Expectation Formation at Times of Economic Change: The Reaction of Firms to New Information, Market Volatility, and Minimum Wages

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Preface

Firms' everyday business is strongly driven by the permanent need of adjustment to changes in the economic environment. This dissertation comprises of four contributions that independently examine the expectation formation of firms in light of new information, the role of market volatility for the expectation formation process, as well as firms' adjustment to changes in policy using the example of changes in minimum wage legislation. Despite their diverse research questions, all contributions demonstrate the usefulness of the firm-level micro data of the IFO Business Survey (IBS) for the understanding of the behavior of firms.

Lucas (1972, 1976) was the first to show the importance of the expectation formation process for the modeling of dynamic processes. The benchmark of rational expectations with full and costless information in the sense of Muth (1961) has—despite its widely undisputed merits—repeatedly failed to predict empirically observed patterns in the behavior of firms and other economic agents, see, e.g., Nerlove (1983). As a response, information frictions have become increasingly popular in macroeconomics to model the expectation formation process in a more realistic way. The most prominent examples of this new class of models are the "sticky information" models of Mankiw and Reis (2002, 2006) and "rational inattention" models in the tradition of Sims (2003) and Woodford (2003). The former assume that agents update their beliefs only irregularly, while the latter endogenize information rigidities as a rational choice of agents in presence of costly gathering and procession of information.

In contrast to this progress in economic theory, empirical evidence on the expectation formation process of firms is still surprisingly scarce. Recent literature has mainly focused on firms' expectations regarding economy wide aggregates such as inflation, total output, and aggregate stock market returns (e.g., Ben-David et al., 2013; Coibion and Gorodnichenko, 2012, 2015; Coibion et al., 2015) or examined the determinants of individual expectations (e.g., Malmendier and Nagel, 2016). Lacking appropriate data, little is known about the determinants of firms' expectations regarding their own future conditions; in spite of their undisputed role for firms' investment, hiring, and pricing decisions. The first two chapters of this dissertation aim to contribute to the recent literature that

opens the black-box of the expectation formation process with the help of survey data.

The first chapter, which is based on joint work with Lukas Buchheim, examines the role of aggregate and disaggregate information for expectation formation of firms. Although neglected in standard economic theory, the distinction between aggregate, industry-wide information and disaggregate information referring to the levels of firms or sub-industries has shown to be important, for example, the explain coordination motives of firms (Hellwig and Veldkamp, 2009) or business cycle comovement (Veldkamp and Wolfers, 2007).

However, empirical evidence on the importance of aggregate and, in particular, disaggregate information for firms' expectations is scarce. This is mainly due to limited availability of micro data on both firm's expectations as well as proxies for firms' information sets. To circumvent this constraint, we make use of the panel structure of the IBS. While time fixed effects allow for a flexible assessment of aggregate information in firms' expectations, the future realizations of firms' business conditions orthogonal to time fixed effects serve as a proxy for today's disaggregate information. This dataset allows us to explore two closely related sets of questions concerning firms' expectation formation: First, to which degree are firms' expectations affected by disaggregate information? Second, what is the causal effect of new information regarding a disaggregate demand shock on expectations?

Regarding the first question, we find that disaggregate information is an important component of firms' expectations across all empirical specifications. Controlling for aggregate information at fairly narrow industry-levels reveals that firms strongly rely on the disaggregate part of their information set when forming their expectations for the next six months. Hereby, firms' expectations are more strongly associated with disaggregate information about the near future (one quarter ahead) than with information about the more distant future (two quarters ahead). In addition, we show that aggregate and disaggregate information are roughly equally important for explaining variation in expectations by means of the marginal R^2 of the measures for information as well as a Shapley variance decomposition.

In answering the second question, we are the first to document a causal effect of new information on firms' expectations in a real world setting. For this purpose, we examine retail firms' expectation adjustment to information about a large demand shock. Namely, a three percentage point increase in German VAT in January 2007. Announced well in advance, the VAT shock constitutes a rare natural experiment because non-durable good retailers were largely unaffected by this policy, while retailers of durable goods faced predictable pull forward effects in demand. Hence, the quality of information about future demand exogenously differed between both groups of firms. We identify the causal effect of this increase in quality of information on expectations in a difference-in-differences design

by exploiting the similarity of durable and non-durable good retailers during all other periods. We find that treated retailers of durable goods become more forward-looking once the demand shock enters their expectation window. The effect is quantitatively large and the increased weight of disaggregate information in expectations is entirely driven by the disaggregate information about the more distant future. Overall, the results suggest that firms are sensitive to the quality of disaggregate information when forming their expectations.

While Chapter 1 mainly focuses on the importance of disaggregate information for the expectation formation of firms, Chapter 2 asks the more general question whether the way these expectations are formed is consistent with rational models of information frictions in the tradition of Mankiw and Reis (2002) and Sims (2003). More specifically, Chapter 2 examines whether firms allocate more attention to shocks that are more volatile when forming their expectations as they have a higher marginal benefit from new information—a prediction common to this class of models. Therein, Chapter 2 is the first to use firm-level expectations data to provide empirical evidence on this mechanism.

The results show that firms in generally more volatile markets are better in predicting their own future business conditions. This finding is reflected in a strongly increased degree to which ex post realized business conditions are associated with previous expectations of these firms. This increased information content of expectations can be observed irrespectively of using firm-specific or sector-specific measures of market volatility. The former is based on firm-specific backlog of orders; the latter are either calculated from industry-level revenue data or based on industry-averages of firms' reported business conditions. Moreover, the relationship appears to be quite stable across firms in all important sectors of the economy. This suggests that information frictions play an important role for the expectation formation of firms. Seen through the lens of the models in the tradition of Mankiw and Reis (2002) and Sims (2003), firms in more volatile markets rationally invest more resources (or a larger part of their limited attention) into the costly collection and processing of information about the future development of their businesses resulting in increased information content of expectations.

While the first two chapters examine the expectation formation of firms, Chapter 3 contributes to the literature on the economic effects of minimum wages that was spurred by the seminal study of Card and Krueger (1994). Although being neglected in large parts of the literature on minimum wage effects, prices have been perceived as an important margin of adjustment for firms (see, for example, the seminal paper of Aaronson, 2001). However, previous studies that found evidence in favor of pass-through on prices usually did not jointly assess the price and employment response at the firm-level. In addition, they mainly focused at the price response to changes in existing minimum wages of firms

in highly affected industries, such as restaurants (e.g., Aaronson, 2001, Lemos, 2006, Aaronson et al., 2008, and Fougère et al., 2010) and retailers (Leung, 2016 and Montialoux et al., 2017).

Chapter 3 analyzes the introduction of statutory minimum wages in Germany in 2015. This offers a unique opportunity to take a broader perspective on these issues, as the new statutory minimum wage was directly set to the average level of OECD countries (see OECD, 2015). As a result, firms in a wide range of sectors were affected by this policy. The differential degree to which firms' were affected by the minimum wage introduction can be identified by means of sectorally and regionally disaggregated wage data. Moreover, the firm-level micro data of the IBS contain monthly information on both price changes as well as expected changes in the number of employees. This allows for a joint analysis of these two potentially important margins of adjustment to minimum wages.

Based on a generalized difference-in-differences estimation strategy, I only find a very modestly negative and insignificant effect of the minimum wage introduction on firms' planned employment changes. While a negative employment effect cannot be ruled out with certainty in light of potential measurement error in the treatment intensity measure, this finding points into the direction of a prominent strand of papers including Card and Krueger (1994, 2000), Dube et al. (2010), and Allegretto et al. (2011) who find that minimum wages do not inevitably destroy jobs. Moreover, Chapter 3 adds to initial evidence in favor of moderate employment effects in response to the introduction of minimum wages in Germany, e.g., Bossler and Gerner (2016).

However, Chapter 3 is the first to provide credibly identified evidence for substantial price pass-through in response to the introduction of statutory minimum wages in Germany. The minimum wage-induced price reaction of affected firms is quantitatively large and firms appear to have rolled over a non-negligible share of increased labor costs to prices. Conditional on the same degree of affectedness, the strength of the minimum wage effect on the probability to increase prices does not differ between manufacturing firms and service companies as well as between firms in West and East Germany. This result thus provides evidence in favor of the external validity of the previously cited studies that document strong minimum wage effects on prices in a much narrower subset of highly affected industries.

All chapters of this dissertation exploit the panel dimension of the IBS and therein provide examples for the variety of potential research questions that can be addressed based on its micro data. The survey is unique in asking a sample of approximately 7000 firms that is representative for the German economy at monthly frequency. In light of high response rates, low attrition, and a large variety of questions covered by the survey, the IBS is ideally suited for micro-econometric analysis of firms in all sectors of the economy.

Despite of these advantages, researchers usually restricted their analysis to the subset of manufacturing firms instead of using the entire sample of firms covered by the IBS, e.g., Pesaran and Timmermann (2009), Bachmann et al. (2013b), Carstensen et al. (2013), Strasser (2013), Fidrmuc and Hainz (2013), and Bachmann and Elstner (2015).

Chapter 4 of this dissertation describes how two major obstacles that have prevented panel data research based on the universe of all firms in the IBS can be removed: namely, heterogeneities (1) across different sector-specific surveys of the IBS in the level of analysis (product vs. firm) and (2) in the industry classification schemes used in the micro data. For this purpose, the level of analysis of the most important industry surveys covering manufacturing, retail/wholesale, and services is transferred to the firm-level by means of aggregation. Moreover, the sector identifiers contained in the micro data are transferred to the official German industry classification systems of 2003 and 2008.

The resulting harmonized dataset expands the scope for economic research based on the micro data of the IBS as it allows for a joint analysis of firms in all main sectors of the economy—a prerequisite for the analyses presented in the first three chapters of this dissertation. Adjusting for a break in the methodology of the survey in 2006, the value added of this harmonization procedure is largest for the micro data of the retail and wholesale survey as it allows to link firms' responses before and after the methodological break which was previously not feasible. Moreover, the uniform coding of firms according to the standard German industry classification systems of 2003 and 2008 is useful for at least two reasons. On the one hand, fixed effects can be applied at different aggregation levels to flexibly control for industry-specific components, such as industry-wide information in firms' expectations as implemented in the first chapter. On the other hand, the firms in the IBS can be merged to industry-level data from other sources such as market volatility measures based on sectoral revenue data used in Chapter 2 or data on the industry-specific wage distribution in the firms' location exploited in Chapter 3 to identify the "bite" of the minimum wage introduction.

Moreover, Chapter 4 exploits the harmonized firm-level dataset to shed light on the interpretation of the most widely used variables in the IBS, i.e., firms' assessments about their current business conditions as well as their expectations for the next six months. The results speak in favor of interpreting these variables as firms' assessment of current and expected future levels of revenues. Despite of the potentially misleading wording of the questions, it is hence very unlikely that business expectations capture the expected change in reported current business conditions. Empirical studies that examine the relationship of firms' reported current and expected business conditions should hence interpret these variables as referring to the similar dimension of the same latent variable.

Chapter 1

Disaggregate Information and Firms' Expectation Formation*

1.1 Introduction

Firms' expectations regarding their own future business conditions are an important determinant of their investment, hiring, and pricing decisions. Yet, empirically little is known about which types of information are incorporated in these expectations. Firms may gather their information from diverse sources such as news articles, market sentiment, their order books or their own market research. Put in more abstract terms, firms may rely on both aggregate, industry-wide information (public industry benchmarks, private signals strongly correlated across firms, or market sentiment) and disaggregate information (idiosyncratic or sub-industry level information orthogonal to aggregate information) when forming their expectations.[1]

Uncovering the role of aggregate and disaggregate information for expectation formation is challenging, however, because it requires micro data on both firm's expectations as well as proxies for firms' information sets. The limited availability of such data is one of the main constraints for the empirical study of firms' expectations.[2] We circumvent this constraint by exploiting the panel dimension of the IFO Business Survey (IBS). This survey is unique in asking a sample of around 7000 firms that is representative for

*This chapter is based on joint work with Lukas Buchheim.

[1]The distinction between aggregate and disaggregate information has proven to be important. On the one hand, a focus on aggregate information may be optimal if it helps firms to coordinate (Veldkamp and Wolfers, 2007; Hellwig and Veldkamp, 2009) or when it can be acquired and processed more cheaply than disaggregate information. On the other hand, a focus on aggregate information may fuel animal spirits and amplify or cause news-driven business cycles (e.g., Angeletos and La'O 2013; Beaudry and Portier, 2014, provide a survey of the literature).

[2]The most common surveys (Survey of Professional Forecasters, Livingston Survey) elicit expectations about economy-wide aggregates like inflation, output growth, or stock prices. This data is hence not suitable to study the role of aggregate and disaggregate information for expectation formation.

the German economy about both their current and their expected business conditions at high, monthly, frequency. The panel structure of the data thus allows us to flexibly and precisely learn about aggregate information via time fixed effects, whereas the future realizations of firms' business conditions (net of time fixed effects) serve as a proxy for today's disaggregate information.

This chapter utilizes this dataset to learn more about how important aggregate and, in particular, disaggregate information are for the expectation formation of firms. We address two questions. First, to which extent is disaggregate information reflected in firms' expectations? And second, what is the causal effect of news about a disaggregate demand shock on expectations?

Our first finding is that disaggregate information is an important component of firms' expectations. Specifically, there is a strong association between expectations and the measure of disaggregate information—future firm-specific business realizations—across all empirical specifications. The result is particularly noteworthy for the main specification that controls for aggregate information via time fixed effects at the fairly narrow two-digit industry level of the German official industry classification, because it implies that firms within a given two-digit industry (e.g., manufacture of furniture) strongly rely on those components of their information sets that are orthogonal to the industry-specific information when forming their expectations.[3] Given the high dimension of the time fixed effects, this set of orthogonal, disaggregate information is typically a small subset of the information contained in firms' private signals (from, e.g., their order books), as the latter are often highly correlated within industries.

Moreover, additional analyses reveal that firms' expectations, which cover a six month window, are more strongly associated with disaggregate information about the near future (one quarter ahead) than with information about the more distant future (two quarters ahead). We also compare the extent to which information at the aggregate and disaggregate level are successful in explaining variation in expectations both via the marginal R^2 of the measures for information and a Shapley variance decomposition. Both comparisons show that, overall, aggregate and disaggregate information are roughly equally important for explaining variation in expectations. Across industries, the share of variance explained by disaggregate information is lowest in industries with arguably the strongest aggregate component in business conditions (services and manufacturing) and highest in industries

[3]The WZ 03 classification of the German Statistical Office (*Klassifikation der Wirtschaftszweige 2003*) used in this chapter largely corresponds to NACE Rev. 1.1 (the European Industry Classification System). The WZ 03 two-digit codes (*divisions*) are, in general, more narrow than the NAICS (North American Industry Classification System) two-digit codes (*sectors*). Often, WZ 03 two-digit *divisions* are comparable to NAICS three-digit *subsectors* (NAICS version of 2002); for example, in manufacturing there are 23 WZ 03 two-digit *divisions*, 3 NAICS two-digit *sectors*, and 21 NAICS three-digit *subsectors*. In total, there are 60 WZ 03 two-digit *divisions* and 20 (103) NAICS two-digit (three-digit) *subsectors*.

with a weak aggregate component (retail and wholesale).

To answer the second question, we use the sample of retail firms to provide causal evidence of how expectations react to information about a large demand shock: the demand effects of the three percentage point increase in the German VAT in January 2007, which was announced in late 2005. The VAT shock led to a differential treatment regarding the quality of information about future demand available to durable and non-durable good retailers. While durable good retailers experienced predictable pull-forward effects in demand—as manifested in strong demand increases before the VAT increase and strong demand reversals thereafter—non-durable good retailers were largely unaffected by the shock.[4] In contrast, the business conditions and expectations of durable and non-durable good retailers follow similar trends at all other times. We exploit this similarity of durable and non-durable retailers in a difference-in-differences design to identify the causal effect of the VAT-induced increase in the quality of information on expectations.

The main finding is that the treated durable goods retailers become more forward-looking once the demand shock enters the expectation window and, hence, information of higher quality is available to them. The effect is quantitatively large, as the weight of disaggregate information in explaining expectations doubles. The increased weight of disaggregate information in expectations is thereby entirely driven by the disaggregate information about the more distant future, possibly reflecting the fact that high-quality information about the VAT-induced demand shock was available from early on.

This chapter is the first to document the causal effect of new information on firms' expectations in a real world setting. Identifying this effect is challenging because the information sets of firms are typically unobservable and data on firms' expectations is scarce. The VAT-induced demand shock in Germany is thus a rare natural experiment for which both changes in firms' information sets can be inferred and high frequency data on firms' expectations exists. By showing that firms become more forward-looking when new (and precise) information becomes available, this chapter complements recent work by Coibion et al. (2015) who demonstrate by means of survey experiments that firms rationally adjust their expectations in response to additional information.[5]

This chapter contributes to the study of the determinants of firm's expectations by showing that disaggregate and aggregate information are equally important drivers of expectations. Taking a similar perspective as this chapter, Fuhrer (2015) argues that expectations are influenced by the consensus of past forecasters, one important type

[4]D'Acunto et al. (2016) document a sizable increase in consumers' readiness to spend on durable goods in response to the expected price increase due to the VAT change.

[5]In parallel work with the IBS data, Triebs and Tumlinson (2016) use the German reunification in 1990 as a natural experiment. They show that it took firms from the former East German states between two and five years to learn forecasting their business situation within the new capitalist environment they faced after 1990.

of aggregate information. Fuhrer's and our focus on the determinants of expectations thus complements the literature on survey expectations of firms and professional forecasters that tests specific models of expectation formation by inquiring whether relevant information is neglected in agents' expectations (see Pesaran and Weale, 2006, for a literature review). For example, Coibion and Gorodnichenko (2012, 2015), Andrade and Le Bihan (2013), and Dovern et al. (2015) test the implication of models of sticky information (Mankiw and Reis, 2002) and rational inattention (Sims, 2003; Woodford, 2003; Maćkowiak and Wiederholt, 2009, 2015) that expectations react sluggishly to shocks. Similarly, Bacchetta et al. (2009), Gennaioli et al. (2015), and Massenot and Pettinicchi (2016) test—and reject—the implication of rational expectations that forecast errors are uncorrelated with past observables.[6]

While work on the determinants of firms' expectations is rather scarce, a number of recent papers is concerned with the determinants of consumer expectations. D'Acunto et al. (2016) study the adjustment of consumers' inflation expectations to the German VAT shock of 2007 and the ensuing effects on the willingness to purchase durable goods. There is also an increasing number of works that examine the impact of past personal experiences on expectations (e.g., Ehrmann and Tzamourani, 2012; Malmendier and Nagel, 2016; Kuchler and Zafar, 2015) or the adjustment of consumer expectations to new information in survey experiments (e.g., Armantier et al., 2016; Cavallo et al., 2017; Armona et al., 2016).

The knowledge about the degree to which aggregate and disaggregate information influence expectations may contribute to a better understanding of macroeconomic dynamics in several ways. Veldkamp and Wolfers (2007) argue that the distinction between aggregate and disaggregate information is important for understanding the extent of synchronized price movements, which amplify the business-cycle co-movement across sectors. Similarly, learning about disaggregate shocks to large individual firms can help anticipate business cycle movements if these shocks cause non-negligible general equilibrium effects because they are "granular" in the sense of Gabaix (2011). Finally, our results suggest that disaggregate information is a time-varying source of cross-sectional heterogeneity in expectations, which, in turn, exhibits stable correlations with the fluctuations of aggregate variables (e.g., Mankiw et al., 2004; Bachmann et al., 2013b; Ben-David et al., 2013; Bachmann et al., 2017). As such, this chapter complements the works by Ito (1990), Patton

[6]Another strand of the literature evaluates the forecasting properties of survey expectations. Recent examples of this line of work are Ang et al. (2007) and Faust and Wright (2013), who show that inflation expectations are among the best available predictors of realized inflation. In contrast, Greenwood and Shleifer (2014) find a strong negative correlation between investors' expectations of stock market returns and the realized returns. In classical work, König et al. (1981) and Nerlove (1983) show strong bivariate associations between different outcome variables (prices, business conditions) and the corresponding expectations.

and Timmermann (2010), and Bachmann and Elstner (2015) who demonstrate that time-constant differences in firms' optimism and pessimism as well as persistent differences in priors are important drivers for cross-sectional disagreement.

The next section describes the survey data of the IBS used in this chapter. Section 1.3 develops a simple conceptual framework to dissect the impact of disaggregate and aggregate information on expectations. Section 1.4 utilizes this framework in panel regressions to quantify the effect of both types of information in general. In Section 1.5 we exploit the natural experiment given by the German VAT increase in 2007 to estimate the causal effect of new information on expectations. The last section concludes.

1.2 Data

The main data source of this chapter is the micro data of the IFO Business Survey (IBS). The IBS is conducted monthly, and is primarily used to construct the IFO Business Climate Index, Germany's most important lead indicator of economic activity (see Becker and Wohlrabe, 2008, for details on the survey). The IBS is divided into four industry surveys that cover the main sectors of the economy (manufacturing, services, retail/wholesale, construction), with each encompassing a sample of more than thousand firms representative for the German economy. Due to methodological peculiarities of the construction survey, our analysis focuses on data from the manufacturing (IBS-IND, 2015), services (IBS-SERV, 2015), and retail/wholesale (IBS-TRA, 2015) surveys.

The main data of interest are the firms' responses to questions regarding their realized and expected general business conditions. Specifically, every month all firms in the sample of the IBS are asked to provide an assessment of their current *realized business conditions*, which can be either bad (encoded as -1), normal (0), or good (1). Using a similar three point scale, the IBS also elicits firms' *expected business conditions* for an expectation window of six months.[7] In our interpretation, the categorical variables on firms' general business conditions and expectations are informed by the same latent variable that is likely related to the profitability of firms.[8] Bolstering this interpretation, Chapter 4 reports that

[7]Given that our main analysis rests on linear econometric models, quantitative data would be preferable to the qualitative data of the IBS. However, quantitative data on firms' expectations of comparable sectoral depth and long time horizon, which is required for the analyses of this chapter, is unavailable. Given these data constraints, we carefully verify that employing linear models delivers reliable results. The application of the Frisch–Waugh–Lovell Theorem in Section 1.4.1 shows that the data is consistent with the symmetry assumption imposed by linear models.

[8]The exact wording of the question regarding firms' realized business conditions is as follows: *"Current situation: We evaluate our current business condition (latest business trends) as [1] good, [0] satisfactory (typical for the season), [-1] bad."* The question regarding expectations, in turn, is: *"Expectations for the next 6 months: After elimination of purely seasonal fluctuations the development of our business will be [1] more favorable, [0] about the same, [-1] more unfavorable."* Hence, the wording of the question regarding expectations seemingly seeks to elicit the change in business conditions. This would be incon-

the sector aggregates of business conditions and expectations from the IBS closely follow the log deviation from trend of sector-specific aggregate revenue. Similarly, Abberger et al. (2009) find, in a meta survey of the retail/wholesale sample, that firms mostly refer to their current and expected profits and sales when they answer the questions of the IBS.

Our sample consists of all firms in the micro data of the IBS between March 2005 and October 2015 that remain in the sample for at least one year. The latter restriction is needed, because most of the empirical models include reported business conditions for the past six months (including the current month) and the following six months. For the same reason, the first month of the sample, March 2005, is the sixth month after the launch of the survey for the service sector in October 2004. Accordingly, our sample ends in October 2015 as, at the time of writing, the micro data were available until April 2016. The sample is large, comprising of, on average, 2400 manufacturing firms, 2170 service firms, and 1330 retailers/wholesalers per month. We harmonize the data over time and across the industry surveys following the procedure presented in Chapter 4. This primarily involves assigning the industry code of the official German industry classification system (*Klassifikation der Wirtschaftszweige 2003*, abbreviated as WZ 03, which closely follows the European industry classification NACE Rev. 1.1) to each firm based on the internal industry classification system of the IFO Institute. We also collapse the product-level surveys conducted in the retail and wholesale sector prior to 2006 to the firm level.

Sample attrition is low. Table 1.A.1 in Appendix 1.A shows that roughly 90 percent of firms remain in the sample after one year, with the number of firms declining by five to six percentage points per year thereafter. The average spell length of firms in our sample is more than five years. If firms are in the sample, they also have a high response rate: they answer the survey in more than three out of four months.[9] We linearly interpolate missing observations as long as the answers are missing for at most two consecutive months.

The empirical analyses of this chapter seek to explain the variation in expectations

sistent with our interpretation that both categorical survey responses are informed by the same latent variable. However, Chapter 4 documents several facts that favor our interpretation. First, the aggregate expectations lead the aggregate conditions by several months in each sector-specific survey, while the correlation between aggregate expectations and aggregate changes in business conditions over the past six months is highest at contemporaneity. Second, there is a positive association between current business conditions and expectations in the micro data, consistent with both referring to the same persistent latent variable. If expectations were referring to changes in business conditions, however, we would expect mean reversion, and, hence, a negative association between current conditions and expectations. Third, a horse race between both interpretations in the micro data clearly favors both variables being driven by the same latent variable. Last, but not least, the practitioners at the IFO Institute agreed with our interpretation in private conversations. This also manifests itself in the calculation of the IFO Business Climate Index, which is a weighted average of the elicited business conditions and expectations. Taking the average of these two variables is most sensible if they represent the same latent variable.

[9] Across industry surveys, the average sample spell and response rates, respectively, are as follows: manufacturing: 6.3 years and 81 percent; services: 5.4 years and 75 percent; retail/wholesale: 5.3 years and 81 percent.

Table 1.1: Transition Frequencies

		Conditions Next Period			Expectations Next Period		
		1	0	-1	1	0	-1
Current	1	0.233	0.064	0.003	0.130	0.074	0.007
Conditions/	0	0.064	0.410	0.045	0.071	0.481	0.062
Expectations	-1	0.003	0.046	0.133	0.009	0.060	0.106
	Sum	0.300	0.520	0.181	0.210	0.615	0.175

Notes: This table shows the transition frequencies of reported realized business conditions and expected business conditions. The left (right) panel shows the frequencies of reported business conditions (expected business conditions) in the next reported month for each possible current report of business conditions/expectations. Since these statistics are derived from the time dimension of the panel dataset, the overall frequencies of reported future conditions/expectations displayed in the last row (*Sum*) are equal to the overall frequencies for the current conditions/expectations, which are, for this reason, omitted.

about firms' future business conditions with variation in future realized business conditions. The bulk of the variation to be explained as well as the identifying variation is thereby provided by the variation of the firms' survey responses over time. Table 1.1 displays this variation by reporting the aggregate transition frequencies between the categorical values of both the realized (left panel) and expected business conditions (right panel) from one month to the next.[10] The table shows that reported business condition change frequently. The business conditions differ between the current and next month in between two to three out of ten months, regardless of whether they currently report bad, normal, or good conditions. The conditional transition frequencies of expectations are almost identical if current expectations equal zero, and are slightly higher—one change in reported expectations in four out of ten months—when expectations are either good or bad. This results in a slightly lower fraction of normal realized conditions vis-a-vis normal expectations (0.52 vs. 0.61), possibly reflecting the shorter reporting window of realized conditions than the expectation window (one month vs. six months). Considering that firms report different realized or expected business conditions in at least two out of ten months but remain in the sample for more than five years on average, there is hence sufficient (within firm) variation both in the dependent and the independent variables of interest.

[10]The transition frequencies within each of the three industry surveys are similar to the aggregate, as Table 1.A.2 in Appendix 1.A shows.

1.3 Expectations and Disaggregate Information: Conceptual Framework and Empirical Model

This section presents a conceptual framework that establishes why, exploiting panel data, future realized business conditions can be used as a proxy for disaggregate information. This framework also governs the choice of the empirical model for the remainder of the chapter.

1.3.1 Conceptual Framework

Denote firm i's realized business condition at time t by $y_{i,t}$ and note that realized business conditions can be decomposed into an aggregate component a_t and a disaggregate component $d_{i,t}$. Hence, $y_{i,t} = a_t + d_{i,t}$, with $d_{i,t}$ orthogonal to a_t. We assume that the future aggregate and disaggregate business conditions at $t+1$, a_{t+1} and $d_{i,t+1}$, both consist of known, orthogonal components denoted by $\hat{a}_t^{t+1}$ and $\hat{d}_{i,t}^{t+1}$, and unknown shocks denoted by α_{t+1} and $\delta_{i,t+1}$, respectively. We call $\hat{a}_t^{t+1}$ aggregate information, and $\hat{d}_{i,t}^{t+1}$ disaggregate information; α_{t+1} and $\delta_{i,t+1}$ are normal, independent and zero mean shocks with variances σ_α^2 and σ_δ^2.[11] Given the information known at t, the expected business conditions at $t+1$ are hence given by $E_t[y_{i,t}] = E_t[a_{t+1}] + E_t[d_{i,t+1}] = \hat{a}_t^{t+1} + \hat{d}_{i,t}^{t+1}$.

When reporting their expectations in t, firms use their information as embodied in $\hat{a}_t^{t+1}$ and $\hat{d}_{i,t}^{t+1}$, but also make an error $\varepsilon_{i,t}$ that has a zero mean. Firm i's observed expectations $\hat{y}_{i,t}^{t+1}$ are hence given by

$$\hat{y}_{i,t}^{t+1} = \hat{a}_t^{t+1} + \hat{d}_{i,t}^{t+1} + \varepsilon_{i,t}. \tag{1.1}$$

The challenge for assessing the importance of aggregate and disaggregate information for expectation formation is that firms' information sets $(\hat{a}_t^{t+1}, \hat{d}_{i,t}^{t+1})$ are, in general, unobservable. Our empirical strategy exploits two ideas to overcome this constraint. First, with panel data it is possible to non-parametrically identify the aggregate information $\hat{a}_t^{t+1}$ via time fixed effects. Second, given this and the information structure, future firm-specific realized business conditions can serve as a proxy for the disaggregate information.

To formally see these points, consider the following empirical model that regresses expectations at t, $\hat{y}_{i,t}^{t+1}$, on date fixed effects ψ_t and ex post realizations $y_{i,t+1}$:

$$\hat{y}_{i,t}^{t+1} = \psi_t + \beta_1\, y_{i,t+1} + \epsilon_{i,t}. \tag{1.2}$$

[11] Note that $\hat{a}_t^{t+1}$ and $\hat{d}_{i,t}^{t+1}$ represent the knowledge of firm i. As this chapter is concerned with identifying the sources of information that govern firms' expectations and not with firms' forecast precision or forecast errors, we are agnostic about whether firms know the entire learnable information (as implied by, e.g., models of rational expectations), or only subsets of it (as implied, e.g., by models of rational inattention).

By the Frisch-Waugh-Lowell Theorem, we have that β_1 can also be identified via

$$\hat{\nu}_{i,t} = \beta_1 \, \nu_{i,t} + \eta_{i,t}. \tag{1.3}$$

Here, $\hat{\nu}_{it}$ and ν_{it} are the residuals of regressing expectations and future realizations, respectively, on date fixed effects

$$\begin{aligned} \hat{y}_{i,t}^{t+1} &= \hat{\lambda}_t + \hat{\nu}_{i,t} \\ y_{i,t+1} &= \lambda_t + \nu_{i,t}. \end{aligned}$$

Given the definition of observed expectations in (1.1) and due to the independence of $\hat{a}_t^{t+1}$ and $\hat{d}_{i,t}^{t+1} + \varepsilon_{i,t}$, we have that $\hat{\lambda}_t \xrightarrow{p} \hat{a}_t^{t+1}$ and, hence, $\hat{\nu}_{it}, \xrightarrow{p} \hat{d}_{i,t}^{t+1} + \varepsilon_{i,t}$. By a similar argument, it holds that $\nu_{i,t} \xrightarrow{p} d_{i,t+1} = \hat{d}_{i,t}^{t+1} + \delta_{i,t+1}$. Hence, (1.3) becomes equivalent to

$$\hat{d}_{i,t}^{t+1} = \beta_1 \, (\hat{d}_{i,t}^{t+1} + \delta_{i,t+1}) + (\eta_{i,t} - \varepsilon_{i,t}).$$

We conclude that, after controlling for time fixed effects, future firm-specific future realized business conditions are indeed a proxy for disaggregate information $\hat{d}_{i,t}^{t+1}$, albeit with classical "measurement error" given by the disaggregate shock $\delta_{i,t+1}$. As a consequence, the coefficient of future realizations will reflect attenuation bias. Specifically, since the true coefficient of regression $\hat{d}_{i,t}^{t+1}$ on itself equals one, we have that $\beta_1 \to 1 \times \frac{Var(\hat{d}_{i,t}^{t+1})}{Var(\hat{d}_{i,t}^{t+1}) + \sigma_\delta^2}$, where the latter term is the attenuation factor.

Thus, there are three important observations that can be drawn from the analysis above. First, with panel data it is possible to use future firm-specific business conditions as a proxy for disaggregate information. This is because time fixed effects non-parametrically filter out both aggregate information $\hat{a}_t^{t+1}$ and aggregate business conditions a_{t+1} in the application of the Frisch-Waugh-Lowell Theorem. Second, the size of the coefficient of the ex post realized business conditions can be interpreted as a measure of how well informed firms are about their future (disaggregate) business conditions. *Ceteris paribus*, firms are better informed about their disaggregate business conditions if the variance of the disaggregate shock σ_δ decreases. This leads to an increase in the attenuation factor $\frac{Var(\hat{d}_{i,t}^{t+1})}{Var(\hat{d}_{i,t}^{t+1}) + \sigma_\delta^2}$, and hence to an increase of β_1.[12] Third, due to the attenuation bias, the marginal R^2 of using future realized conditions as a proxy for disaggregate information is a lower bound of the variance explained by disaggregate information $\hat{d}_{i,t}^{t+1}$.

[12] While the inclusion of an additional regressor into (1.3) alters the definition of the attenuation factor, the conclusion that a decrease in σ_δ implies an increase in β_1 remains valid as long as the disaggregate shock $\delta_{i,t}$ is uncorrelated with the additional regressor.

1.3.2 Empirical Model

The empirical model that guides the empirical analyses throughout the chapter closely follows the conceptual framework outlined above. Specifically, we estimate a slightly modified version of (1.2) to test whether expectations primarily reflect aggregate information at the industry level or disaggregate information orthogonal to industry-specific information.

The empirical model is the following:

$$\begin{aligned}\text{Expectations}_{i,t}^{+6m} = \\ \beta_1 \,\text{Conditions}_{i,(t+1,t+6)} + \beta_2 \,\text{Conditions}_{i,(t,t-5)} + m_i + a_t \times \mathbb{1}(\text{Subsector}_i) + \varepsilon_{i,t}. \quad (1.4)\end{aligned}$$

As for the conceptual framework (1.2), the dependent variable of the empirical model (1.4) are firm i's expectations stated at the monthly date t, which cover an expectation window of six months. As in (1.2), moreover, we non-parametrically identify the aggregate information at the two-digit level of the German industry classification system of 2003, which is roughly equivalent to three-digit NAICS *subsectors* (see Footnote 3), via the subsector-specific time fixed effects $a_t \times \mathbb{1}(\text{Subsector}_i)$.[13] Furthermore, we proxy for disaggregate information via the ex post realization of business conditions during the expectation window of the following six months, as given by $\text{Conditions}_{i,(t+1,t+6)}$. $\text{Conditions}_{i,(t+1,t+6)}$ is calculated as the moving average of the monthly reports of business conditions between the months $t+1$ and $t+6$.

We modify the conceptual framework (1.2) slightly by including firm fixed effects m_i and the six month moving average of current and past realized business conditions, $\text{Conditions}_{i,(t,t-5)}$, as additional independent variables. The firm fixed effects m_i filter out a constant firm-specific tendency of expectations that may be caused by structural factors like an (un)successful business model as well as persistent firm-specific optimism or pessimism (as documented by Bachmann and Elstner, 2015). The past business conditions control for adaptive expectations or the effect of past (disaggregate) information on expectations. This ensures that the proxy for disaggregate information, $\text{Conditions}_{i,(t+1,t+6)}$, predominantly captures the effect of newly relevant information that is not included in past conditions on expectations. That being said, none of our results qualitatively depend on the inclusion of either m_i or $\text{Conditions}_{i,(t-5,t)}$ in the empirical model.

Finally, note that the empirical model (1.4) is linear irrespective of the discrete and ordinal nature of the data. This choice is driven by the non-existence of standard methods

[13] To keep the notation lean, we abuse notation slightly and assign the same letter to different (but related) parameters and variables. For example, in the empirical model (1.4), a_t denotes the time fixed effect, while in the conceptual framework a_t denotes the aggregate business conditions. To avoid confusion, parameters will be uniquely defined within the subsections of the chapter.

for the estimation of fixed effects models with non-binary ordinal data. While Riedl and Geishecker (2014) find that linear panel data models generally perform quite well in comparable settings with large cross-sections and long time series (large N and T), it is *a priori* not clear that assuming linearity is appropriate in the context of this study. We therefore verify in Section 1.4.1 that the linear model is consistent with the variation present in the data.

1.4 Panel Results

This section documents the strong association between disaggregate information and firms' expectations. The analysis begins with an application of the Frisch-Waugh-Lowell Theorem in a regression anatomy exercise that displays the substantial degree of identifying variation in the data. In addition, the analysis verifies that the linearity imposed by the empirical model (1.4) is reflected in the data despite its categorical nature. Then, we turn to the direct estimation of the main empirical model (1.4) and corresponding model variants to quantify the strength and statistical significance of the positive association between firms' expectations and disaggregate information. Finally, a comparison of the variance in expectations explained by disaggregate and aggregate information reveals that both sources of information influence expectations to a similar degree.

