report specifications that instead use the loan spread orthogonalized w.r.t. the bond spread (the Baa spread) in the forecasting regressions.

	Forecast horizon: h = 3m					
	IP	IP	IP	IP	IP	IP
	(1)	(2)	(3)	(4)	(5)	(6)
ΔS_t^{Loan}	-0.397					
	(-4.585)					
ΔS_t^{Bond}		-0.292				
		(-2.729)				
$\Delta S_t^{Loan,\text{ orthog. w.r.t Bond}}$			-0.291	-0.252		
			(-2.618)	(-2.342)		
$\Delta S_t^{Loan,\text{ orthog. w.r.t Baa}}$					-0.242	-0.154
					(-2.268)	(-2.140)
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓
Bid-Ask				✓		✓
SP500				✓		✓
VIX				✓		✓
Adjusted R^2	0.154	0.085	0.081	0.171	0.056	0.141
Incremental R^2	+0.151	+0.082	+0.079	+0.168	+0.053	+0.139
Observations	281	281	281	281	281	281

Out of sample

Next, we provide indicative evidence that the loan spread's predictive power extends to out-of-sample forecasts. Out-of-sample performance is measured via an expanding window. Specifically, we start with 60 months of data and forecast the dependent variable one step ahead, i.e., over the next three-months. We then compare the forecast to the actual growth rate and calculate the forecast error. We repeat this procedure rolling forward one month at a time. This yields a vector of forecast errors across different training/testing windows that can be used for root mean squared error (RMSE) comparisons across models. We use a sample period from 1999:11 to 2020:01, due the to significant variation in dependent variables introduced by the COVID-19 shock as show in Figure 1.14.

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

Consistently across all macro variables, the model with the loan spread returns the lowest

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

Table 1.26: **Out-of-sample**

This table computes the out of sample performance of each forecasting regression. The unit of observation is the monthly level t. The sample period is 1999:11 to 2020:01. The dependent variable in Panel A is the three-month-ahead percentage change in industrial production (IP) i.e., the growth from $t-1$ to $t+3$. Panel B uses total industrial capacity utilization (TCU), Panel C uses new orders for capital goods (ex. defence) (NEW), Panel D uses total business inventories (INV), Panel E uses ISM manfacturing (ISM-MAN) and Panel F uses ISM non-manfacturing (ISM-NMAN). Column (1) calculates the out of sample RMSE via cross validation using a rolling window and a one step ahead horizon. Within each panel we compare three models: "Baseline" contains only one-period lag of the dependent variable, i.e., growth from $t-2$ to $t-1$, the term spread, i.e., the difference between 10-year and three-month U.S. Treasury, and the real FFR, i.e., the effective federal funds rate minus realized inflation. "Baseline + PC Bond spreads" adds the first principal component extracted from $\Delta S_t^{Baa\text{-}Aaa}$, $\Delta S_t^{HY\text{-}AAA}$, and ΔS_t^{Bond}, and "Baseline + S_t^{Loan}" uses S_t^{Loan}. Normalized CV RMSE, scales the CV RMSE by the standard deviation of the dependent variable in order to compare across panels. Column (3) is a t-test of a difference in the mean RMSE between "Baseline + PC Bond spreads" and "Baseline + S_t^{Loan}"

	OOS horizon: h = 3 month		
	CV RMSE	Normalized CV RMSE	$T-stat(p-value)$
	(1)	(2)	(3)
Panel A. IP			
Baseline	0.0125	0.7033	-
Baseline + $\Delta S_t^{Bond\ PC}$	0.0125	0.7027	-
Baseline + ΔS_t^{Loan}	0.0113	0.6359	$-2.836(0.005)$
Panel B. TCU			
Baseline	0.9751	0.6807	-
Baseline + $\Delta S_t^{Bond\ PC}$	0.9775	0.6823	-
Baseline + ΔS_t^{Loan}	0.9009	0.6289	2.482(0.014)
Panel C. NEW			
Baseline	0.1036	0.7878	-
Baseline + $\Delta S_t^{Bond\ PC}$	0.1031	0.7839	-
Baseline +ΔS_t^{Loan}	0.0985	0.7493	$-1.773(0.085)$
Panel D. INV			
Baseline	0.0098	0.5158	-
Baseline + $\Delta S_t^{Bond\ PC}$	0.0097	0.5142	-
Baseline + ΔS_t^{Loan}	0.0092	0.4838	$-1.652(0.100)$
Panel E. ISM-MAN			
Baseline	3.5860	0.7343	-
Baseline + $\Delta S_t^{Bond\ PC}$	3.3507	0.6861	-
Baseline +ΔS_t^{Loan}	3.3923	0.6946	$-0.38(0.703)$
Panel F. ISM-NMAN			
Baseline	2.7997	0.70853	-
Baseline + $\Delta S_t^{Bond\ PC}$	2.5973	0.6573	-
Baseline +ΔS_t^{Loan}	2.5542	0.6464	0.5479(0.583)

Loan vs bond spread dynamics

Section 4.3 of the main paper discusses the forecasting power at various forecast horizons in a local projection framework. Specifically, Figure 5 of the main paper 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. In Figure 1.17 we repeat this exercise, but add in the first bond PC, and again plot the coefficient on the loan spread. Therefore, Figure 1.17 highlights the forecasting power of the loan spread at various forecasting horizons, above and beyond the bond market.

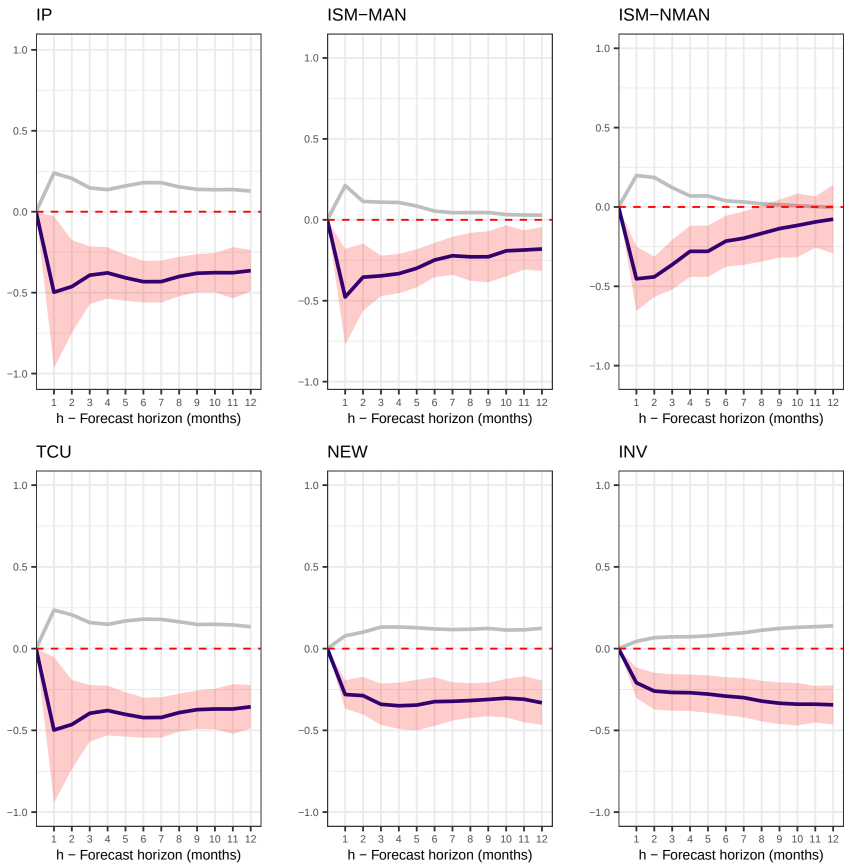


Figure 1.17: **Local Projections and Incremental R-squared**
This figure plots the impulse response function using a Jordà (2005) local projections framework (blue line) and the incremental adjusted R^2 (black line). In each figure, the dependent variable is the h-month ahead growth in the macro variable. Each specification includes the bond spread PC. 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 gray 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 2023:03.

Excess loan premium

We follow Gilchrist and Zakrajšek (2012) and decompose the loan spread into two components: a component that captures changes in default risk based on the fundamentals of a firm or differences in contractual terms and a residual component that captures the price of risk above a default risk premium. We source estimates for firm level distance-to-default (DtD) from NUS-CRI, which estimates DtD based on an adjusted Merton (1974) model.[51]

Decomposition: To isolate the portion of the loan spread driven by variation in the expected default of the firm or contractual terms, we regress the natural logarithm of the loan spread of loan k on the firm level distance-to-default ($\overline{DD}_{it}$), if available, otherwise we use the average distance-to-default across all firms in the industry in the respective month ($\overline{DD}_{bt}$) in it's place. We further include a squared term ($\overline{DD}^2_{it/bt}$) to capture a possible non-linear effect of DD on loan spreads, as well as the volatility of DD across firms in the industry (σDD_{bt}). We run the following regression

$$ln\ S_{it}[k] = \alpha_b + \beta_1\ \overline{DD}_{it/bt} + \beta_2\ \overline{DD}^2_{it/bt} + \beta_3\ \sigma DD^2_{bt} + \gamma^{'} Z_{it}[k] + \epsilon_{it}[k]. \tag{1.8}$$

Table 1.27 shows the results of these regressions. Column (1) begins by including only the DD regressors. As expected, a higher DD reduces loan spreads and the positive coefficient on $\overline{DD}^2_{it/bt}$ is consistent with a non-linear effect. Column (2) then adds a vector of loan-level control variables ($Z_{(it)}[k]$), including the (log) loan amount, the (log) age of the issue and (log) AISD. Column (3) further includes a dummy variable indicating whether the loan includes financial covenants, is a secured loan, and is senior. The signs of the coefficients are as expected: larger loans or those that are secured have lower loan spreads (although the secured effect is not statistically significant). Loans with a higher initial spread (AISD) also trade at higher spreads in the secondary market. The coefficients for the covenant and seniority indicators are insignificant. Loan terms have considerable explanatory power for spreads increasing the adjusted R^2 to about 34%. Column (4) further includes fixed effects for loan type, borrower industry, and loan rating category. The main results remain unchanged. We use the results from column 4 to calculate the predicted loan spread as

[51] The CRI database, the Credit Research Initiative of the National University of Singapore, available at: http://nuscri.org. See CRI documentation for details.

Table 1.27: **Decomposing the loan spread**

This table shows the results of the loan spread decomposition based on Gilchrist and Zakrajšek (2012). The dependent variable is the loan spread for facility i at time t. $\overline{DD}_{bt}$ is the firm level distance-to-default (if available), otherwise we use the average distance-to-default across all firms in the industry in the respective month ($\overline{DD}_{bt}$) in it's place. $\overline{DD}_{bt}^2$ is the distance to default squared. σDD_{bt} is the volatility of DD_{bt} across firms in the same industry. $AISD$ is the all-in-spread-drawn measured in basis points. *Age* is measured as the time elapsed since the loan is first reported in Dealscan. *Amount* is measured as the par amount of the loan at issuance. *Covenants* is a dummy variable that equals 1 if the loan contract includes covenants. *Secured* is a dummy variable that equals 1 if the loan is secured by collateral. *Senior* is a dummy variable that equals 1 if the loan is senior. t-statistics, based on time and loan clustered standard errors, are reported in parentheses.

Panel A. Decomposing loan spreads	(1)	(2)	(3)	(4)	(5)
$\overline{DD}_{bt}$	−0.139	−0.174	−0.173	−0.166	
	(−19.070)	(−24.820)	(−25.000)	(−25.140)	
$\overline{DD}_{bt}^2$	0.004	0.007	0.007	0.007	
	(6.727)	(12.490)	(12.600)	(12.600)	
σDD_{bt}	−0.038	−0.095	−0.095	−0.092	
	(−6.482)	(−21.900)	(−22.340)	(−24.010)	
$Ln(AISD)$		0.709	0.715	0.579	0.665
		(34.180)	(31.770)	(21.860)	(28.610)
$Ln(Age)$		0.070	0.070	0.060	0.078
		(28.110)	(28.140)	(28.040)	(29.970)
$Ln(Amount)$		−0.107	−0.107	−0.107	−0.102
		(−14.970)	(−14.820)	(−16.250)	(−13.790)
$Secured(0/1)$			−0.033	−0.004	0.030
			(−1.326)	(−0.156)	(1.161)
$Covenants(0/1)$			0.013	0.016	0.044
			(0.851)	(1.130)	(2.808)
$Senior(0/1)$			0.027	0.033	0.029
			(0.320)	(0.791)	(0.640)
Loan type fixed effects	No	No	No	Yes	No
Industry fixed effects	No	No	No	Yes	No
Rating fixed effects	No	No	No	Yes	No
Adjusted R^2	0.054	0.396	0.396	0.457	0.314
Observations	258,496	256,965	256,965	256,965	256,965

$$\hat{S}_{bt}^{Loan} = \exp\left[\hat{\beta}_1\ \overline{DD}_{it/bt} + \hat{\beta}_2\ \overline{DD}_{it/bt}^2 + \hat{\beta}_3\ \sigma DD_{bt}^2 + \hat{\gamma}'\, Z_{it}[k] + \frac{\hat{\sigma^2}}{2}\right] \tag{1.9}$$

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

To show the robustness of our ELP results w.r.t different spread decomposition models, we implement an alternative model. The key ingredient of the decomposition is the proxy for firm default risk. In the baseline specification we use the issuers' distance-to-default (DTD) following Gilchrist and Zakrajšek (2012). An alternative measure of firm default risk is the issuer's CDS spread. The CDS spread might be a more timely measure compared to DTD. Because entity level CDS are available for only a select number of borrowers, we again construct CDS spreads at the industry level and use CDS spreads in place of DTD in calculating our ELP. The correlation between ELP from CDS and ELP from DTD is 0.76. We repeat our baseline forecasting regressions using this alternative ELP definition. Table 1.28 reports our baseline result using DTD in Panel A, and the alternative decomposition using CDS in Panel B. Results are similar across both measures.

Table 1.28: **Alternative credit-spread decomposition**

Panel A of this table mirrors Table 5, Panel A, in the main paper. Panel B reports the same model but uses issuer CDS spreads instead of DTD in the credit spread decomposition.

	Forecast horizon: h = 3 month					
	IP	PEMP	UE	TCU	NEW	INV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Using DTD (baseline)						
ΔELP_t	-0.251	-0.254	-0.191	-0.113	-0.248	-0.213
	(-2.892)	(-3.104)	(-2.523)	(-2.118)	(-3.501)	(-3.215)
$\Delta \hat{S}_t^{Loan}$	-0.157	-0.185	-0.037	-0.098	-0.028	-0.023
	(-1.590)	(-1.902)	(-0.565)	(-1.944)	(-0.294)	(-0.307)
Adjusted R^2	0.159	0.201	0.175	0.603	0.254	0.234
Observations	272	272	272	272	272	272
Panel B. Using CDS						
ΔELP_t	-0.324	-0.319	-0.224	-0.164	-0.267	-0.238
	(-3.375)	(-3.410)	(-2.967)	(-3.138)	(-3.857)	(-3.587)
$\Delta \hat{S}_t^{Loan}$	0.016	-0.010	0.051	0.027	-0.017	0.066
	(0.150)	(-0.099)	(0.852)	(0.656)	(-0.236)	(0.796)
Adjusted R^2	0.176	0.193	0.185	0.615	0.236	0.243
Observations	267	267	267	267	267	267
Controls in Panel A-B:						
Term Spread	✓	✓	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓

Chapter 2

Market Segmentation and Cross-predictability

Alessandro Spina [1]

Abstract

I examine how information diffuses slowly across financial markets by testing for cross-predictability in asset prices. I find an increase in loan spreads of upstream industries can predict an increase in loan spreads of downstream industries, but only in the post-2010 period. The emergence of predictability coincides with an increase in institutional investor activity in the loan market. Furthermore, I find cross-predictability within equity returns has disappeared over the same period. These results indicate that information diffusion varies across asset classes and this, in part, has been influenced by changes in the structure of markets.

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2.1 Introduction

In a perfect world, new information is immediately incorporated into security prices by market participants. This assumption of complete, frictionless markets has been challenged by ample empirical evidence that information can take time to be fully integrated, leading to cross-predictability in returns. This "information segmentation" hypothesis has been extensively tested in equity markets. Cross-predictability has been documented between the returns of economically connected firms by Cohen and Frazzini (2008), and related industries by Menzly and Ozbas (2010). However, over the last two decades, an active secondary market has developed, where U.S. corporate syndicated loans are traded like securities. The availability of granular data on loan prices now allows the study of cross-predictability in the loan market. The study of information dynamics in credit markets is particularly interesting as it is not clear *a priori* what to expect. Institutional dominance in credit markets may encourage information dissemination, yet the inherent illiquidity and opacity of credit markets might impede such information diffusion.

In this paper I examine the hypothesis that information diffuses slowly, by testing whether asset prices in one industry can predict prices in a related industry. I test the ability of loan spreads to predict loans spreads in other industries and find that predictability depends on the period investigated. I then test if a similar time dependence can be found in equity markets, and I find that this is indeed the case. I hypothesize and deliver some preliminary evidence that the changes in market structure can explain these patterns.

First, I test information segmentation *within* the loan market. I test the ability of industry-specific loan spreads to predict industry-specific loan spreads in economically related industries. I use the Bureau of Economic Analysis (BEA) Input-Output tables to identify the connections between upstream and downstream industries. Over the full sample, 1999 - 2022, I find loan spreads of upstream industries do not predict future changes in the loan spread of downstream industries.

However, this sample period has seen significant changes to the structure of the loan market suggesting that information segmentation may have changed over time. Collateralised Loan Obligation (CLO) managers have become the largest investor in the syndicated loan market, now accounting for approximately 70% of all loan holdings[2]. Trading in secondary

[2] https://www.stlouisfed.org/en/on-the-economy/2019/october/syndicated-loans-us

loan markets has increased from $100bill(USD) in 2000 to over $823bill(USD) in 2022, see Saunders *et al.* (2023). Focusing on the post-2010 period, I find a 100bps increase in the loan spread of upstream industries is associated with a 32bps increase in the loan spread of downstream industries in the following month. A potential explanation for cross-predictability is industry specialization by loan market investors. If CLO managers specialise along industry lines, an informative signal arising in one industry is received first by CLO managers specializing in that industry, leading to cross-predictability in loan spreads. I find evidence that CLO managers do specialize across industries. Using the measure of excess specialization from Blickle *et al.* (2023), I find CLO managers tend to over-invest in certain industries relative to the industry's market share. CLO manager specialization, coupled with the rapid increase in CLO manager trading, may explain the emergence of cross-predictability post-2010.

Second, I test information segmentation *across* the loan and equity market. Specifically, I test whether industry loan spreads can predict the same industry's future equity returns. Addoum and Murfin (2020) show that syndicated loan prices have the ability to predict future equity returns at the firm level. They examine a subset of firms with both loans and public equity outstanding and find information in publicly available loan prices predicts equity returns one month ahead. However, it is not clear if this pattern is unique to a subset of public firms or if there is information in the broader sample of loan spreads. This paper broadens the scope by considering the entire universe of secondary market-traded loans. Over the full 1999 - 2022 sample, I find no evidence that industry loan spreads predict industry equity returns. However, a significant change occurred in 2015, when the Wall Street Journal (WSJ) ceased publication of weekly loan prices, which informed the cross-market arbitrage of Addoum and Murfin (2020). It is plausible that this effectively increased search costs to any cross-market trading strategy. Consistent with this hypothesis, I find cross-predictability does appear post-2015. Specifically, a 100bps increase in loan spread predicts an 127bps higher equity return in the following month. This suggests that market integration across equity and loan markets deteriorated in the post-publication sample as frictions increased Shleifer and Vishny (1997).

Third, I test information segmentation *within* the equity market. Given the changes in cross-predictability I document in the loan market, I revisit cross-predictability in equity returns. Employing a sample period from 1962 to 2005, akin to Menzly and Ozbas (2010), I find a 100 basis points increase in upstream industry returns predicts a 16 basis points increase in downstream industry equity returns the following month. This aligns with the 11bps increase documented by Menzly and Ozbas (2010). However, extending the analysis to an out of sample period from 2005 to 2022, reveals equity returns in upstream industries no longer predict equity returns in downstream industries. This disappearance in predictability suggests equity markets have experienced a reduction in information segmentation, potentially facilitated by the rise of industry mutual funds and ETFs over this period[3].

The conflicting results in the loan and equity market, suggest market liquidity and market structure may interact in complex ways. Equity and loan markets have both experienced an increase in trading volume over the sample period studied, but cross-predictability patterns have diverged in the two markets. This suggests that information segmentation may initially increase at low levels of market liquidity, but at some point, further improvements in liquidity lead a decrease in market segmentation. This is consistent with an inverse-U shape relationship between liquidity and market segmentation, which can reconcile the different results I find across markets.

Fourth, I test if industry loan spreads can predict industry level economic activity. Saunders *et al.* (2023) establish that the aggregate loan spread has predictive power for aggregate economic activity. However, I argue that aggregation excludes useful information for prediction for at least three reasons. First, aggregate asset prices might not reflect the true sectorial distribution of economic activity. Second, aggregate fluctuations may have their origin in more granular sectorial shocks Gabaix (2011), Acemoglu *et al.* (2012). Third, sectorial shocks can come in two types: shocks which have a symmetric or asymmetric impact across industries. In line with this view, I find that industry specific loan spreads contain predictive power for industry level economic activity above and beyond aggregate loan spreads. Interestingly, no analogous pattern is found in industry equity returns, suggesting there is useful information in the cross-section of loan spreads, but not in the cross-section of equity returns.

This paper contributes to a large literature which explores what information is embedded in asset prices and how it diffuses across markets. Hong and Stein (1999) introduce a model with multiple investors in which information gradually spreads, generating return

[3] State Street's series of industry ETFs was launched in 1999, Vanguard's industry ETFs launched in 2004, and Blackrock's industry ETF's in 2000.

predictability. Menzly and Ozbas (2010) test this idea empirically and find that stocks in economically related industries cross-predict each other's equity returns. Similarly, Cohen and Frazzini (2008) identify firm's principal customers to identify a set of economically related firms, and show return cross-predictability. In this paper, I am the first, to the best of my knowledge, to study cross-predictability in credit markets.

Another strand of literature explores information integration across asset classes, with Linda Allen and Weintrop (2008) comparing loan and equity returns following earnings announcements and Altman *et al.* (2010) studying loan and bond returns around default events. However, these studies focus on specific information events, whereas this paper emphasizes tests of information integration more broadly. Allen and Gottesman (2006) investigate integration across the loan and equity market from 1999-2003 using Granger causality tests, but find no particular market consistently dominates the other. Addoum and Murfin (2020) test if loan prices can predict future equity returns for a set of public firms with both loans and public equity. In this paper, I extend these tests, to include all loans in a wider sample period covering 1999-2023. In a related paper, Hong *et al.* (2007) find that selected industry stock returns do have predictive power for future aggregate market returns. They find important macroeconomic information can arise in particular industries, but it takes time to spread to the rest of the market. This paper differs from Hong *et al.* (2007), in that I focus on the cross-predictability across industries, and across markets.

This paper is also related to an extensive forecasting literature which has documented the predictive power of a range financial market variables for economic activity, 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); Saunders *et al.* (2023). This literature has typically focused on aggregate asset prices, which I argue conceals useful information. I extend these tests to the industry level and document the additional predictive power in the cross-section of loan spreads.

The rest of the paper proceeds as follows. Secion 3.2 describes the data. Section 2.3.1 tests whether loan spreads can predict loan spreads of related industries. Section 2.3.2 tests whether loan spreads predict equity returns. Section 2.3.3 the test the diffusion of information across the equity market. Section 2.3.4 tests if loan spreads can predict economic activity. Section 3.7 provides concluding remarks.

2.2 Data

2.2.1 Industry economic data

The main source of economic data at the industry level comes from the Bureau of Economic Analysis (BEA). To define upstream and downstream industries I use the series of Input-Output (IO) Tables. IO data summarise the flow of commodities from production through intermediate use by industries to purchases by final users. Using the IO tables I can identify an industry's supplier industries directly by observing the flow of goods and services between industries. The IO tables consist of two sets of tables, labelled the "Make" and "Use" tables. The "Make" table shows the production of commodities by industries. The "Use" table shows the uses of commodities by intermediate and final users. These data are provided as a set of tables for each year. Figure 2.12 of the Online Appendix, provides a snapshot of the 2021 edition of the "Use" table. Specifically, Figure 2.12 reports the dollar-value of the inter-industry flows of goods. The airline industry depicted in the top-left panel, reveals that the industries most used by the airline industry are, Transport (TRANS), Food and Accommodation (FOOD), Financial Services (FIN), and Manufacturing (MAN). IO tables are available every year from 1999 to 2022.

The second key dataset from the BEA I make use of are the industry level economic aggregates. Since 2005, the BEA have published quarterly total gross output (TGO) and value added (VA) at a disaggregated industry level. TGO is essentially a measure of an industry's sales. These statistics capture an industry's total sales to consumers and other final users (found in GDP), as well as sales to other industries (intermediate inputs not counted in GDP). VA is a measure of the gross output of an industry less its intermediate inputs, i.e. the contribution of an industry to gross domestic product (GDP). The BEA reports quarterly TGO and VA for 88 industries which can be collapsed down to 15 industry groupings. For the majority of analysis in this paper I will aggregate data to the 15-industry level. I choose a 15-industry classification to ensure sufficient sample size within each industry to create a loan spread measure. Figure 2.13 plots TGO and VA over time for each industry, both time series are measured in "real" (in billions of $USD 2012 dollars) and are seasonally adjusted. Figure 2.14 show the proportion of TGO attributed to each industry over time. It reveals that MAN, FIN, and SERV are the top three industries and contribute the most to total aggregate TGO.

2.2.2 Industry credit spreads

I use industry loan spreads constructed by Saunders *et al.* (2023) using Loan Syndication and Trading Association (LSTA) data. LSTA provide observations of daily price quotes for the universe of loans traded in the secondary market [4]. Saunders *et al.* (2023) construct monthly loan spreads from 1999-2022 using the bottom-up methodology described by Gilchrist and Zakrajšek (2012). Firms are classified into one of 15 industry categories adopted by the BEA using firm SIC codes. Saunders *et al.* (2023) then construct a set of 15 industry specific loan spreads, by taking a monthly equal-weighted average of all loan spreads available in a given industry-b in month-t. Specifically, the industry loan spread is defined as:

$$S_{b,t}^{Loan} = \frac{1}{N_t} \sum_{b} \sum_{i} S_{i,t} \tag{2.1}$$

where $S_{i,t}$ denotes the loan spread of loan-i at time-t, and N is the number of loans available in each industry-b in each month-t. Figure 2.1 plots the loan spreads for each industry over time. Figure 2.15 plots the proportion of traded syndicated loans that belong to each industry. Saunders *et al.* (2023) create an aggregate loan spread as a simple equal-weighted average of all loan spreads available each month.

2.2.3 Industry bond returns

I construct corporate bond spreads using TRACE and WRDS Bond Return data from 2002 to 2022. Consistent with standard practice, TRACE price data are first cleaned according to the procedure documented by Dick-Nielsen (2014). Bond spreads are constructed in the same bottom-up approach as for loans. Bonds are assigned to one of the 15 BEA industry classifications using firm SIC codes. To construct a set of 15 industry specific bond spreads, I take a monthly equal-weighted average of all bond spreads available in a given industry-b in month-t. Figure 2.2 plots the bond spreads for each industry over time.

[4] Saunders *et al.* (2023) provide a full description of the secondary market for syndicated loans. Loans are 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.

2.2.4 Industry equity returns

I construct industry equity returns using CRSP-COMPUSTAT (CCM) monthly return data from 1962 to 2022. I use NYSE, Amex, and NASDAQ listed stocks only. Firms in the bottom 25th percentile of market capitalization are removed to reduce the impact of small stocks. Stocks are assigned to one of the 15 BEA industry classifications using SIC codes. Using monthly total returns (TRT1M), I construct industry specific equity returns by taking a value-weighted average of all returns within each industry-b, in each month-t. Figure 2.3 plots equity returns for each industry over time.

