Firm expectations about production and prices: Facts, determinants, and effects*

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Abstract

This chapter revisits recent work on firm expectations about firm-specific developments regarding future production and prices. We focus on existing studies based on survey data that provide a direct measure of expectations. First, we provide an overview of existing studies and revisit robust empirical observations for the ifo survey of German firms. This allows us to establish five facts regarding firm expectations and expectation errors. Second, we use the same data set to revisit key results regarding the formation of firm expectations and their effects. Firm expectations react strongly to firm-specific developments, aggregate variables are less important. There is also strong evidence that firm decisions are driven by firm expectations, both in terms of first and second moments.

Keywords: Firm expectation, survey data, expectation error, expectation formation, firm decisions, production, prices
JEL-Codes: D84, E71, D21

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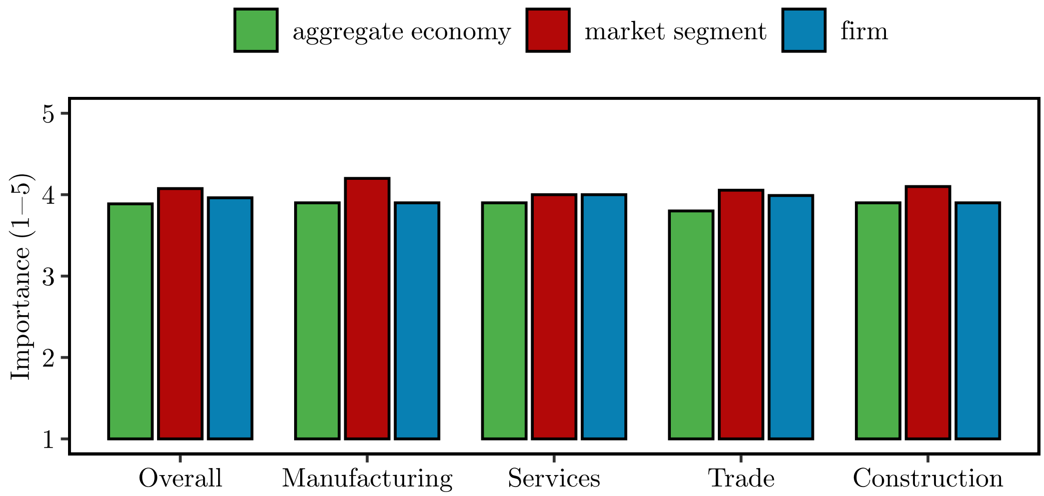
1 Introduction

According to theory, firm expectations take center stage in firm decisions. At a very basic level, almost all firm decisions take place under uncertainty, are inherently dynamic, and are taken in a forward looking manner—at least in modern macroeconomic models. Examples include decisions on such fundamental matters as production, investment, hiring, as well as prices (e.g., Lucas 1973; Kydland and Prescott 1982; Mortensen and Pissarides 2009; Woodford 2003). Of course, this fact has not been lost on empirical researchers. Yet, influenced by the rational expectations revolution of the 1970s, empirical work has often shied away from assessing expectations data directly. Instead, it typically confronted predictions of economic theory based on assumptions regarding the expectation formation process with the data—formally or informally (e.g., Smets and Wouters 2007; Blanchard et al. 2013; Angeletos et al. 2020). Only recently has the literature begun to assess expectations directly on the basis of survey data. This development is facilitated by more and richer surveys becoming available. At the same time, the increased interest has triggered the design of new surveys and survey strategies, some of which we review below.

Before going there, we stress that this chapter is concerned with firm expectations about firm-specific developments and, here in particular, with expectations about firms' future production and prices. This sets it apart from work which focuses on firm expectations about the aggregate economy, say, inflation or GDP. In that area, influential work has also turned to survey data in order to confront theory with direct evidence (Coibion et al. 2018; Tanaka et al. 2020; Coibion et al. 2020a). It is surveyed systematically elsewhere in this handbook. In our view, the case for focusing on firm-specific developments is straightforward when it comes to expectations. For—as soon as we depart from the representative-agent paradigm—firm-specific developments are no longer necessarily the same across firms. As a result, expectations about them are potentially heterogeneous, too. It remains an open question to what extent firm expectations and, in turn, firm behavior is driven by firm-specific developments compared to aggregate developments. We will encounter this question at various instances below.

We motivate our study of firm expectations of firm-specific developments with recent survey evidence. To this end, we included a special question in the October 2020 wave of the ifo survey of German firms (discussed in detail below). Specifically, in response to the question what matters for their production and pricing decisions, some 1,500 German firms answered that firm-specific developments are at least as important as developments of the aggregate economy (see also Freuding et al. 2021). Sectoral developments are also considered important. Figure 1.1 illustrates this result graphically. It also shows that responses do not differ much across sectors. Against this background, it seems worthwhile to carefully revisit

Figure 1.1: What matters for firm decisions



Notes: responses to special question in the October 2020 wave of the ifo Survey of German firms. Question read: "How important are the following domains for your production and/or pricing decisions?", with answer scale 1 to 5. Categories: recent developments in the aggregate economy, the firm's market segment, and within the firm. Based on 1666 responses.

existing evidence regarding firm expectations about firm-specific developments in particular.

We do so in what follows. Because the existing literature on the issue is still in a somewhat early stage, we additionally complement our discussion of existing work with new evidence based on the ifo survey of German firms. The ifo survey is one of the oldest and largest survey of firms currently available. It is based on a firm survey which has been conducted since 1949 and whose design has since then been adopted by other surveys as well (Becker and Wohlrabe 2008). We provide details about this survey and others in Section 2 and use the ifo survey to establish a number of stylized facts in Section 3. Importantly, in doing so we build heavily on existing work and merely revisit facts that have been noted by several authors and for various surveys. Our aim is to provide a common and coherent perspective as we establish these facts robustly on the basis of a common data set.

We are able to establish five stylized facts. First, unconditionally firms' expectation errors are unbiased, that is, mostly not significantly different from zero. This results emerges robustly also for various subsets of firms. Second, survey responses are informative in that they outperform static and adaptive expectations in terms of forecasting firm-specific developments. Third, larger and older firms tend to do even better in terms of forecasting. Fourth, the dispersion and volatility of expectations and expectation errors is countercyclical, in line with the notion that uncertainty increases during recessions. Fifth, we find that firms make predictable forecast errors. It turns out that past information about firms' own variables, in particular, predict expectation errors. This stands in contrast to lags of macroeconomic indicators, which do not contain much information that helps to predict expectation errors.

In the second part of the chapter, we seek to shed light on both the formation of expectations (Section 4) and the effects of expectations on firm decisions (Section 5). We again stick to our strategy and revisit the results of earlier work on the basis of the ifo survey. As we do so, we focus on the main results in the literature but also offer some additional findings which are of particular interest in the context of our survey.

A first important result concerning the information formation process is that firm-specific variables account for almost all the variation in firm expectations. Aggregate indicators hardly play any role. We establish this result as we estimate a simple probit model that features firms' output and price expectations as the dependent variable. Taken at face value, this finding may seem to conflict with the evidence shown in Figure 1.1. Yet, in light of our econometric analysis, one may conclude that once one controls for firm-specific developments, the aggregate economy ceases to be of importance for firm expectations. A second important result concerns the responsiveness of firm expectations to news. Here we revisit some recent results of the literature which has mostly been concerned with professional forecasters (Coibion and Gorodnichenko 2015; Bordalo et al. 2020). As a noteworthy exception, Born et al. (2021) rely on the ifo survey to study the response of forecast errors to forecast revisions (news) and we revisit their main finding: firms tend to overreact to firm-specific news, but underreact to news about the aggregate economy.

Eventually, we care about firm expectations to the extent that they matter for actual outcomes—an issue we revisit last following earlier work by Enders et al. (2021). Here two results are key. First, firm expectations about future production significantly impact current production and pricing decisions. Second, this also holds for expectations which turn out to be incorrect from an ex-post point of view. This suggests that expectations not only operate as a transmission channel of news but also as a genuine source of shocks. There is also evidence that expectations are key for firms' investment decisions and, lastly, we revisit evidence for the effect of uncertainty on firm decisions put forward by Bachmann et al. (2019).

Before getting started, we stress two caveats. First, our analysis is limited to empirical work on firm expectations that uses survey data. Rather than relying on surveys, one may measure expectations or, likewise, confidence through proxies extracted from observable behavior (e.g., Malmendier and Tate 2005a,b; Hirshleifer et al. 2012). However, a distinct and attractive feature of survey data is that it provides a direct measure of expectations. Hence, our focus. Second, we note that firms and firm expectations serve as the primitives of our analysis. This implies that we abstract from within-firm dynamics and management practices and personality traits of CEOs, although we acknowledge that this, too, is a fascinating area of research (e.g., Bloom and Reenen 2007; Kaplan et al. 2012).

2 Surveying firm expectations

This section starts with an overview over existing surveys that ask firms about their expectations regarding their own variables. It then introduces the ifo Business Expectations Panel (BEP), a widely employed firm survey, which we will use throughout the chapter to replicate the most importing findings in the literature and to generate some new results in a single data set. We end the section by discussing approaches to construct firm expectation errors.

2.1 Background

There are a few surveys that started collecting data in the 1950s–70s. They were set up to provide early and additional information about the current state of the economy, given that the official statistics were incomplete and available only with a considerable lag (INSEE 2007; Nerb and Sauer 2020). In these early surveys, firms could typically provide qualitative answers only, that is, firms could state whether they expect, e.g., prices or production to increase, stay the same, or decrease. Similarly, the business situation can be expected to become better, stay the same, or deteriorate and firms can evaluate inventories as being too low, adequate, or too high, etc. Corresponding to the questions on expectations, realizations were typically surveyed in the same way, such that firms could, e.g., report if production had risen, fallen, or stayed the same. Nerb and Sauer (2020) document that the decision for this format was taken in order to increase the return rate and because of the inclusion of question regarding subjective evaluations of, for instance, the current business situation and adequate inventories. Qualitative answers allow firms to weigh different aspects depending on current circumstances in a flexible manner. By aggregating answers regarding current and expected firm-specific variables, the surveys turned out to have a high predictive value for sector-wide or even national economic developments (see Abberger and Wohlrabe 2006; Henzel and Rast 2013, for the ifo survey).

Over time, the large potential for empirical economic analysis of business surveys became more apparent (see, e.g., Nerb 1987; Seiler and Wohlrabe 2013, for the ifo survey).[1] Naturally, the missing quantitative values reduced the scope for potential analyses, such that several surveys have added quantitative questions, in case they were not included before.[2] In this case, respondents are asked to provide a number or to choose from predefined ranges for, e.g., expectations of sales growth. Providing predefined ranges to elicit point estimates involves potential pitfalls, as the provision of ranges may have a bearing on the elicited answers

[1]Unfortunately, this is not necessarily true for the micro data, which, after aggregation, was often not kept for later use.

[2]For instance, the ifo survey and the CBI Industrial Trends Survey introduced quantitative questions in 2005 and 2008, respectively.

(Schwarz et al. 1985). Even more recently, business-cycle research highlighted the role of uncertainty for economic developments (Bloom 2009), such that several surveys now ask for probability distributions in addition to point forecasts. That is, survey participants are asked to assign probabilities to either several bins that cover predefined ranges for the future realizations of the variable of interest (e.g., *Business Inflation Expectations Survey*) or to freely selected bins (*Survey of Business Uncertainty*). To calculate the resulting uncertainty, assumptions have to be made about the probability-mass distribution inside the bins (Krüger and Pavlova 2020). Furthermore, it should be taken into account whether survey participants are likely to form their probability distributions with formal models or not, as this can have an impact on, e.g., reported uncertainty (Glas and Hartmann 2021).

Table 2.1 provides an overview over existing firm surveys that are available for economic research.[3] We order them by their inception date, although the quality and scope of the initial waves may be much reduced (if they are available at all) relative to subsequent waves. We also provide details on the covered country, included variables, the frequency, and whether the survey asks for qualitative or quantitative expectations, or additionally elicits probability distributions.

2.2 Example: The ifo Business Expectations Panel

In the following sections, we will provide an overview over the existing literature on firm expectations regarding their own variables and replicate the most importing findings in a single data set. Because of its large coverage in terms of firms, firm-specific variables, and its time dimension, we chose the Business Expectations Panel of the LMU-ifo Economics and Business Data Center (BEP or ifo survey from now on). It is based on the ifo Business Climate Survey, one of the oldest firm surveys around. Specifically, the BEP combines survey data from the Business Climate Survey and balance sheet data from the Amadeus and Hoppenstedt databases (EBDC-BEP 2019). Because the wording of the questions and possible answers differs somewhat across sectors, we focus on the manufacturing sector for our analysis, the sector with the largest number of firms and the longest time dimension. Since the BEP combines annual balance-sheet data with the monthly survey data, we use the most recent balance-sheet data at a given point in time to avoid using information that is not yet available when firms report expectations. The BEP starts in January 1980, with the last observation available to us being in June 2019. The unit of observation in the manufacturing survey of the BEP is a product.[4]

[3] We only consider those surveys that include questions about firms' own variables and whose firm-level answers are generally provided to researchers.

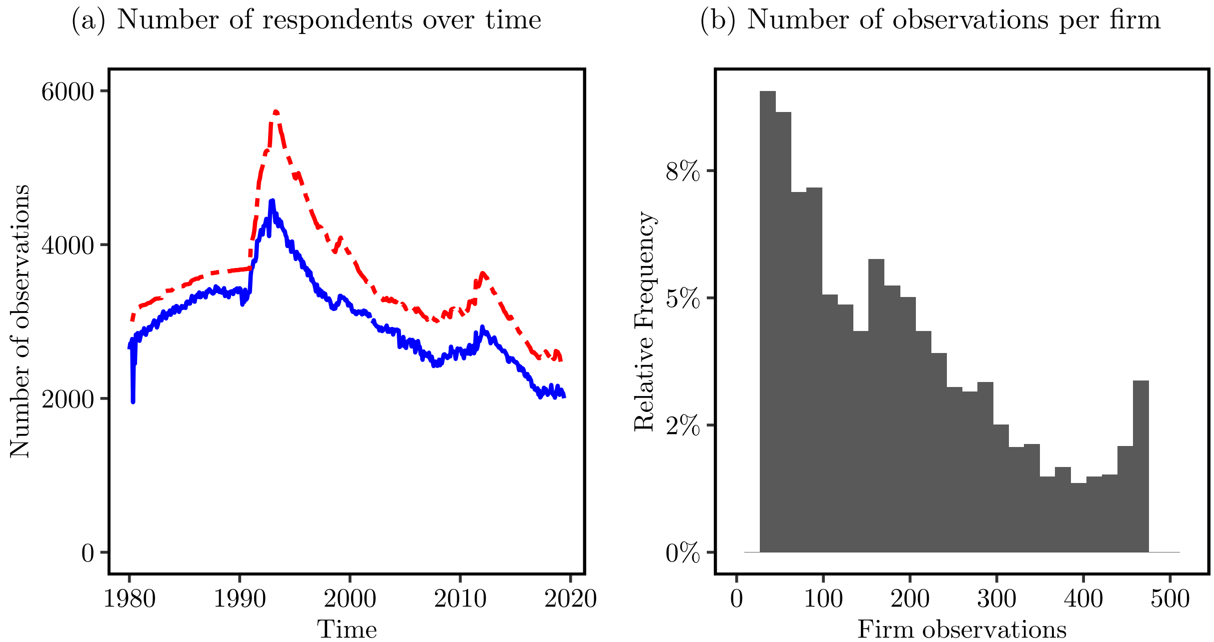
[4] Hence, some firms respond to several questionnaires each month. In our sample, however, this is the case for less than 10% of firms. In our analysis below, we refer to the individual observation as a "firm" in order to ease the exposition.

