How economic expectations react to news: Evidence from German firms*

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Abstract

How do firms adjust their expectations as new information arrives? The response of forecast errors to news provides useful insights: if firms process news immediately and correctly, news will not predict forecast errors. Yet we find that micro news, that is, news regarding firm-specific developments, give rise to negative forecast errors. Instead, macro news induce positive forecast errors. This implies that expectations overreact to micro news, but underreact to macro news. We establish these results for a large survey of German firms and put forward a general equilibrium model with dispersed information and overconfidence to rationalize the evidence. In the model, overconfidence raises the output dispersion across firms but dampens aggregate fluctuations.

Keywords: Firm expectations, survey, overreaction, underreaction, micro news, macro news, overconfidence, amplification, business cycle

JEL-Codes: D84, C53, E71

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1 Introduction

How do people adjust their expectations about the economy as new information comes in? During the last decade the literature has increasingly turned to survey data in order to address this question. The full information rational expectation (FIRE) hypothesis serves as the point of departure. According to this benchmark, expectations are adjusted correctly and instantaneously in the face of new information and, hence, forecast errors should not be predictable on the basis of news. By now it is well established that actual expectations fail to meet the FIRE benchmark because news—as reflected in current forecast revisions—predict forecast errors. On average, expectations tend to underreact to news in the sense that forecast revisions predict positive forecast errors, suggesting that information rigidities are not trivial (Coibion and Gorodnichenko, 2012, 2015). Expectations of individual forecasters, however, tend to overreact to news and the literature is currently exploring explanations that can account for both observations jointly (Bordalo et al., 2020; Broer and Kohlhas, 2020; Kohlhas and Walther, 2021).

In this paper, we revisit the issue while offering a fresh perspective. Namely, rather than studying the expectations of professional forecasters as existing studies do, we turn to firm expectations. In this way we may learn about the expectation formation of actual decision makers and the factors that influence their expectations. The basis of our analysis is the ifo survey of German firms. This has two important implications. First, we work with a rich data set that samples responses of some 1,500 respondents in each month (rather than the limited set of professional forecasters) and covers 15 years of data. Second, we focus on firm expectations about firm-specific developments, notably firms' output, rather than on expectations about aggregate developments. As we investigate how firm expectations react to news, we distinguish between micro and macro news. Micro news concern firm-specific developments, macro news concern the aggregate economy. We find that this distinction is essential for the expectation formation process: firm expectations overreact to micro news, but simultaneously underreact to macro news. In the second part of the paper, we study these results and their implications through the lens of a general equilibrium model. In order to account for simultaneous over- and underreaction to micro and macro news the model features overconfidence in the expectation formation process as suggested by Broer and Kohlhas (2020). The general equilibrium perspective allows us to explore the implications for the business cycle. We find, in particular, that overconfidence raises the volatility of output across firms, that is, it serves as an amplification mechanism of firm-level innovations. At the same time, it lowers (raises) the volatility of aggregate output in response to noise (technology innovations).

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 other surveys as well (Becker and Wohlrabe, 2008). Our 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 issue 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. We measure news as follows. Micro news are given by firms' current forecast revision about future production. This information is by definition available in the current period. We measure macro news as the surprise component of the ifo index, measured as the innovation in the index relative to 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 are very similar in nature, 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. For these reasons, both micro and macro news should not predict the forecast error under the FIRE hypothesis. And yet, on the basis of firm-level and panel regressions, we find robustly that they do.

More importantly still, they do so differently. 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, expectations do not fully account for macro news as they become available: they underreact. 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. Instead there is more heterogeneity in the response to macro news.

We put forward a general equilibrium model in order to rationalize our findings and explore their implications. The model builds on earlier work by Lorenzoni (2009) and Broer and Kohlhas (2020). In contrast to the models in these studies, however, it delivers analytical results for the general equilibrium. There are two key features. First, 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. Second, we assume that firms overestimate the informational content of their own developments regarding the aggregate state but underestimate that of the public signal.

Under these assumptions, we are able to derive a number of closed-form results. First, we show that the model can account for the survey evidence. Second, we spell out the implications for the business cycle. In particular, we show that aggregate output reacts less to noise in the public signal, a common measure of demand shocks (Enders et al., 2021b; Lorenzoni, 2009). 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. It becomes also less efficient, compared to a full-information setup. A direct implication is that overconfidence may cause some of the high idiosyncratic volatility of outcome variables observed at the firm level (Bachmann and Bayer, 2013; Bloom et al., 2018). This is noteworthy because in accounting for this volatility, existing work resorts to highly dispersed firm-level TFP, which is notoriously hard to measure. The model also predicts aggregate fluctuations to be more efficient: they are less driven by public noise, while reactions to noise in the private information cancel across firms. Furthermore, the overreaction to micro news implies stronger and more efficient price movements in case of aggregate innovations in technology.

Our paper relates to recent attempts to reassess the information formation process of economic agents, informed by survey evidence suggesting 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; Kohlhas and Walther, 2021). Other models, by contrast, allow for behavioral aspects in the expectation formation process (for instance, Azeredo da Silveira and Woodford, 2019; Bordalo et al., 2019; Shiller, 2017). Under certain conditions behavioral models and incomplete information models give rise to equivalent equilibrium effects (Angeletos and Huo, 2021).

There is also earlier work on firm expectations based on the ifo index. Massenot and Pettinicchi (2018) regress, in turn, 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.

The remainder of this paper is organized as follows. We provide details about the ifo survey and our data in Section 2. 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.

2 Data

The analysis is based on two main data sources. First, the monthly ifo Business Climate Survey (ifo survey) which is a— mostly qualitative—firm survey[1] that is well established in the literature.[2] Here, we restrict ourselves to firms in the manufacturing sector (IBS-IND, 2020) for which we observe production expectations and realizations.

Second, we draw on the Bloomberg consensus survey for the ifo Business Climate Index (ifo index) to extract the surprise component of the monthly releases. This Bloomberg survey consists of roughly 40 professional forecasters that can change their forecast up to the release of the index. Choosing the ifo index as a proxy for macro news has three substantial advantages in our setting: 1) The ifo index is an indicator with highly predictive power for the German economy (Lehmann, 2020). 2) The media attention of the ifo index is very high, for instance it is listed as one of Bloomberg’s "12 Global Economic Indicators to Watch"[3]. In addition, the news is available to the firms at very low costs: The participants receive the results directly from the ifo Institute. 3) The release of the ifo index is, by definition, between 2 survey waves (at the end of each month).[4] Thereby, we achieve a clear information

[1]A nice feature is that the survey is predominately filled out by senior management (Sauer and Wohlrabe, 2019).

[2]For instance, Bachmann et al. (2013) analyze uncertainty and its impact on production, Bachmann and Elstner (2015) study the presence of expectation biases, Bachmann et al. (2019) find links between uncertainty and price setting, Enders et al. (2019) examine the impact of MP announcements on expectations, Enders et al. (2021a) highlight the importance of expectations on production and pricing decisions, Buchheim et al. (2020) analyze expectations at the start of the Covid-19 pandemic, and Link et al. (2021) document facts about the degree of firms’ information frictions compared to households.

[3]https://www.bloomberg.com/graphics/world-economic-indicators-dashboard/

[4]To illustrate: In the first three weeks of month t, firms fill out the survey (wave t). At the end of month t, the ifo Institute releases the ifo index (containing the answers of wave t) and newspapers report about it and most of time also refer to the median expectations from professional forecasters. About a week later (now, we are in month $t + 1$), firms start to fill out the survey (wave $t + 1$) while having the most recent release of the ifo index in their information set.

structure and can also check whether firms update their expectations in response to the ifo index.

Restricted by the availability of Bloomberg forecasts for the ifo index, our sample ranges over 15 years from April 2004 to December 2019. In the ifo survey, the two main variables that we exploit are qualitative questions about the production expectation in the next three months and production realizations in the past month. The questions are as follows (translated):

Expectations for the next 3 months:
Our production is expected to be [1] increasing, [0] not changing or [-1] decreasing.

Review - tendencies in (last month):
Compared to (month before previous month) our production increased [1], stayed about the same [0] or decreased [-1].

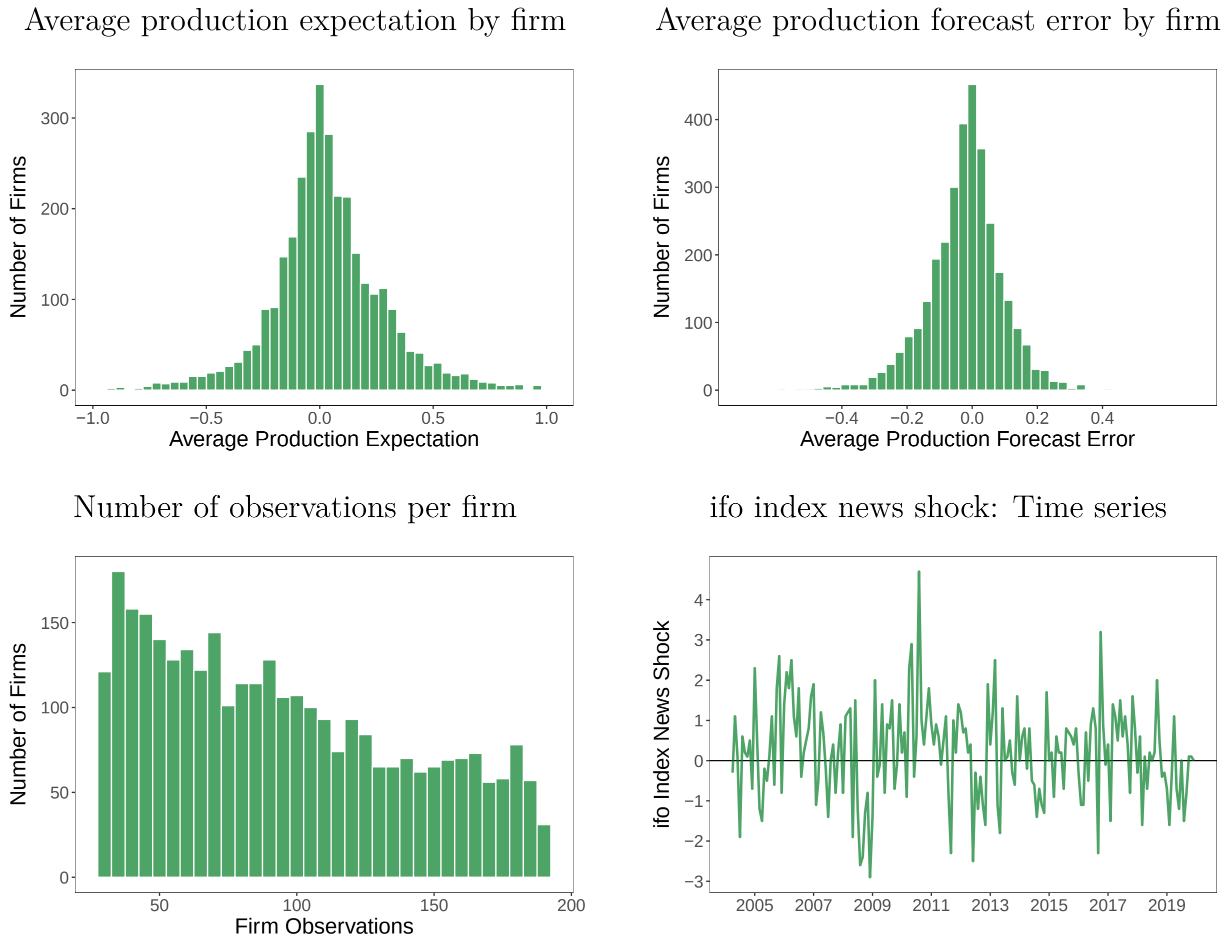
We can then calculate the production forecast error :