1.4.1 Regression Anatomy of the Identifying Variation

Section 1.3 argues that the effect of disaggregate information on expectations can be identified via the partial correlation of expectations and future realized business conditions with both variables purged for their aggregates via time fixed effects. We now bring this analysis to the data and analyze the empirical correlation between purged current expectations $\hat{\nu}_{i,t}$ and purged future business conditions $\nu_{i,t}$, our proxy for disaggregate information. In the context of the empirical model (1.4), $\hat{\nu}_{i,t}$ and $\nu_{i,t}$ are thereby defined as the residuals of the following regressions:

$$\text{Expectations}_{i,t}^{+6m} = \hat{\beta}_2 \, \text{Conditions}_{i,(t,t-5)} + \hat{m}_i + \hat{a}_t \times \mathbb{1}(\text{Subsector}_i) + \hat{\nu}_{i,t} \quad (1.5)$$

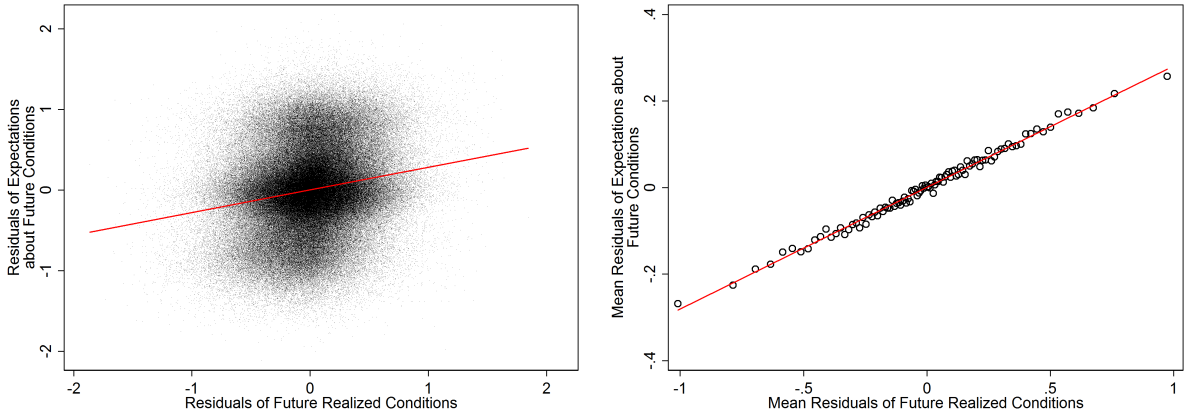
$$\text{Conditions}_{i,(t+1,t+6)} = \tilde{\beta}_2 \, \text{Conditions}_{i,(t,t-5)} + \tilde{m}_i + \tilde{a}_t \times \mathbb{1}(\text{Subsector}_i) + \nu_{i,t}. \quad (1.6)$$

Given this, note that the linear projection of $\hat{\nu}_{i,t}$ on $\nu_{i,t}$ corresponds to the effect of disaggregate information on expectations, because for β_1 from (1.4) it holds that $\beta_1 = \frac{Cov(\hat{\nu}_{i,t},\nu_{i,t})}{Var(\hat{\nu}_{i,t})}$ by the Frisch-Waugh-Lowell Theorem.[14]

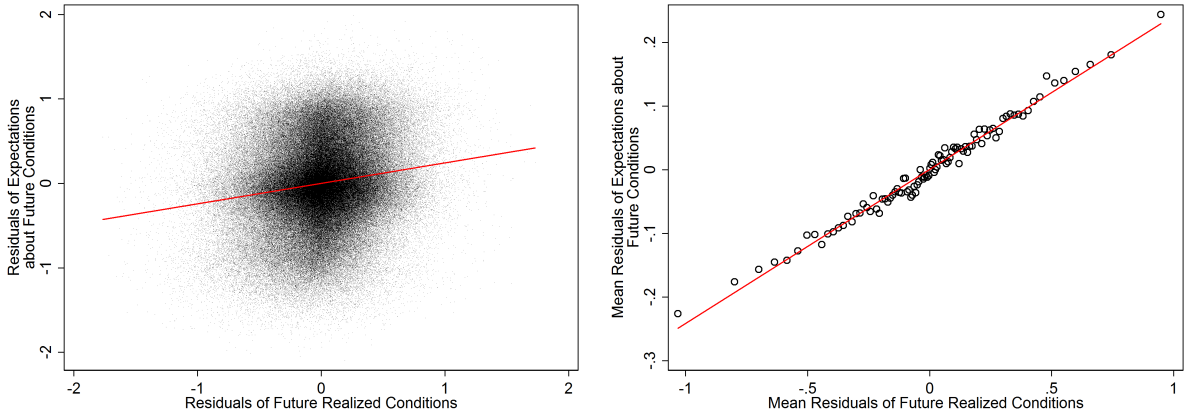
[14] Angrist and Pischke (2008) provide a detailed discussion of the theorem and its usefulness for assessing the identifying variation.

Figure 1.1: Regression Anatomy

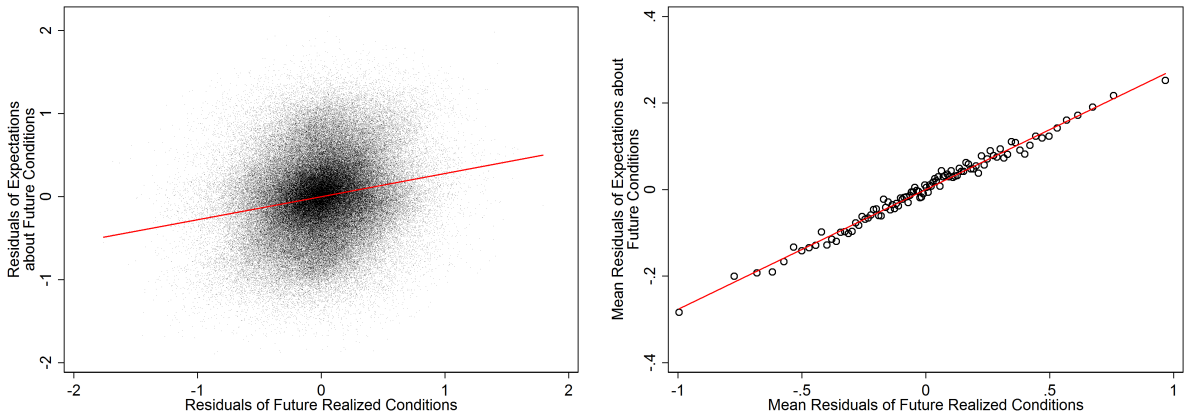
Panel A: Manufacturing



Panel B: Services



Panel C: Retail and Wholesale



Notes. The left figures plot, for each sector-specific survey of the IBS, firms' six month ahead expectations at t (purged for firm fixed effects and date fixed effects at the firms' two-digit industry level as well as current and past conditions according to (1.5)) against the future realized business conditions between $t+1$ and $t+6$ (purged for the same variables as expectations according to (1.6)). The right figures group the residuals of the ex post conditions by percentile and plot, conditional on the percentile, the means of the purged expectations against the means of ex post realized business conditions. The straight lines in both panels represent the regressions of purged expectations on purged future conditions.

The left panels of Figure 1.1 plot, separately for each sector-wide survey, the purged expectations $\hat{\nu}_{i,t}$ against the proxy for disaggregate information $\nu_{i,t}$. The large dispersion of $\nu_{i,t}$ along the horizontal axis reveals that there is sufficient identifying variation in the disaggregate component of the future realized business conditions even after filtering out the aggregate variation at the subsector level. In addition, the regression lines in these figures, the slopes of which are between 0.25 (services) and 0.29 (manufacturing and retail/wholesale), indicate that there is a strong positive association between disaggregate future realizations, the proxy for disaggregate information, and firms' expectations. Yet, this positive association is somewhat masked by the large visible dispersion of $\hat{\nu}_{i,t}$ that is due to the large number of observations (between approximately 160'000 in the retail/wholesale survey and 310'000 in the manufacturing survey). It is hence not clear whether the positive correlation between disaggregate information and expectations is due to outliers or non-linearities—potentially originating from the categorical nature of the data—, or whether the positive and linear association is a general and robust feature of the data.

To reduce noise in both dimensions, the right panels of Figure 1.1 group the purged future conditions $\nu_{i,t}$ by percentiles and plot, conditional on the percentile of $\nu_{i,t}$, the means of the purged expectations $\hat{\nu}_{i,t}$ against the means of the purged future business conditions. Evidently, the correlation of these conditional means is highly linear in all industry surveys and tightly clustered around the linear projections of $\hat{\nu}_{i,t}$ on $\nu_{i,t}$. The average effect of the proxy for disaggregate information on firms' expectations is thus constant across the entire domain of disaggregate information, suggesting that the estimation of linear models is appropriate despite the categorical nature of the data.

1.4.2 Disaggregate Information Is Strongly Associated with Expectations

We now proceed to document the main findings of this section. Column (5) of Table 1.2 reports the complete estimates of the empirical model (1.4). As became clear in the regression anatomy exercise, there is a strong positive association between firms' expectations and the future realized business conditions, the proxy for disaggregate information after controlling for aggregate information via the time fixed effects. Because the standard deviations of expectations and realized conditions are of similar magnitude, the estimated coefficients imply that a one standard deviation change in realized conditions (disaggregate information) is associated with an adjustment of expectations by between 0.25 (services) and 0.29 (manufacturing and retail/wholesale) in the same direction. The effects are precisely estimated with standard errors more than one order of magnitude

Table 1.2: Firms' Expectations and Disaggregate Information

	Expected Business Conditions for the Next 6 Months				
	Panel A: Manufacturing				
	(1)	(2)	(3)	(4)	(5)
$\text{Conditions}_{t+1,t+6}$	0.41***		0.39***		0.29***
	(0.015)		(0.018)		(0.0067)
$\text{Conditions}_{t,t-5}$	-0.13***	0.060***	-0.15***	0.048***	-0.098***
	(0.013)	(0.015)	(0.014)	(0.0094)	(0.0091)
R^2	0.102	0.231	0.285	0.304	0.329
Adjusted R^2	0.102	0.220	0.275	0.288	0.313
Firm FE		yes	yes	yes	yes
Time*2dig-Sector FE				yes	yes
Observations	334542	336014	334473	333426	331899
	Panel B: Services				
$\text{Conditions}_{t+1,t+6}$	0.35***		0.31***		0.25***
	(0.013)		(0.016)		(0.0085)
$\text{Conditions}_{t,t-5}$	-0.090***	0.017	-0.14***	0.0079	-0.11***
	(0.012)	(0.013)	(0.012)	(0.0092)	(0.0079)
R^2	0.075	0.304	0.333	0.350	0.368
Adjusted R^2	0.075	0.292	0.321	0.332	0.350
Firm FE		yes	yes	yes	yes
Time*2dig-Sector FE				yes	yes
Observations	304136	306462	303936	306066	303548
	Panel C: Retail and Wholesale				
$\text{Conditions}_{t+1,t+6}$	0.35***		0.33***		0.29***
	(0.010)		(0.011)		(0.0079)
$\text{Conditions}_{t,t-5}$	0.22***	0.35***	0.21***	0.32***	0.21***
	(0.011)	(0.013)	(0.013)	(0.012)	(0.011)
R^2	0.237	0.381	0.413	0.414	0.436
Adjusted R^2	0.237	0.371	0.404	0.403	0.426
Firm FE		yes	yes	yes	yes
Time*2dig-Sector FE				yes	yes
Observations	180400	181156	180339	180930	180115

Notes: $\text{Conditions}_{t+1,t+6}$ is the mean of ex post realized business conditions in the following six months which is the proxy for disaggregate information. $\text{Conditions}_{t,t-5}$ is defined accordingly. "Time*2dig-Sector FE" are time fixed effects at the two-digit industry level. Standard errors are two-way clustered at the levels of firms and dates. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

smaller than the point estimates.[15] Note also that, conditional on future business conditions within the expectation window, expectations seem to exhibit mean reversion with respect to current and past conditions in the manufacturing and service surveys, while they follow current conditions more closely in the retail/wholesale survey.

In Column (5), we non-parametrically control for aggregate information (and aggregate realizations) via high dimensional time fixed effects at the subsector level. For this reason, the coefficient of future realized conditions captures the degree of information about disaggregate outcomes reflected in the expectations. Column (3), in turn, estimates the same coefficient without the time fixed effects. Then, the coefficient reflects the impact of information regarding the firms' total future conditions, i.e., the sum of aggregate and disaggregate conditions, on their expectations. The increase in the coefficient of future realized conditions hence indicates, plausibly, that firms expectations reflect the future total conditions more strongly than only the disaggregate conditions.[16] Finally, the comparison of the results in Columns (3) and (1) reveals that the coefficient of future realized conditions increases slightly if we remove the firm fixed effects from the set of covariates. This indicates that both expectations and business outcomes are partly determined by firm-specific conditions like, for example, the general success of their business model.[17]

Next, we take a closer look at the time horizon of the disaggregate information reflected in the expectations. To this end, we split the proxy of disaggregate information, the ex post realized business conditions in the following six months, into business realizations one quarter and two quarters ahead (denoted by $\text{Conditions}_{i,(t+1,t+3)}$ and $\text{Conditions}_{i,(t+4,t+6)}$, respectively). For symmetry, we proceed similarly with current and past conditions. The results in Table 1.3 show that firms' expectations about the following six months are more strongly associated with disaggregate information about the business conditions one quarter ahead than with the conditions two quarters ahead. The difference is least pronounced in the service and manufacturing surveys, where firms potentially face a relatively steady business environment, than in the retail/wholesale survey, where the business environment potentially fluctuates with higher frequency. Overall, however, the result is consistent with the hypothesis that firms are, in general, better informed about the near than the more distant future.

[15] Standard errors are two-way clustered along the firm and time dimensions following Dube et al. (2010) and Cameron et al. (2011). This adjusts for serial correlation of standard errors within firms as well as correlations of errors within time periods.

[16] Following the conceptual framework in Section 1.3.1 and interpreting the coefficient of future conditions as an attenuation factor, the result implies that the ratio of the variance of the aggregate shock $(\alpha_{t+1} + \delta_{i,t+1})$ to the variance of aggregate information $(\hat{a}_t^{t+1} + \hat{d}_{it,}^{t+1})$ is smaller than the ratio of the variance of the disaggregate shock $\delta_{i,t+1}$ to the variance of disaggregate information, $\hat{d}_{i,t}^{t+1}$. While this finding is plausible, it is by no means obvious.

[17] The remaining results of Table 1.2 in Columns (2) and (4) will be useful in the analysis of the variance explained in the next subsection.

Table 1.3: Firms' Expectations and Disaggregate Information: Different Forecast Horizons

	Expected Business Conditions for the Next 6 Months		
	Panel A: Manufacturing	*Panel B: Services*	*Panel C: Retail and Wholesale*
$\text{Conditions}_{t+4,t+6}$	0.11***	0.11***	0.079***
	(0.0056)	(0.0062)	(0.0060)
$\text{Conditions}_{t+1,t+3}$	0.17***	0.15***	0.18***
	(0.0054)	(0.0061)	(0.0053)
$\text{Conditions}_{t,t-2}$	0.0055	-0.060***	0.27***
	(0.0073)	(0.0077)	(0.0081)
$\text{Conditions}_{t-3,t-5}$	-0.11***	-0.066***	-0.055***
	(0.0066)	(0.0065)	(0.0068)
Time*2dig-Sector FE	yes	yes	yes
Firm FE	yes	yes	yes
R^2	0.332	0.370	0.449
Adjusted R^2	0.316	0.352	0.439
Observations	318100	283688	172487

Notes: $\text{Conditions}_{t+4,t+6}$ is the mean of ex post reported business conditions in four to six months in the future. $\text{Conditions}_{t+1,t+3}$, $\text{Conditions}_{t,t-2}$, and $\text{Conditions}_{t-3,t-5}$ are defined accordingly. $\text{Conditions}_{t+1,t+3}$ and $\text{Conditions}_{t+4,t+6}$ serve as proxies for disaggregate information. "Time*2dig-Sector FE" are time fixed effects at the two-digit industry level. Standard errors are two-way clustered at the levels of firms and dates. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Appendix 1.B, we perform various robustness checks all of which leave the results unchanged. Table 1.B.1 shows that the parameter estimates are largely independent of the exact specification of the time fixed effects, including the introduction of time fixed effects at the state level. In addition, sample attrition should be of little concern, as the results are identical for subsamples of firms that are observed for sufficiently long time periods. Table 1.B.2 demonstrates that the main results are robust to changes in the vector of covariates. For example, we show that controlling for aggregate, industry-wide observations by means of industry-level revenues instead of the industry-level fixed effects leads to similar results with coefficients approaching the ones reported in Column (3) of Table 1.2. This is not surprising, as industry-level revenues plausibly proxy only for parts of the aggregate information available to firms. We also control for lagged expectations or separately for current and past business conditions, with both specifications leading to results very close to the findings reported in this section. Finally, Table 1.B.3 confirms that firms' expectations are associated with disaggregate information independent of their current business situation.

1.4.3 Variance Explained by Aggregate and Disaggregate Information

This section assesses the relative importance of disaggregate information in comparison to aggregate, industry-wide information for explaining variation in firms' expectations. For this purpose, we first take a look at the marginal R^2 of these variables. Comparing Columns (2) and (4) of Table 1.2 shows that the aggregate and industry-level conditions captured by the time fixed effects add between 3.3 (retail/wholesale) and 7.3 (manufacturing) percentage points to the fraction of overall variance explained. Comparing Columns (4) and (5), the marginal R^2 of disaggregate information as proxied by the realized future business conditions is between 1.8 (services) and 2.5 (manufacturing) percentage points. Hence, the marginal R^2 of disaggregate information amounts to between one third (manufacturing) and two thirds (retail/wholesale) of the marginal R^2 of the aggregate information at the subsector level.

To put these numbers in perspective, recall from the conceptual framework in Section 1.3.1 that the estimated marginal R^2 of disaggregate information is a lower bound for its true marginal R^2. The reason is that the proxy for disaggregate information, the ex post realized business conditions, induces attenuation bias for the coefficient of disaggregate information. In contrast, the estimated marginal R^2 of aggregate information closely approximates its true value, because the time fixed effects capture the variance explained by aggregate information flexibly and non-parametrically.

The extent to which proxying for information via future realized conditions leads to underestimating the true marginal R^2 can be gauged from comparing the marginal R^2 of the time fixed effects—i.e., the comparison of Columns (2) and (4)—with the marginal R^2 of realized conditions without time fixed effects—i.e., the comparison of Columns (2) and (3). Without the inclusion of time fixed effects, the realized conditions are a proxy for the sum of disaggregate *and* aggregate information. Nevertheless, the marginal R^2 of proxying for *both* disaggregate and aggregate information is smaller than the marginal R^2 of flexibly accounting for *only* the aggregate conditions via the fixed effects. This suggests that the empirical framework severely underestimates the variance explained by disaggregate information. Seen in this light, the prominent role of disaggregate information in explaining variance in expectations is even more remarkable.

Broadening the perspective, it is also instructive to ask how much of the variance in expectations is explained by the future realized business conditions *per se*, i.e., when they are not necessarily interpreted as a proxy for (disaggregate) information. The answer to this question is not trivial, as the contribution of the future conditions to the share of total variance explained depends on the order with which the covariates are included in the estimation. This is because the identifying variation of each additional covariate is its

Table 1.4: Generalized Shapley Decomposition of the Variance Explained

	Average Marginal Contribution to R^2 (in % of R^2)		
	Manufacturing	*Services*	*Retail and Wholesale*
$\text{Conditions}_{t+1,t+6}$	16.6	10.7	21.5
$\text{Conditions}_{t,t-5}$	3.8	3.1	17.2
Time*2dig-Sector FE	19.2	13.1	8.2
Firm FE	60.4	73.2	53.0
R^2	0.329	0.368	0.436
Observations	331899	303548	180115

Notes: $\text{Conditions}_{t+1,t+6}$ is the mean of ex post reported business conditions in the following six months. $\text{Conditions}_{t,t-5}$ is defined accordingly. "Time*2dig-Sector FE" are time fixed effects at the two-digit industry level.

partial variation that is uncorrelated with the covariates already included in the model. Clearly, the (partial) identifying variation of each additional covariate declines with the number of covariates already included.

A recent method to deal with this issue is the generalized Shapley value decomposition approach suggested by Shorrocks (2013).[18] Given groups of covariates defined by the researcher, this method decomposes the overall model R^2 into the relative contributions of each group. Applied to our setting, the generalized Shapley value corresponds to the *average* marginal contribution of each group of covariates to the overall model R^2 across all possible sequences of adding these groups to the empirical model.

We compute the generalized Shapley values for the following four groups of covariates: (A) the realized future business conditions ($\text{Conditions}_{i,(t+1,t+6)}$), (B) the current and past business conditions ($\text{Conditions}_{i,(t,t-5)}$), (C) the set of industry-specific time fixed effects ($a_t \times \mathbb{1}(\text{Subsector}_i)$), and (D) the set of firm fixed effects (m_i).[19] Table 1.4 displays the results of this variance decomposition. Clearly, the firm-specific future business conditions and the aggregate information as captured by the time fixed effects both contribute a similar—and sizable—share to the total variance explained. Specifically, the future business conditions contribute, on average, 21.5 percent to the total variance explained in the retail/wholesale survey, and 19.2 and 10.7 percent, respectively, in the manufacturing

[18] Huettner and Sunder (2012) illustrate this approach and review findings of the literature on its desirable properties such as efficiency, monotonicity, and equal treatment of groups as well as of players within groups.

[19] Given this grouping, the generalized Shapley values are computed as follows. Within each of the $4! = 24$ permutations of groups (ABCD, ABDC, ..., DCBA), the respective groups are sequentially added to the regression model and the marginal contribution of each group of covariates to the overall model R^2 is determined. Each group's Shapley value is then given by the average marginal contribution over all permutations of groups.

and services surveys. The aggregate effects at the two-digit industry level contribute, on average, between 8.2 percent (retail/wholesale) and 16.6 percent (manufacturing) to the total variance explained. These statistics are hence consistent with the notion that the manufacturing and services sectors are more exposed to the aggregate business environment than the retail and wholesale sectors. Nevertheless, across all industry surveys, firm-level information as captured by future realized business conditions seems to be an important driver of expectations.[20]

1.5 The Effect of Information on Expectation Formation: Quasi-Experimental Evidence

The previous section has shown that firms' expectations reflect information about firm-specific future business conditions that are orthogonal to aggregate or sector-specific fluctuations. As such, firms are at least partially forward-looking when forming their expectations during "normal times." During these periods, however, it is likely that information about future business conditions is imprecise as well as costly to gather and process. In the remainder of the chapter, we study an episode during which a subset of firms had precise and salient information about a disaggregate demand shock and ask how firms incorporate this new information into their expectations.

It is difficult to identify the causal effect of a change in available information on expectations in the field, predominantly because the information sets of firms are unobservable to the researcher. Although aggregate shocks are often observable and can, at times, be anticipated, they affect all firms at the same time so that the effect of new information becomes indistinguishable from the potential impact of other sources of aggregate fluctuations. Hence, it requires information about a disaggregate information shock that affects a well-defined subset of firms to learn more about how expectations react to changes in the quality of available information.

The announcement of the newly formed German government in November 2005 to raise the VAT from 16 percent to 19 percent as of January 2007 constitutes such a disaggregate information shock.[21] It is well known that increases in the VAT heterogeneously affected

[20] The decomposition exercise also reveals the very prominent role of time-invariant firm-level factors in explaining variation in firms' expectations. At least one fifth of the variation in expectations is explained by firm fixed effects which accounts for between 53.0 percent (retail/wholesale) and 73.2 percent (services) of the overall R^2. The importance of firm fixed effects is not surprising. As shown in Section 1.2, firms frequently report that they expect normal business conditions. Hence, firm fixed effects close to zero presumably "explain" many of the observations with $\text{Expectations}_{i,t}^{+6m} = 0$. In addition, the firm fixed effects also account for the general success of firms' business strategies in the medium and long run as well as for systematic, time-invariant expectation biases (Bachmann and Elstner, 2015, find the latter to be quite prevalent).

[21] During the 2005 election campaign, Ms. Merkel's Christian Democrats (CDU) promised to lower

business conditions of retail firms depending on the type of products they sell. While firms trading with durable goods usually face a large pull-forward effect in demand resulting in sizable fluctuations of their business conditions, firms trading with non-durable goods are typically not affected.[22] For the case of the German VAT reform, this asymmetric effect has been documented by D'Acunto et al. (2016) who find a sizable increase in consumers' readiness to spend on durable goods in advent of the tax rise. Moreover, they do not find evidence for intra-temporal substitution from non-durable to durable goods. Because such pull-forward effects in demand are a common result of VAT increases, they were easy to predict for Germany's durable good retailers, so that the VAT shock led to a differential treatment regarding the quality of information about future demand available to durable and non-durable good retailers.

1.5.1 Empirical Strategy: Difference-in-Differences

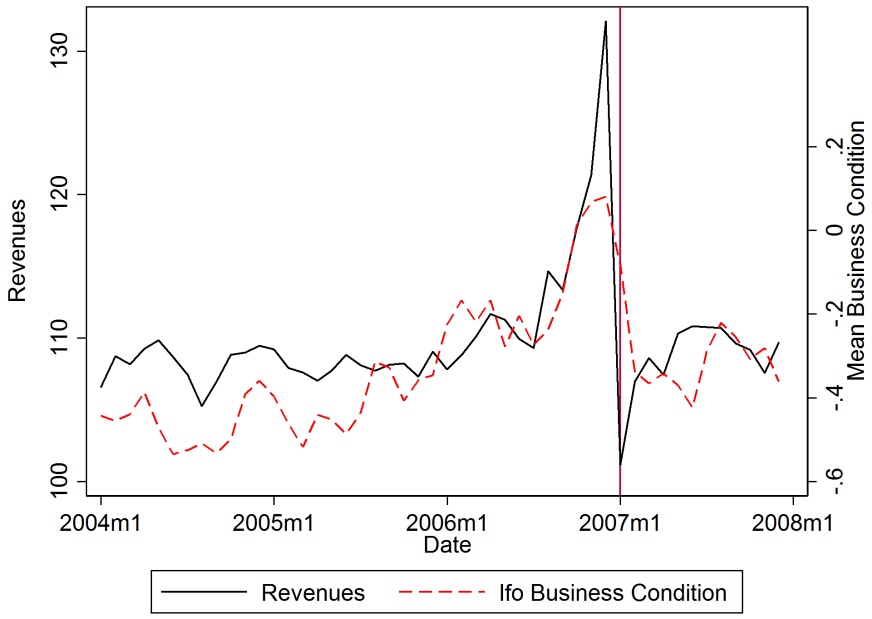
We seek to identify the causal effect of the VAT-induced increase in the quality of information on expectations in a difference-in-differences (DiD) design. For this purpose, we assign firms to treatment and control groups based on the findings of Carare and Danninger (2008) and a report of the German central bank (Bundesbank, 2008). Both studies document that the pull-forward effect in demand was strongest in sales of new cars followed by sales of furniture, furnishings, electronic household appliances, and construction material. Accordingly, we assign approximately 220 retailers of cars, furniture, and electronics to the treatment group to which we henceforth refer as "durable good retailers." The remaining 340 retail firms are assigned to the control group.[23] As the

non-wage labor costs and to refinance the decrease in revenue via an increase in the VAT by 2 percent (CDU/CSU, 2005, p. 13). All other parties with a path to being part of a ruling coalition after the election (Social Democrats, Greens, and Liberals) were in strong opposition to the proposed VAT increase (see, e.g., SPD, 2005, p. 39). As none of the blocks (CDU/CSU & Liberals or Social Democrats & Greens) gained an absolute majority in parliament (*Bundestag*), Christian Democrats and Social Democrats formed a "grand coalition" headed by the new chancellor Ms. Merkel and decided to increase VAT by 3 percent in order to consolidate the federal budget; the non-wage labor costs were lowered by only 1 percent. The draft of the law was accepted by the federal cabinet on February 22, 2006, and was passed into law by the two chambers of parliament on May 19th (*Bundestag*) and June 16th (*Bundesrat*). Given the broad majority of the coalition in both chambers, parliamentary approval of the tax increase did not come as a surprise to the public. D'Acunto et al. (2016) provide a more detailed discussion and documentation of unexpectedness and purposes of the 2007 VAT increase.

[22] In Germany, virtually all durable goods are taxed with the full VAT of 19 percent. A sizable fraction of non-durables such as food, newspapers, and flowers are taxed with a reduced rate of 7 percent that has not been changed since 1983.

[23] Specifically, we define firms as being "treated" if they are classified as being part of the following sectors of the German industry classification system of 2003 (*WZ 03*): "50.1 Sale of motor vehicles," "52.44 Retail sale of furniture, lighting equipment, and household articles," and "52.45 Retail sale of electrical household appliances and radio and television goods" (Destatis, 2003). We do not include firms in WZ 03 group "52.46 Retail sale of hardware, prints and glass" to the treatment group, as the IBS does not contain observations of firms in this group at the time of the VAT increase.

Figure 1.2: The VAT-Induced Demand Effects



Notes: This figure plots the time series of aggregated revenues in the sectors "treated" by the VAT change (black line) against reported business conditions of "treated" firms in the IBS as given by the average responses of retailers of cars, furniture, and electronics in a range between -1 (bad), 0 (normal), and 1 (good conditions). The aggregate revenue series displayed here weights the sector-specific revenues by the share of "treated" firms in the respective sectors in the IBS. The vertical red line corresponds to the date of the VAT increase (January 2007).

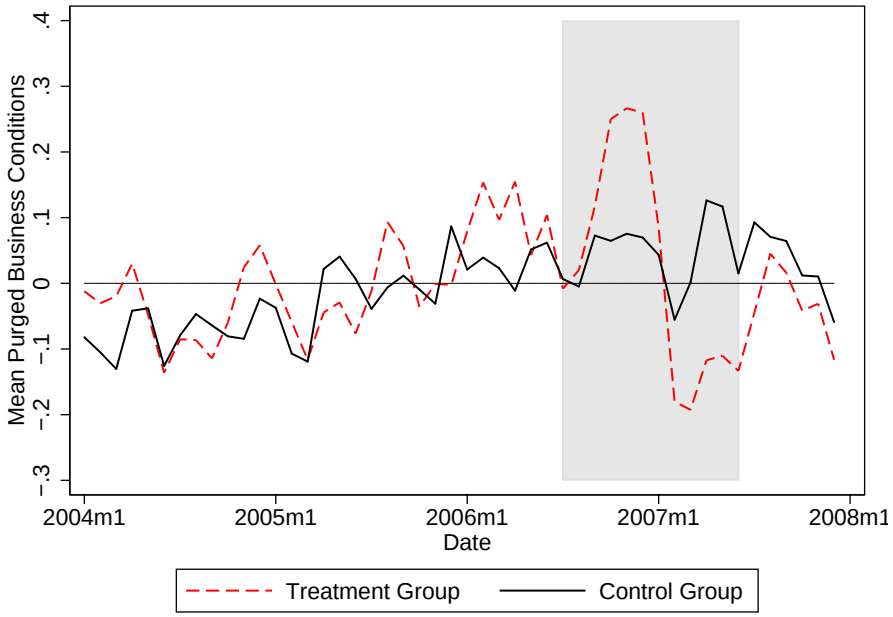
VAT increase aimed at the consolidation of the federal budget, the policy intervention neither intended to facilitate or suppress sales in specific retail sectors nor was it related to economic conditions in these sectors. The "assignment" of firms to the "treatment" can hence be considered as exogenous.

We further restrict the data set that we use for the analysis of the VAT shock to retail firms' expectations reported the latest in December 2007 in order to exclude the repercussions of the 2008 financial crisis from the six-month expectation window. In order to be able to observe pre-trends in firms' expectations and current conditions of sufficient length, we extend the data set to earlier periods covering expectations reported in January 2004 and thereafter.[24]

Figure 1.2 compares the business conditions of "treated" firms reported to the IBS to aggregate revenues of durable good retailers. To this end, we construct a measure of aggregate revenue in the "treated" sectors by weighting sector-specific revenue series

[24]The restricted data set hence covers reported business conditions between August 2003 and June 2008. Another reason for the extension of the data set towards earlier periods is that this raises the number of time periods to 48, satisfying the rule of thumb from the literature that the number of clusters should not fall far below 50. In Appendix 1.C.3, we show that the results are virtually the same when using the same start date (March 2005) as in the previous sections.

Figure 1.3: Identifying Variation in Business Conditions



Notes: The dashed red line plots the mean of business conditions reported by treated firms (durable good retailers) from the IBS, purged for past conditions and firm fixed effects. The solid black line plots the same variable for firms in the control group (all other retail firms). The shaded area corresponds to the treatment period between July 2006 and June 2007.

received from the German Statistical Office with the corresponding share of "treated" firms per sector in the IBS.[25] Clearly, the assessments of current business conditions in the IBS, although qualitative in nature, closely track aggregate revenues in the corresponding sectors. In particular, both time series display a sharp increase in advent of the VAT change in the beginning of 2007, followed by a sharp downswing in the months thereafter.[26]

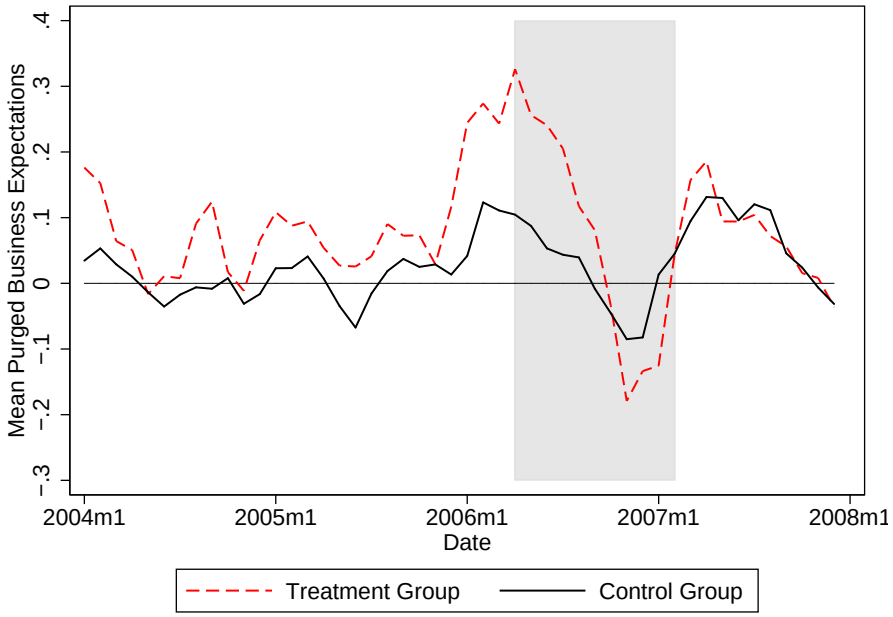
The identifying variation exploited in the DiD estimation is the difference in reported business conditions of durable and non-durable good retailers during the treatment period. Figure 1.3 illustrates this variation by plotting the business conditions of treated and untreated firms that are purged for the past business conditions and firm fixed effects.[27] Evidently, the purged current business conditions of treated and untreated firms follow similar trends with the notable exception of the treatment period defined as the six months

[25]The revenue data are available from the German Federal Statistical Office as monthly time-series at the industry level according to the more recent German industry classification system of 2008 (*WZ 08*), which largely corresponds to the European classification NACE Rev. 2. The displayed time series in Fig. 1.2 is calculated using the revenue time series of the WZ 08 sectors "45.1 Sale of cars," "47.54 Retail trade with electronic household appliances," and "47.59 Retail trade with furniture" weighted by the number of firms in the respective sectors observed in the IBS.

[26]Figure 1.C.1 in Appendix 1.C.1 plots revenues and average reports of current business conditions in the retail industries unaffected by the VAT change.

[27]Specifically, Figure 1.3 plots the residuals of the following linear model, averaged separately for treated and untreated firms: $\text{Conditions}_{i,t} = \hat{\xi}_1 \, \text{Conditions}_{i,(t-1,t-6)} + \hat{m}_i + \hat{\varepsilon}_{i,t}$.

Figure 1.4: Common Trend in Expectations



Notes: The dashed red line plots the mean of expectations for the next 6 months from the IBS as reported by treated firms (durable good retailers) purged for past and current conditions and firm fixed effects. The solid black line plots the same variable for firms in the control group (all other retail firms). The shaded area corresponds to months when the six-month expectation window covers at least four months of the demand shock's treatment period between July 2006 and June 2007, i.e., expectations reported between April 2006 and February 2007.

before and after the VAT increase on January 1^{st}, 2007. During this period, the business conditions of the treated firms are highly non-linear. Due to the overall similarity of all retail firms, non-durable good retailers, which were not affected by the VAT increase, seem to be a well-suited control group that can be used to filter out aggregate trends and different sources of shocks during the treatment period.

Next, we show that the expectations of treated and control firms follow a common trend when the VAT-induced demand shock is outside of the expectation window—the key assumption for the identification of causal effects in a DiD design. To inspect the common trend in expectations, we purge firms' expectations for current conditions and past trends as well as time-invariant firm characteristics captured by firm fixed effects, as before.[28] Figure 1.4 plots the mean purged expectations separately for durable good retailers and all other retail firms. Clearly, the expectations do not differ substantially between both groups before the end of 2005. If anything, the expectations of treated firms already start appreciating in November 2005. Interestingly, this perfectly coincides with the announcement of the VAT increase. Hence, the common trend assumption is very

[28]These purged expectations correspond to the residuals of the following regression: $\text{Expectations}_{i,t}^{+6m} = \tilde{\xi}_1 \, \text{Conditions}_{i,(t,t-5)} + \tilde{m}_i + \tilde{\varepsilon}_{i,t}$.

likely to hold.

We exploit this similarity of durable and non-durable retail firms to study the adjustment of expectations to the VAT-induced differential treatment regarding the quality of information about future demand. In order to elicit whether firms "treated" with the information shock become more forward-looking once the time of the demand shock enters the expectation window of six months, we compute the difference-in-differences of the coefficients of both the future and the current/past realized business conditions. For this purpose, we extend the main empirical model (1.4) to the following standard DiD framework:

$$\begin{aligned}\text{Expectations}_{i,t}^{+6m} = \\ \boldsymbol{\gamma_1}' \mathbf{Conditions}_{i,t} + \boldsymbol{\gamma_2}' \mathbf{Conditions}_{i,t} \times \mathbb{1}(\text{Durable}_i) + \boldsymbol{\gamma_3}' \mathbf{Conditions}_{i,t} \times \mathbb{1}(\text{VAT}_t) \\ + \boldsymbol{\delta}' \mathbf{Conditions}_{i,t} \times \mathbb{1}(\text{Durable}_i) \times \mathbb{1}(\text{VAT}_t) + a_t + m_i + \varepsilon_{i,t}, \quad (1.7)\end{aligned}$$

As before, $\text{Expectations}_{i,t}^{+6m}$ captures firm i's expectations for the next 6 months as reported in the IBS. The column vector $\mathbf{Conditions}_{i,t}$ contains all measures of business conditions employed in the respective empirical specification. Moreover, the indicator $\mathbb{1}(\text{Durable}_i)$ equals one if the firm is a treated durable good retailer and zero otherwise, and the indicator $\mathbb{1}(\text{VAT}_t)$ equals one if $t \in [2006m4, 2007m2]$, i.e., if the six-month expectation window covers at least four months of the demand shock's "treatment" period between July 2006 and June 2007. Lastly, a_t and m_i denote the time and firm fixed effects, and $\varepsilon_{i,t}$ is the error term.[29] The vector $\boldsymbol{\delta}$ contains the coefficients of interest that capture the adjustment of expectations to the VAT information shock by affected firms.

1.5.2 The Causal Effect of More Precise in Information on Expectations

In a first step, we focus on adjustments in the respective weights that durable good retailers put on information regarding their future business conditions as well as current and past conditions when forming expectations. Hence, the column vector $\mathbf{Conditions}_{i,t}$ in model (1.7) equals $(\text{Conditions}_{i,(t+1,t+6)}, \text{Conditions}_{i,(t-5,t)})^T$.

