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Article — Published Version

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Economic Inquiry

Provided in Cooperation with:

John Wiley & Sons

Suggested Citation: Buchholz, Manuel; Tonzer, Lena; Berner, Julian (2021) : Firm-specific forecast errors and asymmetric investment propensity, Economic Inquiry, ISSN 1465-7295, Wiley Periodicals, Inc., Hoboken, USA, Vol. 60, Iss. 2, pp. 764-793, <https://doi.org/10.1111/ecin.13045>

This Version is available at:

<https://hdl.handle.net/10419/264530>

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ORIGINAL ARTICLE

Firm-specific forecast errors and asymmetric investment propensity

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Funding information

Open access funding enabled and organized by Projekt DEAL.

Abstract

This paper analyzes how firm-specific forecast errors derived from survey data of German manufacturing firms over 2007–2011 relate to firms' investment propensity. Our findings reveal that asymmetries arise depending on the size and direction of the forecast error. The investment propensity declines if the realized situation is worse than expected. However, firms do not adjust investment if the realized situation is better than expected suggesting that the uncertainty component of the forecast error counteracts good surprises of unexpectedly favorable business conditions. This asymmetric mechanism can be one explanation behind slow recovery following crises.

KEYWORDS

firm investment, forecast errors, microeconomic survey data, risk climate, uncertainty

JEL CLASSIFICATION

D22, D84, E32

1 | MOTIVATION

During the financial crisis of 2007/2008 and the subsequent European sovereign debt crises, negative news about future economic developments accumulated, and uncertainty increased significantly. In this paper, we use survey data of German manufacturing firms over the period 2007–2011 from the Halle Institute for Economic Research (IWH) risk climate survey to derive firm-specific forecast errors and analyze how they relate to firms' propensity to invest. While forecast errors inform about whether firms have formed too optimistic or too pessimistic expectations, these errors also reveal that firms faced uncertainty when deriving their forecasts. Thus, this paper aims at documenting and analyzing asymmetries in the relation between forecast errors and investment; exploring, in particular, the role of uncertainty and its interaction with positive and negative surprises. Understanding how forecast errors relate to firms' investment behavior and, ultimately, macroeconomic outcomes is key to mitigating economic fluctuations and slow recovery.

Abbreviations: FE, forecast error; IWH, Halle Institute for Economic Research.

Managing Editor: Qinglai Meng

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Similar to Bachmann et al. (2013), we construct absolute forecast errors firms make when evaluating their business conditions. These forecast errors might not only capture a “surprise component” driving a wedge between expected and actual outcome but also a firm-specific “uncertainty component.” The reason is that a larger absolute forecast error reflects less predictability and thus higher uncertainty from the perspective of the individual firm (Jurado et al., 2015; Kalay et al., 2018). We exploit a unique element of the survey data to construct an ex-ante measure of uncertainty. This helps validating that firms’ absolute forecast errors, which are derived from an ex-post perspective, comprise an uncertainty component that potentially compensates for a positive news effect.

Focusing on the relation between forecast errors and investment at the firm level, we contribute to the scarce literature analyzing asymmetric effects of forecast errors. For example, Tanaka et al. (2020) study effects of forecasting ability on Japanese firms’ profitability and productivity. They find a negative effect for both positive and negative forecast errors, which is weaker in the case of unexpectedly high economic growth. We add to their study by focusing on firm investment and providing an explanation for asymmetric effects. The explanation draws, amongst others on Forni et al. (2017), who show that at the aggregate level large news shocks translate into increased uncertainty. This implies that the positive effect of good news on economic activity can be dampened by larger uncertainty. We complement their study by showing empirically that such interactions of surprise and uncertainty components inherent in firm-specific forecast errors matter at the micro level. Our study thereby furthers understanding of the dynamics of firms’ investment responses during and in the aftermath of a recession.

In our analysis, we first derive firm-specific forecast errors firms make when evaluating their business condition and verify the validity of its information content. The forecast error reflects the difference between a firm’s expectation about a variable and incoming data for that variable. When incoming data are worse (better) than the firm’s previous expectations, then the forecast error is negative (positive). In line with findings by, for example, Coibion and Gorodnichenko (2012), we find that firms adjust their expectations with a lag to economic shocks, whereas this under-reaction might be due to information rigidities. More firms make negative forecast errors at the beginning of the crisis period, that is, firms expected the situation to be better than actually realized. In the aftermath of the crisis, a higher fraction of firms makes positive forecast errors suggesting that firms become too pessimistic or overreact following a sequence of bad shocks, which would be in line with the mechanism proposed by Gennaioli et al. (2015). On average, the share of firms making a larger forecast error, whether positive or negative, is higher during crisis times.

Second, we analyze whether there is a relation between firm-specific forecast errors and firm investment. Importantly, larger absolute forecast errors contain two components: First, they reflect deviations from expectations, due to for example positive or negative surprises. Second, they reveal that predictability has declined and thus the level of firm-specific uncertainty has increased such that firms can become more cautious in their investment decisions and decide to “wait and see.” Our results show that firms are less likely to increase investment following the realization of a larger absolute forecast error. However, already simple descriptive statistics point into the direction that the relation between investment and firm-specific forecast errors is more complex and that the surprise and the uncertainty components of the forecast error interact.

Extending our regression analysis accordingly, we find that investment relates in an *asymmetric* way to forecast errors, depending on the size and direction of the forecast error. If the absolute forecast error increases and has a negative sign, that is, the firm faces a negative surprise, firms’ investment propensity declines significantly. This result suggests that the surprise and uncertainty components work in the same direction given negative news. If forecast errors are positive and increasing, that is, the realized situation is better than expected, firms do not adjust their investment plans. Thus, the uncertainty and surprise components work in opposite direction whereas larger uncertainty seems to compensate the realization of unexpectedly favorable business conditions such that, ultimately, firms do not invest more.

Given that the fraction of firms making positive forecast errors is higher after the peak of the crisis, we provide micro evidence that positive surprises may not be sufficient to stimulate investment in an environment of heightened uncertainty. This observation can constitute a potential reason behind sluggish recovery at the macro level in the aftermath of financial crises (Forni et al., 2017; Meinen & Roehle, 2017; Reinhart & Rogoff, 2014). A high level of pessimism triggered by a recession can be reflected in an underestimation of future prospects. In principle, such an underestimation implies a positive surprise from the perspective of the individual firm, whereas the positive surprise itself might spur investment in the aggregate. At the same time, however, uncertainty increases during crisis times, which might reduce incentives to invest and slowdown economic recovery. In this respect, we provide micro-level evidence confirming the findings by Forni et al. (2017) that output responses to large news shocks are asymmetric. The underlying

mechanism is that uncertainty arises from news in such a way that good news and its positive impact are counteracted by the uncertainty effect, while the negative impact of bad news is strengthened.

While it is well established that aggregating firm-level forecast errors yields a proxy for uncertainty, our paper proposes that, also at the firm level, they contain a surprise but also an uncertainty component. To validate that the firm-specific forecast error contains an uncertainty component, we take advantage of the fact that our data set contains a question about how firms judge the stability of expectations about future developments (henceforth: stability of expectations). This can be interpreted as an *ex-ante* measure of firm-specific uncertainty. Firms that consider their expectations about future developments to be stable assume to make a smaller forecast error. This *ex-ante* measure is highly correlated with the (ex-post) forecast error speaking to the idea that forecast errors contain not only a news but also an uncertainty component. Analogously to our results for firms' forecast error, a higher level of *ex-ante* uncertainty, that is, a lower perceived stability of expectations, reduces firms' investment propensity.

The data we rely on is a unique data set based on firm-level survey data of German firms. The "IWH risk climate survey" was obtained from the IWH. It offers various advantages that allow one to assess the relation between firm-specific forecast errors and investment behavior. First, at a half-yearly frequency, it spans the period from the first quarter of 2007 to the third quarter of 2011, such that we can compare the evolution of firms' forecast errors and investment responses starting from a non-crisis period, covering the financial crisis, and entering a recovery phase. While the German economy recovered relatively fast after the crisis, investment has remained below pre-crisis levels (Banerjee et al., 2015). This weakness in investment is similar to other European countries and the United States (Barkbu et al., 2015; OECD, 2015). Additionally, the crisis came unexpectedly, which provides an exogenous event that drives firms' forecast errors independently of firm-specific characteristics. Second, we have a large number of small and medium-sized manufacturing firms located in different parts of Germany, which gives a sufficient degree of heterogeneity.

The paper relates to two main strands of literature. The first strand of literature analyzes investment behavior of firms under uncertainty. Uncertainty is often found to have a weakening effect on investment (Bernanke, 1983; Bloom et al., 2007; Carlsson, 2007; Ghosal & Loungani, 2000; Guiso & Parigi, 1999; Kellogg, 2014; Koetse et al., 2006; Leahy & Whited, 1996; Lensink et al., 2005).¹ The reason is that if uncertainty is high, firms tend to "wait and see" instead of investing more, particularly if investment decisions are irreversible (Bloom, 2009; Bloom et al., 2018; Stokey, 2016). The negative effect of uncertainty on investment and output growth is confirmed at the macro level (Bachmann et al., 2013; Born & Pfeifer, 2014; Christiano et al., 2014; Fernández-Villaverde, 2011). We add to this strand of literature in that we analyze the asymmetric effects of firm-specific forecast errors at the micro level taking into account their surprise and uncertainty components.

The second strand of literature is related to firm-specific determinants of investment behavior, such as the financing situation and risk aversion. Firms' investment responses might depend on both internal financing resources and access to external funds and their costs. Financial frictions can impose constraints on firms that result in reduced investment (Arellano et al., 2019; Gilchrist et al., 2014). Additionally, risk aversion can be a key determinant of firms' investment behavior. The more risk-averse a firm is, the less willing the firm is to invest. The effect of uncertainty on investment is likely to change with firms' risk aversion (Panousi & Papanikolaou, 2012). This is particularly important in crisis times, when uncertainty tends to increase and firms become more risk-averse (Guiso et al., 2018).² We contribute to the literature on the determinants of firm investment by asking whether investment responses are correlated with firm-specific forecast errors, while controlling for financing constraints and risk aversion.

The paper is structured as follows. In Section 2, we describe the data with a particular focus on the IWH risk climate survey. Furthermore, we present descriptive statistics related to the research questions. We show how forecast errors and investment responses evolved over time and across firms. Section 3 explains the regression model and shows the results. Section 4 concludes the paper.

2 | DATA DESCRIPTION AND SUMMARY STATISTICS

This section first describes the IWH risk climate survey, the construction of the underlying survey and its coverage. Second, we explain the computation of firm-level forecast errors. Third, we provide descriptive evidence for the relationship between firms' ability to forecast and their propensity to invest.

2.1 | IWH risk climate survey

The risk climate survey of the IWH covers the period from 2007Q1 to 2011Q3.³ Surveys were conducted every half a year in spring (April) and autumn (October), and we have data for 10 different waves.⁴ Variables used in the analysis are described in Appendix A1. The survey was sent to the executive directors of manufacturing firms. If firms did not respond to two continuous waves, they were dropped from the sample.⁵ Firms could respond by sending a fax or letter or by answering online. For the first two waves, only selected sectors of the manufacturing industry are included. The subsequent eight waves include firms of all sectors, for example, chemical, leather, wood, and engineering, as listed in Appendix A2. Firms were chosen based on a random sampling procedure.⁶

The survey has two main components: First, it contains “core” questions asking firms about their evaluation of current business conditions and the economic situation, their expectations with respect to future development, their judgment of the stability of the expected development, and the resulting implications for the firm. All of these questions are asked with reference to the general business and economic conditions of the firm and subcategories such as production, revenues, or competition. Firms also give an evaluation of their willingness to take risks, whether they have achieved their targeted amount of revenues, and how they expect their investment behavior to evolve. In general, firms have five answer options to indicate whether they expect, for example, a (strong) deterioration (−/−−), no change (0), or a (strong) improvement (+/++) of future business and economic conditions.

Second, questions are asked about the firm's sector, the most important product, the amount of revenue in the last accounting year, and the share of revenue generated abroad. Furthermore, we know whether the firm has participated in the survey, which allows calculating response rates to individual questions. For example, we find that among the participating firms, the share of firms not responding to the question on expected investment behavior is less than 3%. We also know the location of the firm (Eastern or Western Germany), and in which size range the firm falls in terms of employees. “Small” covers firms with 1–4 or 5–24 employees, “medium” refers to firms with 25–74 employees, and “large” covers firms with more than 74 employees. Summary statistics of the number of reporting firms by wave and the share of firms across subcategories, such as the number of employees, can be found in Table 1.⁷ From this table, it can be seen that the survey contains mostly smaller firms.

