Expectations and Bank Lending*

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December 2021

Abstract

We study the properties and the impact of lenders' expectations using a new dataset on banks' economic projections about all MSAs in the US, reported annually for normal and downside scenarios. By combining these projections with comprehensive information on bank lending, we document several findings. First, banks' expectations about economic conditions under normal and downside scenarios have different determinants (e.g., opposite loading on MSA outcomes in the Great Recession). Second, expectations at a given point in time display substantial dispersion, across banks for the same MSA and across MSAs for the same bank. Third, firms have lower loan growth when their banks are more pessimistic about the downside scenario. The results hold with firm-year fixed effects: for the same firm in a given year, there is less lending from more pessimistic banks. Lenders' pessimism is also associated with higher interest rates, which further indicate reductions in credit supply. Moreover, there are negative real effects on firm-level total borrowing and capital expenditures, especially among firms with limited sources of financing, and on MSA-level output growth. Finally, banks that were more pessimistic about the downside pre-COVID have fewer past due loans after the pandemic (stronger balance sheets), but continue to lend less due to persistent pessimism.

*We thank Juliane Begenau, Anil Kashyap, Kathrin Schlafmann, Andrei Shleifer, Alp Simsek, Amir Sufi, and seminar participants at Arizona State University, Bank of Canada, Barcelona GSE COVID conference, Baruch, Blue Collar Working Group, Bocconi, Birmingham, BU Questrom, Cass Business School London, CEBI Workshop on Subjective Beliefs, Central Bank of Chile, Chicago Booth, CREI, EPFL, Federal Reserve Board, Federal Reserve Bank of New York, Goethe University Frankfurt, HKUST, IMF, Johns Hopkins, London Business School, Minnesota Carlson, NBER Summer Institute, Notre Dame Mendoza, Norges Bank, Society for Economic Dynamics Annual Meeting, Triangle Macro-Finance Workshop, and UNSW for helpful comments. We are grateful to Grace Brang, Bianca He, Ammon Lam, Femi Ogunrinu, and Julien Weber for excellent research assistance. The views stated herein are those of the authors and are not necessarily the views of the Federal Reserve Board or the Federal Reserve System.

1 Introduction

Credit supply is a central issue in finance and macroeconomics (Gertler and Kiyotaki, 2010; Schularick and Taylor, 2012; Mian, Sufi and Verner, 2017). Lenders' expectations are often thought to be an important driver of credit supply (Minsky, 1977; Kindleberger, 1978; Greenwood and Hanson, 2013; Cheng, Raina and Xiong, 2014; Bordalo, Gennaioli and Shleifer, 2018; Fahlenbrach, Prilmeier and Stulz, 2018). However, a major challenge for empirical analyses is the lack of data that can directly measure lenders' expectations and demonstrate their impact.[1] In comparison, there has been abundant data about lenders' balance sheet conditions and correspondingly a vibrant stream of research along this dimension (Kashyap and Stein, 2000; Khwaja and Mian, 2008; Jiménez, Ongena, Peydró and Saurina, 2012; Chodorow-Reich, 2014). In addition, for lending decisions, beliefs about the downside are key (Gennaioli, Shleifer and Vishny, 2012; Simsek, 2013, 2021), but empirical work on such beliefs is relatively limited in general.

In this paper, we use new data to investigate banks' expectations and their effects on lending. The data captures the economic projections of the largest lenders in the US for nearly all metropolitan statistical areas (MSAs). Moreover, it includes expectations about both normal and downside conditions: banks provide their assessment under the baseline scenario (i.e., macroeconomic conditions similar to the average expectations of professional forecasters) and the severely adverse scenario (i.e., a major recession). This data is part of the wide range of information collected by the Federal Reserve, and it is available annually since 2014. The primary outcome is the house price index (HPI) growth of the MSA, and an additional outcome is the unemployment rate. We then link this dataset on banks' economic projections to comprehensive data on their lending decisions, often viewed as the US "credit registry." In particular, this lending data reports not only loans but also financial information of firms (e.g., capital expenditures), so we can investigate how lenders' expectations affect both credit supply and ultimately real outcomes. It contains a large number of borrowers including many private firms. Finally, while most of our sample covers an economic boom, we also study lending decisions in light of the negative shock due to the COVID-19 outbreak.

[1] Accordingly, researchers have used a number of approaches to indirectly show that lenders' expectations can be important for credit supply (Fahlenbrach and Stulz, 2011; Greenwood and Hanson, 2013; Cheng, Raina and Xiong, 2014; Ma, 2015; Bordalo, Gennaioli and Shleifer, 2018; Fahlenbrach, Prilmeier and Stulz, 2018; Richter and Zimmermann, 2020; Carvalho, Gao and Ma, 2020; Maxted, 2020; Krishnamurthy and Li, 2020; Bordalo, Gennaioli, Shleifer and Terry, 2021; Gulen, Ion and Rossi, 2021).

We perform three sets of analyses. First, we examine the determinants and properties of lenders' expectations, for both the normal (baseline) scenario and the downside (severely adverse) scenario. Second, we investigate how lenders' expectations affect subsequent lending outcomes (e.g., loan volume and interest rates) and real effects. The data also allows us to test whether lenders' expectations about the downside are especially relevant for credit supply (Simsek, 2013). Third, we study the role of lenders' expectations in the COVID-19 setting.

Starting with the determinants of lenders' expectations, we find that downside projections for HPI and unemployment are more pessimistic on average for MSAs that had worse outcomes in the Great Recession. In contrast, baseline projections are better on average for these MSAs, which is consistent with a greater post-crisis rebound in these areas. In other words, the downside and baseline expectations can respond differently to past shocks. This empirical finding departs from predictions of Gaussian models where a given shock shifts all moments of subjective expectations in the same direction. The result resonates with models that allow separate movements in expectations about downside tails, such as Kozlowski, Veldkamp and Venkateswaran (2020) where tail expectations can have lasting "scars" by past tail events and Krishnamurthy and Li (2020) who consider expectations about a downside illiquidity shock.

Since banks report their economic projections to the Fed, a standard concern is whether they engage in "window dressing." For instance, banks with weaker balance sheets (e.g., lower capital ratios) or higher existing loan exposures to an MSA may want to paint a rosier picture. We do not find such evidence (if anything, banks provide more conservative projections in areas with high past loan exposures). In addition, the primary purpose of the MSA-level economic projections is to help banks better evaluate their business risks; the capital requirement is determined by the Fed's own model. Accordingly, incentives for window dressing are not clear for the regional economic projections, as such behavior will not reduce a bank's capital requirement.

Finally, we find significant heterogeneity in lenders' expectations. While we cannot easily pin down whether the expectations are "rational"—since we do not have lenders' information sets and the rationality of beliefs about tails is by design difficult to assess—the substantial dispersion in the data points to deviations from the simple full information rational expectations (FIRE) benchmark. Different banks may receive different signals about economic conditions, or may update their views differently with respect to a given signal (Woodford, 2003; Scheinkman and Xiong, 2003). The evidence also resonates with large dispersion in other settings including investors' beliefs about stock returns (Giglio, Maggiori, Stroebel and Utkus, 2021) and professional forecasters' expectations about macroeconomic outcomes (Coibion and Gorodnichenko, 2015; Bordalo, Gennaioli, Ma and Shleifer, 2020; Farmer, Nakamura and Steinsson, 2021).

We then turn to the relationship between banks' expectations and lending decisions. We exploit idiosyncratic variations in banks' expectations to sharpen identification (e.g., we control for local conditions using MSA-year fixed effects and further control for firm-year fixed effects among firms with multiple lenders). In terms of timing, banks' economic projections are collected at the beginning of each year and we use them to study subsequent loan growth and other outcomes in the rest of the year. Among large banks, it is a long-standing business practice to develop internal proprietary regional economic analyses that are shared among lending staff, so bank-level expectations can influence lending decisions across the bank.

We find that a firm's total loan growth is lower when its lenders' economic projections about the downside severely adverse scenario are more pessimistic. For a one inter-quartile change in lenders' projections, the annual loan growth on average changes by 3.3 percentage points. This economic magnitude is meaningful, compared to the average annual loan growth of 0.2 percentage points and a raw inter-quartile range of 9.7 percentage points. We also show that banks' economic projections only affect firms' subsequent loan growth, and they are not correlated with past loan growth (which further alleviates the concerns that banks use their projections to justify prior exposures). Moreover, we find that the loan growth of small firms is especially sensitive to lenders' expectations about a firm's particular MSA, whereas the loan growth of large firms is more sensitive to lenders' expectations about the overall US economy (measured by the average MSA projection). Finally, in addition to the quantity of lending, we also observe higher loan rates when lenders are more pessimistic, especially among firms with limited substitution such as small firms and bank-dependent firms. This finding provides additional evidence that lenders' expectations affect the supply of credit (rather than pessimistic lenders are matched with firms with low credit demand).

We further enhance empirical identification of credit supply effects by studying lending from different banks *to the same firm in the same year*. We control for firm-year fixed effects to tease out the impact of a firm's specific conditions or credit demand in a given year, following Khwaja and Mian (2008). For loan growth, we find that the coefficients on lenders' expectations are similar with and without firm-year fixed effects (despite a large change in R^2); they are also similar in loan-level and firm-level regressions. These results offer more reassurance that lenders' economic projections affect credit supply, and their variations (within an MSA-year) are not correlated with unobserved borrower characteristics including credit demand (Altonji, Elder and Taber, 2005; Oster, 2019).

Interestingly, we do not find a significant relationship between lenders' expectations about the *baseline* scenario and lending decisions. The finding suggests that expectations about *downside tails* play an especially important role for lending, and only analyzing expectations about central tendencies is insufficient. It echoes the theoretical insight that lenders' beliefs about the downside are crucial (Simsek, 2013).

