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Firms' expectations on the availability of credit since the financial crisis

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Abstract

Using a large set of firm-level survey data from the euro area since 2009, we analyse how firms use their information to form expectations on the availability of bank finance. Our results suggest that firms update what otherwise look like adaptive expectations on the basis of the latest information in their information set. As in the previous literature, the hypothesis that expectations fulfil the (orthogonality) conditions of the rational expectations hypothesis is rejected by the data. We find evidence that this is not only due to information imperfections but also to some type of misspecification of the expectations' model that firms are using. In addition, we find some evidence that companies that have not used bank finance recently tend to do worse at forecasting its availability next period. To test how policy announcements may affect expectations, we concentrate on the possible effects of the ECB policy announcements of summer 2012, which included among other things the announcement of the European Central Bank's Outright Monetary Transactions Program (OMT). Using a difference-in-differences approach, we find evidence of forward-looking expectations. In particular, shortly after the OMT announcement the forecast of "informed" firms were more upbeat compared to the control group of firms. This moreover was true in both vulnerable and non-vulnerable countries, suggesting that it was the relevance of the information about the future of the banking system that most mattered for expectations at the time, more than the immediate impact of the announced policy measures.

JEL Classification: C83, D22, D84

Keywords: expectation formation, policy announcements and survey data

Non-technical summary

Overreaction of expectations and miscalculation of risk are believed to have played a significant role in the business cycle both in the period of rapid growth in early 2000s and, thereafter, in the recession and recovery.

In this paper we explore how firms formed their expectations about the availability of bank finance since the financial crisis. The expectations on the availability of bank finance are of utmost importance, particularly, for smaller firms' decisions on the timing of investment and production and hence also for the transmission of financial shocks and monetary policy to the real economy. Our analysis is based on a large sample of euro area non-financial companies surveyed in the ECB/EC "Survey on the Access to Finance of Enterprises" (SAFE) between 2009 and 2018. We relate the individual replies on the expected external financing conditions to a set of proxies of the (idiosyncratic) information available to each respondent at the time the survey took place.

Our main results show that firms update their expectations on the basis of the latest information in their information set. The same set of information is however also correlated to the expectation error, even after controlling for country and business cycle effects. This suggests that, when forming their expectations, firms do not use efficiently ("correctly") the information at their disposal. We conclude therefore that the deviation from the rational expectations hypothesis is not only due to informational frictions, but also to some type of misspecification of their expectation formation model. In particular, we find that in the period under consideration, firms tended to give too much weight on the information more easily accessible and understandable. This included information on sales and profits of the respective firm and the general economic environment, less so information about financial market conditions. This would be in line with behavioural theories of decision making that emphasise the importance of heuristics.

We also find some evidence that firms that have not used bank finance recently tend to do worse at forecasting their availability next period. This supports the idea that proximity/familiarity with the banking system provides to companies insights and information that are useful for forecasting future financial conditions. Instead we reject the hypothesis that companies that report that they will need bank finance (next period) forecast its availability more accurately, as one might have expected from models of rational inattention. We also find no evidence of a "wave of pessimism" or "optimism" having an important effect on expectations.

Finally, as a natural experiment, we explore whether firms' expectations concerning the future availability of bank finance changed following the policy announcements of the European Central

Bank in summer 2012 (among other on the Outright Monetary Transactions Program). The question is clearly of relevance to the wider issue of how and how fast communication on policies may affect the decisions of businesses. Using a difference in differences model, we find some evidence that following the policy announcements, “informed” firms revised positively their expectations, possibly anticipating in part the turning point in the financial conditions, otherwise only detectable in the data of the next survey wave. This was true in both vulnerable and non-vulnerable countries.

1. Introduction

The analysis of expectations has received fresh impetus since the last financial crisis. Overreaction of expectations and miscalculation of risk are believed to have played a significant role in the business cycle both in the period of rapid growth and, thereafter, in the recession and recovery (Gennaioli and Schleifer, 2018). Empirical work on expectations has also benefited by the advent of survey data, important for micro empirical studies. The emphasis has been primarily on financial markets and households, rather than on non-financial companies, mainly because of the relative unavailability of data for the latter (Pesaran and Weale, 2006 and Coibion *et al.*, 2018). At least in theory, however, the expectations of non-financial companies are just as important – if not more so – for the propagation of shocks and policies to the economy, for example, in decisions of companies to invest or hire, postpone and revise production plans and build inventories up. Expectations about the external financial conditions, in particular, are important for decisions on the timing of investment and production and hence also on the transmission of financial shocks and monetary policy to the real economy.

In what follows, we use new survey data to explore how non-financial companies form their expectations on the availability of bank finance. The dataset provides only qualitative information, but has four important features that make it particularly useful for the study of expectations. First, the expectations on the availability of bank finance are in many cases a more relevant financial variable than the more commonly analysed expectations of market interest rate or inflation, particularly when it comes to small and medium enterprises (SMEs). Second, the survey provides reasonably good (qualitative) proxies of the idiosyncratic information of each respondent at the time of his/her reporting of forecasts. As will become apparent below, the idiosyncratic information of companies is particularly important when testing expectations models with incomplete information. Third, the survey provides information on how relevant banking finance is to the company, which is potentially an important factor determining the effort companies place in collecting or processing information and in forming expectations ("inattention"). Fourth, the dataset has a broad coverage of non-financial companies across Europe over a time span of 10 years (2009-2018). In particular, it covers all company size classes, down to companies with one employee, in different non-financial sectors. The motivation for looking specifically at the expectations of SMEs is that they play a very significant role in employment and output creation. The multi-country data allow us to better control for the country specific business cycle.

The paper contributes to the existing literature of expectations in different ways.

First, the paper suggests that the expectations of non-financial companies are neither in line with rational expectations hypothesis (REH) nor are they based on a simple autoregressive model. Firms seem to update their expectations on the basis of the latest information in their information set, but the forecast error is also correlated with the same information set even after controlling for country and business cycle effects. This set contains only information that companies are known to have possessed at the time of forming their expectations and that had also been identified as relevant for the availability of external finance in the past. This finding indicates that deviations from the rational expectations hypothesis are unlikely to be only due to information imperfections (e.g sticky information or inattentiveness to news), but are possibly also due to some misspecification of the expectations' model that firms are using.

Interestingly, we also find no evidence of a "wave of pessimism" during the recession that would have led companies to underpredict the future availability of finance. If anything, we find evidence that during the recession companies expected financial conditions to return to "normal" faster (or, equivalently, they were repeatedly surprised to the negative).

Second, we find some evidence that companies that have not used bank finance recently tend to do worse at forecasting its availability next period. This supports the idea that proximity/familiarity with the banking system provides to companies insights and information that are useful for forecasting future financial conditions. Instead we reject the hypothesis that companies reporting that they need bank finance can forecast its availability more accurately, as one might have expected from models of rational inattention.

Finally, we explore whether the expectations of non-financial companies concerning the future availability of bank finance changed following the policy announcements of the European Central Bank of summer 2012. The question is clearly of relevance to the wider issue of how and how fast communication on policies may affect the decisions of businesses. We find some evidence of forward-looking expectations. Following the OMT announcement, firms seem to have revised positively their expectations, in particular "informed" firms, i.e. the ones that were in close contact and had active dealings with banks during the period of the policy announcements.

The structure of the paper is as follows. Section 2 overviews the main issues of the relevant literature while section 3 describes our dataset. Section 4 introduces the basic empirical models of expectations and presents the main econometric results. In section 5 we test the rational expectations hypothesis while in section 6 we explore the role of asymmetric information and inattention using a suggested new metric on the "inaccuracy" of expectations. Finally, in section 7 we discuss the possible effect on expectations of policy announcements on expectations - in this case, the ECB policy announcements of summer 2012, among else on the Outright Monetary Transactions. Section 8 concludes.

2. From heuristics to rational expectations and back

The analysis of the expectation formation of companies and households has a very long tradition in economics. Broadly speaking and no matter what the variables of interest were, one of the main underlying issues in this literature has always been whether the expectation formation is "model-based" and "forward-looking" or, instead, more based on some type of "heuristics" and "backward-looking", e.g. based on statistical regularities observed in the past. A policy-related question has been to what extent and how fast forecasts of companies and households react to the arrival of news, policy announcements and business shocks.

For the most part, the early literature concerned forecasts by financial market participants and households, mainly of macroeconomic variables such as inflation, interest rates or output growth. The discussion of the last 10 years on the transmission of "unconventional" monetary policy measures to real activity and/or the advent of new survey data has brought attention also to the expectations of non-financial businesses (Bachmann and Elstner, 2015; Boneva *et al.*, 2016; Massenot and Pettinicchi, 2018; Coibion et al, 2018).[1] As in the earlier literature, one important focus has been on the expectations of macroeconomic variables, but subject to data availability, expectations of variables more directly relevant to the credit channel have also been examined (Dunkelberg and Scott, 2009; Ferrando *et al.*, 2019). As Dunkelberg and Scott point out, the credit channel is particularly important for SMEs that rely heavily on bank loans. The way these enterprises form their expectations may well differ from the way larger institutions or professional forecasters do.

In the early analysis, empirical models of expectations clustered around two main streams. The first was based on extrapolative models originating, among others, from the work of Cagan (1956) and Nerlove (1983). In the simplest form, extrapolative models assume that the most readily available and least costly information about a future value of a variable (in levels or in growth rates) is to be found in its current and past values. Variations of the extrapolative model may also include a long term "normal" or steady state value that may "anchor" expectations. The expected long term steady state may, in turn, be time-varying and may be modelled on the basis of other information available at the

[1] A parallel and closely related literature has looked at companies' own plans, for example, on investment (Schankerman, 2002, Dave, 2011).

time forecasts are formed, which is then the “forward-looking” part within an extrapolative model. In adaptive expectations, on the other hand, the relevant forecasters are thought to revise their forecast also on the basis of the current (or past) forecast errors, which introduces another “backward looking” element. Thus, in a more general form, forecasts in an empirical extrapolative model are a function of the current (and previous) observations of the respective variable, previously held forecasts (or forecast errors) and possibly other current and past information considered relevant for the long term equilibrium.

A second stream of the analysis of expectations made reference to the theoretical framework of the rational expectation hypothesis (REH), as introduced by Muth (1961). Expectations are formed rationally if the subjective forecast of the forecaster is equal to the mathematical expectation of the relevant variable, conditional on the set of information relevant for the forecast. For most intends and purposes, this is understood to mean that the forecasters form their expectations by using a model that is close to the true structure of the economy (the true data generating mechanism). The implication is that rationally formed expectations should be unbiased predictors of the relevant variables and the ex post forecast errors should be orthogonal to information available at the time of forming the forecasts. In this sense, rational expectations are forward-looking.