To check whether our sample is likely to produce relevant results, we compare it to the universe of manufacturing firms in Germany using data from the federal statistical office (Online Appendix). This shows that smaller-sized firms account for a sizeable share of total manufacturing firms and thus play a non-negligible role in the manufacturing sector. Average revenue is obviously lower for smaller firms but can be reconciled with the numbers in the IWH survey. Finally, the distribution of firms across sectors in the survey data is very similar to the one obtained from official data for the whole German manufacturing sector. This supports the appropriateness of the random sampling procedure and the representativeness of this sample of smaller firms.⁸

TABLE 1 Distribution of firms across subcategories of employees and wave

Wave	Emp < 4	5 ≤ Emp ≤ 24	25 ≤ Emp ≤ 49	50 ≤ Emp ≤ 74	Emp ≥ 75	n.a.	Total #
2007q1	5	36	26	10	23	1	442
2007q3	16	43	18	5	17	1	661
2008q1	17	40	17	6	16	5	848
2008q3	16	37	14	4	15	13	1006
2009q1	19	42	12	4	12	11	1212
2009q3	19	42	12	4	10	13	1182
2010q1	13	21	42	11	3	10	1241
2010q3	21	44	10	5	10	10	1161
2011q1	19	43	10	4	11	13	1301
2011q3	21	41	12	3	10	13	1212

Note: This table shows the distribution of firms across different subcategories of firm size measured by the number of employees and by wave (in %). The last column shows the total number of firms that have participated in the survey across the different waves from 2007Q1 to 2011Q3.

Given that the survey is conducted for a limited number of firms, including mostly smaller firms, besides the representativeness of the sample also the validity of the responses is crucial for further analysis. To verify whether we can rely on firms' responses, we use our data to reconstruct the balance on which the well-known Ifo business climate index for the Germany economy is based.⁹ This allows us to compare the evolution of the original Ifo business climate balance to our reconstructed balance, whereas the two series are remarkably similar (Figure B3 in the Online Appendix). This gives us confidence in the validity of the survey outcome obtained from the IWH risk climate survey. The only discrepancy arises in the level, which can be explained by the fact that, in contrast to the Ifo business climate survey, we have mostly smaller firms in our sample, which are more likely to be too optimistic in their expectations (Bachmann & Elstner, 2015).

2.2 | Firms' forecast errors

Following Bachmann et al. (2013), we compute forecast errors regarding the firms' overall economic situation for each firm at each point in time from the survey responses. The firm-specific forecast error compares the firm's expected situation with the actual situation one period later. More specifically, the forecast error in period t is computed by subtracting the expected situation for t made by the firm in the previous period $t - 1$ from the firm's actual situation in t . This forecast error has five different categories and ranges from "FE -2" (situation was worse than expected) to "FE 2" (situation was better than expected). A detailed explanation of the calculation can be found in Appendix A3.

This measure is, hence, a firm-specific forecast error with two components. First, positive (negative) values in t reflect that there was a positive (negative) surprise compared to firms' expectation in $t - 1$. Second, a larger absolute forecast error reflects less predictability and thus higher uncertainty from the perspective of the individual firm. The uncertainty component is hence measured from an *ex-post* perspective, as the forecast error compares the realized situation in period t with the expected situation in $t - 1$. In further analysis, the forecast error will be linked to investment responses in period t . This approach underlies the assumption that a firm, being aware of having made a forecast error, incorporates this into its investment decisions. This assumption is plausible as long as a firm realizing that past expectations have been "wrong" projects this experience into the future. In this case, *ex-post* forecast errors matter for future decision-making.

Alternatively, we use an *ex-ante* measure of uncertainty based on how firms evaluate the stability of their expectations about future developments, and we refer to this variable as "stability of expectations." If a firm considers its expectations about future developments very unstable, this signals a high level of future uncertainty. In contrast, a firm that believes in the stability of its expectations about future developments perceives less uncertainty regarding its predictions. Hence, the IWH risk climate survey has the advantage that we can use the *ex-ante* measure of uncertainty to validate that the firm-level forecast error contains not only a surprise component but also an uncertainty component, which is derived from an *ex-post* perspective.¹⁰ The correlation coefficient between these two measures is -0.15 (see Table B1 in the Online Appendix) revealing that a higher absolute forecast error relates negatively to firms' stability of expectations. A strong co-movement over time across firms is shown in Figure 1, where we have multiplied the average value of the stability of expectations by minus one to compare the dynamic pattern. This result corroborates the idea that the forecast error contains an uncertainty component also at the firm level because part of its information content is reflected in firms' *ex-ante* perception of uncertainty (see also Section 3.1).

Table 2 shows the distribution of the forecast error based on the overall economic situation of the firm for each wave. Because the survey starts in the first quarter of 2007 (2007q1) and because we do not have firms' expectations from the previous quarter, the series of forecast errors starts from the second wave. The percentage share of firms by size of the forecast error is depicted in the columns of the table. Across the whole sample, the share of firms that had a forecast error of zero is highest, with an average of 60%. If we look at the distribution by wave, asymmetric patterns arise. At the beginning of the crisis 2008q3/2009q1, the share of firms with a negative forecast error is relatively higher compared to other waves. This suggests that more firms expected the situation to be better than realized and underestimated the crisis effect ($>20\%$ for FE -1, $>5\%$ for FE -2). Yet, in the following quarters 2009q3/2010q1, more firms had worse expectations about the future than what was realized ($>20\%$ for FE 1, $>3\%$ for FE 2).

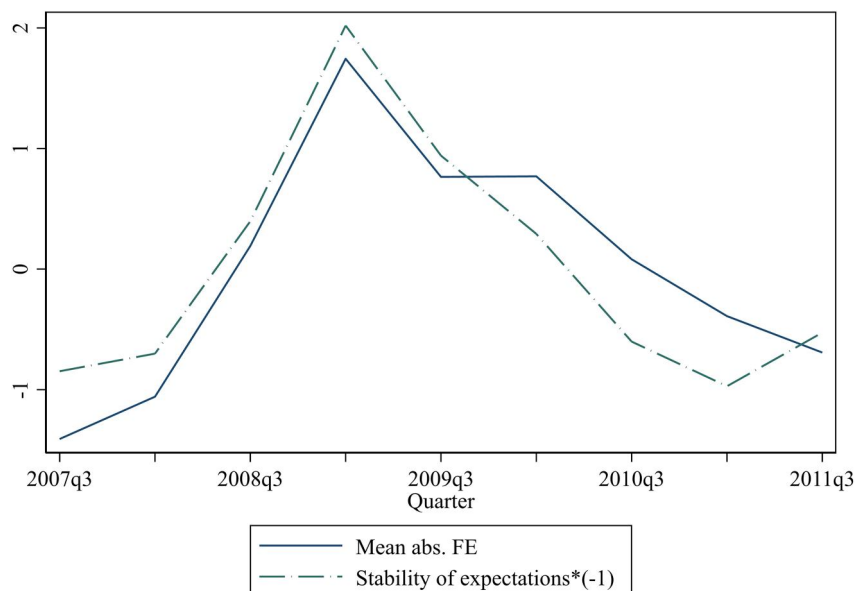


FIGURE 1 Ex-post and ex-ante uncertainty measure. This figure shows the mean absolute forecast error, which captures an uncertainty component from an ex-post perspective (blue, solid line). The ex-ante uncertainty measure corresponds to firms' stability of expectations and its average value is multiplied by minus one and depicted by the green, dotted line. Both variables are standardized and derived from the Halle Institute for Economic Research risk climate survey. For more information, see the data description in the appendix of the paper [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 2 Summary statistics for firms' forecast error

Quarter	Wave	FE -2	FE -1	FE 0	FE 1	FE 2	Total
2007q1	1
2007q3	2	2.8	19.2	69.2	8.4	0.5	100
2008q1	3	1.4	16.1	66.3	14.1	2.0	100
2008q3	4	5.2	21.4	58.8	12.9	1.7	100
2009q1	5	6.9	24.9	47.6	18.3	2.3	100
2009q3	6	3.2	16.2	53.3	24.1	3.2	100
2010q1	7	1.7	19.2	52.6	22.4	4.1	100
2010q3	8	2.5	18.5	57.8	18.8	2.4	100
2011q1	9	2.5	17.6	63.1	13.2	3.6	100
2011q3	10	3.1	19.2	64.6	11.1	1.9	100
2007q3–2011q3	Total	3.3	19.1	58.3	16.7	2.6	100

Note: This table shows the distribution of firms by the size of the forecast error derived from the question on the overall situation of the firm. The forecast error is divided into five categories and ranges from FE -2 (realized situation worse than expected) to FE 2 (realized situation better than expected). The columns show the percentage share of firms which made the respective forecast error for each wave and, in the lowest row, across the whole sample period from 2007Q3 to 2011Q3. Since 2007q1 has been the first wave and we do not have expectations for the preceding quarter, the forecast errors can only be calculated starting from 2007Q3. For visibility, numbers we specifically refer to in the text are depicted in bold.

This demonstrates that during tranquil times, a large number of firms predict the future well. When a shock is occurring, firms do not immediately adjust expectations and forecast errors increase. This underreaction might be due to information frictions as proposed by Coibion and Gorodnichenko (2012, 2015). Forecast errors evolve in the course of crisis times as follows: at the beginning of a crisis, firms are too optimistic, while in the aftermath of the crisis, they become too pessimistic and overreact once bad shocks accumulate. A possible explanation for such overreaction in the aftermath of financial crises could be that firms change their beliefs about the probability of being in a distress period. For example, Gennaioli et al. (2015) show in a theoretical model that only a sequence of bad news causes a change in

investors' beliefs. However, as soon as investors adapt their beliefs, the adjustment is relatively strong and investors overreact. The pattern of forecast errors derived from our data is in line with the findings by Massenet and Pettinicchi (2018). Using the Ifo business survey of manufacturing firms in Germany, these authors find evidence for overoptimism and overpessimism evolving with the business cycle.

We use the *firm-level* data and derive three cross-sectional measures at the *aggregate level* to provide further evidence that the survey responses as well as the way the forecast error is computed deliver reliable information. In line with the related literature, higher uncertainty is thereby assumed to be reflected by, on average, larger and/or more disperse forecast errors/expectations across firms.¹¹ Figure 2 shows that aggregate uncertainty measures computed based on the survey data increase with the onset of the financial crisis and until 2008/2009 before declining again.¹² For comparability with other commonly used uncertainty measures, we also depict stock market volatility of the DAX. It can be seen that the time pattern of the uncertainty measures derived from our survey data closely tracks the development of stock market volatility. This finding supports results by Tanaka et al. (2020) showing for Japanese survey data that the average of firms' absolute forecast errors evolves similar to stock market volatility.

2.3 | Investment responses

Firms' ability to forecast and the level of uncertainty might transmit to investment behavior. To obtain a first visual impression of the relation between aggregate uncertainty and investment, we plot the mean absolute forecast error and the cross-sectional dispersion of the forecast error against the percentage change in gross investments in Germany using data from the German federal statistical office (Figure 3). Similar to related work, our aggregate measures for uncertainty derived from survey data are countercyclical (Bachmann et al., 2013; Bloom, 2014).¹³ However, less evidence exists on the link between investment and firm-specific forecast error once accounting for the surprise and uncertainty components.

