

Overreaction in Expectations: Uncertainty and Experimental Evidence ^{*}

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Abstract

This paper studies overreaction in firm expectations and how it varies with uncertainty. Using a firm panel that links forecasts, realizations, and firm-level uncertainty, I show that firms overreact to the information reflected in their forecast revisions. Specifically, upward revisions predict future realizations that are below forecasts. However, overreaction is weaker, not stronger, when uncertainty increases. When perceived uncertainty rises, the estimated degree of overreaction falls. This evidence is therefore consistent with diagnostic expectations, in which agents overweight states made more likely by new information, while challenging the Smooth Diagnostic Expectations prediction that uncertainty should strengthen overreaction. I then link the firm panel to an information-provision experiment on U.S. tariffs. Overreactors respond differently to experimentally provided information, but not by reacting more to all signals; their responses are muted compared with those of non-overreacting firms. This result shows that firm overreaction measured from historical forecast errors and revisions captures a behavioral type that predicts responses in a controlled information environment.

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1 Introduction

A central lesson of behavioral economics is that beliefs are not formed from information alone. They are shaped by memory, experience, and attention. Individuals do not merely condition on all available data; they retrieve particular past events, overweight salient or accessible experiences, and form judgments from what comes to mind (Gennaioli and Shleifer, 2010; Bordalo, Gennaioli and Shleifer, 2020). This idea appears in experience-based learning (Malmendier and Nagel, 2011, 2016), where lifetime economic conditions impact the beliefs and decisions of agents, and in memory-based models, where probability judgments depend on the examples retrieved from memory rather than only on objective frequencies (Bordalo et al., 2023). Yet much less is known about how these forces operate when decision-makers face environments that have become harder to predict and evaluate. Does uncertainty make economic agents rely more heavily on heuristics? Or does uncertainty discipline beliefs? I study that question in the context of firms.

Diagnostic expectations (Bordalo, Gennaioli and Shleifer, 2018) provide a natural framework for studying this issue. They build on the representativeness heuristic—the tendency for news to selectively bring related past experiences to mind. Concretely, under diagnostic expectations, new information shifts agents’ beliefs too strongly toward the outcomes it makes more probable (Bordalo et al., 2020). In the canonical empirical benchmark, Bordalo et al. (2020) use the Coibion and Gorodnichenko (2015) regression of forecast errors on forecast revisions to study whether forecasters under- or overreact to news. They show that individual forecasters overreact, as upward forecast revisions predict future realizations that are below forecasts. They interpret this pattern as diagnostic overreaction to information. The central object in that literature is therefore not simply biased expectations, but a particular behavioral distortion: excessive movement of beliefs toward states that become more likely with incoming information.

The existing evidence leaves open an important behavioral question: is overreaction stable, or does it vary with the uncertainty faced by the economic agent? The answer matters because it determines whether estimates of overreaction obtained in one environment carry over to another, and whether belief distortions are stronger or weaker in uncertain environments. This answer need not be mechanical. On one view, uncertainty should magnify diagnostic overreaction. When the relevant environment becomes harder to assess, the set of plausible states expands, tail outcomes may become easier to imagine, and recent signals may appear more representative of a changed distribution. This is the force emphasized

by Bianchi, Ilut and Saijo (2024), where higher conditional uncertainty gives representativeness more scope to distort beliefs relative to a reference information set. On another view, uncertainty may reduce overreaction. Agents may respond to uncertainty by acquiring additional information or by placing less weight on signals they regard as noisy. Models of rational inattention and endogenous information acquisition allow attention and information demand to respond to economic conditions (Maćkowiak, Matějka and Wiederholt, 2023), while experimental evidence shows that higher perceived uncertainty can raise firms' demand for information (Mikosch et al., 2024).¹ Whether uncertainty amplifies or attenuates overreaction is therefore an empirical question.

Firms are a useful setting for distinguishing these forces because their expectations are decision-relevant beliefs. They enter firm-specific choices such as pricing, production, orders, and investment. This does not imply that firms are perfectly rational. But it does imply that forecast mistakes have direct consequences for firms' own outcomes. This makes firms a particularly informative setting for testing whether overreaction is stronger or weaker in more uncertain environments.

Smooth Diagnostic Expectations (Bianchi, Ilut and Saijo, 2024) provides the sharpest benchmark for the amplification view. Its key departure from the standard formulation of diagnostic expectations concerns the construction of the reference distribution. Standard diagnostic expectations evaluate states using the earlier conditional mean but the variance implied by current information. Bianchi, Ilut and Saijo (2024) instead form the reference distribution entirely under the earlier information set, allowing current and reference beliefs to differ in both their conditional means and variances. As a result, the primitive diagnosticity parameter, which governs the distortion strength, need not vary over time for the effective degree of overreaction to be state dependent. For a given revision in the conditional mean, overreaction is weaker when current beliefs are relatively precise and stronger when current variance is high relative to the variance of the reference distribution. In the forecast-error-on-revision regression, this amplification mechanism has a direct empirical implication: the slope on forecast revisions should become more negative in high-uncertainty states, or when current uncertainty rises relative to the relevant reference point.

I test these predictions using the KOF Business Tendency Survey, a monthly panel of Swiss firms that elicits qualitative expectations and their subsequent realizations. The panel

¹Work on behavioral attenuation shows that responsiveness to economic fundamentals falls with cognitive uncertainty, although cognitive uncertainty is conceptually distinct from uncertainty about the economic environment (Enke and Graeber, 2023; Enke et al., 2024).

structure allows me to construct forecast errors and forecast revisions for the same firm over time, and therefore to test for overreaction at the firm level. Moreover, the survey asks about firms’ own perceived uncertainty. I use these responses (i) to identify firm-specific high-uncertainty states and (ii) to measure firm-specific changes in consecutive uncertainty levels. Thus, the data allow me to ask whether a firm’s tendency to overreact to information, as reflected in its forecast revisions, changes when that same firm reports facing a more uncertain environment.

The main result is that overreaction is weaker with increases in uncertainty. Firms do overreact on average, as upward revisions in expected orders predict future realizations below forecasts. This finding aligns the firm-level evidence with the individual-level overreaction documented by Bordalo et al. (2020) for professional forecasters.² The novel result concerns how this overreaction varies with uncertainty. In high-uncertainty states, the forecast-error slope is not more negative. More importantly, when the uncertainty rises for a firm, the slope becomes significantly less negative. Put differently, firms continue to display overreaction, but the implied diagnosticity parameter falls when uncertainty increases. The evidence therefore supports diagnostic expectations as a description of firm belief formation, while running against the Smooth Diagnostic Expectations prediction that uncertainty should strengthen overreaction to news.

I then leverage a setting that is rarely available in expectation data: an information-provision experiment linked to the same firm panel. The experiment was embedded in the KOF survey and randomly assigned firms to one of two U.S. tariff scenarios. After receiving the treatment, firms reported beliefs about turnover, investment, and prices. I use the panel to classify firms as overreactors to firm-specific information, based on whether their historical forecast revisions predict subsequent forecast errors in the direction of overreaction. The experiment therefore provides a test of whether overreaction measured from naturally occurring forecast errors predicts how firms process newly supplied information.

The experimental evidence shows that overreaction has predictive content, but not in the form of a general tendency to react more to all information. Holding fixed the information treatment, firms classified as overreactors report different expectations from other firms. Across most outcomes, their responses are closer to zero. This pattern is robust to controlling for firms’ exposure to the U.S. market. Thus, overreaction to firm-specific information is not merely a reduced-form feature of historical forecast errors; it predicts belief updating in a

²Born et al. (2022) find similar results for German firms.

experimentally controlled information environment.

This paper contributes to the literature on diagnostic expectations by studying the state dependence of overreaction.³ The theory builds on models of representativeness and selective memory, including Gennaioli and Shleifer (2010) and Bordalo et al. (2016), where judgments are distorted by reference groups and selectively retrieved information. Diagnostic expectations apply this logic to economic forecasting and have been used to explain credit cycles, stock returns, macroeconomic forecast errors, bubbles, and bond market puzzles (Bordalo, Gennaioli and Shleifer, 2018; Bordalo et al., 2019, 2020, 2021; d’Arienzo, 2020). Recent work embeds the same distortion in richer macroeconomic environments, including New Keynesian models and heterogeneous-firm credit cycles (L’Huillier, Singh and Yoo, 2024; Bordalo et al., 2026*b*). My contribution is to bring direct evidence on the uncertainty-dependence and behavioral content of overreaction to this literature.

