Bank beliefs and firm lending: evidence from Italian loan-level data

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Abstract

We use a novel loan-level dataset containing borrower-specific probability of default to accurately measure lenders' expectations. The analysis is based on a learning model where bankers endowed with diagnostic expectations receive noisy signal about firms' fundamentals and estimate their probability of default. The evidence suggests that banks could be subject to expectational distortions: (i) intermediaries tend to overreact to both micro and macro news, overestimating (underestimating) borrowers' defaults after negative (positive) signals; (ii) the degree of overreaction is heterogenous among banks; (iii) overreacting bankers decrease (increase) interest rates more than rational ones and the probability of issuing a new loan rises (fall) when bankers receive positive (negative) signals. We rationalize these results with the structural estimation of a model of banking competition where banks' profits depends on borrowers' creditworthiness.

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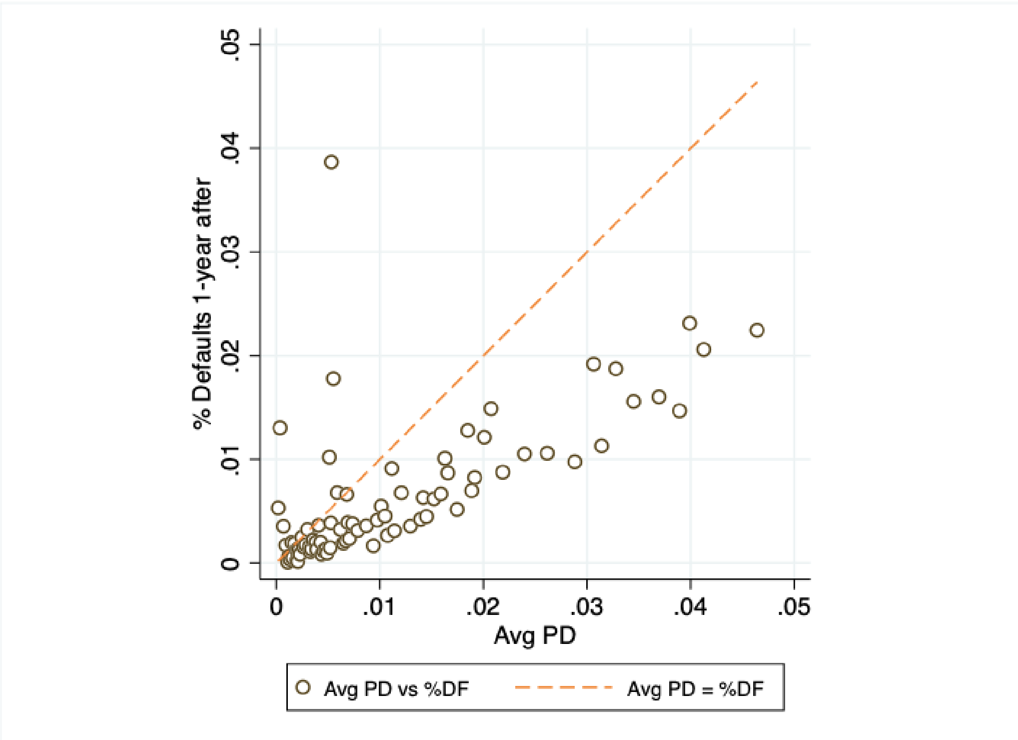
1 Introduction

Lending decisions reflect what lenders think about borrowers' creditworthiness (Minsky, 1986). While there is some evidence (Bordalo et al., 2018; Richter and Zimmermann, 2019; Ma et al., 2021) that bankers tend to over-extrapolate when looking at *aggregate* credit allocation, few studies have quantitatively measured the extent of this distortion and its effect on the price and quantity of credit for *loan level* portfolios. Although macroeconomic or bank-level variables coming e.g., from surveys can unveil salient features of lenders' expectation, credit institutions typically lend based on a mix of hard and soft information (Albareto et al., 2011) which varies substantially in the cross-section of borrowers and that more aggregate data may fail to capture.

Figure 1: Probability of default and realized default rates by centiles



Notes: The chart shows the frequency of the probability of default and default rate realized one year after, by centiles. Rational expectations would require points to be on the 45°-degree line. Points on the left of the 45°-degree line show underestimation of the PD with respect to realized defaults, while points on the right show overestimation. Sorce: our elaborations on AnaCredit.

The starting point of our analysis is a simple aggregate assessment of banks' average forecasting ability of borrowers' credit risk. If bankers' expectations were fully rational, then all points in figure 1, similarly to a quantile-quantile plot, should be aligned on the 45°-degree line where realized one-year ahead default shares are equal to their forecast, as measured by the 1-year probability of default (PD). We find instead that lenders tend to over-estimate defaults for ex-ante riskier borrowers, while safer borrowers show more dispersion with some over- and under-estimation.

Motivated by this fact we ask the following questions: (i) can we consistently measure the bias in lenders' expectations? (ii) In which cases is this distortion greatest? (iii) To what extent does deviation from full rationality affect interest rates and the probability of issuing new loans? Using a novel granular (loan-level) dataset from Italy where credit institutions report their estimates of the probability of default for around 760k monthly non-financial firms, we show that banks' beliefs are consistent with a simple model of diagnostic expectations and that this deviation from rationality can have a sizable impact on the cost of credit and its allocation.

To measure beliefs, following Bordalo et al. (2019) we build a learning model where banks receive noisy signals on borrowing firms' fundamentals to forecast firms' defaults. We test for an extrapolative belief formation process, according to which bankers revise the probability of default 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), this mechanism relies on the "kernel of truth" property, according to which bankers over-estimate the probability of firm's future cashflows realizations whose likelihood has increased the most in light of recent news: the banker acts in the correct direction of news, but he does it with exaggeration.

Using two alternative sources of signals or "news", 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 incoming standard deviation of micro news makes a banker overreact on average between 20 to 250 basis points (bps) more in the determination of the PD relative to a rational one[1]. The effect is weaker for macro news (2-10 bps) but still economically and statistically significant.

Our results also show that the degree of overreaction is heterogeneous for both the cross-section of borrowers and banks. Distortions are more pronounced in the tails of the distribution, i.e., for less- and more-risky firms, and for borrowers with smaller loan size exposures,

[1] The higher effects in absolute value refer to the sample partition where we consider only negative news.

younger credit age and located in the South and Center of Italy. While on average lenders in our sample tend to overreact to news, and some banks (which we call "diagnostic") particularly so, there are also some that do not (and that we call "rational")[2].

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 between 3.5 and 7 basis points and increase the probability of issuing a new loan by about 0.4%-0.6% compared to rational lenders. Results for macro news are qualitatively similar but of smaller magnitude likely due to the lower signal-to-noise ratio of this type of news.

Finally, we rationalize our reduced-form findings with a structural model of imperfect competition of the banking sector. We follow Crawford et al. (2018) but extend their model to incorporate the richer behavioral side 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 belief distortions. Symmetrically, the probability of issuing a new loan would increase by 1.7%.

Literature Review Our paper relates to three main strands of literature. First, it is directly linked to papers that explore bankers' beliefs. Fahlenbrach et al. (2018) and Richter and Zimmermann (2019) examine lenders' expectations through measures of bank's profitability and business activity, loan growth and CEO's expectations. Ma et al. (2021) uses survey data from bankers on MSA's conditions. Our contribution to this literature is measuring more granularly the expectations about the risk assessment of borrowers through the PD,

[2] Following Coimbra and Rey (2017), we potentially identify an additional channel of banks' heterogeneity.

instead of appealing to credit spreads, loan growth or returns on equity measures that are not bankers' direct forecasts. Loan-level data complements more standard survey information on managers expectations about macroeconomic and lending conditions since it represents actual lending decisions, and it can be used to look at how beliefs are heterogeneous across bank- and borrower-characteristics.

Second, we refer to the literature which studies departures from full information rational expectations and diagnostic expectations: Gennaioli and Shleifer (2010), Gennaioli et al. (2012), Greenwood and Shleifer (2014), Coibion and Gorodnichenko (2015), Gennaioli et al. (2016),Bordalo et al. (2016), Bordalo et al. (2019), Bordalo et al. (2020). We add to this line of research an empirical insight on lenders' beliefs using micro data. We are able to study how beliefs vary on the basis of borrowers' characteristics and show that lenders expectations overreact to news.

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), Bordalo et al. (2018), Greenwood et al. (2019), Krishnamurthy and Li (2020). Our analysis does not cover an entire credit cycle, nonetheless our results are indicative through the counterfactual exercises (and conservative in estimates) of what can happen during boom and bust phases: an increase of positive/negative news would amplify the overreaction of creditors, leading to intensified distortions in loans' prices and quantities.
We refer also to a structural estimation literature, in which the main source of inspiration for our model is Crawford et al. (2018).

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 robustness exercises.

2 Data

2.1 Anacredit

The main dataset used in this project is the Italian section of AnaCredit, which is a credit registry managed by the ECB with the aim of collecting 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 on these loans; for each borrower banks are asked to report several characteristics among which the sector of economic activity (2-digit Ateco), the age and the geographical location and also the default status, which in our setting is a binary indicator.

Furthermore, banks that use the so-called Internal Ratings Based approach (IRB - Basel Committee (2001)) also report each month the 1-year ahead probability of default (PD) for each borrower. Since the PD is the key variable in our empirical analysis, we restrict our attention to Italian IRB banks that overall account for around 80% of total assets. Every month we have on average banks' PDs for 760,000 borrowers. Table 1 contains several summary statistics about the dataset.

Data ranges from June 2018 onwards. The main analysis uses data until the start of the Covid-19 in Italy (Q2 2020)[3].

Other datasets used are Italian credit registry, Cerved credit data and Istat.

2.2 Istat

From Istat we retrieve the index of industrial production in Italy. This index is released monthly at Nace 4-digit level (NACE activities B, C and D) and collects volumes of production from mining and manufacturing for firms with more than 20 employees. The measure can be considered as a macro news that banks receive from these sectors. We can only use the Nace 2-digit granularity to match the index with our bank-firm data. The measure of news is defined as the percentage quarterly difference of the index for each 2-digit sub-sector

[3]We expanded the analysis also beyond the beginning of Covid-19. Full-sample findings can be found in section 6.