2.3 Results

2.3.1 Loan market: Cross-industry predictability

The empirical tests in this section use a series of panel regressions to predict industry loan spreads using loan spreads of supplier industries. The underlying idea being that information, once revealed, takes times to diffuse across the loan market leading to cross-predictability in loan spreads. I construct a unique supplier loan spread for each industry. The supplier loan spread is constructed as a weighted average of loan spreads from supplier industries, where the weights are given by the flow of goods and services between industries from the IO tables. Formally, the supplier loan spread is defined as:

$$S_{b,t}^{LoanSuppliers} = \frac{C_b}{\sum C_b} S_{b,t}^{Loan} \tag{2.2}$$

where $S_{b,t}^{Loan}$ is the loan spread for industry-b in month-t, C_b is the flow of goods/services from a supplier industry into industry-b, and $\sum C_b$ is the sum of all goods/services from all industries into industry-b. I then define $S_{b,t}^{LoanSuppliers}$ as the weighted loan spread in month-t of industry-b's supplier industry loan spreads. I use the annual IO tables from 1999 to 2022, lagged by one year, as typically IO tables are released with a lag. Using annual BEA tables ensures the weight an industry contributes to the supplier loan spread can change year-to-year reflecting any shifts in the economic relations between industries. However, the

IO connections are typically stable year to year[5]. I then adopt a similar approach as Menzly and Ozbas (2010), and estimate variants of the following panel regression:

$$\Delta S^{Loan}_{b,t+1} = \alpha_b + \alpha_t + \beta_1 \Delta S^{Loan}_{b,t} + \beta_2 \Delta S^{LoanSuppliers}_{b,t} + \epsilon_{b,t} \tag{2.3}$$

where $\Delta S^{Loan}_{b,t+1}$ is the change in industry-b's loan spread from t to $t+1$, $\Delta S^{Loan}_{b,t}$ is the lagged change in industry-b's loan spread from $t-1$ to t, and $\Delta S^{LoanSuppliers}_{b,t}$ is the lagged change in supplier loan spread for industry-b from $t-1$ to t. The coefficient of interest in this case is β_2. Table 2.1, column 1 begins by regressing future changes in industry b's loan spread on only lagged changes of the industry's own spread. This reveals there is still some degree of serial correlation, even in changes in spreads. Column 2 introduces the supplier loan spread. The positive coefficient on the supplier loan spreads suggests that an increase in the loan spread of supplier industries is associated with a future increase in industry-b's loan spread. Note the coefficient is double in size (0.417) and statistically significant compared to column 1. In column 3, I combine an industry's own lagged spread and the lagged supplier loan spread, including both lagged spreads controls for any momentum in industry loan spreads. This results in the own-industry loan spread becoming insignificant. However, the most detailed specification in column 4 adds time and industry fixed effects and reveals no significant cross-prediction in loan spreads. Once common time-trends are accounted for, it appears the loan spreads of upstream industries do not predict the loan spreads of downstream industries across the full sample period[6].

However, the syndicated corporate loan market has witnessed significant changes in the composition of investors and market structure over the sample period. One of which has been the rise of CLO managers as the dominant investor in the loan market, accounting for approximately 70% of all loan holdings. Trading in secondary loan markets has increased from \$100bill(USD) in 2000 to over \$823bill(USD) in 2022, see Saunders *et al.* (2023). This

[5] In untabulated results, I repeat the baseline specification using different editions of the IO tables or using a time series average of all IO tables. It does not affect the main result.

[6] Hong *et al.* (2007) showed that industry stock returns can predict aggregate market stock returns. In particular, select industries more exposed to the economic cycle, such as Metals, Retail, Commercial Real estate can predict market stock returns. This specialised information is reflected in industry returns first, before the economic shock spreads across the wider economy. In untabulated results, I find no relationship between lagged industry spreads and aggregate spreads. It does not appear that some industries are systematically reacting earlier to an economic shock.

raises the possibility that cross-predictability in loan spreads has been affected by changes in market structure.

To study this question, I split the data into two sample periods: pre and post 2010. I split the data at 2010 as the post global financial crisis period saw a rapid rise in the size and dominance of the CLO market[7], and it marks the publication of Menzly and Ozbas (2010). Results remain unchanged if I shift the cutoff date earlier or later[8]. Table 2.1 column 5 confirms that in a pre-2010 sample, there is no cross-predictability in the loan market. Interestingly, column 6 reveals that post-2010 there is evidence of cross-predictability. Post-2010, a 100bps increase in supplier loan spread is associated with a 32bps increase in downstream industry loan spread the subsequent month. This provides evidence that information diffusion within the loan market may have indeed changed over time, coinciding with the increased influence of CLO managers.

While this is suggestive evidence, it does not preclude alternative explanations for the change in cross-predictability. I next test for cross-predictability in the corporate bond market, to check if the increase in cross-predictability was a common pattern across credit markets or unique to the loan market. Importantly, the composition of bond investors has remained relatively stable over the last 20 years, compared to the syndicated loan market (see Kubitza (2023)). Corporate bonds are typically held by long-term investors such as insurance companies and pension funds[9]. If corporate bond spreads also show an increase in cross-predictability over the same time period, this would reject the hypothesis that investor composition alone was driving the change in cross-predictability in the loan market. I construct industry corporate bond spreads using the same methodology as for loan spreads. The supplier bond spread is constructed in the same way, using the lagged annual IO tables as weights. Table 2.2 repeats the same set of tests as in Table 2.1, but for the corporate bond market. Focusing on the most detailed specification with time and industry fixed effects, column 4, reveals no cross-predictability in corporate bond spreads over the same sample period. Furthermore, when split into pre-2010 (column 5) and post-2010 (column 6), bond

[7] The CLO market grew from a post-crisis trough of $263 USD billion to $910 USD billion as of June 2022 according to https://www.guggenheiminvestments.com/perspectives/portfolio-strategy/understanding-collateralized-loan-obligations-clo. CLO deals issued from 2010 onwards, are often referred to as CLO-2.0. CLO-2.0 deals increased credit support and shortened the period in which loans could be reinvested.

[8] In untabulated results, I shift the cut-off date +/- 2 years, and find the result is unchanged. If anything, the statistical significance is stronger when the cut-off date is shifted later.

[9] https://bfi.uchicago.edu/wp-content/uploads/2022/01/BFI_WP_2022-17.pdf

spreads show no change in cross-predictability over the two sub-periods. The lack of significant results in the bond market relative to the loan market, provides evidence that the increase in loan spread cross-predictability was driven by forces unique to the loan market. Section 2.3.1 will further discuss the potential role of CLO manager specialization as a driver of cross-predictability.

Next, I check the impact of stale loan price. Loan price quotes, collected and disseminated daily by the LSTA, could be slow to update as surveyed broker/dealers take time to adjust their quotes. If certain industries systematically differ in the staleness of loan prices, this might drive cross-predictability. Figure 2.4 plots the proportion of loan prices that remain unchanged relative to the prior week, for each industry. On average, over the entire sample, 56% of loan prices remain unchanged from the previous week. Comparing the pre- and post-2010 reveals a slight increase in staleness (unconditional average across all industries increases from 49% to 62%). However, more importantly this proportion remains similar across all industries. It is unlikely that a change in price staleness alone could explain the emergence of cross-predictability.

This also raises the concern that the cross-predictability across industries could be driven by changes in market liquidity. In the equity literature, it has been shown that large stocks lead small stocks due to differences in liquidity Lo and MacKinlay (1990)). While it is true that the loan market is generally less liquid than bond or equity markets, this is unlikely to explain the cross-predictability findings within the loan market. To rule out this explanation I examine the bid-ask spread in loan prices across industries. The LSTA report bid and ask quotes for each loan daily, allowing me to construct average bid-ask spread at the industry-month level. Figure 2.5 highlights no systematic difference in bid-ask spread across industries in the pre and post-2010 sample.

CLO manager specialization

How do the results discussed in Section 2.3.1 fit with existing models of information diffusion? To obtain predictability in a limited information model, two assumptions are required Menzly and Ozbas (2010). First, different industries must have correlated fundamentals, so that an informative signal arising in one industry has useful information about the future state of another industry. Second, investors must be informationally segmented, so that an informative signal is received by specialist investors in that industry before non-specialist investors. This information segmentation leads new information to be incorporated in a piecemeal fashion, generating cross-predictability in returns. The following section provides evidence for these two assumptions.

First, for there to be cross-predictability across industries, informative signals need to be dispersed among informed investors. This market segmentation could be driven by investor inattention or investor specialization. The inattention hypothesis predicts faster information diffusion in the presence of a greater number of informed investors, who are then capable of incorporating relevant information into asset prices in a timely manner. In equity markets this is typically proxied by the number of analysts covering a firm. However, credit markets typically lack the institution of the sell-side analyst report. Therefore, differences in analyst coverage cannot be used as a proxy for investor attention in the loan market. However, the syndicated loan market is comprised primarily of institutional participant's including CLO managers, Pension Funds, Hedge Funds, and Insurance companies. CLO managers actively trade their loan portfolio over the reinvestment stage of the CLO life (See Kundu (2022)). Furthermore, CLO managers are required to hold a stake in the equity tranche of the CLO, and so directly benefit from active management of the CLO portfolio of loans. CLO managers have a clear incentive to monitor and pay attention to all loans. Therefore, it is unlikely that CLO manager inattention could explain market segmentation.

An alternative explanation is loan market investors specialize along industry lines. In the syndicated loan market, the dominant investors are CLO managers. Approximately 70% of syndicated loans are owned by CLO structures [10], making CLO the dominant market player for syndicated loans. To test whether CLO managers specialize along industry lines, I use micro-data on CLO holdings and trades from the Creditflux CLO-i database to measure how diversified CLO holdings and trades are across industries.

Figure 2.6 reports the average number of industries held within a CLO over it's lifetime. This is an upper bound, as at any given point in time the CLO manager may be invested in smaller subset of industries. Starting with some descriptive statistics, Figure 2.6 highlights that a large number of CLO managers are well diversified, holding loans in approximately 30 out of 41 possible industries over the CLO's entire lifetime. In any given month, CLO managers own an average of 27 out of 41 industries. Also of interest is the long tail of

[10] https://www.stlouisfed.org/en/on-the-economy/2019/october/syndicated-loans-us

less diversified CLOs. Approximately, 30% of CLO's own loans in 26 or fewer industries over the CLO's lifespan. This suggests that some CLOs focus on a subset of industries and do not hold a perfectly diversified portfolio of loans across sectors. This is not to say that CLO have no knowledge about industries they do not currently hold loans in, only that information acquisition and processing may be somewhat segmented enough to slow information diffusion.

I also examine trading behaviour by CLOs. I find CLO trades are also highly concentrated amongst a subset of industries. Figure 2.7 reports the average number of industries traded (either buy or sell) within a CLO over it's lifetime. The typical CLO trades 10 industries over it's lifetime. In any given month, CLO's trade, on average, 8 industries. Compared to holdings, this confirms that CLO managers trades are focused on an even narrower subset of industries then their holdings. This further suggests CLO manager develop specialist knowledge in a subset of industries.

An alternative approach to measuring the degree of concentration in CLO portfolio holdings, is to calculate the deviation of the CLO's industry allocation from the industry's total market size. I adopt the measure used by Blickle *et al.* (2023) to measure bank portfolio specialization. This is measured as:

$$\text{Excess Specialization} = \frac{LoanAmount_{i,b,t}}{\sum LoanAmount_{i,b,t}} - \frac{LoanAmount_{b,t}}{\sum LoanAmount_{b,t}}, \tag{2.4}$$

$\frac{LoanAmount_{i,k,t}}{\sum LoanAmount_{i,k,t}}$ is the share of CLO i's portfolio invested in industry b in month t relative to the CLO's total holdings. $\frac{LoanAmount_{b,t}}{\sum LoanAmount_{b,t}}$ is the share of all CLO lending to industry b in month t relative to all CLO lending. The difference is how much a CLO's share in an industry differs from the entire CLO market. I refer to this as the "excess" specialization. Figure 2.8 plots the average "excess" specialization across all CLOs for the industry they are most invested in i.e., their top industry. First, the majority of CLO's have a positive excess specialization, i.e. they hold their "favourite" industry in a bigger share than the aggregate CLO market implies. The average CLO invests 7.5p.p more of its portfolio in its most favoured industry, than would be expected if they held every industry in line with aggregate CLO holdings. This suggests that CLO, like banks in Blickle *et al.* (2023), tend to specialise somewhat in industries for which they have developed specialist knowledge. This is not surprising given the costs to information acquisition and monitoring required across a portfolio of syndicated loans.

I next address the question of whether economically related industries have correlated fundamentals. Industries closely related to each other along the supply chain are likely to be exposed to correlated cashflow shocks, a key ingredient for cross-predictability Menzly and Ozbas (2010). To test whether industries have correlated fundamentals, I combine industry level economic data on TGO and VA from the BEA, to estimate the following panel regression:

$$Y_{b,t} = \alpha_b + \alpha_t + \beta_1 Y_t^{Market} + \beta_2 Y_{b,t}^{Suppliers} + \epsilon_{b,t} \tag{2.5}$$

where $Y_{b,t}$ is the level of TGO/VA for industry-j in quarter-t. I compute the Y_t^{Market} as the aggregate level of TGO/VA by summing across all industries in quarter-t. I compute the $Y_{b,t}^{Suppliers}$ for each industry by weighting the industry level TGO/VA with the flow of goods and services from the BEA input-output tables, similar to the approach in Section 2.3.1. An industry fixed effect, α_b is also included. The results in Table 2.3 confirm the finding that industries connected economically have positively correlated fundamentals. Specifically, industries along the supply chain have positively correlated fundamentals over and above the aggregate TGO and VA.

In summary, the dominant investor in the loan market, CLO's, exhibit patterns of industry specialization in their holdings and trading behaviour. The increase in the holdings of CLO managers, coincides with the appearance of cross-predictability in loan spreads. Meanwhile, the bond market, which did not see a shift in investor composition, did not see any change in cross-predictability over the same period. While this is not causal evidence for what is driving the cross predictability in loan spreads, it does suggest changes in market structure may have played a role.

2.3.2 Cross-market predictability

In this section I test information segmentation *across* corporate loan and equity markets, by testing if industry loan spreads predict future equity returns of the same industry. In perfect frictionless markets, information about firm value is reflected into each of the firm's underlying securities Merton (1974). However, if markets are imperfect, it can take time for information in one asset class to be incorporated in another Allen and Gottesman (2006). Addoum and Murfin (2020) show that syndicated loan prices have the ability to predict future returns at the firm level. They examine a set of firms with both loans and public equity outstanding. They find that material non-public information reflected in loan prices takes more than a month to appear in the price of the same firm's equity. Their study is motivated by the fact that the syndicated loan market is unique in that loans are not considered securities under the Securities Act of 1933. This makes participants like banks, exempt for from fair disclosure rules, while potentially in the possession of private information. This private information leads loan prices to predict equity prices. However, it is not clear if this pattern is unique to the subset of public firms or if there is information in the broader sample of loans. In other words, is their private information at the firm level only, or is there private information at the industry level which is useful for predicting equity returns? I examine the universe of secondary market traded loans and test whether changes in industry level loan spreads can still predict industry level equity returns. I estimate the following regression:

$$Ret^{Equity}_{b,t+1} = \alpha_b + \alpha_t + \beta_1 \Delta S^{Loan}_{b,t} + Ret^{Equity}_{b,t} + \epsilon_{b,t} \tag{2.6}$$

where $\Delta S^{Loan}_{b,t}$ is the change industry loan spreads from $t-1$ to t. $Ret^{Equity}_{b,t}$ are monthly equity returns from $t-1$ to t. Importantly, I am now forecasting the *same* industry, i.e. I use an industry's loan spread to predict it's future equity return $Ret^{Equity}_{b,t+1}$. I also control for industry fixed effects and common time trends with time fixed effects. Table 2.4, column 1 finds that over the entire sample period, 1999-2022, a negative but insignificant relationship. This is true for equal weighted and value-weighted returns. This suggests that the private information story underpinning the results in Addoum and Murfin (2020), may be applicable to those public firms, but there does not appear to be private information at the industry level in the broader sample of loans.

However, in 2015 the Wall Street Journal (WSJ) ceased publication of weekly movements in loan prices, which informed the cross-market trading strategy used in Addoum and Murfin (2020). Post-2015 loan prices would have only be available to investors with subscriptions to loan pricing services, instead of the publicly available prices in the WSJ. It is plausible that an increase in search costs (or alternatively an increase in investor inattention) would precipitate an increase in cross-market predictability. Therefore, I split the sample into two, pre-2015 covers the sample period used by Addoum and Murfin (2020), and post-2015 a non-overlapping post-publication sample. Table 2.4, column 2 confirms in the first half of the sample there is no significant cross-market predictive ability. However, in the post-2015 sample, column 3 reveals that industry loan spreads do have significant predictive power for equity returns. A 100bps increase in loan spread predicts an 127bps higher equity return in the following month. This is economically significant compared to the unconditional mean industry equity return of 161bps. This supports the notion that elevated frictions to cross-market trading, led to an increase in cross-market predictability Shleifer and Vishny (1997). This evidence suggests market integration remains incomplete across loan and equity markets.

What is the source of information that explain why loan spreads predict equity returns? Allen and Gottesman (2006) propose two explanations, the private information hypothesis and the asymmetric price reaction hypothesis. The private information hypothesis says that the loan market investor possess private information, which is gradually incorporated into markets. The asymmetric price reaction hypothesis results from the fact that loans have limited upside potential, hence loan spreads should be more sensitive to negative information then positive information. This hypothesis suggests that when the information is negative, loan spreads lead equity returns in incorporating the information. Whereas positive information is more relevant to equity investors that benefit from the upside gains from positive information. To test this hypothesis, I further split the sample into months where loan spreads increased or decreased. Table 2.4 columns 4 and 5, further splits the Post-2015 period. Comparing column 4 and 5 reveals that the predictive power of loan spreads is isolated to periods of increases in loan spreads. In column 4, a 100bps increase in loan spreads is associated with a 265bps increase in equity returns the following month. In column 5, which includes only months loan spreads fell, there is no predictive power for equity returns. This is consistent with the asymmetric information hypothesis; loan markets react earlier to negative news (reflected in a widening in spreads) than equity markets.

2.3.3 Equity market: Cross-industry predictability

Having documented changes in cross-predictability in the loan market, I next revisit cross-predictability in equity returns. I first examine cross-predictability in the equity market over the sample period from 1999 to 2022. I adopt the same panel regression as Section 2.3.1, using equity returns in place of changes in credit spreads:

$$Ret^{Equity}_{b,t+1} = \alpha_b + \alpha_t + \beta_1 Ret^{Equity}_{b,t} + \beta_2 Ret^{EquitySuppliers}_{b,t} + \epsilon_{b,t} \tag{2.7}$$

where $Ret^{Equity}_{b,t+1}$ is the industry equity return from t to $t+1$, $Ret^{Equity}_{b,t}$ is the lagged equity return from $t-1$ to t, and $Ret^{EquitySuppliers}_{b,t}$ is the lagged supplier equity return from $t-1$ to t. How I construct industry equity returns is described in Section 3.2 i.e. CRSP value-weighted total returns aggregated to the industry level. Equity return of supplier industries, is constructed the same way as described in Section 2.3.1, using industry equity returns and weights from historical annual IO tables. Table 2.5 repeats the set of panel regressions as in Section 2.3.1. In the most saturated model with industry and time fixed effects, column 4, the coefficient on supplier industry returns is positive, but no longer significant. There appears to be no cross-predictability in equity returns in the sample spanning 1999-2022, in line with the results in the loan market from Table 2.1.

The lack of cross-predictability in equity returns is surprising given the earlier findings of Menzly and Ozbas (2010). One explanation could be the difference in sample periods, as the original study uses equity returns from 1962 to 2005. To test this hypothesis, I apply my specification, i.e. Equation 2.7, on equity returns from 1962 - 2005[11]. Table 2.5, column 5 reveals in this sample period, a 100bps increase in upstream industry returns predicts an 16bps increase in downstream industry equity returns the following month. This is in line with the 11bps increase documented by Menzly and Ozbas (2010). However, Table 2.5, column 6 reveals that in an out of sample period, cross-predictability has largely disappeared. It is interesting to note that the sample period over which cross-predictability in equity

[11] Menzly and Ozbas (2010) use IO tables every 5 years i.e. 2002, 1997, 1992, 1987, 1977, 1972, 1967, 1963, 1958. Since then, the BEA have released historical tables at an annual frequency from 1962 to 1996. For the 1996 to 2005 period I use the weighting implied by the 1996 edition of the IO tables. As mentioned, the year-to-year correlation is extremely high as industry supplier-user connections are relatively stable over time

returns disappears has also coincided with the rise of industry mutual funds/ETF's[12]. The decrease in cross-predictability could be in part driven by post-publication awareness of the trade, combined with reduced transaction costs to exploit any predictability. Similar to the loan market results in Section 2.3, changes in market structure may drive information segmentation in equity markets.

Discussion

How can one reconcile the contrasting patterns of cross-predictability disappearing in equity markets and appearing in loan markets? The divergent results suggests that market liquidity and information segmentation may not be a simple linear relationship. The results presented so far suggest market liquidity and market structure may interact in complex ways to drive patterns in cross-predictability. It is plausible there is an inverse relationship between liquidity and information segmentation. For example, at extremely low levels of liquidity, no information is incorporated into prices (as there is no trading) and information segmentation would also be low, as there is no information to diffuse across the market. At the other extreme, with high levels of liquidity, information can quickly be incorporated across the market, also leading to low information segmentation. The result is an inverse U-shaped function of information segmentation as a function of liquidity. The findings in Section 2.3.3 suggest equity markets are on the downward sloping part of the inverse U-function. Comparing the results from the 1962-2005 to the results from 2005-2022, over this period equity market liquidity improved and transaction costs fell, resulting in lower cross-predictability in equity markets. The findings in Section 2.3.1 suggest the loan market is on the upward sloping part of the inverse U-function. The 1999-2010 sample had low liquidity, low segmentation, and as liquidity improved in the 2010-2022 sample, so did information segmentation. In summary, an increase in liquidity might initially increase information segmentation, but then there will come a point where an increase in liquidity wins out and decreases information segmentation. Loan and equity markets may be at different points on this liquidity versus segmentation trade-off.

[12] State Street's series of industry ETFs was launched in 1999, Vanguard's industry ETFs launched in 2004, and Blackrock's industry ETF's in 2000.

2.3.4 Preditcing industry economic activity

Limits to aggregation

If industry loan spreads can predict loan spreads in related industries and equity returns in the same industry, can industry loan spreads also predict industry economic activity? In this section I test whether corporate loan spreads contain useful information for predicting economic activity. A long line of work in the macroeconomic forecasting literature has tested a range of financial variables that have predictive power for economic activity[13], but they have typically focused on aggregate data. I argue the process of aggregating data obscures useful information for three key reasons.

First, it could be that certain industries are over (or under)-represented in aggregate asset price indexes relative to their true economic contribution. For example, an aggregate loan index (either equal or value-weighted) will place more weight on industries which have more loans outstanding. Figure 2.15 plots the sectoral composition of loans and highlights that MAN an INFO have a disproportionate number of loans outstanding relative to other industries. Patterns in MAN and INFO loans spreads will, therefore, have a disproportionate impact on the aggregate loan spread. Figure 2.14 highlights the economic contribution of each industry to TGO, with FIN, MAN and SERV contributing the most to TGO. The difference in composition between Figure 2.15 and Figure 2.14 suggests an aggregate loan spread index places greater emphasis on certain industries relative to their true economic importance.

Second, it could be that sectoral shocks are more common than aggregate shocks, and these sectoral shocks would be obscured in aggregate indexes. Figure 2.9 highlights recent examples of industry level shocks. The 2001 recession which had its beginnings in the Dot-Com bust, the 2008/9 Global Financial Crisis which had its beginnings in a construction boom, and finally the 2015 Oil-Gas industry collapse following the collapse in the oil price. The blue line indicates the loan spread for the given industry and the black line the aggregate loan spread. Figure 2.9 reveals that industry specific loan spreads reacted relatively early compared to the loan spreads in other industries around industry-specific shocks. These examples suggests that disaggregated industry level data provided a useful signal about the

[13] Friedman and Kuttner (1993); Estrella and Hardouvelis (1991); Gertler and Lown (1999); Gilchrist and Zakrajšek (2012); López-Salido *et al.* (2017); Mueller (2009)

emerging risks in these particular sectors. To provide descriptive statistics on the incidence of industry-specific shocks, I define a "negative shock" at the industry level by counting the number of episodes in which the abnormal equity return of an industry is lower than -10% Iyer *et al.* (2022). I define the abnormal return as the industry equity return minus the SP500 return in a given month. Figure 2.10, top panel, highlights there are 52 (industry-month observations) were abnormal equity returns were lower than -10%. Alternatively, I use a 100bps abnormal increase in industry loan spreads as a "negative shock". I define the abnormal loan spread as the change in industry loan spread minus the change in aggregate loan spread in a given month. Figure 2.10, bottom panel, highlights there are 134 incidences where abnormal industry loan spreads were greater than 100bps. The incidence of negative shocks are more prevalent in certain industries such as ART, AIR, MIN, OIL. Given the frequency of industry-specific shocks, aggregate data may ignore useful signals about emerging risks in the economy.

Third, not all economic shocks are equal. Some shocks affect all industries in the same direction, some affect industries in offsetting directions. For example, the Oil-Gas shock of 2015, was a negative shock for those firms directly linked to the extraction of oil. However, for industries for which energy is a significant input, this same shock was a positive shock. Figure 2.11 contrasts the loans spread for the oil and airlines industry. It is apparent the significant drop in oil prices, while negative for one industry, was positive for the other. This example highlights that different types of industry shocks may cancel out in the aggregate.

Predicting industry economic activity

Given the reasons outlined above, I next test whether industry-specific loans spreads contain information that is useful for predicting industry developments, beyond any information contained in the aggregate macroeconomic variables. I adopt the standard forecasting regression framework:

$$y_{b,t} = \beta_0 + \beta_1 \Delta S_{b,t} + \beta_2 \Delta S_t + \epsilon_{b,t} \tag{2.8}$$

where the dependent variable, y, is either the 1 quarter-ahead growth rate in industry

TGO or VA, i.e., the log growth rate in activity from t to $t+1$. $\Delta S_{b,t}$ is the change in industry loan spread from $t-1$ to t. ΔS_t is the change in the aggregate loan spread from $t-1$ to t. All specifications also include one lag of the dependent variable and time or industry fixed effects, depending on the specification.

Table 2.6 summarises the baseline result. In column 1 I include only the industry loan spread and find an increase in industry specific loan spreads is associated with a decrease in the growth rate of industry specific output in the next quarter, i.e. a 100bps increase in the industry loan spread is associated with a 8 bps decrease in TGO next quarter. This is statistically and economically significant compared to the unconditional average of 47 bps in TGO growth over the next quarter. To test whether there is additional information in the industry level loan spreads, column 2 includes the aggregate loan spread. The coefficient on the industry spread remains negative and significant. Finally, column 3 includes industry and time fixed effects to absorb any common time trends. Column 4-6 repeat the same set of regressions but use industry VA as the dependent variable. Together, Table 2.6 suggests industry specific loan spreads contain useful information for predicting industry level economic activity [14]. The results are agnostic as to which component of credit spreads is reacting early. Credit spreads could change because investors are forecasting a deterioration in borrower health, or it might be that risk premia increase. However, given that not all industry spreads are changing simultaneously, this is more consistent with changes in borrower health, than changes in broad investor risk attitudes.

One may argue that equity markets, being larger and more liquid, should also contain useful information about predicting industry economic activity. Therefore in Table 2.7, I test the ability of industry equity returns to predict industry economic activity. Table 2.7 repeats the specification used in Table 2.6, except replacing loan spreads with equity returns. Column 1/2 (4/5) suggest that an increase in equity returns predicts an increase in TGO (VA) in the next quarter. However, note that in column 2 and 5, once controlling for aggregate equity returns (i.e returns on the SP500), the power of industry equity returns is substantially reduced. Furthermore, with the addition of fixed effects in column 3 and 6, the statistical significance disappears. This suggests that industry specific equity returns do

[14] Saunders *et al.* (2023) employ a simple arithmetic average of all loan spreads available each month to create an aggregate measure. However, as shown in the previous section, industries may differ in their importance and spreads may have a differential information content across sectors. In the Online Appendix the authors provide some evidence that alternative weighting schemes may provide additional prediction power.

not contain much additional information for forecasting industry level activity beyond the market return.

The results extend to forecast horizons greater than one quarter. Figure 2.16 of the Online Appendix, plots the coefficients at various horizons from h=0 to h=10 quarters ahead for both loan spreads (top panel) and equity returns (bottom panel). Figure 2.16 adopts the specification used in column 1 and 3 of Table 2.6 and 2.7, i.e pooled OLS . Interestingly, the predictably extends to longer horizons, peaking at 6 quarters ahead. Both loan spreads and equity returns show a similar patter, with forecasts peaking at the 6-quarter horizon.