More broadly, the paper contributes to behavioral theories of belief updating. Afrouzi et al. (2023) use various experiments to show that overreaction is a robust feature of expectations when information sets and data-generating processes are controlled. Ba, Bohren and Imas (2024) show that cognitive constraints can generate either overreaction or underreaction depending on the learning environment, while Kohlhas and Walther (2021) show how asymmetric attention can reconcile extrapolation with underreaction. Closely related work on forecaster behavior, memory, and probability judgments emphasizes that expectations depend on how agents represent the problem, retrieve examples, and process statistical information (Broer and Kohlhas, 2024; Bordalo et al., 2025, 2026*a,c*). My paper adds to this literature by studying whether a naturally measured behavioral distortion varies with uncertainty and predicts belief updating beyond the setting in which it is measured. In this sense, the paper also connects to experience-based learning, where beliefs depend on the information agents have lived through and made psychologically available (Malmendier and Nagel, 2011, 2016).

This work also contributes to the literature using information-provision experiments to study expectations.⁴ In macroeconomics, information treatments have been used to study household inflation expectations (Armantier et al., 2016; Cavallo, Cruces and Perez-Truglia, 2017), the effect of monetary policy communication (Coibion, Gorodnichenko and Weber, 2022), people’s understanding of inflation (Binetti, Nuzzi and Stantcheva, 2024), recession

³For an overview of diagnostic expectations see Bordalo, Gennaioli and Shleifer (2022).

⁴For recent discussions of information-provision experiments and survey methods, see Fuster and Zafar (2023), Haaland, Roth and Wohlfart (2023), Stantcheva (2023), and Coibion and Gorodnichenko (2026).

expectations (Roth and Wohlfart, 2020), housing-market beliefs (Armona, Fuster and Zafar, 2019), endogenous information acquisition (Fuster et al., 2022), and subjective models of the macroeconomy (Andre et al., 2022). A growing firm-level branch of this literature studies how firms update beliefs and decisions after receiving information about the economy or facing experimentally induced uncertainty: Coibion, Gorodnichenko and Kumar (2018) study firms’ updating after information about macroeconomic conditions, Coibion, Gorodnichenko and Ropele (2020) use repeated information treatments about inflation, Mikosch et al. (2024) study information acquisition and uncertainty among firms and households, and Dibiasi, Mikosch and Sarferaz (2025) use a survey experiment to study how an uncertainty shock affects firm beliefs. My contribution is to link an information-provision experiment to a long firm panel, using the panel to measure overreaction and asking whether this behavioral type predicts responses to randomized information.

The rest of the paper is organized as follows. Section 2 describes the firm panel, the empirical strategy, and the linked information-provision experiment. Section 3 presents the panel evidence on uncertainty and overreaction and uses the experiment to test whether firm overreaction measured in the panel predicts belief updating in response to experimentally supplied information. Section 4 concludes.

2 Data and Measurement

The empirical design combines a long firm panel with an information-provision experiment. The panel allows me to measure overreaction from firms’ own forecast errors and forecast revisions, and to ask whether this overreaction varies with uncertainty. The experiment then provides a controlled information environment in which to test whether the overreaction measured in the panel predicts belief updating. This section introduces the panel setting, defines the forecast-error and uncertainty measures, and describes the construction of behavioral types used in the experimental analysis.

2.1 The KOF Business Tendency Survey

The empirical setting is the KOF Business Tendency Survey (KOF BTS), a long-running firm survey conducted by the KOF Swiss Economic Institute at ETH Zurich. Since the 1950s, the monthly survey has collected information on Swiss firms’ assessments, expectations, and

business plans. The survey questions capture qualitative firm-level developments in variables such as demand, production, sales prices, and the general business situation. This structure is well suited to studying belief formation because it links firms' expectations about future outcomes to subsequent reported realizations for the same variables. In addition, the survey contains direct questions on firms' self-reported uncertainty, which allow me to study whether overreaction varies with the uncertainty perceived by the firm.

Participation is voluntary and based on a firm panel. For panel maintenance, firms are sampled from a business register using strata defined by industry and employment size, measured in full-time equivalents, although firms may also join the panel through self-registration. Responding firms do not receive monetary compensation, but they are given access to aggregated results from the survey waves in which they participate. Since the value of this informational return depends on the accuracy and truthfulness of participants' responses, the survey design mitigates incentives for strategic misreporting. The analysis focuses on firms in the manufacturing sample, corresponding to section C of the NACE Rev. 2 classification.

2.2 Forecast Errors, News, and Self-Reported Uncertainty

The empirical object of interest is the extent to which firms' forecast errors are predictable from information available when forecasts are formed. This is the test first proposed by Coibion and Gorodnichenko (2015) and later used by Bordalo et al. (2020) to distinguish underreaction from overreaction beyond merely the consensus forecast. The logic is simple. If forecasts incorporate information rationally, revisions in beliefs should not predict subsequent forecast errors. If forecasts overreact, upward revisions should be followed by realizations that fall short of forecasts; if forecasts underreact, upward revisions should be followed by realizations that exceed forecasts.

I apply this test at the firm level. Let $y_{t+h|t}^i$ denote firm i 's forecast for variable y at time t for h periods ahead, y_{t+h}^i the corresponding realization, and $FR_{t,h}^i = y_{t+h|t}^i - y_{t+h|t-1}^i$ be firm i 's forecast revision for that variable from $t-1$ to t for time $t+h$. The Bordalo et al. (2020) individual-level specification can then be written as

$$y_{t+h}^i - y_{t+h|t}^i = \beta_0 + \beta_1 FR_{t,h}^i + \varepsilon_{t+h}^i, \quad (1)$$

The forecast error is defined as realization minus forecast, namely $FE_{t+h}^i = y_{t+h}^i - y_{t+h|t}^i$. With this convention, a negative forecast error means that the firm’s forecast was too high relative to the subsequent realization, while a positive forecast error means that the forecast was too low.

Under full-information rational expectations, $\beta_1 = 0$. A positive coefficient indicates underreaction: upward revisions predict positive forecast errors. A negative coefficient indicates overreaction: upward revisions predict negative forecast errors. In the diagnostic-expectations interpretation, $\beta_1 < 0$ captures excessive sensitivity of beliefs to information.

A distinctive feature of the KOF data is that the same survey also elicits firms’ uncertainty. Firms are asked every month whether predicting the future development of their business situation is “easy”, “rather easy”, “rather difficult”, “difficult” (see Appendix D for the exact question wording). I construct two firm-level uncertainty measures from these responses. First, I define a high-uncertainty indicator U_t^i equal to one if firm i reports at time t that predicting the future development of its business situation is “rather difficult” or “difficult,” and zero otherwise. Second, I exploit the ordered nature of the response. Let S_t^i denote the ordered response to the uncertainty question, coded so that higher values correspond to greater difficulty of prediction. I define the change in uncertainty as $G_t^i = S_t^i - S_{t-1}^i$. Positive values of G_t^i therefore indicate that the firm reports a higher level of uncertainty than in the previous month.

These two measures allow me to test complementary predictions of diagnostic expectations under uncertainty. The high-uncertainty indicator U_t^i captures whether diagnostic overreaction is stronger in high uncertainty states. The change in uncertainty G_t^i captures whether diagnostic overreaction varies when uncertainty rises or falls. This distinction is useful because Smooth Diagnostic Expectations (Bianchi, Ilut and Saijo, 2024) link the strength of diagnosticity to uncertainty relative to a reference information set. In the present setting, the theory predicts that the slope relating forecast errors to forecast revisions should become more negative when firms report high uncertainty, and especially upon increases in uncertainty. The KOF panel is therefore useful not only because it contains forecast errors and revisions at the firm level, but because it observes these objects together with both levels and changes in firms’ perceived uncertainty.

A key difference to the Bordalo et al. (2020) setting is that the forecasts and realizations are not about aggregate variables but are instead firm-specific. Firm forecast errors may therefore reflect both firm-specific information and changes in the aggregate environment.

To separate these two components, I augment the individual error-revision regression with a measure of aggregate information, A_t . Following Born et al. (2022), I measure A_t using the first difference in the KOF business situation index. Controlling for A_t , the coefficient on $FR_{t,h}^i$ captures the relation between forecast errors and the firm-specific component of the firm's own revision.

I estimate the following specification using the two alternative measures of uncertainty described above. Let Q_t^i denote either the high-uncertainty state, U_t^i , or the change in uncertainty, G_t^i . Both variables are coded so that higher values correspond to higher perceived uncertainty. The estimating equation is

$$y_{t+h}^i - y_{t+h|t}^i = \beta_0 + \beta_1 FR_{t,h}^i + \beta_2 A_t + \beta_3 Q_t^i + \beta_4 (FR_{t,h}^i \times Q_t^i) + \beta_5 (A_t \times Q_t^i) + \varepsilon_{t+h}^i. \quad (2)$$

The coefficients β_1 and β_4 provide the main test of uncertainty-dependent diagnostic overreaction. When $\beta_1 < 0$, firms overreact to firm-specific information: positive revisions predict negative future forecast errors. The interaction coefficient β_4 measures how this overreaction changes as uncertainty increases. The implied diagnosticity parameter is

$$\theta(Q) = -(\beta_1 + \beta_4 Q). \quad (3)$$

Thus, the implied diagnosticity parameter is increasing in uncertainty if $\beta_4 < 0$ and decreasing in uncertainty if $\beta_4 > 0$.