$$e_{t,h} = \begin{cases} 0 & \text{if } \operatorname{sgn}(x_{t,h}) = x_{t,h|t} \\ \frac{1}{h}(x_{t,h} - x_{t,h|t}) & \text{else ,} \end{cases} \tag{1}$$

where we follow the error definition of Bachmann et al. (2013). Here, $x_{t,h|t}$ is the production forecast of a firm at time t over the horizon h (3 months in our case), $x_{t,h}$ is the sum of monthly production realisations in these h months, and *sgn* denotes the sign function and returns 1,0, or -1. A firm has made no expectation error if the sign of the production expectation equals the sign of the aggregate production realisations within the forecast horizon. In the case of different signs, the expectation error is quantified by the monthly average of the difference between the aggregate realization $x_{t,h}$ and the expectation $x_{t,h|t}$. Hence, the error can take values between $4/3$ and $-4/3$ in the case of a forecast horizon of three months. For a firm to be included in the estimation, we require at least 30 observations and a non-zero variance of forecast errors and forecast revisions, that is, a firm must have revised its expectation at least once. We obtain a panel with roughly 1600 firm-level observations each month. In addition, we draw on information about the number of employees of the firms and the sector they are operating in.

The top row of Figure 1 shows the distribution across firms for the average production expectation (left panel) and the average production forecast error (right panel) over time. Both distributions are roughly symmetric and peak at zero. While the dispersion of average

Figure 1: Descriptive statistics



Notes: Top row: distribution across firms; the left panel shows the distribution of the average production expectation of firms over time, the right panel shows the distribution of the average production forecast error of firms over time. Bottom row: firm observations and shock variation; the left panel illustrates the number of observations in the ifo Business Climate Survey for the manufacturing sector across both panel dimensions, the right panel shows the ifo Business Climate Index news shock (ifo index - median of Bloomberg consensus survey) over time.

expectations is substantial, the average forecast errors are centered around zero. In the full sample, the average production forecast error is -0.019 and thereby, as expected, close to zero. The standard deviation amounts to 0.37 and in 57% of the observations, firms did not make a forecast error.

To analyze firms' expectation updating after they receive macro news, we calculate the ifo index news shock by subtracting the median Bloomberg professional forecaster expectation of the index from the realized ifo index value. Importantly, we pull the ifo index shock one month forward since then it is in the information set of firms before they report their production expectations (see footnote 4). By using this data source, we implicitly assume that the expectations of professional forecasters about the macro economy in Germany are on average the same as for firms up to the release to new information.

The bottom row of Figure 1 summarizes our two data sources. In the left panel, we display the information about the panel dimension of the ifo survey. On average, we observe a firm over more than 90 months and one quarter of firms are more than 125 months in the sample. This strong panel dimension allows us to run firm-by-firm regressions and is a sign of good quality of the survey data. In the right panel, the ifo index news shock is depicted over time. The surprise component of the ifo index is fluctuating around zero and is weakly positively autocorrelated. This is in line with information rigidities and consistent with e.g. Coibion and Gorodnichenko (2012, 2015).

3 Empirical Analysis

In this section, we first introduce our empirical framework before presenting the results for our baseline as well as robustness checks.

3.1 Framework

For the empirical analysis, as discussed in the introduction, we rely on a version of the regression that has been popularized by Coibion and Gorodnichenko (2015). The purpose is to assess whether *news* predict forecast errors. Under full the information rational expectations (FIRE) benchmark, they should not because all information is processed correctly and instantaneously upon arrival. While the original estimation by Coibion and Gorodnichenko (2015) has been estimated on average responses of professional forecasters in the SPF, later studies have stressed the importance also consider the forecast errors of individual forecasters (Bordalo et al., 2020; Broer and Kohlhas, 2020). However, our approach differs from the existing literature because we analyze forecast errors of a *firm-specific* variable—namely firms' own production—instead of macro variables such as inflation. In addition, the distinction between micro and macro news takes center stage in our analysis.

Formally, we estimate the following relationship:

$$x^i_{t+h} - x^i_{t+h|t} = \beta^i_0 + \beta^i_1 micro\_news^i_{t,h} + \beta^i_2 macro\_news_t + v^i_{t+h} \; . \tag{2}$$

In the expression above, $x^i_{t+h} - x^i_{t+h|t}$ is the forecast error of firm i of its own production between month t and month $t+h$. $micro\_news^i_{t,h}$ denotes micro, that is, firm-specific, news, and $macro\_news_t$ captures news about the aggregate economy, both become available in period t. The error term v^i_{t+h} is assumed to have zero mean and strictly positive variance. We estimate the β-coefficients using the observations for individual firms and report estimates for individual firms as well as for a panel-specification in which case we pool observations.

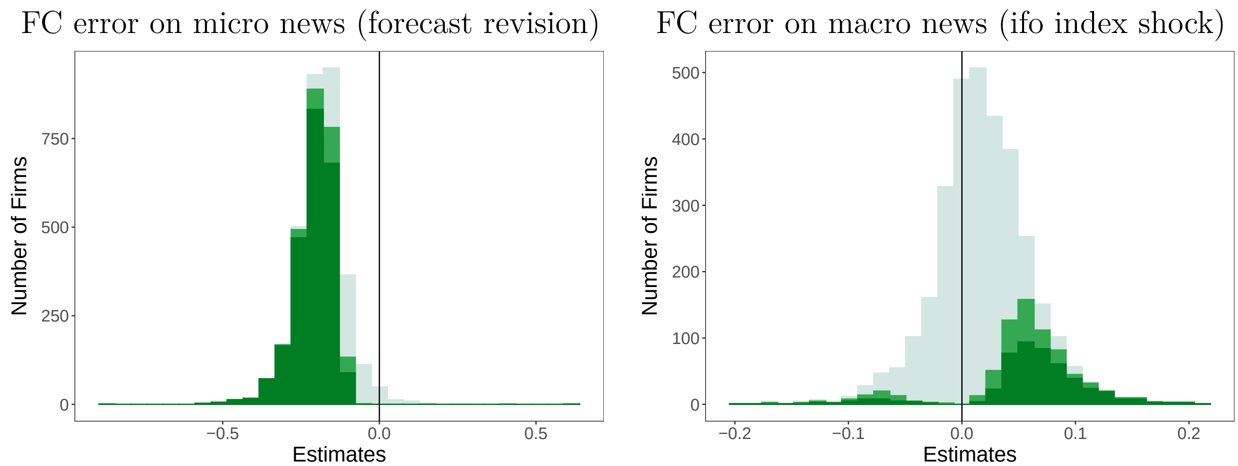
We compute news on the basis of firms' forecast revisions in month t, relative to the previous month $t-1$, $FR^i_{t,h}$. In our survey, the forecasting horizon changes every month as firms report the expected change of production over the next three months. Formally, revisions are thus given by: $FR^i_{t,h} = (x^i_{t+h|t} - x^i_{t-1+h|t-1})$. Since we seek to measure news, we ideally would like to compute the forecast revision for fixed-horizon forecasts. But since these data are not available, we acknowledge this as a limitation of our data set and continue under the assumption that the overlap of the forecasting periods is sufficiently large for forecast revisions to reflect a meaningful update in terms of information (rather than merely a change of the forecasting horizon). In addition, we stress that, because of the nature of the survey, our measure of the forecast error is based on qualitative responses (see Section 2 above). Likewise, we define the forecast revision based on qualitative responses. Formally, we have $FR^i_{t,h} = \text{sgn}(x^i_{t+h|t} - x^i_{t-1+h|t-1}) \in \{+1, 0, -1\}$. The revision is positive (negative) when the forecast in t is larger (smaller) than the forecast in $t-1$.

We measure macro news by the surprise component of the ifo index (introduced in Section 2). Importantly, $macro\_news_t$ is the ifo index shock that was released at the end of last month ($t-1$) and is therefore in the information set of the firms when they respond to the survey in month t.

In general, the forecast revision $FR^i_{t,h}$ may be caused by micro and macro news: firms simply revise their outlook about their own production. But because our model (2) features macro news as a distinct regressor, we may rely on $FR^i_{t,h}$ to measure the effect of micro news on forecast errors. Hence, we interpret the estimate of β^i_1 as a measure of the effect of firm-specific news. In a alternative specification, we estimate Equation (2) on pooled data and add time fixed effects to control for changes in the macro environment more generally.

The interpretation of β_1 and β_2 is straightforward. Under FIRE, the coefficients should not be significantly different from zero since forecast errors are not predictable on the basis of information that is available at the time of the forecast. A positive β-coefficient implies underreaction to the respective news. Conversely, a negative β-coefficient points to an overreaction. To see why, consider the case of a positive macro shock, that is, when the realized ifo index is higher than expected by the median Bloomberg forecaster: $macro\_news_t > 0$. If $\beta^i_2 > 0$, the forecast error responds positively to such a shock, that is, $x_{t+h} > x^i_{t+h|t}$ and one may conclude that the initial revision was too small (underreaction).