After showing how lenders' expectations affect subsequent credit availability through loans, we then investigate their impact on real outcomes. We find that firms' total borrowing and capital expenditures are lower when their lenders are more pessimistic.[2] These real effects are especially pronounced among firms with limited sources of financing, such as small firms and bank-dependent firms. Moving beyond outcomes at the firm level, we also assess the impact of banks' expectations at the MSA-level. We find that in an MSA and a given year, differences in banks' expectations can account for about 20% of the variations in their loan growth. Furthermore, using the granular instrumental variable methodology of Gabaix and Koijen (2020), we find that a one inter-quartile range decrease in lenders' average expectations about a given MSA (value-minus equal-weighted) is associated with a 0.9 percentage point lower MSA-level GDP growth in the next year.

Taken together, the results show that lenders' economic projections affect credit supply through the expectations channel. The findings are difficult to explain if banks construct their projections to lower capital requirements (e.g., under-capitalized banks report more optimistic views), or if pessimistic banks happen to be matched with firms with less credit demand. In particular, lenders' pessimism is associated with not only lower loan growth, but also higher interest rates for firms that cannot easily substitute away. In addition, lending to small firms is shaped by local economic outlooks while

[2]For real effects, we can only perform regressions at the firm level (not at the loan level). The lending regressions at the loan level show that firm-time fixed effects do not make a difference. Accordingly, the firm-level regressions capture well the impact of bank-driven credit supply changes, even though here we cannot control for firm-time fixed effects.

lending to large firms is more sensitive to economy-wide outlooks. Moreover, there are corresponding real effects, especially for firms with limited sources of financing.

Finally, we examine how banks respond to the COVID-19 outbreak, which triggered a large negative shock to the economy. Following the observations of Geanakoplos (2010), one possibility is that lenders who were more optimistic pre-COVID lent more aggressively during the boom, which can make them more vulnerable to the negative shock and less able to lend during the pandemic. We find that banks with more pessimistic downside projections about an MSA before 2020 indeed have had fewer past due loans and loan downgrades since the pandemic, consistent with less risk taking in previous years. However, such effects are modest in magnitude. In the data, lenders that were more pessimistic pre-COVID continue to be more pessimistic and less willing to lend in 2020. In other words, having a smaller amount of past due loans and downgrades (slightly better balance sheet conditions) has not been sufficient to offset the impact of persistent pessimism.

Literature Review. Our work contributes to several strands of research. First, we contribute to the growing amount of research on expectations and economic decisions, which has analyzed firms (Ben-David, Graham and Harvey, 2013; Gennaioli, Ma and Shleifer, 2016), households (Carroll, 2003; Malmendier and Nagel, 2016; Kuchler and Zafar, 2019; Bhandari, Borovička and Ho, 2019; D'Acunto, Hoang, Paloviita and Weber, 2020; Rozsypal and Schlafmann, 2020), and financial market investors (Greenwood and Shleifer, 2014; Giglio et al., 2021; Andonov and Rauh, 2021). As we discuss below, there has been little data to directly investigate lenders' expectations and their impact on credit supply and economic outcomes. In addition, there is also limited empirical research on expectations about tails. We use new data to address these questions, providing systematic evidence on the properties and the effects of lenders' expectations about both normal and downside scenarios.

Second, we contribute to the literature on bank lending. An influential body of work shows that credit market conditions are key to economic outcomes, and many studies investigate how lenders' balance sheet positions shape credit supply.[3] However, there has

[3]See Campello, Graham and Harvey (2010), Schularick and Taylor (2012), Gilchrist and Zakrajšek (2012), Jordà, Schularick and Taylor (2013), Mian, Sufi and Verner (2017), López-Salido, Stein and Zakrajšek (2017), among others for empirical analyses of the impact of credit market conditions, as well as Kiyotaki and Moore (1997), Bernanke, Gertler and Gilchrist (1999), Geanakoplos (2010), Simsek (2013), Bordalo, Gennaioli and Shleifer (2018), Gertler, Kiyotaki and Prestipino (2020), Maxted (2020), Krishnamurthy and Li (2020) among others for theoretical analyses. See Kashyap and Stein (2000), Khwaja and

been limited data to directly examine lenders' expectations, and our study fills this gap. Indeed, research after the financial crisis has often postulated that lenders' expectations are important, but generally reaches this view through indirect evidence. For instance, Fahlenbrach and Stulz (2011) show that incentives cannot fully explain banks' lending decisions in the credit expansion. Cheng, Raina and Xiong (2014) analyze personal housing transactions to document that securitization officers appeared overoptimistic in the boom. Ma (2015) uses bank CEOs' stock and option holdings as proxies of beliefs following Malmendier and Tate (2005), and finds that banks with more optimistic CEOs had higher loan growth in the credit boom. Fahlenbrach, Prilmeier and Stulz (2018) and Richter and Zimmermann (2020) show that banks' balance sheet conditions alone are not sufficient for explaining lending, and analyst forecasts of bank earnings or aggregate forecasts by financial sector CFOs help account for loan growth. We utilize direct and granular data about lenders' expectations, which allows us to pin down their impact on both lending and real outcomes using a variety of empirical strategies.

Third, we contribute to studies about bank lending during COVID-19. Several papers investigate the role of credit lines (Li, Strahan and Zhang, 2020; Chodorow-Reich, Darmouni, Luck and Plosser, 2021; Greenwald, Krainer and Paul, 2021). We document that lenders' expectations continue to be an important determinant of credit supply in this period. In particular, although banks that were more pessimistic pre-COVID have fewer past due loans and downgrades, they continue to lend less due to persistent pessimism. This result further suggests that analyzing expectations (in addition to balance sheet conditions) is important for understanding credit supply.

The rest of the paper is organized as follows. Section 2 describes the data and presents the summary statistics. Section 3 shows the determinants and properties of banks' economic projections. Section 4 analyzes the relationship between banks' expectations and credit supply. Section 5 examines real effects at the firm level and aggregate effects at the MSA level. Section 6 investigates lending decisions during the COVID-19 pandemic. Section 7 concludes.

Mian (2008), Jiménez et al. (2012), Chodorow-Reich (2014), Huber (2018), among others for the impact of banks' balance sheet conditions.

2 Data

Our data has two components. The first part covers banks' economic projections, every year for each MSA. The second part covers loans the banks make and financial information of the borrowers. This section describes the data and summary statistics.

2.1 Banks' Economic Projections

A. Data Source

Our data on banks' economic projections comes from the Federal Reserve's FR Y-14A form, which is part of a wide range of information the Fed collects from bank holding companies in recent years. The Y-14A segment covers banks' quantitative projections for a large set of variables under different macroeconomic scenarios.[4] We focus on the projections about economic conditions across MSAs. The projections are submitted in the first quarter of every year, available to us since 2014. Our sample for Sections 3 to 5 starts in 2014 and ends in 2019 to analyze the pre-COVID period. We then analyze the pandemic period in Section 6.

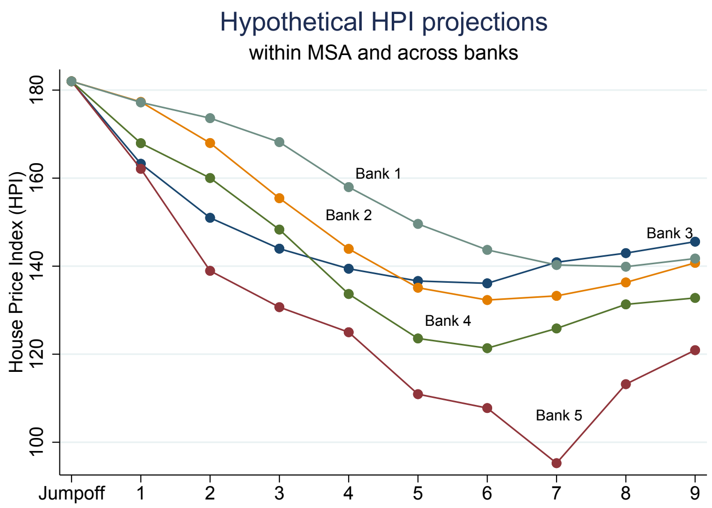
Specifically, we rely on banks' annual projections for three main outcomes. First, banks make projections for each MSA about the house price index (HPI) under the severely adverse scenario, which describes a potential major recession. Second, the majority of banks also report HPI projections under the baseline scenario, which corresponds to macroeconomic conditions in line with consensus forecasts in the Blue Chip Economic Indicators and Blue Chip Financial Forecasts datasets in a given year.[5] Third, most banks report projections of the unemployment rate in each MSA for the severely adverse scenario (for fewer years). For a given scenario, the bank projects the path of the outcome variable over the next nine quarters, and we summarize it using the distance between the jumpoff point (the last quarter of the pre-submission year) and the trough (worst) outcome. Figure 1 shows an illustration of hypothetical paths of the HPI. We define the HPI drop as (jumpoff HPI − min HPI)/jumpoff HPI, which is the percentage change between the actual HPI at the jumpoff point and the trough HPI. A larger

[4] See https://www.federalreserve.gov/apps/reportforms/reporthistory.aspx?sOoYJ+5BzDa2AwLR/gLe5DPhQFttuq/4 for details.

[5] See https://www.federalreserve.gov/publications/stress-test-scenarios-february-2021.htm for a recent example.

Figure 1: An Illustration of Bank Projections

This figure shows an illustration of hypothetical HPI projections for an MSA in a given year. The projection horizon is 9 quarters.



value of this variable means the projection is more pessimistic. We define the unemployment increase as (max unemployment rate − jumpoff unemployment rate), which is the difference between the actual unemployment rate at the jumpoff point and the trough unemployment rate. Again, a larger value of this variable means the projection is more pessimistic. These economic projections reflect MSAs' outcomes conditional on a given macroeconomic condition, instead of the probability of the macro condition.

