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Essays on Expectations in Macroeconomics and Finance

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Abstract

Chapter 1 studies in a cross-sectional analysis lenders' beliefs. We use a novel loan-level dataset containing borrower-specific probability of default that allows to measure accurately lenders' expectations. We found our empirical analysis on a learning model where bankers endowed with diagnostic expectations observe noisy fundamentals from firms and estimate their probability of default. We provide empirical evidence that financial institutions are subject to expectational distortions: banks tend to overreact to both micro and macro news, overestimating (underestimating) borrowers' defaults after negative (positive) signals. We also document that the degree of overreaction is quite heterogenous among banks. In addition, overreacting bankers decrease (increase) interest rates more than rational ones and the probability of issuing a new loan rises (fall) in light of positive (negative) news. We confirm these results with a structural estimation exercise departing from a model of banking competition where banks' profit function depends on borrowers' creditworthiness, driven by the level of banks' expectation distortion and firm-specific economic news.

Chapter 2 investigates bank lending expectations through the Bank Lending Survey and how they react to monetary policy announcements. First we assess whether the belief formation process of banks respects the full-information-rational-expectations paradigm through testing forecast errors predictability. Second we study the reaction of bankers' beliefs to the ECB monetary policy announcements. Preliminary results confirm error predictability in banks' beliefs and amplification of beliefs' distortion when monetary policy announcements are perceived as pure monetary shocks. We preliminary describe the mechanism underlying empirical findings through a macro model with risky debt and non-rational expectations.

Chapter 3 combines non-rational expectations and financial constraints in a simple 3-periods macro model that reconciles with a Minsky cycle. Financial crises have unveiled the central role of determinants such as debt and sentiment in macro dynamics. This paper incorporates both features under the formulation of overreacting expectations to good news and financial constraints in a unique theoretical environment. The model shows that sentiment originates the boom phase through inflated beliefs on the reselling value of the home-equity asset purchased. A reversal of expectations to rationality induces agents to self-constrain their borrowing capacity when they realize that past debt demand was blown up. This mechanism provides the formation of a new equilibrium driven by the collateral limit which provides a lower demand for debt and force the agent to reduce consumption.

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, raise (diminish) loan size 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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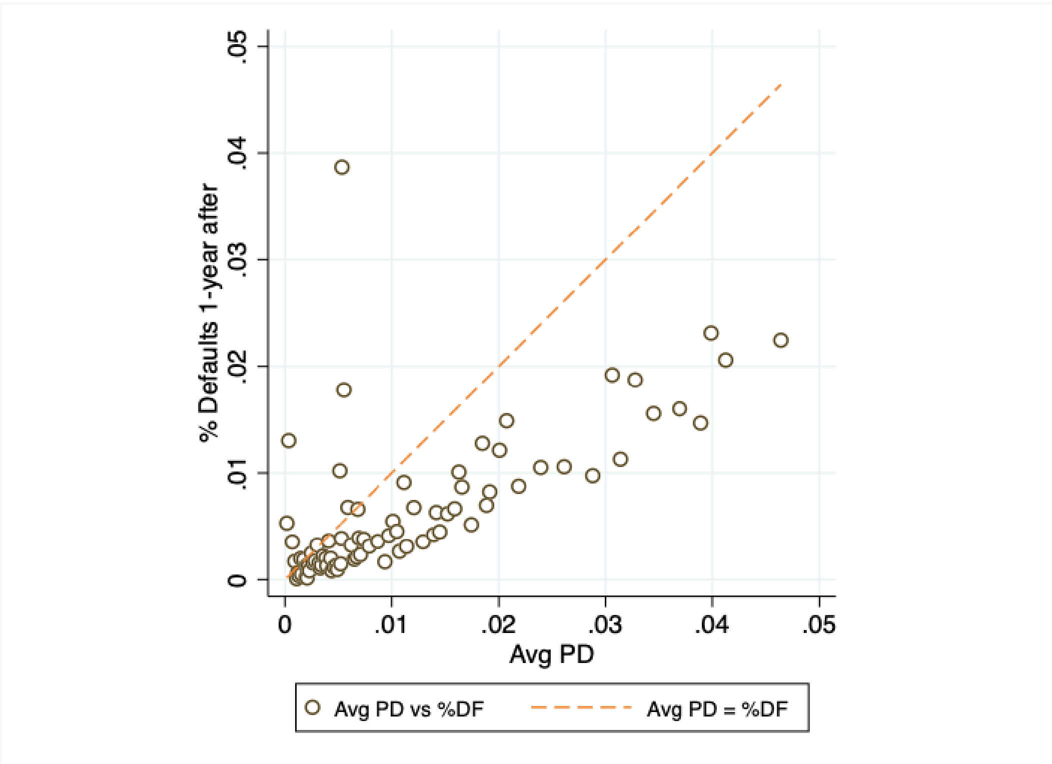
1 Introduction

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 120 to 250 basis points (bps) more in the determination of the PD relative to a rational one.

Regarding borrowers' heterogeneity, distortions are more pronounced towards firms located in the South and Center of Italy. Our results 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 call "diagnostic") particularly do so, there are also some that do not (and that we call "rational")[1].

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)

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

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 4.9 and 9.3 basis points, increase the the loan size by 1.08% and 4.82% and raise the probability of issuing a new loan by about 1.20% compared to rational lenders. Results obtained with macro news as the main information driver confirm qualitatively the estimates of the micro 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 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 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, 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 (*Analytical Credit Datasets*), a credit registry managed by the ECB, which manages, through NCBs (National Central Banks), the collection of 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. In the Italian section there are around 250 reporting entities.

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 such as the sector of economic activity (Nace 2-digit) and the headquarters' geographical location.

Among the reporting entities, we select only those banks that use their internal procedures to compute the probability of default (PD) according to the so-called Internal Ratings Based approach (IRB - Basel Committee (2001)).

Given the big amount of observations in the original Anacredit, we made an additional random selection among IRB banks to get our baseline sample, which contains more than 3 million observations at the loan-level and more than one million 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)[2]. We decided to restrict the main analysis to this period due to the introduction of the *Moratoria*, a policy that the Italian Government introduced in March 2020[3] to relief firms and households hurt by the pandemics. Regarding non-financial corporations, focus of this paper, only small and medium enterprises could apply for *Moratoria*.

In each of the 12 periods used for the baseline estimations, the dataset contains around 75,000 different firms, affiliated to 9 banks, operating in 83 different Nace sectors and scattered over the 107 Italian provinces. The average loan size is around euro 45,000 and ranges from euro 25,000 to 700,000,000. Average interest rate in the panel is 2.97%. Credit age, defined as the difference in quarters between the reporting date and the date of origination of the debt position, ranges from zero to over 40 years.

Other datasets used are the Istat Index of Production (sales), Italian credit registry, Cerved credit data and Taxia. From Istat we retrieve the index of industrial production for manufacturing and construction sectors and sales' index for services in Italy. These indexes are used as macroeconomic signals, as outlined in paragraph 4. Both indexes are released monthly at Nace 4-digit level for manufacturing, construction and services for firms with more than 20 employees. We intend the measure as a macro signal that banks receive from these sectors. We use the Nace 2-digit granularity to match the index with our bank-firm data. The measure of the macro signal is defined as the percentage quarterly difference of the index for each 2-digit sub-sector for which the index is available: $News_t^s = \frac{idx_t^s - idx_{t-1}^s}{idx_{t-1}^s}$, where t is the quarter. Merging Anacredit with Istat dataset, the number of firms roughly decrease to 58,000 units from 75,000. Remained Nace sectors are 52 from the 83 of the original Anacredit. Lost of data is

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

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

mainly due to missing sectors in the Istat dataset, which does not produce the index for minor sectors. The average macro signal is around 3.2%, and the same measure lagged by one period is 1.8%. Other variables are relatively in line with the main Anacredit dataset aggregated at the borrower level. Specific summary statistics can be read in table 14 in the appendix. Italian Credit registry, Cerved credit data and Taxia are described and used in the section dedicated to the structural estimation.

2.2 Probability of default

The probability of default is a bank-borrower variable, meaning that each bank computes this measure for each borrower with an outstanding position. The PD is the forecast about the one-year-ahead default status, which is a binary variable taking values 0 or 1. The default status kicks in after 90-180 days of unpaid loan instalment and/or the bank deems the borrower *unlikely to pay*.

Statistics The discrepancy between the actual default rate and the estimated probability of default makes us question about banks' forecast errors, as outlined in the introduction by figure 1 and whether banks are sensitive to signals. From summary statistics available in table 1 - Panel 1, we can notice that the average level of PD in the sample is 0.04, while average default is slightly higher than 0.02. The PD is sticky over time, as creditworthiness does not necessarily change every quarter for every borrower. Still, it is not completely static: we document that the PD lag-1 and lag-2 autocorrelation are 0.9 and 0.8, respectively. They decrease to 0.77 and 0.63 when the sample is restricted to observations where forecast error is available (this is the selection we use in our main specification in section 4). The bottom PD decile is 0.019%, while the top one measures around 6%. Forecast errors appear to be monotonically decreasing on PD deciles and range from the first the top decile between -0.04 and -0.0015.

In terms of geographical heterogeneity, we report 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 12 in Appendix. The same monotonicity is reported also for the dispersion of such variables. Regarding economic sectors, construction reports the highest average level of PD and PD dispersion, while manufacturing shows the lowest ones. Banks show higher forecast errors for firms operating in construction and agriculture/mining. Summary statistics at the sector level and a full list of Nace sectors in the dataset are available in table 13 in Appendix.

Overall, bankers 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.

Table 1: **Summary statistics**

	N	Mean	p10	p25	p50	p75	p90	Max	Min	SD
					Panel 1: Borrower-level data					
Pd	1,206,271	0.0436	0.0019	0.0038	0.0091	0.0216	0.0617	1	0	0.1509
Default	597,558	0.0227	0	0	0	0	0	1	0	0.1489
FcstError	597,558	-0.00002	-0.0399	-0.019	-0.0069	-0.0034	-0.0015	1	-1	0.1448
PdNews	1,039,960	-0.0039	-0.0061	0	0	0	0.0049	1	-1	0.0661
log(Loansize)	1,206,271	11.59	9.79	10.49	11.51	12.61	13.73	20.36	4.40	1.67
InterestRate	1,206,271	0.0297	0.0060	0.0125	0.0239	0.0405	0.0614	0.9990	-0.0368	0.0234
CreditAge	1,206,271	10.42	1	2	5	12	26	185	0	14.25
					Panel 2: Loan-level data					
Pd	3,666,408	0.0581	0.0022	0.004946	0.0116	0.0329	0.0804	1	0	0.1789
FcstError	1,860,176	0.00761	-0.0617	-0.026911	-0.0112	-0.0045	-0.0016	1	-1	0.1830
PdNews	3,318,026	-0.0060	-0.0087	0	0	0	0.0044	1	-1	0.0773
log(Loansize)	3,666,408	10.66	7.94	9.40	10.75	12.10	13.21	20.36	4.40	2.13
InterestRate	3,666,408	0.0338	0.0000	0.0117	0.0275	0.0504	0.0754	2.4640	-0.561146	0.0282
CreditAge	3,666,408	6.84	0	1	3	7	16	185	0	12.39

Notes: This table shows summary statistics for variables aggregated at the borrower-level and at the loan-level. Deciles are based on the PD distribution. 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. PD 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.

PD origination There are several points to stress about the probability of default. To begin, survey data are today largely used in macroeconomics to study agents' expectations. We prove that other measures can be used to study expectations besides survey data or financial derivative prices. To the best of our knowledge, this paper represents the first attempt to leverage this particular data type in studying agents' expectations. The PD is a measure produced by credit risk models and can be revised judgementally by loan officers. The probability of default is by definition a forecast on the likelihood that a single counterpart defaults one year-ahead and is a measure upon which banks found their business and supervisory authority control capital requirements needed to ensure a valid assessment of risk. The first point ensures the forecasting nature of the variable, while the second confirms the relevance of the measure. In particular, the PD in our dataset originates from banks using Internal Rating Based approach. Only banks that meet stringent conditions regarding disclosure, governance, and model screening ability can use the IRB approach. 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[4]. Specifically, the PD is used to compute the risk-weighted-assets for corporate, sovereign and bank exposures[5].

One concern that may arise is the strategic behaviour of banks in reporting the probability of default to supervisors, borrowers or competitors. With publicly available data, signalling to other banks a specific behaviour for competition purposes is a possibility. Since the PD is reported only to the supervisory authority and not made public, we rule out any concern that could materialise with respect or other peers. Similarly, borrowers are not informed about the level of their PD, so it is unlikely that the firm would react to the assessment of the PD. Conversely, there are several points we make to address and mitigate the potential concern regarding the reporting to supervisors. First, the PD is used for the calculation of capital requirements: the higher the PD, the more capital requirements. A strategic reporting would imply a lower-than-due level of PD, as the bank would lower the amount of capital requirements and potentially increase its profitability. However, we report, on average, a higher probability of default than realized defaults in the sample. Second, the first objective of the paper is documenting the sensitivity of forecast errors to information to prove the presence of a deviation from full-information-rational expectations hypothesis, not measuring the accuracy of banks' forecasting. In addition, in section 6.1 we introduce an additional exercise employing alternative data sources, which serves to address the issue. The model of expectations described in the next section aims at describing in a plausible way the driving mechanism behind the sensitivity that banks may have when receive signals from firms' 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

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

[5]The general formula used to compute capital requirements, according to the PD and other variables 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 og 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. More details are accessible at BIS documentation on the calculation of risk-weighted assets for credit risk Basel Committee on Banking Supervision (2023)

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 applied 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 selec-

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

tively 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.

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

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 $FE_{t+1|t}^{\theta,i} = z_{t+1} - \widehat{PD}_{t+1|t}^\theta$ with respect to the probability of default. Then, for each firm $i = 1, \ldots, N$ and bank $b = 1, \ldots, B$ we have

$$FE_{t+1|t}^{\theta,i,b} \approx K\theta \frac{1}{\widehat{\Omega}^{1/2}} \phi\left(\frac{a}{\widehat{\Omega}^{1/2}}\right) I_t^{i,b} + w_{t+1}^{i,b} \tag{5}$$

where $w_{t+1}^{i,b}$ 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 $\beta_1 = 0$ 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

[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 $\hat{x}_{t+1|t}^\theta$.

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:

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

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

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 2020-Q2 to discard confounding 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.

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

Control variables like loan size and credit age are contained in $\mathbf{\Gamma}'\mathbf{X}$ alongside bank, sector, province, borrower and time fixed effects. The main regressor $News_t$ is a measure of innovation that the bank receives about each firm i in each period t. We validate our borrower-specific measure of $News_t$ in the Appendix - Proofs.

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.

Each Panel of table 2 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 (we refer to it as the *micro* or *PD news*), 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 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. 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. 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. Loan size is negatively correlated to forecast errors, which indicates that banks err less with more exposed borrowers when are subject to news, although coefficients are significant only for the first two specifications of the Panel B. Results in Panel A of table 2 suggest that for a standard deviation increase in news, the forecast error of a diagnostic banker increases by 120 to 250 basis points more than a non-diagnostic banker (Panel

[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 one of them.

A). The effect is stronger in Panel B where the sample is limited to negative news, reaching between 300 and 620 basis points. In Panel C the effect is lower and stands at 3-30 basis points. The effect is always more intense in the specification with borrower fixed effects (last column on the right of table 2). Expressing the results differently, when news increases by one standard deviation, bankers predict a default rate that is 1.2% to 2.5% lower than what a rational forecaster would anticipate. [9]

To corroborate our findings, we also use an alternative aggregate measure of news. We define with *macro* or *sector news* the quarter-on-quarter variation of industrial production index $News_t = \frac{Idx_t - Idx_{t-4}}{Idx_{t-4}} * 100$. The index granularity is at the Nace 2-digit level and is computed for firms in the manufacturing and construction sectors, while an equivalent sales index is given for firms in the services sectors. Table 3 delivers results comparable to table 2. The samples used in the two specifications do not coincide perfectly, as some of the sectors in the Anacredit dataset are not given by the Istat measure (agriculture for instance), and some sectors in Istat are not represented in Anacredit (for a better comprehension of the sectors tables 15 and 16 are provided in Appendix). Coefficients of the macro news are positive and significant in all the specifications of Panel A and B of figure 3. They are positive but not significant in Panel C. The signs of loan size coefficients are negative but not significant everywhere and credit age estimates are overall ambiguous. Regarding the magnitude of the macro news, an increase in of one standard deviation in news (panel A) generates an increase in forecast error of 18 basis points; this number itself does not say a lot. Considering that the average FE in the same sample is 22 basis points, it means that an increase of one standard deviation in macro news generates an error around 80% in forecast error, on average. The effect is larger when the sample is restricted for negative news (panel B) and mitigated for positive news (Panel C). We tried other different variables as proxies for the innovation, left for a robustness exercise in Robustness, section 6.

[9] We report the main standard deviation measures used for the coefficients' interpretation. Measures are those of the subsample used for estimates reported in tables 2 and 3, meaning where forecast error is non-missing and period goes from 2018-Q3 to 2020-Q2.

	St. Dev. (non-missing FE & date $\leq$ 2020Q2)		
	All *News*	$News < 0$	$News \geq 0$
PD News	0.04	0.06	0.025
Macro News	0.14	0.10	0.10

Table 2: **Forecast Errors Predictability - PD News**

	$FE^{\theta,i}_{t+12\|t}$		
	Panel A: All PD News		
$News_t$	0.300***	0.302***	0.629***
	(0.0348)	(0.0348)	(0.0215)
log(Loan Size)	-0.0003	-0.0001	-0.00009
	(0.0002)	(0.0002)	(0.0002)
Credit Age	-0.00003	-0.00001	0.000003
	(0.00002)	(0.00002)	(0.00001)
N	472392	472392	467512
	Panel B: Negative PD News		
$News_t$	0.490***	0.492***	1.045***
	(0.0530)	(0.0530)	(0.0247)
log(Loan Size)	-0.0014***	-0.0014***	-0.00046
	(0.0004)	(0.0004)	(0.000748)
Credit Age	-0.00004	-0.00003	0.00002
	(0.00004)	(0.00004)	(0.00003)
N	113176	113176	95797
	Panel C: Non-Negative PD News		
$News_t$	0.00843	0.0110	0.124***
	(0.0250)	(0.0243)	(0.0247)
log(Loan Size)	-0.0003	-0.00006	-0.00002
	(0.0002)	(0.0002)	(0.00019)
Credit Age	-0.000003	0.00002	-0.000008
	(0.00003)	(0.00002)	(0.00002)
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 provides coefficient estimates of the main 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. Period used goes from 2018-Q3 to 2020-Q2. The dependent variable is Forecast Error and it is computed as the difference between Default at $t+1$ and PD at t. The main regressor PD News is borrower-specific. 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. Errors are clustered at the Nace 2-digit level.

