Quantifying Qualitative Survey Data with Panel Data Structure*

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Abstract

We develop a novel methodology to quantify forecasts based on qualitative survey data. The methodology is generally applicable when quantitative information is available on the realization of the forecasted variable, for example from firm balance sheets. The method can be applied to a wide range of panel datasets, including qualitative surveys on firm-level forecasts or household expectations. As an application, we employ a panel of Greek manufacturing firms and quantify firms' forecast errors of own sales growth. In this context, we conduct a variety of exercises to demonstrate the methodology's validity and accuracy.

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1 Introduction

Given the dynamic nature of economic decisions, expectations play a major role in economic behavior. Economic models that describe economic agents' behavior are naturally dynamic and contain assumptions about expectations. Many papers have emphasized the importance of obtaining evidence on expectations formation that is independent of model assumptions (see Nerlove (1983) and Manski (2004) among others). This makes the use of survey data on expectations particularly useful. However, since survey-based measures for expectations are typically categorical, some important questions cannot be answered. For instance, whether firms make substantial errors in their forecasts and what are their statistical properties. Our paper provides a remedy to this obstacle, as we develop a novel methodology that converts categorical survey data on expectations to continuous quantities. Given the broad agreement in the profession on the advantages and usefulness of quantitative forecasts, there is a recent move towards surveys designed to include quantitative features. As the move to quantitative surveys is recent, they do not not provide long time series or historical data. Furthermore, many useful surveys remain qualitative. Therefore, our methodology will remain relevant and important in the future.

We propose a novel methodology that uses qualitative survey data on the direction of firm sales growth forecasts and quantitative data on realized sales growth from financial statements, to derive a quantitative estimate for firms' sales growth forecasts. We apply this method to a dataset that matches confidential information on firms' monthly qualitative forecasts on their own sales growth together with annual quantitative balance-sheet information on sales growth. The dataset covers Greek manufacturing firms for the period of 1998 to 2015.

In order to quantify the survey responses we extend the methodology by Pesaran (1987) and Smith and McAleer (1995) who aggregate qualitative firm observations cross-sectionally to derive quantitative time series. We extend their work and show how the panel dimension of our dataset can be retained. We use higher-frequency (monthly) qualitative survey data on expected sales growth together with lower-frequency (annual) quantitative data on realized sales growth to estimate quantified expected annual sales growth. Retaining the panel dimension comes with new challenges, such as dealing with unobserved heterogeneity and an omitted variable problem. This requires identifying assumptions that allow us to derive two nonlinear equations. The first one relates observed quantitative annual sales growth to observable variables and the second one relates unobserved quantitative expected sales growth to observable variables. The key is that both of these relationships depend on the same parameters. Then, we estimate the common parameters from the first equation using Nonlinear Least Squares (NLS), and use these estimated parameters in the second equation to derive fitted values for quantitative expectations on sales growth.

This methodology can be applied to a wide range of applications and datasets and is not limited to quantifying firm forecasts. The only requirement is that the researcher can combine two types of data: (i) categorical survey data on expectations, with high time-series frequency within each unit; (ii) quantitative realizations of the corresponding variables with lower time-series frequency within each unit. Effectively, our quantification model aggregates the higher frequency qualitative responses into the lower frequency quantitative variable. For example, in our paper, we aggregate the categorical survey expectations from the firm-month frequency to the firm-year frequency that the quantitative realizations have. We additionally demonstrate that our quantification methodology is applicable to datasets with high- and low-frequency panels that have short time-series dimension.

We provide evidence of external validity and accuracy for our methodology in four ways. First, we show that our quantified estimates on sales growth expectations are fully consistent in terms of sign with the corresponding qualitative survey-based expectations. Second, in an analysis of firm sales growth, we construct a small dataset of UK manufacturing firms that contains monthly qualitative survey expectations and the annual realizations from balance sheets, which allows us to use our methodology to derive estimates for annual forecast errors. Importantly, for each firm, the dataset also includes annual quantitative survey expectations, which we employ as a benchmark. Comparing our estimated annual forecast errors with the directly observable benchmark forecast errors confirms the accuracy of our quantification methodology. Such an exercise can only be conducted using a dataset that includes quantitative forecasts, made by the same forecaster at a high as well as a lower frequency. In practice, this is challenging to do due to the rare availability of such data on quantitative firm-level expectations. In fact, this dearth of data highlights the need for and value of our quantification methodology, which allows researchers to utilize the large number of qualitative surveys to quantify expectations. Third, we perform a Monte Carlo exercise that provides a benchmark based on simulated data. We find forecast errors based on our methodology are highly accurate when compared with forecast errors based on the underlying artificial 'true' data. Fourth, we run extensive robustness checks and provide additional evidence which add validity to the assumptions that underpin our model.

Quantifying forecast errors using qualitative survey data is a very important matter for many questions, but there has been little work on this and no generally accepted methodology.[1] Theil (1952) and Anderson Jr (1952) developed the so called 'probability method'. It provides the theoretical grounds for the 'balance statistics' that are widely used for the published business and consumer sentiment indexes. Pesaran (1987) provides a useful analysis of the limitations of this approach (see also Pesaran and Weale (2006)). A very useful first step to overcoming such limitations is Bachmann and Elstner (2015). They first restrict their survey sample to firms that reported expected output to be unchanged over the following three months. Then, they classify non-zero percentage change of firm's reported utilization as a forecast error. This technique has some limitations compared to our quantification method. Our method does not only deliver continuous forecast errors but also expectations themselves. Furthermore, it is not limited to the quantification of firms' production, but can be applied to any variable in principle, given the data requirements outlined above. Importantly, our method can be used on the entire sample rather than only on a potentially small subset of firms.

Important early work on the use and pitfalls of survey data to analyze how firms form expectations includes de Leeuw and McKelvey (1981) and Nerlove (1983). Our work is part of a now fast growing literature that uses information from surveys to understand firms' decision making. Born et al. (2023) use German data from the IFO Business Survey to study how firms' expectations about future production affect their current decisions on production and price setting. Tanaka et al. (2020) use novel Japanese data to study how firm characteristics affect their GDP forecasts. To the best of our knowledge, these two datasets are the only ones constructed so far to contain categorical firm survey data with corresponding quantitative data, e.g. from balance sheets or national accounts. We contribute to the survey literature by providing a novel

[1]While this holds in the context of the quantification of individual qualitative forecasts, there is a large literature on the quantification approaches for the cross-sectional disagreement measured via qualitative survey responses, see e.g. Mokinski et al. (2015) and the references therein.

dataset that combines responses to a rich firm-level survey with the corresponding balance sheet information for Greece. Our empirical results point to the importance of further work on merging existing quantitative datasets with qualitative survey data.[2] Applying our quantification methodology would then allow for a deeper understanding of how firms or households form expectations and their economic impact. There are many other contributions in the literature that use survey data to help our understanding of firm-level and aggregate variables. Enders et al. (2019) for example use German data from the IFO Business Survey to study how monetary policy announcements affect firms' expectations. Bachmann and Zorn (2020) use the IFO Investment Survey to understand the drivers of aggregate investment. Bloom et al. (2019) use survey responses to understand the causes and consequences of Brexit for the UK economy. Coibion et al. (2018) study how firms form expectations about macroeconomic conditions using novel survey evidence from New Zealand.

The rest of the paper is organized as follows. Section 2 discusses the data. Section 3 lays out our methodology to quantify firms' forecasts and describes the characteristics of the estimated forecasts and the resulting forecast errors. Section 4.1 applies our quantification methodology to derive quantitative forecasts of Greek firms' own sales growth. Section 4.2 provides evidence of external validity, validity and accuracy of our methodology and some robustness checks. Section 5 provides concluding remarks.

2 Data

Our dataset is constructed by merging two databases that cover Greek firm-level data. The first database includes annual information on firm-level balance sheets and income statements. We obtain this data from ICAP S.A., a private consultancy firm, which collects and digitalizes this information from official publicly available records. The financial statements are compiled by certified auditors (chartered accountants) and are used, among other things, for reporting to tax authorities and investors, by commercial banks for credit decisions, and by the central bank for credit rating information. They are available to us at an annual frequency from 1998 to 2015, which determines the time span of our sample. As such, our dataset includes

[2] A novel dataset that combines households' survey based inflation expectations with administrative data has recently been developed in Vellekoop and Wiederholt (2019).

two distinct episodes of the Greek economy, a long boom up to 2008 and the subsequent severe recession. We use firm-level sales from the financial statements, which is deflated using the implicit gross value added deflator from Eurostat.[3]

The second database comprises firms' responses to a monthly survey conducted by the Foundation for Economic and Industrial Research (IOBE). This survey is used by IOBE to construct the much-followed business climate index for the Greek economy since 1985 and is part of the European Commission's business climate index for the European Union.[4] All survey questions concern current, past or expected future firm-level developments. The survey does not include any questions about aggregate macroeconomic or sector-level conditions. Since participation is confidential and voluntary, firms have no strategic interest in misreporting. Further details about the survey are provided in the Online Appendix A.1.

IOBE classifies firms in four broad sectors — manufacturing, construction, retail trade, and services — and sends out surveys that include somewhat different questions across these sectors. We focus on the manufacturing sector as this sector's survey includes questions about anticipated and current sales developments. Responses to these two questions, and the fact that the question on current sales has a direct counterpart in the financial statements data, are key for the quantification of forecast errors.[5] The relevant (translated) questions in the survey are

> Question A.2: *During the previous 3 months, your total sales have increased/remained unchanged/decreased.*
>
> Question D.2: *During the next 3 months, you expect your total sales to increase/remain unchanged/decrease.*

These qualitative survey responses are coded in the data as +1/0/-1 indicating increase/remain unchanged/decrease,

[3]Nominal and real (2005 base year) value added for Greece is available from Table 'nama_10_a64'.

[4]The survey is commissioned by the European Commission and conducted for the Greek economy in compliance with the guidelines of the European Commission's Directorate General for Economic and Financial Affairs (see DGECFIN (2017)). A corresponding survey is conducted for the European Commission for example for the United Kingdom by the Confederation of British Industry and for Germany by the IFO Institute.

[5]The manufacturing sector is also the largest of these broad sectors as it includes 38% of survey observations and 36% of observations in the financial statements data.

respectively. In the following, we label the variables that include the responses of firm i in month m to questions A.2 XS_{im}, and to question D.2 XS^e_{im}. The qualitative survey variable on current sales developments, XS_{im}, has a direct quantitative counterpart with sales growth, denoted as x_{iy} for firm i in year y, in the financial statements. For the remainder of the paper, variables in capital letters denote qualitative variables and lower case letters stand for quantitative variables.

Under a confidentiality agreement, we were given access to the un-anonymized survey data. Using the firm's unique tax identifier, we merged their survey responses with the respective balance sheet data. Details about the cleaning procedures for the two parts of our dataset are outlined in the Online Appendices A.2 and A.3. Our cleaned and merged dataset includes 799 firms with 25,764 monthly responses from the survey on the above two questions and 4,104 annual balance sheet observations on sales. Table 1 provides an overview of the firms in our sample. Our sample includes very small firms but also large firms with close to 4,000 employees and annual sales turnover of over six billion Euros. On average, firms respond in six out of the 11 months in which surveys are sent out. In the Online Appendix A.4 we provide evidence that our sample is representative for the manufacturing sector and establish in several exercises the high quality of the survey responses. In the Online Appendix B.5 we show the distribution of survey expectations on sales growth and documents their evolution over time.

Table 1: Sample Characteristics.

	Min.	Max.	Mean	Median	St. Dev.
Firm-Year Characteristics					
# of Employees	1	3,811	162	75	278
Real Sales (in thousands, 2005 Euros)	6	6,710,000	29,100	7,202	179,000
Survey Responses per Annum	3	11	6	6	3
Firm Level Characteristics					
Age at First Appearance in Sample	0	110	25	24	17
Time-Series Length in Sample (Years)	1	18	5	4	4

3 Quantitative Forecast Errors

The forecast error on sales growth is defined as the difference between actual sales growth and its forecast for the corresponding period. Evaluating the size of firms' forecast errors hence requires quantitative data on sales growth forecasts and their subsequent realization. While the financial statements data provide an annual quantitative measure for the latter, quantitative data on firm's sales growth forecasts is not readily available. In this section we develop a novel quantification methodology to derive a quantitative estimate for firms' sales growth forecasts.

3.1 Quantifying Expected Sales Growth

Consider the expected annual growth rate of sales for firm i in year y, $x^e_{iy} \triangleq \mathbb{E}\big[x_{iy}|\mathcal{F}_{i,y-1}\big]$, that is based on an information set $\mathcal{F}$ at the end of year $y-1$. Additionally, we define firm i's expectation about average sales growth in the next three months as $x^e_{im} \triangleq \mathbb{E}\big[x_{i,\{m,m+1,m+2\}}|\mathcal{F}_{i,m-1\in y}\big]$, where $x_{i,\{m,m+1,m+2\}}$ is the average growth rate of sales for the following three-month period. Note that this expectation is formed based on an information set at the end of month $m-1$. This quantitative monthly sales forecast is consistent, in terms of the information set and forecasting horizon, with the qualitative survey forecast XS^e_{im}.

One can describe a firm's expected annual sales growth with its monthly components as

$$x^e_{iy} = \mathbb{E}_{i,y-1} \sum_{m\in y} x^e_{im}. \tag{1}$$

Intuitively, equation (1) states that the forecast that a firm makes in $y-1$ for the whole of year y can be decomposed to its forecast in $y-1$ about its subsequent monthly frequency forecasts made during y. For further details, see also Online Appendix B.1. To simplify our exposition, we ignore for now any seasonality in the monthly growth rates, but we address this at a later step when we discuss our estimation strategy.

While we do not observe quantitative expectations of sales growth in equation (1) — x^e_{iy} and x^e_{im} — our dataset includes qualitative survey responses on the expected change in sales, $XS^e_{i,m}$. The aim of this section is to derive a quantitative estimate for annual expected sales growth, x^e_{iy}, using the observed qualitative survey responses and the realised annual sales growth rates from the firm's financial statements.

As a first step towards this, we follow Pesaran (1987) and assume that for each firm its monthly expected sales growth rates are linearly positively correlated with the corresponding annual expected sales growth. We also allow for this linear correlation to be asymmetric, as in Smith and McAleer (1995), depending on whether the quantitative monthly expectation variable is positive, $x_{im}^{e,+}$, or negative, $x_{im}^{e,-}$. This is the first identifying assumption (ID1) we make to quantify firms' forecast errors. It can be formalized as

$$x_{im}^{e,+} = \alpha + \gamma_1 x_{iy}^{e} + \nu_{im}^{+}, \qquad \text{and} \qquad x_{im}^{e,-} = -\beta + \gamma_2 x_{iy}^{e} + \nu_{im}^{-}, \qquad \text{[ID1]} \tag{2}$$

where ν_{im}^{+} and ν_{im}^{-} are the error terms.[6] Any potential monthly serial autocorrelation and correlation across firms (month-specific fixed effects) in these error terms are not of concern, because we show later that the aggregation at the firm-year frequency eliminates them. We further allow for the coefficients α, β, γ_1 and γ_2 to differ across boom and bust periods (1998-2008 and 2009-2015 in our sample). We will specify this at the end of this section, but refrain from accounting for this state dependence in the notation for now to ease the exposition.

Equations (2) are not formulated to conduct any inference about how firms make their monthly forecasts, but merely to reflect that for each firm the annual expected growth rate should be correlated with the corresponding monthly components. In fact, this linear correlation in equations (2) can be used to eliminate the unobserved variable x_{im}^{e} from equation (1). If we rewrite x_{im}^{e} as $x_{im}^{e} = x_{im}^{e,+} + x_{im}^{e,-}$ in the sum operator of equation (1) and also combine it with (2) we obtain (detailed derivations are shown in Appendix A)

$$x_{iy}^{e} = \frac{\alpha P_{iy} - \beta N_{iy}}{1 - \gamma_1 P_{iy} - \gamma_2 N_{iy}} + \xi_{iy}, \qquad \text{with} \qquad \xi_{iy} = \frac{\psi_i}{1 - \gamma_1 P_{iy} - \gamma_2 N_{iy}}, \tag{3}$$

where ψ_i is the unobserved firm heterogeneity (fixed effect), and we define

$$P_{iy} \triangleq \sum_{m \in y} \mathbb{1}_{[XS_{im}^{e}=1]}, \qquad \text{and} \qquad N_{iy} \triangleq \sum_{m \in y} \mathbb{1}_{[XS_{im}^{e}=-1]}, \tag{4}$$

to ease the notation. P_{iy} (N_{iy}) denotes the number of months per year that record a rise (decline) in expected sales of firm i. These qualitative variables are directly available from the survey data so that we can observe P_{iy} and N_{iy}.