An area of many subsequent analyses of expectations has focused on the use of information by forecasters. Timely information is thought to be costly and difficult to collect and interpret, more so for some forecasters than for others. Thus, even if forecasters use the information efficiently, as suggested by the REH, it could still be the case that some forecasters react more slowly to news than others, as they become aware of the relevant information with a delay. Moreover, if the information they receive is noisy, they may discount its importance hedging their bets, what may result again to aggregate expectations being regressive (Mankiw and Reis, 2002; Coibion and Gorodnichenko, 2015). As a result, following a shock, the mean forecast of a variable will be muter compared to the actual response of the underlying variable. “Sticky” information may also be the outcome of rational inattention (Sims, 2003; Cobion et, 2018), in the sense that forecasters may choose to invest less in the acquisition of information if it is not very relevant for their purposes or if a cost-benefit analysis does not justify more attention and costs.

Though the bulk of the recent micro-literature on expectations has focused on asymmetric and incomplete information, these are by no means the only reasons why expectations may deviate from the REH. A different but related reason may be limits in the decision maker’s capability of processing all the information needed for rational expectations. In other words, even if economic decision makers had free and full access to the complete information on the current state of the world, their forecast may still deviate from what one would expect under the REH because their inference models may diverge from the true data generating mechanism. As Evans and Honkapohja (2001) note, most agents may lack sophistication to form expectations rationally because this requires agents to possess too much knowledge about the true structure and probability distribution of the economy that not even econometricians succeed to estimate perfectly.

More fundamentally, behavioural economics, drawing from psychology, has increasingly challenged the hypothesis of an ever-optimising agent in favour of models relying more on associative thinking and heuristics. To quote Kahneman (2011, pp. 97-98): "The technical definition of *heuristic* is a simple procedure that helps find adequate, though often imperfect, answers to difficult questions." Based on the "representativeness" heuristic developed by Kahneman and Tversky (1974), Bordalo *et al.* (2017) develop a model of diagnostic expectations that seeks to explain in particular why in the aftermath of a tail event (such as the collapse of Lehmann Brothers), expectations seem to shift suddenly and the subjective probability of such an event happening again seems to be overestimated.[2]

Conceptually, the hypotheses of imperfect information but "rational" (ever-optimising) forecasters and the one of imperfect forecast models (with or without perfect information) are rather similar. Moreover, in reality, imperfect information and imperfect models may well reinforce each other. The distinction between the two is akin to what Handel and Schwartzstein (2018) call "frictions or mental gaps" as sources of non-optimal decision-making. Empirically, the two may have somewhat different implications however.[3] At the level of the individual forecaster, a rational expectations/incomplete information model implies that the individual forecast error should not be systematically correlated with the information the forecaster *actually* had at the time of the forecast. If this were not the case, the rational forecaster could have improved (optimised) the forecast model using information in his/her possession at the time of the forecast. On the contrary, an "imperfect" forecast model may well result to an inefficient use of information actually available to the forecaster at the time of the forecast.

Below we rely on this latter observation to test whether any deviation from the REH at the level of individual firms is likely to have been the result only of imperfect information or also of some type of imperfect inference model.

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[2] This would be in line with evidence by Shiller (1981) and others that expectations seem to be at times more volatile than the underlying variable (Gennaioli and Shleifer, 2018).

[3] Drawing from the sticky information and the noisy-information models, Coibion and Gorodnichenko (2015) argue, for instance, that the aggregate forecast error in each period should only depend on the aggregate forecast revision in that period. Testing this hypothesis, they find evidence in support of the rational expectations/incomplete information models.

3. Data description and summary statistics

The data at our disposal comes from the "Survey on the Access to Finance of Enterprises" (SAFE) run jointly by the ECB and the European Commission.[4] The SAFE is a semi-annual survey on the financial conditions faced by non-financial firms in eleven euro area countries, Austria, Belgium, France, Finland, Germany, Greece, the Netherlands, Ireland, Italy, Portugal and Spain. In our analysis we consider the survey waves 1 to 18, covering the period from beginning of 2009 until March 2018. Firms in the survey sample are randomly selected from the Dun and Bradstreet database. The sample is stratified by firm-size class, economic activity, and country. Sample sizes for each economic activity are chosen to guarantee satisfactory representation across the four largest industries: manufacturing, construction, trade and services[5]. Also, the sample sizes are selected on the basis of representation at the country/size level. The specific individual that is surveyed in each firm is a top-level executive, usually a CFO or CEO. In smaller enterprises, this is often the owner. The questionnaire is administered in the local language.

At the beginning of the survey a bit more than 5000 firms were interviewed, but this number has increased over time reaching more than 10.000 since 2014. We exclude companies for which bank finance was considered "not relevant" and were therefore not asked the relevant subsequent questions about bank finance expectations. Thus, the starting sample has somewhat below 100.000 observations across 55.000 firms. Although we cover a relatively long time span of semi-annual data from 2009 to 2018, we do not get a rich panel structure in the dataset due to the fact that the sample includes a rotating panel of enterprises, aiming at obtaining more accurate estimators at aggregate level. Depending on the variables of interest, the sample falls somewhat above 20.000 observations when all firms are excluded that are not present at least in two consecutive waves. It falls below 10.000 when at least three consecutive waves are needed. Most firms in the sample are small and medium enterprises (SMEs), two thirds of which have less than 50 employees and the overwhelming majority of them being older than 10 years. They are also mostly financially autonomous and not belonging to a business group or venture capitalist.

The main variables of interest are the expected change in the availability of bank finance in the next six months (compared to the last six months) and the perceived respective actual change in the last six

[4] The survey's main results are published in the ECB website every six months. For more information on the survey and its individual waves, see http://www.ecb.europa.eu/stats/money/surveys/sme/html/index.en.html.
[5] These four groups cover the Nave 2 rev. sections mining, manufacturing, electricity, gas and water supply, wholesale and retail trade, repair of motor vehicles and motorcycles, transport, and other services to businesses or persons, such as hotels, restaurants or IT services. It excludes businesses operating in agriculture, public administration and financial services.

months (compared to the six preceding months)[6]. Both are discrete variables taking the values -1, 0, 1 for answers "deteriorated/remained unchanged/improved". Close to half of our observations in both variables are zeros. Despite the business cycle, companies in our sample often did not observe and did not expect their access to bank finance to change significantly, which does not mean that the cost did not change. This is perhaps to be expected in a bank-based system, where bank-company relationships are relatively stable. The prevalence of "no change" answers may also indicate, however, that firms choose the middle category of "no change" for a wide range of outcomes where a respective continuous variable may have been reported with small changes.

Figure 1 shows the two variables, aggregated for each wave. The vertical line identifies the seventh wave, the fieldwork of which took place in September 2012, shortly after the announcement of the European Central Bank of the start of the Outright Monetary Transactions programme. The possible effects of this announcement are considered in more detail in the last section of the paper.

[FIGURE 1]

At the aggregate level, there is little to suggest that expectations lead the actual change in the availability of bank finance. Also, the expected change has remained above the actual change for most of the period until late 2015, an issue we consider in more detail below. The micro data from the panel of firms (present in at least two consecutive waves) show that lagged expectations have a somewhat higher dispersion than ex post changes in the same variable, which is in accordance with the literature that finds expectations to be more volatile than the underlying variables (Bachmann *et al.*, 2013; Bordalo *et al.*, 2017). However, the available categorical information does not allow us to duel into this issue any further.

The SAFE survey also collects information on the factors companies consider to have affected the availability of bank finance in the previous period and whether these factors have deteriorated/remained unchanged/improved in the last six months[7]. The factors include the (1) general economic outlook (insofar as it affects the availability of external financing), (2) the enterprise-specific outlook with respect to the sales and profitability or business plan (again insofar as it affects the availability of external financing for the company), (3) willingness of banks to provide credit to the enterprise, (4) the enterprise's own capital (capital provided by the owners or shareholders of the enterprise) and (5) the enterprise's credit history. Figure 2 shows the aggregated data for these factors.

[6] In the SAFE questionnaire, these are questions Q9_a and Q23_b, respectively.
[7] This is question Q11 in the SAFE questionnaire.

[FIGURE 2]

Broadly speaking, all five variables, when aggregated, show a similar pattern as those in Figure 1. The two variables that refer more to the (macro) environment, namely the general economic environment and the willingness of banks to provide credit, show more pronounced movements over the cycle than is the case for the three firm-specific factors. From the latter, sales and profits of firms also show marked variation over the cycle.

Table 1 shows the summary statistics of the main variables and dummies used in the models below.

[TABLE 1]

4. "News" and expectations

If we denote the availability of bank finance for firm *i* at time *t* as $y_{i,t}$, the two main (latent) variables of interest can be defined as

$$R_{i,t} = y_{i,t} - y_{i,t-1}$$

$$E_{i,t} = y_{i,t}^{\boldsymbol{exp}} - y_{i,t}$$

The superscript *exp* denotes the forecast of the availability of bank finance as of *t* for *t*+1. Variable R_{it} denotes the "realised" change in bank finance availability for company *i* over the last six months, while E_{it} denotes the expected change over the next six months. We may further define the forecast error of company *i* at time *t* as:

$$FE_{i,t} = R_{i,t} - E_{i,t-1}$$

If we denote by Ω_{it} the change between *t*-1 and *t* in the factors affecting bank finance availability of company *i*, in line with what was said in section 2 above, a basic underlying model of expectations can be written as follows.

(1) $$E_{i,t} = f\{R_{i,t}, \Omega_{i,t}, FE_{i,t}, u_{i,t}\}$$

where $u_{i,t}$ is a random error. In words, the expected change in the availability of bank finance by company *i* as of time *t*, E_{it}, is a function of the (realised) change in the availability of bank finance for company i at time t ($R_{i,t}$), the "news" (changes in the information set of company i) at t compared to the previous period ($\Omega_{i,t}$) and the last forecast error ($FE_{i,t}$).[8]

It is important to note that (1) is a growth model with all variables expressed in changes because this is how the information is available to us from the survey. In particular, we only know if the firm expects bank finance availability to have improved, remained the same or deteriorated and similarly for the past values and the other independent variables. However, one may consider that expectations are also likely to be affected ("anchored") by a long term "normal level" of bank availability. We return to this issue below.