Discussion

What is the benefit of using industry level loan spreads and who would find these results useful? First, policy makers including central bankers would benefit from tracking industry level spreads to obtain a better understanding of the state of the economy. Furthermore, industry spreads may provide insights into the transmission mechanisms of monetary policy be tracking conditions in interest rate sensitive sectors. Second, bank loan officers would be a user of industry information given their role in allocating credit. For example, Blickle *et al.* (2023) show that loan portfolios of bank do show a tendency to specialise in certain industries. Industry credit spreads would provide loan officers with an additional barometer of conditions in each industry. Also, industry spreads are correlated across related industries, which is important for banks to manage cross-correlation between loans in their portfolio.

2.4 Conclusion

In this paper I study information segmentation *within* and *across* asset classes and provide new evidence on the gradual diffusion of information hypothesis. I study the ability of loan spreads to predict loans spreads in other industries and finds that predictability depends on the period investigated. I then test if a similar time dependence can be found in equity markets, and I find that this is indeed the case. I hypothesize and deliver some preliminary evidence that the change in market structure can explain these patterns. The lack of cross-predictability in equity returns coincides with the publication of Menzly and Ozbas (2010), and a rapid increase in the range of available industry mutual funds/ETF's to investors. At the same time, the emergence of cross-predictability in the loan market coincides with the rise of CLO managers. I provide evidence that CLO investors specialise somewhat along industry lines.

I also study the ability of industry loan spreads to predict the future equity returns of the same industry. In a fully integrated market such cross-market predictability should not be apparent. The fact that I find some predictive power remains suggests market integration remains incomplete across equity and loan markets. Finally, I test the ability of industry loan spreads to predict industry economic activity. I show that industry-specific loan spreads contain information for forecasting economic activity not captured in aggregate prices.

There results highlight the role of market structure in the diffusion of information across markets. The divergence in cross-predictability across the equity and loan market, suggest that market liquidity and information segmentation may not be a simple linear relationship. While the equity and loan market, have both experienced an increase in trading volume and market size over the sample period studied, key market players and market structures have changed significantly. One hypothesis is that information segmentation may initially increase at low levels of market liquidity, but at some point, further improvements in liquidity lead a decrease in information segmentation. I leave it to further research to further explore these ideas further.

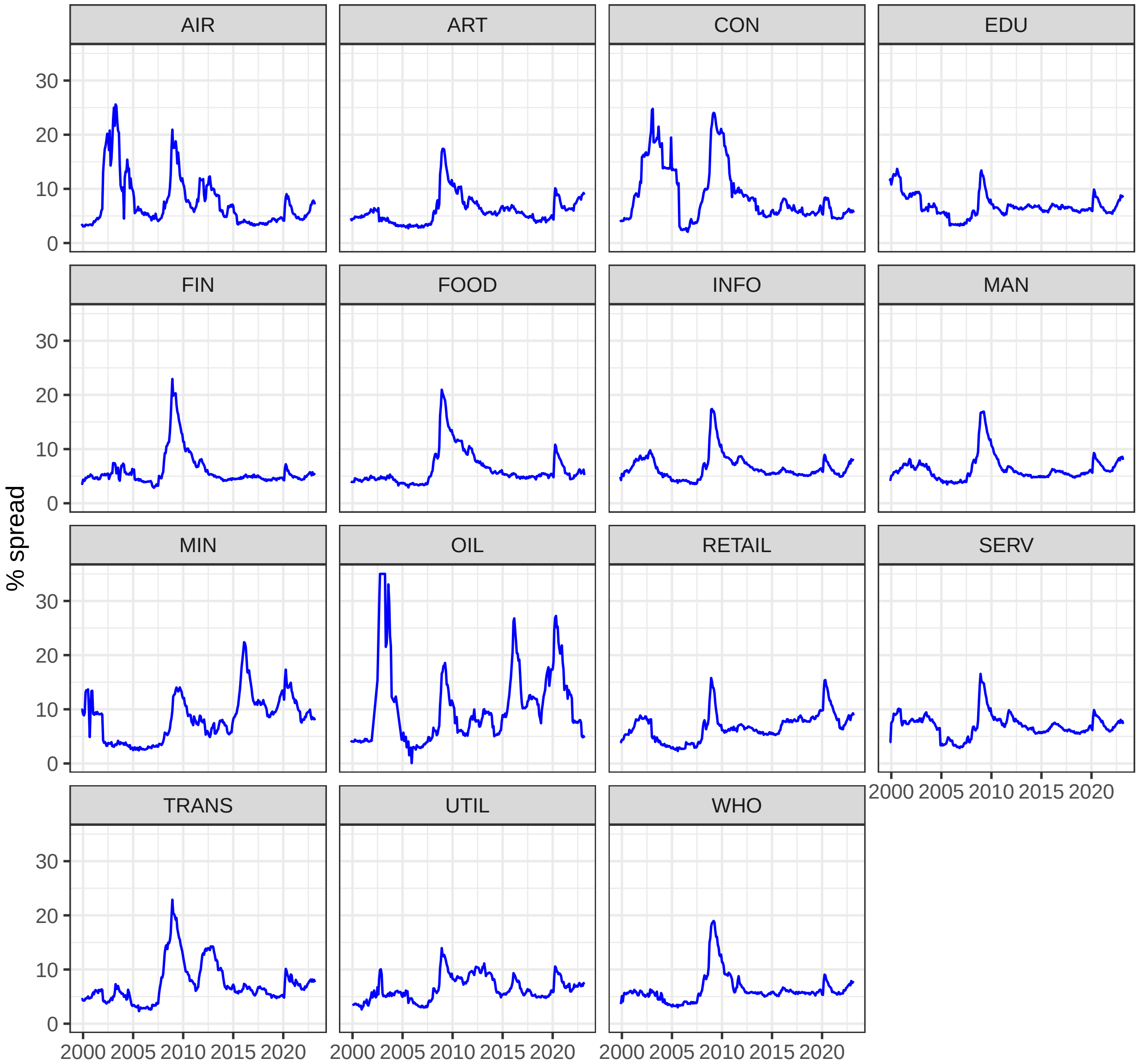

Figure 2.1: **Industry loan spreads**
This figure plots the industry level loan spreads for each BEA industry. Industry level loan spreads are calculated using the bottom-up methodology of Gilchrist and Zakrajšek (2012) with LSTA data. Sample period 1999:11 to 2023:03

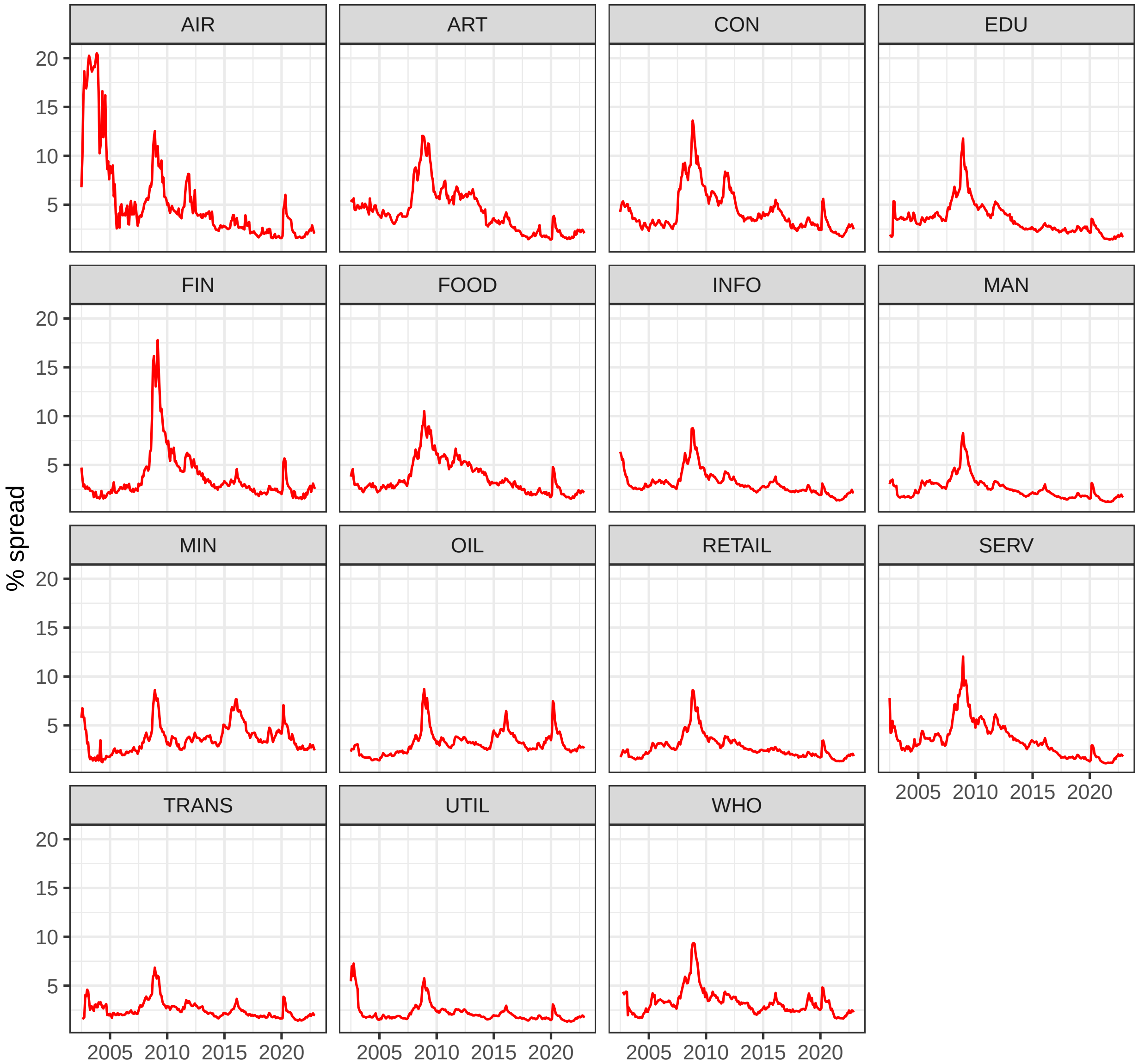

Figure 2.2: **Industry bond spreads**
This figure plots the industry level bond spreads for each BEA industry. Industry level bond spreads are calculated using the bottom-up methodology of Gilchrist and Zakrajšek (2012) with TRACE data. Sample period 2003:03 to 2022:12

Figure 2.3: **Industry equity returns**
This figure plots the industry level equity returns for each BEA industry. Industry level equity returns are calculated as a value-weighted average of individual firm monthly total returns from COMPUSTAT-CRSP. Sample period 1999:11 to 2023:03

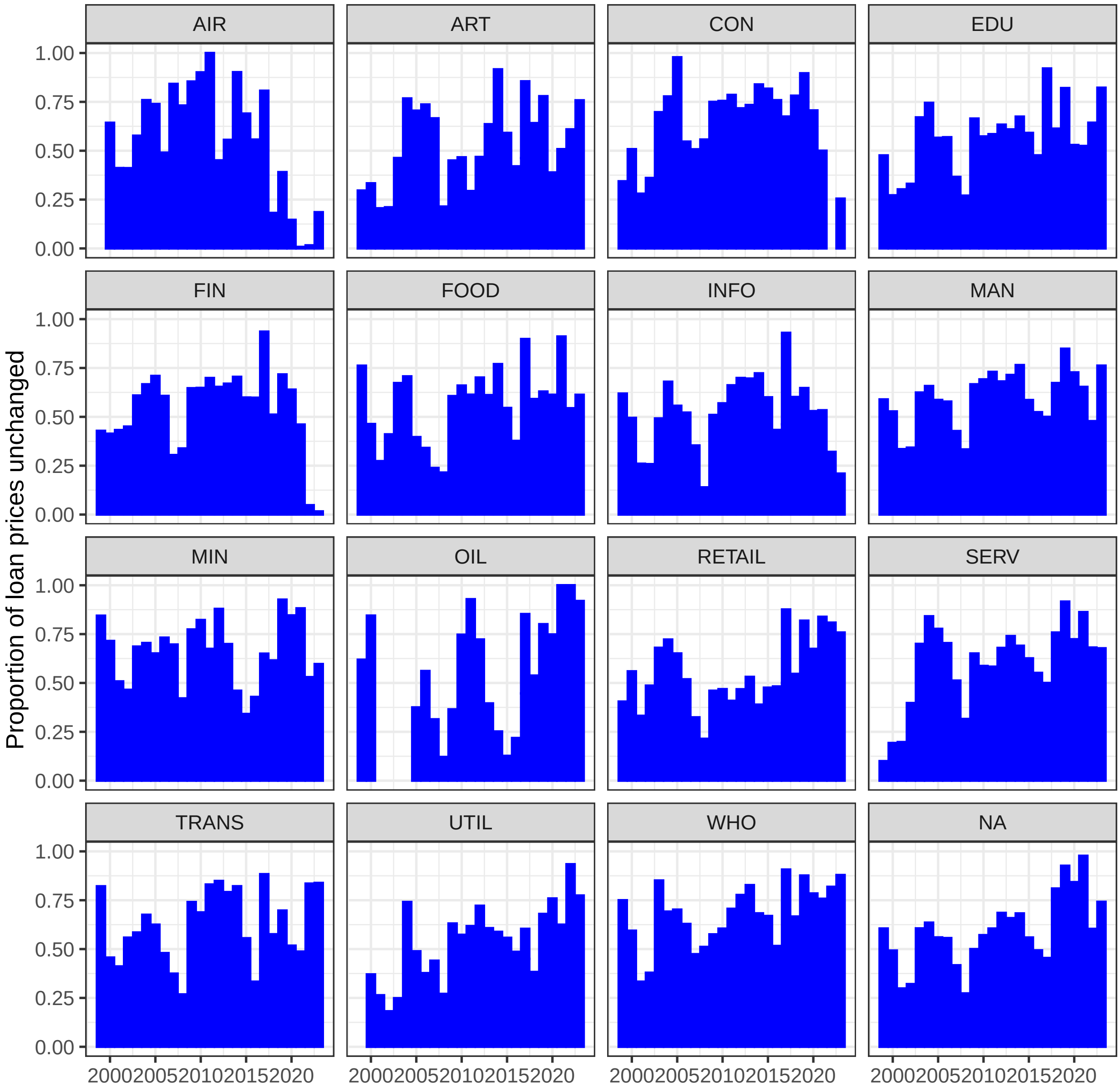

Figure 2.4: **Stale loan price quotes**
This figure plots the proportion of loans, within an industry, with an unchanged price relative to the prior week. Daily loan quotes come from the LSTA quotes data. Sample period 1999:11 to 2023:03.

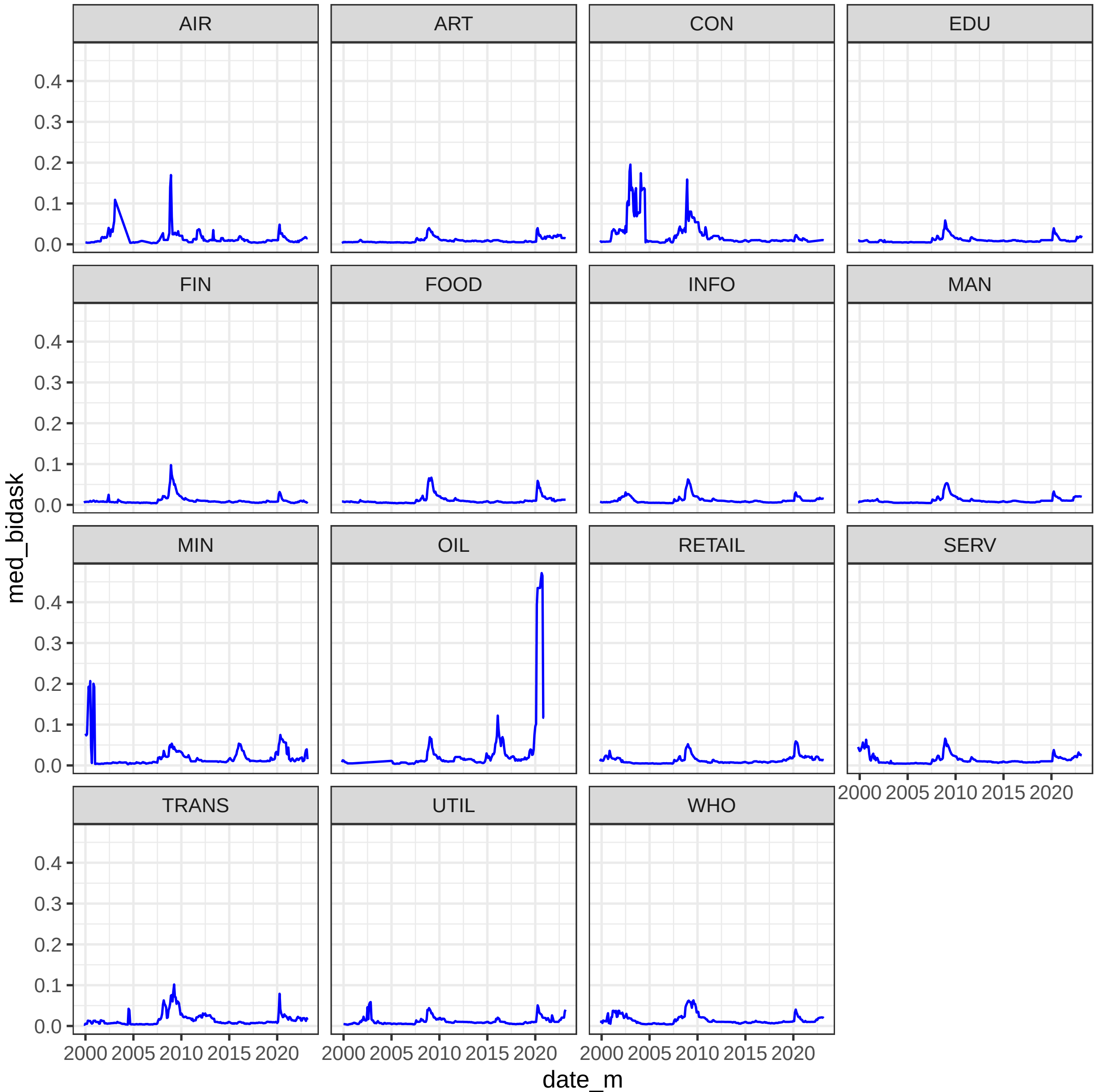

Figure 2.5: **Loan bid-ask spread**
The figure plots median monthly bid-ask spread for loans in each industry. Monthly bid and ask quotes come from the LSTA quotes data. Sample period 1999:11 to 2023:03

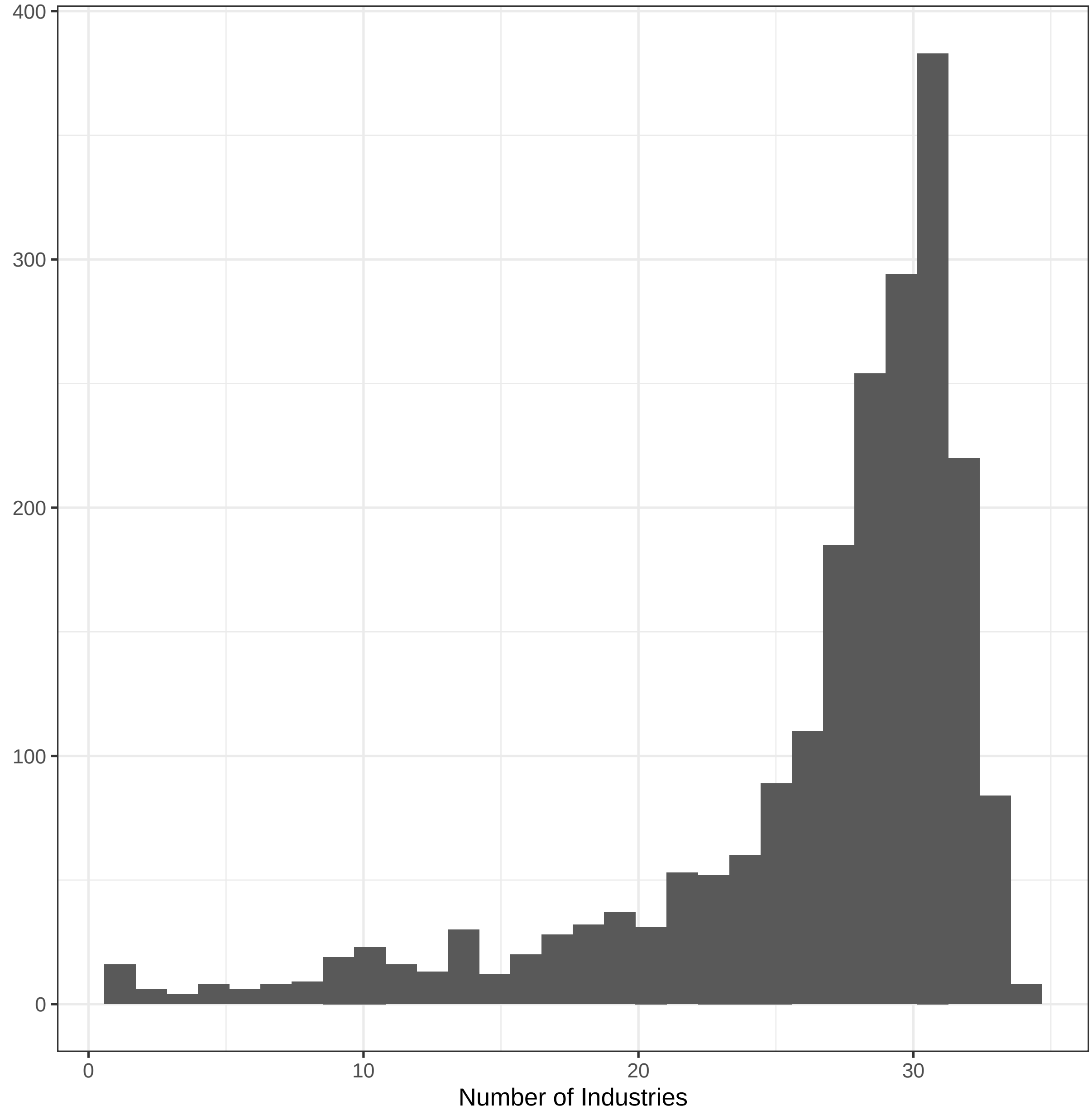

Figure 2.6: **CLO holdings**
This histogram plots the distribution of the average number of industries held by a CLO manager over the CLO's lifetime. CLO holdings data are collected monthly. Each loan is classified into one of 41 industry categories assigned by LPC Dealsan.

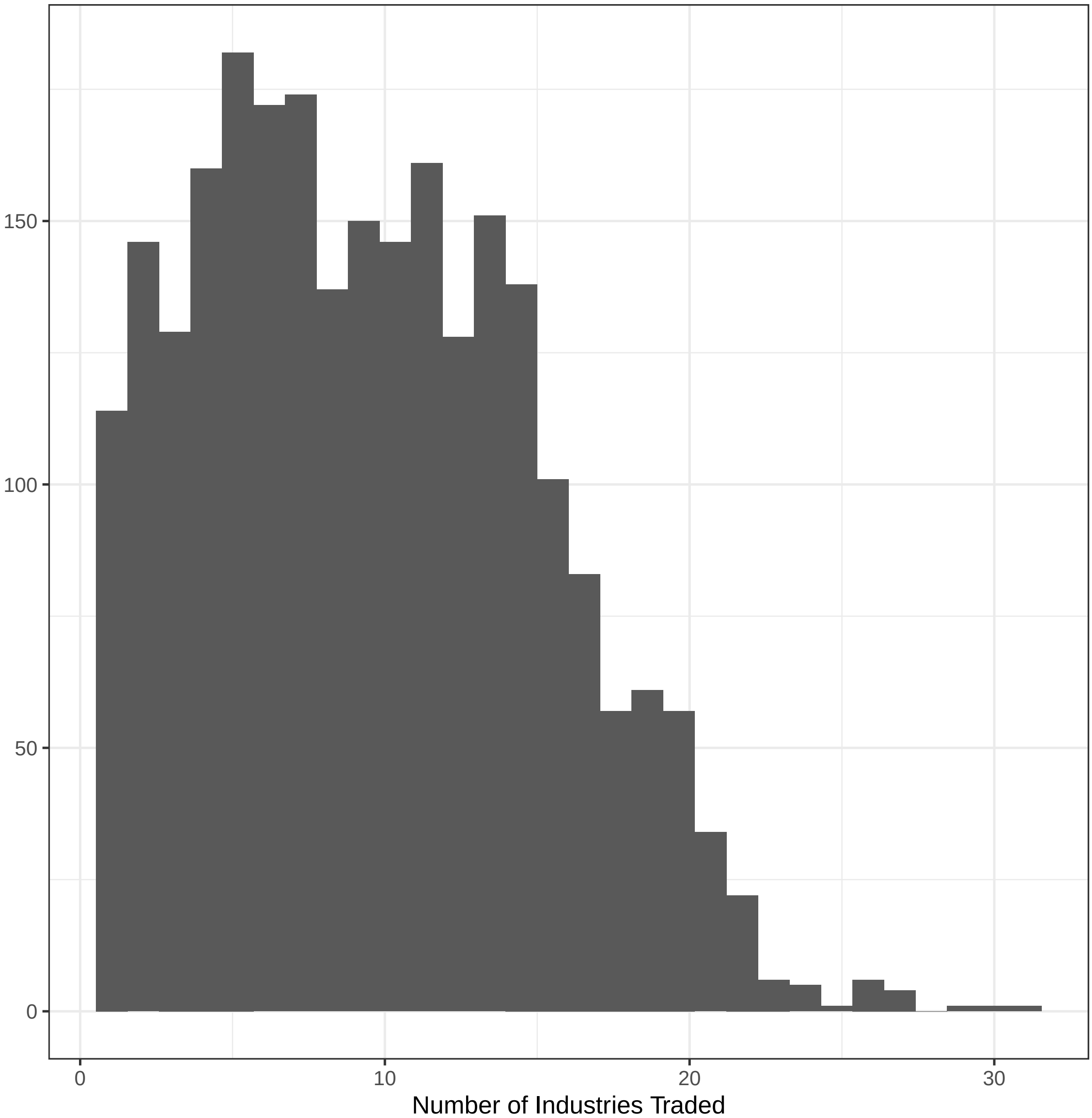

Figure 2.7: **CLO trades**
This histogram plots the distribution of the average number of industries traded by a CLO manager over the CLO's lifetime. CLO trading data are collected monthly. Each loan is classified into one of 41 industry categories assigned by LPC Dealsan.

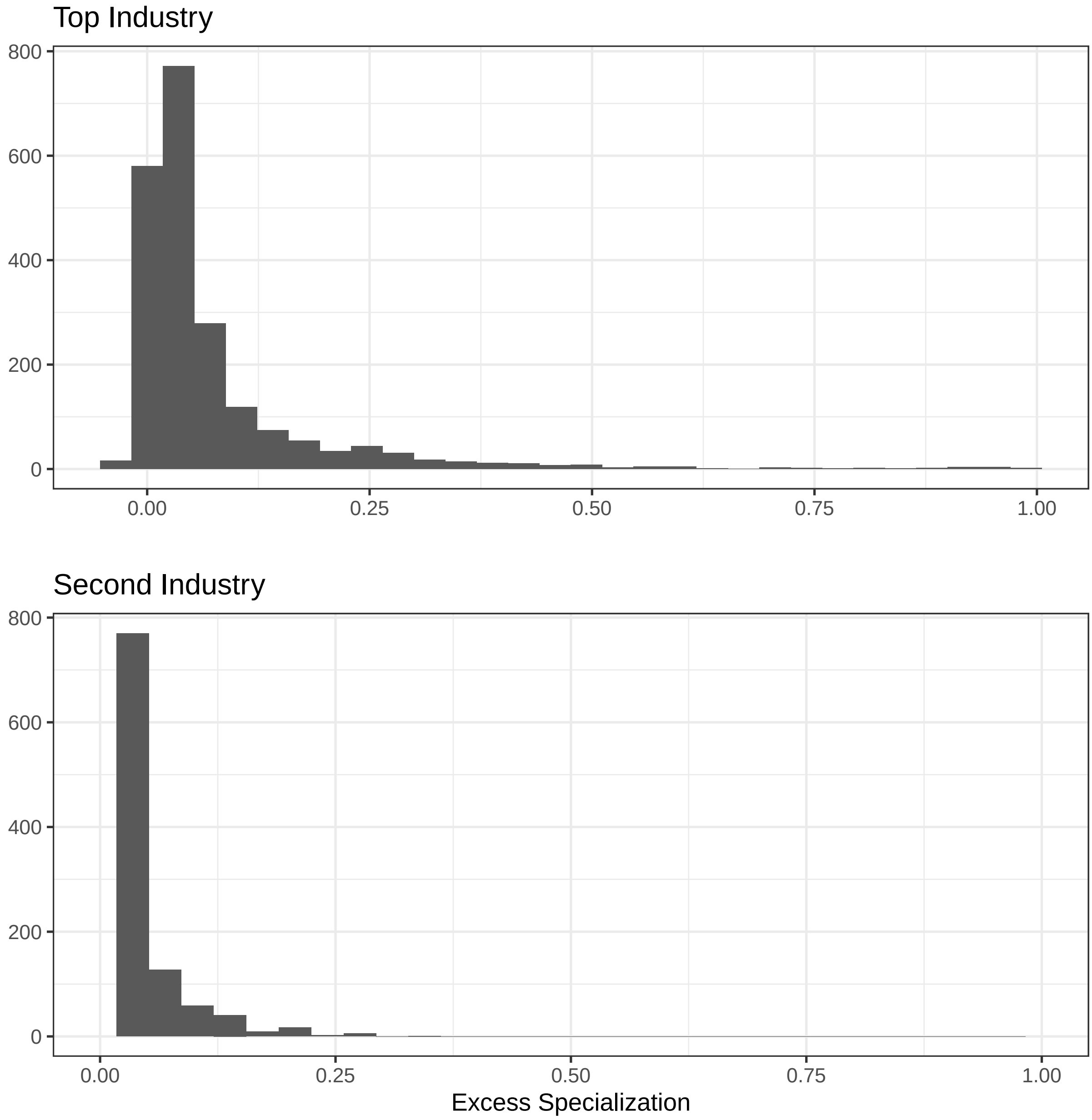

Figure 2.8: **CLO holdings - Excess Specialization**
This figure plots the the "excess" specialization measure from Blickle *et al.* (2023) to measure the concentration in CLO portfolio holdings. Excess specialization measures how much a CLO's share in an industry differs from the entire CLO market. The top panel plots a histogram of excess specialization for each CLO's most held industry. The bottom panel plots a histogram of excess specialization for each CLO's second most held industry.