Table 2.1: Surveys on firm expectations about their own variables

Name	Country	Expectation Variables	From	Freq.	Format	Maintained by
ifo Business Climate Survey	Germany	output, prices, employment, business situation	1949	m	ql, qt 2005+	ifo
Tankan Survey	Japan	sales, exports, exchange rates for exports, profits, investment	1951	q	ql, qt	METI
CBI Industrial Trends Survey	UK	wages, employment, unit cost, prices, outputs, new orders, capacity utilisiation	1958	q	ql, qt 2008+	Confederation of British Industry
Monthly outlook survey in industry	France	sales, prices, employment, cash flow situation, delivery times, inventories, payment deadlines	1962	m	ql, qt	INSEE
Survey of Industrial Trends	Australia	output, employment, prices, stocks, overtime	1966	m	ql	Australian Chamber of Commerce
Business Outlook Survey	US	general business conditions, shipments, prices, employment	1968	m	ql	Fed Philadelphia
Survey of Production Forecast	Japan	production	1971	m	qt	METI
Survey on Industrial and Service Firms	Italy	investments, employment, turnover, capacity utilization, finances	1972	a	qt	Banca d'Italia
ifo Investment Survey	Germany	investment	1973	s	qt	ifo
Basic Survey on Overseas Business Activities	Japan	sales	1995	a	qt	METI
Basic Survey of Japanese Business Structure and Activities	Japan	employment, business activities, R&D	1997	a	qt	METI
Survey on Inflation and Growth Expectations	Italy	inflation, economic situation, own prices, demand, investment and employment	1999	q	ql, qt	Banca d'Italia
Monitoraggio Economia e Territorio	Italy	sales, prices	2008	a	ql, qt	MET Research Center
Management and Organizational Practices Survey	US	management practices, production, performance indicators	2010	5a	ql	U.S. Census Bureau
Business Inflation Expectations Survey	US	unit costs	2011	m	qt, d	Fed Atlanta
Survey of Business Uncertainty	US	employment, sales, investment	2014	m	d	Fed Atlanta
Bundesbank Online Panel - Firms	Germany	employment, sales, inputs, finances, inventories	2020	i	ql	Bundesbank

Notes: surveys for firms own variables. Frequencies (Freq.) are monthly (m), quarterly (q), semi-annually (s), annually (a), and irregular (i). The Management and Organizational Practices Survey is conducted every five years (5a). Formats are qualitative (ql), quantitative (qt), and distributional (d), or combinations thereof. Data for research are not necessarily available since the starting date, e.g., the ifo Business Climate Survey was launched in 1949, with data since 1980 being available for research. METI is the Ministry of Economy, Trade and Industry in Japan.

Figure 2.1: BEP observations across both panel dimensions



Notes: observations of the ifo Business Expectations Panel (BEP) across time and firms. Left panel: number of actual (solid blue) and target observations (dashed red). The number of actual observations is the number of firms that respond in a given month. Target observations equal the number of firms that are in the survey during a given month. Due to the harmonization of survey periods introduced by the European Union, no survey was conducted in December 2001. We set the value to missing in this plot.

In the following, we produce a set of descriptive statistics for the BEP sample. Figure 2.1 displays the number of respondents over time (left panel). The blue line represents the actual number of responses per month, while the red dashed line shows the target observations, that is, the number of firms that are in the survey during a given month. Hence, the difference between the two lines is due to firms that temporarily do not return the questionnaire. Target and actual observations are usually relatively closely aligned, that is, the response rate is unusually high. Furthermore, the median firm responds in 92% of the months they are in the panel. The ifo institute enlarged the panel significantly at various points in time. Clearly visible are enlargements at the beginning of the 1980s and after the German reunification in 1990. The right panel of Figure 2.1 shows the number of responses per firm. While there are many firms that participate only a few times in the survey, there is still a relatively high number of firms that answered the survey more than 100 and up to 500 times.

Table 2.2: Definitions of qualitative expectation errors

Source	Agg. realization	Expectation error	Production		Prices	
	$x^i_{t,h} = f(\varsigma^i_{t,h})$	$e^i_{t,h} = f(x^i_{t,h}, x^i_{t,h\|t})$	μ	σ	μ	σ
Nerlove (1983)	$\text{sgn}(\varsigma^i_{t,h})$	$\text{sgn}(x^i_{t,h} - x^i_{t,h\|t})$	-0.05	0.65	-0.04	0.65
Bachmann et al. (2013)	$\varsigma^i_{t,h}$	0 if $\text{sgn}(x^i_{t,h}) = \text{sgn}(x^i_{t,h\|t})$ $\frac{1}{h}(x^i_{t,h} - x^i_{t,h\|t})$ else	-0.03	0.35	-0.02	0.24
Massenot and Pettinicchi (2018)	$\frac{1}{h}\varsigma^i_{t,h}$	$x^i_{t,h} - x^i_{t,h\|t}$	-0.04	0.53	-0.09	0.41

Notes: schemes for the computation of expectation errors from qualitative surveys like the BEP. Realizations for one month are denoted by $x^i_{t,1} \in \{-1, 0, +1\}$, expectations for h months ahead are denoted by $x^i_{t,h|t} \in \{-1, 0, +1\}$. To account for the difference in reference periods and the qualitative nature, schemes first aggregate monthly realizations over h months and then compare aggregate realizations to expectations. Aggregate realizations $x^i_{t,h}$ are based on the sum of monthly changes over h months $\varsigma^i_{t,h} = \sum_{j=1}^{h} x^i_{t+j,1}$. Nerlove (1983) and Kawasaki and Zimmermann (1986) set $x^i_{t,h}$ to missing when there are opposite signs in the sum. sgn denotes the sign function and returns 1,0, or -1. The last four columns report the mean (μ) and standard deviation (σ) for expectation errors in the BEP.

2.3 Expectation errors

In the following sections, we review literature that employs statistics on expectation errors and also ourselves make extensive use of expectation errors in our empirical analyses. Therefore, we now describe alternative ways to compute expectations errors in the BEP and provide descriptive statistics.

In Table 2.2, we collect information on how previous studies have calculated qualitative expectation errors in the ifo survey. The survey asks for the expected change of a variable (production, prices, business situation, etc.) in the next h months, compared to now. We therefore define as $x^i_{t,h|t}$ the expectation of firm i in month t regarding the change of the firm-specific variable x^i from month t to the period from month $t+1$ until $t+h$. It can take the values -1 (expected decrease), 0 (no expected change), or 1 (expected increase). The realized change—as reported by the firm—of variable x^i from month $t-1$ to month t is denoted by $x^i_{t,1}$. Aggregating this change over the h months in question yields $\varsigma^i_{t,h} = \sum_{j=1}^{h} x^i_{t+j,1}$. Different studies have used different ways how to define a forecast error $e^i_{t,h}$ based on transformations $x^i_{t,h} = f(\varsigma^i_{t,h})$ of $\varsigma^i_{t,h}$, where $x^i_{i,h}$ is the respective definition of the aggregate realization over the h months. Nerlove (1983) compares the (aggregate) sign of $\varsigma^i_{t,h}$ with that of the expectation $x^i_{t,h|t}$.[5] In their definition, the firm has made no expectation error if the two signs align. If not, they assign a forecast error that can be positive or negative (-1 or 1). Bachmann et al. (2013) proceed in a slightly different way. They too assign no expectation error if the sign of the aggregate realization $\varsigma^i_{t,h}$ equals that of the expectation $x^i_{t,h|t}$. In case of differing signs, however, they quantify the expectation error by assigning the monthly average of the

[5]Kawasaki and Zimmermann (1986) employ the same definition.

difference between the aggregate realization $x^i_{t,h}$ and the expectation $x^i_{t,h|t}$. It can therefore take values between $\pm(h+1)/h$. Massenot and Pettinicchi (2018) define the expectation error as the difference between the monthly average of the aggregate realization $\varsigma^i_{t,h}/h$ and the expectation $x^i_{t,h|t}$, such that the error may take values between -2 and 2. Note that with this definition, the error is zero only if the realization of the change takes the expected value in each of the h months. In what follows, we base our calculations on the definition of Bachmann et al. (2013).

As can be seen in the last four columns of Table 2.2, the mean and the standard deviation of the expectation errors for production and prices are fairly comparable across definitions. Similarly, the empirical correlation between the values of the aggregate realization are equal to or above 98%, while the correlation between the resulting expectation errors are 84% at a minimum. The means of the expectation errors for production and prices, independent of the definition, are close to zero. We systematically explore this and related facts in the next section.

3 Stylized facts

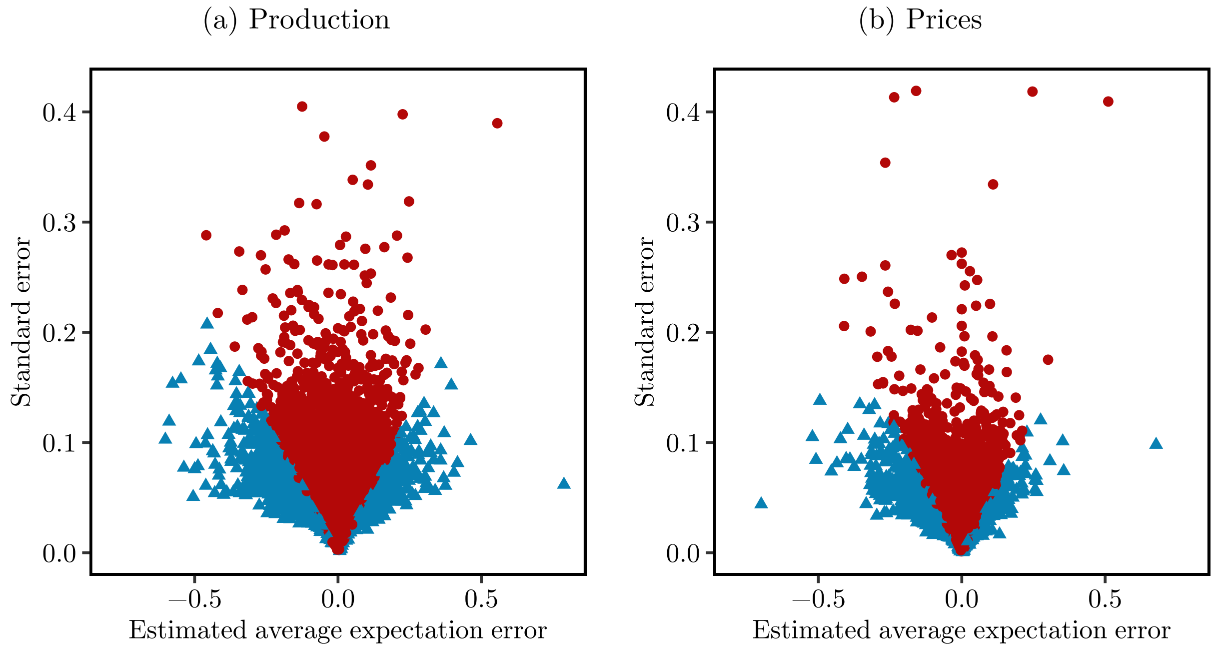
There are a number of facts about firm expectations that have been discussed in the existing literature. In this section, we collect them in order to establish a set of stylized facts about firms' expectations and expectation errors about their own production and prices. We focus on five facts that we represent using one consistent data set, i.e., the ifo Business Expectations Panel (BEP) introduced in the previous section.

Fact 1 - Unbiasedness. *Unconditionally, firms' expectation errors are small and almost always insignificant.*

The question whether firm expectations are unbiased has received considerable attention in the literature. Based on ifo survey data, Bachmann and Elstner (2015) find that more than two-thirds of firms in their sample of German manufacturing firms do not systematically over- or underpredict their production growth one-quarter ahead. Using the same data, Massenot and Pettinicchi (2018) also find that, on average, firms do not make unconditional expectations errors. Altig et al. (2020b) and Barrero (2021) again find little evidence of an unconditional bias in expected firm-level sales growth rates, using data from the Survey of Business Uncertainty. Chen et al. (2020) document for a panel dataset of Japanese firms small forecast errors on average. Andrade et al. (2021) show for French firms that there is a strong positive relationship between firms' anticipated and ex-post price changes.

Turning to our own evidence, Figure 3.1 shows the estimated firm-level average expectation

Figure 3.1: Average firm-level expectation errors



Notes: firm-level average expectation errors. Horizontal axis: mean expectation error; vertical axis: Newey-West standard error. Color and shape of each point indicate if the average is significantly different from 0 at the five percent level (blue triangles) or not (red circles). Plot shows only firms with standard errors in between the 0.5 and 99.5 quantiles. For each firm, we use the longest sequence of non-missing errors to estimate the mean forecast error.

errors for production (left panel) and prices (right panel). Specifically, each marker in the figure represents the regression of a firm's expectation error on a constant, with the estimate of the constant measured on the horizontal axis and the estimate of its Newey-West standard error on the vertical axis. We use blue triangles to indicate that the estimate of the constant is statistically significant. Red circles mark the average expectation errors which are statistically insignificant. The estimated average forecast errors are evenly distributed around zero, with a share of insignificant estimated average expectations errors for production and prices of 78 and 80 percent, respectively. Moreover, the significant errors are more or less evenly distributed around zero. Together, this seems to suggest that, overall, firms' expectations are unbiased.

Table 3.1 reports estimates for various subgroups of firms. We first distinguish between firms of different size, measured in terms of number of employees. This is followed by slicing according to the distribution of employees, sales, and assets. Lastly, we look separately at firms in the western and (former-socialist) eastern part of Germany. Overall, we always find small estimated average expectation errors.[6]

[6] In Table A.2 in the appendix, we additionally distinguish firms according to their manufacturing subsector and find similar results.