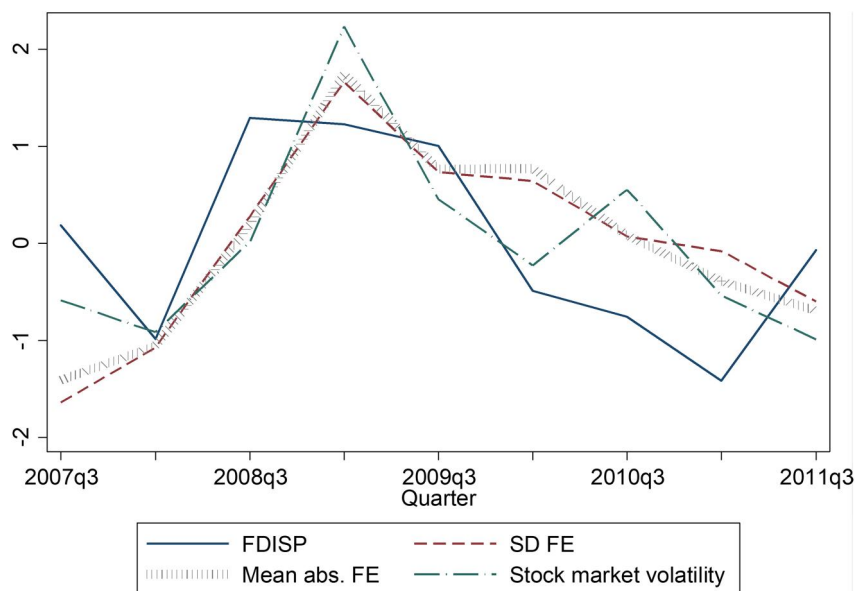


FIGURE 2 Aggregate uncertainty measures across time. This figure shows the three different measures for aggregate uncertainty which are calculated as follows: First, we compute firms' forecast errors (FE). It compares the expected situation with the realized situation one period later. Second, we take the mean of the absolute forecast error (*Mean abs. FE*, gray dotted line) and the standard deviation across these firm-specific forecast errors (*SD FE*, red dashed line). Alternatively, we show the forecast dispersion (*FDISP*, blue solid line) which measures the dispersion of expectations across all firms in each period (Bachmann et al., 2013). All of these series are standardized (zero mean, unit standard deviation). The green dashed line is the VDAX volatility index as obtained from Datastream [Colour figure can be viewed at wileyonlinelibrary.com]

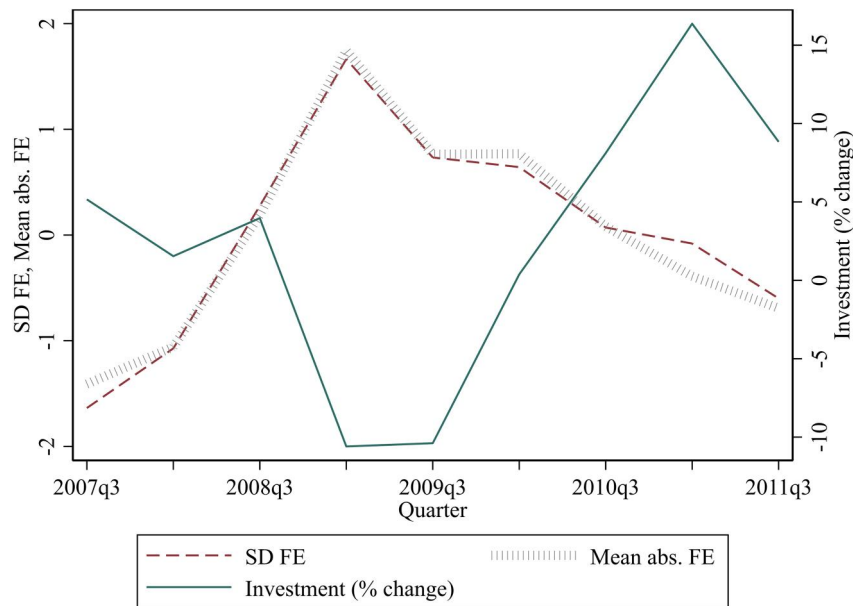


FIGURE 3 Survey based uncertainty measures and investment. This figure shows the pattern of the aggregate uncertainty measures derived from the survey responses and the evolution in the volume of gross investment (percentage change, year-on-year). The standardized uncertainty measures (left axis) comprise the mean absolute forecast error (gray, dotted line) and the standard deviation of firms' forecast errors (red, dashed line). The change in the investment volume is depicted by the green, solid line (right axis applies). Information on the volume of gross investment in billion Euros for the non-governmental sector is obtained from the German federal statistical office (www.destatis.de/EN) [Colour figure can be viewed at wileyonlinelibrary.com]

Figure 4 relates the investment propensity to the size of the firm's forecast error regarding its overall economic situation. A reduction in planned investment volumes compared to the previous year is coded with a minus (−/−−), zero stands for no change (0), and a plus sign indicates an increase in planned investment volumes (+/++). The forecast error measures the difference between the expected and realized economic situation. Therefore, negative values signal that the actual situation was worse than expected (FE −2 and FE −1), and positive values signal that the actual situation was better than expected (FE 1 and FE 2).

The fraction of firms that intend to reduce investment compared to the previous year is higher if the forecast error is negative, meaning that firms were too optimistic regarding future development (upper left panel).¹⁴ However, the converse does not hold true: firms with a positive forecast error do not decide to increase investment relatively more (lower right panel). This suggests that the negative experience of being too optimistic ex-ante makes firms more uncertain and more reluctant to increase planned investment ex-post. Meanwhile, firms that experience a better outcome than expected are unlikely to project this “positive surprise” into the future by increasing their investment. The sheer fact that a firm made an error in its forecast—even when the actual realization turns out to be better than expected—dampens or at least does not increase the investment propensity. This *asymmetric* relation between forecast error and investment response hints at a possible interaction of the surprise and uncertainty components, and the next section studies whether these patterns can be validated using a regression framework.¹⁵

3 | REGRESSION DESIGN AND RESULTS

In this section, we present the econometric model to analyze whether firms' forecast errors relate to investment propensity, and how the surprise and uncertainty components interact when it comes to investment decisions. We start with a baseline model in which the expected change in the investment volume is the dependent variable and our explanatory variable of interest is the firm's absolute forecast error. We then disaggregate the forecast error into positive and negative components to verify the existence of asymmetric effects. Finally, we use firms' perceived stability of expectations as an ex-ante measure of uncertainty and conduct further robustness tests regarding, for example, alternative mechanisms likely to produce asymmetric investment responses such as financial frictions.

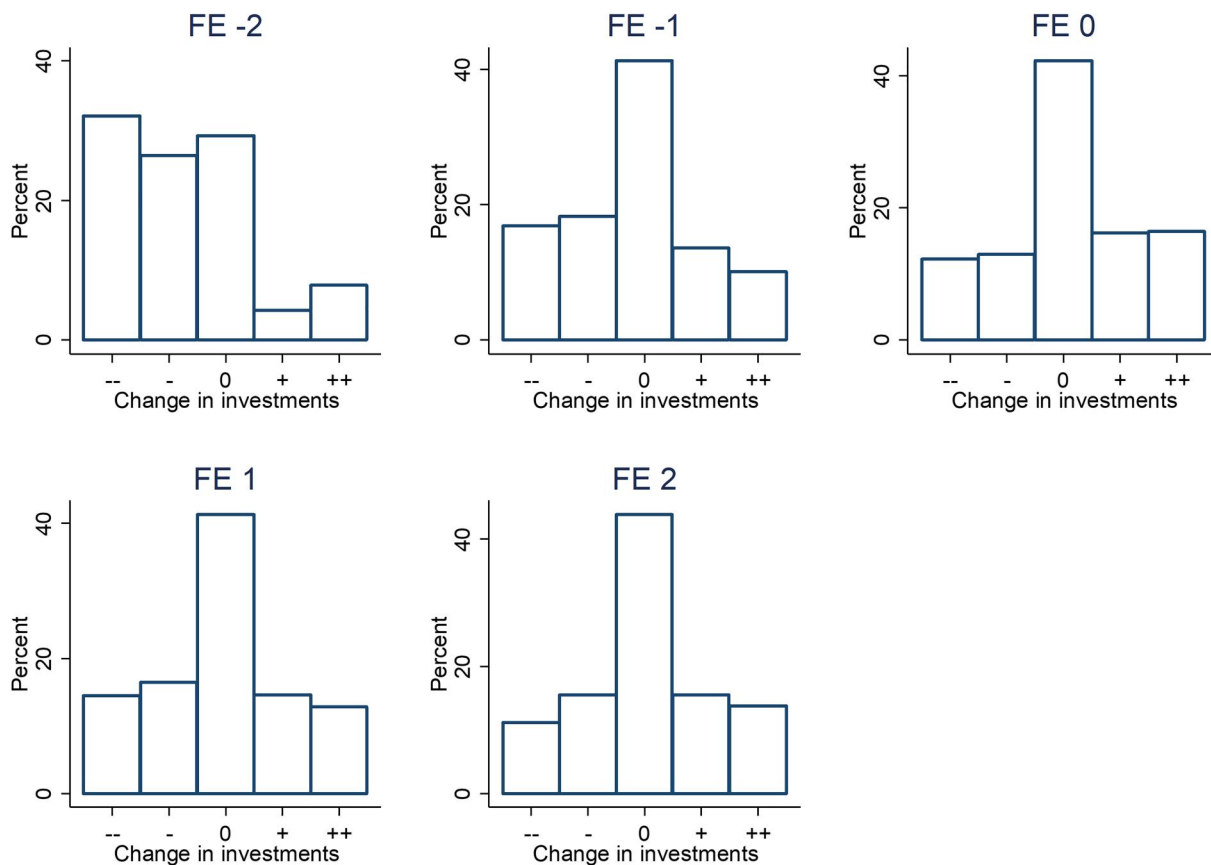


FIGURE 4 Planned investment change by size of forecast error regarding overall economic situation. This figure shows the distribution of firms' planned changes in investment compared to the previous business year for different sizes of the firm-specific forecast error based on the question on the firm's overall economic situation. A (strong) reduction in planned investments corresponds to minus (−/−−), zero stands for no change (0), and plus for a (strong) increase in planned investments (+/++). The forecast error measures the difference between the actually realized situation in t and the expected economic situation in $t - 1$ for period t . Negative values signal that the realized situation was worse than expected (FE −2 and FE −1), positive values signal that the realized situation was better than expected (FE 1 and FE 2) [Colour figure can be viewed at wileyonlinelibrary.com]

3.1 | The effect of firms' forecast errors on investment

To analyze the relation between firm-specific forecast errors and investment, we use an ordered probit regression framework and set up the following empirical model¹⁶:

$$Investment_{i,t} = \alpha + \delta' * CUR_{i,t} + \lambda' * EXP_{i,t} + \sigma * FirmRev_{i,t} + \gamma * RiskAttitude_{i,t} + \beta * Abs. FE_{i,t} + \tau_t + \omega_j + \epsilon_{i,t} \quad (1)$$

where $Investment_{i,t}$ is our dependent variable, denoting the expected change in the investment volume of firm i in period t measured on an ordinal scale. This scale has five outcome categories and ranges from a (strong) decrease to no change to a (strong) increase.

One limitation of the survey is that we have no information on realized investment volumes, only on the firm's assessment of changes in the investment volume. While realized investment would be a nice complement, correctly modeling the link between uncertainty today and realized—but most likely delayed—investment volumes is not straightforward due to confounding factors. Hence, relating firm-specific forecast errors to qualitative but immediate reactions of firms regarding their investment decisions can be of advantage from an identification perspective. This holds as long as the qualitative variable contains information that is actually reflected in future investment volumes, that is, if managers “put the plan into action.” Comparing the average investment response in the survey and realized changes in gross investments in the German non-governmental sector shows that the survey responses are a good predictor of realized investment volumes at the aggregate level.¹⁷

Our main explanatory variable is the firm's forecast error, $Abs. FE_{i,t}$, and we take the absolute value of the five category forecast error.¹⁸ Hence, higher values indicate a larger forecast error, that is, the actual situation differs more from the expected one. We expect that firms that learn in period t that they made a larger absolute forecast error with respect to their expectations in period $t - 1$ are less likely to invest in period t . This might occur because they become more careful after having realized their misjudgment.

To ensure that the estimated coefficient of the forecast error reflects the relation between firm-specific forecast error and investment and is not distorted by the effect of other factors, we include a set of control variables. Most importantly, we control for the firm's *Risk Attitude* $_{i,t}$. In the baseline specification, we use firms' current risk attitude. The variable has five outcome categories, where higher values indicate that firms are more willing to take risks. In robustness tests, we also control for the expected change in risk attitude. We expect that the higher the risk attitude of firms, the more likely they will increase their investment. If firms are risk-averse and returns are uncertain, they might delay current investments (Panousi & Papanikolaou, 2012).

