

Firm Expectations and News: Micro v Macro*

Benjamin Born, Zeno Enders, Manuel Menkhoff,
Gernot J. Müller, and Knut Niemann

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Abstract

How do expectations about the economy adjust to news? In this paper, we turn to firm expectations about their production and establish that the *type* of news matters—firm expectations overreact to micro news but underreact to macro news. We obtain these results based on a large survey of firm expectations. We define micro news as new information about firm-specific developments, while macro news are surprise innovations to an aggregate indicator. In violation of the full-information rational expectation hypothesis, both type of news predict forecast errors. But while micro news predict negative forecast errors, macro news predict positive forecast errors. We show that a general equilibrium model can rationalize the patterns in the data once we assume that firms suffer from “island illusion”.

Keywords: Firm expectations, survey, overreaction, underreaction, micro news, macro news, island illusion, business cycle

JEL-Codes: D84, C53, E71

*Born: Frankfurt School of Finance & Management, CEPR, CESifo, and ifo Institute, b.born@fs.de, Enders: Heidelberg University and CESifo, zeno.enders@uni-heidelberg.de, Menkhoff: ifo Institute and LMU Munich, menkhoff@ifo.de, Müller: University of Tübingen, CEPR, and CESifo, gernot.mueller@uni-tuebingen.de, Niemann: University of Tübingen, knut.niemann@uni-tuebingen.de. We thank Rüdiger Bachmann, Christian Conrad, Alexandre Kohlhas, and participants at various conferences and seminars for very useful comments. Financial support by the German Science Foundation (DFG) is gratefully acknowledged. The usual disclaimer applies.

1 Introduction

The question of how expectations about the economy adjust to news is key when it comes to understanding the expectation-formation process. Accordingly, it has received considerable attention in recent work. The full information rational expectation (FIRE) hypothesis serves as a natural benchmark. Under FIRE, expectations adjust correctly and instantaneously in the face of new information and, as a result, forecast errors are not predictable on the basis of news. By now it is well established that actual expectations—as measured by survey data—fail to meet the FIRE benchmark. On average, expectations tend to underreact to news in the sense that forecast revisions predict positive forecast errors, suggesting that it takes time to process information in contrast to what the *full information* assumptions implies (Coibion and Gorodnichenko 2012, 2015). Expectations of individual forecasters, however, tend to overreact to news—suggestive of a departure from *rationality*—and the literature is currently exploring explanations that can account for both observations jointly (Bordalo et al. 2020; Broer and Kohlhas 2022).

In this paper, we offer a new perspective. Existing studies focus on expectations of macroeconomic outcomes, maintained by professional forecasters. Instead, we turn to firm expectations about firm-specific developments. This has two advantages. First, we are able to distinguish between micro and macro news. Micro news concern firm-specific developments, macro news concern the aggregate economy. Both matter for firm-specific developments and, by implication, impact firm expectations. Second, focusing on firm expectations (rather than on professional forecasters) allows us to exploit a much larger and richer data set and to probe into the role of (firm) heterogeneity for the expectation-formation process. Specifically, our sample is based on the ifo survey of German firms and features responses of some 1,500 observations in each month and covers 15 years of data.

We find that the distinction between micro and macro news is essential for the expectation-formation process: firm expectations overreact to micro news, but simultaneously underreact to macro news. This feature emerges robustly across a variety of specifications and for all firm types that we consider (e.g., small and large, young and old). We use the cross-section of firms to establish real effects of the biased expectations: larger biases are associated with lower profits and higher production volatility. In the second part of the paper, we study these results through the lens of a general equilibrium model. The model builds on the noisy and dispersed information model of Lorenzoni (2009) but assumes, in addition, that firms suffer from “island illusion”: They perceive what’s happening to them as less common than it actually is. This departure from rational expectations allows the model to predict simultaneous over- and underreaction to micro and macro news—in line with the evidence.

In the first part of the paper, we establish new evidence on how firm expectations react to news based on the ifo survey of German firms. It is one of the oldest and largest surveys of firms currently available. It is based on a survey which has been conducted since 1949 and whose design has since then been adopted by surveys around the world (Becker and Wohlrabe 2008). Our monthly sample runs from April 2004 to December 2019. We consider some 1500 observations each month and focus on firms' expectations about how their production will evolve over the next 3 months. Firms respond to these questions qualitatively. This raises some issues when it comes to defining forecast errors, which we address in Section 2.

In order to study the response of expectations to news, we rely on the empirical framework introduced by Coibion and Gorodnichenko (2015), which is by now widely used in the literature. The idea is straightforward: we regress firms' forecast errors on today's news. For this purpose, we first compute the revisions of firms' production expectations in a given month. To the extent that news are processed, they will be reflected in these revisions. However, the news may be about firm-specific developments (micro news) or about the aggregate economy (macro news). We isolate the micro component by removing the (time-)fixed effect in the forecast revision that is common to all firms. We measure macro news, in turn, as the surprise component of the ifo index, a widely watched indicator of the German business cycle compiled on the basis of the ifo survey, relative to professional forecasts for the ifo index, available from the Bloomberg consensus survey. Two aspects are important to note. First, the ifo index is compiled by aggregating expectations across firms in the survey such that micro and macro news rely on the same source but differ in the level of aggregation. Second, regarding the timing, we note that macro news are released at the end of the previous month and are thus available as firms report their forecast in the current month—just like micro news. For these reasons, both micro and macro news should not predict the forecast error under the FIRE hypothesis. And yet, our first key result, based on firm-level and panel regressions, is that they do so robustly.

Our second result, is that they do so in systematically different ways. Macro news have a positive effect on forecast errors. Intuitively, if there is a positive surprise in the current ifo index, chances are high that actual production exceeds production expectations over the course of the next three months. In this sense, firm expectations do not fully account for macro news as they become available: they underreact to macro news. Micro news, instead, have a negative effect on the forecast error, that is, an upward revision of production expectations tends to be followed by a worse-than-expected output performance. Firm expectations respond too strongly to micro news, they overreact. We find that these patterns are a robust feature of our data set. They emerge if we include micro and macro news jointly in the regression, but also if we consider them in isolation. In this case, we include time-fixed

effects to control for aggregate developments as we estimate the effect of micro news on forecast errors. We also allow positive and negative news to have different effects, but find them to be largely symmetric. Finally, we investigate whether effects differ across firms of different sizes and find that they do not in case of micro shock.

The estimated response coefficients provide a measure for the “micro bias” and the “macro bias” in firms’ expectation formation process and we study how these biases evolves over time. We find that they do not change signs. Their size varies considerably, however. The macro bias is largest during the Great Recession. This observation casts doubt on the hypothesis that rational inattention is driving our results. We also exploit the fact that we can estimate the bias for each firm and assess how it relates to firm level outcomes. We find, in particular, that a larger micro bias is associated with lower profits and both, micro and macro biases are associated with higher firm-level volatility. These findings show that expectation and, more specifically, expectation errors matter for firm outcomes, in line with earlier findings based on the ifo survey (Bachmann et al. 2013; Enders et al. 2022; Born et al. 2022).

In the last part of the paper, we put forward a general equilibrium model in order to rationalize our findings. The model builds on earlier work by Lorenzoni (2009) but assumes that firms suffer from island illusion. At a methodological level, our model differs from earlier attempts to account for overreaction such as Broer and Kohlhas (2022) or Bordalo et al. (2020) in that it offers a full-fledged general equilibrium framework. This is essential in the context of our analysis as it allows us to account for the cross-equation restrictions which govern the impact of micro and macro news on firm expectations. In the model, information is dispersed across firms. Firms observe their own developments plus a public signal and use this information to forecast the aggregate state of the economy. Prices are sticky and firms are assumed to adjust production in order to meet demand given posted prices. As a result, the aggregate state of the economy is important for firms when it comes to forecasting their own production. As a distinct feature, we assume that firms suffer from “island illusion:” They underestimate the relative importance of aggregate developments for their own developments.

We think of island illusion as an instance of salience, which Taylor and Thompson (1982) define as “the phenomenon that when one’s attention is differentially directed to one portion on the environment rather than to others, the information contained in that portion will receive disproportionate weighing in subsequent judgments” (see also Bordalo et al. 2013). More specifically, Bordalo et al. (2022) note that “a stimulus is salient when it attracts the decision maker’s attention “bottom up,” automatically and involuntarily.” Our results are consistent with the view that firm-specific developments attract firms’ attention bottom-up and are thereby salient—featuring disproportionately in firms’ judgements—while other sources of information have to be gathered and proceeded actively.

The model is sufficiently stylized and can be solved in closed form. In particular, we show that it predicts firm expectations to overreact to micro news and to underact to macro news, in line with the evidence. Moreover, we spell out the implications for the business cycle. For instance, we show that aggregate output reacts less to noise in the public signal, a common measure of demand shocks (Lorenzoni 2009; Enders et al. 2021). At the same time, due to the overreaction to micro news, the dispersion of output innovations across firms is amplified relative to the noisy-information, rational-expectations benchmark. A direct implication is that island illusion may cause some of the high idiosyncratic volatility of outcome variables observed at the firm level (Bloom et al. 2018; Bachmann and Bayer 2013).

The paper is organized as follows. In the remainder of the introduction we place the paper in the context of the literature. Section 2 provides details about the ifo survey and our data set. In Section 3, we introduce our empirical framework and present the results. We develop and solve a general equilibrium model with dispersed information and overconfidence in Section 4. A final section offers some conclusions.

Related Literature. Recent work points to non-trivial departures from the FIRE benchmark. Some authors emphasize that a (rational) focus on certain sectors/media distorts the information formation process (Chahrour et al. 2021). In related work, Kohlhas and Walther (2021) put forward a model of asymmetric attention which rationalizes the observation that professional forecasts of output growth underreact to forecast revisions (news) but overreact to recent realizations of output growth. They stress, however, that asymmetric attention arises naturally in a rational framework. Other recent models, instead, allow for behavioral aspects in the expectation formation process (for instance, Shiller 2017; Bordalo et al. 2019; Azeredo da Silveira and Woodford 2019). Under certain conditions behavioral models and incomplete information models give rise to equivalent equilibrium effects (Angeletos and Huo 2021). Carroll et al. (2020) put forward a model of sticky expectations to account for evidence on consumption dynamics. A key assumption in their analysis is that information about macroeconomic quantities arrives only occasionally. Farmer et al. (2021) rationalize forecasting anomalies in a model with learning.

There is also earlier work on firm expectations based on the ifo index, surveyed by Born et al. (2022). Massenet and Pettinicchi (2018), in particular, regress expectations and forecast errors on past changes of the business situation (rather than on forecast revisions) and find the regression coefficient is positive and significant and robustly so across a number of specifications. They refer to this result as “over-extrapolation”. Enders et al. (2019), in turn take a macro perspective and document that the response of firm expectations to monetary policy shocks is non-linear in the size of the shock.

2 Measuring forecast errors and news

In this section, we first introduce our data set which is centered around the ifo survey of German firms. We also provide details on the construction and descriptive statistics of firms' forecast errors and the news measures on which our analysis in Section 3 is centered.