The FR-Y14A form is submitted as part of the Federal Reserve's stress test process; correspondingly, our data covers the largest lenders in the US (rather than small regional banks). In constructing the projections, a bank should consider historical data and multiple factors, sources, and events that can generate business risks. It should take into account potential risks on a forward-looking basis (instead of just applying a simple transformation to past realizations) and is advised to consider its vulnerabilities (e.g., should not be excessively optimistic about areas where it has large exposures). If banks' reports differ significantly from the supervisory projections, they may need to provide explanations in order to reconcile the differences. Overall, the primary use of the MSA-level economic projections is to help banks evaluate their business risks. The Fed uses its own model to calculate capital shortfalls, so even if a bank manipulates its regional economic projections, the final capital shortfall will not be affected by this behavior. Accordingly, window dressing incentives may not be clear for these MSA-level economic projections. We investigate the empirical determinants of banks' MSA-level projections

Table 1: Summary Statistics of Bank Projections

Panel A shows the mean, standard deviation and quartiles of banks' MSA-level projections for severely adverse (SA) house price index (HPI) drop, baseline HPI drop, and severely adverse unemployment increase. Panel B shows dispersion of projections within MSA-year, bank-MSA, and bank-year. The odd columns show the average standard deviations of projections within each unit; the even columns show the R^2 from MSA-year, bank-MSA, and bank-year fixed effects respectively.

Panel A. Basic Statistics

	# MSAs (1)	# Banks (2)	N (3)	mean (4)	p50 (5)	sd (6)	25th (7)	75th (8)
SA HPI Drop	392	11	19,609	19.75	19.96	9.16	14.25	25.31
Baseline HPI Drop	392	8	14,975	-0.60	-0.66	1.66	-1.19	-0.05
SA Unempl Incr	392	8	9,439	4.72	4.74	2.00	3.53	5.85

Panel B. Heterogeneity

	MSA-Year		Bank-MSA		Bank-Year	
	Within SD	FE R^2	Within SD	FE R^2	Within SD	FE R^2
	(1)	(2)	(3)	(4)	(5)	(6)
SA HPI Drop	7.80	0.36	5.78	0.60	6.39	0.46
Base HPI Drop	1.09	0.17	1.13	0.28	0.97	0.13
SA Unempl Incr	1.29	0.56	1.37	0.43	1.75	0.27

in Section 3.1 and do not find indications of distorted reporting incentives. We also demonstrate in Sections 4 and 5 that these projections are closely connected to banks' lending decisions, and the results are not easily explained by window dressing behavior.

B. Summary Statistics

We present summary statistics of the projections in Table 1, Panel A. For the HPI projections under the severely adverse scenario, there are 11 banks and around 20,000 bank-MSA-year observations. The mean is about 20%: on average, the HPI is expected to decline by 20% for the average MSA in this case. The HPI projections under the baseline scenario have 8 banks and close to 15,000 bank-MSA-year observations. The mean is about -1%: that is, the HPI is expected to grow by about 1% per year on average in the baseline case. The unemployment rate projection under the severely adverse scenario is available for 8 banks and fewer years, with about 10,000 bank-MSA-year observations. The mean is about 5%: the unemployment rate is expected to increase by 5 percentage points on average in this scenario. Table 1, Panel B, shows that there is substantial dispersion among the projections (e.g., across different banks for the same MSA in a given year), which we discuss more in Section 3.2.

In Table 2, we show the basic relationship among the three types of projections as

Table 2: Relationship between Different Projections

This table shows shows MSA-bank-year level regressions of the severely adverse (SA) house price index (HPI) drop projections on the severely adverse unemployment increase projections in Panel A, as well as on the baseline HPI drop projections in Panel B.

Panel A. SA HPI Drop and SA Unemployment Increase

	SA HPI Drop					
	(1)	(2)	(3)	(4)	(5)	(6)
SA Unemp Incr	0.693***	0.238***	0.861***	0.163***	0.393***	0.531***
	(0.038)	(0.049)	(0.039)	(0.059)	(0.04)	(0.047)
R^2	0.292	0.203	0.425	0.181	0.595	0.807
Fixed effects	Bank	MSA	Bank*Year	MSA*Year	MSA*Bank	B*Y, M*Y, M*B

Panel B. SA HPI Drop and Baseline HPI Drop

	SA HPI Drop					
	(1)	(2)	(3)	(4)	(5)	(6)
Base HPI Drop	0.489***	0.488***	0.265***	0.267***	0.994***	0.722***
	(0.055)	(0.054)	(0.05)	(0.058)	(0.047)	(0.035)
R^2	0.218	0.256	0.418	0.247	0.578	0.837
Fixed effects	Bank	MSA	Bank*Year	MSA*Year	MSA*Bank	B*Y, M*Y, M*B

a consistency check. We see that the HPI projections and unemployment projections under the severely adverse scenario are positive correlated: banks generally expect the HPI drop to be larger in MSAs where they expect the unemployment rate increase to be larger. This holds regardless of the fixed effects used (the magnitude of the relationship is larger for the same bank-year across MSAs, and smaller for the same MSA-year across banks). In addition, the HPI projections under the severely adverse scenario and those under the baseline scenario are also positively correlated: banks generally expect that places with weaker performance in the baseline scenario to also suffer more in the severely adverse scenario. In sum, these results show that the projections seem internally consistent (both within banks and across banks).

2.2 Loans and Borrowers

A. Data Source

We collect data about the loans made by our sample banks and about the borrowers from the Federal Reserve's FR Y-14H1 form. This comprehensive lending data is analogous to a "credit registry; it covers about 70% of corporate loans in the US and has been described in detail in several recent papers (Chodorow-Reich et al., 2021; Caglio et al., 2021). It records the amount, pricing, and security of the loan, as well as standard financial information of the borrower firm. In our sample period, banks' risky lending is primarily concentrated in corporate loans, so we focus on them in our analysis. Moreover, different from data on household loans, our data has a number of firms with multiple loans across banks, which is important for the empirical identification of credit supply effects.

B. Summary Statistics

Table 3 presents summary statistics of borrower characteristics (Panel A) and loan characteristics (Panel B). The median borrower has $14 million assets, which represents a relatively small firm (in comparison, the median assets of Compustat firms in this period are $325 million and larger than the top quartile of firms by size in our sample). About 80% of the median firm's total debt is loans from banks in our sample, so firms in this sample are fairly dependent on banks. The median book leverage is about 31% and return on asset is 11%, which are representative of US non-financial firms. About 10% of firms have loans from multiple banks in our sample (i.e., banks with MSA-level economic projections) and they account for nearly 40% of the total number of loans; the other firms have one bank in our sample (they may have other banks outside of our sample). The median loan size is $3.6 million, which is within the limit of a small business loan. About 15% of the loans are secured by real estate (or similarly for real estate purposes).

3 Properties of Lenders' Economic Projections

In this section, we study the properties of banks' economic projections. Section 3.1 analyzes their determinants. Section 3.2 shows the substantial heterogeneity among the projections.

3.1 Determinants of Banks' Projections

In Table 4, we investigate what factors shape the projections. We study three sets of variables. The first set is recent MSA economic conditions, including MSA HPI growth and unemployment rate in the past year. This set of variables examines if the projections extrapolate recent economic trends. The second set is economic conditions during the

Table 3: Summary Statistics of Firms and Loans

This table presents summary statistics of borrower firms in our sample (Panel A) and loans in our sample (Panel B). Mean, standard deviation, and quartiles are displayed. The number of banks restricts to banks with MSA-level projections.

Panel A. Borrower Firm Characteristics

	mean	p50	sd	p25	p75
Assets (Million)	1343.0	14.0	9704.0	6.0	63.0
Sales Growth (%)	15.0	8.9	24.9	1.0	21.5
Return on Assets (%)	15.7	10.9	17.4	5.1	20.2
Book Leverage (%)	34.5	31.3	26.8	10.1	55.2
Loan Share in Total Debt (%)	63.7	80.5	39.2	23.8	100.0
Number of Banks	1.2	1.0	0.9	1.0	1.0
Average Annual Loan Growth (%)	0.2	-0.4	32.7	-7.4	2.3

Panel B. Loan Characteristics

	mean	p50	sd	p25	p75
Loan Size (Million)	15.48	3.61	44.31	1.64	12.00
Loan Rate (%)	3.58	3.50	1.48	2.53	4.40
Secured by Real Estate (1/0)	0.14				
Loan for Real Estate Purpose (1/0)	0.14				
Unsecured (1/0)	0.22				

Great Recession. This set of variables studies the impact of adverse conditions in the past. The third set is balance sheet conditions, including Tier 1 capital ratio, ROA, asset size, and existing loan exposures in an MSA.

Impact of Past MSA Conditions. For the severely adverse projections, we find that MSA economic conditions in the previous financial crisis have a significant impact. In particular, the HPI projections for the severely adverse scenario are worse among MSAs where HPI growth from 2006 to 2009 was lower. Similarly, the unemployment projections for the severely adverse scenarios are worse among MSAs where the unemployment rate increased by more from 2006 to 2009. In terms of economic magnitude, a one standard deviation change in the HPI growth and the unemployment rate increase from 2006 to 2009 is on average associated with a 0.22 and 0.58 standard deviation change in the severely adverse HPI and the unemployment projection, respectively.[6]

For the baseline HPI projections, the results are the *opposite*: on average HPI growth under the baseline scenario is expected to be higher in MSAs where HPI growth from

[6]The standard deviation of HPI growth from 2006 to 2009 is 13.8%, and the standard deviation of the severely adverse HPI drop projection is 9.16% (see Table 1). $-0.149 \times 13.8/9.16 = -0.22$. The standard deviation of unemployment rate increase from 2006 to 2009 is 2%, and the standard deviation of the severely adverse unemployment increase projection is also 2% (see Table 1). $0.578 \times 2/2 = -0.578$.