Additionally, we include a vector of firm-level controls that capture firms' current ($CUR_{i,t}$) and expected ($EXP_{i,t}$) assessments of key business conditions and economic variables, namely, competition, financing possibilities, cost of raw materials and inputs, and the overall economic situation in Germany. The inclusion of these variables capturing current assessment and expectations allows us to disentangle the role of firm-specific forecast errors from the immediate effect of economic conditions on investment decisions as well as from the current impact of large shocks or tail events on firms' expectations and consequently their investment behavior (Orlik & Veldkamp, 2014; Ranci re et al., 2008). The variable $FirmRev_{i,t}$ indicates the approximate revenue and is grouped in five different categories (see Online Appendix, Table B3).¹⁹ Firm revenue is highly correlated with the number of employees such that this variable should capture both firms' financial revenues and size. It thus controls for firm-specific characteristics that are potentially related to firms' ability to forecast.

The baseline model is augmented by sector fixed effects ω_j and time fixed effects τ_t . This allows us to control for sector-specific characteristics that are common to all firms in that sector as well as aggregate dynamics that affect all firms alike. Standard errors are clustered by firm and alternatively by sector.

Our results yield new insights regarding the relation between firm investment and firm-specific forecast errors. Certainly, the survey data limit the scope to easily identify causal effects, for example, as we do not observe firm-specific balance sheet data. However, we exploit several options to extract confounding factors, by for example including time fixed effects, and to establish a clear link between firm-specific forecast errors and investment decisions. For example, there can be an endogenous interaction between firm-specific beliefs and economic activity as shown by Fajgelbaum et al. (2017). The timing of our variables might not fully eliminate such concerns, but helps reducing them substantially. From the perspective of firm i , its investment plan is unlikely to drive aggregate outcomes, and thus channel back to firm-specific uncertainty. Furthermore, simultaneity concerns are mitigated, as the dependent variable gives information about *planned* behavior: The firm will probably not contribute to aggregate investment until the next period when it will have implemented its plans. In addition, a reverse effect from firms' assessment of their *future* investment volume to the already determined forecast error seems unlikely. A further supporting factor is that our sample period starts with the financial crisis period, which constitutes an unexpected shock and thus introduces some exogenous element. The latter certainly affects forecasts errors significantly and in an unexpected way and thus helps investigating the relation with firms' investment propensity.

3.1.1 | Baseline specification

Table 3a shows results for the baseline specification, including the forecast error in absolute terms, which ranges from zero (the situation at time t is equal to the expected situation at time $t - 1$) to two (the situation at time t is better/worse than the expected situation at time $t - 1$). It can be seen that a higher value of the absolute forecast error relates negatively to the propensity to invest. The coefficient of the absolute value of firm-specific forecast errors remains negative and significant if we control for time and sector fixed effects (Column 2). In case we cluster standard errors at the sector level controlling for possible error correlation across firms within a sector, the coefficient of the forecast error remains significant at the 5% level (Column 3). To obtain information on the quantitative impact, Table 3b shows marginal effects of the forecast error according to the outcome category of the investment response.²⁰ The results show that a one-unit-larger absolute forecast error reduces the probability to invest more by 1.8 percentage points, on average (Column 5).

We also obtain significant results for the other control variables. A currently (or expected) more favorable competitive situation, a good financing situation, and a good situation of the German economy are positively related to

TABLE 3 Investment propensity and forecast error

(a) Regression results						
Main expl. variable	Absolute FE			Asymmetric FE		
	(1)	(2)	(3)	(4)	(5)	(6)
Current situation						
Competition	0.082*** (0.026)	0.075*** (0.027)	0.075* (0.041)	0.075*** (0.026)	0.064** (0.027)	0.064 (0.041)
Financing	0.190*** (0.025)	0.187*** (0.026)	0.187*** (0.026)	0.186*** (0.025)	0.180*** (0.026)	0.180*** (0.027)
Cost of material	-0.107*** (0.024)	-0.072*** (0.027)	-0.072*** (0.021)	-0.109*** (0.024)	-0.070** (0.027)	-0.070*** (0.022)
German economy	0.198*** (0.025)	0.125*** (0.029)	0.125*** (0.028)	0.193*** (0.025)	0.113*** (0.029)	0.113*** (0.029)
Expected change						
Competition	0.090*** (0.032)	0.093*** (0.034)	0.093*** (0.031)	0.095*** (0.032)	0.101*** (0.034)	0.101*** (0.030)
Financing	0.126*** (0.033)	0.111*** (0.035)	0.111*** (0.031)	0.129*** (0.033)	0.116*** (0.035)	0.116*** (0.030)
Cost of material	-0.053** (0.025)	-0.035 (0.027)	-0.035* (0.018)	-0.051** (0.025)	-0.033 (0.027)	-0.033* (0.019)
German economy	0.053* (0.027)	0.041 (0.031)	0.041 (0.026)	0.055** (0.028)	0.048 (0.031)	0.048* (0.027)
Firm controls						
Revenue	-0.058*** (0.016)	-0.040** (0.017)	-0.040* (0.022)	-0.057*** (0.016)	-0.038** (0.017)	-0.038* (0.022)
Risk and FE						
Risk attitude	0.185*** (0.021)	0.188*** (0.022)	0.188*** (0.026)	0.187*** (0.021)	0.192*** (0.022)	0.192*** (0.026)
Absolute FE	-0.088*** (0.031)	-0.080** (0.033)	-0.080** (0.034)			
Forecast error <0				-0.160*** (0.039)	-0.177*** (0.041)	-0.177*** (0.045)
Forecast error ≥0				-0.010 (0.039)	0.026 (0.042)	0.026 (0.034)
Observations	3636	3308	3308	3636	3308	3308
Pseudo R-squared	.07	.08	.08	.07	.08	.08
SE clustered by sector	-	-	x	-	-	x
Sector-fixed effects	-	x	x	-	x	x
Time-fixed effects	-	x	x	-	x	x

TABLE 3 (Continued)

(b) Marginal effects of absolute forecast error					
Outcome category	(1) Strong decrease	(2) Decrease	(3) No change	(4) Increase	(5) Strong increase
Absolute forecast error	0.017*** (0.006)	0.010*** (0.004)	0.001 (0.001)	-0.010*** (0.003)	-0.018*** (0.006)
Observations	3636	3636	3636	3636	3636
(c) Marginal effects of asymmetric forecast error					
Outcome category	(1) Strong decrease	(2) Decrease	(3) No change	(4) Increase	(5) Strong increase
Forecast error <0	0.031*** (0.008)	0.018*** (0.004)	0.001 (0.001)	-0.017*** (0.004)	-0.033*** (0.008)
Forecast error ≥0	0.002 (0.007)	0.001 (0.004)	0.000 (0.000)	-0.001 (0.004)	-0.002 (0.008)
Significantly different:	Yes	Yes	No	Yes	Yes
<i>p</i> -Value	.001	.001	.219	.002	.001
Observations	3636	3636	3636	3636	3636

Note: (a): Dependent variable is the change in investment measured on an ordinal 5 categories scale. A (strong) reduction in investments corresponds to minus (-/-), zero stands for no change (0), and plus for a (strong) increase in investments (+/++). In columns 1–3, independent variable is the forecast error in absolute terms, such that higher values indicate a larger forecast error, that is, the actual situation is different than the expected one. In columns 4–6, we make a distinction between a forecast error that is greater than or equal to zero and negative forecast errors. We control for a set of variables (competition, financing, cost of material, German economy) regarding the current situation and the expected change, both are also measured on a 5 category scale, where the lowest outcome stands for a very bad situation/strong worsening and the highest outcome for a very good situation/strong improvement. Furthermore, we control for the revenue and the risk attitude. We include no fixed effects, or sector and time fixed effects as indicated at the bottom of the table. The time span reaches from 2007 until 2011. Standard errors (SE) are clustered by firm and depicted in parentheses, except for columns 3 and 6, where standard errors are clustered by sector. The *p*-values are as follows: ****p* < .01, ***p* < .05, **p* < .1. (b): This table shows marginal effects of the absolute forecast error on investment across all outcome categories of investment. The marginal effects are shown for the regression model without any fixed effects (Table 3a, column 1). The standard errors are clustered by firm and depicted in parentheses. The *p*-values are as follows: ****p* < .01, ***p* < .05, **p* < .1. (c): This table shows marginal effects of the forecast error on investment across all outcome categories of investment for negative forecast errors and zero/positive forecast errors separately. The marginal effects are shown for the regression model without any fixed effects (Table 3a, column 4). Wald tests are used to test whether marginal effects are significantly different. The standard errors are clustered by firm and depicted in parentheses. The *p*-values are as follows: ****p* < .01, ***p* < .05, **p* < .1.

investment. A negative sign is obtained for improvements in costs of material or higher firm revenue. It is to note that lower (expected) material costs are reflected in a higher value of the variable (as firms positively evaluate the (expected) situation with regard to material costs). The former finding can, on the one hand, imply that firms use their funds to buy material (instead of investing) when material costs are low. On the other hand, it might capture a business cycle component in the sense that material costs go down in crisis times, and so does investment.²¹ The latter finding suggests that it is rather the smaller firms with lower levels of revenue that are more likely to expand and thus invest. As expected, risk attitude has a positive and significant coefficient. Thus, less risk-averse firms show a higher investment propensity. Again, the results do not vary much depending on the choice of fixed effects or the clustering of standard errors. Thus, when controlling for a firm's current and expected situation, its revenue, and sector as well as time fixed effects, we find a significantly negative link between the firm-specific forecast error and investment responses. Following the graphical results in Section 2.3 about the asymmetric relation between investment responses and positive/negative forecast errors, we extend the analysis and disaggregate the forecast error accordingly.

3.1.2 | Disaggregated forecast error and asymmetric investment response

To evaluate what drives the significant coefficient of the forecast error and based on our findings on asymmetric patterns in Section 2.3, we decompose the forecast error. To do so, we control for cases in which the forecast error has been larger or equal to zero (Forecast error ≥ 0) by specifying an indicator variable that is one in these cases and zero

otherwise ($Indicator^{>0}$). In addition, we control for cases in which the forecast error has been smaller than zero (Forecast error < 0) by interacting the absolute forecast error with a correspondingly defined indicator variable ($Indicator^{<0}$).²² The regression model then looks as follows:

$$Investment_{i,t} = \alpha + \delta' * CUR_{i,t} + \lambda' * EXP_{i,t} + \sigma * FirmRev_{i,t} + \gamma * RiskAttitude_{i,t} + \beta_1 * Indicator^{<0} * Abs. FE_{i,t} + \beta_2 * Indicator^{>0} * Abs. FE_{i,t} + \tau_t + \omega_j + \epsilon_{i,t} \quad (2)$$

In doing so, we can disentangle the heterogeneous relation between firm-specific forecast errors and investment depending on whether firms have over- or underestimated the situation. For the interpretation, it is important to note that we still consider the absolute forecast error of the firm; we just differentiate between periods depending on the sign of the forecast error. Otherwise, the regression model remains the same as specified for Equation (1).

Disaggregating the forecast error helps explore how different components of the forecast error interact. If a firm realizes a forecast error, this means that the actual outcome differs from the expected outcome. From this, the firm infers two things:

- Surprise component: expectations regarding business conditions were too pessimistic (positive forecast error) or too optimistic (negative forecast error). How will the firm react? It is plausible to assume that in the first case, the firm tends to increase investment to take advantage of unexpectedly favorable business conditions; in the second case, it would rather reduce investment in the face of unexpectedly poor business conditions.
- Uncertainty component: the firm realizes that its forecast was wrong such that its predictability of future business conditions might have decreased, and thus uncertainty with respect to future outcomes has increased. Based on the concept of uncertainty and the empirical results in the literature, we would expect the firm to decrease investment in the light of higher uncertainty—for example, due to the “wait and see” motive.

Based on this, we conjecture that given a negative forecast error, both the surprise and the uncertainty components work in the same direction with negative implications for investment. In case of a positive forecast error, the surprise and the uncertainty components work in *opposite* directions. Eventually, this means that if the (positive) surprise component dominates, we would expect investment propensity to increase. If the uncertainty component prevails, investment would rather decrease.

Column 4 shows that the coefficient of the forecast error is significantly negative when the actual situation is worse than expected ($FE < 0$) and the result remains robust when adding fixed effects or clustering standard errors at the sector level. Table 3c (upper panel) shows the marginal effects for the negative forecast error by outcome category of the investment variable. A negative forecast error increases the probability to decrease investment by 3.1 percentage points (Column 1). In contrast, no significant result is obtained for a positive forecast error ($FE \geq 0$), and the marginal effects are not significant. Hence, we can confirm that firms' investment propensity shows an *asymmetric pattern depending on the size and direction of the forecast error*.

