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EVIDENCE FROM ITALIAN LOAN-LEVEL DATA

by Paolo Farroni* and Jacopo Tozzo*

Abstract

We use a novel loan-level dataset containing borrower-specific probability of default to estimate a structural learning model where bankers endowed with diagnostic expectations receive noisy signal about firms' fundamentals and assess their creditworthiness. We find that: (i) intermediaries tend to overreact to both micro news and macro signals; (ii) the degree of overreaction is heterogeneous among banks; (iii) overreacting bankers lower (raise) interest rates more than rational ones, increase (decrease) loan size; and (iii) the probability of issuing a new loan rises (falls) when bankers receive positive (negative) signals.

JEL Classification: D22, D84, G21, L13.
Keywords: banks, expectations, credit risk.
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1 Introduction[1]

Lending decisions reflect what lenders think about borrowers' creditworthiness (Minsky, 1986). While there is evidence (Bordalo et al., 2018; Richter and Zimmermann, 2019; Ma et al., 2021) that bankers tend to over-extrapolate when looking at *aggregate* lending outcomes, few studies have quantitatively measured both the extent of this distortion and its effect on the price and quantity of credit for *loan-level* portfolios.

Using a new credit registry from Italy with great detail on lenders' risk assessments for around 760k non-financial firms, in this paper we put forward a new granular measurement of lenders' beliefs which is complementary to more standard survey-based indicators. We then use this measure to test whether banks deviate from full rationality and study the effects of these distortions on credit allocation. The novelty of our approach rests on both matching bankers' expectations with actual credit outcomes at the firm level, and exploiting the vast cross-sectional heterogeneity to quantify the effects of distorted beliefs.

We build a learning model where banks receive noisy signals on borrowing firms' fundamentals and must forecast the defaults of the latter. We test for an extrapolative belief formation process, according to which bankers revise the probability of default (PD) downward (upward) more compared to rational expectations when they receive positive (negative) signals about the borrower. Similarly to previous work on social stereotypes and financial markets (Bordalo et al., 2016, 2018, 2019), our mechanism relies on the "kernel of truth" property: bankers over-estimate the probability of borrowers' future cashflows realizations whose likelihood has increased the most in light of recent news. The agent acts in the correct direction of news, but he does it with exaggeration.

Although other belief formation schemes may be consistent with our empirical findings, we exploit the framework of Bordalo et al. (2018) since it (i) has proved successful in describing expectations of firms, households and other agents (Gennaioli et al., 2016; Bordalo et al., 2019, 2020, 2022; Beutel and Weber, 2023), and (ii) allows for a relatively simple and parsimonious modeling which is especially relevant for our structural estimation.

Using two alternative sources of signals, a micro one (based on the quarterly change in the borrower-level PD) and a macro one (based on the quarterly percentage change of the sector-specific industrial production index) we find that bankers tend to over-extrapolate: an

[1]We want to thank for the precious comments and suggestions Nicola Gennaioli, Max Croce, Luigi Iovino, Elena Carletti, Marco di Maggio, Sidney Ludvigson, Ansgar Walther, Nicola Pavanini, Nicola Borri, Sam Rosen, Stefano Neri, Roberta Zizza, Michele Caivano, Tiziano Ropele, Marianna Riggi and all of the other scholars and colleagues who have contributed to the discussion during the build-up of the manuscript. The views expressed in the article are those of the authors and do not involve the responsibility of the Bank of Italy.

incoming standard deviation of micro news makes a banker overreact on average between 240 to 500 basis points (bps) more in the determination of the PD relative to a rational one.

Our results suggest that distortions tend to be more pronounced towards firms that are ex-ante riskier, smaller, younger and located in the Southern Italy and in the Islands. We also show that the degree of overreaction is heterogeneous among banks. While on average lenders in our sample tend to overreact to news, and some banks (which we denote as "distorted" or "diagnostic") particularly do so, there are also some that do not (and that we call "rational").

We exploit the heterogeneity in banks' belief distortions when looking at the effects of overreaction on credit allocation. The model predicts that there should exist a positive (negative) wedge in the quantity (price) of credit between a diagnostic and rational lender when bankers receive positive signals on a borrower. Our empirical findings for micro news confirm this prediction and show that distorted lenders tend to decrease interest rate by around 5 bps, increase the loan size by 3% to 9% and raise the probability of issuing a new loan by about 1% compared to rational lenders. Results obtained with macro signals as the main information driver qualitatively confirm the estimates based on micro news.

Finally, we rationalize our reduced-form findings with a structural model of imperfect competition of the banking sector. We augment the model of Crawford et al. (2018) by incorporating the behavioural component of our study. The demand side is standard: firms demand unit loans to finance a risky project and must choose one bank among the active ones in their local area (or none, if the "utility" of inaction is high enough). On the supply side, banks compete à la Bertrand-Nash on interest rates and maximize their expected profit based on (i) their degree of belief distortion (if any), (ii) the bank-borrower-specific PD, and (iii) the signal they receive on borrower's fundamentals.

We estimate the model using a subsample of our granular data and conduct some counterfactual exercises. In a scenario where we double the average level of the distortion parameter, our results show that on average positive signals would lead bankers to revise interest rates downward by 42 basis points compared to the baseline case of no change in observed belief distortions. Symmetrically, the probability of issuing a new loan would increase by 1.7%. Although our sample starts in 2018 Q3 and ends in 2020 Q2, this and other counterfactual exercises presented in section 5 help us generalize our empirical findings to the boom/bust phase of the credit cycle when distortions in beliefs may be particularly pronounced or the distribution of borrower signals highly skewed.

Literature Review Our paper relates to three main strands of literature. First, it is directly linked to papers that explore bankers' beliefs. The closest papers to our contribution are Ma et al. (2021) and Falato and Xiao (2023), which examine the impact of banks' expectations on lending outcomes. Ma et al. (2021) use data on US banks' projections on the house price index and unemployment at the metropolitan statistical area (MSA) level. They show that banks' pessimism about downside scenarios significantly reduces credit supply, leading to lower loan volumes, higher rates, and decreased total credit and investment for firms, as well as reduced output. Falato and Xiao (2023) also explore the effects of banks' over-extrapolation using a longer time series of US banks and embed their empirical analysis in a quantitative banking model to assess aggregate implications of their findings.

We differ from these papers by providing a more granular assessment of lenders' beliefs on borrowers' creditworthiness, as we measure expectations through the probability of default which is a direct forecast by banks for each firm in their credit portfolio. Since our sample is representative of the entire borrower population, we can isolate both the demand and the supply of credit and we jointly study their dynamics in our structural model. Moreover, compared to more standard survey information on managers' expectations about macroeconomic and lending conditions, our loan-level data represents actual credit outcomes for a very rich cross-section of borrowers and banks. Becker et al. (2020) also exploit the information content of lenders' risk assessments. They investigate the predictive accuracy of internal credit ratings for firms borrowing from a large Swedish bank over the period 2004-2012, despite not focusing on bankers' expectations and credit outcomes.

Our approach differs from the one of Falato and Xiao (2023) precisely because we exploit borrowers' heterogeneity to quantify the effects of distortions in lenders' beliefs on quantities and prices. In addition, while the existing literature has mainly studied the US lending market, we focus on the Italian economy, which has one of the largest banking sector in Europe.

Other papers that examine lenders' expectations are Fahlenbrach et al. (2018) and Richter and Zimmermann (2019). Fahlenbrach et al. (2018) use measures of bank profitability, business activity, and loan growth to show that banks with ex-ante high credit growth tend to ex-post underperform compared to banks with ex-ante lower credit growth. They then use analysts' forecasts for banks earnings-per-share (EPS) to show that bankers, analysts, and investors are overoptimistic about the risk of loans extended during bank-level periods of high loan growth. Richter and Zimmermann (2019) show a positive connection between future lending volumes and current expected earnings measured thorough a survey of CFOs consistently with extrapolative expectations.

Our work goes a step further by linking beliefs about creditworthiness to interest rates and loan quantities at the borrower level, thereby eliminating the risk of contamination from other factors when evaluating earnings alone. Moreover, we can quantify (extrapolative) expectation distortions on both the optimism and pessimism side, whereas Ma et al. (2021), Fahlenbrach et al. (2018), and Richter and Zimmermann (2019) focus more on one of the two. Furthermore, to the best of our knowledge, we are the first ones to explicitly embed a diagnostic learning model in a structural banking model in the spirit of Bordalo et al. (2018) and Bordalo et al. (2019).

Second, we refer to the literature that studies departures from full information rational expectations (FIRE) and diagnostic expectations. To assess lenders' beliefs, we empirically test deviations from FIRE similarly to Coibion and Gorodnichenko (2015) and Greenwood and Shleifer (2014), and follow the theoretical models presented in the works of this literature as in Gennaioli and Shleifer (2010), Gennaioli et al. (2012), Bordalo et al. (2019), and Bordalo et al. (2020) among others. Our main contribution is to extend the empirical and theoretical frameworks developed in this literature to a different type of agent, namely banks, whose expectational distortions' can have a sizable influence on credit dynamics.

Third, our paper relates to the literature on credit cycle and sentiment. The importance of lenders beliefs' in credit supply has been introduced by Minsky (1977) and Kindleberger (1978), who laid the foundation of financial crisis and irrational manias. After the financial turmoil of 2008, this literature has developed extensively with the works of Baron and Xiong (2017), López-Salido et al. (2017), Greenwood et al. (2019), Krishnamurthy and Li (2020). In this paper we provide an empirical assessment of the main theories postulated in the sentiment-driven credit supply literature. Finally, De Marco et al. (2023) provide evidence complementary to our findings that banks lending to overconfident borrowers are more likely to experience ex-post defaults.

The paper proceeds as follows: section 2 describes data and stylized facts, section 3 presents the econometric model. Section 4 exhibits our main findings. Section 5 illustrates the results from the structural estimation exercise and section 6 presents additional robustness exercises.

2 Data

The main dataset used in this project is the Italian section of AnaCredit (*Analytical Credit Datasets*), a European credit registry centrally managed by the ECB which collects detailed and fully harmonized monthly information on individual loans granted by euro area banks to legal entities whose total debt exposure exceeds 25,000 euros. The project to establish a euro-area credit registry was initiated in 2011 and data collection started in September 2018. For all credit contracts banks are asked to report a wealth of information concerning, *inter alia*, the outstanding amount of loans and the interest rates charged, the borrower's probability of default and its default status, the sector of economic activity, and the headquarters' location. In this project we focus only on credit to non-financial corporations since households are not legal entities and are therefore outside the scope of AnaCredit.

Notwithstanding the availability of monthly data, our sample is at a quarterly frequency to allow for enough time variation in our variables of interest and runs from September 2018 until the start of Covid-19 in Italy (June 2020). We decided to focus on this period due to the introduction between March and June 2020 of (i) state guarantees on new loans and (ii) payment moratoria on existing obligations[2]. Together with the disruptions due to the pandemic, both relief programs may have perturbed the expectation formation process of banks (and the ex-post default status of borrowers) by hindering the usual flow of hard/soft information[3] in the case of moratorium or by softening the initial credit screening in the presence of a state guarantee. Nonetheless, in the appendix we expand our analysis until 2023 Q2 and our main results are broadly unchanged.

Among the reporting entities in AnaCredit, we select only those banks that use the so-called Internal Ratings Based approach (IRB - Basel Committee (2001)) for capital requirements and estimate the (regulatory) probability of default which is our main variable of interest. Given the very large amount of observations, we further randomly subset 10% of borrowers out of the IRB data ending up with an average of 75,000 different firms per quarter, representative of all economic sectors and Italian provinces, and a total of more than 9 million distinct (loan-level) observations. Accounting for mergers and consolidating data at the banking group level, our final sample consists of 9 banking groups (hereafter, simply banks) that represent on average around 75% of total credit to Italian non-financial firms.

Table 1 reports several summary statistics for our entire sample until 2023 Q2. The average interest rate in our panel is 3.01%. Firm total assets, sales and age – which banks directly report in Anacredit - vary substantially in our sample, ranging from young, micro enterprises to older and larger establishments. The probability of default also features a large cross-sectional heterogeneity with a median of about 1.1% and the 1st and 9th decile at 0.18% and 9.4%. From

[2]The first moratorium was introduced in March 2020 with the decree "D.L. Cura Italia". The initial validity of the policy was 6 months, but other extensions were granted until the end of 2021.

[3]E.g., for a position "frozen" under a moratorium arrears or the system-wide performing status as recorded in the national credit registry are no longer updated.

Table 1: Summary statistics

	N	SD	p10	p25	Mean	Median	p75	p90
				Panel A: Borrower-level				
PD (%)	1,781,934	6.24	0.18	0.41	4.35	1.08	3.13	9.4
FE	1,052,831	0.16	-0.055	-0.023	-0.004	-0.009	-0.003	-0.001
Micro News	1,535,413	0.081	-0.01	0	-0.005	0	0	0.007
Macro Signal	979,430	0.386	-0.161	-0.08	0.032	0.017	0.094	0.176
log(Assets)	1,740,645	2.33	12.04	13	14.2	14.16	15.48	16.84
log(Sales)	1,919,865	2.18	11.67	12.58	13.9	13.78	15.17	16.6
Firm Age (y)	2,186,757	14.56	4.95	9.74	21.3	18.79	30.49	40.17
Credit Age (y)	2,186,656	9.43	0.92	2.12	6.64	4.34	8.46	14.38
N bnk	2,186,757	1.4	1	1	1.9	1	2	4
				Panel B: Loan-level				
log(Loan)	9,566,288	3.11	6.18	8.59	9.51	10.13	11.3	12.53
r (%)	9,493,287	2.39	0.32	1.18	3.01	2.53	4.42	6.07
LTV	6,960,478	0.42	0.13	0.34	0.77	0.63	1	1.19
Maturity (y)	9,566,288	9.08	0.29	0.71	5.62	4.38	6.26	15.01
log(Impairment)	9,091,110	2.72	0.69	1.39	3.73	3.43	5.41	7.46

Notes: This table shows summary statistics for selected borrower- (panel A) and loan-level variables (panel B) for our full sample. PD is the probability that a borrower will default in 1 year, FE is the forecast error, Micro News is our main measure of news with positive values implying a (perceived) decrease in borrowers' credit risk. Macro Signal is the one-quarter percentage difference in the industrial production index for manufacturing firms, and in the value added for services sector firms. We refer to paragraph 2 and following ones for a detailed discussion of these variables. Log(Assets), log(Sales) and "Firm Age" (in years) are firm characteristics reported directly by banks in AnaCredit. "N bnk" denotes the number of IRB banks to which a borrower is affiliated, and "Credit Age" is the length of tenure for any given bank-firm pair measured as the difference in years between the reporting date and the oldest available debt contract. "log(Loan)" is the outstanding nominal amount in log units, r the annualized agreed interest rate, and LTV denotes the loan-to-value for those instruments with a positive amount of allocated credit protection. Finally, "Maturity" is the original maturity in years of the contract, and "log(Impairment)" is a measure of expected loss in log units according to accounting practices.

a time series perspective the PD is quite persistent but revisions do occur since already at lag 2 the autocorrelation decreases to 0.24 from 0.52. These revisions are particularly relevant for our scope since they are at the core of our definition of borrower-level news.