Figure 2: Over- and underreaction to news



Notes: The left panel shows the distribution of firm-level estimates β_1^i of Equation (2) (without $macro\_news_t$). The right panel shows the distribution of firm-level estimates β_2^i of Equation (2) (without $micro\_news_{t,h}$).

3.2 Results

We begin the analysis by estimating Equation (2) firm by firm, separately for micro news and macro news.[5] Figure 2 shows the results for forecast revisions, that is, micro news, on the left and for the ifo index shock, that is, macro news, on the right. In both instances, we show the distribution of the estimated β-coefficients across firms. The (light) green bars depict the number of estimates that are significant at the (10%) 5% level. First, we observe that almost all firm-level regressions yield a significantly negative estimate for forecast revisions in the left panel. This implies that firm expectations overreact to firms' own production forecasts. Second, the right panel shows that most firms underreact to macro news, as captured by the ifo index shock: the estimated coefficients are positive for a large number of firms, while there are almost no significantly negative estimates. Also, the overall distribution of estimates is shifted to the right. Third, especially in the right panel, there is large heterogeneity in the estimates across firms. Besides measurement error, this is an indication for different degrees of underreaction and exposure to changes in the macroeconomy across firms. Figure A.1 in the appendix shows the results when micro and macro news are estimated jointly as in Equation (2). The distribution of estimates is very similar. Hence, the overreaction in expectations is most likely driven by micro news.

In what follows, we run the regressions on pooled data to estimate the respective *average* effect of interest. In all specifications, we allow for firm fixed effects (FE) and cluster

[5] At this point we stress again a benefit of using the ifo survey to address the issue at hand: it features a large number of firms, each of which is in the survey for a fairly long period, see Figure 1 above. This enables us to run firm-by-firm regressions.

Table 1: Over- and underreaction to news

	Forecast (FC) Error				Forecast Revision
	(1)	(2)	(3)	(4)	(5)
Forecast Revision	-0.190***	-0.194***		-0.191***	
	(0.001)	(0.001)		(0.001)	
ifo Index Shock			0.021***	0.022***	0.008***
			(0.0007)	(0.0007)	(0.0007)
Observations	302,737	302,737	302,737	302,737	302,737
R^2	0.15736	0.18834	0.08967	0.16260	0.00212
Within R^2	0.07898	0.08462	0.00498	0.08471	0.00033
Firm FE	✓	✓	✓	✓	✓
Time FE		✓			

Notes: The table shows the effects on the production forecast error (Columns (1)-(4)) and production forecast revision (Column (5)). The full, pooled sample is used. The survey questions and variable definitions can be found in Section 2. Standard errors are clustered on firm level. *** p<0.01, ** p<0.05, * p<0.1.

standard errors at the firm level. Table 1 displays the main results. As it was already visible from the distribution of individual estimates above, firms' forecast revisions are on average significantly negatively related to their forecast errors (see Column (1)). Hence, firms tend to overreact to the total amount of news. In Column (2), we include time fixed effects. They should absorb macro news that affect all firms in the same way. The degree of overreaction even increase only slightly as we include time FE. This implies that the overreaction to the forecast revision is largely driven by firm-specific, that is, micro news.

In contrast, the surprise component of the ifo index is significantly positively related to firms' forecast errors (see Column (3)). This implies that firms underreact to macro news on average, which confirms the finding of the firm-by-firm regressions above. Importantly, the results do not change when the effects of forecast revisions and the ifo index shock are estimated jointly (see Column (4)). Consistent with the results reported in column (2), this illustrates once more that firm-specific news are at the heart of firms' overreaction to the the forecast revisions.

Lastly, Column (5) of Table 1 shows that a positive ifo index shock is associated with an upward revision of the production forecast. This indicates that firms do update their expectations in response to the release of macro news on average. However, firms do not respond strongly enough, otherwise the ifo index shock would not have predictive power regarding firms' forecast errors.

In general, the interpretation of the magnitude of the effects is not straightforward due to the qualitative nature of the variables. However, we note that the magnitude in the variation

Table 2: Positive v negative news

	Forecast (FC) Error				FC Revision
	(1)	(2)	(3)	(4)	(5)
FC Revision × Neg. Revision	-0.187***	-0.192***		-0.188***	
	(0.002)	(0.002)		(0.002)	
FC Revision × Pos. Revision	-0.193***	-0.197***		-0.193***	
	(0.002)	(0.002)		(0.002)	
ifo Index Shock × Neg. Shock			0.034***	0.036***	0.012***
			(0.001)	(0.001)	(0.002)
ifo Index Shock × Pos. Shock			0.011***	0.012***	0.005***
			(0.0010)	(0.0010)	(0.001)
Observations	302,737	302,737	302,737	302,737	302,737
R^2	0.15737	0.18835	0.09017	0.16318	0.00215
Within R^2	0.07899	0.08463	0.00554	0.08533	0.00035
Firm FE	✓	✓	✓	✓	✓
Time FE		✓			

Notes: The table shows the effects on the production forecast error (Columns (1)-(4)) and production forecast revision (Column (5)). Forecast revisions and ifo index shocks are divided into positive($\geq$ 0) and positive values. The full, pooled sample is used. The survey questions and variable definitions can be found in Section 2. Standard errors are clustered on firm level. *** p<0.01, ** p<0.05, * p<0.1.

of the regressors is comparable: a forecast revision is always of size 1 and the average ifo index shock is also roughly of size 1. Thus, the overreaction after forecast revisions has an $\approx$ 9 times larger effect on forecast errors compared to the underreaction after an average ifo index shock. To further help the interpretation of the magnitudes, Tables A.1 and A.2 in the appendix present the results of ordered logit regressions. The main message of these regressions is clear cut and in line with our OLS regressions: Positive forecast revisions are associated with lower odds (exp(estimate) $<$ 1) of an increase in forecast error categories while a positive ifo index shock is associated with higher odds (exp(estimate) $>$ 1).

The results are robust to using manufacturing orders as an alternative measure of macro news, see Table A.3. However, the underreaction is smaller in this case.[6]

The main takeaway from the analysis so far is that firms *underreact* to macro news while simultaneously *overreacting* to firm-specific news. We now check for potential heterogeneity with respect to the over- and underreaction in production expectations of firms to news. In a first step, we separate the production forecast revisions as well as the ifo index shock in to

[6]This could be due to the information structure which is not as clear cut as with the ifo index. Some firms already have the information already at the time of filling out the survey a month before since the manufacturing orders statistics are released at the end of the first week of a month. Moreover, manufacturing orders have lower predictive power for the German economy.

Table 3: Over- and underreaction to news: Split by firm size

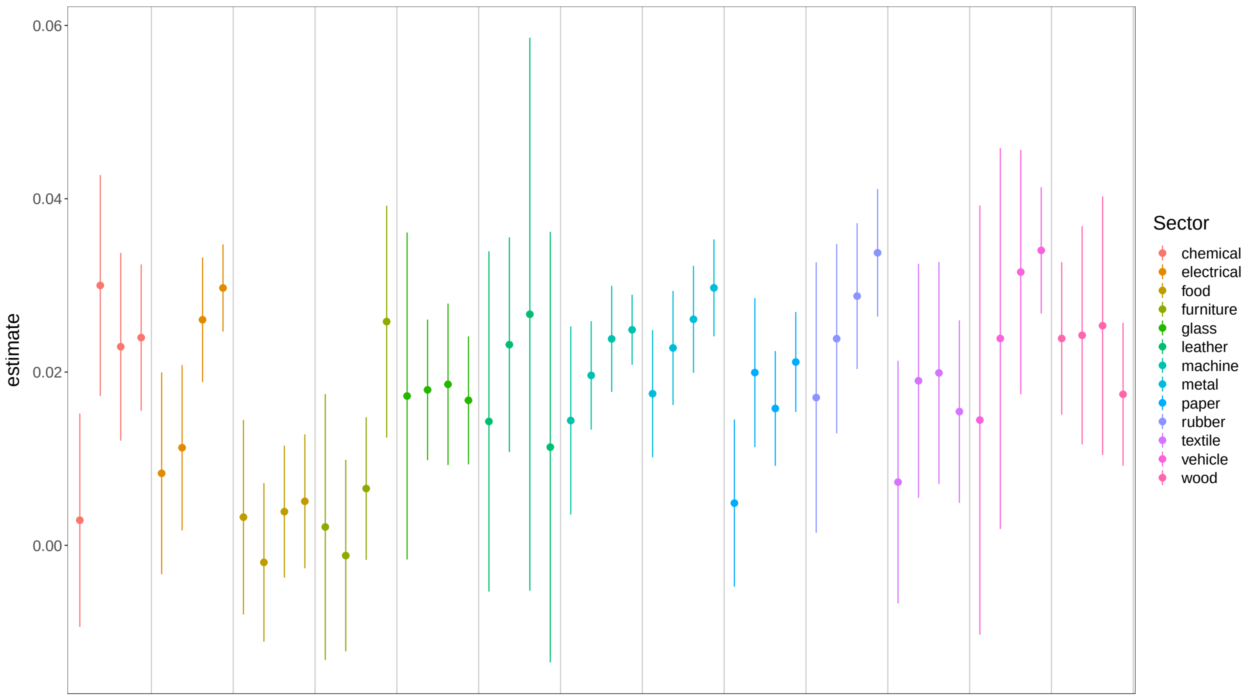
	Forecast (FC) Error				FC Revision
	(1)	(2)	(3)	(4)	(5)
FC Revision × 0-25 P Employees	−0.195***	−0.199***		−0.196***	
	(0.003)	(0.003)		(0.003)	
FC Revision × 26-50 P Employees	−0.188***	−0.192***		−0.189***	
	(0.003)	(0.003)		(0.003)	
FC Revision × 51-75 P Employees	−0.188***	−0.192***		−0.189***	
	(0.003)	(0.003)		(0.003)	
FC Revision × 76-100 P Employees	−0.190***	−0.195***		−0.191***	
	(0.002)	(0.002)		(0.002)	
ifo Index Shock × 0-25 P Employees			0.012***	0.014***	0.007***
			(0.002)	(0.002)	(0.002)
ifo Index Shock × 26-50 P Employees			0.019***	0.020***	0.008***
			(0.001)	(0.001)	(0.002)
ifo Index Shock × 51-75 P Employees			0.021***	0.022***	0.008***
			(0.001)	(0.001)	(0.002)
ifo Index Shock × 76-100 P Employees			0.026***	0.027***	0.008***
			(0.001)	(0.001)	(0.001)
Observations	302,737	302,737	302,737	302,737	302,737
R^2	0.15738	0.18835	0.08989	0.1628	0.0021
Within R^2	0.07899	0.08464	0.00522	0.0850	0.0003
Firm FE	✓	✓	✓	✓	
Time FE		✓			

Notes: The table shows the effects on the production forecast error (Columns (1)-(4)) and production forecast revision (Column (5)). Forecast revisions and ifo index shocks are divided into number of employees quartiles. The full, pooled sample is used. The survey questions and variable definitions can be found in Section 2. Standard errors are clustered on firm level. *** p<0.01, ** p<0.05, * p<0.1.

positive (≥ 0) and negative values. The effect of forecast revisions on forecast errors turns out to be quite symmetric, as visible in Columns (1) and (2) of Table 2. In contrast, there is a strong asymmetry in the underreaction to the ifo index shock. The underreaction is three times larger in the case of negative shocks compared to positive shocks (0.034 / 0.011, see Column (3)). Interestingly, the updating of the production forecast is on average also stronger for negative ifo index shocks than for positive ones (see Column (5)).