This suggests that the significant result found in the baseline specification is mostly driven by negative realizations of the forecast error, which is corroborated by the fact that the marginal effects for the variables *Forecast error* < 0 and *Forecast error* ≥ 0 are significantly different from each other at the 1% level across all possible outcomes of the dependent variable except for the outcome category “no change” (Table 3c). The combination of negative surprises coming in, which yields a negative forecast error, and revealed ex-post uncertainty due to a wrong forecast made in the previous period significantly reduces the probability that firms invest more. By contrast, and similar to Forni et al. (2017), the result suggests that positive surprises or news shocks are compensated by the uncertainty component inherent in a larger forecast error. If the actual situation is better than expected, this does not cause firms to become more optimistic and to invest more. Instead, it seems that firms become more careful due to their incorrect forecast as they perceive a decrease in their ability to forecast. Hence, the well-documented “wait and see” effect of an increase in uncertainty compensates the positive signal of a better-than-expected outcome.²³

The descriptive statistics have shown that positive forecast errors occur predominantly in the aftermath of financial crises (Table 2). If firms become too pessimistic as a response to crisis times, which in turn reduces their investment propensity through the uncertainty channel, this might be one explanation behind the phenomenon of slow recovery in the aftermath of financial crises (Reinhart & Rogoff, 2014). This is in line with the finding of quantitative models that the impact of policy measures is dampened if uncertainty is higher due to firms becoming more cautious (Bloom et al., 2018).²⁴

In this context and regarding external validity, it is important to note that Germany adopted a number of (fiscal) policy measures to stimulate the economy during the crisis. Additionally, the German economy recovered relatively quickly after the global financial crisis compared to other European countries or the USA. Nevertheless, we find a significant relation between firm-specific forecast errors and firms' willingness to invest. This might be because our sample covers mostly smaller firms that had less flexibility in adjusting during the crisis and became more careful in the aftermath of the crisis than the larger export-oriented firms. Nevertheless, Germany might still reflect a lower bound, and in countries more affected by the financial crisis, we would expect stronger effects of firm-specific forecast errors that explain staggered investment in the aftermath of the economic downturn.

3.1.3 | Stability of expectations

Finally, we make use of a unique feature of the survey to corroborate that the forecast error contains an uncertainty component. More specifically, we use the survey responses to the question on the stability of expectations, which provides us an *ex-ante* measure of (perceived) uncertainty from the perspective of the firm. The variable has five possible outcomes and ranges from minus (−/−−) if the stability of expected developments is judged as (very) instable to plus (+/++) if it is evaluated as (very) stable. Table 4a shows that a higher stability of expectations increases the probability to invest more. Hence, if firms believe their expectations are stable, this *ex-ante* certainty translates into increased investment. Table 4b presents marginal effects that are significant across all outcome categories of the

TABLE 4 Stability of expectations as *ex-ante* firm-specific uncertainty

(a) Regression results						
Dependent variable	Investment propensity			Stability of expectations		
	(1)	(2)	(3)	(4)	(5)	(6)
Current situation						
Competition	0.050*** (0.019)	0.048** (0.020)	0.048** (0.022)	0.213*** (0.029)	0.215*** (0.032)	0.215*** (0.026)
Financing	0.118*** (0.018)	0.119*** (0.019)	0.119*** (0.019)	0.277*** (0.027)	0.278*** (0.028)	0.278*** (0.031)
Cost of material	−0.089*** (0.018)	−0.055*** (0.020)	−0.055*** (0.018)	0.034 (0.025)	0.044 (0.028)	0.044* (0.026)
German economy	0.186*** (0.018)	0.111*** (0.021)	0.111*** (0.022)	0.268*** (0.027)	0.249*** (0.032)	0.249*** (0.020)
Expected change						
Competition	0.060*** (0.022)	0.055** (0.024)	0.055*** (0.019)	0.080*** (0.031)	0.068** (0.032)	0.068*** (0.022)
Financing	0.158*** (0.024)	0.131*** (0.026)	0.131*** (0.020)	0.075** (0.033)	0.065* (0.034)	0.065** (0.030)
Cost of material	−0.039** (0.018)	−0.003 (0.020)	−0.003 (0.019)	−0.043* (0.025)	−0.043 (0.027)	−0.043*** (0.016)
German economy	0.057*** (0.019)	0.047** (0.022)	0.047*** (0.017)	0.054* (0.029)	0.061* (0.032)	0.061** (0.026)

(Continues)

TABLE 4 (Continued)

(a) Regression results						
Dependent variable	Investment propensity			Stability of expectations		
	(1)	(2)	(3)	(4)	(5)	(6)
Firm controls						
Revenue	-0.060*** (0.011)	-0.053*** (0.013)	-0.053*** (0.014)	0.105*** (0.018)	0.115*** (0.020)	0.115*** (0.013)
Risk and FE						
Risk attitude	0.169*** (0.015)	0.170*** (0.016)	0.170*** (0.020)	0.091*** (0.023)	0.103*** (0.024)	0.103*** (0.026)
Stability of expectations	0.186*** (0.019)	0.184*** (0.020)	0.184*** (0.015)			
Absolute FE				-0.129*** (0.034)	-0.107*** (0.036)	-0.107** (0.043)
Observations	6959	5991	5991	3604	3279	3279
Pseudo R-squared	.07	.08	.08	.13	.14	.14
SE clustered by sector	-	-	x	-	-	x
Sector-fixed effects	-	x	x	-	x	x
Time-fixed effects	-	x	x	-	x	x
(b) Marginal effects of stability of expectations						
Outcome category	(1) Strong decrease	(2) Decrease	(3) No change	(4) Increase	(5) Strong increase	
Stability of expectations	-0.036*** (0.004)	-0.019*** (0.002)	-0.003*** (0.001)	0.019*** (0.002)	0.040*** (0.004)	
Observations	6959	6959	6959	6959	6959	
(c) Marginal effects of absolute forecast error						
Outcome category	(1) Very instable	(2) Instable	(3) Indifferent	(4) Stable	(5) Very stable	
Absolute forecast error	0.006*** (0.002)	0.019*** (0.005)	0.017*** (0.004)	-0.027*** (0.007)	-0.015*** (0.004)	
Observations	3604	3604	3604	3604	3604	

Note: (a): In columns 1–3, dependent variable is the change in investment measured on an ordinal 5 categories scale. A (strong) reduction in investments corresponds to minus (–/–), zero stands for no change (0), and plus for a (strong) increase in investments (+/++). Independent variable is the stability of expectations (5 categories). (Very) unstable expectations correspond to minus (–/–), zero stands for moderate stability (0), and plus for (very) stable expectations (+/++). In columns 4–6, the stability of expectations is the dependent variable (5 categories). Independent variable is the forecast error in absolute terms, such that higher values indicate a larger forecast error, that is, the actual situation is different than the expected one. We control for a set of variables (competition, financing, cost of material, German economy) regarding the current situation and the expected change, both are also measured on a 5 category scale, where the lowest outcome stands for a very bad situation/strong worsening and the highest outcome for a very good situation/strong improvement. Furthermore, we control for the revenue and the risk attitude. We include no fixed effects, or sector and time fixed effects as indicated at the bottom of the table. The time span reaches from 2007 until 2011. Standard errors (SE) are clustered by firm and depicted in parentheses, except for columns 3 and 6, where standard errors are clustered by sector. The p -values are as follows: *** $p < .01$, ** $p < .05$, * $p < .1$. (b): This table shows marginal effects of the ex-ante firm-specific uncertainty measure captured by the stability of expectations on investment across all outcome categories of investment. The marginal effects are shown for the regression model without any fixed effects (Table 4a, column 1). The standard errors are clustered by firm and depicted in parentheses. The p -values are as follows: *** $p < .01$, ** $p < .05$, * $p < .1$. (c): This table shows marginal effects of the absolute forecast error measure on the stability of expectations across all outcome categories of the variable stability of expectations. The marginal effects are shown for the regression model without any fixed effects (Table 4a, column 4). The standard errors are clustered by firm and depicted in parentheses. The p -values are as follows: *** $p < .01$, ** $p < .05$, * $p < .1$.

investment variable. A higher stability of expectations about future developments thus increases the probability to increase investment by 4 percentage points (Column 5).

Thus, the results obtained from an *ex-ante* measure of firm-specific uncertainty point in the same direction and are consistent with those obtained from our *ex-post* measure, that is, the forecast error. To further validate the concordance of both the *ex-ante* and *ex-post* measures, we use the stability of expectations as the dependent variable in our regression framework. The results in columns 4–6 of Table 4 show that the absolute forecast error has a negative and highly significant coefficient. We take this as evidence that, first, there is a significant relationship between the *ex-ante* measure of uncertainty and the *ex-post* forecast error and that, second, firms that have a larger absolute forecast error are less likely to report stable expectations. This makes intuitive sense because if firms recognize that they have a larger absolute forecast error and thus a higher level of realized uncertainty, this is likely to erode the perceived stability in their expectations today.²⁵

In sum, we find that higher absolute forecast errors relate negatively to firms' investment propensity. We show that looking at the absolute forecast error is insufficient to trace heterogeneous effects. Once we disaggregate positive and negative forecast errors, the investment responses are asymmetric. Overestimations of future conditions relate negatively to the propensity to invest. Underestimations, however, do not improve the propensity to invest. This suggests that better-than-expected developments, or positive surprises, are counteracted by the effect of higher uncertainty reflected by a larger forecast error. We corroborate our finding that the forecast error contains an uncertainty component by relating it to firms' stability of expectations, which is an *ex-ante* measure of uncertainty.

3.2 | Alternative mechanisms

In this section, we discuss alternative mechanisms that could drive our results.²⁶ The literature on firm investment emphasizes the role of financial frictions. In particular, financing constraints bind more after bad shocks, which can also result in an asymmetric relation with firm investment decisions. Results by Alfaro et al. (2018), Arellano et al. (2019), as well as Gilchrist et al. (2014) point to financial frictions as a key mechanism through which fluctuations in uncertainty affect investment dynamics, both at the micro and the macro level. Furthermore, Veldkamp (2005) shows that after a downturn, recovery is slow because the level of information is low, and uncertainty is high, such that lending rates remain at elevated levels and investment remains reduced. To verify that our main results hold even when controlling for the possibility of financial constraints mattering for investment choices simultaneously, we extend our model. We include an interaction of the forecast error and firms' assessment of their financing situation, whereas higher values reflect a better financing situation.²⁷ Regression results containing such an interaction are shown in Table 5 for the absolute and asymmetric forecast errors, whereas the model is otherwise similar to the one presented in Table 3.