Finally, Table 1 shows that borrower-level forecast errors, which we define in the standard way as realized outcome (default) minus its forecast (PD), are almost always negative[4] and are *unconditionally* on average very close to zero. In our main analysis we will show instead that *conditionally* forecast errors display an excess sensitivity to news, meaning that banks tend to over- (under-)estimate the probability of default when they receive negative (positive) signals. In the next paragraphs we provide some more details on the measurement of the PD, news, and forecast errors.

[4]The negativity of forecast errors should not be surprising since the outcome is a binary variable that takes value 1 only in the (rare) case a default occurs.

Focusing on the cross-section of borrowers, we observe a monotonic increasing average probability of default and forecast errors (in absolute value) going from the north to the south of the country, as outlined in table A.1 in the appendix. Dispersion in these variables shows a similar dynamic. There is substantial heterogeneity also across economic sectors: construction has the highest mean PD as well as the highest dispersion, while manufacturing has the lowest PDs. Forecast errors are also higher for firms operating in construction and agriculture/mining. Additional summary statistics at the sector level are available in table A.2 in the appendix together with a description of the relevant sectors according to the NACE classification[5]. Overall, bankers seem to err more on firms that are ex-ante riskier, smaller, with lower credit age, located in the South and Islands and operating in agriculture and construction.

Probability of default The IRB probability of default is the bank's forecast that a borrower or an instrument will default in 1 year as prescribed by Regulation (EU) No 575/2013 (EU Commission, 2013). Since banks in our sample compute and report PDs for a very limited number of instruments, we restrict our analysis to borrower-level PDs which hereafter we simply denote as PD. For borrowers that are already in the default by law the PD is not estimated and fixed at 100%.

While all credit institutions estimate some form of PD or rating, only IRB banks report their estimates in AnaCredit and are allowed to use the PDs as input in the computation of capital requirements[6]. Banks receive permission from the supervisory authority[7] to use the IRB approach if they satisfy stringent requirements, inter alia, on the structure of their rating models, the governance and integrity of their internal process, the timeliness and availability of data, the frequent review and usage of the internal models (EU Commission, 2013; ECB, 2019; EBA, 2017). On the one hand, the granularity of the IRB approach should allow for a more precise estimation of credit risk compared to the fixed portfolio-based risk-weights of the standardized approach. On the other hand, banks may be strategic and under-report the PD to save capital and boost profitability (Behn et al., 2022). We take several steps to mitigate this concern in our sample.

First, we note that existing regulation and supervisory practice already checks whether

[5]NACE is the statistical classification of economic activities in the European Union.

[6]The general formula used to compute risk-weighted-assets for corporate, sovereign and bank exposures is: $\left(LGD \cdot N\left(\frac{G(PD)}{\sqrt{(1-R)}} + \sqrt{\frac{R}{1-R}} \cdot (0.999)\right) - PD \cdot LGD\right) \cdot \frac{1+(M-2.5)\cdot b}{(1-1.5\cdot b)}$, where LGD is the loss given default, $G(PD)$ denotes the inverse cumulative distribution function for a standard normal random variable, b is maturity adjustment and R is an adjustment parameter depending on the PD. For more details see Basel Committee on Banking Supervision (2023)

[7]The Single Supervisory Mechanism (SSM) for Significant Institutions, and National Competent Authorities (NCAs) for Less Significant Institutions.

"the rating systems are incorporated in the relevant processes of the institution within the broader processes of risk management, credit approval and decision-making processes, internal capital allocation, and corporate governance functions" (the so called "use test", EU Commission (2021)). Second, we observe that PDs in our sample are on average *higher* than realized defaults. Finally, in section 6.1 we show that our baseline results are robust when we employ an alternative measure of beliefs based on accounting (IFRS 9) credit ratings that are *not* used in the computation of capital requirements.

Although each bank has its own internal rating system, there are some common general elements that exemplify why the PD is a relevant measure of bankers' beliefs and should complement more standard survey data. First, the probability of default encompasses in a single measure all the internal risk assessments for a specific borrower or pool of borrowers that a bank conducts according to the sound principles outlined above. Second, the PD "cannot be a purely statistical process, but to some extent also has to involve human judgement, to make sure that the models are appropriate for current and foreseeable portfolios and conditions, and that the models are acceptable for business users" (EBA, 2017), although we are not able to disentangle this "soft" component. While other recent works (Becker et al., 2020; Behn et al., 2022) also investigate the role of internal credit ratings, to the best of our knowledge this paper represents the first attempt to leverage firms' default probabilities in studying bankers' expectations.

Forecast errors We construct the forecast error FE for firm i borrowing from bank b in the standard fashion as realized outcome (default) minus forecast (PD): $FE^{i,b}_{t+4} := Def^{i}_{t+4} - PD^{i,b}_{t}$. Note that we adopt the usual convention in the literature and represent the default status of a borrower (Def) as a binary variable that takes value 1 in case of default and 0 otherwise. Hence, forecast errors can range between -1 and 1, and have a fixed forecast horizon of 4 quarters.

With regards to our outcome variable, consistent with Article 178 of Regulation (EU) No 575/2013 (EU Commission, 2013), a bank may report a borrower in default in AnaCredit if either (i) the borrower is 90/180 days in past-due, (ii) the bank deems the borrower "unlikely to pay" or (iii) the borrower is both in past-due and flagged as unlikely-to-pay. Different banks may disagree on the default status of the same borrower[8].

For the sake of our analysis we adopt a broad definition of default: we treat a borrower as in default with respect to the Italian banking system if at least one bank has reported the

[8]E.g., bank 1 may report the borrower as performing (not in default) and bank 2 as unlikely-to-pay.

borrower in one of three default clusters outlined above. The advantage of this definition is that it allows for a standardized and easier comparison across banks. Nevertheless, we explore alternative default definitions, for instance restricting only to borrowers in past-due for more than 90/180 days (see table A.10), and our main results remain robust.

News To study the excess sensitivity of forecast errors to news (or signal) that bank b receives on borrower i we employ two main measures: a "micro" news given by the change in the PD and a "macro" signal based on a sectoral production/sales index

$$MicroNews_t^{i,b} := -(PD_t^{i,b} - PD_{t-1}^{i,b}), \qquad MacroSignal_t^{i,b} := \frac{idx_t^s - idx_{t-1}^s}{idx_{t-1}^s} \tag{1}$$

where idx is the relevant index for sector s where borrower i belongs to.

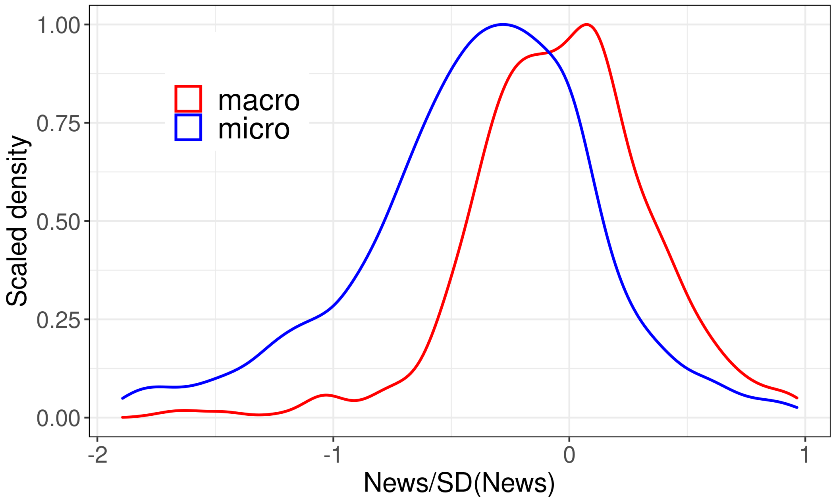
The micro news is our preferred specification that we use throughout the paper (and denote simply by *News*) since (i) it is bank-borrower specific, (ii) has a higher signal-to-noise ratio compared to the macro signal, and (iii) has closer ties with the learning model developed in section 3. While both micro and macroeconomic factors affect credit risk (Hirshleifer and Sheng, 2022), there is some evidence (Bonfim, 2009) that in period of non-excessive credit expansion firm-specific risk drivers, such as a firm's financial structure, profitability, liquidity, recent sales performance, and investment policy, tend to have a better forecasting ability[9]. Since we cannot observe in real time all the relevant borrower-level signals available to banks or can do so only at a very low frequency (annual), we believe that the change in the PD is a reasonably good synthetic indicator of the news a lender has received also in light of the institutional details reported in previous paragraphs.

With regards to the macro signal, we use two main indexes at a NACE 2-digit level of granularity sourced from the Italian statistical agency (Istat): industrial production for manufacturing and construction, and sales for services. These indexes are available at a monthly frequency and are based on the population of firms with more than 20 employees. Merging Anacredit with these data, the number of firms decrease roughly to 58,000 units from 75,000, while the number of sectors to 52 from 83. This data loss is mainly due to limited data availability for minor sectors of the economy.

Comparing the two signals in figure 1 we see that micro signals are on average slightly negative, are more dispersed and are negatively skewed. Macro signals instead have a dis-

[9] This evidence was further reinforced during informal discussions with supervisors and banking officials that mentioned that macroeconomic variables tend to exhibit relatively low explanatory power when it comes to individual-level default prediction, especially compared to idiosyncratic signals such as past credit history, arrears, and firm financials.

Figure 1: Density plot for micro and macro signal



Notes: The figure shows a density plot for micro news and macro signal of eq. (1) scaled by their standard deviation. To compare the two distributions at the same level of granularity we first aggregated micro news at the NACE 2 digit-quarter level. For illustrative purposes the $x-$axis limits are cut at the 2.5% and 97.5% percentile of the entire (micro and macro) news distribution.

tribution skewed to the right, with a positive mean and lower dispersion. Overall, firms for which we can compute the macro signal tend to be moderately less risky, and receive a higher amount of credit and at a lower interest rate compared to the entire population of borrowers (see table A.3).

3 Econometric model

We build a stylized learning model where lenders in each period receive a signal of firms' cashflows, on which lenders try to forecast defaults. As in Bordalo et al. (2019) bankers can form expectations both rationally and according to the so-called representativeness heuristic.

Borrowers default if their cashflows x_t, which we assume follow a simple AR(1) process, fall below an exogenous threshold a. Banks cannot observe directly x_t but only a noisy signal y_t. In state space form the model is

$$\begin{aligned} x_{t+1} &= \rho x_t + v_t, \qquad v_t \sim N(0, \sigma_v^2) \\ y_t &= x_t + w_t, \qquad w_t \sim N(0, \sigma_w^2) \end{aligned} \tag{2}$$

where v_t and w_t are the state and measurement errors, respectively. In this section for ease of notion we normalize the forecast horizon to 1 period so that in time t agents form beliefs about outcomes that realize at $t+1$. We also drop the bank b and borrower i index. In our empirical application of section 4 the forecast horizon is fixed at 4 quarters consistently with our data.

Rational Expectations If bankers are fully rational a standard application of the Kalman filter[10] shows that their beliefs $f(x_{t+1}, I_t)$ given the information set $y^t = \sigma(y_t, y_{t-1}, \dots)$ available to bankers at time t should be normal with mean $\hat{x}_{t+1|t} = \mathbb{E}[x_{t+1}|y^t]$ and variance $\widehat{\Omega}_{t+1|t} = \mathbb{E}(x_{t+1} - \hat{x}_{t+1|t})^2$ satisfying the usual recursions

$$
\begin{aligned}
\hat{x}_{t+1|t} &= \rho \hat{x}_{t|t-1} + K_t I_t \\
\widehat{\Omega}_{t+1|t} &= \rho \widehat{\Omega}_{t|t-1}(\rho - K_t) + \sigma_v^2, \qquad K_t = \frac{\rho \widehat{\Omega}_{t|t-1}}{\widehat{\Omega}_{t|t-1} + \sigma_w^2}
\end{aligned} \tag{3}
$$

where we denote by $I_t = y_t - \mathbb{E}(y_t|y^{t-1}) = y_t - \hat{x}_{t|t-1}$ the news or innovation and by K_t the Kalman Gain. Notice that K_t in equation (3) converges to a steady state value after few iterations in the model. Therefore, we assume $K_t = K$ and hence $\widehat{\Omega}_{t|t-1} = \widehat{\Omega}$ to be a constant in the rest of the paper.

Diagnostic Expectations Before characterizing beliefs for distorted lenders we provide a brief description of diagnostic expectations and refer to (Bordalo et al., 2018, 2019; Gennaioli and Shleifer, 2010) for a comprehensive treatment. Diagnostic expectations are based on the representativeness heuristic of Kahneman and Tversky (1972). An element is representative in a class whenever its relative frequency in that class is much higher compared to a reference class. When forming beliefs the agent (in our setting the banker) assesses the distribution of future state (firms' cashflows) $\hat{x}_{t+1}$ on the basis of realized current state $x_t = \hat{x}_t$. The rational agent predicts the future state using the true conditional distribution $f(x_{t+1}|x_t = \hat{x}_t)$. In our model $f(\cdot)$ is a normal density whose mean and variance are given by $\hat{x}_{t+1|t}$ and $\widehat{\Omega}$ in the Kalman recursions (3).

The diagnostic agent instead has the true distribution $f(x_{t+1}|x_t)$ in the back of his mind, however he selectively recovers and overweights the realizations of the state at $t+1$ that are representative in t. A given state $\hat{x}_{t+1}$ is more representative at t if it's more likely that it occurs under the realized state $(x_t = \hat{x}_t)$ than on the basis of past information $(x_t = \rho \hat{x}_{t-1})$. Hence, *representativeness* of $\hat{x}_{t+1}$ is given by:

$$
R = \frac{f(\hat{x}_{t+1}|x_t = \hat{x}_t)}{f(\hat{x}_{t+1}|x_t = \rho \hat{x}_{t-1})} \tag{4}
$$

[10]See e.g, pp. 82-85 of Durbin and Koopman (2012).

The state is more representative the more its likelihood increases with respect to recent news. Absent any signal, the numerator and denominator coincide leading to the rational expectation case. When the news is good, states in the right tail of the distribution are made more representative, when the news is bad the opposite is true. Hence, a diagnostic agent forms beliefs as if he were using the distorted density

$$f_t^\theta(\hat{x}_{t+1}) = f(\hat{x}_{t+1}|x_t = \hat{x}_t) \cdot \left[\frac{f(\hat{x}_{t+1}|x_t = \hat{x}_t)}{f(\hat{x}_{t+1}|x_t = \rho\hat{x}_{t-1})}\right]^\theta Z$$

where the parameter θ measures the degree of *diagnosticity*, the deviation from the rational expectation case, and Z is a constant ensuring that the distorted density integrates to one. This formula operationalizes the so called "kernel of truth" property, i.e. the agent shifts its beliefs from rational expectations in the direction of the news received.