2.1 The ifo survey

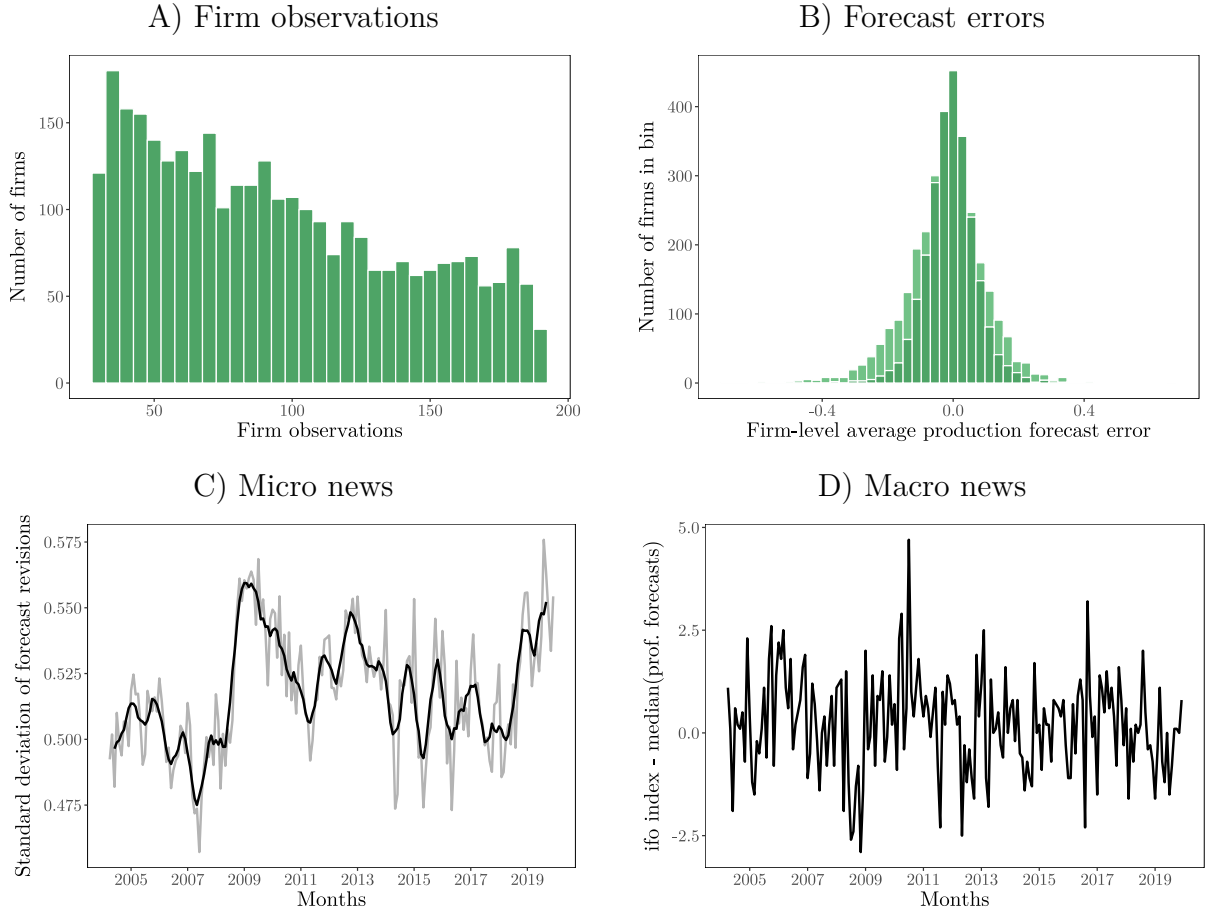
The ifo survey is a mostly qualitative, monthly survey among German firms and representative for the German economy (Hiersemenzel et al. 2022).¹ It was launched in 1949 and the micro-data is available for research since 1980. Participation is voluntary and firms only receive non-monetary compensation in the form of sectoral and aggregate results of the survey. The individual filling a firm's questionnaire is a member of the senior management, 85 percent are CEOs or department heads (Sauer and Wohlrabe 2019). Response rates for the ifo survey are generally high: out of all firms initially contacted in mid 2021, around two thirds returned at least two surveys. For the comparable Survey of Business Uncertainty in the United States, the response rate is around one third only (Altig et al. 2020). Response rates remain high also after initial contact, with an average monthly response rate of 82 percent; the sample attrition is moderate (Enders et al. 2022).

Our analysis—in order to measure firms' forecast errors and news—builds on three main components: (i) the ifo Business Climate *Survey* in the manufacturing sector (IBS-IND 2020, from now on ifo survey), (ii) the ifo Business Climate *Index* (ifo index), and (iii) the Bloomberg consensus forecasts for the ifo index. Our sample is restricted by limited data availability of the Bloomberg forecasts and runs from April 2004 to December 2019.

To measure firm expectations and their forecast errors, we rely on the ifo survey. It features a core set of questions, including questions about expected and actual production, prices, and business situation, where firms can report either an increase, no change, or a decrease. While this makes quantitative statements challenging, the qualitative nature arguably reduces the room for measurement error. In our empirical analysis, we rely on time-series data at the level of individual firms. Therefore, we restrict our sample to those firms which are in the survey for at least 30 months and which exhibit some time-series variation in their expectations and expectation errors. In any given month, this leaves us with more than 1,000 responses and often more than 1,500. Panel A of Figure 1 plots the distribution of firms sorted according to the number of months a firm is in the sample. The

¹Quantitative questions were added in 2005, distributional questions in 2013, see Bachmann et al. (2020, 2021) for details. While the survey is technically at the product level, we follow the literature (for example, Enders et al. 2022; Bachmann et al. 2013; Born et al. 2022) and treat each respondent as a separate firm.

Figure 1: ifo survey, forecast errors, and news



Notes: Panel A: distribution of monthly firm observations, i.e., the number of firms for which a firm-specific time series of certain length is available. Panel B: histogram of firm-level average forecast errors for production. The color indicates if estimates are significantly different from zero at the five percent level (light green) or not (dark green). Panel C: cross-sectional standard deviation of micro news over time, defined as the forecast revision net of time-fixed effects, see Equation (3). The grey line depicts the standard deviation of micro news at a monthly level and the black line depicts the six-month rolling average. Panel D: macro news shocks over time, defined as the surprise in the ifo index compared to median professional forecasts, see Equation (4).

median firm is in the survey for around 90 months and 25 percent of firms are in the survey for more than 130 months. We exploit the fact that we have fairly long time series available for individual firms in our analysis in Section 3. In particular, it allows us to characterize the heterogeneity of the expectation-formation process systematically.

2.2 Forecast errors

To construct firms' forecast errors, we follow the approach of Bachmann et al. (2013) and focus on expected and realized production as reported in the ifo survey. Here, firms report

for their own production the realized change over the previous month $x_{t,1}^i \in \{-1, 0, 1\}$ and the expected change over the following three months $x_{t,3|t}^i \in \{-1, 0, 1\}$ (for the exact wording see Table A.1). To harmonize the time horizons, monthly changes are aggregated over the following three months: $x_{t,3}^i = \sum_{j=1}^3 x_{t+j,1}^i$. Based on this aggregated realized change and the expected change, the forecast error $e_{i,t}$ is then defined as

$$e_{i,t} = \begin{cases} 0 & \text{if } \text{sign}(x_{t,3}^i) = \text{sign}(x_{t,3|t}^i) \\ \frac{1}{3}(x_{t,3}^i - x_{t,3|t}^i) & \text{else.} \end{cases} \quad (1)$$

When the signs of aggregated realized change and expected change coincide, no error is assigned. In all other cases, the forecast error is equal to the difference between aggregated realized and expected change, standardized by the forecasting horizon of three months.

Generally, we find forecast errors to be well-behaved. Panel B of Figure 1 shows the distribution of forecast errors: More than 75 percent of firm-level average forecast errors are not significantly different from zero. And while these forecast errors are based on qualitative rather than quantitative data, the key facts which characterize firms' forecast errors emerge robustly from qualitative and quantitative data and across countries, see Born et al. (2022) for a survey.

2.3 Micro news

Our measure of micro news is based on forecast revisions. Formally, we define the forecast revision of firm i in month t , $FR_{i,t}$, as the first difference of production expectations:

$$FR_{i,t} = \text{sign}(x_{t,3|t}^i - x_{t-1,3|t-1}^i), \quad (2)$$

which is equal to 0 when there is no change in expectations, equal to +1 for an upward revision (for example, from no change in $t-1$ to an increase in t) and equal to -1 for a downward revision (for example, from no change in $t-1$ to decrease in t). Our measure thus relies on current realized and expected production over the next three months, with forecast revisions covering two months. We assume that the overlap in forecasting periods is sufficiently large for forecast revisions to be driven by news and not changes in the forecasting periods.²

Importantly, firms are likely to revise expectations about their own production either

²As a later robustness check, we show that our results also hold for questions about firms' expected business situation. These questions cover the next six months, so the overlap in forecasting periods is five months, which underlines that our results are not driven by changes in the forecasting period.

because their expectations about the macroeconomy change or because they expect changes in their business conditions which are due to idiosyncratic developments. To isolate the latter component—that is to measure *micro news*—we remove time-fixed effects from the forecast revision, as defined in Equation (2):

$$FR_{i,t} = \mu_t + \text{micro news}_{i,t} . \quad (3)$$

In this way, we control for news which are common to all firms (while assuming that macro news load with the same factor for all firms). Panel C of Figure 1 shows how the cross-sectional dispersion of micro news fluctuates over time. It is largest during the Great Recession and towards the end of our sample period.

2.4 Macro news

To measure macro news, we compute the *surprise component* of the *ifo index*. The ifo index is compiled on the basis of the ifo survey by the ifo institute and is a widely watched indicator of the German business cycle (Carstensen et al. 2020; Lehmann 2020). The index is based on firms’ responses about their current business situation and their business expectations over the next 6 months (the exact wording is again in Table A.1).³ The index is defined as follows:

$$\text{business climate}_t = \sqrt{(\text{business situation}_t + 200)(\text{business expectation}_t + 200)} - 200 ,$$

where $\text{business situation}_t$ and $\text{business expectation}_t$ are balances, that is, the share of positive answers (“increase”) minus the share of negative answers (“decrease”) across firms. For publication, the ifo institute reports the business climate as an index relative to a base year, which at the time of writing is 2015 (Sauer and Wohlrabe 2018).

We can measure the surprise component in the ifo index based on professional forecasts for the ifo index, available from the Bloomberg consensus survey. In this survey, professional forecasters can submit and update their forecasts of macroeconomic indicators, for example, GDP, employment, and confidence indexes, up until they are released. In the literature, these forecasts have been used to assess the impact of news on long-term treasury bonds (Altavilla et al. 2017) and stock prices (Elenev et al. 2022; Born et al. 2021; Gilbert et al. 2017; Kurov et al. 2019); see also the construction of uncertainty indexes by Scotti (2016) and the nowcast errors by Enders et al. (2021). For the German ifo index and starting in April 2004, the Bloomberg survey features roughly 40 professional forecasters.

³Since April 2018 the ifo index also includes responses from firms in the service sector (Sauer and Wohlrabe 2018). In the appendix, we show that this does not affect our results.

Table 1: Macro news and forecast revisions

	$\hat{\beta}$	$SE(\hat{\beta})$
Macro News	0.008	0.001
Macro News		
× 1. Quartile by employees	0.007	0.002
× 2. Quartile by employees	0.008	0.002
× 3. Quartile by employees	0.008	0.002
× 4. Quartile by employees	0.008	0.001
Macro News		
× Firm age < 20 years	0.007	0.003
× Firm age < 20 years	0.006	0.001
Macro News		
× Time in survey < half a year	0.015	0.007
× Time in survey \geq half a year	0.008	0.001
Macro News		
× Lower macro importance	0.007	0.001
× High macro importance	0.006	0.003
Macro News		
× Positive sign of news	0.012	0.002
× Negative sign of news	0.005	0.001
Macro News		
× outside Great Recession	0.007	0.001
× during Great Recession	0.012	0.002

Notes: Reaction of forecast revisions to macro news . Firms forecast revisions are regressed on macro news, interactions terms, and firm-fixed effects for each interaction variable separately. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

We measure macro news, as the difference between the published ifo index and the median professional forecast of the ifo index from Bloomberg. The timing is key: In the first three weeks of month $t - 1$, firms respond to the survey. Until the last week of month $t - 1$, professional forecasters submit their forecasts for the ifo index in $t - 1$ to Bloomberg. In the last week of month $t - 1$, the ifo institute then publishes the value of the ifo index. In the first three weeks of month t and after observing the macro news, firms again fill out the ifo survey. Formally, we have

$$\text{macro news}_t = \text{ifo index}_{t-1} - \text{Median}(\text{professional forecasts for ifo index}_{t-1}) . \quad (4)$$

Figure 1, Panel D, depicts our macro-news measure as defined in Equation 4.

Macro news are part of the information set of firms when forecasting their production in t . First, media attention to the index as well as its professional forecasts is high due to its predictive power for the business cycle (see also Footnote 4). The ifo index is ranked among Bloomberg’s “12 Global Economic Indicators to Watch” and news outlets report on both the realized value and, importantly, the professional forecasts.⁴ Second, firms receive the aggregate index (and sectoral results) as their compensation for participating in the survey. Third, regressing forecast revisions on macro news yields significant coefficients (see Table 1). More specifically, in order to investigate systematically how macro news impact firm expectations, we consider a number of specifications allowing for a number of interaction effects as we regress forecast revisions about firms’ own production and business situation on macro news. Across specifications, the coefficients are highly significant and positive (although of limited economic impact). The positive sign shows that after receiving positive macro news in the form of a better-than-expected ifo index, firms revise expectations about their own production and business situation as well.

3 How firm expectations respond to news

In this section, we first introduce the empirical approach. Next, we provide aggregate evidence before zooming in on the firm level and documenting systematic differences in the cross-section and the time-series dimension. Lastly, we show how the reaction to news is related to real activity.