Next, we split the effects of news by firm size, proxied by the number of employees (quartiles). Again, Columns (1) and (2) of Table 3 show that the magnitude of overreaction is on average relatively similar across the firm size distribution. For the ifo index shock, there is clear heterogeneity in the predictability of production forecast errors depending on the firm size. On average, the underreaction for firms in the highest quartile is roughly twice as large as for firms in the lowest quartile (see Columns (3) and (4)), while the forecast updating is of similar size for the four quartiles (Column (5)).

Figure 3: Underreaction to ifo index news shock: Split by sector and firm size



Notes: The figure displays the effect of the ifo index shock on forecast errors and the corresponding 95% confidence bands, split by sectors and firm size that is approximated by the respective quartiles of the number of employees (left to right: q1 to q4).

Last, we interact the employee quartiles with manufacturing sectors to get a full picture of the heterogeneity. For forecast revisions, there is no heterogeneous pattern visible (see Figure A.2 in the appendix). All estimates are significantly negative and clustered between -0.15 and -0.24, which shows again the strong evidence for overreaction of firms to micro news. Figure 3 shows the estimates for the ifo index shock. Here, we make three observations: First, most estimates significantly positive which shows that underreaction is not a phenomenon driven by a few sectors. Second, there are level differences between sectors. Especially the food industry shows only non-significant estimates. This is in line with the fact that the food industry is a non-cyclical industry and hence less impacted by macro shocks. Third, within most sectors, underreaction is again stronger for larger firms. This is particularly visible in large sectors such as the machinery industry.

4 General-Equilibrium Model

In the following we develop a stylized model of noisy information and derive analytical results.[7] We incorporate our empirical findings by introducing overconfidence in own information in the spirit of Broer and Kohlhas (2020). Different to them, however, we consider a general-equilibrium model. In this way we are able to, first, replicate our results for over- and underreactions to micro and macro news on a firm level, and, second, make qualitative statements about the resulting effects on idiosyncratic and aggregate fluctuations in general equilibrium.

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.

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 $1 < n < \infty$.[8] Households have an infinite planning horizon. 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.[9] 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.

Shocks emerge during the second stage. We distinguish between shocks that are directly observable and shocks that are not. Noise and technology shocks are not directly observable in the following sense: information about idiosyncratic productivity (i.e., micro news) is

[7]Lorenzoni (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.

[8]This 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.

[9]As 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.

private to each producer, but, in addition, all agents observe a public signal (i.e., macro news) about average productivity. While the signal is unbiased, it contains an i.i.d. zero-mean noise component. 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 in terms of identification. 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, including the signal, and information contained in the prices of the goods in their consumption bundle. Because the common productivity component is permanent 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

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

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 flow budget constraint 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

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

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 and monetary policy

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

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

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.[10] ν_t is a monetary policy shock that is observable by producers and households alike.

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

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

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.

[10] Pre-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.

4.4 Productivity and overconfidence

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. During stage two of each period, agents observe a public signal about x_t. This represents macro news and takes the form

$$s_t = \varepsilon_t + e_t \ ,$$

where e_t is an i.i.d. noise shock with variance σ_e^2 and mean zero. Producers also observe their own productivity $a_{j,l,t}$. The rational forecast for Δx_t is given by

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

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

$$\bar{\rho}_x^p = \frac{\sigma_\eta^2}{\sigma_e^2 + \sigma_\eta^2 + \frac{\sigma_\eta^2 \sigma_e^2}{\sigma_\varepsilon^2}} \qquad \bar{\delta}_x^p = \frac{\sigma_e^2}{\sigma_e^2 + \sigma_\eta^2 + \frac{\sigma_\eta^2 \sigma_e^2}{\sigma_\varepsilon^2}}.$$

Overconfidence Rather than assuming that expectations are formed in a rational way, however, we suppose that producers are overconfident about the informational content of their own information, that is overconfident in micro news and underconfident in the informational content of macro news.[11] We model this trait by assuming that producer l believes that her private signal $a_{l,t}$ is more precise than it actually is, while she thinks that the public signal s_t is less precise than it is. Specifically, she assumes too low a variance σ_η^2 of the

[11] Broer and Kohlhas (2020) show in a partial-equilibrium setup that relative overconfidence (judging own signals to be more informative than the information of others) can give rise to underconfidence in public signals, while absolute overconfidence (judging own signals to be more informative than they are) leads to overrevisions of expectations. While we model the latter as they do, we take a shortcut for the former and directly assume underconfidence in public signals.

private signal's idiosyncratic component $\eta_{l,t}$ and too a high a the variance σ_e^2 of the public signal's noise component e_t. We assume that all producers are overconfident in the same way and expect other producers to entertain the same beliefs about σ_η^2 and σ_e^2 as they do. We denote these incorrect beliefs about σ_η^2 and σ_e^2 by $\hat{\sigma}_\eta^2 < \sigma_\eta^2$ and $\hat{\sigma}_e^2 > \sigma_e^2$, such that actual expectations of producers are

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

with

$$\rho_x^p = \frac{\hat{\sigma}_\eta^2}{\hat{\sigma}_e^2 + \hat{\sigma}_\eta^2 + \frac{\hat{\sigma}_\eta^2\hat{\sigma}_e^2}{\sigma_\varepsilon^2}} > \bar{\rho}_x^p \qquad \delta_x^p = \frac{\hat{\sigma}_e^2}{\hat{\sigma}_e^2 + \hat{\sigma}_\eta^2 + \frac{\hat{\sigma}_\eta^2\hat{\sigma}_e^2}{\sigma_\varepsilon^2}} < \bar{\delta}_x^p.$$

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. Given that they have also observed the public signal, they can infer the productivity level of each producer in their sample:

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

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. ρ_x^h and δ_x^h are equal across households, see Appendix B. The model nests the case of complete information about all relevant variables for households and producers if $\sigma_e^2 = 0$. If $\sigma_e^2 > 0$, producers will set prices based on potentially overly optimistic or pessimistic expectations of productivity. Consumers also have complete information if $n \to \infty$.

4.5 Market clearing

Goods and labor markets clear in each period:

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

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 Results

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. We obtain the following propositions for which we provide proofs in Appendix C.

Proposition 1 shows that assuming overconfidence, that is $\hat{\sigma}_\eta^2 < \sigma_\eta^2$ and $\hat{\sigma}_e^2 > \sigma_e^2$, generates overreaction to private signals and underreaction to public information by individual firms.

Proposition 1. *Consider the regression*

$$\Delta y_{j,l,t+1} - E_{j,l,t}\Delta y_{j,l,t+1} = \bar{\alpha} + \beta FR_{j,l,t} + \delta s_t + \omega_{j,l,t} \ . \tag{4.1}$$

where $\bar{\alpha}$ is a constant, $\Delta y_{j,l,t+1}$ is the realized change in firm j-specific output and $FR_{j,l,t} = E_{j,l,t}x_{t+1} - E_{j,l,t}x_t$ is the forecast revision of firm j, such that the above equations correspond to the empirical equation (2) *in Section 3. In case of overconfidence ($\hat{\delta}_\eta^2 < \delta_\eta^2, \hat{\delta}_e^2 > \delta_e^2$), we obtain*

$$\beta < 0 \qquad and \qquad \delta > 0 \ .$$

The signs of the coefficients result from the fact that overconfident firms on average overestimate aggregate technology in periods t and $t+1$ following positive innovations in idiosyncratic technology, but underestimate their own output in (the third stage of) period t. Better expected aggregate technology implies lower expected prices of competitors. Since these prices, on average, turn out to be higher than expected in period t, also demand for the own product is higher: current own output is underestimated. This results in a higher-than-estimated growth rate of own output and a negative expectation error. Underconfidence in the public signal, in contrast, lets firms on average underestimate current and future aggregate technology after positive signals, yielding the opposite effect.

Proposition 2 demonstrates that output fluctuations at the firm level are larger due to overconfidence, and inefficiently so. To assess efficiency we benchmark the response of aggregate and idiosyncratic variables against the constrained-efficient outcome in which households and firms possess full information about current variables.[12]

Proposition 2. *The cross-sectional dispersion of output innovations is*

$$\sigma_{\Delta y^j}^2 = \frac{1}{n^2}\left[\gamma(n-1)\Omega + n\delta_x^h(1-\Omega) + \Omega\right]^2 \sigma_\eta^2 \ ,$$

[12]The constrained-efficient outcome is nested in the setup by setting $\sigma_e^2 = 0$ and adjusting the rational-expectations coefficients accordingly, such that $\bar{\rho}_x^p = \bar{\rho}_x^h = 1$ and $\bar{\delta}_x^p = \bar{\delta}_x^h = 0$.

and

$$0 < \Omega = \frac{n - \delta_x^h(1-\alpha)[(n-1)\delta_x^p + 1]}{n\alpha + (1-\alpha)\left\{(1-\delta_x^h)[1+\delta_x^p(n-1)] + (n-1)\gamma(1-\delta_x^p)\right\}} < 1 \ .$$

In case of overconfidence ($\hat{\delta}_\eta^2 < \delta_\eta^2$, $\hat{\delta}_e^2 > \delta_e^2$), Ω takes a higher value relative to the rational-expectations benchmark, such that the cross-sectional dispersion of output increases, i.e.,

$$\frac{\partial \sigma^2_{\Delta y^j}}{\partial \delta_x^p} > 0 \ .$$

The reaction to idiosyncratic technology shocks and the resulting output dispersion in the rational-expectations noisy-information benchmark are inefficiently high. Hence, output dispersion becomes even less efficient with overconfidence.