Probability of default Following Bordalo et al. (2019), we can characterize bankers' beliefs by the distorted density $f^\theta(x, I_t) = f(x, I_t)[R(x, I_t)]^\theta Z$ which is once again normal with the same variance $\widehat{\Omega}$ but distorted mean

$$\begin{aligned} \hat{x}^\theta_{t+1|t} &= \rho\hat{x}_{t|t-1} + (1+\theta)KI_t \\ &= \hat{x}_{t+1|t} + \theta KI_t \end{aligned} \tag{5}$$

Hence, when $\theta > 0$ the agent is distorted or "diagnostic" and over-reacts to information with respect to previous period, while if $\theta = 0$ the agent is rational. Letting z be the default status $z_{t+1} := \mathbb{1}(x_{t+1} < a)$ where a is the default threshold and exploiting the normality of $f(x, I_t)$ and $f^\theta(x, I_t)$, it follows that the probabilities of default for a rational and a distorted borrowers are

$$\begin{aligned} \mathbb{E}_t(z_{t+1}) &= \Phi\left(\frac{a - \hat{x}_{t+1}}{\widehat{\Omega}_t^{1/2}}\right) =: \widehat{PD}_{t+1|t} \\ \mathbb{E}^\theta_t(z_{t+1}) &= \Phi\left(\frac{a - \hat{x}^\theta_{t+1}}{\widehat{\Omega}_t^{1/2}}\right) =: \widehat{PD}^\theta_{t+1|t} \end{aligned} \tag{6}$$

with $\Phi(\cdot)$ the cumulative standard normal distribution. After a linearization and some algebra[11], we obtain an equation that links directly bankers' forecast error $FE^\theta_{t+1|t} = z_{t+1} - \widehat{PD}^\theta_{t+1|t}$

[11] For a complete derivation see the appendix - Proofs.

for both the rational ($\theta = 0$) and distorted lender ($\theta > 0$) to the innovation I_t

$$FE^{\theta,i,b}_{t+1|t} \approx \underbrace{K\theta \frac{1}{\widehat{\Omega}^{1/2}} \phi\left(\frac{a}{\widehat{\Omega}^{1/2}}\right)}_{=:\beta_1} I^{i,b}_t + w^{i,b}_{t+1} \tag{7}$$

where $w^{i,b}_{t+1}$ is an error term, $\phi(\cdot)$ the standard normal density, and i and b denote as usual borrowers and lenders. Since by construction $\widehat{\Omega}_t > 0$, $a > 0$, $K > 0$ and the density is strictly positive, β_1 must have the same sign as the diagnostic parameter θ. Hence, to measure the excess sensitivity of bankers to incoming news we can test the hypothesis $H_0 : (\beta_1 = 0)$ with the following linear regression

$$FE^{\theta,i,b}_{t+1|t} = \beta_0 + \beta_1 I^{i,b}_t + \epsilon^{i,b}_{t+1} \tag{8}$$

and for $\beta_1 \gtrless 0$ lenders overreact (underreact) to incoming information.

Banks' beliefs and lending To characterize the effect of distorted beliefs on credit allocation we assume perfectly competitive markets and refer to section 5 for a more realistic and less stylized structural model where banks compete on prices and enjoy market power. Consider a simple economy where lenders are risk neutral, the gross risk free rate is normalized to 1 and borrowers demand a one-period unitary loan. Assuming competition deprives banks of any surplus, in equilibrium the interest rate r offered by the bank must satisfy the no arbitrage condition $1 = (1 + r_t)\mathbb{E}^{\theta}_t[(1 - z_{t+1})]$ and therefore

$$r_t = \frac{\widehat{PD}_{t+1|t}}{1 - \widehat{PD}_{t+1|t}} = \frac{\Phi\left(\frac{a-\hat{x}_{t+1}}{\widehat{\Omega}^{1/2}_t}\right)}{1 - \Phi\left(\frac{a-\hat{x}_{t+1}}{\widehat{\Omega}^{1/2}_t}\right)}$$

After some algebra and approximations given in appendix - Proofs, we obtain a linearized relationship between interest rate and the probability of default, both for rational and diagnostic agents:

$$r_t \approx \Phi\left(\frac{-a}{\widehat{\Omega}^{1/2}}\right) - \frac{1}{\widehat{\Omega}^{1/2}} \frac{\phi\left(\frac{-a}{\widehat{\Omega}^{1/2}}\right)}{\Phi\left(\frac{-a}{\widehat{\Omega}^{1/2}}\right)^2} \hat{x}_{t+1|t} \tag{9}$$

$$r^{\theta}_t \approx r_t - \underbrace{\frac{K\theta}{\widehat{\Omega}} \frac{\phi\left(\frac{-a}{\widehat{\Omega}^{1/2}}\right)}{\Phi\left(\frac{-a}{\widehat{\Omega}^{1/2}}\right)^2}}_{=:\gamma} I_t \tag{10}$$

Since $K, \Phi(\cdot), \phi(\cdot), \widehat{\Omega}$ are positive by construction, for a positive signal $I_t > 0$ our model predicts a lower interest rate for the diagnostic agent compared to the rational one.

4 Empirical Results

The first testable implication that we bring to the data is the excess sensitivity to news of equation (7). As explained in section 2 our sample starts in September 2018 and ends in 2020-Q2 to discard confounding effects of the Covid-19 in the main analysis; results with the full sample are available in the appendix. Specifically, we estimate

$$FE^{\theta,i,b}_{t+4|t} = \beta_0 + \beta_1 News^{i,b}_t + \mathbf{\Gamma}'\mathbf{X} + \epsilon^{i,b}_{t+4} \tag{11}$$

where $\mathbf{\Gamma}'\mathbf{X}$ is a vector of control variables[12] alongside bank, sector, province, borrower and time fixed effects. Since both dependent and independent variables vary at the bank-borrower(-quarter) level, we collapse the loan dimension so that the number of observations shrinks (sample 1 [13]). As described in paragraph 2 our preferred measure of news is the "micro" news based on the change of the probability of default between consecutive quarters for the same bank-borrower pair. The appendix outlines the relationship between the theoretical innovation I of the model and our empirical proxy. We remark that under rational expectations bankers' forecast errors should not be predictable by variables in their information set ($\beta_1 = 0$) as shown in Born et al. (2023).

Table 2 reports our estimates until 2020 Q2 on three sub-samples according to the sign of the news: both positive and negative news in panel A, and only observations with negative (non-negative) news in panel B (C). When we extend our time series to the last available observation (2023 Q2), our findings are consistent (see table A.6 in the appendix). The news coefficient is always statistically significant and positive for the three panels that include bor-

[12] Our benchmark borrower-level controls are the firm's (log) total sales, size, outstanding credit, length of the relationship with the lender, and lagged credit rating (sample 1, footnote 13). For loan-level regressions we also include the inverse of the loan-to-value (LTV), the loan original maturity, type (e.g., a standard installment loan, a trade receivable, an overdraft, etc.), purpose (e.g., whether the loan is financing import/exports, working capital facility, construction investment, etc.) and type of interest rate (sample 2, footnote 13).

[13] Sample 1: borrower-level units, all observations used. Sample 2: loan-level units, multi-affiliated borrowers with both diagnostic and non-diagnostic banks, new contracts used. We define new contracts as those instruments originated at most 3 quarters before the reference date in order to retain a sufficient number of periods when both rational and distorted banks grant new credit to the same borrower. Sample 3: loan-level units, multi-affiliated borrowers with both diagnostic and non-diagnostic banks, all contracts used. In the regressions where the measure of "macro" signal is used, the number of observations shrinks due to the limited number of sectors available in the Istat dataset, as explained in paragraph 2.

Table 2: Forecast Errors Predictability - Micro News

	(1)	(2)	(3)
		Panel A: All Micro News	
$News_t$	0.300***	0.302***	0.629***
	(0.0348)	(0.0348)	(0.0215)
N	472392	472392	467512
		Panel B: Negative Micro News	
$News_t$	0.490***	0.492***	1.045***
	(0.0530)	(0.0530)	(0.0247)
N	113176	113176	95797
		Panel C: Non-Negative Micro News	
$News_t$	0.00843	0.0110	0.124***
	(0.0250)	(0.0243)	(0.0247)
N	359216	359216	351302
Time FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Sector FE	-	Yes	-
Province FE	-	Yes	-
Borrower FE	-	-	Yes

Notes: This table report estimates of equation (11) where we measure signals using the micro news defined in (1). Our sample runs from from 2018-Q3 to 2020-Q2. Standard errors are in parenthesis and are clustered at the Nace 2-digit level. Sample 1 from footnote 13 is used in Panel A. Samples in Panel B and C are restricted as indicated in each Panel header.

rower fixed effects (column 3)[14]. A positive and significant coefficient implies that bankers overreact to all types of news (positive and negative), i.e., when a distorted lender receives a positive (negative) signal, it tends to decrease (increase) the probability of default more than a purely rational one would. Our estimates suggest that for a standard deviation increase in news of our full sample (0.081, as outlined in table 1), the forecast error of a distorted banker increases by 240 to 500 basis points[15]. more than a non-distorted one (Panel A). The effect is stronger in Panel B where the sample is limited to negative news, reaching between 400 and 850 basis points. In Panel C the effect is lower and stands at 7-100 basis points. Expressing the results differently, when news increase by one standard deviation, bankers predict a default

[14]Whenever we use borrower fixed-effects we cannot include simultaneously bank, province or sector fixed-effects, since the main source of variation comes from the cross-sectional difference among one of them.

[15]We compute the effect as $SD(News) \times \hat{\beta}_1 \times 1e4$, where $SD(News)$ is the standard deviation of the Micro News given in table 1, $\hat{\beta}_1$ is our estimate of the $News$ coefficient, and $1e4$ is a scaling factor to express the result in basis points, e.g. for Panel A, first column: $0.081 \times 0.300 \times 10000 = 243$

Table 3: Forecast Errors Predictability - Macro signal

	(1)	(2)	(3)
	Panel A: All Macro Signal		
$News_t$	0.0134***	0.0132***	0.0131***
	(0.00332)	(0.00322)	(0.00318)
N	488034	488034	488034
	Panel B: Negative Macro Signal		
$News_t$	0.0213**	0.0198**	0.0196**
	(0.00801)	(0.00788)	(0.00744)
N	292871	292871	292871
	Panel C: Non-Negative Macro Signal		
$News_t$	0.00793	0.00751	0.00732
	(0.00780)	(0.00775)	(0.00748)
N	195163	195163	195163
Bank FE	-	Yes	Yes
Province FE	-	-	Yes

Notes: This table report estimates of equation (11) where we measure news using the macro signal defined in (1). Our sample runs from from 2018-Q3 to 2020-Q2. Standard errors are in parenthesis and are clustered at the Nace 2-digit level. Sample 4 from footnote 13 is used in Panel A. Samples in Panel B and C are restricted as indicated in each Panel header.

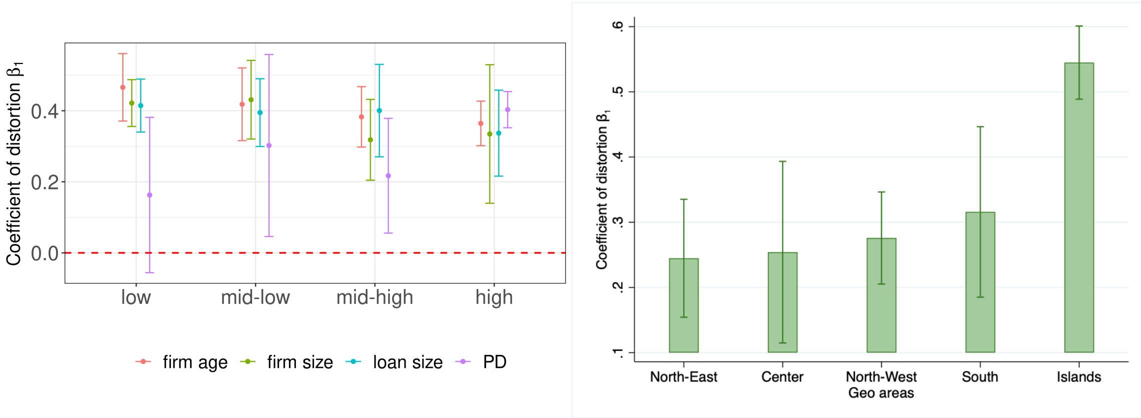
rate that is 2.4% to 5.0% lower than what a rational forecaster would anticipate.

In Panels A and B the effect is also robust for every specification. In Panel C the coefficient becomes significant only when we introduce borrower fixed effects. This is an important finding because it suggests that even if demand-driven components are dampened, expectational distortions by banks still arise and corroborates the use of granular dataset that allow to more easily control for demand-side effects.

To strengthen our results, we re-estimate regression (11) using the macro signal from equation (1). As outlined in paragraph 2, we can estimate this specification only on the subset of firms for which the sector-level production/sales indexes are available. Table 3 reports our main findings. Note that the estimate of the excess sensitivity β_1 are qualitatively similar to those of table 2, but with lower values. Differences in statistical significance and economic magnitudes with respect to table 2 are presumably due to the lower power of aggregate macro signals in explaining borrower-level outcomes.

In a related exercise, Born et al. (2022) also investigate agents' reaction to both micro and macro news. Differently from our setting they focus on non-financial firms and rely on survey

Figure 2: Distortion coefficients by borrower groups



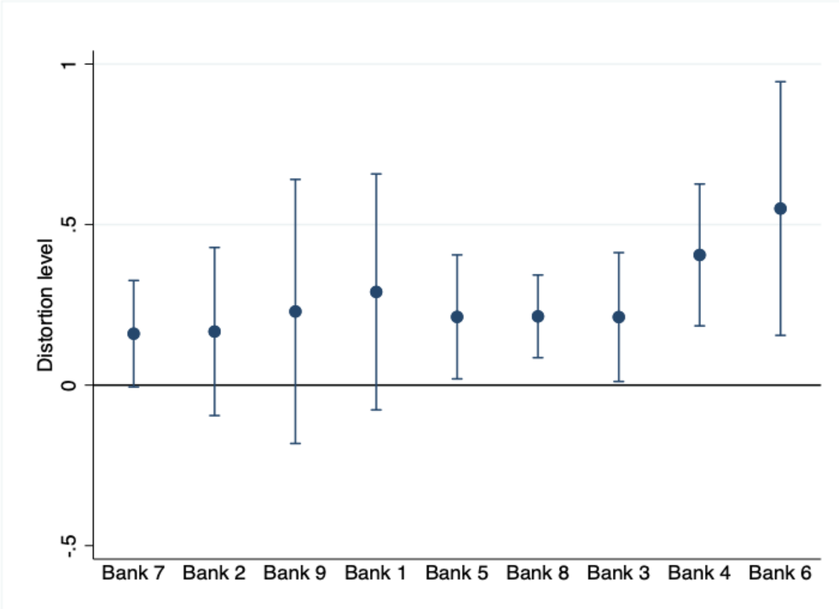
Notes: The figure shows the average level of banks' belief distortion across several dimensions of borrower heterogeneity. For each cluster of firm age and size, PD, loan size (left panel), and headquarters' location (right panel) we separately estimate (11) and report the coefficients $\hat{\beta}_1$ with 95% confidence interval. Standard errors are clustered at NACE 2 digit-level.

data to assess both expectations and news. They show that agents overreact to micro news but underreact to macro signals. Although our results for micro news are consistent with Born et al. (2022), the different type of agents, news measurement and econometric specification do not allow for a straightforward comparison with their findings.