From the survey, we do not observe $E_{i,t}$, $R_{i,t}$ and $\Omega_{i,t}$ directly. We only have the discrete trichotomous representation of these variables (-1, 0, 1). We denote the respective discrete variables as $e_{i,t}$, $r_{i,t}$, $w_{i,t}$. Consequently, we also define the forecast error as:

$fe_{i,t} = r_{i,t} - e_{i,t-1}$

We thus use an ordered logit model, where the probability of $e_{i,t}$ taking the value of -1, 0 or 1 is estimated as a logistic transformation of the linear model $f\{\ \}$ in (1), with all independent variables having being replaced by their discrete representations, $r_{i,t}$, $w_{i,t}$, $fe_{i,t}$.

All regressions also include country-wave-sector dummies. These may capture various macro-economic events as well as any collective waves of "optimism or pessimism" that may be affecting the expectations of firms. To capture some of the effect of the structural characteristics, a set of control dummies is also introduced referring to ownership (family-owned), operational autonomy status, size class and age. Higher lags may also be of importance in an extrapolative model and are tested in the Annex.

It is important to note that the model is written very much from the point of view of the company. The variables in w_i are as reported by company i. If there is sticky, imperfect information or inattention, then each company may perceive, rightly or wrongly, a different set of "news" at each moment in time. Further, all econometric models are estimated by maximum likelihood, applying clustered standard errors at firm level to allow for heteroscedasticity. This accounts also for firm-specific random effects to allow for possible stochastic firm-specific factors, such as some respondents being consistently more "optimists" or more "pessimists".

[8] The forecast error is in principle a feature of adaptive expectations, but in practice it may also correlate to unobserved (structural) characteristics of the company even within a rational expectations' model.

The results of the estimation are presented in Table 2. Column 1 presents a simple version of the extrapolative model in which the expected change in the availability of bank finance in the next period only depends on how this variable changed during the current period. For short, we can call this the autoregressive term. The model also includes the control dummies as explained above.

As expected, past changes in the availability of bank financing and future forecasts of the same variable strongly correlate. When checking the structural firm characteristics, the estimates suggest that, conditional on the autoregressive term, family-based, autonomous and smaller firms expected on average that their availability of bank financing would deteriorate more (or improve less) than their bigger, well-connected counterparts[9]. Perhaps somewhat surprising, the results also suggest that the younger companies tended to have more upbeat expectations about the change in bank financial availability compared to older firms (but see below).

[TABLE 2]

In column 2, the model is extended to include the variables in w_{it} that capture new information in the information set of each company. It turns out that companies do update their expectations on the basis of "news" in their information set. All of the relevant independent variables available from the questionnaire are statistically significant and have the expected (positive) signs. Companies seem to adjust their extrapolative expectations on the basis of what they consider as relevant factors having affected the availability of finance the previous period. A perceived improvement in the last six months in the macro environment, bank credit supply, the company's financial situation or its sales and profits is strongly associated with firms' expectations of better availability of bank finance in the coming period.

It should also be noted that many of the structural characteristics of the firm loose predictive power once the $w_{i,t}$ independent variables are introduced in the regression of column 2. For example, firms' size no longer has a statistically significant effect on firms' expectations. This indicates that size could have been a proxy for different individual factors affecting the availability of bank finance, such as the willingness of banks to provide credit (supply side) or the company's own capital and credit history.

In column 3 of Table 2, we introduce the past forecast error in line with what one may expect in an adaptive expectations model. The number of observations falls sharply because of the lagged dependent variable. This notwithstanding, the main estimated coefficients of interest remain stable and

[9] As for sectoral characteristics, we also run a set of regressions with sectoral dummies standing alone. The results show that firms in the construction and trade sectors reveal significantly negative expectations compared to industry.

statistically significant. The main effect of the lagged dependent variable is that the estimated coefficients of all dummies capturing structural characteristics are no longer statistically significant, as one might expect.

To give an idea of the quantitative impact of the news to expectations, Table 3 reports the average marginal effects per outcome category of the ordered logit model. The forecasted probability that bank finance may increase next period rises by about 4%, other things being equal, when the macro economy is perceived to have had a positive (rather than a stable) effect on the change of bank finance the last six months. Sales and profits are estimated to have a similar marginal impact, while the marginal effect of the perceived willingness of banks to provide loans is above 7%. The marginal effect of financial firm specific variables, such as the credit history and own capital, is below 2%, possibly because these change very little over time.

[TABLE 3]

The results turn out to be robust for different specifications of the model[10]. Table A.1 in the Annex shows the baseline model where a lagged version of each independent variable is introduced. In line with Massenot and Pettinicchi (2017) we find that there is a lagged effect on expectations of past realisations of the same variable as well as lagged sales and profits. As with adaptive expectation, the effect is declining over time (Nerlove, 1983) and the lagged independent variables are no longer statistically significant when a lagged dependent variable is introduced (in column 2). In table A.2 of the Annex, the basic model is re-estimated with OLS as well as a generalised ordered logit. The results broadly confirm again our baseline estimates of Table 2.

5. Information frictions and rational expectations

The econometric results in the previous section suggest that, when forming their expectations, firms use different pieces of recent information, not just the autoregressive/adaptive factors. This result however does not tell us whether firms use this information efficiently in the spirit of rational expectations. To test this, one can follow the now established empirical approach of looking at the properties of the forecast errors.

[10] We run several regressions that explore the cross-industry, cross country and over-time dimensions of the sample (results available upon request). Also, the reported coefficient estimates change very little when the expectation model is augmented with variables on the change of labour and material cost.

Figure 3 shows the aggregate forecast error for each wave and compares this with the change in the realised bank finance, Δr summed over the same set of firms. The aggregate series suggest that forecast errors tend to be correlated over time, contrary to what one would expect from REH.

[FIGURE 3]

Figure 4 allows a closer look at the source of these forecast errors. In particular, the three panels show separately what happened in the availability of bank finance for three different groups of firms each period: the "pessimists" that were forecasting a deterioration in the (change of the) availability of bank finance, those that forecasted that things would stay the same and the "optimists" that forecasted an improvement. Results are shown in each panel as a ratio to all observations of that panel (e.g. in the first panel as a ratio of all "pessimists").

What one can see is that the forecasts of the "pessimists" and the "optimists" were right only about 20%-40% of the time. Most commonly, irrespectively of what was forecasted, the change in the availability of bank finance was reported subsequently to have remained as before (and sometimes moved in the opposite direction). Only in the middle panel, forecasts and realisations seemed to match more often. One can also note that overall the number of times the "optimists" got it wrong are more than that of the "pessimists", especially in the earlier part of the sample period.

[FIGURE 4]

Lui *et al.* (2011) propose two non-parametric tests of rational expectations based on information such as the one presented in Figure 4. These tests essentially come down to whether the forecast turns out to be correct more than 50% of the time or, at least, more often than any of the two possible wrong forecasts (e.g. when forecasting 1, the realised can be 0 or -1). Both tests are based on an assumption that outcomes are independent across firms. As is readily seen from the Figure 4, both tests clearly reject the null of rational expectations. Only in the case of firms expecting "no change" would the null not be rejected, but then the forecasting model would seem rather trivial.

A more standard way of examining the forecast error when testing rational expectations is within a regression model, where the right hand side variables capture all information available at the time the forecast was made. Thus, following the model of the previous section, we estimate the following model:

(2) $$fe_{i,t} = g\{r_{i,t-1}, \mathrm{w}_{i,t-1}, fe_{i,t-1}\}$$

Under rational expectations or indeed under a more general hypothesis that companies use efficiently the information at their disposal, we would expect that the right-hand-side variables in g{ } cannot systematically predict the forecast error $fe_{i,t}$. In particular, we would not normally expect any correlation in the forecast errors unless one believes that there has been a succession of (fundamentally unpredictable) macroeconomic shocks affecting many companies in the same direction. To control for this latter case, we introduce again the country-wave-sector dummies as well as all the dummies capturing the structural characteristics of the company as was the case in Table 2.

Table 4 shows the results of the ordered logit estimation of model (2). In the first column we see that past realisations are negatively related to the expectation error. In other words, firms that reported improved availability of bank loans in the last six months are making, on average, an expectation that proves ex-post to be too “optimistic”.

[TABLE 4]

The size and age variables (not reported) also show a significant correlation with the expectation error. This may suggest that there is systematic correlation of some firm characteristics with the forecast error (Bachmann an Elstner, 2013, 2015). The systematic differences across firms’ age and size could be related for example to limited capacities to collect and process information of younger or smaller firms (Berger and Udell, 1998).

When we expand the list of independent variables (column 2), the significance of past realisations $r_{i,t-1}$ disappears. We observe instead that past information on the other independent variables has predictive power when it comes to the ex post forecast error. This is true, as said, even after controlling for the country/sector business cycle and for the firm structural characteristics. In particular, the variables on the general environment and the profit and sales of the company are negatively correlated with forecast errors, while the opposite is true with the financial variables related directly to bank finance, such as the willingness of banks to provide credit or the effect of the firm’s capital. By contrast, the impact of lagged credit history is not statistically significant. These results are moreover robust to changes in the sample, for example, dropping companies of some countries or some time periods.[11]

One possible explanation is that firms tended to place high weight and overreact to developments in the “real” activity, such as demand, profits and the macro environment, compared to financial variables, notwithstanding the fact that they were forecasting a financial variable, i.e. the availability of bank finance. The reason for this may be that, when making their forecasts, respondents would have

[11] For sake of brevity, results are not reported but are available upon request.

tended to place more weight on something that they believe they know better and they know from the past that it correlates strongly with the variable of interest, rather than trying to use a complex structural model of the economy (Kahneman, 2011). Non-financial companies, particularly smaller ones, are likely to have a better understanding and more faith on their predictions of how the main (real) activity and the macro-environment are developing than what may be happening in the financial markets, particularly in the midst of a financial crisis.

In column 3 of Table 4, the lagged forecast error is also introduced among the independent variables. The results confirm that there is positive correlation of forecast errors. The rest of the estimates change relatively little, at least in qualitative terms.

It is worth noting that the test of REH in Table 4 is more telling than the typical REH tests for two reasons. First, we test for systematic relations between forecast errors and variables in the information set of firms, *conditional on the macro cycle, the industry cycle and the structural characteristics of firms*. Second, the rhs in (2) contains on purpose *only idiosyncratic information that the company is known to have possessed when forming its forecasts and has itself identified as relevant for the availability of bank finance.* Unlike public information often used in this type of tests, there is no doubt that the firms were aware and attentive to this information. It follows that these systematic forecast errors are unlikely to be due only to inattentiveness, sticky or limited information. At least in part, these errors could well be due to some type of "model misspecification", such as the ones described by Kahneman (2011).