Table 3.1: Average expectation errors: sub-groups of firms

		Production			Prices		
Grouped by	Group	N	Median	% insig.	N	Median	% insig.
Overall		5122	-0.0183	77.59	5074	-0.0097	79.96
Number of Employees	Fewer than 50	801	-0.0128	76.40	779	-0.0056	81.51
	50-199	881	-0.0143	76.73	865	-0.0078	81.73
	200-499	410	-0.0097	81.22	410	-0.0048	84.88
	500-999	131	-0.0324	78.63	129	-0.0013	77.52
	More than 1000	95	-0.0041	77.89	93	-0.0051	75.27
Employees (Quartile)	First Quartile	566	-0.0115	77.56	548	-0.0048	81.02
	Second Quartile	588	-0.0172	76.19	578	-0.0085	82.87
	Third Quartile	582	-0.0154	77.15	569	-0.0076	81.20
	Fourth Quartile	582	-0.0097	79.38	581	-0.0039	81.76
Sales (Quartile)	First Quartile	566	-0.0191	74.56	546	-0.0046	82.97
	Second Quartile	576	-0.0147	77.08	557	-0.0071	81.33
	Third Quartile	562	-0.0169	80.25	564	-0.0058	82.27
	Fourth Quartile	571	-0.0159	78.98	574	-0.0063	79.27
Total Assets (Quartile)	First Quartile	672	-0.0159	75.60	652	-0.0070	82.82
	Second Quartile	673	-0.0113	77.86	655	-0.0065	81.07
	Third Quartile	666	-0.0193	78.53	668	-0.0079	83.98
	Fourth Quartile	676	-0.0153	79.29	677	-0.0056	79.03
Location	Eastern Germany	527	-0.0215	79.70	497	-0.0040	89.13
	Western Germany	1050	-0.0123	79.81	1052	-0.0041	82.60

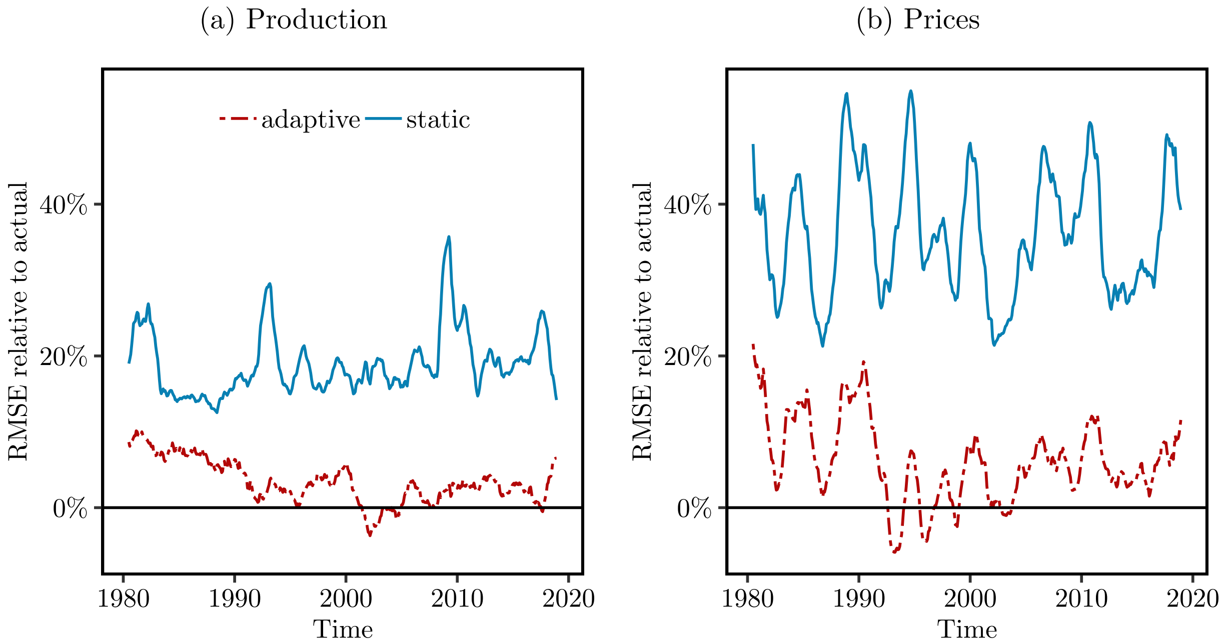
Notes: firm-level average expectation errors; table entries provide number of firms in each subgroup (N), median of their average expectation errors (Median) and share of insignificant average expectation errors (% insig.). When grouping by location we only consider firms that joined the ifo survey after the German reunification.

Fact 2 - Information content. *Firm expectations outperform static and adaptive expectations.*

A natural question to ask is whether firm expectations outperform other benchmark forecast models. Kawasaki and Zimmermann (1986) show that ifo survey-based price expectations beat adaptive expectations, i.e., an approach in which firms use the most recent realization as the forecast. Smith and McAleer (1995) also document the high information content of qualitative survey expectations about firms' output, prices, employment, stocks, and overtime relative to static, i.e., random-walk, expectations, and relative to a number of univariate/multivariate time-series models using the *Confederation of Australian Industries (CAI)/Westpac survey of industrial trends.* Chen et al. (2020) show for Japanese firms that a large majority of firms do not just use their realized sales to forecast next periods sales.

To asses the information content of firm expectations ourselves, we compare firm expec-

Figure 3.2: Performance of firm expectations relative to benchmark models



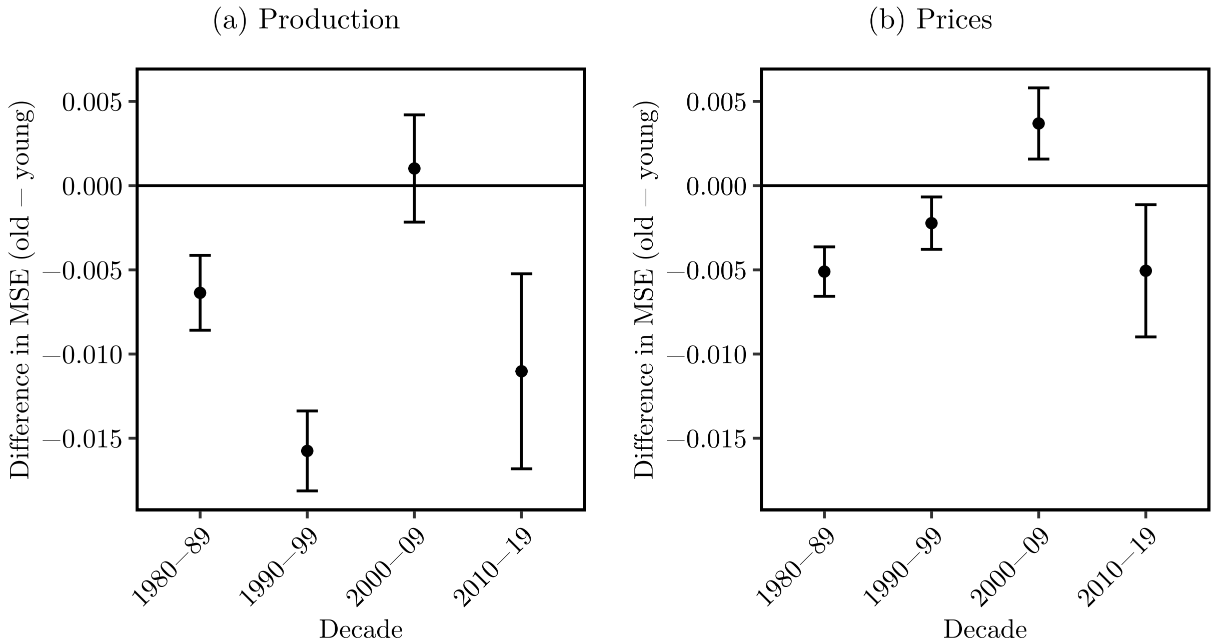
Notes: relative RMSE for production (left panel) and price (right panel) expectations, both for adaptive (red dashed line) and static (blue solid line) expectations. Values above (below) zero mean that the respective benchmark model does not (does) beat the actual survey-based expectations. All series are plotted as moving averages over the previous and the next six months. All values expressed in percent.

tations errors to two of the benchmark models mentioned in the above literature: adaptive and static expectations. Again, under adaptive expectations, firms use the most recent realization as the forecast, while under static (or random-walk) expectations, firms always expect no change. For every month and benchmark model, we compute the root mean squared expectation error (RMSE) across firms and set it in proportion to the RMSE of the actual, i.e., survey-based, firm expectations.

Figure 3.2 shows the relative RMSE for production (left panel) and price (right panel) expectations, both for adaptive (red dashed line) and static (blue solid line) expectations. Values above (below) zero mean that the respective benchmark model does not (does) beat the actual survey-based expectations. While adaptive expectations do better than static expectations, for both the RMSE is larger than the RMSE for actual survey-based expectations, i.e., the relative RMSEs are positive, over most of the sample period.

We have established in Facts 1 and 2 that firm expectations about their own production and prices are quite accurate. Our next fact shows that, however, there is some heterogeneity in forecasting performance across firms.

Figure 3.3: Performance of firm expectations relative to benchmark models



Notes: difference of mean squared expectation errors (MSE) between young and old firms. A firm is considered young when it was founded at most 10 years before the time of being surveyed. For each decade, we split the sample into observations from young and old firms and then compute the difference of the MSEs and its standard error. The point estimate of the difference in MSEs is shown as a dot and the 95 percent confidence intervals as whiskers.

Fact 3 - Experience. *Larger and older firms are better at forecasting their own variables.*

A number of papers have documented that experience matters for the quality of firm expectations about their own variables. Massenot and Pettinicchi (2018) show, based on the ifo survey, that older and larger firms make smaller expectation errors. Bachmann and Elstner (2015) for German firms and Morikawa (2019) for Japanese firms document that larger firms make smaller expectation errors, presumably because they are able to spend more resources on forecasting than smaller firms. Chen et al. (2020) find in a panel of Japanese firms that these increase forecast precision with age. This result is in line with the findings in Triebs and Tumlinson (2013), who provide evidence that firms located in eastern Germany did, relative to their western peers, worse in predicting business conditions early after German reunification, but learned over time and improved their forecasting performance.

For our own analysis, we define a firm to be young when it was founded at most 10 years before the time of being surveyed. In Figure 3.3, we then split, for each decade, the sample into observations from young and old firms and compute the difference of the mean squared expectation errors (MSE) and its standard error, both for production expectations (left panel) and price expectations (right panel). Here, the point estimate of the difference in MSEs is shown as a dot and the 95 percent confidence intervals as whiskers.

Table 3.2: Mean and median squared expectation errors: sub-groups of firms

		Production			Prices		
Grouped by	Group	N	Mean	Median	N	Mean	Median
Overall		5122	0.1278	0.1170	5074	0.0594	0.0372
Number of Employees	Fewer than 50	801	0.1319	0.1197	779	0.0617	0.0363
	50-199	881	0.1299	0.1217	865	0.0615	0.0386
	200-499	410	0.1233	0.1184	410	0.0556	0.0358
	500-999	131	0.1209	0.1052	129	0.0500	0.0372
	More than 1000	95	0.1088	0.0988	93	0.0615	0.0422
Employees (Quartile)	First Quartile	566	0.1312	0.1165	548	0.0622	0.0370
	Second Quartile	588	0.1323	0.1262	578	0.0579	0.0359
	Third Quartile	582	0.1302	0.1216	569	0.0645	0.0406
	Fourth Quartile	582	0.1187	0.1078	581	0.0549	0.0363
Sales (Quartile)	First Quartile	566	0.1348	0.1220	546	0.0587	0.0360
	Second Quartile	576	0.1326	0.1248	557	0.0655	0.0391
	Third Quartile	562	0.1240	0.1147	564	0.0558	0.0375
	Fourth Quartile	571	0.1199	0.1074	574	0.0615	0.0355
Total Assets (Quartile)	First Quartile	672	0.1310	0.1197	652	0.0611	0.0375
	Second Quartile	673	0.1326	0.1209	655	0.0624	0.0375
	Third Quartile	666	0.1284	0.1187	668	0.0589	0.0370
	Fourth Quartile	676	0.1188	0.1082	677	0.0586	0.0361

Notes: firm-level mean and median squared expectation errors; table entries provide summary statistics for the estimates for different subgroups of firms. N denotes the number of firms in each group.

Overall, our findings using the ifo-BEP dataset corroborate the existing literature. Point estimates are mostly below zero, which means that forecast quality as measured by the MSE of production and price expectations is usually higher for older firms compared to younger, less experienced firms. One exception seems to be the Global Financial Crisis around 2008/09. A finding that might deserve some future research.

Looking at the effect of firm size on firms' forecast quality, Table 3.2 reports firm-level mean and median squared expectation errors for different firm sizes. We measure size in terms of the absolute number of employees, as well as where the firm is located in the employee distribution, sales, and total assets. The consistent picture that emerges is that larger firms have smaller MSEs, again in line with the literature.

Our first three facts have focused on the first moment of firm expectations and expectation errors. While the first moment has historically been the focus of most of the literature, recently a number of papers have looked at the dispersion and volatility of firm expectations and expectation errors, e.g., to proxy for firm-level uncertainty (Bachmann et al. 2013). A robust fact has emerged from these studies:

Fact 4 - Countercyclical second moments. *The dispersion and volatility of expectations and expectation errors are countercyclical.*

This fact has been observed using a variety of survey-based measures, which we collect in Table 3.3. A number of these measures go back to an influential paper by Bachmann et al. (2013) and have been used extensively since then (e.g., Enders et al. 2019; Morikawa 2016, 2019). Forecast dispersion $fdisp_t$ is defined as the dispersion of the *level* of expectations across firms, while forecast error dispersion $fedisp_t$ and the mean absolute forecast error mae_t are based on expectation errors. As an alternative measure for the time-series variability in expectation errors, Bachmann et al. (2019) propose to compute the average of firm-specific rolling window standard deviations of forecast errors $stdfe_t$. Panel (a) of Table 3.3 provides an overview over these measures.

Figure A.1 in the appendix plots the various measures computed on the ifo BEP dataset. For readability and comparability, the time series are seasonally adjusted and standardized. Shaded areas mark recessions as dated by the German Council of Economic Experts. Two clear visual patterns emerge. First, all measures increase in recessions and fall in booms, i.e., they show a clear countercyclicality. Second, all errors-based measures are highly correlated, with only the non-error $fdisp_t$-measure showing some divergence.

Panel (b) of Table 3.3 corroborates the visual findings. The first subpanel shows correlation coefficients between the measures, for production on the left and prices on the right-hand side. The error-based measures correlate with coefficients that are always above 0.7 and often higher, while the dispersion of expectation levels is correlated less with the error measures—although still above 0.4.

The countercyclicality of the dispersion and volatility measures can be read off the second subpanel where we report correlation coefficients vis-à-vis common monthly real activity measures: the growth rates of industrial production, hours worked, and employment. Across the board, the signs of the correlation coefficients are negative and mostly significantly so.

Finally, we regress the measures on recession dummies—as dated by the German Council of Economic Experts—and again find a clear increase in dispersion and volatility in economic downturns. Especially so in the Great Recession of 2008/09, where our measures increase by between 8.3 and 25 percent.

Table 3.3: Dispersion and volatility measures

(a) Definitions

Domain	Measure	Definition
firm & time	Absolute forecast error	$\text{absfe}_{i,t} = abs(e^i_{t,h})$
	Rolling window standard deviation	$\text{stdef}_{i,t} = \sqrt{\frac{1}{3}\sum_{k\in\{-3,0,3\}}(e^i_{t+k,h} - \overline{e}^i_{t,h})^2}$
time	Forecast dispersion	$\text{fdisp}_t = \sqrt{\text{frac}^+_t + \text{frac}^-_t - (\text{frac}^+_t - \text{frac}^-_t)^2}$
	Forecast error dispersion	$\text{fedisp}_t = \sqrt{Var(e_{t,h,i\|t})}$
	Mean absolute forecast error	$\text{mae}_t = \frac{1}{n_t}\sum_i \text{absfe}_{i,t}$
	Avg. rolling window standard deviation	$\text{stdfe}_t = \frac{1}{n_t}\sum_i \text{stdef}_{i,t}$

(b) Business cycle properties

	Production				Prices			
Variable	fdisp	fedisp	mae	stdfe	fdisp	fedisp	mae	stdfe
Correlation within measures								
fdisp	1.00	0.69***	0.56***	0.58***	1.00	0.40***	0.60***	0.46***
fedisp		1.00	0.93***	0.73***		1.00	0.94***	0.88***
mae			1.00	0.82***			1.00	0.87***
stdfe				1.00				1.00
Correlation within aggregates								
Δ log Production	−0.12***	−0.04	−0.12***	−0.15***	0.06	−0.07	−0.07	−0.03
Δ log Hours	−0.02	−0.08*	−0.18***	−0.14***	−0.01	−0.03	−0.04	−0.03
Δ log Employment	−0.20***	−0.30***	−0.44***	−0.44***	−0.04	−0.21***	−0.22***	−0.20***
Recession Dummies								
Non-recession Mean	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Recession	0.019***	0.016**	0.043***	0.029***	0.024*	0.061***	0.114***	0.094***
Recession 2008/09	0.083***	0.084***	0.128***	0.140***	0.088***	0.154***	0.246***	0.243***

Notes: in the upper panel, $e^i_{t,h}$ is the forecast error of Bachmann et al. (2013) defined in Table 2.2 and $\overline{e}^i_{t,h}$ is the average forecast error over the current value, its third lag, and its third lead. $\text{frac}^+_t = \sum_i \mathbf{1}(x^i_{t,h|t} = +1)/n_t$ and $\text{frac}^-_t = \sum_i \mathbf{1}(x^i_{t,h|t} = -1)/n_t$ are the shares of expected increases and decreases at time t. Lower panel shows Spearman rank correlation among dispersion measures first, Spearman rank correlation with aggregate business cycle measures second , and regression results using recession dummies third. After standardizing each time series by its non-recession mean, we report coefficients for a general recession dummy and a dummy for the 2008/09 recession. One, two, and three stars (*) correspond to significance on the 10, 5, and 1 percent significance levels.