2006 to 2009 was lower. This is consistent with higher realized HPI growth (stronger recovery) in these MSAs in the sample period, which is expected to continue during normal times. The economic magnitude is smaller: a one standard deviation change in the HPI growth from 2006 to 2009 is on average associated with a 0.06 standard deviation change in the baseline HPI projection.[7]

Overall, in our data MSA economic conditions in the past year do not seem to have a significant impact on the projections, but MSA conditions in the previous crisis play an interesting role. Notably, poor MSA performance during the Great Recession is associated with worse expectations for the severely adverse projections, but not for the baseline projections. The result suggests that expectations about downside and normal conditions can respond differently to past shocks. This finding resonates with the "scarring" effects modeled by Kozlowski, Veldkamp and Venkateswaran (2020), which are especially strong for expectations about downside tails. It also resonates with the model of Krishnamurthy and Li (2020), which features diagnostic expectations about a downside illiquidity state in addition to expectations about regular Brownian shocks.

Impact of Bank Balance Sheets. We do not find evidence that banks window dress their economic projections according to their balance sheet conditions. In particular, one possible concern is that banks may have incentives to report more optimistic projections if they have weaker capital positions or if they have larger past exposures in an area. In the data, we do not find a clear relationship between banks' capital ratios and their economic projections. In addition, if anything, banks appear more conservative in areas where they have larger past exposures, measured as the share of existing loans in an MSA in total loans of the bank (the economic significance is modest: a one standard deviation change in the bank MSA exposure variable, 1.7%, is associated with a 0.05 standard deviation change in the SA HPI projection and a 0.03 standard deviation change in the baseline HPI projection). As discussed in Section 2, window dressing incentives are muted for these MSA-level economic projections (e.g., such window dressing will have little effect on capital requirements, if any). Finally, in unreported results we also do not find significant relationships between banks' projections and branch presence or deposit flows in an MSA, which suggests that banks' economic outlooks are not correlated with their deposit funding conditions and deposit flows do not appear to be the primary

[7]The standard deviation of HPI growth from 2006 to 2009 is 13.8%, and the standard deviation of the baseline HPI projection is 1.66% (see Table 1). $0.007 \times 13.8/1.66 = 0.058$.

Table 4: Properties of Banks' Economic Projections

This table shows regressions of bank projections on MSA and bank attributes. The MSA attributes include MSA house price index (HPI) growth and unemployment rate in the past year, as well as MSA-level HPI growth and unemployment rate increase during the Great Recession (end of 2006 to end of 2009). Bank attributes include lagged bank exposure to the MSA (outstanding commercial loans and commitments in a given MSA as a fraction of total outstanding commercial loans and commitments), lagged Tier 1 capital ratio, lagged return on assets (ROA), and lagged bank size (log assets). We also include lagged projections. Standard errors are double clustered by MSA and bank-year and presented in parentheses.

	HPI Drop		Unempl Incr
	SA	Baseline	SA
	(1)	(2)	(3)
L.MSA HPI Growth	0.126	-0.020	
	(0.112)	(0.015)	
L.MSA Unemployment Rate			-0.199
			(0.161)
HPI Growth 06—09	-0.149***	0.007**	
	(0.032)	(0.003)	
Unemployment Increase 06—09			0.578***
			(0.057)
L.Bank Tier 1	-0.583	0.040	0.128
	(0.402)	(0.032)	(0.121)
L.Bank ROA	-1.363	0.233	-0.605
	(1.865)	(0.140)	(1.100)
L.Bank MSA Exposure	0.292**	0.029***	0.010
	(0.131)	(0.007)	(0.014)
L.Log (Bank Assets)	-0.865	0.462	0.040
	(2.256)	(1.221)	(0.316)
L.Projection	0.612***	0.327***	-0.508
	(0.068)	(0.100)	(0.453)
Observations	9,414	8,273	6,436
R^2	0.559	0.173	0.260

source of information that shapes expectations (at least among these largest banks).

Rationality of Bank Expectations. A natural question is whether banks' expectations are rational. For the severely adverse projections, by definition tail scenarios materialize infrequently and the rationality of these projections is difficult to evaluate. Nonetheless, as we discuss below, there is substantial heterogeneity among these projections (e.g., across different banks for the same MSA in a given year), which indicates that the strong version of full information rational expectations (FIRE) does not hold. For the baseline projections (only available for HPI), we compare them with realized HPI growth as well as with simple linear econometric forecasts based on past HPI growth and other MSA outcomes. Table IA1 uses realized HPI growth to construct the mean-squared error (MSE) of the projections. It shows that the MSE of banks' baseline projections is much smaller than the MSE of simple linear predictions (based on rolling linear forecasting regressions using historical HPI growth, GDP growth, and unemployment rate change). We also find that banks' baseline projections significantly positively predict realized HPI growth, although our sample since 2014 is not necessarily long enough for comprehensive rationality tests. Finally, as we show in Section 4, severely adverse projections (expectations about downside tails) have a strong relationship with lending decisions, whereas baseline projections do not. Therefore, although we find that the baseline projections appear very sensible (e.g., they are not just noise), their rationality may not be the most critical issue; expectations about downside tails are much more important for lending, but their rationality is challenging to pin down.

3.2 Heterogeneity

Finally, we find that the projections display substantial dispersion, which points to prevalent heterogeneity in expectations. The first two columns in Table 1, Panel B, shows the average standard deviation of the severely adverse HPI projections within an MSA-year, as well as the R^2 from MSA-year fixed effects. We observe that the R^2 from MSA-year fixed effects is 36%, indicating that there are considerable differences in the projections across banks for *the same MSA at the same time*. The average within MSA-year standard deviation of 7.8 percentage points is also large, compared to an unconditional inter-quartile range of this variable of around 11.5 percentage points and an unconditional standard deviation of 9.16 percentage points. The middle columns in Panel B of Table 1 show that the R^2 from bank-MSA fixed effects is higher (60%), which could come from sticky experiences banks have in an MSA. Finally, the last two columns point to sizable variations not captured by bank-year fixed effects (the R^2 is 46%). This suggests that there are meaningful variations in the projections about different MSAs that are not captured by a bank's overall conditions in a given year (including balance sheet conditions such as capital positions) or a bank's overall optimism about the economy.

The substantial differences in banks' expectations about the same MSA in a given year indicate deviations from FIRE. This finding resonates with substantial heterogeneity observed in other settings including investors' beliefs about stock returns (Giglio et al., 2021) and professional forecasters' expectations about macroeconomic outcomes (Bordalo et al., 2020). The heterogeneity can arise from different priors, heterogeneous information, or diverse interpretations (Woodford, 2003; Scheinkman and Xiong, 2003; Caballero and Simsek, 2020). We will exploit the heterogeneity across banks below to study how variations in expectations affect lending decisions.

4 Lenders' Expectations and Credit Supply

In this section, we investigate how lenders' expectations affect credit supply. In particular, we focus on idiosyncratic variations in expectations to enhance our empirical identification of the credit supply effects: in all cases, we control for MSA-year fixed effects and exploit differences in lenders' views about the same MSA at the same time. As a result, we tease out MSA-level fundamentals that may affect local economic conditions (including borrower fundamentals such as credit demand) and the common components among banks' projections are dropped. Moreover, for firms with multiple lenders, we also perform tests using firm-time fixed effects to control for time-varying unobserved borrower conditions. Finally, we analyze loan volume as well as interest rates, both of which are key for isolating shifts in the supply of credit. In all of our analyses, lenders' economic projections are reported at the beginning of each year and we measure subsequent lending and other outcomes in the rest of the year. We provide a simple model in Appendix IA2 to illustrate our empirical specifications and outline the empirical predictions for how banks' expectations affect lending outcomes.

4.1 Loan Growth

We start with loan growth and perform our analyses at both the firm level and the loan level. We are interested in firm-level results because many outcomes (e.g., real effects like total credit and investment) are only measured at the firm level. We are also interested in loan-level tests because they can further strengthen our empirical identification: we analyze lending to *the same firm at the same time* by different banks, which is a classic empirical strategy to tease out the influences of credit demand and potential matching between firms and banks.

At the firm level, we test the following regression:

$$LoanGrowth_{i,t} = \alpha_i + \eta_{MSA,t} + \phi_{Ind,t} + \beta BankProjection_{MSA,t-1} + \gamma X_{i,t-1} + \epsilon_{i,t}. \quad (1)$$

The dependent variable $LoanGrowth_{i,t}$ is firm i's annual growth of the total loan amount from banks in our sample (i.e., those with economic projection data available).[8] It measures the commitment amount (which corresponds most closely to credit supply) and is not affected by firms' decisions to draw down credit lines. The key independent variable is $BankProjection_{MSA,t-1}$, which is the weighted average projections of firm i's lenders for its MSA. In each year t, the projections are released in the first quarter, and the preparation process may also include the fourth quarter of year $t-1$. Correspondingly, we calculate $LoanGrowth_{i,t}$ using outstanding loan balances in the third quarter of year t (i.e., after the projections are made), relative to the third quarter of year $t-1$. We control for firm characteristics including lagged firm size (log total assets), ROA, sales growth, and tangible asset share, measured at the end of year $t-1$. We also control for bank characteristics including lagged Tier 1 capital ratio, ROA, existing loan exposure to an MSA (the share of loans in each MSA relative to total loans of the bank), bank size (log total assets); we use weighted average among firm i's lenders if there are multiple lenders. We include firm fixed effects (α_i), MSA-year fixed effects ($\eta_{MSA,t}$), and industry-year fixed effects ($\phi_{Ind,t}$).