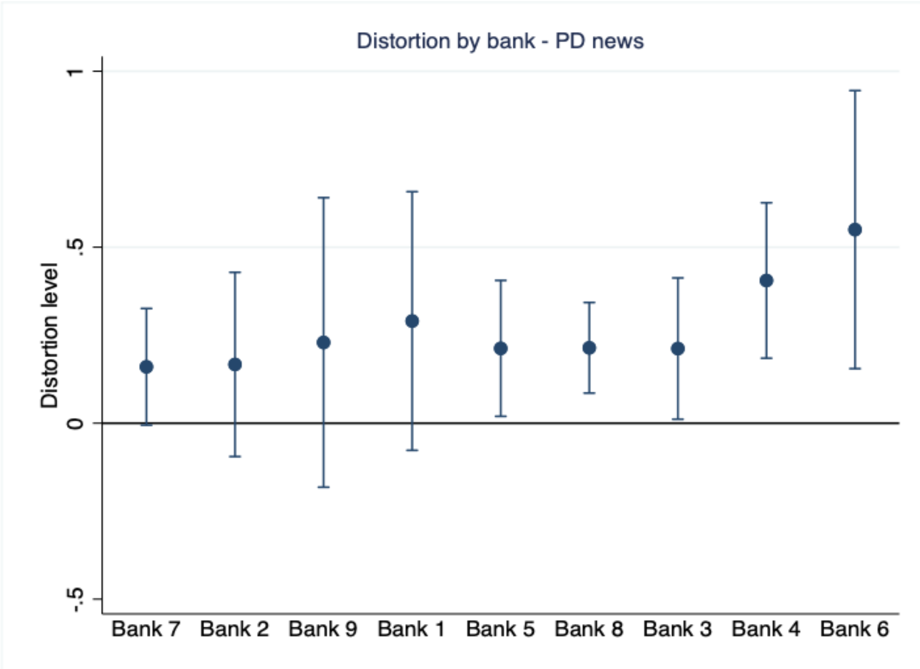
Table 3: **Forecast Errors Predictability - Sector News**

	$FE^{\theta,i}_{t+12\|t}$		
	Panel A: All Sector News		
$News_t$	0.0134***	0.0132***	0.0131***
	(0.00332)	(0.00322)	(0.00318)
log(Loan Size)	-0.0002	-0.0003	-0.0003
	(0.000302)	(0.000275)	(0.0002)
Credit Age	-0.00001 2	-0.00002	-0.00001
	(0.00002)	(0.00002)	(0.00002)
N	488034	488034	488034
	Panel B: Negative Sector News		
$News_t$	0.0213**	0.0198**	0.0196**
	(0.00801)	(0.00788)	(0.00744)
log(Loan Size)	-0.00018	-0.00012	-0.00015
	(0.0003)	(0.0003)	(0.0003)
Credit Age	0.00003	0.00002	0.00003
	(0.00003)	(0.00003)	(0.00003)
N	292871	292871	292871
	Panel C: Non-Negative Sector News		
$News_t$	0.00793	0.00751	0.00732
	(0.00780)	(0.00775)	(0.00748)
log(Loan Size)	-0.00048	-0.00067**	-0.00067**
	(0.000347)	(0.000328)	(0.000309)
Credit Age	-0.00009***	-0.00007**	-0.00007**
	(0.00002)	(0.00003)	(0.00003)
N	195163	195163	195163
Bank FE	-	Yes	Yes
Province FE	-	-	Yes

Notes: This table provides coefficient estimates of the main 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. Period used goes from 2018-Q3 to 2020-Q2. The dependent variable is Forecast error and it is computed as the difference between Default at $t+1$ and PD at t. The main regressor is the macro signal at the sector level computed as the quarter-on-quarter percentage variation. 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. Errors are clustered at the Nace 2-digit level.

4.1 Distortion by bank

Figure 2: **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. 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.

To investigate heterogeneity among banks, we run regression (9) for each bank, to determine a bank-specific diagnostic level. Results are given in figure 2, where we sort banks by β_1 in regression (9). Evidence shows that five out of nine banks display a positive and significant parameter: these banks overreact when receiving news from their customers in attributing them a new probability of default. The level of significant coefficients range between 0.2 and 0.5. These findings confirm that estimates of table 2 are not driven by a single sizeable institution only. We use this outcome to deliver tests on lending variables in subsection 4.2. In the appendix, we replicate the same exercise, this time using macroeconomic news as a regressor.

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 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 differ from those ones 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.

$$r_t^{i,b} = \beta_0 + \beta_1 D_t^b + \beta_2 News_t^{i,b} + \gamma(D_t^b \times News_t^{i,b}) + \mathbf{\Gamma}'\mathbf{X} + \epsilon_t^{i,b} \tag{10}$$

where $D_t^b = \mathbb{1}\{\theta^b = \text{"}high\text{"}\}$ 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 β_1 for each bank b by means of equation (9), (2) sort banks by level of diagnosticity θ, (3) select rational and non-rational banks (where β_1 is 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. Please note that, for each date t, we exclusively consider contracts established by at most 3 quarters between banks and borrowers who already have an existing credit relationship. We confine our analysis to new contracts since it is unfeasible to determine the impact of news on prices for existing contracts, there would have been too many confounders about price determination of older contracts. Moreover, we select borrowers multiaffiliated with at least one rational and one diagnostic bank. This method is similar to that one used by Khwaja and Mian (2008) and allows to dampen demand driven effects. To strengthen our results about potential demand driven outcomes, we add an extra specification in table 4 that includes borrower fixed-effects. Note that the dataset used for this exercise is at the loan-level, which is the reason why the number of observations increases.

Table 4 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): we are interested in assessing the unconditional role of news on price changes. The effect of innovation on interest rate is negative, as expected, and statistically significant: positive news make bankers more optimistic about firms outcomes' and the price of new loans is reduced accordingly. Results in columns 2 and 3 suggest that the interaction coefficient between news and diagnostic firms $News_t \times D_t^b$ is negative and statistically significant at the 1%. 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 rate

Table 4: **Effects on Interest Rates - PD News**

$News_t$	-0.0189***	-0.00850***	0.00331**
	(0.00288)	(0.00161)	(0.00146)
D_t^b		0.00835***	0.00615***
		(0.000491)	(0.000535)
$News_t \times D_t^b$		-0.0121***	-0.00633***
		(0.00399)	(0.00140)
N Obs.	770074	770074	768436
Sector FE	Yes	Yes	-
Province FE	Yes	Yes	-
Time FE	Yes	Yes	Yes
Borrower FE	-	-	Yes

Notes: this table provides estimates of interest rates on news regression. First column shows results of unconditional regression. Second and third 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. Data selection is made on multi-affiliated borrowers to at least one rational and one diagnostic bank whose contracts are younger than 3 quarters. Errors are clustered at the Nace 2-digit level. Significance levels at 1%, 5%, 10% are given by (***), (**), (*) respectively. Contracts signed no more than 3 quarters before the date of reporting are selected for this specification.

to his borrowers between 4.9 to 9.3 basis points on new contracts [10]. We replicate the same exercise with macro news as a robustness check in section 6.

Intensive and extensive margin Similar to the exercise in the previous paragraph, we test whether the level of distortion can impact the size of loans and the probability of issuing new contracts. In equation (11) we use the same logic and sample selection of the interest rate exercise, meaning cutting the sample to new contracts of multi-affiliated borrowers to both pre-identified rational and non-rational banks. Equation (12) is the specification able to capture the effects of diagnostic banks on the probability of issuing new contracts; we use it to grasp the impact on the extensive margin. The variable $NC_t^{i,b}$ is a dummy that takes value 1 when the contract is signed either in the current quarter or in the previous one and works as a dependent variable of a limited probability model. The right-hand side of both equations is the same: there is a regressor that identifies the news, one for the diagnostic bank and a third one for the interaction of the two, together with time, sector, province, and borrower fixed effects in

[10] The effect of the estimate is computed by multiplying one standard deviation of the news to the coefficient. The value of the sd(News)=0.078, so, the total effect on interest rate for the interaction coefficient is $0.078 \cdot -0.0063 = -4.9$bps in column 2 and it is -9.3bps in column 2.

various combinations.

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

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

Results are given in table 5. Unconditional estimates of column 1 are as expected: positive news are associated with higher loan size and probability of new contracts. In Panel A, column 2 and 3 show a positive and significant interaction coefficient between news and diagnosticity ($News_t \times D_t^b$). Conditional on receiving a one standard deviation of positive news, a diagnostic bank increases the loan size of the borrower between 1.08% and 4.82% more than a rational bank[11].

Similarly for Panel B, one standard deviation of positive news is associated with an increase in the probability of signing new contracts of 1.10%-1.20% more with a diagnostic bank than a rational peer[12].

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

[11]The effect is computed multiplying one standard deviation of PD mews (0.078) by the coefficients of table 11, Panel A. The range is given by the adoption of different specifications

[12]The effect is computed multiplying one standard deviation of PD mews (0.082) by the coefficients of table 11, Panel B.

Table 5: **Effects on Quantities**

Panel A: Intensive Margin - Dependent: $log(LoanSize)_t^{i,b}$			
$News_t$	1.248***	0.753***	-0.161***
	(0.112)	(0.111)	(0.0611)
D_t^b		-0.193***	0.0339*
		(0.0403)	(0.0195)
$News_t \times D_t^b$		0.618***	0.139*
		(0.137)	(0.0717)
N Obs.	770074	770074	768436
Sector FE	Yes	Yes	-
Province FE	Yes	Yes	-
Time FE	Yes	Yes	Yes
Borrower FE	-	-	Yes
Panel B: Extensive Margin - Dependent: $NC_t^{i,b}$			
$News_t$	0.193***	0.110***	0.0116
	(0.0139)	(0.0189)	(0.0121)
D_t^b		0.119***	0.0921***
		(0.00710)	(0.00642)
$News_t \times D_t^b$		0.147***	0.132***
		(0.0165)	(0.0336)
N Obs.	1345406	1345406	1345162
Sector FE	Yes	Yes	-
Province FE	Yes	Yes	-
Time FE	Yes	Yes	Yes
Borrower FE	-	-	Yes

Notes: Panel A provides estimates on the intensive margin. Column 1 provides estimate of the unconditional news on quantities. Column 2 and 3 exhibit outcomes of diagnosticity on intensive margin with the regression $log(LoanSize)_t^{i,b} = \beta_0 + \beta_1 D_t^b + \beta_2 News_t^{i,b} + \gamma(D_t^b \times News_t^{i,b}) + \mathbf{\Gamma}'\mathbf{X} + \epsilon_t^{i,b}$. Data selection is made on multi-affiliated borrowers to at least one rational and one diagnostic bank whose contracts are younger than 3 quarters.
Similarly, Panel B contains estimates on the extensive margin. Column 2 and 3 exhibit outcomes of the regression $NC_t^{i,b} = \beta_0 + \beta_1 D_t^b + \beta_2 News_t^{i,b} + \gamma(D_t^b \times News_t^{i,b}) + \mathbf{\Gamma}'\mathbf{X} + \epsilon_t^{i,b}$, respectively. Data selection is made on multi-affiliated borrowers to at least one rational and one diagnostic bank. Errors are clustered at the NACE 2-digit level. Significance levels at 1%, 5%, 10% are given by (***), (**), (*) respectively.

reduced form specification, the PD is in turn a function of bank-specific belief 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 $i = 1, \ldots, I$ operate in markets $m = 1, \ldots, M$ representing geographical provinces, where each bank $j = 1, \ldots, J$ 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 (13):

$$P_{ijm} = \gamma_0 + \gamma_1 T_{ijm} + \gamma_2 L_{ijm} + \lambda_{jm} + \omega_i^p + \tau_{ijm} \tag{13}$$

where ω_i^p, λ_{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 (13) 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:

$$\begin{aligned} U_{ijm}^D = \; & \delta_{jm}^D + \alpha^D(\tilde{P}_{jm} + \tilde{\eta}_1 T_{ijm} + \tilde{\gamma}_2 L_{ijm} + \tilde{\omega}_i^p + \tilde{\tau}_{jm}) + \\ & \eta_1^D T_{ijm} + \eta_2^D L_{ijm} + \eta_3^D Y_i + \eta_4^D \tilde{\omega}_i^p + \nu_{ijm} \\ & = \underbrace{(\delta_{jm}^D + \alpha^D \tilde{P}_{jm})}_{\tilde{\delta}_{jm}^D} + \underbrace{(\eta_1^D + \alpha^D \tilde{\eta}_1)}_{\tilde{\eta}_1^D} T_{ijm} + \underbrace{(\eta_2^D + \alpha^D \tilde{\gamma}_2)}_{\tilde{\eta}_2^D} L_{ijm} + \\ & \eta_3^D Y_i + \underbrace{(\eta_4^D + \alpha^D)}_{\tilde{\eta}_4^D} \tilde{\omega}_i^p + \underbrace{\alpha^D \tilde{\tau}_{jm} + \nu_{ijm}}_{\tilde{\zeta}_{ijm}} \\ & = \tilde{\delta}_{jm}^D + \underbrace{Y_{ijm}^{\prime D} \tilde{\eta}^D}_{V_{ijm}^D} + \zeta_{ijm} \\ \Rightarrow U_{ijm}^D = \; & \tilde{\delta}_{jm}^D + V_{ijm}^D + \zeta_{ijm} \end{aligned} \tag{14}$$

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 (14) independently.

Probability that borrower i chooses bank j in market m is then given by:

$$Pr^D_{ijm} = \frac{\exp(\hat{\tilde{\delta}}^D_{jm}(X^D_{jm}, \tilde{P}_{jm}, \xi^D_{jm}, \alpha^D, \beta^D) + V^D_{ijm}(Y^D_{ijm}, \tilde{\eta}^D))}{1 + \sum_l \exp(\hat{\tilde{\delta}}^D_{jm}(X^D_{jm}, \tilde{P}_{jm}, \xi^D_{jm}, \alpha^D, \beta^D) + V^D_{ijm}(Y^D_{ijm}, \tilde{\eta}^D))} \tag{15}$$

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[13]. 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 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 ra-

[13]See Albareto et al. (2011)

tional 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 (16) is mathematically derived as equation (6):

$$PD_{ji}^{\theta} \approx PD_{ji}^{re} + \beta(\theta) I_i \tag{16}$$

Estimates of the structural model are outlined in table 6. 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 7. 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 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

Table 6: **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 7: **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.

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 2, 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[14] 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} 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 8 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.

[14]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 8: **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	-	Yes	No	Yes	Yes	Yes
Time FE	-	-	Yes	Yes	-	Yes
Sector FE	-	-	-	-	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.

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 9. The arrival of positive or negative news induced by the release of IFRS9 data makes bankers overreact.

6.3 Lending effects with macro news

In this section we estimate the lending effects of macro news when the institutions are subject to macro news. We report estimates of equations (**??**), (11) and (12) in tables 10 and 10.

Table 9: **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	-	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 $FE^{\theta,i,b}_{t+12|t} = \beta_0 + \beta_1 D1^{i,b} + \beta_2 D2^{i,b} + \mathbf{\Gamma}'\mathbf{X} + \epsilon^{i,b}_{t+12}$, 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.

Concerning interest rates, the sign of coefficients is consistent with the PD news estimation. Following a one standard deviation increase in macro news, diagnostic banks dampen the interest rate on average by 9.5 basis points more than a rational peer[15]. The effect size with micro news ranges between 4.9 and 9.3 bps.

Estimates for the intensive margin are not significant about the relevant coefficient. In the specification with borrower fixed effects the magnitude is roughly at the 0.6%. Extensive margin outcomes deliver a coefficient size that is moderately higher than that one obtained in the exercise with micro news (which was 1.20%): one standard deviation of positive macro news causes a diagnostic bank to increase by 3% the probability of providing new contracts with respect to rational peers.

[15]The standard deviation of macro news in this exercise is equal to 0.19.

Table 10: **Effects on Interest Rates - Macro News**

$News_t$	-0.00290**	0.00244*	0.00382***
	(0.00140)	(0.00125)	(0.000644)
D_t^b		0.00990***	0.00696***
		(0.000672)	(0.000377)
$News_t \times D_t^b$		-0.00527***	-0.00512***
		(0.000996)	(0.000675)
N Obs.	335663	335662	335098
Province FE	Yes	Yes	-
Time FE	Yes	Yes	Yes
Borrower FE	-	-	Yes

Notes: this table provides estimates of interest rates on news regression. First column shows results of unconditional regression. Second and third columns exhibit estimates of regression $r_t^{i,b} = \beta_0 + \beta_1 D_t^b + \beta_2 News_t + \gamma(D_t^b \times News_t) + \mathbf{\Gamma}'\mathbf{X} + \epsilon_t^{i,b}$, where $\mathbf{X}$ is a control matrix which contains also fixed effects. $News_t$ is macro news at the sector level. Data selection is made on multi-affiliated borrowers to at least one rational and one diagnostic bank whose contracts are younger than 3 quarters. Errors are clustered at the province level. Significance levels at 1%, 5%, 10% are given by (***), (**), (*) respectively. Contracts signed no more than 3 quarters before the date of reporting are selected for this specification.

Table 11: **Effects on Quantities - Macro News**

Panel A: Intensive Margin - Dependent: $log(LoanSize)_t^{i,b}$			
$News_t$	-0.127	-0.0557	-0.0700
	(0.114)	(0.109)	(0.0482)
D_t^b		-0.118**	0.0593*
		(0.0588)	(0.0322)
$News_t \times D_t^b$		-0.101	0.0316
		(0.0864)	(0.0402)
N. Obs.	335662	335662	335098
Province FE	Yes	Yes	-
Time FE	Yes	Yes	Yes
Borrower FE	-	-	Yes
Panel B: Extensive Margin - Dependent: $NC_t^{i,b}$			
$News_t$	0.0423	-0.0621**	-0.0773***
	(0.0284)	(0.0265)	(0.0173)
D_t^b		0.130***	0.0968***
		(0.0165)	(0.0134)
$News_t \times D_t^b$		0.162***	0.153***
		(0.0249)	(0.0208)
N Obs.	560081	560081	560022
Sector FE	Yes	Yes	-
Province FE	Yes	Yes	-
Time FE	Yes	Yes	Yes
Borrower FE	-	-	Yes

Notes: Panel A provides estimates on the intensive margin. Column 1 provides estimate of the unconditional news on quantities. Column 2 and 3 exhibit outcomes of diagnosticity on intensive margin with the regression $log(LoanSize)_t^{i,b} = \beta_0 + \beta_1 D_t^b + \beta_2 News_t + \gamma(D_t^b \times News_t^{i,b}) + \mathbf{\Gamma}'\mathbf{X} + \epsilon_t^{i,b}$. Data selection is made on multi-affiliated borrowers to at least one rational and one diagnostic bank whose contracts are younger than 3 quarters.
Similarly, Panel B contains estimates on the extensive margin. Column 2 and 3 exhibit outcomes of the regression $NC_t^{i,b} = \beta_0 + \beta_1 D_t^b + \beta_2 News_t + \gamma(D_t^b \times News_t^{i,b}) + \mathbf{\Gamma}'\mathbf{X} + \epsilon_t^{i,b}$, respectively. Data selection is made on multi-affiliated borrowers to at least one rational and one diagnostic bank. 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 assess lenders' beliefs at a granular level we use banks' estimates of borrowers' probability of default. We prove that this measure can be used to estimate precisely the impact of lenders' expectations on interest rates and loan amounts, differently from lenders' beliefs proxies used in the literature so far. We document that bankers over (under) estimate borrowers' default when receiving negative (positive) news. The bias is more amplified 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. Diagnostic banks receiving positive news exhibit a tendency to reduce borrowers' interest rates by 4.9-9.3 basis points, offer loan amounts higher by 1.08% to 4.82%, and engage in signing 1.20% more contracts compared to rational banks. Results about interest rates and loan size are robust to a sectorial measure of news. We rationalize our empirical outcomes through a structural estimation of a banking competition model that confirms results of the empirical analysis.

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.

Basel Committee on Banking Supervision, "Basel Framework, Calculation of RWA for credit risk," 2023.

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.

Khwaja, Asim Ijaz and Atif Mian, "Tracing the impact of bank liquidity shocks: Evidence from an emerging market," *American Economic Review*, 2008, *98* (4), 1413–42.

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

Tables

Table 12: **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
PdNews	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
PdNews	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
PdNews	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
PdNews	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
PdNews	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. PD 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 13: **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
Pd 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
Pd 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
Pd 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
Pd 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. PD 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 14: **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
PdNews	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. PD 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 15: **Nace classification - 1st part**

Ateco 2-digit	Description 2-digit	Ateco 1-digit	Descripion 1-dig	Ateco macro class	Description macro class
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 16: **Nace classification - 2nd part**

Ateco 2-digit	Description 2-digit	Ateco 1-digit	Descripion 1-dig	Ateco macro class	Description macro class
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.

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

$$\begin{aligned}
z_{t+1} - \mathbb{E}^{\theta}_t(z_{t+1}) &= \underbrace{z_{t+1} - \mathbb{E}_t(z_{t+1})}_{=w_{t+1}} + \mathbb{E}_t(z_{t+1}) - \mathbb{E}^{\theta}_t(z_{t+1}) \\
FE^{\theta}_{t+1|t} &= w_{t+1} + \Phi\Big(\frac{a-\hat{x}_{t+1}}{\Omega_t^{1/2}}\Big) - \Phi\Big(\frac{a-\hat{x}^{\theta}_{t+1}}{\Omega_t^{1/2}}\Big) \qquad (17)
\end{aligned}$$

   Equation (17) 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, (17) 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.

Bankers Expectations and Monetary Policy

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Abstract

This paper investigates bank lending expectations through the Bank Lending Survey and how they react to monetary policy announcements. First we assess whether the belief formation process of banks respects the full-information-rational-expectations paradigm through testing forecast errors predictability. Second we study the reaction of bankers' beliefs to the ECB monetary policy announcements. Results confirm error predictability in banks' beliefs and amplification of beliefs' distortion when monetary policy announcements are perceived as pure monetary shocks. We also describe the mechanism underlying the empirical findings through a macro model with risky debt and non-rational expectations. We show that monetary policy innovations can amplify or mitigate the credit dynamics through lenders' distorted expectations.