The coefficient of interest is positive and significant for all combinations of fixed effects for the full sample (panel A) and for the sub-sample of negative signal (panel B). It remains positive for firms with non-negative signal (panel C) but is no longer significant. Our estimates in panel A suggest that for a standard deviation increase in the signal the forecast error of a diagnostic banker increases by around 50 basis points (bps) more than a non-diagnostic banker. The effect is larger in panel B and more subdued in panel C. Finally, in section 6 we show that our findings are robust to using an accounting-based measure of news.

Given our very large cross-section we can explore *pooled* findings of Table 2 and investigate how banks' excess sensitivity to news varies across borrower and bank characteristics. In figure 2 we re-estimate equation (11) using micro news for borrower clusters, according to firm size, age, location, average PD, and loan size. For every subgroup of borrowers the average level of distortion is always positive and statistically significant except for the borrowers with the lowest pre-determined PD. Looking at point estimates, the excess sensitivity is decreasing with loan size, age and size of the firm, and increasing in the probability of default, but with overlapping confidence intervals. Distortions are also more pronounced for firms residing in the Southern Italy and in Sardinia and Sicily. Overall, these results provide evidence in favor of widespread distortions in banks' beliefs that are *not* explained by observable borrower

Figure 3: Distortion coefficients by bank



Notes: The figure plots the coefficients $\hat{\beta}_1$ with 95% confidence interval of the regression (11) estimated separately for each bank. Institutions are sorted increasingly by $\hat{\beta}_1$. Standard errors are clustered at NACE 2 digit-level. For confidentiality reasons banks are anonymised and are assigned a cardinal identifying number.

characteristics.

Moving to banks' heterogeneity, since we cannot easily correlate bank-level covariates to banks' distortions with the limited number of credit institutions in our sample, in figure 3 we separately re-estimate regression (11) using micro news for each bank. Our results show that five out of nine banks display a positive and significant distortion coefficient with point estimates ranging between 0.2 and 0.5. These findings confirm that estimates of table 2 are not driven by a single outlier institution. We exploit this heterogeneity to test implication (10) on interest rates.

Interest rates To bring equation (10) to the data we estimate

$$r_t^{i,b} = \beta_0 + \beta_1 D_t^b + \beta_2 News_t^{i,b} + \gamma(D_t^b \times News_t^{i,b}) + \mathbf{\Gamma}'\mathbf{X} + \epsilon_t^{i,b} \tag{12}$$

where D_t^b is a dummy variable equal to 1 if a bank has a "high" level of distortion, the term $\mathbf{\Gamma}'\mathbf{X}$ contains various controls (ref. footnote 12 and fixed effects like such as size and credit age, bank, sector, province, and borrower fixed effects. To construct our indicator variable D we exploit the heterogeneity in banks' distortion level $\hat{\beta}_1$ as shown in figure 3 and let $D = 1$ for those banks that have a positive and statistically significant $\hat{\beta}_1$ and 0 otherwise. The main coefficient of interest of equation (12) is γ, which should be interpreted in the canonical difference-in-difference framework: it measures the difference in the average change of the interest rate between more distorted banks (the treated group, $D = 1$) and less distorted ones (the control group, $D = 0$), when receiving positive news versus receiving no news. Note that the same interpretation applies for the respective coefficient of interest in equations (13) and (14).

To avoid dealing with old contracts signed before the start of our sample and whose PD at origination we can no longer observe, we restrict our sample to the subset of instruments originated at most 3 quarters before the current period t (sample 2 in footnote 13). We must include more observations for each new contract (those between t and $t-3$) to capture a sufficient number of matching periods in which the borrower originates new contracts with both a rational and a diagnostic bank. Finally, we select borrowers affiliated with at least one rational $(D = 0)$ and one diagnostic bank ($D = 1$). In one specification we go one step further and also include borrower fixed-effects. This method is similar to that one used by Khwaja and Mian (2008) and allows us to dampen variation coming from demand. Note that differently from the estimation of equation (11) here we do not collapse the loan-level dimension (and therefore the number of observations increases), since we are effectively comparing two contracts signed by the same borrower with a distorted and a rational bank.

Table 4 shows our estimation. In column (1) we assess the *unconditional* effect of news on interest rates controlling for several variables. As expected, the coefficient *News* is negative and statistically significant: if banks receive positive signals, they revise downward the probability of default and the price of new loans is reduced accordingly. In columns (2) and (3) we estimate the full specification (12) with different combinations of fixed effects. Consistent with (10) the estimated parameter $\hat{\gamma}$ for the interaction $News \times D$ is negative and statistically significant at the 1%. According to our results, for a standard deviation increase in news (as outlined in 1) distorted banks on average would decrease interest rates on new loans by around 5 bps, compared to rational lenders when receiving no news. We replicate the same exercise with macro signal as a robustness check in section 6. Furthermore, our findings remain broadly stable also when we extend our time series to 2023 Q2 (see table A.7).

Table 4: Effects on Interest Rates - Micro News

	(1)	(2)	(3)
$News_t$	-0.0186***	-0.0109***	0.00116
	(0.00451)	(0.00262)	(0.00175)
D_t^b		0.0104***	0.00668***
		(0.000624)	(0.000538)
$News_t \times D_t^b$		-0.00860	-0.00631***
		(0.00683)	(0.00199)
N Obs.	551074	551074	550073
Sector FE	Yes	Yes	-
Province FE	Yes	Yes	-
Time FE	Yes	Yes	Yes
Borrower FE	-	-	Yes

Notes: this table provides estimates of (12) where we measure signals using the micro news defined in (1). Sample used is sample 2 as oulined in footnote 13 and runs from 2018-Q3 to 2020-Q2 including all borrowers affiliated with at least one rational ($D = 0$) and one diagnostic bank ($D = 1$). Standard errors in parenthesis are clustered at the NACE 2-digit level.

Quantities Similar to the exercise in the previous paragraph, we investigate the differential impact of news on the size of loan (*LoanSize*) and on the probability of a new loan (*NC*)

$$\log(LoanSize)_t^{i,b} = \beta_0 + \beta_1 D_t^b + \beta_2 News_t^{i,b} + \gamma(D_t^b \times News_t^{i,b}) + \mathbf{\Gamma}'\mathbf{X} + \epsilon_t^{i,b} \tag{13}$$

$$NC_t^{i,b} = \beta_0 + \beta_1 D_t^b + \beta_2 News_t^{i,b} + \gamma(D_t^b \times News_t^{i,b}) + \mathbf{\Gamma}'\mathbf{X} + \epsilon_t^{i,b} \tag{14}$$

where $NC_t^{i,b}$ is a dummy variable equal to 1 if the contract originates either in the current quarter t or in $t-1$. Equations (13) and (14) model the *intensive* and *extensive* margin respectively and the main coefficient of interest γ measures the extent to which more distorted banks (1) increase the size of loans and (2) are more likely to grant new credit in equilibrium, compared to rational lenders after receiving a positive signal.

In (13) we refer to the intensive margin: we restrict our sample in the same fashion of (12) to only new contracts and multi-affiliated borrowers, so that γ represents the equilibrium extra (log-)amount of credit that a distorted bank would grant compared to a rational one after receiving positive news on a borrower (sample 2 in footnote 13). In the estimation of (14) instead, we consider only borrowers that are affiliated to at least one rational and one distorted bank, but do not restrict the pool of contracts (sample 3 in footnote 13).

Note that both (13) and (14) are not fully-fledged demand or supply models but should be read as equilibrium relationships. We postpone the exposition of a structural model of demand

Table 5: Effects on Quantities

	(1)	(2)	(3)
Panel A: Intensive Margin - Dependent: $log(LoanSize)_t^{i,b}$			
$News_t$	1.208***	0.384***	-0.200
	(0.224)	(0.136)	(0.121)
D_t^b		-0.324***	-0.0526**
		(0.0363)	(0.0229)
$News_t \times D_t^b$		1.067***	0.358***
		(0.375)	(0.118)
N Obs.	551074	551074	550073
Panel B: Extensive Margin - Dependent: $NC_t^{i,b}$			
$News_t$	0.212***	0.157***	0.0323*
	(0.0142)	(0.0241)	(0.0176)
	(0.0178)	(0.0140)	(0.00915)
D_t^b		0.00860	0.00656
		(0.0140)	(0.0139)
$News_t \times D_t^b$		0.0803***	0.102**
		(0.0290)	(0.0440)
N Obs.	1139946	1139946	1138960
Sector FE	Yes	Yes	-
Province FE	Yes	Yes	-
Time FE	Yes	Yes	Yes
Borrower FE	-	-	Yes

Notes: this table reports estimates of (13)-(14) in, respectively, panel A and B. We measure signals using the micro news defined in (1). Both panels include observations from 2018-Q3 to 2020-Q2, including all borrowers affiliated with at least one rational ($D = 0$) and one diagnostic bank ($D = 1$). The sample used for panel A is Sample 2, as outlined in footnote 13. The sample used for panel B is Sample 3, where the dependent variable new contract NC is defined as a contract originated in period t and $t-1$. Standard errors in parenthesis are clustered at the NACE 2-digit level.

and supply to section 5.

Table 5 reports our findings for the intensive (panel A) and extensive margin (panel B). Our results remain consistent also when we use all observations until 2023 Q2 (see table A.9 in the appendix). For both panels the unconditional estimates of column (1) are as expected: positive news are associated with larger loan sizes and a higher likelihood of new credit. Focusing on panel A, columns (2) and (3) show a positive and significant interaction coefficient $News_t \times D_t^b$ so that, conditional on receiving a one standard deviation of news, a distorted bank would increase the loan size on average around 3-9% more than a rational bank. Similarly, for Panel B the interaction coefficient of columns (2) and (3) is once again positive and significant, implying that the probability of signing new contracts would increase on average by 1% more for a distorted bank compared to a rational one after receiving a standard deviation of positive news. Section 6 reports our findings using the macro measure of news.

Although our empirical results are motivated by a learning model where banks may overreact to news, they also align with the findings of Ma et al. (2021) who measure expectations based on banks' responses to baseline and downside scenarios of MSA-level economic conditions. While the different methodologies and data do not allow to easily compare results, similarly to Ma et al. (2021) we find heterogeneity in lenders' expectations, and that more pessimistic banks are likely to increase interest rates and reduce loan offerings. Differently from Ma et al. (2021), we exploit our large cross-section of beliefs and loan outcomes to formally test for rationality of expectations. Additionally, our study broadens the understanding of lending decisions by also considering scenarios where banks are more optimistic, an aspect not covered by Ma et al. (2021) due to their exclusive focus on the baseline scenario and the absence of a "best case scenario" in their Federal Reserve survey data. Overall, our approach captures both ends of the spectrum—pessimism and optimism—in banking expectations, effectively reflecting banks' responses to both positive and negative news.

Our results on forecast errors predictability are also broadly in line with those of Falato and Xiao (2023). Using qualitative data on delinquencies and charge-offs by the Federal Reserve's Senior Loan Officer Opinion Survey of Bank Lending Practices (SLOOS), they find that banks were over-optimistic before the financial turmoil of 2008 and over-pessimistic thereafter. In addition, they also find that banks' forecast errors are predictable by lagged loan performance, under-reacting to recent changes (1-year lag) and over-reacting to past ones (2-years lag). Our findings suggest instead that banks systematically tend to overreact, to both micro and macro signals, even when these signals arrive with an higher frequency. This difference likely arises because we measure signals quarterly post-great financial crisis while the survey of Falato and Xiao (2023) runs at annual frequency and spans a longer time period.

5 Structural estimation

We extend our reduced form findings with a model of imperfect competition of the banking sector. We follow the framework originally developed by Crawford et al. (2018) and extend it with supply-side belief distortions.

The structural estimation confirms the empirical findings of section 4, in particular with respect to the average level of the diagnostic parameter. We then use the estimated model to quantify the effects of these distortions on the price and quantity of credit, and to run counterfactual exercises where we (i) increase the average level of belief distortion, (ii) release a positive signal for all borrowers, and (iii) impose full rationality for all banks.

Similarly to Crawford et al. (2018) in the model we adopt several important assumptions. First, we narrow the analysis only to unsecured, short-to-medium term (original maturity between 1 and 5 years) installment loans. For each borrower we also consider only the instrument with the highest outstanding amount[16]. We do this to avoid modeling a more complex, possibly inter-temporal decision process, but we still capture on average around EUR 94 bln out of 600 bln of total outstanding credit in our sample. Second, we assume both firms and banks are risk-neutral, although each bank is endowed with potentially distorted beliefs. Third, banks compete only on the interest rate. In markets with lending exclusivity banks can offer contracts that depend both on the credit amount and price. Instead, with the assumption of price competition, the amount of credit is exogenous and given only by the firm's project requirements. As in Crawford et al. (2018), this assumption is reasonable for the Italian credit market, since firms can open multiple credit relationships with different banks and without lending exclusivity a convex price schedule cannot be enforced (Chiappori and Salanié, 2013).

Demand The demand side is standard. If firm $i = 1, \ldots, I$ operating in market $m = 1, \ldots, M$ borrows from bank $j = 1, 2, \ldots, J$ it receives "utility"

$$U^D_{ijm} = \alpha^D_0 + X'^D_{jm}\beta^D + \xi^D_{jm} + \alpha^D P_{ijm} + Y'^D_{ijm}\eta^D + \nu_{ijm} \tag{15}$$

where X_{jm} is vector of bank-market characteristics, P_{ijm} is interest rate offered by bank j to firm i and market m, ξ_{jm} are bank-market characteristics unobservables to the econometrician, and Y'^D_{ijm} are firm-bank-market characteristics. In our setting we identify all combinations of quarters $t = 1, 2, \ldots, T$ and Italian provinces as a market that for ease of notation we denote simply by m instead of (t, m). Finally, we let $j = 0$ be the outside option of non-borrowing.

Supply On the supply side, banks $j = 1, 2, \ldots, J$ compete à la Bertrand-Nash on prices and set for each market m and firm i an interest rate P_{ijm}. Bank's j expected profits from lending to firm i are

$$\Pi_{ijm} = P_{ijm}Q_{ijm}(1 - PD(\theta_j, I_i)) - MC_{ijm}Q_{ijm}$$

[16]E.g., if a borrower has two loans outstanding for 30k and 120k we only consider the main loan of 120k.

Q_{ijm} represents the expected demand for loan which is equal to the probability borrower i will accept the interest rate offered times the expected amount of loan which we normalize to 1. MC_{ijm} denotes the marginal cost of issuing the loan, and $PD(\theta_j, I_i)$ is as usual the probability the borrower will default. Differently from Crawford et al. (2018), our structural PD is a function of the belief distortion parameter θ_j and of the firm's signal I_i consistently with the learning model of section 3.