Column (1) of Table 1.5 reports the vector of estimated "treatment" effects ($\hat{\boldsymbol{\delta}}$) and documents the main result of this section: Firms "treated" with the shock become significantly more forward-looking once the time of the demand shock enters the six-month expectation window. This manifests itself in a statistically highly significant increase of

[29] Note that all retail firms (with the exemption of car sellers) belong to the same two-digit sector according to the German industry classification system of 2003. Hence, applying date fixed effects only controls for all common components at the level of the overall retail sector at each point in time.

Table 1.5: The Effect of More Precise Information on Expectations: Main Results

	Expected Business Conditions for the Next 6 Months				
		Treated Firms		Control Firms	
	Diff-in-Diff	VAT Period	Control Period	VAT Period	Control Period
	(1)	(2)	(3)	(4)	(5)
$\text{Conditions}_{t+1,t+6}$	0.18***	0.35***	0.23***	0.21***	0.27***
	(0.062)	(0.039)	(0.033)	(0.039)	(0.024)
$\text{Conditions}_{t,t-5}$	-0.16***	0.15***	0.27***	0.29***	0.25***
	(0.050)	(0.046)	(0.036)	(0.033)	(0.030)
Adjusted R^2	0.472	0.472			
Firm FE	yes	yes			
Time FE	yes	yes			
Observations	26688	26688			

Notes: The table summarizes the results from two separate empirical models. Column (1) reports the estimate of the vector $\boldsymbol{\delta}$ in model (1.7), that is the VAT-induced change in the coefficients of future realized business conditions ($\text{Conditions}_{t+1,t+6}$) as well as current and past conditions ($\text{Conditions}_{t,t-5}$) when forming their expectations. These estimates are given by the difference-in-differences of the absolute coefficients reported in Columns (2) through (5). The latter correspond to $\boldsymbol{\psi_1}$, $\boldsymbol{\psi_2}$, $\boldsymbol{\psi_3}$, and $\boldsymbol{\psi_4}$ in model (1.8). The treatment period (VAT period) includes expectations formed between April 2006 and February 2007. The treatment group includesall durable good retailers, and the control groups includes all other retail firms. Standard errors are twoway clustered at the levels of firms and dates. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

0.18 in the weights that durable good retailers put on $\text{Conditions}_{i,(t+1,t+6)}$ when forming their expectations. Hence, firms' expectations are almost twice as sensitive to disaggregate information about future business conditions compared to periods with "average" fluctuations.[30] At the same time, the weight on current and past business conditions ($\text{Conditions}_{i,(t,t-5)}$) becomes considerably smaller and decreases by 0.16.

Next, we confirm that the treatment effect is driven by a change in behavior of the firms in the treated groups during the treatment period (as opposed to a change in behavior of the control group). To this end, we estimate the coefficients of future business conditions $\text{Conditions}_{i,(t+1,t+6)}$ as well as the coefficients of current and past trends $\text{Conditions}_{i,(t,t-5)}$ separately for the treated and control firms during the treatment and control periods.

[30]The analysis of retail firms' expectation formation along the lines of Section 1.4 can be found in Tables 1.C.1 and 1.C.2 in Appendix 1.C.2.

This is achieved via the following empirical model

$$\begin{aligned}\text{Expectations}_{i,t}^{+6m} = \\ \boldsymbol{\psi_1'}\,\mathbf{Conditions}_{i,t} \times \mathbb{1}(\text{Durable}_i) \times \mathbb{1}(\text{VAT}_t) + \boldsymbol{\psi_2'}\,\mathbf{Conditions}_{i,t} \times \mathbb{1}(\text{Durable}_i) \times \mathbb{1}(\text{no VAT}_t) \\ + \boldsymbol{\psi_3'}\,\mathbf{Conditions}_{i,t} \times \mathbb{1}(\text{Non-Durable}_i) \times \mathbb{1}(\text{VAT}_t) + \boldsymbol{\psi_4'}\,\mathbf{Conditions}_{i,t} \times \mathbb{1}(\text{Non-Durable}_i) \\ \times \mathbb{1}(\text{no VAT}_t) + a_t + m_i + \varepsilon_{i,t}, \quad (1.8)\end{aligned}$$

where the indicators $\mathbb{1}(\text{Non-Durable}_i)$ and $\mathbb{1}(\text{no VAT}_t)$ equal one if their counterparts $\mathbb{1}(\text{Durable}_i)$ and $\mathbb{1}(\text{VAT}_t)$ are zero. It is straightforward to see that the differences-in-differences of coefficients the from model (1.8) deliver the same treatment effects as directly estimated in model (1.7), i.e., $\boldsymbol{\delta} = (\boldsymbol{\psi_1} - \boldsymbol{\psi_2}) - (\boldsymbol{\psi_3} - \boldsymbol{\psi_4})$.

The estimation results of (1.8) in Table 1.5, Columns (2) through (5), strongly confirm that the "treated" firms become more forward-looking in response to the VAT-induced increase in the quality of disaggregate information. During those times when the VAT-induced demand shock does not enter the six-month expectation window, the expectations of durable good retailers (Column (3)) and all other retail firms (Column (5)) reflect future as well as current and past business conditions in a comparable manner. Moreover, the forecasting behavior of the firms of the control firms remains stable between the treatment and control periods (Columns (4) and (5)). In contrast, treated firms largely rely on information about two quarter ahead business, when they form their expectations during the treatment period, with the corresponding coefficient increasing to 0.35 (Column (2)). At the same time, the sensitivity of expectations with respect to variation in $\text{Conditions}_{i,(t,t-5)}$ substantially drops to 0.15. This confirms, hence, that the shift in attention towards information about the future observed for firms affected by the demand shock cannot be attributed to general adjustments of the expectation formation process of all retail firms.

1.5.3 Early Anticipation of the VAT-Induced Disaggregate Demand Shock

In a next step, we ask whether information about the VAT-induced disaggregate demand shock is incorporated into expectations from particularly early on. For this purpose, we decompose the measure $\text{Conditions}_{i,(t+1,t+6)}$ into two quarter ahead business conditions ($\text{Conditions}_{i,(t+1,t+3)}$) and one quarter ahead business conditions ($\text{Conditions}_{i,(t+4,t+6)}$). Along the lines of Section 1.3, these ex post realized business conditions can serve as a proxy for the disaggregate information available at t about business conditions in the next quarter and two quarters ahead. We proceed similarly with $\text{Conditions}_{i,(t-5,t}$.

Table 1.6: The Effect of More Precise Information on Expectations: Extended Results

	Expected Business Conditions for the Next 6 Months				
		Treated Firms		Control Firms	
	Diff-in-Diff	VAT Period	Control Period	VAT Period	Control Period
	(1)	(2)	(3)	(4)	(5)
$\text{Conditions}_{t+4,t+6}$	0.17***	0.17***	0.030	0.052*	0.076***
	(0.053)	(0.034)	(0.028)	(0.029)	(0.019)
$\text{Conditions}_{t+1,t+3}$	0.014	0.14***	0.14***	0.16***	0.18***
	(0.046)	(0.029)	(0.022)	(0.023)	(0.015)
$\text{Conditions}_{t,t-2}$	-0.11**	0.16***	0.27***	0.25***	0.25***
	(0.056)	(0.045)	(0.028)	(0.027)	(0.024)
$\text{Conditions}_{t-3,t-5}$	-0.048	-0.012	0.0018	0.0098	-0.025
	(0.041)	(0.033)	(0.021)	(0.023)	(0.019)
Adjusted R^2	0.482	0.482			
Firm FE	yes	yes			
Time FE	yes	yes			
Observations	24798	24798			

Notes: The table summarizes the results from two separate empirical models. Column (1) reports the estimate of the vector $\boldsymbol{\delta}$ in model (1.7), that is the VAT-induced change in the coefficients of two quarter ahead business conditions($\text{Conditions}_{t+4,t+6}$), one quarter ahead business conditions ($\text{Conditions}_{t+1,t+3}$) as well as on current quarter's and past quarter's conditions ($\text{Conditions}_{t,t-2}$ and $\text{Conditions}_{t-3,t-5}$, respectively) when forming their expectations. These estimates are given by the difference-in-differences of the absolute coefficients reported in Columns (2) through (5). The latter correspond to $\boldsymbol{\psi_1}$, $\boldsymbol{\psi_2}$, $\boldsymbol{\psi_3}$, and $\boldsymbol{\psi_4}$ in model (1.8). The treatment period (VAT period) includes expectations formed between April 2006 and February 2007. The treatment group includes all durable good retailers and the control groups includes all other retail firms. Standard errors are twoway clustered at the levels of firms and dates. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.6 reports the results of estimating models (1.7) and (1.8) after inclusion of the more fine-tuned measures of realized business conditions.[31] In "normal" times (Columns (3) and (5)), the two quarter ahead business conditions are only weakly reflected in expectations although firms are asked for their assessment of the next six months. Accordingly, expectations mostly reflect firms' current conditions, and information about business conditions in the near future appears to enter expectations more strongly than information referring to the more distant future. Note also that durable good retailers perform worse than retailers of non-durables in anticipating future business conditions during normal

[31]The column vector $\textbf{Conditions}_i$ in models (1.7) and (1.8) now contains $\text{Conditions}_{i,(t+4,t+6)}$, $\text{Conditions}_{i,(t+1,t+3)}$, $\text{Conditions}_{i,(t,t-2)}$, and $\text{Conditions}_{i,(t-3,t-5)}$. Note that we use the same definition of $\mathbb{1}(\text{VAT}_t)$ as independent variables as in the specification with six-month moving averages of business conditions, so that the interaction terms of $\text{Conditions}_{i,(t+1,t+3)} \times \mathbb{1}(\text{VAT}_t)$ and $\text{Conditions}_{i,(t+4,t+6)} \times \mathbb{1}(\text{VAT}_t)$ refer to realized business conditions during different phases of the shock. A specification with adjusted treatment period dummies that accounts for this issue does not deliver substantially different results. The results are available from the authors on request.

times.

In contrast, at the time of the information shock, the treated firms incorporate information about the VAT-induced demand shock into their expectations from particularly early on, while expectations of unaffected firms remain widely unchanged (Columns (2) and (4)). Strikingly, the disaggregate component of the two quarter ahead business conditions is not only significantly more reflected in the expectations of the treated firms, but is also associated more strongly with expectations than the treated firms' information about the current as well as the one quarter ahead business conditions. This pattern is also reflected in DiD coefficients in Column (1). The weight that durable good retailers put on two quarters ahead business conditions when forming their expectations increases substantially by 0.17. At the same time, the weight of the one quarter ahead business conditions remains virtually unaffected, and the weight on current conditions drops substantially by 0.11.[32]

We conclude that the firms "treated" by the VAT-induced increase in the quality of information become significantly more forward-looking once the time of the disaggregate demand shock enters their six-month expectation window. Appendix 1.C.3 shows that this result is not driven by the choice of the baseline specification. Specifically, the results are robust to the definition of the treatment period (Panel A of Table 1.C.3), the inclusion of wholesale firms to the control group (Panel B), as well as different restrictions on the minimum duration of firms in the sample or controlling for attrition (Panel C). Moreover, the results are robust to restricting the sample to the period used in Section 1.4 (Panel D) as well as by the specification of time fixed effects (Panel E).

1.6 Conclusion

This paper studies the formation of firms' expectations regarding their own future business conditions. First, we document that disaggregate information, proxied by firms' future business conditions orthogonal to aggregate information at the two-digit industry level, is strongly reflected in firms' expectations. We also show that disaggregate information explains an economically significant share of the variance in expectations.

Second, we provide causal evidence of how firms' expectations react to new information about a large disaggregate demand shock: the pull-forward effect in demand for durable good retailers in response to a pre-announced VAT increase in Germany. Exploiting the similarity of retailers of durable and non-durable goods in a difference-in-differences

[32]This result also holds when estimating model (1.7) with monthly measures of realized business conditions. In this setting, the monthly DiD coefficients are amplified in particular in the months $t+5$ and $t+6$, but are close to zero in the months $t+7$ and later. The results are available from the authors on request.

design, we find that firms "treated" with the shock become significantly more forward-looking in advent of the large shifts in demand. In particular, when the information about the shock becomes relevant, durable good retailers put larger weights on the information about the two quarters ahead business conditions when forming their expectations and rely substantially less on information about the current business conditions.

The documented adjustment of expectation formation to the VAT-induced increase in quality of information about future business conditions could be expected for at least two reasons. First, firms may rationally put more weight on more distant shocks at times when these shocks can be predicted more reliably. Similarly, at times when large swings in demand are to be expected, firms should view current conditions as less reliable signals for future conditions and thus weight them less when forming expectations. A second interpretation of the results is that the shift in weights reflects a shift in attention to more distant realizations of shocks. As predicted by theories of rational inattention by Sims (2003), Woodford (2003), and Maćkowiak and Wiederholt (2009, 2015), such shifts may occur if information regarding business conditions in the more distant future becomes either more informative or more cheaply to process; this is likely to be true for the case of the VAT shock. Both somewhat distinct interpretations emphasize that the more forward-looking expectations at times of the VAT shock are a rational response to the change in the information structure firms face.

One way to disentangle these two effects in future work could be to study the adjustment process of firms' expectations in response to pre-announced shocks that vary in their information content or magnitude. If firms were constrained in their ability to gather and process information, these variations should lead to differential costs and benefits of adjusting expectations to those shocks, and, hence, to differential adjustments of expectations conditional on the information structure of the shock. In contrast, unconstrained firms are expected to unconditionally adjust their expectations to shocks. A challenge for this approach is, however, that suitable shocks are notoriously hard to identify. Thus, one would likely have to abandon some credibility in the identification strategy—relative to the cleanly identified VAT shock used in this chapter—in order to perform analyses of this sort. We leave this challenge to future work.

Appendices to Chapter 1

1.A Appendix to Section 1.2: Additional Tables

Table 1.A.1: Attrition

		Fraction of Firms Surviving (in %)									
Start Date	Firms@Start	6m	1yr	2yrs	3yrs	4yrs	5yrs	6yrs	7yrs	8yrs	9yrs	10yrs
2005m3	5701	95.5	91.2	83.9	78.2	72.7	67.9	63.8	59.6	55.4	51.2	46.6
2006m3	6510	95.6	91.2	84.6	78.3	73.0	68.3	63.7	59.1	54.5	49.5	0
2007m3	6822	95.5	92.1	85.1	78.9	73.9	69.0	63.9	58.8	53.4	0	0
2008m3	6974	96.0	92.1	85.4	79.9	74.4	69.0	63.3	57.4	0	0	0
2009m3	7356	95.9	92.6	86.5	80.5	74.5	68.2	61.7	0	0	0	0
2010m3	7752	96.2	93.0	86.3	79.5	72.8	65.9	0	0	0	0	0
2011m3	7827	96.4	92.5	85.3	78.1	70.5	0	0	0	0	0	0
2012m3	8069	95.6	91.8	83.4	75.0	0	0	0	0	0	0	0
2013m3	7880	95.0	90.5	81.4	0	0	0	0	0	0	0	0
2014m3	7468	94.5	89.6	0	0	0	0	0	0	0	0	0
2015m3	6983	88.9	0	0	0	0	0	0	0	0	0	0

Notes: This table displays, for all firms in our sample in March of each year, the percentages of firms that remain in the sample after the passage of different time intervals (between six months and ten years).

Table 1.A.2: Transition Frequencies by Sector

Panel A: Manufacturing

		Conditions Next Period			Expectations Next Period		
		1	0	-1	1	0	-1
Current	1	0.228	0.055	0.002	0.113	0.069	0.007
Conditions/	0	0.055	0.431	0.041	0.067	0.500	0.064
Expectations	-1	0.002	0.041	0.145	0.009	0.062	0.108
	Sum	0.285	0.527	0.188	0.189	0.631	0.179

Panel B: Services

		Conditions Next Period			Expectations Next Period		
		1	0	-1	1	0	-1
Current	1	0.284	0.072	0.003	0.167	0.087	0.008
Conditions/	0	0.072	0.391	0.037	0.084	0.462	0.053
Expectations	-1	0.003	0.037	0.102	0.010	0.051	0.079
	Sum	0.359	0.500	0.142	0.261	0.600	0.140

Panel C: Retail and Wholesale

		Conditions Next Period			Expectations Next Period		
		1	0	-1	1	0	-1
Current	1	0.156	0.067	0.006	0.103	0.061	0.006
Conditions/	0	0.067	0.402	0.067	0.059	0.477	0.071
Expectations	-1	0.006	0.068	0.162	0.006	0.071	0.146
	Sum	0.229	0.537	0.235	0.168	0.609	0.223

Notes: This table shows the transition frequencies of reported realized business conditions and expected business conditions for each industry survey. The left (right) panel shows the frequencies of reported business conditions (expected business conditions) in the next reported month for each possible current report of business conditions/expectations. Since these statistics are derived from the time dimension of the panel dataset, the overall frequencies of reported future conditions/expectations displayed in the last row (*Sum*) are equal to the overall frequencies for the current conditions/expectations, which are, for this reason, omitted.

1.B Robustness Checks for Section 1.4: Panel Results

This section confirms that the main results of Section 1.4, which are documented in Column (5) of Table 1.2, remain unchanged when exposed to a variety of robustness checks. Columns (2), (3), and (4) of Table 1.B.1 document that the coefficient of the disaggregate components of $\text{Conditions}_{i,(t+1,t+6)}$ is unaffected by the specification of the time fixed effect that controls for aggregate information. Relative to the baseline specification in Column (1), the change in the estimated coefficient of $\text{Conditions}_{i,(t+1,t+6)}$ never exceeds 0.01. This holds regardless of whether we control only for a single aggregate time fixed effect in Column (2), about 180 time fixed effects at the three-digit industry level in Column (3), or whether we add 16 time fixed effects, one for each German federal state, in Column (4). The results also remain remarkably stable when we restrict the sample of firms to control for attrition. Neither restricting firms to be in the sample for at least two years in Column (5) nor dropping all obervations of firms within one year of the last firm-specific observation in Column (6) alters the coefficient of interest.

Table 1.B.2 verifies that the benchmark results in Column (1) are unaffected by changing the vector of covariates. In Column (2), we alter the industry definition underlying the time fixed effects from the German industry classification of 2003 (*WZ 03*), which we use throughout the chapter, to the more recent German industry classification of 2008 (*WZ 08*). While this requires additional adjustments of the industry codes in the data of the IBS, doing so leaves the results completely unchanged. In Columns (3) and (4), we directly control for aggregate industry conditions by means of aggregate revenues. To this end, we generate a measure of detrended revenue at the two-digit industry level by computing the log deviation of the monthly revenue data (that is publicly available from the German statistical office for the manufacturing and retail/wholesale sectors) to the industry-specific trend in revenue.[33] Column (3) then adds current (detrended) industry revenues as an additional covariate, while Column (4) includes average future revenues during the expectation window of six months. Note that Columns (3) and (4) do not include time fixed effects, as these are perfectly collinear to the industry-specific revenue data. Unsurprisingly, the coefficients of future realized business conditions in Columns (3) and (4) increase, because the industry-specific revenues only partially capture the industry-specific variation in business conditions. Note also that, as expected, the association between current revenues and expectations is not statistically significant, while the association between future industry-specific revenue levels and expectations is strong. Column (5) accounts for the possibility that firms extrapolate from past expectations when forming their current expectations by controlling for the expectations reported

[33] Following Ravn and Uhlig (2002), the monthly revenue data are detrended using a HP filter with smoothing parameter 129'600.

Table 1.B.1: Panel Regressions: Robustness Checks - Fixed Effects and Attrition

	Expected Business Conditions for the Next 6 Months					
	Panel A: Manufacturing					
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Conditions}_{t+1,t+6}$	0.28***	0.29***	0.27***	0.28***	0.28***	0.29***
	(0.0069)	(0.0072)	(0.0067)	(0.0068)	(0.0069)	(0.0070)
$\text{Conditions}_{t,t-5}$	-0.095***	-0.11***	-0.082***	-0.092***	-0.096***	-0.11***
	(0.0092)	(0.0098)	(0.0086)	(0.0091)	(0.0092)	(0.0096)
R^2	0.329	0.318	0.351	0.334	0.327	0.333
Adjusted R^2	0.313	0.307	0.319	0.314	0.312	0.316
Observations	327369	329927	327006	327369	325191	282368
	Panel B: Services					
$\text{Conditions}_{t+1,t+6}$	0.24***	0.25***	0.23***	0.24***	0.24***	0.25***
	(0.0090)	(0.0093)	(0.0088)	(0.0088)	(0.0090)	(0.0093)
$\text{Conditions}_{t,t-5}$	-0.11***	-0.11***	-0.098***	-0.10***	-0.11***	-0.11***
	(0.0080)	(0.0082)	(0.0077)	(0.0080)	(0.0080)	(0.0085)
R^2	0.367	0.355	0.384	0.372	0.365	0.370
Adjusted R^2	0.350	0.344	0.357	0.350	0.348	0.352
Observations	299011	299398	298566	298881	296522	255611
	Panel C: Retail and Wholesale					
$\text{Conditions}_{t+1,t+6}$	0.28***	0.28***	0.27***	0.28***	0.28***	0.28***
	(0.0082)	(0.0083)	(0.0080)	(0.0081)	(0.0082)	(0.0086)
$\text{Conditions}_{t,t-5}$	0.21***	0.21***	0.22***	0.21***	0.21***	0.21***
	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.012)
R^2	0.437	0.433	0.445	0.444	0.435	0.436
Adjusted R^2	0.426	0.423	0.430	0.427	0.425	0.425
Observations	177330	177553	177330	177330	175852	150254
Firm FE	yes	yes	yes	yes	yes	yes
Time FE		yes				
Time*2dig-Sector FE	yes			yes	yes	yes
Time*3dig-Sector FE			yes			
Time*State FE				yes		
Firm at least 24 Months in Sample					yes	
Firm in Sample for at least one more year						yes

Notes: $\text{Conditions}_{t+1,t+6}$ is the mean of ex post realized business conditions in the following six months which is our proxy for disaggregate information. $\text{Conditions}_{t,t-5}$ is defined accordingly. "Time FE" are aggregate time fixed effects, "Time*2dig-Sector FE" are time fixed effects at the two-digit industry level, and "Time*3dig-Sector FE" are time fixed effects at three-digit industry level, and "Time*State FE" are time fixed effect at the level of the German states. Standard errors are two-way clustered at the levels of firms and dates. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.B.2: Panel Regressions: Robustness Checks - Additional Controls

	Expected Business Conditions for the Next 6 Months						
	Panel A: Manufacturing						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{Conditions}_{t+1,t+6}$	0.28***	0.28***	0.38***	0.36***	0.28***	0.20***	0.24***
	(0.0069)	(0.0068)	(0.018)	(0.012)	(0.0070)	(0.0074)	(0.0070)
$\text{Conditions}_{t,t-5}$	-0.095***	-0.094***	-0.15***	-0.17***	-0.12***		
	(0.0092)	(0.0091)	(0.013)	(0.015)	(0.0095)		
$log(\text{Revenues}_t)$			0.0056				
			(0.12)				
$log(\text{Revenues}_{t+1,t+6})$				0.65***			
				(0.14)			
$\text{Expectations}_{t-6}^{+6m}$					0.060***		
					(0.0057)		
Conditions_t						0.045***	0.11***
						(0.0067)	(0.0059)
$\text{Conditions}_{t-1,t-5}$							-0.17***
							(0.0080)
R^2	0.329	0.329	0.284	0.288	0.331	0.327	0.335
Adjusted R^2	0.313	0.313	0.273	0.277	0.315	0.311	0.319
Observations	327369	327369	327369	327369	306916	327369	324099
	Panel B: Services						
$\text{Conditions}_{t+1,t+6}$	0.24***	0.24***			0.24***	0.20***	0.23***
	(0.0090)	(0.0088)			(0.0094)	(0.0088)	(0.0087)
$\text{Conditions}_{t,t-5}$	-0.11***	-0.099***			-0.13***		
	(0.0080)	(0.0078)			(0.0082)		
$\text{Expectations}_{t-6}^{+6m}$					0.025***		
					(0.0060)		
Conditions_t						-0.013**	0.027***
						(0.0060)	(0.0062)
$\text{Conditions}_{t-1,t-5}$							-0.13***
							(0.0074)
R^2	0.367	0.379			0.374	0.364	0.369
Adjusted R^2	0.350	0.356			0.356	0.347	0.352
Observations	299011	298746			258671	299011	292035
	Panel C: Retail and Wholesale						
$\text{Conditions}_{t+1,t+6}$	0.28***	0.27***	0.32***	0.31***	0.28***	0.21***	0.21***
	(0.0082)	(0.0081)	(0.012)	(0.010)	(0.0086)	(0.0075)	(0.0075)
$\text{Conditions}_{t,t-5}$	0.21***	0.22***	0.21***	0.20***	0.18***		
	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)		
$log(\text{Revenues}_t)$			0.086				
			(0.14)				
$log(\text{Revenues}_{t+1,t+6})$				0.85***			
				(0.21)			
$\text{Expectations}_{t-6}^{+6m}$					0.064***		
					(0.0061)		
Conditions_t						0.25***	0.24***
						(0.0070)	(0.0065)
$\text{Conditions}_{t-1,t-5}$							0.015*
							(0.0090)
R^2	0.437	0.447	0.414	0.416	0.438	0.459	0.459
Adjusted R^2	0.426	0.431	0.404	0.406	0.427	0.449	0.449
Observations	177330	177324	177330	177330	161850	177330	174774
Firm FE	yes	yes	yes	yes	yes	yes	yes
Time*2dig-Sector FE	yes				yes	yes	yes
Time*2dig-Sector FE (WZ08)		yes					

Notes: $\text{Conditions}_{t+1,t+6}$, $\text{Conditions}_{t,t-5}$, Conditions_t, and $\text{Conditions}_{t+1,t-5}$ analogously as in the remainder of the chapter. $log(\text{Revenues}_t)$ is the log deviation of revenues at the two-digit level from its HP-filtered trend (smoothing parameter 129,600); $log(\text{Revenues}_{t+1,t+6})$ is its average between $t+1$ and $t+6$. The revenue data are unavailable for services. $\text{Expectations}_{t-6}^{+6m}$ are the expectations as of $t-6$. "Time*2dig-Sector FE" and "Time*2dig-Sector FE (WZ08)" are time fixed effects at the two-digit industry levels according to the WZ03 and WZ08 classifications, respectively. Standard errors are two-way clustered at the levels of firms and dates. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.B.3: Panel Regressions: Conditional on Normal Current Conditions

	Expectations$_t^{+6m}$	
	Panel A: Manufacturing	
Conditions$_{t+1,t+6}$	0.29***	0.27***
	(0.0057)	(0.0069)
Conditions$_{t,t-5}$	-0.10***	-0.20***
	(0.0065)	(0.0081)
R^2	0.334	0.333
Adjusted R^2	0.317	0.301
Observations	309028	159226
	Panel B: Services	
Conditions$_{t+1,t+6}$	0.24***	0.24***
	(0.0065)	(0.0077)
Conditions$_{t,t-5}$	-0.11***	-0.16***
	(0.0070)	(0.0088)
R^2	0.382	0.387
Adjusted R^2	0.358	0.342
Observations	281142	136299
	Panel C: Retail and Wholesale	
Conditions$_{t+1,t+6}$	0.29***	0.24***
	(0.0071)	(0.0080)
Conditions$_{t,t-5}$	0.20***	0.025**
	(0.010)	(0.010)
R^2	0.437	0.330
Adjusted R^2	0.426	0.306
Observations	164616	85572
Neutral Conditions in t	no	yes
Firm FE	yes	yes
Time*2dig-Sector FE	yes	yes

Notes: Conditions$_{t+1,t+6}$ is the mean of ex post reported business conditions in the following six months. Conditions$_{t,t-5}$ is defined accordingly. "Time*2dig-Sector FE" are time fixed effects at the two-digit industry level. Standard errors are two-way clustered at the levels of firms and dates. The sample in the second column consists only of those firms which currently report normal business conditions, that is those firms for which Conditions$_t = 0$. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

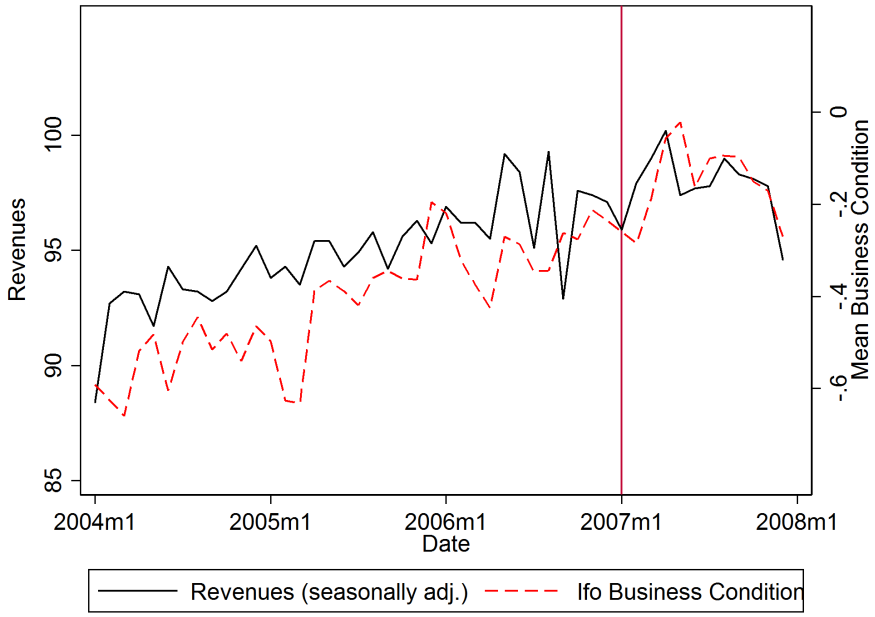
six months ago; these expectations cover an expectation window of the past six months (including the current month). Even though the association between past and current expectations is statistically significant, the association is economically small and does not alter the remaining coefficient estimates or the goodness of fit substantially. In Columns (6) and (7), we separately control for current realized conditions, with and without past conditions. This also has little impact on the parameter estimates of interest.

Finally, we rule out the possibility that firms at the extremes of the distribution of current conditions drive our results. Specifically, one concern could be that firms with unusual good or bad business conditions can expect these conditions to continue to be good or bad in the future with high confidence, and are thus very well informed about their future. Such a mechanism could generate our results, even if all other firms possess no information about their future disaggregate conditions. To deal with this concern, the second column of Table 1.B.3 estimates the main empirical model (1.4) only for those firms that currently report normal conditions. The comparison of the estimates for this restricted sample of firms to the benchmark results in the first column of Table 1.B.3 shows that the effect of disaggregate information on expectation is independent of whether firms currently experience a business as usual or particularly good/bad business conditions.

1.C Appendices to Section 1.5

1.C.1 Additional Description of the VAT Shock

Figure 1.C.1: Effect of VAT Increase in 2007 on Other Retail Firms



Notes: This figure plots the time series of revenues in a subset of sectors "not treated" by the VAT change (black line) against reported business conditions of "untreated" firms in the IBS as given by the average responses to the IBS in a range between -1 (bad), 0 (normal), and 1 (good conditions). The subset of untreated firms displayed here refers to retailers corresponding to the WZ 08 group "47.7 Indoor retail trade with other goods" which contains clothes, shoes, leather goods, pharmaceuticals, medical/ orthopedical/cosmetic goods, flowers/plants/fertilizer/animals, watches/luxury goods, glasses, fotographical/optic goods, art/paintings, antiques, used goods, etc. The vertical red line corresponds to the date of the VAT increase (January 2007).

1.C.2 Panel Results for Subset of Retail Firms

Table 1.C.1: Retail Firms' Expectations and Disaggregate Information

	Expected Business Conditions for the Next 6 Months					
$\text{Conditions}_{t+1,t+6}$	0.29***	0.26***	0.26***	0.26***	0.25***	0.25***
	(0.017)	(0.021)	(0.019)	(0.019)	(0.019)	(0.019)
$\text{Conditions}_{t,t-5}$	0.25***	0.24***	0.25***	0.26***	0.25***	0.26***
	(0.019)	(0.025)	(0.022)	(0.022)	(0.022)	(0.022)
Adjusted R^2	0.205	0.462	0.472	0.476	0.474	0.478
Firm FE		yes	yes	yes	yes	yes
Time FE			yes			
Time*State FE				yes		yes
Time*3digit-Sector FE					yes	yes
Observations	26711	26688	26688	26667	26688	26667

Notes: $\text{Conditions}_{t+1,t+6}$ is the mean of ex post reported business conditions in the following six months. $\text{Conditions}_{t,t-5}$ is defined accordingly. "Time*State FE" and "Time*3digit-Sector FE" are time fixed effects at the state-level or at the 3-digit industry level. The sample includes all retail firms in the IBS between January 2004 and December 2007 that respond to the survey between *t-5* and *t+6*. Standard errors are two-way clustered at the levels of firms and dates. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.C.2: Retail Firms' Expectations and Disaggregate Information: Different Forecast Horizons

	Expected Business Conditions for the Next 6 Months					
$\text{Conditions}_{t+4,t+6}$	0.10***	0.078***	0.072***	0.073***	0.067***	0.068***
	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)
$\text{Conditions}_{t+1,t+3}$	0.18***	0.16***	0.16***	0.16***	0.16***	0.16***
	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
$\text{Conditions}_{t,t-2}$	0.25***	0.23***	0.24***	0.25***	0.25***	0.25***
	(0.019)	(0.021)	(0.017)	(0.017)	(0.018)	(0.017)
$\text{Conditions}_{t-3,t-5}$	0.0037	-0.0047	-0.0088	-0.0030	-0.0055	0.000100
	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Adjusted R^2	0.214	0.471	0.482	0.486	0.484	0.487
Firm FE		yes	yes	yes	yes	yes
Time FE			yes			
Time*State FE				yes		yes
Time*3digit-Sector FE					yes	yes
Observations	24830	24798	24798	24783	24798	24783

Notes: $\text{Conditions}_{t+4,t+6}$ is the mean of ex-post reported business conditions in four to six months in the future. $\text{Conditions}_{t+1,t+3}$, $\text{Conditions}_{t,t-2}$, and $\text{Conditions}_{t-3,t-5}$ are defined accordingly. "Time*State FE" and "Time*3digit-Sector FE" are time fixed effects at the state-level or at the three-digit industry level. The sample includes all retail firms in the IBS between January 2004 and December 2007 that respond to the survey between *t-5* and *t+6*. Standard errors are two-way clustered at the levels of firms and dates. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1.C.3 Robustness Checks for Section 1.5

This appendix performs a series of robustness checks to demonstrate that the results are not driven by the choice of the baseline specification. For this purpose, we estimate the difference-in-differences effect of facing the large pull-forward effect in demand due to the VAT increase on expectations of affected firms under different specifications. The results of all robustness checks are summarized and compared to the benchmark in Table 1.C.3.

To begin with, we show that our results are robust to the definition of the treatment period. First, we symmetrically shorten the treatment period at the beginning and the end by two months each. Hence, we define expectations to cover the period of the pull-forward effect in demand if they are formed between June and December 2006. Although the difference-in-differences effect is estimated based on only 7 instead of 11 treatment months, results are qualitatively similar to the benchmark scenario as can be inferred from Table 1.C.3 Panel A. If anything, the relatively early anticipation of the disaggregate shock is estimated to be even stronger in this setting as the difference-in-differences coefficient for $\text{Conditions}_{i,(t+4,t+6)}$ increases to 0.174. This appreciated treatment effect is not surprising having in mind that expectations formed within this shorter time frame put a relatively higher weight on realized conditions from periods that are closer to the increase in VAT and do not cover realizations from more distant periods when the magnitude of the VAT-induced disaggregate demand shock was smaller.

Second, we define the treatment period asymmetrically such that it covers less months in which expectations are mainly referring to periods with appreciated business conditions during the upward-movement in demand before the VAT increase and more months in which expectations are formed that cover the downswing thereafter. This is done because the appreciating effect on business conditions of treated firms preceding the VAT increase lasted shorter than the period of depreciated business conditions thereafter as documented in Figure 1.3. However, the coefficients in row 2 of Table 1.C.3 Panel A show that choosing the treatment period to asymmetrically capture the upward and downward effects of the VAT increase on business conditions does not change the results, either.

Next, Table 1.C.3 Panel B confirms that our results are robust to the inclusion of wholesale firms to the control group. Using survey responses of all firms in the retail and wholesale survey of the IBS, the majority of firms in the control group are wholesalers whose expectation formation is arguably more dissimilar from durable good retailers than that of other retail firms. The treatment effects in response to the VAT shock, however, do not hinge on this choice and still show the particularly early anticipation of the disaggregate demand shock in expectations of affected firms.

Moreover, the explanatory power of firm fixed effects for expectations is highest for firms that are in the sample for only a few periods by construction. If the treatment

Table 1.C.3: The Effect of More Precise Information on Expectations: Robustness Checks

	Difference-in-Differences Coefficients					
	$\text{Cond}_{t+4,t+6}$	$\text{Cond}_{t+1,t+3}$	$\text{Cond}_{t,t-2}$	$\text{Cond}_{t-3,t-5}$	Obs.	Adj. R^2
Baseline Specification	0.151***	0.0182	-0.135***	-0.0156	24798	0.502
	(0.0585)	(0.0435)	(0.0518)	(0.0454)		
Panel A: Robustness to Choice of Treatment Period						
$\mathbb{1}(\text{VAT}_t) = 1$ if						
$t \in (2006m6, 2006m12)$	0.174***	0.0562	-0.137**	-0.0258	24798	0.503
	(0.0637)	(0.0507)	(0.0667)	(0.0577)		
$t \in (2006m6, 2007m2)$	0.135**	0.0572	-0.136**	0.000913	24798	0.503
	(0.0642)	(0.0443)	(0.0567)	(0.0514)		
Panel B: Robustness to Choice of Control Group						
Control: Other Retail & Wholesale	0.151***	0.0224	-0.116**	-0.0107	50923	0.494
	(0.0449)	(0.0407)	(0.0468)	(0.0333)		
Panel C: Restrictions on Minimum Duration in Sample and Attrition						
Firm at least 24 months in sample	0.176***	0.0331	-0.187***	-0.00133	21270	0.493
	(0.0551)	(0.0479)	(0.0522)	(0.0425)		
Firm covers at least 2006m4-2007m2	0.166***	0.0180	-0.163***	-0.0153	19990	0.493
	(0.0540)	(0.0472)	(0.0514)	(0.0437)		
Firm covers at least 2005m6-2007m12	0.146***	0.0309	-0.171***	0.0135	17923	0.491
	(0.0550)	(0.0494)	(0.0538)	(0.0416)		
Panel D: Robustness to Choice of Time Period Covered By Dataset						
Dataset covers 2005m3-2007m12	0.157**	0.0199	-0.117**	-0.0495	18056	0.510
	(0.0629)	(0.0447)	(0.0548)	(0.0464)		
Panel E: Robustness to Estimation of Fixed Effects						
FE: Firm only	0.234***	-0.00997	-0.165***	-0.0312	24798	0.493
	(0.0718)	(0.0459)	(0.0572)	(0.0469)		
FE: Firm, Time*State	0.143**	0.0215	-0.130**	-0.00821	24783	0.521
	(0.0592)	(0.0438)	(0.0524)	(0.0482)		

Notes: Each row corresponds to the results of one robustness check and reports the respective estimate of the vector $\boldsymbol{\delta}$ in model (1.7), that is the change in the weights, caused by the VAT shock, that firms put on ex post realized business conditions two quarters ahead ($\text{Cond}_{t+4,t+6}$), one quarter ahead ($\text{Cond}_{t+1,t+3}$) as well as on current quarter's and past quarter's conditions ($\text{Cond}_{t,t-2}$ and $\text{Cond}_{t-3,t-5}$, respectively) when forming their expectations. If not stated otherwise all regressions use the baseline specification with (1) firm- and time-fixed effects, (2) the treatment period referring to expectations formed between April 2006 and February 2007, (3) the treatment group entailing all durable good retailers, (4) the control group including all other retail firms, and (5) no restriction on duration of the firm in the sample and attrition. If not stated otherwise, the range of data is restricted to retail frims between January 2004 and December 2007 that respond to the survey between $t-5$ and $t+6$. Standard errors are twoway clustered at the levels of firms and dates. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and control group consisted of different proportions of these short-lived firms, the results might be biased, too. Results in row 1 of Table 1.C.3 Panel C confirm that results are unaffected from restricting the analysis to firms that are in the sample for at least 24 months during the 4 years under consideration (2004-2007).