Fact 5 - Predictability. *Firms make predictable expectation errors.*

The rational expectations hypothesis suggests that expectation errors should not be predictable using variables from an agent's information set that are available at the time of forecasting. However, a number of papers have shown that firms make predictable expectations errors, also when it comes to their own variables. Massenot and Pettinicchi (2018), using the ifo survey for the German manufacturing sector, find that firms extrapolate from past experience too much and end up making predictable expectation errors. Similarly, Barrero (2021), using the *Survey of Business Uncertainty (SBU)* (Altig et al. 2020b), documents that firm managers over-extrapolate, their forecasts are too optimistic after positive shocks and too pessimistic after negative shocks. Boneva et al. (2020), show that UK firms tend to have rational expectations of quantity variables, such as their own employment and new orders, but deviate from rational expectations when it comes to prices, wages, and unit costs.

We re-investigate this question on the dataset used throughout this chapter. The rational expectations hypothesis can be framed in a regression setup as

$$e^i_{t,h} = x^i_t \beta + v^i_t \ , \tag{1}$$

where the forecast error $e^i_{t,h}$ is the dependent variable and x^i_t contains candidate predictors. Under rational expectations, the β-coefficients should not be different from zero.

Table 3.4 lists the variables contained in x_{it} and the resulting regression coefficients. While macroeconomic variables turn out to be mostly insignificant, many firm-specific variables help in predicting expectation errors in production and prices. Overall, about 17 percent of the variance in expectations errors can be explained in our regressions, refuting the thesis that expectation errors are entirely unpredictable.

Table 3.4: Predictability of expectation errors

Variable	Timing	Production estimate	Production t-value	Production p-value	Prices estimate	Prices t-value	Prices p-value
Constant		0.022	1.22	0.22	0.037***	3.14	0.00
IP growth	real-time	0.424*	1.93	0.05	0.165	1.58	0.11
Unemployment rate	t-1	0.002	1.16	0.24	−0.001	-0.86	0.39
PPI growth	t-2	0.005	0.23	0.82	0.036***	3.61	0.00
CPI growth	t-2	−0.016	-1.07	0.29	−0.007	-1.00	0.32
Expectation about own prices	t	0.012***	3.97	0.00	−0.258***	-81.95	0.00
	t-1	−0.001	-0.39	0.70	0.055***	21.63	0.00
	t-2	−0.010***	-3.87	0.00	0.010***	4.23	0.00
	t-3	−0.010***	-3.30	0.00	0.001	0.26	0.79
Expectation about own production	t	−0.301***	-94.38	0.00	0.002	1.22	0.22
	t-1	0.041***	15.97	0.00	−0.001	-0.78	0.43
	t-2	0.007**	2.52	0.01	−0.001	-0.89	0.37
	t-3	−0.004	-1.26	0.21	0.000	-0.19	0.85
Reported business situation	t	0.007**	2.48	0.01	0.004**	2.21	0.03
	t-1	−0.004*	-1.93	0.05	0.000	-0.17	0.87
	t-2	0.004*	1.77	0.08	0.002	1.21	0.23
	t-3	0.019***	5.95	0.00	0.001	0.74	0.46
Reported backlog of orders	t	−0.020***	-7.01	0.00	−0.011***	-6.23	0.00
	t-1	0.001	0.49	0.63	0.000	0.25	0.80
	t-2	0.004**	1.97	0.05	0.000	0.30	0.76
	t-3	−0.007***	-2.85	0.00	−0.001	-0.73	0.47
most recent reported change in production	t	0.038***	12.22	0.00	0.003	1.58	0.12
	t-1	0.025***	8.98	0.00	0.003*	1.75	0.08
	t-2	0.021***	7.83	0.00	0.004**	2.43	0.02
	t-3	0.023***	7.63	0.00	0.001	0.52	0.60
most recent reported change in prices	t	−0.003	-1.11	0.27	0.060***	16.43	0.00
	t-1	−0.003	-1.35	0.18	0.038***	13.73	0.00
	t-2	0.000	-0.08	0.93	0.033***	12.65	0.00
	t-3	−0.003	-0.91	0.36	0.041***	12.20	0.00
Reported change in demand	t	0.048***	16.18	0.00	0.010***	5.45	0.00
	t-1	0.023***	9.39	0.00	0.004**	2.45	0.01
	t-2	0.014***	6.09	0.00	0.002	1.24	0.22
	t-3	0.006**	2.14	0.03	0.001	0.89	0.38
R^2		0.172			0.170		

Notes: predictive regressions for forecast errors for prices and production. For IP growth we use real-time data for the seasonally and calendar adjusted industrial production and compute monthly growth rates that are also reported in the press releases of DESTATIS. We assume that firms update their information set on the day after the release. Since 2005 firms may complete the survey online. Only for these firms the day of completion is known, which is the sample used for this exercise. One, two, and three stars (*) correspond to significance on the 10, 5, and 1 percent significance levels.

4 Expectation formation

In this section, we turn to the expectation formation process of firms with a focus on recent survey evidence. This seems warranted, not least in light of the facts discussed in the previous section. For instance, Fact 5 shows that firms make predictable forecast errors, in conflict with models that assume full information rational expectations (FIRE).

At this point, there is no consensus about an alternative to FIRE. At a very basic level, there is a long tradition of noisy information models. Here, information processing is rational but information incomplete. In the classic contributions by Lucas (1973), Woodford (2002), or Sims (2003), economic actors—and notably firms—process information and update expectations in a rational way. This goes some way to account for the evidence presented above. Likewise, recent contributions emphasize that a (rational) focus on certain sectors/media distorts the information formation process (Chahrour et al. 2020; Kohlhas and Walther 2021). Other models, by contrast, allow for behavioral aspects in the expectation formation process (for instance, Shiller 2017; Bordalo et al. 2019). Under certain conditions behavioral models and incomplete information models give rise to equivalent equilibrium effects (Angeletos and Huo 2021).

In what follows, we seek to inform this discussion by first surveying the evidence on the determinants of expectations. In the second part of this section, we zoom in on the expectation formation process as we discuss recent evidence regarding the response of firms to news, both at the firm level and the aggregate level. As in the previous section, we revisit key findings on the basis of the data set that we have introduced above.

4.1 Determinants of expectations

In what follows, we seek to provide a simple empirical characterization of the determinants of firm expectations. We first focus on the forecast (first moment). Afterwards, we also consider briefly the determinants of firm uncertainty (second moment).

4.1.1 Firm expectations

In terms of expectations, we focus, as before, on firm expectations about production and prices. To set the stage, we perform an analysis based on the ifo survey which builds on earlier work by Enders et al. (2021). Because firm answers in the ifo survey are qualitative only, we estimate an ordered probit model.[7] Specifically, following the notation introduced

[7]Bloom et al. (2020) analyze business expectations that are surveyed as part of the Census Bureau's *Management and Organizational Practices Survey*. For selected years, it elicits point estimates for current-year outcomes and five-point probability distributions for the next. Bloom et al. (2020) find that 85% of

Table 4.1: Determinants of production and price expectations

	Production		Prices	
Variables	Observations	Pseudo R^2	Observations	Pseudo R^2
Survey	181329	0.2523	181276	0.32
Fundamentals	271498	0.00012	277890	0.00008
Macro	337028	0.005	345828	0.007
Survey + Fundamentals	180686	0.252	180633	0.32
Survey + Macro	172428	0.252	172374	0.324
Fundamentals + Macro	254624	0.006	260988	0.007
Survey + Fundamentals + Macro	172327	0.252	171731	0.324

Notes: summary statistics for ordered probit models using expectations about a firm's own production and price as dependent variables. Explanatory variables are combinations of variables from the survey (business situation, orders etc. with up to three lags and interaction terms), firm fundamentals from their balance sheet (debt share, financing coefficient) and macro variables (monthly growth rates of PPI, CPI, and IP and the unemployment rate, each with their publication lag). See Table Table A.4 in the appendix for more details on the variables.

in Section 2.3 and using $j = \{-1, 0, 1\}$ to index the the reported expectation $x^i_{t,h|t}$ about a firm's own price or production, we estimate

$$\begin{aligned} Pr(x^i_{t,h|t} = j) &= Pr(a_{j-1} < x^{i*}_{t,h|t} \leq a_j) \\ &= \Phi(\alpha_j - X'_{it}\beta) - \Phi(\alpha_{j-1} - X'_{it}\beta) \ , \end{aligned} \tag{2}$$

where X_{it} contains the variables which may influence firm expectations, $x^{i*}_{t,h|t}$ is the latent variable, and α_{j-1} and α_j are threshold parameters. Since the set of potential variables is large, we consider different groups of variables and summarize their impact by focusing on the model fit, namely on the pseudo R^2 as defined by McFadden (1974).[8] In terms of explanatory variables X_{it}, we distinguish three sets of variables. The first set contains variables that describe a firm's own condition as reported in the survey, such as, for instance, the current state of business, orders, and capacity utilization. In addition, it includes lags of expected production and prices. It also includes interaction terms that we include on the basis of a log-likelihood test. The second set contains firm fundamentals as reported in the most recent balance sheet data such as, for instance, the debt share. Here our selection of variables follows Enders et al. (2021). Lastly, a third set of variables contains macro variables as observable by firms in real time, notably the unemployment rate in the previous month as well as industrial production. Table A.4 in the appendix provides a full list of variables for each of the three sets.

respondents provide logically sensible responses to our five-point distribution questions, suggesting that most managers can form and express detailed subjective probability distributions.

[8]Formally, we consider: $R^2_{mf} = 1 - \ln L_M / \ln L_0$, where R^2_{mf} is the pseudo R^2, L_M is the likelihood of the model and L_0 is the likelihood of a constant-only model.

We estimate model (2) using all combinations of the three sets of variables and show results in Table 4.1. In the upper part of the table, we look at the different sets in isolation, in the lower part of the table we look at their joint effects. Results are clear cut. The survey responses account for a fairly large share of the variation in firm expectations, with a pseudo R^2 of 25 and 32 percent for production and prices, respectively. If benchmarked against these numbers, the contributions of balance-sheet fundamentals and macro variables appear negligible. To be fair, we should also stress that balance sheet data ("fundamentals") is available only at annual frequency and may therefore not matter much for changes in the short-term outlook of firms over the next three month. Alternatively to using the R^2 to judge the contribution of each group of variables, we additionally checked by how much the share of correctly predicted expectations increases when we include each group one-by-one. When doing so, we again find that the first set of variables helps to increase the performance of the model most strongly.

The result that firm-specific information as reflected in the survey data is a key determinant of firm expectations echos early work based on the ifo survey in the 1950s. Pioneering work, by Anderson et al. (1956a), Anderson et al. (1956b) and somewhat later by Anderson and Strigel (1960), showed that unexpected changes in demand altered firms' production and pricing plans. Also in line with the more recent evidence, this early work established that production plans are more responsive to surprise demand changes than price plans. For the latter costs changes are important. More recently, Massenot and Pettinicchi (2018) document for the ifo survey that business expectations are responsive to past business. Similarly, Boneva et al. (2020) find for UK firms that past orders are important when it comes to accounting for price and wage expectations. Lastly, as they consider Italian firms during the Corona crisis, Balduzzi et al. (2020a) find that financially constrained Italian firms expect to charge higher prices relative to their unconstrained counterparts.

That said, there is also evidence that firm expectations are responsive to macroeconomic developments. Enders et al. (2019), in particular, show that firm expectations respond to monetary policy shocks. Eminidou and Zachariadis (2019) document effects of monetary policy shocks on firms' expectations for a panel of euro area countries. For this purpose they rely on the *Joint Harmonised EU Programme of Business and Consumer Surveys* (BCS). Strasser (2013) uses the ifo survey and investigates to what extent firms' export expectations respond to exchange-rate movements.

Several studies use survey data to explore the impact of the Covid-19 pandemic on firm expectations. For this purpose, Meyer et al. (2021) use the *Business Inflation Expectations Survey* run by the Federal Reserve Bank of Atlanta. Balleer et al. (2020) and the Bundesbank (2021) look at German firms, using ifo data and a newly established survey of German firms, respectively. Likewise, there is also evidence that lockdown measures matter for firm expectations. Buchheim et al. (2020), using ifo data for Germany, show that the announcement of nation-wide school closures on March 13 in response to the pandemic was followed by the largest change in business perceptions by far.

Finally, there is evidence for the role of firms' own sectors or regions as drivers of their expectations. Andrade et al. (2021) stress the importance of industry-level shocks, as distinct from aggregate and firm-specific shocks, for both firm actions and expectations. Their analysis is based on a survey of French firms. Dovern et al. (2020) show for the ifo survey that firms seem to extrapolate from local economic conditions to aggregate growth expectations. In line with theories of rational inattention, expectations are less dispersed for larger firms and those firms whose business depends more on aggregate conditions.

4.1.2 Firm uncertainty

So far, we have focused on the determinants of the first moment of firm expectations, that is, the mean forecast. In addition, there is recent work that has looked into the determinants of the second moment of firm expectations, that is, into firm-level uncertainty. Altig et al. (2020b) survey business executives about their own-firm outcomes with a particular focus on business uncertainty. They find, among other things, that subjective uncertainty is higher when firms' grow faster. Furthermore, Dovern et al. (2020) document a negative relationship between firms' uncertainty about their own business outlook and expectations about GDP growth. There is also survey evidence that specific events raise uncertainty at the firm level, notably in the context of Brexit and Covid-19 (Bloom et al. 2019; Altig et al. 2020a).

4.2 Over- and underreaction to news

In an influential study, Coibion and Gorodnichenko (2015) use a simple diagnostic in order to shed light on the expectation formation process. Specifically, using the Survey of Professional Forecasters (SPF), they regress the upcoming forecast error on the current forecast revision. It turns out that forecast revisions predict forecast errors in the same direction. An upward revision, say, is followed by underprediction of the same variable—forecasters seem to underreact to news, as reflected in the revision. When taken at face value, this finding is in line with rational expectations models featuring noisy information. Yet it has given rise to an intensive debate about the information formation process and motivated new explorations, both empirically and in terms of theory.

In their original contribution, Coibion and Gorodnichenko (2015) study the response of the average forecast error in the SPF to the average forecast revision in the SPF. Against this background, Bordalo et al. (2020) stress that results change—from underreaction to overreaction—once one studies the relationship between forecast errors and forecast revisions *at the level of individual forecasters.* Other work, some of which we discuss below, establishes that whether there is over- or underreaction depends on the nature of the news which forecasters receive. To date, however, most of the evidence is based on the SPF. In what follows, we thus seek to broaden the discussion by turning to firms' forecasts and their expectation formation process.