Table 1: Anacredit Summary statistics

	1st quartile	Median	3rd quartile
N Borrowers	748,741	762,871	781,723
N Bank-Borrowers	7,104	27,098	80,491
N Bank per Borrower	1	2	3
Def. Rate (%)	0.75%	0.87%	1.10%
PD	0.34%	0.94%	2.42%
Loan Size (EUR k)	33.19	84.12	255.25
Int. Rate (%)	1.10%	2.41%	4.98%

Notes: this table provides basic summary statistics of the dataset used in the paper, by quartiles. Default rate, PD and interest rate are expressed in percentages, while loan size in thousands of euro.

for which the index is available:

$$News_t^s = \frac{idx_t^s - idx_{t-1}^s}{idx_{t-1}^s}$$

2.3 PD in the data

As anticipated in the introduction, the motivating evidence for the investigation in bankers' beliefs formation is given by figure 1. The discrepancy between the actual default rate and the probability of default makes us question the differences across the distribution. Table 2 compares the lowest ad highest deciles of firms by bankers' PD forecast error. On average, bankers' forecast errors are lower on the first decile of the distribution (even if more dispersed, as shown in 1), while they tend to widen for the highest decile. On the top decile the average PD is around 5.9%, while bottom decile errors concern low-risky firms (average PD around 0.7%). The average loan size difference among two deciles is euro 67k, with average size higher among less risky firms. Credit age[4] is almost three years higher for bottom decile PD error, while the error is significantly more pronounced for firms located in the South and Center of Italy. Overall, bankers seem to err more on firms that are ex-ante riskier, smaller, with lower credit age, located in the Center and South and not operating in the manufacturing sector (a full list of NACE sectors in available in Appendix).

How does PD change along time and across the distribution? The autocorrelation of the

[4] The "credit age" is defined as the number of years from the time of the first credit relationship between the firm and any bank in the panel.

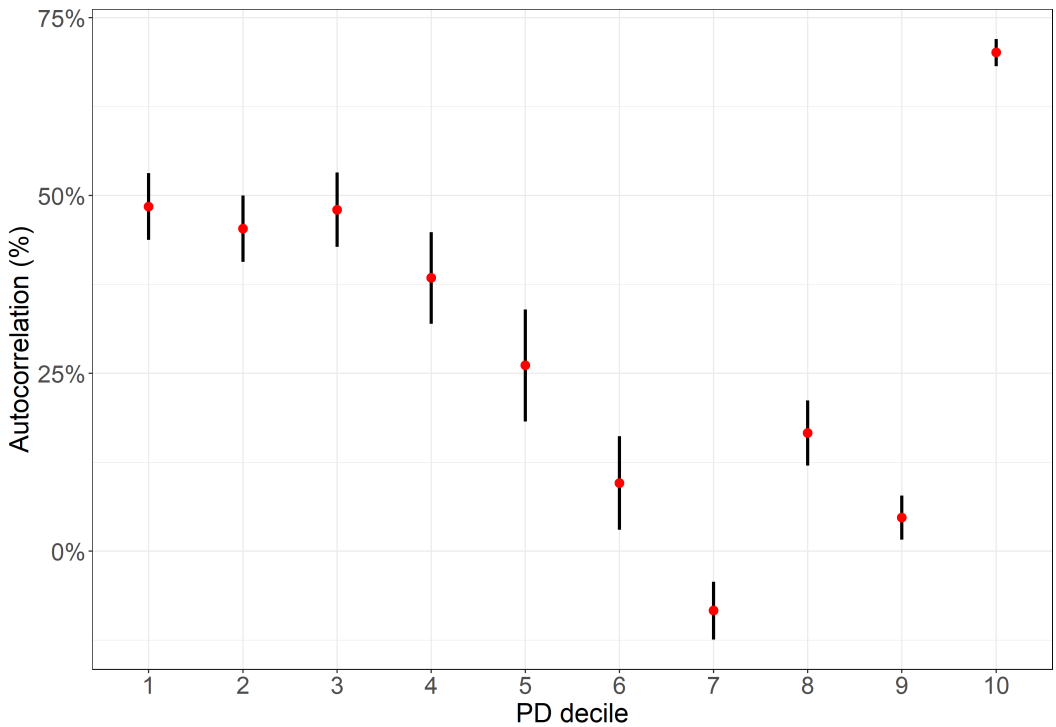
Table 2: Summary Statistics of Lowest and Highest deciles by PD forecast error

	Bottom Decile by PD error	Top Decile by PD error	Top - Bottom
Avg. PD	0.007^{***}	0.059^{***}	0.052^{***}
	(0.000)	(0.000)	(0.000)
Avg. Def. Rate	0.006^{***}	0.038^{***}	0.032^{***}
	(0.000)	(0.003)	(0.003)
Avg. Loan Size (EUR k)	235.90^{***}	168.72^{***}	-67.18^{***}
	(0.084)	(0.122)	(0.087)
Avg. Credit Age	14.462^{***}	11.617^{***}	-2.845^{***}
	(0.369)	(0.384)	(0.328)
Agriculture Sect.	0.047	0.052	0.005
			(0.006)
Construction Sect.	0.097	0.139	0.041
			(0.038)
Manufacturig Sect.	0.268	0.175	-0.094^{***}
			(0.029)
Other Sect.	0.015	0.016	0.001
			(0.003)
Services Sect.	0.572	0.619	0.046
			(0.040)
Geo: Center	0.190	0.228	0.038^{***}
			(0.005)
Geo: North-East	0.260	0.204	-0.056^{***}
			(0.010)
Geo: North West	0.396	0.372	-0.024^{***}
			(0.007)
Geo: South	0.155	0.197	0.042^{***}
			(0.008)

Notes: this table provides summary statistics of firms in the bottom and top deciles of the bankers' PD forecast errors (given by the share of realized defaults less the average probability of default). For industry sectors and geographical locations the table reports the average frequency distribution of borrowers in the relative sector/geo. area. Standard errors are in parenthesis and are clustered at NACE 2 digit-level. Significance levels at 1%, 5%, 10% are given by (***), (**), (*) respectively.

PD by deciles, shows interestigly that for the first three deciles the autocorrelation coefficient is high and stable at 50%, while from the fourth decile on it starts to decrease quite monotonically (figure 2). The high correlation in the last decile is likely due to firms that are close to default, who keep receiving high PD until the failure is made official. This picture is instructive because it shows that bankers do update the PD over time on the basis of incoming information.

Figure 2: PD Autocorrelation



Notes: the figure shows autocorrelation of borrower-specific PD on y-axis, by PD decile on x-axis.

2.4 Focus on the probability of default

Pd origination As mentioned above, the PD in our dataset originates from banks using Internal Rating Based approach and it works as a credit risk parameter to set capital requirements. Only banks that meet stringent conditions regarding disclosure, governance, and model screening ability can use the IRB approach. The PD originating from these models is a measure upon which banks found their business and supervisory authority control capital requirements needed to ensure a valid assessment of risk. After an initial approval process, supervisory authorities (the Single Supervisory Mechanism (SSM) for Significant Institutions, and National Competent Authorities (NCAs) for Less Significant Institutions) regularly validate these models to ensure their on-going respect of prudential requirements[5]. While we cannot completely rule out the possibility that banks are strategic when reporting the PD to supervisors (and therefore in AnaCredit), in section 6.1 we discuss at length factors that mitigate this concern.

So, the PD is a measure produced by credit risk models and can be revised judgementally by loan officers. The model of expectations described in the next section to explain

[5]For further details, we refer to Basel Committee (2001).

forecast distortions embeds a mechanism that overweights most recent news coming from fundamentals.

3 Econometric model

We build a learning model that mimics how banks estimate borrowers' PD. If cashflows fall below a given threshold, the firm defaults. Banks do not directly observe firm's cashflows, but only a noisy signal upon which banks try to forecast default. We add representativeness in bankers' expectations on the basis of Bordalo et al. (2019), to capture how banks can produce distorted PDs. Before introducing the distorted learning process, we design a baseline Kalman filter applied to our case. Suppose the firm's cash flow follows an AR(1) process x_t but the bank cannot observe the process directly, rather only a noisy signal y_t:

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

where v_t and w_t are the state and measurement errors, respectively.
Standard Kalman derivation gives the following recursions in Durbin and Koopman (2012)[6]:

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

where $\hat{x}_{t|t-1} = \mathbb{E}[x_t|y^{t-1}]$, $\widehat{\Omega}_{t|t-1} = \mathbb{E}(x_t - \hat{x}_{t|t-1})^2$ and y^{t-1} is the information set available to bankers at time $t-1$ formed by all signals $y_{t-1}, y_{t-2}, \ldots$
We denote the innovation by $I_t = y_t - \mathbb{E}(y_t|y^{t-1}) = y_t - \hat{x}_{t|t-1}$ and the Kalman Gain by K_t. Notice that K_t in (2) converges to a steady state value after few iterations in the model. Therefore, we assume $K_t = K$ to be a constant in the rest of the paper.

Diagnostic Expectations Diagnostic Expectations is based on the concept of 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. Gennaioli and Shleifer (2010) built an analytical model describing representativeness ap-

[6] Steps of the derivation can be found in ch.4.3, pp. 82-85

plied to belief formation. We refer to Bordalo et al. (2018) for an analytical description of representativeness applied to time-varying economic variables.

Assume that the agent forms beliefs about an economic random variable following an AR(1) process $x_{t+1} = \rho x_t + \epsilon_t$ with $\epsilon_t \sim N(0, \sigma^2)$ and $\rho \in (0, 1)$. The agent assesses the distribution of future state $\hat{x}_{t+1}$ on the basis of realized current state $x_t = \hat{x}_t$. The rational agent predicts the future state using the true conditional distribution $f(x_{t+1}|x_t = \hat{x}_t)$. 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:

$$R = \frac{f(\hat{x}_{t+1}|x_t = \hat{x}_t)}{f(\hat{x}_{t+1}|x_t = \rho \hat{x}_{t-1})} \tag{3}$$

The state is more representative the more its likelihood increases with respect to recent news. In case of absence of news, 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. The overweighting states process is rationalized as if the agent uses a distorted density

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

The formula embeds what is defined as the "kernel of truth" property, i.e. the agent shifts its beliefs from rational expectations in the direction of the news received. Parameter θ measures the degree of *diagnosticity*, the deviation from the rational expectation case. Z is a constant ensuring that the distorted density integrates to one.