3.1 Framework

According to the FIRE benchmark, forecast errors should not be predictable from information available to the forecaster at the time of forecasting. This benchmark has been tested in regressions of forecast errors on observable variables. In their seminal work, Coibion and Gorodnichenko (2015) show that using news as explanatory variables is not just informative about the FIRE benchmark, but also about alternative models of expectation formation. More specifically, they propose regressions of the type

$$e_{i,t} = \beta_0 + \beta_1 \cdot \text{news}_{it} + \varepsilon_{it} , \tag{5}$$

⁴Examples include leading weekly newspapers *Der Spiegel* and *Die Zeit*. *Der Spiegel* (Unternehmen sind wegen vierter Coronawelle äußerst besorgt, 24 November 2021) discusses the November 2021 index value of 96.5 as well as the professional forecast of 96.6. *Die Zeit* (Geschäftsklimaindex überraschend gestiegen, 25 January 2022) reports that, contrary to professional forecasts, the January 2022 index value increased by 0.9 points compared to the previous month.

where e_{it} is a forecast error and $\text{news}_{i,t}$ is some surprise, typically measured by forecast revisions. In this simple, but powerful framework the rational expectations benchmark is that forecast errors are not predictable, so $\beta = 0$. When positive news is followed by positive forecast errors, the revised forecast is too small and there is underreaction to news. Conversely, when positive news is followed by negative forecast errors, the revised forecast is too large and there is overreaction to news. In the existing literature, this idea is commonly applied to professional forecasts from the *Survey of Professional Forecasters* to check for over- or underreaction, where news are measured by forecast revisions. More specifically, Coibion and Gorodnichenko (2015), Broer and Kohlhas (2022), and Angeletos et al. (2021) consider the median (consensus) professional forecast for inflation and find positive regression coefficients. Bordalo et al. (2020) focus on the individual forecasts and generally find negative coefficients pointing towards overreaction at the individual level.

We also build on model (5) but make three innovations relative to earlier work. First, we consider firms, that is, actual decision-makers, rather than professional forecasters. Second, we focus on firm-level variables such as production rather than macro-level variables, for example inflation. Third, we consider two sources of news, micro news, that is, the forecast revision net of time-fixed effects and macro news, that is, the surprise component to the ifo index. This distinction takes center stage in our analysis and yields our baseline regression equation:

$$e_{i,t} = \beta_0 + \beta_1 \cdot \text{micro news}_{i,t} + \beta_2 \cdot \text{macro news}_t + v_{i,t} . \quad (6)$$

Here, $e_{i,t}$ is a firm’s forecast error for its own production defined in Equation (1), micro news is the production forecast revision net of a time-fixed effect, as defined in Equation (3), and macro news is the surprise component in the ifo index of the previous month, as in Equation (4). In what follows, we refer to β_1 as “*micro bias*” and β_2 as “*macro bias*”, since under the FIRE benchmark these coefficients are zero—no variable in a firm’s time- t information set should be able to predict forecast errors. In the previous section, we have argued why both micro and macro news are part of this information set.

3.2 Baseline results

To establish our main result, we first pool observations across time and firms and then estimate equation (6) to assess the average news bias, while allowing for firm-fixed effects. The results are displayed in Table 2. The first column shows that both, micro and macro news, are not priced into expectations correctly and thereby induce predictable, statistically highly significant forecast errors. But while micro news predict negative forecast errors, macro

Table 2: Over- and underreaction to news

	Forecast Error			
	(1)	(2)	(3)	(4)
Micro News	-0.194*** (0.001)	-0.194*** (0.001)		
Macro News	0.021*** (0.0007)		0.021*** (0.0007)	0.022*** (0.0007)
Forecast Revision				-0.191*** (0.001)
Observations	302,737	302,737	302,737	302,737
R ²	0.16471	0.16015	0.08967	0.16260
Within R ²	0.08701	0.08202	0.00498	0.08471
Firm FE	✓	✓	✓	✓

Notes: regression results based on equation (6) using the full pooled sample. Dependent variable is the production forecast error, micro news are forecast revisions net of time-fixed effects and macro news are the surprise component of the ifo index. Column (5) uses raw forecast revisions, i.e., without netting out time-fixed effects, as measure of micro news. Standard errors are clustered on firm level. *** p<0.01, ** p<0.05, * p<0.1.

news predict positive forecast errors. This implies, as explained above, that firms overreact to micro news but underreact to macro news. This results is clear cut and turns out to be robust across a range of alternative specifications. In Section 4 below, we offer a theoretical perspective on this finding, based on a general equilibrium model where firms suffer from island illusion.

Before considering alternative specifications, we note that the biases in our baseline specification are quantitatively meaningful. In general, the economic importance of the biases is not straightforward to assess due to the qualitative nature of the forecast revisions. However, their relative size can be compared. The average absolute size of micro news is 0.296 and leads to a decrease in the forecast error by 0.057 (0.16 standard deviations of the forecast error). The average absolute size of macro news is 0.971 and leads to an increase in the forecast error by 0.02 (0.05 standard deviations of the forecast error). Hence, the effects on forecast errors are not negligible, and, on average, the micro bias has a 2 to 3 times stronger impact on the forecast error compared to the macro bias.

The remaining columns confirm this finding in alternative specifications: the micro bias remains negative and highly significant when excluding macro news (second column). This follows from the fact that the time-series variation is already purged out in the construction of micro news. The macro bias remains positive and significant when including only macro news in the regression (third column) or when using raw forecast revisions to measure micro news (fourth column).

In what follows, we vary specific aspects of the baseline specification to show the robustness of our results. The results are summarized in Table 3. Our baseline results are based on using OLS and the Bachmann et al. (2013) definition of qualitative production forecast errors, see Equation (1). Macro news are the surprise component of the ifo index, and the macro component of forecast revisions is the mean over the entire cross-section. The first panel shows that our results also hold when we treat forecast errors in a more qualitative spirit and use ordered logit rather than OLS for the estimation. The second panel addresses concerns about measurement error. First, in the construction of forecast errors, we set all small forecast errors to zero and thereby consider large forecast errors only. Second, to maintain more variation in forecast errors, we set small forecast errors to zero, when firms expect 'no change' in production. In both cases, we find that our results hold. The third panel varies the definition of macro news. Our results also hold when considering as macro news alternatively the surprise component in manufacturing orders, the first difference of the ifo index or the average forecast revision per sector. The fourth panel shows the results from considering the sectoral forecast revision as macro components rather than the overall mean forecast revision. The fifth and final panel addresses concerns about the data type and the forecast revision. Our baseline relies on qualitative data on production, where we construct forecast revisions from sequential forecasts that overlap by two out of three months. Alternatively, we consider quantitative responses about firm's business situation, where sequential forecast overlap by five out of six months. While the question on realizations asks about levels (with possible answers ranging from 0 (bad) to 100 (good)), the question about expectations is less clear. Here, answers range from 0 (rather less favorable) to 100 (rather favorable), which could be interpreted as both levels and changes.⁵ We construct forecast errors based on both interpretations. For the interpretation of expectations as levels (changes), we subtract from the reported business in $t + 6$ (change between t and $t + 6$) the expectation to obtain the forecast error. Our results are robust to both interpretations.

3.3 Zooming in: Firm-level heterogeneity

We have established our main result based on a sample which pools observations across firms. In what follows, we exploit the fact that we have sufficient time-series observations for each firm to estimate the biases on a firm-level basis. To this end, we go back to our baseline specification and focus on firms' production and the surprise component in the ifo index and apply it to each of the 3,000 firms in our sample of the ifo survey separately.⁶

⁵Link (2020) concludes that responses measure levels of expected revenues.

⁶As discussed in Section 2, our sample includes only firms with at least 30 monthly observations and some variation in their production expectations and forecast errors.

Table 3: Robustness of average biases

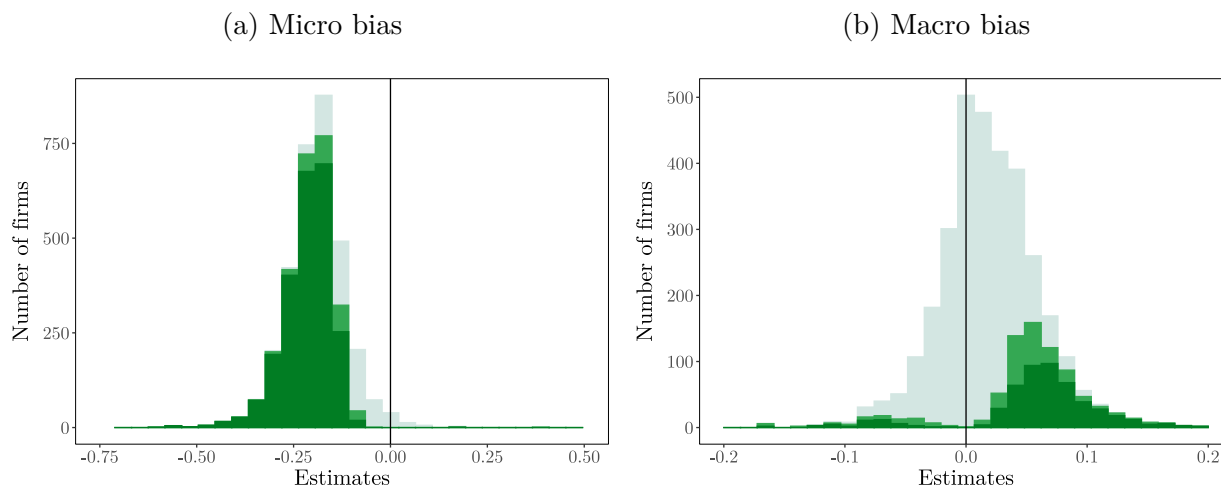
Aspect (Baseline)	Variation	Details	Micro bias	Macro bias
1) Estimation (OLS)				
	ordered logit	Table A.2	-1.16***	0.100***
2) Forecast error (Bachmann et al. 2013)				
	set small errors ($\pm\frac{1}{3}$) to zero	Table A.3	-0.117***	0.018***
	above only for no-change expectations	Table A.4	-0.180***	0.017***
3) Macro News (surprise component in ifo index)				
	surprise component in manuf. orders	Table A.5	-0.194***	0.005***
	first difference of ifo index	Table A.6	-0.194***	0.001***
	average forecast revision	Table A.6	-0.194***	0.308***
	average forecast revision by sector ^a	Table A.6	-0.196***	0.129***
4) Macro component of forecast revision (fixed effect by time)				
	fixed effect by time and sector	Table A.6	-0.196***	0.021***
5) Data type (production (+1, 0, -1))				
	business situation (0-100) as levels	Table A.7	-0.450***	0.687***
	business situation (0-100) as changes	Table A.8	-0.448***	0.697***

Notes: Variations of baseline regression setup. Each column corresponds to an alternative of the baseline results for Equation 6 in Table 2. Micro bias and Macro bias are the coefficients on micro and macro news. ^a In this specification, the macro component of forecast revisions is the time and sector average, which in turn are used as macro news. *** p<0.01, ** p<0.05, * p<0.1.

Figure 2 shows the result: It displays the distribution of estimates for β_1 and β_2 in the left and right panel. Also at the firm level we can reject the FIRE-benchmark: the micro bias is generally negative and highly significant while the macro bias is more heterogeneous with a large surplus of positive (compared to negative) coefficients. More specifically, for the subset of significant estimates, the micro bias is negative for more than 99 percent of firms, while the macro bias is positive for 89 percent of firms. The interpretation of these results is straightforward: firms overreact to micro news and tend to underreact to macro news.

But there is more to be learned about these news biases: where does the heterogeneity of the macro bias stem from, and how do these biases change over time? To address these questions, we re-run the pooled regressions from Table 2 and add interaction terms to check for heterogeneity in the cross-sectional and time-series dimensions. For the cross-section, we consider the number of employees, age, and time in the survey. More specifically, for the number of employees, we distinguish between firms in different quartiles; for age, we subtract from the year of being surveyed the year of reported incorporation and split at firm ages above

Figure 2: Over- and underreaction to news



Notes: The left panel shows the distribution of firm-level estimates β_1^i , based on running Regression (6) for each firm individually. The right panel shows the corresponding distribution of firm-level estimates β_2^i . The grey areas represent insignificant estimates, the light green areas represent estimates that are significant at the 10% level, and the green areas represent estimates that are significant at the 5% level.

and below 20; and for the time in survey, we distinguish between responses submitted during and after the first six months of being in the survey. In addition, we consider heterogeneity regarding the self-reported importance of the business cycle for the firms (see Table A.1 for the wording of the question). For the time-series, we distinguish between positive and negative news, and the period during (outside) the Great Recession.

Table 4 displays the results. To establish a benchmark for the biases, the first row contains the baseline findings from Table 2: On average, firms overreact to micro news (measured by negative news coefficients) and underreact to macro news (positive news coefficients). This general finding also holds across the interaction terms: Both biases are highly significant, and the micro bias is negative while the macro bias is positive. More specifically, the micro bias is robustly negative in the cross-section, that is, across firm size, firm age, time in survey, and importance of the business cycle. Here, the differences are generally not statistically different from each other, and relative deviations are not economically relevant. In the time-series dimension, the micro bias is significantly larger for positive news compared to negative news and during the Great Recession compared to other periods.