For the uncertainty-state specification, $Q_t^i = U_t^i$, so β_1 is the forecast-error slope for firms reporting low-uncertainty and $\beta_1 + \beta_4$ is the slope for firms reporting high-uncertainty. For the uncertainty-change specification, $Q_t^i = G_t^i$, so β_4 captures how the forecast-error slope changes when perceived uncertainty increases. Smooth diagnosticity predicts that uncertainty should amplify overreaction to information. In this notation, the prediction is $\beta_4 < 0$: the slope relating forecast errors to forecast revisions should become more negative as uncertainty increases. Conversely, $\beta_4 > 0$ corresponds to weaker overreaction at higher values of the uncertainty measure: the forecast-error slope becomes less negative and the implied diagnosticity parameter falls.

The aggregate-information terms are interpreted separately. A positive β_2 indicates underreaction to aggregate information, while a negative coefficient indicates overreaction. The interaction β_5 asks whether firms' response to aggregate information also changes when uncertainty is high. Because diagnostic expectations map most directly into overreaction to

the information contained in a firm’s own revision, the paper’s primary test is the pair (β_1, β_4) . The aggregate-information coefficients provide a comparison that distinguishes state-dependent overreaction in firm-specific belief updating from broader changes in sensitivity to the aggregate environment.

In the baseline estimation, equation (2) is augmented with firm and time fixed effects. Because the KOF survey responses are qualitative, forecast errors are constructed from ordered response categories following Bachmann, Elstner and Sims (2013). To construct forecast revisions I follow Born et al. (2022). Appendix B describes the details for constructing forecast errors and revisions from qualitative data. The notation above suppresses these details to keep the mapping between the diagnostic-expectations test and the empirical specification transparent.

2.3 The Vignette Experiment and Behavioral Types

I complement the panel evidence with an information-provision experiment from Abberger et al. (2026). The experiment was embedded in the KOF manufacturing survey and presented to firms participating online. Firms were randomly assigned to one of two tariff scenarios. In the first vignette, respondents were asked to assume that the United States permanently imposes a uniform tariff of 10 percent on goods imported from all countries. In the second vignette, respondents were asked to assume that the United States permanently imposes a 31 percent tariff on goods imports from Switzerland, with imports from other countries facing the tariff rates announced on “Liberation Day.” After the vignette, firms reported how they expected the scenario to affect their turnover, fixed asset investment in Switzerland, and sales prices across destinations.

The experiment is useful to test a distinct implication of diagnostic expectations: overreaction should have behavioral content beyond the forecast-error regression. The vignette setting is not designed to test the uncertainty mechanism studied above. Instead, it provides a separate information environment in which firms face the same externally supplied policy scenario. If overreaction captures a stable feature of belief updating, firms that overreact to firm-specific information in the panel should respond differently to this experimental information than firms that do not.

I construct behavioral types using the firm panel. For each firm i , I estimate the firm-level

analogue of equation (2), omitting the uncertainty terms:

$$y_{t+h}^i - y_{t+h|t}^i = \beta_0^i + \beta_1^i F R_{t,h}^i + \beta_2^i A_t + \varepsilon_{t+h}^i. \quad (4)$$

The coefficient β_1^i measures whether firm i 's forecast errors are predictable from its own forecast revisions, controlling for aggregate information. I classify a firm as an overreactor if the estimated coefficient on its own forecast revision is negative and statistically significant:

$$D_i = \mathbf{1} \left\{ \hat{\beta}_1^i < 0 \text{ and } p(\hat{\beta}_1^i) < \alpha \right\}. \quad (5)$$

This rule is conservative. A firm is classified as an overreactor only when its panel behavior displays statistically significant overreaction to firm-specific information. Firms with negative but imprecisely estimated coefficients are therefore not classified as overreactors.

Let $Z_i^{(k)}$ denote firm i 's response to experimental outcome k , where k indexes the outcomes elicited in the vignette experiment. Let $V_i \in \{0, 1\}$ denote the vignette, with $V_i = 0$ corresponding to the uniform 10 percent tariff scenario and $V_i = 1$ corresponding to the 31 percent Switzerland-specific tariff scenario. The main experimental comparison is the difference in mean responses between overreactors and other firms within the same vignette:

$$\Delta_v^{(k)} = E \left[Z_i^{(k)} \mid D_i = 1, V_i = v \right] - E \left[Z_i^{(k)} \mid D_i = 0, V_i = v \right], \quad v \in \{0, 1\}. \quad (6)$$

This comparison asks whether firms that display overreaction in the panel respond differently to the same information than firms that did not. The design therefore links naturally occurring overreaction to belief updating in an experimentally controlled information environment.

3 Results

In the baseline specification, y denotes incoming orders. Firm forecasts are elicited at a three-month horizon, and realizations are observed monthly. The panel spans April 2004 to April 2026. The uncertainty questions enter the survey in July 2020, so specifications that include U_t^i or G_t^i are estimated on the corresponding shorter sample. In robustness checks, I repeat the analysis using the production firm-level variable.

3.1 Uncertainty and State-Dependent Overreaction

Table 1 reports estimates of equation (2). The dependent variable is the forecast error for incoming orders, defined as the realization minus the firm’s forecast. Recall the sign convention: negative coefficients on information variables indicate overreaction, while positive coefficients indicate underreaction.

The first result is that self-reported uncertainty is systematically related to forecast errors. The coefficient on the high-uncertainty indicator, U_t^i , is negative and statistically significant across specifications. Firms reporting high uncertainty subsequently realize lower orders than they had forecast. In other words, uncertainty is associated with overshooting of the orders variable. This coefficient is not itself a direct test of diagnostic expectations, because it is not attached to a measure of information, such as forecast revisions. It nevertheless shows that self-reported uncertainty contains information about firms’ belief distortions, systematically predicting forecast errors across specifications.

The central diagnostic-expectations test is given by the coefficients on firms’ own forecast revisions. The coefficient on $FR_{t,h}^i$ is negative and statistically significant. Firms therefore overreact to firm-specific information: when firms revise their forecasts for expected orders upward, the subsequent outcomes tend to fall short of those forecasts. This finding is consistent with the individual-level evidence in Bordalo et al. (2020), where negative error-revision slopes indicate overreaction to information.

The high-uncertainty interaction does not support the amplification prediction of smooth diagnosticity. Smooth Diagnostic Expectations (Bianchi, Ilut and Saijo, 2024) predicts that the effective diagnostic distortion should increase when current uncertainty is high relative to the reference information set. In the high-uncertainty-state specification, this prediction corresponds to a more negative forecast-error slope among firms reporting high uncertainty. Empirically, the interaction between $FR_{t,h}^i$ and U_t^i is not statistically significant and its point estimate has the opposite sign. If anything, the forecast-error slope becomes less negative when firms report high uncertainty.

In terms of implied diagnosticity parameters, firms reporting low uncertainty have

$$\theta_L = -\beta_1,$$

while firms reporting high uncertainty have

$$\theta_H = -(\beta_1 + \beta_4).$$

The point estimates imply that the diagnosticity parameter remains positive in high-uncertainty states and, if anything, is smaller than in low-uncertainty states. Thus, the uncertainty-state evidence does not indicate that high uncertainty amplifies overreaction.

The aggregate-information coefficients provide a useful comparison. The coefficient on A_t is positive, indicating underreaction to aggregate information, although its magnitude is much smaller than the coefficient on firms' own forecast revisions. This pattern is consistent with related firm-level evidence in Born et al. (2022), which also finds that firms' forecast errors respond differently to firm-specific and aggregate information. However, the coefficient on A_t becomes statistically insignificant when including interactions with the high-uncertainty indicator. Similarly, the interaction between aggregate information and high uncertainty is statistically indistinguishable from zero and economically small. Thus, as with firms' own revisions, the state-level uncertainty measure provides no evidence that high uncertainty amplifies distortions in the response to aggregate information.

3.2 Increases in Uncertainty

Table 2 replaces the high-uncertainty state U_t^i with the change in perceived uncertainty, G_t^i . This provides a more direct test of the central prediction of Smooth Diagnostic Expectations. The theory links the effective diagnostic distortion to current uncertainty relative to a reference information set, meaning the distortion should be stronger when current uncertainty is higher relative to the reference uncertainty. The change in perceived uncertainty therefore brings the empirical specification closer to this theoretical object.

The results strengthen the conclusion from Table 1. The coefficient on uncertainty-change G_t^i is negative and statistically significant. Firms whose uncertainty increases subsequently realize lower orders than they had forecast. As in the level specification, uncertainty is associated with systematic overshooting. The information coefficients remain stable as well: firms overreact to their own information, as reflected in their forecast revisions, and underreact to aggregate information.