Back to our model, following Bordalo et al. (2019), we can characterize bankers' beliefs by the distorted density

$$f^{\theta}(x, I_t) = f(x, I_t)[R(x, I_t)]^{\theta} Z$$

where x represents firms' cashflows and I_t is the information received at t; $R(x, I_t)$ is the level of representativeness, as in equation (3). When $\theta > 0$ the agent is diagnostic and over-reacts to information with respect to previous period, if $\theta = 0$ the agent is rational.

Given the linearity of the process (1) the rational density $f(x, I_t)$ is normal with variance $\widehat{\Omega}$ and mean $\hat{x}_{t+1|t}$. Following Bordalo et al. (2019), we can characterize the diagnostic density $f^\theta(x, I_t)$ as normal with the same variance $\widehat{\Omega}$ and mean

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

3.1 Kalman filter and the Probability of Default

To compute the probability of default we define z as the default status of any firm: $z_{t+1} = \mathbb{1}(x_{t+1} < a)$. The firm defaults whenever cashflows x_{t+1} are strictly lower than a given threshold $a \in \mathbb{R}$. It follows that the probability of the firm's default is given by

$$\mathbb{E}(z_{t+1}|y^t) = \mathbb{E}_t(z_{t+1}) = \mathbb{P}_t(x_{t+1} < a)$$

Given beliefs $f(x, I_t)$ and $f^\theta(x, I_t)$ (see proof in Appendix - Proofs) we obtain the predicted probability of default for a rational and diagnostic agent[7], respectively. Notice that Φ and ϕ stand for cumulative distribution and density function of a standard normal.

$$\begin{aligned}\mathbb{E}_t(z_{t+1}) &= \Phi\left(\frac{a - \hat{x}_{t+1}}{\Omega_t^{1/2}}\right) = \widehat{PD}_{t+1|t} \\ \mathbb{E}^\theta_t(z_{t+1}) &= \Phi\left(\frac{a - \hat{x}^\theta_{t+1}}{\Omega_t^{1/2}}\right) = \widehat{PD}^\theta_{t+1|t}\end{aligned} \tag{4}$$

From the definition of PD in 4, applying some algebra and approximations (see proof in Appendix - Proofs), we obtain an equation that links directly the innovation I_t to bankers' forecast error $FE^{\theta,i}_{t+1|t} = z_{t+1} - \widehat{PD}^\theta_{t+1|t}$ with respect to the probability of default. Then, for each firm $i = 1, \ldots, N$ and bank $b = 1, \ldots, B$ we have

$$FE^{\theta,i,b}_{t+1|t} \approx K\theta\frac{1}{\widehat{\Omega}^{1/2}}\phi\left(\frac{a}{\widehat{\Omega}^{1/2}}\right)I^{i,b}_t + w^{i,b}_{t+1} \tag{5}$$

where $w^{i,b}_{t+1}$ is an error term. Now, define $\beta_1 := K\theta\frac{1}{\widehat{\Omega}^{1/2}}\phi\left(\frac{a}{\widehat{\Omega}^{1/2}}\right)$. By construction $\widehat{\Omega}_t > 0$, $a > 0$, $K > 0$ and the density is strictly positive. Therefore the only term that could make

[7] As highlighted in the previous paragraph, the agent provided with diagnostic expectations perceives a process that is the distributed as $f^\theta(x, I_t) = f(x, I_t)[R(x, I_t)]^\theta Z$ with mean $\hat{x}^\theta_{t+1|t}$.

$\beta_1 = 0$ is the diagnostic parameter θ. For $\theta > 0$ the agent overreacts to incoming news $I_t^{i,b}$. As a consequence, we can test the hypothesis $H_0 : (\beta_1 = 0)$ with the following linear regression

$$FE_{t+1|t}^{\theta,i,b} = \beta_0 + \beta_1 I_t^{i,b} + \epsilon_{t+1}^{i,b} \tag{6}$$

At each fixed point in time t, with regression (6) we are able to determine whether in our cross-sectional dataset banks respond to firms' news with overreaction measured through the parameter θ. Empirical results are given in section 4.

3.2 Learning process, representativeness and bank lending

We adapt our learning model to real effects, in particular how it influences the interest rates setting for banks that are endowed with diagnostic expectations.

Consider a simple one-period loan when borrowers promise to repay tomorrow $a = L(1 + r)$ for a loan today of size L. Assuming competition deprives lenders of any surplus we have:

$$\begin{aligned} L &= \mathbb{E}[a \cdot \mathbb{1}\{x_{t+1} > a\}] \\ &= a(1 - \widehat{PD}_{t+1|t}) \end{aligned}$$

We also know that the repayment at $t + 1$ will be equal to the loan at $t = 0$ plus a positive interest rate r_t, such that

$$a = L(1 + r_t)$$

Combining the two equations above we get an expression for the risky interest rate, such that:

$$r_t = \frac{\widehat{PD}_{t+1|t}}{1 - \widehat{PD}_{t+1|t}}$$

This equation allows us to derive a direct relationship between the interest rate set by banks and the probability of default implied by the noisy firms' cashflow signal

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

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:

$$r_t \approx \Phi\left(\frac{-a}{\widehat{\Omega}^{1/2}}\right) - \frac{1}{\widehat{\Omega}^{1/2}} \frac{\phi\left(\frac{-a}{\widehat{\Omega}^{1/2}}\right)}{\Phi\left(\frac{-a}{\widehat{\Omega}^{1/2}}\right)^2} \hat{x}_{t+1|t} \tag{7}$$

$$r_t^\theta \approx r_t - \frac{K\theta}{\widehat{\Omega}} \frac{\phi\left(\frac{-a}{\widehat{\Omega}^{1/2}}\right)}{\Phi\left(\frac{-a}{\widehat{\Omega}^{1/2}}\right)^2} I_t \tag{8}$$

Equations (7) and (8) differentiate by the innovation I_t and relative multiplicative parameters. Given positive parameters $K, \Phi(\cdot), \phi(\cdot), \widehat{\Omega}$ by construction, for a positive innovation $I_t > 0$ our model predicts a lower interest rate for the diagnostic agent compared to the rational one.

4 Empirical Results

We preface that while the model forecast horizon is one time period for simplicity, given the nature of the probability of default in our dataset, in the empirical specifications we have a 12 months forecast horizon. Our sample starts in mid-2018 ending in 2019-Q2 to discard counfounding effects of the Covid-19 in the main analysis; results with the full sample are available in section 6.

For an empirical assessment of the model we adapted the equation (6) to our data, which brings to equation (9). The dependent variable is given by the banker's forecast error $FE^\theta_{t+12|t} := z_{t+12} - \widehat{PD}^\theta_{t+12|t}$, where $z_{t+12} = \mathbb{1}(x_{t+12} < a)$ is a dummy that takes value one if the firm defaults at $t+12$ and zero otherwise, and $\widehat{PD}^\theta_{t+12|t}$ is the probability of default for firm i by a banker with diagnostic expectations.

$$FE^{\theta,i,b}_{t+12|t} = \beta_0 + \beta_1 News^{i,b}_t + \mathbf{\Gamma}'\mathbf{X} + \epsilon^{i,b}_{t+12} \tag{9}$$

Controls and bank, sector, province, borrower, time fixed effects are contained in $\mathbf{\Gamma}'\mathbf{X}$. The main regressor $News_t$ is a measure of innovation that the bank receives about each firm i in each period t.

We remark that under rational expectations bankers' forecast errors should not be predictable using variables in the bankers' information set. At the borrower level, we choose as a proxy for the model-based news I_t the one-quarter probability of default difference at the time the forecast $\widehat{PD}^{\theta}_{t+12|t}$ is made, i.e.

$$News_t = -(\widehat{PD}^{\theta}_{t+12|t} - \widehat{PD}^{\theta}_{t+9|t-3}) = -\Delta\widehat{PD}^{\theta}_t$$

This measure captures any new information each banker has incorporated at time t with respect to $t-1$ into the valuation variable used to predict the default status. The negative sign in front of the expression makes $News_t$ a positive news, since a positive $\Delta\widehat{PD}^{\theta}_t$ means higher probability of default, hence a deterioration of credit worthiness.

To corroborate our findings, we use an alternative aggregate measure of news based on the industrial production index for Italian firms.

We also tried different variables as proxies for the innovation, left for a robustness exercise in the Robustness section (6). We validate our borrower-specific measure of $News_t$ in the Appendix - Proofs.

Each Panel of table 3 presents results from the estimation of equation (9), with data selected on the basis of the sign of the news: all news in Panel A, only negative and positive news in Panel B and C respectively. The main regressor is the news coefficient, which is statistically significant and positive for the three panels that include borrower fixed effects (far-right column)[8]. In Panels A and B the effect is also robust for every other specification and the magnitude is higher when we consider only negative news in Panel B. In Panel C the coefficient flips to the right sign and becomes significant when we introduce borrower fixed effects: this is important, because it suggests that even if demand-driven components are dampened, expectational distortions by banks in the direction of over-reaction still arise. This result strengthens the motivation of using such granular dataset in studying lenders' beliefs.

A positive and significant coefficient rejects the null of $\theta = 0$ and suggests that bankers overreact to both positive and negative news about their borrowers. With positive θ the agent forms forecast with diagnostic expectations: he receives a news through a noisy signal and inflates the probability of those states that became more likely in light of recent news.

[8]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 banks.

When the banker gets a positive news, he tends to decrease the probability of default more than he would have done if rational. The converse happens in case of negative news.

Results in Panel A of table 3 suggest that for a standard deviation increase in news (so news becoming more positive), the forecast error of a diagnostic banker increases between 20 and 250 basis points more than a non-diagnostic banker. In other words, for a one s.d. more positive news, bankers forecast a default rate between 0.2% and 2.5% lower than what would have a rational forecaster.