On the other hand, it should also be mentioned that the explanatory power in all regressions in Table 4 is exceptionally low even for this type of models and with largely cross sectional data. This is also confirmed by Table 5, where the reported marginal effects of the various variables are very low. It is therefore difficult to say whether these systematic forecast errors made a material difference to the firms.

[TABLE 5]

One last important comment concerns the time pattern of the forecast errors. As can be seen already at the aggregate level, in Figure 3, forecast errors have been mostly negative during the earlier period, during the recession, and then positive during the recovery. Given that negative forecast errors signify that expectations were better (more "optimistic") than the subsequent realisation of the same variable, the series in Figure 3 would seem to contradict the idea that the recession was marked by a wave of pessimism and vice versa for the recovery. The same observation can be made from Figure 4, where the "optimists" were seen to be those mostly making errors in the midst of the crisis.

This time pattern of the forecast errors is also confirmed by the estimated coefficient of the country-wave dummies of Table 5 (not shown). Conditional on the independent variables and the structural characteristics of companies, throughout the observation period companies have tended to forecast better availability of bank finance than what turned out to be the case, even more so during the years of recession. Also, the estimates suggest that the conditional forecast errors tended to be more negative in the recession for companies in countries under particular stress, such as Greece, Ireland, Italy, Portugal and Italy, , while the opposite was true in the recovery.

The interpretation of this time pattern is not obvious. Either companies across the euro area have tended to be repeatedly surprised by negative shocks more or less throughout the observation period (and in particular during the recession) or – equivalently - companies may have been adjusting their forecast depending on how far they perceived (the *level* of) the availability of finance to be from the "normal" or "long term" equilibrium value. Under the latter hypothesis, when the availability of finance fell sharply below "normal", particularly in vulnerable countries, companies expected a relatively faster recovery, other things being equal. Unfortunately, our data do not provide information on levels but only on changes from one period to another. We have therefore no way to introduce a true error correction term in order to test the latter hypothesis and, as a result, we have to treat the time variation of forecast error (as captured by the country-wave-sector dummies) as essentially unexplained.

The conclusion from this section is that forecast errors are systematically correlated with information known to the firms at the time the expectations were formed. Any deviations from the REH are therefore unlikely to be only due to information frictions. Errors also tend to be serially correlated. This is moreover true, even when controlling for macroeconomic shocks and structural characteristics of the firms. Though these results tend to reject the REH, it is difficult to say how important quantitatively these deviations from the REH are for the single firm.

6. Heterogeneity and attentiveness

Both the hypotheses of rational expectations with incomplete information and that of incomplete forecast models are likely to give rise to more heterogeneity and disagreement among forecasters than would be the case if everyone were using a single (correct) model of the economy and a single (complete) set of information. The rational inattentiveness hypothesis (Sims, 2003) advanced the idea that heterogeneity in expectations is not only due to some random process or structural characteristics of the firm (e.g. size), but also the result of a deliberate choice of different (rational) forecasters to invest in information acquisition.[12] Thus, given the costs of acquiring the relevant data and processing it, rational inattention models suggest that a firm will devote resources to track information and refine its forecasts depending on the effect these would have on profits. This firm is then expected to make systematically less errors in forecasting the variable of interest compared to a firm for which this variable is less relevant. The relevance of the expectations may moreover change over time depending on market conditions (Coibion *et al.*, 2018). In the context of our data, we proxy "relevance" by identifying those cases where a firm reported that it "needs" bank finance in the period ahead.[13]

Relevance and intention to use bank credit may not be the only factors affecting the information and effort put on forecasts. If information about the actual credit conditions is not readily available and requires effort to get, then a close firm-bank relationship may also be of importance. In our sample we have no information on such relation, but we do know whether a firm used bank credit in the period preceding the forecast. We can test therefore whether this recent "familiarity/proximity" to the banking system has an impact on the forecast accuracy of future bank availability. This is somewhat different than the rational inattention hypothesis as it stresses the importance of recent experience, a feature very common in behavioural models of decision making (Gennaioli and Shleifer, 2018). Also, more conventionally, we test whether structural characteristics of the company, e.g. size, age, autonomy, family based may play a role.

To test these hypotheses, we need some metric of forecast accuracy using the categorical data at our disposal. One such measure could be, for example, the absolute value of the forecast error. This is a variable that measures how often companies make a forecast error (e.g. forecasting that bank credit availability will improve when it stayed the same). As a measure of forecast ability, this measure is intuitive but has the drawback that it depends heavily on the stochastic environment within which each company operates. For example, smaller companies may have to live with more unanticipated shocks,

[12] Several streams in the economic literature have long highlighted that there are indeed differences when it comes, for example, to information used to form expectations. Souleles (2004) and Bach and Elstner (2013) find systematic biases of forecast according to consumers' and firms' structural characteristics. The models of Brock and Hommes (1997), Branch (2004) and Dominitz and Manski (2005) all rely on the concept of difference strategies of expectation formation mechanisms according to some degree of information sophistication.
[13] To recall, all firms in our sample have identified bank finance as "relevant" for them, though only about a third has reported in any single period that it "needs" bank finance next period.

which will typically lead to more forecast errors, even if they may otherwise be equally well informed and use the same expectation models as larger firms.

We propose therefore a measure of "relative inaccuracy" of expectations by comparing the (absolute value of the) forecast error with the absolute value of the change in the perceived availability of bank finance r_i. In particular, if we denote with Δr_{it} the change in r_i between $t-1$ and t, we define relative forecast inaccuracy as

$$(3) \qquad P_{i,t} = |fe_{i,t}| - |\Delta r_{i,t}|$$

One intuitive way of thinking of P_i is as a measure of the absolute forecast error of company i compared to the theoretical forecast error the company would have made had it used a naïve expectation model in which the expected change of bank finance availability next period would be the same as the one observed in the current period. Thus, compared to the absolute value of the forecast error, P_i shows the distance not from zero error but from the error from a hypothetical very simple expectations model. As a result, forecast errors carry a higher weight in (3) when they occur in a steady state environment, where the change in the availability of bank finance, r_i, "stays the same" from one period to another. Analogously, the expectations of a company are considered particularly accurate if there is no forecast error in an environment of high fluctuations in the actual value r_i (and thus of high $|\Delta r_i|$). We employ P_i as a (noisy) indicator of expectations inaccuracy. The higher it is, the more inaccurate the forecast of an enterprise is likely to be compared to the counterfactual expectations model.

Figure 5 presents the aggregate data for all three components of equation (3). Note that the dispersion of the actual forecast error has been higher throughout the period than the forecast error from the counterfactual naïve model. This is another way of saying that expectations seem to have been more volatile than the underlying variable. In the period under consideration, the absolute forecast error has tended to fall as firms exited the recession but so did also $|\Delta r_i|$, leaving the average relative inaccuracy with no clear downward trend despite the marked change of the macroeconomic environment.

[FIGURE 5]

To test whether "relevance" of bank finance and "familiarity" with the banking system have a systematic effect on forecast accuracy, the proposed measure of relative forecast inaccuracy is regressed in Table 6 against the relevant proxies as well as proxies of the cost of acquiring and processing information, such as firm age, whether a firm is autonomous or family-owned. Country-wave- industry dummies are included in all regressions to capture the country specific business cycle across separate industry characteristics.

[TABLE 6]

In column (1) of Table 6, we can see that none of the firm characteristics has a significant effect on forecast accuracy, with the possible exception of medium-large companies forming somewhat more accurate forecasts than the small ones as one might expect. In columns (2) and (3), forecast inaccuracy is found to be negatively correlated with both proxies of “familiarity” (recent use) and “relevance” (need of bank credit). Recent familiarity with the banking sector or possible intention to request bank loans are found to be associated with better forecasting ability of companies, confirming the relevance of both backward and forward looking factors affecting forecast accuracy.

Finally, the last column introduces both proxies together. The estimates suggest that mostly firms that have had recent experience and familiarity with banks may be better placed to form more accurate expectations on the availability of future bank finance. This may be because dealing actively with the banking system provides the firm with early information and a better understanding of how the banking system works. Instead, “need of bank loans”, introduced as the proxy of relevance, turns out not to be statistically significant, possibly because the same effect is captured by the variable on “use”, suggesting that (in)attention may not be an important factor in this case. The dimension of the firm also turns out not to be statistically significant when conditioning on the recent use of bank finance, suggesting that it is not size as such that matters for forecast accuracy, but more so whether the firm had recent dealings with banks (which of course larger firms tend to have more).

To explore what might have been different in the expectations of firms that were more familiar with the banking system (because of recent dealings with it), in Table 7 the expectation model of Table 2 (column 2) is re-estimated with a focus on the “informed” firms. In the first column, a dummy is introduced to identify these “informed” firms. The estimated coefficient turns out to be negative and significant. Knowing that companies have tended to be on average “overoptimistic” about the speed with which availability of bank finance would return to “normal”, the negative coefficient suggests that “informed” firms tended to be somewhat more “realistic” and closer to the (ex post) actual change in the availability of bank finance.

The second column in Table 7 re-estimates the same model but only for the subsample of “informed” firms. The results suggest that, structurally, the expectation model of “informed” and “less informed” companies was not very different. Taking into account that estimates are not fully comparable between the two models in columns (1) and (2), it is interesting that the results are very similar despite the fact that only 1/3 of all observations are used in the latter.

[TABLE 7]

Overall, the tentative conclusion from this exercise is that companies that have had recent proximity to banks may have better or additional information that helps them make somewhat more accurate forecast, but there is no evidence that they use fundamentally different expectations models than the rest. Need of bank finance, which was introduced as a proxy of "relevance" and hence of (in)attention, does not have a statistically significant effect when conditioning on the past use of bank finance. The same is true with the size of the firm.

7. Expectations and policy announcements

Expectations have often been discussed in the literature in relation to the effectiveness and speed of transmission of macroeconomic policies to economic activity and, in particular, of monetary policy. One of the main questions in this context remains whether and how fast the financial markets, companies and households anticipate the effects of new macroeconomic policy measures when these are announced. The concept of "forward guidance" in monetary policy and of "anchoring" inflation expectations relies on the very idea that financial market participants, businesses and households can anticipate the effects of a future monetary policy stance based on information communicated by the central bank at an earlier stage.