The key coefficient is the interaction between the firm's own forecast revision and G_t^i .

Table 1: Overreaction in High-Uncertainty States

	Incoming Orders Forecast Error					
	(1)	(2)	(3)	(4)	(5)	(6)
Forecast revision, $FR_{t,h}^i$	-0.0300*** (0.0020)	-0.0303*** (0.0020)	-0.0222*** (0.0037)	-0.0302*** (0.0085)	-0.0222*** (0.0037)	-0.0302*** (0.0085)
Aggregate information, A_t		0.0040*** (0.0003)	0.0013*** (0.0004)	0.0013*** (0.0004)	0.0012 (0.0008)	0.0012 (0.0008)
High uncertainty, U_t^i			-0.0613*** (0.0115)	-0.0614*** (0.0115)	-0.0613*** (0.0115)	-0.0614*** (0.0115)
$FR_{t,h}^i \times U_t^i$				0.0101 (0.0097)		0.0101 (0.0097)
$A_t \times U_t^i$					0.0001 (0.0010)	0.0001 (0.0010)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	2,255	2,252	1,203	1,203	1,203	1,203
Observations	134,904	134,507	32,046	32,046	32,046	32,046

Notes: The table reports regressions of forecast errors for incoming orders on firms' own forecast revisions, aggregate information, self-reported uncertainty, and their interactions. The dependent variable is the realized change in incoming orders minus the corresponding forecast. $FR_{t,h}^i$ denotes the firm's forecast revision, A_t denotes aggregate information, and U_t^i is an indicator for high self-reported uncertainty. Column (6) reports the full specification in equation (2); columns (1)–(5) omit selected terms from the full specification. All specifications include firm, year, and month fixed effects. Standard errors are clustered by firm and A_t is winsorized at the 95 percent level. *p<0.10; **p<0.05; ***p<0.01.

Smooth Diagnostic Expectations predicts that increases in uncertainty should amplify overreaction to information. With the forecast-error convention used here, this corresponds to a negative interaction coefficient: the slope relating forecast errors to forecast revisions should become more negative when uncertainty rises. The data show the opposite. The interaction between $FR_{t,h}^i$ and G_t^i is positive and statistically significant. Thus, upon increases in uncertainty, the forecast-error slope becomes less negative.

Because G_t^i is an ordered change rather than a binary indicator, β_4 measures the change in the forecast-error slope associated with a one-unit increase in perceived uncertainty. The relevant slope is therefore $\beta_1 + \beta_4 G_t^i$. At the estimated coefficients, the slope remains negative for the vast majority of observations, implying that overreaction is weaker, but remains

present, even when firms report larger increases in uncertainty.⁵

Equivalently, the implied diagnosticity parameter falls as perceived uncertainty increases:

$$\theta(G_t^i) = -(\beta_1 + \beta_4 G_t^i).$$

Since $\beta_1 < 0$ and $\beta_4 > 0$, the implied diagnosticity parameter $\theta(G_t^i)$ is decreasing in G_t^i . The diagnosticity parameter remains positive in almost all observed cases, but it falls, not increases, when perceived uncertainty rises.

The aggregate-information interaction is not statistically significant. This sharpens the interpretation of the main result. The attenuation of overreaction as uncertainty rises occurs where diagnostic expectations have the clearest empirical mapping: the relation between firms' own forecast revisions and their subsequent forecast errors. The evidence therefore qualifies smooth diagnosticity in its most direct form. Overreaction to firm-specific information is not stronger when uncertainty rises; it is weaker.

My results are not specific to the baseline fixed-effect structure or to incoming orders. Appendix Tables C.1 and C.2 report the incoming-orders specifications without time fixed effects, while Appendix Table C.3 adds year-month fixed effects. Appendix Tables C.4 and C.5 repeat the analysis using production, the other firm-level variable for which I can construct both forecast errors and forecast revisions. Across specifications, the results are close to the baseline estimates: firms overreact to their own information, but this overreaction is not stronger under higher uncertainty.

Taken together, Tables 1 and 2 deliver a consistent message. Firms overreact to their own information, supporting the diagnostic-expectations view of belief formation. However, overreaction is not stronger in high-uncertainty states and is significantly weaker when firms report an increase in perceived uncertainty. The evidence therefore supports diagnostic expectations as a framework for firm belief formation, while challenging the smooth-diagnosticity prediction that uncertainty should increase the severity of the diagnostic distortion.

⁵ G_t^i takes values on $\{-4, \dots, 4\}$. The marginal effect of forecast revisions, $\beta_1 + \beta_4 G_t^i$, is negative for more than 95 percent of observations.

Table 2: Overreaction upon Changes in Uncertainty

	Incoming Orders Forecast Error			
	(1)	(2)	(3)	(4)
Forecast revision, $FR_{t,h}^i$	-0.0229*** (0.0037)	-0.0228*** (0.0037)	-0.0229*** (0.0038)	-0.0229*** (0.0038)
Aggregate information, A_t	0.0013*** (0.0004)	0.0013*** (0.0004)	0.0013*** (0.0004)	0.0013*** (0.0004)
Changes in uncertainty, G_t^i	-0.0134*** (0.0027)	-0.0134*** (0.0027)	-0.0138*** (0.0027)	-0.0138*** (0.0027)
$FR_{t,h}^i \times G_t^i$		0.0131** (0.0062)		0.0127** (0.0063)
$A_t \times G_t^i$			0.0008 (0.0006)	0.0007 (0.0006)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Number of firms	1,195	1,195	1,195	1,195
Observations	31,414	31,414	31,414	31,414

Notes: The table reports regressions of forecast errors for incoming orders on firms' own forecast revisions, aggregate information, self-reported uncertainty, and their interactions. The dependent variable is the realized change in incoming orders minus the corresponding forecast. $FR_{t,h}^i$ denotes the firm's forecast revision, A_t denotes aggregate information, and G_t^i is the change in self-reported uncertainty. Column (4) reports the full specification in equation (2); columns (1)–(3) omit selected terms from the full specification. All specifications include firm, year, and month fixed effects. Standard errors are clustered by firm and A_t is winsorized at the 95 percent level. *p<0.10; **p<0.05; ***p<0.01.

3.3 Behavioral Types and Responses to Experimentally Provided Information

I next test whether overreaction measured in the panel predicts how firms respond to experimentally supplied information. To do so, I match firms in the KOF panel to the information-provision experiment of Abberger et al. (2026). In that experiment, firms were randomly assigned to one of two tariff scenarios: a uniform 10 percent U.S. tariff on goods imported from all countries, or a 31 percent tariff on goods imports from Switzerland. The original experiment shows that these tariff scenarios affected firms' expectations, with expected declines in real turnover and investment as well as increases in prices, especially for U.S.

sales.

For the present paper, the experiment is useful because it provides a controlled information environment. I classify firms as overreactors using the panel data. Specifically, I estimate equation (4) firm by firm and set $D_i = 1$ if the coefficient on the firm's own forecast revision is negative and statistically significant at the 10% level.

Figure 1 reports mean experimental responses separately by vignette and by behavioral firm type. Across several outcomes, firms classified as overreactors report different adjustments from other firms facing the same information vignette. Table 3 reports the corresponding within-vignette differences in means, estimated from regressions of each outcome on the overreactor indicator within each vignette. The type gaps are highly statistically significant for all but one price-vignette combination.