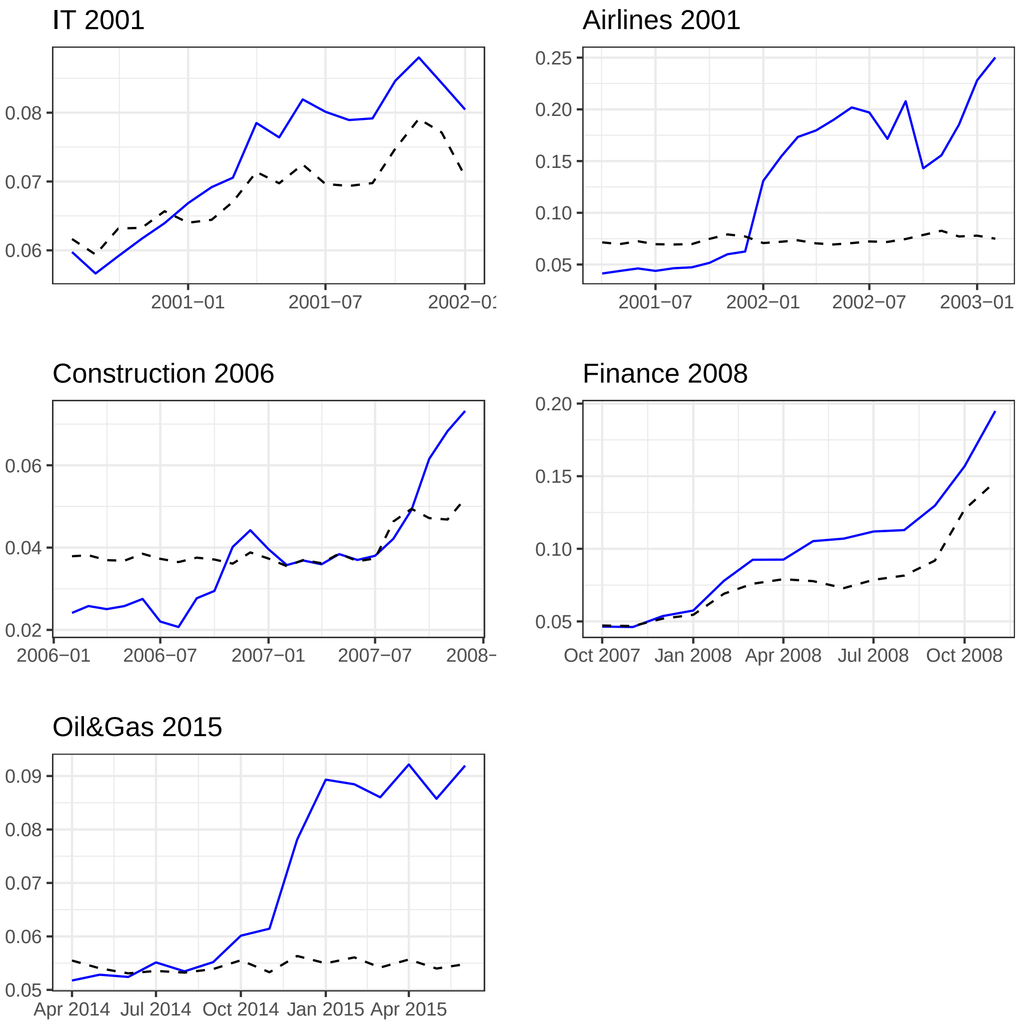

Figure 2.9: **Industry vs Aggregate loan spreads**
Each figure plots the industry specific loan spread (blue) and the aggregate loan spread (black), around five examples of industry specific economic downturns.

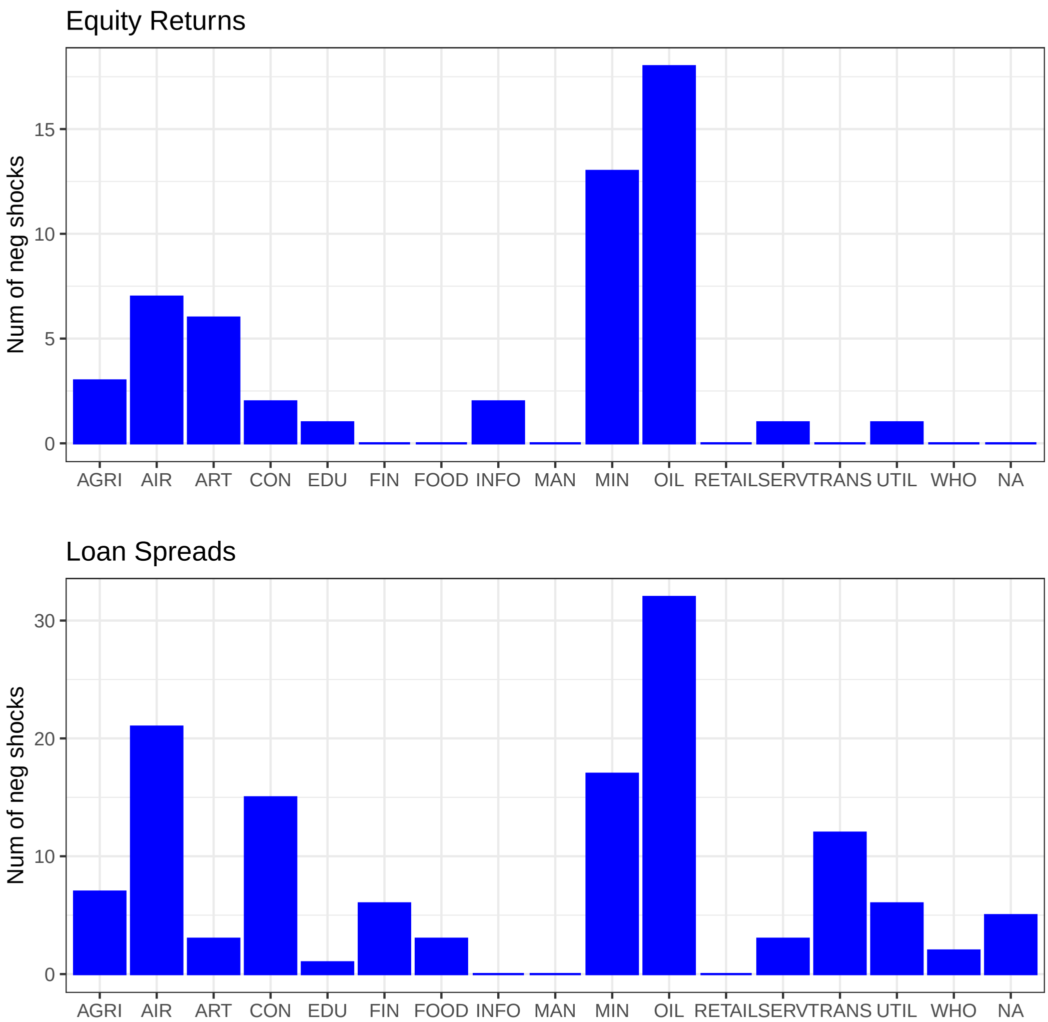

Figure 2.10: **Negative Industry Shocks**
This figure plots the number of negative industry-specific shocks. The top figure plots the incidence of >-10% abnormal equity returns in each industry. Abnormal equity returns are calculated as the difference between the industry equity return and the SP500 return. The bottom figure plots the incidence of >100bps abnormal loan spreads in each industry. Abnormal loan spreads are calculated as the difference between the industry loan spread and the aggregate loan spread.

Figure 2.11: **Airline vs Oil Industry**
This figure plots the loan spread for the Oil&Gas industry and the Airline industry over 2014-2016 in which the global price of oil suffered a significant drawdown.

Table 2.1: **Loan spread cross-predictability**

This table predicts industry loan spreads using the supplier loan spread. The unit of observation is the industry-b, month-t level. The dependent variable, $\Delta S^{Loan}_{b,t+1}$, is the change in loan spread for industry-b from t to $t+1$. The independent variables include lagged changes in industry-b's loan spread from $t-1$ to t, $\Delta S^{Loan}_{b,t}$, and the lagged change in supplier loan spread from $t-1$ to t, $\Delta S^{Loan-Suppliers}_{b,t}$. The supplier loan spread is constructed from supplier industry loan spreads weighted by the flow of goods and services from the lagged annual BEA Input-Output tables. Col(1)-(6) cluster standard errors at the time and industry level. In Column (1)-(4) the sample period is 1999:11 to 2023:03. The sample period for Col(5) is 1999:11 to 2010:01. The sample period for Col(6) is 2010:02 to 2022:12.

Dependent Variable:	$\Delta S^{Loan}_{b,t+1}$					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
	1999:2022	1999:2022	1999:2022	1999:2022	Pre-2010	Post-2010
Variables						
$\Delta S^{Loan}_{b,t}$	0.2178***		0.0979	0.1028	0.0843	0.1670**
	(0.0566)		(0.0745)	(0.0815)	(0.0881)	(0.0697)
$\Delta S^{Loan-Suppliers}_{b,t}$		0.4170***	0.3112***	0.1682	0.1505	0.3279*
		(0.0546)	(0.0685)	(0.1617)	(0.1664)	(0.1855)
Fixed-effects						
industry				Yes	Yes	Yes
date_m				Yes	Yes	Yes
Fit statistics						
Observations	4,168	4,168	4,168	4,168	1,978	2,190
R^2	0.04741	0.06194	0.06753	0.32269	0.27807	0.47695
Within R^2				0.01822	0.01302	0.05137

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2.2: **Bond spread cross-predictability**

This table predicts industry bond spreads using the supplier bond spread. The unit of observation is the industry-b, month-t level. The dependent variable, $\Delta S^{Bond}_{b,t+1}$, is the change in bond spread for industry-b from t to $t+1$. The independent variables include lagged changes in industry-b's bond spread from $t-1$ to t, $\Delta S^{Bond}_{b,t}$, and the lagged change in supplier bond spread from $t-1$ to t, $\Delta S^{Bond-Suppliers}_{b,t}$. The supplier bond spread is constructed from supplier industry bond spreads weighted by the flow of goods and services from the lagged annual BEA Input-Output tables. Col(1)-(6) cluster standard errors at the time and industry level. In Column (1)-(4) the sample period is 1999:11 to 2023:03. The sample period for Col(5) is 1999:11 to 2010:01. The sample period for Col(6) is 2010:02 to 2022:12.

Dependent Variable:	$\Delta S^{Bond}_{b,t+1}$					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
	1999:2022	1999:2022	1999:2022	1999:2022	Pre-2010	Post-2010
Variables						
$\Delta S^{Bond}_{b,t}$	0.1150**		-0.0050	-0.0042	0.0205	-0.1268**
	(0.0544)		(0.0970)	(0.0490)	(0.0590)	(0.0537)
$\Delta S^{Bond-Suppliers}_{b,t}$		0.2774***	0.2819**	-0.0069	-0.0372	0.1584
		(0.0436)	(0.1115)	(0.1724)	(0.2086)	(0.1981)
Fixed-effects						
industry				Yes	Yes	Yes
date_m				Yes	Yes	Yes
Fit statistics						
Observations	3,656	3,656	3,656	3,656	1,511	2,145
R^2	0.01362	0.03664	0.03666	0.40866	0.35269	0.58195
Within R^2				2.51×10^{-5}	0.00040	0.01424

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2.3: **Correlated Fundamentals**

This table examines the contemperaneous correlation in the fundamentals of related industries. The unit of observation is the industry-b, month-t level. The dependent variable $Y_{b,t}$ is the level of OUT/VA for industry-j in quarter-t. I compute the Y_t^{Market} as the aggregate level of OUT/VA by summing across all industries in quarter-t. I compute the $Y_{b,t}^{Suppliers}$ for each industry by weighting the industry level OUT/VA with the flow of goods and services from the BEA input-output tables. All columns cluster standard errors at the time and industry level. The sample period is 2005:03 to 2022:12

Dependent Variables:	$OUT_{b,t}$	$VA_{b,t}$
Model:	(1)	(2)
Variables		
OUT_t^{Market}	0.0247	
	(0.0163)	
$OUT_{b,t}^{Suppliers}$	0.3555*	
	(0.1879)	
VA_t^{Market}		-0.0150
		(0.0344)
$VA_{b,t}^{Suppliers}$		0.5639*
		(0.3083)
Fixed-effects		
industry	Yes	Yes
Fit statistics		
Observations	1,080	1,080
R^2	0.98794	0.98343
Within R^2	0.49093	0.47308

Clustered (industry & date) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2.4: **Predicting Industry Equity Returns**

This table predicts industry equity returns using industry loan spreads. The dependent variable, $Ret_{b,t+1}^{Equity}$ is the industry-b's equity return from t to $t+1$. The indepdendent variables include, $\Delta S_{b,t}^{Loan}$, the change in industry-b's loan spread from $t-1$ to t, and $Ret_{b,t}^{Equity}$ industry-b's equity returns from $t-1$ to t. All specifications include industry and time fixed effects. All columns cluster standard errors are the time an industry level. The sample period in Col(1) is 1999:11 to 2023:03, Col(2) is 1999:11 to 2015:01, and in Col(3)-(5) is 2015:01 to 2023:03.

Dependent Variable:			$Ret_{b,t+1}^{Equity}$		
Model:	(1)	(2)	(3)	(4)	(5)
	1999-2022	Pre-2015	Post-2015	Post-2015	Post-2015
				$\Delta S_{b,t}^{Loan} > 0$	$\Delta S_{b,t}^{Loan} < 0$
Variables					
$\Delta S_{b,t}^{Loan}$	0.1997	0.0541	1.266*	2.656***	-0.3134
	(0.1495)	(0.0910)	(0.6337)	(0.8620)	(0.5237)
$Ret_{b,t}^{Equity}$	-0.0134	0.0154	-0.0231***	-0.1144	-0.0031
	(0.0082)	(0.0358)	(0.0069)	(0.1235)	(0.0018)
Fixed-effects					
industry	Yes	Yes	Yes	Yes	Yes
date_m	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	4,361	2,694	1,455	702	753
R^2	0.31308	0.65113	0.21083	0.25152	0.68563
Within R^2	0.00050	0.00036	0.00247	0.00360	0.00109

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2.5: **Equity returns cross-predictability**

This table predicts industry equity returns using the supplier equity returns. The unit of observation is the industry-b, month-t level. The dependent variable,$\Delta S^{Equity}_{b,t+1}$, is the equity return for industry-b from t to $t+1$. The independent variables include lagged equity return in industry-b from $t-1$ to t, $\Delta S^{Equity}_{b,t}$, and the lagged supplier equity return from $t-1$ to t, $\Delta S^{Equity-Suppliers}_{b,t}$. The supplier equity return is constructed from supplier industry equity returns weighted by the flow of goods and services from the lagged annual BEA Input-Output tables. Col(1)-(6) cluster standard errors at the time and industry level. In Column (1)-(4) the sample period is 1999:11 to 2023:03. The sample period for Col(5) is 1962:01 to 2005:01. The sample period for Col(6) is 2005:01 to 2022:12.

Dependent Variable:	$Ret^{Equity}_{b,t+1}$					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
	1999:2022	1999:2022	1999:2022	1999:2022	1962:2005	2005:2022
Variables						
$Ret^{Equity}_{b,t}$	-0.0291***		0.0070	-0.0152*	0.0156	-0.0146*
	(0.0086)		(0.0132)	(0.0079)	(0.0249)	(0.0082)
$Ret^{Equity-Suppliers}_{b,t}$		-0.0473***	-0.0514***	0.0015	0.1623**	0.0010
		(0.0091)	(0.0136)	(0.0031)	(0.0685)	(0.0037)
Fixed-effects						
industry				Yes	Yes	Yes
date_m				Yes	Yes	Yes
Fit statistics						
Observations	4,170	4,170	4,170	4,170	7,650	3,240
R^2	0.00084	0.00270	0.00273	0.31065	0.65665	0.28785
Within R^2				0.00021	0.00245	0.00020

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2.6: **Predicting Industry Cycles**

This table predicts industry output growth (OUT) and value added (VA) using loan spreads. The dependent variable $Y_{b,t+1}$ is the log growth rate in OUT/VA i.e. growth in real output from t to $t+1$. The independent variables include changes in credit spreads at the industry $\Delta S^{Loan}_{b,t}$ and aggregate level ΔS^{Loan}_{t}. Col(1) and (4) includes only the industry specific spread. Col (2) and (5) adds the aggregate loan spread. Col(3) and (6) include time and industry fixed effects. All specifications include a 1-quarter lag of growth in $Y_{b,t}$. Col(1),(2),(4),(5) use NW standard errors (lag=2), Col(3),(6) clusters standard errors at the time and industry level. The sample period is 2005:03 to 2022:12.

Dependent Variables:	$OUT_{b,t+1}$	$OUT_{b,t+1}$	$OUT_{b,t+1}$	$VA_{b,t+1}$	$VA_{b,t+1}$	$VA_{b,t+1}$
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\Delta S^{Loan}_{b,t}$	-0.0080***	-0.0057**	-0.0039***	-0.0068***	-0.0050**	-0.0036***
	(0.0019)	(0.0023)	(0.0012)	(0.0019)	(0.0022)	(0.0010)
ΔS^{Loan}_{t}		-0.3936			-0.3064	
		(0.3093)			(0.3944)	
Controls						
$Y_{b,t}$	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
industry			Yes			Yes
date			Yes			Yes
Fit statistics						
Observations	1,050	1,050	1,050	1,050	1,050	1,050
R^2	0.04809	0.05047	0.35664	0.03400	0.03510	0.26359
Within R^2			0.00706			0.00531

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2.7: **Predicting Industry Cycles - Equity**

This table predicts industry output growth (OUT) and value added(VA) using equity returns. The dependent variable $Y_{b,t+1}$ is the log growth rate in OUT/VA i.e. growth in real output from t to $t+1$. The independent variables include equity returns at the industry $\Delta S_{b,t}^{Equity}$ and aggregate level ΔS_{t}^{Equity}. Col(1) and (4) includes only the industry specific return. Col (2) and (5) adds aggregate equity returns. Col(3) and (6) include time and industry fixed effects. All specifications include a 1-quarter lag of growth in real $Y_{b,t}$. Col(1),(2),(4),(5) use NW standard errors (lag=2), Col(3),(6) clusters standard errors at the time and industry level. The sample period is 2005:03 to 2022:12.

Dependent Variables:	$OUT_{b,t+1}$	$OUT_{b,t+1}$	$OUT_{b,t+1}$	$VA_{b,t+1}$	$VA_{b,t+1}$	$VA_{b,t+1}$
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$Ret_{b,t}^{Equity}$	0.1359***	0.0715*	0.0446	0.0961*	0.0206	-0.0081
	(0.0441)	(0.0374)	(0.0483)	(0.0510)	(0.0458)	(0.0671)
Ret_{t}^{Equity}		0.1353***			0.1585***	
		(0.0337)			(0.0399)	
Controls						
$Y_{b,t}$	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
industry			Yes			Yes
date			Yes			Yes
Fit statistics						
Observations	1,050	1,050	1,050	1,050	1,050	1,050
R^2	0.07978	0.09563	0.35629	0.03846	0.05510	0.26109
Within R^2			0.00653			0.00193

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

2.5 Online Appendix

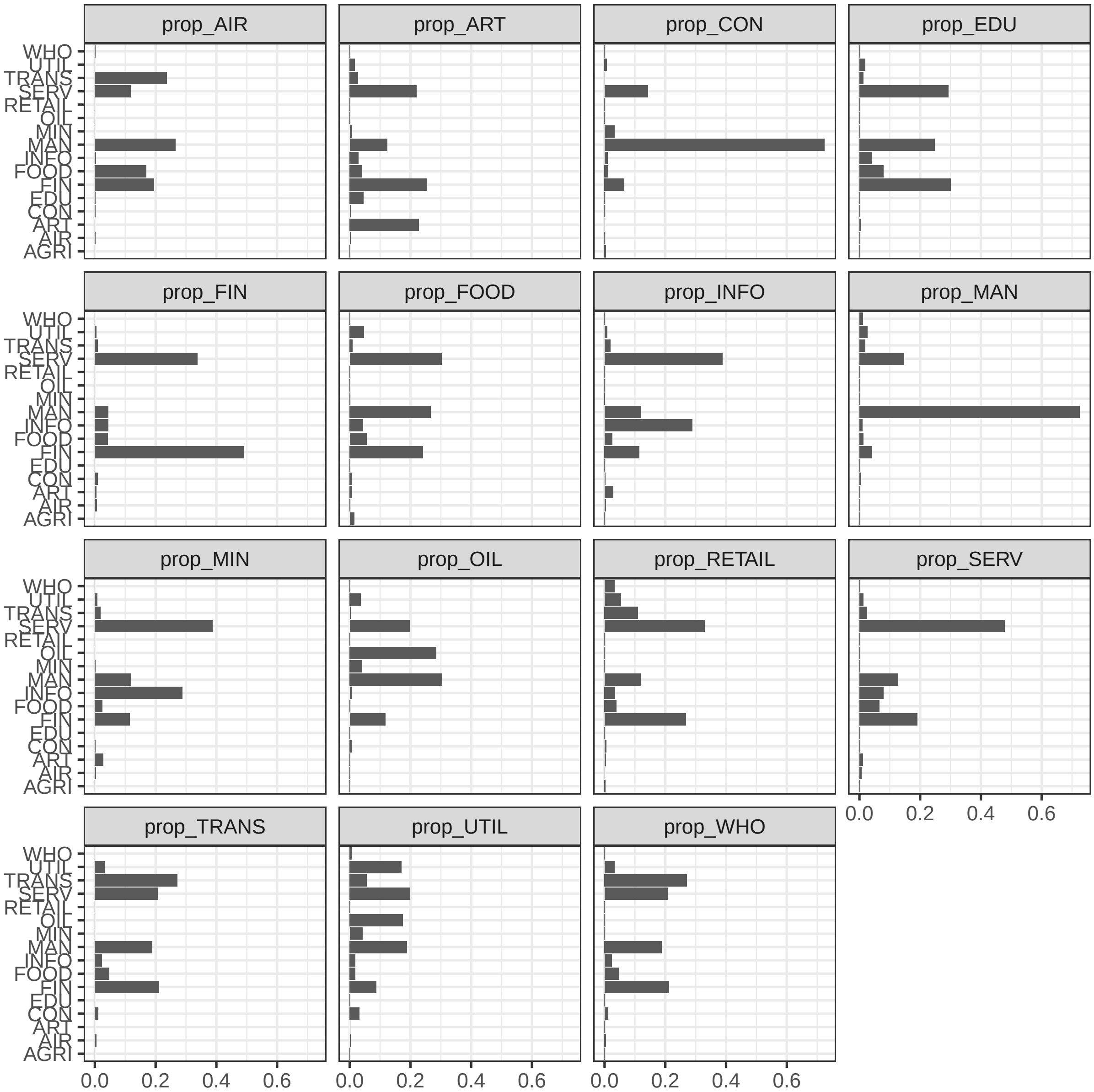

Figure 2.12: **Input-Output Table (2022 Edition**
This figure plots the cross industry usage of inputs from the 2022 edition of the BEA "Use" table from the Input-Output tables. Each sub-panel reports the percentage breakdown of inputs for each industry.