For the macro bias, we find heterogeneity across all interaction variables. Looking at the firm size, underreaction is strictly and statistically significantly increasing across employee quartiles, where the underreaction of the largest firms is twice as strong as that of the smallest firms. Regarding firm age, the statistical difference in the macro biases between young and old firms is only weakly significant, and the relative difference is around ten percent. So

Table 4: Heterogeneity

Interaction	N	Micro News		Macro News	
		$\hat{\beta}_j$	$SE(\hat{\beta}_j)$	$\hat{\beta}_j$	$SE(\hat{\beta}_j)$
News	302,737				
Overall		-0.194***	0.001	0.021***	0.001
News	302,737				
× 1. Quartile by employees		-0.199***	0.003	0.012***	0.003
× 2. Quartile by employees		-0.193***	0.003	0.019***	0.002
× 3. Quartile by employees		-0.192***	0.003	0.021***	0.001
× 4. Quartile by employees		-0.195***	0.002	0.026***	0.001
News	162,776				
× Firm age < 20 years		-0.187***	0.006	0.018***	0.003
× Firm age ≥ 20 years		-0.193***	0.002	0.020***	0.001
News	302,737				
× Time in survey < half a year		-0.195***	0.008	0.032***	0.006
× Time in survey ≥ half a year		-0.194***	0.001	0.021***	0.001
News	129,053				
× Lower macro importance		-0.190***	0.002	0.018***	0.001
× High macro importance		-0.191***	0.005	0.022***	0.002
News	302,737				
× Positive sign of news		-0.199***	0.002	0.011***	0.001
× Negative sign of news		-0.189***	0.002	0.034***	0.001
News	302,737				
× outside Great Recession		-0.191***	0.001	0.016***	0.001
× during Great Recession		-0.211***	0.003	0.039***	0.002

Notes: Baseline regression (Equation (6)) estimated on the full, pooled sample. All regressions include micro and macro news with interaction terms, and firm-fixed effects. Standard errors are clustered at the firm level. N is the number of observations, R^2 is the within- R^2 , $\hat{\beta}_j$ is the point estimate and $SE(\hat{\beta}_j)$ is its standard error. For (quartiles of) the number of employees, we rely on annual questions in the ifo survey. For firm age, we rely on a one-time question about the year the firm was founded. To compute the firm age, we subtract from the year of response the year of foundation. For the Great Recession, we rely on a dummy equal to 1 during the years 2007 to 2008 and 0 else. For macro importance we rely on a one-time question, where firms rank the importance of general economic developments in Germany for their business on a five point scale from very important [1] to unimportant [5]. Macro importance is high when the response was very important. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

there is no clear evidence, that firms learn simply by getting older.⁷ When comparing the overreaction of firms that recently joined the survey (six months) to more tenured firms, we see evidence for learning through the survey effects in the spirit of Kim and Binder (2021), as the overreaction among more tenured firms is roughly one third smaller compared to firms that recently joined the survey. This finding is in line with Massenot and Pettinicchi (2018), who show, for example, that firms’ absolute forecast errors about their own business situation decrease in time passed since entry in the ifo survey. Interestingly, the macro bias is slightly larger for firms that report a high importance of the German business cycle compared to other firms. While one would expect that firms with a stronger exposure to aggregate economic fluctuations are more attentive to macro news, the counteracting force of stronger impact due to underreaction seems to dominate. This channel might also explain the positive relation between macro bias and firm size. In the time-series dimension, the macro bias is three times as large after negative news compared to positive news and just as the micro bias larger during the Great Recession compared to other periods. In summary, overreaction to micro news and underreaction to macro news is a general phenomenon and not specific to certain groups of firms or time periods. However, both deviations from the rational expectations benchmark are larger during bad times.

To get the full picture of the countercyclical degree of miss-reaction, we follow Coibion and Gorodnichenko (2015) in estimating the baseline specification in rolling 5-year windows. Figure 3 shows the resulting time series of micro and macro biases. First, we observe that firms overreact to micro news and underreact to macro news over the entire sample. Second, we see that deviations from the rational expectations benchmark are largest during the Great Recession, in line with the results from Table 4. For macro news however, it is also substantial in economic terms: the macro bias is three times as large during the Great Recession compared to non-recession periods. This is at odds with models featuring rational inattention, since the higher importance of macro news would imply lower information friction during the recession. However, as argued above, neglecting macro news during the Great Recession has a stronger impact on production than in normal times.

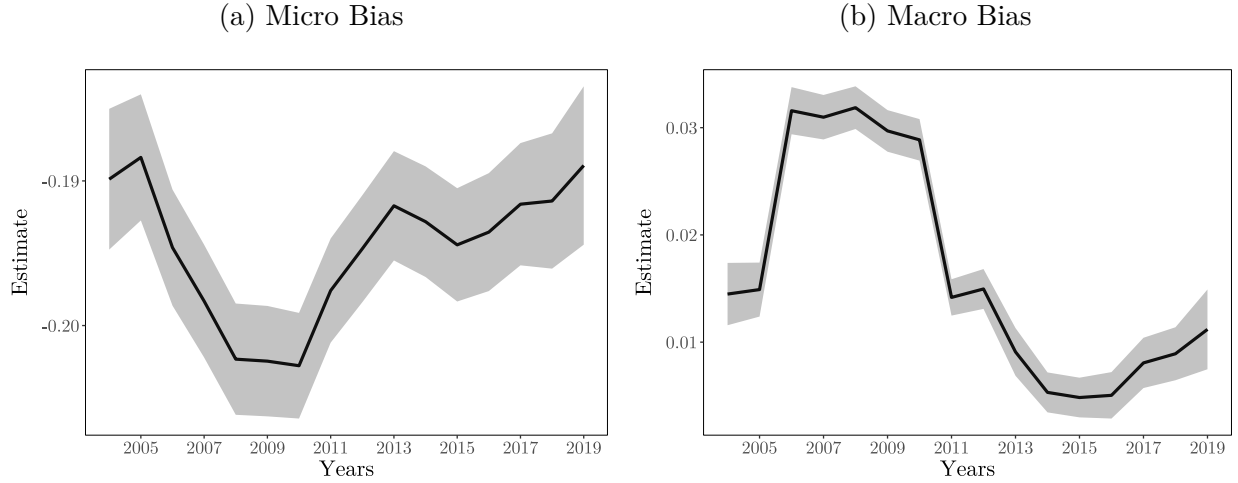
3.4 News biases and real activity

We now investigate to what extent the bias in expectation formation matters for real activity at the firm level.⁸ For this purpose, we relate the micro and macro news bias to (i) profits

⁷For instance, Farmer et al. (2021) show that bayesian learning can potentially explain forecasting anomalies in professional forecasts of aggregate variables.

⁸Related work by Enders et al. (2022), using the same dataset, finds that expectations matter for production and pricing decisions. In what follows we focus on the role of the biases.

Figure 3: Rolling window regressions



Notes: micro and macro news biases over time. The plots show the time-series of news coefficients from rolling window regressions covering centered windows of five years each. Black lines depict point estimates, grey areas correspond to 95% confidence intervals.

Table 5: Over- and underreaction to news and real activity

		mean _i (profits _{it})		sd _i (production _{it})	
Sign of bias		(1)	(2)	(3)	(4)
Constant		0.199 (0.182)		0.406*** (0.010)	
Micro News Bias	$\beta_1 < 0$	1.76** (0.876)	2.36*** (0.842)	-0.250*** (0.045)	-0.248*** (0.046)
Macro News Bias	$\beta_2 > 0$	-0.069 (1.85)	-0.363 (1.83)	1.66*** (0.097)	1.64*** (0.098)
Observations		1,665	1,665	2,204	2,204
R ²		0.003	0.053	0.135	0.154
Within R ²			0.005		0.132
Sector and Size FE			✓		✓

Notes: estimates from linear regressions of average profits (Columns (1) and (2)) and production dispersion (Columns (3)-(4)) of firms on the firm-level estimates of micro and macro news bias. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

and (ii) volatility of output. We rely on the firm-level estimates from Section 3.3 and restrict the sample to firms that overreact to micro news and underreact to macro news, in line with the aggregate findings.

Since 2009, the ifo Business Climate Survey includes a quantitative question on return to sales in the current year.⁹ For each firm, we calculate average profits and regress them on

⁹Return on sales are elicited in May and September. We rely on the September wave, which arguably

the micro and macro news bias estimated in Section 3.3. In addition, we absorb sector and size fixed effects. Columns (1) and (2) in Table 5 display the results. A stronger micro news bias is associated with a significant decrease in average profits, while a stronger macro bias is not significantly related to average profits. In terms of magnitude, a one standard deviation increase in the micro news bias leads on average to a ≈ 0.16 percentage point reduction in profits.

As a second exercise, we calculate the standard deviation of qualitative realized production changes as a proxy for firm-level production volatility. Then, we follow the procedure above and regress it on the micro and macro news bias, estimated in Section 3.3. Columns (3) and (4) in Table 5 display the results. The estimates indicate a tight relation between production volatility and the micro and macro news biases at the firm-level. An increase in the news biases is associated with higher volatility. While the point estimate for the micro news bias is larger than for the macro news bias, a one standard deviation increase in the respective bias increases output volatility slightly more for the macro news bias. Projecting these cross-sectional estimates on the macro level implies higher micro-level volatility in presence of the biases. This is a potential explanation for the high observed idiosyncratic volatility of firm outcome variables (Bachmann et al. 2013; Bloom 2009).

4 Island Illusion: A General Equilibrium Account

In the following we develop a stylized model of noisy information and derive analytical results.¹⁰ To explain our empirical findings, we incorporate the behavioral bias of ‘island illusion’ in the way how firms form expectations and then empirically test additional predictions of the model in the next section. In short, this bias lets firms overestimate the importance of firm-specific variables, compared to aggregate developments. This may happen, since firm-specific developments are more ‘salient’ to decision makers, in contrast to public information.¹¹ This interpretation is in line with findings that direct experience has larger effects on risk perceptions than indirect effects derived from outcomes to others (Smith et al. 2001; Viscusi and Zeckhauser 2015). Different to most of the literature, however, we consider firms’ expectations about their own variables. Since these variables, in particular firm-specific demand, depend on idiosyncratic and aggregate variables, we develop a suitable

contains less expectations and more realizations. In addition, we subtract yearly average profits to ensure that the results are not driven by reverse causality.

¹⁰Lorenzoni (2009) and Coibion and Gorodnichenko (2012) find that models of information rigidities in general, and of noisy information in particular, are successful in predicting empirical regularities of survey data on expectations.

¹¹Bordalo et al. (2020) develop a model of salience, in which certain states of the economy are overly representative to forecasters. In our model, instead, salience is determined by the type of information.

general-equilibrium model. Our model builds on the noisy and dispersed information model of Lorenzoni (2009). As our goal is to derive robust qualitative predictions, we simplify the original model, notably by assuming predetermined rather than staggered prices. As a result, it is possible to solve an approximate model in closed form and to derive analytical predictions regarding over- and underreactions to private and public signals. We also obtain additional predictions that we later test in the data.

4.1 Setup and timing

There is a continuum of islands (or locations), indexed by $l \in [0, 1]$, each populated by a representative household and a unit mass of producers, indexed by $j \in [0, 1]$. Each household buys from a subset of all islands, chosen randomly in each period. Specifically, it buys from all producers on n islands included in the set $\mathcal{B}_{l,t}$, with $1 < n < \infty$.¹² Households have an infinite planning horizon. Each household’s demand is subject to a shock, which consists of an aggregate and an idiosyncratic component. Producers produce differentiated goods on the basis of island-specific productivity, which is determined by a permanent, economy-wide component and a temporary, idiosyncratic component.¹³ Both components are stochastic. Financial markets are complete such that, assuming identical initial positions, wealth levels of households are equalized at the beginning of each period.

The timing of events is as follows: each period consists of three stages. During stage one of period t , information about all variables of period $t-1$ is released. Subsequently, nominal wages are determined and the central bank sets the interest rate based on expected inflation.

The aggregate and idiosyncratic components of productivity materialize in the second stage. Concerning technology, firms can only observe their own productivity (micro news). Additionally, a noisy public signal about the aggregate demand shock is released to firms and households, based on, say, market research (macro news). We allow for one additional generic shock that is observable. To simplify the discussion, we refer to this shock as a “monetary policy shock” with the understanding that other observable shocks would play a comparable role. Given these information sets, producers set prices.

During the third and final stage, households split up. Workers work for all firms on their island, while consumers allocate their expenditures across differentiated goods based on public information and information contained in the prices of the goods in their consumption bundle. Additionally, individual demand shocks influence their consumption decisions. Because the

¹²This setup ensures that households cannot exactly infer aggregate productivity from observed prices. At the same time, individual producers have no impact on the price of households’ consumption baskets.

¹³As argued by Lorenzoni (2009), this setup can account for the empirical observations that the firm-level volatility of productivity is large relative to aggregate volatility and that individual expectations are dispersed.

common productivity component is permanent, demand shocks are purely temporary, and households' wealth and information are equalized in the next period, agents expect the economy to settle on a new steady state from period $t+1$ onward.