TABLE 5 Robustness tests—Financial constraints

(a) Regression results						
Main expl. variable	Absolute FE			Asymmetric FE		
	(1)	(2)	(3)	(4)	(5)	(6)
Current situation						
Competition	0.091*** (0.026)	0.085*** (0.027)	0.085** (0.043)	0.084*** (0.026)	0.074*** (0.027)	0.074* (0.043)
Financing	0.203*** (0.037)	0.196*** (0.039)	0.196*** (0.049)	0.206*** (0.037)	0.198*** (0.039)	0.198*** (0.049)
Cost of material	−0.103*** (0.024)	−0.066** (0.027)	−0.066*** (0.022)	−0.104*** (0.024)	−0.064** (0.027)	−0.064*** (0.023)
German economy	0.206*** (0.025)	0.130*** (0.029)	0.130*** (0.029)	0.201*** (0.025)	0.118*** (0.029)	0.118*** (0.030)

(Continues)

TABLE 5 (Continued)

(a) Regression results						
Main expl. variable	Absolute FE			Asymmetric FE		
	(1)	(2)	(3)	(4)	(5)	(6)
Expected change						
Competition	0.084*** (0.032)	0.086** (0.034)	0.086*** (0.031)	0.088*** (0.032)	0.094*** (0.034)	0.094*** (0.030)
Financing	0.141*** (0.032)	0.127*** (0.034)	0.127*** (0.031)	0.145*** (0.032)	0.132*** (0.034)	0.132*** (0.030)
Cost of material	-0.054** (0.025)	-0.035 (0.027)	-0.035* (0.019)	-0.052** (0.025)	-0.033 (0.027)	-0.033* (0.019)
German economy	0.050* (0.028)	0.039 (0.031)	0.039 (0.026)	0.052* (0.028)	0.046 (0.031)	0.046* (0.027)
Firm controls						
Revenue	-0.051*** (0.016)	-0.032* (0.017)	-0.032 (0.023)	-0.049*** (0.016)	-0.030* (0.017)	-0.030 (0.022)
Risk and FE						
Risk attitude	0.186*** (0.021)	0.189*** (0.022)	0.189*** (0.026)	0.188*** (0.021)	0.193*** (0.022)	0.193*** (0.027)
Absolute FE	-0.184 (0.118)	-0.186 (0.124)	-0.186 (0.117)			
Absolute FE × financing	0.031 (0.039)	0.035 (0.041)	0.035 (0.039)			
Forecast error <0				-0.243 (0.153)	-0.235 (0.159)	-0.235* (0.127)
Forecast error ≥0				-0.004 (0.147)	0.013 (0.157)	0.013 (0.149)
Forecast error <0 × financing				0.028 (0.053)	0.019 (0.056)	0.019 (0.044)
Forecast error ≥0 × financing				-0.003 (0.048)	0.003 (0.052)	0.003 (0.052)
Observations	3636	3308	3308	3636	3308	3308
Pseudo R-squared	.07	.08	.08	.07	.08	.08
SE clustered by sector	-	-	x	-	-	x
Sector-fixed effects	-	x	x	-	x	x
Time-fixed effects	-	x	x	-	x	x
(b) Marginal effects of forecast error conditional on financing						
Outcome category	(1) Strong decrease	(2) Decrease	(3) No change	(4) Increase	(5) Strong increase	
Financing: (very) bad	0.029*** (0.011)	0.013*** (0.005)	-0.008** (0.003)	-0.015*** (0.006)	-0.019** (0.008)	

TABLE 5 (Continued)

(b) Marginal effects of forecast error conditional on financing					
Outcome category	(1) Strong decrease	(2) Decrease	(3) No change	(4) Increase	(5) Strong increase
Financing: middle	0.018*** (0.006)	0.011*** (0.004)	0.000 (0.001)	-0.011*** (0.004)	-0.018*** (0.006)
Financing: (very) good	0.009 (0.008)	0.008 (0.007)	0.004 (0.004)	-0.006 (0.005)	-0.015 (0.013)
Observations	3636	3636	3636	3636	3636
(c) Marginal effects of asymmetric forecast error conditional on financing					
Outcome category	(1) Strong decrease	(2) Decrease	(3) No change	(4) Increase	(5) Strong increase
Marginal effect of forecast error < 0					
Financing: (very) bad	0.044*** (0.013)	0.020*** (0.006)	-0.011*** (0.004)	-0.023*** (0.007)	-0.030*** (0.009)
Financing: middle	0.031*** (0.008)	0.019*** (0.005)	0.001 (0.001)	-0.018*** (0.005)	-0.032*** (0.008)
Financing: (very) good	0.020* (0.012)	0.016* (0.009)	0.009* (0.005)	-0.013* (0.008)	-0.032* (0.018)
Marginal effect of forecast error ≥ 0					
Financing: (very) bad	0.003 (0.014)	0.001 (0.006)	-0.001 (0.004)	-0.001 (0.007)	-0.002 (0.010)
Financing: middle	0.003 (0.007)	0.002 (0.005)	0.000 (0.000)	-0.002 (0.004)	-0.003 (0.008)
Financing: (very) good	0.003 (0.010)	0.002 (0.008)	0.001 (0.004)	-0.002 (0.006)	-0.004 (0.016)
Observations	3636	3636	3636	3636	3636

Note: (a): Dependent variable is the change in investment measured on an ordinal 5 categories scale. A (strong) reduction in investments corresponds to minus (-/-), zero stands for no change (0), and plus for a (strong) increase in investments (+/+). In columns 1–3, independent variable is the forecast error in absolute terms, such that higher values indicate a larger forecast error, that is, the actual situation is different than the expected one. In columns 4–6, we make a distinction between a forecast error that is greater than or equal to zero and negative forecast errors. Compared to the baseline model, an interaction between the forecast error and firms' assessment about their financial situation is included, where the financing variable is set to have three outcomes: (very) bad; middle; (very) good, and higher values indicate a better financing situation. We control for a set of further variables regarding the current situation and the expected change measured on a 5 category scale, where the lowest outcome stands for a very bad situation/strong worsening and the highest outcome for a very good situation/strong improvement. Furthermore, we control for the revenue and the risk attitude. We include no fixed effects, or sector and time fixed effects as indicated at the bottom of the table. The time span reaches from 2007 until 2011. Standard errors (SE) are clustered by firm and depicted in parentheses, except for columns 3 and 6, where standard errors are clustered by sector. The p -values are as follows: *** $p < .01$, ** $p < .05$, * $p < .1$. (b): This table shows marginal effects of the absolute forecast error on investment across all outcome categories of investment and conditional on the assessment of the firm about the financial situation. The marginal effects are shown for the regression model without any fixed effects (Table 5a, column 1). The standard errors are clustered by firm and depicted in parentheses. The p -values are as follows: *** $p < .01$, ** $p < .05$, * $p < .1$. (c): This table shows marginal effects of the forecast error on investment across all outcome categories of investment and conditional on the assessment of the firm about the financial situation for negative forecast errors and zero/positive forecast errors separately. The marginal effects are shown for the regression model without any fixed effects (Table 5a, column 4). The standard errors are clustered by firm and depicted in parentheses. The p -values are as follows: *** $p < .01$, ** $p < .05$, * $p < .1$.

To evaluate the link between the forecast error and firms' investment propensity, we calculate marginal effects conditional on the financing situation. Table 5b shows that, as before, there is a negative relation between the absolute forecast error and investment. This link is particularly strong when financing constraints are present but also remains robust in periods in which firms have a rather neutral assessment of the financing situation. Hence, there seems to be

some enforcing effect of financial constraints on the role of the forecast error. To verify that the asymmetric result is not only due to a more pronounced role of financing constraints, we calculate marginal effects of the two components of the absolute forecast error, again conditional on the financing situation (Table 5c). It turns out, that as before, the link to firms' investment is driven by the negative part of forecast errors. When zooming into the upper panel of Table 5c, it becomes, however, evident that the significance does not depend on the financing situation being tight. In sum, while financial constraints enforce the negative relation between forecast error and investment, the asymmetric result also arises if firms are not financially constrained.

Furthermore, we test whether the established channel is truly independent to aggregate measures of volatility. We include first the measure for stock market volatility to Equation (1), which has the caveat that we can no longer control for time fixed effects, whereas the latter should be the most sophisticated way to control for aggregate developments interfering with our channel of interest. Results in Table 6 show that despite controlling for stock market volatility in columns 1–3, the firm-specific absolute forecast error keeps its sign and remains significant, which is also reflected in

TABLE 6 Stock market volatility

(a) Regression results						
Additional expl. variable	Stock market volatility			High vs. low stock market volatility		
	(1)	(2)	(3)	(4)	(5)	(6)
Current situation						
Competition	0.081*** (0.026)	0.073*** (0.027)	0.073* (0.040)	0.082*** (0.026)	0.074*** (0.027)	0.074* (0.040)
Financing	0.185*** (0.025)	0.190*** (0.026)	0.190*** (0.026)	0.185*** (0.025)	0.190*** (0.026)	0.190*** (0.026)
Cost of material	−0.085*** (0.025)	−0.090*** (0.026)	−0.090*** (0.020)	−0.086*** (0.025)	−0.091*** (0.027)	−0.091*** (0.020)
German economy	0.156*** (0.026)	0.161*** (0.027)	0.161*** (0.036)	0.158*** (0.026)	0.163*** (0.028)	0.163*** (0.036)
Expected change						
Competition	0.084*** (0.032)	0.098*** (0.033)	0.098*** (0.031)	0.083*** (0.032)	0.097*** (0.033)	0.097*** (0.031)
Financing	0.123*** (0.033)	0.114*** (0.034)	0.114*** (0.029)	0.124*** (0.033)	0.114*** (0.034)	0.114*** (0.029)
Cost of material	−0.035 (0.025)	−0.047* (0.026)	−0.047*** (0.016)	−0.032 (0.025)	−0.043 (0.027)	−0.043*** (0.016)
German economy	0.060** (0.028)	0.052* (0.029)	0.052** (0.026)	0.053* (0.028)	0.045 (0.030)	0.045* (0.026)
Firm controls						
Revenue	−0.054*** (0.016)	−0.048*** (0.017)	−0.048** (0.023)	−0.053*** (0.016)	−0.047*** (0.017)	−0.047** (0.023)
Risk and FE						
Risk attitude	0.186*** (0.021)	0.189*** (0.022)	0.189*** (0.026)	0.186*** (0.021)	0.189*** (0.022)	0.189*** (0.025)
Absolute FE	−0.080** (0.032)	−0.081** (0.033)	−0.081** (0.033)	−0.080** (0.032)	−0.080** (0.033)	−0.080** (0.034)

TABLE 6 (Continued)

(a) Regression results						
Additional expl. variable	Stock market volatility			High vs. low stock market volatility		
	(1)	(2)	(3)	(4)	(5)	(6)
Stock market volatility	-0.016***	-0.016***	-0.016***			
	(0.003)	(0.003)	(0.005)			
Stock market volatility \leq p90				-0.011**	-0.011**	-0.011*
				(0.004)	(0.005)	(0.006)
Stock market volatility $>$ p90				-0.014***	-0.014***	-0.014***
				(0.003)	(0.003)	(0.005)
Observations	3636	3308	3308	3636	3308	3308
Pseudo R-squared	.07	.07	.07	.07	.08	.08
SE clustered by sector	-	-	x	-	-	x
Sector-fixed effects	-	x	x	-	x	x
Time-fixed effects	-	-	-	-	-	-
(b) Marginal effects of absolute forecast error						
Outcome category	(1) Strong decrease	(2) Decrease	(3) No change	(4) Increase	(5) Strong increase	
Absolute forecast error	0.015**	0.009**	0.001	-0.009**	-0.016**	
	(0.006)	(0.004)	(0.001)	(0.003)	(0.006)	
Observations	3636	3636	3636	3636	3636	
(c) Marginal effects of high and low stock market volatility						
Outcome category	(1) Strong decrease	(2) Decrease	(3) No change	(4) Increase	(5) Strong increase	
Stock market volatility \leq p90	0.002**	0.001**	0.000	-0.001**	-0.002**	
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	
Stock market volatility $>$ p90	0.003***	0.002***	0.000	-0.001***	-0.003***	
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	
Significantly different:	No	No	No	No	No	
p-Value	.159	.160	.317	.160	.160	
Observations	3636	3636	3636	3636	3636	

Note: (a): Dependent variable is the change in investment measured on an ordinal 5 categories scale. A (strong) reduction in investments corresponds to minus (-/-), zero stands for no change (0), and plus for a (strong) increase in investments (+/++). Independent variable is the forecast error in absolute terms, such that higher values indicate a larger forecast error, that is, the actual situation is different than the expected one. Compared to the baseline model, in columns 1–3, a measure for stock market volatility (VDAX) is added to the model. In columns 4–6, we make a distinction between periods in which stock market volatility is below, respectively above the 90th percentile of the variable over the sample period. We control for a set of variables (competition, financing, cost of material, German economy) regarding the current situation and the expected change, both are also measured on a 5 category scale, where the lowest outcome stands for a very bad situation/strong worsening and the highest outcome for a very good situation/strong improvement. Furthermore, we control for the revenue and the risk attitude. We include no fixed effects, or sector fixed effects as indicated at the bottom of the table. The time span reaches from 2007 until 2011. Standard errors (SE) are clustered by firm and depicted in parentheses, except for columns 3 and 6, where standard errors are clustered by sector. The p -values are as follows: *** $p < .01$, ** $p < .05$, * $p < .1$. (b): This table shows marginal effects of the absolute forecast error on investment across all outcome categories of investment. The marginal effects are shown for the regression model without any fixed effects (Table 6a, column 1). The standard errors are clustered by firm and depicted in parentheses. The p -values are as follows: *** $p < .01$, ** $p < .05$, * $p < .1$. (c): This table shows marginal effects of the high versus low stock market volatility measure on investment across all outcome categories of investment. The marginal effects are shown for the regression model without any fixed effects (Table 6a, column 4). Wald tests are used to test whether marginal effects are significantly different. The standard errors are clustered by firm and depicted in parentheses. The p -values are as follows: *** $p < .01$, ** $p < .05$, * $p < .1$.

the marginal effects in Table 6b. The coefficient of stock market volatility is negative and highly significant. The result suggests that in periods of high aggregate volatility, firms are less likely to increase investment. However, their individually experienced forecast error still contains further information guiding firms' choices.