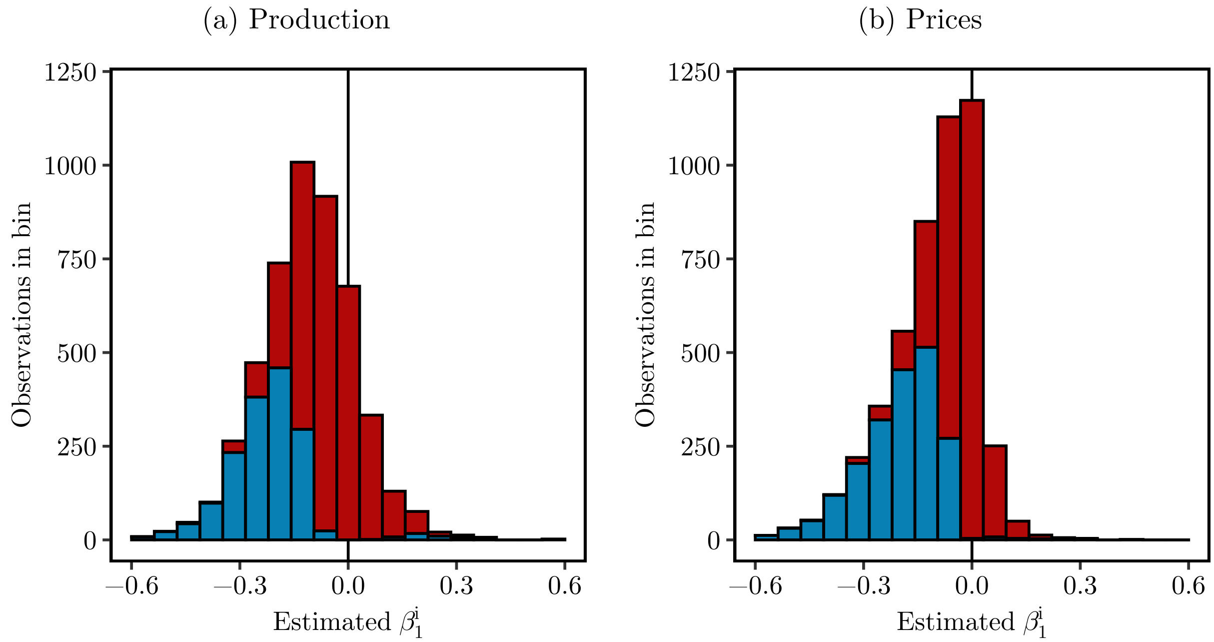
For this purpose we revisit recent evidence established by Born et al. (2021). It is based on the ifo Business Survey Industry. We replicate some of their results for our sample. As in Born et al. (2021), our point of departure is the specification of Bordalo et al. (2020):

$$x_{t+h} - x^i_{t+h|t} = \beta^i_0 + \beta^i_1 FR^i_{t,h} + v^i_{t+h} \ . \tag{3}$$

Here x_t is a (common) variable of interest, index i denotes a specific forecaster/firm, $x_{t+h} - x^i_{t+h|t}$ is the forecast error, $FR^i_{t,h} = (x^i_{t+h|t} - x^i_{t+h|t-1})$ is the forecast revision, and v^i_{t+h} is a zero-mean error. A positive β^i_1-coefficient implies underreaction to the news that is reflected in the forecast revision. To see why, consider the case of a positive forecast revision, that is, the expectation of a variable is revised upward: $FR^i_{t+h} > 0$. For $\beta^i_1 > 0$, the forecast error responds positively to such a revision, that is, $x_{t+h} > x^i_{t+h|t}$ and one may conclude that the initial revision was too small (underreaction). Conversely, a negative β^i_1-coefficient points to an overreaction.

In the context of the ifo survey data there are a number of noteworthy conceptual issues and limitations. First, in contrast to the professional forecasters in the SPF, ifo firms do not forecast the same variable x_{t+h} but each firm forecasts its own target variable x^i_{t+h}, such as its production and prices. Second, the forecasting horizon changes every month as firms predict the change in prices and production over the next three months, so revisions take the form $FR^i_{t,h} = (x^i_{t+h|t} - x^i_{t-1+h|t-1})$. 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). Third, we stress that because of the nature of the survey our measure of the forecast error is based on qualitative responses (see Table 2.2 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 $t-1$. Lastly, given the limited range of responses in the survey, firms which respond either $+1$ (or -1) may not make a positive (negative) forecast error. To account for this complication, we estimate Equation (4) on a

Figure 4.1: Response of forecast error to forecast revision



Notes: histograms of estimated β_1^i-coefficients in firm-level regressions for production and price expectations, see equation (4); sample restricted to firms that initially report no expected change. Coefficients outside of the 1 and 99 percent quantiles (pooled over all subfigures) are dropped. Red is for estimates that are insignificant at the five percent level, blue is for significant estimates.

restricted sample in which we include only those firms which report no expected change in period t: these firms may have revised their expectations upwards or downwards between periods $t-1$ and t and may exhibit a positive or negative expectation error in period $t+1$.[9]

The following regression model sums up our changes relative to the original formulation (3) by Bordalo et al. (2020):

$$e_{t,h}^i = \beta_0^i + \beta_1^i FR_{t,h}^i + v_{t+h}^i \ , \tag{4}$$

where $e_{t,h}^i$ is the forecast error defined in Table 2.2 above.

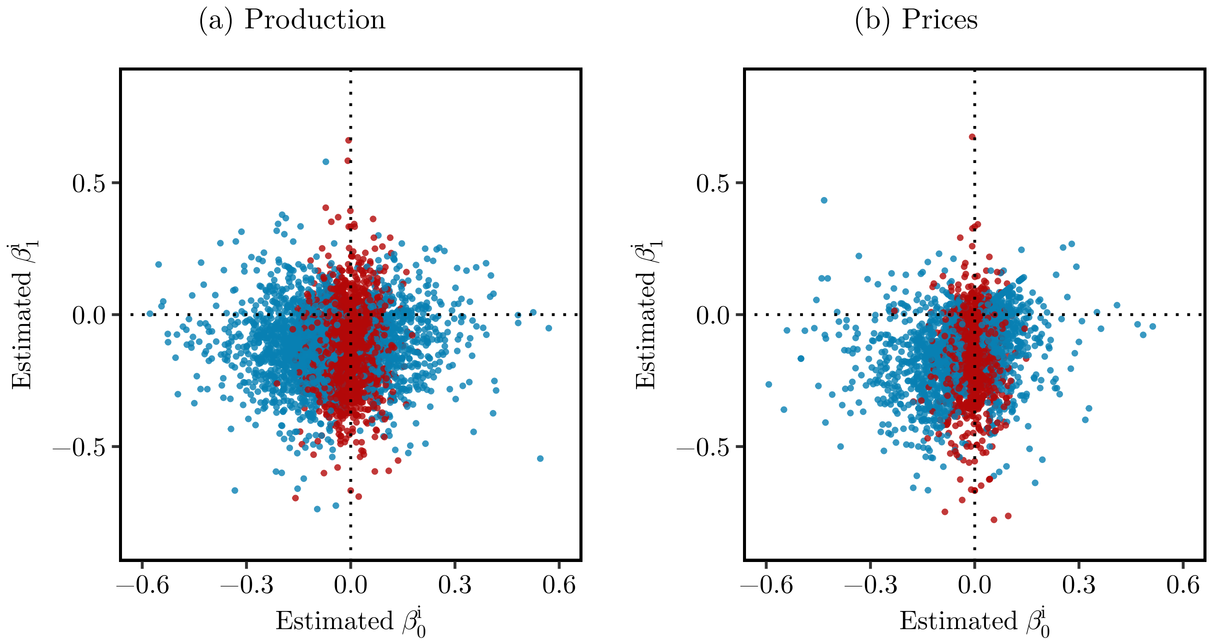
We estimate this equation separately for each firm, for both price and production expectations. At this point we stress a potential benefit of using the ifo survey to address the issue at hand: it features a large number of firms, each of which is in the survey for a fairly long period, see Figure 2.1 above.[10]

Figure 4.1 shows the results for production expectations in the left panel and for price

[9]Still, as Born et al. (2021) show, results do not differ much if the equation is estimated on an unrestricted sample.

[10]For a firm to be considered 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.

Figure 4.2: Point estimates for constant and slope



Notes: estimation of Equation (4) on firm-level observations. Horizontal axis: estimates of β_0^i; vertical axis: estimates of slope coefficient β_1^i. Colors indicate if the constant is significantly different from 0 (blue) or not (red). Plot shows values within the 99.95 quantiles.

expectations in the right panel. In each instance, we show the distribution of the estimates for β_1^i across firms. The mass of firms is characterized by negative betas. We highlight in blue the point estimates which are statistically significant. This is the case for 32 and 41 percent of the firms, respectively. The overall result is in line with Born et al. (2021) and clear cut: firms tend to overreact to news. This is particularly noteworthy because in our analysis news and forecast errors pertain to firms' expectations about their own production and prices rather than the aggregate economy and rational expectations models with noisy information have a hard time rationalizing overreactions. A number of behavioral models have been put forward to account for overreaction in other contexts. Azeredo da Silveira and Woodford (2019), for instance, show that if memory is noisy, current realizations are extrapolated into the future disproportionally. Bordalo et al. (2020), instead, rely on diagnostic expectations to rationalize overreaction. Here, forecasters overweigh the probability of certain states in the light of recent signals.

Figure 4.2 displays additional estimation results that we obtain as we estimate Equation (4). Specifically, in the figure each dot represents the estimate for one firm, with the estimate of the constant β_0^i measured on the horizontal axis, and the estimate of the slope coefficient β_1^i measured along the vertical axis. The estimates of the slope coefficient tend to be negative, as established above. We use the color blue to indicate that the estimate of the constant is

Table 4.2: Underreaction to firm-specific news

		Production			Prices		
Grouped by	Group	N	Mean	Median	N	Mean	Median
Overall		4851	-0.1121	-0.1089	4851	-0.1070	-0.0820
Number of Employees	Fewer than 50	236	-0.1050	-0.1041	236	-0.1029	-0.0777
	50-199	156	-0.0844	-0.0660	156	-0.1108	-0.0827
	200-499	78	-0.0918	-0.0825	78	-0.1059	-0.0739
	500-999	22	-0.1586	-0.1721	22	-0.0826	-0.0693
	More than 1000	5	-0.1433	-0.1833	5	-0.0751	-0.0736
Employees (Quartile)	First Quartile	124	-0.0964	-0.0971	124	-0.1047	-0.0878
	Second Quartile	124	-0.1158	-0.1160	124	-0.1025	-0.0647
	Third Quartile	124	-0.0816	-0.0555	124	-0.1139	-0.0907
	Fourth Quartile	125	-0.1029	-0.1042	125	-0.0978	-0.0667
Sales (Quartile)	First Quartile	107	-0.0989	-0.1029	107	-0.1234	-0.0912
	Second Quartile	112	-0.1016	-0.0846	112	-0.0983	-0.0642
	Third Quartile	109	-0.0999	-0.0903	109	-0.1080	-0.0940
	Fourth Quartile	110	-0.1060	-0.1047	110	-0.1087	-0.0659
Total Assets (Quartile)	First Quartile	130	-0.0962	-0.0955	130	-0.1107	-0.0840
	Second Quartile	131	-0.0979	-0.0987	131	-0.1131	-0.0829
	Third Quartile	130	-0.0954	-0.0870	130	-0.0932	-0.0675
	Fourth Quartile	131	-0.1146	-0.1071	131	-0.1129	-0.0730
Location	Eastern Germany	2203	-0.1121	-0.1099	2203	-0.1060	-0.0806
	Western Germany	1198	-0.1055	-0.1025	1198	-0.1081	-0.0824

Notes: estimation of Equation (4) on firm-level observations. Entries provide summary statistics for the slope estimates based for different subgroups of firms. N denotes the number of firms in each group. When grouping by location we only consider firms that joined the ifo survey after the German reunification

statistically significant. We find that estimates for the intercept are generally well-behaved in the sense that they are scattered evenly around zero. Moreover, we note that there is no systematic pattern which would suggest a specific relationship between the estimate for the slope and the intercept.[11]

Table 4.2 reports estimates for various subgroups of firms. In the top panel we distinguish between firms of different size, measured in terms of number of employees. In the following panels, we again distinguish in terms of size measured by the distribution of employees, sales, and assets. In the the last panel, we distinguish between firms in the western and eastern parts of Germany. In all instances we find that the mean and the median of the estimated slope coefficient is negative and of a similar magnitude. The same holds if we consider distinct sectors, as Table A.5 in the appendix illustrates. We conclude that overreaction of firm expectations to news is a robust and pervasive feature of the data, not driven by a particular group of firms.

[11]The correlation between intercept and slope is 0.03 for production and 0.25 for prices.

Born et al. (2021) also estimate Equation (4) on pooled data while allowing for firm and time fixed effects. For this specification the estimate of β_1^i is significantly negative as well. Born et al. (2021) also investigate the response to "macro news" as distinct from firm-specific news (as reflected in the revision of a firms' own production expectation). They define macro news as the surprise component in the aggregate ifo index. It is computed by subtracting from the monthly release of the ifo index the forecast sampled by Bloomberg in the run up to the release. It turns out that including macro news in equation (4) does not change the response to forecast revisions in a meaningful way. While the coefficient on firms' forecast revision remains significantly negative, the coefficient on macro news is significantly positive—suggesting that firms *underreact* to macro news while simultaneously overreacting to firm-specific news.

The finding that there is simultaneously overreaction to forecast revisions and underreaction to macro news is reminiscent but distinct from the observation for the SPF that there is underreaction to news in the aggregate but overreaction at the level of individual forecasters (Bordalo et al. 2020). Kohlhas and Walther (2021), in turn, also consider the SPF and find that there is underreaction of forecast errors to output growth and underreaction to average forecast revisions, both at the level of individual forecasters.[12] In order to account for this finding, they develop a model where forecasters chose to pay asymmetric attention to certain signals (more to procyclical variables than to countercyclical ones) and, given this choice, update rationally.

Broer and Kohlhas (2020) stress that what they call "overrevision" of individual forecasts may mask both over- and underreactions to salient public signals, as found in the SPF. They extend a model of noisy rational expectations by allowing forecasters to be overconfident about the precision of their own information. In this account, absolute overconfidence (perceiving own information as more informative than it actually is) makes forecaster overreact to private information while relative overconfidence (perceiving own information as more informative than information of others) makes forecasters underreact to public signals which, in turn, are understood to reflect the response of others to their own forecasts. A version of this mechanism has the potential to rationalize our empirical finding of a simultaneous overreaction of firms to firm-specific news and the underreaction to macro news (Born et al. 2021).

[12]Using the ifo survey, Massenot and Pettinicchi (2018) regress, in turn, expectations and forecast errors on past changes of the business situation (rather than on forecast revisions). They find that the regression coefficient is positive and significant and robustly so across a number of specifications. They refer to this result as "over-extrapolation".

5 Firm expectations and firm decisions

As stressed in the introduction, we care about firm expectations because they matter for firm decisions—at least according to theory. For the longest time, the link from economic expectations to actions has been taken for granted. At an empirical level, predictions from models featuring a key role of expectations, for instance the New Keynesian Phillips curve, have been shown to describe the data reasonably well (e.g., Galí and Gertler 1999). Yet, in this case, as in most macroeconometric studies, the structural model is tested jointly with specific assumptions regarding the expectation formation process. There are also numerous purely empirical studies which suggest that, in general, expectations of economic agents are key for the business cycle (see, for instance, Beaudry and Portier 2006; Born et al. 2019; Enders et al. 2020). Instead, *direct* evidence regarding the specific impact of firm expectations on economic decisions is much more scarce. As stressed by Enders et al. (2021), two major difficulties are to blame. First, expectations are not directly observable unless one resorts to specific surveys. Second, expectations are responsive to changes in the economic environment; identifying the causal effect of expectations on economic decisions is therefore challenging.

A few recent studies exploit direct survey evidence to tackle this challenge. In what follows, we seek to provide an overview of recent contributions, first focusing on the effect of firm expectations regarding the developments of firm-specific factors, such as production ("first moment"), on firm decisions. Afterwards, we look into the effect of firm-level uncertainty regarding firm-specific variables on firm decisions ("the second moment", or uncertainty). As before, we replicate key findings of the literature on the basis of our data set but also discuss additional results in passing.

5.1 The effect of firm expectations

A number of studies have established that firms adjust their behavior in response to expected changes in the macroeconomic environment, notably those captured by GDP and inflation movements (Tanaka et al. 2020; Coibion et al. 2020a). The focus of our chapter, however, is on firm expectations regarding their own production and prices, as in the analysis of Enders et al. (2021). In what follows, we thus replicate and extend some key results of their analysis. To set the stage, we outline the econometric strategy of Enders et al. (2021) but keep the exposition short since the original study provides all the details.