4.2 Households

A representative household on island l ("household l ", for short) maximizes lifetime utility, given by

$$U_{l,t} = E_{l,t} \sum_{\tau=t}^{\infty} \beta^{\tau-t} Q_{l,\tau} \ln C_{l,\tau} - \frac{L_{l,\tau}^{1+\varphi}}{1+\varphi} \quad \varphi \geq 0, \quad 0 < \beta < 1,$$

where $E_{l,t}$ is the expectation operator based on household l 's information set at the time of its consumption decision in stage three of period t (see below). $C_{l,t}$ denotes the consumption basket of household l , while $L_{l,t}$ is its labor supply. The demand shock $Q_{l,t}$ consists of an aggregate and a household-specific component. Written in logs, this implies

$$q_{l,t} = q_t + \hat{q}_{l,t},$$

with q_t being an i.i.d. shock with mean zero and variance σ_q^2 . Similarly, $\hat{q}_{l,t}$ is also an i.i.d. shock with mean zero and variance $\sigma_{\hat{q}}^2$. While actual demand, including the shocks, realizes only in stage three of the period, a public signal about the aggregate component is released to firms and households in the second stage, representing macro news.

$$s_t = q_t + e_t,$$

where e_t is an i.i.d. noise shock with variance σ_e^2 and mean zero.

The flow budget constraint of the household is given by

$$E_t \varrho_{l,t,t+1} \Theta_{l,t} + B_{l,t} + \sum_{m \in \mathcal{B}_{l,t}} \int_0^1 P_{j,m,l,t} C_{j,m,l,t} dj \leq \int_0^1 \Pi_{j,l,t} dj + W_{l,t} L_{l,t} + \Theta_{l,t-1} + (1 + r_{t-1}) B_{l,t-1},$$

where $C_{j,m,l,t}$ denotes the amount bought by household l from producer j on island m and $P_{j,m,l,t}$ is the price for one unit of $C_{j,m,l,t}$. At the beginning of the period, the household receives the payoff $\Theta_{l,t-1}$, given a portfolio of state-contingent securities purchased in the previous period. $\Pi_{j,l,t}$ are the profits of firm j on island l and $\varrho_{l,t,t+1}$ is household l 's stochastic discount factor between t and $t+1$. The period- t portfolio is priced conditional on the (common) information set of stage one, hence we apply the expectation operator E_t . $B_{l,t}$ are state non-contingent bonds paying an interest rate of r_t . The complete set of state-contingent securities is traded in the first stage of the period, while state-non-contingent bonds can

be traded via the central bank throughout the entire period. The interest rate of the non-contingent bond is set by the central bank. All financial assets are in zero net supply. The bundle $C_{l,t}$ of goods purchased by household l consists of goods sold in a subset of all islands in the economy

$$C_{l,t} = \left(\frac{1}{n} \sum_{m \in \mathcal{B}_{l,t}} \int_0^1 C_{j,m,l,t}^{\frac{\gamma-1}{\gamma}} dj \right)^{\frac{\gamma}{\gamma-1}} \quad \gamma > 1.$$

While each household purchases a different random set of goods, we assume that the number n of islands visited is the same for all households. The price index of household l is therefore

$$P_{l,t} = \left(\frac{1}{n} \sum_{m \in \mathcal{B}_{l,t}} \int_0^1 P_{j,m,l,t}^{1-\gamma} dj \right)^{\frac{1}{1-\gamma}}.$$

4.3 Producers

Producer j on island l produces according to the following production function

$$Y_{j,l,t} = A_{j,l,t} L_{j,l,t}^\alpha \quad 0 < \alpha < 1,$$

featuring labor supplied by the local household as the sole input. $A_{j,l,t} = A_{l,t}$ denotes the productivity level of producer j , which is the same for all producers on island l . During stage two, the producer sets her optimal price for the current period. Given prices, the level of production is determined by demand during stage three. Since each island is visited by n consumers, the demand shock $q_{j,l,t}$ influencing demand for goods from producer j on island l results, in logs, as

$$q_{j,l,t} = q_t + \sum_{\{m|l \in \mathcal{B}_{m,t}\}} \frac{\hat{q}_{m,t}}{n}.$$

Log-productivity on each island is the sum of an aggregate and an island-specific idiosyncratic component

$$a_{l,t} = x_t + \eta_{l,t},$$

where $\eta_{l,t}$ is an i.i.d. shock with variance σ_η^2 and mean zero. It aggregates to zero across all islands. Idiosyncratic productivity thus represents micro news about the aggregate component x_t , which follows a random walk

$$\Delta x_t = \varepsilon_t.$$

The i.i.d. productivity shock ε_t has variance σ_ε^2 and mean zero. Producers only observe their own productivity $a_{j,l,t}$.

4.4 Island Illusion

The rational forecast for Δx_t is given by

$$\bar{E}_{j,l,t}\Delta x_t = \bar{\delta}_x^p(a_{j,l,t} - x_{t-1}),$$

with $E_{j,l,t}^r$ being the rational expectation of producer j on island l when setting prices (in stage two). The coefficient $\bar{\delta}_x^p$ is the same for all producers and a function of the structural parameters that capture the informational friction. It is non-negative and smaller than unity:

$$\bar{\delta}_x^p = \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_\eta^2}. \quad (7)$$

The rational forecast for q_t is given by

$$\bar{E}_{j,l,t}q_t = \bar{\rho}_q^p s_t, \quad \text{with} \quad \bar{\rho}_q^p = \frac{\sigma_q^2}{\sigma_\varepsilon^2 + \sigma_q^2}.$$

Rather than assuming that expectations are formed in a rational way, however, we suppose that producers are subject to island illusion. Specifically, we assume that producers overestimate the importance of island-specific developments, relative to aggregate developments. We model this trait by introducing producers' biased estimate $\hat{\sigma}_\varepsilon < \sigma_\varepsilon$ and $\hat{\sigma}_q < \sigma_q$, such that producers underestimate the aggregate parts of productivity and demand. Since producers correctly observe the total volatilities of $a_{j,l,t}$ and $q_{l,t}$, this also implies that $\hat{\eta}_\varepsilon > \sigma_\eta$ and $\hat{\sigma}_e > \sigma_e$. Thus, actual expectations are formed according to

$$E_{j,l,t}\Delta x_t = \delta_x^p(a_{j,l,t} - x_{t-1}) \quad E_{j,l,t}q_t = \rho_q^p s_t,$$

with

$$\delta_x^p = \bar{\delta}_x^p = \frac{\hat{\sigma}_\varepsilon^2}{\hat{\sigma}_\varepsilon^2 + \hat{\sigma}_\eta^2} > \bar{\delta}_x^p \quad \rho_q^p = \frac{\hat{\sigma}_q^2}{\hat{\sigma}_\varepsilon^2 + \hat{\sigma}_q^2} < \bar{\rho}_q^p.$$

Consumers Regarding consumers, we assume that they form rational expectations in the following way. While shopping during stage three, they observe a set of prices. They can hence infer the productivity level of each producer in their sample:

$$E_{l,t}\Delta x_t = \delta_x^h \tilde{a}_{l,t},$$

where $\tilde{a}_{l,t}$ is the average over the realizations of $a_{m,t} - x_{t-1}$ for each island m in household l 's sample $\mathcal{B}_{l,t}$. δ_x^h is equal across households, see Appendix B. Consumers have complete information if $n \rightarrow \infty$.

4.5 Monetary policy and Market clearing

The central bank follows an interest-rate feedback rule but sets r_t before observing prices, that is during stage one of period t :

$$r_t = \psi E_{cb,t} \pi_t + \nu_t \quad \psi > 1,$$

where π_t is economy-wide net inflation, calculated on the basis of all goods sold in the economy. The expectation operator $E_{cb,t}$ is conditional on the information set of the central bank. This set consists of information from period $t-1$ only, that is, the central bank enjoys no informational advantage over the private sector.¹⁴ ν_t is a monetary policy shock that is observable by producers and households alike.

Goods and labor markets clear in each period:

$$\int_0^1 C_{j,m,l,t} dl = Y_{j,m,t} \quad \forall j, m \quad L_{l,t} = \int_0^1 L_{j,l,t} dj \quad \forall l,$$

where $C_{j,m,l,t} = 0$ if household l does not visit island m . The asset market clears in accordance with Walras' law.

4.6 Over- and underreaction

We derive a solution of the model based on a linear approximation to the equilibrium conditions around the symmetric steady state; see Appendix B for details. Lower-case letters denote percentage deviations from steady state. In the following, $\Delta y_{j,l,t}$ is the change of output of firm j on island l between periods $t-1$ and t . $FE_{j,l,t} = \Delta y_{j,l,t} - E_{j,l,t} \Delta y_{j,l,t}$ is the forecast error of the same firm regarding its output growth. $FR_{j,l,t} = E_{j,l,t} y_{j,l,t} - E_t y_{j,l,t}$ represents the change in the forecast of the same firm regarding output growth between stage one and stage two of period t , that is, before and after having received the private and public signals. We obtain the following proposition, for which we provide proofs in Appendix C. It

¹⁴Pre-set prices and interest rates allow us to discard the noisy signals about quantities and inflation observed by producers and the central bank in Lorenzoni (2009), simplifying the signal-extraction problem without changing the qualitative predictions of the model. Pre-set wages, on the other hand, guarantee determinacy of the price level. They do not affect output dynamics after noise and technology shocks, because goods prices may still adjust in the second stage of the period.

shows that assuming island illusion, that is $\hat{\sigma}_\varepsilon^2 < \sigma_\varepsilon^2$ and $\hat{\sigma}_q^2 < \sigma_q^2$, generates overreaction to private signals and underreaction to public information by individual firms.

Proposition 1. *Consider the regression*

$$FR_{j,l,t} = \beta FR_{j,l,t} + \delta s_t + \omega_{j,l,t} . \quad (8)$$

where $\Delta y_{j,l,t}$ is the realized change of output of firm j on island l , $FR_{j,l,t}$ is the forecast revision thereof by the same firm, and $\omega_{j,l,t}$ represents a potential error term. In case of island illusion, we obtain

$$\beta < 0 \quad \text{and} \quad \delta > 0 .$$

Intuitively, in a rational-expectations framework, average future forecast errors cannot be predicted by current forecast revisions ($\beta = 0$) or public signals ($\delta = 0$), as firms could otherwise easily improve on their forecasts. However, given that in our model firms display island illusion and therefore underassess the importance of aggregate developments, they place too little weight on the private signal ($\delta_x^p < \bar{\delta}_x^p$) when revising their forecast of aggregate technology, relative to the rational-expectations benchmark. Hence, on average, firms underestimate aggregate technology when they observe a positive surprise in their own technology. Put differently, after a successful technological innovation at the own firm, managers underestimate the potential of competitors to implement a similar reduction in costs. In general equilibrium, this has two partly offsetting effects: on the one hand, firms expect prices of competitors to be on average higher than what they will actually turn out, increasing expected demand for the firms' products. On the other hand, firms expect overall demand to be lower than warranted, reducing expected idiosyncratic demand as well. Taken together, the first effect dominates and firms on average overestimate their future sales after having observed a negative surprise in idiosyncratic technology, yielding $\beta < 0$.

Regarding the effect of the public signal on firms' forecast error, firms again underestimate the role of aggregate developments. That is, they deem aggregate demand shocks to fluctuate less than they actually do. At the same time, they correctly observe the volatility of the signal, such that they overassess the contribution of noise to the signal. Consequently, they pay less attention to the signal than the rational-expectations benchmark would prescribe ($\rho_x^p < \bar{\rho}_x^p$). Following a positive signal, they hence underestimate the increase in demand for their own and their competitors' products. Hence, firms expect own demand and the prices of competitors to be lower than they, on average, realize after a positive signal and therefore underestimate their own output, such that $\delta > 0$.

5 Conclusion

How do firms adjust their expectations as new information arrives? We address this question empirically and provide new evidence on the basis of the ifo survey of German firms. We find robustly that firm expectations overreact to micro news and underreact to macro news, relative to what the full information rational expectation benchmark implies. While recent work has documented overreaction and underreaction to news, this work has typically focused on surveys of professional forecasters. Our evidence instead pertains to firms and hence to actual decision makers.

In the last part of our analysis we take a structural perspective and put forward a general equilibrium model with dispersed information. In the model, firms suffer from island illusion which may be understood as an instance of salience: Firms simply direct more attention to idiosyncratic signals than what would be warranted under FIRE. Under this assumption the model is able to rationalize the key features of the data, in particular overreaction to micro news and underreaction to macro news. Island illusion is also likely to bear implications for policy—an issue we leave for future work to explore.