In what follows, we focus on the announcement effect of monetary policy on business expectations. Apart from being a potentially important channel of policy transmission, announcement effects provide indirect evidence of forward looking expectations (Coibion, 2018). The period covered by our dataset contains a number of important policy announcements and interventions by the European Central Bank the impact of which is widely thought to have been very significant in shaping expectations and affecting the evaluation of risks in the financial markets.[14] The measures agreed upon in the summer of 2012 present a particularly good case study for this. In particular, we explore

[14] For a more detailed description of the several monetary policy decisions taken by the ECB since the breakdown of the financial crisis see Hartmann and Smets (2018). The effect of unconventional monetary policy measures on the financial conditions faced by the firms has specifically received some attention lately (Boneva *et al.*, 2016, Ferrando *et al.*, 2018).

whether, conditional on their information set, firms changed their expectations following the policy announcements of summer of 2012. We do so by employing a difference in differences model in which the treatment group comprises of the "informed" firms identified in the previous section, namely firms that had been using bank finance in the previous period.[15]

To recall, in early 2012, as a result of weak growth and fiscal slippages, risk premia of sovereign bond yields rose sharply in several vulnerable euro area countries seriously hampering the funding of banks in general. Financial tensions were rising fast threatening not only the banking system, but the very unity of the euro area. In the summer of 2012 some important policy decisions were agreed upon and announced. In the end of June 2012, the European Council agreed to create a European banking supervision mechanism and a resolution mechanism, a step towards building a banking union. In early August, the European Central Bank's Governing Council announced it would undertake outright monetary transactions (OMTs), a programme consisting of the purchase of sovereign bonds in secondary markets under strict conditions. Some days before that announcement, the President of the ECB delivered a speech now well-known for the quote "Within our mandate, the ECB is ready to do whatever it takes to preserve the euro. And believe me, it will be enough." The technical framework of OMTs was announced on 6 September 2012. Financial markets are believed to have reacted to these policy announcements and by the end of 2013 government bond yields had returned to pre-crisis levels, despite the fact that the ECB did not actually purchase government bonds through the OMT Program. (Altavilla *et al.*, 2014).

The summer 2012 marks an interesting turning point for the access of companies to bank finance in both "vulnerable" and "non-vulnerable" countries as well as for expectations of future bank credit, as shown in Figure 6.[16]

[15] To be sure, the "difference in differences" estimates below do not necessarily provide watertight evidence of forward-looking expectations. An alternative or complementary interpretation could be that the treatment group of firms were the first to benefit from the effects a policy announcement on the markets and that this was not sufficiently controlled for by the independent variables. If this were to be the case, the evidence suggests heterogeneity in the transmission mechanism rather than heterogeneity in the expectation formation process of "informed" firms.

[16] For completeness, it should be said that the sovereign debt crisis of that period left a damaging legacy, which led the way for a new phase of the crisis. This was characterized by the process of deleveraging of banks in many parts of the euro area – particularly in vulnerable countries – and involved a slow recovery in the lending to the real economy. To address the problem, the ECB sought to affect the whole range of interest rates. In particular, it announced in June 2014 the introduction of a credit easing package, which included targeted longer-term refinancing operations, specifically designed to support bank lending to the private sector. Further measures included an expanded Assets Purchase Program, with monthly purchases of public and private securities. The combined impact of these measures aimed at reducing market and bank-based financing costs, was visible in the continuous increase in the availability of bank loans as also signalled by the firms in our survey.

[FIGURE 6]

The OMT programme did not lead to any actual intervention in the bond market. Also, the single supervisory mechanism became active at a much later stage, in late 2014. Thus, in September 2012, when the fieldwork of the SAFE survey was carried out, no actual intervention had taken place on the basis of these announcements (though ECB policy interest rates had been reduced by 25 basis points in July 2012 and stayed stable thereafter). In the survey of September 2012 (2012w7) more companies than ever (in the history of the survey) reported that the willingness of banks to provide credit had deteriorated in the preceding six months. They also reported a deteriorating general economic environment. In other words, at that stage, conditions "on the ground" had not much improved for firms and policy interventions had not taken place. The econometric strategy consists therefore of identifying whether, conditional on the (otherwise negative) news contained in the right hand side of equation (1), firms' expectations in September 2012 were higher, presumably as a result of anticipating the improvement of borrowing conditions in the months following the policy announcements.

Any macroeconomic effects of these policy announcements cannot be detected in the model, as these are only a part of the macroeconomic environment of summer 2012 and would have been captured by the country-wave-industry dummies of the econometric model. We use therefore, a difference-in-differences model. In particular, in line with what was discussed in the previous section, we test whether the expectations of firms that had used bank credit in the six preceding months changed to the better in the September 2012 survey wave when compared to the control group. The impact on borrowing conditions of a possible intervention of the ECB in the government bond market is unlikely to have been easy to anticipate. It is therefore reasonable to expect that firms that were actively dealing with banks, as discussed in the previous section, would have been the first ones to decouple the financial markets' signal from the noise and adapt their expectations accordingly. As a falsification test, we consider the same model introducing the differences in differences term one wave earlier (in March 2012) and one wave later (in March 2013).

The main results of this exercise can be found in Table 8. Only the estimates for the variables of interest are presented, as the estimated coefficients of the other variables stay very close to those found earlier in Tables 2 and 7.

[TABLE 8]

In the first column, the expectations model is amended to control for the change in expectations of "informed" firms in September of 2012, shortly after the OMT announcement. Notwithstanding that these firms tended to have less optimistic forecasts overall (as was also seen in the previous section), the estimates suggest that their expectations improved in September 2012 more than in the control group (that had no dealings with banks in the preceding six months). Again, in line with the previous section, this could be interpreted as a better ability of the "informed" firms to anticipate the turning point in the availability of finance that followed in late 2012. The next two columns in Table 8 show results of a falsification test. In particular, the treatment groups are now the "informed" companies one wave before (in March 2012) and one wave after (in March 2013). These results suggest that the positive changes in the expectations of the treatment group observed in September 2012 are not statistically significant before or after that survey wave.

Table 9 provides some more information on the underlying mechanism that affected the expectations of "informed" firms in wave 7. We now consider separately the expectations of firms in vulnerable and non-vulnerable countries. A priori one may consider that an intervention of the ECB in the government bond market would have benefited in the first instance banks and companies in vulnerable countries (due to the home bias in government bond holdings) and this is indeed what one could observe in the financial markets. But bonds of vulnerable countries were also held by banks in non-vulnerable countries and more generally the risks of contagion were high given the interconnectedness of the banking system. Looking forward on a longer horizon, therefore, an intervention in the government bond market was likely to affect financial market conditions throughout the euro area. The question is therefore whether companies in both vulnerable and non-vulnerable countries would have perceived this and adjusted their expectations on bank credit availability as a result. Table 9 suggests that this was indeed the case. Conditional expectations of "informed" firms in both vulnerable and non-vulnerable countries were higher in September 2012 than otherwise predicted by the model. These results are complementary to a recent study by Ferrando *et al.* (2019).[17]

[TABLE 9]

The two last columns in Table 9 suggest moreover that the effect of the ECB policy announcements on the expectations of larger firms may have been particularly prominent (and statistically significant) in non-vulnerable countries.[18] This may indicate that large companies in non-vulnerable countries were

[17] Ferrando et al. (2019) find that expectations improved significantly more after the OMT announcement for firms borrowing from banks with high balance sheet exposures to impaired sovereign debt.

[18] To recall from the previous section, in the absence of the variable "use of bank finance", firm size matters for the accuracy of expectations, possibly as another proxy of familiarity and closeness to the banking system.

particularly interested and stood to benefit more from a macroeconomic policy announcement that aimed in the short run at “calming” the markets and avoiding any ripple effects through the financial system of the euro area. Large firms in vulnerable countries, though also benefiting from better financial conditions in general, were still looking at a vulnerable local banking system that would still need to deleverage in the future. The improvement of their expectations from a policy intervention may therefore have been somewhat more muted for the latter.

8. Conclusions

This paper delivers new evidence on the expectations formation of non-financial companies concerning the availability of bank finance based on survey data from 11 euro area countries. The results suggest that non-financial companies do not seem to follow any simple mechanical rule when forming their expectations. The evidence strongly supports the hypothesis that these firms update their expectations on the basis of new information on a wider range of variables than, for example, a simple extrapolative model would have suggested.

As in previous literature, the hypothesis that expectations fulfil the (orthogonality) conditions of the rational expectations hypothesis is rejected by the data. Interestingly, we find evidence that the expectation error is correlated with information that we know companies had in their information set and that firms had identified as relevant for the availability of external finance in the past. This finding indicates that deviations from the rational expectations hypothesis are unlikely to have been solely due to information imperfections (e.g sticky information or inattentiveness to news). They indicate some type of misspecification in the expectations’ model firms are using. In particular, the evidence suggests that in the period under consideration, firms tended to give too much weight on the information more easily accessible and understandable, namely that on the sales and profits of the respective firm and the general economic environment.

We also find that the pattern of forecast errors over time does not fit with what one would expect if there were waves of optimism/pessimism. Either firms were faced with successive unanticipated shocks or, equivalently, they tended to a faster return to “normal” conditions than actually was the case.

Using an indicator of expectations “inaccuracy” at the firm level, we test and find some evidence that companies differ in their ability to forecast the availability of bank finance six months ahead. In particular, smaller firms and/or firms that were recently less exposed to (or had not used) bank finance tend to do worse at forecasting their availability next period. This could be a sign of asymmetric/imperfect information. We cannot confirm, however, if (rational) inattention plays a role. In particular, firms that report that they need bank finance and thus, presumably, have reasons to seek better information do not seem to be any better at forecasting bank finance availability (when we condition on the past use).

In the last section of the paper, the monetary policy announcements of late summer 2012 (among else on the OMT programme) offer an interesting natural experiment to test whether firms incorporate any forward looking elements in their expectations. Using a difference in differences model, we find some evidence that following the policy announcements, "informed" firms revised positively their expectations, possibly anticipating in part the turning point in the financial conditions, otherwise only detectable in the data of next survey wave. This seems to be true in both vulnerable and non-vulnerable countries.

Overall these results suggest that, when forming their expectations, companies seem to combine both backward and forward-looking elements. They also seem to react to recent information, including policy announcements, albeit not in the efficient way one would expect under REH. Moreover, firms seem to differ in their ability to forecast future bank credit availability in a way that changes over time, possibly depending on their information channel at the time of their forecast. Interestingly, monetary policy announcements – in our case a major announcement in a critical moment such as the OMT – do have a direct impact on the expectations of non-financial firms, at least of those better informed and/or larger.

9. References

Altavilla, C., Giannone, D., and Lenza, R. (2014), "The Financial and the Macroeconomic Effects of the OMT Announcements", CSEF Working Paper No. 352.

Bachmann, R., Elstner, S. and Sims, R. (2013), "Uncertainty and Economic Activity: Evidence from Business Survey Data", NBER Working Paper 16143

Bachmann, R., and Elstner, S. (2015), "Firm Optimism and Pessimism", *European Economic Review*, Vol. 79, pp. 297-325.