The first order condition for the maximization of the profit function reads as

$$P_{ijm} = \frac{MC_{ijm}}{1 - PD_{ijm}(\theta_j, I_i)} + \frac{\mathcal{M}_{ijm}}{1 - PD_{ijm}(\theta_j, I_i)} \tag{16}$$

where $\mathcal{M}_{ijm} := -Q_{ijm}/Q'_{ijm}$ is bank j markup on firm i loan. This is the standard Bertrand-Nash pricing equation but where both the marginal cost and the markup are deflated by the probability the borrower will survive. If lenders display overreaction to news ($\theta > 0$) as in our empirical investigation, positive signals will decrease the PD reducing both the effective marginal cost and markups. If the credit market is fairly competitive, beliefs' distortions will act mainly through marginal costs. On the other hand, when competition is low and markups are high, lenders' excess sensitivity to news can help mitigate the upward pressure on prices in good times (positive news), but exacerbate it in bad times (negative news).

Before estimating the model we need to address two additional issues. First, in our data we only observe prices for actual credit relationships, but we also need interest rates offered from banks not chosen by firms. Second, we need to control for the unobserved characteristics ξ^D_{jm} that borrwers take into account and that we cannot observe, as econometricians. While this latter point is standard in the industrial organization literature and will be solved using the toolkit based on Berry et al. (1995), the first one is unique to our setting and we follow the approach of Crawford et al. (2018) to impute the missing prices.

Price imputation The imputation strategy is based on a predictive regression

$$P_{ijm} = \gamma_0 + \gamma_1 T_{ijm} + \gamma_2 L_{ijm} + \lambda_{jm} + \omega^p_i + \tau_{ijm} \tag{17}$$

where ω^p_i, λ_{jm} are firm and bank-market fixed effects, T_{ijm} is tenure of relationship between borrower i and the bank j in market m, L_{ijm} is a categorical variable for clusters of loan size, and τ_{ijm} are prediction errors. In order to identify ω^p_i we estimate this regression on the subsample of firms borrowing from multiple banks, and then use the estimated coefficients to predict prices $\tilde{P}_{ijm}$ offered from banks that firms decided to discard. To predict prices for non-borrowing firms or for firms with a single banking relationship we use a propensity score matching algorithm to impute the missing borrower fixed effects.

A possible caveat of this approach is that it may neglect *soft* information that is unobserved by the econometrician but could be an important component in the bank-firm relationship. Although in our learning model we are not able to distinguish the hard and soft component in the PD estimation, note that since banks in our panel follow the IRB approach ad-hoc human intervention, possibly based only on soft information, should be "appropriately documented and justified" (EBA, 2017). Hence, the effect of one-off adjustments in the final PD reported in AnaCredit should not be unduly large. Furthermore, the use of borrower fixed effects allows us to absorb any time-invariant borrower-specific component unobservable to the econometrician. Since the Italian credit market is strongly characterized by multi-affiliated borrowers, this approach allows us to directly control for the role of soft information in a sizable share of our sample (around 33% of borrowers).

Following Crawford et al. (2018) we proceed in steps: first, we combine the price prediction (17) with firms' utility (15) to arrive at an estimable demand formulation. Second, we construct appropriate moment conditions for both demand and supply for a reasonably simple parametrization of marginal costs and of belief distortions. Finally, we *jointly* estimate all demand/supply parameters using the two-stage procedure and contraction algorithm of Berry et al. (1995) in its GMM formulation as explained in Train (2009). Our focus on the supply and on deviation from full rationality is the major difference from the work of Crawford et al. (2018).

Demand estimation To derive the expression for demand that we can take to the data, we define the baseline bank-market price $\tilde{P}_{jm} := \lambda_{jm}$ as the bank-market fixed effect from (17) so that we can re-write the equation (17) as

$$P_{ijm} = \tilde{P}_{jm} + \tilde{\gamma}_1 T_{ijm} + \tilde{\gamma}_2 L_{ijm} + \tilde{\omega}_i^p + \tilde{\tau}_{ijm}$$

Then, in a control-function spirit we impose a simple linear relationship $\omega_i^D = \eta_4^D \omega_i^p$ between the unobserved component of the price equation ω_i^p and the latent propensity of the firm to demand credit ω_i^D in the bank-firm vector of characteristics $Y_{ijm}^{\prime D}$. The rationale is that both terms (ω_i^p and ω_i^D) are related to soft information available to the bank (but not to the econometrician) and so should be modeled jointly. Hence, the characteristics $Y_{ijm}^D \eta^D$ from (15) become $Y_{ijm}^D \eta^D = \eta_1^D T_{ijm} + \eta_2^D L_{ijm} + \eta_3^D Y_i + \eta_4^D \tilde{\omega}_i^p$ and substituting the last two equations in the firm utility we obtain

$$\begin{aligned}
U_{ijm}^{D} &= \delta_{jm}^{D} + \alpha^{D}(\tilde{P}_{jm} + \tilde{\eta}_1 T_{ijm} + \tilde{\gamma}_2 L_{ijm} + \tilde{\omega}_i^{p} + \tilde{\tau}_{ijm}) + \\
&\quad \eta_1^{D} T_{ijm} + \eta_2^{D} L_{ijm} + \eta_3^{D} Y_i + \eta_4^{D} \tilde{\omega}_i^{p} + \nu_{ijm} \\
&= \underbrace{(\delta_{jm}^{D} + \alpha^{D}\tilde{P}_{jm})}_{\tilde{\delta}_{jm}^{D}} + \underbrace{(\eta_1^{D} + \alpha^{D}\tilde{\eta}_1)}_{\tilde{\eta}_1^{D}} T_{ijm} + \underbrace{(\eta_2^{D} + \alpha^{D}\tilde{\gamma}_2)}_{\tilde{\eta}_2^{D}} L_{ijm} + \\
&\quad \eta_3^{D} Y_i + \underbrace{(\eta_4^{D} + \alpha^{D})}_{\tilde{\eta}_4^{D}} \tilde{\omega}_i^{p} + \underbrace{\alpha^{D}\tilde{\tau}_{jm} + \nu_{ijm}}_{\tilde{\zeta}_{ijm}} \\
&= \tilde{\delta}_{jm}^{D} + \underbrace{Y_{ijm}^{\prime D}\tilde{\eta}^{D}}_{V_{ijm}^{D}} + \zeta_{ijm}
\end{aligned} \tag{18}$$

where $\delta_{jm}^{D} = \alpha_0^{D} + X_{jm}^{\prime D}\beta^{D} + \xi_{jm}^{D}$. Assuming as it is standard in the literature that the residual taste shocks ζ_{ijm} are distributed as a type I extreme value, we arrive at the familiar formulation for the probability that borrower i chooses to borrow from bank j in market m

$$Pr_{ijm}^{D} = \frac{\exp\left(\tilde{\delta}_{jm}^{D}(X_{jm}^{D}, \tilde{P}_{jm}, \xi_{jm}^{D}, \alpha^{D}, \beta^{D}) + V_{ijm}^{D}(Y_{ijm}^{D}, \tilde{\eta}^{D})\right)}{1 + \sum_l \exp\left(\tilde{\delta}_{jm}^{D}(X_{jm}^{D}, \tilde{P}_{jm}, \xi_{jm}^{D}, \alpha^{D}, \beta^{D}) + V_{ijm}^{D}(Y_{ijm}^{D}, \tilde{\eta}^{D})\right)} \tag{19}$$

where $\tilde{\delta}_{jm}^{D}$ are bank-market constants which are a linear function of the unobserved parameter ξ_{jm}^{D} and that we recover through the contraction method from Berry et al. (1995). The intuition to the algorithm is as follows. For given values of the nonlinear parameters $\tilde{\eta}^{D}$, we solve for the mean utility levels $\tilde{\delta}_{jm}^{D}$, that set the predicted market shares equal to the observed market shares. We define the residual ξ_{jm}^{D} as the difference between this valuation and the one predicted by the linear parameters α and β

$$\tilde{\delta}_{jm}^{D} = \alpha_0^{D} + \alpha^{D}\tilde{P}_{jm} + X_{jm}^{\prime D}\beta^{D} + \xi_{jm}^{D}$$

where prices may correlate with the unobservable (to the econometrician) bank-market characteristics ξ_{jm}^{D}. Following Crawford et al. (2018) we use households' deposits (both rates and quantities) as an instrument since they are an important source of funding for banks (Drechsler et al., 2017) and therefore are likely to affect loan pricing. The exclusion restriction rests on the observation that households (not firms) demand deposits and that they value different characteristics (e.g., liquidity and payment services) not available in the loan market for non-financial corporations.

Supply estimation Moving to the supply of credit, using banks' FOC from (16) we need to form moment conditions to estimate in our GMM routine the marginal cost MC and the belief distortion parameter θ. For the marginal cost we adopt a simplifying assumption and impose that θ (i) varies across banks and markets but not borrowers, and (ii) is linear in the cost of funding which we measure with the interest rates paid on deposits at the bank-market level. To identify belief distortions we exploit expression (8) that relates forecast errors of both a rational and distorted bank to the signal I. Recalling that β_1 is a sign-preserving convolution of the primitive distortion parameter θ, and that $\beta_1 = 0$ for a rational lender, subtracting (8) of a distorted banker from the same expression for a non-distorted one we have

$$PD^{\theta}_{ijm} \approx PD^{re}_{ijm} + \beta(\theta) I_i \tag{20}$$

where β is the structural belief parameter that we estimate. Hence, to bring (16) to the data we recast all PDs in difference with respect to the "more rational" lender that we identify as in figure 3. Finally, following section 4 we measure signals I using our micro news. In case of missing data for some bank-borrower pair, we use an imputation strategy based on propensity score matching analogous to the one used in the price predictive regression (17).

Results Table 6 reports our structural estimates. Its upper part contains demand parameters, including firm characteristics, while the bottom part supply ones. As expected, the average price coefficient is negative and significant meaning that higher interest rates negatively impact demand for loans. Other significant parameters are borrower unobserved characteristics, tenure of the relationship, age and sales of the firm. On the supply side, the distortion coefficient is statistically significant and, although negative, has the same interpretation as in table 2: an increase in its (absolute) value causes an upsurge in the equilibrium amount of credit through a lower probability of default assigned by distorted banks compared to a rational peer. Looking at magnitudes, the structural belief distortion parameter is very close to our empirical findings of table 2, column (3) panel A.

Using the estimated structural model we run three main counterfactuals to assess the effect of beliefs distortions on credit allocation. In a first exercise we double the average level of distortions. In this case the model predicts that, conditional on receiving positive news from firms, on average interest rate would drop by 42 basis points and the probability of new loans would increases by 1.7%.

Our second counterfactual consists in shifting to the right by one standard deviation the distribution of news I in our sample. Given our limited time series, this exercise tries to mimic

Table 6: Structural Estimation - Results

Demand		*Supply*	
Tenure	1.658***	Const. (Bel. dist.)	0.039***
	(0.181)		(0.000)
Previous rel.	1.403***	**Belief distortion**	**−0.599***
	(0.387)		(0.018)
Constant	0.940	Const. (Deposit int. rate)	1.003
	(15.644)		(0.873)
Share branches	0.988	Deposit int. rate	1.000
	(1.913)		(13.065)
Avg. Price	−1.442***		
	(0.519)		
Borrower FE	0.899***		
	(0.220)		
Age	0.888***		
	(0.147)		
log Sales	0.890**		
	(0.396)		
log Asset	0.890		
	(1.202)		
Debt Eq.	0.899***		
	(0.136)		

Notes: This table report our estimates of the structural model of (18)-(20). Our sample runs from from 2018-Q3 to 2020-Q2. Standard errors are in parenthesis. Coefficients of demand and supply are displayed in the left and right sides of the table, respectively.

what would happen according to our model in the boom phase of the credit cycle when we expect a large number of firms to signal positive news. Under this scenario, more distorted banks would decrease prices by 32 basis points and increase the likelihood of new credit to firms with positive signals by 4.7% with respect to the benchmark rational lender. Results for the sub-sample of borrowers that still display negative news after the shift are almost symmetric. Compared to our empirical findings of table 4 and 5 our counterfactual increase in news induces a higher decrease (increase) in rates (quantities) with lower asymmetry in the response to positive/negative news. Finally, we shut down all beliefs' distortions, and see how banks respond to a median positive signal. Our model suggests an increase in prices and a mild reduction in quantities.

These three exercises help strengthen the reduced form findings of section 4, confirming that expectational errors could have a sizable impact on credit outcomes in imperfectly competitive markets. Importantly, these counterfactuals provide further evidence that distorted

Table 7: Accounting and prudential PD

	ΔPD_t^{IRB}					
Intercept	3.617***	3.565***	3.829***	3.996***	3.759***	4.182***
	(0.142)	(0.174)	(0.677)	(0.708)	(0.221)	(0.794)
N Obs.	145,429	145,429	145,429	145,429	145,429	145,429
Bank FE	-	Yes	No	Yes	Yes	Yes
Time FE	-	-	Yes	Yes	-	Yes
Sector FE	-	-	-	-	Yes	Yes

Notes: This table reports the intercept β_0 of the following regression: $\Delta PD_t^{IRB,i,b} = \beta_0 + \mathbf{\Gamma}'\mathbf{X} + \epsilon_t^{i,b}$ where $\mathbf{X}$ is a vector of controls including *total loans* and *credit age*. A positive and significant intercept means that whenever banks increase their PD^{EL} we observe a parallel increase in PD^{IRB}. Our sample runs from 2018 Q3 to 2020 Q2 and includes all borrowers that migrate from $S1$ to $S2$. Standard errors are clustered at 2-digit NACE sectors.

expectations among banks have the potential to magnify the boom-bust phase of the credit cycle. These findings suggests that a more resilient and efficient banking system should not be unduly sensitive to credit signals, especially during downturns when lenders may excessively tighten credit supply as a result. Hence, policies aimed at the assessing and curtailing banks' overreaction to news may be particularly valuable.

6 Robustness

Together with the full sample results shown in the appendix, we conduct two other main robustness exercises to strengthen our findings. First, we expand the discussion of section 2 and try to mitigate the concern that banks report the PD strategically. Second, we replicate our rates and quantities regressions of section 4 but using our macro measure of news. Overall our results are robust both to the inclusion of additional data and to alternative news definitions.

6.1 PD and strategic behaviour

One concern when looking at IRB PDs (that in this paragraph we denote PD^{IRB}) is that banks may systematically under-report their "true" credit risk assessment to minimize capital requirements and boost profitability (Behn et al., 2022). While we cannot completely rule out banks' strategic behavior, we take several steps to mitigate this issue.

First, looking at table 2, if anything, banks seem to *over estimate* the probability of default, at least in our sample period. Second, we correlate our PD^{IRB} to another probability of default

Table 8: Forecast errors and accounting news

	$FE^{\theta,i,b}_{t+4\|t}$					
Rating Decrease	-0.002	-0.001	-0.002	-0.002	-0.001	-0.028^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.002)
Rating Increase	-0.002	-0.001	-0.002	-0.002	-0.000	0.004^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N Obs.	1,550,735	1,550,735	1,550,735	1,550,735	1,550,735	821,889
Bank FE	-	Yes	No	-	Yes	-
Sector FE	-	-	Yes	-	Yes	-
Province FE	-	-	-	Yes	Yes	-
Borrower FE	-	-	-	-	-	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table provides coefficient estimates of the regression $FE^{\theta,i,b}_{t+3|t} = \beta_0 + \beta_1 D1^{i,b}_t + \beta_2 D2^{i,b}_t + \mathbf{\Gamma}'\mathbf{X} + \epsilon^{i,b}_{t+3}$, where $D1$ ($D2$) are dummy variables equal to 1 for a rating decrease (increase) and 0 for no change, and $\mathbf{X}$ is a control matrix that includes various controls such as *loan size* and *credit age*. Our sample runs from 2018 Q3 to 2020 Q2. Standard errors are clustered at NACE 2 digit-level.