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A Appendix

Table A.1: Relevant questions from ifo survey

Label Name	Question	Possible answers
Q1 Expected state of business (qualitative)	Plans and Expectations for the next 6 months: Our business situation will be	rather more favorable [1] not changing [0] rather less favorable [-1]
Q2 Expected state of business (quantitative)	Expectations for the next 6 months: In cyclical regards our state of business will be	slider with range 0 [be rather less favorable] to 100 [rather more favorable]
Q3 Realized state of business (qualitative)	Current situation: We evaluate our state of business to be	good [1] satisfiable [0] bad [-1]
Q4 Realized state of business (quantitative)	Current situation: We consider our state of business to be	slider with range good [100] to bad [0]
Q5 Realized production	Review - tendencies in [t-1]: Compared to [t-2] our production	increased [1] stayed about the same [0] decreased [-1]
Q6 Expected production	Plans and Expectations for the next 3 months: Our production is expected to be	increasing [1] not changing [0] decreasing [-1]
Q7 Macro importance	How important is the general economic development in Germany for your business situation?	very important [1] important [2] not as important [3] less important [4] unimportant [5]

Notes: most recent wording of relevant questions from the ifo survey taken from the EBDC Questionnaire manual. t denotes the month of the survey, so in July Q5 asks about the change in June compared to May.

Table A.2: Robustness check: ordered logit

term	estimate	std.error	statistic	coef.type	exp_est
Micro News	-1.16	0.01	-166.78	coefficient	0.31
Macro News	0.11	0.00	35.72	coefficient	1.11
-4/3 -1	-6.06	0.03	-174.39	scale	0.00
-1 -2/3	-3.58	0.01	-338.15	scale	0.03
-2/3 -1/3	-2.47	0.01	-371.28	scale	0.08
-1/3 0	-1.28	0.00	-281.98	scale	0.28
0 1/3	1.53	0.00	315.43	scale	4.61
1/3 2/3	2.73	0.01	374.91	scale	15.33
2/3 1	3.93	0.01	322.62	scale	50.69
1 4/3	6.68	0.05	144.51	scale	795.27

Notes: results using ordered logit to estimate the effect of micro news and macro news on the production forecast error. The last column shows the odds ratios. Rows 3 to 10 depict the cut points of the latent variable. The full, pooled sample is used. The survey questions and variable definitions can be found in Section 2.

Table A.3: Robustness check: alternative production forecast error

	Forecast Error			
	(1)	(2)	(3)	(4)
Micro News	-0.117*** (0.001)	-0.117*** (0.001)		
Macro News	0.018*** (0.0006)		0.018*** (0.0006)	0.018*** (0.0006)
Forecast Revision				-0.115*** (0.001)
Observations	302,737	302,737	302,737	302,737
R ²	0.11483	0.11068	0.07974	0.11352
Within R ²	0.04244	0.03795	0.00449	0.04103
Firm FE	✓	✓	✓	✓

Notes: baseline-setup except small forecast errors ($\pm\frac{1}{3}$) are set to zero. Standard errors are clustered on firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4: Robustness check: alternative production forecast error

	Forecast Error			
	(1)	(2)	(3)	(4)
Micro News	-0.180*** (0.001)	-0.180*** (0.001)		
Macro News	0.017*** (0.0006)		0.017*** (0.0006)	0.018*** (0.0006)
Forecast Revision				-0.176*** (0.001)
Observations	302,737	302,737	302,737	302,737
R ²	0.14873	0.14530	0.07495	0.14684
Within R ²	0.08316	0.07946	0.00369	0.08113
Firm FE	✓	✓	✓	✓

Notes: baseline-setup except small forecast errors ($\pm\frac{1}{3}$) are set to zero when expectations are zero. Standard errors are clustered on firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: Robustness check: alternative macro news

	Forecast Error			
	(1)	(2)	(3)	(4)
Micro News	-0.194*** (0.001)	-0.194*** (0.001)		
Macro News	0.005*** (0.0003)		0.005*** (0.0003)	0.005*** (0.0003)
Forecast Revision				-0.190*** (0.001)
Observations	298,586	298,586	298,586	298,586
R ²	0.16100	0.16006	0.08580	0.15828
Within R ²	0.08321	0.08217	0.00103	0.08023
Firm FE	✓	✓	✓	✓

Notes: baseline-setup except macro news are constructed from the median professional forecast of manufacturing orders. Standard errors are clustered on firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.6: Robustness check: alternative fixed effects and macro news

	(1)	(2)	(3)	(4)	(5)
Micro News	-0.194*** (0.001)		-0.194*** (0.001)	-0.194*** (0.001)	
Macro News	0.021*** (0.0007)	0.021*** (0.0007)			
Micro News (Time X Sector FE absorbed)		-0.196*** (0.001)			-0.196*** (0.001)
Δ ifo Index			0.001*** (0.0002)		
Average Forecast Revision				0.308*** (0.019)	
Average Forecast Revision by Sector					0.129*** (0.013)
Observations	302,737	302,737	301,185	302,737	302,737
R ²	0.16471	0.16555	0.16017	0.16186	0.16169
Within R ²	0.08701	0.08793	0.08214	0.08389	0.08371
Firm FE	✓	✓	✓	✓	✓

Notes: baseline-setup except we control for sectoral news in Column 2, construct macro news as first difference of the ifo index in Column 3, construct macro news as average forecast revision in Column 4, construct macro news as sectoral average forecast revision in Column 5. Standard errors are clustered on firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.7: Robustness check: qualitative expectations about business situation (expectations in levels)

	Forecast Error			
	(1)	(2)	(3)	(4)
Micro News	-0.450*** (0.003)	-0.450*** (0.003)		
Macro News	0.687*** (0.043)		0.683*** (0.042)	0.843*** (0.043)
Forecast Revision				-0.442*** (0.003)
Observations	161,578	161,578	164,675	161,578
R ²	0.32430	0.32210	0.25535	0.32261
Within R ²	0.09227	0.08931	0.00290	0.09000
Firm FE	✓	✓	✓	✓

Notes: baseline-setup expect we consider qualitative data for firms' own business situation rather than their production. Here, firms can report their expected and actual business situation on a scale from 0 to 100. For the exact wording of the questions see Table A.1. We treat both expectations and realizations as measured in levels, so we take the realized level at $t + 6$ and subtract from it the expectation in t to obtain the error in t . Standard errors are clustered on firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.8: Robustness check: qualitative expectations about business situation (change)

	Forecast Error			
	(1)	(2)	(3)	(4)
Micro News	-0.448*** (0.003)	-0.448*** (0.003)		
Macro News	0.697*** (0.043)		0.693*** (0.042)	0.853*** (0.043)
Forecast Revision				-0.440*** (0.003)
Observations	161,399	161,399	164,492	161,399
R ²	0.33211	0.32989	0.26488	0.33054
Within R ²	0.09112	0.08809	0.00298	0.08898
Firm FE	✓	✓	✓	✓

Notes: baseline-setup expect we consider qualitative data for firms' own business situation rather than their production. Here, firms can report their expected and actual business situation on a scale from 0 to 100. For the exact wording of the questions see Table A.1. We treat expectations as measured in changes and realizations as measured in levels, so we take the realized change in business between t and $t + 6$ and subtract from it the expectation in t to obtain the error in t . Standard errors are clustered on firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B Model solution

Below, we provide the proofs for the proposition in Section 4. In a preliminary step, we outline the model solution and key equilibrium relationships. Throughout, we consider a linear approximation to the equilibrium conditions of the model. Lower-case letters indicate percentage deviations from steady state. We solve the model by backward induction. That is, we start by deriving inflation expectations regarding period $t + 1$. Using the result in the Euler equation of the third stage of period t allows us to determine price-setting decisions during stage two. Eventually, we obtain the short-run responses of aggregate variables to unexpected changes in productivity or optimism shocks.

Expectations regarding period $t + 1$. Below, $E_{k,t}$ stands for either $E_{j,l,t}$, referring to the information set of producer j on island l at the time of her pricing decision, or for $E_{l,t}$, referring to the information set of the household on island l at the time of its consumption decision. Variables with only time subscripts refer to economy-wide values. The wage in period $t + 1$ is set according to the expected aggregate labor supply

$$E_{k,t}\varphi l_{t+1} = E_{k,t}(w_{t+1} - p_{t+1} - c_{t+1}).$$

This equation is combined with the aggregated production function

$$E_{k,t}y_{t+1} = E_{k,t}(x_{t+1} + \alpha l_{t+1}),$$

the expected aggregate labor demand

$$E_{k,t}(w_{t+1} - p_{t+1}) = E_{k,t}[x_{t+1} + (\alpha - 1)l_{t+1}],$$

and market clearing $y_{t+1} = c_{t+1}$ to obtain

$$E_{k,t}x_{t+1} = E_{k,t}y_{t+1} = E_{k,t}c_{t+1}. \tag{A-1}$$

Furthermore, the expected Euler equation, together with the Taylor rule, is

$$E_{k,t}c_{t+1} = E_{k,t}(c_{t+2} + \pi_{t+2} - \psi\pi_{t+1}).$$

Agents expect the economy to be in a new steady state tomorrow ($E_{k,t}c_{t+1} = E_{k,t}c_{t+2}$), given the absence of state variables other than technology, which follows a unit root process, and

the demand shock, whose expected value is zero. Ruling out explosive paths yields

$$E_{k,t}\pi_{t+2} = E_{k,t}\pi_{t+1} = 0.$$

Stage three of period t . After prices are set, each household observes n prices in the economy. Since only productivity is idiosyncratic to firms at the time of setting prices, the productivity level $a_{j,l,t} = a_{l,t}$ —which is the same for all producers $j \in [0, 1]$ on island l —can be inferred from each price $p_{j,l,t}$ of the good from producer j on island l . Hence, household l forms its expectations about the change in aggregate productivity according to

$$E_{l,t}\Delta x_t = \delta_x^h \hat{a}_{l,t},$$

where $\hat{a}_{l,t}$ is the average over the realizations of $a_{m,t} - x_{t-1}$ for each location m in household l 's sample $\mathcal{B}_{l,1}$. The coefficients δ_x^h is equal across households and depend on n, σ_ε^2 , and σ_η^2 in the following way:

$$\delta_x^h = \frac{\sigma_\varepsilon^2}{\underbrace{\sigma_\varepsilon^2 + \sigma_\eta^2/n}_{\rightarrow 1 \text{ if } n \rightarrow \infty}}. \quad (\text{A-2})$$

The expectation formation of producers is discussed in the main text. Consumption follows an Euler equation with household-specific inflation, as only a subset of goods is bought. Agents expect no differences between households for $t + 1$, such that expected aggregate productivity and the overall price level impact today's individual consumption. Additionally using $E_{l,t}p_{t+1} = E_{l,t}p_t$ and $E_{l,t}x_{t+1} = E_{l,t}x_t$ gives

$$c_{l,t} = E_{l,t}x_t + E_{l,t}p_t - p_{l,t} - r_t + q_{l,t}. \quad (\text{A-3})$$

Similar to the updating formula for technology estimates, households all relevant available information to form an estimate about the aggregate price level p_t according to

$$E_{l,t}p_t = \delta_p^h \hat{a}_{l,t} + \kappa_p^h w_t + \tau_p^h x_{t-1} - \eta_p^h r_t + \bar{\rho}_p^h s_t + \bar{\delta}_p^h q_{l,t}, \quad (\text{A-4})$$

where the undetermined coefficients $\delta_p^h, \kappa_p^h, \tau_p^h, \eta_p^h, \bar{\rho}_p^h$, and $\bar{\delta}_p^h$ represent the impact of the relevant variable on the expected price level. Combining the above gives

$$c_{l,t} = (1 + \tau_p^h)x_{t-1} + \delta_{xp}^h \hat{a}_{l,t} + \kappa_p^h w_t - (1 + \eta_p^h)r_t - p_{l,t} + \bar{\rho}_p^h s_t + (1 + \bar{\delta}_p^h)q_{l,t} \quad (\text{A-5})$$

where $\delta_{xp}^h = \delta_x^h + \delta_p^h$. We will solve for the coefficients below. Total demand for good j on island l is

$$\begin{aligned} y_{j,l,t} &= -\gamma p_{j,l,t} + \gamma \sum_{m \in \mathcal{B}_{l,t}} \frac{p_{m,t}}{n} + \sum_{m \in \mathcal{B}_{l,t}} \frac{c_{m,t}}{n} \\ &= -\gamma p_{j,l,t} + \gamma \tilde{p}_{l,t} + \tilde{y}_{l,t}, \end{aligned} \quad (\text{A-6})$$

where $\tilde{y}_{l,t}$ is the average consumption level of customers visiting island l , $1/n$ th of which equals $p_{j,l,t}$. The index $\tilde{p}_{l,t}$ is the average price index of customers visiting island l . If customers bought on all (that is, infinitely many) islands in the economy, $\tilde{p}_{l,t}$ would correspond to the overall price level. Given (A-5), we have

$$\begin{aligned} \tilde{y}_{l,t} &= \frac{1}{n} \sum_{m \in \mathcal{B}_{l,t}} [E_{m,t} x_t + E_{m,t} p_t - p_{m,t} - r_t + q_{m,t}] \\ &= \kappa^h + \delta_{xp}^h \sum_{m \in \mathcal{B}_{l,t}} \frac{\hat{a}_{m,t}}{n} - \sum_{m \in \mathcal{B}_{l,t}} \frac{p_{m,t}}{n} + (1 + \bar{\delta}_p^h) \left(q_t + \sum_{m \in \mathcal{B}_{l,t}} \frac{\hat{q}_{m,t}}{n} \right) + \bar{\rho}_p^h s_t. \end{aligned} \quad (\text{A-7})$$