Berger, A and Udell, G. (1998), "The Economics of Small Business Finance: The Roles of Private Equity and Debt Markets in the Financial Growth Cycle", *Journal of Banking and Finance*, Vol. 22, Issues 6-8, pp. 613–673.

Bordalo, P., Gennaioli, N. and Shleifer, A. (2017), "Diagnostic Expectations and Credit Cycles", *The Journal of American Finance Association*, Vol. 73, pp. 199-227.

Boneva, L., Cloyne, J., Weale, M and Wieladek, T. (2016), "The effect of unconventional monetary policy on inflation expectations: Evidence from firms in the United Kingdom", *Journal of Central Banking*, Vol. 12 No 3, pp. 161-195.

Branch, W. A. (2004), "The Theory of Rationally Heterogeneous Expectations: Evidence from Survey Data on Inflation Expectations", *The Economic Journal*, Vol. 114, pp. 592–621.

Brock, W, and Hommes, C. (1997), "A Rational Route to Randomness", *Econometrica*, Vol. 65 No 5, pp. 1059-1096.

Cagan, P. (1956), "The monetary dynamics of hyper-inflation", in Friedman, M. (ed.) *Studies in the Quantity Theory of Money*, University of Chicago Press, Chicago, pp. 25-117.

Coibion, O. and Gorodnichenko, Y. (2015), "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts", *American Economic Review*, Vol. 105 No 8, pp. 2644–2678.

Coibion, O., Gorodnichenko, Y. and Kamdar, R. (2018), "How Do Firms Form Their Expectations? New Survey Evidence", *American Economic Review*, Vol. 108 No 9, pp. 2671-2713

Dominitz, J. and Manski, C. (2005), "Measuring and Interpreting Expectations of Equity Returns". NBER Working Paper 11313.

Dunkelberg, W., and Scott J., (2009), "The response of small business owners to changes in monetary policy", *Business Economics*, Vol. 44, pp. 23-37.

Evans, G.W. and Honkpohja, S. (2001),*Learning and Expectations in Macroeconomics*, Princeton University Press.

Ferrando, A., Popov A. and Udell, G. F. (2018), "Do SMEs Benefit from Unconventional Monetary Policy and How? Micro-Evidence from the Eurozone", *Journal of Money, Credit and Banking*, Vol. 51 No 4, pp. 895-928.

Ferrando A., Popov A. and Udell G. (2019), "A Funding Expectations Channel of Monetary Policy", *Unpublished Manuscript*, ECB.

Gennaioli, N. and Shleifer, A. (2018), *A Crisis of Beliefs*, Princeton University Press.

Handel, B. and Schwartzstein J. (2018), "Frictions or Mental Gaps: What's Behind the Information We (Don't) Use and When Do We Care?", *Journal of Economic Perspectives*, Vol. 32 No 1, pp. 155–178.

Hartmann, P., and Smets, F. (2018), "The first 20 years of the European Central Bank: Monetary Policy", ECB Working Paper Series 2219.

Kahneman, D. (2011), *Thinking Fast and Slow*, Penguin books

Kahneman, D. and Tversky, A. (1974), "Judgment under Uncertainty: Heuristics and Biases", *Science* Vol. 185 No 4157, pp.1124-31.

Lui, S., J. Mitchell, and Weale G. (2011), "The Utility of Expectational Data: Firm-level Evidence using Matched Quantitative-qualitative UK Surveys", *International Journal of Forecasting*, Vol. 27, pp. 1128-1146.

Mackowiak, B. and Wiederholt, M. (2009), "Optimal Sticky Prices under Rational Inattention", *American Economic Review*, Vol. 99 No 3, pp.769-803.

Manski, C. F. (2004), "Measuring Expectations", *Econometrica*, Vol. 72 No 5, pp.1329-1376.

Mankiw, N.G. and Reis, R. (2002), "Sticky information versus sticky prices: a proposal to replace the new Keynesian Phillips curve", *The Quarterly Journal of Economics*, Vol. 117 No 4, pp. 1295-1328.

Massenot, B. and Pettinicchi, Y. (2018), "Can firms see into the future? Survey evidence from Germany", *Journal of Economic Behavior and Organization*, Vol. 145, pp. 66-79.

Muth, J. F. (1961). Rational Expectations and the Theory of Price Movements. Econometrica, 29 (3), 315-335.

Nerlove, M. (1983), "Expectations, Plans, and Realizations in Theory and Practice", *Econometrica*, Vol. 51 No5, pp.1251-1279.

Pesaran, H. M. and Weale, M. (2006), "Survey Expectations", in G. Elliot, Granger C. W. J.and Timmermann A. (Eds.). *Handbook of Economic Forecasting*, North-Holland, Amsterdam.

Shiller, R. J. (1981), "Do Stock Prices Move Too Much to Be Justified by Subsequent Changes in Dividends?", *American Economic Review*, Vol. 71 No 3, pp. 421-36.

Sims. C. A. (2003), "Implications of Rational Inattention", *Journal of Monetary Economics*, Vol 50 No 3, pp. 665-690.

Souleles, N. S. (2004), "Expectations, Heterogeneous Forecast Errors, and Consumption: Micro Evidence from the Michigan Consumer Sentiment Surveys", *Journal of Money, Credit and Banking*, Vol. 36, pp. 39-72.

10. Tables and Figures

Table 1: Summary statistics for the sample used in the analysis

VARIABLES	N	Mean	Std. dev	Min	Max
Dependent Variables					
expectation	33,607	0.051	0.62	-1	1
realisation	32,088	0.032	0.62	-1	1
forecast error	27,499	-0.012	0.76	-2	2
forecast error in absolute value	27,499	0.49	0.59	0	2
change in availability in absolute value	26,068	0.42	0.56	0	2
forecast inaccuracy index	25,280	0.064	0.66	-2	2
Business Conditions					
general economy	45,768	-0.068	0.73	-1	1
willingness of banks to provide credit	36,346	0.020	0.70	-1	1
own capital	46,857	0.14	0.64	-1	1
credit history	45,259	0.16	0.59	-1	1
sales and profit	45,909	0.088	0.72	-1	1
Firm Characteristics					
use of bank loans	46,702	0.30	0.46	0	1
need more bank loans	31,660	0.24	0.43	0	1
credit constraints	33,106	0.13	0.34	0	1
financing pressure	36,594	0.42	0.49	0	1
medium large	47,303	0.65	0.48	0	1
size: micro	47,303	0.34	0.47	0	1
size: small	47,303	0.31	0.46	0	1
size: medium	47,303	0.26	0.44	0	1
size: large	47,303	0.083	0.28	0	1
Age: below 2 years	46,730	0.0090	0.094	0	1
age: 2-4 years	46,730	0.045	0.21	0	1
age: 5-9 years	46,730	0.11	0.31	0	1
age: above 9 years	46,730	0.84	0.37	0	1
Autonomous	47,295	0.86	0.35	0	1
family-owned	47,266	0.81	0.39	0	1
sector: industry	47,303	0.29	0.45	0	1
sector: construction	47,303	0.10	0.30	0	1
sector: trade	47,303	0.26	0.44	0	1
sector: service	47,303	0.34	0.48	0	1

Note: This table presents the summary statistics for the variables used in the empirical tests. All variables are categorical ones; those that take more than 0/1values are ordered. *Expectation* is a firm's expectation on the availability of bank loans to either deteriorate (-1), remain unchanged (0), or improve (1) in the next six months. *Realisation* is a firm's perception on the availability of bank loans to have either deteriorated (-1), remained unchanged (0), or improved (1) in the past six months. *Forecast error* is expressed by the difference between lagged expectations and realisation and takes values -2, -1, 0, 1, 2. *Forecast error in absolute value* takes the values 0, 1, 2. *Change in availability in absolute value* is defined as the difference between actual and lagged realisation and takes values -2, -1, 0, 1, 2. *Forecast inaccuracy index* is defined as the difference between the absolute expectation error and the absolute change in the availability of bank loans and takes values -2, -1, 0, 1, 2. *Use of bank loans* is is equal to 1 if the firm has used bank loans or bank products such as credit lines or overdrafts, respectively, in the past six months. *Credit constraints* is equal to 1 if the firm applied for bank financing in the past 6 months, but its loan application was denied, or it applied and got less than 75% of the requested amount, or it refused the loan because the cost was too high or it was discouraged from applying because of fear of rejection. *Financing pressure* is equal to 1 if firms consider finance as a major problem for their business activity. *Family-owned* is equal to 1 if the company has one owner only, or is run by a family or entrepreneurs. *Autonomous* is equal to 1 if the company an autonomous profit-oriented enterprise, making independent financial decisions. *Industry* is equal to 1 if the company's main activity is in manufacturing or mining. *Construction* is 1 if company's main activity is in construction. *Trade* is equal to 1 if the company's main activity is in wholesale or retail trade. *Service* is equal to 1 if the company's main activity is in transport, real estate, and other services to businesses and persons. *Micro* is equal to 1 if the firm has between 1 and 9 employees. *Small* is equal to 1 if the firm has between 10 and 49 employees. *Medium* is equal to 1 if the firm has between 50 and 249 employees. *Large* is equal to 1 if the firm has 250+ employees. *General economy* is a categorical variable of firms' perception of the general economic outlook during the past six months, which takes values deteriorated (-1), remained unchanged (0), or improved (1). *Willingness of banks to provide credit* is a categorical variable of firms' perception of the willingness of banks to provide credit during the past six months, which takes values deteriorated (-1), remained unchanged (0), or improved (1). *Own capital* refers to firms' perception of the state of their own capital during the past six months and takes values deteriorated (-1), remained unchanged (0), or improved (1). *Credit history* is a categorical variable of firms' perception of their own credit history during the past six months, which takes values deteriorated (-1), remained unchanged (0), or improved (1). *Sales and profit* is a categorical variable of firms' perception of their sales and profits during the past six months, which takes values deteriorated (-1), remained unchanged (0), or improved (1).