Based on the ifo survey, we compare the behavior of firms that report that they expect an increase or a decrease of production to firms that expect production to remain unchanged. A key challenge is to identify variation in expectations that is orthogonal to current fundamentals. For only to the extent that firms are comparable in terms of fundamentals, we may capture the effect of expectations as such. Because the responses regarding expected production are qualitative, we may think of expectations as a kind of "treatment": firms may either expect an increase, no change, or a decrease. Of course, expectations are not literally assigned in a random way. By comparing firms that display the same fundamentals but different expectations, we can nevertheless consider the assignment as random. Formally, we rely on propensity score matching as originally put forward by Rosenbaum and Rubin (1983), see also Caliendo and Kopeinig (2008) and Imbens and Rubin (2015). The idea is to mimic randomized control trials where treatment is actually assigned in a random fashion and hence orthogonal to observable characteristics.

Importantly, while the analysis seeks to control for current fundamentals, it does not require expectations to be unrelated to *future* fundamentals. In fact, future fundamentals may impact current decisions via expectations. In this case expectations operate as a transmission channel for news, rather than as pure expectation shocks or "noise" (Lorenzoni 2009). Enders et al. (2021) account for this distinction by conditioning results on whether firm expectations turn out to be correct from an ex-post point of view or not.

In terms of identification, we rely on two features of the ifo survey. First, the survey features a fairly large set of control variables, including balance-sheet data and received orders of firms. They allow us to approximate the set of fundamentals which matter for firm decisions. Specifically, as discussed above, Enders et al. (2021) estimate a version of the probit model (2) and summarize results by the propensity score, that is, the probability of receiving a treatment given the realization of the fundamentals. We have already estimated a version of the model in the previous section and rely on these estimates in what follows. Second, the timing of survey responses is key: because the large majority of responses to the survey is filed early in the month, they represent expectations before actual production has taken place.[13] For this reason, we can be confident to identify the effect of expectations on production and not the other way around.

In what follows, we modify the analysis of Enders et al. (2021) in two ways. First, for the matching exercise we use data from 1991–2019, that is, three more years of data than in the original study of Enders et al. (2021). Second, rather than using time fixed effects in the estimation of the probit model, we expand our model of Section 4 and use a set of macro variables. We hence directly build on the estimates reported in Section 4, which include the unemployment rate, as well as the monthly growth rates of PPI, CPI and IP. Based on the estimated model, we compute propensity scores for each firm-month observation,

[13] About 50% of firms answer within the first eight days and another 25% answer in the following week. These figures are calculated for those firms that answers the survey electronically, which is the majority by now.

$p(X_{it})$, and match treated and untreated observations using a variant of caliper or radius matching (Caliendo and Kopeinig 2008). We match each treated observation i to all untreated observations k within the same month that satisfy

$$p(X_{it}) - 0.02 \leq p(X_{kt}) \leq p(X_{it}) + 0.02 \ , \tag{5}$$

i.e., we allow for a radius of 0.02. Enders et al. (2021) consider a number of alternative specifications and find that results are generally robust. We compute the average treatment effect on the treated (ATT) for production and pricing decisions.

We show the results in Table 5.1, both for production (columns 3 and 4) and pricing decisions (columns 5 and 6). In the columns labeled "increase", firms report an expected increase in production, in the columns labeled 'decrease", firms report an expected production decline. Recall that expectations about production pertain to the next three months, while we measure the effect of expectations on production and pricing decisions in the current month. The top row of the table reports results for the full sample. We find that expectations of a production increase impact current production and prices positively. Quantitatively our results are very similar to those reported by Enders et al. (2021). This positive effect may reflect a stronger tendency among treated firms to raise production and prices or a reduced tendency to lower production and prices, or both. As they disentangle the two effects, Enders et al. (2021) find that the overall effect is dominated by the increased tendency to raise production and prices. The effect of an expected production decrease on production and prices is negative and quantitatively comparable to that of an expected production increase. In this case, Enders et al. (2021) find that the effect is mostly due to an increased probability of reduction of production and prices (rather than a decreased probability of an increase of production and prices).

Table 5.1 also offers a detailed break-down of the effects of expectations on firm decisions along various dimensions. In this respect, we go beyond the original analysis of Enders et al. (2021). By and large the results are fairly similar across sectors.[14] Furthermore, differences of firms in the former western and eastern parts of Germany are also not dramatic. This is consistent with evidence which suggests that firms located in the eastern part of Germany did worse in predicting business conditions early after German reunification but caught up over time (Triebs and Tumlinson 2013). We also consider a number of indicators related to size and find moderate differences only. However, there is a tendency of larger firms, in

[14]Some of the small differences across sectors could be related to the nature of the output good. Firms in the food sector, for example, react more strongly to expected production decreases than to expected increases. This might be due to the fact that generally food cannot be easily stored. Similarly, furniture is often produced on demand only, which might explain that production reacts less to expectations (and more to actual orders).

Table 5.1: Treatment effects of of increased and decreased production expectations

		Production		Prices	
Grouped by	Group	increase	decrease	increase	decrease
Full sample		0.152***	−0.193***	0.012***	−0.034***
Number of Employees	Fewer than 50	0.140***	−0.175***	0.025***	−0.040***
	50-199	0.154***	−0.207***	0.003	−0.029***
	200-499	0.183***	−0.149***	0.026**	−0.052***
	500-999	0.186***	−0.245***	−0.009	−0.048*
	More than 1000	0.150***	−0.242***	0.092***	0.006
Employees (Quartile)	First Quartile	0.162***	−0.160***	0.033***	−0.051***
	Second Quartile	0.143***	−0.179***	0.015	−0.017
	Third Quartile	0.140***	−0.229***	−0.005	−0.044***
	Fourth Quartile	0.177***	−0.176***	0.030***	−0.035***
Sales (Quartile)	First Quartile	0.159***	−0.159***	0.038***	−0.028**
	Second Quartile	0.128***	−0.191***	0.005	−0.038***
	Third Quartile	0.139***	−0.163***	−0.002	−0.053***
	Fourth Quartile	0.163***	−0.217***	0.013*	−0.024***
Total Assets (Quartile)	First Quartile	0.153***	−0.151***	0.034***	−0.034***
	Second Quartile	0.132***	−0.225***	0.007	−0.028***
	Third Quartile	0.160***	−0.169***	−0.001	−0.048***
	Fourth Quartile	0.159***	−0.211***	0.016**	−0.029***
Location	Eastern Germany	0.146***	−0.149***	−0.002	−0.025**
	Western Germany	0.144***	−0.183***	0.013**	−0.040***
Sector	Chemical	0.145***	−0.120***	0.011	−0.054***
	Electrical	0.157***	−0.184***	−0.005	−0.052***
	Food	0.154***	−0.224***	−0.002	0.037*
	Furniture	0.114***	−0.160***	−0.018	−0.039**
	Glass	0.122***	−0.192***	0.016	−0.024
	Leather	0.294***	−0.294***	−0.033	0.020
	Machine	0.174***	−0.231***	0.029***	−0.035***
	Metal	0.143***	−0.181***	0.030***	−0.043***
	Oil	0.166*	−0.241*	−0.014	−0.133
	Paper	0.133***	−0.152***	−0.006	−0.065***
	Rubber	0.116***	−0.193***	−0.018	0.015
	Textile	0.247***	−0.223***	0.096***	−0.038
	Vehicle	0.197***	−0.244***	0.004	−0.043*
	Wood	0.147***	−0.197***	0.050*	−0.025

Notes: treatment effect of increased and decreased production expectations. Independent of the sample split, all available observations are used for the matching. The treatment effect is then computed using all observations in a given group. Instead of including time fixed-effects, we use the macro variables introduced in the determinants section. When grouping by location we only consider firms that joined the ifo survey after the German reunification. One, two and three stars (*) correspond to significance on the 10, 5, and 1 percent significance levels, respectively.

particular if measured by sales, to adjust production more strongly to expectations—both for positive and negative expectations. This is consistent with Fact 3, established in Section 3 above: because larger firms are better at forecasting their own production, one would expect them to react more strongly to expectations.

Expectations may impact current decisions for two reasons. A first possibility is that expectations reflect *news* that are not yet incorporated in current fundamentals. According to this interpretation firm expectations operate as a transmission channel through which future fundamentals impact current decisions. A second possibility is that expectations are fundamentally unwarranted and as such are genuine *noise*. Enders et al. (2021) assess the distinct role of news and noise for firm decisions on the basis of forecast errors. Specifically, taking an ex-post perspective, they ask whether firms that expect a change in production behave differently vis-à-vis firms which correctly expect production to remain unchanged, once for firms whose expectations of a change turn out to be correct and once for firms with, in hindsight, incorrect expectations. They find that the treatment effect is stronger in case expectations turn out to be correct, but it is also present in case it does not. This finding suggests that expectations impact current firm decisions for both fundamental (news) and non-fundamental reasons (noise).[15]

Generally, in our view, a systematic analysis of how firm expectations about their own variables impact firm decisions based on survey evidence has just started. Boneva et al. (2020) study a survey of UK firms and estimate Phillips-curve relationships to capture the effect of firm expectations on firm decisions. Simlar to the findings above, they also find an effect on firms' pricing decisions. Other papers have established a link between firm expectations and firms' investment decisions. Bachmann and Zorn (2020) do so on the basis of the ifo investment survey. Gennaioli et al. (2015), instead, rely on the *Duke University quarterly survey of Chief Financial Officers*. They stress, in particular, that while CFOs' expectations matter for investment decisions, these expectation cannot be subsumed by traditional variables. Ma et al. (2020) establish a relation between capital investment and sales forecasts using a business survey of Italian firms run by the Bank of Italy.

[15]The authors explain the stronger effect for correct expectations with the fact that, with qualitative data, it remains unobservable how much production is expected to change and how certain firms are about the change. Using quantitative expectation data, available for a subsample, they confirm that expectations of a larger change lead to stronger production adjustments.

5.2 Firm-level uncertainty and firm decisions

In theory, it is not only the first moment of firm-level expectations which matters for firm decisions. The second moment, that is, uncertainty matters, too. In an influential study, Bloom (2009) emphasized the real option value of delaying an (irreversible) investment decision in the face of increased uncertainty. Whether this matters a lot for aggregate dynamics and the business cycle remains controversial (Bachmann and Bayer 2013, 2014; Bloom et al. 2018). A direct empirical assessment of the effect of uncertainty on firm decisions is thus called for in order to advance our understanding of how firm-level expectations influence firm decisions.

An influential study by Bachmann et al. (2013) uses the ifo survey to construct empirical proxies for time-varying business-level uncertainty. The authors employ a VAR model in order to show that uncertainty shocks induce a temporary contraction of aggregate production in the manufacturing sector as well as of employment and hours—consistent with the notion that uncertainty drives firm decisions. Also, they obtain similar results for the US based on the *Business Outlook Survey* maintained by the Federal Reserve Bank of Philadelphia.

Bachmann et al. (2019), in turn, zoom in on the decisions at the firm level, again using the ifo survey. In what follows we reproduce some of their results for our sample. As in the original study, we consider two alternative measures of uncertainty, namely the absolute value of the firms forecast error ($absfe_{i,t}$) and the rolling window standard deviation of forecast errors ($stdfe_{i,t}$), as introduced in Table 3.3 above. Using these two measures of firm-specific uncertainty, the original study by Bachmann et al. (2019) runs a probit regression to assess the impact of uncertainty on pricing decisions. We extend this analysis and consider production decisions as well (TBC).

Table 5.2 shows the results. In line with the results reported by Bachmann et al. (2019), we find that idiosyncratic firm-level volatility raises the probability of a decision to reset prices. This may reflect the fact that firms are exposed to larger shocks as uncertainty (volatility) increases. The results suggests that this "volatility effect" dominates the "wait-and-see" effect, according to which one would expect a reduced probability to adjust prices.[16] Consistently, Bachmann et al. (2019) also find that heightened volatility raises significantly the probability of both price increases and price decreases. In addition, they use quantitative firm pricing data from the German Federal Statistical Office to establish that firms also adjust along the intensive margin and that the aggregate adjustment is mainly driven by firms that decrease their prices after an increase in firm-specific volatility. This is also reflected in the fall in the aggregate price level following an aggregated firm-specific volatility shock.

So far, we have discussed the role of objective uncertainty for firm decisions. Yet, the

[16]See also Vavra (2014) for a model-based analysis of how volatility impacts pricing behavior.

Table 5.2: Firm-specific uncertainty and firm decisions

	Quarterly model		Monthly model		Monthly dummy model
Firm-level controls	ABSFE	STDFE	ABSFE	STDFE	ABSFE
yes	0.008***	0.013***	0.002***	0.003***	0.011**
no	0.014***	0.029***	0.004***	0.008***	0.20***

Notes: summary of probit results from Bachmann et al. (2019). The dependent variable takes the value one if a firm states that it changed its price in the previous period and zero otherwise. Explanatory variables are measures of firm uncertainty at the time of forecasting. ABSFE is the absolute value of the firms forecast error and STDFE is the rolling window standard deviation of forecast errors as defined in Table 3.3. Further controls include time and industry fixed effects and Taylor dummies. Firm level controls consist of reported business situation, business expectations, orders, and changes of input prices. Quarterly and monthly models use the uncertainty measures, the monthly dummy models uses a binary volatility measure equal to one if there is a forecast error in the next period. The table reports marginal effects with standard errors that are robust and clustered on the firm-level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

level of of subjective uncertainty may also matter. Ben-David et al. (2013) find for CFOs in the US that they are severely “miscalibrated”: realized returns lie outside the reported confidence intervals far too often. This, they show, matters for corporate decisions: more miscalibrated managers invest more and tolerate higher leverage.

References

Abberger, Klaus and Klaus Wohlrabe (2006). "Einige Prognoseigenschaften des ifo Geschäftsklimas – Ein Überblick über die neuere wissenschaftliche Literatur". *ifo Schnelldienst 59*, 19–26.

Altig, Dave, Scott Baker, Jose Maria Barrero, Nicholas Bloom, Philip Bunn, Scarlet Chen, Steven J. Davis, Julia Leather, Brent Meyer, Emil Mihaylov, Paul Mizen, Nicholas Parker, Thomas Renault, Pawel Smietanka, and Gregory Thwaites (2020a). "Economic uncertainty before and during the COVID-19 pandemic". *Journal of Public Economics 191*, 104274.

Altig, David, Jose Maria Barrero, Nicholas Bloom, Steven J. Davis, Brent Meyer, and Nicholas Parker (2020b). "Surveying business uncertainty". *Journal of Econometrics forthcoming*.

Anderson, Oskar, Rainald K. Bauer, Hellmuth Führer, and Jens-Peter Petersen (1956a). "Ursachen und Typen kurzfristiger Produktions- und Preisplanrevisionen der Unternehmer". *ifo-Studien 2*, 1–26.

Anderson, Oskar, Hildegard Fürst, and Willi Schulte (1956b). "Zur Analyse der unternehmerischen Reaktionsweise". *ifo-Studien 2*, 129–156.

Anderson, Oskar and Werner H. Strigel (1960). "Empirische Untersuchungen des Unternehmerverhaltens an Hand von Konjunkturtest-Daten". *ifo-Studien 6*, 143–156.

Andrade, Philippe, Olivier Coibion, Erwan Gautier, and Yuriy Gorodnichenko (2021). "No firm is an island? How industry conditions shape firms' expectations". *Journal of Monetary Economics forthcoming*.

Angeletos, George-Marios, Fabrice Collard, and Harris Dellas (2020). "Business-cycle anatomy". *American Economic Review 110* (10), 3030–70.

Angeletos, George-Marios and Zhen Huo (2021). "Myopia and anchoring". *American Economic Review 111* (4), 1166–1200.