The intuition is straightforward: overestimating the informational content of the private signal (i.e., their own technology) implies that producers think that their idiosyncratic and aggregate technology are more aligned than they actually are. In case of positive idiosyncratic technology shocks, they therefore believe other producers to reduce their prices as well. Because of strategic complementarity, they set their own prices inefficiently low, which increases the cross-sectional dispersion of output. Aggregate technology innovations or noise, however, affect all producers in the same way.

Next, we solve for the response of aggregate output to the individual shocks. We then obtain an expression for the variance of output innovations.

Proposition 3. *The variance of aggregate output innovations is given by*

$$\sigma^2_{\Delta y} = \left[\rho_x^h(1-\Omega)\right]^2 \sigma_e^2 + \left[(\delta_x^h + \rho_x^h)(1-\Omega) + \Omega\right]^2 \sigma_\varepsilon^2 + \left[\frac{\alpha}{\alpha + \psi(1-\alpha)}\right]^2 \sigma_\nu^2.$$

In case of overconfidence ($\hat{\delta}_\eta^2 < \delta_\eta^2$, $\hat{\delta}_e^2 > \delta_e^2$), aggregate output fluctuations generated by public noise are muted, while fluctuations generated by innovations in aggregate technology are amplified, that is

$$\frac{\partial(\partial\sigma^2_{\Delta y}/\partial\sigma^2_e)}{\partial \delta_x^p} < 0 \qquad \textit{and} \qquad \frac{\partial(\partial\sigma^2_{\Delta y}/\partial\sigma^2_\varepsilon)}{\partial \delta_x^p} > 0 \ .$$

The reaction to aggregate technology shocks in the rational-expectations noisy-information benchmark is inefficiently low and the reaction to noise shocks inefficiently large. Hence, aggregate output fluctuations become more efficient with overconfidence.

Intuitively, an underreaction to public noise increases efficiency, while the overreaction to noise in private signals cancels out across firms. Additionally, as explained above, overconfident producers believe that their own technology is more correlated with the aggregate technology than it actually is. Following a positive aggregate technology shock, overconfident producers therefore reduce their prices more than in the noisy-information rational-expectations benchmark. Due to the presence of noisy information, however, the individual price reaction in that benchmark is muted relative to the full-information scenario. A stronger price reduction therefore raises efficiency.

Taken together, the model shows that overconfidence leads to more dispersed output across firms. This is noteworthy in light of the high observed idiosyncratic volatility of firm outcome variables (Bachmann and Bayer, 2013; Bloom et al., 2018). To generate this volatility, existing work typically assumes a high cross-sectional dispersion individual technology levels, which is difficult to measure. Overconfidence can, at least partly, be an alternative to this assumption.

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 second part of our analysis we take a structural perspective and augment a general equilibrium model with dispersed information with overconfidence. Because the model is able to account for the evidence, we rely on it to spell out the implications of our findings for the business cycle. In particular, we find that there is amplification of firm-level shocks and an increase in the cross-sectional dispersion of firm outcomes relative to standard models of dispersed information. While this reduces overall efficiency, aggregate fluctuations become more efficient.

While we leave a more systematic analysis of this efficiency insight for future research, it should be said that the predictions of the model have important implications for fiscal and monetary policy: as they have a bearing on aggregate variables only, the predicted inefficiency on the micro level, together with a higher efficiency on the macro level, reduces policy's scope for achieving an efficient outcome for all market participants.

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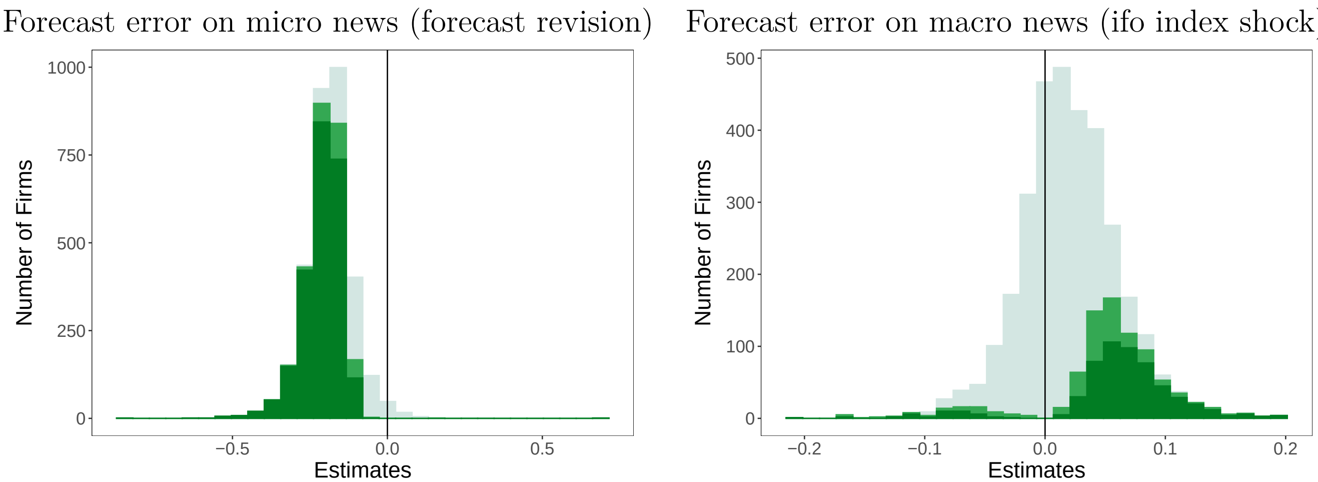
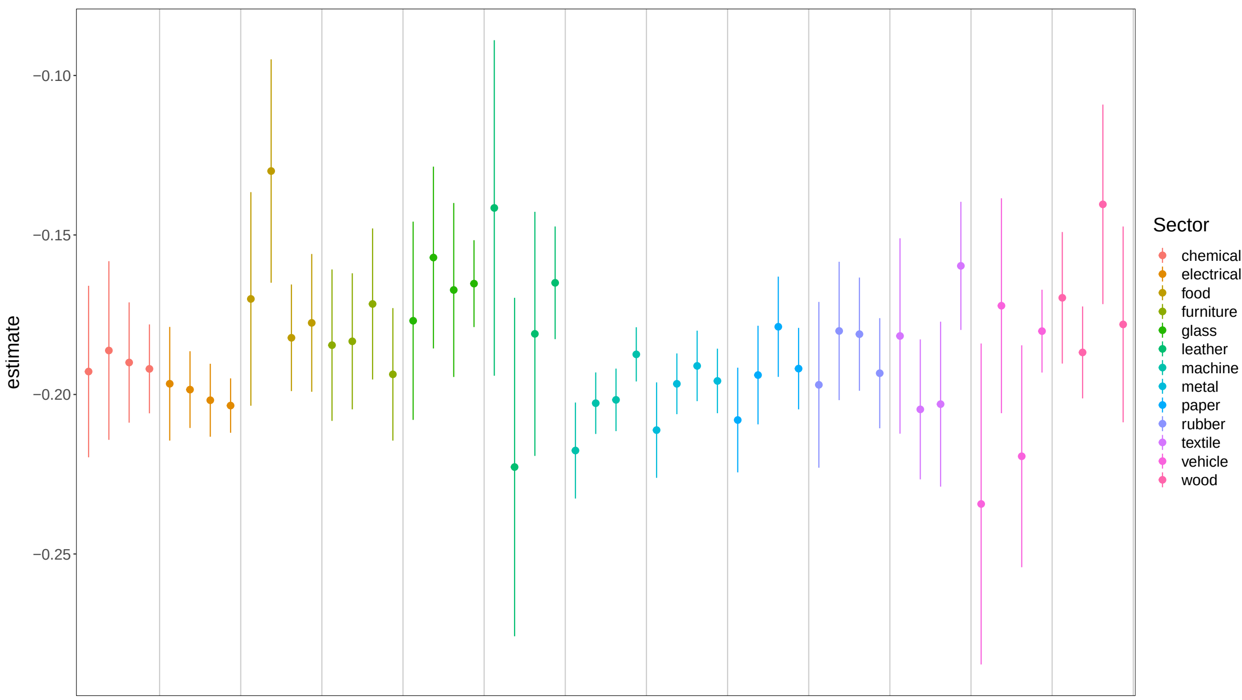
A Appendix

Figure A.1: Predictability of forecast errors: Firm-by-firm regressions (jointly estimated)



Notes: The left panel shows the distribution of firm-level estimates β_1^i of Equation (2). The right panel shows the distribution of firm-level estimates β_2^i of Equation (2).

Figure A.2: Overreaction to forecast revision: Split by sector and firm size



Notes: The figure displays the effect of the ifo index shock on forecast errors and the corresponding 95% confidence bands, splitted by sectors and firm size that is approximated by the respective quartiles of the number of employees (left to right: q1 to q4).