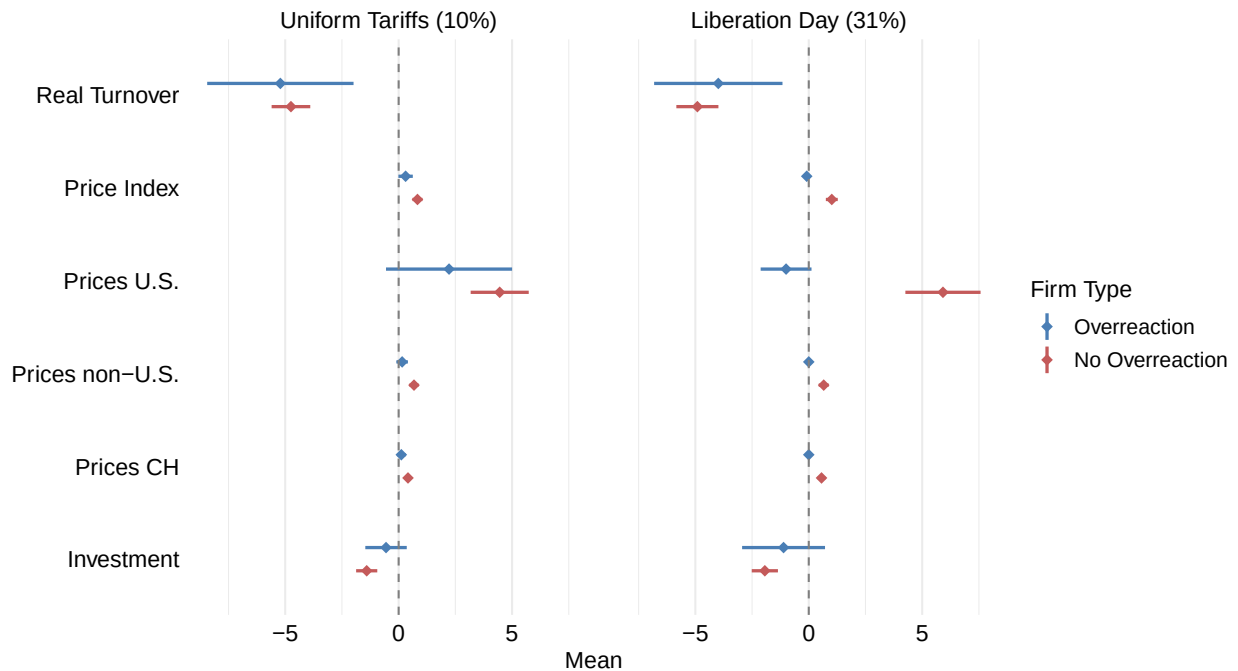


Figure 1: Mean Responses by Behavioral Firm Type

Notes: The figure reports means and 90% confidence intervals for overreacting and non-overreacting firms by their treatment assignment and outcome variable in the vignette experiment of Abberger et al. (2026). A firm is classified as an overreactor when its panel behavior displays statistically significant overreaction to firm-specific information. Firms with less than 10 observations are excluded from the panel. Outcome variables are measured as percentage changes relative to the no-tariff-increase benchmark. Confidence intervals are constructed with heteroskedasticity-robust (HC1) standard errors.

The direction of the heterogeneity is also informative. Whenever the difference between overreactors and other firms is statistically meaningful, the response of overreactors is closer to zero. Thus, overreactors do not appear to be generally more responsive to all information. Rather, they respond less to the experimentally supplied tariff scenario than other firms.

This result is useful for interpreting overreaction. The overreaction documented in the panel concerns firms’ own forecast revisions, which are naturally tied to firm-specific information. The vignette, by contrast, provides an externally supplied policy scenario. The experimental evidence therefore suggests that overreaction is not simply a tendency to move expectations more in response to any information. It captures a behavioral belief-updating type that predicts how firms respond to experimentally controlled information, and in this setting overreactors react less to aggregate policy information.

Table 3: Differences in Experimental Responses by Tariff Vignette

	Uniform tariff (10 %)		“Liberation Day” (31 %)	
	Δ mean	SE	Δ mean	SE
Real turnover	−0.47	1.97	0.92	1.76
Price index	−0.52 **	0.23	−1.10 ***	0.17
Prices: U.S.	−2.23	1.79	−6.92 ***	1.20
Prices: rest of world	−0.52 ***	0.19	−0.66 ***	0.13
Prices: Switzerland	−0.29 **	0.14	−0.56 ***	0.10
Investment	0.85	0.61	0.83	1.14

Notes: The table reports differences in means for overreacting and non-overreacting firms by their treatment assignment in the vignette experiment of Abberger et al. (2026). Positive values indicate higher outcome means for overreacting firms. A firm is classified as an overreactor when its panel behavior displays statistically significant overreaction to firm-specific information. Firms with less than 10 observations are excluded from the panel. Outcome variables are measured as percentage changes relative to the no-tariff-increase benchmark. Heteroskedasticity-robust (HC1) standard errors are reported in adjacent columns. *p<0.10; **p<0.05; ***p<0.01.

A natural concern is that this heterogeneity could be driven by exposure to the U.S. market rather than by firm type. The tariff experiment studied by Abberger et al. (2026) finds that U.S. turnover exposure is an important predictor of experimental responses. I therefore re-estimate the difference-in-means regressions controlling for an indicator equal to one if the firm generates more than 20 percent of its turnover in the United States. Appendix Table C.6 reports the results.

The type differences are essentially unchanged after controlling for high U.S. exposure. For outcomes with statistically significant differences, firms classified as overreactors continue to report responses closer to zero than other firms within the same vignette. The coefficient on high U.S. exposure absorbs an important economic determinant of the tariff response, but it does not explain away the heterogeneity by behavioral type.

A potential concern is that the baseline measure of D_i uses panel observations collected after the experiment, so firm type is not strictly predetermined. Because the experiment occurred near the end of the panel, these observations account for only a small share of the data used to classify firms. Nevertheless, I reconstruct D_i using only pre-experiment panel observations and re-estimate the within-vignette differences in means. Appendix Table C.7 shows that the results are virtually unchanged.

The experimental evidence offers a direct test of whether overreaction captures a behavioral type. The information provided in the vignette concerns a policy scenario rather than firm-specific information, so the result speaks to whether overreaction predicts belief updating outside the environment in which it is measured. Firms classified as overreactors respond differently from other firms to the same information. Thus, overreaction is not merely a reduced-form pattern in survey forecast errors; it also predicts how firms update beliefs in response to experimentally controlled information.

4 Conclusion

This paper reaches two conclusions about firm belief updating. First, firms overreact to the information reflected in their own forecast revisions, but this overreaction weakens rather than strengthens when perceived uncertainty rises. The evidence is therefore consistent with diagnostic expectations as an account of overreaction, while challenging the amplification prediction of Smooth Diagnostic Expectations in this setting. Second, overreaction measured in the firm panel has behavioral content beyond the forecast-error regression used to identify it. It predicts how firms respond to the same experimentally supplied information, although firms classified as overreactors generally respond less, rather than more, to the externally supplied policy scenario. Taken together, these findings suggest that overreaction is state dependent and specific to the information type, rather than a fixed tendency to respond excessively to all information.

An important next step is to identify why overreaction attenuates when subjective uncer-

tainty rises. A natural design would combine an experimental manipulation of uncertainty with information provision, while measuring posterior beliefs, information acquisition, and subsequent decisions. Such a design could help distinguish whether agents respond more cautiously because they regard signals as less precise, seek additional information, or process information more deliberately. Eliciting full subjective distributions could also permit a more direct comparison of current and reference uncertainty, the theoretical object emphasized by Smooth Diagnostic Expectations. Extending these designs to households and linking changes in belief updating to consumption, pricing, or investment decisions would help establish how broadly the attenuation result applies and whether it has meaningful aggregate consequences.

References

- Abberger, Klaus, Arbërim Bibaj, Hans Gersbach, Alexis Perakis, Alexander Rathke, Samad Sarferaz, and Kieran James Walsh. 2026. “Tariffs and Firm Expectations.” *CESifo Working Paper*, 12510. CESifo.
- Afrouzi, Hassan, Spencer Y Kwon, Augustin Landier, Yueran Ma, and David Thesmar. 2023. “Overreaction in Expectations: Evidence and Theory*.” *The Quarterly Journal of Economics*, 138(3): 1713–1764.
- Andre, Peter, Carlo Pizzinelli, Christopher Roth, and Johannes Wohlfart. 2022. “Subjective Models of the Macroeconomy: Evidence From Experts and Representative Samples.” *Review of Economic Studies*, 89(6): 2958–2991.
- Armantier, Olivier, Scott Nelson, Giorgio Topa, Wilbert van der Klaauw, and Basit Zafar. 2016. “The Price Is Right: Updating Inflation Expectations in a Randomized Price Information Experiment.” *Review of Economics and Statistics*, 98(3): 503–523.
- Armona, Luis, Andreas Fuster, and Basit Zafar. 2019. “Home Price Expectations and Behaviour: Evidence From a Randomized Information Experiment.” *Review of Economic Studies*, 86(4): 1371–1410.
- Bachmann, Rüdiger, Steffen Elstner, and Eric R. Sims. 2013. “Uncertainty and Economic Activity: Evidence from Business Survey Data.” *American Economic Journal: Macroeconomics*, 5(2): 217–49.
- Ba, Cuimin, J. Aislinn Bohren, and Alex Imas. 2024. “Over- and Underreaction to Information.” *SSRN Working Paper*, 4274617. Social Science Research Network.
- Bianchi, Francesco, Cosmin L. Ilut, and Hikaru Saijo. 2024. “Smooth Diagnostic Expectations.” *NBER Working Paper*, 32152. National Bureau of Economic Research.
- Binetti, Alberto, Francesco Nuzzi, and Stefanie Stantcheva. 2024. “People’s understanding of inflation.” *Journal of Monetary Economics*, 148: 103652.
- Bordalo, Pedro, Giovanni Burro, Katherine Coffman, Nicola Gennaioli, and Andrei Shleifer. 2025. “Imagining the Future: Memory, Simulation, and Beliefs.” *The Review of Economic Studies*, 92(3): 1532–1563.
- Bordalo, Pedro, John Conlon, Nicola Gennaioli, Spencer Kwon, and Andrei Shleifer. 2026a. “How People Use Statistics.” *The Review of Economic Studies*, 93(1): 250–285.
- Bordalo, Pedro, John J Conlon, Nicola Gennaioli, Spencer Y Kwon, and Andrei Shleifer. 2023. “Memory and Probability.” *The Quarterly Journal of Economics*, 138(1): 265–311.