(PD^{EL}) and test whether forecast errors still display excess sensitivity to news constructed according to the latter. PD^{EL} is the probability of default that banks use to compute the expected loss of a borrower according to the IFRS 9 accounting principle. Since this accounting PD is *not* used to compute capital requirements, it should not be subject to the same degree of strategic behaviour as PD^{IRB}.

Unfortunately, we cannot observe directly PD^{EL} in AnaCredit but we can observe the "rating" class[17] Sn assigned to a specific borrower by the bank: $S1$ corresponds to borrowers with low credit risk, $S2$ to borrowers with a significant increase in credit risk but still performing, and $S3$ to defaulted borrowers. Since the rating is a function of PD^{EL}, we can measure changes in the latter by rating migrations. Our first test is as follows: if a bank recognizes a significant increase in credit risk of some counterparty, which corresponds to a worsening of rating from $S1$ to $S2$, and if IRB models are consistent with accounting practices, we should observe a similar change in PD^{IRB} too.

Table 7 reports our findings. The estimation sample runs from 2018 Q3 to 2020 Q2 and includes only borrowers that migrate from $S1$ to $S2$. The coefficient of interests β_0 is always positive and statistically significant, implying that there is a strong positive correlation between the accounting (EL) and prudential (IRB) PD. Note that we cannot use PD^{EL} to compute fore-

[17] With a slight abuse of terminology we adopt the term "rating" in place of the more correct "staging". Since staging is a loan-level outcome, we pool together loans' staging for each firm to get a borrower-specific measure.

Table 9: Effects on Interest Rates - Macro News

	(1)	(2)	(3)
$News_t$	-0.00405***	-0.000911	0.00187***
	(0.00151)	(0.00123)	(0.000570)
D_t^b		0.0107***	0.00721***
		(0.000715)	(0.000401)
$News_t \times D_t^b$		-0.00637***	-0.00407***
		(0.00111)	(0.000768)
N Obs.	249144	249144	249144
Province FE	Yes	Yes	-
Time FE	Yes	Yes	Yes
Borrower FE	-	-	Yes

Notes: This table provides estimates of (12) where we measure signals using the macro news defined in (1). Sample used is sample 2 as oulined in footnote 13 and runs from 2018-Q3 to 2020-Q2 including all borrowers affiliated with at least one rational ($D = 0$) and one diagnostic bank ($D = 1$). Standard errors in parenthesis are clustered at the NACE 2-digit level. Standard errors in parenthesis are clustered at the province level.

cast errors since the rating classes $S1$ and $S2$ are accounting concepts and – differently from the default status - their physical realizations are not observable.

Finally, we use the IFRS 9 ratings to construct an alternative "micro" news and test for lenders excess sensitivity similarly to equation (11). We look again at the subset of borrowers who flow from one rating class Sn to another as a signal of their creditworthiness. For each borrower-bank pair we measure negative and positive news with two indicator variables equal to 1 in case of a rating decrease ($D1 = 1$) or increase ($D2 = 1$). Borrowers who see their rating class unchanged represent the baseline case of no news ($D1 = 0$ and $D2 = 0$). Notice that since $D1$ signals negative news the expected sign of the overreaction coefficient is negative (an overreaction to negative news induce a higher-than-due PD, hence a negative forecast error). When we introduce fixed effects, the coefficients of both subgroups are statistically significant and correct in sign, as table 8 shows. The arrival of positive or negative "accounting" news makes bankers overreact.

6.2 Lending effects with macro signal

In this section we measure the effects of macroeconomic signals on credit allocations by re-estimating equations (12), (13) and (14) using our macro signal from (1). Tables 9 and 10 report our findings. Our results are qualitatively similar to those of section 4 and confirm that deviation from full rationality can affect credit markets. With regards to interest rates on new contracts, the main coefficient $News \times D$ is both negative and statistically significant consistent with our results for micro news of table 4. Following a one standard deviation increase in macro signal, distorted banks decrease the interest rate on average by 15-20 basis points more than rational ones.

Looking at the amount of credit, on the *extensive* margin (see table 10, panel B) the interaction coefficient is once again positive and statistically significant as in table 5: one standard deviation of positive macro signal leads a diagnostic lender to increase by around 5% the probability of new credit with respect to rational peers. Moving to the *intensive* margin (panel A), our estimates for the main coefficient in our preferred specification with borrower fixed effects (column 3) are still positive but less statistically significant, likely because of a reduction in the number of observations and the lower signal-to-noise ratio of macro signal compared to micro news.

Table 10: Effects on Quantities - Macro Signal

	(1)	(2)	(3)
Panel A: Intensive Margin - Dependent: $log(LoanSize)_t^{i,b}$			
$News_t$	0.240*	0.225*	-0.0537
	(0.130)	(0.116)	(0.0476)
D_t^b		-0.271***	-0.0234
		(0.0619)	(0.0319)
		(0.0588)	(0.0322)
$News_t \times D_t^b$		0.0476	0.0748*
		(0.0856)	(0.0449)
N. Obs.	249144	249144	249144
Panel B: Extensive Margin - Dependent: $NC_t^{i,b}$			
$News_t$	0.0273	-0.0604***	-0.0558***
	(0.0255)	(0.0227)	(0.0202)
D_t^b		0.0462***	0.0447***
		(0.0156)	(0.0155)
$News_t \times D_t^b$		0.148***	0.139***
		(0.0222)	(0.0220)
N Obs.	495717	495717	495717
Sector FE	Yes	Yes	-
Province FE	Yes	Yes	-
Time FE	Yes	Yes	Yes
Borrower FE	-	-	Yes

Notes: This table reports estimates of (13)-(14) in, respectively, panel A and B. Both panels include observations from 2018-Q3 to 2020-Q2, including all borrowers affiliated with at least one rational $(D = 0)$ and one diagnostic bank $(D = 1)$. The sample used for panel A is Sample 2, as outlined in footnote 13. The sample used for panel B is Sample 3, where the dependent variable new contract NC is defined as a contract originated at most 3 periods before t. Standard errors in parenthesis are clustered at the province level.

7 Conclusion

In this paper, we exploit a novel loan-level dataset to assess lenders' beliefs on borrowers' creditworthiness and their effect on interest rates and loan amounts. We provide evidence that our granular metric is a valid measure of expectations and is complementary to survey data and other proxies used in the field so far.

We contribute to the literature of lenders' beliefs and show that bankers over- (under-) estimate borrowers' default when they receive negative (positive) news. The bias is more pronounced when negative news occurs. We also find significant heterogeneity in lenders' levels of overreaction, which we exploit to quantify the effect of expectational distortions on lending prices and quantities. Distorted banks receiving positive news tend to reduce borrowers' interest rates by 5 basis points, offer loan amounts higher by around 3% to 9%, and are 1% more likely to engage in new lending compared to rational banks. Our results are robust to a sectoral measure of news.

Finally, we rationalize our empirical findings through a structural estimation of a banking competition model. In a counterfactual exercise we show that distorted expectations among banks can amplify boom-bust cycles by influencing credit prices and quantities. We conclude that policies related to the identification and mitigation of excessive overreaction by banks could be valuable especially in terms of financial stability and efficient credit allocation.

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A Tables

Table A.1: Summary statistics - By Geographical Area

	N	Mean	p10	p25	p50	p75	p90	Max	Min	SD
					North-East					
PD	342,091	0.0334	0.0015	0.003	0.0068	0.0176	0.0401	1	0	0.1291
Default	177,620	0.0177	0	0	0	0	0	1	0	0.1318
FcstError	177,620	-0.0005	-0.034	-0.0159	-0.0065	-0.0029	-0.0014	1	-1	0.1291
Micro news	297,926	-0.0032	-0.0044	0	0	0	0.0039	1	-1	0.0584
log(Loansize)	342,091	11.76	9.90	10.66	11.69	12.83	13.81	20.03	-1.09	1.70
InterestRate	342,091	0.0263	0.0062	0.0117	0.0208	0.0351	0.0536	0.1950	-0.0032	0.0206
CreditAge	342,091	9.58	1	2	5	12	22	169	0	13.30
					North-West					
PD	413,176	0.0401	0.0015	0.0033	0.0069	0.0201	0.0617	1	0	0.1423
Default	196,917	0.0207	0	0	0	0	0	1	0	0.1426
FcstError	196,917	-0.0009	-0.0389	-0.0179	-0.0066	-0.0030	-0.0013	1	-1	0.1379
Micro news	353,081	-0.0034	-0.0063	0	0	0.000001	0.0049	1	-1	0.0619
log(Loansize)	413,176	11.62	9.76	10.48	11.51	12.67	13.81	20.21	-1.09	1.68
InterestRate	413,176	0.0284	0.0050	0.0115	0.0221	0.0398	0.0602	0.4951	-0.0021	0.0233
CreditAge	413,176	10.74	1	2	5	12	29	161	0	14.89
					Center					
PD	236,584	0.0528	0.002	0.0043	0.0105	0.0282	0.0729	1	0	0.1698
Default	114,885	0.0271	0	0	0	0	0	1	0	0.1626
FcstError	114,885	0.0013	-0.0461	-0.0209	-0.0092	-0.0041	-0.0017	1	-1	0.1571
Micro news	203,457	-0.0046	-0.0074	0	0	0	0.0059	1	-1	0.0709
log(Loansize)	236,584	11.41	9.61	10.30	11.40	12.42	13.52	20.36	-1.79	1.71
InterestRate	236,584	0.0313	0.0055	0.0128	0.0260	0.0438	0.0647	0.3345	-0.0368	0.0244
CreditAge	236,584	10.78	1	2	5	13	28	165	0	14.73
					South					
PD	156,616	0.0565	0.0025	0.00517	0.0122	0.0308	0.0758	1	0	0.1751
Default	78,004	0.0310	0	0	0	0	0	1	0	0.1735
FcstError	78,004	0.0036	-0.0548	-0.0242	-0.0105	-0.0049	-0.0021	1	-1	0.1687
Micro news	135,189	-0.0053	-0.0077	0	0	0	0.0061	1	-1	0.0789
log(Loansize)	156,616	11.49	9.87	10.50	11.51	12.46	13.34	17.90	-0.69	1.53
InterestRate	156,616	0.0349	0.0081	0.0162	0.0300	0.0486	0.0699	0.9999	0.0000	0.0256
CreditAge	156,616	10.58	1	2	6	13	26	185	0	13.38
					Islands					
PD	57,804	0.0567	0.0022	0.0051	0.0141	0.0338	0.0816	1	0	0.1698
Default	30,132	0.0259	0	0	0	0	0	1	0	0.1590
FcstError	30,132	-0.0058	-0.0617	-0.0308	-0.0117	-0.0049	-0.002	1	-1	0.1600
Micro news	50,307	-0.0045	-0.0099	0	0.0000	0.0000	0.0079	1	-1	0.0778
log(Loansize)	57,804	11.3700	9.8200	10.37	11.28	12.32	13.2100	17.72	-0.69	1.5200
InterestRate	57,804	0.04	0.01	0.02	0.03	0.05	0.07	0.17	0.00	0.02
CreditAge	57,804	11.1700	1.0000	2.0000	5.0000	14.0000	33.0000	127.0000	0.0000	15.0300

Notes: This table shows summary statistics of the dataset aggregated at the borrower-level. The PD is the likelihood computed at t of being in default at $t+1$, where t indicates a 12-months period. Default indicates the realized status of default in $t+1$. Fcst Error is computed as the difference between Default at $t+1$ and PD at t. Micro news is the negative difference between PD of the current quarter and PD of the previous quarter. log(Loansize) is the logarithm of the loan size in euro, where the loan size is computed as the sum of commitment at inception and off-balance sheet amount of credit. Credit Age is the difference in months between the reporting date and the date of origination of the debt position.

Table A.2: Summary statistics - By Sector

	N	Mean	p10	p25	p50	p75	p90	Max	Min	SD
					Agriculture and Mining					
PD	52,805	0.0418	0.002	0.0043	0.0100	0.0233	0.0624	1	0	0.1405
Default	27,281	0.0167	0	0	0	0	0	1	0	0.1281
Fcst Error	27,281	-0.0093	-0.0459	-0.0209	-0.0093	-0.0041	-0.0020	1	-1	0.1328
Micro news	45,897	-0.0026	-0.0067	0	0	0	0.0061	1	-1	0.0648
log(Loansize)	52,805	11.73	10.13	10.82	11.67	12.61	13.53	17.73	0.69	1.43
Interest Rate	52,805	0.0305	0.0095	0.0165	0.0263	0.0400	0.0571	0.1700	0	0.0210
Credit Age	52,805	11.42	1	2	6	15	32	116	0	14.01
					Construction					
PD	94,940	0.0670	0.002	0.0041	0.0112	0.0329	0.094	1	0	0.1965
Default	44,314	0.0295	0	0	0	0	0	1	0	0.1691
Fcst Error	44,314	-0.0012	-0.0617	-0.0267	-0.0102	-0.0039	-0.0015	1	-1	0.1640
Micro news	81,005	-0.0049	-0.0085	0	0	0	0.0074	1	-1	0.0756
log(Loansize)	94,940	11.25	9.62	10.22	11.16	12.21	13.20	18.86	0.00	1.59
Interest Rate	94,940	0.0353	0.0080	0.0166	0.0300	0.0491	0.0700	0.4947	0	0.0256
Credit Age	94,940	11.39	1	2	6	14	33	145	0	14.98
					Manufacturing					
PD	468,043	0.0361	0.0015	0.0030	0.0068	0.0189	0.05	1	0	0.1352
Default	239,749	0.0193	0	0	0	0	0	1	0	0.1375
Fcst Error	239,749	0.0002	-0.0374	-0.0159	-0.0063	-0.0028	-0.0013	1	-1	0.1330
Micro news	406,003	-0.0036	-0.0047	0	0	0	0.0039	1	-1	0.0603
log(Loansize)	468,043	11.81	9.89	10.75	11.81	12.90	13.84	20.03	-1.79	1.73
Interest Rate	468,043	0.0262	0.0050	0.0104	0.0200	0.0357	0.0564	1.0000	0	0.0222
Credit Age	468,043	10.07	1	2	5	12	23	185	0	14.10
					Services					
PD	590,483	0.0461	0.002	0.0041	0.0102	0.0242	0.0631	1	0	0.1547
Default	286,214	0.0251	0	0	0	0	0	1	0	0.1565
Fcst Error	286,214	0.0009	-0.0431	-0.0201	-0.0089	-0.0039	-0.0018	1	-1	0.1521
Micro news	507,055	-0.0042	-0.0069	0	0	0	0.0058	1	-1	0.0689
log(Loansize)	590,483	11.47	9.76	10.36	11.41	12.43	13.53	20.37	-1.10	1.65
Interest Rate	590,483	0.0315	0.0068	0.0138	0.0262	0.0435	0.0641	0.3065	-0.0369	0.0239
Credit Age	590,483	10.46	1	2	5	12	27	165	0	14.26

Notes: This table shows summary statistics of the dataset aggregated at the borrower-level. The PD is the likelihood computed at t of being in default at $t+1$, where t indicates a 12-months period. Default indicates the realized status of default in $t+1$. Fcst Error is computed as the difference between Default at $t+1$ and PD at t. Micro news is the negative difference between PD of the current quarter and PD of the previous quarter. log(Loansize) is the logarithm of the loan size in euro, where the loan size is computed as the sum of commitment at inception and off-balance sheet amount of credit. Credit Age is the difference in months between the reporting date and the date of origination of the debt position.