Stage two of period t . During the second stage, firms obtain idiosyncratic signals about their productivity. Firms set prices according to

$$\begin{aligned} p_{j,l,t} &= w_t + \frac{1 - \alpha}{\alpha} E_{j,l,t} y_{j,l,t} - \frac{1}{\alpha} a_{l,t} \\ &\equiv k' + k'_1 E_{j,l,t} \tilde{p}_{l,t} + k'_2 E_{j,l,t} \tilde{y}_{l,t} - k'_3 a_{l,t}, \end{aligned}$$

with

$$k' = \frac{\alpha}{\alpha + \gamma(1 - \alpha)} w_t \quad k'_1 = \frac{\gamma(1 - \alpha)}{\alpha + \gamma(1 - \alpha)} \quad k'_2 = \frac{1 - \alpha}{\alpha + \gamma(1 - \alpha)} \quad k'_3 = \frac{1}{\alpha + \gamma(1 - \alpha)}. \quad (\text{A-8})$$

From here onwards, expressions that are based on common knowledge only (such as k') are treated like parameters in notation terms, i.e., they lack a time index. This facilitates the important distinction between expressions that are common information and those that are not. Evaluating the expectation of firm j about island-specific demand in period t , using

(A-7), results in

$$E_{j,l,t}\tilde{y}_{l,t} = \kappa^h + \delta_{xp}^h \left(\frac{1}{n}(a_{l,t} - x_{t-1}) + \frac{n-1}{n}E_{j,l,t}\varepsilon_t \right) - \left(\frac{1}{n}p_{j,l,t} + \frac{n-1}{n}E_{j,l,t}p_t \right) + \left[(1 + \bar{\delta}_p^h)\rho_q^p + \bar{\rho}_p^h \right] s_t. \quad (\text{A-9})$$

where ρ_q^p is the coefficient used by producers to form expectations about the aggregate demand shock based on the signal, and $\kappa^h = (1 + \tau_p^h)x_{t-1} - (1 + \eta_p^h)r_t + \kappa_p^h w_t$ contains only publicly available information. Furthermore, it is taken into account that the productivity and prices of island l have a non-zero weight in the sample of productivity and price levels observed by consumers visiting island l . Note that producers still take the price index of the consumers as given, since they buy infinitely many goods on the same island.

Note that the expectation error of each firm regarding its island-specific demand is, using equations (A-7) and (A-9)

$$\tilde{y}_{l,t} - E_{j,l,t}\tilde{y}_{l,t} = \frac{n-1}{n}\delta_{xp}^h(\varepsilon_t - E_{j,l,t}\varepsilon_t) - \frac{n-1}{n}(p_t - E_{j,l,t}p_t).$$

Inserting the firm expectation (A-9) into the pricing equation (A-8) yields (here, p_t is the average of the prices charged by producers of all other islands, which is the overall price index)

$$p_{j,l,t} \equiv k + k_1 E_{j,l,t}p_t - k_3 a_{l,t} + k_4 s_t,$$

with

$$\begin{aligned} \Xi &= 1 - \frac{1}{n}(k'_1 - k'_2) & k &= \frac{1}{\Xi} \left\{ k' + k'_2 \kappa^h + \frac{k'_2 \delta_{xp}^h}{n} [(n-1)(1 - \delta_x^p) - 1] x_{t-1} \right\} \\ k_1 &= \frac{n-1}{n\Xi} (k'_1 - k'_2) & k_3 &= \frac{1}{\Xi} \left\{ k'_3 - \frac{k'_2 \delta_{xp}^h}{n} [(n-1)\delta_x^p + 1] \right\} & k_4 &= \frac{k'_2}{\Xi} \left[(1 + \bar{\delta}_p^h)\rho_q^p + \bar{\rho}_p^h \right]. \end{aligned} \quad (\text{A-10})$$

Note that, according to (A-8), $0 < k'_1 - k'_2 < 1$ because $0 < \alpha < 1$ and $\gamma > 1$. Using the definition of k_1 in (A-10), this implies (observe that $n > 1$)

$$0 < k_1 < 1.$$

Aggregating over all producers gives the aggregate price index

$$p_t = k + k_1 \bar{E}_t p_t - k_3 x_t + k_4 s_t,$$

where $\int a_{l,t} dl = x_t$, and $\bar{E}_t p_t = \iint E_{j,l,t} p_t dj dl$ is the average expectation of the price level.

The expectation of firm j of this aggregate is therefore

$$\begin{aligned} E_{j,l,t} p_t &= k - k_3 E_{j,l,t} x_t + k_1 E_{j,l,t} \bar{E}_t p_t + k_4 s_t \\ &= k - k_3 \delta_x^p a_{l,t} - k_3 (1 - \delta_x^p) x_{t-1} + k_1 E_{j,l,t} \bar{E}_t p_t + k_4 s_t. \end{aligned} \quad (\text{A-11})$$

Inserting the last equation into (A-10) gives

$$p_{j,l,t} = k + k_1 k - k_1 k_3 (1 - \delta_x^p) x_{t-1} - (k_3 + k_1 k_3 \delta_x^p) a_{l,t} + k_1^2 E_{j,l,t} \bar{E}_t p_t + (k_4 + k_1 k_4) s_t.$$

To find $E_{j,l,t} \bar{E}_t p_t$, note that firm j 's expectations of the average of (A-11) are

$$E_{j,l,t} \bar{E}_t p_t = k - k_3 (1 - \delta_x^p) (1 + \delta_x^p) x_{t-1} - k_3 \delta_x^{p^2} a_{l,t} + k_1 E_{j,l,t} \bar{E}_t^{(2)} p_t + k_4 s_t.$$

where $\bar{E}^{(2)}$ is the average expectation of the average expectation. The price of firm j is found by plugging the last equation into the second-to-last:

$$\begin{aligned} p_{j,l,t} &= k + k_1 k + k_1^2 k - \left[k_1 k_3 (1 - \delta_x^p) + k_1^2 k_3 (1 - \delta_x^p) (1 + \delta_x^p) \right] x_{t-1} \\ &\quad - \left[k_3 (1 + k_1 \delta_x^p) + k_1^2 k_3 \delta_x^{p^2} \right] a_{l,t} + \left[k_4 + k_1 k_4 + k_1^2 k_4 \right] s_t + k_1^3 E_{j,l,t} \bar{E}^{(2)} p_t. \end{aligned}$$

Continuing like this results in some infinite sums

$$\begin{aligned} p_{j,l,t} &= k \left(1 + k_1 + k_1^2 + k_1^3 \dots \right) \\ &\quad - k_1 k_3 (1 - \delta_x^p) \left[1 + k_1 (1 + \delta_x^p) + k_1^2 (1 + \delta_x^p + \delta_x^{p^2}) + k_1^3 (1 + \delta_x^p + \delta_x^{p^2} + \delta_x^{p^3} \dots) \right] x_{t-1} \\ &\quad - k_3 \left(1 + k_1 \delta_x^p + k_1^2 \delta_x^{p^2} + k_1^3 \delta_x^{p^3} \dots \right) a_{l,t} + \left[k_4 + k_1 k_4 + k_1^2 k_4 + k_1^3 k_4 + \dots \right] s_t \\ &\quad + k_1^\infty E_{j,l,t} \bar{E}^{(\infty)} p_t. \end{aligned}$$

This results in

$$p_{j,l,t} = \frac{k}{1 - k_1} - \frac{k_1 (1 - \delta_x^p)}{1 - k_1} \frac{k_3}{1 - k_1 \delta_x^p} x_{t-1} - \frac{k_3}{1 - k_1 \delta_x^p} a_{l,t} + \frac{1}{1 - k_1} k_4 s_t + \underbrace{k_1^\infty \bar{E}_t^{(\infty)}}_{\rightarrow 0} p_t$$

or

$$p_{j,l,t} = \bar{k}_1 + \bar{k}_3 a_{l,t} + \bar{k}_4 s_t. \quad (\text{A-12})$$

with

$$\bar{k}_1 = \frac{1}{1 - k_1} \left[k - (1 - \delta_x^p) \frac{k_1 k_3}{1 - k_1 \delta_x^p} x_{t-1} \right] \quad \bar{k}_3 = -\frac{k_3}{1 - k_1 \delta_x^p} \quad \bar{k}_4 = \frac{1}{1 - k_1} k_4.$$

The average over all producers yields the aggregate price index as

$$p_t \equiv \bar{k}_1 + \bar{k}_3 x_t + \bar{k}_4 s_t. \quad (\text{A-13})$$

To arrive at qualitative predictions for the impact of the structural shocks ε_t and q_t on output growth and the forecast error, we need to determine the sign and the size of \bar{k}_3 . Note that, according to (A-10),

$$-k_3 = \delta_{xp}^h \frac{k_2' - nk_3'/\delta_{xp}^h + k_2'(n-1)\delta_x^p}{n - (k_1' - k_2')},$$

where the first part of the numerator can be rewritten, by observing (A-8), as

$$k_2' - nk_3'/\delta_{xp}^h = \frac{1 - n/\delta_{xp}^h - \alpha}{\alpha + \gamma(1 - \alpha)}.$$

Using (A-8) and (A-10) thus yields

$$-k_3 = \delta_{xp}^h \frac{(1 - \alpha)[(n-1)\delta_x^p + 1] - n/\delta_{xp}^h}{(n-1)[\alpha + \gamma(1 - \alpha)] + 1}.$$

Plugging this into the definition of \bar{k}_3 in (A-13) gives

$$\bar{k}_3 = \delta_{xp}^h \frac{\frac{(1-\alpha)[(n-1)\delta_x^p+1]-n/\delta_{xp}^h}{(n-1)[\alpha+\gamma(1-\alpha)]+1}}{1 - \delta_x^p \frac{(n-1)(\gamma-1)(1-\alpha)}{(n-1)[\alpha+\gamma(1-\alpha)]+1}}.$$

To obtain $\delta_{xp}^h = \delta_x^h + \delta_p^h$, we need to find the undetermined coefficients of equation (A-4). Start by comparing this equation with household l 's expectation of equation (A-13):

$$E_{l,t} p_t = \underbrace{\bar{k}_1 + \bar{k}_3 x_{t-1}}_{\kappa_p^h w_t + \tau_p^h x_{t-1} - \eta_p^h r_t} + \underbrace{\bar{k}_3 \delta_x^h}_{\delta_p^h} \hat{a}_{l,t} + \underbrace{\bar{k}_4}_{\bar{\rho}_p^h} s_t, \quad (\text{A-14})$$

with $\bar{\delta}_p^h = 0$, since the household knows that price-setters only have the public signal regarding demand, but not any information about actual demand. Hence, $\delta_{xp}^h = \delta_x^h(1 + \bar{k}_3)$. Inserting

this into the above expression for \bar{k}_3 yields

$$\bar{k}_3 \equiv -\frac{n/\Upsilon - \delta_x^h \Psi}{\Phi - \delta_x^h \Psi}, \quad (\text{A-15})$$

with

$$\begin{aligned} \Upsilon &= (n-1)[\alpha + \gamma(1-\alpha)] + 1 > 0 & \Psi &= (1-\alpha)[(n-1)\delta_x^p + 1]/\Upsilon > 0 \\ \Phi &= 1 - \delta_x^p(n-1)(\gamma-1)(1-\alpha)/\Upsilon. \end{aligned}$$

The signs obtain because $n > 1$, $0 < \alpha < 1$, $\delta_x^p > 0$, and $\gamma > 1$. Observe that $\Psi\Upsilon < n$ because $\delta_x^p \leq 1$. Hence, $n/\Upsilon - \delta_x^h \Psi > 0$ because

$$n - \underbrace{\delta_x^h}_{>0, <1} \underbrace{\Psi\Upsilon}_{<n} > 0,$$

implying that the numerator of (A-15) is positive. Turning to the denominator $\Phi - \delta_x^h \Psi$, note that $\Phi - \Psi > 0$. The denominator of (A-15) is therefore positive as well, and we have $\bar{k}_3 < 0$. Next, consider that $n/\Upsilon < \Phi$ and we obtain

$$-1 < \bar{k}_3 < 0.$$

This is a key result for the derivation of the proposition in Appendix C.