- Bordalo, Pedro, Katherine Coffman, Nicola Gennaioli, and Andrei Shleifer.** 2016. “Stereotypes.” *The Quarterly Journal of Economics*, 131(4): 1753–1794.
- Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer.** 2018. “Diagnostic Expectations and Credit Cycles.” *The Journal of Finance*, 73(1): 199–227.
- Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer.** 2020. “Memory, Attention, and Choice.” *The Quarterly Journal of Economics*, 135(3): 1399–1442.
- Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer.** 2022. “Overreaction and Diagnostic Expectations in Macroeconomics.” *Journal of Economic Perspectives*, 36(3): 223–44.
- Bordalo, Pedro, Nicola Gennaioli, Andrei Shleifer, and Stephen J. Terry.** 2026*b*. “Real Credit Cycles.” *American Economic Review*, 116(4): 1274–1308.
- Bordalo, Pedro, Nicola Gennaioli, Florencio Lopez-de-Silanes, Simon G. Schröder, Andrei Shleifer, and Maarten van Rooij.** 2026*c*. “The Psychology of Macroeconomic Expectations.” *NBER Working Paper*, 35214. National Bureau of Economic Research.
- Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta, and Andrei Shleifer.** 2019. “Diagnostic Expectations and Stock Returns.” *The Journal of Finance*, 74(6): 2839–2874.
- Bordalo, Pedro, Nicola Gennaioli, Spencer Yongwook Kwon, and Andrei Shleifer.** 2021. “Diagnostic bubbles.” *Journal of Financial Economics*, 141(3): 1060–1077.
- Bordalo, Pedro, Nicola Gennaioli, Yueran Ma, and Andrei Shleifer.** 2020. “Overreaction in Macroeconomic Expectations.” *American Economic Review*, 110(9): 2748–82.
- Born, Benjamin, Zeno Enders, Manuel Menkhoff, Gernot J. Müller, and Knut Niemann.** 2022. “Firm Expectations and News: Micro v Macro.” *CESifo Working Paper*, 10192. CESifo.
- Broer, Tobias, and Alexandre N. Kohlhas.** 2024. “Forecaster (Mis-)Behavior.” *The Review of Economics and Statistics*, 106(5): 1334–1351.
- Cavallo, Alberto, Guillermo Cruces, and Ricardo Perez-Truglia.** 2017. “Inflation Expectations, Learning, and Supermarket Prices: Evidence from Survey Experiments.” *American Economic Journal: Macroeconomics*, 9(3): 1–35.
- Coibion, Olivier, and Yuriy Gorodnichenko.** 2015. “Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts.” *American Economic Review*, 105(8): 2644–78.
- Coibion, Olivier, and Yuriy Gorodnichenko.** 2026. *Expectations matter: The new causal macroeconomics of surveys and experiments*. Princeton University Press.

- Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber.** 2022. “Monetary policy communications and their effects on household inflation expectations.” *Journal of Political Economy*, 130(6): 1537–1584.
- Coibion, Olivier, Yuriy Gorodnichenko, and Saten Kumar.** 2018. “How Do Firms Form Their Expectations? New Survey Evidence.” *American Economic Review*, 108(9): 2671–2713.
- Coibion, Olivier, Yuriy Gorodnichenko, and Tiziano Ropele.** 2020. “Inflation Expectations and Firm Decisions: New Causal Evidence.” *The Quarterly Journal of Economics*, 135(1): 165–219.
- d’Arienzo, Daniele.** 2020. “Maturity Increasing Overreaction and Bond Market Puzzles.” *SSRN Working Paper*, 3733056. Social Science Research Network.
- Dibiasi, Andreas, Heiner Mikosch, and Samad Sarferaz.** 2025. “Uncertainty Shocks, Adjustment Costs, and Firm Beliefs: Evidence From a Representative Survey.” *American Economic Journal: Macroeconomics*, 17(3): 36–73.
- Enke, Benjamin, and Thomas Graeber.** 2023. “Cognitive Uncertainty.” *The Quarterly Journal of Economics*, 138(4): 2021–2067.
- Enke, Benjamin, Thomas Graeber, Ryan Oprea, and Jeffrey Yang.** 2024. “Behavioral Attenuation.” *NBER Working Paper*, 32973. National Bureau of Economic Research.
- Fuster, Andreas, and Basit Zafar.** 2023. “Survey Experiments on Economic Expectations.” In *Handbook of Economic Expectations*, ed. Rüdiger Bachmann, Giorgio Topa and Wilbert van der Klaauw, 107–130. Academic Press.
- Fuster, Andreas, Ricardo Perez-Truglia, Mirko Wiederholt, and Basit Zafar.** 2022. “Expectations with Endogenous Information Acquisition: An Experimental Investigation.” *The Review of Economics and Statistics*, 104(5): 1059–1078.
- Gennaioli, Nicola, and Andrei Shleifer.** 2010. “What Comes to Mind.” *The Quarterly Journal of Economics*, 125(4): 1399–1433.
- Haaland, Ingar, Christopher Roth, and Johannes Wohlfart.** 2023. “Designing Information Provision Experiments.” *Journal of Economic Literature*, 61(1): 3–40.
- Kohlhas, Alexandre N., and Ansgar Walther.** 2021. “Asymmetric Attention.” *American Economic Review*, 111(9): 2879–2925.
- L’Huillier, Jean-Paul, Sanjay R Singh, and Donghoon Yoo.** 2024. “Incorporating Diagnostic Expectations into the New Keynesian Framework.” *The Review of Economic Studies*, 91(5): 3013–3046.

- Malmendier, Ulrike, and Stefan Nagel.** 2011. “Depression Babies: Do Macroeconomic Experiences Affect Risk Taking?*.” *The Quarterly Journal of Economics*, 126(1): 373–416.
- Malmendier, Ulrike, and Stefan Nagel.** 2016. “Learning from Inflation Experiences.” *The Quarterly Journal of Economics*, 131(1): 53–87.
- Maćkowiak, Bartosz, Filip Matějka, and Mirko Wiederholt.** 2023. “Rational Inattention: A Review.” *Journal of Economic Literature*, 61(1): 226–73.
- Mikosch, Heiner, Christopher Roth, Samad Sarferaz, and Johannes Wohlfart.** 2024. “Uncertainty and information acquisition: Evidence from firms and households.” *American Economic Journal: Macroeconomics*, 16(2): 375–405.
- Roth, Christopher, and Johannes Wohlfart.** 2020. “How Do Expectations about the Macroeconomy Affect Personal Expectations and Behavior?” *Review of Economics and Statistics*, 102(4): 731–748.
- Stantcheva, Stefanie.** 2023. “How to Run Surveys: A Guide to Creating Your Own Identifying Variation and Revealing the Invisible.” *Annual Review of Economics*, 15: 205–234.

Overreaction in Expectations:
Uncertainty and Experimental Evidence
– **Online Appendix** –

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This appendix provides supplementary material. Section A presents descriptive figures. Section B details the construction of forecast errors and revisions from qualitative survey responses. Section C reports supporting regression results. Section D presents the survey questions used in the analysis.