Table A.3: Summary statistics - Anacredit with Macro Indices

	N	Mean	p10	p25	p50	p75	p90	Max	Min	SD
PD	979,430	0.0421	0.0018	0.0036	0.0080	0.0209	0.0617	1	0	0.1476
Dflt	489,526	0.0224	0	0	0	0	0	1	0	0.1480
Fcst Error	489,526	0.0005	-0.0399	-0.0187	-0.0069	-0.0033	-0.0015	1	-1	0.1432
Micro News	845,635	-0.0040	-0.0059	0	0	0	0.0046	1	-1	0.0649
MacroNews	979,430	0.0319	-0.1618	-0.0803	0.0172	0.0943	0.1769	7.3723	-0.8479	0.3864
MacroNewsLag	979,430	0.0183	-0.1631	-0.0930	-0.0028	0.0758	0.1745	7.3723	-0.8479	0.3741
log(Loansize)	979,430	11.60	9.77	10.51	11.51	12.61	13.75	20.37	-1.79	1.68
InterestRate	979,430	0.0291	0.0057	0.0121	0.0230	0.0400	0.0610	1.0000	-0.0368	0.0235
CreditAge	979,430	10.07	1	2	5	12	24	185	0	14.09

Notes: This table shows summary statistics of the Anacredit dataset merged with Istat macro indicators, aggregated at the borrower-level. Macro News is the quarter-on-quarter percentage change of the industrial production (or sales for services) index. The PD is the likelihood computed at t of being in default at $t+1$, where t indicates a 12-months period. Default indicates the realized status of default in $t+1$. Fcst Error is computed as the difference between Default at $t+1$ and PD at t. Micro news is the negative difference between PD of the current quarter and PD of the previous quarter. log(Loansize) is the logarithm of the loan size in euro, where the loan size is computed as the sum of commitment at inception and off-balance sheet amount of credit. Credit Age is the difference in months between the reporting date and the date of origination of the debt position.

Table A.4: Nace classification - 1st part

Nace 2D	Description 2D	Nace 1D	Descripion 1D	Nace macro	Description
1	crop and animal production, hunting and related service activities	A	agriculture, forestry and fishing	AA	agri and mining
2	forestry and logging	A	agriculture, forestry and fishing	AA	agri and mining
3	fishing and aquaculture	A	agriculture, forestry and fishing	AA	agri and mining
5	mining of coal and lignite	B	mining and quarrying	AA	agri and mining
6	extraction of crude petroleum and natural gas	B	mining and quarrying	AA	agri and mining
7	mining of metal ores	B	mining and quarrying	AA	agri and mining
8	other mining and quarrying	B	mining and quarrying	AA	agri and mining
9	mining support service activities	B	mining and quarrying	AA	agri and mining
10	manufacture of food products	C	manufacturing	C	manufacturing
11	manufacture of beverages	C	manufacturing	C	manufacturing
12	manufacture of tobacco products	C	manufacturing	C	manufacturing
13	manufacture of textiles	C	manufacturing	C	manufacturing
14	manufacture of wearing apparel	C	manufacturing	C	manufacturing
15	manufacture of leather and related products	C	manufacturing	C	manufacturing
16	manufacture of wood and of products of wood and cork, except furniture, manufacture of articles of straw and plaiting materials	C	manufacturing	C	manufacturing
17	manufacture of paper and paper products	C	manufacturing	C	manufacturing
18	printing and reproduction of recorded media	C	manufacturing	C	manufacturing
19	manufacture of coke and refined petroleum products	C	manufacturing	C	manufacturing
20	manufacture of chemicals and chemical products	C	manufacturing	C	manufacturing
21	manufacture of basic pharmaceutical products and pharmaceutical preparations	C	manufacturing	C	manufacturing
22	manufacture of rubber and plastic products	C	manufacturing	C	manufacturing
23	manufacture of other non-metallic mineral products	C	manufacturing	C	manufacturing
24	manufacture of basic metals	C	manufacturing	C	manufacturing
25	manufacture of fabricated metal products, except machinery and equipment	C	manufacturing	C	manufacturing
26	manufacture of computer, electronic and optical products	C	manufacturing	C	manufacturing
27	manufacture of electrical equipment and of non-electric domestic appliances	C	manufacturing	C	manufacturing
28	manufacture of machinery and equipment n.e.c.	C	manufacturing	C	manufacturing
29	manufacture of motor vehicles, trailers and semi-trailers	C	manufacturing	C	manufacturing
30	manufacture of other transport equipment	C	manufacturing	C	manufacturing
31	manufacture of furniture	C	manufacturing	C	manufacturing
32	other manufacturing	C	manufacturing	C	manufacturing
33	repair and installation of machinery and equipment	C	manufacturing	C	manufacturing
35	electricity, gas, steam and air conditioning supply	D	electricity, gas, steam and air conditioning supply	SS	services
36	water collection, treatment and supply	E	water supply sewerage, waste management and remediation activities	SS	services
37	sewerage	E	water supply sewerage, waste management and remediation activities	SS	services
38	waste collection, treatment and disposal activities, materials recovery	E	water supply sewerage, waste management and remediation activities	SS	services
39	remediation activities and other waste management services	E	water supply sewerage, waste management and remediation activities	SS	services
41	construction of buildings	F	construction	F	construction
42	civil engineering	F	construction	F	construction
43	specialised construction activities	F	construction	F	construction
45	wholesale and retail trade and repair of motor vehicles and motorcycles	G	wholesale and retail trade repair of motor vehicles and motorcycles	SS	services

Notes: This table shows the complete list of Nace sectors (2007) by Eurostat. Columns 1 and 2 contain the code and the description of the sectors at the 2-digit level; columns 3 and 4 contain the code and the description of sectors at the 1-digit level; column 5 and 6 contain a macro classification: agriculture and mining, construction,. manufacturing and services. Additional information can be obtained at the official page of the Eurostat.

Table A.5: Nace classification - 2nd part

Nace 2D	Description 2D	Nace 1D	Descripion 1D	Nace macro	Description
45	wholesale and retail trade and repair of motor vehicles and motorcycles	G	wholesale and retail trade repair of motor vehicles and motorcycles	SS	services
46	wholesale trade, except of motor vehicles and motorcycles	G	wholesale and retail trade repair of motor vehicles and motorcycles	SS	services
47	retail trade, except of motor vehicles and motorcycles	G	wholesale and retail trade repair of motor vehicles and motorcycles	SS	services
49	land transport and transport via pipelines	H	transportation and storage	SS	services
50	water transport	H	transportation and storage	SS	services
51	air transport	H	transportation and storage	SS	services
52	warehousing and support activities for transportation	H	transportation and storage	SS	services
53	postal and courier activities	H	transportation and storage	SS	services
55	accommodation	I	accommodation and food service activities	SS	services
56	food service activities	I	accommodation and food service activities	SS	services
58	publishing activities	J	information and communication	SS	services
59	motion picture, video and television programme production, sound recording and music publishing activities	J	information and communication	SS	services
60	programming and broadcasting activities	J	information and communication	SS	services
61	telecommunications	J	information and communication	SS	services
62	computer programming, consultancy and related activities	J	information and communication	SS	services
63	information service activities	J	information and communication	SS	services
64	financial service activities, except insurance and pension funding	K	financial and insurance activities	SS	services
65	insurance, reinsurance and pension funding, except compulsory social security	K	financial and insurance activities	SS	services
66	activities auxiliary to financial services and insurance activities	K	financial and insurance activities	SS	services
68	real estate activities	L	real estate activities	SS	services
69	legal and accounting activities	M	professional, scientific and technical activities	SS	services
70	activities of head offices, management consultancy activities	M	professional, scientific and technical activities	SS	services
71	architectural and engineering activities, technical testing and analysis	M	professional, scientific and technical activities	SS	services
72	scientific research and development	M	professional, scientific and technical activities	SS	services
73	advertising and market research	M	professional, scientific and technical activities	SS	services
74	other professional, scientific and technical activities	M	professional, scientific and technical activities	SS	services
75	veterinary activities	M	professional, scientific and technical activities	SS	services
77	rental and leasing activities	N	administrative and support service activities	SS	services
78	employment activities	N	administrative and support service activities	SS	services
79	travel agency, tour operator and other reservation service and related activities	N	administrative and support service activities	SS	services
80	security and investigation activities	N	administrative and support service activities	SS	services
81	services to buildings and landscape activities	N	administrative and support service activities	SS	services
82	office administrative, office support and other business support activities	N	administrative and support service activities	SS	services
84	public administration and defence, compulsory social security	O	public administration and defence compulsory social security	SS	services
85	education	P	education	SS	services
86	human health activities	Q	human health and social work activities	SS	services
87	residential care activities	Q	human health and social work activities	SS	services
88	social work activities without accommodation	Q	human health and social work activities	SS	services
90	creative, arts and entertainment activities	R	arts, entertainment and recreation	SS	services
91	libraries, archives, museums and other cultural activities	R	arts, entertainment and recreation	SS	services
92	gambling and betting activities	R	arts, entertainment and recreation	SS	services
93	sports activities and amusement and recreation activities	R	arts, entertainment and recreation	SS	services
94	activities of membership organisations	S	other service activities	SS	services
95	repair of computers and personal and household goods	S	other service activities	SS	services
96	other personal service activities	S	other service activities	SS	services
97	activities of households as employers of domestic personnel	T	activities of households as employers undifferentiated goods- and services-producing activities of households for own use	SS	services
98	undifferentiated goods- and services-producing activities of private households for own use	T	activities of households as employers undifferentiated goods- and services-producing activities of households for own use	SS	services
99	activities of extraterritorial organisations and bodies	U	activities of extraterritorial organisations and bodies	SS	services

Notes: This table shows the complete list of Nace sectors (2007) by Eurostat. Columns 1 and 2 contain the code and the description of the sectors at the 2-digit level; columns 3 and 4 contain the code and the description of sectors at the 1-digit level; column 5 and 6 contain a macro classification: agriculture and mining, construction,. manufacturing and services. Additional information can be obtained at the official page of the Eurostat.

Table A.6: FE Predictability - Micro News, full sample

	(1)	(2)	(3)
		Panel A: All Micro News	
$News_t$	0.185***	0.187***	0.400***
	(0.012)	(0.012)	(0.008)
N	894148	894148	894148
		Panel B: Negative Micro News	
$News_t$	0.204***	0.205***	0.857***
	(0.020)	(0.020)	(0.017)
N	221097	221097	221097
		Panel C: Non-Negative Micro News	
$News_t$	0.148***	0.150***	0.243***
	(0.015)	(0.014)	(0.013)
N	673051	673051	673051
Time FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Sector FE	-	Yes	-
Province FE	-	Yes	-
Borrower FE	-	-	Yes

Notes: This table report estimates of equation (11) where we measure signals using the micro news defined in (1). As controls we include various fixed effects, loan size, credit age, ... Our sample runs from from 2018-Q3 to 2023-Q2. Standard errors are in parenthesis and are clustered at the Nace 2-digit level.

Table A.7: Effects on Interest Rates - Micro News, full sample

	(1)	(2)	(3)
$News_t$	-0.057^{***}	-0.054^{***}	-0.019^{***}
	(0.007)	(0.007)	(0.003)
D_t^b		-0.005^{***}	-0.002^{***}
		(0.000)	(0.000)
$News_t \times D_t^b$		-0.002	-0.004^{**}
		(0.005)	(0.002)
N Obs.	994969	994969	994969
Sector FE	Yes	Yes	-
Province FE	Yes	Yes	-
Time FE	Yes	Yes	Yes
Borrower FE	-	-	Yes

Notes: this table provides estimates of (12) where we measure signals using the micro news defined in (1). Our sample runs from 2018-Q3 to 2023-Q2 and includes (i) all borrowers affiliated with at least one less distorted ($D = 0$) and one diagnostic bank ($D = 1$), and (ii) all contracts originated no later than 1 quarter before the reporting date. Standard errors are in parenthesis and are clustered at the Nace 2-digit level.

Table A.8: Effects on Spreads - Micro News, full sample

	(1)	(2)	(3)
$News_t$	-0.059^{***}	-0.055^{***}	-0.020^{***}
	(0.007)	(0.007)	(0.003)
D_t^b		-0.006^{***}	-0.003^{***}
		(0.000)	(0.000)
$News_t \times D_t^b$		-0.001	-0.005^{**}
		(0.004)	(0.002)
N	935696	935696	935696
Time FE	Yes	Yes	Yes
Sector FE	Yes	Yes	-
Province FE	Yes	Yes	-
Borrower FE	-	-	Yes

Notes: this table provides estimates of (12) where we measure signals using the micro news defined in (1). The dependent variable is now the interest rate spread $s_t^{i,b} := r_t^{i,b} - r_t^f$ with r_t^f the risk free rate. To construct the spread, we first build risk free yield curves at monthly frequency interpolating via splines the Euribor/Eurirs rates for all maturities ranging from 1 month to 30 years. Then, for a fixed rate instrument we match the loan rate r_t with the risk-free rate r_t^f prevailing at contract inception with maturity equal to the loan original duration. For a floating rate loan we use instead the risk free rate prevailing one month before each observation date and with the same maturity as the loan payment frequency (which is typically below 6 months). Our sample runs from 2018-Q3 to 2023-Q2 and includes (i) all borrowers affiliated with at least one less distorted ($D = 0$) and one diagnostic bank ($D = 1$), and (ii) all contracts originated no later than 1 quarter before the reporting date. Standard errors are in parenthesis and are clustered at the Nace 2-digit level.