Table 2: Expectations on the availability of bank loans

VARIABLES	(1)	(2)	(3)
expectation error			-0.508***
			(0.027)
realisation	1.281***	0.730***	1.228***
	(0.015)	(0.018)	(0.043)
general economy		0.317***	0.341***
		(0.014)	(0.027)
sales and profit		0.329***	0.284***
		(0.014)	(0.026)
willingness of banks to provide credit		0.542***	0.539***
		(0.017)	(0.032)
own capital		0.095***	0.103***
		(0.015)	(0.027)
credit history		0.131***	0.140***
		(0.015)	(0.029)
family-owned	-0.051**	-0.036*	-0.064
	(0.020)	(0.022)	(0.041)
autonomous	-0.057**	-0.067***	-0.057
	(0.024)	(0.025)	(0.049)
size: small	0.096***	-0.002	-0.041
	(0.019)	(0.020)	(0.039)
size: medium	0.197***	0.040*	-0.007
	(0.021)	(0.022)	(0.042)
size: large	0.210***	0.025	-0.057
	(0.030)	(0.031)	(0.058)
age: 2-4 years	-0.182***	-0.100	0.055
	(0.070)	(0.078)	(0.178)
age: 5-9 years	-0.222***	-0.121	-0.015
	(0.066)	(0.074)	(0.171)
age: >9 years	-0.336***	-0.186***	-0.027
	(0.063)	(0.071)	(0.166)
/cut1	-0.136	1.491**	1.954***
	(0.701)	(0.707)	(0.593)
/cut2	3.200***	5.027***	5.721***
	(0.701)	(0.707)	(0.595)
Observations	91,432	83,303	24,630
Country*Wave*Sector Dummy	Yes	Yes	Yes
R^2	0.110	0.148	0.179

Note: This table presents estimates of expectations on the availability of bank loans. The model is estimated using ordered logit. The estimation period is June 2009 –March 2018. All regressions include fixed effects as specified. Standard errors clustered at the firm level appear in parentheses. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 3: Average marginal effects of expectations on the availability of bank loans

VARIABLES	(1) *Exp= -1*	(2) *Exp = 0*	(3) *Exp = 1*
realisation	-0.091***	-0.008***	0.100***
	(0.002)	(0.001)	(0.002)
general economy	-0.040***	-0.004***	0.043***
	(0.002)	(0.000)	(0.002)
sales and profit	-0.041***	-0.004***	0.045***
	(0.002)	(0.000)	(0.002)
willingness of banks to provide credit	-0.068***	-0.006***	0.074***
	(0.002)	(0.001)	(0.002)
own capital	-0.012***	-0.001***	0.013***
	(0.002)	(0.000)	(0.002)
credit history	-0.016***	-0.001***	0.018***
	(0.002)	(0.000)	(0.002)

Note: This table presents the average marginal effects of the estimates of expectations on the availability of bank loans as in Column 2 of Table 2 for each outcome category. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 4: Forecast errors on the availability of bank loans

VARIABLES	(1)	(2)	(3)
lagged forecast error			0.158***
			(0.040)
lagged realisation	-0.076***	-0.033	-0.105*
	(0.024)	(0.031)	(0.061)
lagged general economy		-0.119***	-0.128***
		(0.024)	(0.040)
lagged sales and profit		-0.189***	-0.142***
		(0.023)	(0.037)
lagged willingness of banks to provide credit		0.048*	0.054
		(0.029)	(0.047)
lagged own capital		0.088***	0.126***
		(0.025)	(0.040)
lagged credit history		0.015	-0.016
		(0.027)	(0.044)
/cut1	-3.102***	-3.350***	-4.124***
	(0.656)	(0.771)	(0.901)
/cut2	-0.734	-0.962	-1.641*
	(0.654)	(0.769)	(0.899)
/cut3	1.901***	1.687**	1.149
	(0.654)	(0.769)	(0.899)
/cut4	4.574***	4.377***	4.082***
	(0.655)	(0.770)	(0.902)
Observations	24,940	23,292	9,960
Firm controls	Yes	Yes	Yes
Country*Wave*Sector Dummy	Yes	Yes	Yes
R^2	0.0225	0.0263	0.0423

Note: This table presents estimates of the forecast error on the availability of bank loans. The model is estimated using ordered logit. Firm controls are *family-owned* and *autonomous*. The estimation period is June 2009 –March 2018. See Table 1 for variable definitions. All regressions include fixed effects as specified. Standard errors clustered at the firm level appear in parentheses. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 5: Average marginal effects of forecast errors on the availability of bank loans

VARIABLES	(1) -2	(2) -1	(3) 0	(4) 1	(5) 2
lagged realisation	0.001	0.005	0.000	-0.005	-0.001
	(0.001)	(0.004)	(0.000)	(0.005)	(0.001)
lagged general economy	0.003***	0.016***	0.000	-0.017***	-0.002***
	(0.001)	(0.003)	(0.000)	(0.004)	(0.000)
lagged sales and profit	0.005***	0.026***	0.001	-0.028***	-0.004***
	(0.001)	(0.003)	(0.000)	(0.003)	(0.000)
lagged willingness of banks to provide credit	-0.001*	-0.007*	-0.000	0.007*	0.001*
	(0.001)	(0.004)	(0.000)	(0.004)	(0.001)
lagged own capital	-0.002***	-0.012***	-0.000	0.013***	0.002***
	(0.001)	(0.003)	(0.000)	(0.004)	(0.000)
lagged credit history	-0.000	-0.002	-0.000	0.002	0.000
	(0.001)	(0.004)	(0.000)	(0.004)	(0.001)

Note: This table presents the average marginal effects of the estimates of the forecast error on the availability of bank loans as in Column 2 Table 4 for each outcome category. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 6: Forecast inaccuracy in predicting the availability of bank loans

VARIABLES	(1)	(2) Use of bank loans	(3) Need of bank loans	(4) Use + Need of bank loans
use of bank loans		-0.097***		-0.100***
		(0.028)		(0.030)
need more bl			-0.072**	-0.044
			(0.033)	(0.034)
lagged family-owned	-0.036	-0.032	-0.016	-0.013
	(0.038)	(0.038)	(0.039)	(0.039)
lagged autonomous	0.062	0.071	0.052	0.056
	(0.046)	(0.046)	(0.048)	(0.048)
lagged medium-large	-0.069**	-0.054*	-0.057*	-0.044
	(0.030)	(0.030)	(0.031)	(0.031)
lagged age: 2-4 years	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
lagged age: 5-9 years	0.044	0.026	0.043	0.026
	(0.143)	(0.143)	(0.151)	(0.151)
lagged age: >9 years	-0.052	-0.065	-0.036	-0.050
	(0.134)	(0.135)	(0.141)	(0.141)
/cut1	-3.834***	-3.878***	-3.828***	-3.875***
	(0.691)	(0.692)	(0.690)	(0.693)
/cut2	-0.596	-0.642	-0.593	-0.642
	(0.687)	(0.689)	(0.687)	(0.689)
/cut3	2.438***	2.393***	2.429***	2.381***
	(0.688)	(0.689)	(0.688)	(0.690)
/cut4	5.511***	5.468***	5.493***	5.444***
	(0.692)	(0.693)	(0.692)	(0.694)
Observations	24,940	24,846	23,624	23,545
Country*Wave*Sector Dummy	Yes	Yes	Yes	Yes
R^2	0.0168	0.0171	0.0177	0.0179

Note: This table presents estimates of factors affecting the inaccuracy of forecasting the availability of bank loans. The model is estimated using ordered logit. The estimation period is June 2009 –March 2018. See Table 1 for variable definitions. All regressions include fixed effects as specified. Standard errors clustered at the firm level appear in parentheses. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 7: Expectations on the availability of bank loans when firms made use of bank loans

VARIABLES	(1) All firms	(2) Only firms that used bank loans
use of bank loans	-0.105***	
	(0.016)	
realisation	0.736***	0.628***
	(0.018)	(0.026)
general economy	0.317***	0.308***
	(0.014)	(0.021)
sales and profit	0.329***	0.327***
	(0.014)	(0.021)
willingness of banks to provide credit	0.541***	0.500***
	(0.017)	(0.025)
own capital	0.096***	0.090***
	(0.015)	(0.021)
credit history	0.129***	0.152***
	(0.015)	(0.022)
family-owned	-0.034	-0.058*
	(0.022)	(0.032)
autonomous	-0.060**	-0.057
	(0.025)	(0.039)
size: small	0.008	-0.012
	(0.020)	(0.033)
size: medium	0.058**	0.056
	(0.023)	(0.034)
size: large	0.049	0.069
	(0.032)	(0.044)
age: 2-4 years	-0.103	-0.202
	(0.078)	(0.126)
age: 5-9 years	-0.121	-0.224*
	(0.074)	(0.119)
age: >9 years	-0.183**	-0.285**
	(0.071)	(0.114)
/cut1	1.430**	0.995
	(0.712)	(0.733)
/cut2	4.965***	4.451***
	(0.712)	(0.734)
Observations	82,968	36,007
Country*Wave*Sector Dummy	Yes	Yes
R^2	0.148	0.142

Note: This table presents estimates of expectations on the availability of bank loans considering firms have used bank loans (column 1) and taking only the subsample of firms that have used bank loans (column 2). The model is estimated using ordered logit. The estimation period is June 2009 –March 2018. All regressions include fixed effects as specified. Standard errors clustered at the firm level appear in parentheses. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 8: Non-conventional monetary policy and expectations on the availability of bank loans: Difference-in-Differences

	Use of bank loans	Falsification test	
VARIABLES	(1) (Wave 7 Sept.2012)	(2) Wave 6	(3) Wave 8
use of bank loans	-0.116*** (0.016)	-0.111*** (0.016)	-0.108*** (0.016)
use of bank loans x wave7	0.194*** (0.069)		
use of bank loans x wave6		0.109 (0.071)	
use of bank loans x wave8			0.051 (0.067)
/cut1	1.423** (0.712)	1.426** (0.712)	1.428** (0.712)
/cut2	4.959*** (0.713)	4.961*** (0.712)	4.964*** (0.712)
Observations	82,968	82,968	82,968
Business conditions	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Country*Wave*Sector Dummy	Yes	Yes	Yes
R^2	0.148	0.148	0.148

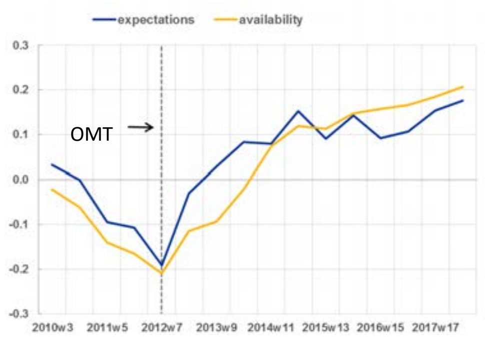
Note: This table presents difference in differences on the expectations on the availability of bank loans. In column (1) the use of bank loans and a dummy that is equal to 1 in 2012 wave 7 (and zero otherwise) are interacted. The wave 7 comes just after the announcement of unconventional monetary policy related to the OMT. In columns (2) and (3) the respective dummy refers to waves 6 and 8 six months before and after the announcement of the OMT program. The estimation period is June 2009 –March 2018. All regressions include fixed effects as specified. Business conditions are a set of variables as defined in Table 1. Standard errors clustered at the firm level appear in parentheses. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 9: Non-conventional monetary policy and expectations on the availability of bank loans among vulnerable and non-vulnerable countries: Difference-in-Differences