We use loan size and credit age as controls in the regression, and time, bank and province fixed effects for specifications with no borrower fixed effects. The credit age coefficient is significant and negative, reconciling with findings of the summary statistics for bottom and top deciles by PD error in Table 2: bankers tend to err less with respect to firms with higher credit age. Having presumably more information on these firms, bankers tend to be more accurate when assessing their creditworthiness. With respect to loan size instead, we find that bankers overreact to incoming news irrespective of the magnitude of new firms' exposures.

We complement these main results with two alternative exercises: (1) explore if overreaction to news is different across the probability of default distribution and (2) whether it entails considerable real effects on prices. The following paragraphs are focused on these aspects.

4.1 News effect across the distribution

To complement the previous analysis we conduct a focus on the cross-sectional effects of the news. Our model (9), allows to test if the overreaction to news is different across the distribution, both relative to banks and borrowers heterogeneity. It is indeed likely that banks overreact to news differently on the basis of being a particular bank or observing at distinct firm characteristics, geographic locations and credit relationships. The first paragraph gives an insight on bank's, while the second one on firm's heterogeneity.

Summary by bank diagnostic level To investigate heterogeneity among banks, we run regression (9) for each bank, to determine a bank-specific diagnostic level. Results are given in figure 3, where we sort banks by $\hat{\theta}$. Results show that six out of nine banks display a positive and significant parameter: these banks overreact when receiving positive or negative

Table 3: Predictability on forecast errors - PD news

	$FE^{\theta,i}_{t+12\|t}$			
	Panel A: All PD News			
$News_t(all)$	0.274***	0.273***	0.274***	0.485***
	(0.0227)	(0.0226)	(0.0226)	(0.00643)
N Obs.	1036314	1036314	1036314	1034841
	Panel B: Negative PD News			
$News_t < 0$	0.562***	0.567***	0.562***	0.946***
	(0.116)	(0.0443)	(0.0442)	(0.0157)
N Obs.	239009	239008	239009	224402
	Panel C: Non-Negative PD News			
$News_t \geq 0$	-0.115***	-0.117***	-0.113***	0.0671***
	(0.0181)	(0.0187)	(0.0183)	(0.0129)
N Obs.	797305	797304	797305	794910
Time FE	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	No
Sector FE	No	Yes	No	No
Province FE	No	No	Yes	No
Borrower FE	No	No	No	Yes

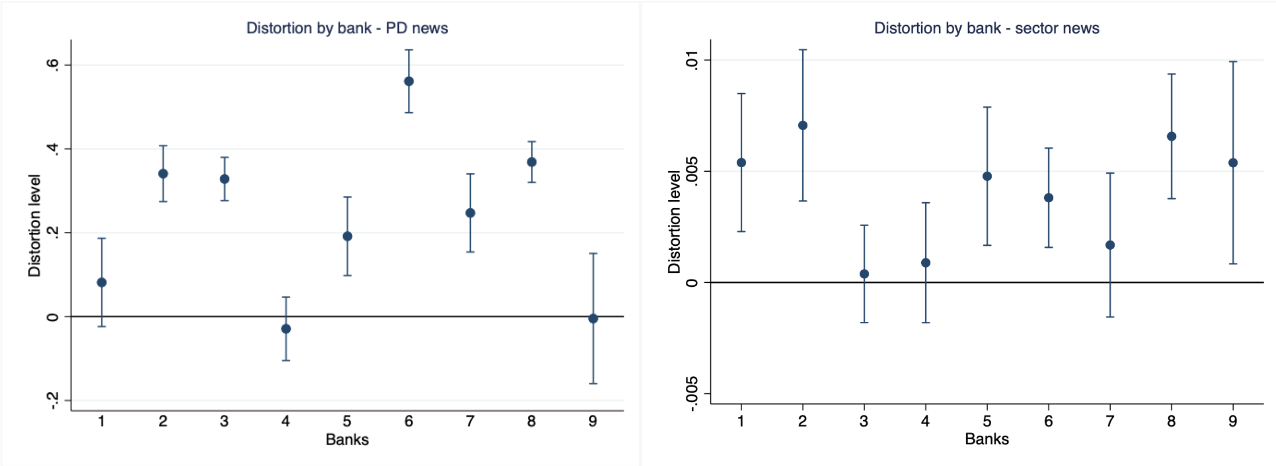
Notes: this table provides coefficient estimates of the regression $FE^{\theta,i,b}_{t+12|t} = \beta_0 + \beta_1 News^{i,b}_t + \mathbf{\Gamma}'\mathbf{X} + \epsilon^{i,b}_{t+12}$, where $\mathbf{X}$ is the controls' matrix that contains also fixed effects. Controls used are loan size, firm credit age, post-Covid-19. Main regressor *News* is borrower specific. Errors are clustered at NACE 2-digit level. Significance levels at 1%, 5%, 10% are given by (***), (**), (*) respectively.

Table 4: Predictability on forecast errors - Sector news

	$FE^{\theta,i}_{t+12\|t}$		
	Panel D: All Sector News		
$News_t(all)$	0.00395***	0.00449***	0.00107*
	(0.000938)	(0.00109)	(0.000403)
N Obs.	505920	505920	505330
	Panel E: Negative Sector News		
$News_t < 0$	0.0105*	0.0101*	-0.00407
	(0.00443)	(0.00433)	(0.00326)
N Obs.	291952	291952	187295
	Panel F: Non-Negative Sector News		
$News_t \geq 0$	0.00613***	0.00702	0.0000911
	(0.00140)	(0.00355)	(0.00166)
N Obs.	213968	213968	212577
Bank FE	No	Yes	No
Province FE	No	Yes	No
Borrower FE	No	No	Yes

Notes: this table provides coefficient estimates of the regression $FE^{\theta,i,b}_{t+12|t} = \beta_0 + \beta_1 News^s_t + \mathbf{\Gamma}'\mathbf{X} + \epsilon^{i,b}_{t+12}$, where $\mathbf{X}$ is the controls' matrix that contains also fixed effects. Controls used are loan size, firm credit age, post-Covid-19. Main regressor *News* is sector specific. Errors are clustered at NACE 2-digit level. Significance levels at 1%, 5%, 10% are given by (***), (**), (*) respectively.

Figure 3: Distortion coefficients by bank



Notes: The figure plots the coefficients $\hat{\beta}_1$ with 95% confidence interval of the regression $FE^{\theta,i}_{t+12|t} = \beta_0 + \beta_1 News^i_t + \mathbf{\Gamma}'\mathbf{X} + \epsilon^i_{t+12}$, estimated by bank. The blue line represents the cutoff between high and low θ banks, i.e. banks with a diagnostic parameter above and below the median. Banks are sorted by $\hat{\theta}$. Standard errors are clustered at NACE 2 digit-level. For confidentiality reasons banks are anonymised and are assigned a cardinal identifying number.

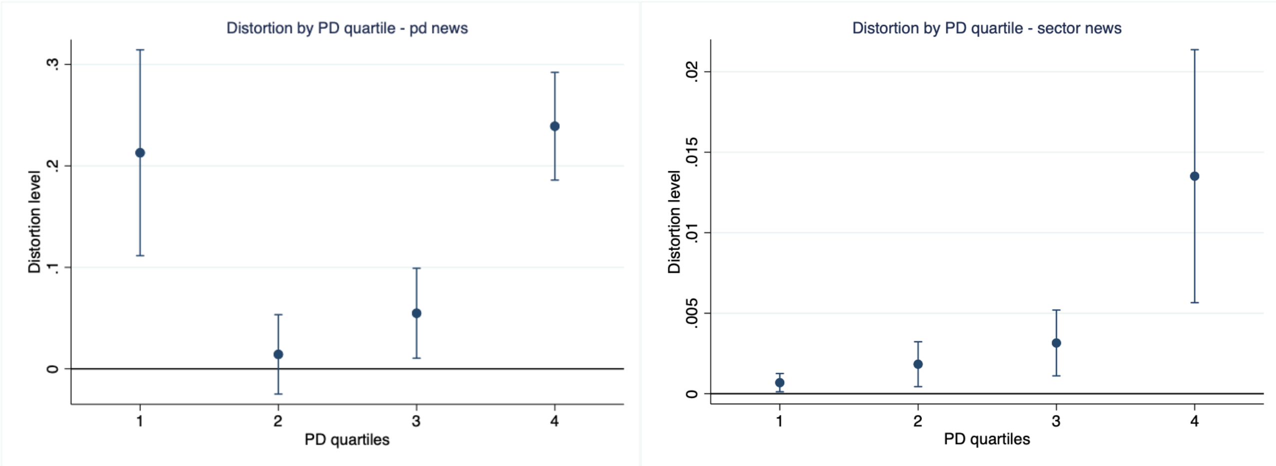
news from their customers in attributing them a new probability of default. The degree of overreaction is different, based on the nature of news received. From figure 3 indeed, banks non reacting to micro-news are 1, 4 and 9, while those non reacting to macro-news are 3, 4 and 7. The dispersion of the coefficients is more pronounced in the left-hand panel of the figure, where we use micro-news. This is not surprising because micro-news varies at the borrower level and the signal-to-noise ratio is likely higher. Overall, overreaction to news seems diffuse among the Italian panel of Anacredit and confirms that results of the previous section are not driven only by a single sizable institution.

News effect (theta) by PD quartile In figure 4, we estimate regression (9) by quartile and plot the news coefficients. Coefficients of distortion based on micro-news are more significant and pronounced in the first and fourth quartiles about PD distribution, while are monotonically increasing based on macro-news. The two sub-figures share that banks overreact more with respect to riskier borrowers, independently on the news type received.

4.2 Effects on lending

Interest rates A natural question about the importance of studying distortions in expectation formation mechanisms is whether they may yield considerable real effects. We try to

Figure 4: Distortion by quartile



Notes: The figure plots the coefficients $\hat{\beta}_1$ with 95% confidence interval of the regression $FE^{\theta,i,b}_{t+12|t} = \beta_0 + \beta_1 News^{i,b}_t + \Gamma'\mathbf{X} + \epsilon^{i,b}_{t+12}$, estimated by PD decile. Standard errors are clustered at NACE 2 digit-level.

address this point in the following exercises. First, we simply regress interest rates on the level of news, to measure how new information impacts bankers' evaluation of credit price, unconditionally. Second, we test whether interest rates set by diagnostic banks receiving news, are different from those set by rational ones.