Second, we divide the stock market volatility measure into periods of low and high volatility, whereas high volatility is defined by a period in which stock market volatility is in the upper tail, that is, larger than its 90th percentile. In columns 4–6, our key result is maintained even when controlling for periods of low versus high stock market volatility. Higher stock market volatility relates negatively to investment propensity, while (and in contrast to the asymmetric forecast error), the marginal effects are not significantly different for low versus high volatility (Table 6c). Hence, also when conducting this horse race type of test, the coefficient of the firm-specific forecast error remains significant and negative.

3.3 | Further robustness tests

We conduct a number of additional tests to check the robustness of our results obtained from the baseline specification (1). Most importantly, despite ordered probit estimation fits well the categorical nature of the dependent variable, we conduct robustness tests relying on linear regression models. This approach has the advantage that firm fixed effects can be included. We do so for the baseline model containing the absolute forecast error as the main explanatory variable of interest and for the model revealing the asymmetric result. Table 7 shows that our results remain robust even when controlling for firm and time fixed effects (columns 1 and 3). Hence, these findings provide evidence that time-invariant, firm-specific characteristics that are not controlled for in ordered probit regressions are no major source of omitted variable bias. We also exploit that

TABLE 7 Robustness tests—Linear estimation

Main expl. variable	Absolute FE		Asymmetric FE	
	SE clustered by firm (1)	SE clustered by sector and time (2)	SE clustered by firm (3)	SE clustered by sector and time (4)
Current situation				
Competition	0.092** (0.036)	0.077* (0.043)	0.076** (0.036)	0.067 (0.043)
Financing	0.215*** (0.039)	0.186*** (0.035)	0.207*** (0.039)	0.179*** (0.034)
Cost of material	−0.120*** (0.033)	−0.072** (0.034)	−0.123*** (0.033)	−0.070** (0.034)
German economy	0.112*** (0.036)	0.125*** (0.032)	0.091** (0.036)	0.113*** (0.033)
Expected change				
Competition	0.074* (0.040)	0.090*** (0.029)	0.076* (0.040)	0.098*** (0.028)
Financing	0.087** (0.041)	0.109** (0.043)	0.087** (0.041)	0.114*** (0.042)
Cost of material	0.006 (0.033)	−0.034 (0.031)	0.008 (0.033)	−0.032 (0.030)
German economy	0.064* (0.035)	0.040 (0.038)	0.064* (0.035)	0.046 (0.039)

TABLE 7 (Continued)

Main expl. variable	Absolute FE		Asymmetric FE	
	SE clustered by firm (1)	SE clustered by sector and time (2)	SE clustered by firm (3)	SE clustered by sector and time (4)
Firm controls				
Revenue	-0.043 (0.052)	-0.040 (0.028)	-0.036 (0.051)	-0.038 (0.027)
Risk and FE				
Risk attitude	0.199*** (0.032)	0.189*** (0.021)	0.197*** (0.032)	0.192*** (0.022)
Absolute FE	-0.066* (0.039)	-0.083*** (0.026)		
Forecast error <0			-0.187*** (0.048)	-0.178*** (0.038)
Forecast error ≥0			0.067 (0.049)	0.023 (0.024)
Observations	3636	3308	3636	3308
R-squared	.16	.21	.17	.21
Firm-fixed effects	x	-	x	-
Sector-fixed effects	x	x	x	x
Time-fixed effects	x	x	x	x

Note: Dependent variable is the change in investment measured on an ordinal 5 categories scale, whereas the model is estimated with ordinary least squares. A (strong) reduction in investments corresponds to minus (-/--), zero stands for no change (0), and plus for a (strong) increase in investments (+/++). Independent variable is the absolute forecast error, and in columns 3 and 4, we make a distinction between a forecast error that is greater than or equal to zero and negative forecast errors. We control for a set of variables (competition, financing, cost of material, German economy) regarding the current situation and the expected change, both are also measured on a 5 category scale, where the lowest outcome stands for a very bad situation/strong worsening and the highest outcome for a very good situation/strong improvement. Furthermore, we control for the revenue and the risk attitude. In columns 1 and 3, the regressions include firm (and thus also sector) and time fixed effects. Standard errors are clustered at the firm level and depicted in parentheses. In columns 2 and 4, we include sector and time fixed effects. Standard errors are clustered by sector and time using two-way clustering and depicted in parentheses. The time span reaches from 2007 until 2011. The *p*-values are as follows: ****p* < .01, ***p* < .05, **p* < .1.

when using a linear model, we can simultaneously control for serial correlation of error terms across time and sector by estimating the model with two-way clustered standard errors.²⁸ Columns 2 and 4 show that results remain again robust.

We conduct further and more technical tests to investigate the robustness of the baseline result, which can be found in the Online Appendix. We repeat the analysis but change the estimation method (Table B5, columns 1–3). First, we use an ordered logit model and second, we estimate the regressions using a random effects ordered probit model. Column 3 shows results if we do not rescale answers; while column 4 is based on even stronger rescaling. This yields a forecast error with either nine or three categories. In column 5, we test whether truncation when calculating the forecast error matters for our results. Furthermore, we limit the sample period and use only observations starting from wave three. From then on, the survey questions and sample composition remain stable (Column 6). In column 7, we limit the estimation to the spring survey to control for the fact that in spring firms are still more likely to plan investment while in autumn their reporting might be already backward looking. In addition, we use the correlated random effects approach to control for the effect of unobserved heterogeneity at the firm level (Column 8).²⁹ Despite these changes, the coefficient of the absolute forecast error remains negative and significant.

To check the stability of our results regarding firms' revenues, we exchange the revenue variable with the achieved sales target (Table B6, column 1). Firms that have not achieved their sales target might be less willing to invest, as their

loss aversion increases and part of this effect might be hidden in the forecast error. Thus, it can be helpful to control for it. The variable has a positive coefficient, that is, firms having achieved their sales target are more likely to increase their investment. However, the effect seems to be of minor importance, as the coefficient is not significant and the result for the absolute forecast error remains significant. When controlling simultaneously for revenue, sales target and employees, the result remains robust (column 2).

The analysis has shown that firms' risk attitude is a significant driver of investment responses. In the case of firms' future investment propensity, both the current risk attitude and firms' expectations about their future risk attitude might be a driving factor. Thus, in Table B6, column 3, we do not control for firms' current risk attitude as done in our baseline regression; rather, we test the robustness of our results when controlling for the expected change in the risk attitude. As expected, the coefficient is positive and significant, reflecting that firms that are becoming less risk-averse are more likely to increase their investment.³⁰

To control for a firm's general forecasting pattern, we include its average forecast error (column 4). This captures whether a firm has been, on average, too pessimistic or too optimistic. However, these robustness tests do not change our main results, namely, that the absolute forecast error significantly undermines firms' willingness to invest.

Furthermore, to verify the asymmetric result for the forecast error, we run regressions only for those observations that show a negative (column 5) or positive (column 6) forecast error. Consistent with our previous results, we can confirm the asymmetric effect: the forecast error shows a negative and significant coefficient when we focus on the negative outcomes. However, the coefficient is insignificant if firms made a positive forecast error, that is, if the actual situation is better than expected.

4 | CONCLUDING REMARKS

This paper analyzes the relation between firm-specific forecast errors and investment behavior based on survey data of German manufacturing firms. We contribute to the literature by shedding light on the interaction between the surprise and uncertainty components inherent in the forecast error. Using data from the IWH risk climate survey offers several advantages. It spans a tranquil and a crisis period (2007–2011), it covers a large number of small and medium-sized firms, and it offers useful survey questions to study the role of firm-specific forecast errors for firms' propensity to invest.

In particular, we derive forecast errors regarding the overall economic situation of a firm and show that investment relates asymmetrically to larger absolute forecast errors: Larger and negative forecast errors, that is, firms facing the negative surprise that the actual situation is worse than expected accompanied by a larger uncertainty component, relate negatively to investment propensity. However, if forecast errors are positive and increasing, that is, the realized situation is better than expected, firms do not adjust their investment upward. Thus, the uncertainty component seems to compensate for the realization of unexpectedly favorable economic conditions (surprise component) such that we do not find firms to invest more. Given that the share of firms with positive forecast errors is higher in the aftermath of the crisis, this finding might explain the slow recovery following economic downturns. Firms remain too pessimistic after the peak of the crisis, which translates into positive forecast errors, and correlates with a higher reluctance to increase investment.

To validate our results and to corroborate that firms' forecast errors contain an uncertainty component, we show that the forecast error yields similar results as an ex-ante measure of uncertainty, which we obtain from the survey responses. We also document that both measures are correlated at the firm level suggesting that forecast errors do not only reflect a surprise component but also a firm-specific uncertainty component. In addition, our results remain robust to a set of various robustness tests.

Accounting for asymmetric effects of firm-specific forecast errors and separating the surprise from the uncertainty component might be an interesting avenue for future research regarding the extension of quantitative macroeconomic models. Furthermore, the study shows interesting dynamics of ex-ante and ex-post forecast errors, which could be explored further regarding the role of learning and expectations in prediction models and their implications for firm behavior.

ACKNOWLEDGMENTS

We thank four anonymous referees, Emmanuelle Auriol, Claudia M. Buch, Andrea Caggese, Valeriya Dinger, Steffen Elstner, Reint Gropp, Michael Koetter, Inge van den Bijgaart and seminar participants at the University of Osnabrück, the Martin-Luther-University Halle, the University of Magdeburg, the University of Duisburg-Essen, and the Annual Meeting of the German Economic Association 2016 for helpful comments as well as the Halle Institute for Economic

Research for providing the data. Hannes Böhm and Friederike Güttner have provided very efficient research assistance. All errors and inconsistencies are solely in our own responsibility.

Open access funding enabled and organized by Projekt DEAL.

CONFLICT OF INTEREST

None.

ENDNOTES

- ¹ While the literature usually finds a negative effect of uncertainty, there is less consensus about whether effects are of sizeable magnitude or not (e.g., Bachmann & Bayer, 2013; Bloom, 2009).
- ² Also in the asset pricing literature, time-varying risk premia have a long tradition, see, for example, Campbell and Cochrane (1999).
- ³ The survey was stopped in 2011 due to organizational changes within the institute.
- ⁴ An example of the survey containing all questions and answer options can be found in the Online Appendix.
- ⁵ Per wave, the data set contains 4302 entries, however, not all firms responded to the survey. The median response rate across all waves is 27%.
- ⁶ The random sampling procedure is based on the distribution of firms in the firm database “MARKUS” of Creditreform and in accordance with the number of firms per sector, firm size, and location in Eastern and Western Germany. Firms are anonymized such that no matching of firm-specific balance sheet data or income statements from other sources is possible.
- ⁷ Obviously, our results will not be representative for large German firms, for example, Ghosal and Loungani (2000) show that profit uncertainty has larger effects on investment in industries with a large share of smaller firms. The distribution of firms across subcategories of revenues and wave can be found in the Online Appendix (Table B3).
- ⁸ Summary statistics and correlations of the variables based on the regression sample (Table B1) as well as information on the distribution of firms across sectors for survey and official data (Table B2; Figures B1 and B2) are provided in the Online Appendix.
- ⁹ While having a broader coverage, the Ifo business climate index does not contain information on the risk attitude and the stability of expectations, which we exploit to construct a measure of firms' ex-ante uncertainty. The construction of the Ifo business climate balance is explained in the Online Appendix and corresponds to the description found here: <https://www.ifo.de/en/survey/ifo-business-climate-index>. We make use of the survey questions on firms' assessment of the current overall situation and the expected development in the following six months to reconstruct the corresponding series from the IWH risk climate survey.
- ¹⁰ Bachmann et al. (2019) take instead the forecast error with respect to period $\tau + 3$, to evaluate the effect on firms' decisions in period τ . This underlies the assumption that firms' perceived level of uncertainty in period τ is captured by the realized forecast error as derived from $\tau + 3$ data. The IWH survey has the advantage that we directly obtain an ex-ante uncertainty measure as perceived by the firm in period t .
- ¹¹ The derivation of these measures follows Bachmann et al. (2013) and it is explained in detail in Appendix A4.
- ¹² The pattern of the aggregate uncertainty measure is similar if we construct a forecast error with three (nine) categories: there is only a downward (upward) shift in the level.
- ¹³ Summary statistics for the distribution of firms' investment responses across answer possibility and wave are available in the Online Appendix (Table B4).
- ¹⁴ Please note that if firms respond that they intend to reduce investment compared to the previous year, this does not necessarily imply that they disinvest in the sense of a declining capital stock.
- ¹⁵ By contrast, for other common determinants of investment such as expectations about the future situation, risk attitude or the financing situation, we find a symmetric relationship with firm investment (see Figures B4–B6 in the Online Appendix).
- ¹⁶ More formally, $Investment_{i,t}$ reflects the continuous latent variable in the ordered probit model, which is linked via the normal distribution function to the five-scale outcome variable on investment, as observed in the data, depending on the internally estimated cutoff points.
- ¹⁷ See Figure B7 in the Online Appendix. Survey data is also used by Chong and Gradstein (2009) to test the impact of volatility on firm growth.
- ¹⁸ Bachmann et al. (2019) proceed similarly and take the absolute value of firms' forecast error.
- ¹⁹ From the survey, we also obtain information on the number of employees and revenue abroad. However, because these variables are highly correlated with revenue, we do not include them simultaneously. See also the robustness section.
- ²⁰ Marginal effects remain stable for the regressions including fixed effects. For brevity, we do not include them, but they can be obtained upon request.