Table A.1: Ordered Logit: Effect of forecast revision on forecast error

term	estim.	std.error	statistic	type	exp(estim.)
Forecast Revision	-1.13	0.01	-163.64	coeff.	0.32
-4/3 | -1	-6.06	0.03	-174.53	scale	0.00
-1 | -2/3	-3.59	0.01	-339.28	scale	0.03
-2/3 | -1/3	-2.47	0.01	-374.16	scale	0.08
-1/3 | 0	-1.29	0.00	-287.42	scale	0.27
0 | 1/3	1.50	0.00	315.48	scale	4.49
1/3 | 2/3	2.70	0.01	374.27	scale	14.86
2/3 | 1	3.89	0.01	321.14	scale	49.03
1 | 4/3	6.64	0.05	143.81	scale	768.36

Notes: The table shows the results using ordered logit to estimate the effect of forecast revisions on the production forecast error. The last column shows the odds ratios. Rows 2 to 9 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.2: Ordered Logit: Effect of ifo index shock on forecast error

term	estim.	std.error	statistic	type	exp(estim.)
ifo Index Shock	0.10	0.00	33.55	coeff.	1.10
-4/3 | -1	-5.88	0.03	-169.47	scale	0.00
-1 | -2/3	-3.41	0.01	-327.25	scale	0.03
-2/3 | -1/3	-2.32	0.01	-360.77	scale	0.10
-1/3 | 0	-1.19	0.00	-272.94	scale	0.31
0 | 1/3	1.43	0.00	306.98	scale	4.16
1/3 | 2/3	2.57	0.01	364.45	scale	13.12
2/3 | 1	3.75	0.01	312.24	scale	42.61
1 | 4/3	6.50	0.05	140.68	scale	662.13

Notes: The table shows the results using ordered logit to estimate the effect of the ifo index shock on the production forecast error. The last column shows the odds ratios. Rows 2 to 9 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: Over- and underreaction to news: Manuf. Orders

	Forecast Error				Forecast Revision
	(1)	(2)	(3)	(4)	(5)
Forecast Revision	-0.190***	-0.194***		-0.190***	
	(0.001)	(0.001)		(0.001)	
Manuf. Orders Shock			0.005***	0.005***	0.002***
			(0.0003)	(0.0003)	(0.0004)
Observations	298,586	298,586	298,586	298,586	298,586
R^2	0.15717	0.18842	0.08580	0.15828	0.00198
Within R^2	0.07902	0.08479	0.00103	0.08023	0.00009
Firm FE	✓	✓	✓	✓	✓
time_id FE		✓			

Notes: The table shows the effects on the production forecast error (Columns (1)-(4)) and production forecast revision (Column (5)). The measure for macro news is month-on-month manufacturing order shocks (realized value - median Bloomberg forecast). The shock is pulled forward one month to assure that it is in the information set of firms The full, pooled sample is used. The survey questions and variable definitions can be found in Section 2. 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 propositions 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

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

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.

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 the productivity signal is public, 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

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

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. The coefficients ρ_x^h and δ_x^h are equal across households and depend on $n, \sigma_e^2, \sigma_\varepsilon^2$, and σ_η^2 in the following way:

$$\rho_x^h = \underbrace{\frac{\sigma_\eta^2/n}{\sigma_e^2 + \sigma_\eta^2/n + \frac{\sigma_e^2\sigma_\eta^2/n}{\sigma_\varepsilon^2}}}_{\to 0 \text{ if } n\to\infty}, \qquad \delta_x^h = \underbrace{\frac{\sigma_e^2}{\sigma_e^2 + \sigma_\eta^2/n + \frac{\sigma_e^2\sigma_\eta^2/n}{\sigma_\varepsilon^2}}}_{\to 1 \text{ if } n\to\infty}. \tag{A-2}$$

The expectation formation of (overconfident) 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. Also 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

$$c_{l,t} = E_{l,t}x_t + E_{l,t}p_t - p_{l,t} - r_t. \tag{A-3}$$

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

$$E_{l,t}p_t = \rho_p^h s_t + \delta_p^h \hat{a}_{l,t} + \kappa_p^h w_t + \tau_p^h x_{t-1} - \eta_p^h r_t. \tag{A-4}$$

Combining the above gives

$$c_{l,t} = (1+\tau_p^h)x_{t-1} + \rho_{xp}^h s_t + \delta_{xp}^h \hat{a}_{l,t} + \kappa_p^h w_t - (1+\eta_p^h) r_t - p_{l,t}, \tag{A-5}$$

where $\rho^h_{xp} = \rho^h_x + \rho^h_p$ and $\delta^h_{xp} = \delta^h_x + \delta^h_p$. We will solve for the undetermined coefficients below. Total demand for good j on island l is

$$y_{j,l,t} = -\gamma(p_{j,l,t} - \tilde{p}_{l,t}) + \tilde{y}_{l,t},$$

where $\tilde{y}_{l,t}$ is the average consumption level of customers visiting island l, which, imposing market clearing, equals output of island l. 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. Since consumers only buy on a subset of islands, the price of their own island has a non-zero weight in their price index, such that

$$y_{j,l,t} = -\gamma \frac{n-1}{n} (p_{j,l,t} - p_t) + \tilde{y}_{l,t}. \tag{A-6}$$

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

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

with

$$k' = \frac{\alpha}{\alpha + \gamma(1-\alpha)} w_t \qquad k'_1 = \frac{\gamma(1-\alpha)}{\alpha + \gamma(1-\alpha)} \qquad k'_2 = \frac{1-\alpha}{\alpha + \gamma(1-\alpha)} \qquad k'_3 = \frac{1}{\alpha + \gamma(1-\alpha)}. \tag{A-7}$$

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 aggregate output in period t, given equation (A-5), results in

$$E_{j,l,t} y_t = \kappa^h + \rho^h_{xp} s_t + \delta^h_{xp} E_{j,l,t} \left(\frac{1}{n} a_{l,t} + \frac{n-1}{n} E_{j,l,t} x_t - x_{t-1} \right) - \left(\frac{1}{n} p_{j,l,t} + \frac{n-1}{n} E_{j,l,t} p_t \right),$$

where $\kappa^h = (1 + \tau^h_p) x_{t-1} - (1 + \eta^h_p) r_t + \kappa^h_p w_t$ contains only publicly available information. Furthermore, it is taken into account that the productivity of island l has a non-zero weight in the sample of productivity 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. Inserting the above into the pricing equation (A-7) yield (here, p_t is the average of the prices charged by producers of all other islands, which is the overall price index as there are infinitely many locations)

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

with

$$\Xi = 1 - \frac{1}{n}(k_1' - k_2') \qquad k = \frac{1}{\Xi}\left\{k' + k_2'\kappa^h + \frac{k_2'\delta_{xp}^h}{n}\left[(n-1)(1-\delta_x^p) - 1\right] x_{t-1}\right\} \tag{A-8}$$

$$k_1 = \frac{n-1}{n\Xi}(k_1' - k_2') \qquad \tilde{k} = \frac{k_2'}{\Xi}\left(\rho_{xp}^h + \delta_{xp}^h \rho_x^p \frac{n-1}{n}\right) \qquad k_3 = \frac{1}{\Xi}\left\{k_3' + \frac{k_2'\delta_{xp}^h}{n}\left[(n-1)\delta_x^p - 1\right]\right\}.$$

Note that, according to (A-7), $0 < k_1' - k_2' < 1$ because $0 < \alpha < 1$ and $\gamma > 1$. Using the definition of k_1 in (A-8), this implies (observe that $n > 1$)

$$0 < k_1 < 1.$$

Aggregating over all producers gives the aggregate price index

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

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

The expectation of firm j of this aggregate is therefore

$$\begin{aligned} E_{j,l,t} p_t &= k + \tilde{k} s_t - k_3 E_{j,l,t} x_t + k_1 E_{j,l,t} \overline{E}_t p_t \\ &= k + \left(\tilde{k} - k_3 \rho_x^p\right) s_t - k_3 \delta_x^p a_{l,t} - k_3 (1-\delta_x^p) x_{t-1} + k_1 E_{j,l,t} \overline{E}_t p_t. \end{aligned} \tag{A-9}$$

Inserting the last equation into (A-8) gives

$$p_{j,l,t} = k + k_1 k - k_1 k_3 (1-\delta_x^p) x_{t-1} + \left[\tilde{k} + k_1\left(\tilde{k} - k_3 \delta_x^p\right)\right] s_t - \left(k_3 + k_1 k_3 \delta_x^p\right) a_t^j + k_1^2 E_{j,l,t} \overline{E}_t p_t.$$

To find $E_{j,l,t}\overline{E}_t p_t$, note that firm j's expectations of the average of (A-9) are

$$E_{j,l,t}\overline{E}_t p_t = k - k_3(1-\delta_x^p)(1+\delta_x^p) x_{t-1} + \left(\tilde{k} - k_3\rho_x^p - k_3 \delta_x^p \rho_x^p\right) s_t - k_3 \delta_x^{p2} a_{l,t} + k_1 E_{j,l,t} \overline{E}_t^{(2)} p_t,$$

where $\overline{E}^{(2)}$ 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:

$$\begin{aligned}p_{j,l,t} = &\left(k + k_1 k + k_1^2 k\right) - \left[k_1 k_3 (1-\delta_x^p) + k_1^2 k_3 (1-\delta_x^p)(1+\delta_x^p)\right] x_{t-1} \\ &+ \left[\tilde{k} + k_1\left(\tilde{k} - k_3\rho_x^p\right) + k_1^2\left(\tilde{k} - k_3\rho_x^p - k_3\delta_x^p\rho_x^p\right)\right] s_t \\ &- \left(k_3 + k_1 k_3 \delta_x^p + k_1^2 k_3 \delta_x^{p2}\right) a_{l,t} + k_1^3 E_{j,l,t}\overline{E}^{(2)} p_t.\end{aligned}$$

Continuing like this results in some infinite sums

$$\begin{aligned}p_{j,l,t} =& k\left(1 + k_1 + k_1^2 + k_1^3 \dots\right) \\ &- k_1 k_3 (1-\delta_x^p)\left[1 + k_1(1+\delta_x^p) + k_1^2(1+\delta_x^p+\delta_x^{p2}) + k_1^3(1+\delta_x^p+\delta_x^{p2}+\delta_x^{p3}\dots)\right] x_{t-1} \\ &+ \left[\tilde{k} + k_1\left(\tilde{k} - k_3\rho_x^p\right) + k_1^2\left(\tilde{k} - k_3\rho_x^p - k_3\delta_x^p\rho_x^p\right) + k_1^3\left(\tilde{k} - k_3\rho_x^p - k_3\rho_x^p\delta_x^p - k_3\rho_x^p\delta_x^{p2}\right) + \dots\right] s_t \\ &- k_3\left(1 + k_1\delta_x^p + k_1^2\delta_x^{p2} + k_1^3\delta_x^{p3}\dots\right) a_{l,t} + k_1^\infty E_{j,l,t}\overline{E}^{(\infty)} p_t.\end{aligned}$$