A further potential issue is attrition. Given that the sample is unbalanced, some firms drop or enter the sample during the time period under consideration. If attrition was correlated with the outcomes of the treatment, our results would be biased. We control for attrition by restricting the analysis to firms that neither drop nor enter the sample during the treatment period (row 2 of Table 1.C.3 Panel C) as well as the period between June 2005 and December 2007 in row 3, i.e., the treatment period ± 10 months. As shown by the difference-in-differences coefficients, the particularly early and relatively better anticipation of the disaggregate demand shock due to the VAT increase is estimated to be even stronger once attrition is controlled for.

Furthermore, Table 1.C.3 Panel D confirms that our results are robust to the choice of the time period covered by the dataset. Restricting the dataset to firms between March 2005, i.e., the first period of the joint data set including all industry surveys used in Section 1.4, and December 2007 and thereby reducing the length of the pre-treatment period by half, the treatment effects in response to the VAT shock are virtually left unchanged despite of the reduced number of observations in the control period.

In a last step, we estimate the treatment effects using different empirical specifications of fixed effects in model (1.7). Table 1.C.3 Panel E shows that the treatment effects explain an even more pronounced early anticipation of the pull-forward effect in demand of affected firms once only firm fixed effects are applied and time fixed effects are excluded. In contrast, applying time fixed effects interacted with regional identifiers at the level of federal states leads to slightly weaker, albeit still statistically significant results.[34]

In sum, all robustness checks confirm that firms "treated" by the VAT-induced increase in the quality of information about future business conditions become significantly more forward-looking once the time of the disaggregate demand shock enters their expectation window of six months. While fluctuations one to three months ahead are, if anything, only reflected slightly more than in "normal" times, current conditions are reflected significantly less by expectations and ex post realized business conditions four to six month in the future are significantly better anticipated in all specifications.

[34]Note that time fixed effects interacted with sectoral identifiers are not sensible at levels that are more disaggregate than the two-digit level, which exactly refers to the group of all retail firms, as the treatment and control group are defined along these dimensions.

Chapter 2

Market Volatility, Information Frictions, and the Information Content of Firms' Expectations

2.1 Introduction

Information frictions have become increasingly popular in macroeconomics to model the expectation formation process of firms and other economic agents more realistically compared to the usual full-information rational expectations approach. However, these frictions—often modeled as capacity constraints or costly acquisition and processing of information—are usually rationalized on intuitive grounds because empirical evidence on the importance of information rigidities for the expectation formation process of firms is scarce. This chapter aims at narrowing this gap by providing evidence that firms form expectations regarding their own future business conditions consistently with rational models of information frictions.

For this purpose, I test whether firms allocate more attention to shocks that are more volatile—a prediction that different types of these models share and that has not been tested at the firm level, yet.[1] For example, Reis (2006) shows that in the "sticky information model" of Mankiw and Reis (2002) "more volatile shocks lead to more frequent updating since inattentiveness is more costly in a world that is rapidly changing" (Reis, 2006, p. 803). Moreover, calibrating a "rational inattention model" à la Sims (2003), Maćkowiak and Wiederholt (2009) show that firms allocate a low degree of attention to monetary policy shocks because of their relatively low volatility which explains why

[1] To my knowledge, Maćkowiak et al. (2009) is the only paper that directly assessed the relationship between volatility and information frictions. Using industry-level data in a dynamic factor model, they find that the speed of response of a sectoral price index to aggregate shocks is increasing in the standard deviation of sectoral inflation due to aggregate shocks.

responses to monetary policy are exceptionally sluggish and persistent. The results presented in this chapter provide evidence in favor of this prediction by documenting that the degree to which firms' expectations reflect information about future business conditions is strongly increasing in the volatility of market conditions firms are generally exposed to.

This chapter contributes to a small, but growing literature on the importance of information frictions for the expectation formation of firms. Identifying this relationship is challenging because the information sets of firms are typically unobserved and data on firms' expectations is scarce. In line with my results, Kacperczyk et al. (2016) document that mutual funds managers allocate their attention rationally. Moreover, Sarte (2014) finds evidence for notable information lags consistent with Mankiw and Reis (2002) in manufacturing firms' information sets by contrasting industry-level time series on production with survey-based balance indices. Analyzing errors in inflation forecasts of firms in the semiannual Livingston survey, Coibion and Gorodnichenko (2012, 2015) find that the importance of information frictions for firms' inflation forecasts is comparable to what can be found in survey data of professional forecasters, consumers, and central bankers. Lastly, Chapter 1 documents that firms adjust their expectation formation to the availability of precise information about future demand which is consistent with the presence of information frictions.

The remainder of the chapter is structured as follows. In the next section, I describe the data and present the empirical framework. Section 2.3 discusses the empirical findings. Finally, Section 2.4 relates these findings to the literature and concludes.

2.2 Data and Empirical Framework

I use the micro data of the IFO Business Survey (IBS) that is unique in asking a large and representative sample of German firms about current realizations and six-month-ahead expectations of their business conditions at monthly frequency.[2] Aiming for a high level of generality, the analysis focuses on the three main surveys of the IBS covering manufacturing firms (IBS-IND, 2015), retailers and wholesalers (IBS-TRA, 2015), and service

[2]See Becker and Wohlrabe (2008) for details of the survey. I use the following questions: (Q1) *"Current situation: We evaluate our current business condition as [1] good, [0] satisfactory, [-1] bad."* and (Q2) *"Expectations for the next 6 months: After elimination of purely seasonal fluctuations the development of our business will be [1] more favorable, [0] about the same, [-1] more unfavorable."* Importantly, firms appear to refer to the same latent variable when answering (Q1) and (Q2) despite of the potentially misleading wording. As can be inferred from Figure 2.1 and discussed in detail in Chapter 4, it is very unlikely that (Q2) captures the expected change in (Q1). Moreover, the manufacturing survey is at the product level similarly to the retail/wholesale survey until January 2006. For the sake of uniformity, I aggregate the data to the firm level. See Chapter 4 for details on the aggregation and the procedure how industry identifiers contained in the micro data are transferred to the official German industry classification system of 2008 ("WZ 08") that corresponds to NACE Rev. 2.

Figure 2.1: Time Series of Average Realized Business Conditions and Expectations

Notes: Time series of mean reports on expected business conditions and current business conditions of firms in the respective industry surveys of the IBS after purging for firm fixed effects as well as month fixed effects.

providers (IBS-SERV, 2015). The sample is restricted to firms that responded to the survey for at least one year as well as to dates and sectors that can be matched to all volatility measures described below. The final data set comprises of on average 1300 manufacturing firms per month between 1992 and 2015, 520 retail and wholesale firms between 1995 and 2015, and 990 service providers between 2004 and 2015.[3] Figure 2.1 displays the time series of average realized business conditions as well as six-month-ahead expectations of the firms in the sample after purging for month fixed effects (deseasonalization) and firm fixed effects.

Each firm i is matched to two proxies that capture the general level of market volatility specific to its industry s, the first based on external administrative revenue data and the second constructed from the IBS itself. Moreover, a firm-specific market volatility measure can be constructed for the subset of manufacturing firms. The market volatility measures are defined as follows:

1. $\sigma_{i\in s}^{\text{Revenues}}$: standard deviation of monthly indices of seasonally adjusted total revenues in each industry. The time series are obtained from the German Federal Statistical Office and allow for the computation of $\sigma_{i\in s}^{\text{Revenues}}$ at the four-digit industry level according to the German industry classification system of 2008. No rule without exemption: for service providers, the revenue data are of much lower quality such that $\sigma_{i\in s}^{\text{Revenues}}$ can only be calculated based on quarterly data at the two-digit industry level.[4]

[3]Overall, attrition is low and firms respond quite regularly: manufacturing (average duration in IBS: 13.1 years/response rate: 88%), retail and wholesale (7.3/78%), services (5.7/76%). As the empirical approach requires data from 12 consecutive months, I linearly interpolate missing survey data if answers are missing for at most two consecutive months. Chapter 4 shows that interpolated observations do not differ from original reports in a systematic way.

[4]The following time series of seasonally adjusted revenue indices are downloaded from Destatis' GENESIS database: manufacturing (code 42152/period 1992-2015/monthly frequency/4-digit industry level), retail and wholesale (45211,45212,45214/1995-2015/monthly/4-digit), and services (47414/2005-

2. $\sigma_{i \in s}^{\text{IFO Index}}$: standard deviation of the industry-specific analog of the "IFO Business Situation Index"—a widely-recognized business indicator of the German economy based on the IBS—which corresponds to the average reported realized business conditions of all firms in the same four-digit industry after deseasonalization using industry-specific month fixed effects. To ensure that volatility is not driven by non-response or entry and exit of firms, the analysis is restricted to industries with at least 20 firms at all dates.

3. $\sigma_i^{\text{Backlog}}$: firm-specific market volatility based on a supplementary question in the manufacturing survey of the IBS which asks firms once per quarter for a *quantitative* assessment of their backlog of orders as measured in months of production. First, these reports are deseasonalized using quarter fixed effects for each firm. Then, $\sigma_i^{\text{Backlog}}$ is calculated for firms that reported their backlog of orders at least 12 times.

In order to test whether the information content of firms' expectations increases with the market volatility they generally face, I estimate the following empirical model for each volatility measure[5]

$$\begin{aligned}\text{Expectations}_{i,t}^{+6m} = \beta_1 \times \text{Conditions}_{i,(t+1,t+6)} + \gamma_1 \times \text{Conditions}_{i,(t+1,t+6)} \times \sigma_i \\ + \beta_2 \times \text{Conditions}_{i,(t,t-5)} + \gamma_2 \times \text{Conditions}_{i,(t,t-5)} \times \sigma_i + \alpha_i + \varepsilon_{i,t}, \quad (2.1)\end{aligned}$$

where $\text{Expectations}_{i,t}^{+6}$ denotes firm i's expectations for the next 6 months reported in month t to the IBS. $\text{Conditions}_{i,(t+1,t+6)}$ summarizes ex post realized business conditions in the six months following reporting month t. $\text{Conditions}_{i,(t,t-5)}$ covers business conditions between $t-5$ and t. I construct the measures $\text{Conditions}_{i,(t+1,t+6)}$ and $\text{Conditions}_{i,(t,t-5)}$ as moving averages of the realized business conditions reported to the IBS. In order to estimate the volatility effect, $\text{Conditions}_{i,(t+1,t+6)}$ and $\text{Conditions}_{i,(t,t-5)}$ are interacted with one of the market volatility measures σ_i constructed above. Lastly, I add firm fixed effects α_i to capture systematic, time-invariant expectation biases of firms documented by Bachmann and Elstner (2015).

As model (2.1) controls for current and past conditions as well as firm fixed effects, the coefficient β_1 can be interpreted as the magnitude to which firms incorporate information about future business conditions available at date t into their expectations that is neither

2015/quarterly/2-digit). I detrend all time series using the log-deviation from an HP-filtered trend with smoothing parameter $\lambda = 129,600$ (1,600) for monthly (quarterly) data as suggested by Ravn and Uhlig (2002).

[5]To correct for potential correlation in the error terms, I follow Cameron et al. (2011) in twoway-clustering standard errors at the levels of firms and dates. Moreover, the fixed effects model is estimated with ordinary least squares because of the non-existence of standard methods for the estimation of fixed effects models with non-binary ordinal data. Chapter 1 discusses this choice in greater detail.

captured by current conditions or past trends, nor due to time-invariant firm-specific effects. Consequently, the information content of expectations is estimated to $\hat{\beta}_1 + \hat{\gamma}_1 \times \sigma_i$, where the coefficient γ_1 captures the degree to which the expectations of firms in highly volatile markets contain more information relative to firms in more stable markets. For the sake of interpretability of the coefficients, the volatility measures are standardized such that they take the values of zero and one for the firms at the 10^{th} and 90^{th} percentile of their distribution, respectively.

2.3 Results

The results are presented in Table 2.1. Panel A reports results for manufacturing firms, while Panels B and C cover the samples of retail and wholesale firms as well as service companies, respectively. As documented in Columns (1) of each panel, six-month-ahead expectations strongly reflect the corresponding variation in ex post realizations of future business conditions after controlling for current and past conditions as well as firm fixed effects, i.e., $\hat{\beta}_1 > 0$.[6] Hence, the expectations of firms in all industry surveys of the IBS contain a substantial degree of information about future business conditions available at t which is in line with and discussed in detail in Chapter 1.

The estimation of model (2.1) delivers a strongly positive correlation between industry-specific market volatility and the information content of expectations that is robust for firms in all sector-specific surveys of the IBS, see Columns (2) and (3) of each panel.[7] In the manufacturing survey, expectations of firms at the 90^{th} percentile of the distribution of the respective volatility measure reflect variation in ex post realized conditions by roughly 60% more than firms at the 10^{th} percentile, i.e., $\hat{\gamma}_1/\hat{\beta}_1 = 0.57$ (0.62) using $\sigma_{i\in s}^{\text{Revenues}}$ ($\sigma_{i\in s}^{\text{IFO Index}}$). For the subset of retail and wholesale firms, the estimated volatility effects are of comparable size as the interaction term $\hat{\gamma}_1$ takes the values of 0.14 and 0.16 for the measures $\sigma_{i\in s}^{\text{Revenues}}$ and $\sigma_{i\in s}^{\text{IFO Index}}$, respectively.

The estimated effects are more heterogeneous for firms in the services survey. Using the survey-based market volatility measure $\sigma_{i\in s}^{\text{IFO Index}}$ delivers a significant and strongly posi-

[6] The standard deviations of $\text{Expectations}_{i,t}^{+6m}$ and $\text{Conditions}_{i,(t+1,t+6)}$ are of comparable size. Hence, a one standard deviation increase in $\text{Conditions}_{i,(t+1,t+6)}$ is *ceteris paribus* associated with an appreciation of expectations by $\hat{\beta}_1$ standard deviations.

[7] Potentially, the documented effects could reflect a mechanical artifact of the trichotomous nature of the survey data if (a) the composition of survey responses differed substantially between firms in highly volatile and less volatile markets and (b) a higher share of extremely positive or negative business conditions resulted in a higher estimated correlation between expectations and ex post realized business conditions. As documented in Table 2.A.1 in the Appendix, the fraction of reported non-neutral business conditions is not robustly higher for firms in markets with high volatility compared to their counterparts in more stable markets. It is thus very unlikely that the results are driven by the categorical nature of the data.

Table 2.1: Effect of Market Volatility on the Information Content of Firms' Expectations

Dependent Variable: Expected Business Conditions in Next 6 Months							
	Panel A: Manufacturing						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{Conditions}_{t+1,t+6}$	0.37***	0.30***	0.26***	0.32***	0.34***	0.28***	0.25***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.017)	(0.012)	(0.012)
$\text{Conditions}_{t+1,t+6} \times \sigma_{i\in s}^{\text{Revenues}}$		0.17***				0.15***	
		(0.017)				(0.018)	
$\text{Conditions}_{t+1,t+6} \times \sigma_{i\in s}^{\text{IFO Index}}$			0.16***				0.14***
			(0.017)				(0.018)
$\text{Conditions}_{t+1,t+6} \times \sigma_{i}^{\text{Backlog}}$				0.11***	0.14***	0.077***	0.067***
				(0.014)	(0.024)	(0.014)	(0.014)
Observations	370283	370283	370283	370283	127365	370283	370283
Firms	2574	2574	2574	2574	492	2574	2574
R^2	0.235	0.237	0.238	0.236	0.225	0.238	0.238
Control for Current & Past Realiz.	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes
Firms in Sample: 1992-2015	no	no	no	no	yes	no	no
	Panel B: Retail & Wholesale				Panel C: Services		
	(1)	(2)	(3)		(1)	(2)	(3)
$\text{Conditions}_{t+1,t+6}$	0.30***	0.25***	0.23***		0.30***	0.29***	0.20***
	(0.011)	(0.012)	(0.015)		(0.018)	(0.018)	(0.023)
$\text{Conditions}_{t+1,t+6} \times \sigma_{i\in s}^{\text{Revenues}}$		0.14***				0.033	
		(0.026)				(0.022)	
$\text{Conditions}_{t+1,t+6} \times \sigma_{i\in s}^{\text{IFO Index}}$			0.16***				0.14***
			(0.029)				(0.027)
Observations	130122	130122	130122		125337	125337	125337
Firms	1642	1642	1642		2044	2044	2044
R^2	0.362	0.365	0.366		0.345	0.345	0.346
Control for Current & Past Realiz.	yes	yes	yes		yes	yes	yes
Firm FE	yes	yes	yes		yes	yes	yes

Notes: $\text{Conditions}_{t+1,t+6}$ is the mean of ex post realized business conditions in the following six months. Market volatility measures refer to volatility at the levels of industries ($\sigma_{i\in s}^{\text{Revenues}}$ and $\sigma_{i\in s}^{\text{IFO Index}}$) as well as firms ($\sigma_{i}^{\text{Backlog}}$) and are constructed as described in the main text. All specifications control for current and past realized business conditions interacted with the respective volatility measures in line with the empirical model (1). Standard errors are twoway-clustered at levels of firms and dates. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

tive volatility effect of $\hat{\gamma}_1 = 0.14$. According to this estimate, service providers in highly volatile industries (90^{th} percentile of $\sigma_{i\in s}^{\text{IFO Index}}$) form expectations that reflect variation in ex post realized conditions by roughly 70% more than firms in very stable industries (10^{th} percentile). In contrast, the volatility effect is estimated to be only slightly positive ($\hat{\gamma}_1 = 0.033$) and statistically indistinguishable from zero when using $\sigma_{i\in s}^{\text{Revenues}}$ as volatility measure. As the revenue data for the service sector are only available at quarterly frequency and at the more aggregated level of two-digit industries, $\sigma_{i\in s}^{\text{Revenues}}$ might probably fail to closely track the market volatility that is perceived by firms. Hence, the estimate is most plausibly attenuated due to measurement error.

Moreover, the information content of expectations regarding their future business conditions is also strongly correlated with the firm-specific market volatility measure $\sigma_{i}^{\text{Backlog}}$.

As displayed in Column (4) of Panel A, the volatility effect is estimated to $\hat{\gamma}_1 = 0.11$. In the baseline specification, however, manufacturing firms are in the sample during different periods of time. Hence, $\sigma_i^{\text{Backlog}}$ does not allow to distinguish different degrees of market volatility firms are generally exposed to from time-varying market volatility that is potentially correlated across firms. To accommodate this concern, I further restrict the sample to manufacturing firms that have been in the sample throughout the entire period between 1992 and 2015. Interestingly, the results for the remaining 492 firms displayed in Column (5) indicate an even stronger relationship between firm-specific market volatility and the information content of firms' expectations ($\hat{\gamma}_1 = 0.14$).

Taking the results based on firm-specific as well as industry-specific market volatility measures together delivers additional interesting insights. Despite the fact that both types of measures arguably capture different dimensions of the market volatility firms are exposed to, which manifests in a low correlation of 0.26 (0.32) between $\sigma_i^{\text{Backlog}}$ and $\sigma_{i\in s}^{\text{Revenues}}$ ($\sigma_{i\in s}^{\text{IFO Index}}$), the information content of expectations increases significantly in both measures.[8] Moreover, the estimated volatility effects stay significantly positive once each industry-level volatility measure competes in a horse-race with the firm-specific measure $\sigma_i^{\text{Backlog}}$, see Columns (6) and (7) of Panel A. Arguably, all volatility measures thus only capture the volatility in market conditions that is actually perceived by firms with (classical) measurement error. The results should hence be interpreted as a lower bound of the "true" volatility effect.

The results are robust to various robustness checks that are summarized in Table 2.2. First, the results do not appear to be mainly driven by the global financial crisis starting in 2008 that depressed business conditions differently across firms and industries. Coibion and Gorodnichenko (2015) find evidence that information frictions decrease during recessions because economic agents have higher incentives to become better informed about economic conditions. If the degree to which firms were affected by the crisis on the one hand was correlated with this increase in attentiveness and on the other hand largely explained the heterogeneity in the market volatility measures constructed above, the volatility effect documented in Table 2.1 could be largely associated to the financial crisis rather than to differences in the market volatility firms generally face throughout the entire time period. To mitigate this concern, the analysis is restricted to volatility

[8] On the one hand, $\sigma_i^{\text{Backlog}}$ might capture each firm's market volatility more precisely than the industry-specific measures as their market conditions might only be imperfectly correlated with overall conditions in their industry. On the other hand, $\sigma_i^{\text{Backlog}}$ is based on self-reported assessments of firms' backlog of orders which are likely to describe their market conditions only with error. In contrast, the industry-level market volatility measures are usually strongly correlated with each other ($\rho(\sigma_i^{\text{IFO Index}}, \sigma_{i\in s}^{\text{Revenues}}) = 0.7$ for manufacturing firms and 0.96 for retail and wholesale firms) and hence seem to incorporate roughly comparable components of firms' market volatility. For firms in services, this correlation is substantially lower ($\rho(\sigma_i^{\text{IFO Index}}, \sigma_{i\in s}^{\text{Revenues}}) = 0.47$) which is most likely due to the low quality of administrative revenue data.

Table 2.2: Robustness Checks

Dependent Variable: Expected Business Conditions in Next 6 Months							
	Manufacturing			Retail & Wholesale		Services	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Sample Excluding Financial Crisis 2008-2010						
$\text{Conditions}_{t+1,t+6}$	0.30***	0.25***	0.30***	0.25***	0.22***	0.26***	0.21***
	(0.010)	(0.012)	(0.011)	(0.014)	(0.017)	(0.016)	(0.016)
$\text{Conditions}_{t+1,t+6} \times \sigma_{i\in s}^{\text{Revenues}}$	0.089***			0.098***		-0.028*	
	(0.015)			(0.027)		(0.015)	
$\text{Conditions}_{t+1,t+6} \times \sigma_{i\in s}^{\text{IFO Index}}$		0.15***			0.12***		0.054**
		(0.019)			(0.028)		(0.022)
$\text{Conditions}_{t+1,t+6} \times \sigma_{i}^{\text{Backlog}}$			0.11***				
			(0.014)				
Observations	334246	334246	334246	111920	111920	86072	86072
R^2	0.236	0.236	0.236	0.371	0.372	0.368	0.368
	Panel B: Sample Restricted to 2005-2015						
$\text{Conditions}_{t+1,t+6}$	0.35***	0.33***	0.36***	0.29***	0.29***	0.29***	0.20***
	(0.022)	(0.021)	(0.023)	(0.017)	(0.018)	(0.018)	(0.023)
$\text{Conditions}_{t+1,t+6} \times \sigma_{i\in s}^{\text{Revenues}}$	0.096***			0.10***		0.033	
	(0.019)			(0.036)		(0.022)	
$\text{Conditions}_{t+1,t+6} \times \sigma_{i\in s}^{\text{IFO Index}}$		0.13***			0.094**		0.14***
		(0.026)			(0.036)		(0.027)
$\text{Conditions}_{t+1,t+6} \times \sigma_{i}^{\text{Backlog}}$			0.097***				
			(0.019)				
Observations	120970	120970	120970	72499	72499	125337	125337
R^2	0.283	0.284	0.282	0.390	0.389	0.345	0.346
	Panel C: $\sigma_{i\in s}^{Revenues}$ and $\sigma_{i\in s}^{IFO\ Index}$ Constructed at Three-Digit Level						
$\text{Conditions}_{t+1,t+6}$	0.30***	0.28***	0.33***	0.27***	0.26***	0.29***	0.22***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.013)	(0.019)	(0.023)
$\text{Conditions}_{t+1,t+6} \times \sigma_{i\in s}^{\text{Revenues}}$	0.13***			0.058***		0.034*	
	(0.014)			(0.017)		(0.019)	
$\text{Conditions}_{t+1,t+6} \times \sigma_{i\in s}^{\text{IFO Index}}$		0.15***			0.069***		0.14***
		(0.018)			(0.021)		(0.029)
$\text{Conditions}_{t+1,t+6} \times \sigma_{i}^{\text{Backlog}}$			0.089***				
			(0.011)				
Observations	533589	533589	533589	261706	261706	135918	135918
R^2	0.237	0.237	0.236	0.390	0.389	0.339	0.340
	Panel D: Number of Firms per Industry and Date $\geq$ 10						
$\text{Conditions}_{t+1,t+6}$	0.32***	0.28***	0.33***	0.27***	0.26***	0.28***	0.22***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.013)	(0.021)	(0.022)
$\text{Conditions}_{t+1,t+6} \times \sigma_{i\in s}^{\text{Revenues}}$	0.12***			0.11***		0.025	
	(0.014)			(0.024)		(0.025)	
$\text{Conditions}_{t+1,t+6} \times \sigma_{i\in s}^{\text{IFO Index}}$		0.15***			0.082***		0.12***
		(0.016)			(0.020)		(0.027)
$\text{Conditions}_{t+1,t+6} \times \sigma_{i}^{\text{Backlog}}$			0.087***				
			(0.012)				
Observations	527163	527163	527163	173847	173847	135404	135404
R^2	0.238	0.239	0.237	0.382	0.381	0.345	0.346
Control for Current & Past Realiz.	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes

Notes: $\text{Conditions}_{t+1,t+6}$ is the mean of realized conditions in the following six months. If not stated otherwise, $\sigma_{i\in s}^{\text{Revenues}}$, $\sigma_{i\in s}^{\text{IFO Index}}$, and $\sigma_{i}^{\text{Backlog}}$ are constructed as described in the main text, i.e., (1) based on the entire time period covered by each sector-specific survey, (2) at the four-digit industry level (exemption: $\sigma_{i\in s}^{\text{Revenues}}$ in services), (3) $\sigma_{i\in s}^{\text{IFO Index}}$ is constructed for four-digit industries with at least 20 firms at any date. All specifications control for firm fixed effects as well as current and past realized conditions interacted with the respective volatility measures as in model (1). Standard errors are clustered at levels of firms and dates. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

measures calculated based on data prior to January 2008 and after December 2010. Moreover, business expectations reported to the IBS during this period are excluded from the regression. The results displayed in Panel A show that the effect of market volatility on the information content of firms' expectations is of comparable magnitude, albeit slightly smaller, once the period of the financial crisis is excluded from the analysis.

Second, the estimated volatility effects for firms in the manufacturing survey as well as in the retail/wholesale survey stay highly significant once their samples are restricted to the shorter time period that is covered by the services survey (2005-2015). The fact that the coefficients displayed in Panel B are slightly lower than in the baseline specification is potentially due to the shorter time series that are used for the calculation of the market volatility measures which hence might capture the volatility that is generally perceived by the firms with relatively more measurement error.

Third, the results are robust to the choice of less restrictive requirements for the calculation of the market volatility measures. Panel C summarizes the estimated volatility effects if the industry-level volatility measures are calculated based on time series at the more aggregated level of three-digit industries, while Panel D covers firms that are in four-digit industries with at least 10 firms at each date. Despite the fact that the underlying time series potentially do not track the actual market conditions of the firms as closely as in the baseline scenario, the estimated volatility effects for both robustness specifications are only slightly attenuated, but still of comparable size.[9]

2.4 Discussion

The findings have important implications as they highlight the relevance of information frictions for the expectation formation process of firms and provide empirical support for models that implicitly or explicitly take these frictions into account. Seen through the lens of this class of models in the tradition of Mankiw and Reis (2002) and Sims (2003), firms in more volatile markets *rationally* invest more resources (or a larger part of their limited attention) into the costly collection and processing of information about their future business conditions resulting in increased information content of their expectations. Although this pattern is robustly documented for all important sectors of the economy and a wide range of different specifications, the results suggest the need for more research on

[9]The only notable exemption are the estimated volatility effects for retail and wholesale firms which are still significantly positive, but drop by more than half of their respective magnitudes once $\sigma_{i\in s}^{\text{Revenues}}$ and $\sigma_{i\in s}^{\text{IFO Index}}$ are calculated at the three-digit industry level. By the nature of the industry classification system, the three-digit industry groups of retailers and wholesalers usually cover four-digit groups that are much more heterogeneous compared to their counterparts in manufacturing or services sectors. Hence, the market volatility measures capture the actual volatility the respective firms face with relatively more error resulting in more strongly attenuated coefficients.

the mechanisms behind the expectation formation process of economic agents. Using high-frequency data on market conditions at very disaggregate levels of even higher quality, which hopefully become available in the future, should hence highlight the importance of information frictions for expectation formation even further.

Appendix to Chapter 2

Table 2.A.1: Composition of Reported Conditions: High vs. Low Volatility Markets

	Manufacturing			Retail and Wholesale		Services	
Volatility Measure x_i	$\sigma_{i\in s}^{\text{Revenues}}$	$\sigma_{i\in s}^{\text{IFO Index}}$	$\sigma_{i}^{\text{Backlog}}$	$\sigma_{i\in s}^{\text{Revenues}}$	$\sigma_{i\in s}^{\text{IFO Index}}$	$\sigma_{i\in s}^{\text{Revenues}}$	$\sigma_{i\in s}^{\text{IFO Index}}$
Frac. "Neutral" if $x_i \leq$ Median	0.5391	0.5459	0.5322	0.4908	0.4553	0.4672	0.4486
Frac. "Neutral" if $x_i >$ Median	0.5004	0.4962	0.5071	0.5471	0.5459	0.5234	0.5283
Difference	-0.0387***	-0.0498***	-0.0252***	0.0563***	0.0906***	0.0562***	0.0797***
	(0.0084)	(0.0083)	(0.0084)	(0.0201)	(0.0129)	(0.016)	(0.013)

Notes: Fraction of "neutral conditions" among the answers to Q2 of firms in markets with volatility above the median compared to their counterparts with market volatility below the median according to the volatility measure indicated above each column. Level of significance of a two-sided t-test on the significance of the difference between both fractions: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 3

The Price and Employment Response of Firms to the Introduction of Minimum Wages

3.1 Introduction

In light of increasing wage inequality, minimum wages have become an increasingly popular tool for public policy during the last decades. However, its economic consequences are still hotly debated. Spurred by the seminal paper of Card and Krueger (1994), who cast doubt on the conventional wisdom that minimum wages inevitably destroyed jobs, the literature has mainly focused on the question whether a negative effect on the overall level of employment can be detected (e.g., Neumark and Wascher, 2000, 2008; Neumark et al., 2014) or not (e.g., Card and Krueger, 1994, 2000; Dube et al., 2010; Allegretto et al., 2011).[1] Although being neglected in most papers on minimum wage effects, prices have been perceived as an important margin of adjustment for firms (see, for example, the seminal paper of Aaronson, 2001). However, previous studies mainly focused at the price response to changes in existing minimum wages of firms in highly affected industries, such as restaurants (e.g., Aaronson, 2001, Lemos, 2006, Aaronson et al., 2008, and Fougère et al., 2010) and retailers (Leung, 2016 and Montialoux et al., 2017).

This chapter takes a step in this direction by examining the price and employment response of firms in the manufacturing as well as services sector to the introduction of statutory minimum wages in Germany in 2015. This policy intervention offers a unique opportunity to take a broader perspective on these issues, as the new statutory minimum wage was directly set to the average level of OECD countries, see OECD (2015). Thereby,

[1] See Neumark et al. (2014) and Card and Krueger (2015) for recent summaries and discussions of the literature on employment effects of minimum wages.

firms across a wide range of industries were affected by this policy which permits for a more general analysis of minimum wage effects that goes beyond the restaurant and retail sector.

Uncovering the response of firms to the introduction of minimum wages requires micro data on employment and prices at the firm-level. As the availability of disaggregated producer price data is limited, the price adjustment of firms to the introduction of statutory minimum wages in Germany has not been studied in the literature, yet. I circumvent this constraint by making use of the IFO Business Survey (IBS).[2] This survey is unique in repeatedly asking a large sample of approximately 5000 German manufacturing and services firms about both their planned changes in employment and prices at high, monthly, frequency. The IBS is thus ideally suited for an assessment of the minimum wage-induced reaction of firms in different regions and sectors of the economy along two potentially important margins of adjustment: their number of employees and their prices.

Moreover, the identification of each firm's degree of affectedness by the minimum wage introduction is essential for the analysis of their reaction. Following the "minimum wage bite" approach proposed by Card (1992), I construct a firm-level treatment intensity measure based on regionally and sectorally disaggregated wage data: the fraction of full-time employees that previously earned a gross wage below the newly introduced minimum wage of €8.50 per hour in each firm's industry and location. This treatment intensity measure identifies a substantial degree of variation between firms within different industries and regions that can be exploited empirically to assess the firm-level response to the minimum wage.

I find striking evidence in favor of a minimum wage-induced effect on prices based on a generalized difference-in-differences estimation strategy. Specifically, the probability that firms planned to increase their prices during the period around the introduction in January 2015 is strongly significantly associated with their relative degree of affectedness by the new statutory minimum wage. Interestingly, the price reaction of affected firms is found to be comparably strong in manufacturing and services as well as in West and East Germany given the same degree of affectedness. Moreover, firms in the manufacturing sector, which additionally provide information on realized price changes to the IBS, are found to have stuck to their plans and indeed increased their prices in response to the statutory minimum wage.

The price effect of the minimum wage introduction is considerably large. Exploiting the fact that average reported price changes in the IBS closely track *quantitative* changes

[2]The IBS has already been used for the evaluation of industry-specific minimum wages in the construction sector by Werner and Sell (2015). However, their identification of "treated" firms only relies on the fact whether a minimum wage has been introduced in their industry or not. Hence, they neither observe whether the minimum wage is binding for the firm, nor the intensity to which it is affected.

in industry-level producer price indices, the minimum wage-induced effect on the overall level of producer prices is approximated to roughly 0.2%. This effect is sizable in light of the fact that average wages of full-time employees increased by approximately 0.6%. Hence, price pass-through appears to have been an important margin of adjustment for firms in response to the new minimum wage.

In contrast to the strong and sizable effect on prices, the minimum wage effect on affected firms' planned employment changes is estimated to be only very modestly negative and insignificant. In light of potential measurement error in the firm-specific treatment intensity measure, however, a negative employment reaction cannot be ruled out with certainty. Irrespectively, the probability that firms increased their prices is much larger compared to the probability that they planned to reduce their number of employees.

This chapter contributes to the most extensive part of the minimum wage literature that is interested in net employment effects. Documenting that firms did not cut back their employment plans substantially, my results point into the direction of a prominent strand of papers including Card and Krueger (1994, 2000), Dube et al. (2010), and Allegretto et al. (2011). Moreover, the chapter adds to first evidence on the German introduction of statutory minimum wages that detected only moderately negative effects on the total number of employees. Using data on employment relationships from the Federal Employment Agency in a descriptive analysis, vom Berge et al. (2016) find a loss of approximately 94,000 marginal employment relationships followed by a prolonged, but attenuated downward trend until the third quarter of 2015.[3] Comparably, Bossler and Gerner (2016) estimate that 60,000 jobs were lost (marginally employed plus regular jobs) based on the IAB Establishment Panel which equals to 0.18% of all German employees and is only statistically significant for East Germany.

Interestingly, the documented employment effects of the minimum wage introduction in Germany are much weaker than previously predicted by a series of studies. For example, Knabe et al. (2014) predicted a job loss of up to 910,000 employees of which 251,000 were regular jobs prone to social security, while Arni et al. (2014) expected a total job loss of 570,000. The discrepancy between ex ante simulated losses and ex post estimated employment effects can potentially by explained by the fact that these models did not incorporate any other adjustment mechanism besides the layoff of workers that allowed firms to react to increased labor costs.[4] In turn, my findings provide evidence for the

[3]Moreover, vom Berge et al. (2016) could not find negative effects for employment relationships prone to social security in the short run. In turn, roughly 50% of the marginally employment relationships lost were converted to "regular" jobs prone to social security. In addition, they find that the job loss was greatest in industries and regions with the lowest average wages.

[4]Alternative explanations for this gap include that short-run elasticities of employment with respect to minimum wage increases may differ from long-run elasticities as highlighted by Sorkin (2015), or that the assumption of competitive, neoclassical labor markets in the models' baseline specifications might

importance of one particular margin of adjustment for affected firms that was not considered in these simulation models: firms appear to have compensated their increased labor costs—at least partially and in the short run—by raising prices.

Providing the first credibly identified evidence for substantial price effects of the introduction of statutory minimum wages in Germany, this chapter contributes to the literature that aims to improve the general understanding of minimum wage effects and, in particular, the importance of pass-through on prices. During the last years, there has been accumulating evidence that prices are an important margin of adjustment for firms that face a minimum wage-induced increase in labor costs. So far, the price effect has almost exclusively been documented for (fast food) restaurants or retailers based on disaggregated city/region-level CPI data (Aaronson, 2001; Lemos, 2006) or store-level prices of different products (Dube et al., 2007; Aaronson et al., 2008; Fougère et al., 2010; Allegretto and Reich, 2016; Leung, 2016; Montialoux et al., 2017). For other sectors of the economy, existing evidence on pass-through on prices is far less clear.[5] For example, Wadsworth (2010) does not find significant short-run effects on prices in several low-wage industries in response to increases in the British national minimum wage based on industry-level price data. In contrast, I use firm-level data and provide evidence that firms' price response does not differ substantially between the manufacturing and services sector given their degree of affectedness by the minimum wage.

Moreover, this chapter contributes to an increasing literature that more generally highlights the relevance of additional channels of adjustment besides the extensive margin of employment, such as labor market flows (Portugal and Cardoso, 2006; Brochu and Green, 2013; Dube et al., 2016; Meer and West, 2016), firm profitability (Draca et al., 2011), tax evasion (Tonin, 2011), hygiene in fast food restaurants (Chakrabarti et al., 2017), or substitutability of jobs by machines (Lordan and Neumark, 2017).[6] For the case of the German statutory minimum wage, there is evidence that affected firms also reacted along various dimensions. For example, vom Berge et al. (2016) and Garloff (2016) document that marginal employment relationships are substituted by regular jobs. Moreover, Bellmann et al. (2017) find that affected firms reduced employer-financed training programs, while Gürtzgen et al. (2016) document that skill requirements for vacant and newly filled low-wage positions increased after the introduction of the German statutory minimum

not be appropriate in the context of minimum wages as, e.g., argued by Manning (2003).