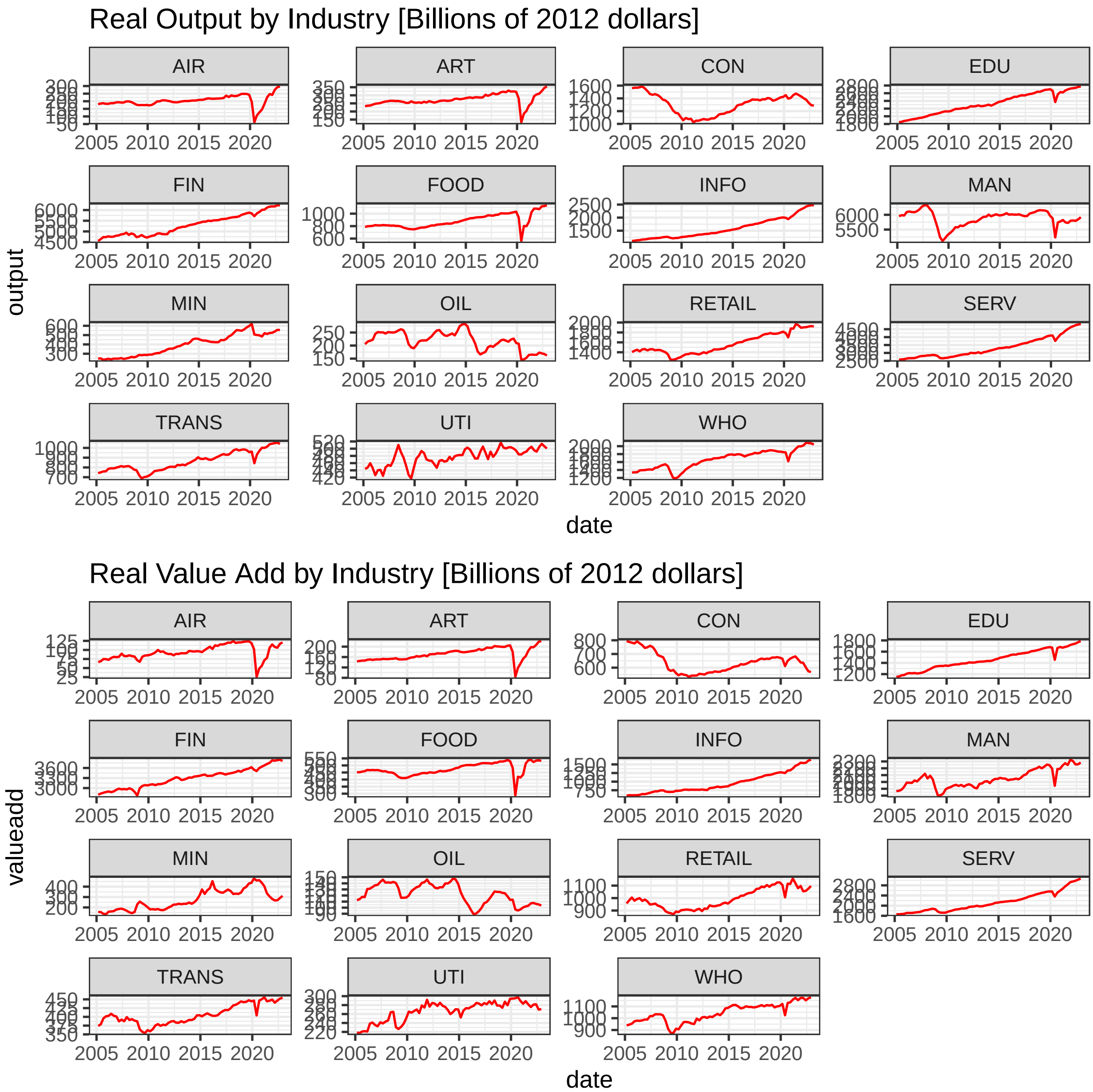

Figure 2.13: **Industry Output and Value Add (Levels)**
This figure plots the level of (Real) Value Added and (Real) Output by BEA industry. Underlying data comes from the BEA and is measured in billions of 2012 dollars, seasonally adjusted at annual rates. Sample period 2005:03 to 2022:09

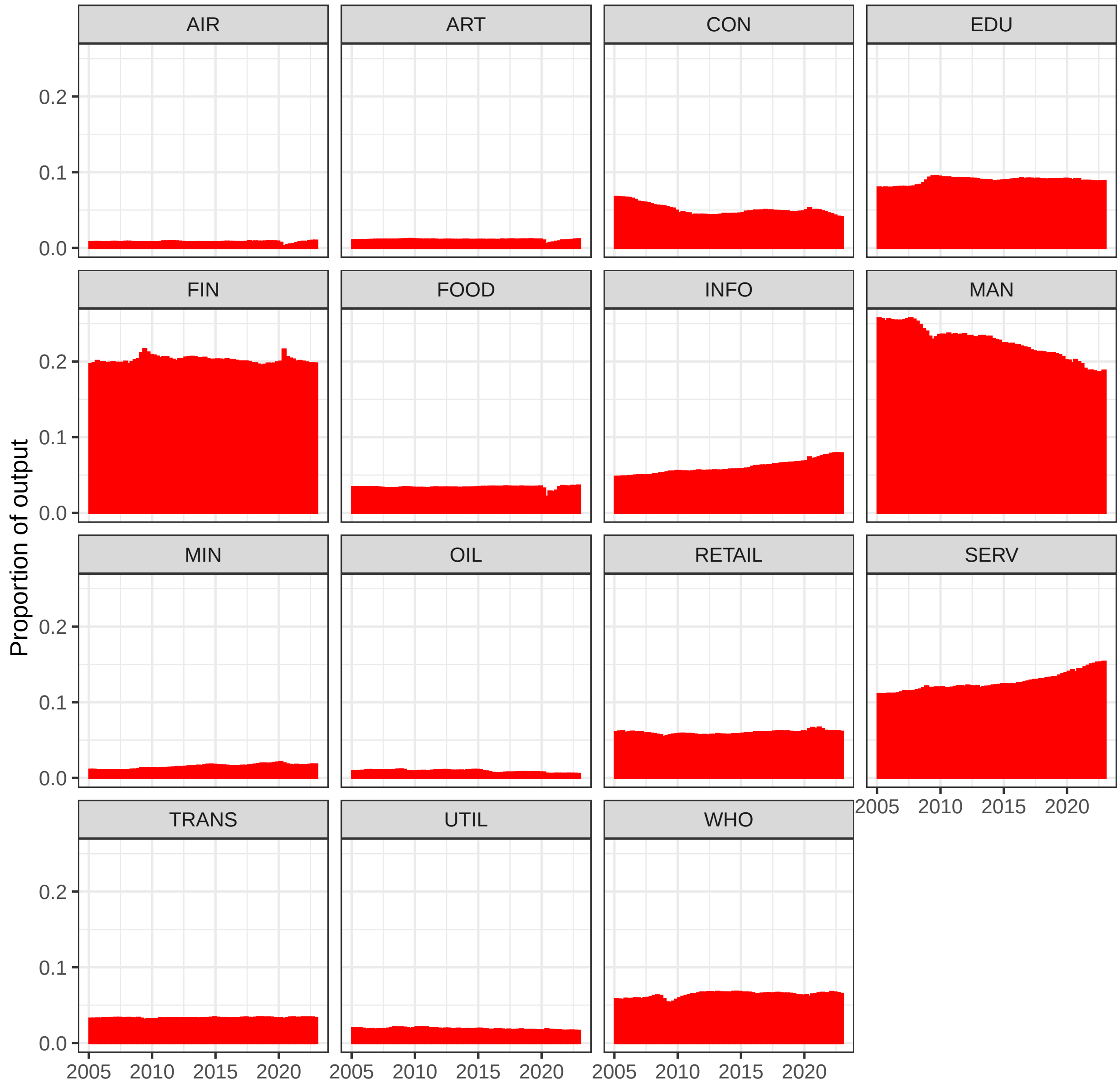

Figure 2.14: **Composition of industry output**
This figure plots the proportion of industry output associated with each industry. Data are based on BEA industry level output data. Sample period 1999:11 to 2022:09

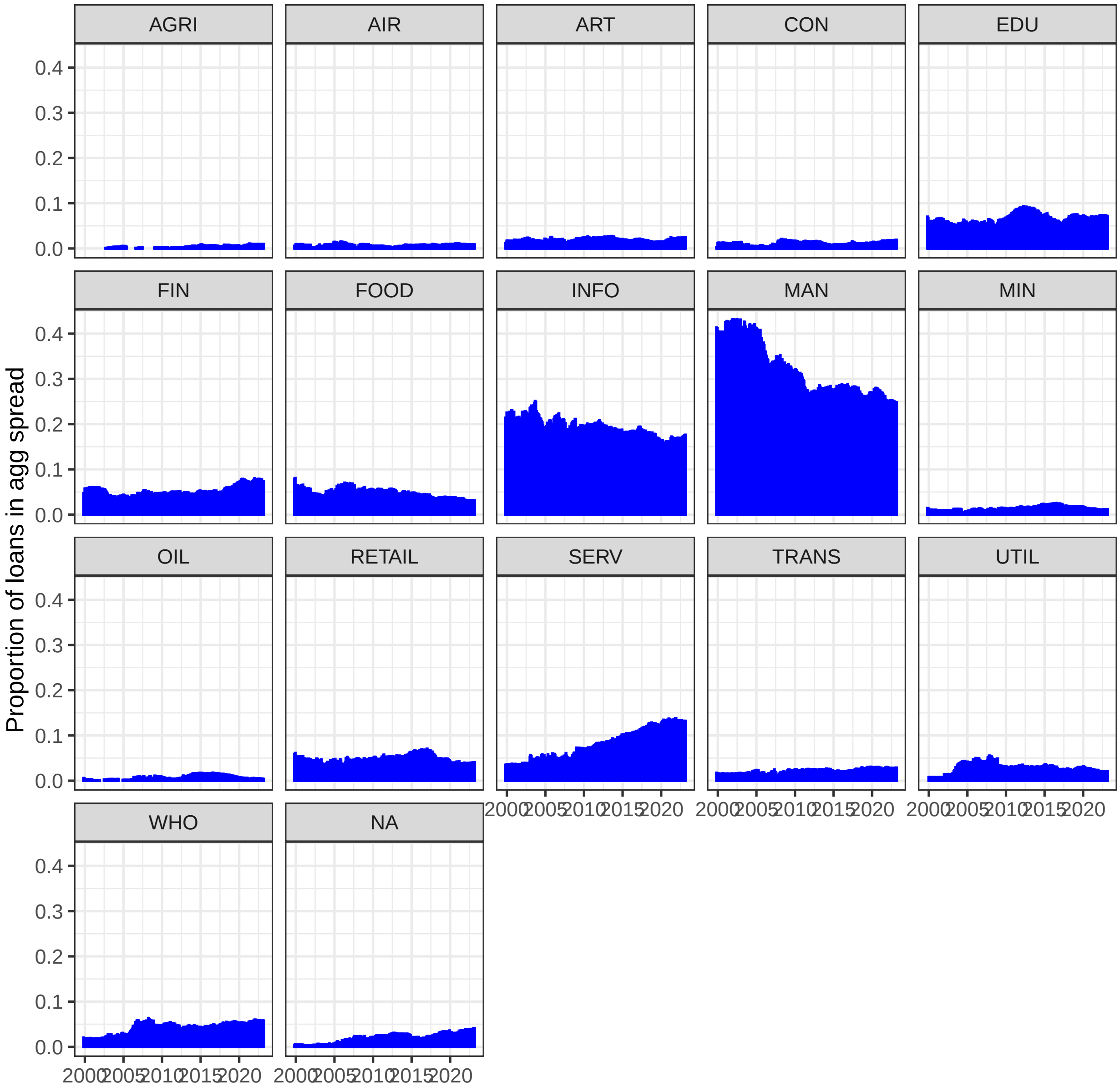

Figure 2.15: **Composition of the aggregate loan spread**
This figure plots the proportion of loans that belong to each industry. Saunders *et al.* (2023) aggregate loan spread is a simple equal-weighted average of all loan spreads available each month. This figure shows how representative this aggregate loan spread is of each industry. Sample period 1999:11 to 2022:09

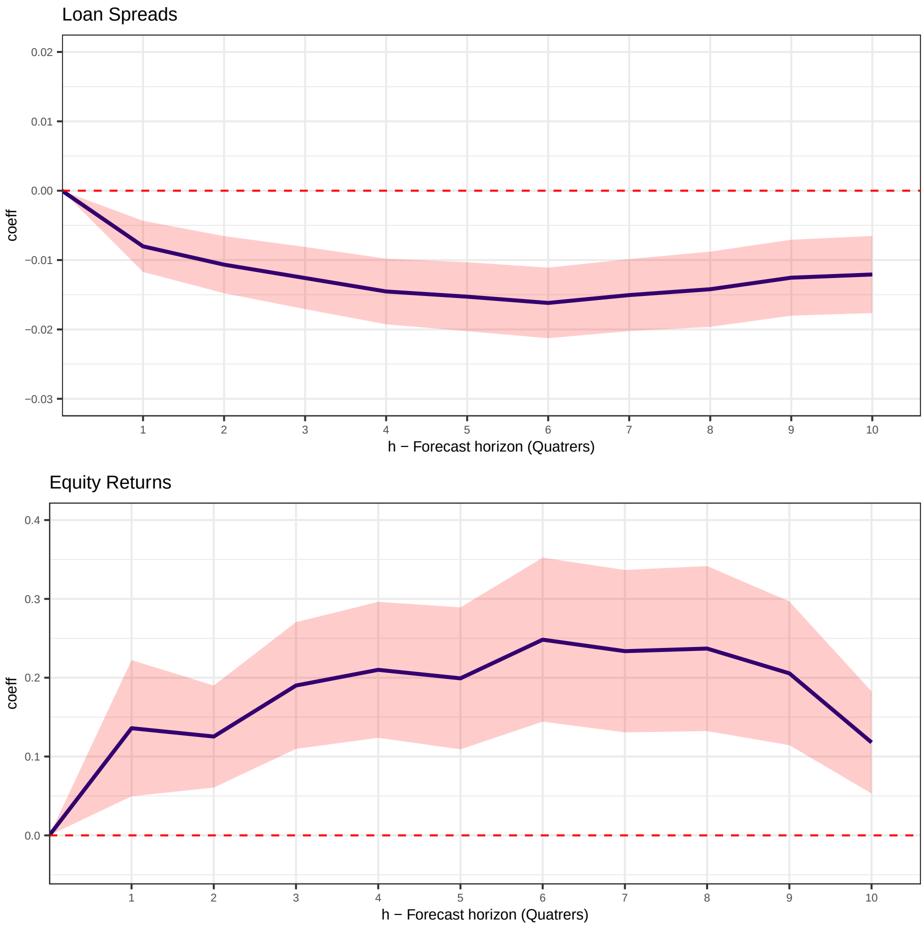

Figure 2.16: **Alternative forecast horizons**
This figure plots the coefficient on the baseline forecasting regression in Table 1, at various forecast horizons from h=0 to h=10.

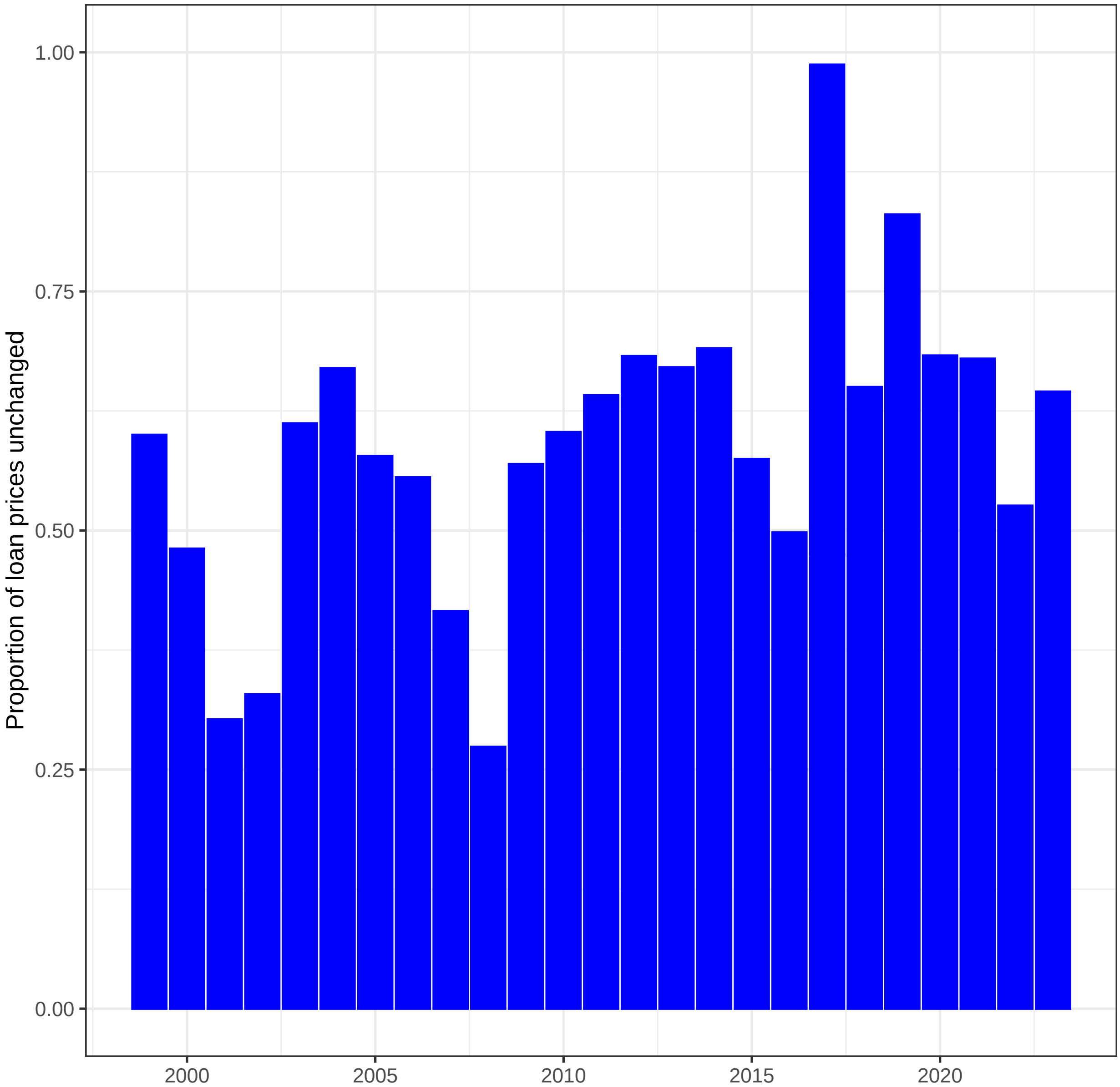

Figure 2.17: **Staleness in loan price quotes**
This figure plots the proportion of loans within an unchanged price relative to the week prior. Daily loan quotes come from the LSTA quotes data. Sample period 1999:11 to 2022:12

Chapter 3

Heterogenous Expectation Formation

Alessandro Spina [1]

Abstract

I use forecasts from the Wall Street Journal economic survey to study how respondents develop expectations of macroeconomic variables. Existing studies have typically assumed that forecasts from any given firm are coming from the same individual. In reality, employee turnover within surveyed firms is common. By tracking the turnover in survey respondents, I find that the degree of underreaction or overreaction measured in forecasts is influenced by the relative experience of the respondent. Furthermore, I find differences in respondent's subjective perception of the Federal Reserve's reaction function. These findings show that heterogeneity amongst respondents cannot be ignored when studying expectation formation.

[1] I thank David Lando, Julian Terstegee, Peter Norman Sørensen and seminar participants at UNSW for their helpful suggestions. I gratefully acknowledge support from the Center for Financial Frictions (FRIC), grant no. DNRF102.

3.1 Introduction

How agents develop expectations about the future matters for economics and finance. An approach to testing the expectation formation process was popularized by Coibion and Gordonichenko (2015), in which they measure the correlation between forecast revisions and subsequent forecast errors from macroeconomic surveys. Under the full-information rational expectations (FIRE) model, forecast revisions should not predict future forecast errors. When the correlation is positive, upward revisions predict higher realizations compared to the forecast, implying the forecaster underreacted to new information. When the correlation is negative, upward revisions predict lower realizations compared to the forecast, implying the forecaster overreacted to new information. A growing literature has documented evidence that expectations of macroeconomic variables do not adhere to what FIRE models predict, i.e. the correlation between forecast error and revision is non-zero; see Coibion and Gordonichenko (2015), Fuhrer (2018), Bordalo *et al.* (2020).

Existing studies have typically employed survey data from monthly macroeconomic surveys of professional forecasters. However, studies of expectations have commonly assumed that forecasts from any given firm are coming from the same individual over the whole sample period. In reality, a given firm's survey respondent, changes over time with natural employee turnover. What does predictability of forecast errors teach us about how respondents form expectations, if the underlying respondent is continually changing? If expectations are formed in a similar way across respondents, turnover of respondents can be safely ignored. However, if there are differences across respondents, then ignoring turnover may lead to mismeasurement of any systematic predictability. Respondent heterogeneity could be driven by respondent's own experiences Malmendier and Nagel (2011), or the type of firm an respondent is employed by Gleason and Lee (2003).

In this paper, I use the method of Coibion and Gordonichenko (2015) to test if the expectation formation process is systematically different in the cross section of survey respondents. In other words, I test if the implicit assumption of the homogenous respondent biases tests of systematic predictability. I take advantage of a seldom used survey of macroeconomic forecasts, the Wall Street Journal's (henceforth WSJ) monthly survey of macroeconomic forecasts. There are two benefits to using the WSJ survey over more commonly used surveys such as Blue Chip Economics (BCE), Survey of Professional Forecasters (SPF), and Consensus Economics (CE). First, the WSJ survey is a monthly survey which allows the study of expectation formation at a higher frequency than the quarterly SPF. Second, the WSJ survey reports the name of each respondent from each firm, which is not available in the SPF or BCE surveys [2]. Identification of the respondents allows me to proxy for respondent's relative survey experience by tracking the length of time the same individual has contributed forecasts to the WSJ survey. I show that the individual providing forecasts on behalf of a firm does regularly change and those changes matter, as "new" respondents tend to form their expectations differently than more experienced respondents.

Tests of the expectations formation process can be run at either the aggregate level (consensus forecasts) or at the individual level (individual forecasts). Bordalo *et al.* (2020) argue that tests at the consensus or individual level are informative about different departures from FIRE. Tests at the individual level are informative about departures from rationality, while tests at the aggregate level are informative about the role of information rigidities. In this paper I also use both consensus forecasts and individual forecasts. I document four main results.

First, I study systematic predictability in forecast errors at the individual level, ignoring respondent turnover. I find that individual forecasters show a mix of underreaction and overreaction to news. The 12-month ahead forecasts of the consumer price index (CPI), federal funds rate (FFR), and payroll employment (PEMP) show evidence of overreaction (i.e. upward revisions predict a negative forecast error). While 12-month ahead forecasts of 10-year US Treasuries (UST), Gross Domestic Product (GDP), Oil (OIL), and unemployment rate (UERATE) show evidence of underreaction (i.e. upward revisions predict a positive forecast error). These findings support the notion that respondents are not fully rational in how they form expectations. However, the findings stand in contrast to the overreaction documented by Bordalo *et al.* (2020). Is this difference explained by some structural difference between respondent in the WSJ survey and other macroeconomic surveys? If I condition on a set of overlapping firms that appears in both the BCE survey and WSJ survey, I find the pattern of underreaction is even stronger relative to the broader sample.

Second, I test for systematic differences in the predictability of forecast errors in the cross section of respondents. The implicit assumption in existing studies is that respondent

[2] Blue Chip Financial do provide the name of the contributing forecaster, but BCE and SPF do not. However, Blue Chip Financial focus on market interest rates and do not cover forecasts of key macro variables covered in BCE

turnover does not affect the measurement of forecast errors. I show that across all firms (long-term contributing firms), 25% (44%) of respondents turned over at least once over the sample. I take advantage of the variation in respondent experience this creates to split the sample in two and repeat the tests of forecast error predictability. I find that once I remove the "less-experienced" respondents (under 12-months) from the sample, there is a consistent pattern of underreaction to information across all variables. While the initial results, ignoring respondent turnover, showed a mix of overreaction and underreaction, once less-experienced respondents are removed, the pattern is one of underreaction.

A potential explanation for respondent underreaction is that survey respondents produce forecasts, not to minimize forecast error, but to optimize on wages, credibility, and job security (see, Lamont (2002), Morris and Shin (2002)). Reputational or career concerns may lead respondents to gradually adjust their public forecasts towards their true beliefs, leading to a pattern of underreaction. This is particularly plausible given the unique feature of the WSJ survey that makes respondent's name publicly available along with their forecast. There may be a reputational cost to providing a forecast that is seen as extreme relative to consensus. Therefore, the public nature of the WSJ survey itself, may in part, explain the WSJ respondent's tendency to underreact to information. To test this I implement the test proposed by Lamont (2002) and Mitchell and Pearce (2007), in which I regress a respondent's absolute forecast deviation from consensus on the number of surveys a respondent has participated in. I find that as respondents participate in more surveys, their forecasts tend to deviate less from the consensus forecast. This opens up a possible reconciliation between the overreaction documented by Bordalo *et al.* (2020), and the underreaction I find. It could be that respondent tend towards overreaction when forecasts are strictly anonymous, but when forecasts are public, reputational concern outweigh any tendency to extrapolate forecasts. These findings suggest that survey structure and panel composition matter for the interpretation of tests of expectation models Engleberg *et al.* (2009).

Third, I also study systematic predictability in forecast errors at the consensus level. Tests at the consensus level are informative about the role of information rigidities. Coibion and Gordonichenko (2015) focus on the role of informational rigidities in affecting forecasts, while maintaining individual rationality via Bayesian updating. They find evidence of under-reaction in consensus forecasts, which they interpret as evidence for departures from full information. I repeat the same tests using consensus forecast and find no evidence of overreaction or underreaction. Combined, these findings suggest that over the sample period, WSJ respondents do deviate from rationality, but there is no evidence of information frictions.

Fourth, I use respondent's *joint* forecast revisions to understand subjective perceptions about the Federal Reserve's (Fed) monetary policy reaction function. Introduced in the seminal work of Taylor (1993), the Taylor Rule, implies the Fed's interest rate policy ought to be closely related to changes in inflation and output levels. By studying how survey respondents vary their joint forecasts of FFR, CPI, GDP and UE, I can understand which variables respondents believe are important, i.e., I can back out respondent's subjective Fed reaction function. This question is explored by Bauer *et al.* (2022) in the time series. Bauer *et al.* (2022) find that perceptions of the Fed monetary policy rule are indeed time varying which has implications for asset pricing and monetary policy transmission. In contrast, I examine how perceptions of the Fed reaction function are systematically different in the cross-section of forecasters. I find that the type of organization the forecasters belong to affects their perceptions of the Fed reaction function. Respondents employed by 'Banks' and "Consultants', adjust their joint forecasts in a manner consistent with the belief that the Fed follows a Taylor Rule, i.e., when their FFR forecast is revised it tends to occur with joint revisions to their CPI and UE forecasts. In contrast, respondents employed by "Non-bank Financials", do not adjust their joint forecasts commensurate with a Taylor Rule, i.e., there is no relationship between their CPI, UE, and FFR forecasts. This suggests that the organization a respondent belongs to can shape incentives and how expectations about monetary policy are formed. Furthermore, I find that a respondent's relative experience also influences their perception of the Fed's reaction function. More experienced respondents (over 12-months) perceive the Fed to follow a traditional Taylor Rule approach, however, less experienced respondents (under 12-months) show no correlation between their joint forecasts. This finding further highlights how respondents appear to learn over time how to best incorporate new information into their forecasts.

This paper contributes to the existing literature in four ways. First, it contributes to the study of bias in expectations. A growing literature has documented deviations from models of rational expectations (see, among others, Pesaran and Weale, 2006; Coibion and Gordonichenko, 2015; Fuhrer, 2018; Bordalo *et al.*, 2020). The findings in this paper challenge the notion that overreaction to news is the dominant bias when forming expectations.

Second, this paper tests the hypothesis that expectation formation is heterogeneous in the cross-section of survey respondents. I find it is the more experienced forecasters that show a structural pattern of underreaction to new information. This implies panel composition may have implications for the growing body of research, that uses macroeconomic surveys to study deviations from FIRE models. Third, this paper's findings add to the existing literature on forecaster bias. Using survey data to test expectation models suffers from a joint hypothesis problem i.e. the implicit assumption is the forecaster has rational expectations *and* reports these expectations truthfully Lamont (2002). Lamont (2002) find older forecasters deviate more from consensus, Mitchell and Pearce (2007) find older forecasters are closer to consensus. My findings include a sample period after the publication of these papers and find evidence in support of the Mitchell and Pearce (2007) finding. These results are consistent with a model of reputational/career concerns, suggesting care must be taken when using survey data to draw broad conclusions about agent expectations. Finally, this paper contributes to the understanding of monetary policy communication. One of the key changes in monetary policy over the last two decades has been the increasing focus on communication and transparency with the market Nakamura and Steinsson (2018). This has made it increasingly important to understand how investors perceive the central bank's reaction function. I find that respondent's perception of the Fed reaction function is different depending on their employer organization's type and experience in forecasting.

3.2 Data

The WSJ has run a survey of macroeconomic forecasts for 35 years[3]. From the mid-1980s through 2002, the survey's frequency was twice a year. From 2003 through March 2021, it was conducted monthly. The survey asks between 50-70 individuals[4] to forecast a range of economic indicators, for example; quarterly and annual gross domestic product (GDP), the consumer price index (CPI), unemployment rate (UNRATE), monthly change in nonfarm payrolls (PEMP), the midpoint of the range for the federal funds rate (FFR), closing yield on 10-year Treasury Notes (10YRUST), and others. Some questions, such as GDP, have

[3] Data are publicly available on the WSJ website: https://www.wsj.com/articles/economic-forecasting-survey-archive-11617814998

[4] Mitchell and Pearce (2007) confirm from a WSJ source, that the selection of survey respondents does not depend on respondent past performance. The WSJ tries to sample a broad pool of forecasters, including chief economists from the major financial institutions.

been asked throughout the life of the survey. Others, such as the exchange rate for Euros to U.S. dollars, were asked only for a short time. Panel participants come from a range of organizations including financial intermediaries and consulting firms. Online Appendix B provides a full list of firms and the number of times each has contributed to the WSJ survey.

A typical question asks respondents for their forecast for a given macro variable at multiple fixed horizons. For example, in the February 2020 edition of the survey, respondents were asked for the forecasts of the unemployment rate in June 2020, Dec 2020, June 2021, Dec 2021 and June 2022. The impact of a fixed-date forecast is that the forecast horizon h will change month to month. To deal with this I take advantage of the term structure of forecasts provided each month. I linearly interpolate between forecasts provided to achieve a forecast for the same h-horizon ahead every month. That way the predictability regressions discussed in Section 3.3 always use forecasts with the same forecast horizon-h over time.

3.2.1 Comparisons between surveys

In this section I describe the commonly used survey data used to test models of expectation formation and how the WSJ survey data is unique. The SPF is a commonly used survey of macroeconomic forecasts administered by the Federal Reserve Bank of Philadelphia. The SPF is a quarterly survey of approximately 40-50 respondents. Each forecaster is anonymous and identified only by an ID. The industry the forecaster belongs to is flagged as either financial, non-financial or other. Otherwise, the exact identity of the participating firms is unknown. Forecasts are provided for the current quarter out to four quarters ahead. Variables are typically measured as the average level over a given quarter i.e. the one quarter ahead unemployment rate forecast is the average level of the unemployment rate over the next three months. The WSJ survey used in this paper differs from SPF along several dimensions. First, the WSJ is a higher frequency survey conducted monthly. Second, the WSJ allows the identification of the firm and individual contributing to the survey. Thirdly, the WSJ typically provides a point estimate of the future macro variable, whereas SPF report forecasts of quarterly averages. To address the concern that forecasts from the WSJ are somehow structurally different from the SPF, Figure 3.10 and 3.11 compare the consensus forecasts for UE and UST across the two surveys. The high correlation for forecasts across the two surveys suggests that forecasts from WSJ respondents are not structurally different from participants in other surveys.