From equations (7) and (8), we derived a regression to measure the impact of diagnostic parameter on the level of interest rates.

$$r^{i,b}_t = \beta_0 + \beta_1 D^b_t + \beta_2 News^{i,b}_t + \gamma(D^b_t \times News^{i,b}_t) + \Gamma'\mathbf{X} + \epsilon^{i,b}_t \tag{10}$$

where $D^b_t = \mathbb{1}\{\theta^b = \text{“}high\text{''}\}$ identifies banks with high level of distortion. The idea is to test whether diagnostic expectations measured through different parameters θ have heterogenous effects on interest rates. To pursue this test, we: (1) estimate θ^b for each bank b by means of equation (9), (2) sort banks by level of diagnosticity θ, (3) select banks rational and non-rational banks (θ statistically different from zero) and (4) run regression (10), whose coefficient of interest γ gives us the impact of innovation absorbed through diagnostic expectations on the level of interest rates. Notice that, for each date t, we select only new contracts stipulated among banks and borrowers who had already an existing credit relation. We restrict to new contracts only because it is not possible to identify news effects on prices on outstanding contracts. Therefore, the banker receives information about the borrower between $t-1$ and t and formulates an interest rate for the new contract in t.

Table 5 contains two sections with results on interest rates. The first column shows a simple regression between interest rates and news only (controlled by several variables), which is not derived by any model. We are interested in a first place in assessing the "unconditional" role of news on price changes. The effect of innovation on interest rate is negative, as expected, but not statistically significant: positive news make bankers more optimistic about firms outcomes' and price to new loans are reduced accordingly.

Results in columns 2-4 suggest that the interaction coefficient between news and diagnostic firms $News_t \times D_t^b$ is negative and statistically significant at the 10%, 5%, 1% levels respectively. The interpretation of this coefficient reads as follows: distorted banks compared to rational ones, conditional on the arrival of one standard deviation of positive news, tend to decrease on average the interest rates to his borrowers between 3.5 to 6.8 basis points on first contract signed [9]. In the last column, borrower-fixed effects are introduced to capture any potential unobserved demand-driven effect hidden to the econometrician.

In panel B we run the same regression, substituting the borrower-specific news with the sector-specific one. The level of significance for the coefficient of interest is lower from column 2 to 4, but in the last specification, where the coefficient is significant at the 1% level, the magnitude is comparable to that in panel A: an increase of one standard deviation in news causes a 7 basis points[10] additional decrease in the interest rate offered on new loans by diagnostic banks.

To conclude, expectations-distorted banks receiving positive news decrease on average interest rates on new contracts compared to non-rational banks.

Quantities Similar to the exercise in the previous paragraph, we test whether the level of distortion can impact the bank's probability of issuing new contracts[11]. We derive a regression of equation (10) type, where the dependent variable is a *new contract*. The idea is to test whether a distorted bank receiving a positive news tends to have a different lending behaviour with respect to a rational one. In the regression we run $NC_t^{i,b} = 1$ if the contract is new and 0 otherwise, while the regressors take the same meaning of the rate regression

[9] The effect of the estimate is computed by multiplying the standard deviation of the news to the coefficient. The value of the sd(News)=0.02 in panel A, while 0.017 is the value of the interaction coefficient in panel A when borrower-fixed effects are introduced. The total effect on interest rate can be read as $0.2 * 0.017 = 3.5bp$. Standard deviation may slightly change depending on how data are selected for the ongoing exercise.

[10] Standard deviation of macro news is different from that of micro, this is why different coefficients leads to the same marginal effects on interest rates.

[11] Here we do not restrict the panel to new contracts only.

Table 5: Effects on Interest Rates

	$r^{i,b}$			
	Panel A: PD News			
$News_t$	-0.00694	0.000338	0.00556	0.00471
	(0.00450)	(0.00546)	(0.0102)	(0.00611)
D_t^b		0.00212***	0.00166***	-0.00101***
		(0.000123)	(0.000602)	(0.000264)
$News_t \times D_t^b$		-0.0279***	-0.0338**	-0.0169*
		(0.00638)	(0.0166)	(0.00946)
N Obs.	186096	190596	190596	186096
Sector FE	No	No	Yes	No
Province FE	No	No	Yes	No
Time FE	Yes	No	No	Yes
Borrower FE	Yes	No	No	Yes
	Panel B: Sector News			
$News_t$	0.00396***	0.00474***	0.00374**	0.00645***
	(0.000999)	(0.000789)	(0.00155)	(0.00128)
D_t^b		0.00591***	0.00507***	0.00420***
		(0.000179)	(0.000679)	(0.000453)
$News_t \times D_t^b$		-0.00121	-0.000395	-0.00321***
		(0.000885)	(0.00135)	(0.000910)
N Obs.	111334	112080	112080	111334
Sector FE	No	No	Yes	No
Province FE	No	No	Yes	No
Borrower FE	Yes	No	No	Yes

Notes: this table provides estimates of interest rates on news regression. First column shows results of unconditional regression. 2-4 columns exhibit estimates of regression $r_t^{i,b} = \beta_0 + \beta_1 D_t^b + \beta_2 News_t^{i,b} + \gamma(D_t^b \times News_t^{i,b}) + \mathbf{\Gamma}'\mathbf{X} + \epsilon_t^{i,b}$, where $\mathbf{X}$ is a control matrix which contains also fixed effects. Panel A uses PD news (borrower-specific), panel B sector-specific news. Errors are clustered at the NACE 2-digit level. Significance levels at 1%, 5%, 10% are given by (***), (**), (*) respectively.

(10) in a linear probability framework.

$$NC_t^{i,b} = \beta_0 + \beta_1 D_t^b + \beta_2 News_t^{i,b} + \gamma(D_t^b \times News_t^{i,b}) + \mathbf{\Gamma}'\mathbf{X} + \epsilon_t^{i,b} \tag{11}$$

The main coefficient of interest is the interaction (γ) between distorted bank and the level of news. Table 6 shows in panel A the coefficients when using the firm-specific news: unconditionally, when positive news reaches banks, the probability of a new contract increases, regardless if a bank is rational or diagnstic. Moreover, when a distorted bank receives a positive news from firms, it tends to increase the probability of signing new contracts more than their rational peers. To quantify this effect, as in the rates exercise, we multiply one standard deviation of news to the coefficient estimate. Being affiliated to an expectation-distorted bank increases (reduces) the probability of signing a new contract by 0.4% to 0.6%. Note that the first coefficient $News_t$ in the panel has not the expected sign from columns 2 to 4.

Sector-level results in Panel B are not completely in line with those of Panel A, likely due to the lower signal-to-noise ratio of the aggregate measure of news.

5 Structural estimation

We extend our reduced form findings with a model of imperfect competition of the banking sector. Designing a model of credit demand and supply is crucial to estimate the extent of expectations' distortions on real effects and to run counterfactuals. We borrow the structural design from Crawford et al. (2018), developed to analyse asymmetric information in the loan market, specifically adverse selection. The model is appropriate for our goal since it allows to introduce lending imperfect competition. The empirical environment is familiar too, since the application is over the Italian banking market.

The model is composed of firms and banks. Demand of credit is represented by firms, which ask for loans to finance a risky project to a single bank for their main line of credit. They decide how much to use of the credit line and whether to repay or default. Banks compete à la Bertrand-Nash on interest rates. The banks' profit function of our model differs from the model of Crawford et al. (2018) for risky revenues, which in our case depend on borrower's specific probability of default and level of measurable information received. As outlined in the reduced form specification, the PD is in turn a function of bank-specific belief

Table 6: Effects on Quantities

	$NC^{i,b}$			
	Panel A: PD News			
$News_t$	0.112***	-0.0821***	-0.0702	-0.0759*
	(0.0104)	(0.0268)	(0.0508)	(0.0422)
D_t^b		-0.0120***	-0.00973	-0.0103*
		(0.000573)	(0.00621)	(0.00553)
$News_t \times D_t^b$		0.225***	0.210***	0.155**
		(0.0291)	(0.0695)	(0.0594)
N Obs.	2075790	2075790	2075790	2075747
Sector FE	No	No	Yes	No
Province FE	No	No	Yes	No
Time FE	Yes	Yes	Yes	Yes
Borrower FE	No	No	No	Yes
	Panel B: Sector News			
$News_t$	-0.0347***	-0.0692***	-0.0646***	-0.0454***
	(0.00168)	(0.00561)	(0.0133)	(0.0109)
D_t^b		0.0244***	0.0272***	0.0178***
		(0.00122)	(0.00328)	(0.00452)
$News_t \times D_t^b$		0.00308	0.000927	-0.0165
		(0.00626)	(0.0153)	(0.0125)
N. Obs	1206816	667225	667225	667169
Sector FE	No	No	Yes	No
Province FE	No	No	Yes	No
Time FE	Yes	Yes	Yes	Yes
Borrower FE	No	No	No	Yes

Notes: this table provides estimates of interest rates on news regression. First column shows results of unconditional regression. 2-4 columns exhibit estimates of regression $NC_t^{i,b} = \beta_0 + \beta_1 D_t^b + \beta_2 News_t^{i,b} + \gamma(D_t^b \times News_t^{i,b}) + \mathbf{\Gamma}'\mathbf{X} + \epsilon_t^{i,b}$, where $\mathbf{X}$ is a control matrix which contains also fixed effects. Panel A uses PD news (borrower-specific), panel B sector-specific news. Errors are clustered at the NACE 2-digit level. Significance levels at 1%, 5%, 10% are given by (***), (**), (*) respectively.

distortion.