[6]For our dataset this assumption directly links to the monthly survey forecasts in which the information updates each month. However, for other datasets this can be relaxed to

$$\mathbb{E}_{i,y-1} x_{im}^{e,+} = \alpha + \gamma_1 x_{iy}^{e} + \mathbb{E}_{i,y-1}\nu_{im}^{+}, \quad \text{and} \quad \mathbb{E}_{i,y-1} x_{im}^{e,-} = -\beta + \gamma_2 x_{iy}^{e} + \mathbb{E}_{i,y-1}\nu_{im}^{-}, \tag{3'}$$

We thank an anonymous referee for pointing this out.

To derive equation (3), we have additionally assumed that

$$\mathbb{E}_{i,y-1} P_{iy} = P_{iy} \quad \text{and} \quad \mathbb{E}_{i,y-1} N_{iy} = N_{iy}, \tag{5}$$

where both sides of these two equations refer to firm forecasts. The assumption embedded in equation (5) is that, during year y, firm i makes as many forecasts of positive and negative sales growth when responding to the survey as it expected to do at the end of year $y-1$. Note that the assignment to individual months of positive and negative forecasts is unconstrained by (5) as long as the proportion is constant. Intuitively, equation (5) states that firms do not drastically update their information during year y when making monthly forecasts. This may happen because updating information on a monthly basis is costly. In Online Appendix B.3, we provide some analysis supporting that this assumption is realistic for our dataset.[7]

To estimate equation (3) we need to take some additional steps since we do not observe quantitative expectations of annual sales growth, x^e_{iy}, in the data. In fact, deriving quantitative sales growth expectations was our goal in the first place. Instead, if we had estimates for the parameters and knowledge of the error term — and given that we observe P_{iy} and N_{iy} — we could use equation (3) to derive fitted values for x^e_{iy}. The next steps of the derivation are undertaken to facilitate exactly this.

We know that for each firm i, realized sales growth in year y is the sum of expected sales growth in that year and a forecast error, $x_{iy} = x^e_{iy} + x^{fe}_{iy}$. Using this expression to replace x^e_{iy} in equation (3) yields after rearranging

$$x_{iy} \quad = \quad \frac{\alpha P_{iy} - \beta N_{iy}}{1 - \gamma_1 P_{iy} - \gamma_2 N_{iy}} + x^{fe}_{iy} + \xi_{iy}. \tag{6}$$

In principle, this equation can be estimated, as the financial statements data includes quantitative information about realized annual sales growth, x_{iy}. While the forecast error, x^{fe}_{iy}, is still unobserved, estimating equation (6) without this variable is simply an omitted variable problem that adds to the error term. In the next part of this subsection, we discuss this omitted variable problem and deal with unobserved firm

[7]The assumption in equation (5) might be violated during major events (e.g. the 2020-2021 pandemic) when a large shift of expectations can occur within that turbulent year. We recommend dropping these years from the estimation sample. In our dataset, the rapid expansion of the noughties in Greece (until 2008) was followed by a bust and a prolonged contraction (output declined more than 25% by the end of 2014). For this reason we split our sample in two periods, 1999-2008 and 2009-2015, when we estimate the parameters α, β, γ_1 and γ_2.

heterogeneity in ξ_{iy} to obtain an expression of equation (6) that can be estimated.

Omitted Variable Problem. To ease the notational burden in this section, we use equation (3) to define the conditional expectation of the quantitative sales growth expectations as

$$\tilde{x}^e_{iy} \triangleq \mathbb{E}\big[x^e_{iy}\big|P_{iy}, N_{iy}\big] = \frac{\alpha P_{iy} - \beta N_{iy}}{1 - \gamma_1 P_{iy} - \gamma_2 N_{iy}}, \tag{7}$$

which can be thought as the 'econometrician's estimate' of the firm's expectation.

To obtain consistent estimates of the parameters in equation (6), we need the composite error term $x^{fe}_{iy} + \xi_{iy}$ to be mean independent of the non-linear function $\tilde{x}^e_{iy}$ (see Davidson and MacKinnon (2004)). We proceed now to show this. Note that the forecast error, x^{fe}_{iy}, is mean independent from the forecast x^e_{iy}.[8] Since $\mathbb{E}\big[x^{fe}_{iy}\big|x^e_{iy}\big] = 0$ holds, it also implies that the firm's forecast error is mean-independent from the econometrician's estimate of that forecast, $\mathbb{E}\big[x^{fe}_{iy}\big|\tilde{x}^e_{iy}\big] = 0$. We provide a proof of this statement in Online Appendix B.2 using the law of iterated expectations and the fact that in our model the econometrician's estimate of the firm's forecast is not more informed than the firm's as it is based on the firm's own monthly forecasts. Intuitively, firms' expected sales growth, x^e_{iy}, whether rational or, not cannot ex-ante forecast their forecast error, otherwise firms would have incorporated this information in their expectation to reduce the forecast error. The same must hold then also for any estimates, $\tilde{x}^e_{iy}$, of firms' sales growth expectations.

Having established the forecast error's mean independence of $\tilde{x}^e_{iy}$, and in order to obtain consistent estimates of the parameters in equation (6), it remains to be shown that $\mathbb{E}\big[\xi_{iy}\big|\tilde{x}^e_{iy}\big] = 0$. A sufficient condition for mean independence of the error term, $\mathbb{E}\big[\xi_{iy}\big|\tilde{x}^e_{iy}\big] = 0$, to hold is that $\mathbb{E}[\xi_{iy}|\{XS^e_{im}\}_{m\in y}] = 0$. In Online Appendix B.2 we provide a formal proof of this statement. This leaves us with the task to control for the unobserved firm heterogeneity that is likely to make ξ_{iy} correlated with $\{XS^e_{im}\}_{m\in y}$. We turn to this next.

Unobserved Firm Heterogeneity. From equation (3), we know that the numerator of the error term ξ_{iy} is the unobserved firm heterogeneity ψ_i. We need to account for the effect of the unobserved heterogeneity

[8] Indeed, $\mathbb{E}\big[x^{fe}_{iy}\big|x^e_{iy}\big] = \mathbb{E}\big[x_{iy} - x^e_{iy}\big|x^e_{iy}\big] = x^e_{iy} - x^e_{iy} = 0$. This does not imply rational expectations, because mean independence from the firm's forecast does not imply mean independence from the information set that was used by the firm for that forecast. However, it has implications for the loss function of the firm's forecasts, for example, a quadratic loss function can result in $\mathbb{E}\big[x^{fe}_{iy}\big|x^e_{iy}\big] = 0$.

which is in fact an omitted variable and is endogenous. The reason is that firm heterogeneity is related to the entire history of XS^e_{im}, so that $\mathbb{E}[\psi_i|\{XS^e_{im}\}_{m=1,\ldots,T_i}] \neq 0$. Note that the notation $\{XS^e_{im}\}_{m=1,\ldots,T_i}$ denotes the entire history of months m for variable XS^e_{im}, where T_i is firm i's total number of monthly observations.[9]

To control for unobserved heterogeneity, we need to approximate $\mathbb{E}[\psi_i|\{XS^e_{im}\}_{m=1,\ldots,T_i}]$. The structure of the non-linear equation (3) that we want to estimate does not allow us to derive an estimator for ψ_i analytically, and we cannot use dummy variables either, because the cross-sectional dimension is very large. A widely used approximation for this purpose is the one suggested in Mundlak (1978).[10] The original Mundlak (1978) specification is linear, but in the following we additionally include a second-order term due to the non-linearity of equation (3), and we show later in Section 4.2.4 that this quadratic approximation is adequate. Therefore, our second identifying assumption is that the conditional expectation of the unobserved firm heterogeneity in the error term ξ_{iy} is

$$\mathbb{E}[\psi_i|\{XS^e_{im}\}_{m=1,\ldots,T_i}] \;=\; \delta_1\overline{XS^e_i} + \delta_2(\overline{XS^e_i})^2, \qquad \text{[ID2]}$$

where δ_1 and δ_2 are coefficients. This results in the following auxiliary regression for ψ_i

$$\psi_i \;=\; \delta_1\overline{XS^e_i} + \delta_2(\overline{XS^e_i})^2 + \omega_i, \tag{8}$$

where ω_i is the the part of the firm-specific heterogeneity that is mean independent from the survey expectations, that is $\mathbb{E}[\omega_i|\{XS^e_{im}\}_{m=1,\ldots,T_i}] = 0$; and $\overline{XS^e_i} = \frac{1}{T_i}\sum_{m=1}^{T_i} XS^e_{im}$ is the simple arithmetic mean of the survey variable XS^e_{im} across time for each firm i. Intuitively, ID2 and equation (8) control for the firms' forecasting behavior and their overall firm-specific optimism or pessimism when they respond to the survey. We can now substitute equation (8) for ψ_i in the numerator of ξ_{iy}, obtaining

$$\xi_{iy} = \frac{\delta_1\overline{XS^e_i} + \delta_2(\overline{XS^e_i})^2 + \omega_i}{1 - \gamma_1 P_{iy} - \gamma_2 N_{iy}}. \tag{9}$$

[9]This notation is distinct from $\{XS^e_{im}\}_{m\in y}$, used above, which refers to all months m in year y.

[10]See e.g. Bartelsman et al. (1994), Semykina and Wooldridge (2010), Kosova (2010) and Triguero and Córcoles (2013)). The Mundlak (1978) approximation is the standard tool used in non-linear models in panel data. In linear models, it is equivalent to the least squares dummy variable and the standard within estimator.

The Final Equation to be Estimated. As we have provided a way to approximate the unobserved firm heterogeneity, we can now derive the final equation to be estimated. We substitute equation (9) into equation (6) and obtain

$$x_{iy} \quad = \quad \frac{\alpha P_{iy} - \beta N_{iy} + \delta_1 \overline{XS_i^e} + \delta_2 (\overline{XS_i^e})^2}{1 - \gamma_1 P_{iy} - \gamma_2 N_{iy}} + \tilde{\xi}_{iy}, \tag{10}$$

where

$$\tilde{\xi}_{iy} = x_{iy}^{fe} + \frac{\omega_i}{1 - \gamma_1 P_{iy} - \gamma_2 N_{iy}}. \tag{11}$$

Overall, equation (10) is estimable because the error term $\tilde{\xi}_{iy}$ is mean-independent of the explanatory variables. We provide a formal proof of this statement in Online Appendix B.2. This addresses the issue of the unobserved heterogeneity in equation (6), so that we can obtain consistent estimates of the coefficients of interest, α, β, γ_1 and γ_2.[11]

Controlling for seasonality. The exposition above describes our quantification method, yet we can refine it by controlling for the seasonality in the monthly forecasts of the firm. We define the weights

$$\mathcal{W}_{im}^{+} = W_{im} \mathbb{1}_{[XS_{i,m}^e = +1]}, \qquad \text{and} \qquad \mathcal{W}_{im}^{-} = W_{im} \mathbb{1}_{[XS_{i,m}^e = -1]}. \tag{12}$$

They consist of two components. The first component in each weight, W_{im}, accounts for the fact that some months have a higher level of firm sales than others and therefore represent a larger share of the final annual outcome, which is the seasonality. It is defined as

$$W_{im} \triangleq \frac{w_{im}}{\sum_{m \in y} w_{im}}, \tag{13}$$

where w_{im} is the ratio of the seasonally unadjusted over the seasonally adjusted real gross value added. Intuitively, when this ratio exceeds unity, unadjusted gross value added is higher than the seasonally adjusted one, meaning that during this month value added is above normal levels due to seasonality, and this month is more important than others for the annual outcome. Our theoretical decomposition allows for individual

[11] The error term, $\tilde{\xi}_{iy}$, in equation (10) is likely to be heteroscedastic and autocorrelated within each firm. When we estimate such an equation, we will use the heteroscedasticity robust estimator for the standard errors, which addresses both problems — this robust estimator treats errors as clustered within cross-sectional units.

weights for each firm i, but in our practical implementation below, data availability limits the design of w_{im} to be the same across all firms in the manufacturing sector at quarterly frequency.[12] The second component of the weights $\mathcal{W}_{im}^{+}$ and $\mathcal{W}_{im}^{-}$ is the indicator variables that we used in deriving equation (3) and correspond to expectations of positive or negative sales growth.

The introduction of the seasonal weights does not affect the algebraic manipulations that lead to equation (3) nor does it affect our omitted variable problem and the approximation of the firm-specific heterogeneity. One simply has to use these weights to compute the variables P_{iy} and N_{iy} for equation (10) as follows

$$P_{iy} = \sum_{m \in y} \mathcal{W}_{im}^{+}, \qquad \text{and} \qquad N_{iy} = \sum_{m \in y} \mathcal{W}_{im}^{-}. \tag{14}$$

Summary of the Quantification Method. We have derived two nonlinear equations. Equation (10) relates observed quantitative annual sales to observable variables and the identifying assumption ID2 ensures that the coefficient estimates are consistent. Equation (3) relates unobserved quantitative expected sales growth to observable variables. The key is that both of these relationships depend on the same parameters. We estimate the parameters from equation (10) using Nonlinear Least Squares (NLS), and use these estimated parameters in equation (3) to derive fitted values for quantitative expectations on sales growth.

The practical implementation of the estimation methodology to derive quantitative forecasts on sales growth can be summarized in the following steps:

1. Compute the weighted shares of months per year that record a rise (decline) in expected sales P_{iy} (N_{iy}) from survey data, using equation (14), with the weights defined in equations (12) and (13).

2. Compute the firm heterogeneity proxies, $\overline{XS_i^e}$ and $(\overline{XS_i^e})^2$, based on the arithmetic mean (across time for each firm i) of the qualitative survey variable XS_{im}^e .

3. Estimate equation (10) using NLS. Run the estimation separately for the boom ($y \leq 2008$) and bust period ($y > 2008$).[13]

[12] We use 2-digit seasonally unadjusted and adjusted real gross value added for the manufacturing sector from Eurostat, Table 'namq_10_a10' for Greece, both in 2005 Chain Linked Volumes. We use value added since information on sales is not available at monthly or quarterly frequency.

[13] In Online Appendix B.4 we outline an alternative procedure that allows the parameters to be state dependent and tests for

4. Use the NLS estimated coefficients of equation (10) to compute the fitted values, $\hat{x}^e_{iy}$, for quantified sales growth forecasts from equation (3).

Our parameter estimates of the NLS estimation of equation (10) are documented in Section 4.1.1 below. The difference between the sales growth rate available from the financial statements, x_{iy}, minus the quantified forecast on sales growth for the corresponding year, $\hat{x}^e_{iy}$, then gives the quantified forecast error on sales growth, $\hat{x}^{fe}_{iy}$.

Our methodology to quantify forecasts and forecast errors is generally applicable to variables other than sales growth. It is applicable to any qualitative (survey based) variable on future developments, as long as a quantitative corresponding variable on realization is available at a lower frequency. Even in datasets where the time dimension of the panels is short, our methodology remains applicable. First, if the dimension of the panel with the high-frequency observations is 'shorter' than the monthly frequency in our data, then there would be some loss of accuracy in the estimated parameters of the NLS equation. We show that the loss of accuracy is small using a Monte Carlo simulation in Section 4.2.2. Second, where the low-frequency panel is short, there are no consequences for accuracy nor for consistency. Indeed, to achieve consistency we have shown that the omitted variable problem can be ignored and the unobserved firm heterogeneity can be proxied with the Mundlak (1978) fixed effects proxy. The omitted variable is not affected by the time-series length of the panels, and equation (8) would still provide a valid proxy of the unobserved firm heterogeneity if the time-series length per panel at the low-frequency data was short.

4 Application of the Quantification Methodology

In this section, we apply our quantification methodology using the data set introduced in Section 2. We estimate Greek firms' forecast errors of their own sales growth in Section 4.1.1 and provide the reader with an overview about the panel-data estimates in Section 4.1.2. Section 4.2 uses the forecast error estimates for Greek firms, as well as artificially generated data, and data of UK firms for various tests on the accuracy and validity of our quantification methodology.

these state dependencies.

4.1 An application on Greek firms' forecasts of own sales growth

4.1.1 Baseline Nonlinear Least Squares Estimation Results

Table 2 reports the results of the NLS estimation of equation (10). Column (1) shows estimation results for the boom period up to 2008 and column (2) for the following recession. As a reminder, α and $-\beta$ are the constant terms in the positive and negative continuous monthly forecasts of ID1. We observe that the constant of the positive monthly forecasts is larger during the boom than in the bust which is consistent with our economic intuition. Moreover, the constant of the negative monthly forecast is lower during the bust than in the boom, which is also consistent with our economic intuition.