A standard concern for such specifications is potential matching between banks and firms: maybe banks that are more pessimistic about a location happen to be matched with firms with lower quality and lower credit demand. To address the concerns about credit demand, we follow the empirical strategies in prior work (Khwaja and Mian, 2008) and zoom in on firms with multiple lenders. In these cases, we can use firm-year fixed effects to tease out the influences of credit demand. In other words, we test loan-level regressions for those firms with multiple lenders and apply firm-year fixed effects:

$$LoanGrowth_{i,j,t} = \alpha_{i,t} + \eta_{MSA,t} + \xi_{MSA,j} + \beta BankProjection_{MSA,j,t-1} + \gamma X_{i,t-1} + \epsilon_{i,t}. \quad (2)$$

Now the dependent variable $LoanGrowth_{i,j,t}$ is firm i's annual loan growth from bank j, and the key independent variable $BankProjection_{MSA,j,t-1}$ is the projection of lender j for firm i's MSA. In particular, $\alpha_{i,t}$ is firm-year fixed effects (so firm-level controls are all dropped). We also include bank-MSA fixed effects ($\xi_{MSA,j}$), which will absorb any invariant attributes at the bank-MSA level. This means that we also remove from the projections the possible influence of a bank's business model, geographic specialization,

[8] We use the formula $LoanGrowth_{i,t} = (Loan_{it} - Loan_{it-1})/(0.5Loan_{it} + 0.5Loan_{it-1})$, where $Loan_{it}$ is total loan amount in year t and $Loan_{it-1}$ is total loan amount at the same time in year $t-1$. This formula allows us to accommodate cases where the loan balance in year $t-1$ is zero.

Table 5: Bank Expectations and Firm-Level Loan Growth

This table presents firm-level loan growth regressions following the specification in Equation (1). SA HPI Drop, Baseline HPI Drop, and SA Unempl Incr are the severely adverse HPI drop projection, baseline HPI drop projection, and severely adverse unemployment rate increase projection, respectively (if there are multiple lenders, the variable is the weighted average of their projections). A larger value means more pessimistic projections. Firm controls include lagged firm ROA, sales growth, and fixed asset ratio (property, plant, and equipment in total assets). Standard errors clustered by MSA are presented in parentheses.

	Firm-Level Loan Growth				
	(1)	(2)	(3)	(4)	(5)
SA HPI Drop	-0.277***		-0.275***		-0.266**
	(0.033)		(0.069)		(0.106)
Baseline HPI Drop		0.238	0.050		
		(0.263)	(0.268)		
SA Unempl Incr				-3.139***	-2.852***
				(1.012)	(1.065)
L.Bank Tier 1	-0.318	-1.418***	-0.887***	-1.235***	-1.077***
	(0.213)	(0.186)	(0.259)	(0.202)	(0.222)
L.Bank ROA	0.067***	0.035**	0.085***	-0.319***	-0.257***
	(0.016)	(0.017)	(0.019)	(0.068)	(0.096)
L.Bank MSA Exposure	-0.434**	-0.731***	-0.682***	0.122	0.086
	(0.217)	(0.172)	(0.188)	(0.550)	(0.438)
L.Log (Bank Assets)	-17.725***	-26.414***	-29.545***	-21.972***	-21.570***
	(1.886)	(3.179)	(4.130)	(2.567)	(2.519)
Firm Controls			Yes		
Fixed Effects			Firm, MSA*Year, Industry*Year		
Observations	333,593	240,978	239,361	183,558	182,738
R^2	0.191	0.210	0.211	0.283	0.281

or past crisis experience in a given MSA.

A. Firm-Level Results

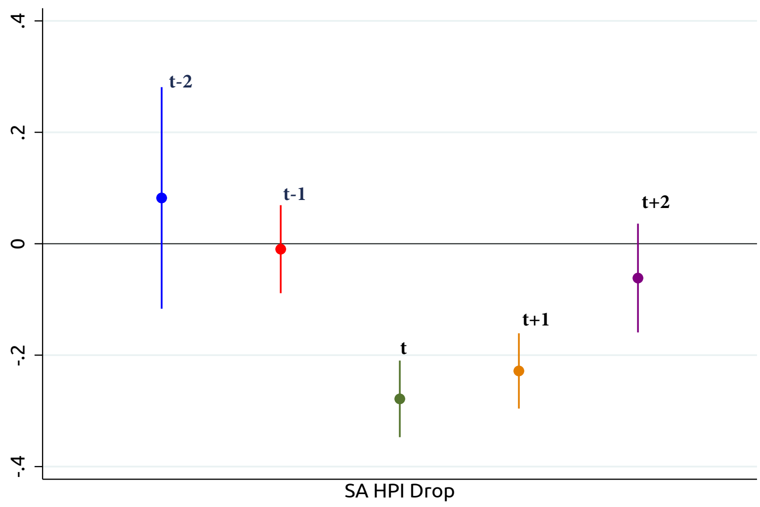
Table 5 presents the firm-level results. Column (1) shows that when lenders' severely adverse HPI projections decrease by 1 percentage point, firm-level annual loan growth is lower by around 0.3 percentage points. Accordingly, if these projections change by one inter-quartile range (roughly 11 percentage points), loan growth would be lower by 3.3 percentage points. This magnitude is meaningful, compared to average firm-level annual loan growth of about 0.2 percentage points and a raw inter-quartile range of 9.7 percentage points.[9] Columns (2) and (3) show that baseline HPI projections, on the other hand, do not have any significant impact on loan growth. Finally, columns (4) and (5) show that when lenders' severely adverse projections of the unemployment rate are lower, firm-level loan growth also declines.

In Figure 2, we plot the regression coefficients β on bank projections in Equation (1),

[9]The raw standard deviation of loan growth is more affected by extreme values, so we do not use it as the benchmark for economic magnitudes.

Figure 2: Loan Growth Over Time

This figure plots the coefficient β on bank projections in Equation (1) when loan growth is measured in year $t-2$ to $t+2$. The vertical bars indicate 95% confidence intervals.



using loan growth in different years (from $t-2$ to $t+2$) on the left hand side. We show that bank projections are not correlated with loan growth in the past. Rather, when banks are pessimistic, only subsequent loan growth is affected. These results verify that banks with different levels of optimism or pessimism are not simply matched to firms that always have higher or lower loan growth. In addition, they suggest that the projections are not just driven by banks having particular business models in an MSA (and therefore always lend a lot or lend a little). Finally, they also further alleviate the concern that banks report more optimistic projections to justify higher past lending.

Overall, we find that downside tail projections are closely linked to banks' lending decisions, while baseline projections do not play a significant role in our data. This finding is in line with the observation that the downside is most payoff relevant for lenders and correspondingly downside expectations are crucial for lending (Simsek, 2013). It also underscores the importance of measuring and analyzing expectations about downside tails.

B. Loan-Level Results

In Table 6, we zoom in at the loan-level dimension for each firm in a given year to enhance our empirical identification. In particular, we use firms with multiple lenders and compare the results with and without firm-year fixed effects (columns (3) and (4) compared with columns (1) and (2)). Studying loan-level variations within the same firm is a classic empirical strategy in prior work to tease out the potential influence of credit

Table 6: Bank Expectations and Loan Growth: Firms with Multiple Banks

This table presents loan-level loan growth regressions following the specification in Equation (2). SA HPI Drop, and SA Unempl Incr are the severely adverse HPI drop projection and unemployment rate increase projection at the MSA-bank-year level. A larger value means more pessimistic projections. Standard errors clustered by firm and bank-year are presented in parentheses.

	Loan Growth			
	(1)	(2)	(3)	(4)
SA HPI Drop	-0.235**		-0.260**	
	(0.101)		(0.113)	
SA Unempl Incr		-0.743***		-1.005***
		(0.254)		(0.277)
L.Bank Tier 1	-1.034*	0.507	-1.078	0.858
	(0.591)	(0.737)	(0.685)	(0.986)
L.Bank ROA	7.031	-10.715	8.354	-15.514
	(8.475)	(12.571)	(10.254)	(16.292)
L.Bank MSA Exposure	0.376	1.153**	0.391	1.089*
	(0.235)	(0.438)	(0.282)	(0.601)
L.Log (Bank Assets)	-21.800**	-15.302***	-20.817**	-20.142**
	(9.087)	(4.080)	(9.379)	(7.367)
Fixed Effects	Bank*MSA, MSA*Year			
	Firm, Industry*Year		Firm*Year	
Observations	180,301	79,338	180,301	77,577
R^2	0.110	0.184	0.346	0.479

demand. Comparing the results with and without firm-time FE provides information about whether pessimistic lenders happen to be matched with firms that have less credit demand. We find that the coefficients on bank projections are similar with and without firm-year fixed effects (despite a substantial increase in R^2). These results offer more reassurance that lenders' economic projections affect the supply of credit, and their variations (within an MSA-year) do not seem to be correlated with unobserved borrower characteristics and credit demand (Altonji, Elder and Taber, 2005; Oster, 2019). We also provide further evidence for credit supply effects in Section 4.2 by studying loan rates.

C. Are HPI Projections Only about Real Estate Value?

Since the main economic projection variable in our data focuses on the HPI, we also check the mechanisms of its effects. Specifically, one possibility is that HPI projections reflect expectations about the value of real estate collateral, in which case they will be particularly relevant for lending against real estate. Another possibility is that HPI projections capture expectations about MSA-level economic conditions more generally (e.g., they are correlated with unemployment rate projections as shown in Table 2, Panel A), in which case their impact will not be confined to loans against real estate.

In Table IA2, we test Equation (1) separately for the growth of real estate and non-real estate loans. In columns (1) and (2), we split loans based on whether they are for real estate purpose. In columns (3) and (4), we split loans based on whether they are secured by real estate. We find that HPI projections are relevant for both real estate and non-real estate loans, so HPI projections are not just about the value of real estate collateral. The coefficients are larger in the regressions of real estate loans, which can be affected by both the real estate value channel and the general economic condition channel.