[5]There is one notable exemption: Harasztosi and Lindner (2015) find evidence for minimum wage-induced increases in prices of Hungarian manufacturing firms, which are calculated based on an annual survey covering volumes and values of production for different products. Moreover, Lemos (2008) provides a survey of almost thirty studies on the price effect, which, however, usually rely on price data at rather aggregated industry levels and thus cannot exploit heterogeneity in firms' price reaction resulting from within-industry variation in the degree to which firms are affected by minimum wages.

[6]See Metcalf (2008) and Schmitt (2015) for a more complete and more extensive overview of the literature on the importance of different margins for firms' reaction to minimum wages.

wage. Complementing these findings by highlighting the importance of firms' price reaction shows that an exclusive focus on employment outcomes steps short of telling the full story of minimum wage effects.

The remainder of the chapter is structured as follows. Section 3.2 provides information about the institutional background of the introduction of statutory minimum wages in Germany in 2015. Section 3.3 describes the data as well as the identification of firms' degree of affectedness by the minimum wage. Section 3.4 specifies the empirical strategy and Section 3.5 documents the effect of the minimum wage introduction on the pricing and employment policies of firms. Section 3.6 provides an approximation of the quantitative size of the price effect. Finally, Section 3.7 performs diverse robustness checks and Section 3.8 concludes.

3.2 The New Statutory Minimum Wage in Germany: Institutional Background

Accompanied by a controversial public debate, a statutory minimum wage of €8.50 came into force in Germany on January 1, 2015. This introduction constituted a paradigm shift in the history of German labor market policy as wages had previously been determined almost exclusively through collective bargaining agreements between unions and employer associations. Until then, minimum wages were only in force in a small number of industries provided that a wage floor, which was part of a collective bargaining agreement, was declared as binding for the rest of the industry based on the "Posted Workers Act" ("*Arbeitnehmer-Entsendegesetz*" AEntG).[7]

In contrast to the history of statutory minimum wages in other countries, which is most extensively studied in the U.S., the U.K., and France, the German introduction of 2015 is unique with respect to the degree to which firms faced changes in labor costs. According to the "OECD Employment Outlook 2015," the German statutory minimum wage was directly set to a level that resulted in a minimum-to-median wage ratio of 0.48. This level is lower than in France (0.62), close to the U.K. and the average across OECD countries (0.49), and much higher than in the U.S. (0.36), see OECD (2015). While the level of the national minimum wage has been historically quite stable at low levels in the U.S. and high levels in France, the British statutory minimum wage has been introduced

[7]Prior to 2015, industry-specific minimum wages had been in place for instance in the construction and roofing sector, in commercial cleaning, security, and laundry services, as well as in a number of handicraft sectors. These industry-specific minimum wages were allowed to differ between regions, e.g., between West and East Germany. Moreover, an industry-specific minimum wage had been introduced in the care industry in 2010 that was not based on a collective bargaining arrangement, but implemented following a proposal of a commission installed by the Federal Ministry of Labor and Social Affairs in accordance with §12 AEntG.

at lower levels (0.42) in 1999 and steadily increased to the current level. Hence, none of these countries observed variation in national minimum wages during the last decades that were comparable to the case of the introduction of statutory minimum wages in Germany.

The new statutory minimum wage is set at a uniform level in (almost) all industries and across all regions. The German system is hence different from the U.S., where the national minimum wage can be trumped by higher rates set at the levels of states or cities. Compared to other countries, the German system is most similar to the British, as the wage floor is set at a national level and a commission decides on changes of its rate. In Germany, this commission is composed of unions and employer associations and takes advice from independent experts.

While the statutory minimum wage in general applies to all industries, there are exemptions for sectors that previously agreed on industry-specific wage floors below the level of €8.50 per hour. These sectors, including agriculture, forestry, gardening, the meat industry, manufacturing of textiles and clothing, temporary work agencies, hair dressers, and laundries, were conceded to delay their compliance to the statutory minimum wage until the end of 2016.[8] In order to prevent malpractice, the minimum wage law was accompanied by strict obligatory requirements for firms to document daily working hours of each employee with a gross monthly wage below €2,958.[9]

The introduction of the minimum wage was implemented in the following way: after the federal election ("*Bundestagswahl*") of September 22, 2013, the chairmen of the conservative parties (*CDU* and *CSU*) and the social democrats (*SPD*) signed a coalition agreement on November 27, 2013 containing the intention to introduce a statutory minimum wage of €8.50 on January 1, 2015. The Federal Cabinet proposed the minimum wage law ("*Mindestlohngesetz*" MiLoG) on April 2, 2014, containing all relevant regulations regarding its introduction and details on the exemptions. In light of the overwhelming majority of the "Grand Coalition" in both chambers of parliament, *Bundestag* and *Bundesrat* finally approved the law on July 3 and July 11, 2014 without major changes.

[8]Moreover, there are additional exemptions from the minimum wage for long-term unemployed during the first six months of re-employment, employees below the age of 18 years without training qualification, employees in vocational training, and internships compulsory for school programs, apprenticeship, or academic studies.

[9]According to the National Regulatory Control Council ("*Nationaler Normenkontrollrat*"), the introduction of the statutory minimum wage in 2015 and its first adjustment in 2017 imposed annual compliance costs of €6.3 billion on firms (National Regulatory Control Council, 2017, p.19).

3.3 Data and Identification of Firms' Affectedness by the Minimum Wage

3.3.1 Micro Data of the IFO Business Survey

The IFO Business Survey (IBS) has been conducted since 1949 in order to construct the IFO Business Climate Index which is the most recognized lead indicator for economic activity in Germany (see Becker and Wohlrabe (2008) for details of the survey). Each month, firms from all sectors of the economy are*, inter alia*, asked for an assessment of their expected changes in employment and prices of their products or services. The IBS is divided into four industry surveys that cover the main sectors of the economy (manufacturing, services, retail/wholesale, construction). In order to assess the firm-level effects of the minimum wage introduction in the relevant sectors of the economy, I use data of the two surveys covering (a) manufacturing firms (IBS-IND, 2015) and (b) service companies (IBS-SERV, 2015).[10] Furthermore, I exclude firms from the sample if they were operating in industries that were allowed to pay wages below the statutory minimum wage of €8.50 per hour during a transition phase until the end of 2016.[11]

Restricting the sample to the period between January 2010 and December 2015 as well as to firms that responded at least 12 months to the survey, the dataset comprises of approximately 5000 firms per month (on average 2550 manufacturers and 2400 service companies).[12] Attrition is very low in the restricted data set (firms are observed for almost 5 years on average) and response rates to the survey are relatively high despite of the fact that participation is voluntary (firms answer the questionnaire in more than four out of five months on average).

[10] I do not use data from the construction survey because these firms already had to adhere to an industry-specific minimum wage of €11.15 (€10.75) per hour in West (East) Germany in January 2015. Moreover, retailers and wholesalers are excluded—despite of the fact that especially retail firms were strongly affected by the minimum wage—as the direct effect of minimum wages through higher labor costs cannot be disentangled from price increases of the products they sell, which have potentially been produced by firms affected by the minimum wage.

[11] Specifically, I exclude firms in the two-digit industries WZ08-13 "Manufacture of textiles," WZ08-14 "Manufacture of wearing apparel," WZ08-78 "Temporary employment agencies and other employment activities," WZ08-96 "Other personal service activities" (85% of all employees belong to WZ08-9602 "Hairdressing") as well as the three-digit industry WZ08-101 "Processing and preserving of meat and production of meat products." Firms in these sectors do not constitute a valid control group as their industry-specific minimum wages have been increased in steps during the treatment period to approach the level of the statutory minimum wage by the end of 2016.

[12] The micro data do not allow to discriminate between subsidiaries of the same company in different locations and other firms. The term "firm" used in this chapter hence refers to both types of entities. Moreover, the manufacturing survey of the IBS is at the product level and not at the firm level. However, only 0.4% of all observations between 2010 and 2015 refer to multiple products of the same firm at a given point in time. Following the procedure described in Chapter 4, these observations are aggregated to the firm level by taking means across products and rounding to the next integer.

The anonymized micro data of the IBS allow to track firms over the entire time span in the sample. The data contain information on firms' main sector of business following the standard German industry classification system of 2008 (WZ 08) which largely corresponds to the European NACE Rev. 2 classification scheme.[13] In addition, I gained access to confidential information about the firms' location at the level of counties. These regional and sectoral identifiers permit to merge firms to wage statistics at the level of industries and counties as described in Section 3.3.2.

The analysis of firms' responses to the minimum wage mainly focuses on the following questions regarding expected changes in prices and employment contained in the IBS:[14]

Q1 *"Expectations for the next 3 months: The prices of our goods/services will [1] increase, [0] stay the same, or [-1] decrease."*

Q2 *"Expectations for the next 3 months: The number of employees will [1] increase, [0] stay the same, or [-1] decrease."*

Clearly, realized changes in prices and employment would be preferable relative to the expected changes stated in Q1 and Q2. While realized changes in prices and employment are not covered in both industry surveys of interest, firms in the manufacturing survey are asked to additionally state whether the prices of their products [1] increased, [0] stayed the same, or [-1] decreased during the previous month. As the majority of affected firms operate in the services sector, the baseline analysis is restricted to minimum wage effects on the pricing plans of firms in both industry surveys. In turn, the price realizations are used in Section 3.5.3 to demonstrate that—within the subset of manufacturing firms—the effect of the minimum wage introduction on firms' pricing plans is accompanied by a comparably strong effect on realized price changes.

Moreover, the data is categorical and effects estimated based on these variables hence cannot be interpreted quantitatively without further assumptions. However, there is no dataset available that contains quantitative producer price data at the level of firms in different industries. For example, the micro data underlying the German producer price

[13]Firms in the services survey have been coded with respect to the older "WZ2003" classification scheme until March 2011. The assignment of these firms to identifiers according to the "WZ2008" classification scheme is described in Chapter 4.

[14]The wording of the questions slightly differs between the manufacturing survey and the services survey but is largely comparable. The translated questions in the respective surveys are listed in Appendix 3.A. Moreover, I use firms' assessment of their current backlog of orders to control for the demand they face which is also measured at a trichotomous scale ("[1] comparatively large, [0] sufficient (typical for the season), or [-1] too small"). I further examine the effect of the minimum wage introduction on firms' reported current business conditions being either "[1] good, [0] satisfactory, or [-1] bad" as well as their expectations regarding their business conditions in the next six months as part of the analysis in Section 3.5.

index hosted by the Federal Statistical Office are not available for research purposes. In contrast, the micro data of the consumer price index are available at the "Research Data Centers" of the Federal Statistical Office but the prices of goods and services cannot be linked to the location of the producing firm or service provider, which is essential for the identification of the degree to which firms are affected by the minimum wage. Hence, the micro data of the IBS appear to be the best source of price data in order to study the pass-through of minimum wages on prices at the firm-level in Germany.

In contrast to the outstanding nature of the price data, the IBS data on expected employment changes are inferior to employment data from other sources. For example, there are quantitative micro data on firm-level employment available in the "IAB Establishment Panel" hosted by the Institute for Employment Research in Nuremberg, which are used in other studies on the effect of the introduction of the minimum wage in Germany, e.g., Bossler (2017) and Bossler and Gerner (2016). However, this dataset does not contain data on prices and cannot be matched to the micro data of the IBS. Still, the employment data in the IBS are useful enough to verify the finding of Bossler (2017) and Bossler and Gerner (2016) that the effect of the statutory minimum wage on the employment level was very weak and only slightly negative.[15]

Importantly, the qualitative expected price and employment changes as reported to the IBS on average closely track actually realized price and employment changes observed in administrative data. For the case of manufacturing firms, Figure 3.1 plots the time series of average answers to Q1 and Q2 against the annualized percentage change in producer prices and the number of employees relative to the level three months before, respectively.[16] As the time series are strongly correlated, the survey questions appear to be useful indicators of firms' pricing and employment policies. This close relationship is exploited in Section 3.6 to approximate the quantitative size of the price effect documented in Section 3.5.

[15]It is important to note that the survey question on expected employment changes (Q2) is asked in a rather vague way and only refers to the "number of employees." Hence, Q2 does not allow to discriminate between different types of employment relationships, which is potentially an important margin of adjustment for firms affected by the minimum wage as shown by other studies on the German minimum wage, such as vom Berge et al. (2016) and Garloff (2016).

[16]The German Federal Statistical Office provides time series of producer price indices ($PPI_{s,t}$) and the number of employees ($Empl_{s,t}$) at the level of two-digit industries s which are downloaded from Destatis' GENESIS database (prices: code "61241-0002;" employment: code "42111-0004"). Aggregated time series on producer prices of service companies are not available for most sub-industries of the services sector. As described in Section 3.6, the time series of industry-level indices are weighted by the average share of manufacturing firms in the respective sectors of the IBS in order to get an aggregate time series that is representative for the firms in the survey. The employment time series is purged by month fixed effects for seasonal adjustment. During the time period of the baseline sample (January 2010 until December 2015), the time-series correlation between realized price (employment) changes and average price (employment) expectations in the IBS is highest at the first (second) lag of price (employment) expectations with $\rho = 0.87$ ($\rho = 0.90$).

Figure 3.1: Average Employment and Price Expectations Compared to Quantitative Data

Notes: The left (right) figure plots time series of the realized change in producer prices (in the number of employees) in the manufacturing sector relative to three months before (solid line; left axis) against time series of mean reported price expectations (employment expectations) of firms in the manufacturing survey of the IBS (dashed line; right axis). The German Federal Statistical Office provides time series of producer price indices and the number of employees at the two-digit industry level. For aggregation, the time series are weighted by the average share of manufacturing firms in the respective sectors of the IBS. The employment time series is purged using month fixed effects for seasonal adjustment.

3.3.2 Identification of Firms' Affectedness by the Minimum Wage

In order to evaluate the reaction of firms to the introduction of the statutory minimum wage, the degree to which each firm is affected by this policy intervention needs to be identified. Unfortunately, the IBS does not include any information about wages or labor costs at the firm level. I circumvent this constraint by following the minimum wage "bite" approach of Card (1992), a standard method for the identification of heterogeneity in treatment intensity with respect to minimum wages. Utilizing data on the wage distribution at disaggregated levels of industries and regions, I construct a treatment intensity measure specific for each firm: the fraction of full-time employees that earned a gross wage below the newly introduced minimum wage of €8.50 per hour in the firms' industry and location prior to its introduction.[17]

The underlying idea of the treatment intensity measure is that firms in industry-region cells with a higher fraction of full-time employees that earned less than €8.50 in 2013 are plausibly more strongly affected by the minimum wage than their counterparts in cells with a smaller fraction of affected full-time employees, *ceteris paribus*. Due to data limitations described below, the treatment intensity measure is not based on wage data of part-time employees and marginally employed workers despite of the fact that these

[17]Closest to my specification, Garloff (2016) uses administrative wage data of full-time employees at the level of labor market regions, age-cohorts and gender in order to analyze the relationship between (un-)employment growth and the "bite" of the German statutory minimum wage at the regional level.

groups were more strongly affected by the minimum wage as for example documented by Brenke (2014) and Falck et al. (2013).[18] However, the relative wage levels of part-time and full-time employees are plausibly strongly correlated across firms in different sectors and regions. In turn, the treatment intensity measure should be strongly correlated with the relative increase in labor costs faced by affected firms that wanted to leave the composition and size of their workforce unchanged.[19] In order to identify the *ex ante* "bite" of the minimum wage introduction, I use data on wages in 2013 instead of 2014, as affected firms might have adjusted their wages towards the new minimum wage of €8.50 already in the period prior to its introduction in January 2015.

Importantly, the treatment intensity measure only captures the direct effect on firms' labor costs. In turn, it abstracts from other effects such as spillovers through potentially more expensive inputs or additional costs for firms to comply with the administrative requirements of the minimum wage law. Another indirect effect of the minimum wage introduction which is beyond the scope of this chapter is its effect on labor supply.

The treatment intensity measure is calculated based on data of gross monthly wages paid in each two-digit industry at the level of counties (NUTS-3-regions) as well as labor market regions in 2013.[20] The Federal Employment Agency provides this data along with information on wages at the following percentiles: $p \in \{10, 20, 30, 40, 50, 60, 80\}$ (Federal Employment Agency, 2016). The data is collected via the reporting procedure of the social security system ("*Meldeverfahren zur Sozialversicherung*") in order to determine unemployment benefits and social security contributions. Every firm is required by law to report the gross wage that each of its employees earned in a given year. In addition, firms need to provide information about the duration of the employment relationship and whether the employee worked full-time or part-time.[21] As the reports do not contain detailed information on hours worked, the analysis needs to be restricted to gross monthly wages for full-time workers. Moreover, distributional parameters of wages are only available for sector-region combinations with at least 1000 full-time employees due

[18] Relatedly, Müller and Steiner (2013) show that the relative ordering in the "bite" of the minimum wage introduction between different skill groups, gender, and the employment types of full-time, part-time, and marginally employed workers is largely unaffected by the choice of hypothetical levels of the wage floor using SOEP data.

[19] In order to capture firms in industry-region cells that paid full-time employees more than €8.50 per hour but arguably needed to increase the wages of part-time employees and marginally employed workers, I also construct the treatment intensity measure based on thresholds above €8.50. The results are presented in Section 3.7.

[20] There are 96 labor market regions ("*Raumordnungsregionen*") in Germany that typically describe commuting zones. On average, they consist of approximately 4 out of a total number of 402 counties (295 "*Landkreise*" and 107 "*kreisfreie Städte*").

[21] The reporting procedure only refers to employees prone to social security and does hence not include wages of marginally employed workers ("*Mini-Jobs*") as well as self-employed. Unfortunately, data on wages in these groups are not available at disaggregated levels of industries and regions.

to data protection issues. Despite of this restriction, wage data at the levels of two-digit industries and counties cover 72.1% of all full-time employed workers in Germany. At the level of labor market regions, 93.0% of full-time employed workers can be assigned to the wage distribution in their two-digit industry. In the baseline specification, I therefore use the industry-specific wage distribution at the county-level and replace missing values by wage data at the level of labor market regions. In addition, robustness checks solely using wage data at the levels of labor market regions or counties are presented in Section 3.7.

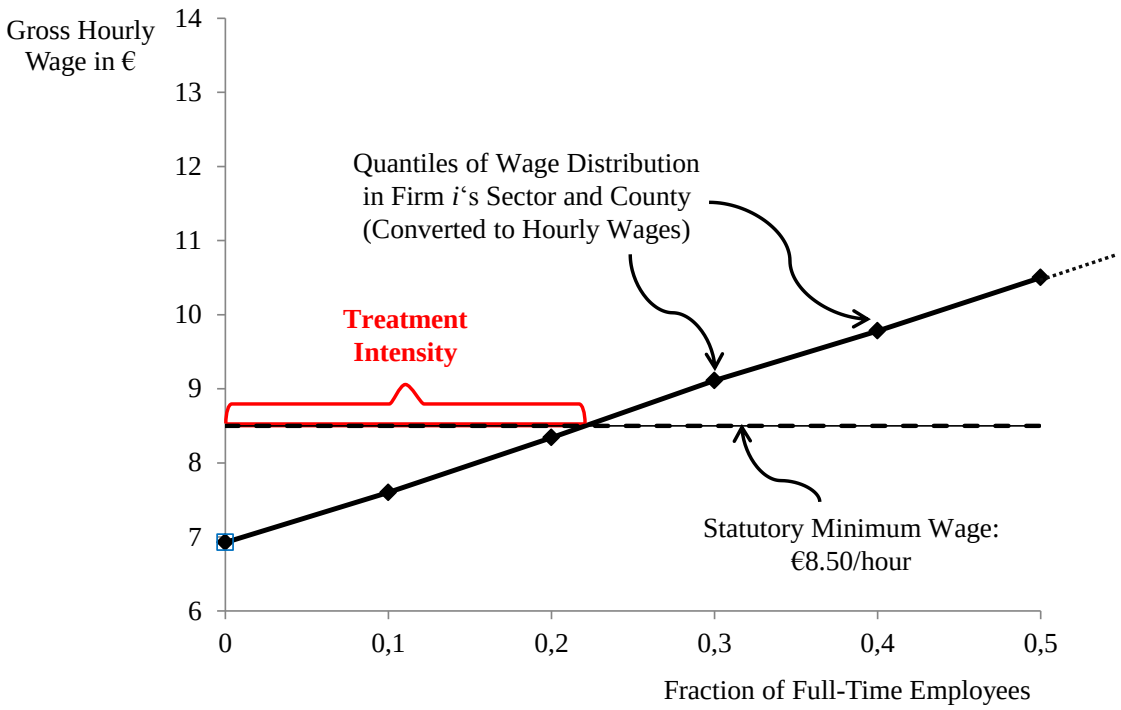
Next, monthly wages are converted to hourly wages by means of the number of paid working hours per month collected by the Quarterly Earnings Survey ("*Vierteljährliche Verdiensterhebung*"). This survey, which is conducted by the statistical offices of the federal states, covers 40,500 German firms (7.4% of all firms) and is representative at the level of two-digit industries in both East and West Germany.[22] After calculating the average amount of monthly working hours in 2013 for each industry in West and East Germany, the monthly wages at each percentile are transformed to an hourly basis for each sector-region cell, i.e., to $w_{s,r}(p)$ which denotes the p^{th} percentile of hourly wages in sector s and region r (counties or labor market regions).

Then, the fraction of full-time employees that earned a gross hourly wage of less than €8.50 is calculated for each sector-region combination. Figure 3.2 provides an illustration of the procedure that is based on two assumptions about the shape of the wage distribution: first, the wage level of employees between any two percentiles for which wage data are available is approximated by linear interpolation. Second, the wage level at the minimum of the wage distribution $w_{s,r}(0)$ is assumed to be related to the wage at the 10^{th} percentile similarly as $w_{s,r}(10)$ is related to $w_{s,r}(20)$, i.e., $w_{s,r}(0)/w_{s,r}(10) = w_{s,r}(10)/w_{s,r}(20)$. Accordingly, the wage level at the maximum of the wage distribution is assumed to be $w_{s,r}(100)/w_{s,r}(80) = w_{s,r}(80)/w_{s,r}(60)$.[23] Given these assumptions, the fraction of full-time employees that earned less than €8.50 per hour in 2013 in each sector-region cell—

[22]The quality of the data on working hours is perceived to be very high as response to the survey is compulsory. The data is available online through the GENESIS database of the Federal Statistical Office (code 62321) and described in more detail here: https://www.destatis.de/EN/FactsFigures/NationalEconomyEnvironment/EarningsLabourCosts/Methods/QuarterlyEarningsSurvey.html.

[23]It is important to note that the relative ordering of sector-region combinations with respect to their fraction of full-time employed that earned less than €8.50 does not hinge on the choice of $w_{s,r}(0)$ and $w_{s,r}(100)$. I also computed TI_i assuming that $w_{s,r}(0) = 0.9 * w_{s,r}(10)$ or $w_{s,r}(0) = 0.7 * w_{s,r}(10)$ and the relative ordering of sector-region cells did not change substantially. Moreover, robustness checks presented in Section 3.7 show that the main effects of this study do not hinge on the assumptions about $w_{s,r}(0)$.

Figure 3.2: Illustration of the Identification of Firms' Affectedness by the Minimum Wage



Notes: This diagram illustrates the identification of firms' affectedness by the minimum wage indicated by the red line ("Treatment Intensity") for the example of firms in industry "55 Accommodation/Lodging" in county "09180 Garmisch-Partenkirchen." The black rhombi refer to the deciles of the wage distribution of full-time employees in 2013 after conversion to hourly wages. The wage levels between the deciles given in the data are linearly interpolated, while the values for the minimum and maximum of the wage distribution are calculated as described in the main text.

henceforth denoted as $TI_{s,r}$—can be derived from the intercept theorem:

$$TI_{s,r} = \begin{cases} 0 & \text{if } \bar{w}_{min} \leq w_{s,r}(0) \\ p + 0.1 * \frac{\bar{w}_{min} - w_{s,r}(p)}{w_{s,r}(p+10) - w_{s,r}(p)} & \text{if } w_{s,r}(p) < \bar{w}_{min} \leq w_{s,r}(p+10) \wedge p \in \{10, 20, 30, 40, 50\} \\ p + 0.2 * \frac{\bar{w}_{min} - w_{s,r}(p)}{w_{s,r}(p+20) - w_{s,r}(p)} & \text{if } w_{s,r}(p) < \bar{w}_{min} \leq w_{s,r}(p+20) \wedge p \in \{60, 80\} \\ 1 & \text{if } w_{s,r}(100) \leq \bar{w}_{min} \end{cases} \tag{3.1}$$

where $\bar{w}_{min}$ denotes the level of the new statutory minimum wage of €8.50 per hour.

Weighting the treatment intensity measure $TI_{s,r}$ by the number of full-time employees in each sector-region cell yields that 4.0% of all full-time employees in West Germany and 15.6% in East Germany earned less than €8.50 per hour prior to the introduction of the statutory minimum wage.[24] These numbers are remarkably close to Falck et al. (2013),

[24]Within the manufacturing and services industries relevant for this study, i.e., industries that were not conceded to delay their compliance to the federal level of €8.50 per hour until the end of 2016, these numbers are still 2.4% and 12.1% of full-time employees in West and East Germany, respectively. Throughout the chapter, the term "East Germany" refers to the federal states of Mecklenburg-West Pomerania, Brandenburg, Saxony-Anhalt, Saxony, and Thuringia, while "West Germany" covers the area

Table 3.1: Variation in Treatment Intensity

	Total		Manufacturing		Services		West Germany		East Germany	
	# Firms	%	# Firms	%	# Firms	%	# Firms	%	# Firms	%
Firms	3825	.	2039	.	1786	.	3292	.	533	.
$TI = 0$	2733	71.5	1668	81.8	1065	59.6	2588	78.6	145	27.2
$TI \in (0, 0.1)$	545	14.2	212	10.4	333	18.6	382	11.6	163	30.6
$TI \in (0.1, 0.2)$	339	8.9	121	5.9	218	12.2	211	6.4	128	24.0
$TI \in (0.2, 0.3)$	85	2.2	11	0.5	74	4.1	53	1.6	32	6.0
$TI \in (0.3, 0.5)$	96	2.5	18	0.9	78	4.4	53	1.6	43	8.1
$TI \in (0.5, 1)$	27	0.7	9	0.4	18	1.0	5	0.2	22	4.1

Notes: Distribution of firms (in January 2015) across different groups of treatment intensity as captured by the percentage of full-time employees in their two-digit industry and region that earned less than €8.50 per hour in 2013.

who find that 4.2% and 15.5% of all full-time employees earned less than €8.50 per hour in 2013 in West and East Germany, respectively, based on individual-level wage data from the German Socio-Economic Panel (SOEP).

Finally, each firm i in the IBS is matched to the respective level of treatment intensity of its sector-region cell $TI_{i \in SR}$ (henceforth denoted as TI_i). Overall, 84.5% of all manufacturing firms and service companies in the IBS can be matched to a measure that proxies the degree of affectedness by the minimum wage introduction. Moreover, the frequency of matches is relatively homogeneous across sectors (86.1% of manufacturing firms vs. 82.7% of service companies) as well as between West Germany (85.3%) and East Germany (80.0%).

The treatment intensity measure captures a substantial degree of variation in the degree to which firms were affected by the minimum wage. As summarized in Table 3.1, approximately three out of ten firms in the sample had to increase wages of full-time employees by at least some degree due to the minimum wage if they wanted to leave the number and composition of their workforce unchanged. In turn, approximately seven out of ten firms are perceived as unaffected in the baseline specification of TI_i. Among firms with $TI_i > 0$, roughly half of the affected firms had to increase wages of more than 10% of their full-time employees due to the minimum wage, *ceteris paribus*. Moreover, a group of approximately 210 (120) firms had been very strongly affected as they operated in sector-region cells in which more than 20% (30%) of full-time employees were affected by the minimum wage.

Moreover, there is a sufficient degree of variation in TI_i that allows for separate analyses of the response of manufacturing firms relative to service companies as well as firms in

of the Federal Republic of Germany prior to the reunification in 1990 plus Berlin, which is organized as a single county.

West Germany relative to their counterparts in the East. In general, service providers—of which approximately 40% are perceived as being affected—have been affected more strongly by the minimum wage than manufacturing firms (roughly 20%).[25] In addition, one out of five firms in West Germany was affected according to TI_i, while almost three out of four East German firms were affected to at least some degree. Conditional on being affected ($TI_i > 0$), however, the variation in TI_i is roughly comparable between firms in the different subsets as the mean treatment intensity among affected firms is 0.113 and 0.150 in the subset of manufacturing firms and service companies as well as 0.123 and 0.165 for firms East and West Germany, respectively.

The plausibility of the firm-specific treatment intensity measure is confirmed by making use of firms' responses to a series of special questions in the IBS regarding their assessment of the upcoming introduction of the statutory minimum wage that has been conducted in November 2014. In these supplementary questions, firms were asked whether their company is affected by the new regulation and how they planned to react in case of being affected, e.g., whether they planned to reduce their workforce or working hours, to cut bonus payments or investment volumes, or to increase prices.[26]

As sketched in Table 3.2 and documented in further detail in Appendix 3.B, the probability that firms stated to be affected by the minimum wage increases substantially in TI_i. While only 17% of firms stated to be affected if they operated in sector-region combinations in which no full-time employee earned less than €8.50 in 2013, this probability increases to 81% for firms in sector-region cells with more than 30% of full-time employees being treated. At the same time, firms that were affected to a larger degree as captured by TI_i appear to be hit differently by the minimum wage: once stating to be affected, they are substantially more likely to take action through decreases in employment, increases in prices, reductions in investment, or cuts in special payments. In contrast, the majority of firms that reported to be affected by the minimum wage despite of $TI_i = 0$ did not plan to react to the minimum wage introduction. Arguably, these firms were only affected indirectly by the minimum wage or perceived themselves as being affected because of the

[25] Furthermore, there is also substantial variation in firms' proxied treatment intensity within the different two-digit industries of the manufacturing and services sector, see Table 3.D.1 in Appendix 3.D.

[26] The question about firms' affectedness neither provides any information about the intensity to which firms are affected, nor contains any information about the channels through which firms are affected, as can be inferred from the English translation of the supplementary questions in Appendix 3.B. Moreover, the questions regarding firms' planned reaction to the introduction of the minimum wage are restricted to affected firms and one direction. For example, affected firms could only state whether they planned to reduce their number of employees or not. If firms were operating in monopsonistic labor markets, however, they should be expected to increase their labor demand in response to a binding minimum wage at sufficiently low levels as argued by Manning (2003). Hence, the supplementary questions on the minimum wage introduction themselves do neither permit an identification of firms' kind and degree of affectedness, nor allow for causal inference on the firm-level response of the minimum wage introduction due to missing counterfactuals as well as one-sided questions.

Table 3.2: Plausibility Check of the Treatment Intensity Measure

	Treatment Intensity (TI)			
Treatment Intensity $TI \in$	[0%]	(0%,20%]	(20%,30%]	(30%,100%)
prob("Affected" = 1)	0.171	0.374	0.597	0.811
prob("Plan to Adjust Business" = 1|"Affected" = 1)	0.455	0.525	0.739	0.833
prob("Do Not Plan to React" = 1|"Affected" = 1)	0.545	0.475	0.261	0.167

Notes. "Treatment Intensity" refers to the fraction of full-time employees that earned an hourly gross wage of less than €8.50 in 2013 in each firm's two-digit industry and region. *prob*("Affected" = 1) displays the probability that a firm responded to be "affected" by the minimum wage in the special questions of the IBS in November 2014 depending on its proxied treatment intensity as indicated at the top of each column. *prob*("Plan to Adjust Business" = 1|"Affected" = 1) captures the probability that "affected" firms stated to plan to react in at least one of the following ways: reduction in staff, reduction in working hours, price increases, decreased investment volume, cuts in bonus payments, or other action. *prob*("Do Not Plan to Adjust Business" = 1|"Affected" = 1) is defined accordingly.

obligatory and time-consuming documentation requirements. Overall, this evidence confirms that TI_i plausibly captures the degree to which firms are directly affected by the introduction of the minimum wage through the channel of increased labor costs.

3.4 Empirical Strategy

The goal of the empirical strategy is to evaluate whether firms that were more strongly affected by the introduction of the statutory minimum wage in Germany were more likely to increase prices or to change their number of employees. For this purpose, I use a generalized difference-in-differences (DiD) framework to estimate how strongly the intensity to which firms are affected by the minimum wage introduction (TI_i) is associated with firms' pricing and employment plans, denoted β. Before examining the dynamic response of firms, I start with the estimation of the average effect of the minimum wage on firms' price and employment expectations during the year around its introduction in January 2015, relative to "normal" times outside this window.

The estimation of β is based on the following empirical model

$$Y_{i,t}^{+3m} = \beta \times TI_i \times \mathbb{1}(t \in (2014m7, 2015m6)) + \gamma \times \text{Demand}_{i,t} + \alpha_i + \delta_t \times \mathbb{1}(\text{Sector}_i) + \delta_t \times \mathbb{1}(\text{State}_i) + \varepsilon_{i,t}, \quad (3.2)$$

where the dependent variable $Y_{i,t}^{+3m}$ denotes either firm i's expected change in the price of its products (or provision of its services) in the next three months ("Price Exp.$_{i,t}^{+3m}$") or firm i's expected change in employment ("Empl. Exp.$_{i,t}^{+3m}$") as reported to the IBS questions Q1 and Q2 in month t. As described in Section 3.3.1, both variables take values on a trichotomous scale ([1] "increase", [0] "stay the same", [-1] "decrease").

To estimate the minimum wage effect, I interact the firm-specific treatment intensity measure TI_i with a dummy variable for the treatment period between six months before and after the introduction of the minimum wage in January 2015. This standard method for the identification of the treatment effect of an intervention in a DiD design delivers an estimate of β, relative to the dates outside the treatment period and after controlling for all other covariates (Angrist and Pischke, 2008).

The set of control variables in the baseline specification of model (3.2) includes current demand of each firm ($\text{Demand}_{i,t}$) as reported to the IBS, firm fixed effects α_i, and date fixed effects δ_t at the levels of two-digit industries as well as federal states. Firm-specific demand controls for the fact that price or employment changes are potentially demand-driven. As documented in Section 3.5, $\text{Demand}_{i,t}$ itself is not affected significantly by the introduction of statutory minimum wages. In addition, firm fixed effects capture time-invariant firm-specificities such as persistent optimism or pessimism of firms that has been found to be important for the understanding of expectations in the IBS by Bachmann and Elstner (2015). Furthermore, date fixed effects at the levels of two-digit industries as well as federal states flexibly control for industry-specific and state-specific fluctuations that similarly influence the pricing and employment policies of all firms in each industry or region irrespective of TI_i. Notably, the date fixed effects also eliminate the entire variation in firms' price and employment plans due to aggregate fluctuations or other policies at the national level.

After evaluating the average effect of the minimum wage on firms' price and employment policies by means of model (3.2), I estimate the dynamic response of firms along these margins over time. Specifically, the price and employment effects induced by the minimum wage, denoted β_t, are estimated for each month relative to September 2013, the month of the federal election. For this purpose, the DiD framework of model (3.2) is augmented in a standard way given by

$$Y_{i,t}^{+3m} = \sum_{t:t\neq 2013m9} \beta_t \times TI_i \times \mathbb{1}(\text{Date}_t) + \gamma \times \text{Demand}_{i,t} + \alpha_i + \delta_t \times \mathbb{1}(\text{Sector}_i) + \delta_t \times \mathbb{1}(\text{State}_i) + \varepsilon_{i,t}, \quad (3.3)$$

where the treatment intensity measure TI_i is interacted with date dummies ($\mathbb{1}(\text{Date}_t)$). The empirical model (3.3) delivers estimates of β_t both for the dates before and after September 2013. Consequently, the sequence of estimates after September 2013 should capture the effects of the statutory minimum wage on price and employment plans of firms. In contrast, estimates for the dates prior to the federal election in 2013 should be equal to zero because the introduction of the statutory minimum wage was not expected at that time.

Despite of the discrete and ordinal nature of the data, both empirical models (3.2) and (3.3) are estimated using ordinary least squares. This choice is due to the fact that standard methods for the estimation of generalized DiD models with fixed effects and non-binary ordinal data are not established in the literature, yet. However, Riedl and Geishecker (2014) find that linear panel data models generally perform quite well in comparable settings with large cross-sections and long time series. In addition, standard errors are multi-way clustered at the levels of counties, two-digit industries and dates.[27]

3.5 Minimum Wage Effects at the Firm Level

This section presents the main findings of the study. The empirical analysis in Section 3.5.1 shows that the introduction of the statutory minimum wage went along with substantial increases in the probability that affected firms planned to increase their prices which is accompanied by at most very weak adjustments of their employment policies. Interestingly, the minimum wage effect on pricing and employment plans are homogeneous across firms in the manufacturing and services sectors as well as between firms in West and East Germany, as documented in Section 3.5.2. Importantly, estimating the price effect based on realized price changes of firms in the subsample of manufacturing firms delivers results that are comparable to the baseline specification that uses price expectations, as demonstrated in Section 3.5.3.

3.5.1 Firms' Adjustment of Price and Employment Plans

The estimation of the baseline model (3.2) reveals a strongly positive relationship between the degree to which firms were affected by the minimum wage introduction and their probability to plan price increases during the next three months. The results for the baseline specification are displayed in Column (1) of Table 3.3. The average treatment effect on planned price changes reported between July 2014 and June 2015 is estimated to $\hat{\beta} = 0.4$. This price effect is not only statistically significant at the 1%-level, but also economically substantial and quantitatively large, as will be shown in the quantification exercise conducted in Section 3.6.

[27] As highlighted by Bertrand et al. (2004), serially correlated error terms might cause severe inconsistencies in the estimated coefficients even after controlling for fixed effects. In my setting, the OLS standard errors are subject to different sources of possible bias which are taken into account via multi-way clustering as proposed by Dube et al. (2010) and Cameron et al. (2011). First, the treatment intensity measure (TI_i) varies between two-digit industries and counties only. Hence, error terms are clustered at the level of two-digit industries and counties. Moreover, there might be a concern that common shocks lead to a downward bias in standard errors which is controlled for by additionally clustering along the time dimension.