For the terms in the third line, we have

$$\begin{aligned}&\tilde{k} + k_1\left(\tilde{k} - k_3\rho_x^p\right) + k_1^2\left(\tilde{k} - k_3\rho_x^p - k_3\delta_x^p\rho_x^p\right) + k_1^3\left(\tilde{k} - k_3\rho_x^p - k_3\rho_x^p\delta_x^p - k_3\rho_x^p\delta_x^{p2}\right) \\ &+ k_1^4\left(\tilde{k} - k_3\rho_x^p - k_3\rho_x^p\delta_x^p - k_3\rho_x^p\delta_x^{p2} - k_3\rho_x^p\delta_x^{p3}\right)\dots \\ =&\tilde{k}(1 + k_1 + k_1^2 + k_1^3 \dots) - \left(k_1 k_3\rho_x^p + k_1^2 k_3\rho_x^p + k_1^3 k_3\rho_x^p \dots\right) \\ &- \left(\delta_x^p k_1^2 k_3\rho_x^p + \delta_x^p k_1^3 k_3\rho_x^p + \delta_x^p k_1^4 k_3\rho_x^p \dots\right) - \left(\delta_x^{p2} k_1^3 k_3\rho_x^p + \delta_x^{p2} k_1^4 k_3\rho_x^p + \delta_x^{p3} k_1^5 k_3\rho_x^p \dots\right)\dots \\ =&\tilde{k}(1 + k_1 + k_1^2 + k_1^3 \dots) - k_1 k_3\left(\frac{\rho_x^p}{1-k_1} + \frac{\rho_x^p\delta_x^p k_1}{1-k_1} + \frac{\rho_x^p\delta_x^{p2}k_1^2}{1-k_1}\dots\right) \\ =&\frac{\tilde{k}}{1-k_1} - \frac{k_1 k_3\rho_x^p}{1-k_1}\left(1 + \delta_x^p k_1 + \delta_x^{p2}k_1^2 \dots\right) \\ =&\frac{\tilde{k}}{1-k_1} - \frac{k_1 k_3\rho_x^p}{(1-k_1)(1-\delta_x^p k_1)}.\end{aligned}$$

Proceeding similarly with the terms in the other lines results in

$$p_{j,l,t} = \frac{k}{1-k_1} - \frac{k_1(1-\delta_x^p)}{1-k_1}\frac{k_3}{1-k_1\delta_x^p}x_{t-1} + \frac{1}{1-k_1}\left(\tilde{k} - \rho_x^p\frac{k_1 k_3}{1-k_1\delta_x^p}\right)s_t - \frac{k_3}{1-k_1\delta_x^p}a_{l,t} + \underbrace{k_1^\infty\overline{E}_t^{(\infty)}}_{\to 0} p_t$$

or

$$p_{j,l,t} = \bar{k}_1 + \bar{k}_2 s_t + \bar{k}_3 a_{l,t}. \qquad \text{(A-10)}$$

with

$$\bar{k}_1 = \frac{1}{1-k_1}\left[k - (1-\delta_x^p)\frac{k_1 k_3}{1-k_1\delta_x^p}x_{t-1}\right] \quad \bar{k}_2 = \frac{1}{1-k_1}\left(\tilde{k} - \rho_x^p\frac{k_1 k_3}{1-k_1\delta_x^p}\right) \quad \bar{k}_3 = -\frac{k_3}{1-k_1\delta_x^p}.$$

Setting idiosyncratic technology shocks equal to zero in order to track the effects of aggregate shocks and observing that all firms then set the same price gives

$$p_t \equiv \bar{k}_1 + \bar{k}_2 s_t + \bar{k}_3 x_t. \tag{A-11}$$

To arrive at qualitative predictions for the impact of the structural shocks ε_t and e_t on output growth and the nowcast error, we need to determine the sign and the size of $\bar{k}_3$. Note that, according to (A-8),

$$-k_3 = \delta^h_{xp} \frac{k'_2 - nk'_3/\delta^h_{xp} + k'_2(n-1)\delta^p_x}{n - (k'_1 - k'_2)},$$

where the first part of the numerator can be rewritten, by observing (A-7), as

$$k'_2 - nk'_3/\delta^h_{xp} = \frac{1 - n/\delta^h_{xp} - \alpha}{\alpha + \gamma(1-\alpha)}.$$

Using (A-7) and (A-8) thus yields

$$-k_3 = \delta^h_{xp} \frac{(1-\alpha)[(n-1)\delta^p_x + 1] - n/\delta^h_{xp}}{(n-1)[\alpha + \gamma(1-\alpha)] + 1}.$$

Plugging this into the definition of $\bar{k}_3$ in (A-11) gives

$$\bar{k}_3 = \delta^h_{xp} \frac{\frac{(1-\alpha)[(n-1)\delta^p_x + 1] - n/\delta^h_{xp}}{(n-1)[\alpha+\gamma(1-\alpha)]+1}}{1 - \delta^p_x \frac{(n-1)(\gamma-1)(1-\alpha)}{(n-1)[\alpha+\gamma(1-\alpha)]+1}}.$$

To obtain $\delta^h_{xp} = \delta^h_x + \delta^h_p$, we need to find the undetermined coefficients of equation (A-4). Start by comparing this equation with household l's expectation of equation (A-11):

$$E_{l,t} p_t = \underbrace{\bar{k}_1 + \bar{k}_3 x_{t-1}}_{\kappa^h_p w_t + \tau^h_p x_{t-1} - \eta^h_p r_t} + \underbrace{\left(\bar{k}_2 + \bar{k}_3 \rho^h_x\right)}_{\rho^h_p} s_t + \underbrace{\bar{k}_3 \delta^h_x}_{\delta^h_p} \hat{a}_{l,t}. \tag{A-12}$$

Hence, $\delta^h_{xp} = \delta^h_x(1 + \bar{k}_3)$. Inserting this into the above expression for $\bar{k}_3$ yields

$$\bar{k}_3 \equiv -\frac{n/\Upsilon - \delta^h_x \Psi}{\Phi - \delta^h_x \Psi}, \tag{A-13}$$

with

$$\Upsilon = (n-1)[\alpha + \gamma(1-\alpha)] + 1 > 0 \qquad \Psi = (1-\alpha)[(n-1)\delta^p_x + 1]/\Upsilon > 0$$
$$\Phi = 1 - \delta^p_x(n-1)(\gamma-1)(1-\alpha)/\Upsilon.$$

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-13) is positive. Turning to the denominator $\Phi - \delta_x^h\Psi$, observe that $\Phi - \Psi > 0$. The denominator of (A-13) is therefore positive as well, and we have $\overline{k}_3 < 0$. Next, consider that $n/\Upsilon < \Phi$ and we obtain

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

This is a key result for the derivation of propositions 1-3; see Appendix C. Multiplying the nominator and the denominator of the fraction in equation (A-13) by Υ and rewriting gives the expression for Ω used in Proposition 2.

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

$$E_t y_t = E_t x_t - \psi E_t \pi_t.$$

Remember that the monetary policy shock emerges after wages are set. Its expected value before wage-setting is zero. Using $E_t x_t = E_t y_t$ (which results from combining labor supply and demand with the production function), we obtain

$$E_t \pi_t = 0.$$

Nominal wages are set in line with these expectations. We thus have determinacy of the price level. The central bank also expects zero inflation in the absence of monetary policy shocks. To find the effects of monetary policy shocks on the interest rate, including feedback effects via changes in expected inflation, note that, according to equation (A-12),

$$\overline{k}_1 + \overline{k}_3 x_{t-1} = \kappa_p^h w_t + \tau_p^h x_{t-1} - \eta_p^h r_t,$$

where, observing equations (A-7), (A-8), and (A-11),

$$
\begin{aligned}
\overline{k}_1 =& \frac{1}{(1-k_1)\Xi}\left[\frac{\alpha}{\alpha+\gamma(1-\alpha)}+k_2'\kappa_p^h\right]w_t - \frac{k_2'(1+\eta_p^h)}{(1-k_1)\Xi}r_t \\
&+\frac{1}{(1-k_1)\Xi}\left\{k_2'(1+\tau_p^h)+k_2'\delta_{xp}^h\left[\frac{n-1}{n}(1-\delta_x^p)-1\right]-\frac{(1-\delta_x^p)k_1k_3\Xi}{1-k_1\delta_x^p}\right\}x_{t-1}.
\end{aligned}
$$

We can hence determine the coefficient η_p^h as

$$
-\eta_p^h = \frac{k_2'(1+\eta_p^h)}{(1-k_1)\Xi} = \frac{\alpha-1}{\alpha},
$$

which is the impact of r_t on the price level. To finally determine the response of r_t, use this insight in the Taylor rule, resulting in

$$
r_t = \psi\frac{\alpha-1}{\alpha}r_t + \nu_t = \frac{\alpha}{\alpha+\psi(1-\alpha)}\nu_t. \tag{A-14}
$$

C Proofs

Proof of Proposition 1 Calculating the expectation error for idiosyncratic output, using demand equation (A-6) and the expectation of future output (A-1), yields

$$
\begin{aligned}
&\Delta y_{j,l,t+1} - E_{j,l,t}\Delta y_{j,l,t+1} = y_{j,l,t+1} - y_{j,l,t} - E_{j,l,t}x_{t+1} + E_{j,l,t}y_{j,l,t} \\
&= y_{j,l,t+1} - E_{j,l,t}x_{t+1} - \gamma\frac{n-1}{n}\left(p_t - E_{j,l,t}p_t\right) - \tilde{y}_{l,t} + E_{j,l,t}\tilde{y}_{l,t} \\
&= f_{t+1} + x_t - E_{j,l,t}x_t + \gamma\frac{n-1}{n}\Omega\left(\varepsilon_t - E_{j,l,t}\varepsilon_t\right) - \frac{n-1}{n}\left(\delta_{xp}^h + \Omega\right)\left(\varepsilon_t - E_{j,l,t}\varepsilon_t\right) \\
&= f_{t+1} + \varepsilon_t - E_{j,l,t}\varepsilon_t - \frac{n-1}{n}\left[(1-\gamma)\Omega + \delta_x^h(1-\Omega)\right]\left(\varepsilon_t - E_{j,l,t}\varepsilon_t\right) \\
&\equiv f_{t+1} + (1-\Lambda)\left(\varepsilon_t - E_{j,l,t}\varepsilon_t\right),
\end{aligned}
$$

where the third equation uses equation (A-11) for aggregate prices, the definition of $\Omega = -\overline{k}_3$ and the Euler equations (A-5) of customers of island l. The fourth equation employs the definition of δ_{xp}^h, see (A-12). $f_{t+1} = f(\varepsilon_{t+1}, e_{t+1}, \eta_{j,l,t+1})$ is a combination of variables of period $t+1$. The effect $1-\Lambda$ of the expectation error regarding aggregate technology innovations $\varepsilon_t - E_{j,l,t}\varepsilon_t$ on the expectation error regarding own output is positive if

$$
\gamma - 1 > \delta_x^h\frac{1-\Omega}{\Omega}. \tag{A-15}
$$

Since

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

inequality (A-15) is fulfilled if

$$n-(1-\alpha)[(n-1)\delta_x^p+1]\delta_x^h > \delta_x^h(n-1)(1-\alpha)(1-\delta_x^p)$$

or

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

which is correct, such that $1-\Lambda > 0$. Forecast revisions are given by

$$\begin{aligned} E_{j,l,t}y_{j,l,t+1} - E_{j,l,t-1}y_{j,l,t} &= E_{j,l,t}x_t - E_{j,l,t-1}x_{t-1} \\ &= (\rho_x^p + \delta_x^p)\varepsilon_t + \rho_x^p e_t + \delta_x^p \eta_{j,l,t} - g_{t-1}, \end{aligned}$$

where g_{t-1} is a function of variables of period $t-1$.