Table 2: NLS Estimation of Equation (10).

	(1)	(2)
Coefficients	Dependent Variable: x_{iy}	
α	0.190**	0.104**
β	0.151*	0.238***
δ_1	-0.0255	-0.127***
δ_2	-0.00215	-0.0530
γ_1	-0.366	-0.446
γ_2	-0.179	0.0712
Firm-Year Observations	2,471	1,397
R^2	0.043	0.057
Period	$y \leq 2008$	$y > 2008$

Fixed effects proxies of equation (10) are omitted – but are included in the estimation – to maintain a simple representation. We use robust standard errors and ***, ** and * indicates 1%, 5% and 10% significance. Column (1) shows results for the boom period up to 2008 and column (2) for the following recession.

4.1.2 Descriptive Statistics on the Quantified Forecast Errors

Figure 1 shows the distribution of forecast errors. We report moments on this distribution in Table 3. The average forecast error in our sample is zero and slightly larger than the median (-0.03). This implies that the median forecast on sales growth is three percentage points more optimistic than the subsequent realization. Overall, a number of forecast errors made by firms are small (in absolute value), as these are centred close to zero, but still a significant number of forecast errors made are quite substantial given the high standard deviation. A non-negligible number of firms make forecast errors that imply 50% higher or lower sales than expected.

In Table 3 we also observe that the mean value of the quantified forecast errors does not appear to be countercyclical and their standard deviation is not procyclical as the literature has found (see for example Bachmann et al. (2013)). We note, however, that the observable survey-based forecast errors do not appear to have these properties either, which suggests it is not the quantification that has eliminated these properties. We also note that the case of Greece is particularly different from other developed economies, because it experienced a prolonged period of expansion (boom) that was followed by a prolonged and particularly severe contraction (bust).

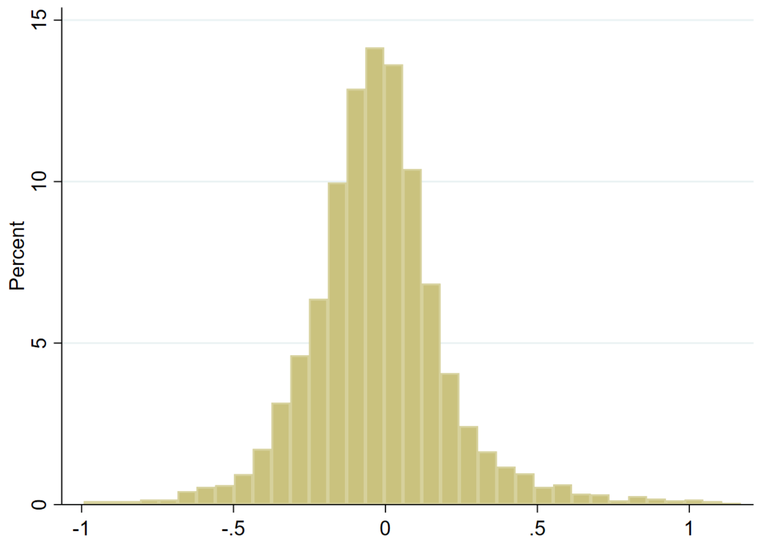

Figure 1: **Distribution of Annual Quantified Sales Growth Forecast Errors.** The 1% of forecast errors at the top of the distribution are omitted to ease visibility.

Table 3: Descriptive Statistics for Quantified Sales Growth Forecast Errors.

	Mean	Median	Stand. dev.
Full Sample	0.00	-0.03	0.34
Boom	0.01	-0.02	0.34
Bust	-0.02	-0.05	0.35

The boom (bust) period spans the years 1998-2008 (2009-2015).

4.2 External validity, validity of our assumptions and robustness checks

In this section, we conduct a number of of exercises to demonstrate the external validity of our quantification methodology. First, we use the qualitative firm forecast data from the survey as a benchmark and test whether our quantified estimates are accurate in terms of the sign of expected sales growth. In the second type, we test the accuracy of our quantification methodology in terms of the magnitude of firm growth forecasts. We do so by conducting a Monte Carlo experiment using artificial datasets, and also by employing our methodology on a dataset of UK firms for which qualitative monthly and quantitative annual survey forecasts are directly available.

Additionally, we run a number of robustness checks to demonstrate that our quantified forecast errors remain robust to relaxing some of our assumptions. First, we use alternative weights to compute the variables P_{iy} and N_{iy} for equation (10). Second, we use a cubic approximation of the Mundlak (1978) fixed effects that proxy for the unobserved firm-specific heterogeneity. Third, we relax our assumption that the parameters α, β, γ_1 and γ_2 are common for all firms and allow them to vary with i.

4.2.1 Directional Consistency of Estimated Forecasts with the Survey Data.

We can use the observed survey data on the direction of expected sales growth to benchmark how well our quantified forecasts match the direction of expected sales growth. To facilitate the comparison of the monthly survey data with our annual forecast estimates, we annualize the survey responses by computing a weighted yearly average $\sum_{m\in y} \mathcal{W}_{im}[XS^e_{im}]$, where the weights are based on equation (14). The distributions of the raw monthly and annualized survey expectations are reported in the Online Appendix B.5. While the annualized survey forecasts cannot provide a detailed indication about the size of the forecasts, as they are based on trinomial and purely qualitative monthly data, they can still be informative about the direction of the observed forecasts.

To benchmark our estimates of quantified forecasts against the annualized survey-based qualitative forecasts, we split responses in each of these two variables into three categories — positive, zero or negative — and cross-tabulate the three directions. Table 4 reports how well our quantified forecasts match the direction of the annualized observable ones. The main diagonal shows the share of observations that are directionally consistent across the two variables when classified as either positive, zero or negative. Overall, the direction of our quantified forecasts are highly consistent with the ones of the annualized survey responses — their direction coincides for 93.98% of all observations (the sum of the main diagonal).

The small share of observations for which the directions do not coincide can be explained by the absence of information on scale in the qualitative survey data. In practice, even if the majority of all monthly forecasts in one year point in the same direction, a single large monthly forecast in the opposite direction could dominate the annual response. This however cannot be captured by annualizing purely qualitative monthly forecasts. For this reason, we also report in Table 4 results based on a restricted sample that only includes annualized observations for years in which all underlying monthly survey responses indicated sales forecasts in the same direction. This ensures that the direction implied by the annualized survey data is accurate for all considered observations. Panel B shows results for this restricted sample which comprises 26% of the observations of the full sample used in Panel A. It is evident that now the direction of all quantified forecasts is consistent with the ones of the annualized survey responses.[14]

Table 4: Directional consistency between survey-based sales forecasts and forecasts based on different quantification methodologies (share in total observations)

	Entire Sample			**Restricted Sample**		
	Panel A: NLS			**Panel B: NLS**		
	Negative	Zero	Positive	Negative	Zero	Positive
Negative Forecasts	23.94%	0.00%	1.45%	11.21%	0.00%	0.00%
Zero Forecasts	0.26%	14.71%	0.34%	0.00%	56.96%	0.00%
Positive Forecasts	3.98%	0.00%	55.33%	0.00%	0.00%	31.83%
	Directional Consistency: 93.98%			Directional Consistency: 100.00%		

Rows refer to forecasts on sales growth based on annualized weighted average of the firm-month survey responses. Variables in columns refer to estimates for quantified sales growth forecasts using Non-Linear Least Squares. The restricted sample only considers annualized survey observations for which, in a given year, all underlying monthly observations report forecasts in the same direction.

Overall, our exercise shows that forecasts based on our quantification methodology are fully consistent with the direction of sales growth implied by the qualitative survey responses. We next turn to a Monte Carlo exercise that uses simulated data to infer how precisely our estimates match the magnitude of underlying true forecast errors.

[14] Results are fully directionally consistent even if we consider annualized observations for which at least 67% of all underlying monthly survey responses of a particular year indicated sales forecasts in the same direction. This comprises 39% of the observations of the full sample used in Panel A.

4.2.2 Monte Carlo Experiment.

It is important to understand how well forecast errors based on our methodology match, in terms of magnitude, true quantitative forecast errors. In practice, this is challenging to do due to the unavailability of data on quantitative firm-level expectations. This dearth of data was, indeed, the key motivation for developing the quantification methodology proposed in this paper. The vast majority of surveys contain qualitative questions about firms' future developments. If quantitative survey-based expectations are available at all, then they either focus on aggregate rather than firm-specific variables or have an extremely limited sample size. To overcome this obstacle, we perform a Monte Carlo exercise that provides a benchmark based on simulated data. In particular, we simulate data on firm (continuous) annual sales growth realizations, as well as corresponding qualitative and quantitative expectations. We then use the data on realized sales growth and qualitative expectations as inputs to the quantification methodology of Section 3.1 and generate estimates for quantified sales growth expectations. Subsequently, we evaluate the accuracy of the estimated forecast errors in comparison to those based on the underlying artificial 'true' data.

We generate 1,000 sets of random artificial data, each one of which mimics the structure of the true dataset in terms of number of firms and its unbalanced nature of firm-year-month observations. Details about the data generation are provided in the Online Appendix B.6. This Appendix documents that the underlying processes and their calibration to generate the artificial data are carefully guided by the characteristics and statistics of the observable financial statements and the survey data. We further highlight in this appendix that the simulated datasets match closely moments and statistics in the empirical data that have not been targeted during the calibration.

Panels A and B of Table 5 show the distribution of the true forecast error and of the estimated ones, all based on the artificial datasets. The mean and median of their distribution are very close — for both moments the difference is only about one percentage point of sales growth. This is very small, particularly when recalling from Figure 1 and Table 3 that the absolute median forecast error in our data is three percentage points and the empirical distribution has non-negligible mass at forecast error values as large as 50 percentage points of sales growth. The close correspondence between the estimated and the true forecast error can also be illustrated in a scatter plot. Figure 2 contains the scatter plot for one artificial dataset (randomly chosen among the 1,000 draws). The forecast error pairs conform to the 45 degree line (red) quite closely.

Table 5: Distribution of the estimated quantitative forecast error and the true quantitative forecast error (both based on artificial data)

	5%	10%	25%	Median	Mean	75%	90%	95%
	Panel A: True forecast errors							
Average	-0.654	-0.510	-0.268	0.000	0.002	0.269	0.511	0.654
St. dev.	0.018	0.014	0.012	0.011	0.009	0.012	0.014	0.018
	Panel B: Quantification using all monthly survey responses							
Average	-0.646	-0.501	-0.259	0.011	0.013	0.281	0.524	0.669
St. dev.	0.014	0.011	0.010	0.009	0.008	0.010	0.012	0.014
	Panel C: Quantification using only quarterly survey responses							
Average	-0.645	-0.499	-0.254	0.018	0.020	0.291	0.536	0.682
St. dev.	0.019	0.015	0.013	0.013	0.011	0.014	0.017	0.021

We report the average and standard deviation (St. dev.) across 1,000 random samples of artificial data of the descriptive statistics.

In Panel C of Table 5 we show the distribution of the estimated quantitative forecast error and the true quantitative forecast error when using *only the quarterly survey responses*. We do this exercise to assess the degree of the loss of accuracy in the case that the dimension of the panel with the qualitative survey-based observations is 'shorter' than the monthly frequency that we have in our data. Observe that the two distributions of the quantified forecast errors in Panels B and C are very close so any measurement error resulting from using quarterly instead of monthly observations is not substantial. Also the standard deviation of the moments across the 1,000 trials of the Monte Carlo are slightly higher in Panel C than B. This is to be expected because the reduction in the survey-based observations will result in losses in efficiency.

4.2.3 Validating Forecast Error Accuracy and ID1 in a Sample of UK Firms.

As explained above, the vast majority of firm-level surveys contain only qualitative questions. If surveys have quantitative features, these are typically limited. While this highlights the importance of developing methodologies to quantify qualitative survey responses, it makes it difficult to validate our methodology

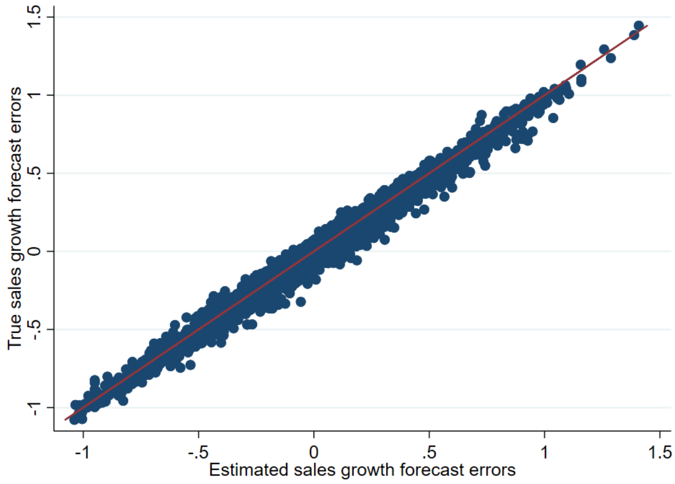

Figure 2: **Pairs of true and estimated sales growth forecast errors based on artificial data.** The figure shows all points in the dataset (we randomly selected one of the 1,000 draws for the datasets). The 45^o line is shown in red.

against survey-based quantitative forecast errors. In principle, we can do so if a dataset contains firm-level information on (i) monthly qualitative survey based forecasts for the three-month period ahead, (ii) quantitative annual survey forecasts, and (iii) annual realizations of the underlying variable. We have managed to obtain this information for a very limited sample of firms in the UK manufacturing sector. To the best of our knowledge, this is the only dataset that contains all three types of data required to inspect the accuracy of our methodology. In particular, we consider quantitative annual forecasts on firm's own turnover growth from the Management and Expectations Survey which was conducted by the Office for National Statistics (ONS) in 2017. During the same year, the Confederation of British Industry (CBI) independently collected qualitative monthly survey forecasts on firm's output growth.[15] To obtain the annual realizations on turnover growth we match the survey data with the Financial Statements from Bureau Van Dijk's FAME dataset.[16] Since the ONS and CBI surveys are conducted independently, the resulting matched sample is very small. It consists of 173 firm-month observations for qualitative survey forecasts on output growth, and 47 observations for annual quantitative forecasts on turnover growth and the corresponding realizations.

[15]Details about the ONS survey can be found in Awano et al. (2018) and Bloom et al. (2021). The CBI's survey on forecasts has a similar structure as the one from the IOBE for Greece, as both are used to construct EU-wide index of business climate by the Directorate-General for Economic and Financial Affairs (see DGECFIN (2017)).

[16]We thank Nick Bloom, Paul Mizen, Rebecca Riley and Michael Mahony for sharing the survey data and linking tables.

Table 6: Distribution of the difference between the estimated quantitative forecast error and the observed quantitative forecast error in a sample of firms in the UK manufacturing sector.

5%	10%	25%	Median	Mean	75%	90%	95%
-0.135	-0.128	-0.052	-0.001	-0.004	0.052	0.098	0.129

First, we implement our quantification methodology as follows. In the interest of statistical power, we fit the non-linear equation (10) to the realized turnover growth from FAME for a sample of 2,502 firm-year observations, for the period from 2000 until 2016. We then compute the forecast errors according to the methodology outlined in Section 3.1 for the 47 firms for which qualitative monthly survey forecasts are available. We compare these forecast error estimates with the quantitative forecast errors from the ONS survey. The distribution of the differences between the estimated and survey-based forecast errors is summarized in Table 6. Both, the mean and median of this distribution are very close to zero. Given that the ONS survey-based forecast errors have a mean of zero and a standard deviation of 0.31, the overall distribution for differences in forecast errors shown in Table 6 is rather tight. This is striking also because the monthly survey question is concerned with output growth and the annual survey question with turnover growth, which are closely related, but may not be perceived by respondents as exactly equal.[17]

Second, we give evidence that supports our identifying assumption ID1 that the monthly expectations during a given year are linearly correlated with the corresponding annual expectations about the same year. We find that the monthly qualitative survey forecasts are correlated with their annual quantitative counterparts. We also find that this linear correlation does not vary within the year.[18]

4.2.4 Robustness Checks

Alternative Weighting Schemes. This section shows results based on two alternative weighting schemes used in equation (14). In particular, while our baseline weighting controls for seasonalities within the year, we consider as an alternative that all observations are weighted equally per year as well as with decreasing monthly weights.

[17]In Online Appendix B.7, we show the close correspondence between the imputed and the true forecast errors in the MES and CBI data illustrated in a scatter plot.

[18]We have more details about this exercise in Online Appendix B.8.