Table 3.3: Minimum Wage Effects at the Firm-Level: Baseline Results

	Planned Price Change Next 3 Months				Planned Empl. Change Next 3 Months			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$TI \times \mathbb{1}(t \in \{2014m7, 2015m6\})$	0.40***	0.37***	0.39***	0.41***	-0.0100	-0.019	-0.062	0.00082
	(0.10)	(0.11)	(0.074)	(0.11)	(0.070)	(0.079)	(0.051)	(0.082)
R^2	0.331	0.321	0.328	0.347	0.350	0.311	0.348	0.365
Control for $\text{Demand}_{i,t}$	yes	no	yes	yes	yes	no	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
Time*Sector FE	yes	yes	yes	yes	yes	yes	yes	yes
Time*State FE	yes	yes	no	no	yes	yes	no	no
Time*Region FE	no	no	no	yes	no	no	no	yes
Observations	280541	287020	280541	280447	280500	287035	280500	280407

Notes: The dependent variables are planned price or employment changes during the next 3 months as reported to the IBS. "TI" is the proxy of each firm's degree of affectedness by the minimum wage introduction and "$\mathbb{1}(t \in \{2014m7, 2015m6\})$" is a dummy that is one during the treatment period. "$\text{Demand}_{i,t}$" is firms' current backlog of orders as reported in the IBS. "Time*Sector FE," "Time*State FE," and "Time*Region FE" are time fixed effects at the levels of two-digit industries, federal states, and labor market regions, respectively. Standard errors are multiway clustered at the sector, county, and date levels. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The estimated minimum wage effect on firms' price expectations of $\hat{\beta} = 0.4$ can be interpreted as follows: Suppose a firm is located in a sector-region cell in which 25% of all full-time employees earned an hourly wage of less than €8.50 in 2013, i.e., $TI_i = 0.25$. Relative to the time period before and after the twelve-month window around January 2015, this firm reported planned price changes—scaled as "[1] increase," "[0] stay the same," "[-1] decrease"—that were *ceteris paribus* increased by 0.1 on average ($\hat{\beta} \times TI_i = 0.4 \times 0.25 = 0.1$). Within the 1-year window around January 2015, the average number of months in which affected firms reported planned price changes of a one-step higher category—i.e., increased instead of constant or constant instead of decreased prices—compared to the counterfactual scenario in absence of the minimum wage is given by $\hat{\beta} \times TI_i \times 12$ months. Hence, firms with $TI_i = 0.25$ reported planned price changes of a one-step higher category in on average 1.2 months compared to the planned price changes they would have reported if the minimum wage was not affecting them.

The estimated effects of the introduction of minimum wages on firms' pricing plans are constant for different specifications of the baseline empirical model (3.2): neither dropping the control for firm-specific demand in Column (2), nor controlling for time-specific fluctuations at the more aggregate federal level in Column (3) as well as at the more disaggregate level of labor market regions in Column (4) substantially affects the results.

In contrast, the relationship between the intensity to which firms were affected by the minimum wage introduction and their probability to report planned employment changes is not found to differ relative to other time periods. As documented in Column (5) of Table

Table 3.4: Minimum Wage Effects at the Firm-Level: Increases vs. Decreases

	Price Exp.$_t^{+3m}$			Employment Exp.$_t^{+3m}$		
	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	$= 1$	$\neq -1$	Baseline	$= 1$	$\neq -1$
$TI \times \mathbb{1}(t \in \{2014m7, 2015m6\})$	0.40***	0.30***	0.096***	-0.0100	-0.051	0.041
	(0.10)	(0.085)	(0.036)	(0.070)	(0.032)	(0.048)
Demand$_{i,t}$	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
Time*Sector FE	yes	yes	yes	yes	yes	yes
Time*State FE	yes	yes	yes	yes	yes	yes
R^2	0.331	0.303	0.334	0.350	0.334	0.285
Observations	280541	280541	280541	280500	280500	280500

Notes: The dependent variables are planned price or employment changes during the next 3 months as reported to the IBS. In Columns (2), (3), (5), and (6) the respective dependent variable is binarized as indicated above each column. "TI" is the proxy of the firm's degree of affectedness by the minimum wage introduction and "$\mathbb{1}(t \in \{2014m7, 2015m6\})$" is a dummy that is one during the treatment period. "Demand$_{i,t}$" is firms' current backlog of orders as reported in the IBS. "Time*Sector FE," "Time*State FE," and "Time*Region FE" are time fixed effects at the levels of two-digit industries, federal states, and labor market regions, respectively. Standard errors are multiway clustered at the sector, county, and date levels. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.3, the average treatment effect on planned employment changes reported between July 2014 and June 2015 is only slightly negative and statistically indistinguishable from zero. Again, the results are robust to the different specifications summarized in Columns (6) through (8). Notably, the estimated effect on planned employment changes is more negative in the specification that does not control for variation at regional levels, see Column (7). However, the estimated effect of $\hat{\beta} = -0.062$ is still insignificant (p-value=0.21).

The minimum wage-induced effect on pricing plans mostly stems from additional price increases. Table 3.4 summarizes the results of estimating model (3.2) separately for binarized dependent variables that either capture planned increases in prices, i.e., using a dummy $\mathbb{1}(\text{Price Exp.}_t^{+3m} = 1)$, or refer to planned changes that are non-negative, i.e., $\mathbb{1}(\text{Price Exp.}_t^{+3m} \neq -1)$. As displayed in Columns (2) and (3), three quarters of the price effect can be attributed to additional reports of planned price increases, while one quarter of the effect is due to the fact that firms planned to decrease their prices less frequently compared to the counterfactual scenario without the minimum wage. In turn, affected firms appear to have reported to plan to increase as well as decrease their number of employees less frequently in response to the minimum wage introduction. As documented in Columns (5) and (6), both effects are not statistically different from zero, however, and almost perfectly cancel each other out.

Furthermore, the minimum wage introduction does not appear to have had a strong effect on firms' realized and expected revenues as well as current demand. Table 3.5

Table 3.5: Minimum Wage Effects at the Firm-Level: Other Dependent Variables

	Conditions_t	$\text{Expectations}_t^{+6m}$	Demand_t
$TI \times \mathbb{1}(t \in \{\underline{t}, \bar{t}\})$	0.0043	-0.099	-0.059
	(0.10)	(0.12)	(0.068)
Begin Treatment Period ($\underline{t}$)	2014m10	2014m7	2014m10
End Treatment Period ($\bar{t}$)	2015m9	2015m6	2015m9
Control for $\text{Demand}_{i,t}$	yes	yes	no
Firm FE	yes	yes	yes
Time*Sector FE	yes	yes	yes
Time*State FE	yes	yes	yes
R^2	0.632	0.359	0.454
Observations	281823	280482	282178

Notes: The dependent variables are current business conditions, expected business conditions for the next six months, as well as current backlog of orders as reported to the IBS. "TI" is the proxy of each firm's degree of affectedness by the minimum wage introduction and "$\mathbb{1}(t \in \{\underline{t}, \bar{t}\})$" is a dummy that is one during the treatment period between $\underline{t}$ and $\bar{t}$. "Time*Sector FE", "Time*State FE", and "Time*Region FE" are time fixed effects at the levels of two-digit industries, federal states, and labor market regions, respectively. Standard errors are multiway clustered at the sector, county, and date levels. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

summarizes the results of the estimation of model (3.2) using additional variables from the IBS as dependent variable. On the one hand, TI_i is not associated with differences in firms' current business conditions ($\text{Conditions}_{i,t}$) during the period around the introduction of the minimum wage, which are very closely related to the level of revenues as demonstrated in Chapter 4. On the other hand, firms reported slightly more negative expected business conditions for the next six months ($\text{Expectations}_{i,t}^{+6m}$) as well as current backlog of orders ($\text{Demand}_{i,t}$) if they were more heavily affected by the minimum wage. However, these effects are not statistically significant irrespective of using the baseline specification presented in Table 3.5 or alternative specifications displayed in Table 3.D.3 in Appendix 3.D.

Dynamic Response of Price and Employment Plans

Next, I estimate the dynamic response of firms' price and employment plans over time by means of model (3.3). The estimated sequences of treatment effects β_t relative to the baseline period in September 2013 are plotted in Figure 3.3 along with the 95%-confidence intervals.

The positive effect on planned price changes is clearly concentrated in the time period around the introduction of the minimum wage in January 2015, as can be inferred from the left-hand graph of Figure 3.3. Overall, the price expectations of firms are not correlated with the treatment intensity measure prior to the federal election in September 2013.[28]

[28]Comparably, placebo tests based on the empirical model (3.2) do not deliver any statistically signif-

Figure 3.3: Dynamic Response of Minimum Wage Effects at the Firm-Level

Notes: The figure plots the coefficients of the dynamic treatment effect of the minimum wage introduction in January 2015 as estimated in model (3.3). The dependent variables are firms' planned price or employment changes during the next 3 months as reported to the IBS. The effects are estimated relative to September 2013, the month of the federal election. The vertical lines in April 2014 and January 2015 indicate the months of the decision of the federal cabinet containing the relevant details of the minimum wage law and the month of its introduction, respectively. The shaded areas indicate the treatment period used in model (3.2). The thin lines display the 95%-confidence intervals based on standard errors clustered at the sector, county, and date levels.

Hence, affected firms did not follow a different pre-trend in their pricing plans relative to their unaffected counterparts and after controlling for firm-specific demand as well as firm fixed effects and industry-specific as well as state-specific trends. Moreover, the coalition agreement of November 2013 stating the introduction of the statutory minimum wage by January 2015 does not seem to have had an immediate effect on price expectations of affected firms. Instead, the treatment effect on firms' pricing plans has been appreciating over the course of 2014 as more details about the minimum wage law, which was proposed by the federal cabinet in April 2014 and finally approved in July 2014, became available and the introduction date approached. Unsurprisingly, the treatment effect on pricing plans has been strongest between the last quarter of 2014 and the second quarter of 2015. Finally, the pass-through on prices appears to have been completed during the second half of 2015 when the estimated effect of the minimum wage on firms' planned (additional) price changes for the next three months approached zero again.

In contrast, the dynamic response of firms' employment plans to the introduction of statutory minimum wages does not deliver a comparably strong pattern. As displayed in the right-hand graph of Figure 3.3, firms that were affected more strongly did not report employment plans that were significantly deteriorated relative to September 2013 after controlling for firm-specific demand, firm fixed effects as well as general trends in their

icant relationship between TI_i and average pricing plans during the twelve months around January 2012, January 2013, and January 2014 relative to all other dates, see Table 3.D.2 in Appendix 3.D.

industry and federal state. Interestingly, a significantly negative treatment effect can be detected in October 2014—exactly three months prior to the introduction of the minimum wage. In all remaining months around January 2015, however, the estimated treatment effects are insignificant. Moreover, employment expectations of affected firms generally tended to deteriorate during autumn in all previous years. The negative coefficient in October 2014 could thus just capture a degree of seasonality in employment plans that is not captured by the control variables of model (3.3).

In opposition to the case of estimated price responses, the choice of the baseline date is crucial for the estimation of the dynamic employment effects. The reason is that the estimated relationship between employment expectations and firms' treatment intensity had been very volatile in the period before the minimum wage was announced.[29] The results presented in Figure 3.3 show that the planned employment changes of firms were positively—and compared to all other periods unusually strongly—associated with TI_i during the months prior to the federal election in September 2013 although the minimum wage could not have been expected by then. In contrast, choosing November 2013—the month of the signing of the coalition treaty—as baseline period, the estimated treatment effect on employment responses would be positive at almost all dates during 2014 and 2015. Hence, a negative employment reaction of firms in response to the introduction of minimum wages cannot be ruled out with certainty, but can only be detected using baseline dates that are arguably less realistic than in the benchmark scenario.

Note on Measurement Error

It is important to note that the estimated coefficients regarding the treatment effect are likely to be biased towards zero due to measurement error in the treatment intensity measure. TI_i only imperfectly captures the degree to which firms are affected by the minimum wage for various reasons. First, measurement error originates from the fact that TI_i is constructed from wage data of full-time employees at the levels of two-digit industries as well as counties or labor market regions. Thus, labor costs for part-time employees and marginally employed workers as well as heterogeneity in payment schemes between firms within each sector-region cell is not reflected in TI_i. Second, TI_i only captures the direct effect of the minimum wage introduction on the wage bill of firms and thereby abstracts from additional effects such as spillovers through potentially more expensive inputs or compliance costs originating from the documentation requirements formulated in the minimum wage law.

[29] Importantly, firms' employment plans were *on average* not related to TI_i prior to the policy intervention. As shown in Table 3.D.2 in Appendix 3.D, placebo tests based on the empirical model (3.2) do not deliver any statistically significant relationship between the treatment intensity measure and average employment plans during the twelve months around January 2012, January 2013, and January 2014.

In light of the resulting attenuation bias, the estimated coefficients should be viewed as a lower bound of the "true" size of the treatment effects on planned employment and price changes. Hence, the insignificant (but throughout most specifications negative) coefficient on employment expectations does not generally rule out that negative employment effects could be detected if firms' affectedness to the minimum wage introduction was observed without measurement error. Importantly, the relative magnitude of the price and employment effect should be largely unaffected by the fact that TI_i is measured with error.

3.5.2 Minimum Wage Effects in Different Sectors and Regions

The existing literature on the price effect of minimum wages is mainly drawing on evidence from highly affected industries such as fast food restaurants (e.g., Aaronson, 2001 and Aaronson et al., 2008 for the U.S., Lemos, 2006 for Brazil, and Fougère et al., 2010 for France) or retailers (Leung, 2016 and Montialoux et al., 2017). The main advantage of these studies is that they can exploit a large number of changes in (already existing) minimum wages in order to identify price effects. At the same time, the analysis is naturally restricted to industries with a high fraction of minimum wage workers because changes in minimum wages are usually small and thus do not strongly affect firms in other industries.

In contrast, the introduction of statutory minimum wages in Germany offers scope for a separate analysis of firm-level minimum wage effects in the services sector compared to the less strongly affected manufacturing sector. As documented in Section 3.3.2, there is a large degree of variation in the treatment intensity measure in both sectors which allows to investigate whether the reaction to the minimum wage introduction differed between manufacturing firms and service companies given their level of TI_i. In order to estimate the minimum wage-induced adjustment of pricing and employment plans separately for firms in manufacturing and services, denoted β^M and β^S, the baseline empirical model (3.2) is adjusted as follows

$$\begin{aligned} Y_{i,t}^{+3m} = \beta^M \times TI_i \times \mathbb{1}(t \in (2014m7, 2015m6)) \times \mathbb{1}(\text{Manuf.}_i) \\ + \beta^S \times TI_i \times \mathbb{1}(t \in (2014m7, 2015m6)) \times \mathbb{1}(\text{Services}_i) \\ + \gamma \times \text{Demand}_{i,t} + \alpha_i + \delta_t \times \mathbb{1}(\text{Sector}_i) + \delta_t \times \mathbb{1}(\text{State}_i) + \varepsilon_{i,t}, \quad (3.4) \end{aligned}$$

where the dummies $\mathbb{1}(\text{Manuf.}_i)$ and $\mathbb{1}(\text{Services}_i)$ equal one if firm i operates in the manufacturing or services sector, respectively. The results are summarized in Table 3.4, where Columns (1) and (4) replicate the results for the baseline estimation and Columns (2) and (5) provide the estimated treatment effects in the adjusted empirical model (3.4).

Table 3.6: Minimum Wage Effects at the Firm-Level in Different Sectors and Regions

	Price Expectations$_t^{+3m}$			Empl. Expectations$_t^{+3m}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$TI \times \mathbb{1}(t \in \{2014m7, 2015m6\})$	0.40***			-0.0100		
	(0.10)			(0.070)		
$TI \times \mathbb{1}(t \in \{2014m7, 2015m6\}) \times \mathbb{1}$(Manuf.)		0.41***			0.079	
		(0.13)			(0.091)	
$TI \times \mathbb{1}(t \in \{2014m7, 2015m6\}) \times \mathbb{1}$(Services)		0.39**			-0.084	
		(0.15)			(0.096)	
$TI \times \mathbb{1}(t \in \{2014m7, 2015m6\}) \times \mathbb{1}$(West)			0.41***			0.080
			(0.14)			(0.17)
$TI \times \mathbb{1}(t \in \{2014m7, 2015m6\}) \times \mathbb{1}$(East)			0.40***			-0.0095
			(0.10)			(0.070)
R^2	0.331	0.331	0.331	0.350	0.351	0.351
Control for Demand$_{i,t}$	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
Time*Sector FE	yes	yes	yes	yes	yes	yes
Time*State FE	yes	yes	yes	yes	yes	yes
H0: Coefficients Equal: p-value		0.928	0.948		0.202	0.576
Observations	280541	280541	280541	280500	280500	280500

Notes: The dependent variables are planned price or employment changes during the next 3 months as reported to the IBS. "TI" is the proxy of each firm's degree of affectedness by the minimum wage introduction and "$\mathbb{1}(t \in \{2014m7, 2015m6\})$" is a dummy that is one during the period between July 2014 and June 2015. "$\mathbb{1}(Manuf.)$," "$\mathbb{1}(Services)$," "$\mathbb{1}(West)$," and "$\mathbb{1}(East)$" are dummies for firms in manufacturing, services, West Germany, and East Germany, respectively. "Demand$_{i,t}$" is firms' current backlog of orders as reported in the IBS. "Time*Sector FE" and "Time*State FE" are time fixed effects at the levels of two-digit industries and federal states. Standard errors are multiway clustered at the sector, county, and date levels. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results show that manufacturing firms and service providers responded to the introduction of the statutory minimum wage in a comparable way. In both sectors, affected firms planned to increase prices significantly more often than they would have done if they were not affected. The estimated adjustment of pricing plans of manufacturing firms induced by a given degree of treatment intensity is $\hat{\beta}^M = 0.41$. Despite of being treated less on average, the treatment effect is not statistically different from the price reaction of service companies ($\hat{\beta}^S = 0.39$). *Ceteris paribus*, manufacturing firms thus planned to increase prices with roughly the same probability as service firms that were affected to a comparable degree. Moreover, the minimum wage introduction did not result in significantly depreciated employment plans of firms in both samples as can be inferred from the insignificant coefficients in Column (5) of Table 3.1 which are not statistically different from each other at the 10% level.

Next, I evaluate whether the reaction to the minimum wage introduction differed between firms in West and East Germany given their level of TI_i. As documented in

Table 3.1, firms in West Germany were on average less strongly affected by the introduction of statutory minimum wages than their counterparts in the East. However, there is sufficient variation in TI_i across firms in both regions that allows for the estimation of minimum wage effects separately for firms in West and East Germany. Along the lines of model (3.4), the treatment interaction term is multiplied with dummies indicating whether firms are located in West or East Germany.

The results show that the reaction of affected firms regarding their pricing and employment plans did not differ between firms in East and West Germany given their degree of affectedness. As displayed in Columns (3) and (6) of Table 3.4, the respective coefficients of the treatment effects are of comparable size for firms in both regions. For the same degree of TI_i, the probability to plan to increase prices due to the minimum wage was hence comparably strong for firms in the East and the West. Moreover, a significantly negative effect on firms' employment plans cannot be detected for firms in any of the two regions.

3.5.3 Realized Price Changes of Manufacturing Firms

The previous analysis documented a strongly positive effect on the probability that affected firms *planned* to increase the prices of their goods or services in response to the introduction of minimum wages in Germany in January 2015. As described in Section 3.3.1, the focus on *expected* rather than *realized* price changes results from the design of the IBS: While firms in both surveys covering manufacturers and service companies are asked about their expected price changes in the next three months, realized price changes are only extracted from firms in the manufacturing survey. As the majority of firms that are affected by the minimum wage introduction operate in the services sector, it is reasonable to include them into the baseline sample and restrict the main analysis to firms' pricing plans. However, it is *a priori* not clear whether firms indeed realized the price changes they previously planned in response to the minimum wage. In order to accommodate this concern, I make use of the realized price changes reported by firms in the manufacturing survey of the IBS.

Before estimating the effect of the minimum wage introduction on realized prices of manufacturing firms, the general relationship between firms' realized and expected price changes is assessed. While firms are asked whether they plan to change their prices during the *next three months*, the question on price realizations refers to the change in *the previous month*. Unsurprisingly, firms report to expect price changes (20.4% of reports) during the next three month more often than they state to have changed prices during the previous month (16.9%). Consequently, the variation in price expectations is larger than in reported price realizations, which is important for the interpretation of the estimated

Table 3.7: Price Expectations and Realized Price Changes in the Subsequent 3 Months

	Obs.	Fractions of Mean Realized Price Changes b/w $t+1$ & $t+3$			Sum
		> 0	$= 0$	< 0	
Price Exp.$_t^{+3m} = 1$	15975	0.64	0.33	0.03	1
Price Exp.$_t^{+3m} = 0$	93079	0.10	0.82	0.08	1
Price Exp.$_t^{+3m} = -1$	7447	0.04	0.28	0.68	1

Notes: This table contrasts the micro data of expected price changes during the next three months stated in t with the mean reported (monthly) price changes during the following three months, i.e., between $t+1$ and $t+3$. The sample is restricted to manufacturing firms that reported price expectations in t as well as price realizations in the subsequent three months.

treatment effects.

In general, firms are relatively good in predicting changes of their prices during the next three months. This can be inferred from Table 3.7 that contrasts the price expectations reported by manufacturing firms in month t and their average reported price changes in the subsequent three months.[30] In total, firms stick to their pricing plans in 79% of the cases. Specifically, if firms planned to increase (decrease) their prices, they reported price increases (decreases) thereafter in 64% (68%) of all periods, while they did not change their prices during 82% of the periods after reporting that they did not plan to change prices. These descriptive results are in line with Pesaran and Timmermann (2009) who find evidence for a high degree of predictability in the price data of the IBS using more involved statistical tests. Hence, it is very likely that affected firms stuck to their plans and increased prices in response of the introduction of minimum wages.[31]

Next, the effect of the minimum wage introduction on realized price changes of manufacturing firms is estimated along the lines of the baseline empirical model (3.2). Besides using the respective reports to the IBS as dependent variable, the window of the treatment period is forwarded by three months in order to accommodate for the different time period covered by the survey question.

The results presented in Table 3.8 demonstrate that manufacturing firms reported to have indeed increased their prices in response to the introduction of minimum wages in

[30]This comparison assumes that positive and negative changes are of comparable size and can hence be weighted equally. This assumption is not too restrictive given the fact that less than 1% of all price expectations are followed by realizations in the subsequent three months that contained at least one positive and one negative realized price change.

[31]Furthermore, the number of "unexpected" price increases (in total 10,224 observations consisting of 10% of the cases following a "neutral" price expectation and 4% of those following "negative" plans) strongly outweighs the 5751 cases in which firms previously planned to increase prices without sticking to their plans. Hence, it is likely that some firms increased their prices due to the minimum wage although they did not plan to do so.

Table 3.8: Minimum Wage Effect on Realized Price Changes of Manufacturing Firms

	Change in Prices_t^{-1m}
$TI \times \mathbb{1}(t \in \{2014m10, 2015m9\})$	0.34**
	(0.15)
R^2	0.288
Control for $\text{Demand}_{i,t}$	yes
Firm FE	yes
Time*Sector FE	yes
Time*State FE	yes
Observations	150051

Notes: The dependent variable is the realized price change during the previous month as reported by firms in the manufacturing survey of the IBS. "TI" is the proxy of each firm's degree of affectedness by the minimum wage introduction and "$\mathbb{1}(t \in \{2014m10, 2015m9\})$" is a dummy that is one during the period between October 2014 and September 2015. "$\text{Demand}_{i,t}$" is firms' current backlog of orders as reported in the IBS. "Time*Sector FE" and "Time*State FE" are time fixed effects at the levels of two-digit industries and federal states, respectively. Standard errors are multiway clustered at the sector, county, and date levels. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

January 2015. The estimated coefficient of the treatment effect of $\hat{\beta} = 0.34$ is significant at the 5%-level. Relative to all other periods when the minimum wage was not affecting them, a hypothetical firm with $TI_i = 0.25$ reported realized price changes of a one-step higher category—i.e., increased instead of constant or constant instead of decreased prices—in one additional month on average ($\hat{\beta} \times TI_i \times 12m = 0.34 \times 0.25 \times 12m = 1.02m$) between October 2014 and September 2015.

This estimate of the minimum wage effect on realized price changes is remarkably close to the effect on expected price changes during the next three months ($\hat{\beta} = 0.41$) documented in Section 3.5.1. In light of less variation in one-month realized price changes compared to three-month price expectations, it is not surprising that the estimated minimum wage effect on realized price changes is slightly smaller than the effect on expectations. As shown in the next section, however, the quantitative size of the overall effect on producer prices in the manufacturing sector is the same irrespectively of being estimated based on price changes in the previous month or price expectations.

Hence, firms appear to have increased their prices in response to the introduction of minimum wages to the same degree as they had previously planned. As survey data on realized price changes are not available for service firms in the IBS, this finding can only be verified for the subset of manufacturing firms. However, it is very unreasonable to assume that service companies differed from their counterparts in the manufacturing sector with respect to the degree to which their minimum wage-induced adjustment of pricing plans resulted in actual price increases.

3.6 Quantification of the Minimum Wage Effect on Producer Prices

In order to gain insights about the economic dimension of the price effect documented previously, this section provides an approximation of the quantitative size of the increase in producer prices. As the micro data of the IBS do not contain information about the size of price changes, I exploit the fact that aggregated survey responses regarding price changes closely track *quantitative* changes in price indices from administrative sources.

As aggregated time series on producer prices in most sub-industries of the services sector are not available, a quantitative counterpart to the reported price changes in the IBS based on administrative producer price data can only be constructed for manufacturing firms. For this subset, I use monthly time series of producer price indices ($PPI_{s,t}$) at the level of two-digit industries s provided by the German Federal Statistical Office.[32] In order to track the average reported prices of firms as closely as possible, the industry-level time series are weighted by the share of manufacturing firms in the respective sectors of the IBS (ω_s), i.e., $\overline{PPI}_t = \sum_s \omega_s PPI_{s,t}$.

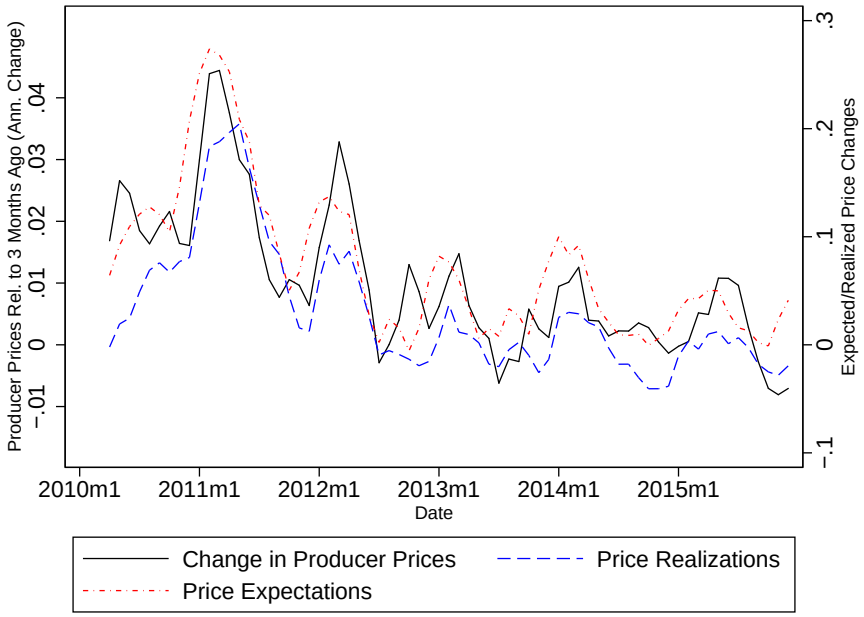
The time series of average expected and realized price changes of manufacturing firms reported to the IBS ($\overline{\text{Price Exp.}}_t^{+3m}$ and $\overline{\text{Price Realiz.}}_t^{-1m}$) are strongly correlated with annualized changes in the time series of weighted producer prices ($\Delta\overline{PPI}_t$), see Figure 3.4. As documented in Table 3.D.4 in the Appendix, the time series correlation between $\Delta\overline{PPI}_t$ and average price expectations in the IBS is highest if price expectations are lagged by one month ($\rho(\overline{\text{Price Exp.}}_t^{+3m}, \Delta\overline{PPI}_t) = 0.87$), while the correlation with average price realizations is highest at contemporaneity ($\rho(\overline{\text{Price Realiz.}}_t^{-1m}, \Delta\overline{PPI}_t) = 0.86$).[33]

Based on these time series, I estimate semi-elasticities that map qualitative survey

[32] For the manufacturing sector, price data are available at Destatis' GENESIS database (code "61241-0002"). If anything, time series on producer prices in the services sector are only available for very few, mostly industry-related services. In these cases, however, the data are only available at quarterly frequency and at inhomogeneous aggregation levels. Moreover, price data for services that enter the consumer price index are available. These time series are not useful for my analysis because they are not necessarily limited to domestic service providers and because they are coded according to a classification system that cannot directly be linked to two-digit industries of the WZ2008 classification.

[33] Note that the aggregate price change used here ($\Delta\overline{PPI}_t$) is the annualized percentage change of the current price level relative to three months in the past, which fits the average survey data on price realizations better than monthly changes in producer price indices, see Table 3.D.4 in Appendix 3.D. It is important to note that it is not reasonable to estimate a semi-elasticity mapping qualitative survey responses to changes in producer price indices separately for each industry because the number of firms in the IBS is too low in most two-digit industries. Consequently, the changes in industry-level producer price indices do not fit with the mean reported price changes of firms in the respective sectors due to the trichotomy of the survey data.

Figure 3.4: Comparison between Expected/Realized Price Changes and Quantitative Data



Notes: The figure plots time series of the realized change in producer prices in the manufacturing sector relative to three months before (black solid line) against time series of average realized price changes (blue dashed line) and expected price changes (red dotted line) reported by firms in the manufacturing survey of the IBS. The German Federal Statistical Office provides time series of producer price indices at the two-digit industry level. For aggregation, the industry-specific price indices are weighted by the average share of manufacturing firms in the respective sectors of the IBS.

responses to quantitative changes in producer price indices, which are defined as follows

$$\hat{\psi}^{Exp} := \frac{\mathrm{d}\Delta\overline{PPI}_t}{\mathrm{d}\overline{\text{Price Exp.}}_t^{+3m}} = 0.147 \text{ and } \hat{\psi}^{Realiz} := \frac{\mathrm{d}\Delta\overline{PPI}_t}{\mathrm{d}\overline{\text{Price Realiz.}}_t^{-1m}} = 0.169. \tag{3.5}$$

Reflecting the lower volatility in average price realizations, the semi-elasticity that links reported price changes to changes in producer prices is higher ($\hat{\psi}^{Realiz} = 0.169$) than for the case of price expectations ($\hat{\psi}^{Exp} = 0.147$). Hence, an appreciation of average price expectations (realizations) in the IBS by 0.1 over the course of 12 months can be associated with an increase in producer prices by roughly 1.5 (1.7) percent.

The estimated semi-elasticities $\hat{\psi}^{Exp}$ and $\hat{\psi}^{Realiz}$ can be used to approximate the quantitative size of firms' price increases in response to the introduction of minimum wages. Assuming (a) that the average size of price changes due to the minimum wage introduction did not differ from "normal" price changes and (b) that price changes of manufacturing firms and service providers are on average of similar size, the minimum wage-induced price reaction of each firm (ΔP_i) can be quantified using the following relationship:

$$\Delta P_i = \hat{\psi} \times \hat{\beta} \times TI_i, \tag{3.6}$$

where $\hat{\psi}$ refers to either $\hat{\psi}^{Exp}$ or $\hat{\psi}^{Realiz}$ and $\hat{\beta}$ is the treatment effect on firms' planned (or realized) price changes estimated in the previous section based on model (3.2).

The approximated price effect is considerably large. For example, firms that operate in sector-region combinations in which one out of four full-time employees was affected by the minimum wage ($TI_i = 0.25$) increased their prices by approximately 1.5% in response to the minimum wage. In line with the results in Section 3.5.3, the price effect of manufacturing firms does not differ substantially once it is approximated using survey data on expected or realized price changes.[34]

3.6.1 Average Price Effect Across All Firms in the Sample

Next, the average size of price increases of all firms in the sample is approximated. Plugging the average degree of treatment intensity of all firms ($\overline{TI} = 0.039$) into equation (3.6) delivers an average price increase of 0.23%. As the average degree to which firms were affected by the minimum wage largely differed between West and East Germany as well as between manufacturing firms and service providers, the average price effect is heterogeneous among these groups. As displayed in Panel A of Table 3.9, firms in West Germany are estimated to have increased their prices by only 0.15% in response to the minimum wage introduction, while the price reaction of East German firms was much stronger (+0.71%). Moreover, manufacturing firms (+0.12%) appear to have raised their prices less strongly than firms in services (+0.35%). Again, estimating the overall price effect for manufacturing firms based on realized price changes rather than expectations delivers comparable results.

Comparing these estimates to the approximate extent of the wage increase in response to the minimum wage introduction indicates that firms passed through a substantial share of their increased labor costs to the prices of their products and services. Assuming that the number and composition of workers did not change, the average increase in total wage costs of all firms in the sample induced by the minimum wage can be approximated to 0.70%.[35] Admittedly, this calculation only delivers a very rough estimate of the true increase in labor costs firms faced on average. On the one hand, the estimate provides a lower bound of the true increase in the wage bill because the more strongly affected wages of part-time employees and marginally employed workers are not considered. On

[34] Inserting the estimated coefficients of the price effect for manufacturing firms from Tables 3.6 and 3.8 to equation (3.6) gives $\Delta P_i^{Exp} = 0.147 \times 0.409 \times TI_i = 0.060 \times TI_i$ and $\Delta P_i^{Realiz} = 0.169 \times 0.338 \times TI_i = 0.057 \times TI_i$.

[35] Each firm's approximate increase in wage costs is calculated based on the wage data presented in Section 3.3.2, i.e., the wage distribution of full-time employees in each firm's two-digit industry and region in 2013. In Figure 3.2, the minimum wage-induced increase in the wage bill corresponds to the fraction of (a) the area between the wage distribution of 2013 in each firm's sector-region combination and the new minimum wage of €8.50/hour and (b) the integral below the entire support of the wage distribution.

Table 3.9: Quantitative Effect of Minimum Wage on Overall Level of Producer Prices

	Quantification of Price Effect Based on					
	Price Expectations					Price Realizations
	Total	Manuf.	Services	West	East	Manuf.
PPI-Semi-Elasticity ($\hat{\psi}$)	0.147	0.147	0.147	0.147	0.147	0.169
Treatment Effect ($\hat{\beta}$)	0.400	0.409	0.392	0.407	0.400	0.338
Panel A: Average Price Effect of All Firms in Sample						
Mean Treatment Intensity ($\overline{TI}$)	0.039	0.02	0.06	0.024	0.121	0.02
Average Price Effect ($\Delta\overline{P}$ in %)	0.23	0.12	0.35	0.15	0.71	0.12
Panel B: Minimum Wage Effect on Revenue-Weighted Producer Price Index						
Revenue-Weighted Treatment Intensity ($\widetilde{TI}$)	0.029	0.014	0.051	0.023	0.100	0.014
Overall Price Effect ($\Delta\widetilde{P}$ in %)	0.17	0.08	0.31	0.14	0.59	0.08

Notes: This table summarizes the estimated minimum wage effect on the overall level of producer prices. The "PPI-Semi-Elasticity ($\hat{\psi}$)" refers to the degree to which changes in average price expectations in the IBS translate to changes in producer price indices. $\hat{\psi}$ can only be estimated for manufacturing firms and is assumed to be constant across all sectors and regions. The "treatment effects ($\hat{\beta}$)" correspond to the estimated coefficients of Table 3.6 and 3.8. "$\overline{TI}$" is the average treatment intensity of all firms in the IBS and "$\widetilde{TI}$" refers to the revenue-weighted average treatment intensity of all industry-region combinations.

the other hand, the estimate is upward biased because of potential non-compliance of firms and because of the fact that wage increases that would have taken place in absence of the minimum wage are not taken into account. However, it is reasonable to argue that the order of magnitude of the true increase in wage costs is roughly captured by this estimate. In light of this, an average price increase of 0.23% appears to be relatively strong and non-negligible.[36]

3.6.2 Minimum Wage Effect on Overall Producer Prices

In a next step, I examine the effect of the minimum wage introduction on the overall level of producer prices in Germany. For this purpose, the average degree of treatment intensity of all industry-region combinations ($\widetilde{TI}$) is inserted to equation (3.6). To capture the level of overall producer prices as closely as possible, the treatment intensity of each industry-region combination is weighted by revenues in each cell.[37] Similarly to Section 3.6.1, $\widetilde{TI}$

[36]In order to calculate the exact share of firms' additional labor costs that is passed through to prices, additional information on other input costs besides labor as well as the development of firms' revenues or profits would be needed. Unfortunately, this additional information is not available at the corresponding level of analysis.

[37]Revenue data are received from Destatis' GENESIS database (code "73321") at the level of two-digit industries and federal states. From this, revenue weights are calculated for each county-sector combination using the county's share of the total number of employees in the respective industry of its federal state. Moreover, I adjust the revenue weights for the fact that wage data are missing more often

is also calculated separately for the manufacturing sector and the services sector as well as for West and East Germany.

The results of this quantification exercise presented in Panel B of Table 3.9 show that overall producer prices in Germany increased by approximately 0.17 percent in response to the introduction of statutory minimum wages in January 2015. Again, producer prices were more strongly increased in East Germany (+0.59%) compared to West Germany (+0.14%) as well as in the services sector (+0.31%) in relation to the manufacturing sector (+0.08%). The estimated effect on the overall level of producer prices is slightly lower than the average price effect across all firms in the IBS displayed in Panel A. This difference can be rationalized by the fact that revenues are higher in industry-region combinations which were less strongly affected by the minimum wage. However, the order of magnitude of both estimates is comparable.

The estimated size of the minimum wage-induced increase in producer prices is remarkably close to the prediction of the "German Council of Economic Experts." In their annual report to the federal government published two months prior to January 2015, they predicted an additional increase in CPI inflation by 0.2 percentage points in response to the introduction of the statutory minimum wage (c.f. Sachverständigenrat, 2014, p. 107).[38] Hence, the back-of-the-envelope calculation of the price effect does not seem to deliver unreasonable results despite of the very strong assumptions needed to interpret the effects found in the qualitative survey data in a quantitative way.

3.7 Robustness

This study documents that affected firms increased their prices in response to the introduction of the statutory minimum wage in Germany, while their employment reaction appeared to be—if anything—only very modestly negative on average and insignificant. Besides providing additional insights about the firms' reaction, this section conducts several robustness checks that confirm the main findings with respect to firms' adjustment of pricing and employment plans. In addition, Table 3.D.5 in Appendix 3.D summarizes the results of all robustness checks with respect to realized price changes in the subset of manufacturing firms which are comparable to the findings presented in the following.

First, the results do not change once I control for attrition. If dropout of firms from the sample was correlated with the degree to which they were affected by the minimum wage introduction, the results of the baseline specification could be biased. To accommodate this concern, I restrict the sample to firms that stay in the dataset until December 2015.

in East Germany compared to West Germany. For details, see Appendix 3.C.