Azeredo da Silveira, Rava and Michael Woodford (2019). "Noisy memory and over-reaction to news". *AEA Papers and Proceedings 109*, 557–61.

Bachmann, R., Steffen Elstner, and Eric R. Sims (2013). "Uncertainty and economic activity: Evidence from business survey data". *American Economic Journal: Macroeconomics 5* (2), 217–249.

Bachmann, Rüdiger, Benjamin Born, Steffen Elstner, and Christian Grimme (2019). "Time-varying business volatility and the price setting of firms". *Journal of Monetary Economics 101*, 82–99.

Bachmann, Rüdiger and Steffen Elstner (2015). "Firm optimism and pessimism". *European Economic Review 79*, 297–325.

Bachmann, Rüdiger and Christian Bayer (2013). "'Wait-and-see' business cycles?" *Journal of Monetary Economics 60* (6), 704–719.

——— (2014). "Investment dispersion and the business cycle". *American Economic Review 104* (4), 1392–1416.

Bachmann, Rüdiger, Steffen Elstner, and Atanas Hristov (2017). "Surprise, surprise - Measuring firm-level investment innovations". *Journal of Economic Dynamics and Control 83*, 107–148.

Bachmann, Rüdiger and Peter Zorn (2020). "What drives aggregate investment? Evidence from German survey data". *Journal of Economic Dynamics and Control 115*, 103873.

Balduzzi, Pierluigi, Emanuele Brancati, Marco Brianti, and Fabio Schiantarelli (2020a). "The economic effects of covid-19 and credit constraints: evidence from Italian firms' expectations and plans". IZA Discussion Paper 13629.

Balduzzi, Pierluigi, Emanuele Brancati, and Fabio Schiantarelli (2020b). "Financial markets, banks' cost of funding, and firms' decisions: lessons from two crises". *Journal of Financial Intermediation 36*, 1–15.

Balleer, Almut, Sebastian Link, Manuel Menkhoff, and Peter Zorn (2020). "Demand or supply? price adjustment during the Covid-19 pandemic". Covid Economics: Vetted and Real-Time Papers, 31, 59–102.

Barrero, Jose Maria (2021). "The micro and macro of managerial beliefs". *Journal of Financial Economics forthcoming*.

Beaudry, Paul and Franck Portier (2006). "Stock prices, news, and economic fluctuations". *American Economic Review 96* (4), 1293–1307.

Becker, Sasha O. and Klaus Wohlrabe (2008). "Micro data at the Ifo Institute for Economic Research - The 'ifo business survey' usage and access". *Schmollers Jahrbuch-Zeitschrift für Wirtschafts- und Sozialwissenschaften 182* (2), 307–319.

Ben-David, Itzhak, John R. Graham, and Campbell R. Harvey (2013). "Managerial miscalibration". *Quarterly Journal of Economics 128* (4), 1547–1584.

Bennett, Adam (1984). "Output expectations of manufacturing industry". *Applied Economics 16* (6), 869–879.

Blanchard, Olivier, Jean-Paul L'Huillier, and Guido Lorenzoni (2013). "News, noise, and fluctuations: An empirical investigation". *American Economic Review 103* (7), 3045–3070.

Bloom, Nicholas (2009). "The impact of uncertainty shocks". *Econometrica 77* (3), 623–685.

Bloom, Nicholas, Philip Bunn, Scarlet Chen, Paul Mizen, Pawel Smietanka, and Gregory Thwaites (2019). "The impact of Brexit on UK firms". Staff Working Paper 818. Bank of England.

Bloom, Nicholas, Steven J. Davis, Lucia Foster, Brian Lucking, Scott Ohlmacher, and Itay Saporta Eksten (2020). “Business-level expectations and uncertainty”. NBER Working Paper 28259.

Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J. Terry (2018). “Really uncertain business cycles”. *Econometrica 86* (3), 1031–1065.

Bloom, Nicholas and John Van Reenen (2007). “Measuring and explaining management practices across firms and countries”. *Quarterly Journal of Economics 122*, 1351–1408.

Boneva, Lena, James Cloyne, Martin Weale, and Tomasz Wieladek (2020). “Firms’ price, cost and activity expectations: evidence from micro data”. *The Economic Journal 130* (627), 555–586.

Bordalo, Pedro, Nicola Gennaioli, Yueran Ma, and Andrei Shleifer (2020). “Overreaction in macroeconomic expectations”. *American Economic Review 110* (9), 2748–82.

Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta, and Andrei Shleifer (2019). “Diagnostic expectations and stock returns”. *The Journal of Finance 74* (6), 2839–2874.

Born, Benjamin, Zeno Enders, Manuel Menkhoff, Gernot J. Müller, and Knut Niemann (2021). “Over- and underreaction to news: Evidence from German firms”. Mimeo.

Born, Benjamin, Gernot J Müller, Moritz Schularick, and Petr Sedláček (2019). “The Costs of Economic Nationalism: Evidence from the Brexit Experiment”. *The Economic Journal 129* (623), 2722–2744.

Brancati, Emanuele, Emanuela Marrocu, Manuel Romagnoli, and Stefano Usai (2018). “Innovation activities and learning processes in the crisis: evidence from italian export in manufacturing and services”. *Industrial and Corporate Change 27* (1), 107–130.

Broer, Tobias and Alexandre N. Kohlhas (2020). “Forecaster (mis-)behavior”. Mimeo.

Buchheim, Lukas, Carla Krolage, and Sebastian Link (2020). “Sudden stop: when did firms anticipate the potential consequences of COVID-19?” CESifo Working Paper 8429.

Bundesbank, Deutsche (2021). “Assessments and expectations of firms in the pandemic: findings from the Bundesbank Online Panel Firms ”. Monthly report, April.

Caliendo, Marco and Sabine Kopeinig (2008). “Some practical guidance for the implementation of propensity score matching”. *Journal of Economic Surveys 22* (1), 31–72.

Chahrour, Ryan, Kristoffer Nimark, and Stefan Pitschner (2020). “Sectoral media focus and aggregate fluctuations”. Mimeo.

Chen, Cheng, Tatsuro Senga, Chang Sun, and Hongyong Zhang (2020). “Uncertainty, imperfect information, and expectation formation over the firm’s life cycle”. Mimeo. Queen Mary University.

Coibion, Olivier and Yuriy Gorodnichenko (2015). “Information rigidity and the expectations formation process: A simple framework and new facts”. *American Economic Review 105* (8), 2644–2678.

Coibion, Olivier, Yuriy Gorodnichenko, and Saten Kumar (2018). “How do firms form their expectations? new survey evidence”. *American Economic Review 108* (9), 2671–2713.

Coibion, Olivier, Yuriy Gorodnichenko, and Tiziano Ropele (2020a). “Inflation expectations and firm decisions: new causal evidence”. *Quarterly Journal of Economics 135* (1), 165–219.

——— (2020b). “Inflation expectations and firm decisions: New causal evidence”. *The Quarterly Journal of Economics 135* (1), 165–219.

Dovern, Jonas, Lena Müller, and Klaus Wohlrabe (2020). “How do firms form expectations of aggregate growth? new evidence from a large-scale business survey”. CESifo Working Paper 8179.

EBDC-BEP (2019). “Business Expectations Panel 01/1980 – 06/2019, LMU-ifo Economics & Business Data Center, Munich”. *doi: 10.7805/ebdc-bep-2019*.

Eminidou, Snezana and Marios Zachariadis (2019). “Firms’ expectations and monetary policy shocks in the eurozone”. University of Cyprus Working Papers in Economics 02-2019.

Enders, Zeno, Franziska Hünnekes, and Gernot J. Müller (2019). “Monetary policy announcements and expectations: Evidence from German firms”. *Journal of Monetary Economics 108*, 45–63.

——— (2021). “Firm expecations and economic activity”. Mimeo, University of Tübingen.

Enders, Zeno, Michael Kleemann, and Gernot J. Müller (2020). “Growth expectations, undue optimism, and short-run fluctuations”. Review of Economics and Statistics, forthcoming.

Freuding, Julia, Raffaela Seitz, and Klaus Wohlrabe (2021). “Was steckt hinter dem ifo Geschäftsklima? Einschätzungen der Unternehmen zu ihrer aktuellen Lage und Erwartungen”. *ifo Schnelldienst 74* (08), 40–45.

Galí, Jordi and Mark Gertler (1999). “Inflation dynamics: a structural econometric analysis”. *Journal of Monetary Economics 44* (2), 195–222.

Gennaioli, Nicola, Yueran Ma, and Andrei Shleifer (2015). “Expectations and investment”. *NBER Macroeconomics Annual 2015, Volume 30*. NBER Chapters. National Bureau of Economic Research, 379–431.

Glas, Alexander and Matthias Hartmann (2021). “Uncertainty measures from partially rounded probabilistic forecast surveys”. Mimeo.

Henzel, Steffen R. and Sebastian Rast (2013). “Prognoseeigenschaften von Indikatoren zur Vorhersage des Bruttoinlandsprodukts in Deutschland”. *ifo Schnelldienst 66*, 39–46.

Hirshleifer, David, Anieg Low, and Siew Hong Teoh (2012). "Are overconfident CEOs better innovators?" *The Journal of Finance 67* (4), 1457–1498.

Imbens, Guido W. and Donald B. Rubin (2015). *Causal inference in statistics, social, and biomedical sciences*. Cambridge University Press.

INSEE (2007). "The French business survey on the situation and outlook in industry: methodology". *Insee Méthodes 117*.

Kaplan, Steven N., Mark M. Klebanov, and Morten Sorensen (2012). "Which CEO characteristics and abilities matter?" *Journal of Finance 67*, 973–1007.

Kawasaki, Seiichi and Klaus F. Zimmermann (1986). "Testing the rationality of price expectations for manufacturing firms". *Applied Economics 18* (12), 1335–1347.

Kohlhas, Alexandre and Ansgar Walther (2021). "Asymmetric attention". *American Economic Review*, forthcoming.

Krüger, Fabian and Lora Pavlova (2020). "Quantifying subjective uncertainty in survey expectations". KIT Working Paper in Economics 139.

Kydland, Finn E. and Edward C. Prescott (1982). "Time to build and aggregate fluctuations". *Econometrica 50* (6), 1345–1370.

König, Heinz, Marc Nerlove, and Gilles Oudiz (1981). "On the formation of price expectations". *European Economic Review 16* (1), 103–138.

Lorenzoni, Guido (2009). "A theory of demand shocks". *American Economic Review 99* (5), 2050–2084.

Lucas, Robert E. (1973). "Some international evidence on output-inflation tradeoffs". *The American Economic Review 63* (3), 326–334.

Lui, Silvia, James Mitchell, and Martin Weale (2010). "Qualitative business surveys: signal or noise?" *Journal of the Royal Statistical Society: Series A (Statistics in Society) 174* (2), 327–348.

Ma, Yueran, Tiziano Ropele, David Sraer, and David Thesmar (2020). "A quantitative analysis of distortions in managerial forecasts". NBER Working Paper 26830.

Malmendier, Ulrike and Geoffrey Tate (2005a). "CEO overconfidence and corporate investment". *The Journal of Finance 60* (6), 2661–2700.

——— (2005b). "Does overconfidence affect corporate investment? CEO overconfidence measures revisited". *European Financial Management 60* (11), 649–659.

Massenot, Baptiste and Yuri Pettinicchi (2018). "Can firms see into the future? Survey evidence from Germany". *Journal of Economic Behavior & Organization 145*, 66–79.

McFadden, Daniel (1974). "Conditional logit analysis of qualitative choice behavior". *Frontiers in Econometrics*.

McIntosh, James, Fabio Schiantarelli, and William Low (1989). "A qualitative response analysis of UK firms' employment and output decisions". *Journal of Applied Econometrics 4* (3), 251–264.

Meyer, Brent H., Brian Prescott, and Xuguang Simon Sheng (2021). "The impact of the COVID-19 pandemic on business expectations". *International Journal of Forecasting*.

Morikawa, Masayuki (2016). "Business uncertainty and investment: Evidence from Japanese companies". *Journal of Macroeconomics 49*, 224–236.

——— (2019). "Uncertainty over production forecasts: An empirical analysis using monthly quantitative survey data". *Journal of Macroeconomics 60*, 163–179.

Mortensen, Dale and Christopher Pissarides (2009). "Job creation and job destruction in the theory of unemployment". *The Review of Economic Studies 63* (2), 397–415.

Nerb, Gernot (1987). "Der Konjunkturtest im Lichte neuerer wirtschaftstheoretischer Ansätze". *ifo Studien 32*, 27–40.

Nerb, Gernot and Stefan Sauer (2020). "Einführung in die ifo Umfragen". *Handbuch der umfragebasierten konjunkturforschung*. Ed. by Georg Goldrian. Vol. 88. ifo Beiträge zur Wirtschaftsforschung. ifo Institut für Wirtschaftsforschung. Chap. 200, 1–8.

Nerlove, Marc (1983). "Expectations, plans, and realizations in theory and practice". *Econometrica 51* (5), 1251–1279.

Rosenbaum, Paul R. and Donald B. Rubin (1983). "The central role of the propensity score in observational studies for causal effects". *Biometrika 70* (1), 41–55.

Schwarz, Norbert, Hans-J. Hippler, Brigitte Deutsch, and Fritz Strack (1985). "Effects of category range on reported behavior and comparative judgments". *The Public Opinion Quarterly 49* (3), 388–395.

Seiler, Christian and Klaus Wohlrabe (2013). "Das ifo Geschäftsklima und die deutsche Konjunktur". *ifo Schnelldienst 66* (18), 17–21.

Shiller, Robert J. (2017). "Narrative economics". *American Economic Review 107* (4), 967–1004.

Sims, Christopher A. (2003). "Implications of rational inattention". *Journal of Monetary Economics 50* (3). Swiss National Bank/Study Center Gerzensee Conference on Monetary Policy under Incomplete Information, 665–690.

Smets, Frank and Rafael Wouters (2007). "Shocks and frictions in US business cycles: A Bayesian DSGE approach". *American Economic Review 97* (3), 586–606.

Smith, Jeremy and Michael McAleer (1995). "Alternative procedures for converting qualitative response data to quantitative expectations: an application to australian manufacturing". *Journal of Applied Econometrics 10* (2), 165–185.

Strasser, Georg (2013). “Exchange rate pass-through and credit constraints”. *Journal of Monetary Economics 60* (1). Carnegie-NYU-Rochester Conference, 25–38.

Tanaka, Mari, Nicholas Bloom, Joel M. David, and Maiko Koga (2020). “Firm performance and macro forecast accuracy”. *Journal of Monetary Economics*, forthcoming.

Thomas, D. G. (1995). “Output expectations within manufacturing industry”. *Applied Economics 27* (5), 403–408.

Triebs, Thomas P and Justin Tumlinson (2013). “Learning to forecast the hard way—evidence from German reunification”. NBER Working Paper 19209.

Vavra, Joseph (2014). “Inflation dynamics and time-varying volatility: new evidence and an Ss interpretation”. *Quarterly Journal of Economics 129* (1), 215–258.

Woodford, Michael (2002). “Imperfect common knowledge and the effects of monetary policy”. Princeton: Princeton University Press, 25–58.

——— (2003). *Interest and prices.* Princeton University Press.