The decreasing monthly weights are motivated by the fact that an expected increase in sales in the first months of the year might have a larger effect on the overall forecast of sales growth for the entire year. For example, consider a case (a) in which a firm expects an increase in sales in the first three months of the year and then monthly sales are expected to stabilise at a higher level for the rest of the year. Consider also and alternative example, case (b) where the same firm would expect monthly sales to remain constant during the first nine months of the year and expect an increase in the last three months. The true expected sales growth for the entire year would be higher in case (a) than in case (b), but the quantified expectations from our methodology would be equal for the two cases as the variables P_{iy} and N_{iy} would also be equal between case (a) and case (b).

To control for this, in our robustness exercise we apply weights in equation (13) that are decreasing with the months. That is, January has a weight of $w_{im} = 12$; February has $w_{im} = 11$; March has $w_{im} = 10$; ...; December has $w_{im} = 1$.

Table 7 shows the distribution of the quantified forecasts using (i) our baseline weighting scheme, (ii) constant monthly weights, and (iii) decreasing monthly weights. We observe that the differences in the three distributions are minimal. That is, the quantified forecast errors are robust to using alternative weighting schemes.

Table 7: Distribution of baseline quantified forecast errors and quantified forecasts based on alternative weighting schemes.

	Min	5%	10%	25%	Median	Mean	75%	90%	95%	Max
Baseline	-0.993	-0.370	-0.282	-0.148	-0.028	-0.001	0.093	0.243	0.407	5.226
Constant weighting	-0.992	-0.370	-0.281	-0.147	-0.027	-0.001	0.093	0.242	0.407	5.226
Decreasing weighting	-0.967	-0.363	-0.276	-0.141	-0.025	0.004	0.100	0.248	0.419	5.226

Cubic approximation of firm fixed effects. To control for unobserved heterogeneity, we employ a quadratic approximation. In this section, we show that a finer approximation of the firm fixed effect is not required. In Table 8, we re-estimate our baseline equation (10) including the cubic term $(\overline{XS_i^e})^3$ to proxy for the firm fixed effect. That is

$$x_{iy} = \frac{\alpha P_{iy} - \beta N_{iy} + \delta_1 \overline{XS_i^e} + \delta_2 (\overline{XS_i^e})^2 + \delta_3 (\overline{XS_i^e})^3}{1 - \gamma_1 P_{iy} - \gamma_2 N_{iy}} + \tilde{\xi}_{iy}, \quad (15)$$

where

$$\tilde{\xi}_{iy} = x_{iy}^{fe} + \frac{\omega_i}{1 - \gamma_1 P_{iy} - \gamma_2 N_{iy}}.$$

The estimates clearly demonstrate that the coefficient of the cubic term is not statistically significant in any of the periods. The estimates are not sensitive to the inclusion of the cubic term and are close to those reported in Table 2.

Table 8: Robustness check: Cubic approximation of firm-level fixed effects.

Coefficients	Dependent Variable: x_{iy}	
α	0.196*	0.104**
β	0.151*	0.241***
δ_1	-0.0334	-0.147***
δ_2	-0.0104	-0.0380
δ_3	0.0225	0.0521
γ_1	-0.406	-0.370
γ_2	-0.215	0.0505
Firm-Year Observations	2,471	1,397
R^2	0.043	0.057
Period	$y \leq 2008$	$y > 2008$

Table shows estimates of estimates of equation (15). We use robust standard errors and ***, ** and * indicates 1%, 5% and 10% significance. Columns (1) and (3) show results for the boom period up to 2008 and columns (2) and (4) for the following recession.

Correlated Random Coefficients. We turn now to relaxing our assumption that the parameters α, β, γ_1 and γ_2 are common for all firms and allow them to vary with i.

Beginning with the the parameters α and β, the unobserved heterogeneity we capture in equation (8) and ID2 controls for having distinct α and β for each i. One can decompose the error terms of equations (2) as standard in the literature, which will make α and β varying for each i and which is essentially how the ordinary 'firm fixed effects' work. This is how we introduce the unobserved firm heterogeneity.

Let us now examine the possibility that the parameters γ_1 and γ_2 vary with i in equations (3). Suppose that the true coefficients in the population are $\gamma_{1i} = \gamma_1 + \tilde{\gamma}_{1i}$ and $\gamma_{2i} = \gamma_2 + \tilde{\gamma}_{2i}$, where $\tilde{\gamma}_{1i}$ and $\tilde{\gamma}_{2i}$ are centred around 0 and distinguish the firm-specific component from the common one. We can rewrite the final equation that we will estimate as

$$x_{iy} = \frac{\alpha P_{iy} - \beta N_{iy} + \delta_1 \overline{XS_i^e} + \delta_2 (\overline{XS_i^e})^2}{1 - \gamma_{1i} P_{iy} - \gamma_{2i} N_{iy}} + \tilde{\xi}_{iy}$$
$$= \frac{\alpha P_{iy} - \beta N_{iy} + \delta_1 \overline{XS_i^e} + \delta_2 (\overline{XS_i^e})^2}{1 - \gamma_1 P_{iy} - \gamma_2 N_{iy} - \tilde{\gamma}_{1i} P_{iy} - \tilde{\gamma}_{2i} N_{iy}} + \tilde{\xi}_{iy},$$

where

$$\tilde{\xi}_{iy} = x_{iy}^{fe} + \frac{\omega_i}{1 - \gamma_1 P_{iy} - \gamma_2 N_{iy} - \tilde{\gamma}_{1i} P_{iy} - \tilde{\gamma}_{2i} N_{iy}}.$$

Owing to the sample restrictions in our data and the non-linear form of our model we are unable to model the term $-\tilde{\gamma}_{1i} P_{iy} - \tilde{\gamma}_{2i} N_{iy}$ for each firm by estimating for instance the non-linear equation for each firm independently.

As a robustness check of the consistency of our estimates, we approximate the firm-specific components of γ_1 and γ_2 using two firm-specific variables: (i) the age of the firm in its first appearance in the sample, age_i, (ii) and the size of the firm in its first appearance in the sample measured as the decile (values 1-10) of the value of the firm's real total net assets, K_i. We report that firms stay in the sample for on average 5 years and during this period we do not observe large swings in their net assets growth (each firm grows on average by 3.8% during its presence in the survey sample), so their decile size in the first appearance in the sample remains a reliable proxy for the size of the firm during its overall sample presence. Essentially, we assume that $\gamma_{1i} = \gamma_1 + \tilde{\gamma}_1 \cdot Z_i$ and $\gamma_{2i} = \gamma_2 + \tilde{\gamma}_2 \cdot Z_i$, where $Z_i = age_i, K_i$. That is, we assume a specific form for $\tilde{\gamma}_{1i}$ and $\tilde{\gamma}_{2i}$ in which age or size captures the firm specific effect. We used age because there is evidence in the literature that it affects forecast accuracy (see Tanaka et al. (2020)) and size following our economic intuition that larger firms might have more resources to make more rational forecasts. Then, we estimate in Table 9 the following equation

$$x_{iy} = \frac{\alpha P_{iy} - \beta N_{iy} + \delta_1 \overline{XS_i^e} + \delta_2 (\overline{XS_i^e})^2}{1 - \gamma_1 P_{iy} - \gamma_2 N_{iy} - \tilde{\gamma}_1 \cdot Z_i \cdot P_{iy} - \tilde{\gamma}_2 \cdot Z_i \cdot N_{iy}} + \tilde{\xi}_{iy}, \tag{16}$$

with $Z_i = age_i, K_i$.

In Table 9, we show that the estimates of α and β and their significance during both the boom and the bust periods are very close to the ones we obtained from our baseline model in Table 2, while the coefficients $\tilde{\gamma}_l$ are not significant. At first look, the estimates of γ_1 and γ_2 in the new equation are different. However, if we compute the quantities $\gamma_l + \tilde{\gamma}_l \cdot \overline{Z_i}$, $l = 1, 2$ which is equivalent to the assumptions of or baseline estimates, then these quantities are very close to the ones we obtained in the baseline estimation — see Table 10.[19] The exception is $\gamma_1 + \tilde{\gamma}_1 \cdot \overline{age_i}$ and only during the boom period, which has a smaller magnitude than the baseline estimate. Overall, our robustness check suggests that our baseline estimates are unaffected by using age to proxy for firm-specific γ_1 and γ_2.

Table 9: NLS Estimation of Equation (16) – Robustness for firm-varying γ_1 and γ_2.

	(1)	(2)	(3)	(4)
Coefficients	Dependent Variable: x_{iy}			
	$Z_i = age_i$		$Z_i = K_i$	
α	0.176**	0.109**	0.193**	0.105**
β	0.141**	0.232***	0.145*	0.241***
δ_1	-0.0255	-0.128***	-0.0209	-0.130***
δ_2	-0.0321	-0.0579	-0.00824	-0.0477
γ_1	0.555	-0.883	-0.198	-0.717
γ_2	0.363	0.0438	0.449	0.155
$\tilde{\gamma}_1$	-0.0330*	0.0161	-0.0376	0.0521
$\tilde{\gamma}_2$	-0.0201	0.00196	-0.130	-0.0194
Firm-Year Observations	2,461	1,395	2,461	1,395
R^2	0.047	0.057	0.043	0.056
Period	$y \leq 2008$	$y > 2008$	$y \leq 2008$	$y > 2008$

The table shows estimates of equation (16). Columns (1) and (2): $Z_i = age_i$, i.e. age of the firm in its first appearance in the sample. Columns (3) and (4): $Z_i = K_i$, i.e. the size of the firm in its first appearance in the sample (decile of real total net assets). Columns (1) and (3) show results for the boom period up to 2008 and columns (2) and (4) for the following recession. We use robust standard errors and ***, ** and * indicates 1%, 5% and 10% significance.

5 Conclusion

In this paper, we develop a novel methodology to quantify qualitative survey data on expectations. This methodology is applicable generally when quantitative information is available on the realization of the

[19] $\overline{Z_i}$ is the average age ($Z_i = age_i$) across the sampled firms and is equal to 25 years; or the average decile of total net assets ($Z_i = K_i$) which is equal to 5.

Table 10: Calculating firm-varying γ_1 and γ_2 at the average, $\gamma_l + \tilde{\gamma}_l \cdot \overline{Z_i}$ with $l = 1, 2$ and $Z_i = age_i, K_i$.

	(1)	(2)	(3)	(4)	(5)	(6)
	$Z_i = age_i$		$Z_i = K_i$		Baseline, $\tilde{\gamma}_l = 0$	
	Boom	Bust	Boom	Bust	Boom	Bust
$\gamma_1 + \tilde{\gamma}_1 \cdot \overline{Z_i}$	-0.19	-0.39	-0.4	-0.467	**-0.366**	**-0.446**
$\gamma_2 + \tilde{\gamma}_2 \cdot \overline{Z_i}$	-0.14	0.09	-0.2	0.06	**-0.179**	**-0.071**

age_i is the firm's age at the first appearance in the sample with an average of 25 years across firms; K_i is the firm's decile of total net assets at the first appearance in the sample with an average of 5 across firms.

forecasted variable. We apply this methodology to Greek firm data on sales growth. The survey of firm expectations we use for Greek firms is similar in structure to the ones used by all European Union countries at a monthly frequency. A key component of our methodology to produce quantified expectations estimates of sales growth using the qualitative survey data is to combine firm balance sheet data on realized sales.

Once we have quantitative estimates of firms' forecasts and forecast errors, we can answer important questions about firm expectations formation and economic behavior. Do firms make errors in forecasting their future sales that are predictable and display autocorrelation? If so, what does that reveal about firm behavior and the way they form expectations? In particular, does firms' behavior conform to the Full Information Rational Expectations (FIRE) hypothesis? What are the causes of forecast errors, and how do these errors affect firm production, investment, and financing decisions? These are important questions to be pursued in future research.

A Appendix: Derivation of Equation (3)

This section shows how equation (3) can be derived using equations (1) and (2).

First, note that we can rewrite (1) as follows

$$x^e_{iy} = \mathbb{E}_{i,y-1} \sum_{m \in y} \left[x^{e,+}_{im} + x^{e,-}_{im} \right], \tag{17}$$

and we can naturally ignore the terms where $x^e_{im} = 0$.

Let us now use the indicator variables that take a value of unity if the expected sales growth rate x^e_{im} is either positive, $\mathbb{1}_{[x^e_{im}>0]}$, or negative, $\mathbb{1}_{[x^e_{im}<0]}$. Because we observe in the surveys the direction of x^e_{im}, we have that $\mathbb{1}_{[x^e_{im}>0]} = \mathbb{1}_{[XS^e_{i,m}=+1]}$ and $\mathbb{1}_{[x^e_{im}<0]} = \mathbb{1}_{[XS^e_{i,m}=-1]}$. Given the nature of the indicator variables, we can rewrite equation (17) as follows

$$x^e_{iy} = \mathbb{E}_{i,y-1} \sum_{m \in y} \left[\mathbb{1}_{[XS^e_{i,m}=+1]} x^{e,+}_{im} + \mathbb{1}_{[XS^e_{i,m}=-1]} x^{e,-}_{im} \right]. \tag{18}$$

Second, we take expectations of equations (2), which become

$$\mathbb{E}\left[x^{e,+}_{im} | \mathcal{F}_{i,y-1}\right] = \alpha + \gamma_1 x^e_{iy} + \mathbb{E}_{i,y-1}\nu^+_{im}, \quad \text{and} \quad \mathbb{E}\left[x^{e,-}_{im} | \mathcal{F}_{i,y-1}\right] = -\beta + \gamma_2 x^e_{iy} + \mathbb{E}_{i,y-1}\nu^-_{im}. \tag{19}$$

Then, we substitute equation (19) into (17)

$$x^e_{iy} = \mathbb{E}_{i,y-1} \sum_{m \in y} \mathbb{1}_{[XS^e_{i,m}=+1]} \left[\alpha + \gamma_1 x^e_{iy} + \nu^+_{im} \right] + \mathbb{E}_{i,y-1} \sum_{m \in y} \mathbb{1}_{[XS^e_{i,m}=-1]} \left[-\beta + \gamma_2 x^e_{iy} + \nu^-_{im} \right].$$

Then, we obtain

$$\begin{aligned} x^e_{iy} &= \left[\alpha + \gamma_1 x^e_{iy}\right] \mathbb{E}_{i,y-1} \sum_{m \in y} \mathbb{1}_{[XS^e_{im}=1]} + \mathbb{E}_{i,y-1} \sum_{m \in y} \mathbb{1}_{[XS^e_{im}=1]} \nu^+_{im} \\ &+ \left[-\beta + \gamma_2 x^e_{iy}\right] \mathbb{E}_{i,y-1} \sum_{m \in y} \mathbb{1}_{[XS^e_{im}=-1]} + \mathbb{E}_{i,y-1} \sum_{m \in y} \mathbb{1}_{[XS^e_{im}=-1]} \nu^-_{im}. \end{aligned} \tag{20}$$

To simplify the notation, we define

$$P_{iy} \triangleq \sum_{m \in y} \mathbb{1}_{[XS^e_{im}=1]}, \qquad \text{and} \qquad N_{iy} \triangleq \sum_{m \in y} \mathbb{1}_{[XS^e_{im}=-1]},$$

where P_{iy} (N_{iy}) denotes the share of months within a year that indicate a rise (fall) in *expected* sales.

Next we assume that (equation (5) in main text)

$$\mathbb{E}_{i,y-1} P_{iy} = P_{iy} \quad \text{and} \quad \mathbb{E}_{i,y-1} N_{iy} = N_{iy},$$

where both sides of these equations refer to firm forecasts.