The model estimation confirms the empirical findings of section (4), in particular with respect to the average level of the diagnostic parameter. Finally, we use our model to quantify the effects of these distortions on prices and quantities and conduct counterfactual exercises. In the model we adopt several important assumptions: first, we narrow the analysis on the first credit line (visible in the data) each firm opens with banks. We do this to avoid the dynamic dimension and reduce the complexity of the problem. Second, we assume both firms and banks are risk-neutral. Third, banks compete only on the interest rate. In markets with lending exclusivity bank can offer contracts that depend both on credit amount and price. Instead, with our assumption the amount of credit is exogenous and given only by the firm's project requirements. As in Crawford et al. (2018), the Italian credit market justifies this assumption, since it is not a market with lending exclusivity, as firms can open multiple credit lines with different banks. As in Chiappori and Salanié (2013), with no contract exclusivity convex price schedule cannot be enforced.

Demand Firms $i = 1, \dots, I$ operate in markets $m = 1, \dots, M$ representing geographical provinces, where each bank $j = 1, \dots, J$ supply loans. Demand estimation is composed of one main equation that represents firm's utility from the credit line. It depends on loan price and market-bank characteristics.

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

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 are bank-market characteristics unobservables to the econometrician; Y'^D_{ijm} are firm-bank-market characteristics.

Supply On the supply side, banks 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 firm i is

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

Q_{ijm} represents the expected demand for loan, given by demand probability times expected amount of loan used by firm i and MC_{ijm} is the marginal cost the bank pays on issuing the loan. Probability of default $PD(\theta_j, I_i)$ depends from the bank-specific parameter of belief distortion θ_j and firm's news I_i. The first order condition for the maximization of the profit function reads as

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

where $\mathcal{M}_{ijm} = -Q_{ijm}/Q'_{ijm}$ is the bank's j markup on firm i loan. The equation tells us that the interest rate is formed of an effective marginal cost and a markup components, similarly to Bertrand-Nash pricing equation, augmented by the presence of the probability of default of the borrowers.

Recall that the probability of default depends negatively (positively) on positive (negative) news and positive belief distortion. The pricing equation tells us that, conditional on having a positive news, distorted beliefs ($\theta > 0$) tend to reduce both the marginal cost and the markup components. High level of competition implies low margins, which induce the belief distortion to have an effect mainly through the marginal cost channel. On the other hand, when competition is low and markups are high, beliefs' distortion can help to mitigate the markup component in good times (positive news), but exacerbating it in bad times (negative news).

Estimation of demand requires knowledge of contract prices, which give rise to several considerations. First, the borrower-bank price observed in our dataset is the equilibrium price, but to estimate the model, prices offered from banks not chosen by firms are also needed. Second, it is likely there are unobserved characteristics to us econometricians on the demand-side. Following Crawford et al. (2018), we adopt measures to avoid the risk of incurring in inaccurate price predictions.

Loan pricing reflects borrower specific components, such as customer's riskiness, bank-specific characteristics, as the degree of expectations' distortion, and bank-borrower relationship features. The price prediction is tightly linked to how we treat information in the bank-borrower-econometrician relationship. Crawford et al. (2018) claim that the determinants of loan prices are a combination of *hard* information, those observed by firms, banks and econometricians, and *soft* information, which are unobserved by the econometrician, but known by banks and borrowers. Designing a loan pricing model bears the risk of neglecting some of the information that could be in possess of the bank, but invisible to us (*soft*).

To mitigate this concern, first note that banks in our panel follow the IRB approach and it is reasonable to believe they make predominantly use of *hard* information (even if the *soft* component cannot be removed a priori though). A large survey by Albareto et al. (2011) indeed shows how large banks in Italy tend to use the following source of information to assess the creditworthiness of new loan applicants, by order of importance: 1- financial statement data, 2- credit relations with the entire system, 3- statistical-quantitative methods, 4- qualitative information, 5- availability of guarantees, 6- first-hand information (branch-specific). Second, we include in the analysis only the first and main credit line a firm borrows, to omit any dynamic from the bank-borrower relationship. Also, we introduce firm fixed effects to absorb any borrower-specific component unobservable to the econometrician. The institutional environment favours the use of fixed effects, given that the Italian market is strongly characterized by multi-affiliated borrowers (confirmed by our data, where single borrower-bank relationships account only for around 10%). After this premise, we can now present the price prediction model: price P_{ijm} charged to firm i by firm j in market m is an OLS model as described by equation (12):

$$P_{ijm} = \gamma_0 + \gamma_1 T_{ijm} + \gamma_2 L_{ijm} + \lambda_{jm} + \omega_i^p + \tau_{ijm} \tag{12}$$

where $\omega_i^p, \lambda_{ijm}$ are firm and bank-area-time fixed effects, T_{ijm} is tenure of relationship between borrower i and the bank j in market m; L_{ijm} is loan size and τ_{ijm} are prediction errors. Using estimated coefficients of (12) we can predict prices $\tilde{P}_{ijm}$ offered from banks that firms decided to discard.

Another required exercise is predicting prices for non-borrowing firms. We adopted a propensity score matching, using similar characteristics between borrowing and non-borrowing firms to predict price of contracts that would have been offered to firms that have not received them. Similarly, we use the same method to retrieve information and probability of default for firms with no relations with some banks.

First stage estimation We estimate the demand for credit lines in a two-step estimation, as in Train (2009). In the first step we estimate the firm-level parameters and recover bank-market specific constants with the contraction method as in Berry et al. (1995), which represents the dependent variable of the second-step estimation, recovering the price coefficient α^D in the demand function (5).

Estimation faces two obstacles: first, endogeneity of price should be taken into account;

second, as we did in the price prediction equation, we need to account for potential "soft" information, unobserved by the econometrician. Besides the prediction accuracy, it is important to account for possible *soft* information since they could give rise to omitted variable problem in the demand estimation. In what follows we try to get rid of this issue, as in Crawford et al. (2018).

The price prediction equation allows to disentangle between a bank-market and bank-market-borrower component:

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

where the term $\tilde{\omega}_i^p$ is estimated firm fixed effects from pricing equation. Since "soft" information are observed by bank (and not by us), we can include them in a variable $\omega^D = \eta_4^D \omega_i^p$, dependent on the component responsible for pricing.

All of the firm level components determining the demand are then given by:

$$
Y_{ijm}^D = \eta_1^D T_{ijm} + \eta_2^D L_{ijm} + \eta_3^D Y_i + \eta_4^D \tilde{\omega}_i^p
$$

Including the last two equations in the demand estimation equation yields:

$$
\begin{aligned}
U_{ijm}^D &= \delta_{jm}^D + \alpha^D(\tilde{P}_{jm} + \tilde{\eta}_1 T_{ijm} + \tilde{\gamma}_2 L_{ijm} + \tilde{\omega}_i^p + \tilde{\tau}_{jm}) + \\
&\quad \eta_1^D T_{ijm} + \eta_2^D L_{ijm} + \eta_3^D Y_i + \eta_4^D \tilde{\omega}_i^p + \nu_{ijm} \\
&= \underbrace{(\delta_{jm}^D + \alpha^D \tilde{P}_{jm})}_{\tilde{\delta}_{jm}^D} + \underbrace{(\eta_1^D + \alpha^D \tilde{\eta}_1)}_{\tilde{\eta}_1^D} T_{ijm} + \underbrace{(\eta_2^D + \alpha^D \tilde{\gamma}_2)}_{\tilde{\eta}_2^D} L_{ijm} + \\
&\quad \eta_3^D Y_i + \underbrace{(\eta_4^D + \alpha^D)}_{\tilde{\eta}_4^D} \tilde{\omega}_i^p + \underbrace{\alpha^D \tilde{\tau}_{jm} + \nu_{ijm}}_{\tilde{\zeta}_{ijm}} \qquad (13) \\
&= \tilde{\delta}_{jm}^D + \underbrace{Y_{ijm}^{\prime D} \tilde{\eta}^D}_{V_{ijm}^D} + \zeta_{ijm} \\
\Rightarrow U_{ijm}^D &= \tilde{\delta}_{jm}^D + V_{ijm}^D + \zeta_{ijm}
\end{aligned}
$$

Parameters $\tilde{\eta}^D$ are a mixture of direct effect of firm and firm-bank covariates on demand and indirect effects through pricing. Differentiating these channels in step 2 of the estimation gives demand-only specific parameters η^D. In addition, as standard in the literature, we assume error ζ_{ijm} is distributed as a type I extreme value. Finally, parameter α^D must be estimated in the second step of the estimation, since not part of equation (13) independently. Probability that borrower i chooses bank j in market m is then given by:

$$Pr^D_{ijm} = \frac{\exp(\hat{\tilde{\delta}}^D_{jm}(X^D_{jm}, \tilde{P}_{jm}, \xi^D_{jm}, \alpha^D, \beta^D) + V^D_{ijm}(Y^D_{ijm}, \tilde{\eta}^D))}{1 + \sum_l \exp(\hat{\tilde{\delta}}^D_{jm}(X^D_{jm}, \tilde{P}_{jm}, \xi^D_{jm}, \alpha^D, \beta^D) + V^D_{ijm}(Y^D_{ijm}, \tilde{\eta}^D))} \tag{14}$$

where $V^D_{ijm} = Y'^D_{ijm}\tilde{\eta}^D$ and $\hat{\tilde{\delta}}^D_{jm}$ are specific constants recovered through the contraction method from Berry et al. (1995).

Second stage estimation We use instrumental variable estimation to recover structural parameters in demand equation. In the first stage we find constants $\hat{\tilde{\delta}}^D_{jm}$, which contain bank-market-time covariates X^D_{jm} and bank-market-time specific component of predicted prices $\tilde{P}_{jm}$. We IV-regress constants on bank-market components using cost-shifters as instruments, where cost-shifters are interest rates on deposits:

$$\hat{\tilde{\delta}}^D_{jm} = \alpha^D_0 + \alpha^D \tilde{P}_{jm} + X'^D_{jm}\beta^D + \xi^D_{jm}$$

where ξ^D_{jm} is the structural error term. As indicated in Crawford et al. (2018), unobserved structural error term can be interpreted as the borrower's unobserved valuation of bank's characteristics, affecting bank's interest rates. ξ^D_{jm} can also include market specific errors. Bank and market fixed effects could solve this endogeneity concern. However, correlation between these bank-market errors can be solved through the use of an instrumental variable that represent households' deposits. Households' deposits are an important source of banks' capital and affect the lending conditions of branches[12]. The exclusion restriction is given by the fact that households' deposits respond to different market characteristics than the firm loans. Hence, as the instrumental variable for loan prices we use bank specific interest rate on households' deposits.