	VULNERABLE COUNTRIES		NON-VULNERABLE COUNTRIES	
VARIABLES	(1) wave7 x use of bank loans	(2) wave7 x size	(3) wave7 x use of bank loans	(4) wave7 x size
medium-large		-0.004		0.014
		(0.026)		(0.024)
use of bank loans	-0.050**		-0.180***	
	(0.023)		(0.022)	
medium large x wave7		0.187*		0.374***
		(0.104)		(0.100)
use of bank loans x wave7	0.215**		0.166*	
	(0.099)		(0.095)	
/cut1	1.974***	2.025***	1.419*	1.686**
	(0.287)	(0.270)	(0.750)	(0.740)
/cut2	5.308***	5.362***	5.146***	5.405***
	(0.289)	(0.272)	(0.751)	(0.741)
Observations	39,767	40,520	43,201	44,068
Business conditions	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Country*Wave*Sector Dummy	Yes	Yes	Yes	Yes
R^2	0.155	0.155	0.139	0.139

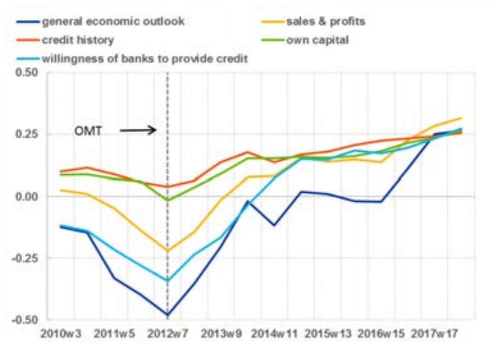
Note: This table presents difference in differences on the expectations on the availability of bank loans, where the use of bank loans and a dummy for medium and large firms are interacted with a dummy is equal to 1 in 2012 wave7, immediately after the announcement of unconventional monetary policy related to the OMT and zero otherwise. The sample is split between vulnerable countries (Greece, Ireland, Italy, Spain and Portugal) and non-vulnerable countries (Austria, Belgium, Germany, Finland, France and the Netherlands). The model is estimated using ordered logit. The estimation period is June 2009 –March 2018. All regressions include fixed effects as specified. Business conditions are a set of variables as defined in Table 1. Standard errors clustered at the firm level appear in parentheses. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Figure 1: Firms' expectations of bank loan availability over time *(net percentages)*



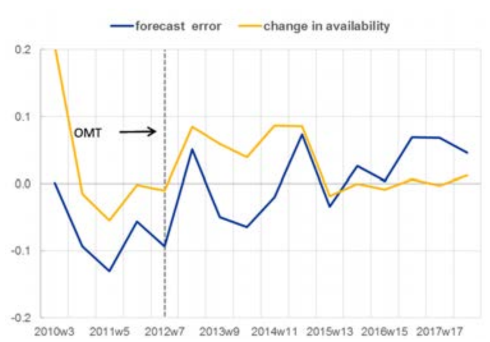
Note: The net percentage is the difference between the percentage of enterprises reporting an increase for a given factor and the percentage reporting a decrease. See Table 1 for variable definitions.

Figure 2: Firms' perceptions of business and market conditions over time *(net percentages)*



Note: The net percentage is the difference between the percentage of enterprises reporting an increase for a given factor and the percentage reporting a decrease. See Table 1 for variable definitions.

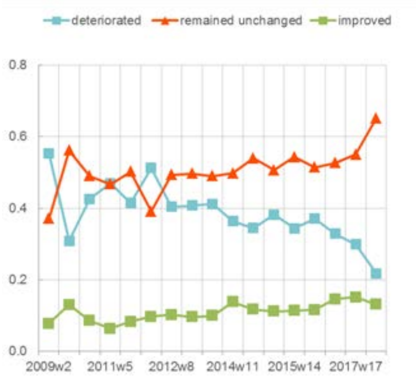
Figure 3: Firms' forecast errors and changes in actual availability of bank loans *(net percentages)*



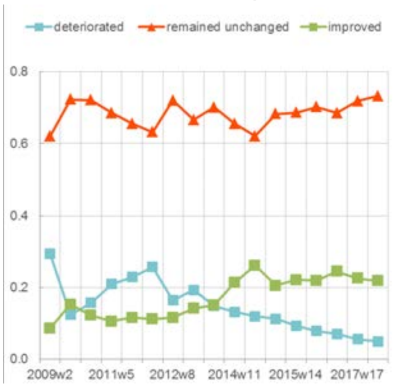
Note: The net percentage is the difference between the percentage of enterprises reporting an increase for a given factor and the percentage reporting a decrease. See Table 1 for variable definitions.

Figure 4: Availability of bank loans given expectations - Pessimists, no-change and optimists

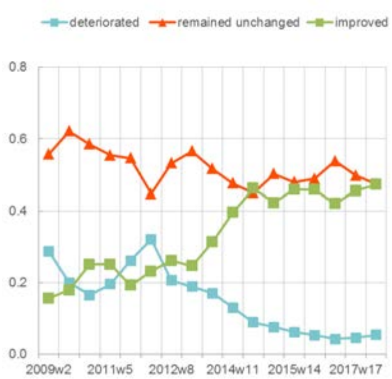
Pessimists



No- changes

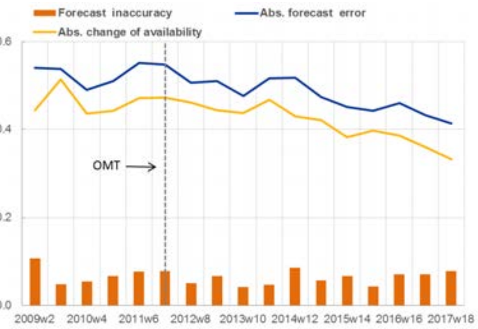


Optimists



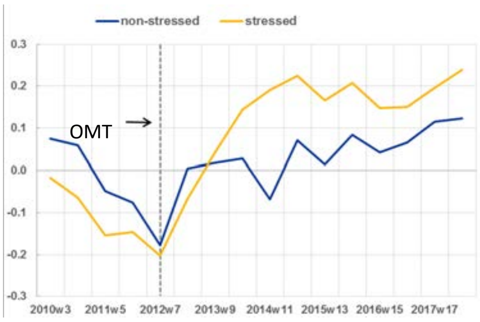
Note: Proportions of firms that report bank availability to improve, to remain unchanged or to deteriorate conditional to their expectations six months before. Pessimists (Optimists) are firms that were expecting a deterioration (improvement); no-changes are firms that were expecting broadly unchanged availability.

Figure 5: Firms' forecast errors and changes in the availability of bank loans - in absolute value and forecast inaccuracy index



Note: See Table 1 for variable definitions.

Figure 6: Firms' expectations of bank loan availability over time- vulnerable and non-vulnerable countries *(net percentages)*



Note: The net percentage is the difference between the percentage of enterprises reporting an increase for a given factor and the percentage reporting a decrease. The vertical line is at for wave 2012w7, immediately after the policy announcements of summer 2012, including on the OMT. The sample is split between vulnerable countries (Greece, Ireland, Italy, Spain and Portugal) and non-vulnerable countries (Austria, Belgium, Germany, Finland, France and the Netherlands). See Table 1 for variable definitions.

11. Annex

Table A.1: Robustness on expectations: Added lagged dependent variables

VARIABLES	(13) Exp	(24) Exp
lagged expectation		0.512***
		(0.031)
realisation	0.733***	0.713***
	(0.038)	(0.038)
lagged realisation	0.122***	0.031
	(0.033)	(0.034)
general economy	0.340***	0.331***
	(0.029)	(0.029)
lagged general economy	0.053*	0.016
	(0.027)	(0.028)
sales and profit	0.286***	0.275***
	(0.028)	(0.028)
lagged sales and profit	0.073***	0.040
	(0.026)	(0.027)
willingness of banks to provide credit	0.529***	0.530***
	(0.035)	(0.035)
lagged willingness of banks to provide credit	0.046	-0.013
	(0.031)	(0.032)
own capital	0.109***	0.104***
	(0.030)	(0.031)
lagged own capital	0.010	-0.006
	(0.029)	(0.030)
credit history	0.147***	0.149***
	(0.031)	(0.031)
lagged credit history	0.000	-0.005
	(0.029)	(0.029)
/cut1	2.858***	3.525***
	(0.768)	(0.796)
/cut2	6.590***	7.313***
	(0.771)	(0.798)
Observations	21,977	21,543
Firm controls	Yes	Yes
Country*Wave*Sector Dummy	Yes	Yes
R^2	0.174	0.184

Note: This table presents estimates of expectations on the availability of bank loans with added lagged independent variables. The models are estimated using ordered logit. The estimation period is June 2009 –March 2018. See Table 1 for variable definitions. All regressions include fixed effects as specified. Standard errors clustered at the firm level appear in parentheses. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table A.2: Robustness of expectations: Different estimation models

VARIABLES	(1) ols	(2) gologit	(3) gologit
		Exp = 0	*Exp = 1*
realisation	0.184***	0.942***	0.539***
	(0.005)	(0.026)	(0.022)
general economy	0.083***	0.477***	0.222***
	(0.004)	(0.020)	(0.016)
sales and profit	0.087***	0.332***	0.332***
	(0.004)	(0.014)	(0.014)
willingness of banks to provide credit	0.139***	0.803***	0.356***
	(0.004)	(0.025)	(0.020)
capital	0.025***	0.087***	0.087***
	(0.004)	(0.015)	(0.015)
credit history	0.034***	0.043**	0.233***
	(0.004)	(0.020)	(0.019)
/cut1			
/cut2			
Constant	1.166***	-2.405***	-4.149***
	(0.179)	(0.628)	(0.627)
Observations	83,303	83,303	83,303
Firm controls	Yes	Yes	Yes
Country*Wave*Sector FEs	Yes	Yes	Yes
R^2	0.24	0.159	0.159

Note: This table presents estimates of expectations on the availability of bank loans by different econometric estimation models. Column 1 presents the baseline model of expectations, estimated by ordinary least squares and column 2 and 3 by generalised ordered logit, with *expectation* =-1 as reference category. The estimation period is June 2009 –March 2018. See Table 1 for variable definitions. All regressions include fixed effects as specified. Standard errors clustered at the firm level appear in parentheses. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

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