*Bocconi University and Bank of Italy. I want to thank Bank of Italy for the kind concession of the iBLS dataset. The views expressed in the manuscript are those of the authors and not those of the Bank of Italy. Please do not circulate this draft.

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1 Introduction

In recent years, there has been a growing focus on the formation of beliefs within the realm of economics. While agents' expectations have held a central position in macroeconomic modeling ever since the Lucas critique emerged in the 1970s, it's worth noting that limited attention had been directed toward scrutinizing the mechanisms underlying the formation of these beliefs. Notably, the literature concerning lenders' expectations has remained relatively modest due to data constraints, with only a handful of exceptions such as Ma et al. (2021), Richter and Zimmermann (2019), Fahlenbrach et al. (2018) and Farroni and Tozzo (2022). Furthermore, a significant gap persists in our understanding of the primary drivers shaping bankers' expectations about future credit developments.

In light of this backdrop, this paper postulates that monetary policy plays a pivotal role in shaping bankers' expectations and endeavors to explore the extent and manner through which this influence emerges, specifically via monetary policy announcements.

The primary objectives of this study are two-fold. Firstly, utilizing the time-series nature of the dataset, the research seeks to empirically test the evolution of belief formation mechanisms among the prominent European banks roughly over the last twenty years. Secondly, the study examines the impact of monetary policy announcements on bankers' expectations. Building upon the standard tests of rationality that have become commonplace in the literature since Coibion and Gorodnichenko (2015), this research augments these tests by considering the interaction of monetary policy shocks. This interaction is employed to uncover whether such shocks significantly impact the predictability of forecast errors.

In this context, the study addresses several key questions: How do Euro Area bankers form their beliefs? Are there consistent deviations from the full-information rational expectations hypothesis? Do distortions in beliefs exhibit substantial variations across countries? How do banks' expectations shift in response to monetary policy announcements? And further, do distortions in banks' beliefs display systematic fluctuations in response to monetary shocks?

To address these questions, this study relies on the individual Bank Lending Survey dataset, a comprehensive survey conducted at the Euro-Area level. This dataset has been collected since 2002 and features pertinent forward-looking inquiries that serve as reliable proxies for bankers' forecasts.

This research is guided by two primary motivations. Firstly, given that bankers' decisions wield a significant influence over credit supply, and consequently over the real components of the economy, a thorough understanding of the questions posed above is crucial. This influence has been well-documented in the works of Kiyotaki and Moore (1997), Schularick and Taylor (2012), Mian et al. (2017), Baron and Xiong (2017) or López-Salido et al. (2017), and other related literature. Secondly, considering the strong interlinkages between bankers' activities and decisions made by monetary authorities, it is reasonable to hypothesize that bankers' expectations are inherently intertwined with the actions of these authorities. Consequently, this study's central inquiry revolves around determining whether policy actions contribute to exacerbating potential distortions in bankers' expectations.

To mitigate any concerns of reverse causality that may arise from the commercial-central bank relationship, this study employs exogenous monetary policy shocks identified by Altavilla et al. (2019a). These shocks are extracted from a dataset comprising intraday market movements, utilizing high-frequency financial data. Shocks are identified within a time window surrounding ECB policy announcements, as conveyed through press releases and press conferences on pre-determined Governing Council dates.

The empirical analysis involves assessing the predictability of forecast errors using a range of various tests, employing both standard specifications found in the literature (similar to Gennaioli et al. (2016) and Bordalo et al. (2020)) as well as an ordered probit approach, in alignment with the qualitative nature of the dataset. The study's findings highlight a tendency for agents to overreact to recent news in terms of forecast revisions. This overreaction is symmetrically manifested regardless of whether the news is positive or negative. The paper posits that this overreaction can be conceptualized through a model of diagnostic expectations, wherein agents tend to overweight the likelihood of events whose probabilities have most prominently increased in the recent past. This concept suggests that a banker who revises credit standard forecasts upwards or downwards tends to systematically overestimate these revisions with respect to realized values.

The second exercise introduces monetary policy shocks into the forecast predictability regression, utilizing fixed effects and probabilistic models. The analysis progresses in two steps: firstly, by examining the correlation between the plain monetary shocks identified by Altavilla et al. (2019a) and forecast error predictability, and secondly, by isolating pure monetary shocks based on the findings of Jarociński and Karadi (2020). These pure monetary shocks are those that respond solely to the Odyssean nature of policy announcements, where interest rates and stocks move in opposing directions. Conversely, shocks containing an informational component leading to co-movement between interest rates and stocks are termed Delphic. The study leverages a shock composition method following Ottonello and Winberry (2020) and Enders et al. (2019) to quantify the magnitude of these shocks over quarters. The results underscore the role of monetary policy announcements in predicting bankers' forecast errors, particularly when pure monetary (Odyssean) shocks are considered.

Our study introduces a comprehensive macro model, underpinned by two distinct representative agents—a borrower and a lender. The borrower represents a firm seeking debt to fuel its risky projects, while the lender is risk-neutral and deep pocketed. Notably, our model accounts for the presence of diagnostic expectations within agents' belief formation, akin to prior work by Bordalo et al. (2022). To construct the foundation for the model's risky debt aspect, we draw inspiration from Arellano (2008) and Arellano (2019). This forms the basis onto which we develop the non-rational expectations component. Additionally, our model integrates a monetary dimension in which the central bank wields control over the real interest rate, subject to independent and identically distributed (IID) shocks, thus augmenting the framework with monetary policy dynamics. Through the model's solutions and policy functions we observe the impact of varying the diagnostic parameter for different levels of productivity. Under diagnostic expectations, agents view lower past shock levels as positive news due to distorted beliefs, while higher past shock levels relative to the present are considered negative news. The presence of diagnostic expectations significantly alters outcomes. When the current shock is higher the past one, the policy function for capital exceeds the rational expectations-based optimal capital, but decreases for lower shocks, stabilizing at zero for highly negative news. Negative news signifies the disparity between shocks in two time periods. The dividend level diverges notably from rational expectations, lower for negative past news and slightly higher for positive news. From the lender's perspective, a positive past shock raises debt prices (lower perceived risk), while a higher past shock relative to the present increases perceived risky debt. Diagnostic expectations introduce complexity to risky debt assessment, impacting borrowing and lending patterns in economic phases. Monetary policy news magnifies these effects, influencing lenders' pricing decisions, particularly during unfavorable economic conditions marked by higher interest rates due to negative news about borrower fundamentals. This integrated insight emphasizes the interactions between risky debt, diagnostic expectations, and monetary policy dynamics.

In summary, this paper delves into the intricate dynamics of bankers' beliefs, investigating their formation mechanisms over time and scrutinizing the impact of monetary policy announcements on these beliefs. By addressing critical questions related to belief formation, this research contributes to a deeper understanding of the factors influencing credit supply, economic performance, and the interplay between bankers' expectations and central bank actions.

2 Data

We aim to answer the questions raised in this study by using different sets of data. Initially, we turn to the Bank Lending Survey (BLS), a survey conducted by the European Central Bank (ECB) since 2002, encompassing a sample of approximately 140 banks representative of both the Euro Area and national credit markets. The dataset is characterized by a quarterly frequency, with banks granted a window of about two weeks at the end of each quarter to furnish their responses to their respective national counterparts. The questionnaire encompasses inquiries pertaining to credit conditions, both generally concerning the market landscape and specifically focused on the surveyed bank. Notably, the survey comprises 18 questions concerning conditions in the preceding quarter and an additional 4 questions oriented towards the upcoming quarter.

Central to our analysis are forward-looking questions concerning credit criteria for both firms and households, which we utilize as proxies for banks' expectations. Specifically, within the BLS framework, questions Q8 and Q9 pertain to firms, while questions Q21 and Q22 address households' credit conditions. As the latter two, Q9 and

Q22, delve into banks' anticipations regarding demand conditions, our focal point remains on Q8 and Q21, which offer a more discerning insight into beliefs on the supply side.

- (Q8) Please indicate how you expect your bank's credit standards as applied to the approval of loans or credit lines to enterprises to change over the next three months. Please note that we are asking about the change in credit standards, rather than about their level.
- (Q21) Please indicate how you expect your bank's credit standards as applied to the approval of loans to households to change over the next three months. Please note that we are asking about the change in credit standards, rather than about their level.
- (Q9) Please indicate how you expect demand for loans or credit lines to enterprises to change at your bank over the next three months (apart from normal seasonal fluctuations)? Please refer to the financing need of enterprises independent of whether this need will result in a loan or not.
- (Q22) Please indicate how you expect demand for loans to households to change over the next three months at your bank (apart from normal seasonal fluctuations). Please refer to the financing need of households independent of whether this need will result in a loan or not.

The nature of each answer is qualitative and allows responders to assign a value on a five-level ordered scale $\{-2, -1, 0, +1 + 2\}$[1]. The dataset contains also questions about the present state of the forward-looking variables. This allows us to compute forecast errors.

Second, we use a dataset containing monetary announcements to measure their impact on bank lending. Attached to Altavilla et al. (2019a) authors published the so called "Euro Area Monetary Policy Dataset", which collects market data changes around monetary event windows (press release, press conference and overall event) of the ECB Governing Council. Variables contained are OIS, Euro Area major countries sovereign rates, stock indexes, main exchange rates. This dataset will be used to identify monetary shocks within each quarter.

3 Empirical Strategy

The empirical strategy is thought to be divided in two main parts. First, we test error predictability of banks' forecasts, through standard specifications given by the literature, as in Gennaioli et al. (2016) and Bordalo et al. (2020). Second, we study how

[1] In the original dataset we have classes values from 1 to 5, we rescaled them by a constant of -3 for easier interpretation.

banks' expectations are affected by monetary policy shocks following Ottonello and Winberry (2020) and Enders et al. (2019).

3.1 Forecast errors predictability

Forecast error predictability is analyzed with standard specifications in the literature, as in Gennaioli et al. (2016) and Bordalo et al. (2022). Shortly, if agents are endowed with rational expectations forecast errors should be unpredictable, i.e. orthogonal to all information available at the time when the forecast is made. Hence, the correlation between forecast errors and information set when the forecast is made signals distorted expectations. Time length of our panel allows us to test whether forecast errors are predictable. Recall that BLS runs with a quarterly frequency since Q4 of 2002: time span allows us to measure beliefs across different credit cycles.

To test forecast errors predictability we regress forecast errors on forecast revisions, where revision here is to be intended as the difference between the forecast today and one one quarter before: $\Delta F = F_t - F_{t-1}$. We run this test by two main specifications. First, through a standard ols, pooled and with various aggregations, with and without different combinations of fixed effects. Second, with an ordered probit model to take better into consideration the qualitative nature of the variables. The first specification is given by

$$FE_{i,t+1} = \beta_0 + \beta_1 \Delta F_{i,t} + \Gamma' X + \varepsilon_{i,t+1} \tag{1}$$

where i are individual observations X is a vector of covariates including controls, $y_{i,t+1}$ is the realized value of the forecast $F_{i,t}$ and $FE_{i,t+1} = y_{i,t+1} - F_{i,t}$. A significant coefficient β_1 different from zero assesses potential deviations from rational expectations. According to rational expectation hypothesis, forecast errors at $t+1$ should be unpredictable based on information available at t. In particular, the interpretation of (1) can be read as follows. Regressor $\Delta F_{i,t} > 0 (< 0)$ signals an increase (decrease) on credit standards for firms or borrowers. If this is associated with $FE_{t+1|t} < 0$ ($FE_{t+1|t} > 0$), it signals an optimistic (pessimistic) behaviour of the agent and the coefficient β_1 is therefore negative.

$$\left.\begin{array}{l}\text{Cred. Stand. worsening} \Rightarrow \Delta F_{i,t} < 0 \\ \text{Pessimistic agent} \Rightarrow FE_{i,t+1|t} = y_{t+1} - \hat{y}_{t+1|t} > 0\end{array}\right\} \Rightarrow \beta_1 < 0$$

$$\left.\begin{array}{l}\text{Cred. Stand. improvement} \Rightarrow \Delta F_{i,t} > 0 \\ \text{Optimistic agent} \Rightarrow FE_{i,t+1|t} = y_{t+1} - \hat{y}_{t+1|t} < 0\end{array}\right\} \Rightarrow \beta_1 < 0$$

Differently from the standard literature on distorted expectations, we also run an ordered probit model as in Altavilla et al. (2019b). We decide to run an ordered probit since the nature of our dataset is qualitative, so we are able to determine the probability of association between specific levels of the regressor and the dependent variable. In the probabilistic analysis, since the frequency of top and bottom answer's levels in our variables of interest is low (-2 and +2 values), we collapse them in each nearest class so that variables Q8, Q21 (and variables of the realized values accordingly) are defined for values $\{-1, 0, +1\}$. As a consequence, forecast error is defined over five (or three if we repeat the collapsing exercise) classes.

Given a latent variable

$$FE^*_{i,t+1|t} = \beta_0 + \beta_1 \Delta F_{i,t} + u_{i,t+1} \tag{2}$$

where i identifies observation and classes $c = \{-2, -1, 0, 1, 2\}$ are possible values of the latent variables classes. $FE_{i,t+1|t} = c$ if $\alpha_{c-1} < FE^*_{i,t+1|t} < \alpha_c$. The probability that observation i selects class c is given by

$$\begin{aligned}\mathbb{P}(FE_{i,t+1|t} = c) &= \mathbb{P}(\alpha_{c-1} < FE^*_{i,t+1|t} < \alpha_c) \\ &= \Phi(\alpha_c - \mathbf{\Delta F'_{i,t}}\beta_1) - \Phi(\alpha_{c-1} - \mathbf{\Delta F'_{i,t}}\beta_1)\end{aligned}$$

In this case the coefficients (margins) of the regression report the probability associated between each class of the predictor with every category of the dependent variable. As shown in the results' session, an optimistic agent would show a probability associated between positive forecast revision and negative forecast errors much higher than the probability associated between the same revision and positive errors.

3.2 Monetary policy

To test whether monetary policy announcements amplify distortions in lenders' expectations, we add to equation (2) a monetary policy measure as an additional regressor. The first monetary specification reads as

$$FE^{*}_{i,t+1|t} = \beta_0 + \beta_1 \Delta F_t + \beta_2 \Delta OIS^{m}_{t} + \epsilon_{i,t+1} \tag{3}$$

where ΔOIS^{m}_{t} is a measure for interest rates changes in the monetary window for rates with maturity $m = \{3M, 2Y\}$, measured in the *Euro Area Monetary Policy Database* in Altavilla et al. (2019a) that we call *monetary surprise* hereafter. We use two different ways to aggregate monetary surprises: 1- we sum all surprises between two BLS survey dates; 2- we make a weighted sum of monetary surprises in quarter t for each governing council τ (there are more Governing Council events for each quarter), through the following expression

$$\Delta OIS^{m}_{t} = \sum_{\tau} w(\tau) \varepsilon_{\tau,t}$$
$$w(\tau) = \frac{\Delta bls_t - \Delta gc(\tau)_t}{\Delta bls_t}$$

Δbls_t is the number of days between two consecutive closing dates of bls survey; bls_t is the closing date of the survey; $\Delta gc(\tau)_t = bls_t - gc_{\tau,t}$, i.e. days difference between closing date and governing council. In every interval between two survey closing dates (approx. 1 quarter), we have τ Governing Councils, and the respective shock ε_{τ}. The closer the Governing Council to the survey closing date, the higher $w(\tau)$ - the more the shock is weighted.

The second monetary specification includes a multiplicative dummy to the monetary surprise that identify a pure monetary shock, following the deconstruction of variables' response in the monetary-event window of the Governing Council, as in Jarociński and Karadi (2020). Monetary surprises can be the result of both pure monetary (Odyssean) or information (Delphic) shock. When changes in interest rates and stock index move in opposite direction in the window, the surprise is interpreted as monetary rather than having an hidden informational content on the state of the economy and $M_t^{pure} = 1$ identifies a pure monetary shock.

$$FE^*_{i,t+1|t} = \beta_0 + \beta_1 \Delta F_t + \beta_2 \Delta OIS_t^m \times M_t^{pure} + \epsilon_{i,t+1} \quad (4)$$

4 Results

4.1 Predictability

We present results from ols specification (1). Figure 1 show coefficients of the baseline pooled ols regression with fixed effects. Coefficients are always and significantly negative, even if our main interest lies on the *supply* survey question. Supply questions are those ones in which bankers are asked about the credit standards supply, so questioned directly on their actions. Demand questions instead are about what they think about the credit standard demand from households and firms. Estimates are about each subgroup with respect to which bankers are required to answer. In particular, for firms bankers are asked about the standards of *overall credit, SMEs, big firms, short and long term credit*. For households bankers are asked about *credit for housing* and *consumption*. The figure report negative coefficient for both firms and households in all the different questions regarding credit standards. Negative coefficients are interpreted as an overall overreaction to news by agents (where the news has to be interpreted as the revision of the forecast): when the revision of the forecast is positive, agents tend to have a negative forecast error one period ahead, which means that the forecast has been on average above than the realized value, suggesting an optimistic behaviour in part of bankers. When the revision is negative, agents tend to show positive forecast errors, i.e. an on average lower than due forecast suggesting a pessimistic sentiment.

We also report results of the baseline regression run by country in figure **??**. Estimates suggest that the behaviour of bankers' by country is in part heterogeneous in magnitude, but overall the picture is not so distant from what we observe in figure 1. The different colours of the estimates represent a pooled ols specification (in blue) and an aggregate one (in red) where individual observations have been aggregated by time and country. The second specification is run with a robustness intent[2]; larger standard

[2]With aggregate variables the regression may give a different sign of the coefficient, suggesting a different underlying mechanism of expectation distortion, such as lack of full-information as in Coibion and Gorodnichenko (2015) and also discussed by Bordalo et al. (2020).

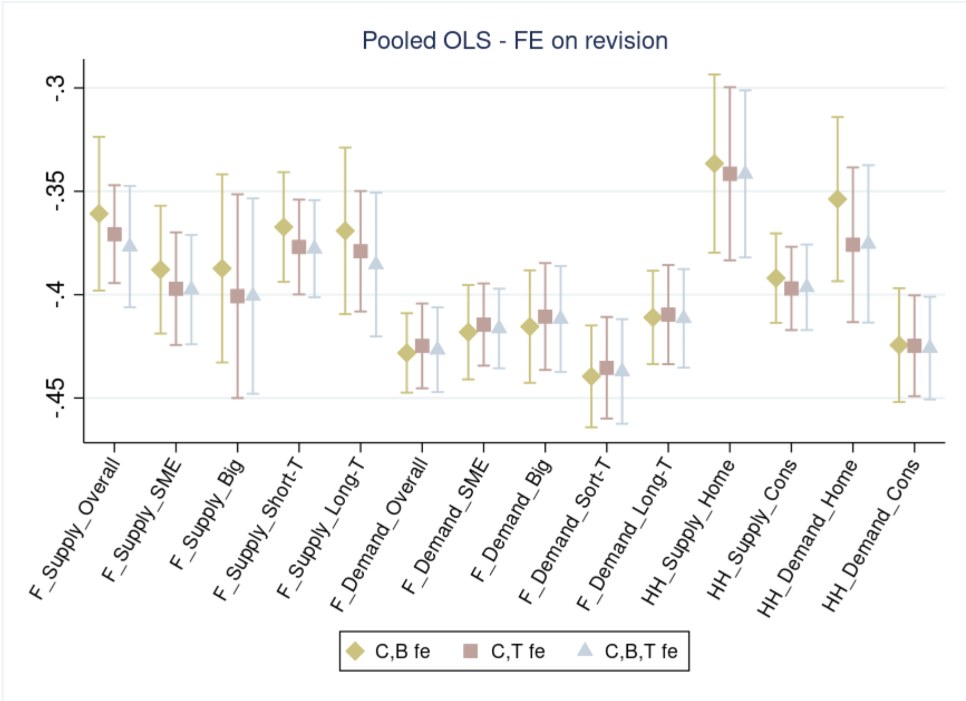


Figure 1: Figure shows coefficients of the regression $FE_{i,t+1} = \beta_0 + \beta_1 \Delta F_{i,t} + \Gamma' X + \varepsilon_{i,t+1}$ for each different question in the survey. Significance is at 1% level. Negative coefficients are interpreted as overreaction to news by bankers. Different colours represent different fixed effects combinations: $\{C, B, T\} = \{Country, Bank, Time\}$.

errors make several coefficients non significant, even if the remaining significant ones are close in magnitude to the first specification and always negative, confirming the overreacting behaviour of the respondents.