This assumption allows us to rearrange equation (20) to solve for x_{iy}^e:

$$x_{iy}^e = \frac{\alpha P_{iy} - \beta N_{iy}}{1 - \gamma_1 P_{iy} - \gamma_2 N_{iy}} + \xi_{iy}, \qquad \text{with} \qquad \xi_{iy} = \frac{\mathbb{E}_{i,y-1} \sum_{m \in y} \left(\mathbb{1}_{[XS_{i,m}^e = +1]} \nu_{im}^+ + \mathbb{1}_{[XS_{i,m}^e = -1]} \nu_{im}^- \right)}{1 - \gamma_1 P_{iy} - \gamma_2 N_{iy}}.$$

We can rewrite the term $\left(\mathbb{1}_{[XS_{i,m}^e = +1]} \nu_{im}^+ + \mathbb{1}_{[XS_{i,m}^e = -1]} \nu_{im}^- \right)$ with a more compact representation that is standard in the literature, by decomposing it into a firm-specific component ψ_i, a time-specific term ψ_m and an idiosyncratic term ψ_{im}. We obtain

$$\mathbb{E}_{i,y-1} \sum_{m \in y} \left(\mathbb{1}_{[XS_{i,m}^e = +1]} \nu_{im}^+ + \mathbb{1}_{[XS_{i,m}^e = -1]} \nu_{im}^- \right) = \sum_{m \in y} \mathbb{E} \left(\psi_i + \psi_m + \psi_{im} \middle| \mathcal{F}_{i,y-1} \right),$$

by the definition of the conditional expectation, with $\mathcal{F}_{i,y-1}$ being the information set of firm i in year $y - 1$. This leaves us with

$$\mathbb{E}_{i,y-1} \sum_{m \in y} \left(\mathbb{1}_{[XS_{i,m}^e = +1]} \nu_{im}^+ + \mathbb{1}_{[XS_{i,m}^e = -1]} \nu_{im}^- \right) = \psi_i,$$

because the firm's expectation of the shocks ψ_m and ψ_{im} in $y - 1$ for the months of the following year y is 0. Note, that the expectation of ψ_m and ψ_{im} conditional on last year's information is 0, as firms cannot predict shocks. Mathematically, the random shocks ψ_m and ψ_{im} are by definition mean-independent of the firm's information set in $y - 1$. Note that $\mathbb{E}\psi_m = \mathbb{E}\psi_{im} = 0$, because $\mathbb{E}\nu_{im}^+ = \mathbb{E}\nu_{im}^+ = 0$ from the structure of equations (2). Therefore,

$$\xi_{iy} = \frac{\psi_i}{1 - \gamma_1 P_{iy} - \gamma_2 N_{iy}},$$

where the firm fixed effect is a source of endogeneity, but we control for it at a later step. The error term ξ_{iy} also indicates that any potential serial correlation in the monthly errors ν_{im}^+ and ν_{im}^+ that is not the result of the firm-specific unobserved heterogeneity is eliminated and is not of concern.

This completes the derivation of equation (3) in Section 3.1.

References

Anderson Jr, O. (1952). The business test of the IFO-Institute for economic research, Munich, and its theoretical model. *Revue de l'Institut International de Statistique*, 20(1):1–17.

Awano, G., Bloom, N., Dolby, T., Mizen, P., Riley, R., Senga, T., Van, J., Reenen, J. V., and Wales, P. (2018). A firm-level perspective on micro-and macro-level uncertainty. *ESCoE Discussion Pape*, 10.

Bachmann, R. and Elstner, S. (2015). Firm optimism and pessimism. *European Economic Review*, 79:297–325.

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

Bachmann, R. and Zorn, P. (2020). What drives aggregate investment? Evidence from german survey data. *Journal of Economic Dynamics and Control*, 115:103873.

Barrero, J. M. (2019). The micro and macro of managerial beliefs. *Stanford Institute for Economic Policy Research — Working Paper No. 19-010*.

Bartelsman, E. J., Caballero, R. J., and Lyons, R. K. (1994). Customer-and supplier-driven externalities. *The American Economic Review*, 84(4):1075–1084.

Bloom, N., Bunn, P., Chen, S., Mizen, P., Smietanka, P., and Thwaites, G. (2019). The impact of brexit on uk firms. *National Bureau of Economic Research Working Paper*.

Bloom, N., Kawakubo, T., Meng, C., Mizen, P., Riley, R., Senga, T., and Van Reenen, J. (2021). Do well managed firms make better forecasts? Technical report, National Bureau of Economic Research.

Born, B., Enders, Z., Müller, G. J., and Niemann, K. (2023). Firm expectations about production and prices: Facts, determinants, and effects. In *Handbook of Economic Expectations*, pages 355–383. Elsevier.

Coibion, O., Gorodnichenko, Y., and Kumar, S. (2018). How do firms form their expectations? New survey evidence. *American Economic Review*, 108(9):2671–2713.

Davidson, R. and MacKinnon, J. G. (2004). *Econometric theory and methods*, volume 5. Oxford University Press New York.

de Leeuw, F. and McKelvey, M. J. (1981). Price expectations of business firms. *Brookings Papers on Economic Activity*, 1981(1):299–314.

DGECFIN (2017). The joint harmonised EU programme of business and consumer surveys: User guide. *European Commission: Directorate-General for Economic and Financial Affairs*.

Diebold, F. X. and Mariano, R. S. (1995). Comparing predictive accu racy. *Journal of Business and Economic Statistics*, 13(3):253–263.

Enders, Z., Hünnekes, F., and Müller, G. J. (2019). Monetary policy announcements and expectations: Evidence from German firms. *Journal of Monetary Economics*, 108:45–63.

Kosova, R. (2010). Do foreign firms crowd out domestic firms? Evidence from the Czech Republic. *The Review of Economics and Statistics*, 92(4):861–881.

Manski, C. F. (2004). Measuring expectations. *Econometrica*, 72(5):1329–1376.

Mokinski, F., Sheng, X. S., and Yang, J. (2015). Measuring Disagreement in Qualitative Expectations. *Journal of Forecasting*, 34(5):405–426.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica*, pages 69–85.

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

Pesaran, M. H. (1987). *The limits to rational expectations*. Blackwell Publishers.

Pesaran, M. H. and Weale, M. (2006). Survey expectations. *Handbook of economic forecasting*, 1:715–776.

Semykina, A. and Wooldridge, J. M. (2010). Estimating panel data models in the presence of endogeneity and selection. *Journal of Econometrics*, 157(2):375–380.

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

Tanaka, M., Bloom, N., David, J. M., and Koga, M. (2020). Firm performance and macro forecast accuracy. *Journal of Monetary Economics*, 114:26–41.

Theil, H. (1952). On the time shape of economic microvariables and the Munich business test. *Revue de l'Institut International de Statistique*, 20(2):105–120.

Triguero, A. and Córcoles, D. (2013). Understanding innovation: An analysis of persistence for Spanish manufacturing firms. *Research Policy*, 42(2):340–352.

Vellekoop, N. and Wiederholt, M. (2019). Inflation expectations and choices of households. *SAFE Working Paper*.

Appendix (for Online Publication)

A Data

In the following we provide further details about the conduct of the IOBE survey (Section A.1) and the cleaning procedures on the IOBE and ICAP data (Sections A.2 and A.3). Section A.4 provides additional information about our matched sample and discusses representativeness and quality of survey responses.

A.1 Details on the Survey Data

The firm-level survey data are collected every month by IOBE. IOBE sends surveys to a sample of firms included in the ICAP firm directory. This directory covers more than 75% of the economy's output. The sample of surveyed firms is chosen to represent the distribution of firm sizes in terms of gross value added in each 2-digit sector. Every 4-5 years it is replenished by removing those firms who never replied and those who have stopped replying. These are replaced with new firms, following the same sampling principles, while the firms that have been responsive are retained in the sample. According to IOBE researchers, the response rate is somewhat smaller than 20% which is in line with response rates of surveys conducted for the European Commission in other countries.

IOBE send surveys by mail and email between the 22th and the 25th of each month – surveys refer to the following month. More than 80% of firms that reply do so by the 15th of the month the survey refers to, and more than 95% reply by the 20th. Responses that arrive well past the month they refer to, are dropped by the IOBE as it is unclear to which month responses refer. Less than 10% of responses are received by email. The vast majority of surveys are completed on paper and returned by mail in a prepaid envelope. The IOBE requests that surveys are completed by managers or a person who has complete knowledge of the entire activity of the surveyed firm.

Surveys are conducted monthly with the exception of August. In August the majority of firms are closed as managers and employees take their annual leave. For this reason, there are no surveys sent out at the end of July to record the responses for August. IOBE uses imputation methods to produce data for August and for monthly non-responses.[20] We will remove imputed observations in the cleaning section A.2.

A.2 Cleaning the Survey Data

The wording of the survey question is so that it asks about sales expectations for the next three months. This means expectations that include the last two months of a year would also be concerned with sales in the first one or two months of the following year. Similarly, the survey questions about realized sales asks about sales in the previous three months, so that responses at the beginning of the year may include sales developments of months in the previous year. For this reason we make adjustments to the submitted responses on realizations and forecasts in the concerning months, which are standard treatment of survey data in the literature. For forecasts, we multiply the survey variable with $2/3$ in November and with $1/3$ in December, as only two thirds and one thirds respectively, of the period over which expectations are recorded, belongs to the current calendar year. For realizations a similar argument applies and we set the responses in January to missing and use this observation with weight 1 in the final month of the preceding year. We further multiply recorded responses by $1/3$ in February, and $2/3$ in March. The intuition is that e.g. the response submitted in beginning to mid-February will cover sales relizations that concern November to January and hence only one out of three months included in the response is concerned with the current year. The underlying assumption for our adjustment is that the respondents attach the same weight to the three months covered in their response. This is a standard assumption in the survey literature and implicitly assumed for example in Bachmann et al. (2013) and Massenot and Pettinicchi (2018).

IOBE uses imputation techniques for missing monthly responses and for August, a month for which they do not send out surveys. We set to missing all the survey variables of the firm-month observations that were imputed.

Finally, we have set to missing all firm-month observations in one particular year if we have less than three monthly survey responses of this firm within the year. This was necessary because our quantification aggregates (and quantifies) the firm-month observation to the firm-year frequency. The informativeness of

[20]This is standard practice of survey providers. Lui et al. (2011) for example report that for the UK business climate survey, the Confederation of British Industry (who administer the survey) also implements imputation techniques for missing data.

this aggregation is rather limited when during the year, a firm has responded only once or twice. These cleaning steps leave us with 1,093 firms in the manufacturing sector that provide survey responses.

A.3 Cleaning the Financial Statements Data

We have financial statements data available from ICAP. In the following we outline the consecutive steps undertaken to prepare and clean the financial statements database. Prior to these steps this data comprised 1,219 firms with 18,786 firm-year observations in the manufacturing sector. After the cleaning we retained all 1,219 firms and 18,213 firm-year observations.

1. The way the data is recorded, Net Worth is included in Total Liabilities. Therefore, Total Net Assets should equal Total Liabilities, i.e. $TotalNetAssets_{i,y} = TotalLiabilitiess_{i,y}$, for every the firm i, year y. For the firm i-year y observations for which $TotalNetAssets_{i,y} \neq TotalLiabilitiess_{i,y}$, we replaced their values with those from an alternative Balance Sheet data-base of Hellastat S.A.[21,22] We confirmed that for the replaced values of $TotalNetAssets_{i,y}$ and $TotalLiabilitiess_{i,y}$ the equality holds, and that the net value of the sub-categories included in the Assets sum up to the Total Net Assets. If these variables did not add up, we set to missing all the financial statement variables of these firm-year observations.

2. The following equality should hold:

   $TotalGrossSales_{i,y} = GrossOpertingProfit_{i,y} + CostOfSoldGoods_{i,y}$, for every the firm i, year y. For the observations for which the above equality does not hold, we replaced their values with those from Hellastat. Then we confirmed that for the replaced values of $TotalGrossSales_{i,y}$, $GrossOpertingProfit_{i,y}$ and $CostOfSoldGoods_{i,y}$ the equality holds. If these variables did not add up, we set to missing all the financial statement variables of these firm-year observations.

[21]Non-satisfaction of the accounting identity is entirely due to human error, and since the data providers are different, the person making the error is also different, so we can assume that the two data-bases do not include the same errors.

[22]Hellastat S.A. is a private consultancy firm collecting and digitalizing the financial statements from official and publicly available sources. This database is very similar to our ICAP data, but includes a less detailed break-down of financial statement variables.

3. We set to missing all the financial statement variables for the firm-year observations for which the following equality does not hold.

$$
\begin{aligned}
&TotalNetValueOfFixedAssets_{i,y} + TotalAccumulatedDepreciation_{i,y}\\
=&GrossValueOfMachinery\&Equipment_{i,y} + GrossValueOfBuilding\&Facilities_{i,y}\\
&+ GrossValueOfIntangibleAssets_{i,y} + ValueOfLand_{i,y} + ValueOfHoldings_{i,y}\\
&+ ValueOfLongTermReceivables_{i,y}
\end{aligned}
$$

4. For some firm-year observations the NACE classification was the version 1 or its Greek analogue, STAKOD 2003. We used ELSTAT (2002), EUROSTAT (2008a) and EUROSTAT (2008b) to translate all NACE classifications to NACE v. 2.

5. $GrossDepreciablePropertyValue_{i,y}$ is defined as the sum of the Gross Values of Building & Facilities, Machinery & Equipment and Intangible Assets, for every firm i, year y. We set to missing all the financial statement variables for the firm i-year y observations for which at least one of the Gross Depreciable Property, the Gross Sales, the Total Net Fixed Assets, the Total Net Assets or the Owner's Equity is lower or equal to 0, as this would indicate that the firm was under dissolution in that year.

6. To derive values of Real Total Net Assets, Real Owner's Equity, Real Total Sales we used the annual implicit gross added value deflator (ratio of nominal over real value) from Eurostat Table nama_10_a64 for Greece. To derive Real Total Net Fixed Assets and Real Gross Depreciable Property we used the implicit deflator of capital stocks from Eurostat Table nama_10_nfa_st.

7. In the final cleaning steps, we deal with extreme observations that likely result from miscoding. When the growth rate of any the following variables was at the lower 0.5% of its empirical distribution we set to missing all the financial statement variables: Real Total Net Assets, Real Total Net Fixed Assets, Real Gross Depreciable Property, Real Owner's Equity, Real Total Sales.

8. When the real growth rate of any the following variables was at the upper 1% of its empirical distribution we set to missing all the financial statement variables: Real Total Net Fixed Assets, Real Gross

Depreciable Property, Real Total Sales.

A.4 The Matched Sample and Quality of Survey Responses

We match firms' financial statements data with the corresponding survey responses using the firm's unique tax identifier. As described in Section A.2, our cleaned survey data comprised 1,093 firms. We could match 73.1% of these firms (76.7% of the firm-month observations), so that the sample for which we have both survey and financial statement data comprises of — after the cleaning procedures described above — 799 firms in the manufacturing sector with 25,764 monthly responses from the survey on the two questions A.2 and D.2 and 4,104 annual balance sheet observations on sales. This section first establishes that our sample is representative for the manufacturing sector. Then we evaluate the quality of survey responses.

Representativeness. We evaluate representativeness of our sample in a number of ways using data from the survey and the financial statements.

First, we report a time-series correlation of 0.95 between the official IOBE business sentiment index for the manufacturing sector and a recalculated sentiment index based on our manufacturing sector dataset.[23] This high correlation shows that our dataset is still highly representative when responses are aggregated, even though we abstain from using the imputed survey responses and we dropped observations if firms responded fewer than three times in a calendar year. Second, we report a correlation of 0.64 between the average real growth rate of output in our sample as reported in the financial statements and the corresponding manufacturing sector output growth from Eurostat.[24] We perform this comparison using output since Eurostat only publishes sales for the Greek manufacturing sector from 2008. Third, to further examine the

[23]The monthly sentiment index for the manufacturing sector is computed as $\frac{QS_{im}+QS^e_{im}-INV_{im}}{3}$, where INV_{im} corresponds to the question *'The level of finished goods inventories you deem it is...'* with the possible responses being above/at/below normal levels and coded as $+1/0/-1$, respectively; and QS_{im} corresponds to the survey question *'For the preceding 3 months you assess that your production did...'*, QS^e_{im} corresponds to the question *'For the next 3 months you foresee that your production will...'*, and the possible responses are rise/no change/fall, coded as $+1/0/-1$, respectively.

[24]Output from the financial statements is the sum of sales plus the contemporaneous first difference of final goods inventories. We deflated the firm-year output of the financial statements using the ratio of the nominal over real (chain linked volumes) gross value added at the NACE 2-digit level. We use the simple arithmetic mean of the firm-year observations to obtain the average growth rate of our sample. The manufacturing growth rate of real output from Eurostat for Greece is from Table nama_10_a64.

representativeness of our final sample we study the share of each 2-digit sector in the total manufacturing sector sales. We compare the contributions based on our sample with the ones from the official Eurostat data. Table 1.A exemplifies these statistics for two years — 2009 and 2012 — and we observe that most of the shares based on our dataset are close to the ones reported by Eurostat with few exceptions of over- and under- representativeness.

Table 1.A: Share of NACE 2-digit industry sales in the total manufacturing sales in years 2009 and 2012.