The BCE is an alternative macroeconomic survey. The BCE is a monthly survey of approximately 40-50 respondents from a range of private and public sector institutions. Each forecaster is identified by the firm contributing the forecasts, but the individual name of the forecaster is not provided[5]. Forecasts are typically provided as the year-on-year growth rate of a variable over the calendar year. Other variables are defined as the average of the calendar year. The WSJ survey used in this paper also differs from BCE survey along a number of dimensions. First, BCE allows identification of firms, but not of individuals contributing. Second, WSJ provides forecasts along a range of fixed dates (i.e. allowing for a fixed forecast window using the interpolation described in Section 3.2), whereas BCE provide forecasts for a single fixed period i.e., the forecast horizon is changing survey to survey.

3.2.2 Panel composition

In this section I discuss the composition of the WSJ panel of respondents. I begin by categorizing all survey respondents into four groups based on the firm type: 'Bank', 'Non-bank Financial', 'Consultant', and 'Private' [6]. Figure 3.1 highlights how the composition of the panel has changed over time. Figure 3.1 shows a clear trend away from Banks and Other Financials and towards Consulting and Private firms.

How often do the respondents for a given firm change? If respondents change infrequently than the implicit assumption of a homogenous individual may be warranted. Figure 3.2 highlights how frequently firms change forecaster, i.e. a measure of staff turnover. The top panel reveals that of the 160 firms that submitted a forecast to the WSJ survey, 40(25%) changed forecaster at least once over the sample period in which they contributed forecasts. I identify a change in forecaster by a change in the name of the respondent providing forecasts for a given firm. However, it should be noted a number of firms only enter the WSJ panel for a short period, and then drop out. To account for this, the bottom panel of Figure 3.2 conditions on those "long-term contributing" firms that contributed to the WSJ survey for at least 4 years. Amongst these firms, 35 out of 80 (44%) changed forecaster at least

[5] Blue Chip Financials forecasts do provide the name of the contributing forecaster, but the Blue Chip Economic forecasts and SPF do not. Blue Chip Financials survey focuses on forecasts of interest rate variables and so does not cover many of the economic variables covered by the Blue Chip Economic survey.

[6] See Online Appendix B provides a full list of firms and the number of times each has contributed to the WSJ survey

once over the sample period in which they contributed forecasts. Figure 3.2 highlights staff turnover is frequent within the panel of forecast contributors. It is this variation in forecaster "experience" I will exploit to test for differences in expectation formation.

3.3 Forecast error on forecast revision regressions

What does the predictability of forecast errors reveal about how individuals form expectations? Coibion and Gordonichenko (2015) proposed a method of regressing future forecast errors on current forecast revisions. Their predictability regression takes the following form:

$$FE_{t+h} = \beta_0 + \beta_1 FR_{t,h} + \epsilon_{t,t+h}, \tag{3.1}$$

Under the full information rational expectations (FIRE) model the forecast error is unpredictable, and the regression coefficient should be $\beta_1 = 0$, i.e. each agent rationally updates with all information available. When $\beta_1 > 0$, upward revisions predict higher realizations relative to forecasts, meaning the agents underreacted to information relative to FIRE. This means agents systematically did not adjust the forecast by enough in the right direction. When $\beta_1 < 0$, upward revisions to forecasts predict lower realizations relative to forecasts, meaning agents overreacted to new information.

The predictability regression in Equation 3.1, can be run at either the aggregate level (using consensus forecasts) or at the individual level (using individual forecasts), with each testing a different departure from the FIRE model. Coibion and Gordonichenko (2015) focus on only the aggregate level version, because their focus is on the role of informational rigidities in affecting forecasts, while maintaining individual rationality via Bayesian updating. Information rigidity models fall into two camps, the sticky-information model of Mankiw and Reis (2002) and the noisy-information model of Woodford (2003). Under either one of these models, Coibion and Gordonichenko (2015) argue that there should be no predictability at the individual level. Under sticky information, agents either do not update their information and so there is no forecast revision, or if they do update, they update directly to the rational forecast in which case there will also be no predictability. Hence, the predictability of the consensus forecast error using consensus forecast revisions, is an emergent property of the aggregation across individuals, not a property of the individual forecasts.

To analyze forecast error predictability at the consensus level I denote the consensus forecast made at time t about the future value of a variable h-periods ahead as $x_{t+h|t}$. This is an equal-weighted average of all forecasts made by survey respondents at time t. The consensus forecast of the same variable in the previous period $t-1$ is then denoted $x_{t+h|t-1}$. The h-period consensus forecast revision is then defined as $FR_{t,h} = (x_{t+h|t} - x_{t+h|t-1})$. The actual value of the variable at time $t+h$ is denoted x_{t+h} and the h-period ahead consensus forecast error is then defined as $FE_{t+h} = (x_{t+h} - x_{t+h|t})$. The predictability of consensus forecast errors is measured using the following regression:

$$FE^{i}_{t+h} = \beta^{c}_{0} + \beta^{c}_{1} FR^{i}_{t,h} + \epsilon^{i}_{t,t+h}, \tag{3.2}$$

This framework was extended by Bordalo *et al.* (2020) who argue that different tests are informative about different departures from FIRE. Tests at the aggregate level are informative about the role of information rigidities. Tests at the individual level are informative about departures from rationality. To analyze forecast error predictability at the individual level I define the forecast revisions at the individual level, $FR^{i}_{t,h} = (x^{i}_{t+h|t} - x^{i}_{t+h|t-1})$, and the forecast error at the individual level as $FE^{i}_{t+h} = (x^{i}_{t+h} - x^{i}_{t+h|t})$. The following specification is then estimated on the pooled sample:

$$FE^{i}_{t+h} = \beta^{p}_{0} + \beta^{p}_{1} FR^{i}_{t,h} + \epsilon^{i}_{t,t+h}, \tag{3.3}$$

3.4 Predictability in forecast errors

In this section I use the Coibion and Gordonichenko (2015) regression framework to test for overreaction or underreaction in the expectations of all respondents to the WSJ survey. I first estimate the predictability regression at an individual level using Equation (3.2) across seven macroeconomic variables with sufficient coverage in the WSJ survey data. The forecasting horizon is the interpolated 12 months ahead ($h = 12$). All data are winsorized, as GC style regressions are highly sensitive to outliers Kucinskas and Peters (2023), Juodis and Kucinskas (2023) [7].

Individual level Figure 3.3 plots the point estimates and confidence intervals for the coefficient β_1^p from Equation (3.2). The standard errors are clustered at the forecaster and time level. The first finding is that at the individual level the estimated coefficient for β_1^p are mixed. Figure 3.3 reveals that individual's forecasts of UST, GDP, OIL and UE tend to underreact ($\beta_1^p > 0$) to information at the 12-month ahead horizon, while CPI, FFR and PEMP overreact ($\beta_1^p < 0$) to new information. This in contrast to Bordalo *et al.* (2020) who find that for 14 out of 22 variables, individual's forecasts tend to overreact ($\beta_1^p < 0$). One explanation for the discrepancy could be that the WSJ survey includes forecasts from a different set of firms than covered by Bordalo *et al.* (2020). To control for this, Figure 3.4 repeats the regressions, but includes only WSJ survey respondents who also appear in the BCE survey. I hand match firm names from the BCE and WSJ surveys and find 70 out of 175 (40%) of firms overlap. When conditioning on this subset of firms, I find a pattern of underreaction across all seven variables, albeit PEMP and UE are statistically insignificant [8]. Conditioning on the same set of respondent firms, the WSJ survey and BCE survey reveal very different patterns in expectation formation. Overall, we see at the individual level a mix of overreaction or underreaction, especially amongst the overlapping set of forecasters. This evidence suggests some deviation from rational expectations, but in the direction of underreaction.

Term structure of expectations Next I examine the degree of underreaction or overreaction across different forecast horizons, i.e., I establish a "term-structure" of deviations from rational expectations. Typically, predictive regressions in the form of Equation 3.2 focus on one particular forecast horizon. However, it is plausible that the degree of deviations from FIRE models varies depending on the forecast horizon considered. I begin by plotting the point estimates and confidence intervals for the β_1^p coefficient across horizons ($h = 1, 2, 3, 4, 5$) quarters ahead in Figure 3.5. Interestingly, the degree of overreaction or underreaction is sensitive to the exact forecast horizon chosen. In particular, UST, GDP and OIL forecasts at short and longer horizons can have opposite signs. This evidence suggests that the exact

[7] Juodis and Kucinskas (2023) argue that when expectations are measured with error, the CG regression suffers from a nonclassical measurement-error problem that can spuriously yield negative coefficients.

[8] Bordalo *et al.* (2020) use the BCE survey data for two variables (FFR and 10YRUST) which are also part of the WSJ survey. If I compare my results on these two variables I find FFR has the same sign as reported by Bordalo *et al.* (2020), whereas 10YRUST has the opposite sign.

nature of the deviation from rational expectations may differ between short-run and long-run forecasts.

Consenus forecast regression Next, I estimate the predictability regression at the aggregate level (Equation 3.3). Figure 3.6 plots the point estimates and confidence intervals for β_1^c. I find that at the aggregate level, for six out of seven macroeconomic variables the estimated coefficient β_1^c is statistically indifferent from zero. Figure 3.7 repeats the test but restricts the sample to overlapping firms which also appear in the BCE survey. I find the same pattern, β_1^c is statistically indifferent from zero for six out of seven macroeconomic variables. As described above, $\beta_1^c \neq 0$ would be consistent with information frictions. Figure 3.6 and 3.7 suggest no information frictions in contrast to the findings of Bordalo *et al.* (2020) and Coibion and Gordonichenko (2015). This leads to the question, is there something unique about the respondents to the WSJ survey or has the information environment in which forecasts are produced changed?[9] One important difference is the sample period covered in Bordalo *et al.* (2020) and this paper. In Bordalo *et al.* (2020) survey data from SPF start in 1968, and survey data from BCE start in 1981. WSJ survey data only starts in 2002. One explanation of the difference in results, could be that information is faster and easier to be incorporated by survey respondents, reflected in a decreasing β_1^c over time.

Summary Tests at the consensus level are ultimately a test of the full information assumption, whereas tests at the individual level are a test of the rational expectations assumption. At the consensus level I find little evidence of systematic overreaction or underreaction to information. At the individual level, I observe underreaction to information. This suggests no information frictions, in contrast to the findings of Coibion and Gordonichenko (2015). My findings do align with Bordalo *et al.* (2020), in that we both find deviations from rationality at the individual level. However, I find underreaction in expectations which does not fit their model of diagnostic expectations leading to overreaction in expectations. In order to rationalise both these findings, I need a model of expectation formation that excludes limits to information processing (to capture the absence of overreaction or underreaction at the consensus level), but does have some deviation from rationality (to capture the underreaction prevalent at the individual level). Section 3.5.1 further discusses potential explanations to reconcile these findings.

[9] For example the ubiquitous Bloomberg Terminal has reduced barriers to information propagation and immediacy.

3.5 Forecaster experience

In this section I test whether the pattern of overreaction or underreaction to new information is related to how experienced the forecaster is. To proxy for experience, I count the number of times a respondent has participated in the WSJ economic survey. This proxy captures the experience of WSJ respondents *relative* to other WSJ respondents. This relative measure of experience is still potentially relevant dimension of experience, given the literature exploring analyst herding behaviour Lamont (2002). I start with a definition which labels any respondent as "new" in the first 12 surveys they start providing forecasts for a given firm. This definition excludes the first observed respondent for each firm, as I am unable to identify their survey history. Any subsequent respondent after the initial respondent, can be classified as a "new" respondents. Therefore, this definition requires a firm to have at least one change in respondent over the sample period to have any respondent potentially classified as "new". Firms for which the respondent's name remains constant across the entire sample, can never be classified as "new" under this definition.

To test this hypothesis, I repeat Equation 3.2 for the two sub-groups of "less-experienced" and "more-experienced". Figure 3.8 plots the β_1^p coefficients across these two groups where "less-experienced" is defined as respondents in their first 12 months. The first finding is that the "less-experienced" group show a different pattern compared to the "more-experienced" group. For the less experienced group, all coefficients for β_1^p are statistically indifferent from zero, suggesting no deviation from rationality. In contrast, the left panel of Figure 3.8 highlights for the "more-experienced group", all seven variables show a pattern of underreaction to new information. This difference in sign (and size) of regression coefficients across the two groups reveals the process of information incorporation is related to the individual's experience. One concern with Figure 3.8 may be that the type of firm differs between the sample in the less-experienced and more-experienced groups. Figure 3.14 of the Online Appendix, further compares new respondents in the first 12 months (LHS panel), to the *same* respondent after their first 12 months (RHS panel). This removes any firms which never have a "new" respondent, i.e. never change respondent over the sample. The overall result remains unchanged, with underreaction to new information emerging as the dominant pattern in expectations.

Next, I check the sensitivity of the previous result to the cutoff used to define more or less experienced respondents. I repeat the predictive regressions, but use an expanding definition of "less-experienced". In Figure 3.9 I define "less-experienced" as individuals in either their first 6, 12, 18, or 24 months of participating in the WSJ survey. For the variables CPI, UERATE, OIL and PEMP we see the greatest amount of overreaction or underreaction occurs when I define "less-experienced" as in their first 6 surveys, albeit the small sample makes these estimate particularly noisy. By widening the definition to cover individuals in their first 24 month we see the degree of overreaction and underreaction begins to stabilise. This suggests that there is something unique about the newest respondents who have joined the WSJ panel, their forecasts appear more susceptible to deviations from the FIRE model. It suggests that forecasters are themselves "learning" the optimal way to process information and update forecasts[10].

3.5.1 Reputational concerns

In Section 3.4 I observe underreaction to information, which does not fit the Bordalo *et al.* (2020) model of diagnostic expectations. In order to explain the findings of this paper, I need a model of expectation formation that includes some deviation from rationality, in the direction of underreaction.

What alternative explanations could reconcile these findings and help explain why the experience of forecasters matters for their expectation formation? Lamont (2002) suggests that survey respondents may produce forecasts, not to minimize some forecast error, but instead to optimize on wages, credibility and job security. New forecasters may wish to mark their tenure by initially making bold forecasts to build a reputation, but quickly converge towards consensus over time for fear of reputational/career concerns. Morris and Shin (2002) also suggest individuals may wish to stay close to consensus for fear of standing out [11]. This channel is potentially potent for the WSJ survey in particular, given the respondent's name is made public, along with their forecast. The public nature of the WSJ survey may explain the respondent's tendency to underreact to information, as there may be a reputational cost to providing a forecast that is seen as extreme relative to consensus.

[10] Furthermore, I check if there are any systematic difference in expectation formation across organization type. As documented in Figure 3.1, respondents belong to variety of types of organization, so I split survey respondents into four groups based on what type of organization they belong to. Figure 3.15 reveals no systematic differences across groups.

[11] Keynes(1936): "Worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally."

To test this idea I repeat the test introduced by Lamont (2002) and Mitchell and Pearce (2007), in which I regress an individual's absolute forecast deviation from consensus on the number of surveys an individual has participated in [12] The regression takes the following form:

$$F_i - F_{c,(-i)} = \beta_0^p + \beta_1^p AGE_{i,t} + \beta_2^p AVEDEV_{c(-i),t} + \epsilon_{t,t+h}^i, \tag{3.4}$$

The dependent variable is the absolute difference between respondent-i's time-t forecast the consensus time-t forecast excluding respondent-i. AGE is the number of WSJ surveys the respondent has participated in. $AGEDEV_{-i}$ is the average absolute deviation of the time-t forecasts from the consensus time-t forecast, excluding the ith respondent. The coefficient of interest is β_1^p, which captures how respondent's forecasts relative to consensus change over time.

Table 3.4 reveals a statistically significant negative coefficients between deviation from consensus and number of surveys participated in for five out of seven macroeconomic variables. A negative coefficient indicates the more surveys an individual has participated in, the closer they tend to be to the consensus forecast. In terms of economic magnitudes, an additional 1 year participating, is associated with a forecast 12bps closer to the consensus CPI forecast. This is the opposite result compared to Lamont (2002), who finds that as forecasters participates in more surveys, they tend to become more radical and deviate further from consensus. However, Table 3.4 is consistent with the findings of Mitchell and Pearce (2007) who find that forecasters deviate *less* from consensus as they age. Interestingly, Mitchell and Pearce (2007) use the same WSJ survey data as used in this paper, but over a different sample period from 1989 to 2002. This evidence confirms the original findings of Mitchell and Pearce (2007) in an out of sample period.

This suggests that over time, respondents who continue to contribute to the WSJ survey, may become more concerned with maintaining their reputation as a forecaster who is not radical. This made lead respondents to underreact to new information for fear of standing out from the consensus forecast. This provides a simple mechanism to reconcile the findings

[12] Lamont(2002) uses data from Business Week annual year end outlook issue from 1971-1992 which did publish the forecasters name. However, the survey is limited to GNP, Unemployment and CPI forecasts for 12months ahead.

in this paper with Bordalo *et al.* (2020). They find typically find overreaction when analyst's forecasts are anonymous (as is the case in the BCE and SPF) surveys. In Section 3.4 I find that underreaction is prevalent when respondent's name are public (as in the WSJ survey). It is plausible that in the WSJ survey, career concerns play a more important role, biasing expectations towards underreaction.

3.6 Perceptions of the Fed reaction function

One of the key developments in monetary policy over the last two decades has been the improvements in policymaker communication and transparency. An increasing focus on the information channel of monetary policy has made it important to understand how financial market participants perceive the central bank's reaction function in order to understand how monetary policy is transmitted Nakamura and Steinsson (2018). However, when studying perceptions of monetary policy, do perceptions of the Fed reaction function differ between individuals? The previous section established that expectation formation can differ depending on an individual's experience. In this section, I ask the same question, does a respondent's level of experience affect their perceptions of how the Fed sets policy?

Monetary economists have proposed monetary rules like the Taylor Rule Taylor (1993). This implies that changes in the fed funds rate forecasts should be associated with contemporaneous changes in forecasts for inflation, employment, and output. By studying how survey respondents vary their *joint* forecasts of the fed funds rate and other macro variables, I can understand which variables respondents believe are important to the Fed, i.e. back out the survey respondent's subjective perception of the Fed reaction function. This question has been explored by Bauer *et al.* (2022) in the time series. They find that perceptions of the Fed policy rule are indeed time varying. I extend these findings and examine how perceptions of the Fed's reaction function are systematically different across the cross-section of forecasters.

I begin by measuring the contemporaneous correlation between changes in respondent's forecasts. In each specification I regress an individual's forecasted change in the fed funds rate, i.e. the difference between actual FFR in month t and the forecasted FFR at $t+12$, on the forecasted change in UNRATE and CPI forecasted over the same 12-month window. Each specification includes respondent and time fixed effects. The contemporaneous correlation between an individual's joint changes in FFR and UNRATE/CPI forecasts reveals what individuals think the Fed is more likely to respond to over the next 12-months. Table 3.1, column 1 - 3 examine the contemporaneous correlation between UE, CPI and GDP independently. Column 1 indicates an 1% increase in the UE over the next 12 months is associated with a 12bps decrease in FFR. Column 2 finds a 1% increase in CPI over the next 12 months is associated with a 16bps increase in FFR. Column 3 finds a 1% increase in GDP over the next 12 months is associated with a 5bps increase in FFR. This is consistent with the notion that individuals expect the Fed to target both parts of the dual mandate. An increase in the UNRATE forecast tends to occur with a contemporaneous decrease in the FFR forecast over the next 12 months. Similarly, an increase in CPI forecasts tends to occur with a contemporaneous increase in the FFR forecasts. Columns 4 and 5 include both variables jointly and finds the same result.

By Firm type: Does the type of organization for which an respondent is employed affect their perceptions of the Fed reaction function? To test this, I classify all respondent into four types of organization (Bank, Non-bank Financial, Consultant and Private) and repeat the previous regressions. Table 3.2 summarises the results by organization type. Table 3.2, column 1 indicates respondents belonging to Banks, adjust their forecasts as if the Fed followed a traditional Taylor Rule. An increase in UERATE is associated with a significant decrease in FFR, while a increase in CPI is associated with a significant increase in FFR. Interestingly, Non-bank Financials in column 2, show no contemporaneous relationship. This suggests respondents from this group either do not think the Fed reaction function follows the traditional Taylor Rule, or they do not adjust their forecasts in a consistent way across variables. In column 3, Consultants, also adjust their forecasts as if the Fed followed a traditional Taylor Rule. However, it is interesting to note, the stronger relationship between CPI and FFR forecasts for the Consultant group. Finally, column 4 reveals forecasts by Private respondents respond to changes in CPI, but not to changes in UERATE. Taken together, this suggests that respondents from different organizations adjust their forecasts very differently, meaning they perceive the Fed reaction function very differently. Is there something in the incentives or constraints respondents face in each type of organization that would lead to patterns found? For example, one potential explanation could be that Banks are overly sensitive to loan losses on mortgages/loans which are highly exposed to employment conditions in the economy. This leads respondents from Banks to place more focus on the Fed reacting to employment variables.

By Individual experience: Does the forecasting experience of the individual influence their perceptions of the Fed reaction function? To test this, I split respondents into two groups based on experience. "Less-experienced" are those individuals in their first 12 months of participating in the WSJ survey, the "more-experienced" group is everybody else. Table 3.3 summarises the results by individual experience. Col(1) of Table 3.3 reveals the "less-experienced" group show no significant correlation in how the adjust their joint forecasts. In other words, their forecasts of changes in FRR are independent of changes to their forecasts of PEMP and CPI. This in stark contrast to the "more-experienced" group in Col(2) who tend to adjust their joint forecasts consistent with the Fed following a Taylor rule. It appears forecasters learn over time and adjust their forecasts to be more in line with a Taylor Rule.

3.7 Conclusion

Using data from the WSJ economic survey, I revisit the question of how agents form expectations. Existing empirical studies have typically assumed that forecasts from any given firm are coming from the same individual. In reality, I show that employee turnover within surveyed firms is common. By tracking the turnover in survey respondents, I am able to identify individuals and show that the degree of underreaction or overreaction measured in forecasts, is influenced by the relative experience of the respondent. Furthermore, I find differences in respondent's subjective perception of the Federal Reserve's reaction function.

Together these findings raise interesting questions about the study of expectation formation. First, the results presented in this paper provide further evidence for underreaction in expectations. Overreaction may not be the dominant paradigm when it comes to forming expectations and further research is required to understand what drives the mixed results. Second, survey design, whether respondents are anonymous or identified, may in part explain the mixed results in the literature. This suggests that respondent's incentives must be considered when studying expectation formation across differently structured surveys. Furthermore, if the panel composition of respondents is changing over time, then care must be taken when interpreting tests of expectation formation. Third, differences in respondent's subjective perception of the Fed's reaction function, has implications for monetary policy communication. The Fed's communication policy over the last decade has been built around improving the transparency with which the Fed communicate their own beliefs, with the aim that market participants use this to guide their own expectations of the path of future policy. However, the findings presented in this paper suggests some respondents either do not believe the Fed follows a Taylor Rule, or update their joint forecasts in manner inconsistent with a Taylor Rule. I leave it to future research to further study exactly how respondent's beliefs align with the beliefs of the Fed.

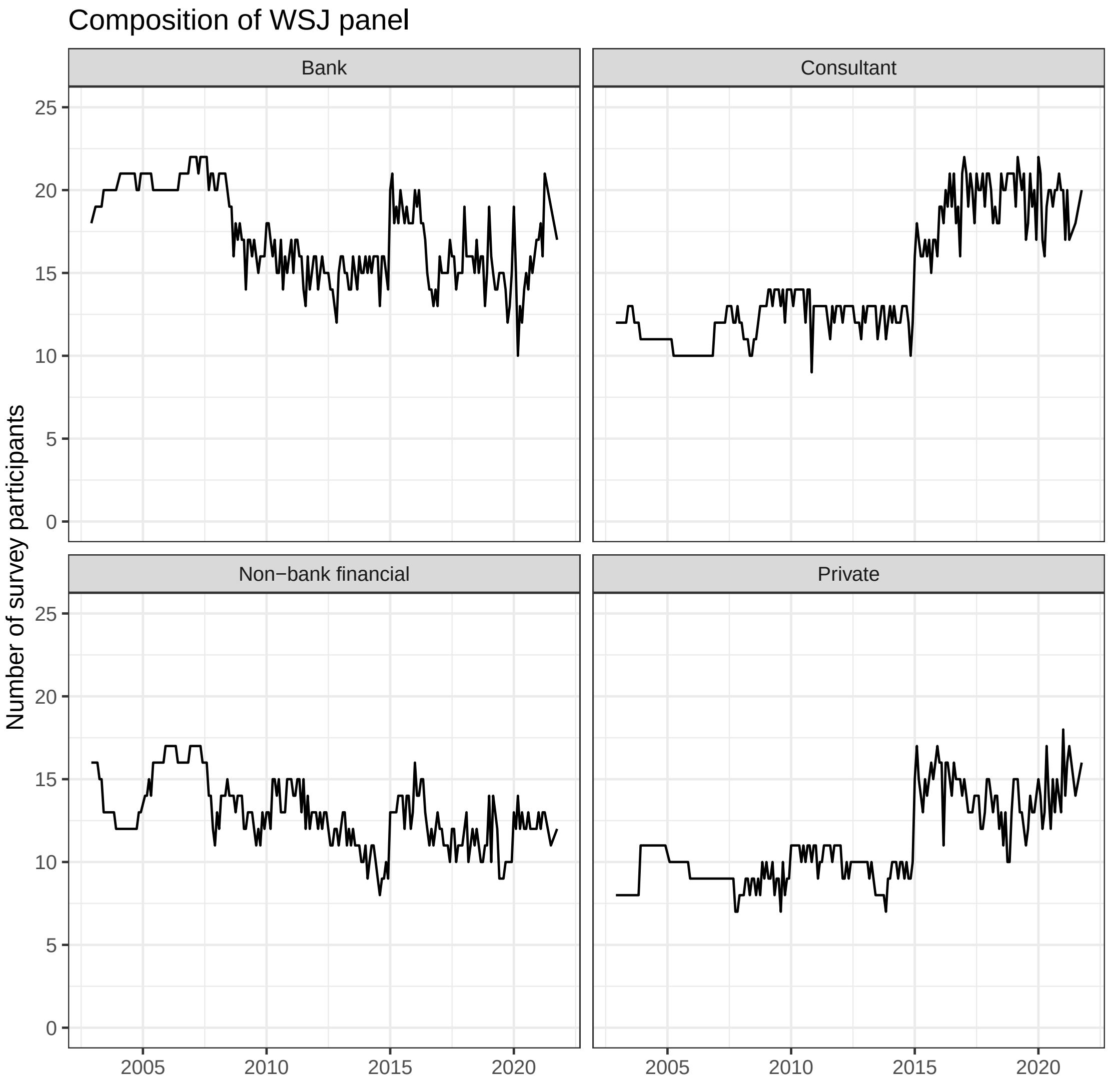

Figure 3.1: **Panel composition of WSJ Economic Survey**
This figure plots the number of respondents to the WSJ survey across organization type over time. The sample period is December 2002 to October 2021.