Estimation and results Besides estimation of demand described in the paragraphs above that accurately follows the work of Crawford et al. (2018), our estimation is characterized

[12]See Albareto et al. (2011)

by a slightly different supply equation. Equation (5) is dependent on the borrower's creditworthiness and nests both the level of the bank specific expectations' distortion θ_j and the borrower information I_i. We can define the level of distorted probability of default as a function of the rational probability of default plus a distortion parameter that guides the reaction to firm-specific news. Note that for this equation and the estimation results the interpretation of the coefficient goes in the other direction: when news is positive, the level of PD for distorted banks decreases more than for rational ones, as a direct effect of overreaction. We are opting for this formulation because the firm-specific news and the level of belief distortion never enter independently in our economic model, rather only through the probability of default. Expressing the distorted PD as the composition of a rational PD and a theta-dependent parameter which reacts to news, allow us to include both variables in the model and estimate the coefficient of belief distortion. Equation (15) is mathematically derived as equation (6):

$$PD_{ji}^{\theta} \approx PD_{ji}^{re} + \beta(\theta) I_i \tag{15}$$

Estimates of the structural model are outlined in table 7. 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. At the same time, increase of distortion (given by parameter *Belief Distortion*), causes an increase of loan demand though the dampening of probability of default assigned by banks.

We further conduct some counterfactual exercise where we make vary several components to the detect the response of the model; results are given by table 8. As a first exercise we double the level of beliefs' distortion to understand the reaction of loan quantities and prices. Results show that doubling the level of distortion, conditional on receiving a positive news from firms, interest rate tend to drop by 42 basis points and the probability of having a new bank-borrower relationship increases by 1.7%, on average.

The second exercise we run through the model consists in increasing the news by one standard deviation. Receiving a positive one standard deviation news makes diagnostic banks decrease price by 32.4 basis points and increase the likelihood of new bank-borrower relationship by 4.7%, compare to the average rational. Results for a negative news are almost symmetric. In the empirical analysis our findings display instead a higher level of

Table 7: Structural Estimation - Results

		Prob. borr-bank relationship
Demand param.	Tenure	1.658^{***}
		(0.181)
	Previous rel.	1.403^{***}
		(0.387)
	Constant	0.940
		(15.644)
	Share branches	0.988
		(1.913)
	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)
Supply param.	Const. (Bel. dist.)	0.039^{***}
		(0.000)
	Belief distortion	$\mathbf{-0.599}^{***}$
		(0.018)
	Const. (Deposit int. rate)	1.003
		(0.873)
	Deposit int. rate	1.000
		(13.065)

This table presents estimate of the structural model.

Table 8: Counterfactuals - Results

	ΔP	ΔQ
Exercise 1		
News	-0.419^{***}	0.017^{***}
	(0.162)	(0.003)
Bank FE	Yes	Yes
Market FE	Yes	Yes
Exercise 2		
Diagn. Bnk $\|\Delta News > 0$	-0.324^{***}	0.047^{***}
	(4.141)	(0.314)
Diagn. Bnk $\|\Delta News < 0$	0.268^{***}	-0.051^{***}
	(4.380)	(0.346)
Exercise 3		
Median News	1.671^{*}	-0.004^{*}
	(0.999)	(0.002)
Bank FE	Yes	Yes
Market FE	Yes	Yes

This table shows coefficient estimates of the structural model for three different counterfactual exercises investigating the effects on prices and quantities on diagnostic banks, keeping the rational banks as benchmark. In Exercise 1 we double the size of the average estimated expectational distortion parameter *theta* for diagnostic banks, conditional on receiving a positive news. In the Exercise 2 we perturb the model with a *News* increase of one standard deviation, both positive and negative. In Exercise 3 we shut down the coefficient *theta* for previously identified diagnostic banks and see how their lending decisions would react in absence of the expectation distortion.

asymmetry in favour of the negative news and are overall weaker in magnitude. Third, we shut down the distortion parameter for the banks identified as distorted in the reduced form analysis, and see how these banks react in prices and quantities to a median positive news. The reaction our model suggests is an increase in prices and a mild reduction in quantities. In absence of their distortion, diagnostic banks would price their loans on average 167 basis points more than a rational bank. The three exercises above strengthen the reduced form findings of section 4, confirming that expectational errors in the banks' prediction of the probability of default is a channel well identifiable through a structural model of lending imperfect competition.

6 Robustness

We conduct several robustness exercises to strengthen our main results. First, we try to mitigate the concern that PD does not deviate from realized default rates only because of banks' strategic behaviour. Second, we try an alternative measure of news with respect to the two used in the main specifications. Third, we use the entire dataset length, so including Covid-19, to investigate how results may vary. Overall we do not find significant variations and findings confirm outcomes of the main analysis.

6.1 PD and strategic behaviour

One concern when looking at IRB PDs (the PD in Anacredit, we call it in this paragraph PD^{IRB}) is that banks may systematically under-report their "true" credit risk assessment to minimize capital requirements (Behn et al. (2021)). While we cannot completely rule out banks' strategic behaviour, we take several steps to mitigate this concern.

First, looking at figure 1 and table 3, if anything, banks seem to *over estimate* the probability of default, at least in our sample period. Second, we compare our PD^{IRB} to another probability of default, which banks use to compute the expected loss of a borrower according to the IFRS 9 accounting principle, and that here we will call PD^{EL}. PD^{EL}, which is computed quarterly, is *not* used to compute capital requirements and therefore should not be subject to the same degree of strategic behaviour as PD^{IRB}. Note that the PD^{EL} is unobservable in AnaCredit. What we can observe is the "rating" class[13] 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. The rating class is directly linked to PD^{EL}, so we can use the observed class as a good proxy for the IFRS 9 associated probability of default. From one period to another, if the PD^{EL} changes, we are able to observe it through the corresponding change in the assigned rating class Sn.

Our 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 consistent change in PD^{IRB}

[13] 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: Test on banks' strategic behaviour

	ΔPD^{IRB}_{t+3}					
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	No	Yes	No	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	No	Yes
Sector FE	No	No	No	No	Yes	Yes

Notes: This table reports the coefficients of the following regression: $\Delta PD^{IRB,i,b}_{t+3} = \beta_0 + \mathbf{\Gamma}'\mathbf{X} + \epsilon^{i,b}_t$ where $\mathbf{X}$ is a vector of controls including *total loans* and *credit age*. The regression is estimated only on the subsample with a $\Delta PD^{EL} > 0$: a positive and significant intercept means that whenever banks increase their PD^{EL} we observe a parallel increase in PD^{IRB}, too. Standard errors are clustered at 2-digit NACE sectors.

too. In our specification we select the subsample of borrowers that migrate from $S1$ to $S2$. We then use as a dependent variable the quarterly change of the PD^{IRB}, ΔPD^{IRB}_{t+3} and some controls as regressors. Table 9 shows the results: a positive and significant intercept has to be interpreted as a positive correlation between the variation in PD^{EL} and PD^{IRB}. This finding suggests to reject that banks are not overly strategic when reporting the PD^{IRB} to the supervisory authority.

6.2 News proxy with IFRS9 accounting data

As in the previous section, we use the rating class Sn given by IFRS9 accounting data for a different scope. We aim to find a measure that replaces the news measure $News_t$ for an additional robustness exercise. We look again at the subset of borrowers who flow from one rating class Sn to another as a signal of null/negative/positive news. Borrowers who pass to a more-risky rating class constitute a negative news ($D1$ = Rating Decrease), those who pass to a less-risky rating class a positive one ($D2$ = Rating Increase) for the bank. Borrowers who see their rating class unchanged represent the baseline case of no news. Notice that, since $D1$ signals negative news, the expected right coefficient for overreaction would be of negative sign (an overreaction to negative news induce a higher-than-due PD, hence a negative forecast error).

$$FE^{\theta,i,b}_{t+12|t} = \beta_0 + \beta_1 D1^{i,b} + \beta_2 D2^{i,b} + \mathbf{\Gamma}'\mathbf{X} + \epsilon^{i,b}_{t+12}$$

When we introduce fixed effects, the coefficients of both subgroups are statistically significant and correct in sign, as confirmed in table 10. The arrival of positive or negative news induced by the release of IFRS9 data makes bankers overreact.

Table 10: Test on alternative News measure

	$FE^{\theta,i,b}_{t+12\|t}$					
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	No	Yes	No	No	Yes	No
Sector FE	No	No	Yes	No	Yes	No
Province FE	No	No	No	Yes	Yes	No
Borrower FE	No	No	No	No	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table provides coefficient estimates of the regression $FE^{\theta,i,b}_{t+12|t} = \beta_0 + \beta_1 D1^{i,b} + \beta_2 D2^{i,b} + \mathbf{\Gamma}'\mathbf{X} + \epsilon^{i,b}_{t+12}$, where $\mathbf{X}$ is the controls matrix can include *loan size* and *credit age* and bank, sector, province and/or borrower fixed effects. Standard errors are clustered at NACE 2 digit-level. Significance levels at 1%, 5%, 10% are given by (***), (**), (*) respectively.

6.3 Using the full sample

As an additional test, we replicate our main results from regressions (9) and (10) extending our sample to 2021(Q1), i.e. including also the Covid-19 shock[14]. Our results are left unaffected to those found in the pre-Covid sample. Table 11 confirms the overreaction of bankers' to news arrival; given an increase in the news standard deviation, the forecast error increases by 420 basis points. Table 12 instead, shows a very similar result to that one obtained in the main analysis.

One possible explanation for the very high degree of overreaction using the full-sample can be that banks, under the Covid-19 shock revised upward PDs while realized default rates did not increase as expected because of public intervention[15]. Finally, interest rates

[14]We believe it is reasonable to pinpoint the first data under Covid-19 with the third quarter of 2020. First partial lockdown measures in Italy started in March 2020 and we assume bankers' beliefs remained unvaried for several months thereafter.

[15]Since the beginning of the pandemics, Italian government has put in place a moratorium on outstanding banking debts positions.