The sign of β of regression (4.1) 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

$$\begin{aligned} &\frac{Cov((\rho_x^p + \delta_x^p)\varepsilon_t + \rho_x^p e_t + \delta_x^p \eta_{j,l,t} - g_{t-1}, \varepsilon_t + e_t)}{Var(s_t)} \\ =&\rho_x^p + \delta_x^p \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_e^2} \\ \equiv&\rho_x^p + \Lambda_1. \end{aligned}$$

The residual of this regression can therefore be written as $\delta_x^p a_{j,l,t} - \Lambda_1 s_t$, with $\Lambda_1 > 0$. The sign of the coefficient β of regression (4.1) then depends on the sign of

$$\begin{aligned} &Cov(f_{t+1} + (1-\Lambda)(\varepsilon - E_{j,l.t}\varepsilon_t), \delta_x^p a_{j,l,t} - \Lambda_1 s_t) \\ =&(1-\Lambda)\delta_x^p Cov((\varepsilon - E_{j,l.t}\varepsilon_t), a_{j,l,t}) - (1-\Lambda)\Lambda_1 Cov((\varepsilon - E_{j,l.t}\varepsilon_t), s_t). \end{aligned}$$

The first covariance can be written as

$$\begin{aligned} &= Cov\left(\varepsilon_{j,l,t} - (\rho_x^p + \delta_x^p)\varepsilon_{j,l,t} - \rho_x^p e_t - \delta_x^p \eta_{j,l,t}, \varepsilon_t + \eta_{j,l,t}\right) \\ &= (1-\rho_x^p - \delta_x^p)\sigma_\varepsilon^2 - \rho_x^p \delta_\eta^2 \\ &= \frac{\hat\sigma_e^2(\hat\sigma_\eta^2 - \sigma_\eta^2)}{\hat\sigma_e^2 + \hat\sigma_\eta^2 + \frac{\hat\sigma_e^2\hat\sigma_\eta^2}{\hat\sigma_\varepsilon^2}}. \end{aligned}$$

This expression is zero for rational expectations ($\hat{\sigma}_\eta^2 = \sigma_\eta^2, \hat{\sigma}_e^2 = \sigma_e^2$) but negative for overconfidence in private signals ($\hat{\sigma}_\eta^2 < \sigma_\eta^2$).

The second covariance can be written as

$$
\begin{aligned}
&= Cov\left(\varepsilon_{j,l,t} - (\rho_x^p + \delta_x^p)\varepsilon_{j,l,t} - \rho_x^p e_t - \delta_x^p \eta_{j,l,t}, \varepsilon_t + e_t\right) \\
&= (1 - \rho_x^p - \delta_x^p)\sigma_\varepsilon^2 - \rho_x^p \sigma_e^2 \\
&= \frac{\hat{\sigma}_\eta^2(\hat{\sigma}_e^2 - \sigma_e^2)}{\hat{\sigma}_e^2 + \hat{\sigma}_\eta^2 + \frac{\hat{\sigma}_e^2\hat{\sigma}_\eta^2}{\hat{\sigma}_\varepsilon^2}}.
\end{aligned}
$$

This expression is zero for rational expectations ($\hat{\sigma}_\eta^2 = \sigma_\eta^2, \hat{\sigma}_e^2 = \sigma_e^2$) but positive for underconfidence in public signals ($\hat{\sigma}_e^2 > \sigma_e^2$). Together, this shows that $\beta < 0$.

The sign of δ regression (4.1) can similarly be determined. We first regress the signal on forecast revisions, yielding the regression coefficient

$$
\frac{Cov((\rho_x^p + \delta_x^p)\varepsilon_t + \rho_x^p e_t + \delta_x^p \eta_{j,l,t} - g_{t-1}, \varepsilon_t + e_t)}{Var((\rho_x^p + \delta_x^p)\varepsilon_t + \rho_x^p e_t + \delta_x^p \eta_{j,l,t} - g_{t-1})} \equiv \Lambda_2.
$$

The residual of this regression can therefore be written as $(1 - \Lambda_2\rho_x^p)s_t - \Lambda_2\delta_x^p a_{j,l,t}$, with $\Lambda_2 > 0$. The sign of the coefficient δ of regression (4.1) then depends on the sign of

$$
\begin{aligned}
&Cov(f_{t+1} + (1 - \Lambda)(\varepsilon - E_{j,l.t}\varepsilon_t), (1 - \Lambda_2\rho_x^p)s_t - \Lambda_2\delta_x^p a_{j,l,t}) \\
= &- (1 - \Lambda)\Lambda_2\delta_x^p Cov((\varepsilon - E_{j,l.t}\varepsilon_t), a_{j,l,t}) + (1 - \Lambda)(1 - \Lambda_2\rho_x^p)Cov((\varepsilon - E_{j,l.t}\varepsilon_t), s_t).
\end{aligned}
\tag{A-16}
$$

As shown above, this expression is zero for rational expectations. Furthermore, the entire first term is positive for overconfidence in private signals. The sign of the second term depends on the sign of $1 - \Lambda_2\rho_x^p$. Note that

$$
\begin{aligned}
\Lambda_2\rho_x^p &< 1 \\
((\rho_x^p)^2 + \delta_x^p\rho_x^p)\sigma_\varepsilon^2 + (\rho_x^p)^2\sigma_e^2 &< (\rho_x^p + \delta_x^p)^2\sigma_\varepsilon^2 + (\rho_x^p)^2\sigma_e^2 + (\delta_x^p)^2\sigma_\eta^2 + Var(g) \\
-\delta_x^p(\rho_x^p - \delta_x^p)\sigma_\varepsilon^2 &< (\delta_x^p)^2\sigma_\eta^2 + Var(g),
\end{aligned}
$$

which is correct, proving that $1 - \Lambda_2\rho_x^p > 0$, such that the second term of inequality (A-16) is positive for underconfidence in public signals and hence $\delta > 0$ in regression (4.1). ■

Proof of Proposition 2 Calculating the deviations of idiosyncratic from aggregate demand, using demand equation (A-6), yields

$$y_{j,l,t} - y_t = -\gamma \frac{n-1}{n} \left(p_{j,l,t} - p_t\right) + \tilde{y}_{l,t} - y_t.$$

Combining equation (A-10) for idiosyncratic prices and equation (A-11) for aggregate prices yields

$$p_{j,l,t} - p_t = \overline{k}_3 \eta_{j,l,t},$$

while $\tilde{y}_{l,t} - y_t$ can be derived with, imposing market clearing, the Euler equations (A-5) of customers of island l

$$\tilde{y}_{l,t} - y_t = \delta^h_{xp}(\tilde{a}_{l,t} - x_t) - \tilde{p}_{l,t} + p_t = \delta^h_{xp}\eta_{j,l,t} - (p_{j,l,t} - p_t)/n,$$

since $p_{j,l,t}$ corresponds to the price of all firms on island l. Combining all this with the definition of δ^h_{xp}, see (A-12), yields

$$\begin{aligned} y_{j,l,t} - y_t &= -\gamma \frac{n-1}{n} \overline{k}_3 \eta_{j,l,t} + \delta^h_x (1 + \overline{k}_3) \eta_{j,l,t} - (p_{j,l,t} - p_t)/n \\ &= \frac{1}{n} \left[\gamma(n-1)\Omega + n\delta^h_x (1 - \Omega) + \Omega \right] \eta_{j,l,t}. \end{aligned}$$

The cross-sectional output dispersion results directly from this equation and is given in the proposition. Its derivative with respect to Ω results as

$$\frac{\partial \sigma^2_{\Delta y^j}}{\partial \Omega} = \gamma(n-1) + 1 - n\delta^h_x,$$

which is positive, since $n(\gamma - \delta^h_x) > \gamma - 1$. Furthermore,

$$\frac{\partial \Omega}{\partial \rho^p_x} = 0 \qquad \frac{\partial \Omega}{\partial \delta^p_x} > 0.$$

The latter is true if

$$\gamma - 1 > \delta^h_x \frac{1 - \Omega}{\Omega}, \tag{A-17}$$

which was shown in the Proof for proposition 1, completing the proof. ■

Proof of Proposition 3 Aggregating individual Euler equations (A-3) over all individuals, using (A-11), (A-12), and (A-14), gives

$$\begin{aligned} y_t =& E_{l,t}x_t + E_{l,t}p_t - p_t - r_t \\ =& x_{t-1} + \rho_x^h(1+\overline{k}_3)s_t + \left[\delta_x^h + \overline{k}_3(\delta_x^h - 1)\right]\varepsilon_t - \frac{\alpha}{\alpha+\psi(1-\alpha)}\nu_t \\ =& x_{t-1} + \underbrace{\rho_x^h(1+\overline{k}_3)}_{>0} e_t + \underbrace{\left[\delta_x^h + \rho_x^h - \overline{k}_3(1-\delta_x^h-\rho_x^h)\right]}_{>0}\varepsilon_t \underbrace{-\frac{\alpha}{\alpha+\psi(1-\alpha)}}_{<0}\nu_t, \end{aligned} \tag{A-18}$$

where $1-\delta_x^h-\rho_x^h > 0$ because of (A-2). Note that, if households have full information ($n \to \infty$), we get $\rho_x^h \to 0$ and $\delta_x^h \to 1$. Defining $\Omega \equiv -\overline{k}_3$, we can write

$$y_t = x_{t-1} + \rho_x^h(1-\Omega)e_t + \left[(\delta_x^h + \rho_x^h)(1-\Omega) + \Omega\right]\varepsilon_t - \frac{\alpha}{\alpha+\psi(1-\alpha)}\nu_t.$$

The signs indicated above result from $0 < \Omega = -\overline{k}_3 < 1$ (derived in Appendix B). This formula also determines the variance of aggregate output innovations. ■