D. Role of Local versus Economy-Wide Projections

Our data on expectations capture banks' economic outlooks for each MSA. Accordingly, it is natural to think that these regional economic projections are especially relevant for lending to smaller firms that operate in a given area. On the other hand, for lending to larger firms that may operate across the country, economy-wide economic outlooks can be more relevant. We examine this issue in Table 7. In particular, we use the specification in Equation (1). On the right hand side we now have both the projection for a given MSA (based on the firm's headquarters) and the average projection a bank has across all MSAs in a given year which proxies for its economy-wide economic outlook. Indeed, we find that lending to small firms (assets less than \$50 million) is significantly affected by the local MSA-level economic outlook. Lending to large firms, conversely, is not significantly related to the local economic outlook, whereas the economy-wide economic outlook plays a more important role.

Overall, these findings are consistent with the mechanisms of lender expectations shaping lending decisions. They also further address the concern that banks' economic projections are affected by their balance sheet conditions. For instance, if banks' projections are simply driven by their balance sheet strength (e.g., capital ratios), then the average projection in a given bank-year should be correlated with lending to all firms, which we do not find to be the case.

4.2 Loan Rates

To provide further evidence that lenders' expectations shift credit supply, we analyze their relationship with loan rates. In particular, if pessimistic lenders cut loan supply, then we would expect them to charge higher interest rates. Firms with limited ability to substitute to other sources of financing will have to pay higher interest rates. Firms with

Table 7: Lending to Small and Large Firms

This table presents annual regressions of firm-level loan growth. In addition to the variables in Equation (1) and Table 5, we also include the average HPI drop for each bank-year as a measure of economy-wide outlook of a bank in a given year. Small (large) is total assets less than (greater than) 50 million dollars. Standard errors clustered by MSA are presented in parentheses.

	All (1)	Small (2)	Large (3)
SA HPI Drop	-0.169***	-0.155***	-0.165
	(0.044)	(0.043)	(0.142)
Average HPI Drop for Bank-Year	-0.129	-0.085	-0.379*
	(0.081)	(0.071)	(0.213)
Fixed Effects	Firm, MSA*Year, Industry*Year		
Observations	333,593	232,279	100,914
R^2	0.192	0.196	0.197

greater ability to substitute may switch to other forms of financing, in which case loan volume will fall but observed loan rates may not increase substantially (i.e., borrowers shift away from pessimistic banks and therefore will not pay higher loan rates). On the other hand, if the loan growth results reflect that pessimistic banks are somehow matched with borrowers with less credit demand, we would not observe higher loan rates associated with pessimistic banks.

Table 8 presents the results of the relationship between banks' economic projections and the average loan rates a firm pays.[10] We find that interest rates are indeed higher when banks are more pessimistic. In particular, this relationship is especially pronounced among firms with limited sources of financing, such as small firms, bank-dependent firms, and risky firms. These results provide further support that banks' expectations affect the supply of credit.

4.3 Other Outcomes

Finally, our main data on banks' expectations captures their economic outlooks for each MSA (which are relevant for lending to firms in the area), not their beliefs about a particular firm. We use additional information on banks' assessment of the loss given default (LGD) and probability of default (PD) for each loan. We find that banks with more pessimistic severely adverse economic projections also expect a higher loss given default, though not necessarily a higher probability of default. This result is in line with

[10]We present the interest rate regressions at the firm level, not the loan level, because within a firm the interest rate differences among different loans could also be driven by the seniority of different loans (which is not fully available in the data).

Table 8: Bank Expectations and Loan Rates

Firm-level regressions of average loan rates on lenders' expectations. SA HPI Drop is the severely adverse HPI drop projection (weighted average among lenders if there are multiple lenders). Standard errors are clustered by MSA. Small (large) is total assets less than (greater than) 50 million dollars. Bank dependent is yes if loans are more than 50% of total debt. NonIG and IG are based on internal risk ratings, which map into noninvestment grade and investment grade. Firm controls include lagged firm ROA, sales growth, and fixed asset ratio (property, plant, and equipment in total assets). Standard errors clustered by MSA are presented in parentheses.

	All	Size		Bank Dependent		Risk	
		Small	Large	Yes	No	NonIG	IG
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SA HPI Drop	0.006**	0.010**	0.001	0.011**	0.002	0.007***	-0.001
	(0.003)	(0.004)	(0.001)	(0.005)	(0.002)	(0.003)	(0.003)
L.Bank Tier 1	-0.042**	-0.050	-0.018*	-0.090	-0.009**	-0.031**	-0.090**
	(0.019)	(0.031)	(0.010)	(0.059)	(0.004)	(0.013)	(0.037)
L.Bank ROA	-0.001	-0.001	-0.002	-0.004***	-0.001*	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L.Bank MSA Exposure	0.013*	0.026**	-0.008	0.051**	-0.007	0.017**	0.001
	(0.007)	(0.013)	(0.005)	(0.022)	(0.007)	(0.008)	(0.007)
L.Log (Bank Assets)	0.064	-0.063	0.241	-0.050	0.331*	0.137*	-0.017
	(0.077)	(0.066)	(0.188)	(0.121)	(0.183)	(0.082)	(0.124)
Firm Controls				Yes			
Fixed Effects			Firm, MSA*Year, Industry*Year				

the fact that the severely adverse economic projections reflect how much economic outcomes are expected to change conditional on a major recession, rather than the expected probabilities of a major recession. In addition, our results above suggest that pessimistic banks already lend less in the first place, yet they still expect higher loss given default. Relatedly, because LGD and PD assessment reflect banks' views *conditional on their lending decisions*, it is difficult to use them as a main expectation measure for explaining lending decisions. In comparison, the data on banks' economic projections captures their ex ante expectations about economic fundamentals in an area, which are more suitable for studying how beliefs affect lending decisions.

5 Real Effects

After analyzing the impact of banks' expectations on loan supply, we further investigate the real effects at the firm level and the aggregate effects at the MSA level.

Table 9: Firm-Level Total Leverage and Capital Expenditures

This table presents firm-level regressions. The outcome is total borrowing (normalized by total book assets) in Panel A and capital expenditures (normalized by lagged book assets) in Panel B. The control variables are the same as those in Table 5. Standard errors clustered by MSA are presented in parentheses.

Panel A. Total Borrowing

	All	Size		Bank Dependent		Risk	
		Small	Large	Yes	No	NonIG	IG
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SA HPI Drop	-0.038***	-0.048***	-0.006	-0.037***	-0.027	-0.037***	-0.011
	(0.010)	(0.013)	(0.014)	(0.011)	(0.030)	(0.010)	(0.021)
Bank Controls	Yes						
Firm Controls	Yes						
Fixed Effects	Firm, MSA*Year, Industry*Year						
Observations	199,260	137,039	59,298	142,994	45,101	41,283	70,459
R^2	0.844	0.837	0.877	0.828	0.904	0.893	0.886

Panel B. Capital Expenditures

	All	Size		Bank Dependent		Risk	
		Small	Large	Yes	No	NonIG	IG
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SA HPI Drop	-0.007**	-0.012***	0.004	-0.009**	-0.015*	-0.015**	0.015**
	(0.003)	(0.003)	(0.008)	(0.004)	(0.008)	(0.006)	(0.007)
Bank Controls	Yes						
Firm Controls	Yes						
Fixed Effects	Firm, MSA*Year, Industry*Year						
Observations	203,534	140,879	59,690	146,844	45,408	42,776	71,964
R^2	0.491	0.353	0.552	0.479	0.543	0.487	0.543

5.1 Firm-Level Real Effects

At the firm level, our data covers not only the loans that firms have, but also firm outcomes including total credit and capital spending. In Table 9, we document how lenders' expectations affect firm-level real outcomes. Panel A shows that total credit declines when a firm's lenders are ex ante more pessimistic, especially for firms with limited sources of financing, such as small firms, risky firms, and bank-dependent firms. Panel B shows that there is also a negative impact on capital expenditures, more pronounced for firms with limited sources of financing.

5.2 Regional Aggregate Effects

We then evaluate MSA-level aggregate effects of lenders' expectations. We start with assessing how much of the variations in banks' lending in an MSA each year can be accounted for by differences in their expectations. For each MSA-year, the standard deviation of idiosyncratic variations in banks' severely adverse HPI projections (i.e., removing MSA-year fixed effects from the raw projections) is 7.24 percentage points; the standard deviation of idiosyncratic variations in banks' loan growth (i.e., removing MSA-year fixed effects from each bank's loan growth in an MSA-year) is 12 percentage points. In Section 4 we find that loan growth changes by around 0.3 percentage points for a one percentage point change in lenders' severely adverse HPI projections. Accordingly, differences in expectations measured by our data translate into 18% ($7.24 \times 0.3/12$) of the differences in banks' loan growth.

In addition, we examine implications of banks' expectations for MSA-level real outcomes. We continue to exploit the idiosyncratic component of lenders' expectations for empirical identification, and utilize the methodology of granular instrumental variables by Gabaix and Koijen (2020). In particular, for each MSA (i) and year (t), we denote projections of banks j as η_{ijt}. We form the instrument (G_{it}) for lenders' expectations at the MSA-year level ($\overline{\eta_{it}}$) by taking the difference between the market-share weighted average and the equal weighted average of bank projections:

$$G_{it} = \sum_{j=1}^{N} m_{ijt-1}\eta_{ijt} - \frac{1}{N}\sum_{j=1}^{N} \eta_{ijt},$$

where m_{ijt-1} is bank j's market share in MSA i by the end of year $t-1$. The instrument G_{it} thus captures the impact of the idiosyncratic components of lenders' expectations, and it is particularly influenced by the idiosyncratic component of the expectations of the largest lenders in an MSA.