Table 11: Effect of news on forecast errors - Full Sample

	$FE^{\theta,i}_{t+12\|t}$					
$News_t(all)$	0.315***	0.320***	0.315***	0.316***	0.321***	0.534***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.005)
N	3,069,663	3,069,663	3,069,663	3,069,663	3,069,663	1,626,921
Bank FE	No	Yes	No	No	Yes	No
Sector FE	No	No	Yes	No	Yes	No
Province FE	No	No	No	Yes	Yes	No
Borrower FE	No	No	No	No	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table provides coefficient estimates of the regression $FE^{\theta,i}_{t+12|t} = \beta_0 + \beta_1 News^i_t + \mathbf{\Gamma}'\mathbf{X} + \epsilon^i_{t+12}$, where $\mathbf{X}$ is the controls matrix and includes sector, province and/or borrower fixed effects. The regression is run using the full sample period. Standard errors are clustered at the borrower level. Significance levels at 1%, 5%, 10% are given by (***), (**), (*) respectively.

seem to have changed homogeneously among banks and decreased on average moderately because of public intervention.

Table 12: Effects on interest rates - Full Sample

	$r^{i,b}_t$					
$News_t$	−0.030***	−0.027***	−0.029***	−0.026***	−0.024***	−0.004
	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.004)
D^b_t	0.005***	0.007***	0.004***	0.005***	0.006***	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
$News_t \times D^b_t$	−0.020	−0.017	−0.020	−0.024	−0.021	−0.023*
	(0.014)	(0.013)	(0.014)	(0.016)	(0.014)	(0.013)
N	204,693	204,693	204,693	204,693	204,693	108,487
Bank FE	No	Yes	No	No	Yes	No
Sector FE	No	No	Yes	No	Yes	No
Province FE	No	No	No	Yes	Yes	No
Borrower FE	No	No	No	No	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: In this table we report estimates of the regression $r^{i,b}_t = \beta_0 + \beta_1 D^b_t + \beta_2 News^{i,b}_t + \gamma(D^b_t \times News^{i,b}_t) + \mathbf{\Gamma}'\mathbf{X} + \epsilon^{i,b}_t$, where $\mathbf{X}$ is a control matrix which contains also fixed effects. The regression is run using the full sample period. Errors are clustered at the NACE 2-digit level. Significance levels at 1%, 5%, 10% are given by (***), (**), (*) respectively.

7 Conclusion

In this paper, we contribute to the literature of lenders' beliefs and show that bankers overreact to news on borrowers' creditworthiness consistently with a learning model of diagnostic expectations. To measure lenders' beliefs at a granular level we use banks' estimates of borrowers' probability of default. We document that bankers over (under) estimate borrowers' default when receiving negative (positive) news, and that this bias is stronger for negative news and riskier borrowers. We also find significant heterogeneity in lenders' levels of overreaction, which we exploit to quantify the effect of expectational distortions on prices and quantities. Finally, we rationalize our empirical results through a structural estimation of a banking competition model.

There are several natural extensions of this work. First, we limited our analysis to the Italian banking sector, but other belief distortions (if any) may characterize credit markets in other developed or developing economies. Second, our study focuses on the cross-section of borrowers (and banks). If a longer time series were available, extending our loan-level analysis to longer time periods may prove valuable to develop a more complete understanding of the boom-bust phases of the credit cycle.

References

Albareto, Giorgio, Michele Benvenuti, Sauro Mocetti, Marcello Pagnini, and Paola Rossi, "The organization of lending and the use of credit scoring techniques in Italian banks," *Journal of financial transformation*, 2011, pp. 143–57.

Baron, Matthew and Wei Xiong, "Credit expansion and neglected crash risk," *The Quarterly Journal of Economics*, 2017, *132* (2), 713–764.

Basel Committee, "The Internal Ratings-Based Approach," *BIS Publications*, 2001, p. 108.

Behn, Markus, Rainer FH Haselmann, and Vikrant Vig, "The limits of model-based regulation," *Journal of Finance, Forthcoming, LawFin Working Paper*, 2021, (20).

Berry, Steven, James Levinsohn, and Ariel Pakes, "Automobile prices in market equilibrium," *Econometrica*, 1995, *63* (4), 841–90.

Bordalo, Pedro, Katherine Coffman, Nicola Gennaioli, and Andrei Shleifer, "Stereotypes," *The Quarterly Journal of Economics*, 2016, *131* (4), 1753–1794.

_ , Nicola Gennaioli, and Andrei Shleifer, "Diagnostic expectations and credit cycles," *The Journal of Finance*, 2018, *73* (1), 199–227.

_ , _ , Rafael La Porta, and Andrei Shleifer, "Diagnostic expectations and stock returns," *The Journal of Finance*, 2019, *74* (6), 2839–2874.

_ , _ , Yueran Ma, and Andrei Shleifer, "Overreaction in macroeconomic expectations," *American Economic Review*, 2020, *110* (9), 2748–82.

Chiappori, Pierre-André and Bernard Salanié, "Asymmetric Information in Insurance Markets: Empirical Assessments," *Handbook of Insurance: Second Edition*, 2013, pp. 397–422.

Coibion, Olivier and Yuriy Gorodnichenko, "Information rigidity and the expectations formation process: A simple framework and new facts," *American Economic Review*, 2015, *105* (8), 2644–78.

Coimbra, Nuno and Hélene Rey, "Financial cycles with heterogeneous intermediaries," Technical Report, National Bureau of Economic Research 2017.

Crawford, Gregory, Nicola Pavanini, and Fabiano Schivardi, "Asymmetric Information and Imperfect Competition in Lending Markets," *American Economic Review*, 2018, *108* (7), 1659–1701.

Durbin, James and Siem Jan Koopman, *Time series analysis by state space methods*, Oxford university press, 2012.

Fahlenbrach, Rüdiger, Robert Prilmeier, and René M Stulz, "Why does fast loan growth predict poor performance for banks?," *The Review of Financial Studies*, 2018, *31* (3), 1014–1063.

Gennaioli, Nicola and Andrei Shleifer, "What comes to mind," *The Quarterly journal of economics*, 2010, *125* (4), 1399–1433.

_ , _ , and Robert Vishny, "Neglected risks, financial innovation, and financial fragility," *Journal of Financial Economics*, 2012, *104* (3), 452–468.

_ , Yueran Ma, and Andrei Shleifer, "Expectations and investment," *NBER Macroeconomics Annual*, 2016, *30* (1), 379–431.

Greenwood, Robin and Andrei Shleifer, "Expectations of returns and expected returns," *The Review of Financial Studies*, 2014, *27* (3), 714–746.

_ , Samuel G Hanson, and Lawrence J Jin, "Reflexivity in credit markets," Technical Report, National Bureau of Economic Research 2019.

Kahneman, Daniel and Amos Tversky, "Subjective probability: A judgment of representativeness," *Cognitive Psychology*, 1972, *3* (3), 430–454.

Kindleberger, Charles, "Manias, Panics, and Crashes," 1978.

Krishnamurthy, Arvind and Wenhao Li, "Dissecting mechanisms of financial crises: Intermediation and sentiment," Technical Report, National Bureau of Economic Research 2020.

López-Salido, David, Jeremy C Stein, and Egon Zakrajšek, "Credit-market sentiment and the business cycle," *The Quarterly Journal of Economics*, 2017, *132* (3), 1373–1426.

Ma, Yueran, Teodora Paligorova, and José-Luis Peydro, "Expectations and bank lending," *Work. Pap., Chicago Booth Sch. Bus., Chicago Google Scholar Article Location*, 2021.

Minsky, Hyman P, "The Financial Instability Hypothesis: An Interpretation of Keynes and an Alternative to "Standard" Theory," *Nebraska Journal of Economics and Business*, 1977, pp. 5–16.

_ , "Stabilizing an Unstable Economy: The Lessons for Industry, Finance and Government," *Hyman Minski Archives*, 1986.

Richter, Björn and Kaspar Zimmermann, "The profit-credit cycle," *Available at SSRN 3292166*, 2019.

Train, Kenneth E., "Discrete choice methods with simulation," *New York: Cambridge University Press*, 2009.

Appendix

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 $\mathbb{E}_t(z_{t+1})$.)

$$\begin{aligned}
z_{t+1} - \mathbb{E}_t^{\theta}(z_{t+1}) &= \underbrace{z_{t+1} - \mathbb{E}_t(z_{t+1})}_{=w_{t+1}} + \mathbb{E}_t(z_{t+1}) - \mathbb{E}_t^{\theta}(z_{t+1}) \\
FE^{\theta}_{t+1|t} &= w_{t+1} + \Phi\Big(\frac{a - \hat{x}_{t+1}}{\Omega_t^{1/2}}\Big) - \Phi\Big(\frac{a - \hat{x}^{\theta}_{t+1}}{\Omega_t^{1/2}}\Big) \qquad (16)
\end{aligned}$$

   Equation (16) 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 $\Phi\left(\frac{a-\hat{x}_{t+1}}{\Omega_t^{1/2}}\right)$ and $\Phi\left(\frac{a-\hat{x}^{\theta}_{t+1}}{\Omega_t^{1/2}}\right)$ gives:

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

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

From the last two expressions, (16) becomes

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

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.

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

Model - Real effects

Non linear relation for interest rate looks like

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

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

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

$$r_t^\theta \approx r_t - \frac{\theta K_t}{\Omega^{1/2}} \frac{\phi\left(\frac{a}{\Omega^{1/2}}\right)}{\Phi\left(\frac{a}{\Omega^{1/2}}\right)^2} I_t$$

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.

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$$

$$y_i = \gamma_0 + \gamma_1 z_i + v_i$$

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 (4)

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

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.

Tables

Table 13: Nace Sectors

1-Digit Code	Description
A	Agricolture, forestry, fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity and gas
E	Water supply and waste management
F	Construction
G	Wholesale retail
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support activities
O	Public administration and defense
P	Education
Q	Human health and social works
R	Arts, entertainment and recreation
S	Other service activities
T	Activities of households and employers
U	Activities of extraterritorial organizations

Notes: This table shows the list of NACE differentiation of economic activity. More information can be obtained at the official page of European Commission.