We now turn to \bar{k}_4 . First observe that

$$\begin{aligned} \Xi &= 1 - \frac{1}{n}(k'_1 - k'_2) \\ &= \frac{[(n-1)\gamma + 1](1-\alpha) + n\alpha}{n[\alpha + \gamma(1-\alpha)]} > 0 \end{aligned}$$

and

$$k_1 = \frac{(n-1)\varepsilon(1-\alpha) + (n-1)\alpha + 1 - n}{(n-1)\varepsilon(1-\alpha) + (n-1)\alpha + 1} < 1.$$

Thus,

$$\begin{aligned} \bar{k}_4 &= \frac{1}{1-k_1} \frac{k'_2}{\Xi} [\bar{k}_4 + \rho_q^p] \\ &= \frac{k'_2}{(1-k_1)\Xi - k'_2} \rho_q^p. \end{aligned}$$

Since $k'_2 > 0$, for $\bar{k}_4 > 0$, we need to show that

$$(1 - k_1)\Xi > k'_2$$

or

$$n\alpha^2 > -\alpha(1 - \alpha)[(n - 1)\gamma + 1],$$

which is true, such that $\bar{k}_4 > 0$.

Stage one of period t As information sets of agents are perfectly aligned during stage one, we use the expectation operator E_t to denote (common) stage-one expectations in what follows. Combining the results regarding expectations about inflation in period $t + 1$ with the Euler equation, the Taylor rule, and the random-walk assumption for x_t gives, see equation (A-3),

$$E_t c_t = E_t y_t = E_t x_t + (1 - \psi)E_t \pi_t + E_t q_t.$$

Remember that the monetary policy shock emerges after wages are set. Its expected value before wage-setting is zero, just like the expected value of the demand shock, as the signal is not yet released. Labor supply is given by

$$\varphi E_t l_t = E_t (w_t - p_t - c_t + q_t).$$

This equation can be combined with the aggregated production function

$$E_t y_t = E_t (x_t + \alpha l_t),$$

the expected aggregate labor demand

$$E_t (w_t - p_t) = E_t [x_t + (\alpha - 1)l_t],$$

and market clearing $y_t = c_t$ to obtain

$$\varphi E_t l_t = E_t (x_t + (\alpha - 1)l_t - c_t) + q_t$$

or

$$E_t y_t = E_t x_t.$$

Comparing this expression to the Euler equation, we get

$$E_t \pi_t = 0.$$

Nominal wages are set in line with these expectations. We thus have determinacy of the price level. The central bank then sets its interest rate based on expected inflation.

C Proofs

Proof of Proposition 1 Calculating the average expectation error of firms for idiosyncratic output, using demand equation (A-6), the island-specific demand (A-7), and the price-level equation (A-13), yields

$$\begin{aligned} FE_{j,l,t} &= \Delta y_{j,l,t} - E_{j,l,t} \Delta y_{j,l,t} = \gamma \frac{n-1}{n} (p_t - E_{j,l,t} p_t) + \tilde{y}_{l,t} - E_{j,l,t} \tilde{y}_{l,t} \\ &= \frac{n-1}{n} \left[(\gamma - 1) \bar{k}_3 + \delta_x^h (1 + \bar{k}_3) \right] (\varepsilon_t - E_{j,l,t} \varepsilon_t) + q_t - E_{j,l,t} q_t + \sum_{m \in \mathcal{B}_{l,t}} \frac{\hat{q}_{k,t}}{n} \\ &\equiv \Lambda (\varepsilon_t - E_{j,l,t} \varepsilon_t) + q_t - E_{j,l,t} q_t + \sum_{m \in \mathcal{B}_{l,t}} \frac{\hat{q}_{k,t}}{n}, \end{aligned} \quad (\text{A-16})$$

where the Euler equations (A-5) of customers of island l is used in the second equation. The effect Λ of the expectation error regarding aggregate technology innovations $\varepsilon_t - E_{j,l,t} \varepsilon_t$ on the expectation error regarding own output is negative if

$$\gamma - 1 > -\delta_x^h \frac{1 + \bar{k}_3}{\bar{k}_3}. \quad (\text{A-17})$$

Since

$$-\frac{1 + \bar{k}_3}{\bar{k}_3} = \frac{(n-1)(1-\alpha)(\gamma-1)(1-\delta_x^p)}{n - \delta_x^h(1-\alpha)[(n-1)\delta_x^p + 1]},$$

inequality (A-17) is fulfilled if

$$1 > \delta_x^h (1 - \alpha),$$

which is correct, such that $\Lambda < 0$. The gap between expected own and aggregate output can be calculated using (A-6), (A-9), (A-12), and (A-13):

$$\begin{aligned} E_{j,l,t} y_{j,l,t} - E_{j,l,t} y_t &= -\gamma \frac{n-1}{n} (p_{j,l,t} - E_{j,l,t} p_t) + E_{j,l,t} \tilde{y}_{l,t} - E_{j,l,t} y_t \\ &= \frac{1}{n} \left[-\gamma(n-1)\bar{k}_3 + \delta_x^h(1 + \bar{k}_3) - \bar{k}_3 \right] E_{j,l,t} \eta_{l,t} \end{aligned}$$

$$\equiv K_1 E_{j,l,t} \eta_{l,t}. \quad (\text{A-18})$$

Aggregating individual Euler equations (A-3) over all individuals, using (A-13), and (A-14) gives aggregate output as

$$\begin{aligned} y_t &= E_{l,t} x_t + E_{l,t} p_t - p_t - r_t + q_t \\ &= x_{t-1} + \underbrace{\left[\delta_x^h - \bar{k}_3(1 - \delta_x^h) \right]}_{>0} \varepsilon_t + q_t \underbrace{- \frac{\alpha}{\alpha + \psi(1 - \alpha)}}_{<0} \nu_t. \end{aligned}$$

Note that, if households have full information ($n \rightarrow \infty$), we get $\delta_x^h \rightarrow 1$ and $y_t = x_t - \nu_t \alpha / (\alpha + \psi(1 - \alpha))$. The signs indicated above result from $0 < -\bar{k}_3 < 1$ (derived above).

Forecast revisions are then given by the change in expectations between before and after receiving the private and public signals (that is, between stage one and stage two). The last equation implies

$$E_{j,l,t} y_t - x_{t-1} = \left[\delta_x^h - \bar{k}_3(1 - \delta_x^h) \right] E_{j,l,t} \varepsilon_t + \rho_q^p s_t - \frac{\alpha}{\alpha + \psi(1 - \alpha)} \nu_t.$$

Using this equation together with equation (A-18) in the forecast revision gives

$$\begin{aligned} FR_{j,l,t} &= E_{j,l,t}(y_{j,l,t} - y_{j,l,t-1}) - E_t(y_{j,l,t} - y_{j,l,t-1}) = E_{j,l,t} y_{j,l,t} - E_{j,l,t} y_t + E_{j,l,t} y_t - E_t y_t \\ &= K_1 E_{j,l,t} \eta_{l,t} + \left[\delta_x^h - \bar{k}_3(1 - \delta_x^h) \right] E_{j,l,t} \varepsilon_t + \rho_q^p s_t - \frac{\alpha}{\alpha + \psi(1 - \alpha)} \nu_t. \end{aligned}$$

Since

$$E_{j,l,t} \varepsilon_{l,t} = \delta_x^p (\varepsilon_t + \eta_{l,t}) \quad E_{j,l,t} \eta_{l,t} = (1 - \delta_x^p) (\varepsilon_t + \eta_{l,t}) \quad (\text{A-19})$$

we can write the above as

$$\begin{aligned} FR_{j,l,t} &= K_1 (1 - \delta_x^p) (\varepsilon_t + \eta_{l,t}) + \left[\delta_x^h - \bar{k}_3(1 - \delta_x^h) \right] \delta_x^p (\varepsilon_t + \eta_{l,t}) + \rho_q^p s_t - \frac{\alpha}{\alpha + \psi(1 - \alpha)} \nu_t \\ &\equiv X_1 \varepsilon_t + X_1 \eta_{l,t} + X_1^q q_t + X_1^q e_t^q + K_\nu \nu_t. \end{aligned}$$

with

$$X_1 = K_1 (1 - \delta_x^p) + \left[\delta_x^h - \bar{k}_3(1 - \delta_x^h) \right] \delta_x^p \quad X_1^q = \rho_q^p \quad K_\nu = -\frac{\alpha}{\alpha + \psi(1 - \alpha)} \nu_t.$$

Similarly, making use of (A-19), the forecast error (A-16) can be written as

$$FE_{j,l,t} = \Lambda [(1 - \delta_x^p)\varepsilon_t - \delta_x^p\eta_{l,t}] + (1 - \rho_q^p)q_t - \rho_q^p e_t + \sum_{m \in \mathcal{B}_{l,t}} \frac{\hat{q}_{k,t}}{n}.$$

The sign of β of regression (8) can then be determined in two steps. Since both independent variables, forecast revisions and the signal, are correlated, we first regress forecast revisions on the signal, yielding the regression coefficient

$$\begin{aligned} Coef_1 &= \frac{Cov(FR_{j,l,t}, s_t)}{Var(s_t)} \\ &= \frac{X_1^q \sigma_q^2 + X_1^q \sigma_e^2}{\sigma_q^2 + \sigma_e^2} \\ &= X_1^q. \end{aligned}$$

The residual of this regression can therefore be written as $FR_{j,l,t} - Coef_1 s_t$. The sign of the coefficient β of regression (8) then depends on the sign of

$$\begin{aligned} &Cov(FE_{j,l,t}; FR_{j,l,t} - Coef_1 s_t) \\ &= Cov(FE_{j,l,t}; FR_{j,l,t}) - Coef_1 Cov(FE_{j,l,t}, s_t) \\ &= \underbrace{(X_1^q - Coef_1)}_{=0} R_e^q + \underbrace{\Lambda X_1}_{<0} \underbrace{R_\eta}_{>0} < 0, \end{aligned}$$

with

$$R_\eta = (1 - \delta_x^p)\sigma_\varepsilon^2 - \delta_x^p\sigma_\eta^2.$$

The signs obtain from $\Lambda < 0$ and

$$\begin{aligned} K_1 &= \frac{1}{n} [-\gamma(n-1)\bar{k}_3 + \delta_x^h(1 + \bar{k}_3) - \bar{k}_3] > 0 \\ X_1 &= K_1(1 - \delta_x^p) + [\delta_x^h - \bar{k}_3(1 - \delta_x^h)] \delta_x^p > 0 \end{aligned}$$

as well as

$$R_\eta > 0 \quad \text{if} \quad \frac{\hat{\sigma}_\eta^2}{\hat{\sigma}_\varepsilon^2} > \frac{\sigma_\eta^2}{\sigma_\varepsilon^2},$$

which results from the assumption of island illusion. Hence, $\beta < 0$.

The sign of the coefficient δ of regression (8) can equivalently be derived by first regressing the forecast revision on the signal, which gives the coefficient

$$\begin{aligned} \text{Coe}f_2 &= \frac{\text{Cov}(FR_{j,l,t}, s_t)}{\text{Var}(FR_{j,l,t})} \\ &= \frac{X_1^q \sigma_q^2 + X_1^q \sigma_e^2}{X_1^2 \sigma_\varepsilon^2 + X_1^2 \sigma_\eta^2 + (X_1^q)^2 \sigma_q^2 + (X_1^q)^2 \sigma_e^2 + (K_\nu)^2 \sigma_\nu^2}, \end{aligned}$$

which is positive since $X_1^q > 0$. The sign of δ in regression (8) then depends on the sign of

$$\begin{aligned} &\text{Cov}(FE_{j,l,t}; s_t - \text{Coe}f_2(FR_{j,l,t})) \\ &= \text{Cov}(FE_{j,l,t}; s_t) - \text{Coe}f_2 \text{Cov}(FE_{j,l,t}, FR_{j,l,t}) \\ &= \underbrace{(1 - \text{Coe}f_2 X_1^q)}_{>0} \underbrace{R_e^q}_{>0} - \underbrace{\text{Coe}f_2}_{<0} \underbrace{\Lambda X_1}_{<0} R_\eta, \end{aligned}$$

with

$$R_e^q = (1 - \rho_q^p) \sigma_q^2 - \rho_q^p \sigma_{e,q}^2.$$

The signs obtain because

$$1 - \text{Coe}f_2 X_1^q = \frac{(K_\nu)^2 \sigma_\nu^2 + X_1^2 \sigma_\varepsilon^2 + X_1^2 \sigma_\eta^2}{X_1^2 \sigma_\varepsilon^2 + X_1^2 \sigma_\eta^2 + (X_1^q)^2 \sigma_q^2 + (X_1^q)^2 \sigma_{e,q}^2 + (K_\nu)^2 \sigma_\nu^2},$$

which is positive but smaller than unity, and

$$R_e^q > 0 \quad \text{if} \quad \frac{\hat{\sigma}_e^2}{\hat{\sigma}_q^2} > \frac{\sigma_e^2}{\sigma_q^2},$$

which results from the assumption of island illusion. Hence, $\delta > 0$. ■