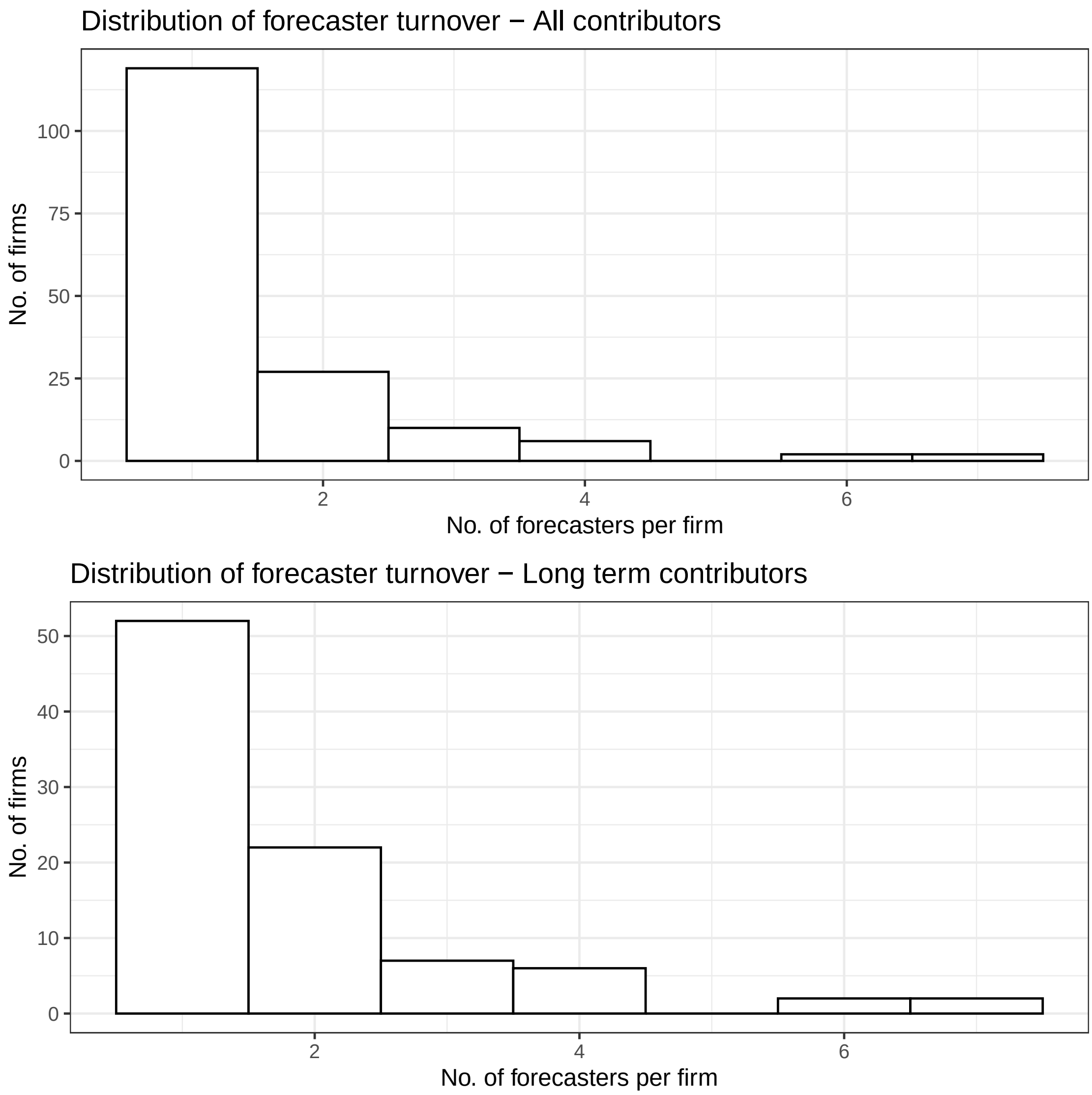

Figure 3.2: **Respondent turnover**
This figure highlights the turnover in respondents over time. The top figure plots how often a given firm changes the forecaster (identified by name of the respondent changing). The bottom panel conditions on only those firms that contribute to the WSJ survey over a long period of time (>4years). The sample period is December 2002 to October 2021.

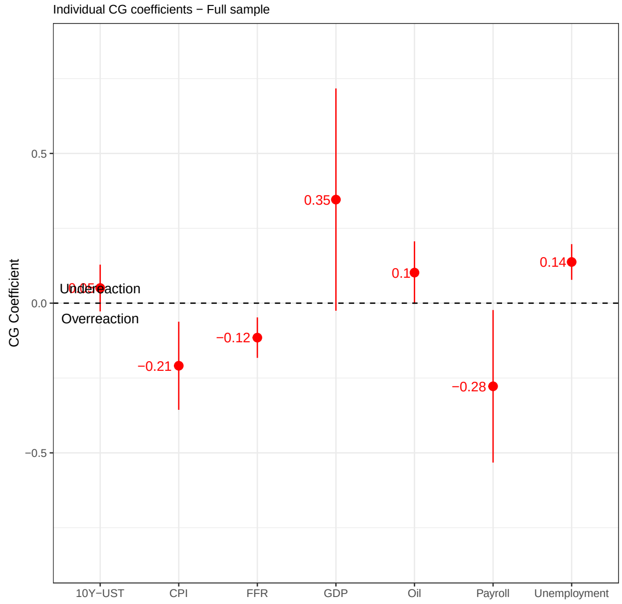

Figure 3.3: **Forecat Error on Forecast Revision Regression (Individual)**
This figure plots the regression coefficients of forecast error on forecast revision at the individual level. The dots represent the coefficient β_1^p from Equation (3.3), the bars are confidence intervals based on clustered standard errors at the individual-time level. The forecast horizon is 12 month ahead ($h = 12$). $\beta_1^p > 0$ implies forecasters tend to underreact, $\beta_1^p < 0$ implies forecasters tend to overreact. The sample period is January 2003 to December 2021.

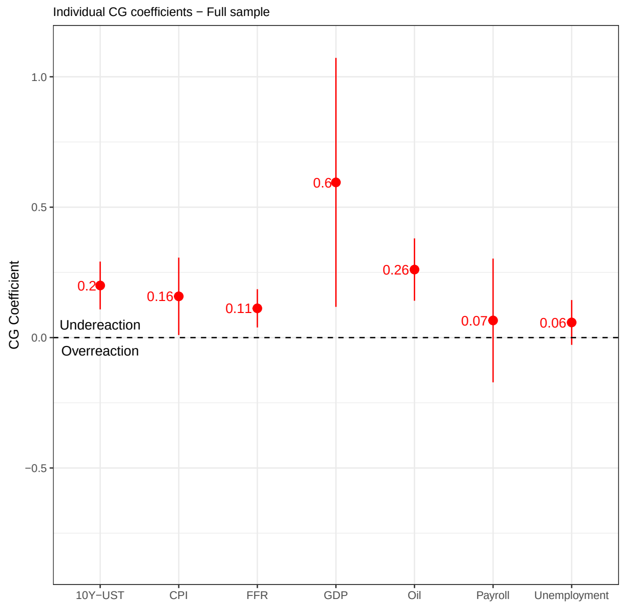

Figure 3.4: **Forecat Error on Forecast Revision Regression (Individual)**
This figure plots the regression coefficients of forecast error on forecast revision at the individual level, but only using the same firms which appear in the Blue Chip Economics survey. The dots represent the coefficient β_1^p from Equation (3.3), the bars are confidence intervals based on clustered standard errors at the time level. The forecast horizon is 12 month ahead ($h = 12$). $\beta_1^p > 0$ implies forecasters tend to underreact, $\beta_1^p < 0$ implies forecasters tend to overreact. The sample period is January 2003 to December 2021.

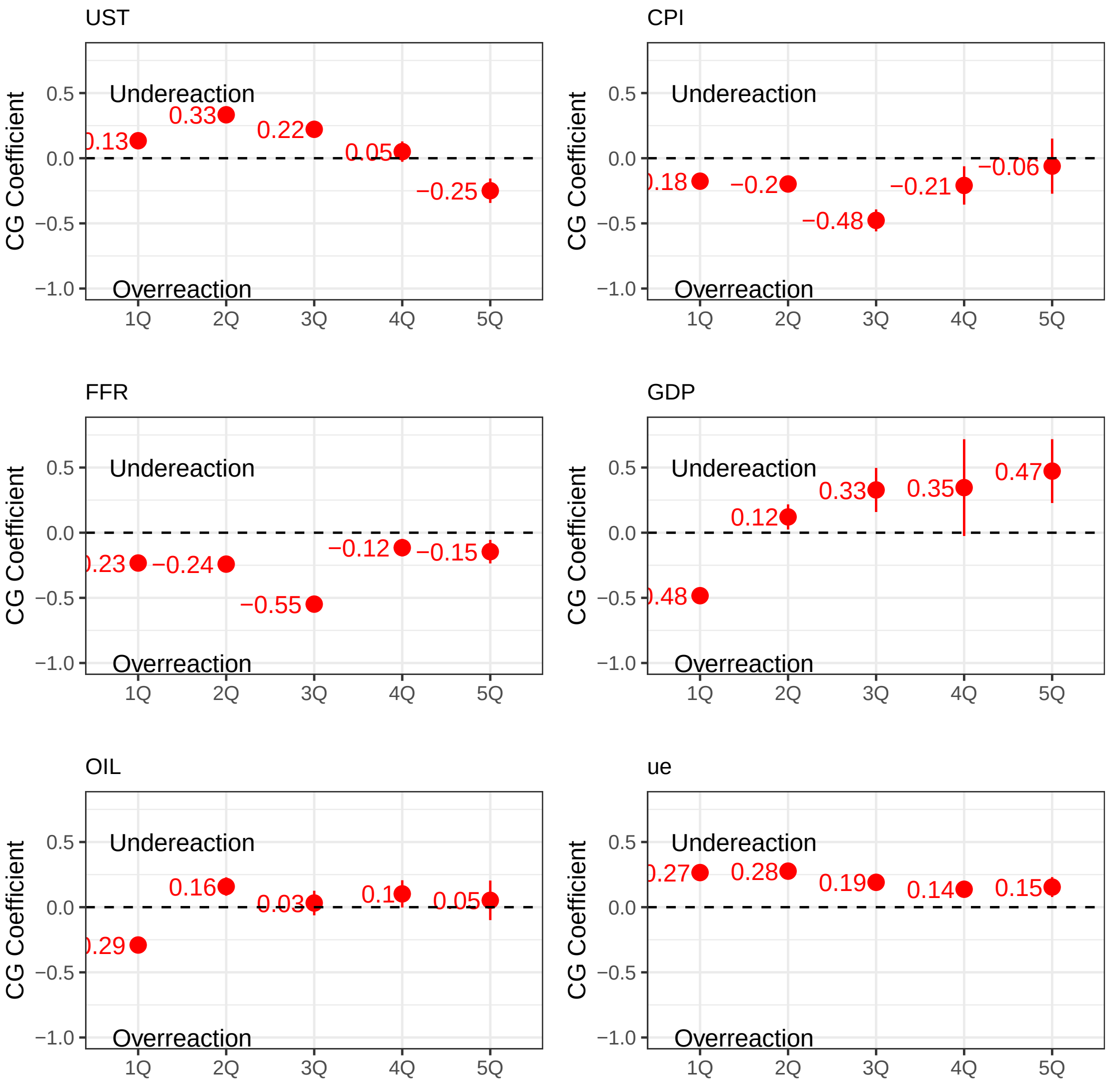

Figure 3.5: **Forecat Error on Forecast Revision Regression (Individual)**
This figure plots the regression coefficients of forecast error on forecast revision at the individual level for various forecast horizons. The dots represent the coefficient β_1^p from Equation (3.3), the bars are confidence intervals based on clustered standard errors at the individual-time level. $\beta_1^p > 0$ implies forecasters tend to underreact, $\beta_1^p < 0$ implies forecasters tend to overreact. The sample period is January 2003 to December 2021.

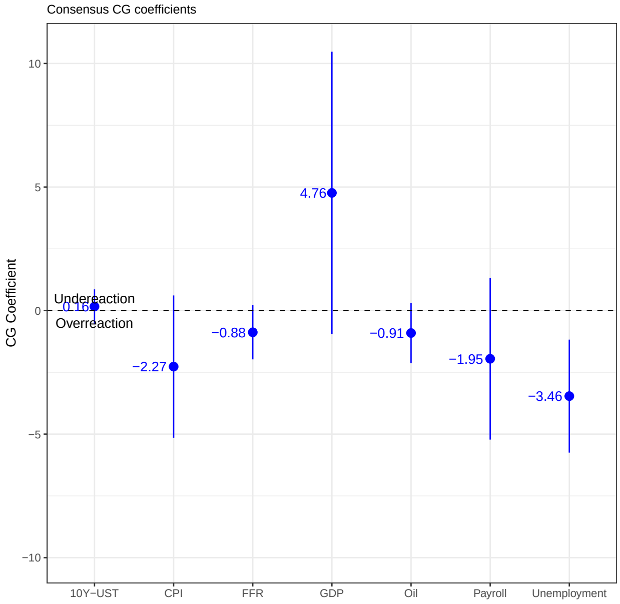

Figure 3.6: **Forecat Error on Forecast Revision Regression (Consenus)**
This figure plots the regression coefficients of forecast error on forecast at the consensus level. The dots represent the coefficient β_1^c from Equation (3.2), the bars are confidence intervals based on clustered standard errors at the individual-time level. The forecast horizon is 12 month ahead ($h = 12$). $\beta_1^c > 0$ implies forecasters tend to underreact, $\beta_1^c < 0$ implies forecasters tend to overreact. The sample period is January 2003 to December 2021.

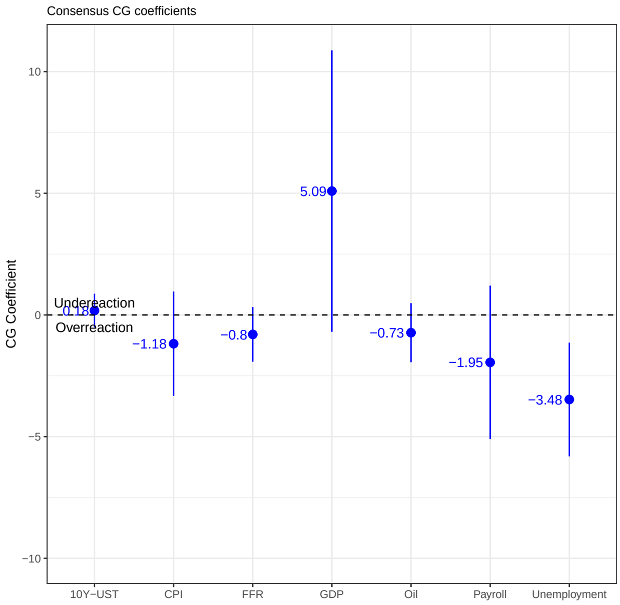

Figure 3.7: **Forecat Error on Forecast Revision Regression (Consensus)**
This figure plots the regression coefficients of forecast error on forecast at the consensus level, but only using the same firms which appear in the Blue Chip Economics survey. The dots represent the coefficient β_1^c from Equation (3.2), the bars are confidence intervals based on clustered standard errors at the time level. The forecast horizon is 12 month ahead ($h = 12$). $\beta_1^c > 0$ implies forecasters tend to underreact, $\beta_1^c < 0$ implies forecaster tend to overreact. The sample period is January 2003 to December 2021.

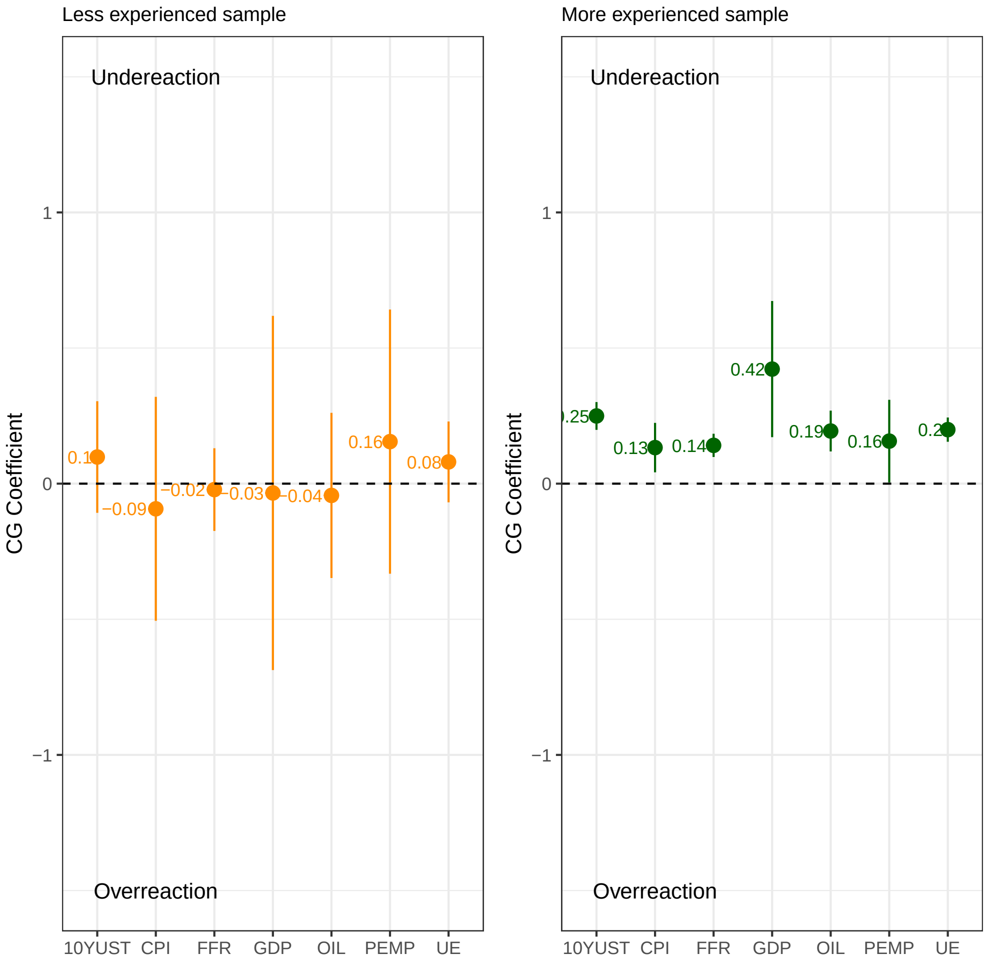

Figure 3.8: **Error on Revision Regression Split by Experience**
This figure plots the regression coefficients of forecast error on forecast revision at the individual level split by the experience of the individual. Less-experienced are those respondents in their first year of participating in the WSJ survey. The dots represent the coefficient β_1^p from Equation (3.3), the bars are confidence intervals based on clustered standard errors at the individual-time level. $\beta_1^p > 0$ implies forecasters tend to underreact, $\beta_1^p < 0$ implies forecasters tend to overreact. The sample period is January 2003 to December 2021

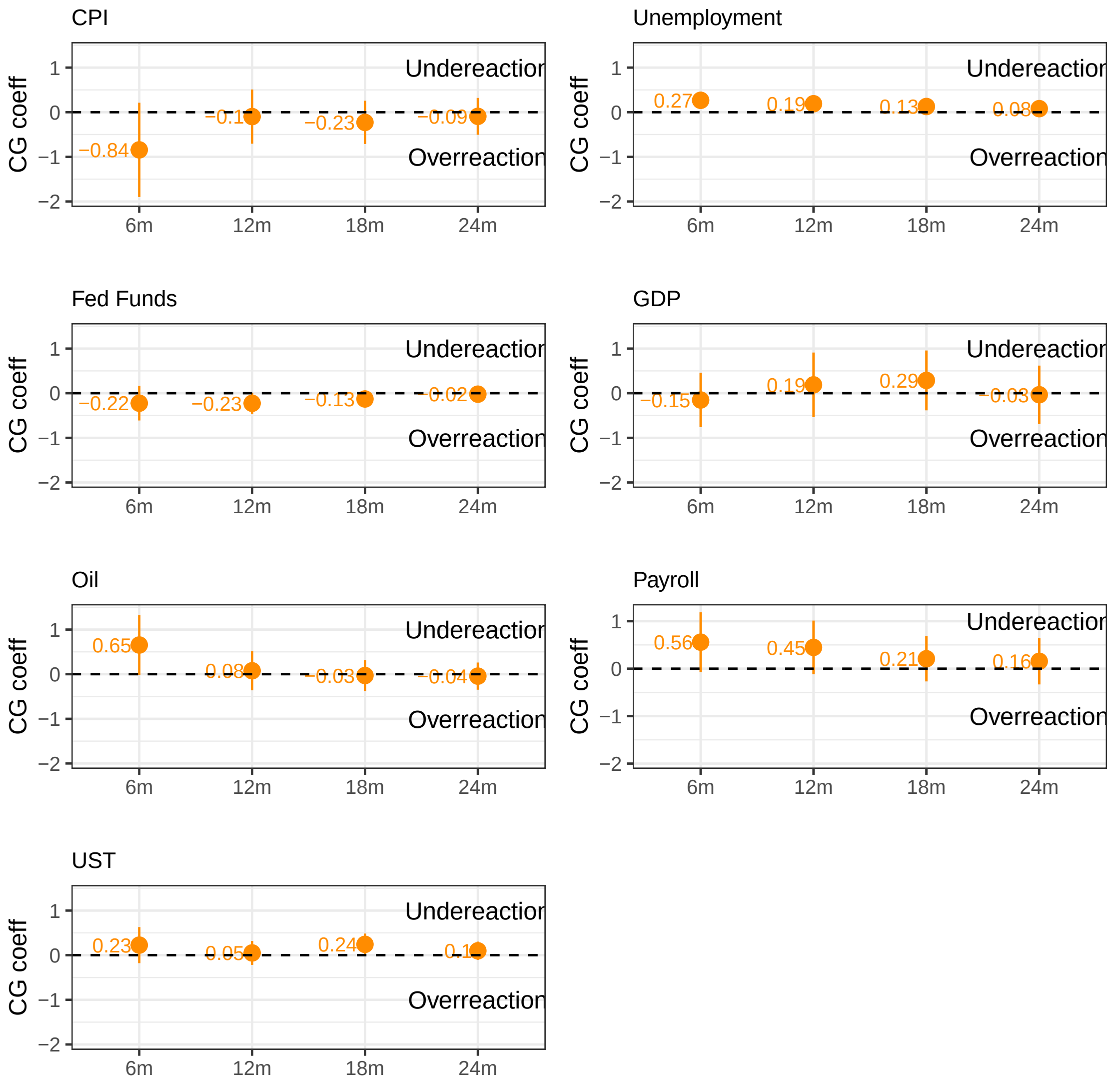

Figure 3.9: **Error on Revision Regression Split by Experience**
This figure plots the regression coefficients of forecast error on forecast revision at the individual level split by the experience of the individual, using various definitions of experience. The dots represent the coefficient β_1^p from equation (3.3), the bars are confidence intervals based on clustered standard errors at the individual-time level. $\beta_1^p > 0$ implies forecaster tend to underreact, $\beta_1^p < 0$ implies forecasters tend to overreact. The sample period is January 2003 to December 2021

Table 3.1: **Co-movement between joint forecasts**

This table compares the joint forecasts revisions across macroeconomic variables. The dependent variable is the 12 month ahead forecast change in federal funds rate (FFR), i.e. the difference between actual FFR in month t and the respondent's forecast of FFR at $t + 12$ measured in percentage points. The independent variables include, the change in unemployment rate (UE), consumer price index (CPI), and gross domestic product (GDP) forecasted over the same 12-month window. Col (1) - (3) considers the variables seperatly, Col (4) and (5) considers the variables jointly. All specifications include respondent and time fixed effects. The sample period is 2002:12 to 2021:10.

Dependent Variable:			ΔFFR_{12m}		
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
ΔUE_{12m}	-0.1147**			-0.0963**	
	(0.0513)			(0.0443)	
ΔCPI_{12m}		0.1616***		0.1437***	0.1559***
		(0.0229)		(0.0218)	(0.0230)
ΔGDP_{12m}			0.0458**		0.0373**
			(0.0186)		(0.0180)
Fixed-effects					
Respondent	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	3,755	3,755	3,755	3,755	3,755
R^2	0.68606	0.68988	0.67881	0.69710	0.69200
Within R^2	0.03232	0.04408	0.00998	0.06636	0.05064

Clustered (survey_date_m) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3.2: **Co-movement between joint forecasts**

This table compares the joint forecasts revisions across macroeconomic variables. The dependent variable is the 12 month ahead forecast change in federal funds rate (FFR), i.e. the difference between actual FFR in month t and the respondent's forecast of FFR at $t + 12$ measured in percentage points. The independent variables include, the change in unemployment rate (UE), and consumer price index (CPI) forecasted over the same 12-month window. Column (1) includes respondents belonging to Banks. Column (2) includes respondents belonging to Non-bank Financials. Column (3) includes respondents belonging to Consultant. Column (4) includes respondents belonging to Private firms. All specifications include respondent and time fixed effects. The sample period is 2002:12 to 2021:10.

Dependent Variable:		ΔFFR_{12m}		
Model:	(1)	(2)	(3)	(4)
Firm Type:	(Bank)	(Non-Bank Fin)	(Consultant)	(Private)
Variables				
ΔUE_{12m}	-0.1402**	-0.0854	-0.0684*	-0.1444
	(0.0547)	(0.0669)	(0.0341)	(0.0904)
ΔCPI_{12m}	0.1069***	0.0992	0.1967***	0.0964**
	(0.0309)	(0.0677)	(0.0442)	(0.0451)
Fixed-effects				
Respondent	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,121	861	1,005	768
R^2	0.78412	0.74062	0.70187	0.68145
Within R^2	0.06916	0.03340	0.09498	0.06776

Clustered (name & survey_date_m) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3.3: **Co-movement between joint forecasts**

This table compares the joint forecasts revisions across macroeconomic variables. The dependent variable is the 12 month ahead forecast change in federal funds rate (FFR), i.e. the difference between actual FFR in month t and the respondent's forecast of FFR at $t + 12$ measured in percentage points. The independent variables include, the change in unemployment rate (UE), and consumer price index (CPI), forecasted over the same 12-month window. Column (1) includes only "less-experienced" respondents (under 12months). Column (2) includes only "more-experienced" respondents (over 12months). All specifications include respondent and time fixed effects. The sample period is 2002:12 to 2021:10.

Dependent Variable:	ΔFFR_{12m}	
Model:	(1)	(2)
Respondent Type:	Under-12months	Over-12months
Variables		
ΔUE_{12m}	-0.0649	-0.0962**
	(0.0484)	(0.0473)
ΔCPI_{12m}	0.0006	0.1512***
	(0.0446)	(0.0284)
Fixed-effects		
Respondent	Yes	Yes
Time	Yes	Yes
Fit statistics		
Observations	406	3,349
R^2	0.88297	0.69620
Within R^2	0.01770	0.06941

Clustered (name & survey_date_m) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3.4: **Deviation from consensus forecast**

This table compares an individual's absolute forecast deviation from consensus to the number of surveys an individual has participated in. The dependent variable is the absolute difference between respondent-i's time-t forecast and the consensus time-t forecast excluding respondent-i. AGE is the number of WSJ surveys the respondent has participated in. $AGEDEV_{-i}$ is the average absolute deviation of the time-t forecasts from the consensus time-t forecast, excluding the ith respondent. Columns (1) - (7) repeat the regression for each variable in the WSJ survey. The sample period is 2002:12 to 2021:10.

Dependent Variable:	Abs deviation from consensus						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CPI	UERATE	FFR	GDP	OIL	PEMP	UST
Variables							
AGE	-0.001***	0.001	-0.001***	0.000	-0.023**	-96.268***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.010)	(28.161)	(0.000)
$AGEDEV_{-i}$	-0.081	0.058***	0.024***	0.011	0.061**	-0.184***	0.014
	(0.063)	(0.014)	(0.008)	(0.069)	(0.030)	(0.021)	(0.010)
Fixed-effects							
Respondent	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	8,941	5,689	6,613	4,005	3,830	7,912	2,416
R^2	0.27750	0.29878	0.26177	0.23790	0.35065	0.37547	0.32087
Within R^2	0.01896	0.09077	0.02299	0.00184	0.06807	0.22009	0.02477

Clustered (name & survey_date_m) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

3.8 Online Appendix A

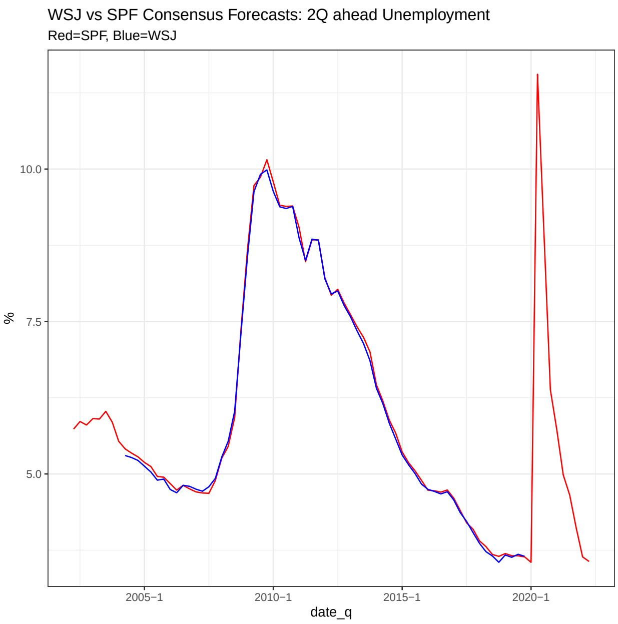

Figure 3.10: **Forecasts from WSJ and SPF (Unemployment)**
This figure plots the two quarter ahead forecasts for the unemployment rate from the WSJ survey (blue) and SPF survey (red).