Table IA4 presents the results for the MSA-level annual loan growth in column (1) and GDP growth in column (2). We see that when lenders are more pessimistic, MSA-level overall loan growth is lower, which verifies the impact on bank lending. Moreover, subsequent MSA-level GDP growth is also lower. In particular, if the MSA-level severely adverse HPI projections fall by one inter-quartile range, the MSA-level GDP growth would be 0.9 percentage point lower in the following year. That is, we find economically and statistically significant results of bank expectations on the economy at the loan level, the firm level, and the MSA level.

6 Credit Supply during COVID-19

Finally, we analyze how lenders' expectations affect credit supply in 2020 following the COVID-19 outbreak. Our main sample of 2014 to 2019 covers a period of relative economic prosperity, and the COVID-19 outbreak generated a sudden negative shock. A classic mechanism in credit cycles is that optimistic lenders who were aggressive during the boom years tend to be more vulnerable to negative shocks (Geanakoplos, 2010; Simsek, 2013). Accordingly, their ability to lend may be especially affected in a recession, which can amplify the severity of the recession. We utilize our data to investigate this mechanism in the COVID-19 crisis.

6.1 Pre-COVID Optimism and Loan Losses

We begin by examining whether banks' pre-COVID optimism affected their loan performance during the COVID-19 crisis. In Table 10, we study the relationship between banks' pre-COVID optimism and loan outcomes in 2020. For each loan, we use an indicator variable that equals one if the loan is past due in 2020 as the dependent variable in Panel A,[11] and another indicator variable that equals one if the loan receives a downgrade in 2020 as the dependent variable in Panel B. The independent variable of interest is the lender's pre-COVID optimism, measured as the average severely adverse HPI or unemployment increase projection in 2014 to 2019. We also control for bank characteristics by the end of 2019 and firm characteristics by the end of 2019 in columns (2) and (4); these control variables are the same as those we used in earlier regressions.

Table 10 shows that lenders who were more optimistic pre-COVID indeed have worse loan performance in 2020: their loans are more likely to be past due and to receive downgrades. This result is consistent with the view that optimistic lenders during the boom tend to be hit harder by negative shocks. For a one interquartile range change in the average pre-COVID projections, the probability of past due increases by 0.1 to 0.2 percentage points and the probability of downgrade increases by one to three percentage points. The overall fraction of past due loans increased from around 0.6% pre-COVID

[11] A loan in considered past due if principal or interest payments are past due 30 days or more.

Table 10: Pre-COVID Bank Optimism and Loan Performance in 2020

This table presents loan level regressions in the four quarters of 2020. In Panel A, the outcome variable is equal to one if the loan is past due and zero otherwise. In Panel B, the outcome variable is equal to one if the loan is downgraded and zero otherwise. The independent variables include the lender's average severely adverse HPI and unemployment increase projections in the pre-COVID years (2014 to 2019). They also include bank characteristics by the end of 2019 and firm characteristics by the end of 2019 (ROA, sales growth, fixed assets over total assets, size measured as log total assets) in columns (2), (4), (6), and (8); these controls are the same as those in Table 5. MSA by quarter and industry by quarter fixed effects are included. Standard errors clustered by MSA are presented in parentheses.

Panel A. Past Due in 2020

	Past Due			
	(1)	(2)	(3)	(4)
SA HPI Drop 14-19	-0.0001***	-0.00012*		
	(0.000)	(0.000)		
SA Unempl Incr 15-19			-0.0004	-0.0007**
			(0.000)	(0.000)
Bank Tier 1 (2019)	-0.00003	0.00092***	-0.0000	0.0003
	(0.000)	(0.000)	(0.000)	(0.000)
Bank ROA (2019)	-0.00163**	-0.00498***	0.0013	-0.0047***
	(0.001)	(0.001)	(0.001)	(0.001)
Bank MSA Exposure (2019)	-0.00002	-0.00007	0.0005***	0.0005**
	(0.000)	(0.000)	(0.000)	(0.000)
Log (Bank Assets) (2019)	0.00114***	0.00156***	0.0011**	-0.0006
	(0.000)	(0.000)	(0.000)	(0.001)
Firm Controls	No	Yes	No	Yes
Fixed Effect	MSA×Quarter, Industry ×Quarter			
Observations	398,687	247,703	264,648	173,559
R^2	0.007	0.008	0.010	0.002

Panel B. Downgrade in 2020

	Downgrade			
	(1)	(2)	(3)	(4)
SA HPI Drop 14-19	-0.0005***	-0.0034***		
	(0.000)	(0.000)		
SA Unempl Incr 15-19			-0.0094***	-0.0112***
			(0.001)	(0.001)
Bank Tier 1 (2019)	0.0100***	-0.0075***	0.0033***	0.0035***
	(0.000)	(0.001)	(0.000)	(0.001)
Bank ROA (2019)	-0.0062***	-0.0467***	0.0088***	0.0030
	(0.002)	(0.003)	(0.003)	(0.004)
Bank MSA Exposure (2019)	-0.0002	0.0009**	0.0031***	0.0005
	(0.000)	(0.000)	(0.000)	(0.001)
Log (Bank Assets) (2019)	-0.0075***	0.0101***	-0.0109***	-0.0068***
	(0.001)	(0.001)	(0.001)	(0.002)
Firm Controls	No	Yes	No	Yes
Fixed Effect	MSA×Quarter, Industry ×Quarter			
Observations	408,694	265,038	278,496	193,268
R^2	0.037	0.051	0.039	0.041

to around 0.75% in 2020; the overall fraction of downgrades increased from 7% pre-COVID to 12% in 2020. Accordingly, the effects associated with pre-COVID optimism are economically meaningful but not drastic; indeed the overall increase in past due and downgrades are mild, in part due to the large-scale fiscal and monetary responses.

6.2 Bank Lending since COVID-19 Outbreak

We then ask whether pre-COVID optimists had limited capacity to lend in 2020 due to the higher past due and downgrades they experienced. In Table 11, we find that the pre-COVID optimists continued to lend more in 2020 (and the pre-COVID pessimists continued to lend less): firms with more optimistic lenders had higher loan growth and vice versa. As before, the loan growth variable includes both outstanding loans and loan commitments, so this variable is not affected by firms' discretionary draw-downs of credit lines during the pandemic (Greenwald et al., 2021; Chodorow-Reich et al., 2021). Overall, the data suggests that the balance sheet effects due to pre-COVID optimism do not dominate in the COVID recession. The direct effects of lenders' expectations continue to play a primary role.

Table 11: Loan Growth in 2020

This table shows firm-level regressions for loan growth in 2020. Loan growth is measured relative to the same period one year ago. The independent variables are the same as those in Table 10. They are value-weighted averages of a firm's lenders by the end of 2019 if the firm had multiple banks. MSA by quarter and industry by quarter fixed effects are included. Standard errors clustered by MSA are presented in parentheses.

	Firm-Level Loan Growth			
	(1)	(2)	(3)	(4)
SA HPI Drop 14-19	-0.232***	-0.183***		
	(0.018)	(0.018)		
SA Unempl Incr 14-19			-2.188***	-1.940***
			(0.163)	(0.182)
Bank Tier 1 (2019)	0.515***	0.556**	-0.053	-0.071
	(0.065)	(0.265)	(0.130)	(0.158)
Bank ROA (2019)	0.030	-1.647**	5.071***	2.530**
	(0.512)	(0.720)	(0.473)	(0.989)
Bank MSA Exposure (2019)	0.093	0.250	0.328**	0.359
	(0.185)	(0.232)	(0.158)	(0.262)
Log (Bank Assets) (2019)	-0.447*	-0.187	3.604***	2.990***
	(0.266)	(0.379)	(0.336)	(0.312)
Firm Controls	No	Yes	No	Yes
Fixed Effect	MSA×Quarter, Industry ×Quarter			
Observations	185,862	125,957	136,847	97,032
R^2	0.005	0.012	0.007	0.012

7 Conclusion

We study the properties and impact of lenders' expectations using new data on the largest banks' economic projections about all MSAs in the US, reported annually for both the baseline scenario and the severely adverse scenario. We show that expectations about economic conditions under normal (baseline) and downside (severely adverse) scenarios respond differently to past shocks. In particular, expectations about the downside are more pessimistic if MSAs had worse outcomes in the previous crisis, but this is not the case for expectations about the baseline. This result points to the importance of analyzing expectations about not only central tendencies but also other parts of the distribution. We also find substantial dispersion in the projections at a given point in time, for the same MSA across banks and for the same bank across MSAs. This finding resonates with models of heterogeneous information and belief disagreement, and aligns with belief heterogeneity documented in other settings such as investors' expectations of stock returns and professional forecasters' expectations of macroeconomic outcomes.

Moreover, we document the effects of lenders' expectations on credit supply and economic outcomes. The granularity of the data and the substantial idiosyncratic variations in lenders' expectations help us isolate the credit supply effects. The rich data also shows that expectations about the downside tail scenarios are especially important for lending. We present a number of findings. First, we show that firms have lower loan growth when lenders are more pessimistic about the downside. To enhance identification, we also document that for the same firm in a given year, there is less lending from more pessimistic banks after controlling for firm-year fixed effects. Second, lending to small firms is mainly affected by expectations about the firm's own MSA, while lending to large firms is more affected by expectations about the national economic condition. Third, lenders' pessimism is also associated with higher interest rates. Small and bank-dependent firms have limited ability to substitute and pay higher loan rates in equilibrium. Fourth, despite less lending, more pessimistic banks still expect a higher loss given default on their loans. Fifth, lenders' pessimism has negative real effects on firm-level total borrowing and capital expenditures, especially among firms with limited sources of financing. Finally, there are corresponding negative real effects on MSA-level output growth. Overall, we find that differences in expectations can account for a sizable fraction of the variations in banks' lending growth to firms in an MSA in a given year (around 20% in our data); firms' outcomes are also significantly affected.