	2009		2012	
NACE Code	Sample Data	Eurostat Data	Sample Data	Eurostat Data
10	13.35%	20.23%	16.01%	19.74%
11	10.11%	3.94%	6.03%	2.98%
12	2.67%	1.01%	1.60%	0.74%
13	1.99%	1.93%	1.94%	1.26%
14	0.58%	3.16%	0.29%	1.84%
15	0.74%	0.50%	0.20%	0.21%
16	0.95%	1.50%	0.06%	0.82%
17	1.63%	2.02%	0.89%	1.76%
18	0.84%	1.63%	0.30%	1.06%
19	19.71%	21.77%	45.19%	36.54%
20	5.58%	4.44%	4.22%	3.48%
21	10.70%	2.63%	6.08%	1.80%
22	2.42%	3.24%	2.17%	3.04%
23	6.95%	5.90%	1.92%	2.78%
24	7.23%	7.49%	1.19%	8.62%
25	6.93%	7.60%	7.29%	5.31%
26	2.60%	0.68%	1.00%	0.68%
27	0.68%	2.49%	0.57%	2.68%
28	2.14%	2.39%	1.57%	1.68%
29	0.53%	0.51%	0.25%	0.27%
30	0.39%	1.12%	0.78%	0.36%
31	0.62%	1.76%	0.21%	0.91%
32	0.38%	0.96%	0.23%	0.58%
33	0.28%	1.11%	0.00%	0.87%

For our sample, total manufacturing sales is the sum of sales of all firms in a particular year. The shares reported show the sum of sales in a 2-digit sector over total manufacturing sales in our sample for a particular year. The shares in the 'Eurostat' columns are the corresponding ratios based on Eurostat sales data based on Table sbs_sc_sca_r2 for Greece.

Quality of Survey Responses. In this section we first establish that the survey responses are consistent across different questions and then, we show they are consistent with data from the financial statements.

In the spirit of Coibion et al. (2018) we use a regression-based approach to evaluate the consistency of the survey responses across questions. We conduct two exercises to establish consistency that will jointly cover around two thirds of the survey questions. Turning to the first exercise, economic intuition suggests that if a firm expects excess future production capacity relative to sales, it is more likely to (i) report higher than normal inventory levels (ii) expect a drop in the sales (iii) expect it will have to decrease employment (iv) have lower capacity utilization that would allow it to increase production if need be. To confirm that this economic intuition holds in our data we estimate the following linear equation:

$$D3_{im} = \beta_0 + \boldsymbol{\beta}\Big[INV_{im}, XS^e_{im}, L^e_{im}, U_{im}\Big]' + \psi_i + \psi_y + \eta_{im}, \tag{21}$$

where the vector $\boldsymbol{\beta} = [\beta_1, \beta_2, \beta_3, \beta_4]$, ψ_i and ψ_y control for firm and year fixed effects respectively, and η_{im} is the idiosyncratic error. The variables $D3_{im}$, INV_{im}, XS^e_{im}, L^e_{im}, and U_{im} denote current production capacity, inventory level, sales, the number of employees, and capital utilization of firm i in month m and are derived from survey questions.[25]

We estimate equation (21) twice: first, by eliminating ψ_i using standard fixed effects tools and second, by substituting NACE sector dummies for ψ_i. In Panel A of Table 2.A we report the results from estimating equation (21). We observe that the signs of the variables under examination are as expected based on the economic intuition outlined above and that all estimates are statistically significant at the 1% level. The relatively low R^2 indicates that there are other factors that explain expected movements in production capacities. However, for the purpose of verifying the consistency of survey answers we are only interested in the directional relationship between variables.

In the second exercise, we focus on production. When we observe an increase in production, economic intuition indicates one factor behind this could be a rise in capacity utilization. We check this by estimating the following linear equation:

$$QS_{im} = \beta_0 + \beta_1[U_{i,m-1} - U_{i,m-3}] + \psi_i + \psi_y + \eta_{im}, \tag{22}$$

where U_{im} corresponds to the survey question asking about the percentage of capacity utilization for firm i in month m, QS_{im} indicates the change in past production, ψ_i and ψ_y control for firm and year fixed

[25] The precise questions are as follows. INV_{im}, question E.1: *'The level of your final goods inventories is: above normal/normal/below normal'*. $D3_{im}$, question E.2: *'Given the outstanding orders you have at the moment and the possible evolution of demand during the next months, the current production capacity is more than sufficient/sufficient/insufficient'*. XS^e_{im} refers to question D.2 outlined in the main body. L^e_{im}, question D.3: *'During the next 3 months, you expect your number of employees to increase/remain unchanged/decrease'*. In these questions, a numerical value -1 refers to reduction or lower than normal level or insufficient production capacity as appropriate; $+1$ refers to an increase or higher than normal level or more than sufficient as appropriate; and 0 refers to no change or normal level or sufficient capacity as appropriate. U_{im}, question E.3: *'During the ongoing period, what is your percentage (%) utilization of your production capacity?*. Firms respond to this question with a quantitative answer.

effects respectively, and η_{im} is the idiosyncratic error.[26] As previously, we estimate equation (22) in two ways: firstly, we eliminate ψ_i using standard fixed effects tools and secondly, we substitute NACE sector dummies for ψ_i. Results are reported in Panel B of Table 2.A. These are in line with economic intuition: an increase in production is positively and significantly correlated with a reported three-month increase in capacity utilization (from $m-3$ to $m-1$) over the same time horizon.

Table 2.A: Consistency of survey responses across questions

PANEL A: Dependent Var. $D3_{im}$			**PANEL B:** Dependent Var. QS_{im}		
INV_{im}	0.137***	0.140***	$U_{i,m-1} - U_{i,m-3}$	0.00506***	0.00508***
XS^e_{im}	-0.0485***	-0.0489***			
L^e_{im}	-0.179***	-0.185***			
U_{im}	-0.00418***	-0.00413***			
Constant	0.336***	0.242***	Constant	0.277***	0.363***
RE/FE	FE	RE	RE/FE	FE	RE
NACE FE	NO	YES	NACE FE	NO	YES
Observations	22,168	22,168	Observations	9,411	9,411
Overall R^2	0.243	0.262	Overall R^2	0.0537	0.0767
Number of firms	791	791	Number of firms	627	627

Estimations with NACE FE were made with Random Effects pool OLS (RE). All variables (apart from NACE 2-digit code) are survey questions. NACE fixed effects are taken at the 2-digit level. Fixed year effects are omitted to simplify representation but are included in the estimation. $D3_{im}$ is the sufficiency of production capacity; U_{im} is the percentage capacity utilization; QS_{im} is the recent change of production; INV_{im} is the level of inventories; SS^e_{im} is a forecast about sales; L^e_{im} is a forecast about the number of employees. Complete details about the exact wording of the questions are in the text of this section. *** denotes significance at the 1% level.

Having substantiated the consistency of survey responses across questions, we now turn to evaluating their consistency with the information in the financial statements. Annual sales growth of firm i in the income statements, x_{iy}, should be positively correlated with the survey question A.2 concerning the evolution of current sales, XS_{im}.

We examine this by estimating the following linear equations

$$XS_{im} = \beta_0 + \beta_1 x_{iy} + \psi_i + \psi_y + \eta_{im}, \tag{23}$$

where ψ_i and ψ_y control for firm and year fixed effects respectively and η_{im} is the idiosyncratic error. As previously, we estimate equation (23) in two ways, using standard fixed effects tools or NACE sector dummies. To estimate this regression, the firm-year observations from financial statements are treated as the same for each month in a particular year. We can do so as the survey data is qualitative while the data

[26] QS_{im} corresponds to question A.1: *'During the previous 3 months, your production, has increased/remained unchanged/decreased.'*

from financial statements is quantitative and we are simply interested in a correlation between the two. In Table 3.A, we observe that the monthly responses are positively and highly significantly correlated with the growth rates from the financial statements. In other words, qualitative survey responses on changes in current sales and production are on average consistent with their quantitative counterparts reported in the financial statements.

Table 3.A: Consistency of survey responses with variables in financial statements

	Dependent Variable XS_{im}	
x_{iy}	0.221***	0.227***
Constant	0.155***	0.223***
Observations	24,261	24,261
Number of Firms	785	785
Overall R^2	0.0670	0.0801
RE/FE	FE	RE
NACE FE	NO	YES

Estimations with NACE FE were made with Random Effects pool OLS (RE). NACE fixed effects are taken at the 2-digit level. Fixed year effects are omitted to simplify representation but are included in the estimation. x_{iy} is gross sales growth from financial statements. Significance at the 1% level is indicated by ***.

Overall, based on the results in Tables 2.A and 3.A, we find that survey responses are consistent, both with each other within the questionnaire, but also with the information in the financial statements. In addition, the fact that survey responses are positively correlated with the corresponding financial statement variables is consistent with the information from IOBE that surveys are completed by executives who have a complete overview about the firm's activities. We can draw this conclusion, because the financial statements are published after the respondents fill in the survey.

B Quantification of Forecast Errors

B.1 Derivation of equation (1)

Our decomposition is motivated by the compound growth approximation formula, $(1+r)^n = 1 + n \cdot r$, for r being the growth rate and n the number of periods.

In a similar manner, we can decompose the realised annual growth rate x_{iy} into the sum of the monthly growth rates. That is

$$x_{iy} = \sum_{m \in y} x_{im}. \tag{24}$$

Next, by using the definition of our annual forecast, $x^e_{iy} \triangleq \mathbb{E}_{i,y-1}\big[x_{iy}\big] = \mathbb{E}\big[x_{iy}|\mathcal{F}_{i,y-1}\big]$, and equation (24), we obtain

$$x^e_{iy} = \mathbb{E}_{i,y-1} \sum_{m \in y} x_{im}. \tag{25}$$

Intuitively, equation (25) states that the annual forecast for the whole of year y is equal to the forecast of the monthly growth rates within year y.

Note that we can re-write x_{im} as $\frac{1}{3}x_{im} + \frac{1}{3}x_{im} + \frac{1}{3}x_{im}$. As a result,

$$\sum_{m \in y} x_{im} = \left[\frac{1}{3}x_{i,m1} + \frac{1}{3}x_{i,m1} + \frac{1}{3}x_{i,m1}\right] + \left[\frac{1}{3}x_{i,m2} + \frac{1}{3}x_{i,m2} + \frac{1}{3}x_{i,m2}\right] + ... + \left[\frac{1}{3}x_{i,m12} + \frac{1}{3}x_{i,m12} + \frac{1}{3}x_{i,m12}\right], \tag{26}$$

where $m1, m2, ..., m12 \in y$ indicating respectively the first, second, ..., twelfth months within year y. If we rearrange equation (26), we obtain

$$\begin{aligned} \sum_{m \in y} x_{im} = & \left[\frac{1}{3}x_{i,m1} + \frac{1}{3}x_{i,m1}\right] + \frac{1}{3}x_{i,m2} \\ & + \left[\frac{1}{3}x_{i,m1} + \frac{1}{3}x_{i,m2} + \frac{1}{3}x_{i,m3}\right] + \left[\frac{1}{3}x_{i,m2} + \frac{1}{3}x_{i,m3} + \frac{1}{3}x_{i,m4}\right] + ... + \\ & + \left[\frac{1}{3}x_{i,m10} + \frac{1}{3}x_{i,m11} + \frac{1}{3}x_{i,m12}\right] + \left[\frac{1}{3}x_{i,m11} + \frac{1}{3}x_{i,m12}\right] + \left[\frac{1}{3}x_{i,m12}\right]. \end{aligned} \tag{27}$$

We have also defined $x_{i,\{m,m+1,m+2\}}$ as the average growth rate of sales for the following three-month period, i.e. $x_{i,\{m,m+1,m+2\}} = \left[\frac{1}{3}x_{i,m+1} + \frac{1}{3}x_{i,m+2} + \frac{1}{3}x_{i,m+3}\right]$. Plugging this into (27), we obtain

$$\sum_{m \in y} x_{im} \approx \sum_{m \in y} x_{i,\{m,m+1,m+2\}}. \tag{28}$$

So, from equations (25) and (28),

$$x^e_{iy} \approx \mathbb{E}_{i,y-1} \sum_{m \in y} x_{i,\{m,m+1,m+2\}}. \tag{29}$$

Finally, from the law of iterated expectations we have that

$$\mathbb{E}_{i,y-1} \sum_{m \in y} x_{i,\{m,m+1,m+2\}} = \mathbb{E}_{i,y-1} \sum_{m \in y} \mathbb{E}\big[x_{i,\{m,m+1,m+2\}}|\mathcal{F}_{i,m-1 \in y}\big] = \mathbb{E}_{i,y-1} \sum_{m \in y} x^e_{im},$$

because $\mathcal{F}_{i,y-1} \subseteq \mathcal{F}_{i,m-1 \in y}$. Plugging this into equation (28) gives us equation (1).

The approximation of equations (27) and (29) are consistent with our treatment of the survey data for the months of November and December, which are weighted with 2/3 (1/3)) which is standard in the literature — for details see Online Appendix A.2. Similarly, we have used an alternative weighting scheme where January and February have a lower weight to account for the components $\left[\frac{1}{3}x_{i,m1} + \frac{1}{3}x_{i,m1}\right] + \frac{1}{3}x_{i,m2}$ in equation (27). Our baseline estimates are robust to this alternative weighting (output omitted but can be made available upon request).

B.2 Proofs Related to the Estimation of Equation (6)

Statement 1. If $\mathbb{E}\left[x_{iy}^{fe}\middle|x_{iy}^{e}\right] = 0$, then $\mathbb{E}\left[x_{iy}^{fe}\middle|\mathcal{H}\left(x_{iy}^{e}\right)\right] = 0$ for any Borel measurable function $\mathcal{H}$. Therefore, $\mathbb{E}\left[x_{iy}^{fe}\middle|\tilde{x}_{iy}^{e}\right] = 0$ ($\tilde{x}_{iy}^{e}$ is defined in equation (7) in the main text).

Proof. Firstly, note that the underlying mathematical form of this (and any) conditional expectation is $\mathbb{E}\left[x_{iy}^{fe}\middle|x_{iy}^{e}\right] = \mathbb{E}[x_{iy}^{fe}|\sigma(x_{iy}^{e})]$, where $\sigma(x_{iy}^{e})$ is the minimal sigma-algebra generated by x_{iy}^{e}. Intuitively, all the information that x_{iy}^{e} can convey. Then from the Doob-Dynkin Lemma (see Proposition 3 in Rao and Swift (2006)) we know that $\sigma\left(\mathcal{H}\left(x_{iy}^{e}\right)\right) \subset \sigma(x_{iy}^{e})$ for any Borel measurable function $\mathcal{H}$. As a result, from the general form of the Law of Iterated Expectations, we get $\mathbb{E}\left[x_{iy}^{fe}\middle|\mathcal{H}\left(x_{iy}^{e}\right)\right] = \mathbb{E}\left[\mathbb{E}\left[x_{iy}^{fe}\middle|x_{iy}^{e}\right]\middle|\mathcal{H}\left(x_{iy}^{e}\right)\right] = 0$. Next, we know that $\tilde{x}_{iy}^{e}$ is a Borel measurable function of XS_{im}^{e} for $m \in y$.[27] Also, XS_{im}^{e} is a Borel measurable function of x_{iy}^{e} (from ID1).[28] Overall, we have that $\sigma(\tilde{x}_{iy}^{e}) \subset \sigma(\{XS_{im}^{e}\}_{m\in y}) \subset \sigma(x_{iy}^{e})$, for $m \in y$. Therefore, $\mathbb{E}\left[x_{iy}^{fe}\middle|\tilde{x}_{iy}^{e}\right] = 0$. This completes the proof.

Statement 2. If $\mathbb{E}\left[\xi_{iy}\middle|\{XS_{im}^{e}\}_{m\in y}\right] = 0$, then $\mathbb{E}\left[\xi_{iy}\middle|\mathcal{H}\left(\{XS_{im}^{e}\}_{m\in y}\right)\right] = 0$ for any Borel measurable

[27]This follows from the fact that $\tilde{x}_{iy}^{e}$ is a composition of the following three Borel functions: the numerator, the denominator and a function of type $1/f(\cdot)$. The latter, $1/f(\cdot)$, although not continuous it is still Borel measurable. The numerator and the denominator are Borel measurable, because they are continuous functions of XS_{im}^{e}: they are linear (continuous) functions of P_{iy} and N_{iy} which are also linear functions (continuous) of XS_{im}^{e}.

[28]This is true because XS_{im}^{e} is a composition of Borel measurable functions. In ID1, the quantitative monthly forecast, x_{im}^{e}, is a linear (continuous) function of the x_{iy}^{e}, hence Borel measurable. Depending on the value of x_{im}^{e}, then, XS_{im}^{e} takes the discrete values $\{-1, 0, +1\}$. We can see XS_{im}^{e} as a composition of indicator functions of x_{im}^{e}. Indicator functions are Borel measurable.

function $\mathcal{H}$. Therefore, $\mathbb{E}\left[\xi_{iy}\middle|\tilde{x}^e_{iy}\right] = 0$.