[38] Unfortunately, the report only includes a prediction for consumer prices rather than producer prices and does not provide details on how the prediction of the minimum wage effect is performed.

The estimated minimum wage effect on firms' price and employment expectations are very close to the results of the baseline regression as shown in Columns (1) and (2) of Tables 3.10 and 3.11.

Second, the results are robust to the choice of the aggregation level in the wage data used for the construction of the treatment intensity measure. As described in Section 3.3.2, 53.9% (84.5%) of all firms in the manufacturing and services surveys of the IBS can be matched to administrative, industry-specific wage data at the level of the county (labor market region) they are located in. Trading off the higher coverage of wage data at the level of labor market regions and the fact that firm-level wages are better reflected by the county level data, the baseline specification uses county-level wage data once they are available and replaces missing values by wage data at the more aggregated level of labor market regions. If wage data at the level of labor market regions are used to determine TI_i for all firms instead, the results do not change substantially. As can be inferred from Column (3) of Tables 3.10 and 3.11, the estimated coefficient on the treatment effect on pricing and employment plans is slightly smaller in absolute value in both cases. This can be attributed to additional measurement error in TI_i.

As expected, the estimated minimum wage effects on firms' pricing and employment reaction are stronger if the construction of TI_i is restricted to industry-specific wage data at the county level. Capturing the actual treatment intensity of firms with less measurement error reduces the attenuation bias in the estimated coefficient. Regarding the price reaction of firms, the treatment effect is estimated to $\hat{\beta} = 0.56$, see Column (4) of Table 3.10. Consequently, the approximated effect on the level of overall producer prices is stronger (+0.21%) compared to the baseline specification (+0.17%). For the case of employment expectations, the estimated treatment effect increases in absolute value to $\hat{\beta} = -0.06$, see Column (4) of Table 3.11. Although the estimate is still insignificant, I cannot rule out that firms' employment reaction would be estimated to be significantly negative if firms' treatment intensity was observed without measurement error. Hence, the results of the baseline specification are likely to reflect a lower bound of the true extent of firms' price and employment reaction to the introduction of minimum wages.

Third, the results are robust to the choice of different "virtual" minimum wage levels $\bar{w}_{min}$ for the construction of TI_i. If TI_i measures the fraction of all full-time employees that earned less than €6.50 or €7.50 in 2013, the treatment intensity measure only captures firms that are affected very strongly by the introduction of a minimum wage of €8.50 per hour. Unsurprisingly, the estimated effect on the overall price level is smaller (+0.08% for $\bar{w}_{min} =$ €6.50 and +0.12% for $\bar{w}_{min} =$ €7.50) because fewer firms are considered as being affected. Further, the estimated employment reaction among these highly treated firms is more negative than in the baseline specification ($\hat{\beta} = -0.15$ and $\hat{\beta} = -0.08$) but still

Table 3.10: Firms' Price Response to the Minimum Wage Introduction: Robustness

	Planned Price Change in Next 3 Months									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Specification	Baseline	No Attrition	Wage Data		Threshold $\bar{w}$				$w(p0)$	
			Region	County	6.50€	7.50€	9.50€	10.50€	$0.7w(p10)$	$0.9w(p10)$
$TI \times \mathbb{1}(t \in \{2014m7, 2015m6\})$	0.40***	0.42***	0.38***	0.56***	0.89***	0.58***	0.26***	0.17**	0.46***	0.39***
	(0.10)	(0.098)	(0.10)	(0.15)	(0.24)	(0.14)	(0.092)	(0.075)	(0.12)	(0.10)
$\text{Demand}_{i,t}$	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time*Sector FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time*State FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.331	0.325	0.331	0.332	0.331	0.331	0.331	0.331	0.331	0.331
Observations	280541	227216	280541	173051	280541	280541	280541	280541	280541	280541
PPI-Semi-Elasticity ($\hat{\psi}$)	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147
Mean Treatment Intensity ($\overline{TI}$)	0.039	0.039	0.04	0.031	0.007	0.018	0.068	0.105	0.064	0.037
Average Price Effect ($\Delta\overline{P}$ in %)	0.231	0.238	0.222	0.256	0.095	0.157	0.264	0.262	0.438	0.211
Revenue-Weighted TI ($\widetilde{TI}$)	0.029	0.029	0.03	0.026	0.006	0.014	0.048	0.073	0.035	0.026
Overall Price Effect ($\Delta\widetilde{P}$ in %)	0.168	0.175	0.165	0.209	0.075	0.12	0.186	0.181	0.236	0.148

Notes: The dependent variable is expected price changes during the next 3 months as reported to the IBS. "TI" is the proxy of firms' degree of affectedness by the minimum wage introduction and "$\mathbb{1}(t \in \{2014m7, 2015m6\})$" is a dummy that is one during the treatment period. "$\text{Demand}_{i,t}$" is firms' current backlog of orders as reported in the IBS. "Time*Sector FE" and "Time*State FE" are time fixed effects at the levels of two-digit industries and federal states, respectively. "$\hat{\psi}$" denotes the semi-elasticity that maps changes in average price expectations to quantitative producer prices. "$\overline{TI}$" and "$\Delta\overline{P}$" refer to the average treatment intensity and approximated minimum wage-induced price increase of all firms in the sample. "$\widetilde{TI}$" and "$\Delta\widetilde{P}$" reflect the overall treatment intensity in the economy and the overall effect of producer prices based on revenue weights for each county-industry cell as described in Section 3.6.2. Standard errors are multiway clustered at the sector, county, and date levels. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

insignificant, see Columns (5) and (6) of Table 3.11. Despite of being insignificant, this points into the direction that deteriorated employment plans were—if anything—more likely to occur among very strongly affected firms.

If the treatment intensity measure is calculated based on minimum wage thresholds above €8.50, TI_i assigns a positive degree of affectedness to firms that operate in industries and regions where all full-time employees earned wages slightly above the minimum wage prior to its introduction. However, it is reasonable to argue that these firms employed at least some part-time employees or marginally employed workers that previously earned less than €8.50. The results in Columns (7) and (8) of Table 3.10 indicate that price expectations in the period around the minimum wage introduction reacted less sensitive to a given variation in TI_i based on the thresholds of $\bar{w}_{min} =$ €9.50 and €10.50 compared to the baseline specification. Naturally, the average degree of treatment intensity across all firms $\overline{TI}(\bar{w}_{min})$ as well as the revenue-weighted mean of overall treat-

Table 3.11: Employment Response to the Minimum Wage Introduction: Robustness

	Planned Employment Change in Next 3 Months									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Specification	Baseline	No Attrition	Wage Data		Threshold $\bar{w}$				$w(p0)$	
			Region	County	6.50€	7.50€	9.50€	10.50€	$0.7w(p10)$	$0.9w(p10)$
$TI \times \mathbb{1}(t \in \{2014m7, 2015m6\})$	-0.0100	0.0035	-0.0040	-0.060	-0.15	-0.078	-0.0056	-0.00027	-0.026	-0.025
	(0.070)	(0.069)	(0.076)	(0.10)	(0.15)	(0.088)	(0.055)	(0.044)	(0.075)	(0.065)
$\text{Demand}_{i,t}$	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time*Sector FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time*State FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.350	0.340	0.350	0.364	0.351	0.351	0.350	0.350	0.350	0.350
Observations	280500	227248	280500	173019	280500	280500	280500	280500	280500	280500

Notes: The dependent variable is the expected employment change during the next 3 months as reported to the IBS. "TI" is the proxy of firms' degree of affectedness by the minimum wage introduction and "$\mathbb{1}(t \in \{2014m7, 2015m6\})$" is a dummy that is one during the treatment period. "$\text{Demand}_{i,t}$" is firms' current backlog of orders as reported in the IBS. "Time*Sector FE" and "Time*State FE" are time fixed effects at the levels of two-digit industries and federal states, respectively. Standard errors are multiway clustered at the sector, county, and date levels. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

ment intensity $\widetilde{TI}(\bar{w}_{min})$ is much larger in these specifications, i.e., $\overline{TI}(9.50) = 0.068$ and $\overline{TI}(10.50) = 0.105$ as well as $\widetilde{TI}(9.50) = 0.048$ and $\widetilde{TI}(10.50) = 0.073$. Unsurprisingly, the overall effect on producer prices is larger (+0.19% and +0.18%) compared to the baseline scenario (+0.17%). This small difference indicates that the lion's share of the price effect is generated by firms that were already captured by the baseline specification of the treatment intensity measure. Abstracting from firms that were affected by the minimum wage only through higher wage costs for part-time employees or marginally employed workers does hence not appear to be a major concern.

Fourth, the results are robust to different assumptions about the minimum of the wage distribution $w(0)$ which is not given in the wage data. The baseline specification is based on the assumption that $w(0)$ is related to the wage at the 10^{th} percentile ($w(10)$) in the same way as $w(10)$ is related to wages at the 20^{th} percentile. In this specification, the minima of the wage distribution on average corresponded to approximately 85% of the wage rates at the 10^{th} percentile. As documented in Columns (9) and (10) of Tables 3.10 and 3.11, the results are very close to those of the baseline specification once the wage curve below the 10^{th} percentile is assumed to be either steeper (with $w(0) = 0.7 \times w(10)$) or flatter (with $w(0) = 0.9 \times w(10)$).

3.8 Conclusion

This chapter studies the response of manufacturing firms and service companies to the introduction of statutory minimum wages in Germany in 2015. The analysis focuses on two potential margins of adjustment for firms in response to minimum wage-induced increases in labor costs: changes in the number of employees and pass-through on prices. For this purpose, the study makes use of the micro data of the IFO Business Survey that is unique in containing information on price changes at the level of firms across a wide range of sectors and regions at high, monthly, frequency.

Identifying each firm's degree of affectedness by means of sectorally and regionally disaggregated wage data, I find strong evidence for price pass-through of affected firms. Based on a generalized difference-in-differences estimation strategy, I find that the probability that firms increased their prices is strongly associated with the intensity to which they were affected by the minimum wage introduction. Conditional on the same degree of affectedness, the price effect does not differ between manufacturing firms and service companies as well as between firms in West and East Germany. This provides evidence in favor of the external validity of other studies that document strong minimum wage effects on prices based on data from single sectors only, such as restaurants (e.g., Aaronson, 2001, Lemos, 2006, Aaronson et al., 2008, and Fougère et al., 2010) and retailers (Leung, 2016 and Montialoux et al., 2017). In addition, exploiting the strong correlation between qualitative survey data and administrative producer price indices reveals that the minimum wage-induced price reaction of affected firms is quantitatively large and increased the overall level of producer prices in Germany by roughly 0.2%.

In contrast to the pronounced price reaction, I only find a very modestly negative and insignificant effect of the minimum wage introduction on firms' planned employment changes. While a negative employment effect cannot be ruled out with certainty in light of potential measurement error in the treatment intensity measure, this finding points into the direction of a prominent strand of papers including Card and Krueger (1994, 2000), Dube et al. (2010), and Allegretto et al. (2011) who find that minimum wages do not inevitably destroy jobs. Moreover, the chapter adds to first evidence in favor of moderate employment effects in response to the introduction of minimum wages in Germany by Bossler and Gerner (2016) and vom Berge et al. (2016) that were much weaker than previously predicted by Knabe et al. (2014) and Arni et al. (2014).

Overall, the results suggest that price pass-through is an important margin of adjustment for firms in response to minimum wages because affected firms appear to have (at least partially and in the short-run) compensated their increased labor costs more often by raising prices than by reducing their number of employees. This highlights that the joint assessment of different potential adjustment channels is a fruitful avenue of research

to gain a comprehensive understanding of firms' response to minimum wages. Ideally, this approach would include quantitative micro data on producer prices at very disaggregated levels, which hopefully become available in the future, along with firm-level data on employment stocks and flows as well as further important dimensions such as investment, quality of outputs, and different characteristics of jobs and workers. While data on many of these aspects are being collected, they are either not available or can only hardly be matched to other sources of micro data, yet. I leave this challenge to future work.

Appendices to Chapter 3

3.A Survey Questions Used in the Study

The following set of questions, which are asked regularly on a monthly basis in the IBS, are used in this chapter (English translation of German original):

Services Survey (S):

S:Q1 Price Expectations:
"During the next 3 months, the prices of our services will [1] increase, [0] stay the same, or [-1] decrease."

S:Q2 Employment Expectations:
"During the next (2-3) months, the number of employees will [1] increase, [0] stay the same, or [-1] decrease."

S:Q3 Current Backlog of Orders:
"We evaluate our backlog of orders as [1] comparatively large, [0] sufficient (typical for the season), or [-1] too small."

S:Q4 Current Business Situation:
"We evaluate our current business situation as [1] good, [0] satisfactory (typical for the season), or [-1] bad."

S:Q5 Expected Business Situation:
"During the next six months, our business situation will be [1] more favorable, [0] stay the same, or [-1] more unfavorable."

Manufacturing Survey (M):

In the manufacturing survey, firms are asked for assessments regarding specific products. However, only 0.43% of all observations between 2010 and 2015 refer to multiple products for the same firm at a given point in time. Following the procedure described in Chapter 4, these observations are aggregated to the firm level by taking means across products and

rounding to the next integer.

M:Q1 Price Expectations:
"During the next 3 months, the domestic (net) sales prices for product X will—in consideration of changes in conditions—probably [1] increase, [0] roughly stay the same, or [-1] decrease."

M:Q1a Realized Price Changes [only asked in manufacturing survey]:
"During the past month, the domestic (net) sales price for product X—in consideration of changes in conditions— [1] increased, [0] stayed the same, or [-1] decreased."

M:Q2 Employment Expectations:
"During the next 3 months, the number of employees for the production of product X will [1] increase, [0] roughly stay the same, or [-1] decrease."

M:Q3 Current Backlog of Orders:
"We evaluate our backlog of orders for product X as [1] comparatively large, [0] sufficient (typical for the season), or [-1] too small."

M:Q4 Current Business Situation:
"We evaluate the current business situation for product X as [1] good, [0] satisfactory, or [-1] bad."

M:Q5 Expected Business Situation:
"Expectations for the next six months: the business situation for product X will be [1] more favorable, [0] stay the approximately same, or [-1] more unfavorable."

3.B Plausibility of the Treatment Intensity Measure: Supplementary Evidence

This appendix complements the evidence presented in Section 3.3.2 regarding the plausibility of the treatment intensity measure TI_i by making use of firms' responses to a series of special questions in the IBS. Specifically, the IBS version of November 2014 has been complemented by the following set of questions referring to firms' assessments about the upcoming introduction of the statutory minimum wage in January 2015 (English translation of German original):[39]

SQ1: *"The statutory minimum wage will be introduced on January 1st, 2015. Is your company affected by this regulation? [1] yes, [0] no."*

"If yes, which actions are you going to undertake in reaction to the introduction of the minimum wage (multiple answers possible)?

SQ2: *No action planned: [1] yes.*

SQ3: *Reduction in staff: [1] yes.*

SQ4: *Reduction in working hours: [1] yes.*

SQ5: *Price increases: [1] yes.*

SQ6: *Decreased investment volume: [1] yes.*

SQ7: *Cuts in bonus payments: [1] yes.*

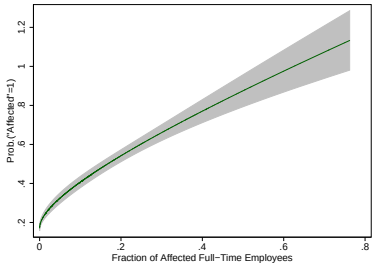
SQ8: *Other action: [1] yes."*

As the functional form of the relationship between TI_i and the frequency to which firms answered questions SQ1, SQ3, SQ4, and SQ5 in the affirmative is not clear *a priori*, I estimate a fractional polynomial of degree two of TI_i without adding any further covariates. Figure 3.B.1 plots the resulting curves of the mean probability to affirm to the respective special question at different levels of TI_i along with the 95%-confidence

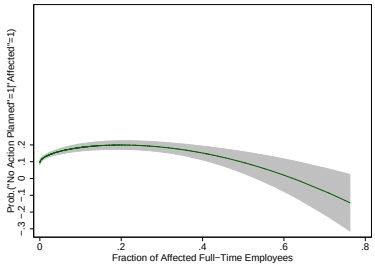
[39] See Erthle et al. (2014) for a description and summary statistics of the minimum wage-related special questions in the IBS of November 2014 as well as Sauer and Wojciechowski (2016) for a descriptive analysis based on these data.

Figure 3.B.1: Relationship between TI_i and Firms' Responses to Minimum Wage Related Special Questions in the IBS

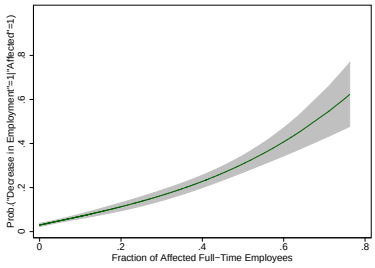
SQ1: Probability of "Affectedness"



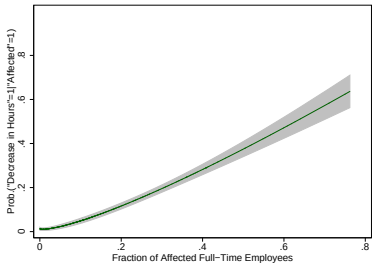
SQ2: No Action Planned if "Affected"



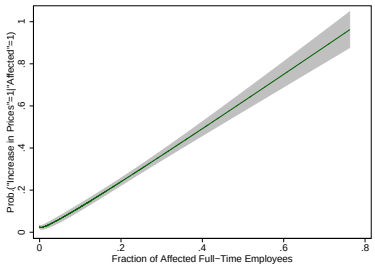
SQ3: Planned Empl. Decreases if "Affected"



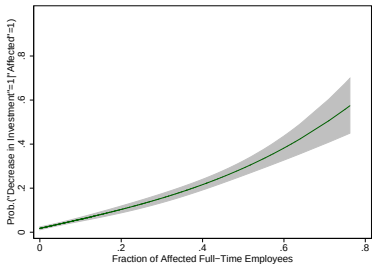
SQ4: Planned Decrease in Working Hours if "Affected"



SQ5: Planned Increase in Prices if "Affected"



SQ6: Planned Decrease in Investment if "Affected"



Notes: The figure plots the predicted probabilities (green line) to affirm to the respective special question indicated above each graph by estimating a fractional polynomial of degree two of TI_i, i.e., the fraction of full-time employees affected by the minimum wage, without adding any further covariates. The shaded area covers the 95%-confidence interval of the predicted probabilities.

intervals. In addition, Table 3.B.1 summarizes the average frequencies of responses at different levels of TI_i. The question about firms' affectedness (SQ1) neither provides any information about the intensity to which firms are affected nor contains any information about the channels through which firms are affected. As can be inferred from Figure 3.B.1 and Table 3.B.1, the probability that firms stated to be affected by the minimum wage increases substantially in TI_i. The majority among the 17% of firms that reported to be affected by the minimum wage despite of $TI_i = 0$ did not plan to react to the minimum wage introduction. Arguably, these firms were only affected indirectly by the minimum wage or perceived themselves as being affected because of the obligatory and time-consuming documentation requirements.

Table 3.B.1: Plausibility Check of the Treatment Intensity: Extended Results

	Treatment Intensity (TI)			
Treatment Intensity $TI \in$	[0%]	(0%,20%]	(20%,30%]	(30%,100%)
prob("Affected" = 1)	0.171	0.374	0.597	0.811
prob("No Action" = 1|"Affected" = 1)	0.545	0.475	0.261	0.167
prob("Staff Reduction" = 1|"Affected" = 1)	0.176	0.165	0.261	0.322
prob("Hours Reduction" = 1|"Affected" = 1)	0.07	0.123	0.239	0.389
prob("Price Increase" = 1|"Affected" = 1)	0.152	0.272	0.565	0.644
prob("Reduction in Investment" = 1|"Affected" = 1)	0.104	0.13	0.261	0.311
prob("Reduction in Special Payments" = 1|"Affected" = 1)	0.156	0.215	0.326	0.411

Notes. "Treatment Intensity" refers to the fraction of full-time employees that earned an hourly gross wage of less than €8.50 in 2013 in each firm's two-digit industry and county. *prob*("Affected" = 1) displays the probability that a firm responded to be "affected" by the minimum wage in the special questions of the IBS in November 2014 depending on its proxied treatment intensity as indicated at the top of each column. *prob*("No Action" = 1|"Affected" = 1), etc. are defined accordingly.

Moreover, the probability that "affected" firms according to SQ1 stated to react to the minimum wage introduction increases along all margins covered by the supplementary questions SQ3 through SQ7. Interestingly, the probability of stating to increase prices (SQ5) increases most strongly in TI_i. Albeit reacting less strongly compared SQ5, the probabilities of affected firms to confirm to plan reductions in employment (SQ3), cuts in working hours (SQ4), decrease investment (SQ6), or reduce special payments (SQ7) also increases in TI_i.

However, interpreting these correlations in a causal way is potentially misleading because the questions regarding firms' planned reactions to the introduction of the minimum wage (SQ3-SQ7) are restricted to affected firms and one direction. For example, affected firms could only state whether they planned to reduce the number of employees or not. If firms were operating in monopsonistic labor markets, however, they should be expected to *increase* their labor demand in response to a minimum wage that is binding at sufficiently low levels (Manning, 2003). If a non-negligible fraction of affected firms operated in such monopsonistic labor markets, the fraction of firms that planned to decrease their labor demand could hence be accompanied by a fraction of firms that planned to increase labor demand resulting in a total employment effect that potentially cancels out. Hence, the supplementary questions on the minimum wage introduction themselves do not allow for causal inference on the firm-level response of the minimum wage introduction due to missing counterfactuals as well as one-sided questions.

3.C Revenue-Weighted Average Treatment Intensity of the German Economy

This appendix presents the calculation of the revenue-weighted average treatment intensity of all industry-region combinations ($\widetilde{TI}$) that is used for the quantification of the minimum wage effect on the overall level of producer prices in Section 3.6.2. To capture overall producer prices as closely as possible, the treatment intensity of each industry-county combination is weighted by the revenues generated in each cell, denoted $\widetilde{revenues}_{s,c}$. As data on industry-specific revenues are not available at the level of counties and the treatment intensity measure cannot be constructed for all industry-county combinations due to data protection issues, the revenue weights are approximated as described in the following.

Revenue data are received from Destatis' GENESIS database (code "73321") at the level of two-digit industries s and federal states f ($revenues_{s,f}$) for 2013, the year used for the construction of $TI_{s,c}$. In order to put an appropriate weight on each $TI_{s,c}$, the state-level revenue weights $revenues_{s,f}$ are assigned to each county in proportion to its relative size in the federal state.[40] This relative size is approximated by the share of full-time employees in each county working in the industry of interest, denoted $employees_{s,c}$. The employment data are included in the wage data set received from the Federal Employment Agency (2016). From this, the total number of full-time employees represented by industry-specific wage data can be calculated for each federal state, i.e., $employees_{s,f} = \sum_{c \in f}(employees_{s,c} | w_{s,c} \notin \{\emptyset\})$.

Assuming that the industry-specific treatment intensity in counties not covered by wage data is similar to the average treatment intensity in all other counties of the federal state, the revenue weight for treatment intensities in counties for which wage data are available ($w_{s,c} \notin \{\emptyset\}$) is given by

$$revenues_{s,c} = revenues_{s,f} \times \frac{employees_{c,s}}{employees_{s,f}}.$$

However, there are industry-federal state cells for which wage data are not available in any county or labor market region. Specifically, federal state-level revenue data cannot be matched to treatment intensity measures in at least one of the respective federal state's counties in 12.0% (7.4%) of all East (West) German industry-federal state combinations. As workers were more strongly affected in East Germany, the calculated $\widetilde{TI}$ would hence be downward biased without adjustment of this asymmetry in the availability of wage

[40] As in the baseline specification, empty county-level cells are replaced by wage data at the level of labor market regions.

data. In order to correct this bias, the revenue weights ($revenues_{s,c}$) of counties in East German federal states are inflated by the inverse of the proportion of industry-specific revenues in East Germany that can be assigned to wage data in any East German federal state, i.e.,

$$\xi_{s,East} = \frac{\sum_{f \in \{East\}} revenues_{s,f}}{\sum_{f \in \{East\}} (revenues_{s,f} | w_{s,f} \notin \{\emptyset\})},$$

where $w_{s,f} \notin \{\emptyset\}$ denotes that industry-specific wage data are available in at least one county of state f. $\xi_{s,West}$ is defined accordingly for the case of industry-federal state combinations in West Germany.

The resulting revenue weight for $TI_{s,c}$ in each industry-county cell is hence given by

$$\widetilde{revenues}_{s,c} = revenues_{s,f} \times \frac{employees_{c,s}}{employees_{s,f}} \times \xi_{s,EW},$$

where $\xi_{s,EW}$ refers to $\xi_{s,East}$ or $\xi_{s,West}$ if county c is located in East or West Germany, respectively.

3.D Supplementary Tables

Table 3.D.1: Variation in Firms' Treatment Intensity In Different Industries

Two-Digit Industry (WZ 2008)	# Firms	% Firms with Fraction of Affected Full-Time Employees =0%	>0%	>10%	>20%	>30%	>50%
Panel A: Firms in Manufacturing Survey of IBS							
10 Food products	66	1.5	98.5	71.2	34.8	30.3	9.1
11 Beverages	12	91.7	8.3	0	0	0	0
12 Tobacco products	2	100	0	0	0	0	0
15 Leather products (& related)	1	100	0	0	0	0	0
16 Wood & products of wood (excl. furniture)	57	87.7	12.3	3.5	1.8	1.8	0
17 Paper & paper products	76	81.6	18.4	15.8	0	0	0
18 Printing and reproduction of recorded media	97	79.4	20.6	7.2	0	0	0
19 Coke and refined petroleum products	1	100	0	0	0	0	0
20 Chemicals and chemical products	118	87.3	12.7	3.4	0	0	0
21 Basic pharmaceutical products & preparations	16	68.8	31.3	0	0	0	0
22 Rubber and plastic products	180	73.9	26.1	12.2	1.1	0	0
23 Other non-metallic mineral products	116	81	19	0	0	0	0
24 Basic metals	92	91.3	8.7	0	0	0	0
25 Fabricated metal products, except machinery & equipment	302	73.2	26.8	12.9	0	0	0
26 Computer, electronic and optical products	95	80	20	7.4	0	0	0
27 Electrical equipment	174	93.1	6.9	3.4	1.1	0	0
28 Machinery and equipment n.e.c.	448	98	2	0	0	0	0
29 Motor vehicles, trailers and semi-trailers	82	89	11	0	0	0	0
30 Other transport equipment	9	100	0	0	0	0	0
31 Furniture	44	75	25	9.1	6.8	6.8	0
32 Other Manufacturing	44	45.5	54.5	20.5	15.9	6.8	6.8
33 Repair and installation of machinery and equipment	7	71.4	28.6	0	0	0	0
Panel B: Firms in Services Survey of IBS							
35 Electricity, gas, steam, and air conditioning supply	7	100	0	0	0	0	0
38 Waste collection, treatment and disposal activities; materials recovery	61	72.1	27.9	6.6	0	0	0
41 Construction of buildings	13	84.6	15.4	7.7	0	0	0
43 Specialised construction activities	14	71.4	28.6	7.1	0	0	0
45 Wholesale and retail trade and repair of motor vehicles and motorcycles	1	0	100	100	100	0	0
49 Land transport and transport via pipelines	131	1.5	98.5	71.8	22.9	5.3	0
50 Water transport	2	100	0	0	0	0	0
51 Air transport	3	100	0	0	0	0	0
52 Warehousing and support activities for transportation	127	76.4	23.6	7.9	.8	0	0
53 Postal and courier activities	8	0	100	37.5	0	0	0
55 Accommodation	89	1.1	98.9	78.7	40.4	14.6	5.6
56 Food and beverage service activities	57	0	100	100	100	93	15.8
58 Publishing activities	14	92.9	7.1	7.1	0	0	0
59 Motion picture, video & TV programme production, sound recording & music publishing	10	0	100	10	0	0	0
60 Radio and Television	7	100	0	0	0	0	0
61 Telecommunications	6	100	0	0	0	0	0
62 Computer programming, consultancy and related activities	247	91.5	8.5	1.2	0	0	0
63 Information service activities	15	73.3	26.7	0	0	0	0
64 Financial service activities, except insurance and pension funding	49	100	0	0	0	0	0
65 Insurance, reinsurance and pension funding, except compulsory social security	1	100	0	0	0	0	0
66 Activities auxiliary to financial services and insurance activities	11	90.9	9.1	0	0	0	0
68 Real estate activities	61	26.2	73.8	24.6	0	0	0
69 Legal and accounting activities	72	25	75	22.2	8.3	0	0
70 Activities of head offices; management consultancy activities	90	87.8	12.2	1.1	0	0	0
71 Architectural and engineering activities; technical testing and analysis	350	88.3	11.7	0	0	0	0
72 Scientific research and development	39	97.4	2.6	0	0	0	0
73 Advertising and market research	61	70.5	29.5	6.6	0	0	0
74 Other professional, scientific and technical activities	22	13.6	86.4	13.6	0	0	0
77 Rental and leasing activities	25	64	36	16	0	0	0
79 Travel agency, tour operator and other reservation service and related activities	36	52.8	47.2	0	0	0	0
80 Security and investigation activities	12	0	100	83.3	41.7	41.7	25
81 Services to buildings and landscape activities	55	0	100	100	40	23.6	0
82 Office administrative, office support and other business support activities	47	0	100	55.3	17	6.4	0
84 Public administration and defence; compulsory social security	3	100	0	0	0	0	0
85 Education	14	92.9	7.1	0	0	0	0
86 Human health activities	5	0	100	40	40	0	0
87 Residential care activities	3	33.3	66.7	0	0	0	0
88 Social work activities without accommodation	2	0	100	50	0	0	0
90 Creative, arts and entertainment activities	9	55.6	44.4	0	0	0	0
92 Gambling and betting activities	2	0	100	100	100	100	50
93 Sports activities and amusement and recreation activities	4	0	100	100	25	0	0
94 Activities of membership organisations	3	100	0	0	0	0	0

Notes. Distribution of firms in the IBS surveys covering the manufacturing and services sectors within different two-digit industries with respect to their treatment intensity. As the composition of firms is varying over time, this table displays the distribution of firms that reported to the IBS in January 2015.

Table 3.D.2: Minimum Wage Effects at the Firm-Level: Placebo Tests

	Price Exp.$_t^{+3m}$				Employment Exp.$_t^{+3m}$			
	Placebo			Treatment	Placebo			Treatment
Begin Period ($\underline{t}$)	2011m7	2012m7	2013m7	2014m7	2011m7	2012m7	2013m7	2014m7
End Period ($\bar{t}$)	2012m6	2013m6	2014m6	2015m6	2012m6	2013m6	2014m6	2015m6
$TI \times \mathbb{1}(t \in \{\underline{t}, \bar{t}\})$	-0.053	-0.063	0.013	0.40***	-0.15	0.052	0.042	-0.0100
	(0.059)	(0.081)	(0.060)	(0.10)	(0.093)	(0.053)	(0.051)	(0.070)
R^2	0.331	0.331	0.331	0.331	0.351	0.351	0.350	0.350
Control for Demand$_{i,t}$	yes	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
Time*Sector FE	yes	yes	yes	yes	yes	yes	yes	yes
Time*State FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	280541	280541	280541	280541	280500	280500	280500	280500

Notes: This table summarizes the results of estimating the minimum wage effect in model (3.2) during different placebo periods. The dependent variables are planned price or employment changes during the next 3 months as reported to the IBS. "TI" is the proxy of each firm's degree of affectedness by the minimum wage introduction and "$\mathbb{1}(t \in \{\underline{t}, \bar{t}\})$" is a dummy that is one during the time period between $\underline{t}$ and $\bar{t}$ as indicated above each column. "Demand$_{i,t}$" is firms' current backlog of orders as reported in the IBS. "Time*Sector FE" and "Time*State FE" are time fixed effects at the levels of two-digit industries and federal states, respectively. Standard errors are multiway clustered at the sector, county, and date levels. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.D.3: Minimum Wage Effect on Other Variables - Robustness

	Conditions$_{i,t}$				Expectations$_t^{+6m}$				Demand$_t$		
$TI \times \mathbb{1}(t \in \{\underline{t}, \bar{t}\})$	0.0043	-0.028	-0.0058	-0.0049	-0.099	-0.11	-0.068	-0.091	-0.059	0.019	-0.12
	(0.10)	(0.12)	(0.070)	(0.10)	(0.12)	(0.11)	(0.099)	(0.12)	(0.068)	(0.056)	(0.086)
Begin Period ($\underline{t}$)	2014m10	2014m10	2014m10	2014m10	2014m7	2014m7	2014m7	2014m7	2014m10	2014m10	2014m10
End Period ($\bar{t}$)	2015m9	2015m9	2015m9	2015m9	2015m6	2015m6	2015m6	2015m6	2015m9	2015m9	2015m9
Control for Demand$_{i,t}$	yes		yes	yes	yes		yes	yes			
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time*Sector FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time*State FE	yes	yes			yes	yes			yes		
Time*Region FE				yes				yes			yes
R^2	0.632	0.508	0.630	0.640	0.359	0.351	0.356	0.373	0.454	0.451	0.466
Observations	281823	291683	281823	281728	280482	290263	280482	280386	282178	282178	282083

Notes: The dependent variables are current business conditions, expected business conditions for the next six months, as well as current backlog of orders as reported to the IBS. "TI" is the proxy of the each firm's degree of affectedness by the minimum wage introduction and "$\mathbb{1}(t \in \{\underline{t}, \bar{t}\})$" is a dummy that is one during the treatment period between $\underline{t}$ and $\bar{t}$. "Time*Sector FE," "Time*State FE," and "Time*Region FE" are time fixed effects at the levels of two-digit industries, federal states, and labor market regions, respectively. Standard errors are multiway clustered at the sector, county, and date levels. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.D.4: Cross-Correlation Between Time Series of Average Reports to IBS and Changes in Quantitative Price Data

Panel A: Changes in PPI Relative to 3 Months Before							
Lag i	-3	-2	-1	0	1	2	3
$\rho(\overline{\text{Price Exp.}}_{t-i}^{+3m}, \Delta\overline{PPI}_t)$	0.554	0.678	0.782	0.858	**0.870**	0.781	0.579
$\rho(\overline{\text{Price Realiz.}}_{t-i}^{-1m}, \Delta\overline{PPI}_t)$	0.731	0.805	0.854	**0.855**	0.745	0.536	0.333

Panel B: Changes in PPI Relative to Previous Month							
Lag i	-3	-2	-1	0	1	2	3
$\rho(\overline{\text{Price Realiz.}}_{t-i}^{-1m}, \Delta\overline{PPI}_t)$	0.621	0.635	0.699	0.610	0.396	0.238	0.158

Notes: Cross-correlogram of time series of changes in weighted producer prices ($\Delta\overline{PPI}_t$) relative to three months ago (Panel A) or one month ago (Panel B) and average expected price changes for the next three months ($\overline{\text{Price Exp.}}_t^{+3m}$) or average realized price changes during the previous month ($\overline{\text{Price Realiz.}}_t^{-1m}$) as reported to the IBS. The sample is restricted to manufacturing firms between January 2010 and December 2015.

Table 3.D.5: Firms' Price Response to the Minimum Wage Introduction: Robustness

	Realized Price Change During Previous Month									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Specification	Baseline	No Attrition	Wage Data		Threshold $\bar{w}$				$w(p0)$	
			Region	County	6.50€	7.50€	9.50€	10.50€	$0.7w(p10)$	$0.9w(p10)$
$TI \times \mathbb{1}(t \in \{2014m10, 2015m9\})$	0.34**	0.35**	0.25	0.60***	0.92***	0.54***	0.21	0.16	0.49***	0.32**
	(0.15)	(0.15)	(0.15)	(0.14)	(0.00072)	(0.11)	(0.14)	(0.11)	(0.14)	(0.14)
$\text{Demand}_{i,t}$	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time*Sector FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time*State FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.288	0.277	0.288	0.283	0.288	0.288	0.288	0.288	0.288	0.288
Observations	150051	122576	150051	92479	150051	150051	150051	150051	150051	150051
PPI-Semi-Elasticity ($\hat{\psi}$)	0.169	0.169	0.169	0.169	0.169	0.169	0.169	0.169	0.169	0.169
Mean Treatment Intensity ($\overline{TI}$)	0.02	0.021	0.02	0.018	0.002	0.007	0.041	0.07	0.045	0.019
Average Price Effect($\Delta\overline{P}$ in %)	0.116	0.122	0.085	0.182	0.028	0.061	0.144	0.192	0.374	0.104
Revenue-Weighted TI ($\widetilde{TI}$)	0.014	0.014	0.015	0.013	0.001	0.005	0.026	0.041	0.018	0.012
Overall Price Effect ($\Delta\widetilde{P}$ in %)	0.079	0.081	0.062	0.128	0.022	0.05	0.09	0.113	0.149	0.069

Notes: The dependent variable is the reported change in prices in the previous month as reported by manufacturing firms. "TI" is the proxy of each firm's degree of affectedness by the minimum wage introduction and "$\mathbb{1}(t \in \{2014m10, 2015m9\})$" is a dummy that is one during the treatment period. "$\text{Demand}_{i,t}$" is firms' current backlog of orders as reported in the IBS. "Time*Sector FE" and "Time*State FE" are time fixed effects at the levels of two-digit industries and federal states, respectively. "$\hat{\psi}$" denotes the semi-elasticity that maps changes in average price expectations to quantitative producer prices. "$\overline{TI}$" and "$\Delta\overline{P}$" refer to the average treatment intensity and approximated minimum wage-induced price increase of all firms in the sample. "$\widetilde{TI}$" and "$\Delta\widetilde{P}$" reflect the overall treatment intensity in the economy and the overall effect of producer prices based on revenue weights for each county-industry cell as described in Section 3.6.2. Standard errors are multiway clustered at the sector, county, and date levels. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 4

Harmonization and Interpretation of the IFO Business Survey's Micro Data

4.1 Introduction

The micro data of the IFO Business Survey (IBS) provide a multitude of opportunities for evidence-based research in various fields of economics. The survey is unique in asking a large sample of firms that is representative for the German economy at monthly frequency about, *inter alia*, current trends and expectations for the development of their general business situation as well as their volume of production, demand situation, and changes in employment and prices. The IBS is divided into four industry surveys that cover the main sectors of the economy (manufacturing, services, retail/wholesale, construction), with each being accompanied by regularly asked industry-specific special questions that, for example, refer to constraints to business activity or credit supply by banks. At times, the IBS is supplemented by questions about recent events such as the integration of refugees into the German labor market or the introduction of statutory minimum wages in 2015.[1] The IBS is ideally suited for micro-econometric analysis as the response rate of firms is high, attrition is low, and the anonymized micro data allow to track firms over the entire time span in the sample.