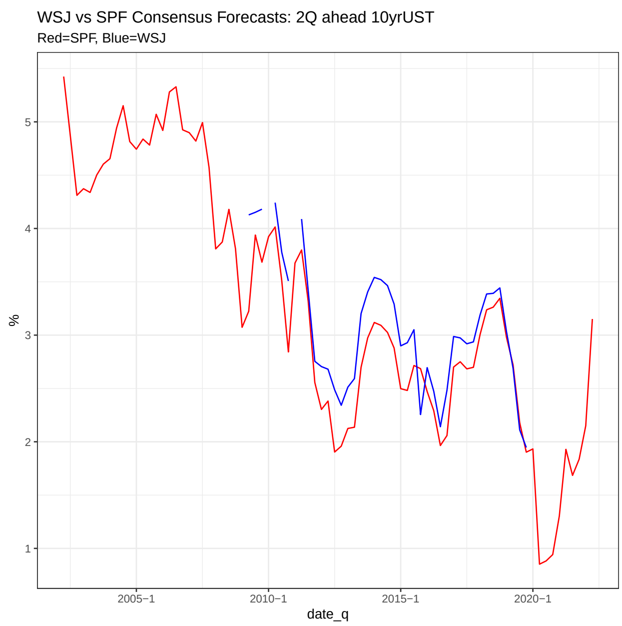

Figure 3.11: **Forecasts from WSJ and SPF (10yrUST)**
This figure plots the two quarter ahead forecasts for the 10yr UST from the WSJ survey (blue) and SPF survey (red).

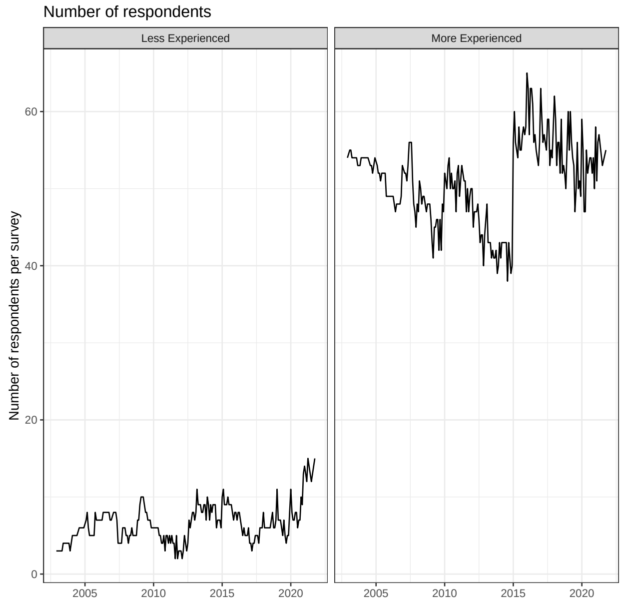

Figure 3.12: **Number of respondents per survey**
This figure plots the number of less experienced (under 24 months) and more experienced (over 24 months)...

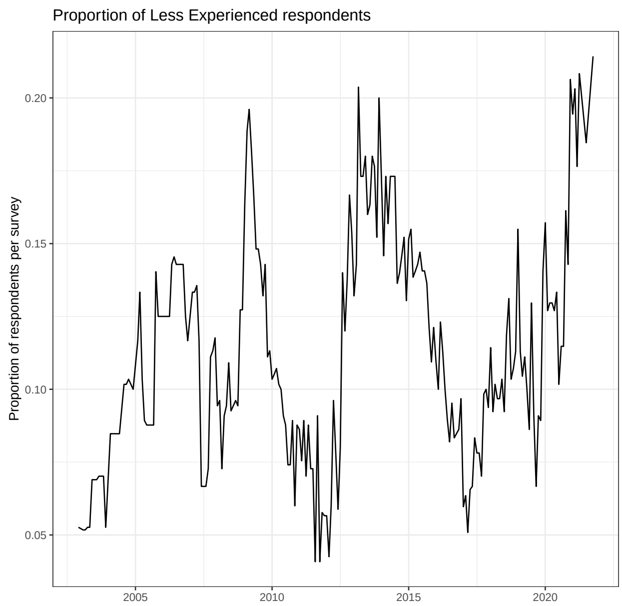

Figure 3.13: **Number of respondents per survey**
This figure plots the number of less experienced (under 24 months) and more experienced (over 24 months)...

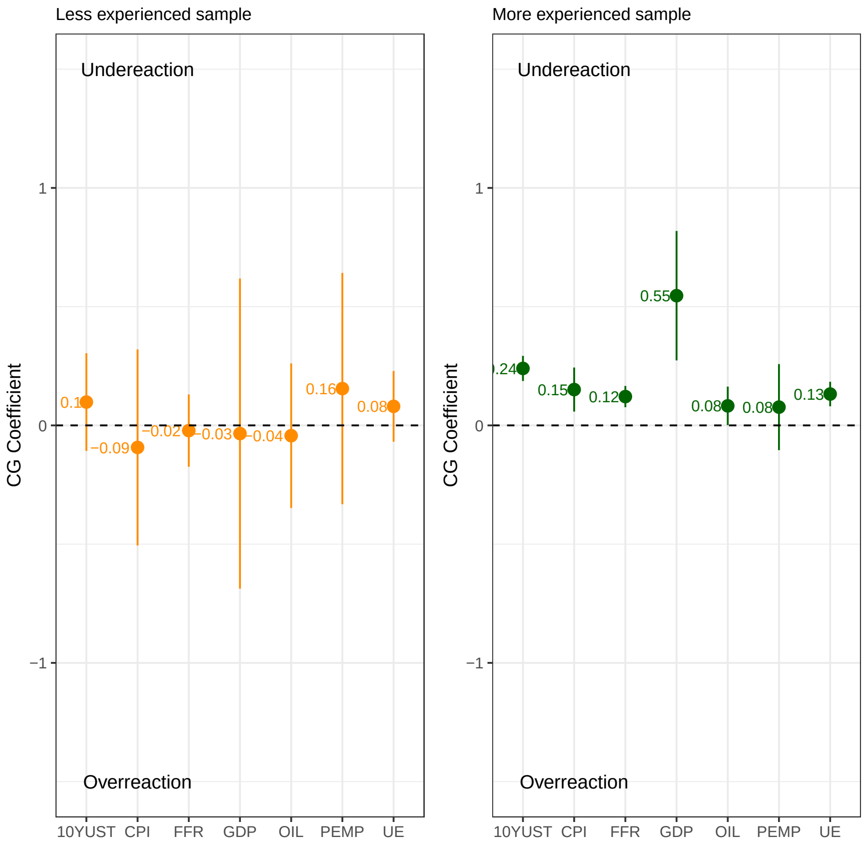

Figure 3.14: **Error on Revision Regression Split by Experience**
This figure plots the regression coefficients of forecast error on forecast at the individual forecaster level split by the experience of the individual. Less-experienced are those respondents in the first 12surveys. The more experienced are the same respondent after their first 12 surveys. The dots represent the coefficient β_1^p from equation (2), the bars are confidence intervals based on clustered standard errors at the individual-time level. A $\beta_1^p > 0$ implies forecaster tend to underreact, a $\beta_1^p < 0$ implies forecaster tend to overreact. The sample period is January 2003 to December 2021

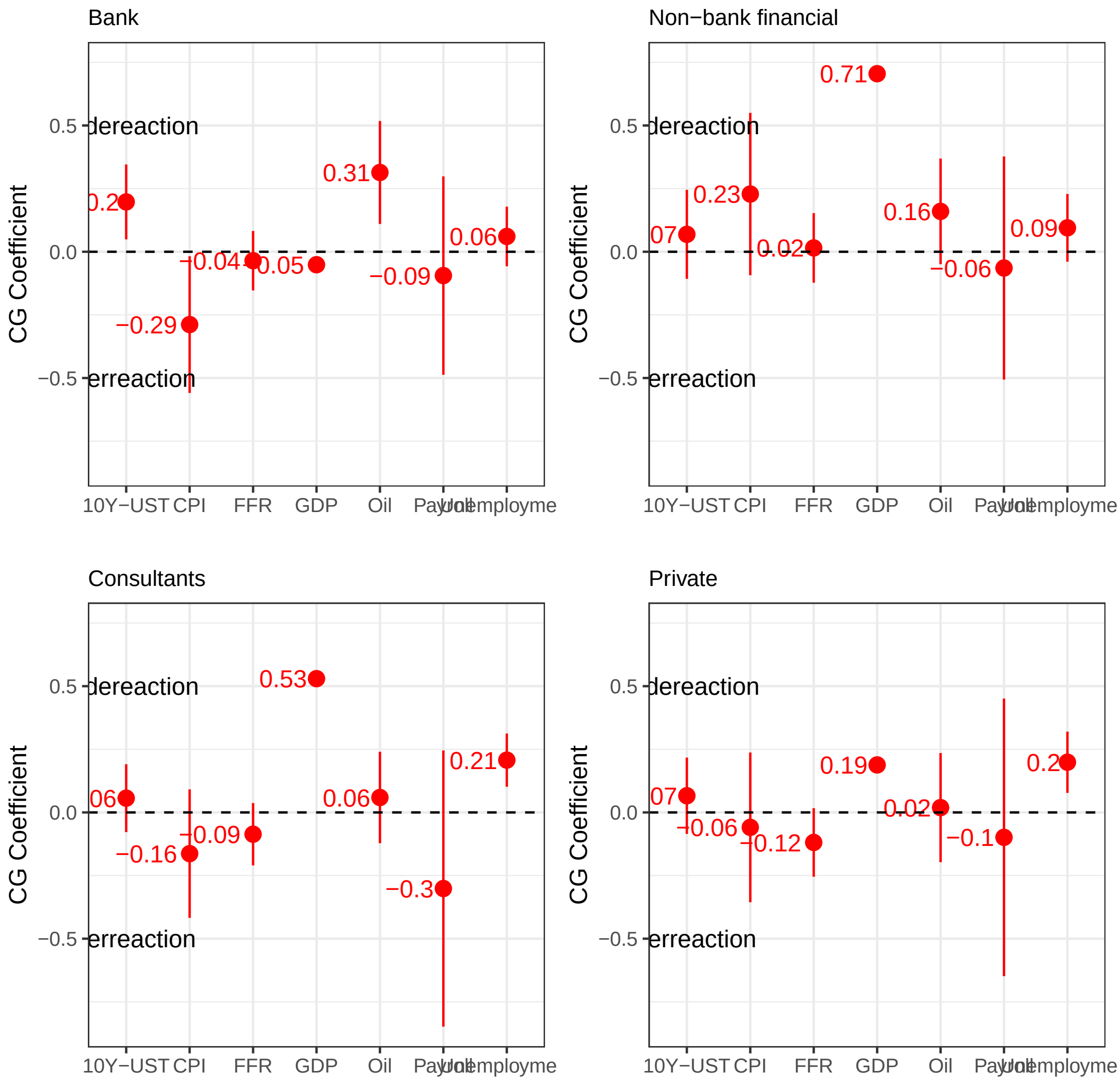

Figure 3.15: **Error on Revision Regression Split by Firm Type**
This figure plots the regression coefficients of forecast error on forecast at the individual forecaster level split by organization type of the individual. The dots represent the coefficient β_1^p from equation (2), the bars are confidence intervals based on clustered standard errors at the individual-time level. A $\beta_1^p > 0$ implies forecaster tend to underreact, a $\beta_1^p < 0$ implies forecaster tend to overreact. The sample period is January 2003 to December 2021

3.9 Online Appendix B

	Firm Name	N_CPI	N_UE	N_FFR	N_PEMP	N_GDP	N_UST	Type
1	ABNAMRO	6.00	6.00	6.00	5.00	6.00	6.00	Bank
2	ACCuttsAssociatesLLC	17.00	17.00	17.00	17.00	17.00	17.00	Consultant
3	ACTResearch	76.00	76.00	76.00	69.00	76.00	76.00	Consultant
4	AGEdwards	48.00	45.00	47.00	7.00	47.00	42.00	Non-bank financial
5	AGaryShillingCoInc	10.00	10.00	10.00		10.00	5.00	Non-bank financial
6	AllianceBernstein	136.00	133.00	136.00	112.00	136.00	135.00	Non-bank financial
7	AmericanChemistryCouncil	74.00	74.00	74.00	71.00	74.00	74.00	Private
8	AmericanExpress	29.00	29.00	29.00		29.00	24.00	Non-bank financial
9	AmeripriseFinancial	113.00	110.00	112.00	97.00	112.00	111.00	Non-bank financial
10	AmherstPierpontSecurities	6.00	6.00	6.00	6.00	6.00	6.00	Non-bank financial
11	ArgusResearchCorp	10.00	10.00	10.00		10.00	5.00	Consultant
12	Avidbank	131.00	126.00	129.00	102.00	130.00	129.00	Bank
13	BBVA	77.00	77.00	77.00	74.00	77.00	77.00	Bank
14	BMOCapital	65.00	65.00	65.00	61.00	65.00	65.00	Non-bank financial
15	BNPParibas	130.00	129.00	130.00	128.00	129.00	128.00	Bank
16	BankOneNA	18.00	18.00	18.00		18.00	13.00	Bank
17	BankofAmerica	207.00	204.00	205.00	147.00	206.00	198.00	Bank
18	BankoftheWest	54.00	54.00	54.00	51.00	54.00	54.00	Bank
19	BarclaysCapital	154.00	151.00	153.00	94.00	153.00	142.00	Bank
20	BearStearns	57.00	54.00	56.00	15.00	56.00	50.00	Bank
21	BostonCollege	5.00	5.00	5.00	5.00	5.00	5.00	Private
22	CSFB	114.00	113.00	114.00	26.00	114.00	93.00	Bank
23	CaliforniaLutheranUniversity	30.00	30.00	30.00	27.00	30.00	30.00	Private
24	CaliforniaStateUniversity	118.00	118.00	118.00	118.00	118.00	118.00	Private
25	CamilliEconomics	12.00	11.00	13.00	8.00	12.00	12.00	Consultant
26	CapitalEconomics	142.00	140.00	141.00	113.00	142.00	140.00	Consultant
27	CatawbaCollege	1.00	1.00	1.00	1.00	1.00	1.00	Private
28	ChamberofCommerce	58.00	59.00	59.00	5.00	59.00	59.00	Private
29	Citigroup	49.00	46.00	48.00	5.00	48.00	43.00	Bank
30	ClaymoreSecurities	8.00	7.00	8.00		8.00	8.00	Non-bank financial
31	CombinatoricsCapital	126.00	123.00	125.00	109.00	125.00	124.00	Non-bank financial
32	ComericaBank	197.00	193.00	197.00	154.00	197.00	190.00	Bank
33	ConsumerElectronicsAssociation	1.00	1.00		1.00	1.00	1.00	Private
34	Corelogic	65.00	65.00	65.00	61.00	65.00	65.00	Consultant
35	CreditAgricoleCIB	130.00	130.00	130.00	54.00	130.00	87.00	Bank
36	CreditSuisse	82.00	78.00	81.00	64.00	81.00	80.00	Bank
37	DaiwaCapital	72.00	72.00	72.00	69.00	72.00	72.00	Bank
38	DaiwaCapitalMarketsAmerica	6.00	6.00	6.00	6.00	6.00	6.00	Bank
39	DecisionEconomicsInc	214.00	211.00	213.00	169.00	213.00	207.00	Consultant
40	DeloitteInsights	6.00	6.00	6.00	6.00	6.00	6.00	Consultant
41	DeloitteLP	60.00	60.00	60.00	57.00	60.00	60.00	Consultant
42	DeutscheBank	210.00	208.00	210.00	162.00	210.00	201.00	Bank
43	DianeSwonkAssociatesLLC	22.00	22.00	22.00	21.00	22.00	22.00	Consultant
44	DuPontCompany	21.00	21.00	21.00		21.00	16.00	Private
45	EatonCorp	186.00	186.00	188.00	145.00	188.00	182.00	Private
46	EconForecasterLLC	13.00	13.00	13.00	13.00	13.00	13.00	Consultant
47	Econoclast	214.00	211.00	213.00	168.00	213.00	207.00	Consultant

48	EconomicAnalysis	213.00	210.00	212.00	168.00	212.00	205.00	Consultant
49	EconomicOutlookGroup	60.00	60.00	60.00	57.00	60.00	60.00	Consultant
50	EconomicandRevenueForecastCouncil	40.00	40.00	40.00	40.00	40.00	40.00	Private
51	Economycom	30.00	29.00	30.00		30.00	25.00	Consultant
52	EncimaGlobal	48.00	48.00	48.00	48.00	48.00	48.00	Consultant
53	Equifax	31.00	32.00	32.00	31.00	32.00	32.00	Non-bank financial
54	ErnstYoung	15.00	15.00	15.00		15.00	10.00	Consultant
55	EvansCarrollAssociates	3.00	3.00	3.00		3.00		Non-bank financial
56	FannieMae	207.00	204.00	206.00	159.00	206.00	201.00	Non-bank financial
57	FedExCorp	108.00	105.00	107.00	76.00	107.00	106.00	Private
58	FirstTrustAdvisors	183.00	181.00	182.00	169.00	182.00	181.00	Non-bank financial
59	FordMotorCorp	20.00	19.00	20.00		20.00	20.00	Private
60	FriedmanBillingsRamsey	10.00	9.00	10.00	3.00	10.00	10.00	Non-bank financial
61	GeorgiaStateUniversity	74.00	69.00	74.00	70.00	74.00	74.00	Private
62	GoldmanSachs	198.00	195.00	197.00	151.00	197.00	189.00	Bank
63	GrantThornton	42.00	42.00	42.00	39.00	42.00	42.00	Consultant
64	GriffinKubikStephensThompsonInc	23.00	23.00	23.00		23.00	18.00	Consultant
65	HSBCSecurities	41.00	41.00	41.00	38.00	41.00	39.00	Bank
66	HanmiBank	32.00	29.00	31.00	9.00	31.00	30.00	Bank
67	HighFrequencyEconomics	193.00	191.00	193.00	139.00	193.00	187.00	Consultant
68	IHSGlobalInsight	184.00	180.00	184.00	141.00	185.00	178.00	Consultant
69	ING	6.00	6.00	6.00	6.00	6.00	6.00	Bank
70	ITGInvestmentResearch	17.00	17.00	17.00	17.00	17.00	16.00	Consultant
71	IndependentConsultant	10.00	10.00	10.00	7.00	10.00	10.00	Consultant
72	InternationalCouncilofShoppingCenters	99.00	97.00	98.00	86.00	98.00	97.00	Non-bank financial
73	JPMorgan	120.00	118.00	119.00	111.00	119.00	118.00	Bank
74	Jefferies	2.00	2.00	2.00	2.00	2.00	2.00	Bank
75	Jeffries Company	15.00	15.00	15.00	1.00	15.00	10.00	Bank
76	JimOSullivan	6.00	6.00	6.00	6.00	6.00	6.00	Non-bank financial
77	KPMG	48.00	49.00	50.00	44.00	48.00	50.00	Consultant
78	KeystoneBusinessIntelligenceIndia	34.00	31.00	33.00	9.00	33.00	32.00	Consultant
79	KudlowCoLLC	56.00	53.00	55.00	14.00	55.00	50.00	Non-bank financial
80	LBMCLLC	5.00	5.00	5.00		5.00		Non-bank financial
81	LaSalleConsultingGroup	4.00	4.00	4.00		4.00	4.00	Consultant
82	LehmanBrothers	61.00	58.00	60.00	19.00	60.00	54.00	Bank
83	LombardStreetResearch	2.00	2.00	2.00	1.00	2.00	2.00	Consultant
84	LoyolaMarymountUniversity	1.00	1.00	1.00	1.00	1.00	1.00	Private
85	MFGlobal	21.00	21.00	21.00	20.00	21.00	21.00	Bank
86	MFRInc	140.00	139.00	140.00	59.00	140.00	139.00	Consultant
87	MScience	3.00	3.00	3.00	3.00	3.00	3.00	Consultant
88	MacroEconGlobalAdvisors	123.00	123.00	124.00	120.00	124.00	123.00	Consultant
89	MacroeconomicAdvisers	183.00	183.00	175.00	140.00	186.00	170.00	Consultant
90	MariaFioriniRamirezInc	52.00	49.00	51.00	10.00	51.00	45.00	Consultant
91	MerrillLynch	57.00	54.00	55.00	7.00	56.00	48.00	Bank
92	MesirowFinancial	128.00	125.00	127.00	107.00	127.00	126.00	Non-bank financial
93	MetLifeInvestmentManagement	10.00	6.00	10.00		2.00	10.00	Non-bank financial
94	MoodysInvestorsService	209.00	207.00	210.00	166.00	210.00	204.00	Non-bank financial
95	MorganStanley	143.00	142.00	145.00	98.00	143.00	134.00	Bank
96	MortgageBankersAssociation	204.00	201.00	203.00	169.00	203.00	202.00	Private
97	NEMA	100.00	104.00	104.00	102.00	103.00	103.00	Private

98	NaroffEconomicAdvisors	70.00	68.00	71.00	68.00	71.00	70.00	Consultant
99	NaroffEconomicsLLC	6.00	6.00	6.00	6.00	6.00	6.00	Consultant
100	NatWestMarkets	15.00	16.00	16.00	11.00	15.00	14.00	Bank
101	NationalAssociationofHomeBuilders	70.00	71.00	71.00	60.00	71.00	70.00	Private
102	NationalAssociationofManufacturers	72.00	72.00	72.00	69.00	72.00	64.00	Private
103	NationalAssociationofrealtors	207.00	203.00	205.00	160.00	202.00	199.00	Private
104	NationalAutoDealerAssociation	25.00	28.00	28.00	23.00	28.00	26.00	Private
105	NationalBankofKuwait	15.00	15.00	15.00	15.00	15.00	15.00	Non-bank financial
106	NationalCityCorporation	65.00	62.00	64.00	23.00	64.00	58.00	Bank
107	NationalElectricalManufacturersAssociation	1.00	1.00	1.00	1.00	1.00	1.00	Private
108	NationalRetailFederation	81.00	81.00	81.00	77.00	81.00	81.00	Private
109	NationwideInsurance	100.00	100.00	100.00	97.00	100.00	100.00	Non-bank financial
110	Natixis	24.00	24.00	24.00	21.00	24.00	24.00	Bank
111	NomuraSecuritiesInternational	201.00	200.00	203.00	155.00	202.00	196.00	Bank
112	NorthCarolinaATStateUniversity	6.00	6.00	6.00	6.00	6.00	6.00	Private
113	NorthernTrust	7.00	7.00	7.00	7.00	7.00	7.00	Bank
114	OxfordEconomics	77.00	77.00	77.00	74.00	77.00	77.00	Consultant
115	PIMCO	5.00	5.00	5.00		5.00		Non-bank financial
116	PNCFinancialServicesGroup	161.00	158.00	161.00	116.00	161.00	156.00	Non-bank financial
117	PangeaMarketAdvisory	5.00	5.00	5.00	5.00	5.00	5.00	Consultant
118	PantheonMacroeconomic	86.00	86.00	86.00	83.00	86.00	86.00	Consultant
119	ParsecFinancialManagement	127.00	127.00	127.00	124.00	127.00	127.00	Non-bank financial
120	PernaAssociates	121.00	118.00	120.00	79.00	120.00	114.00	Non-bank financial
121	PictetWealthManagement	8.00	7.00	9.00	1.00	8.00	9.00	Non-bank financial
122	PierpontSecurities	129.00	129.00	129.00	126.00	129.00	129.00	Non-bank financial
123	PointLomaNazareneUniversity	71.00	71.00	71.00	68.00	71.00	71.00	Private
124	PrestigeEconomicsLLC	1.00	1.00	1.00	1.00	1.00	1.00	Consultant
125	PrudentialEquityGroup	46.00	43.00	45.00	5.00	45.00	40.00	Non-bank financial
126	RBCCapital	17.00	17.00	17.00	13.00	17.00	17.00	Bank
127	RBSGreenwichCapital	30.00	29.00	30.00	29.00	30.00	29.00	Bank
128	RDQEconomics	71.00	71.00	71.00	69.00	71.00	71.00	Consultant
129	RSMUSLLP	17.00	17.00	17.00	17.00	17.00	17.00	Non-bank financial
130	RSQEUofMichigan	61.00	58.00	60.00	16.00	60.00	54.00	Private
131	Rabobank	15.00	15.00	17.00		17.00		Bank
132	RobertFryEconomicsLLC	53.00	53.00	53.00	50.00	53.00	53.00	Consultant
133	RoyalBankofScotland	33.00	33.00	33.00	8.00	33.00	28.00	Bank
134	SPGlobalRatings	5.00	5.00	5.00	5.00	5.00	5.00	Non-bank financial
135	SSEconomics	29.00	29.00	29.00	27.00	29.00	29.00	Consultant
136	Scotiabank	57.00	57.00	57.00	55.00	57.00	57.00	Bank
137	SkolkovoInstituteforEmergingMarketStudies	46.00	46.00	46.00	46.00	46.00	45.00	Private
138	SocieteGenerale	197.00	198.00	200.00	145.00	200.00	193.00	Bank
139	StMarysUniversity	6.00	6.00	6.00	6.00	6.00	6.00	Private
140	StandardChartered	1.00	3.00	11.00	4.00	7.00	11.00	Non-bank financial
141	StandardandPoors	176.00	178.00	179.00	129.00	180.00	172.00	Non-bank financial
142	SterneAgee	42.00	54.00	57.00	24.00	57.00	55.00	Non-bank financial
143	StraszheimGlobalAdvisors	35.00	34.00	35.00		35.00	30.00	Non-bank financial
144	SwissRe	96.00	91.00	95.00	53.00	95.00	89.00	Non-bank financial
145	TDSecurities	27.00	27.00	28.00	28.00	28.00	26.00	Non-bank financial
146	TSLombard	46.00	47.00	47.00	43.00	47.00	47.00	Consultant
147	TheConferenceBoard	197.00	199.00	202.00	135.00	203.00	189.00	Consultant

148	TheEconomicOutlookGroup	3.00	3.00	3.00	3.00	3.00	3.00	Consultant
149	TheHeritageFoundation	17.00	17.00	18.00	17.00	18.00	17.00	Private
150	TheNorthernTrust	196.00	192.00	195.00	155.00	195.00	193.00	Bank
151	ThrutheCycle	2.00	2.00	2.00	2.00	2.00	2.00	Consultant
152	TuftsUniversity	49.00	50.00	50.00	49.00	48.00	48.00	Private
153	UBS	140.00	136.00	140.00	89.00	140.00	134.00	Bank
154	UCLAAndersonforecast	210.00	208.00	210.00	166.00	210.00	204.00	Private
155	UCRiversideSchoolofBusiness	14.00	14.00	14.00	13.00	14.00	14.00	Private
156	USTrust	49.00	46.00	48.00	7.00	48.00	43.00	Private
157	UniversityofCentralFlorida	123.00	123.00	123.00	119.00	123.00	123.00	Private
158	UniversityofNorthCarolinaandSIOR	38.00	36.00	37.00		37.00	32.00	Private
159	VanderbiltUniversity	160.00	157.00	159.00	117.00	159.00	153.00	Private
160	Visa	18.00	18.00	18.00	18.00	18.00	18.00	Non-bank financial
161	WachoviaCorp	66.00	63.00	65.00	28.00	65.00	64.00	Bank
162	WayneHummerInvestments	105.00	102.00	104.00	63.00	104.00	98.00	Non-bank financial
163	WellsFargo	213.00	210.00	212.00	168.00	212.00	206.00	Bank
164	WesternCarolinaUniversityandParsecFinancialManagement	34.00	33.00	34.00	30.00	34.00	33.00	Private
165	WilmingtonTrust	7.00	4.00	7.00	4.00	5.00	7.00	Non-bank financial
166	WintrustWealthManagement	14.00	14.00	14.00	14.00	14.00	14.00	Non-bank financial
167	WoodleyParkResearch	21.00	20.00	21.00	21.00	21.00	21.00	Consultant
168	WrightsideAdvisors	8.00	8.00	8.00	8.00	8.00	8.00	Consultant
169	WrightsonICAP	180.00	178.00	178.00	165.00	179.00	178.00	Consultant
170	iCIMS	4.00	4.00	4.00	4.00	4.00	4.00	Private
171	NationalAssociationofRealtorsr		1.00	1.00	1.00	1.00	1.00	Private
172	StifelNicoulasandCompanyInc		2.00	2.00	2.00	2.00	2.00	Non-bank financial
173			1.00			1.00	1.00	
174	TuftsUniversityandAlphaEconomicForesights					1.00	1.00	Private
175	TuftsUniversityandBostonCollege					1.00	1.00	Private

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