Finally, heatmap matrices (figure 2) show the coefficients (margins) of the second specification given by equation (2). The probability that negative news represented by $\Delta F_t < 0$ in the top matrix (in red) is associated to positive or null forecast error is sensibly higher than the probability associated with negative forecast error. The converse is true when $\Delta F_t > 0$ in the bottom matrix (in green): when the revision of the forecast is positive, such that bankers expect that credit standards ameliorate, they tend to most likely report a negative forecast error one period ahead, certifying that the realization of credit standards has been lower than hypothesised. Coefficients are obtained by running pooled ordered probit regressions including every country and period in the panel. The colour scale of the matrix boxes report the magnitude of the coefficients and the positive news matrix shows more distinct results than the negative one. Hence, bankers tend to be more optimistic when they receive positive news than pessimistic when they receive negative ones.

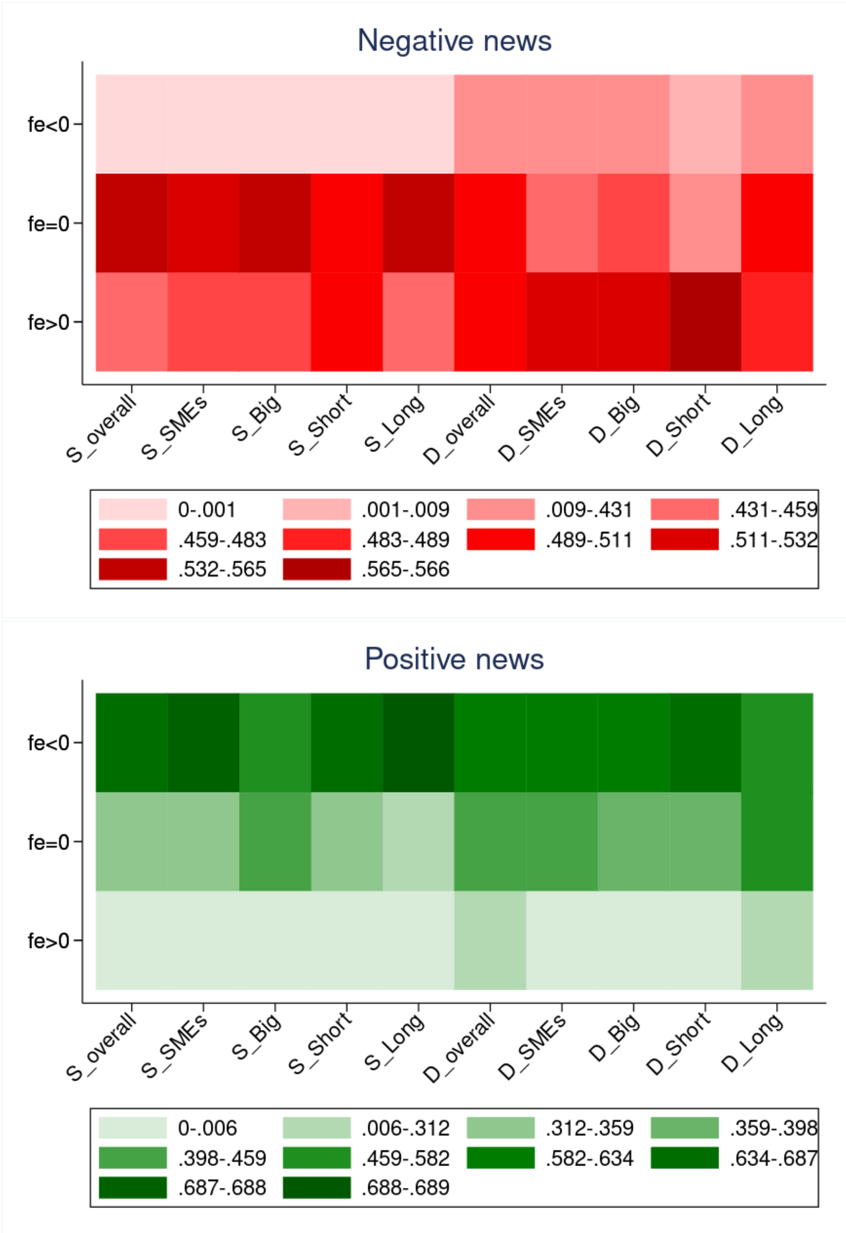


Figure 2: Figure shows probability associated to positive and negative ΔF_t with forecast errors. Probability that negative news ($\Delta F_t < 0$) is associated to positive forecast error is higher than probability associated with negative forecast error. The converse is true when $\Delta F_t > 0$ in the bottom figure.

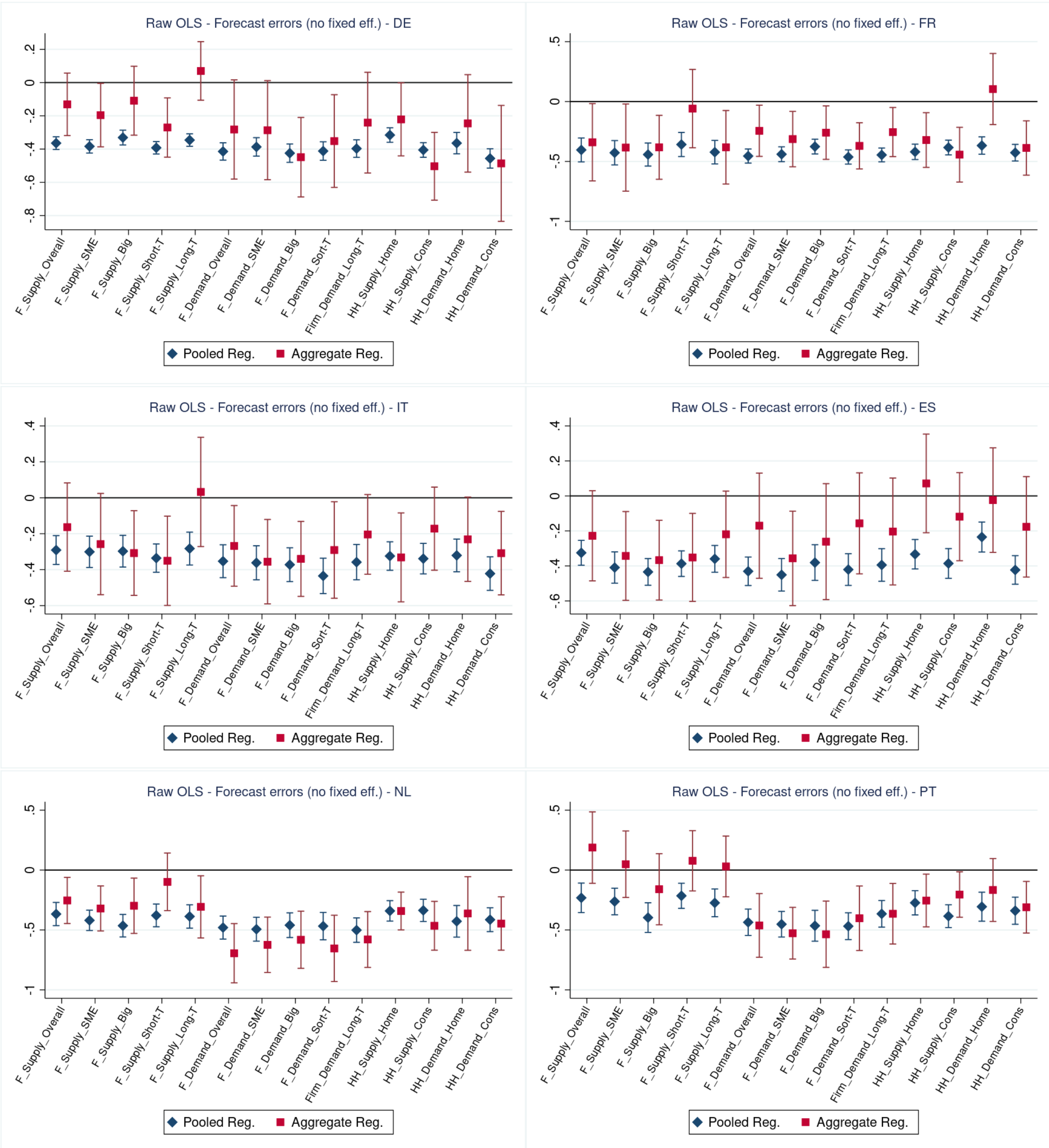


Figure 3: Figure shows baseline OLS regression (1) of forecast errors predictability for different countries of the EU. Coefficients are of a pooled regression and an aggregate regression, where in the latter observations are averaged by country and time.

4.2 Monetary

Results from figures 4 and 5 confirm that monetary surprises correlates with banks' forecast errors' predictability. Heatmap matrices show probability associated to tightening monetary shocks OIS (coefficients β_2 in (3) and (4)) with forecast errors. Tightening monetary shock has to be intended as a negative news for credit standards: we associate an increase in interest rates with the worsening of credit standards, both for firms and households. Probability that tightening shock is associated to positive or null forecast error is higher than probability associated with negative forecast error for variables on supply forecasts (at least for supply related questions).

In the right hand panels we show result for the monetary surprise interacted with a dummy equal to one when changes in interest rates and stock index move in opposite direction, as in Jarociński and Karadi (2020). We pursue this exercise because monetary surprises can be the result of both pure monetary (Odyssean) and information (Delphic) shock. $M_t^{pure} = 1$ should identify a pure monetary shock. Higher marginal effects for coefficients associated with positive forecast errors seem to confirm an active role of monetary policy announcements on the predictability of banks' forecast errors. In other words, monetary policy announcements polished by the information component increase banks expectations' distortions: when the ECB announces monetary policy tightening, banks decrease credit standards by more than what they would do with no monetary announcement and if endowed with rational expectations.

Results of the monetary analysis do not show significance of the coefficients and it is not easy to straightforwardly link them to a real numeric interpretation. However, it gives a clear sign of the effects included in the specifications. We take this empirical exercise as a motivation for the model in the next session. The underlying mechanism is based on the idea that if subjective beliefs of the lenders are somehow distorted, monetary surprises received by the central bank may amplify the effects of these distortions according to the changes in credit standards of the supply side.

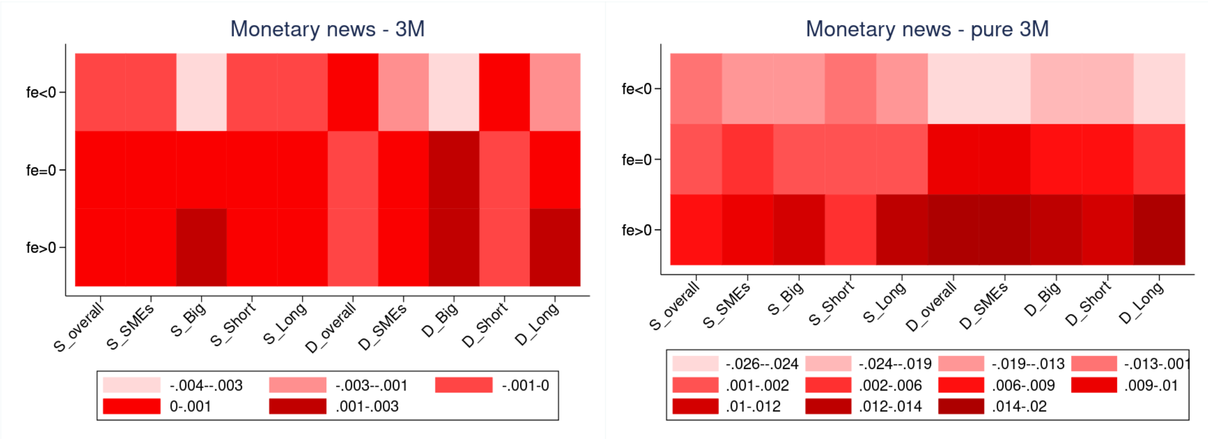


Figure 4: Figure shows probability associated to tightening monetary shock OIS - 3 months with forecast errors. Probability that tightening shock is associated to positive or null forecast error is higher than probability associated with negative forecast error.

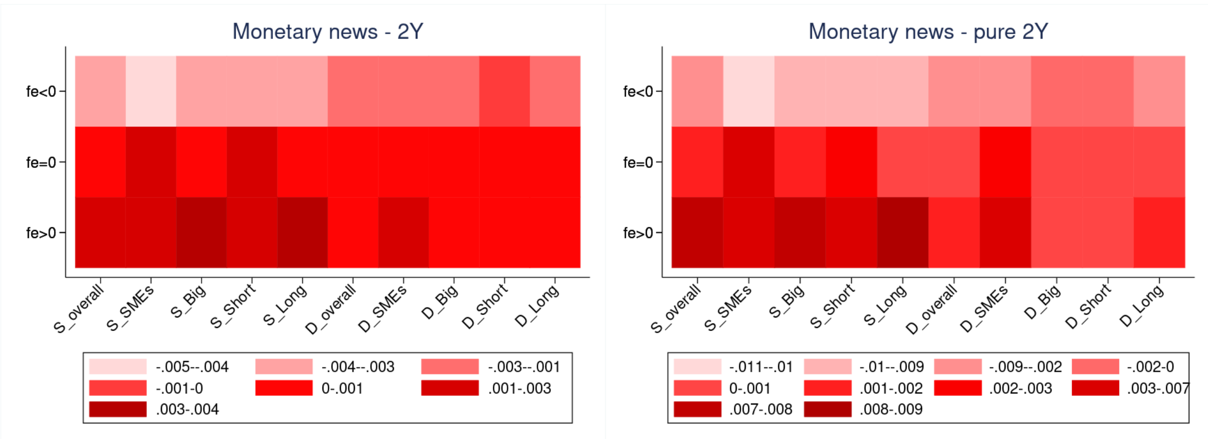


Figure 5: Figure shows probability associated to tightening monetary shock OIS - 2 years with forecast errors. Probability that tightening shock is associated to positive or null forecast error is higher than probability associated with negative forecast error. *D* and *S*

5 The Macro Model

We develop a macro model with two representative agents, a borrower and a lender. The borrower is a firm that needs debt to finance its risky projects, the lender is a deep pocketed and risk-neutral. In addition, agents are endowed with diagnostic expectations. The risky debt part of the model is built on Arellano (2008), (2019), on top of which we add the non-rational expectations' component as in Bordalo et al. (2022) and a monetary component where the central bank controls the real interest rate, subject to an IID shock.

5.1 Diagnostic expectations

Diagnostic Expectations are based on the concept of *representativeness* heuristics, disclosed by Kahneman and Tversky in the early seventies - Kahneman and Tversky (1972). An element is representative in a class whenever it is diagnostic, i.e. it's relative frequency in that class is much higher than in another reference class. Gennaioli and Shleifer (2010) built an analytical model describing representativeness applied to belief formation.

The agent forms beliefs estimating the distribution of a generic future state conditional on the present state, in comparison with the distribution of the past.

The agent knows the true distribution of the state in the future ($f(x_{t+1}|x_t)$), however he selectively recovers the realizations of the state at $t+1$ that are more representative in t with respect to the past state x_{t-1}.

When the agent forms his expectations, he assess the distribution of the future state X_{t+1} given current conditions $X_t = x_t$. When the agent is rational, he solves the problem by using conditional distribution $f(X_{t+1} = x_{t+1}|X_t = x_t)$. In the case of diagnostic agent instead, he selectively retrieves and overstates future states x_{t+1} that are representative at time t with respect to information held at $t-1$.

Specifically, under the assumption of $x_t \sim AR(1)$, the reference state to be $X_t = \rho x_{t-1}$. Representativeness of x_{t+1} is given by:

$$\frac{f(X_{t+1} = x_{t+1}|X_t = x_t)}{f(X_{t+1} = x_{t+1}|X_t = \rho x_{t-1})} \tag{5}$$

The state is more representative the more it is its likelihood with respect to recent news. In case of absence of news, numerator and denominator coincide, there is no state more representative than others, 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 [3]

$$f_t^{\theta} x_{t+1} = f(X_{t+1} = x_{t+1} | X_t = x_t) \left[\frac{f(X_{t+1} = x_{t+1} | X_t = x_t)}{f(X_{t+1} = x_{t+1} | X_t = \rho x_{t-1})} \right]^{\theta} \frac{1}{Z} \tag{6}$$

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.

5.2 Firm

Firm is subject to a macro TFP shock z following an AR(1) process.

$$\log z' = \rho_z logz + \varepsilon_z', \quad \varepsilon_z' \sim N(0, \sigma_z^2), \quad \rho_z \in (0,1) \tag{7}$$

Agents are endowed with diagnostic expectations, so, given the $AR(1)$ TFP process, the diagnostic process becomes:

$$\log z' | (\log z, \varepsilon_z) \sim N(\rho_z(\log z + \theta\varepsilon_z), \sigma_z^2) \tag{8}$$

If $\theta = 0$ agents are rational, while if $\theta > 0$ agents are diagnostic and they forecast the future level of productivity z' overweighting current news given by ε_z.
Low of motion for capital is given by $k' = i + (1-\delta)k, \quad \rho_z \in (0,1)$. Output depends on the unique input k and the level of macro productivity: $y = zk^{\alpha}$. Investments involve quadratic adjustment costs $AC(i,k) = \frac{\eta_k}{2}(\frac{i}{k})^2 k$.

The firm finances their project with risky debt and maximize current and expected profits. Every period each firm can decide whether to repay or default. If a firm de-

[3] Where Z is a normalizing constant ensuring diagnostic density integrates to one.

faults, assets are partially recovered by lenders and the firm restarts with zero capital and zero debt in the following period. If a firm repays, it chooses how much to invest and to borrow in the next period. Every period the dividend is given by output plus additional debt b' minus investment, adjustment costs and repaid previous period debt.

$$d = y - AC(i,k) + q(z,k',b')b' - i - b \tag{9}$$

Following Gomes2001, if dividends are negative, the firm issues equity at a cost $IC(d) = \mathbb{1}(d < 0)(\eta_f + \eta_v|d|)$, where η_f, η_v represent the fixed and variable components of the issuing cost respectively.

Firm's problem is about maximizing next period capital and debt over four state variables, given by the current level of debt b, the exogenous state z, the level of capital k and the previous exogenous state z_{-1}. The recursive firm's problem is given by

$$V^{\theta}(b,z,k,z_{-1}) = \max\{V^{\theta}_{D}(z,z_{-1}), V^{\theta}_{ND}(b,z,k,z_{-1})\} \tag{10}$$

$$V^{\theta}_{D}(z,z_{-1}) = 0 + \frac{1}{1+R}\mathbb{E}[V(0,z',0,z)|(z,z_{-1}] \tag{11}$$

$$V^{\theta}_{ND}(b,z,k,z_{-1}) = \max_{d,b',k'}\{d - IC(d) + \frac{1}{1+R}\mathbb{E}[V(b',z',k',z)|(z,z_{-1}]\} \tag{12}$$

When the value of non-defaulting is greater or equal than the defaulting option, the continuation value is as in equation (12). The firm optimizes current profit and future ones, choosing the best future level of debt and capital. When the firm defaults, assets are partly recovered by the lender according to parameter $gamma \in (0,1)$. The firm does not produce for one period, has zero debt and capital and the next period restarts with positive debt and capital. Equation (10) identifies the policy $df(b',z',k',z)$, where the firm chooses optimally to default when $V^{\theta}_{D} > V^{\theta}_{ND}$. The other policy functions are $b'(b,z,k,z_{-1}), k'(b,z,k,z_{-1})$.

5.3 Lender

The endogenous risky debt price is given by a condition that sets the expected rate of return on debt equal to the risk-free rate, subject to the monetary authority shock. The recovery rate of firm's asset is governed by parameter γ. The zero-profit condition for the lender is therefore:

$$b'(1+r^{rfree}) = \mathbb{E}[df(b',z',k',z)\mathcal{R}(b',k')|z,z_{-1}] + b'\mathbb{E}[(1+r^{risky})(1-df(b',z',k',z))|z,z_{-1}] \tag{13}$$

and the price of the risky debt, for agents endowed with diagnostic expectations, is

$$q^{\theta}(b',z',k',z) = \frac{1}{1+r}\mathbb{E}^{\theta}[1+df(b',z',k',z))(\mathcal{R}(b',k')-1)|z,z_{-1}] \tag{14}$$

where $df(\cdot)$ is the borrower's defaulting policy rule, $\mathcal{R}(\cdot)$ is the recovery rate and $r = r^{rfree}$ the real interest rate set by the central bank and subject to the monetary shock.