A Descriptive Figures

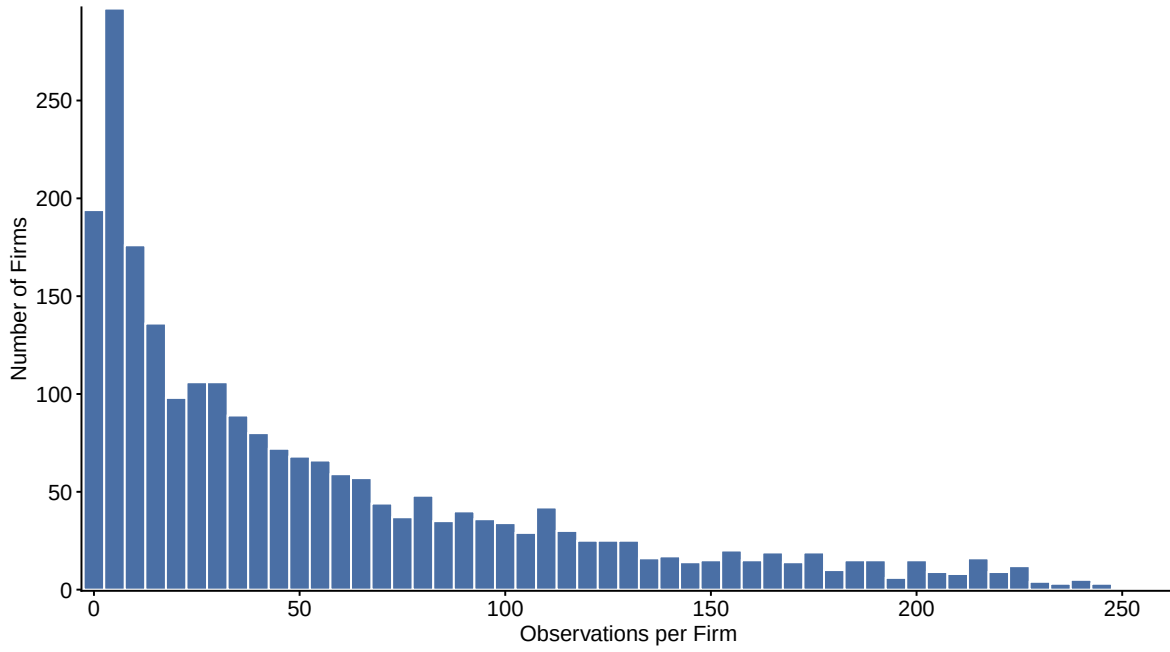


Figure A.1: Distribution of Firm Observations

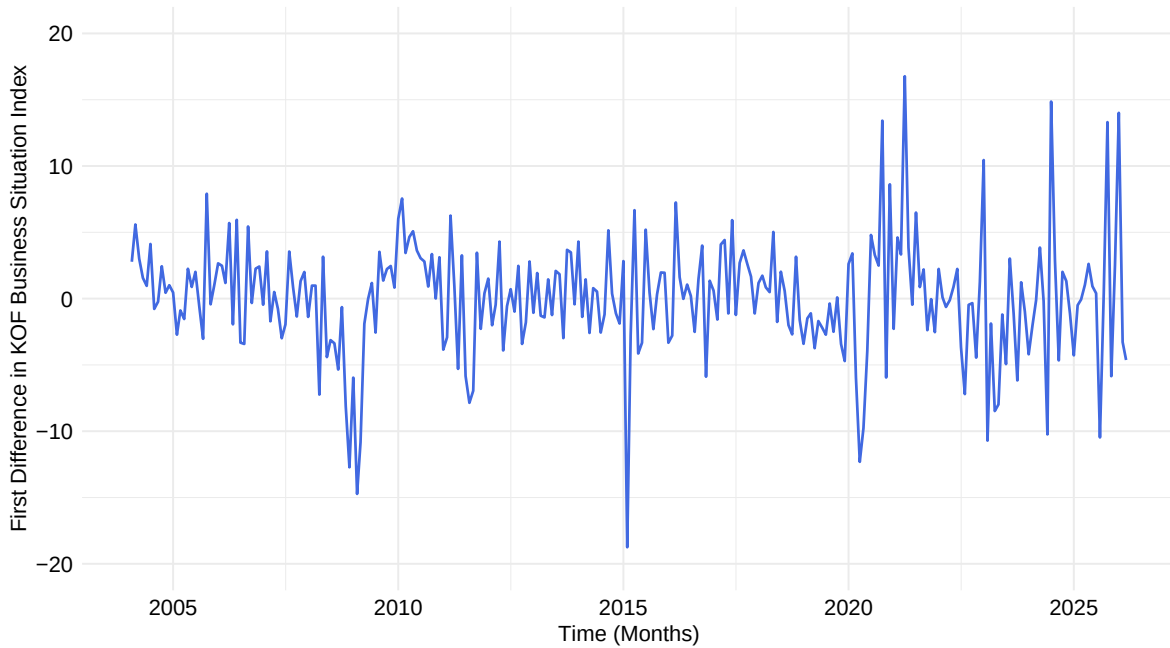


Figure A.2: Aggregate News A_t Over Time

B Constructing Forecast Errors and Forecast Revisions from Qualitative Survey Data

Section 2 abstracts from several implementation issues that arise from the qualitative nature of the survey responses. First, firms report the expected direction of change over the next three months, whereas realizations refer to the previous month. The response categories are coded as +1, 0, and -1 for “increase,” “remain the same,” and “decrease,” respectively. Constructing forecast errors therefore requires aggregating the monthly realizations over the horizon covered by the forecast. I follow the procedure of Bachmann, Elstner and Sims (2013), summarized in Panel (a) of Table B.1. Moreover, forecast revisions are constructed by mapping changes between successive qualitative forecasts into $\{-1, 0, +1\}$. I use the procedure of Born et al. (2022), reported in Panel (b) of Table B.1. As is standard in this literature (Coibion and Gorodnichenko, 2015; Bordalo et al., 2020), the horizons of successive forecasts do not perfectly overlap.

Table B.1: Construction of Forecast Errors and Forecast Revisions

(a) Forecast Errors

Forecast at $t - 3$, $F_{t t-3}^i$	Realization at t , $R_t^i = \sum_{s=0}^2 y_{t-s}^i$		
	> 0	$= 0$	< 0
+1 (Increase)	0	$-\frac{1}{3}$	$\frac{R_t^i - 1}{3}$
0 (Same)	$\frac{R_t^i}{3}$	0	$\frac{R_t^i}{3}$
-1 (Decrease)	$\frac{R_t^i + 1}{3}$	$\frac{1}{3}$	0

(b) Forecast Revisions

Forecast at $t - 1$, $F_{t+2 t-1}^i$	Forecast at t , $F_{t+3 t}^i$		
	Decrease	Same	Increase
Decrease	0	+1	+1
Same	-1	0	+1
Increase	-1	-1	0

Notes: Panel (a) reports the construction of forecast errors following Bachmann, Elstner and Sims (2013). $F_{t|t-3}^i \in \{-1, 0, +1\}$ denotes firm i 's qualitative forecast, made at $t - 3$, for the direction of change over the three-month period ending at t . The corresponding realization is $R_t^i = \sum_{s=0}^2 y_{t-s}^i$, where $y_{t-s}^i \in \{-1, 0, +1\}$ is the firm's monthly qualitative realization. The forecast error is zero when the expected direction coincides with the sign of the cumulative realization. The remaining cells report the discrepancy normalized by the length of the forecast horizon. Panel (b) reports the construction of forecast revisions following Born et al. (2022). The revision is defined as $\text{sign}(F_{t+3|t}^i - F_{t+2|t-1}^i) \in \{-1, 0, +1\}$. The notation F distinguishes forecasts, which refer to three-month intervals, from the monthly realizations denoted by y .

C Supporting Results

Table C.1: Robustness for High-Uncertainty States – No Time Fixed Effects

	Incoming Orders Forecast Error					
	(1)	(2)	(3)	(4)	(5)	(6)
Forecast revision, $FR_{t,h}^i$	-0.0317*** (0.0020)	-0.0319*** (0.0020)	-0.0244*** (0.0037)	-0.0324*** (0.0085)	-0.0244*** (0.0037)	-0.0324*** (0.0085)
Aggregate information, A_t		0.0046*** (0.0003)	0.0023*** (0.0004)	0.0023*** (0.0004)	0.0020** (0.0009)	0.0020** (0.0009)
High uncertainty, U_t^i			-0.0606*** (0.0115)	-0.0607*** (0.0115)	-0.0607*** (0.0115)	-0.0608*** (0.0115)
$FR_{t,h}^i \times U_t^i$				0.0101 (0.0097)		0.0101 (0.0097)
$A_t \times U_t^i$					0.0004 (0.0010)	0.0004 (0.0010)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No	No	No
Month fixed effects	No	No	No	No	No	No
Number of firms	2,255	2,252	1,203	1,203	1,203	1,203
Observations	134,904	134,507	32,046	32,046	32,046	32,046

Notes: The table reports regressions of forecast errors for incoming orders on firms' own forecast revisions, aggregate information, self-reported uncertainty, and their interactions. The dependent variable is the realized change in incoming orders minus the corresponding forecast. $FR_{t,h}^i$ denotes the firm's forecast revision, A_t denotes aggregate information, and U_t^i is an indicator for high self-reported uncertainty. Column (6) reports the full specification in equation (2); columns (1)–(5) omit selected terms from the full specification. All specifications include firm fixed effects and standard errors are clustered by firm. A_t is winsorized at the 95 percent level. *p<0.10; **p<0.05; ***p<0.01.