After studying the pre-COVID years with favorable macroeconomic conditions, we then investigate lending during the pandemic. In the data, banks that were more pessimistic pre-COVID have had fewer past due loans and loan downgrades, consistent with less risk taking in previous years. However, this balance sheet effect is not sufficient to offset the impact of persistent pessimism, and these banks continue to lend less. This evidence further suggests that expectations can play a key role for credit supply, and balance sheet conditions are not the only story.

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Internet Appendix

IA1 Additional Results

Table IA1: Mean Squared Error of Baseline HPI Projections

This table shows the mean and median (across MSAs and years) of the squared forecast errors of the baseline HPI projections $(HPI_{it} - F_{t-1}HPI_{it})^2$ (where HPI_{it} denotes the actual HPI growth for MSA i in year t measured as the percentage change between the current HPI and the minimum HPI over the next nine quarters, and $F_{t-1}HPI_{it}$ denotes the baseline HPI projection which captures the percentage change between the current HPI and the minimum HPI over the next nine quarters). In the first row, the projection is the individual baseline HPI projection for MSA i in year t by bank j. In the second row, the projection is the average HPI projection for MSA i in year t by all banks with baseline HPI projections. In the third row, the projection is based on rolling linear forecasting regressions using HPI growth, GDP growth, and unemployment rate change in each MSA in the twelve months before the year t projection.

	Mean (1)	Median (2)
Individual Bank Projection	4.97	1.26
Average Bank Projection	3.29	1.30
Poor Man	9.26	5.63

Table IA2: Real Estate Loans and Non-Real Estate Loans

This table presents annual firm-level regressions using the specification in Equation (1). The outcome variable is the firm-level loan growth of loans for real estate purpose in column (1), loans for non-real estate purpose in column (2), loans secured by real estate in column (3), and loans not secured by real estate in column (4). The control variables are the same as those in Table 5. Standard errors clustered by MSA are presented in parentheses.

	Real Estate Purpose		Secured by Real Estate	
	Yes	No	Yes	No
SA HPI Drop	-0.972**	-0.520**	-0.505***	-0.239***
	(0.467)	(0.228)	(0.195)	(0.057)
Controls	Firm Variables, Bank Variables			
Fixed Effects	Firm, MSA*Year, Industry*Year			
Observations	63,864	285,977	66,403	275,589
R^2	0.746	0.329	0.411	0.227

Table IA3: Bank Expectations and Estimates of LGD and PD

Firm-level regressions of average lender assessment of loss given default (columns (1) and (2)) and probability of default (columns (3) and (4)). The independent variables are the same as those in Table 5.

	LGD		PD	
	(1)	(2)	(3)	(4)
SA HPI Drop	0.106***		0.014	
	(0.018)		(0.010)	
SA Unempl Incr		0.253**		-0.074
		(0.107)		(0.045)
L.Bank Tier 1	-0.602***	-1.033***	0.004	-0.122***
	(0.194)	(0.062)	(0.023)	(0.042)
L.Bank ROA	0.215***	-0.237***	0.001	-0.054***
	(0.018)	(0.066)	(0.005)	(0.017)
L.Bank MSA Exposure	0.018	-0.284***	0.006	-0.042
	(0.046)	(0.107)	(0.014)	(0.059)
L.Log (Bank Assets)	1.260	6.921***	0.519*	1.535***
	(1.174)	(0.427)	(0.267)	(0.285)
Firm Controls	Yes			
Fixed Effects	Firm, MSA*Year, Industry*Year			
R^2	0.689	0.855	0.689	0.721
Observations	272,943	178,195	277,428	182,719

Table IA4: MSA-Level Aggregate Effects

This table shows annual MSA-level regressions of real outcomes, using the granular instrumental variable approach of Gabaix and Koijen (2020). The first column shows the first stage. The second and third columns show instrumented regressions where the outcome is subsequent MSA-level loan growth and GDP growth respectively.

	First Stage	IV	
	$\overline{\eta_{it}}$	MSA Loan Growth	MSA GDP Growth
G_{it}	1.576***		
	(0.067)		
$\overline{\eta_{it}}$ (Instrumented)		-0.404**	-0.091***
		(0.188)	(0.034)
L.MSA HPI Growth	0.395***	0.513***	0.180***
	(0.029)	(0.138)	(0.028)
L.MSA GDP Growth	0.024	0.096	0.118***
	(0.027)	(0.107)	(0.036)
Fixed Effects		Year	
Observations	2,280	2,280	2,280

IA2 Simple Model

We present a simple toy model to illustrate our empirical specifications in Section 4 and outline the empirical predictions for how banks' expectations affect lending outcomes.

IA2.1 Setup

We consider two states: 1) the macroeconomic distress state, which has probability p and maps into the severely adverse scenario; 2) the normal state, which has probability $1-p$ and maps into the baseline scenario. For simplicity, we assume there is no default in the normal state and default happens in the macroeconomic distress state, and the bank can recover $(1-\lambda)$ fraction of loan. The severely adverse projection captures the bank's expectation about λ: if a bank is optimistic, then it thinks λ is small. We denote this expectation to be λ^e. We assume banks are risk neutral.

If the loan size is L, then the bank' break-even condition is:

$$(1-p)(1+r)L + p(1-\lambda^e)L - \alpha L^2 = L, \tag{IA1}$$

where r is the loan rate. The term αL^2 allows for potential additional funding costs for loans. If $\alpha = 0$, then the loan supply curve is flat.

Then the interest rate the bank would charge is:

$$1 + r = [1 - p(1-\lambda^e) + \alpha L]/(1-p). \tag{IA2}$$

IA2.2 One Bank Case

We consider a risk neutral firm that uses L to invest, with a production function $f()$ where $f' > 0$ and $f'' < 0$. When there is a single bank, then the firm's problem is:

$$\max_{L} \ (1-p)[f(L) - (1+r)L]. \tag{IA3}$$

This means the equilibrium loan amount L^* is given by:

$$f'(L^*) = \frac{1 - p(1-\lambda^e) + \alpha L^*}{1-p}. \tag{IA4}$$

The comparative static with respect to the bank expectation λ^e is:

$$\left[f''(L^*) - \frac{\alpha}{1-p}\right] \frac{L^*}{\partial \lambda^e} = \frac{p}{1-p}, \tag{IA5}$$

therefore $\frac{L^*}{\partial \lambda^e} < 0$. This shows that equilibrium loan size will be smaller when the bank is more pessimistic.

For the equilibrium interest rate, we have:

$$\frac{\partial r^*}{\partial \lambda^e} = \frac{p}{1-p} + \frac{\alpha}{1-p}\frac{\partial L^*}{\lambda}. \tag{IA6}$$

The two terms on the right hand side reflect two forces. The first term reflects the direct force: a more pessimistic bank expects more losses in the severely adverse state and wants to charge a higher interest rate. The second term reflects the indirect force: the loan rate also depends on the loan size when the bank faces funding costs (i.e., $\alpha > 0$). This term pushes in the other direction: when the bank is more pessimistic, the equilibrium loan size L^* will decrease, which alleviates the upward pressure on loan rates. As a result, if the bank's funding cost curve is not too steep (i.e., α small), then the equilibrium loan rate will be higher when the bank is more pessimistic.

Finally, it is also possible that banks impose quantity-based borrowing constraints (in addition to charging higher loan rates when the downside is larger as in Equation (IA2)). For instance, the borrowing constraint could state that a firm cannot borrow more than $\bar{L}(\lambda^e)$, where $\bar{L}$ is higher when the bank is more optimistic (λ^e smaller). Such borrowing constraints can be another driver of reductions in lending when the bank is more pessimistic.

IA2.3 Multiple Banks or Funding Sources

We now consider the case where the firm can obtain funding from multiple sources.

Syndicated loan. In the case of a syndicated loan, the interest rate is uniform in a given tranche (i.e., for all participating banks). In this case, Equation (IA1) shows that a given bank i will be willing to contribute $L_i = [(1-p)(1+r) + p(1-\lambda_i^e) - 1]/\alpha_i$. This shows that all else equal, a bank will be willing to fund a larger amount if it is more optimistic.

Substituting among different banks and funding sources. In the simplest case, we can think of a firm following a pecking order and using the cheapest source of financing first, which will make the firm favor more optimistic banks. In the extreme case of small or opaque firms that do not have multiple relationship banks, the firm may not be able to substitute at all (so we are effectively back to the one bank case). On the other hand, some firms may be able to substitute more freely as soon as their existing lenders become too pessimistic, and the substitution may occur among banks or between banks and capital markets (e.g., bond markets or equity markets).

IA2.4 Mapping to Empirical Analyses in Section 4

In our regression analyses in Section 4.1, we think of L^* as net lending per year. We normalize it by lagged total loan amount outstanding. Accordingly, in Section 4.1, loan growth (net lending relative to lagged loan amount outstanding) is the left-hand-side variable (as shown in Equations (1) and (2)). At the firm level, we expect to see a reduction in the equilibrium quantity of lending when lenders are more pessimistic. This can happen in the single bank case as shown by Equation (IA5). It can also happen if the firm can substitute to other sources of financing (e.g., nonbank lenders or bond markets). At the loan level (for firms with multiple banks), we expect to see that more pessimistic banks lend less to the same firm at a given point in time. This can happen in the syndicated loan case. It can also happen when firms are able to substitute among different banks.

In Section 4.2, we also analyze equilibrium loan rates as the left-hand-side variable. For firms that cannot substitute, we would expect the observed loan rate to be higher when lenders are more pessimistic, as long as the direct effect in Equation (IA6) dominates. For firms that can substitute between different sources of financing, we may not expect the observed loan rate to change significantly as the firm can walk away from more pessimistic lenders.