5.4 Monetary policy

The central bank controls the real interest rate, which is made of the natural real interest rate directly controlled by the monetary authority and an error ν_t arising from the monetary authority announcements.

$$r = r^n + \nu, \quad \nu \sim^{iid} N(0, \sigma_\nu^2) \tag{15}$$

5.5 Model solution

The model is solved numerically with value function iteration. The equilibrium of the model is given by

- firm policies $b'(\cdot), k'(\cdot), df(\cdot)$;
- firm value functions $V^{\theta}_{ND}, V^{\theta}_{D}, vf^{\theta}$;
- lender price schedule q^{θ};

such that, taking as given lender's price schedule, firm policies and value functions satisfy equations (10)-(12) and taking as given firm policies, the lender price satisfies the zero-profit condition of equation (14). The procedure works as follows:

1. Guess the value function vf and the pricing rule $q(\cdot)$;

2. Update the default V_D and non-default V_{ND} value functions for each combination of $(b, z, k, z_{-1}, b', k')$;

3. Using these two functions update the value function vf, the default rule $df(\cdot)$ and the pricing function $q(\cdot)$;

4. check for convergence;

We apply standard discretization for debt and capital grids, while we use Tauchen revised method to discretize current and past productivity levels[4]. The calibration used for the baseline solution is that one offered by Bordalo et al. (2022).

In Figure 6, we present the outcomes of a model simulation, where we explore distinct values of the diagnostic parameter (θ)—specifically, zero ($\theta = 0$, reflecting rational expectations) and one ($\theta = 1$, representing diagnostic expectations). Notice that the level of the diagnostic parameter used in this simulation is the same for the borrower and the lender. In the case of the diagnostic expectations (DE) model, we visualize policy functions for varying levels of past Total Factor Productivity (TFP) denoted as z_{-1}. The interpretation of the results follows: when the past shock level is lower than the current shock level, the agent, influenced by distorted beliefs, interprets this as positive news; conversely, if the past shock level is higher than the present one, the agent perceives it as negative news.

Clearly, the presence of diagnostic expectations significantly alters the model's solution. When the present shock is higher than the past shock, the policy function for capital (depicted in subplot 1) markedly exceeds the optimal capital under rational expectations calibration. In contrast, when the shock is lower, the optimal capital decreases, eventually reaching a stable zero level for highly negative news. Notably, such negative news is construed as the difference between the shocks in the two time periods. Consequently, the dividend level (subplot 3) diverges substantially from the rational expectations model — lower in scenarios of negative news from the past and slightly higher when the news is positive. Turning to the lender's perspective, a positive past shock leads to an increase in the price of debt (implying reduced perceived

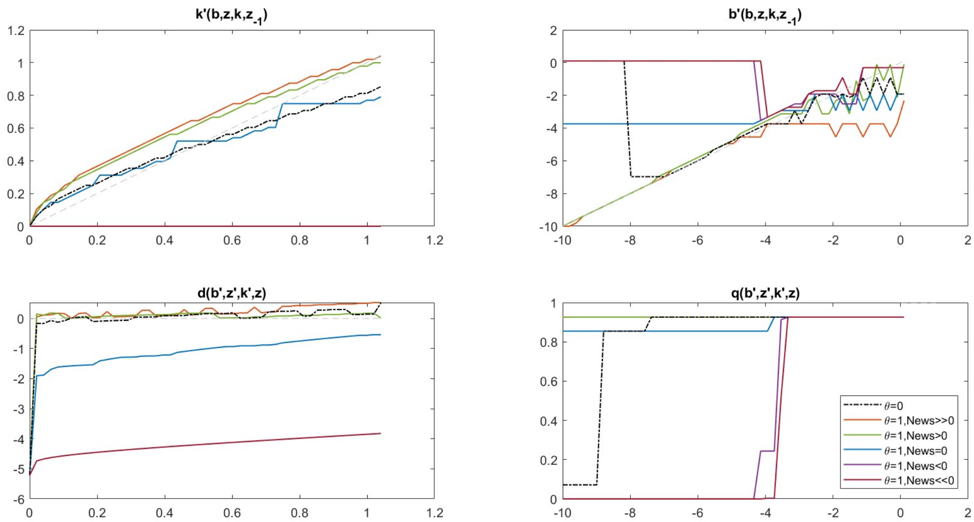
[4]In the diagnostic setting, an extra state variable given by the past state is added to the problem. Therefore, for each exogenous level of current productivity there are n exogenous levels of the last period's productivity to deal with.

riskiness), while a higher past shock relative to the present one corresponds to a perception of significantly increased risky debt.

Regarding the broader economic dynamics, diagnostic expectations introduce an additional layer of complexity through the lens of risky debt. During favorable economic periods, borrowers seek increased debt, and lenders are inclined to offer it at lower prices due to the lowered perceived risk. Conversely, in economic downturns, the opposite pattern prevails. This observation is consistent with the findings of Bordalo et al. (2022). The influence of monetary policy news accentuates these effects by affecting lenders' pricing decisions.

With respect to the monetary policy dynamics, they interfere with the debt pricing on the first term of the right-hand-side of equation 14. Consider the next results as being conditional on having a positive TFP shock. The announcement shock may hit in two ways. If $\nu > 0$, the announcement has a mitigation effect on the debt price. Conversely, when $\nu < 0$, the announcement has an amplification effect on the debt price. This dynamic occurs unconditionally of the nature of the lender's expectations. When we consider the monetary and the expectations channel jointly, since the expectations channel is always amplifying, if the monetary announcement is positive, the expectational distortion is mitigated, converging to the rational benchmark. If instead the monetary announcement is negative, the expectational distortion is amplified even more intensely. Even a modest negative impact on the interest rate gets enlarged in the diagnostic equilibrium, influencing debt levels and prices. Overall, the model prescribes results that can be twofold, based on the sign of the monetary shock. However, from the empirical analysis we observe that the amplification mechanism of the model is prevailing, as banks tend to amplify their expectational distortions when they are hit by monetary policy announcements.

Figure 6: Model simulation policy functions



Notes: The figure shows policy functions of the model simulation. Different lines show results of the simulation for different levels of the TFP shock. In the NW and NE panel is provided the policy function for capital and debt depending on k and b respectively. Panel in SW shows the policy function for dividends of the firm depending on k, SE panel shows the equilibrium price.

6 Conclusions

This paper delves into examining the rationality of subjective beliefs held by major lenders in the Euro Area. This investigation is conducted through an empirical analysis of the iBLS survey. The primary focus is on determining whether it is possible to predict forecast errors made by bankers participating in the survey. The results affirm the presence of predictability in forecast errors, taking the form of lender overreaction. This overreaction is quantified by negative coefficients in ordinary least squares (OLS) regressions. As an alternative approach, an ordered probit model is employed to better align with the qualitative characteristics of the dataset. Interestingly, the direction of the results remains consistent: there is a notably higher probability that positive (negative) news corresponds to negative (positive) forecast errors, as opposed to null or positive (negative) forecast errors. Moreover, we prove the uniformity of this behavior across European banks. By examining regressions at the country level, it becomes evident that most survey questions exhibit negative coefficients similar to those observed in the pooled baseline regression. These coefficients range from -0.2 to -0.5. On the other hand, the coefficients in the aggregate regression are less pronounced in magnitude and significance.

The paper's second innovative empirical exercise involves investigating whether distortions in short-term lenders' expectations are influenced by monetary policy announcements. Initial analysis reveals a higher likelihood of a connection between positive forecast errors and monetary surprises compared to negative ones. Furthermore, when announcements are categorized as Delphic or Odyssean, a polarization of the aforementioned effect is observed. By isolating the monetary surprise from potential informational content, a clearer understanding of the purely monetary nature of the shock is obtained, shedding light on the "negative" news that impact lenders' credit standards.

Ultimately, the paper presents a straightforward macroeconomic model aimed at elucidating the mechanism underlying the empirical findings, where agents are endowed with diagnostic expectations, firms can default on risky debt, and a lenders are subject to monetary policy shocks. Higher shocks due to expectations' distortions lead to markedly excessive capital policy function compared to rational expectations. Lower shock reduces optimal capital, reaching stable zero for very negative news. Dividend level diverges greatly — lower for negative past news, slightly higher for positive news. Positive past shock increases debt price (reduced risk), higher past shock raises risky debt perception.

Diagnostic expectations add complexity to risky debt dynamics. In prosperous times, borrowers demand more debt and invest more, lenders offer at lower prices due to lower risk perception. In downturns, opposite pattern emerges. Conditional on receiving a positive monetary policy shock (risk free rate higher), diagnostic expectations amplify this channel through lenders' pricing. Lenders perceive borrowers more risky than the rational baseline, and therefore set higher risky interest rates, implying defaults for a higher number of TFP states.

The paper shows how monetary policy innovations can be absorbed by banks' expectations and how these can amplify the credit dynamics when lenders are endowed with non-rational beliefs.

References

Altavilla, Carlo, Luca Brugnolini, Refet S Gürkaynak, Roberto Motto, and Giuseppe Ragusa, "Measuring Euro Area Monetary Policy," *Journal of Monetary Economics*, 2019, p. 53.

_ , Matthieu Darracq Pariès, and Giulio Nicoletti, "Loan supply, credit markets and the euro area financial crisis," *Journal of Banking & Finance*, 2019, *109*, 105658.

Arellano, Cristina, "Default Risk and Income Fluctuations in Emerging Economies," *American Economic Review*, June 2008, *98* (3), 690–712.

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

Bordalo, Pedro, Nicola Gennaioli, Andrei Shleifer, and Stephen J Terry, "Real credit cycles," 2022.

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

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.

Enders, Zeno, Franziska Hünnekes, and Gernot J. Müller, "Monetary policy announcements and expectations: Evidence from german firms," *Journal of Monetary Economics*, December 2019, *108*, 45–63.

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.

Farroni, Paolo and Jacopo Tozzo, "Bank beliefs and firm lending: evidence from Italian loan-level data," *Working Paper*, 2022.

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

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

Jarociński, Marek and Peter Karadi, "Deconstructing Monetary Policy Surprises—The Role of Information Shocks," *American Economic Journal: Macroeconomics*, April 2020, *12*, 1–43.

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

Kiyotaki, Nobuhiro and John Moore, "Credit cycles," *Journal of political economy*, 1997, *105* (2), 211–248.

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.

Mian, Atif, Amir Sufi, and Emil Verner, "Household debt and business cycles worldwide," *The Quarterly Journal of Economics*, 2017, *132* (4), 1755–1817.

Ottonello, Pablo and Thomas Winberry, "Financial Heterogeneity and the Investment Channel of Monetary Policy," *Econometrica*, 2020, *88*, 2473–2502.

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

Schularick, Moritz and Alan M Taylor, "Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008," *American Economic Review*, 2012, *102* (2), 1029–61.

Appendix

Table 1: Marginal effects of Monetary Policy on Credit - Firms

	Overall Credit	SMEs	Big Firms	Short T.	Long T.
			Panel A: $\Delta \mathbf{OIS}_{\mathbf{t}}^{\mathbf{2Y}}$		
$FE_{t+1\|t} = -2$	-0.000266**	-0.000413***	-0.000489***	-0.000145*	-0.000412***
	(0.0000945)	(0.000122)	(0.000141)	(0.0000685)	(0.000119)
$FE_{t+1\|t} = -1$	-0.00900***	-0.00906***	-0.0104***	-0.00820***	-0.00859***
	(0.00173)	(0.00182)	(0.00177)	(0.00169)	(0.00174)
$FE_{t+1\|t} = 0$	0.00175**	0.00247***	0.00217***	0.00195**	0.00160**
	(0.000592)	(0.000674)	(0.000657)	(0.000614)	(0.000559)
$FE_{t+1\|t} = +1$	0.00722***	0.00680***	0.00844***	0.00622***	0.00718***
	(0.00139)	(0.00137)	(0.00143)	(0.00129)	(0.00145)
$FE_{t+1\|t} = +2$	0.000297**	0.000209*	0.000335**	0.000177*	0.000217*
	(0.000107)	(0.0000857)	(0.000117)	(0.0000783)	(0.0000895)
			Panel B: $\Delta \mathbf{OIS}_{\mathbf{t}}^{\mathbf{2Y}} \times \mathbf{M}_{\mathbf{t}}^{\mathbf{pure}}$		
$FE_{t+1\|t} = -2$	-0.000462**	-0.000796***	-0.000837***	-0.000255*	-0.000845***
	(0.000149)	(0.000231)	(0.000209)	(0.000122)	(0.000221)
$FE_{t+1\|t} = -1$	-0.0158***	-0.0177***	-0.0180***	-0.0147***	-0.0180***
	(0.00297)	(0.00297)	(0.00312)	(0.00297)	(0.00342)
$FE_{t+1\|t} = 0$	0.00309*	0.00481**	0.00375*	0.00349**	0.00340*
	(0.00126)	(0.00148)	(0.00146)	(0.00123)	(0.00150)
$FE_{t+1\|t} = +1$	0.0127***	0.0132***	0.0145***	0.0111***	0.0150***
	(0.00248)	(0.00214)	(0.00242)	(0.00232)	(0.00285)
$FE_{t+1\|t} = +2$	0.000533**	0.000407*	0.000581**	0.000323*	0.000461*
	(0.000178)	(0.000161)	(0.000217)	(0.000144)	(0.000189)
N	5439	5439	5439	5439	5439

Notes: This table reports estimates of ordered probit regression for firms' credit, with latent variable $FE^*_{i,t+1|t} = \beta_0 + \beta_1 F_t + \beta_2 \Delta OIS_t^{2Y} + \epsilon_{i,t+1}$ in Panel A. For panel B, the dependent latent variable is given by $FE^*_{i,t+1|t} = \beta_0 + \beta_1 F_t + \beta_2 \Delta OIS_t^{2Y} \times M_t^{pure} + \epsilon_{i,t+1}$. Columns report independent variables, i.e. OIS variation and OIS variation interacted with pure monetary shock. Rows report dependent variables. Each coefficient has to be interpreted as the probability effect the independent has on the specific class of $FE_{i,t+1|t}$. Standard errors are in parenthesis and are clustered at bank-level. Significance levels at 1%, 5%, 10% are given by (***), (**), (*) respectively.

Table 2: Marginal effects of Monetary Policy on Credit - HH

	Weighted Avg News		Total Quarter News	
	Cr. Housing	Cr. Consumption	Cr. Housing	Cr. Consumption
		Panel A: $\Delta \mathbf{OIS}_t^{2Y}$		
$FE_{t+1\|t} = -2$	-0.000131	-0.000137*	-0.0000716*	-0.0000599*
	(0.0000801)	(0.0000690)	(0.0000322)	(0.0000269)
$FE_{t+1\|t} = -1$	-0.00316	-0.00386*	-0.00172**	-0.00169**
	(0.00178)	(0.00163)	(0.000655)	(0.000595)
$FE_{t+1\|t} = 0$	0.000182	0.000718	0.0000985	0.000313*
	(0.000195)	(0.000379)	(0.0000984)	(0.000149)
$FE_{t+1\|t} = +1$	0.00300	0.00319*	0.00164**	0.00139**
	(0.00169)	(0.00135)	(0.000623)	(0.000493)
$FE_{t+1\|t} = +2$	0.000107	0.0000882	0.0000585*	0.0000385
	(0.0000679)	(0.0000505)	(0.0000280)	(0.0000202)
		Panel B: $\Delta \mathbf{OIS}_t^{2Y} \times \mathbf{M}_t^{pure}$		
$FE_{t+1\|t} = -2$	-0.000563**	-0.000445**	-0.000226**	-0.000155**
	(0.000189)	(0.000164)	(0.0000706)	(0.0000587)
$FE_{t+1\|t} = -1$	-0.0136***	-0.0127***	-0.00547***	-0.00442***
	(0.00368)	(0.00330)	(0.00131)	(0.00119)
$FE_{t+1\|t} = 0$	0.000790	0.00236	0.000317	0.000822
	(0.00118)	(0.00130)	(0.000470)	(0.000459)
$FE_{t+1\|t} = +1$	0.0129***	0.0105***	0.00519***	0.00365***
	(0.00343)	(0.00264)	(0.00121)	(0.000959)
$FE_{t+1\|t} = +2$	0.000460**	0.000291*	0.000184**	0.000102*
	(0.000175)	(0.000137)	(0.0000672)	(0.0000480)
N	5439	5439	5439	5439

Notes: This table reports estimates of ordered probit regression for households' credit, with latent variable $FE^*_{i,t+1|t} = \beta_0 + \beta_1 F_t + \beta_2 \Delta OIS_t^{2Y} + \epsilon_{i,t+1}$ in Panel A. For panel B, the dependent latent variable is given by $FE^*_{i,t+1|t} = \beta_0 + \beta_1 F_t + \beta_2 \Delta OIS_t^{2Y} \times M_t^{pure} + \epsilon_{i,t+1}$. Columns report independent variables, i.e. OIS variation and OIS variation interacted with pure monetary shock. Rows report dependent variables. Each coefficient has to be interpreted as the probability effect the independent has on the specific class of $FE_{i,t+1|t}$. Standard errors are in parenthesis and are clustered at bank-level. Significance levels at 1%, 5%, 10% are given by (***), (**), (*) respectively.

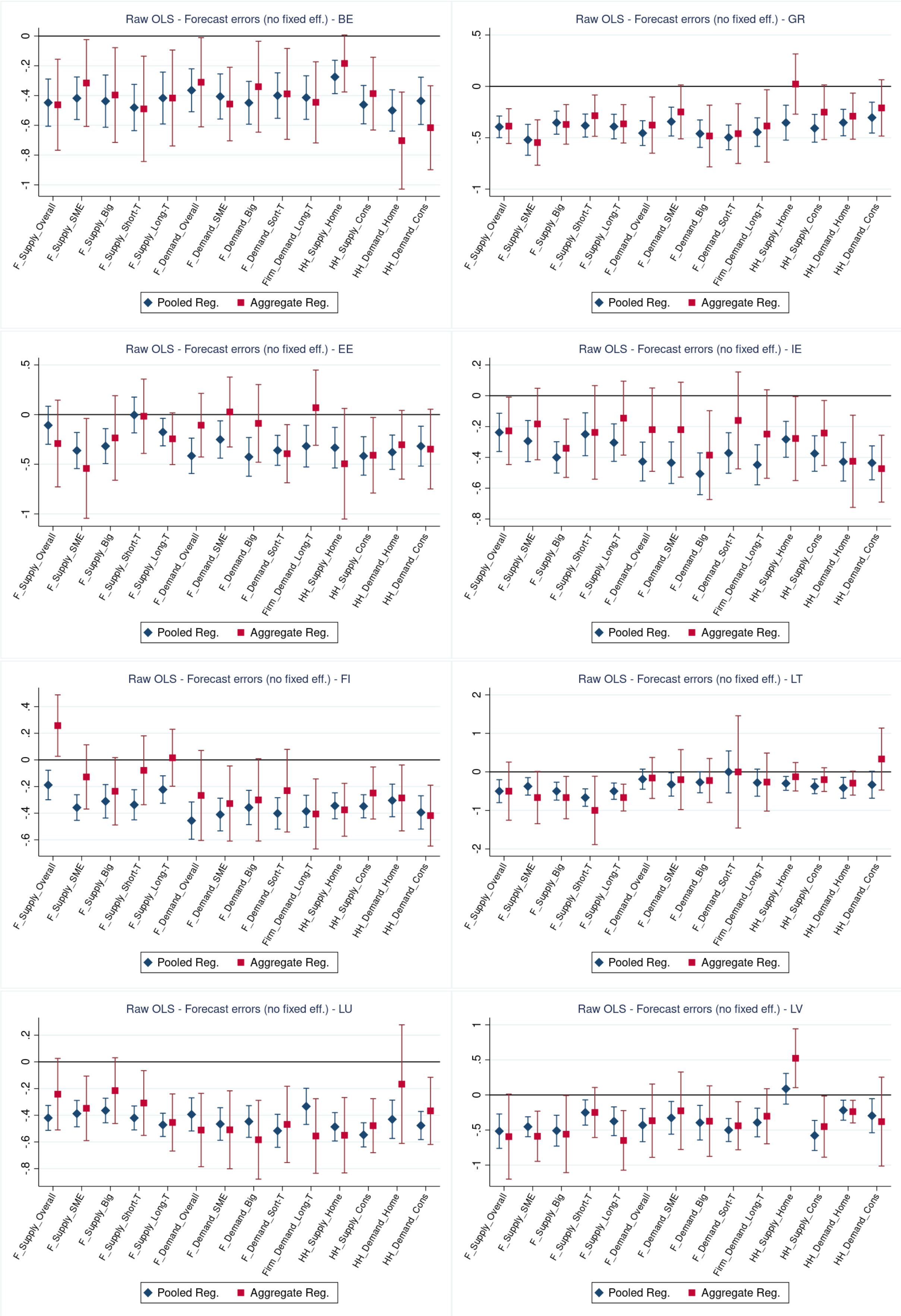


Figure 7: Figure shows baseline OLS regression (1) of forecast errors predictability for additional countries of the EA. Coefficients are of a pooled regression and an aggregate regression, where in the latter observations are averaged by country and time.