- ²¹ For example, Rotemberg and Woodford (1999) find that marginal costs based on material costs and inventories rise during cyclical expansions affecting output cyclicality. While it is standard in the literature to consider the effect of input costs of labor or capital, limited evidence exists on the specific relevance of costs of material.
- ²² This approach is similar to Tanaka et al. (2020) who study the link between absolute GDP growth forecast errors and total factor productivity, respectively performance, for a sample of Japanese firms.
- ²³ The results support the findings by Foerster (2014) showing asymmetric effects of uncertainty on economic activity from a macro perspective.
- ²⁴ Asymmetric effects of increased volatility on stock returns have been found in the asset pricing literature, one reason being the time-varying risk premia (see e.g., Bekaert & Wu, 2000; Campbell & Hentschel, 1992). Rancière et al. (2008) use the skewness of credit growth instead of the variance to capture asymmetric effects of systemic risk on per capita GDP growth.
- ²⁵ Please note that the ex-ante measure of uncertainty helps tracing out that the ex-post forecast error contains an uncertainty component. Yet, it cannot be divided into a positive and negative surprise component, and thus cannot be used to test for interactions of surprise and uncertainty components.
- ²⁶ We thank two anonymous referees for their suggestions in that regard.
- ²⁷ In this model, the variable “financing” is defined to have three categories, where the lowest reflects (very) bad and the highest (very) good conditions. Consequently, marginal effects of the forecast error conditional on the financing situation can be presented in a more visible way.
- ²⁸ The model has been estimated with the cluster2 command in Stata using the ado-file provided by Mitchell A. Petersen.
- ²⁹ The correlated random effects model goes back to Mundlak (1978) and provides an alternative to the fixed-effects estimator. It allows controlling for unobserved individual heterogeneity but does not suffer from the incidental parameter problem. See Wooldridge (2019) for nonlinear models (such as ordered probit) for the case of unbalanced panels. Technically, the correlated random effects model controls for unobserved individual heterogeneity by including all time-varying explanatory variables along with their individual-specific mean over time.
- ³⁰ To check whether firm investment plans also depend on past conditions, we conducted robustness tests including lags of the dependent variable and the other controls, whereas results for the forecast error remained robust. Firms’ investment propensity in period $t - 1$ positively and significantly relates to investment propensity in period t . The inclusion of both lagged dependent and controls reduced the significance of the coefficient of interest to the 10% level.
- ³¹ For a detailed description of the construction of our forecast errors, see the next section in the appendix.
- ³² We check whether this truncation affects our regression result by excluding those firm observations for which rescaling leads to a forecast error of zero. The results are only marginally affected both in terms of estimated coefficients and standard errors. Results are available in Table B5 in the Online Appendix.
- ³³ Furthermore, the forecast error has the same range as the other variables, which benefits consistency and eases interpretation. Alternatively, we compute a forecast error that has nine categories and ranges from “FE -4” to “FE 4,” or three categories ranging from “FE -1” to “FE 1.” The main result remains robust using these alternatively calculated forecast errors (see Table B5 in the Online Appendix).

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

How to cite this article: Buchholz, M., Tonzer, L. & Berner, J. (2022) Firm-specific forecast errors and asymmetric investment propensity. *Economic Inquiry*, 60(2), 764–793. Available from: <https://doi.org/10.1111/ecin.13045>

APPENDIX A

A1 | Data description

The data used in this paper come from the IWH risk climate survey. The data set is confidential and cannot be distributed to external researchers. It can be accessed at the IWH in accordance with the research data center. It covers a large sample of small and medium-sized firms active in the German manufacturing sector. The survey waves were conducted bi-annually starting in 2007Q1 and ending in 2011Q3. For illustration, we have added a survey at the end of the paper. In the analysis, the ordering of the answers to questions four and five have been reversed in contrast to the ordering in the survey sheets to make it consistent with the ordering of the remaining survey questions and facilitate interpretation.

Variable name	Measurement	Interpretation	Survey question
Dependent variable			
Change in investment	--/-/0/+/++	--	Strong decrease ++ Strong increase 6
Risk attitude and forecast errors ³¹			
Risk attitude	--/-/0/+/++	--	Very low willingness to take risks ++ Very high willingness to take risks 3
Expected change in risk	--/-/0/+/++	--	Strong decrease ++ Strong increase 4
Forecast error	-2/-1/0/1/2	-2	Situation worse than expected 2 Situation better than expected Own calculation
Stability of expectations	--/-/0/+/++	--	Very instable ++ Very stable 2.1
Current situation			
Competition	--/-/0/+/++	--	Very bad ++ Very good 1.1.3a
Financing	--/-/0/+/++	--	Very bad ++ Very good 1.1.4a
Cost of material	--/-/0/+/++	--	Very bad ++ Very good 1.1.5a
German economy	--/-/0/+/++	--	Very bad ++ Very good 1.2a
Expected change			
Competition	--/-/0/+/++	--	Strong deterioration ++ Strong improvement 1.1.3b
Financing	--/-/0/+/++	--	Strong deterioration ++ Strong improvement 1.1.4b
Cost of material	--/-/0/+/++	--	Strong deterioration ++ Strong improvement 1.1.5b
German economy	--/-/0/+/++	--	Strong deterioration ++ Strong improvement 1.2b
Firm controls			
Revenue (see Table B3)	5 categories	1	Revenue <250 k € 5 5 bn € <Revenue 10
Employees	5 categories	1	Employees <5 5 74 <Employees 9
Sales target	--/-/0/+/++	--	Absolutely not achieved ++ Absolutely achieved 5
East/west dummy		0	Located in Western Germany 1 Located in Eastern Germany

A2 | Sector description

This table shows the sectors of the manufacturing industries based on the classification scheme WZ2008 of the German federal statistical office (www.destatis.de/EN).

Sector number	Sector name
10	Manufacture of food products
11	Manufacture of beverages
12	Manufacture of tobacco products
13	Manufacture of textiles
14	Manufacture of wearing apparel
15	Manufacture of leather and related products
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c.
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing
33	Repair and installation of machinery and equipment

A3 | Calculation of the forecast error

For the calculation of the forecast error, we exploit that in the survey each firm had to evaluate its *current situation* on an ordinal scale. There were five possible answers ranging from “--” (very bad situation) to “++” (very good situation). The firm also had to evaluate the *expected change of the situation* over the following 6 months. Again, the possible answers range from “--” to “++,” with “--” representing a strong worsening of the situation, “0” corresponding to no change, and a clear improvement coded with “++.” To calculate the forecast error, we proceed in three steps.

First, to have a numerical scale for the calculation, we *recode and rescale* the survey answers. This means that we recode the plus and minus scale for the question on the actual situation and the question on the expected change of the situation into numbers: -- corresponds to 1; - to 2; 0 to 3; + to 4; ++ to 5. We then rescale the answers on the actual situation to a simpler scale with three categories. 1 and 2 are rescaled to 1 (bad situation), 3 to 2, and 4 and 5 are rescaled to 3 (good situation). For consistency, we rescale the answers on the expected change to a three-category scale reflecting the direction of the change: 1 and 2 are rescaled to -1 (worsening), 3 to 0, and 4 and 5 are rescaled to 1 (improvement). This step can be summarized as follows:

	Survey answer	Recoding	Rescaling
Very good situation/strong improvement	++	5	3 (1)
Good situation/improvement	+	4	
Neutral/no change	0	3	2 (0)
Bad situation/worsening	–	2	1 (–1)
Very bad situation/strong worsening	--	1	

Second, given that we only know the firm's answer on the expected change of its situation, we have to *derive the expected situation*. To do so, we calculate the expected value in $t - 1$ for time period t by summing the actual situation in $t - 1$ and the direction of the expected change in $t - 1$: *Expected situation for t in $t - 1$ (3 categories) = actual situation in $t - 1$ (3 categories) + expected change in $t - 1$ (3 categories)*. We set the value for the expected situation back to scale if the actual situation is evaluated as good (bad) and an improvement (deterioration) is expected. The reason is that this would imply the expected situation to be at a value of 4 (0), which is out of range of the previously defined three categories scale of the actual situation going from 1 to 3. In this case, all values for the expected situation of 4 (0) are truncated to 3 (1), that is, to “good” (“bad”).³²

Third, we can now *compute the forecast error* in period t with five resulting categories by subtracting the expected situation for t made by the firm in the previous period $t - 1$ from the firm's actual situation in t : *Forecast error in t (5 categories) = actual situation in t (3 categories) – expected situation for t in $t - 1$ (3 categories)*. This forecast error has five different categories (FE –2, FE –1, FE 0, FE 1, FE 2). Negative values mean that the actual situation of the firm is worse than expected. Positive values indicate that the actual situation of the firm is better than expected. For illustration, we provide a brief example of the calculation steps below. The previously described rescaling results in a forecast error with five categories. This computation of the forecast error has the advantage of presenting a sufficient degree of variation without having to make too many assumptions on the scaling and of circumventing the problem of few observations in the tails.³³

Example:

Period $t - 1$: Boom period

- Actual situation is 4 (good) and expected change is 3 (no change).
- Rescale actual situation to 3 (good) and expected change to 0 (no change).
- Calculate the expected situation in period $t - 1$ for period t : $= 3 + 0 = 3$ (good).

Period t : The crisis hits

- Actual situation is 2 (bad) and recoded to 1.
- Subtract expected situation in $t - 1$ from actual situation in t : $= 1 - 3 = \text{“FE } -2\text{.”}$
- A forecast error of –2 indicates that the actual situation is (much) worse than expected.

A4 | Calculation of the aggregate uncertainty measures

Mean of absolute forecast errors

The aggregate measures derived from the firm-specific forecast error are calculated for any given quarter t by calculating, first, the mean of the absolute value of the firm-specific forecast error.

$$\text{Mean abs. } FE_t = \text{mean}\left(\left| \text{forecast error}_{i,t} \right|\right)$$

By taking the absolute value, a higher mean implies that on average more firms have made larger forecast errors irrespective of whether the forecast errors have been negative or positive.

Standard deviation of forecast errors

Second, we take the firm-specific forecast errors and compute the standard deviation.

$$SD FE_t = SD(\text{forecast error}_{i,t})$$

Dispersion of expectations

While the former measures are based on firm-specific forecast errors, the forecast dispersion (*FDISP*) measures the divergence of the firms' expected changes for each quarter *t*. The formula looks as follows:

$$FDISP_t = \sqrt{Frac_t^+ + Frac_t^- - (Frac_t^+ - Frac_t^-)^2}$$

$Frac_t^+$ = fraction of the participants that expect an enhancement.

$Frac_t^-$ = fraction of the participants that expect a worsening.

The higher the *FDISP_t*, the more diverging are the expectations. This forecast dispersion measure (*FDISP*) refers to Bachmann et al. (2013).