Proof. From the Doob-Dynkin Lemma (see Proposition 3 in Rao and Swift (2006)) and the Law of Iterated Expectations we obtain the first part that $\mathbb{E}\left[\xi_{iy}\middle|\{XS^e_{im}\}_{m\in y}\right] = 0$ implies $\mathbb{E}\left[\xi_{iy}\middle|\mathcal{H}\left(\{XS^e_{im}\}_{m\in y}\right)\right] = 0$ for any Borel measurable function $\mathcal{H}$ — the proof is the same as that of Statement 1. From the proof of Statement 1 we also know that $\sigma(\tilde{x}^e_{iy}) \subset \sigma(\{XS^e_{im}\}_{m\in y})$. As a result, $\mathbb{E}\left[\xi_{iy}\middle|\tilde{x}^e_{iy}\right] = \mathbb{E}\left[\mathbb{E}\left[\xi_{iy}\middle|\{XS^e_{im}\}_{m\in y}\right]\middle|\tilde{x}^e_{iy}\right] = 0$. This completes the proof.

Statement 3. The error term $\tilde{\xi}_{iy}$ in equation (10) is mean-independent of the explanatory variables. We provided a way to approximate the unobserved firm heterogeneity, and we derived the final estimable equation (10). For equation (10), by the same principles as for Statements 1 and 2, it suffices to prove that $\mathbb{E}[\tilde{\xi}_{iy}|\{XS^e_{im}\}_{m\in y}] = 0$. Then, $\tilde{\xi}_{iy}$ is also mean-independent of all the right hand side variables of equation (10). This means that the NLS error $\tilde{\xi}_{iy}$ is also mean independent of the rational function on the right hand side of (10), which satisfies Davidson and MacKinnon (2004)'s condition for consistency (equation (6.29)). Indeed, from equation (11)

$$\begin{aligned}
\mathbb{E}\left[\tilde{\xi}_{iy}|\{XS^e_{im}\}_{m\in y}\right] &= \mathbb{E}\left[x^{fe}_{iy}|\{XS^e_{im}\}_{m\in y}\right] + \mathbb{E}\left[\frac{\omega_i}{1-\gamma_1 P_{iy} - \gamma_2 N_{iy}}\middle|\{XS^e_{im}\}_{m\in y}\right] \\
&= 0 + \frac{1}{1-\gamma_1 P_{iy} - \gamma_2 N_{iy}}\mathbb{E}\left[\omega_i\middle|\{XS^e_{im}\}_{m\in y}\right] \\
&= 0,
\end{aligned}$$

where the terms P_{iy} and N_{iy} 'go outside' the conditional expectation as they are functions of XS^e_{im}, $m \in y$, and therefore $\sigma(\{XS^e_{im}\}_{m\in y})$-measurable. This follows from the Doob-Dynkin Lemma and the standard properties of the conditional expectations. From Statement 1 we have that $\mathbb{E}\left[x^{fe}_{iy}|\{XS^e_{im}\}_{m\in y}\right] = 0$. Note that $\{XS^e_{im}\}_{m\in y} \subset \{XS^e_{im}\}_{m=1,2,\dots,T_i}$ which implies that $\sigma\left(\{XS^e_{im}\}_{m\in y}\right) \subset \sigma\left(\{XS^e_{im}\}_{m=1,2,\dots,T_i}\right)$. Therefore, from ID2 and the Law of Iterated Expectations we have that $\mathbb{E}\left[\omega_i\middle|\{XS^e_{im}\}_{m\in y}\right] = 0$. This completes the proof.

B.3 How realistic is the assumption in equation (5)?

To examine how reasonable is the assumption behind equation (5), we regress realized annual sales growth on survey-based sales growth forecasts in two sub-samples. The first sub-sample contains the survey-based forecasts of months January to June, and the second one the survey-based forecasts of months July to December. If firms significantly update their annual forecasts within the year then arguably the assumption in equation (5) would be violated. This is because firms would have updated their annual forecasts, and as a result their subsequent monthly qualitative forecasts following their information update. If this is the case, forecasts from the second half of the year will be more strongly correlated with annual sales growth than will forecasts from the first half, because the forecasts later in the year will be based on information more strongly correlated with the overall sales growth of that year.

As a measure of this correlation we use the R-squared from each regression. The fixed-effects regression of annual sales growth on survey-based forecasts of months January to June gives an overall R^2 of 5.96%. The fixed-effects regression of annual sales growth on survey-based forecasts of months July to December gives an overall R^2 of 5.52%. Both regressions also include a constant and fixed year effects. Clearly, the forecasts made in the second half of the year are if anything less correlated with the overall annual sales growth during that same year. This suggests that our assumption is reasonable and that the monthly forecasts made towards the end of a year are not more informative about the overall sales growth of that year.

Additionally, we conduct a Diebold and Mariano (1995) test (DM) comparing the squared forecast errors computed using: (i) the survey-based expectations from January to June of each year and each firm; (ii) the survey-based expectations from July to December. We essentially split our sample in two, and we implement our quantification methodology — as we describe it in Section 3 — in each sub-sample obtaining distinct forecast errors from each one of them. Then we compute the difference of the two squared forecast errors and we run a random effects regression of that difference on a constant. The estimated value of the constant is -0.001 with two-tailed p-value 0.21 indicating that it is not statistically significant. This means that the squared forecast errors from using the first six months are not more accurate that those from using the second semester. If firms drastically update their information within a year, as well as their overall forecast for the whole year, then we would expect their forecasts later in that year to be more accurate than those in the first half of that year. The DM test we conducted rejects this, which implies that during a year, firms do not drastically update their information.

B.4 Testing and allowing for state dependent parameters in the non-linear quantification equation

We outline a more general method that future applications could use to introduce a state dependency in parameters α, β, γ_1 and γ_2 under the assumption that

$$\begin{aligned} x_{im}^{e,+} &= \alpha + \tilde{\alpha}\mathbb{1}_y^U + \gamma_1 x_{iy}^e + \tilde{\gamma}_1 \mathbb{1}_y^U x_{iy}^e + \nu_{im}^+, \\ \text{and} \qquad x_{im}^{e,-} &= -\beta - \tilde{\beta}\mathbb{1}_y^U + \gamma_2 x_{iy}^e + \tilde{\gamma}_2 \mathbb{1}_y^U x_{iy}^e + \nu_{im}^-, \end{aligned} \tag{3*}$$

where $\mathbb{1}_y^U$ is an indicator variable taking value 1 in year y the economy experienced a sizeable aggregate shock. Note that the term $\mathbb{1}_y^U$ can theoretically be further elaborated or expanded (e.g. different indicators for positive and negative aggregate events). However, in practice one needs to remain frugal with the additional parameters that they introduce in the NLS model, because the limited sample size can make the estimates unreliable.

We propose the following steps:

Step 1: **Identify years with aggregate shocks.** Use a variable that identifies aggregate state-dependencies. For instance, for the Greek economy, one can use the 'OECD based Recession Indicators for Greece', 'GRCREC' series, published by the Federal Reserve Economic Data (FRED). Use this variable to identify years with an aggregate shocks setting $\mathbb{1}_y^U = 1$.

Step 2: **Obtain estimates of the parameters.** Using (3*) from above and equation (1) from the main body of the paper, follow the same algebraic manipulations and assumptions to derive the final estimable equation:

$$x_{iy} = \frac{\alpha P_{iy} + \tilde{\alpha}\mathbb{1}_y^U P_{iy} - \beta N_{iy} - \tilde{\beta}\mathbb{1}_y^U N_{iy} + \delta_1 \overline{XS_i^e} + \delta_2 (\overline{XS_i^e})^2}{1 - \gamma_1 P_{iy} - \tilde{\gamma}_1 \mathbb{1}_y^U P_{iy} - \gamma_2 N_{iy} - \tilde{\gamma}_2 \mathbb{1}_y^U N_{iy}} + \tilde{\xi}_{iy}. \tag{30}$$

Step 3: **Test the significance** of the state dependent parameters $\tilde{\alpha}$, $\tilde{\beta}$, $\tilde{\gamma}_1$ and $\tilde{\gamma}_2$ using standard tools.

Step 4: **Computing quantified forecasts.** If the state-dependent parameters are statistically significant, obtain the quantified forecasts using the estimated parameters and P_{iy} and N_{iy} from the survey data, without using the fixed effects proxies as in our baseline application. That is,

$$\hat{x}^e_{iy} = \frac{\alpha P_{iy} + \tilde{\alpha}\mathbb{1}^U_y P_{iy} - \beta N_{iy} - \tilde{\beta}\mathbb{1}^U_y N_{iy}}{1 - \gamma_1 P_{iy} - \mathbb{1}^U_y P_{iy} - \gamma_2 N_{iy} - \tilde{\gamma}_2\mathbb{1}^U_y N_{iy}}. \quad (31)$$

B.5 Statistics on Forecasts and Forecast Errors

Statistics on Survey Forecasts. This section provides an overview about the information on sales forecasts in the survey. The left subplot of Figure 1.B shows the distribution of monthly responses to survey question D.2 on firms' expected sales during the next three months. These possible responses, increase/no change/decline, are coded as +1/0/1, respectively. The right subplot of Figure 1.B shows the distribution of annualized survey forecasts based on the same question. We annualize the monthly survey responses by computing a weighted yearly average $\sum_{m\in y} W_{im}[XS^e_{im}]$, where the weights are based on equation (14). The right subplot of Figure 2.B documents the number of survey responses on sales expectations (survey question D.2) per year. The number of responses is relatively constant across our sample. Towards the end of the sample it is somewhat lower. The reason is that responses are digitized only about 2 years after they have been received. At the time we obtained the data not all responses at the end of the sample had been digitized. The left subplot of Figure 2.B shows for each year the share of survey responses on sales growth expectations that indicate an increase/unchanged/decrease (shown in green/orange/blue). The share of optimistic (pessimistic) responses is higher in the first (second) half of our sample, consistent with the strong boom that ended in 2008 and the following severe depression.

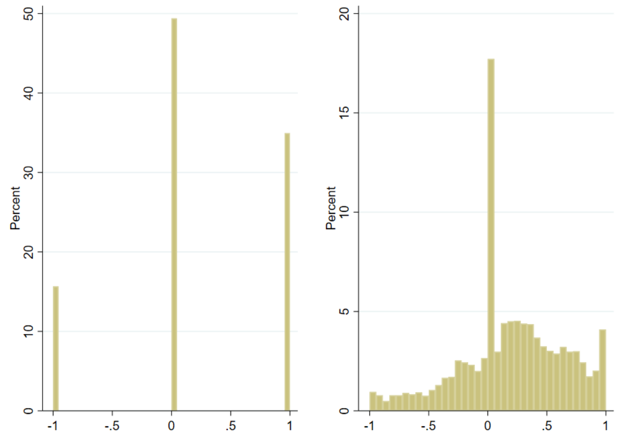

Figure 1.B: **Distribution of Sales Forecasts based on Qualitative Survey Data.** The figure on the left shows the distribution of firm-month sales forecasts based on survey question D.2. The figure on the right shows the distribution of the survey based firm-year sales forecasts when the monthly survey responses are annualized using a yearly weighted average.

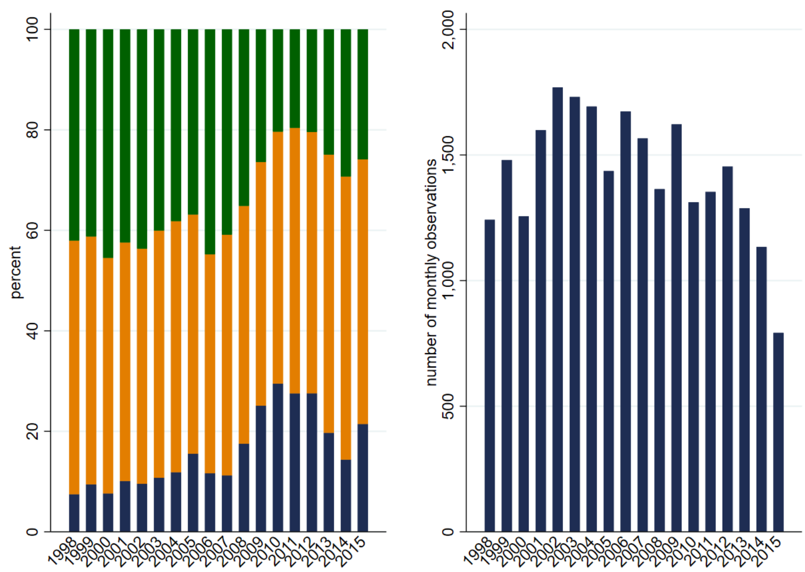

Figure 2.B: **Qualitative Survey Responses on Expected Sales Growth over Time (Survey Question D.2).** The figure on the left shows the responses indicating an increase/unchanged/decrease in green/orange/blue as share of total monthly observations per year. The figure on the right shows the total number of monthly survey responses per year distribution of firm-month sales forecasts based on survey question D.2.

B.6 Accuracy of the Quantification Methodology: Monte Carlo Exercise

In this section, we describe how artificial data is generated and subsequently used to evaluate the precision of our methodology to quantify qualitative forecasts. We first document details of the data generating process and its calibration. Finally, we discuss results that stress the robustness of the evidence shown in Table 5.

Generating Artificial Data. The following outlines how we generate artificial data on firm's (continuous) sales growth, z_{iy}, as well as corresponding qualitative expectations, ZS^e_{iy}, and quantitative expectations, z^e_{iy}. The realized sales growth and the qualitative expectations are then used as inputs to the quantification methodology in Section 3.1 to generate estimates for quantified sales growth expectations, $\hat{z}^e_{iy}$. This allows us to evaluate the accuracy between these estimates, $\hat{z}^e_{iy}$, and the actual underlying expectations, z^e_{iy}.

Our dataset on Greek firms' sales growth is an unbalanced panel with 799 firms, 4,104 firm-year observations and 25,764 firm-month observations that spans 18 years. The final artificial datasets that we generate exactly matches this structure. We further take into account that the first eleven years in our sample were a boom period and the last seven years a severe bust. We start with generating a balanced panel that spans 20 years, where the first two years are used to inform lagged values. We now document how each of the three artificial variables is generated.

First, we generate artificial data for firm's sales growth, z_{iy}, based on an AR(1) process. We use the MA(∞) representation

$$z_{iy} = \sum_{l=0}^{y-1} \theta^l (\varepsilon_{i,y-l} + \varpi_i), \quad \text{for } y > 1; \qquad \text{and} \qquad z_{iy} = \varepsilon_{i0} + \varpi_i \quad \text{for } y = 1.$$

This is guided by the evidence in Section B.6.1 (Table 6.B) that this process explains the data well.[29] The innovations $\varepsilon_{iy} \sim N\big((1-\theta)\mu, (1-\theta^2)\sigma^2\big)$ are i.i.d. and $\varpi_i \sim N(0, \sigma^2_{\varpi_i})$ is unobserved firm heterogeneity.

Second, we generate firms' annual quantitative sales growth forecasts based on the process

$$z^e_{iy} = (1-\theta)\mu + \theta z_{i,y-1} + \varpi^e_i + \varepsilon^e_{i,y-1},$$

where ϖ^e_i is the unobserved firm heterogeneity, which can be seen as firm-specific degree of optimism or pessimism. The innovations $\varepsilon^e_{iy} \sim N(0, \sigma^2_{\varepsilon^e_{iy}})$ are i.i.d. and capture any additional information the

[29]Using an AR(2) process to generate the artificial data does not materially affect the performance of our quantification methodology. Results are discussed below and shown in Table 5.B.

firm might include in its forecast. There is no means of inferring the underlying process for expectation formation from the data. However, since realized sales growth in the data is well explained by an AR(1) process, it seems likely that such a process is also used by firms to form expectations.

Third, we generate the qualitative monthly expectations, ZS^e_{im}. These expectations need to correspond to the annual quantitative forecasts z^e_{iy}. For this reason, we first generate firms' monthly quantitative forecasts, z^e_{im}, and map these into qualitative categories (decline/unchanged/increase) in a second step. Firms' monthly quantitative expectations, conditional on their forecast for the whole year, are generated as

$$z^e_{im} = \mu + \gamma z^e_{iy} + \varepsilon^e_{im},$$

where $\varepsilon^e_{im} \sim N(0, \sigma^2_{\varepsilon^e_{im}})$ are i.i.d. and capture any additional information that the firm includes in its forecast. Note that this procedure to link the artificial annual and monthly observations derives closely from Pesaran (1987).