Diagnostic expectations and credit constraints

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Third Chapter
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Abstract

This study combines non-rational expectations and financial constraints in a simple 3-periods macro model that reconciles with a Minsky cycle. Financial crises have unveiled the central role of determinants such as debt and sentiment in macroeconomic dynamics. This paper incorporates both features under the formulation of overreacting expectations to good news and financial constraints in a unique theoretical environment. The model shows that sentiment originates the boom phase through inflated beliefs on the reselling value of the home-equity asset purchased. A reversal of expectations to rationality induces agents to self-constrain their borrowing capacity when they realize that past debt demand was blown up. This mechanism provides the formation of a new equilibrium driven by the collateral limit which provides a lower demand for debt and force the agent to reduce consumption.

1 Introduction

After the financial crisis of 2008, some economic phenomena that had been forgotten or neglected in previous years have been debated and deeply studied anew. Debt and sentiment are unequivocally two of these topics, dug out in the last decade in macroeconomics and finance. The Great recession has brought together about the crucial role of debt in the determination of a financial crises. Regarding sentiment, there has been less production in the literature so far, but progress has been made, for instance, with the work of Gabaix (2020), López-Salido et al. (2017), Gennaioli and Shleifer (2020) or Kaplan et al. (2020). Since 1977, a strong and enlightening contribution on the field was brought by Hayman Minsky with Minsky (1977). The author designed a clear connection between debt and optimism emerging in any pre-crises period of a financial downturn, as well-established in Minsky and Kaufman (2008). Minsky claimed that capitalist economies recurrently fall into financial crisis that are jointly determined by investors euphoria disposition, rising asset prices and blowing up debt. The crises appear when players of the game realize that asset prices are inconsistently high with respect to the real underlying values and the leverage becomes unsustainable. The literature subsequently defined the time in which the castle falls as the *Minsky moment*. Simultaneously, evenly important and critical is the aftermath of the crisis. When the economy bursts, phenomena such financial constraints and de-leveraging play their role. Due to exogenous motives or agents recognition of the inflated value of their assets, excessive optimism leave the place to de-leveraging processes and downturn of real outcomes.

The objective of this paper is to mimic this well-known dynamic in a theoretical model based on households consumption and investments in home-equity asset. The mechanism of the crisis is described by a baseline three-period model. Between first and second period the booming phase of the crises appears. There are borrowers who take on debt by savers; due to positive news in the first period, borrowers expect a future surge in the price of their asset. The rise is motivated exclusively by optimism of the agents, that realizes through extrapolative beliefs. Since the main scope of borrowing is to buy a real asset, demand of debt increases as a result of the common belief that value of the assets will increase in the second period. How does the crisis originate? Agents get acquainted of the overvalued price of their assets and start to deleverage. Thus, they end up to be borrowing constrained as a result of the recognition of their distorted beliefs.

The paper is linked to several strand of literature in macroeconomics and finance. First, it is to evidence a growing literature on the role of expectations in financial crisis with respect to home assets and debt dynamics. From the paper of López-Salido et al. (2017) that investigates the role of credit-market sentiment as a source of macroeconomic risk in the last century, recent developments have shown the role of non-rational expectations in the crisis dynamics. As important examples, Kaplan et al. (2020) has reconciled a model of housing market boom-and-bust with data in the US, while Farhi and Werning (2020) focuses on the positive policies that can be undertaken by central authorities in the event of a Minsky cycle.

Further, there is a wide set of articles on non-rational expectations in macroeconomics, which is filled by the seminal work of Kahneman and Tversky (1972) that gave the birth to the concept of representativeness. Later on, representativeness has been used to design a theory of non-rational expectations developed starting by Gennaioli and Shleifer (2010) and collected in Gennaioli and Shleifer (2020). Diagnostic expectations is a belief formation mechanism that overweights future outcomes that are more likely in response of incoming news. In Bordalo et al. (2018a), the paper is evocative of the Minsky cycle. It treats a neoclassical model of credit cycle with diagnostic expectations. Moreover, an heterogeneous firms model with diagnostic expectation is proposed in Bordalo et al. (2019), where dynamics of spreads and leverage are accounted. Together with Bordalo et al. (2018b), where evidence of forecast errors predictability and forecast revisions is empirically proven, these papers contribute to the determination of diagnostic expectations in credit cycles. While they mostly look into the supply-side of the economy, my paper introduces diagnosticity on consumers side, evidencing a novel duty in relation with collateralized home-equity debt. Surely, the role of this literature in the paper is to motivate the boom phase of the cycle. With overreaction to news on the exogenous price process, borrowers overvalue their assets and increase their demand for debt.

Another stream of literature regards the role of debt and financial constraints and this part is linked with the second part of the model. Agents become borrowing constrained, affecting output through dynamics occurring in the credit market. Among others, Eggertsson and Krugman (2012) focuses on the importance of credit constraints for impatient agents during the bust phase. My paper aims attention at the boom phase too, completing the cycle of the crisis. Monacelli (2009) introduces collateral constraints in a New Keynesian environment where the collateral plays a role in the response of durable consumption to monetary shocks. In Guerrieri and Lorenzoni (2017), which shows the effects of credit crunch on consumer spending with heterogeneous agents, credit tightening is motivated by an exogenous unexpected financial shock. These papers prove the negative impact of financial constraints on aggregate demand and several other outcomes, however the shock is motivated by monetary or income shocks. This paper instead, identifies in the reversal of distorted expectations the cause of credit constrained agents. In the first period borrowers form beliefs overvaluing the future price of assets, while in the second they self-constrain through deleveraging, as a result of their self-realization of distorted beliefs.

Results of the model show that: 1- there is an increase in the demand of debt in good times by borrowers, who forecast a higher reselling value of their home-equity asset based on incoming positive news. 2- expectations can act as an endogenous driver for equilibrium variation. Changing their belief formation process, which in the paper is represented by a reversal from diagnosticity to rationality, can act as a crucial disturbance to the model dynamics. 3- Credit market works as a vehicle both for the belief formation process and output dynamics. Credit constraints are confirmed as an important source of demand tightening.

The paper is structured as follows: in section 2 is presented a series of empirical result in support of the paper's theoretical reasoning. Section 3 describes the belief formation process. In section 4 the baseline model is presented. Additionally, in section 5 an intuition of a more complex framework including inflation and endogenous production is given, with the aim of expand the research in a well-defined model with production in the future. In section 6 there are conclusions.

2 The Great Recession: evidence of the cycle

Vast literature has been produced during the last decade to prove an existing link between the rising of debt, booming economic activity and subsequent downturn. In the following paragraph a broad crises pattern is designed, starting from the most relevant empirical findings.

Pre-crisis A result using long-run data is given by Schularick and Taylor (2012) and predicts that credit booms happening in the previous five years of the event rise up the probability to incur into a financial crisis.

Facts about the first phase are well-documented in the extensive work of Mian and collegues such as Mian and Sufi (2011), Mian and Sufi (2014), Mian (2016), Mian et al. (2017). First, in the US, such as in other advanced economies, between 2002-2006 there was an expansion of credit mortgage supply due to non-visible increased economic conditions of the borrowers. In Mian and Sufi (2011) the growth of debt, mostly driven by home purchases, lines up on the 34% with respect to the previous 4-year period. Second, a strong correlation between household debt rise and upsurge of house price has been documented. The authors claim a clear causal relationship going from the former to the latter. Moreover, effect of rising home prices on borrowing concentrates more on owners with lower credit scores and high propensity of credit cards usage, opening up to heterogeneity of homeowners. Finally, existing homeowners leveraged out their day-by-day growing home-asset price. The evidence above is also accompanied by extremely low credit spreads between 2002-2006, in particular subprime mortgage spread.

The crisis hits When the boom debt burst, the main reported effects are an increase in the default rate, a fall on the debt to GDP rate and consequent drop of GDP and employment. The correlation between debt boom and GDP downturn has been documented by Mian et al. (2017), which shows how a credit boom ignites GDP on the short term and brings it at the same pre-crisis level after five years[1]. On the longer term, the GDP falls even under the pre-shock level, validating the permanent impact of the debt boom. In Jordà et al. (2013) is shown that the 5-years aftermath of the crisis measures a decline of 8% on real GDP. Moreover, Mian and Sufi (2014) exhibit a direct link between the deterioration of household balance sheets given by home-equity value loss and the slump on post-2009 employment.

Motivation The recognition of these empirical results is a good starting point upon which justify the theoretical background of this paper. There are heterogeneous consumers in their net debt position. Borrowers take on debt from savers; during the booming phase there are no borrowing limits, house prices increase thanks to overoptimism as well as debt demand, on the basis of the aforementioned empirical results. Why the crisis happen? Consumers get aware of their biased beliefs and start deleveraging, self-imposing a borrowing constraint based on the value of their home-equity value. The proposition reflects a demand-shock driven model that leads to an increase of the interest rate in the first place and a consecutive fall on the bust phase. Additionally, as the borrowing capacity reduces, consumption drops and negative impact on GDP is served in the last period.

3 Diagnostic expectations

Diagnostic Expectations is based on the concept of *representativeness* heuristics, disclosed by Kahneman and Tversky in the early seventies - Kahneman and Tversky (1972). An element is representative in a class whenever it is diagnostic, i.e. it's rel-

[1] The study is based on a VAR analysis and is conducted on a country-level panel dataset including 900 country-years over the 1960-2012 period.

ative frequency in that class is much higher than in another reference class. Gennaioli and Shleifer (2010) built an analytical model describing representativeness applied to belief formation.

The agent forms beliefs estimating the distribution of a generic future state conditional on the present state, in comparison with the distribution of the past.

The agent knows the true distribution of the state in the future ($f(x_{t+1}|x_t)$), however he selectively recovers the realizations of the state at $t+1$ that are more representative in t with respect to the past state x_{t-1}.

When the agent forms his expectations, he assess the distribution of the future state X_{t+1} given current conditions $X_t = x_t$. When the agent is rational, he solves the problem by using conditional distribution $f(X_{t+1} = x_{t+1}|X_t = x_t)$. In the case of diagnostic agent instead, he selectively retrieves and overstates future states x_{t+1} that are representative at time t with respect to information held at $t-1$.

Specifically, under the assumption of $x_t \sim AR(1)$, the reference state to be $X_t = \rho x_{t-1}$. Representativeness of x_{t+1} is given by:

$$\frac{f(X_{t+1} = x_{t+1}|X_t = x_t)}{f(X_{t+1} = x_{t+1}|X_t = \rho x_{t-1})} \tag{1}$$

The state is more representative the more it is its likelihood with respect to recent news. In case of absence of news, numerator and denominator coincide, there is no state more representative than others, 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 [2]

$$f_t^\theta x_{t+1} = f(X_{t+1} = x_{t+1}|X_t = x_t)\left[\frac{f(X_{t+1} = x_{t+1}|X_t = x_t)}{f(X_{t+1} = x_{t+1}|X_t = \rho x_{t-1})}\right]^\theta \frac{1}{Z} \tag{2}$$

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. Param-

[2]Where Z is a normalizing constant ensuring diagnostic density integrates to one.

eter θ measures the degree of diagnosticity, the deviation from the rational expectation case.

4 A 3-period model of household debt

The following paragraph describes the baseline model of the paper. The timing evolves in three periods: $t = \{0, 1, 2\}$. This setting is helpful in describing the how the crisis originates; in particular, between t time 0 and 1 the boom phase occurs, between time 1 and 2 the bust happens. There are two representative household types: saver and borrower. The latter takes loans from the saver to finance a home-equity asset at a risk-free rate, which is supplied in fixed quantity at an exogenous fluctuating price. While the nature of the saving attitude in the literature is usually motivated by a different level of impatience among housholds, in this model the level of impatience is the same as in Farhi and Werning (2020); the borrower is pushed by the need of housing services, while the saver does not. Endowment is also exogenous for both agents.

At time zero the borrower is endowed with extrapolative expectations over the price of home assets. Led by a sentiment of optimism on the future expected price of home-asset, the borrower pushes up the demand of debt in the credit market[3], determining a higher equilibrium level of debt and interest rate. The crisis hits at time 1. How? Unexpectedly, the borrower at time $t = 1$ becomes rational and he realizes he invested disproportionately in housing service, as a result he decides to self-constrain his borrowing capacity. Here lies the novelty of the paper with respect to those models in the literature that have largely studied household deleveraging, such as Eggertsson and Krugman (2012) and Guerrieri and Lorenzoni (2017). Borrower bounds above his borrowing by the future level of present asset, used as a collateral as in Kiyotaki and Moore (1997) and many others later. Since the *rational* expected future asset-price is lower than the *diagnostic* price (through which the first equilibrium was formed), the constraint that depends on the future value of the asset shrinks. Consequently, a new

[3] In Mian (2016) has been shown that existing homeowners borrowed extensively against the rise of house equity value, during the pre-financial crisis of 2008.

equilibrium originates at $t = 2$ from the variation of the expectation formation process. The entire mechanism determines the realization of a boom between period zero and one and a bust phase between time one and two. As in Eggertsson and Krugman (2012), in the bust phase of the model aggregate demand is concerned by a drop of consumption driven by borrowers and cannot be compensated by savers if the real interest rate does not fall sufficiently down. In the following paragraphs I present features and results of the model.

Exogenous price The exogenous price process originating from distorted expectations can be though as something of this form:

$$g^{\theta}_{t+1} = g_{t+1} + \theta g_t$$
$$\frac{q^{\theta}_{t+1}}{q_t} = \frac{q_{t+1}}{q_t} + \theta \frac{q_t}{q_{t-1}}$$

where g^{θ}_{t+1} is the distorted rate of growth of future asset price and θ is the parameter regulating the diagnosticity degree. In the baseline model, since only the borrower presents distorted expectations at time zero, we precisely define the price process as follows: at time zero, given q_{-1}, the expected future home-asset price of period one is given by

$$\frac{q^{\theta}_{1}}{q_0} = \frac{q_1}{q_0} + \theta \frac{q_0}{q_{-1}} \tag{3}$$

Where q_1 is intended as the rational expectation future price benchmark.

Preferences In the baseline model preferences depend only on consumption and they are shared among types. Consumption function of each agent is logarithmic.

$$U(c^i) = \ln(c^i_0) + \beta \ln(c^i_1) + \beta^2 \ln(c^i_2) \tag{4}$$

Budget constraints The saver's budget constraint is made of saver's income, consumption and saving flows. Income in given by an exogenous endowment. In period

1 and 2 saver benefits from borrower's interest rate paid on debt issued

$$t = 0: \quad C_0^S + S_0 \leq Y_0^S \tag{5}$$

$$t = 1: \quad C_1^S + S_1 \leq Y_1^S + (1 + r_0)S_0 \tag{6}$$

$$t = 2: \quad C_2^S \leq Y_2^S + (1 + r_1)S_1 \tag{7}$$

The borrower's spending is composed by non-durable consumption and home-equity asset in period zero. The borrower buys the home asset through a mortgage issued by the saver. Home asset is supplied at a fixed quantity $\bar{K}$. The time zero mortgage is paid back to saver in period one, when a new loan is issued for the incoming period. Home asset investment follows a low of motion: depreciated equity asset of period zero is sell off at period one and new asset is purchased at time one.

The borrower is unconstrained in period zero, i.e. the potential constraint is high enough that does not affect the desired demand of debt. [4]

$$t = 0: \quad C_0^B + q_0 K_0 \leq Y_0^B + B_0 \tag{8}$$

$$t = 1: \quad C_1^B + q_1[K_1 - (1 - \delta)K_0] + (1 + r_0)B_0 \leq Y_1^B + B_1 \tag{9}$$

$$t = 2: \quad C_2^B + (1 + r_1)B_1 \leq Y_2^B + q_2(1 - \delta)K_1 \tag{10}$$

Agents' problem The problem of the saver is standard. He maximises her utility under her budget constraints, choosing how much of her endowment Y_t^s to allocate between consumption and saving in each period. There is no uncertainty about the future for the saver. Optimality conditions are represented by Euler equations between each period.

$$\frac{1}{C_t^S} = \beta(1 + r_t)\frac{1}{C_{t+1}^S} \tag{11}$$

At time zero the problem of the borrower is standard too. He takes out loan from

[4] At time zero, the borrower is unconstrained. Actually the maximum constraint to be considered is $(1 + r_0)B_0 = q_1^\theta K_0$. Since the agent expects q_1^θ to rise consistently, B_0 can be thought as bounded by a very large amount that completely satisfy agent's demand. It represents the equilibrium maximum level of debt demand, assuming Walras Law.

the saver, and together with the amount of endowment Y_t^B, he decides how to invest it either in consumption or on home-equity asset. The difference with saver's problem is expressed by the presence of the investment in home-equity asset K_t in the first two periods. The optimality conditions consist of an Euler equation between each period and a no-arbitrage equation between the cost of debt and home-equity asset (see Appendix 1.A). Jointly, the equations create a link between the marginal utility of present and future consumption.

$$\frac{1}{C_0^B} = \beta(1+r_t)\frac{1}{C_1^B} \tag{12}$$

Equation (12) states that one marginal unit of additional consumption can be saved and postponed in the future through home-asset market, since $(1+r_t) = \frac{q_{t+1}^{\theta}}{q_t}(1-\delta)$. An additional unit of endowment under extrapolative expectations makes perceive the marginal utility level of consumption today equal to a relatively higher level of consumption tomorrow.

Just from this simple expression it is easy to grab the potential of an extrapolative expectation mechanism that distorts expected future prices with respect to the rational benchmark: assuming positive theta, at optimum the value of future consumption becomes higher.

4.1 Ex-ante equilibrium

The motivation for *ex-ante* equilibrium is based on the fact that borrower does not know to change his expectations, becoming rational - and hence self-constrain - before period one comes. Therefore, an *ex-ante* competitive equilibrium is defined by sequences of allocations $\{C_t^i\}_{t=0}^2, \{K_t, B_t, S_t\}_{t=0,1}$ and prices $\{r_t, q_t\}_{t=0,1}$ such that agents maximize their expected utility (4) subject to their intertemporal budget constraints given by equations (5)-(7) and (8)-(10).

The markets of goods, debt and assets clear at each date t. Market clearing condition for goods is given by

$$C_t^S + C_t^B = Y_t^{\text{tot}} = Y_t^S + Y_t^B \tag{13}$$

Debt market clearing yields $B_t = S_t = D_t$ in $t = \{0, 1\}$. Assets are in fixed supply, so that $K_t = \bar{K}$ for $t = \{0, 1\}$ as in Bianchi and Mendoza (2010).

In each period the equilibium level of debt and interest rate on the credit market depends positively on the reselling value of the home-equity asset. It follows that, since the price of future home-equity asset is distorted by extrapolation governed by θ, the equilibrium bundle on the credit market will see in each period a higher-than-rational issuance of debt at an higher interest rate. The borrower's grade of optimism drives the demand for debt and saver is favourable to accord it for a higher price.

A demand curve expression is derived for interest rate at time zero which includes equilibrium levels of interest rate and debt at time one too

$$1 + r_0 = \frac{Y_1^B + f(q_1^\theta, q_2^\theta)}{\eta B_0 + \gamma} \tag{14}$$

Where the entire formula is provided in Appendix A.1 and $\frac{\partial(1+r_0)}{\partial q_1^\theta} > 0$ and $\frac{\partial(1+r_0)}{\partial q_2^\theta} > 0$. $\eta = \frac{1+\beta+\beta^2}{1+\beta}$ and $\gamma = \beta(Y_0^B - q_0\bar{K})$.

Equation (14) outlines the negative relation between interest rate and debt quantity at time zero and the positive influence of future asset prices on time zero equilibrium level. Real interest rate is higher than it would be under the rational case, since the home-equity expected price is inflated by distorted beliefs (assuming a positive news occurring among period minus one and zero, i.e. $\theta > 0$). Extrapolation illustrates how optimism influences the credit market, shifting upwards the credit demand curve: any given level of debt demanded is accompanied by an higher level of real interest rate. The mechanism develops on demand side, the saver holds rational expectations and responds to demand inputs of the borrower on the credit market.