Appendix

Table A.1: Additional information on relevant surveys

Name	Selected Literature	Sectors	Resp.*	Firm Size
ifo Business Climate Survey	Nerlove (1983), Kawasaki and Zimmermann (1986), Bachmann et al. (2013), Massenot and Pettinicchi (2018), and Enders et al. (2019, 2021)	industry, construction, trade, services, insurance	9,000	
Tankan Survey	Morikawa (2016)	not restricted	11,000	medium to large
CBI Industrial Trends Survey	Bennett (1984), McIntosh et al. (1989), Thomas (1995), Lui et al. (2010), and Boneva et al. (2020)	manufacturing	400-500	not restricted
Monthly outlook survey in industry	König et al. (1981), Nerlove (1983), and Andrade et al. (2021)	manufacturing and extraction	1,600	
Survey of Industrial Trends	Smith and McAleer (1995)			
Business Outlook Survey	Bachmann et al. (2013)	manufacturing	250	100+ employees
Survey of Production Forecast	Morikawa (2019)	manufacturing		
Survey on Industrial and Service Firms		manufacturing, construction, non-financials	5,000	20+ employees
ifo Investment Survey	Bachmann et al. (2017)	manufacturing and mining	2,000	
Basic Survey on Overseas Business Activities	Chen et al. (2020)			
Basic Survey of Japanese Business Structure and Activities		not restricted		
Survey on Inflation and Growth Expectations	Coibion et al. (2020b)	manufacturing	1,000	50+ employees
Management and Organizational Practices Survey	Bloom et al. (2020)	manufacturing	37,000	not restricted
Business Inflation Expectations Survey		not restricted	300	not restricted
Survey of Business Uncertainty	Altig et al. (2020b)	not restricted	1,300	
Bundesbank Online Panel - Firms		not restricted		
Monitoraggio Economia e Territorio	Balduzzi et al. (2020b) and Brancati et al. (2018)	manufacturing and services	25,000	not restricted

Notes: *Resp. refers to current respondents per wave.

Table A.2: Summary statistics on firm-level average forecast errors

		Production			Prices		
Grouped by	Group	N	Median	% insig.	N	Median	% insig.
Sector	Chemical	226	-0.0087	83.19	226	-0.0048	78.32
	Electrical	599	-0.0194	78.80	600	-0.0101	82.00
	Food	277	-0.0198	80.51	278	-0.0092	81.29
	Furniture	242	-0.0187	74.79	237	-0.0084	83.97
	Glass	288	-0.0201	76.04	294	-0.0102	79.25
	Leather	63	-0.0111	73.02	62	0.0064	77.42
	Machine	772	-0.0155	80.83	766	-0.0032	84.20
	Metal	612	-0.0129	78.43	583	-0.0104	79.59
	Oil	14	-0.0275	92.86	13	-0.0000	92.31
	Paper	710	-0.0248	75.49	700	-0.0269	72.86
	Rubber	333	-0.0171	76.58	328	-0.0146	79.57
	Textile	315	-0.0261	73.33	329	-0.0108	82.37
	Vehicle	130	0.0031	74.62	128	-0.0021	82.03
	Wood	209	-0.0333	76.56	207	-0.0210	69.08

Notes: estimation of firm-level average forecast errors, entries above provide summary statistics for the estimates for different subgroups of firms. N denotes the number of firms in each group. Sectors are from Bachmann et al. (2019).

Table A.3: Summary statistics on firm-level average squared forecast errors

		Production			Prices		
Grouped by	Group	N	Mean	Median	N	Mean	Median
Sector	Chemical	226	0.1279	0.1152	226	0.0783	0.0498
	Electrical	599	0.1195	0.1083	600	0.0474	0.0332
	Food	277	0.1314	0.1262	278	0.0588	0.0329
	Furniture	242	0.1353	0.1281	237	0.0406	0.0292
	Glass	288	0.1209	0.1073	294	0.0586	0.0349
	Leather	63	0.1127	0.1052	62	0.0490	0.0357
	Machine	772	0.1209	0.1058	766	0.0477	0.0319
	Metal	612	0.1301	0.1156	583	0.0625	0.0354
	Oil	14	0.1054	0.0788	13	0.1557	0.1086
	Paper	710	0.1321	0.1243	700	0.0692	0.0521
	Rubber	333	0.1369	0.1289	328	0.0695	0.0473
	Textile	315	0.1203	0.1118	329	0.0618	0.0330
	Vehicle	130	0.1185	0.1065	128	0.0422	0.0283
	Wood	209	0.1400	0.1299	207	0.0739	0.0496

Notes: estimation of firm-level average squared forecast errors, entries above provide summary statistics for the estimates for different subgroups of firms. N denotes the number of firms in each group. Sectors are from Bachmann et al. (2019).

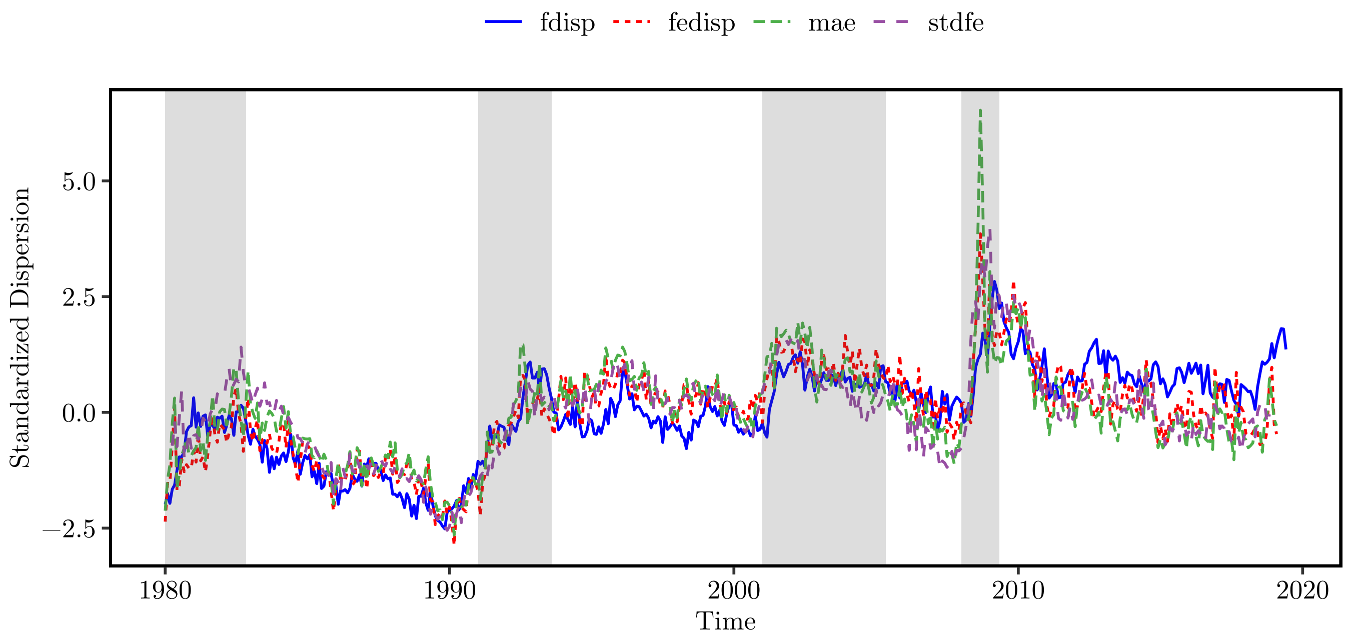
Table A.4: Definition of variable blocks

Block	Variable	Description	Frequency	Periods
Survey	Business Situation		monthly	t to t-3
	Realized Production		monthly	t to t-2
	Expected Production		monthly	t-1 to t-3
	Realized Prices		monthly	t to t-2
	Orders		monthly	t to t-3
	Foreign Orders		monthly	t to t-3
	Demand		monthly	t to t-2
	Capacity		monthly	t-1 to t-3
	Expected Prices		monthly	t-1 to t-3
	Employees		annual	
	Avg. Business Situation	two-digit sector level	monthly	t
	Sectoral Fixed Effects			
Fundamentals	Financing Coefficient	$\frac{\text{Liabilities - Provisions}}{\text{Equity + Provisions}}$	annual	
	Debt Share	$\frac{\text{Total debt}}{\text{Assets}}$	annual	
	Total Assets		annual	
Macro	PPI Growth	versus previous month	monthly	t-2
	CPI Growth	versus previous month	monthly	t-2
	Unemployment		monthly	t-1
	IP Growth	versus previous month	monthly	t-2

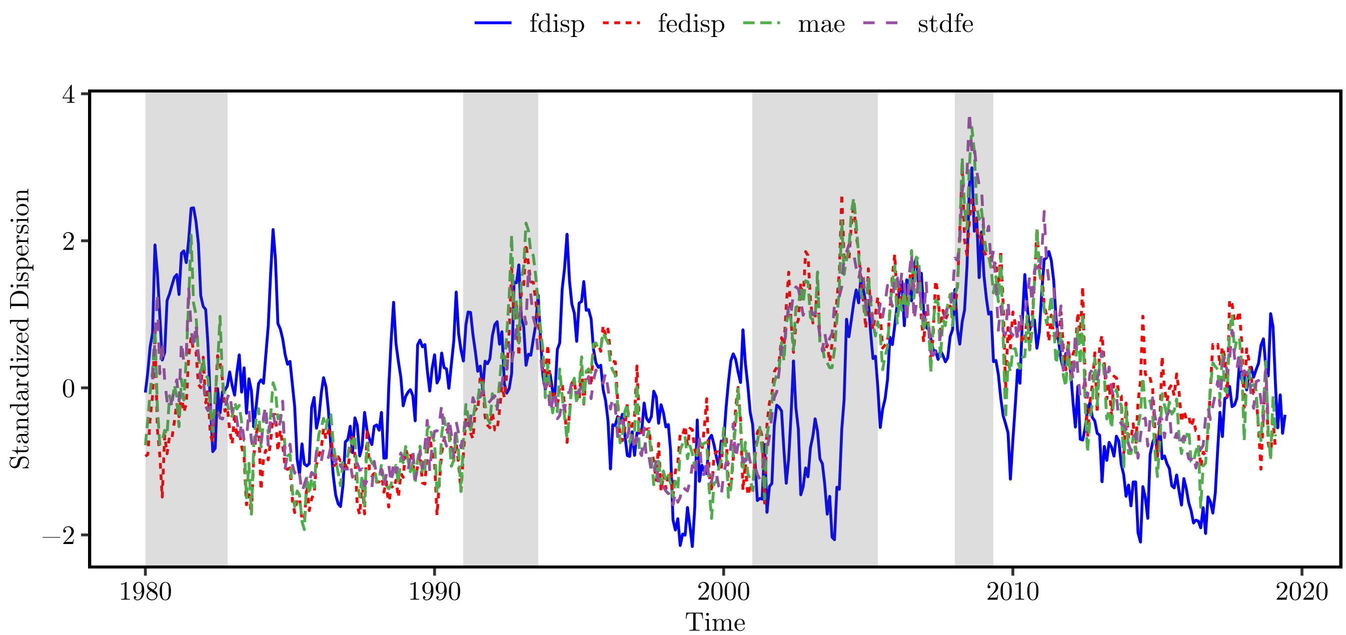
Notes: components of the three variable blocks considered as explanatory variables in the ordered probit. The survey and fundamental blocks are taken from Enders et al. (2021).

Figure A.1: Dispersion of expectations and their errors

(a) Dispersion in production



(b) Dispersion in prices



Notes: time-series of dispersion measures in expectation (errors) for prices and production. Time series are seasonally adjusted (X13-ARIMA-SEATS) and standardized. Shaded areas mark recessions as dated by the German Council of Economic Experts (see Bachmann et al. 2013).

Table A.5: Summary statistics firm-level slope estimates by sector

		Production			Prices		
Grouped by	Group	N	Mean	Median	N	Mean	Median
Sector	Chemical	271	-0.1113	-0.1105	271	-0.1025	-0.0718
	Electrical	515	-0.1147	-0.1131	515	-0.1078	-0.0876
	Food	358	-0.1092	-0.1108	358	-0.1043	-0.0786
	Furniture	238	-0.1082	-0.1018	238	-0.1117	-0.0817
	Glass	262	-0.1090	-0.0980	262	-0.1170	-0.0931
	Leather	86	-0.1309	-0.1266	86	-0.0880	-0.0523
	Machine	646	-0.1185	-0.1111	646	-0.1088	-0.0813
	Metal	719	-0.1073	-0.1105	719	-0.1052	-0.0773
	Oil	11	-0.0541	-0.0443	11	-0.1178	-0.0508
	Paper	574	-0.1111	-0.1060	574	-0.1102	-0.0892
	Rubber	343	-0.1167	-0.1097	343	-0.1125	-0.0885
	Textile	265	-0.1042	-0.0924	265	-0.1064	-0.0825
	Vehicle	144	-0.1113	-0.1172	144	-0.1042	-0.0755
	Wood	248	-0.1263	-0.1272	248	-0.1042	-0.0862

Notes: summary statistics for the slope estimates from the forecaster-by-forecaster regressions in Equation (4) for different groups of firms. N denotes the number of firms in each group.

Table A.6: Summary statistics firm-level constant estimates

		Production			Prices		
Grouped by	Group	N	Mean	Median	N	Mean	Median
Overall		4851	-0.0317	-0.0263	4851	-0.0093	0.0056
Number of Employees	Fewer than 50	236	-0.0236	-0.0155	236	0.0005	0.0062
	50-199	156	-0.0237	-0.0274	156	0.0048	0.0133
	200-499	78	0.0068	-0.0023	78	0.0065	0.0094
	500-999	22	-0.0200	-0.0299	22	-0.0004	-0.0071
	More than 1000	5	-0.0148	-0.0344	5	-0.0132	-0.0090
Employees (Quartile)	First Quartile	124	-0.0232	-0.0103	124	-0.0057	0.0053
	Second Quartile	124	-0.0240	-0.0188	124	0.0092	0.0123
	Third Quartile	124	-0.0242	-0.0264	124	0.0011	0.0115
	Fourth Quartile	125	-0.0032	-0.0232	125	0.0058	0.0099
Sales (Quartile)	First Quartile	107	-0.0192	0.0000	107	0.0002	0.0052
	Second Quartile	112	-0.0258	-0.0111	112	0.0032	0.0079
	Third Quartile	109	-0.0127	-0.0150	109	0.0024	0.0103
	Fourth Quartile	110	-0.0311	-0.0325	110	-0.0095	0.0065
Total Assets (Quartile)	First Quartile	130	-0.0196	0.0002	130	-0.0058	0.0051
	Second Quartile	131	-0.0270	-0.0220	131	0.0018	0.0105
	Third Quartile	130	-0.0104	-0.0153	130	0.0107	0.0134
	Fourth Quartile	131	-0.0311	-0.0265	131	-0.0092	0.0093
Location	Eastern Germany	2203	-0.0256	-0.0208	2203	-0.0060	0.0070
	Western Germany	1198	-0.0373	-0.0303	1198	-0.0126	0.0038
Sector	Chemical	271	-0.0446	-0.0291	271	-0.0162	0.0060
	Electrical	515	-0.0435	-0.0315	515	-0.0113	0.0051
	Food	358	-0.0225	-0.0230	358	-0.0070	0.0046
	Furniture	238	-0.0269	-0.0231	238	-0.0113	0.0076
	Glass	262	-0.0343	-0.0128	262	-0.0097	0.0056
	Leather	86	-0.0395	-0.0264	86	-0.0120	0.0113
	Machine	646	-0.0239	-0.0230	646	-0.0052	0.0046
	Metal	719	-0.0303	-0.0231	719	-0.0104	0.0057
	Oil	11	0.0085	-0.0230	11	0.0035	0.0185
	Paper	574	-0.0322	-0.0304	574	-0.0119	0.0032
	Rubber	343	-0.0318	-0.0265	343	-0.0123	-0.0000
	Textile	265	-0.0370	-0.0276	265	-0.0067	0.0065
	Vehicle	144	-0.0360	-0.0332	144	-0.0096	0.0021
	Wood	248	-0.0317	-0.0233	248	-0.0063	0.0100

Notes: summary statistics for the estimates of the constant from the forecaster-by-forecaster regressions in Equation (4) for different groups of firms. When grouping by location we only consider firms that joined the ifo survey after the German reunification.