The only purpose for which the quantitative monthly expectations z^e_{im} have been generated, is to match these into three categories (*decline/unchanged/increase*) to derive qualitative monthly expectations, ZS^e_{im}. This mapping is constructed so that resulting proportions of observations in the three categories correspond to the proportion of *decline* responses, $C^-\%$, and the proportion of *increase* responses, $C^+\%$, in our survey data. In particular, we assign $ZS^e_{im} = 1$ for the largest $C^+\%$ of values in z^e_{im}; and $ZS^e_{im} = -1$ for the smallest $C^-\%$ of values in z^e_{im}. Since the percentage share of *unchanged* observations in the survey data equals 100-$C^+\%$-$C^-\%$, for the remaining observations in the middle of the distribution of z^e_{im} we set the corresponding $ZS^e_{im} = 0$.

Finally, for the three variables based on artificial data — z_{iy}, z^e_{iy} and ZS^e_{im} — we drop the appropriate observations so that we derive an unbalanced panel of artificial data that exactly corresponds to the structure of firm-year-month observations in our observable dataset.[30] We repeat the steps above to generate 1,000 random samples of artificial datasets. Then, for each sample, we use z_{iy} and ZS^e_{im} as input to our quantification methodology and compare the resulting estimate for quantitative sales growth expectations, $\hat{z}^e_{iy}$, with the true underlying expectations, z^e_{iy}.

[30]Prior to this, we have also dropped all observations of the first two years which had only been employed to inform values of lagged variables.

Calibration. To generate the artificial data we need to calibrate a number of parameters. This exercise is closely informed by our financial statements data on annual sales growth realizations and the survey data on monthly qualitative expectations. Based on the estimates reported in Table 6.B, we set the autocorrelation coefficient in the AR(1) process for artificial sales growth, z_{iy}, to $\theta = -0.1$. The parameters μ and σ, that govern the moments of the corresponding innovations, are calibrated to match the respective moments in our sales growth data from the financial statements. Since particularly the mean differs across the boom and bust periods in our sample, we differentiate between these episodes and set $\mu = 0.077$ ($\mu = -0.059$) and $\sigma = 0.391$ ($\sigma = 0.401$) during the boom (bust) period.[31] The standard deviation of the unobserved firm heterogeneity, σ_{ϖ_i}, is set to 0.129 to match the standard deviation of the firm-specific cross-time average of sales growth in the financial statements data.

Since the artificially generated qualitative and quantitative expectations variables are linked, we jointly calibrate the remaining parameters that correspond to these variables to match a number of statistics in our data. We first discuss the parameters that govern the process for annual sales growth expectations. The firm specific optimism/pessimism, ϖ_i^e, should be related to the average firm-specific performance, ϖ_i. We scale $\varpi_i^e = 0.5 \cdot \varpi_i$ so that the standard deviation of the firm-specific average of the artificial monthly qualitative expectations is close to the corresponding statistic in the observable dataset (0.431 vs. 0.422). The standard deviation of the innovation, $\sigma_{\varepsilon_{iy}^e} = 0.02$, is calibrated so that the standard deviation of the firm-year averages of the monthly qualitative expectations in the artificial data will be close to the one in the observable data (0.515 vs. 0.478).

Next, we turn to the remaining parameters required to generate the monthly expectations. The standard deviation of the innovations, $\sigma_{\varepsilon_{im}^e}$, is set to 0.05, based on the within-year variation of the monthly qualitative survey responses. We measure this variation as the arithmetic mean of the squared difference between the monthly survey responses and their firm-year average (0.211 in the artificial data vs. 0.259 in the survey responses). The parameter γ is calibrated to 0.8 so that the correlation between realized annual sales growth and the qualitative monthly expectation responses in the artificial data matches the corresponding

[31] Apart from the mean μ, and the shares C^+ and C^-, the statistics used to calibrate the parameters in this section are very similar across boom and bust episodes which is why we refrain from a differentiation for these parameters.

correlation in our observable dataset.[32]

Table 4.B: Calibrated parameters to generate artificial data

Parameter	Value	Matched Moment from Financial Statements (FS) or Survey Data
μ	0.077 (-0.059)	Mean in boom (bust) period of sales growth from financial statements
σ	0.391 (0.401)	Standard deviation in boom (bust) period of sales growth from financial statements
θ	-0.1	Autocorrelation estimates (see Table 6.B) of sales growth from financial statements
σ_{ϖ_i}	0.129	Standard deviation of firm-specific cross-time average of sales growth in the FS
ϖ_i^e	$0.5\sigma_{\varpi_i}$	Scaled to match std. dev. of firm-specific average of monthly qual. survey expectations
$\sigma_{\varepsilon_{iy}^e}$	0.02	Std. dev. of the firm-year averages of the monthly qualitative survey expectations
$\sigma_{\varepsilon_{im}^e}$	0.05	Mean of squared difference between monthly survey responses and their firm-year average
γ	0.8	Correlation: annual sales growth from FS and qualitative monthly survey expectations
C^+	38% (24%)	Percentage share of positive monthly responses in the survey data during boom (bust)
C^-	11% (24%)	Percentage share of negative monthly responses in the survey data during boom (bust)

All calibrated parameters and the moments we target are summarized in Table 4.B. Our calibration strategy carefully ensures close correspondence of the artificially generated data with our observable dataset. This is achieved by matching statistics that concern, amongst others, relations between qualitative survey expectations and quantitative realizations, as well as monthly and annual data. We now evaluate the appropriateness of the calibration and the assumptions on underlying processes by evaluating how well the artificial data conforms to statistics in the observable data that are not targeted. We document three such statistics. First, for the error of the regression of monthly qualitative forecasts on annual sales growth realizations, the unobserved firm heterogeneity accounts for 35% of its variance in the artificial data vs. 33% in the dataset that comprises information from the survey and the financial statements.[33] Second, the coefficient of the regression of annualized survey responses on sales growth realizations is 0.169 in the artificial data vs. 0.193 in the observed data.[34] Third, in the error term of the latter regression (ZS_{iy}^e on z_{iy}) unobserved firm heterogeneity accounts for 56% of its variance vs. 58% in the observed data. The close correspondence between artificial and observed data in all three statistics is reassuring about the adequacy of our calibration. The second statistic particularly corroborates our calibration of γ, while the first and

[32] In particular, we run the regression $XS_{im}^e = \beta_0 + \beta_1 x_{iy} + \phi_i + \eta_{im}$ where ϕ_i controls for firm fixed effects and η_{im} is an idiosyncratic error.

[33] Using the notation for the artificial variables the regression is: $ZS_{im}^e = \beta_0 + \beta_1 z_{iy} + \phi_i + \eta_{im}$. The corresponding variables in our empirical dataset have been denoted XS_{im}^e on x_{iy} in the main body.

[34] Using the notation for the artificial variables the regression is $ZS_{iy}^e = \beta_0' + \beta_1' z_{iy} + \phi_i' + \eta_{iy}'$. Where ZS_{iy}^e is the firm-year arithmetic mean of the monthly survey responses.

third statistics support our calibration of the variance of the unobserved firm heterogeneity.

Alternative Data Generating Process. Table 5 in the main body demonstrates, based on artificial data, a close correspondence between the estimated and the true quantitative forecast errors. The artificial data on sales growth has been generated based on the above AR(1) process. We now demonstrate robustness to an alternative Data Generating Process. We relax the AR(1) assumption and generate sales growth based on the AR(2) process $z_{iy} = 1.2\mu - 0.2z_{i,y-1} - 0.1z_{i,y-1} + \varepsilon_{iy} + \varpi_i$. Note that the sales growth expectations are still generated based on the process as shown above which introduces predictability and autocorrelation in the forecast errors. Table 5.B shows the distribution of the difference between the estimated quantitative forecast error and the true quantitative forecast error when the artificial data is generated based on the AR(2) process. Overall, results are robust to this change, and the estimated forecast errors still correspond closely to the underlying true forecast errors.

Table 5.B: Distribution of the difference between the estimated quantitative forecast error and the true quantitative forecast error — alternative data generation

5%	10%	25%	Median	Mean	75%	90%	95%
-0.085	-0.065	-0.033	0.000	-0.002	0.031	0.058	0.075
(0.011)	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)

We report the average across 1,000 sets of artificial data of the descriptive statistics. Standard deviations across the 1,000 sets for these statistics are reported in parenthesis. Sales growth realizations are generated based on an AR(2) process.

B.6.1 Autocorrelation of Sales Growth

In Table 6.B we report estimates for the autocorrelation of sales growth. We use the Arellano and Bover (1995) Two Step Forward Orthogonal Deviations GMM (FOT). We use distinct number of lags (for instruments) for robustness (see Roodman (2009), Caselli and Tesei (2016)). Additionally, because of the small number of firms (relatively to the moment conditions) we collapse the instruments and we use the Windmeijer (2005) corrected standard errors (Roodman (2009), Caselli and Tesei (2016)). Finally, for the realizations, we use the first differences as instruments as the instruments in levels indicated serial autocorrelation in the error. Table 6.B shows that annual real sales growth from the financial statements has a negative autocorrelation, and the estimated coefficient is robust to different lag lengths. Overall, we find the result of negative autocorrelation in sales growth is very robust and close to -0.10. This is consistent with evidence on other datasets in the literature, see e.g. Barrero (2019).

Table 6.B: Autocorrelation of firms' realized sales growth

	(1)	(2)	(3)
Estimation		FOT	
Stand. Errors		2-step, Windmeijer corrected	
Lags as Instruments	2-11	2-6	2-4
	Dependent Variable: Sales Growth, x_{iy}		
$x_{i,y-1}$	-0.0995***	-0.103***	-0.0997***
Constant	–	–	–
Observations	13,994	13,994	13,994
# of Firms	1,214	1,214	1,214
Over-identified	Yes	Yes	No
Hansen p-value	0.251	0.0369	N.A.
m2 test p-value	0.553	0.617	0.549

Estimates are obtained using the Arellano and Bover (1995) 2-Step Forward Orthogonal Deviations GMM (FOT). y fixed effects are included in all estimations, but are omitted. We use distinct number of lags (for instruments) for robustness, all are collapsed. The instruments are lagged first differences of the right hand side variable dated as indicated. The Arellano-Bond p-value (m2 test) shows no serial correlation of order 2 in the errors. x_{iy} is the sales growth observed from the financial statements. ***, ** and * indicates statistical significance at the 1%, 5% and 10% level, respectively.

B.7 MES and CBI Data: Scatter plot

Figure 3.B shows the pairs of imputed — from our quantification model using CBI qualitative survey data — and observed sales growth forecast error in the MES and CBI data. We observe that the observed and the imputed values are closely around the 45^o line (red).

Finally, note that the annual forecasts were recorded by the MES during mid-2017 and we check their correlation with the qualitative survey responses recorded by the CBI during the same year. However, the 2017 MES also records the expected annual sales growth for 2018. Even though this sample is too limited to allow for implementation of our quantification method due to limited matching with the realizations from the FAME dataset, we can use it to test our ID1. We run the same checks on the linear correlation and the ordered probit between: (i) the qualitative forecasts collected by the CBI during 2018; (ii) the one-year

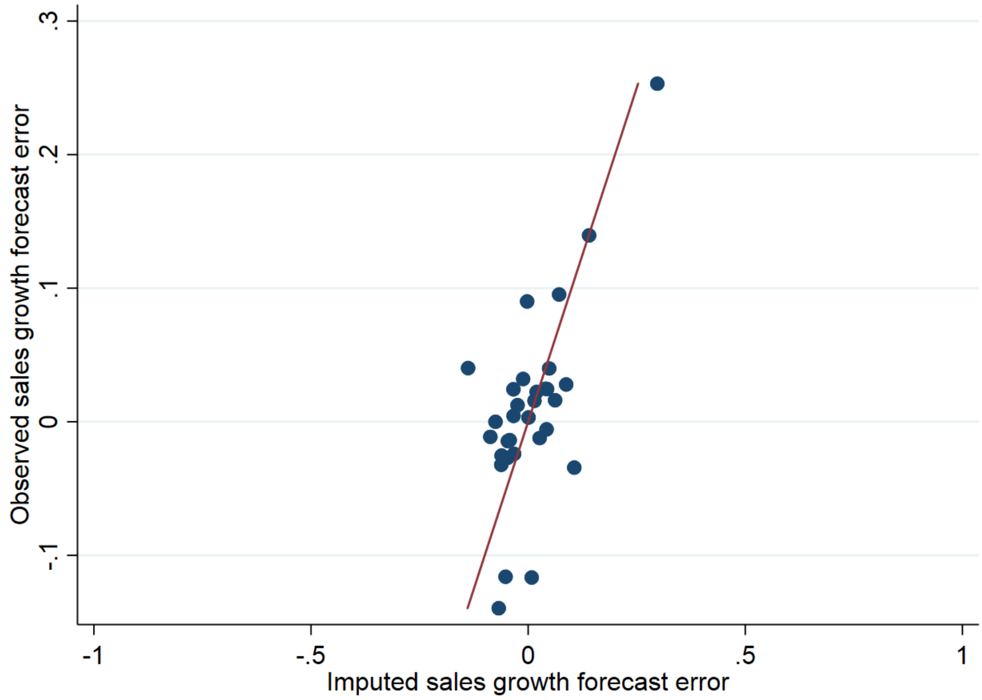

Figure 3.B: **Pairs of true and estimated sales growth forecast errors based on the MES and CBI data.** The 45^o line is shown in red.

ahead annual forecasts concerning 2018 collected by the MES in 2017. We obtain similar results validating our assumption: (i) in the linear regression, correlation is 0.16 also sig. at 1%; (ii) in the ordered probit, the Wald Chi-sq. (1 degree of freedom) is 18.88.

B.8 Testing ID1: Relation between Monthly and Annual Survey Forecasts

With the matched CBI and MES data we can test our ID1 that the monthly expectations during a given year are correlated with the corresponding annual expectations about the same year. This pair of data combines qualitative monthly and their corresponding quantitative annual firm-level expectations, a combination suitable for testing ID1.

To verify this assumtpion, we first estimate a linear regression using the same observations we use to test our quantification in the UK sample. We regress the monthly qualitative survey responses recorded during 2017 on the quantitative annual forecast for 2017, and we find there is a positive correlation of 0.27 significant at 1%. Second, given the qualitative nature of the survey forecasts, we estimate an ordered probit model of the monthly forecasts on the observed annual quantitative forecast. This ordered probit model also verifies our assumption (Wald chi-squared statistic for the whole ordered probit model with 1 degree of freedom is 7.25). Third, we test whether the linear correlation changes with each quarter. To do so, we follow the standard procedure: we include dummy variables for the three quarters multiplied with the quantitative annual forecast on the right-hand side (interaction terms), as well as the dummies alone. None of the coefficients of the dummy variables was statistically significant, which means that the degree of correlation between the monthly and the annual forecast does not change throughout the year.

Finally, note that the annual forecasts were recorded by the MES during mid-2017 and we check their correlation with the qualitative survey responses recorded by the CBI during the same year. However, the 2017 MES also records the expected annual sales growth for 2018. Even though this sample is too limited to allow for implementation of our quantification method due to limited matching with the realizations from the FAME dataset, we can use it to test our ID1. We run the same checks on the linear correlation and the ordered probit between: (i) the qualitative forecasts collected by the CBI during 2018; (ii) the one-year ahead annual forecasts concerning 2018 collected by the MES in 2017. We obtain similar results validating our assumption: (i) in the linear regression, correlation is 0.16 also sig. at 1%; (ii) in the ordered probit, the Wald Chi-sq. (1 degree of freedom) is 18.88.

References in the Appendix

Arellano, M. and Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1):29–51.

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

Caselli, F. and Tesei, A. (2016). Resource windfalls, political regimes, and political stability. *Review of Economics and Statistics*, 98(3):573–590.

Coibion, O., Gorodnichenko, Y., and Kumar, S. (2018). How do firms form their expectations? New survey evidence. *American Economic Review*, 108(9):2671–2713.

Davidson, R. and MacKinnon, J. G. (2004). *Econometric theory and methods*, volume 5. Oxford University Press New York.

ELSTAT (2002). Statistical classification of the branches of economic activity: Stakod 2003. Technical report, Hellenic Statistical Authority.

EUROSTAT (2008a). Correspondence table nace rev. 1.1 - nace rev. 2. Technical report, EUROSTAT: The Statistical Office of the European Union.

EUROSTAT (2008b). Nace rev. 2: Statistical classification of economic activities in the european community. Technical report, EUROSTAT: The Statistical Office of the European Union.

Lui, S., Mitchell, J., and Weale, M. (2011). Qualitative business surveys: signal or noise? *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 174(2):327–348.

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

Pesaran, M. H. (1987). *The limits to rational expectations*. Blackwell Publishers.

Rao, M. M. and Swift, R. J. (2006). *Probability theory with applications*, volume 582. Springer Science & Business Media.

Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, 71(1):135–158.

Windmeijer, F. (2005). A finite smple correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, 126(1):25–51.