The picture illustrates the interaction between debt demand and supply curves and the action of diagnostic expectations on the price process that drives up the overall equilibrium level. For any level of debt at time zero, there is a higher level of real interest rate in period. The story here meets the empirical findings of Mian and Sufi

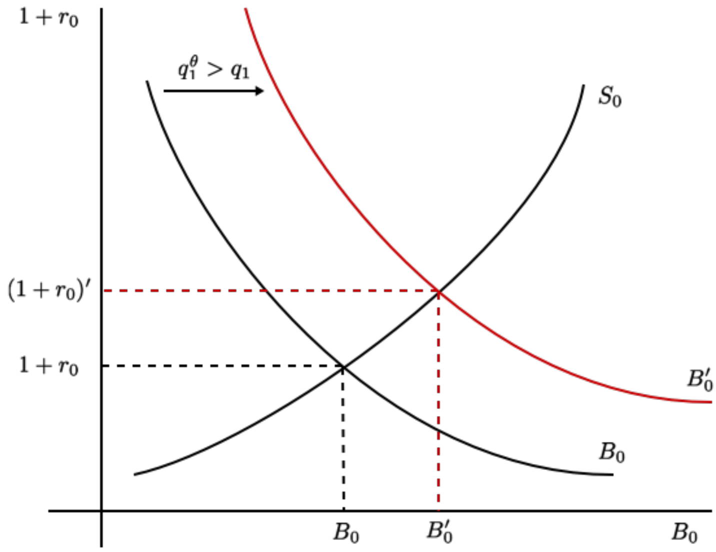

Figure 1: Demand and supply credit curves. Optimism makes the demand curve shift up as a result of inflated future home-asset price.

(2011) and Mian (2016): households expect their home-equity asset price to grow in the future and they use it to leverage and increase debt demand and consumption spending, as happened to home prices in the pre-crisis period lasting from 2002-06, both in the US and in several other advanced economies.

At time one, the equilibrium level of interest rate is given by

$$(1+r_1) = \frac{Y_2^{\text{tot}} + q_2^\theta(1-\delta)\bar{K}}{\beta[Y_1^{\text{tot}} - q_1^\theta \delta \bar{K}]} \tag{15}$$

This result shows how the interest rate in equilibrium at time one positively correlates with home-asset prices. The level of interest rate given equation (15) is the equilibrium rate at time one that is forecast as the intertemporal problem is given by the agent. However, that equilibrium will never be reached, since substituted by the new-equilibrium formed through different borrower's expectations in period one. Comparing the *old* given by equation (15) with the *ex-post* equilibrium will provide the degree of action of the expectation formation mechanism.

To resume, in period zero, after observing a positive news on the level of home-asset value, borrowers tend to be optimistic about the future level of prices. The intertemporal equilibrium shows a positive shift in credit demand at time zero, which is led by agent's optimism captured by home-asset prices. The entire mechanism generates what we refer as a *boom* phase.

4.2 The crisis and the aftermath

When period one comes, borrower becomes rational and makes himself aware that his expected future home-asset price in period zero was too high and inflated by the excessive optimism. The process of extrapolation mechanism has driven the borrower to over-demand credit; consequently, he decides to de-leverage when rationality comes in period one. How? He imposes himself a binding financial constraint, given by the future value of its home asset.

While the literature modeled so far deleveraging shocks with exogenous financial disturbances of different nature, this model provides an endogenous tractability of the problem. There is no external financial shock here hitting the asset value owned by the household. Differently, the mechanism driving the deleveraging process has its roots on decision maker beliefs about the price of equity-asset.

Hence, what I refer to the *bust* phase, originates from a reversal of non-rational expectations followed by a credit self-constraint. Rationality initiates a reversal of the price trend: since the q_1^{θ} is considered to be inflated, the expected future asset value will be $q_2 < q_1^{\theta}$. Moreover, the borrowing limit is bounded above by the net resell value of the asset holdings that works as a collateral, and its reduction automatically dampens debt demand cutting down borrower's spending capacity. As a consequence, if the reduction is high enough, the constraint changes the equilibrium level on the credit market, reducing both the levels of price and debt quantity issued.

When period one comes, the borrower faces the financial constraint (16) and a new equilibrium has to be determined.

$$(1 + r_1)B_1 \leq q_2(1 - \delta)K_1 \tag{16}$$

The borrower maximises $U(C_1^B, C_2^B)$ under (9), (10) and (16) determining a new equilibrium on the credit and goods market. Credit and goods market clear and asset is exogenously suppplied.

With the binding borrowing limit, the distorted Euler delivers a marginal utility of consumption[5] higher than the marginal utility of saving. Hence, the binding constraint limits the consumption needs of the borrower. The pseudo-Euler between period one and two looks as

$$\frac{1}{C_1^B} = \beta(1 + r_1)\frac{1}{C_2^B} + \psi \tag{17}$$

Merging the saver's Euler equation (11), which defines an optimality condition between period one and two, together with the constraint (16) and the credit market clearing at $t = 1$, an expression for the new credit demand interest rate is derived.

$$(1 + r_1) = \frac{Y_2^S + [q_2((1 - \delta) + \beta) + \beta q_1]\bar{K}}{\beta[Y_1^S + (1 + r_0)B_0]} \tag{18}$$

The credit price depends positively both on q_1 and future rationally-expected price q_2. Which means, a reduced q_2 lowers the equilibrium level of interest rate on the credit market.

If the expected price of future asset is considerably lower than period one price, the equilibrium on the credit market can change as shown in figure 2 Consumption of the borrower will be reduced as a consequence of the reduced borrowing capacity. The standard Euler condition for the borrower is no longer valid in the second period because of the binding borrowing constraint, as shown by equation (17). Consumption

[5]The right hand side of equation (17) is disturbed by the positive term $\psi = \beta(1 + r_1)\frac{\lambda_1^b}{\lambda_2}\frac{1}{c_2}$, which makes the marginal utility of current consumption higher of the marginal utility of moving one unit of consumption in the future. λ_1^b and λ_2 are the multipliers on the borrowing constraint and period 2 budget constraint, respectively.

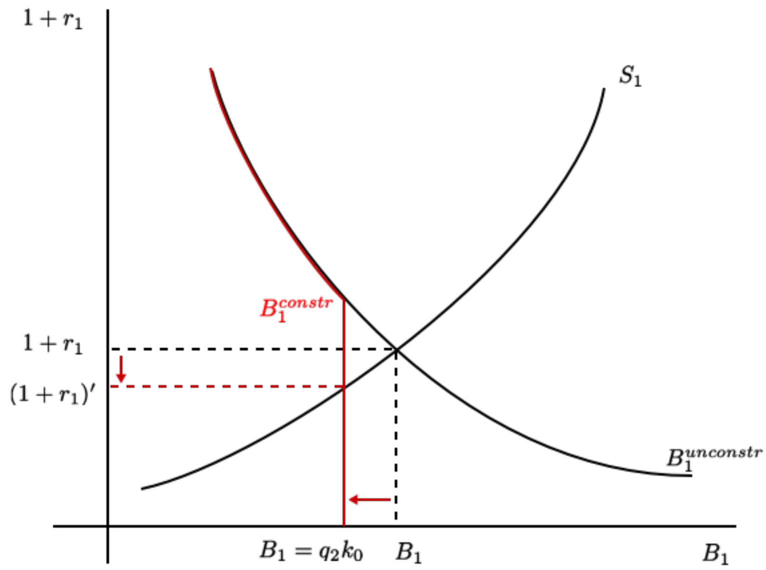

Figure 2: Demand and supply at period 1. Deleveraging is generated by revision of borrower's expectations.

in period one is obtained by the budget and credit limit and it looks as follows

$$c_1 = Y_1 - (1 + r_0)B_0 + \frac{q_1 + q_2}{1 + r_1}(\bar{K}) \tag{19}$$

Clearly consumption in period one positively correlates with the future-reselling asset price, and if q_2[6] is reduced, the consequence is a shrink in consumption too.

The overall level of consumption could potentially be left unvaried due to an increase of saver's consumption. However, if the binding constraint is tight enough, i.e. if the difference among distorted and rational asset-price is considerable, the overall consumption drops if the level of the real interest rate does not fall sufficiently down.

To resume, the model shows the implications of expectations reversals, which are at the core of the analysis. First, distorted beliefs lead to a different *ex-ante* equilibrium with respect to what would originate under rationality. Second, a change of the belief formation process can divert the equilibrium of the economy previously determined and lead to aggregate adjustments on real variables.

[6]Here q_2 is intended to be as the rationally expected future price.

5 Risky debt model

We present a 2-agent model where agents are a borrower and a saver; they differ in the discount factor, higher for the patient agent: $\beta^b < \beta^s$. Agents receive and share an identical income shock. Both borrowers are endowed with diagnostic expectations driven by the parameter θ.

Borrower Borrower can default or repay. Exogenous state is income y which follows an AR(1) with i.i.d. shocks $\varepsilon \sim N(0,1)$. Endogenous state is borrowing $b > 0$. Controls are future borrowing and consumption.
First decision rule of the borrower is between defaulting or repaying. V_c is the value of continuing to be on the market repaying, V_d is the value of defaulting.

$$V^b(b,y) = \max\{V_c(y,b'), V_d(y)\} \tag{20}$$

If the borrower defaults in one period, next period re-enters the market with an exogenous probability $\psi > 0$. Income of defaulted borrower is a function of the exogenous income including a penalty.

$$\begin{aligned} V_d(y) &= \max_c u(c) + \beta^b \mathbb{E}_t^\theta[\psi V^b(0,y') + (1-\psi)V_d(y')] \\ s.t. \quad & c^b = y^{def} \end{aligned}$$

If the borrower repays, he maximises the value of consumption and future borrowing holdings. The borrower faces a borrowing constraint that can be or not binding. We will mainly focus on biding constraints, where $b \geq 0$.

$$\begin{aligned} V_c(b,y) &= \max_{b',c} u(c) + \beta^b \mathbb{E}_t^\theta[V^b(b',y')] \\ s.t. \quad & c + b = y + q(b',y)b' \\ & b \leq Z \end{aligned}$$

Saver Saver, as borrower, is subject to endowment shock y. He maximizes its value function through the optimal value of saving and consumption.

$$V^s(b,y) = \max_{b',c} u(c^s) + \beta^s \mathbb{E}_t^{\theta}[V^s(b',y')]$$
$$s.t. \quad c^s + q(b',y)b' = y + b$$

Pricing Since the borrower can default, this is a model with risky debt. Riskiness is given by the endogenous borrower's probability of default. Debt price is given by a combination of the risk-free interest rate and the probability of the default (PD).

$$q(b',y) = \frac{1 - PD(b',y)}{1+r} \tag{21}$$

Equilibrium Equilibrium of the model consists of value functions $V_c(b,y)$, $V_d(y)$, $V^b(b,y)$, a default rule and policy functions c^b, b' for the borrower, value function V^s and policy functions c^s, b' for the saver, a pricing function $q(y,b')$, such that:

- given the default rule, the pricing function satisfies equation (21);
- given the function (21) and default rule, the value functions V_c, V_d, V^b satisfy the borrower's Bellman equations and b'^b, c^b are the associated policy functions;
- given the function (21) and default rule, the value function V_s satisfies the saver's Bellman equation and b'^s, c^s are the associated policy functions;
- debt market clears: $\phi b^s = (1-\phi)b^b$;
- consumption market clears: $y = c^{tot}$, where $c^{tot} = \phi c^s + (1-\phi)c^b$.

6 Model results

The model is solved numerically through value function iteration. Solution of he model is a set of value functions, policy functions and a sequence of debt prices. As the equilibrium conditions specify, these objects must satisfy the maximization of the borrower's and saver's optimal conditions, as well as the pricing equation. The iterative procedure reads as follows: there is a guess for the default state of the borrower, which determines the probability of the default of the borrower, given the transition probabilities of the exogenous income state. The probability of default allows to compute the equilibrium debt price. Then, the optimal value of defaulting and non-defaulting for the borrower are derived and the maximum between the two is kept for each specific iteration. Distance between old and new value function is computed. After, a similar iteration for the saver starts, with the only difference that here there is no default value. An algorithm of this type is executed both for the rational and diagnostic agents, where the distinction is given by an additional state, the past income state. Indeed, diagnostic expectations affect the future value function $V(y', b')$ which depends both on states y and y_{-1} and dependence on previous state y_{-1} is governed by the parameter θ.

In the next section main results from the baseline model, which has the following features:

1. The two agents differ for their discount rate β;
2. Agents are endowed with diagnostic expectations;
3. Borrowing constraint is binding, which means b=Z. The coding procedure adopted fixes the borrowing limit from a given point to the end of the grid[7].

It follows that the main analysis are focused on the differences between diagnostic expectations and the rational benchmark, and baseline model with and without borrowing constraints.

6.1 Numerical solutions description

In figure 3 value functions (repaying value function for borrower). The function is decreasing in the amount of debt to repay for the borrower, while the converse is true for the saver. Diagnostic expectations work as exhibited by the lines in the charts.

[7] In the main calibration the constraint binds at 60% of the maximum value of the grid.

The agent extrapolates from past income states: when t exogenous state is higher than $t-1$, the agent perceives as if he receives a positive news and inflate the probability of being in a good state tomorrow, shifting upward the perceived value function with respect to the rational benchmark. The converse happens when the news received is negative, he overestimates the probability of bad states in the future and the perceived value function is lower than the rational. This mechanism will be repeated in all of the following the model results'. As for the value function, differences among low and high income states in t are not relevant, while the interval of the different curves is larger for the borrower. This implies that the borrower tends to be more news-sensitive in the value of consumption.

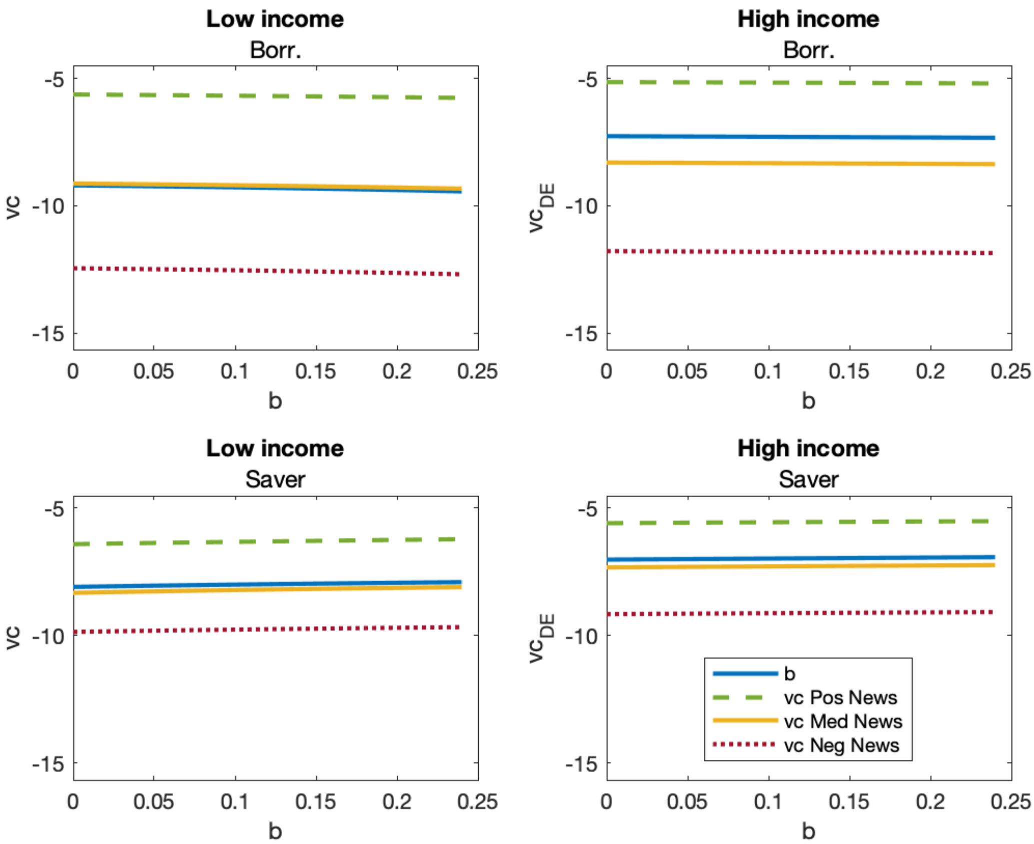

Figure 3: Value function for borrower (v.f. of repaying) and saver. Graphs shows rational benchmark and effects of diagnostic expectations for low and high income states. Domain of the state space takes 20 values, low reference state is 5 and high reference state is 15. Bad, median and good news regards states with the following distances with respect to the references: $[-2, 0+2]$.

Diagnosic expectations impact aggregate demand evidently compared to the rational benchmark. An overestimation of better future states of the economy following good states is characterized by a present expansion of the aggregate demand and the converse is true when the economy is doing poorly. There is however a difference between borrower's and saver's respective demands. Borrower's consumption under diagnostic expectations changes sharply along the income distribution conditional on two factors mainly: the level of news received from past state and incorporated in expectations of future states, and the probability of default. When the latter tends to zero, borrower's demand steps up due to the lower cost of debt repayment. Also, demand on default states is consistently reduced because borrowers are subject to an income penalty. Saver's demand instead is smoother and lower on average: it is lower because, given the same amount of income shock, the saver saves. It is smoother because it is not subject to the penalties, since borrowers never default.

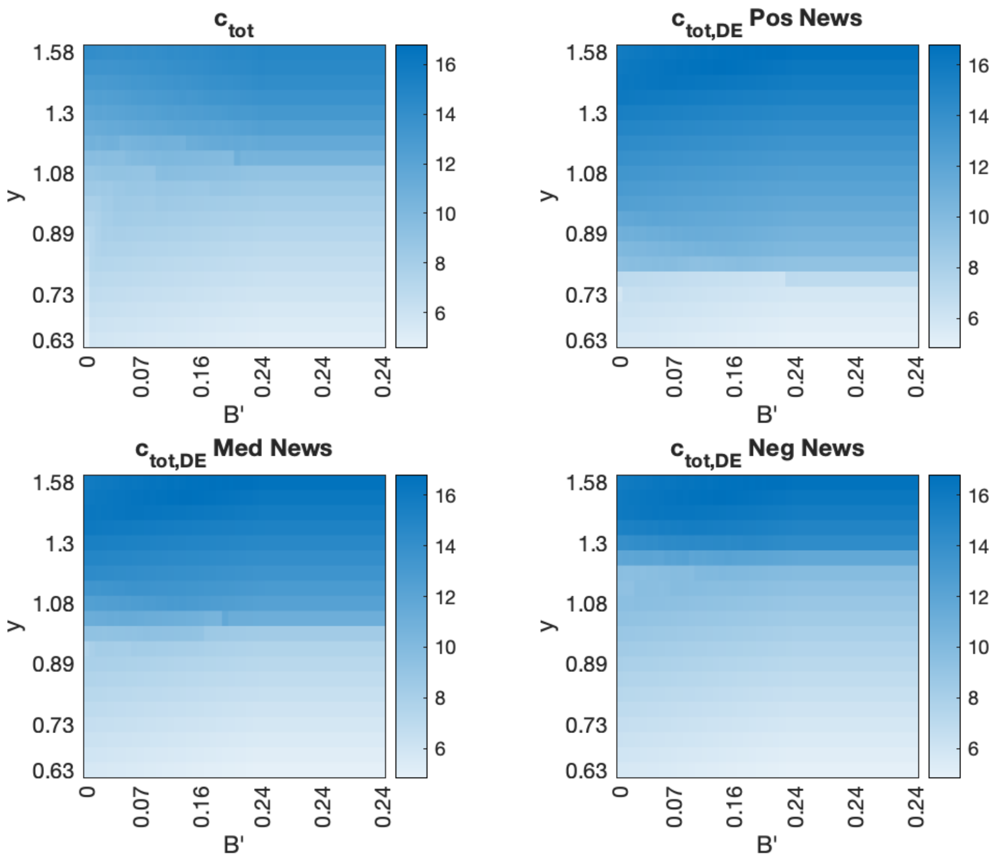

Figure 4: Aggregate demand. Graphs show rational benchmark and effects of diagnostic expectations for all income states. Domain of the state space takes 20 values, low reference state is 10 and high reference state is 15. Bad, median and good news regards states with the following distances with respect to the references: $[-3, 0+3]$.