Table C.2: Robustness for Changes in Uncertainty – No Time Fixed Effects

	Incoming Orders Forecast Error			
	(1)	(2)	(3)	(4)
Forecast revision, $FR_{t,h}^i$	-0.0250*** (0.0038)	-0.0250*** (0.0038)	-0.0251*** (0.0038)	-0.0250*** (0.0038)
Aggregate information, A_t	0.0020*** (0.0004)	0.0020*** (0.0004)	0.0020*** (0.0004)	0.0020*** (0.0004)
Changes in uncertainty, G_t^i	-0.0141*** (0.0027)	-0.0141*** (0.0027)	-0.0145*** (0.0027)	-0.0144*** (0.0027)
$FR_{t,h}^i \times G_t^i$		0.0116* (0.0062)		0.0112* (0.0063)
$A_t \times G_t^i$			0.0007 (0.0006)	0.0007 (0.0006)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No
Month fixed effects	No	No	No	No
Number of firms	1,195	1,195	1,195	1,195
Observations	31,414	31,414	31,414	31,414

Notes: The table reports regressions of forecast errors for incoming orders on firms' own forecast revisions, aggregate information, self-reported uncertainty, and their interactions. The dependent variable is the realized change in incoming orders minus the corresponding forecast. $FR_{t,h}^i$ denotes the firm's forecast revision, A_t denotes aggregate information, and G_t^i is the change in self-reported uncertainty. Column (4) reports the full specification in equation (2); columns (1)–(3) omit selected terms from the full specification. All specifications include firm fixed effects and standard errors are clustered by firm. A_t is winsorized at the 95 percent level. *p<0.10; **p<0.05; ***p<0.01.

Table C.3: Robustness for Uncertainty – Year-Month Fixed Effects

	Incoming Orders Forecast Error				
	(1)	(2)	(3)	(4)	(5)
Forecast revision, $FR_{t,h}^i$	-0.0300*** (0.0019)	-0.0228*** (0.0037)	-0.0304*** (0.0086)	-0.0234*** (0.0037)	-0.0234*** (0.0037)
High uncertainty, U_t^i		-0.0624*** (0.0115)	-0.0625*** (0.0115)		
$FR_{t,h}^i \times U_t^i$			0.0096 (0.0097)		
Changes in uncertainty, G_t^i				-0.0130*** (0.0027)	-0.0130*** (0.0027)
$FR_{t,h}^i \times G_t^i$					0.0128** (0.0062)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes	Yes	Yes
Number of firms	2,255	1,203	1,203	1,195	1,195
Observations	134,904	32,046	32,046	31,414	31,414

Notes: The table reports regressions of forecast errors for incoming orders on firms' own forecast revisions, self-reported uncertainty, and their interactions. The dependent variable is the realized change in incoming orders minus the corresponding forecast. $FR_{t,h}^i$ denotes the firm's forecast revision, U_t^i is an indicator for high self-reported uncertainty, and G_t^i is the change in self-reported uncertainty. All specifications include firm and year-month fixed effects. Relative to equation (2), the aggregate information variable A_t is absorbed by the year-month fixed effects and is therefore omitted; specifications also omit interactions involving A_t . Standard errors are clustered by firm. *p<0.10; **p<0.05; ***p<0.01.

Table C.4: Robustness for High-Uncertainty States – Alternative Outcome

	Production Forecast Error					
	(1)	(2)	(3)	(4)	(5)	(6)
Forecast revision, $FR_{t,h}^i$	-0.0231*** (0.0018)	-0.0235*** (0.0018)	-0.0164*** (0.0034)	-0.0153** (0.0069)	-0.0165*** (0.0034)	-0.0153** (0.0069)
Aggregate information, A_t		0.0027*** (0.0003)	0.0005 (0.0004)	0.0005 (0.0004)	0.0002 (0.0007)	0.0002 (0.0007)
High uncertainty, U_t^i			-0.0631*** (0.0106)	-0.0631*** (0.0106)	-0.0632*** (0.0106)	-0.0632*** (0.0106)
$FR_{t,h}^i \times U_t^i$				-0.0014 (0.0083)		-0.0014 (0.0083)
$A_t \times U_t^i$					0.0004 (0.0009)	0.0004 (0.0009)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	2,226	2,223	1,182	1,182	1,182	1,182
Observations	131,241	130,866	30,573	30,573	30,573	30,573

Notes: The table reports regressions of forecast errors for production on firms' own forecast revisions, aggregate information, self-reported uncertainty, and their interactions. The dependent variable is the realized change in production minus the corresponding forecast. $FR_{t,h}^i$ denotes the firm's forecast revision, A_t denotes aggregate information, and U_t^i is an indicator for high self-reported uncertainty. Column (6) reports the full specification in equation (2); columns (1)–(5) omit selected terms from the full specification. All specifications include firm, year, and month fixed effects. Standard errors are clustered by firm and A_t is winsorized at the 95 percent level. *p<0.10; **p<0.05; ***p<0.01.

Table C.5: Robustness for Changes in Uncertainty – Alternative Outcome

	Production Forecast Error			
	(1)	(2)	(3)	(4)
Forecast revision, $FR_{t,h}^i$	-0.0154*** (0.0034)	-0.0153*** (0.0034)	-0.0153*** (0.0034)	-0.0152*** (0.0034)
Aggregate information, A_t	0.0006 (0.0004)	0.0006 (0.0004)	0.0006 (0.0004)	0.0006 (0.0004)
Changes in uncertainty, G_t^i	-0.0039* (0.0023)	-0.0039* (0.0023)	-0.0043* (0.0023)	-0.0043* (0.0023)
$FR_{t,h}^i \times G_t^i$		0.0142** (0.0060)		0.0139** (0.0060)
$A_t \times G_t^i$			0.0007 (0.0006)	0.0007 (0.0006)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Number of firms	1,174	1,174	1,174	1,174
Observations	29,972	29,972	29,972	29,972

Notes: The table reports regressions of forecast errors for production on firms' own forecast revisions, aggregate information, self-reported uncertainty, and their interactions. The dependent variable is the realized change in production minus the corresponding forecast. $FR_{t,h}^i$ denotes the firm's forecast revision, A_t denotes aggregate information, and G_t^i is the change in self-reported uncertainty. Column (4) reports the full specification in equation (2); columns (1)–(3) omit selected terms from the full specification. All specifications include firm, year, and month fixed effects. Standard errors are clustered by firm and A_t is winsorized at the 95 percent level. *p<0.10; **p<0.05; ***p<0.01.

Table C.6: Robustness for Differences in Experimental Responses – Tariff Exposure

	Uniform tariff (10 %)		“Liberation Day” (31 %)	
	Δ mean	SE	Δ mean	SE
Real turnover	−0.72	1.92	0.77	1.42
Price index	−0.44 **	0.19	−1.07 ***	0.26
Prices: U.S.	−2.13	1.79	−6.64 ***	1.37
Prices: rest of world	−0.53 ***	0.20	−0.61 ***	0.14
Prices: Switzerland	−0.27 *	0.15	−0.59 ***	0.11
Investment	0.77	0.64	0.81	1.16

Notes: The table reports differences in means for overreacting and non-overreacting firms by their treatment assignment in the vignette experiment of Abberger et al. (2026). **The difference-in-means regressions control for an indicator equal to one if the firm generates more than 20 percent of its turnover in the United States.** Positive values indicate higher outcome means for overreacting firms. A firm is classified as an overreactor when its panel behavior displays statistically significant overreaction to firm-specific information. Firms with less than 10 observations are excluded from the panel. Outcome variables are measured as percentage changes relative to the no-tariff-increase benchmark. Heteroskedasticity-robust (HC1) standard errors are reported in adjacent columns. *p<0.10; **p<0.05; ***p<0.01.

Table C.7: Robustness for Differences in Experimental Responses – Pre-experiment Panel

	Uniform tariff (10 %)		“Liberation Day” (31 %)	
	Δ mean	SE	Δ mean	SE
Real turnover	0.63	2.33	2.32	1.54
Price index	−0.63 ***	0.22	−1.11 ***	0.17
Prices: U.S.	−0.73	3.42	−6.88 ***	1.18
Prices: rest of world	−0.46 **	0.23	−0.65 ***	0.13
Prices: Switzerland	−0.25	0.17	−0.56 ***	0.10
Investment	0.61	0.79	−0.36	1.53

Notes: The table reports differences in means for overreacting and non-overreacting firms by their treatment assignment in the vignette experiment of Abberger et al. (2026). Positive values indicate higher outcome means for overreacting firms. A firm is classified as an overreactor when its **pre-experiment** panel behavior displays statistically significant overreaction to firm-specific information. Firms with less than 10 observations are excluded from the panel. Outcome variables are measured as percentage changes relative to the no-tariff-increase benchmark. Heteroskedasticity-robust (HC1) standard errors are reported in adjacent columns. *p<0.10; **p<0.05; ***p<0.01.

D The Survey Questions

Question on Realized Incoming Orders

In the past month compared to the previous incoming orders have:

- increased
- remained the same
- declined

Question on Realized Production

In the past month compared to the previous production has:

- increased
- not changed
- decreased

Question on Future Development

To predict the future development of our business situation is currently:

- easy
- rather easy
- rather difficult
- difficult

Question on Incoming Orders Expectations

It is likely that in the next 3 months incoming orders will:

- increase
- remain the same
- decrease

Question on Production Expectations

It is likely that in the next 3 months production will:

- increase
- remain the same
- decrease