Table A.9: Effects on Quantities, full sample

	(1)	(2)	(3)
Panel A: Intensive Margin - Dependent: $log(LoanSize)_t^{i,b}$			
$News_t$	2.054***	2.028***	0.749***
	(0.236)	(0.232)	(0.140)
D_t^b		0.214***	−0.018
		(0.070)	(0.044)
$News_t \times D_t^b$		0.093	0.320*
		(0.297)	(0.177)
N Obs.	1013357	1013357	1013357
Panel B: Extensive Margin - Dependent: $NC_t^{i,b}$			
$News_t$	0.036***	0.036***	0.034**
	(0.008)	(0.010)	(0.016)
D_t^b		0.031***	0.047***
		(0.012)	(0.013)
$News_t \times D_t^b$		0.027	0.037**
		(0.019)	(0.018)
N Obs.	4400813	4400813	4400813
Time FE	Yes	Yes	Yes
Sector FE	Yes	Yes	-
Province FE	Yes	Yes	-
Borrower FE	-	-	Yes

Notes: this table reports estimates of (13)-(14) in, respectively, panel A and B. We measure signals using the micro news defined in (1). Our sample for panel B runs from from 2018-Q3 to 2023-Q2 and includes all borrowers affiliated with at least one rational ($D = 0$) and one diagnostic bank ($D = 1$). The sample for panel A is a subset of the one used for panel B further restricted to all contracts originated no later than 3 quarters before the reporting date. Standard errors are in parenthesis and are clustered at the Nace 2-digit level.

Table A.10: Forecast Errors Predictability - alternative default definition

	(1)	(2)	(3)
$News_t$	0.207^{***}	0.205^{***}	0.197^{***}
	(0.006)	(0.006)	(0.004)
N	894148	894148	894148
Time FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Sector FE	-	Yes	-
Province FE	-	Yes	-
Borrower FE	-	-	Yes

Notes: This table report estimates of equation (11) where we measure signals using the micro news defined in (1). We compute forecast errors as $FE^{i,b}_{t+4} = \widetilde{Def}^{i,b}_{t+4} - PD^{i,b}_t$ where $\widetilde{Def}^{i,b}$ is an indicator variable equal to 1 if bank b reports borrower i in past-due for more than 90/180 days. As controls we include various fixed effects, loan size, credit age, ... Our sample runs from from 2018-Q3 to 2023-Q2. Standard errors are in parenthesis and are clustered at the Nace 2-digit level.

B Proofs

Model - main

1. Proof Normalizing PD (eq 8,9).

   By definition $x_{t+1} \sim N(\hat{x}_{t+1}, \Omega)$. It follows that the standardized variable for x_{t+1} is $x^s = \frac{x_{t+1} - \hat{x}_{t+1}}{\Omega^{1/2}}$. The conditional expectation of firm's default status, i.e. the probability of default, is derived as

$$
\begin{aligned}
\mathbb{E}(z_{t+1}|y^t) &= \mathbb{P}(x_{t+1} < a) \\
&= \mathbb{P}(\Omega^{1/2} x^s + \hat{x}_{t+1} < a) \\
&= \mathbb{P}\Big(x^s < \frac{a - \hat{x}_{t+1}}{\Omega^{1/2}}\Big) \\
&= \Phi\Big(\frac{a - \hat{x}_{t+1}}{\Omega^{1/2}}\Big)
\end{aligned}
$$

2. Taylor approximation, complete.

   From the definition of z_{t+1} and $\mathbb{E}_t(z_{t+1})$, we can decompose their sum as follows (recall that from the starting equations describing the noisy process $u_{t+1} = z_{t+1} - x_{t+1}$, which here is interpreted as the difference between z_{t+1} and $\mathbb{E}_t(z_{t+1})$.)

$$
\begin{aligned}
z_{t+1} - \mathbb{E}_t^{\theta}(z_{t+1}) &= \underbrace{z_{t+1} - \mathbb{E}_t(z_{t+1})}_{=w_{t+1}} + \mathbb{E}_t(z_{t+1}) - \mathbb{E}_t^{\theta}(z_{t+1}) \\
FE^{\theta}_{t+1|t} &= w_{t+1} + \Phi\Big(\frac{a - \hat{x}_{t+1}}{\Omega_t^{1/2}}\Big) - \Phi\Big(\frac{a - \hat{x}^{\theta}_{t+1}}{\Omega_t^{1/2}}\Big) \qquad \text{(B.1)}
\end{aligned}
$$

   Equation (B.1) says that the forecast error of the diagnostic bankers increases the more (1) the signal is noisy and (2) the greater is the difference between the standard and diagnostic probability of default.

   Applying a Taylor approximation to function $\Phi(\cdot)$ around $\mathbf{x_0}$, for constant A, multiplicative vector $\mathbf{B}$ and each component j of $\mathbf{x_0}$. Suppose w.l.o.g. that $\mathbf{x_0} = \mathbb{E}(\hat{x}_{t+1|t} \quad I_t)' = (0 \quad 0)'$. We obtain a linear expression that reads as

$$
g(\hat{x}_{t+1}, I_t) = \Phi(A + \mathbf{B}'\mathbf{x}) \approx \Phi(A + \mathbf{B}'\mathbf{x_0}) + \sum_j B_j \phi(A + \mathbf{B}'\mathbf{x_0}) \times (x - x_{0j})
$$

which, applied to $\Phi\Big(\frac{a-\hat{x}_{t+1}}{\Omega_t^{1/2}}\Big)$ and $\Phi\Big(\frac{a-\hat{x}^{\theta}_{t+1}}{\Omega_t^{1/2}}\Big)$ gives:

$$\begin{aligned}\Phi\Big(\frac{a-\hat{x}_{t+1}}{\Omega_t^{1/2}}\Big) \approx\; &\Phi\Big(\frac{a}{\Omega^{1/2}}-\frac{1}{\Omega^{1/2}}\hat{x}_{0,t+1}\Big)\\ &+\frac{1}{\Omega^{1/2}}\phi\Big(\frac{a}{\Omega^{1/2}}-\frac{1}{\Omega^{1/2}}\hat{x}_{0,t+1}\Big)(\hat{x}_{t+1}-\hat{x}_{0,t+1})\\ &=\Phi\Big(\frac{a}{\Omega^{1/2}}\Big)-\frac{1}{\Omega^{1/2}}\phi\Big(\frac{a}{\Omega^{1/2}}\Big)\hat{x}_{t+1}\end{aligned}$$

$$\begin{aligned}\Phi\Big(\frac{a-\hat{x}^{\theta}_{t+1}}{\Omega_t^{1/2}}\Big) &= \Phi\Big(\frac{a-\hat{x}_{t+1}-\theta K_t I_t}{\Omega_t^{1/2}}\Big)\\ &\approx \Phi\Big(\frac{a}{\Omega^{1/2}}-\frac{1}{\Omega^{1/2}}\hat{x}_{0,t+1}-\frac{1}{\Omega^{1/2}}K_t\theta I_{0,t}\Big)\\ &-\frac{1}{\Omega^{1/2}}\phi\Big(\frac{a}{\Omega^{1/2}}-\frac{1}{\Omega^{1/2}}\hat{x}_{0,t+1}\Big)(\hat{x}_{t+1}-\hat{x}_{0,t+1})\\ &-\frac{1}{\Omega^{1/2}}K_t\theta\phi\Big(\frac{a}{\Omega^{1/2}}-\frac{1}{\Omega^{1/2}}K_t\theta I_{0,t}\Big)(I_t-I_{0,t})\\ &=\Phi\Big(\frac{a}{\Omega^{1/2}}\Big)-\frac{1}{\Omega^{1/2}}\phi\Big(\frac{a}{\Omega^{1/2}}\Big)\hat{x}_{t+1}-\frac{1}{\Omega^{1/2}}K_t\theta\phi\Big(\frac{a}{\Omega^{1/2}}\Big)I_t\end{aligned}$$

From the last two expressions, (B.1) becomes

$$\begin{aligned}FE^{\theta}_{t+1|t} &\approx w_{t+1}+\Phi\Big(\frac{a}{\Omega^{1/2}}\Big)-\frac{1}{\Omega^{1/2}}\phi\Big(\frac{a}{\Omega^{1/2}}\Big)\hat{x}_{t+1}\\ &-\Phi\Big(\frac{a}{\Omega^{1/2}}\Big)+\frac{1}{\Omega^{1/2}}\phi\Big(\frac{a}{\Omega^{1/2}}\Big)\hat{x}_{t+1}+\frac{1}{\Omega^{1/2}}K_t\theta\phi\Big(\frac{a}{\Omega^{1/2}}\Big)I_t\\ &\approx w_{t+1}+\theta\underbrace{\frac{1}{\Omega^{1/2}}}_{>0}\underbrace{K_t}_{>0}\underbrace{\phi\Big(\frac{a}{\Omega^{1/2}}\Big)}_{>0}I_t\end{aligned}$$

In the last expression, the only term that can make the overall coefficient equal to zero is *theta*. Therefore, we safely derive our last form of the equation and link it to the an empirical expression as described in the main model section.

$$FE^{\theta}_{t+1|t}=K_t\theta\frac{1}{\Omega^{1/2}}\phi\Big(\frac{a}{\Omega^{1/2}}\Big)I_t+w_{t+1}$$

Model - Real effects

Non linear relation for interest rate looks like

$$r_t=\frac{\Phi\Big(\frac{a-\hat{x}_{t+1}}{\Omega_t^{1/2}}\Big)}{1-\Phi\Big(\frac{a-\hat{x}_{t+1}}{\Omega_t^{1/2}}\Big)}$$

From the previous proofs we know that, linearizing the cumulative distribution function around a fixed point through a Taylor approximation, we obtain

$$\Phi(A + \mathbf{B}'\mathbf{x}) \approx \Phi(A + \mathbf{B}'\mathbf{x_0}) + \sum_j B_j \phi(A + \mathbf{B}'\mathbf{x_0}) \times (x - x_{0j})$$

If the pdf $\phi(\cdot)$ is symmetric around its mean, we obtain

$$\begin{aligned} r_t &\approx \frac{\Phi\left(\frac{a}{\Omega_t^{1/2}}\right)}{1 - \Phi\left(\frac{a}{\Omega_t^{1/2}}\right)} - \frac{1}{\Omega^{1/2}} \frac{\phi\left(\frac{a}{\Omega^{1/2}}\right)}{\Phi\left(\frac{a}{\Omega^{1/2}}\right)^2} \hat{x}_{t+1|t} \\ r_t^\theta &\approx r_t - \frac{\theta K_t}{\Omega^{1/2}} \frac{\phi\left(\frac{a}{\Omega^{1/2}}\right)}{\Phi\left(\frac{a}{\Omega^{1/2}}\right)^2} I_t \end{aligned}$$

The last one can be adapted as a linear regression where the only possible term equal to zero is the parameter θ

$$r_t^\theta = \beta_0 + \theta \cdot \beta_1 \widehat{PD}_{t+1|t} + \beta_2 I_t + \epsilon_t$$

Innovation as PD Variation

In our empirical exercise, we define as the main measure for innovation

$$I_t = -(\widehat{PD}^\theta_{t+11|t-1} - \widehat{PD}^\theta_{t+8|t-4}) = -\Delta \widehat{PD}^\theta_{t+3}$$

Consider two standard OLS univariate regressions, with a common dependent variable y_i and two different regressors x_i, z_i respectively.

$$\begin{aligned} y_i &= \beta_0 + \beta_1 x_i + \varepsilon_i \\ y_i &= \gamma_0 + \gamma_1 z_i + v_i \end{aligned}$$

where $x_i \perp \varepsilon_i, x_i \perp v_i$. Now get the coefficient of the second regression in terms of covariance and variance of the variables involved and make some substitutions

$$\begin{aligned}
\gamma_1 &= \frac{Cov(y_i, z_i)}{Var(z_i)} \\
&= \frac{Cov(\beta_1 x_i + \varepsilon_i, z_i)}{Var(z_i)} \\
&= \beta_1 \frac{\sigma_{xz}}{\sigma_z^2} \\
\Rightarrow \beta_1 &= \frac{\sigma_z^2}{\sigma_{xz}} \gamma_1
\end{aligned}$$

If $\sigma_{xz} = Cov(z_i, x_i) > 0$, then between coefficients β_1 and γ_1 we have a positive relationship.

We do the same with the regressions obtained from the theoretical and empirical models, respectively:

$$\begin{aligned}
FE^{\theta,i}_{t+1|t} &= \beta_0 + \beta_1 I^i_t + \varepsilon_i \\
FE^{\theta,i}_{t+1|t} &= \gamma_0 + \gamma_1 News^i_t + v_i \\
\Rightarrow \gamma_1 &= \beta_1 \frac{Cov(News^i_t, I^i_t)}{Var(News^i_t)}
\end{aligned}$$

So, if $Cov(News^i_t, I^i_t) > 0$, we have a positive relationship between the main variable of theoretical and the empirical model. Recall the definition of the theoretical news in the empirical model, which can be written also as a combination of the first difference of rational PDs and innovations

$$News_t = -\Delta\widehat{PD}^{\theta}_{t+1|t} = -(B(\hat{x}_{t+1|t} - \hat{x}_{t|t-1}) + C(I_t - I_{t-1}))$$

For coefficients $A, B, C \in \mathbb{R}^+$ and K be the steady state value of the Kalman gain, we substitute the formulation of $News_t$ in the covariance between news and inovation, and get

$$\begin{aligned}
Cov(News_t, I_t) &= \mathbb{E}[Cov_{t-1}(News_t, I_t)] + Cov(\mathbb{E}_{t-1}[News_t], \underbrace{\mathbb{E}_{t-1}[I_t]}_{=0}) \\
&= \mathbb{E}[Cov_{t-1}(News_t, I_t)] \\
&= \mathbb{E}[BCov_{t-1}(-(\hat{x}_{t+1|t} - \hat{x}_{t|t-1}), I_t) - C \cdot Cov_{t-1}(I_t - I_{t-1}, I_t)] \\
&= \mathbb{E}[BCov_{t-1}(-((\rho-1)\hat{x}_{t|t-1} + KI_t), I_t) - CVar_{t-1}(I_t)] \\
&= \mathbb{E}[-BKVar_{t-1}(I_t) - CVar_{t-1}(I_t)] \\
&= -Bk\mathbb{E}[Var_{t-1}(I_t)] - C\mathbb{E}[Var_{t-1}(I_t)] \\
Cov(News_t, I_t) &= -(BK + C)\mathbb{E}[Var_{t-1}(I_t)]
\end{aligned}$$

Recalling from equation (6)

$$\begin{aligned}\widehat{PD}^{\theta}_{t+1|t} &= \Phi\Big(\frac{a-\hat{x}^{\theta}_{t+1}}{\Omega_t^{1/2}}\Big)\\ &\approx \underbrace{\Phi\Big(\frac{a}{\Omega^{1/2}}\Big)}_{=:A}\underbrace{-\frac{1}{\Omega^{1/2}}\phi\Big(\frac{a}{\Omega^{1/2}}\Big)}_{=:B}\hat{x}_{t+1|t}\underbrace{-K\theta\frac{1}{\Omega^{1/2}}\phi\Big(\frac{a}{\Omega^{1/2}}\Big)}_{=:C}I_t\end{aligned}$$

It follows that the covariance between news and innovation is positive.

$$Cov(News_t, I_t) = \underbrace{-(BK+C)}_{>0}\underbrace{\mathbb{E}[Var_{t-1}(I_t)]}_{>0} > 0$$

This result proves that the measure $News_t = -\Delta\widehat{PD}^{\theta}_{t+1|t}$ used in the empirical exercise is a valid alternative to the innovation of the theoretical model, given that their covariance is strictly positive.

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