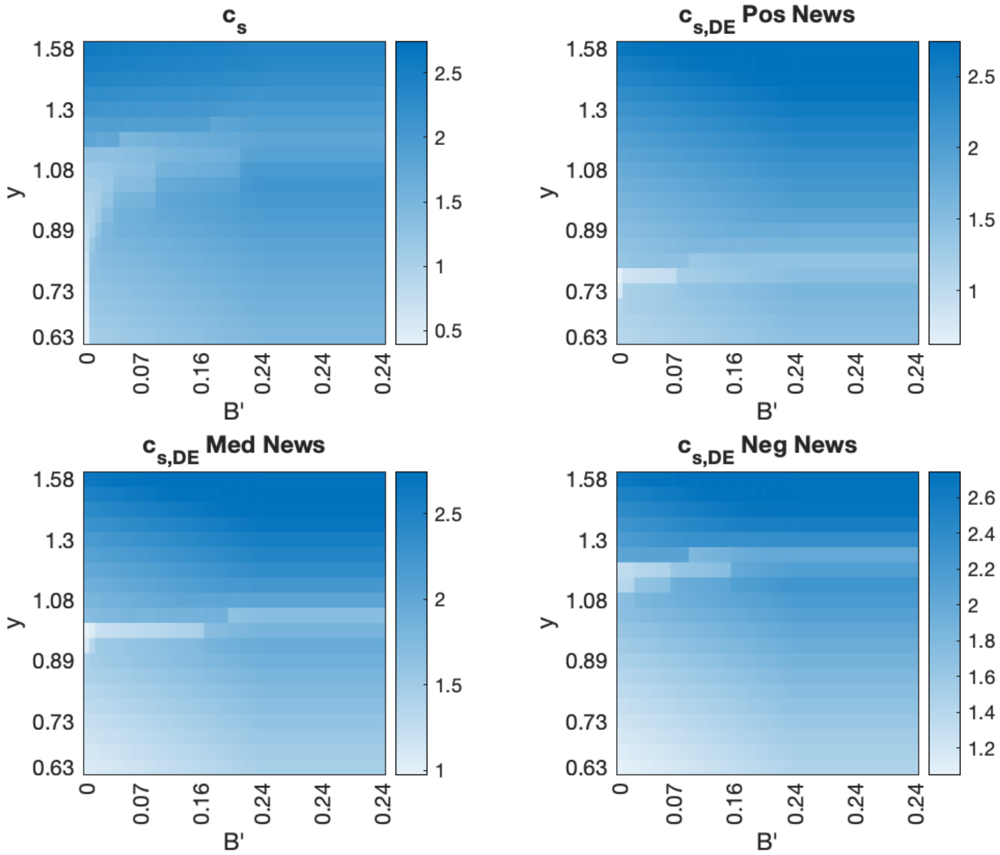

Figure 5: Saver's demand. Graphs show rational benchmark and effects of diagnostic expectations for all income states. Domain of the state space takes 20 values, low reference state is 10 and high reference state is 15. Bad, median and good news regards states with the following distances with respect to the references: $[-3, 0+3]$.

Figure 7 reports the probability of default distribution $PD(y, b')$ of the rational expectation case and three diagnostic states. As expected, in the rational case the probability of default is decreasing on the level of income and the borrowing amount. This variable is crucial to understand the innovations introduced by the model: diagnostic expectations and borrowing constraints. The former allows to investigate how sentiment motives in part of agents impact on the riskiness of debt: when agents receive a positive income shock, they incorporate higher likelihood of future good states in their expectations and so decreasing the perceived probability of default, all other things constant. Incorporating diagnostic expectations in a risky debt model thus have important implications for the equilibrium level of aggregate variables that depend on risky debt, such as the amount of debt and consumption. The mis-perception of risky

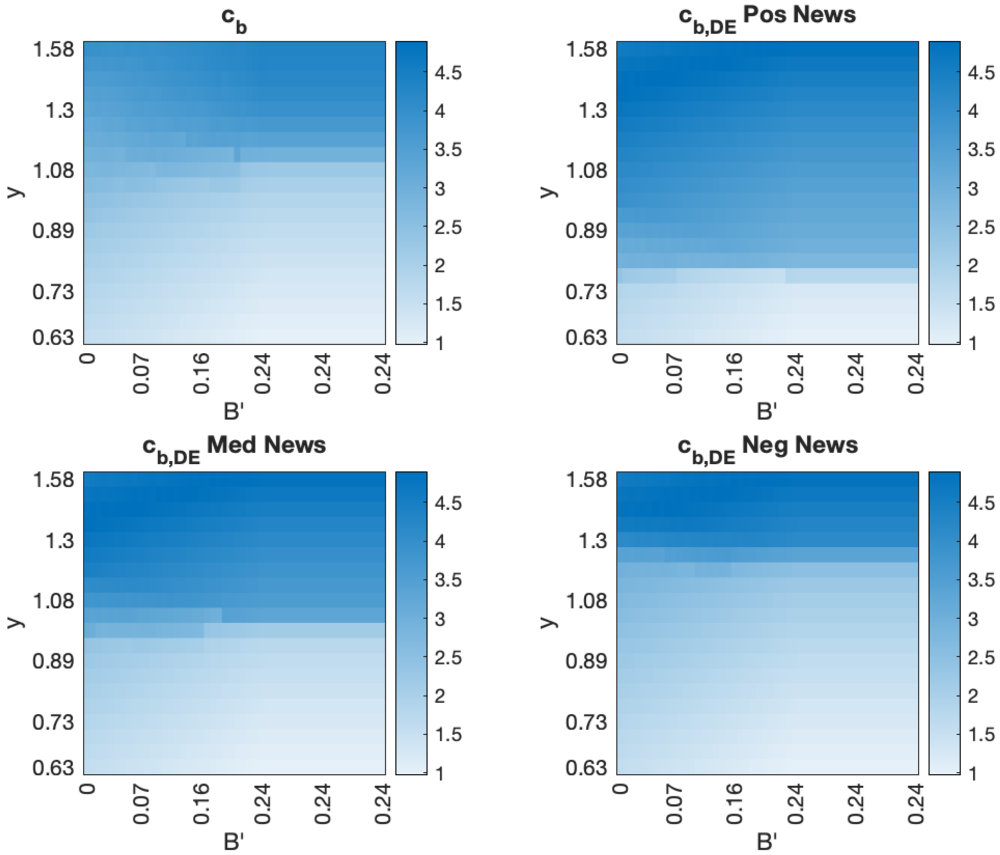

Figure 6: Borrower's demand. Graphs show rational benchmark and effects of diagnostic expectations for all income states. Domain of the state space takes 20 values, low reference state is 10 and high reference state is 15. Bad, median and good news regards states with the following distances with respect to the references: $[-3, 0+3]$.

debt, when risk is underestimated, generates a lower level of debt price and an higher aggregate demand compared to the rational case. Therefore, diagnostic expectations amplify trends of the economy in both directions.

Borrowing constraint instead works on the right hand side of the borrowing distribution, setting a limit for high borrowing states and reducing the probability of default for riskier borrowers. Combined with diagnostic expectations it has a boosting effect for positive news scenario, because it reduces the amount of defaulting states, while it mitigates negative scenario, since perceived number of defaulters is lower. At the same time, when the economy is in its bust moment, borrowing constraints reduces the overall amount of borrowing lent out, contributing to economy shrinking together with pessimism generated by the non-rational expectations.

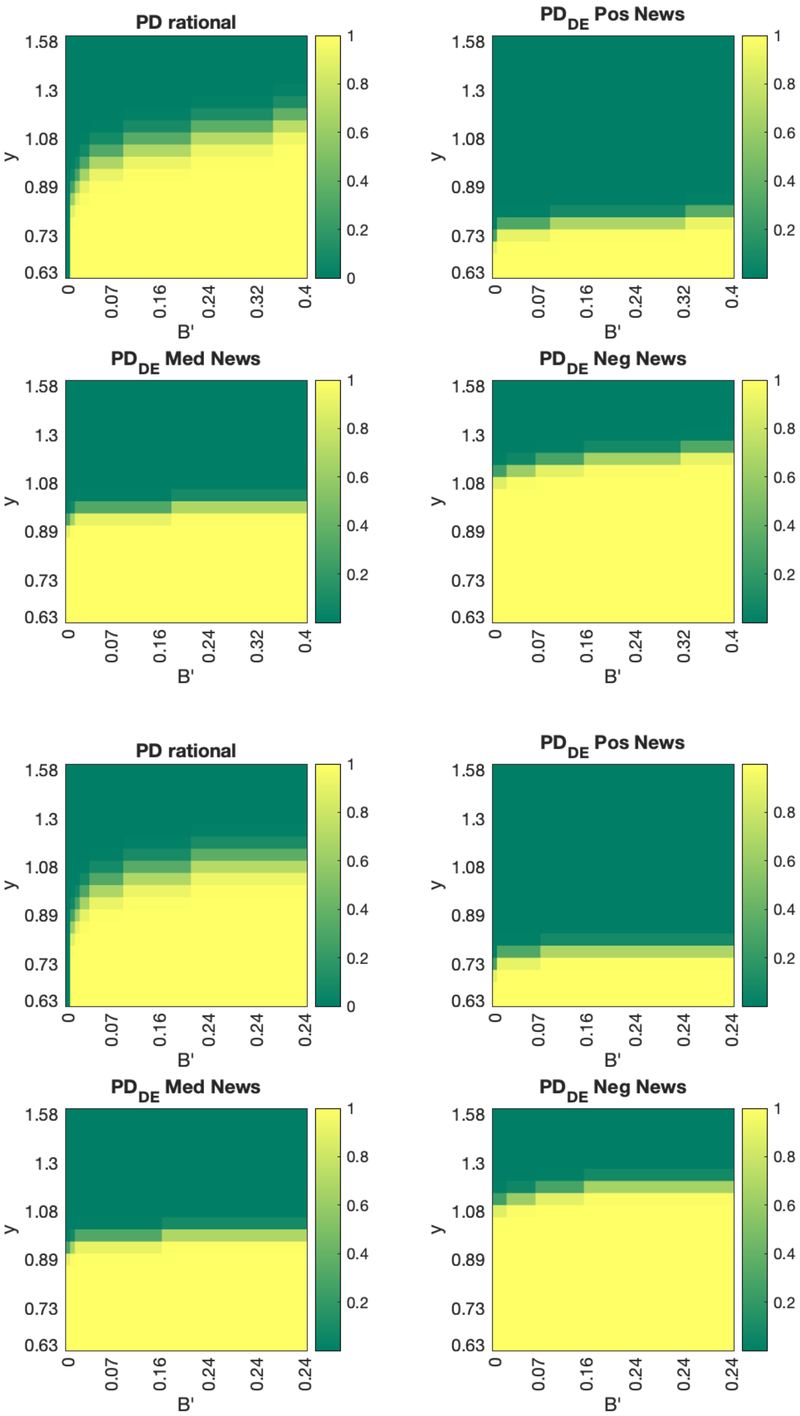

Figure 7: Probability of default. Four graphs in the upper part of the figure show unconstrained model results, while lower ones are cases when borrowing constraints are in place. Graphs shows rational benchmark and effects of diagnostic expectations for all income states. Domain of the state space takes 20 values, low reference state is 10 and high reference state is 15. Bad, median and good news regards states with the following distances with respect to the references: $[-3, 0 + 3]$.

Conclusions and forward developments

This paper aims at showing the effects of introducing diagnostic expectations in a two-agent borrowing-saving economy with risky debt. Diagnostic expectations amplify the pattern of the cycle by an overestimation by agents of future better/worse states. When a positive income shock comes, borrowers' forecasts inflate the probability of positive future shocks, and increase their demand for future debt, as well as current consumption, amplifying aggregate demand and the overall level of riskiness. Borrowing constraints help reducing the Forward developments include a time series simulation of the model and the introduction of housing as an additional state variable, where the borrowing constraint is given by a collateral constraint, as outlined in the 3-periods model. In addition, an empirical analysis will be pursued to document the main theoretical findings.

References

Bianchi, Javier and Enrique G. Mendoza, "Overborrowing, Financial Crises and 'Macro-prudential' Taxes," June 2010, (16091).

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

_ , _ , _ , and Stephen J Terry, "Real credit cycles," *Harvard University*, 2019.

_ , _ , Yueran Ma, and Andrei Shleifer, "Over-reaction in Macroeconomic Expectations," Technical Report w24932, National Bureau of Economic Research, Cambridge, MA August 2018.

Calza, Alessandro, Tommaso Monacelli, and Livio Stracca, "HOUSING FINANCE AND MONETARY POLICY," *Journal of the European Economic Association*, 2013, *11* (s1), 101–122.

Eggertsson, Gauti B. and Paul Krugman, "Debt, Deleveraging, and the Liquidity Trap: A Fisher-Minsky-Koo Approach*," *The Quarterly Journal of Economics*, August 2012, *127* (3), 1469–1513.

Farhi, Emmanuel and Ivan Werning, "Timing a Minsky Cycle," 2020.

Gabaix, Xavier, "A Behavioral New Keynesian Model," *American Economic Review*, August 2020, *110* (8), 2271–2327.

Gennaioli, Nicola and Andrei Shleifer, "What Comes to Mind," *The Quarterly Journal of Economics*, 11 2010, *125* (4), 1399–1433.

_ and _ , *A Crisis of Beliefs*, Princeton University Press, 2020.

Guerrieri, Veronica and Guido Lorenzoni, "Credit Crises, Precautionary Savings, and the Liquidity Trap*," *The Quarterly Journal of Economics*, August 2017, *132* (3), 1427–1467.

Jordà, Oscar, Moritz Schularick, and Alan M. Taylor, "When Credit Bites Back," *Journal of Money, Credit and Banking*, December 2013, *45* (s2), 3–28.

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

Kaplan, Greg, Kurt Mitman, and Giovanni L. Violante, "The Housing Boom and Bust: Model Meets Evidence," *Journal of Political Economy*, 2020, *forth.*

Kiyotaki, Nobuhiro and John Moore, "Credit Cycles," *Journal of Political Economy*, April 1997, *105* (2), 211–248.

López-Salido, David, Jeremy C. Stein, and Egon Zakrajšek, "Credit-Market Sentiment and the Business Cycle*," *The Quarterly Journal of Economics*, August 2017, *132* (3), 1373–1426.

Mian, Atif, "Household Debt and Defaults from 2000 to 2010: The Credit Supply View," 2016, p. 49.

_ , Amir Sufi, and Emil Verner, "Household Debt and Business Cycles Worldwide*," *The Quarterly Journal of Economics*, 05 2017, *132* (4), 1755–1817.

_ and _ , "House Prices, Home Equity-Based Borrowing, and the US Household Leverage Crisis," *American Economic Review*, August 2011, *101* (5), 2132–56.

_ and _ , "What Explains the 2007–2009 Drop in Employment?," *Econometrica*, 2014, *82* (6), 2197–2223.

Minsky, Hyman P., "The Financial Instability Hypothesis: An Interpretation of Keynes and an Alternative to "Standard" Theory," *Nebraska Journal of Economics and Business*, 1977, *16* (1), 5–16.

Minsky, Hyman P and Henry Kaufman, *Stabilizing an unstable economy*, Vol. 1, McGraw-Hill New York, 2008.

Monacelli, Tommaso, "New Keynesian models, durable goods, and collateral constraints," *Journal of Monetary Economics*, March 2009, *56* (2), 242–254.

Notarpietro, Alessandro and Stefano Siviero, "Optimal Monetary Policy Rules and House Prices: The Role of Financial Frictions," *Journal of Money, Credit and Banking*, 2015, *47* (S1), 383–410.

Schularick, Moritz and Alan M. Taylor, "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008," *American Economic Review*, April 2012, *102* (2), 1029–61.

Appendix A.

6.2 Model 1 - Agent's maximization problem

First phase maximization: saver and borrower maximize utility under budget constraint choosing how much to consume and how much to invest in the 3 periods time of the model. Saver problem is reported, borrower's is similar. Lagrangian and first order conditions are:

$$\mathcal{L} = \max_{C_0,C_1,C_2,S_0,S_1} u(C_0) + \beta u(C_1) + \beta^2 u(C_2) +$$
$$\lambda_0[Y_0 - C_0 - S_0] + \lambda_1[Y_1 + (1+r_0)S_0 - C_1 - S_1]\lambda_2[Y_2 + (1+r_1)S_1 - C_2]$$

$$\frac{1}{C_t} = \lambda_t$$
$$\beta\frac{1}{C_{t+1}} = \lambda_{t+1}$$
$$(1+r_t) = \frac{\lambda_t}{\lambda_{t+1}}$$

It follows that optimality Euler condition derived from focs and the two budget constraints give the necessary and sufficient conditions to compute the optimal levels of saving and consumption in terms of income flows and interest rates (and asset levels for the borrower). Standard Euler looks as

$$\frac{1}{c_t} = \beta(1+r_{t+1})\frac{1}{c_{t+1}}$$

In the bust phase the problem is similar for saver, except for the fact that it is a 2-period problem.
The problem of the borrower instead looks different after the boom because the borrowing constraint is added to the maximization.

$$\mathcal{L} = \max_{C_1,C_2,S_1} u(C_1) + \beta u(C_2) + \lambda_1^a[Y_1 + S_1 - C_1 - q_1(K_1 - (1-\delta)K_0) - (1+r_0)B_0] +$$
$$\lambda_1^b[\frac{1}{1+r_1}q_2(1-\delta)K_1] + \lambda_2[Y_2 + q_2(1-\delta)K_1 - C_2 - (1+r_1)B_1]$$

As a result, the derived pseudo-Euler looks as follows

$$\frac{1}{C_1} = \beta(1+r_1)\frac{1}{C_2} + \beta(1+r_1)\frac{\lambda_1^b}{\lambda_2}\frac{1}{C_2}$$

6.3 Borrower's Maximization

The following reported equations are the equilibrium expression for unknown variables of the three period model, i.e. $\{C_0^B, C_1^B, C_2^B, B_0, B_1\}$.

$$C_0^B = \frac{R_0R_1y_0^b + R_1y_1^b + y_2^b + (1-\delta)(q_2k_1 + R_1q_1k_0) - R_1(q_1k_1 + R_0q_0k_0))}{R_0R_1(\beta^2+\beta+1)} \tag{22}$$

$$C_1^B = \beta \frac{R_0 R_1 y_0^b + R_1 y_1^b + y_2^b + (1-\delta)(q_2 k_1 + R_1 q_1 k_0) - R_1(q_1 k_1 + R_0 q_0 k_0))}{R_1(\beta^2 + \beta + 1)} \tag{23}$$

$$C_2^B = \beta^2 \frac{R_0 R_1 y_0^b + R_1 y_1^b + y_2^b + (1-\delta)(q_2 k_1 + R_1 q_1 k_0) - R_1(q_1 k_1 + R_0 q_0 k_0))}{(\beta^2 + \beta + 1)} \tag{24}$$

$$B_0 = \frac{-(1+\beta) R_0 R_1 y_0^b + R_1 y_1^b + y_2^b + (1-\delta) q_2 k_1 + (1-\delta) R_1 q_1 k_0 - R_1 q_1 k_1 + \beta(1+\beta) R_0 R_1 q_0 k_0}{R_0 R_1(\beta^2 + \beta + 1)} \tag{25}$$

$$B_1 = \frac{\beta^2 R_0 R_1 y_0^b - \beta^2 R_1 y_1^b + (1+\beta) y_2^b + (1-\delta)(1+\beta) q_2 k_1 + R_0 R_1 \beta^2 q_0 k_0 + R_1 \beta^2 q_1 k_1 - (1-\delta)\beta^2 R_1 q_1 k_0}{R_1(\beta^2 + \beta + 1)} \tag{26}$$

6.4 Saver's Maximization

$$C_0^S = \frac{y_2^s + R_1 y_1^s + R_0 R_1 y_0^s}{R_0 R_1(\beta^2 + \beta + 1)} \tag{27}$$

$$C_1^S = \beta \frac{y_2^s + R_1 y_1^s + R_0 R_1 y_0^s}{R_1(\beta^2 + \beta + 1)} \tag{28}$$

$$C_2^S = \beta^2 \frac{y_2^s + R_1 y_1^s + R_0 R_1 y_0^s}{\beta^2 + \beta + 1} \tag{29}$$

$$S_0 = \frac{\beta(1+\beta) R_0 R_1 y_0^s - R_1 y_1^s - y_2^s}{R_0 R_1(\beta^2 + \beta + 1)} \tag{30}$$

$$S_1 = \frac{\beta^2 R_0 R_1 y_0^s + \beta^2 R_1 y_1^s - (1+\beta) y_2^s}{R_1(\beta^2 + \beta + 1)} \tag{31}$$