Despite of these advantages, researchers usually restricted their analysis to the subset of manufacturing firms instead of using the universe of firms covered by the IBS, e.g., Pesaran and Timmermann (2009), Bachmann et al. (2013b), Carstensen et al. (2013), Strasser (2013), Fidrmuc and Hainz (2013), and Bachmann and Elstner (2015). This is

[1]The IBS has been conducted since 1949 in order to construct the IFO Business Climate Index which is the most recognized lead indicator for economic activity in Germany, see Becker and Wohlrabe (2008) for details on the survey. Moreover, refer to Seiler (2012) for a description of the different datasets of anonymized micro data including the IBS that can be accessed under strict non-disclosure agreements on-site the IFO Institute in Munich, Germany.

mainly due to the fact that the sector-specific surveys of the IBS differ with respect to the time period covered as well as the set of questions asked. In addition, panel data research based on the universe of all firms in the IBS is prevented by the fact that the sector-specific surveys are heterogeneous in the level of observational units (product vs. firm) as well as in the industry classification systems used in the micro data.

The first goal of this chapter is to prepare the micro data of the IBS for a joint econometric analysis of firms across its most important industry surveys. In order to ensure a high level of generality, I focus on data in the three main covering (a) manufacturing firms (IBS-IND (2015)—monthly micro data available since 1980), (b) retailers and wholesalers (IBS-TRA (2015)—since 1990), and (c) service companies (IBS-SERV (2015)—since 2004).[2] For this purpose, I harmonize the level of observational units across industry surveys by aggregation to the firm-level. Thereby, I adjust for a break in the methodology of the retail and wholesale survey in 2006. This adjustment is necessary for a joint analysis of the time periods before and after the break.[3]

Moreover, I harmonize the sector identification variables in the micro data of the IBS that are originally coded according to heterogeneous classification systems within and across the different sector-specific surveys. The respective codes are transferred to the German standard classification systems of 2003 and 2008 (henceforth, *WZ 03* and *WZ 08*), which largely correspond to the European "NACE Rev. 1.1" and "NACE Rev. 2" classification systems.[4] Codifying all firms to a unique classification system serves mainly two purposes: on the one hand, fixed effects can be applied along the same level of industry aggregation in order to flexibly control for industry-specific variation of any kind. On the other hand, the IBS data can be merged to industry-level data from other sources which are usually coded according to *WZ 03* and *WZ 08*.[5]

The second goal of this chapter is to utilize the harmonized firm-level dataset to

[2]I do not use data from the construction survey due to a lack of comparability to the other sector-specific surveys of the IBS.

[3]For example, Chapter 1 makes use of this adjustment when examining the anticipation effects of the increase in German value added taxes in 2007 based on firms' responses between January 2004 and December 2007. In contrast, Schenkelberg (2014) does not adjust for the methodological break and restricts her analysis to the micro data of the retail and wholesale survey prior to 2006.

[4]The NACE (European Industry Classification System) two-digit codes (*divisions*) are, in general, more narrow than the NAICS (North American Industry Classification System) two-digit codes (*sectors*). Often, NACE two-digit *divisions* are comparable to NAICS three-digit *subsectors*; for example, in manufacturing there are 24 "NACE Rev. 2" two-digit *divisions*, 3 NAICS two-digit *sectors*, and 21 NAICS three-digit *subsectors*. In total, there are 88 "NACE Rev. 2" two-digit *divisions* and 99 NAICS three-digit *subsectors*.

[5]For example, the study in Chapter 3 matches firms in the IBS to data on the distribution of wages in their industry and location in order to identify the degree to which firms are affected by the introduction of statutory minimum wages in Germany in 2015. Moreover, Chapter 2 examines the relationship between market volatility and the information content of firms' expectations in the IBS based on industry-level revenue data from administrative sources.

shed light on the interpretation of the most widely used variables in the IBS, i.e., firms' assessments about their current business conditions as well as their expectations for the next six months. Previous literature has been silent on the issue of interpretation in spite of the rather vague wording of these questions with respect to the dimension and the benchmark of the latent variable. Specifically, it is not unambiguous whether these variables have to be interpreted as *changes* relative to an (unspecified) baseline date or in *levels*, e.g., as a deviation from the trend. For this purpose, I proceed in two steps: first, I analyze the relationship between average time series of both questions and industry-level revenue data. Then, I provide insights from panel regressions at the firm-level. The results suggest that it is most reasonable to interpret both questions in levels rather than assuming that the expectations question captures the expected change in the level of business conditions. Obviously, this finding has direct implications for the specification of both econometric models, which use the micro data of IBS, and forecasting models, which include time series based on the survey questions, alike.

The remainder of this chapter is organized as follows: Section 4.2 describes the harmonization procedure of the micro data of the different sector-specific surveys. Then, Section 4.3 evaluates the interpretation of the survey questions regarding firms' current and expected future business conditions. Section 4.4 concludes.

4.2 Preparing the IBS Micro Data for Panel Research

The goal of this section is to prepare the micro data of the IBS for a joint econometric analysis of firms across its most important sector-specific surveys. This task includes two challenges. First, the level of observational units is heterogeneous between the industry surveys and, more importantly, changed over time in the retail and wholesale survey. Section 4.2.1 addresses this problem. Second, the micro data contain information on each firm's main sector of business based on different classification systems across the industry surveys. Section 4.2.2 describes how firms in the IBS are assigned to official industry classification systems based on this information. Finally, Section 4.2.3 provides descriptive statistics of the harmonized micro data of the IBS.

In principle, the harmonization procedure applies to all survey questions. For the sake of convenience, the description is exemplified using the following questions from the IBS:

Q1 *"Current situation: We evaluate our current business condition (latest business trends) as [1] good, [0] satisfactory (typical for the season), [-1] bad."*

Q2 *"Expectations for the next 6 months: After elimination of purely seasonal fluctuations, the development of our business will be [1] more favorable, [0] about the same, [-1] more unfavorable."*

Table 4.1: Multiple Reported Expectations per Firm and Date: Within-Firm Correlation

	Manufacturing 1990-2015	Services 2004-2015	Retail/Wholesale 1990-2006
# Firm-Date Combinations	968255	325536	238971
# Firm-Date Comb. w. Multiple Reported Expectations	7657	1030	117930
- of Which All Reports Refer to Same Category	6512	841	97129
- of Which Reports Refer to Distinct Categories	1145	189	20801
Fraction of Expectations Diverging from Mode Expectation in Case of Multiple Reports	0.067	0.056	0.063

Notes: This table summarizes the degree to which firms in the different sector-specific surveys provided multiple reports regarding their business expectations for the next six months (Q2) at the same date, i.e., multiple reported expectations per firm-date combination. The frequencies are comparable once computed for the case of Q1 and hence not displayed here. Statistics on firms in the retail and wholesale survey are not displayed for the period after the methodological break in February 2006 as firms always reported to the IBS once per month.

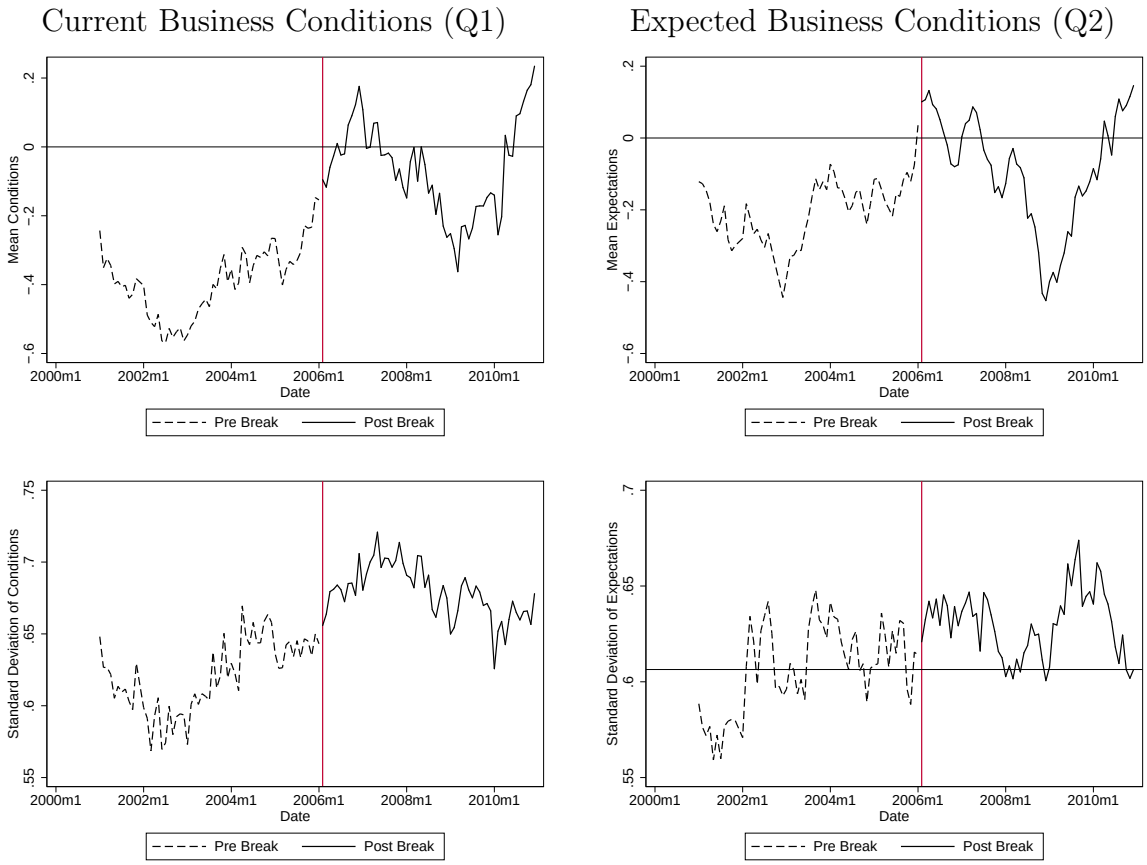
4.2.1 Standardization of Observational Units to the Firm Level

The level of observational units slightly differs across the sector-specific surveys of the IBS as questions either refer to the firm as a whole or to specific products of the firm. Aiming at the construction of a homogeneous data set, I define the firm as the unit of observation and aggregate the micro data to this level. As the anonymized micro data of the IBS do not allow to sharply discriminate between subsidiaries of the same company in different locations and firms reporting to the IBS in one location only, the term "firm" refers to both types of entities interchangeably. As the identification of manufacturing firms is not unambiguous in many cases during the 1980s, I restrict the dataset to observations since 1990.[6]

To begin with, I have to cope with a methodological change in the retail/wholesale survey of the IBS: Since February 2006, firms have been asked to answer each survey question only once while referring to the firm as a whole. Before this date, firms were asked to answer the same set of questions several times for different products on the same questionnaire. As summarized in Table 4.1 for the example of answers to Q2, almost half of the firms (49%) provided assessments of expected business conditions with respect to more than one product per point in time prior to the break.

[6]The micro data of the IBS usually contain an anonymized identification variable "idnum" which originates from IFO's address database. This variable is needed to unambiguously discriminate between firms because the firm-specific identifiers in the IBS micro data ("runnum") of firms that dropped out of the survey could potentially have been assigned to newly entering firms. As the identifier "idnum" is not available for many manufacturing firms during the 1980s, the dataset is restricted to observations since 1990 for which the identifier "idnum" is available. This restriction is not too restrictive in light of the fact that administrative data at the industry-level are only available according to the *WZ 03* and *WZ 08* classification systems since the early 1990s in most cases.

Figure 4.1: Correction of the Methodological Break in Retail/Wholesale Survey



Notes: The figures plot the cross-sectional means (upper graphs) and standard deviations (lower graphs) of current business conditions (left) and expected business conditions (right) of retail and wholesale firms over time. Before January 2006, the reports to the retail and wholesale survey of the IBS referred to different products of the firms. This data is aggregated to the firm level by taking means and rounding to the next integer. Cross-sectional means and standard deviations of the aggregated data are plotted using a dashed line. Accordingly, the solid lines display the cross-sectional means and standard deviations of reports of retail and wholesale firms after February 2006 that referred to the firm as a whole.

Importantly, the answers before the methodological break were almost perfectly correlated within firms at a given point in time. If retail or wholesale firms provided assessments with respect to multiple products at the same date, they reported exactly the same expected business conditions for all products in more than 82% of cases, see Table 4.1. In turn, only 6% of the product-specific expectations differed from the mode expectation of each firm at a given date.

In order to use the entire universe of the micro data in the retail/wholesale survey, I aggregate the data before January 2006 to the firm level by taking arithmetic means of the answers. In light of the strong within-firm correlation in case of multiple reports at a given date, it is reasonable to assume that the current and expected business conditions of each firm are well captured by the average reports with respect to different products. In

case of dissimilar assessments referring to different products, I round the mean response to the next integer. This includes that a mean of "-0.5" is rounded to "-1" for the sake of symmetry. Figure 4.1 plots the time series of cross-sectional means and standard deviations of aggregated reported business conditions and expectations of retail and wholesale firms over time. The graphs indicate that the methodological break between January and February 2006 did not generate differing patterns in the data and that the data before January 2006 can be aggregated to the firm-level without major concerns.[7]

In contrast, the aggregation to the firm-level is more straightforward in the case of the manufacturing and services surveys of the IBS. While the questions in the services survey refer to the firm as a whole, firms in the manufacturing survey are asked for an assessment regarding a specific product. As the latter usually refers to the main product of the firm and firms are usually observed only once per month in the survey, the responses of manufacturing firms are interpreted as referring to the current and expected business conditions of the firm as a whole. In 0.8% (0.3%) of all reporting periods, however, the micro data in the manufacturing (services) survey contain multiple reports per firm at a given date. As documented in Table 4.1, simultaneous reports are usually identical. In turn, only 7% of these multiple reports differ from the mode of the firms' other business expectations reported at the same point in time. Similar to the procedure in the retail and wholesale survey, the small number of multiple observations per reporting month is aggregated to the firm level by taking means and rounding to the next integer.

4.2.2 Harmonization of Industry Classification Systems

As the organization of sector identifiers strongly differs between the different sector-specific surveys of the IBS, I describe the procedure of the assignment of firms to the official *WZ 03* and *WZ 08* classification systems separately for each survey.

Manufacturing Survey

The transfer of sector identifiers to the official *WZ 03* and *WZ 08* classification systems is most straightforward for firms in the manufacturing survey. In the micro data, information about each firm's main sector of business activity is contained in three variables denoted "sector_wz93," "sector_wz08," and "sector_ifo." Importantly, these variables do not only contain sector codes, but also include verbal descriptions for each sector. While "sector_wz93" and "sector_wz08" contain five-digit codes that are roughly equivalent to the official older classification system of 1993 (*WZ 93*) as well as to *WZ 08*, "sector_ifo"

[7]Moreover, the distribution of reported business conditions and expectations for the next six months is similar before and after the break. During the twelve months before the break, firms reported non-neutral current (expected) business conditions in 49% (40%) of the cases. In the year after the break, these numbers were largely comparable (47% and 41%).

refers to a four-digit code that provides additional details about the good produced by the firm. In more than 99% of the observations, all three identifiers are given simultaneously in the dataset.

Based on this information, each observation is assigned to the respective *WZ 08* sector. To begin with, I use the "*WZ 93→WZ 03*" conversion table provided by the Federal Statistical Office, see Destatis (2003) p. 548ff.[8] In some cases, however, the variable "sector_wz93" is empty or only provides information at the three-digit level. I circumvent this problem by using more precise information contained in the variables "sector_wz08" and/or "sector_ifo" to group the observation to the corresponding four-digit group according to *WZ 03*.[9]

In turn, the variable "sector_wz08" is used to assign each observation to a *WZ 08* sector. Again, information from the other sector identifiers is used once the observation cannot directly be grouped to a four-digit *WZ 08* sector based on information contained in "sector_wz08."

Overall, more than 99% of all observations in the manufacturing survey can be assigned to sector identifiers of both classification systems that are informative at least at the four-digit level.

Services Survey

The organization of sector identifiers in the micro data of the services survey differs from the manufacturing survey as there is only one identifier available at any given point in time. Firms have been coded with respect to the *WZ 08* classification system only since April 2011. Before this date, the micro data contain sector identifiers according to the older *WZ 03* classification system.[10]

Updating the sector identifiers in 2011, the practitioners of the IFO Institute assigned each firm "by hand" to the *WZ 08*-industry that was most consistent with its actual business. Hence, the transfer of firms from *WZ 03* to *WZ 08* does not necessarily coincide

[8] In fact, the *WZ 03* classification system is only marginally different from the older *WZ 93*, while the replacement of *WZ 03* by *WZ 08* constituted a major re-organization of the classification system.

[9] For example, an observation classified as "sector_wz93=29400 Manufacture of machine tools" and "sector_wz08=28410 Manufacture of metal forming machinery" is grouped to the *WZ 03*-industry "29420 Manufacture of machine-tools for metalworking." Moreover, if information is only available at the three-digit level in all sector identifiers, I group this observation to the most general four-digit code, e.g., "1530(0) Processing and preserving of fruit and vegetables" is grouped to "1533(0) Processing and preserving of fruit and vegetables, not elsewhere classified." Obviously, this adjustment is only relevant if administrative data at the four-digit level is merged to the firms in the IBS because the code "15.30" does not exist in the official version of the *WZ 03* classification system.

[10] In a small number of cases, the respective variables "sector_wz03" and "sector_wz08" only provide information at the two-digit or three-digit level. As in the case of the manufacturing survey, I group these observations to the most general four-digit code, e.g., "6200(0) Computer programming, consultancy and related activities" is grouped to "6209(0) Other information technology and computer service activities."

with the official conversion table provided by the Federal Statistical Office. Therefore, it is convenient to assign each firm's post-break *WZ 08* identifier to the period before the break. Following this procedure, 78% of all observations prior to March 2011 can be matched to sector identifiers according to *WZ 08*. The remaining observations are assigned to the mode *WZ 08* identifier of firms in the same three-digit industry according to *WZ 03*. Accordingly, the pre-break *WZ 03* identifiers are forwarded to the post-break era.

Retail and Wholesale Survey

The methodological break in the questionnaires of the retail and wholesale survey in 2006 involves a change in the organization of sector identifiers. Since February 2006, firms have been classified according to the *WZ 03* classification system. During this period, *WZ 03*-specific identifiers can directly be used without major corrections and transferred to the *WZ 08* classification using the "*WZ 03*→*WZ 08*" conversion table provided by the Federal Statistical Office, see Destatis (2008) p. 663ff.[11]

Until January 2006, each observation is classified in accordance with an IBS-specific product classification system that is more detailed than the *WZ 03* or *WZ 08* industry classifications. The respective identifier, denoted as "sector_ifo," contains a verbal description of the good and is usually accompanied with a variable, denoted "typtra," indicating whether the firm is a retailer or a wholesaler. I assign each combination of "sector_ifo" and "typtra" to the corresponding *WZ 03* and *WZ 08* identifiers "by hand."

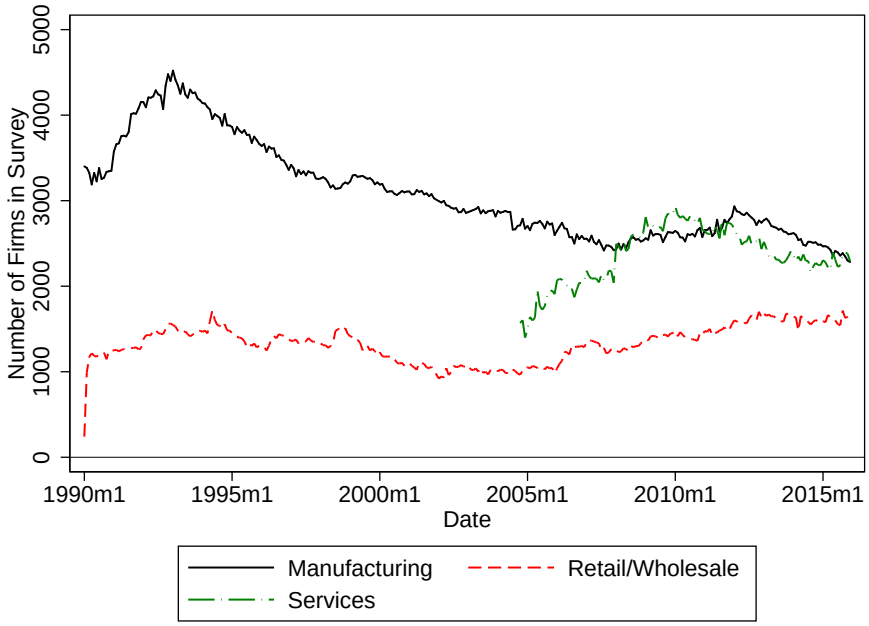
To complicate things, retail and wholesale firms in East Germany were coded differently prior to 2006. In contrast to their counterparts in West Germany, the variable "sector_ifo" is very close to the *WZ 03* classification system in the case of East German firms. For example, the code "sector_ifo=[51550] chemical products" can only be found for East German firms. Therefore, this observation is assigned to the *WZ 03*-industry "[51550] Wholesale of chemical products." In contrast, the combination "sector_ifo=[51590] cosmetic articles and personal hygiene articles" and "typtra=1" (retail) is unique to West German firms and hence assigned to the *WZ 03*-industry "[52331] Retail sale of cosmetic and toilet articles."[12]

In order to finalize the standardization of observational units to the firm-level described

[11] In order to be able to match data from administrative sources at the four-digit level to the micro data of the IBS, I need to correct for minor deviations of the sector identifier in the IBS from the official *WZ 03* system. For example, the IBS-codes "[50131] Retail sale of new motor vehicles" and "[50132] Retail sale of used motor vehicles" are assigned to the official *WZ 03*-code "[50103] Retail sale of motor vehicles."

[12] Moreover, there is a third classification that covers all East German firms until June 1998 on a very rough scale that cannot be transferred to the more precise *WZ 03* and *WZ 08* classification systems. The sector identifier of these firms is set to missing.

Figure 4.2: Number of Firms in the Different Sector-Specific Surveys of the IBS



Notes: This figure plots the number of firms in the respective sector-specific surveys of the IBS over time conditional on responding to the survey in at least two months.

in Section 4.2.1, firms with multiple observations per period in time, which potentially are grouped to different sector identifiers, are assigned to unique *WZ 03* and *WZ 08* codes in each period. I proceed in the following steps: first, I use the sector identifier referring to the first product of each firm in every period if all sector identifiers are identical or within the same four-digit group. Second, I match the sector identifiers of firms that are still ambiguous to the unique identifier of February 2006 if the firm "survives" the methodological break. Third, if firms are not observed after the break in 2006 and observations are not within the same four-digit sector, but in the same three-digit group, I assign the firm to the mode sector of all observations at a given point in time. Lastly, the remaining observations are grouped to a unique sector identifier by hand.[13]

4.2.3 Descriptive Statistics of Harmonized IBS Micro Data

The harmonized sample of the IBS comprises of on average approximately 5500 reports of firms per month between 1990 and 2015 if the data is restricted to firms that responded to the survey in at least two months. As displayed in Figure 4.2, the number of reporting firms per survey period is largest in the manufacturing survey (on average approximately 3100 firms), but steadily declining over time. In contrast, the number of firms in the retail and wholesale survey has been relatively constant (on average roughly 1300 firms). Moreover, an average number of 2300 firms has responded to the services survey since its introduction in October 2004.

Conditional on responding to the survey more than once, attrition is very low and firms are observed for 7.5 years on average.[14] While attrition of firms is not found to be random, dropout of firms does not appear to be problematic for most research questions. As documented in Column (1) of Table 4.2, firms reported current business conditions—coded on a trichotomous scale with values $\{-1, 0, 1\}$—that were significantly worse by -0.12 on average during the last month in the sample compared to the mean of reported business conditions in all other observations.[15] However, dropout of firms does not appear to be driven by industry-specific shocks because the estimated average condition in the month prior to firms' dropout is largely unaffected by the inclusion of date fixed effects at the level of four-digit industries, see Column (2). In contrast, the coefficient drops by more than half after controlling for firm fixed effects in Column (3). Hence, firms that drop out of the sample generally performed worse during all other periods compared to the remaining firms. Furthermore, the pattern of attrition does not appear to have changed substantially over time. As can be inferred from Table 4.A.1 in the Appendix, the survival rates are rather constant across different cohorts of firms.

Moreover, the response rates to the survey are relatively high despite of the fact that participation is voluntary. On average, firms answer the questionnaire in 80.3% of months

[13] If the remaining firms have distinct sector identifiers in less than three months, these observations are assigned to the sector code of the previous month. Moreover, there are 23 retailers of food in the groups *WZ 03*:52110/ *WZ 08*:47110 ("Retail sale in non-specialized stores with food, beverages or tobacco predominating") and *WZ 03*:52200/ *WZ 08*:47200 ("Retail sale of food, beverages and tobacco in specialized stores") which are manually assigned to group *WZ 03*:52270/ *WZ 08*:47290 "Other retail sale of food, beverages and tobacco in specialized stores." In addition, 27 retailers of cars and motorcycles including their maintenance are sorted to *WZ 03*:50103/ *WZ 08*:45110 "Retail sale of cars." The remaining firms with ambiguous sector identifiers are assigned to groups *WZ 03*:52120/ *WZ 08*:47789 "Other retail sale" if they are retailers or *WZ 03*:51900/ *WZ 08*:46900 "Other wholesale" if they are wholesalers.

[14] The average duration in the data set of firms in the different sector-specific surveys respectively is 9.4 years (manufacturing), 6.5 years (retail and wholesale), and 5.4 years (services).

[15] The respective empirical model reads: $\text{Conditions}_{i,t} = (\beta_0+)\beta_1 \times \mathbb{1}(\text{Last Observation of Firm in Sample}_i) + (\alpha_i + \delta_t \times \mathbb{1}(\text{Sector}_i)) + \varepsilon_{i,t}$, where $\text{Conditions}_{i,t}$ denotes current business conditions as reported to Q1, $\mathbb{1}(\text{Last Observation of Firm in Sample}_i)$ is a dummy that is one during the last date firm i is observed in the sample and α_i and $\delta_t \times \mathbb{1}(\text{Sector}_i)$ are firm fixed effects and time fixed effects at the four-digit industry level.

Table 4.2: Relationship Between Business Conditions and Sample Attrition

	Current Business Condition$_t$		
	(1)	(2)	(3)
$\mathbb{1}$(Last Observation of Firm in Sample$_i$)	-0.12***	-0.10***	-0.044***
	(0.0051)	(0.0050)	(0.0044)
Constant	yes		
Firm FE			yes
Time*4-dig. Sector FE		yes	yes
R^2	0.095	0.224	0.462
Observations	1698864	1698864	1692297

Notes: The dependent variable is the firms' reported current business situation to Q1 of the IBS. $\mathbb{1}$(Last Observation of Firm in Sample$_i$) is a dummy that is one during the last date firm i is observed in the sample. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and response rates do not differ substantially between firms in the industry surveys on manufacturing (82.0%), retail and wholesale (79.0%), and services (77.1%). Even though the response rate of firms is high, researchers working with the micro data of the IBS might need to deal with non-response of firms if their empirical approach is based on firms' reports to the IBS in several consecutive months, for example. In order not to lose too many observations, one possibility is to linearly interpolate missing answers to the survey question of interest as long as the gap in the data is shorter than a predefined number of periods. If missing answers to Q1 are interpolated as long as answers are missing for at most two consecutive months, for example, the "artificial" response rate increases to 87.6% on average. As documented in Figure 4.A.1 in the Appendix, the interpolated responses do not differ substantially from the answers originally contained in the dataset.[16]

4.3 Interpretation of Current and Expected Business Conditions in the IBS

This section uses the harmonized firm-level data of the IBS in order to shed light on the interpretation of the survey questions regarding firms' assessments about their current business conditions (Q1) as well as their expectations for the next six months (Q2). Unfortunately, the wording of the questions is rather vague with respect to the dimension

[16]See Seiler (2014) for a more detailed analysis on the determinants of non-response in the IBS. Moreover, Seiler and Heumann (2013) provide a statistical analysis of different imputation methods and conclude that the bias due to non-response does not significantly reduce the forecasting performance of the IFO Business Climate Index that is based on the micro data of the IBS.

and the benchmark of the latent variable firms are supposed to refer to in Q1 and Q2.[17] On the one hand, the wording of Q1 appears to ask for an assessment of the *level* of firms' current business conditions, e.g., as being "good." However, Q1 does not set a benchmark to which firms should relate this level, for example as a deviation from the trend. On the other hand, Q2 is formulated using relative terms such as "more favorable" but does not provide an explicit benchmark, either. The more natural interpretation is that firms relate the expected development of their business conditions during the next six months to the situation prevalent in the reporting month. In this case, Q2 would capture the expected *change* in business conditions. However, it is also reasonable that firms opting for "[1] more favorable" in Q2 expect that their business conditions in the next six months will be more favorable compared to the trend. Then, Q2 would capture the expected *level* of future business conditions.

The majority of studies that used the IBS data at aggregated levels implicitly interpreted both survey questions along the same dimension. For example, there is a large literature on the forecasting properties of the "IFO Business Climate Index" (henceforth, IBC) which is calculated as a weighted average of firms' responses to Q1 and Q2.[18] These studies relate the IBC to time series such as aggregate production indices or GDP. Thereby, the respective authors implicitly assume that the IBC can be interpreted in a sensible way, i.e., that Q2 is not capturing the expected change in Q1.[19]

While time series of aggregated survey results have frequently been used in the literature, micro-econometric analyses that exploit the cross-sectional variation in firms' responses to Q1 and Q2 are rare. In the majority of these cases, the relationship between current and expected business conditions is not at the heart of the econometric analysis and reports to Q1 (or Q2) serve as covariates that control for firm-specific business conditions in other contexts.[20] These studies usually do not provide an interpretation of the

[17]It is important to note that the IFO Institute deliberately does not provide a latent variable when asking Q1 and Q2 in order to capture the "sentiment" of firms as closely as possible in the "IFO Business Climate Index." Given this flexibility, each firm can assess its current and expected business conditions according to the variable that is most relevant in the context of its business. I thank Klaus Wohlrabe from the IFO Institute for pointing this out.

[18]See Abberger and Wohlrabe (2006) for a survey of the literature on the forecasting properties of the IBC. Precisely, the IBC is calculated as the average between the weighted mean of firms' reported current business conditions from Q1 and the weighted mean of firms' business expectations from Q2.

[19]In contrast, the "IFO Business Cycle Clock," which portrays the two components of the IBC in a four-quadrant scheme, provides an exemption. For example, Abberger and Nierhaus (2011) follow this method and relate average reports to Q1 to the deviation of real GDP from its trend as well as Q2 to changes in this measure.

[20]For example, Fidrmuc and Hainz (2013) control for firms' reported business conditions when assessing the effect of banking regulation on cross-border lending. The same applies to Bachmann et al. (2013a) and Kleemann and Wiegand (2014) who use answers to Q1 and Q2 as covariates when examining the relationship between business volatility and price setting of firms as well as the role of real effects for credit supply, respectively. A notable exemption is Buchen (2013), who analyzes the relationship between mass media and the expectation formation of firms. Her dependent variable is based on Q2, while firms'

survey questions as the reading of their main results is not depending on this issue.

The following analysis takes a step in the direction of a better understanding of the interpretation of Q1 and Q2. First, Section 4.3.1 summarizes evidence from the analysis of time series of average reported realized and expected business conditions and exploits the newly-created possibility to match industry-specific revenue data to the IBS. Second, Section 4.3.2 provides insights from panel regressions at the firm-level.

4.3.1 Insights from Aggregate Time Series

This section provides evidence for the interpretation of the survey questions Q1 and Q2 by means of analyzing firms' average reports of current and expected future business conditions. For this purpose, I exploit the possibility that administrative data of industry-level revenues can be matched to the harmonized IBS data and compared to average responses of firms. Moreover, the relationship between Q1 and Q2 is directly examined by comparing the time series of average reported current and expected future business conditions.

4.3.1.1 Current Conditions: Relation to Administrative Revenue Data

In a meta-study of the retail and wholesale survey conducted by Abberger et al. (2009), firms stated to mostly refer to profits or revenues when being asked for an assessment of their current business situation in Q1 of the IBS. Unfortunately, firm-level data on revenues or comparable measures are not available at monthly frequency. I circumvent this problem by using monthly time series of seasonally adjusted revenues ($\text{Revenues}_{s,t}$) at the level of four-digit industries s in the manufacturing as well as retail/wholesale sector provided by the German Federal Statistical Office. In lack of more detailed data, I furthermore use quarterly data of seasonally adjusted revenues at the two-digit industry level in the services sector.[21] For the sake of comparability to the time series of average reported business conditions ($\overline{\text{Cond}}_t$), the industry-level time series are weighted by the share of firms in the respective sectors of the IBS (ω_s), i.e., $\overline{\text{Revenues}}_t = \sum_s \omega_s \text{Revenues}_{s,t}$.[22] In

reported business conditions (Q1) are in the control vector. However, her paper neither provides an interpretation of Q1 and Q2, nor displays the coefficient that captures the relationship between current conditions and expectations.

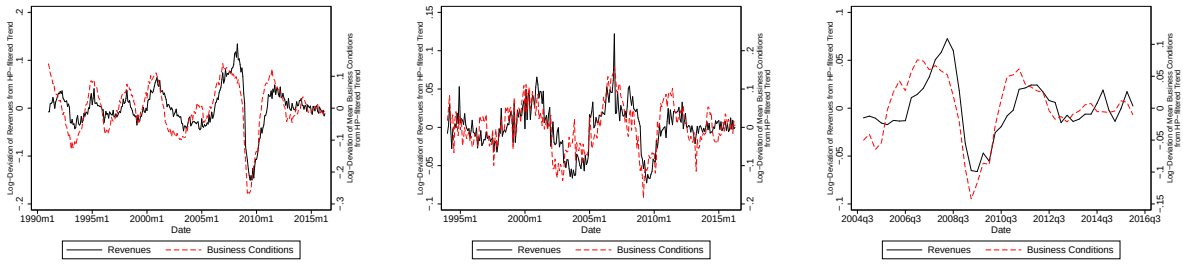
[21] The following time series of seasonally adjusted revenue indices are downloaded from Destatis' GENESIS database: Manufacturing (code 42152/period 1992-2015/monthly frequency/4-digit industry level) as well as Retail and Wholesale (45211,45212,45214/1994-2015/monthly/4-digit), and Services (47414/2005-2015/quarterly/2-digit). In turn, average conditions are deseasonalized using fixed effects for each month.

[22] It is important to note that it is not reasonable to compare average business conditions and revenues separately for each industry because the number of firms in the IBS is too low in most four-digit industries. Consequently, the correlation between both time series is usually quite low due to the trichotomy of the survey data.

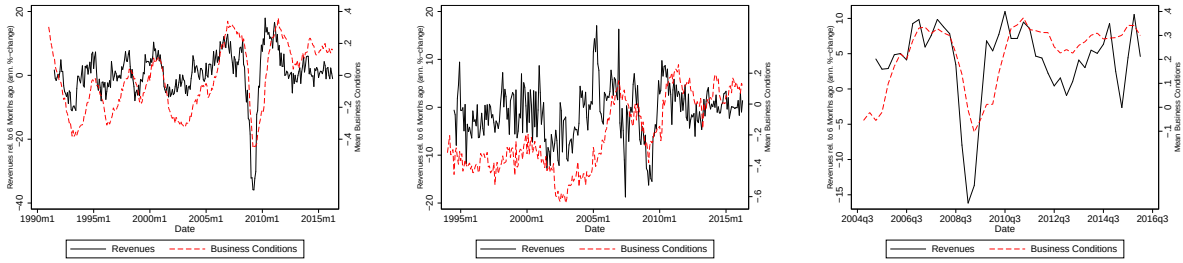
Figure 4.3: Average Business Conditions Relative to Administrative Revenue Data

Manufacturing Retail & Wholesale Services

Panel A: Mean Realized Business Conditions vs. Level of Revenues



Panel B: Mean Realized Business Conditions vs. Past Changes in Revenues



Notes: Panel A plots the mean current business conditions as reported to Q1 in the IBS (right axis) against the mean of industry-specific, seasonally adjusted revenue indices weighted by the number of firms in each industry (left axis). Mean business conditions are deseasonalized by purging for month fixed effects. For the subset of services firms, mean business conditions are transferred to quarterly frequency by taking means as revenue data are only available on a quarterly basis. Both time series are detrended using the log-deviation from an HP-filtered trend with smoothing parameter $\lambda = 129,600$ (1,600) for monthly (quarterly) data. Panel B plots mean current business conditions (right axis) against the annualized change in weighted revenues relative to six months before reporting date t (left axis).

the case of the services survey, the time series of average business conditions is transferred to quarterly frequency by taking means.

On average, the level of reported business conditions closely tracks the variation in administrative revenue data. This can be inferred from Panel A of Figure 4.3, which displays the detrended time series $\overline{\hat{\text{Cond}}}_t$ and $\overline{\hat{\text{Revenues}}}_t$, i.e., the log-deviation of average conditions and revenues from an HP-filtered trend with the standard smoothing parameters of $\lambda = 129,600$ (1,600) for monthly (quarterly) data suggested by Ravn and Uhlig (2002). Both series are strongly correlated despite of the fact that the IBS data are only qualitative in nature and the revenue data are quantitative. In the case of the manufacturing and services surveys, $\overline{\hat{\text{Cond}}}_t$ precede $\overline{\hat{\text{Revenues}}}_t$ and the time series correlation is highest if average business conditions are lagged by three months/one quarter, i.e., $\rho(\overline{\hat{\text{Revenues}}}_t, \overline{\hat{\text{Cond}}}_{t-3}) = 0.85$ and 0.84, respectively. In the case of the retail and wholesale sector, the time series correlation is highest at contemporaneity ($\rho(\overline{\hat{\text{Revenues}}}_t, \overline{\hat{\text{Cond}}}_t) = 0.72$) although revenues and average business conditions fluctuate

much more erratically around their trends.[23]

Further, the relationship between average reported business conditions and past changes in revenues is examined. As shown in Panel B of Figure 4.3, $\overline{\text{Cond}}_t$ is positively correlated with the time series of annualized changes in weighted revenues relative to six months before reporting date t, denoted $\Delta\overline{\text{Revenues}}_{t,t-6}$. In contrast to the "level"-interpretation of Panel A, average reported conditions lag past changes in revenues by four months in the case of the manufacturing survey, six months in the retail/wholesale survey, and one by quarter in the services survey. While the correlation between both series is still relatively high (albeit lower than in Panel A) in the case of the manufacturing and services surveys ($\rho(\Delta\overline{\text{Revenues}}_{t-4,t-10}, \overline{\text{Cond}}_t) = 0.72$ and $\rho(\Delta\overline{\text{Revenues}}_{t-3,t-9}, \overline{\text{Cond}}_t) = 0.70$), the relationship is much weaker in the subset of retail and wholesale firms ($\rho(\Delta\overline{\text{Revenues}}_{t-6,t-12}, \overline{\text{Cond}}_t) = 0.39$). The comparison of average business conditions and revenue data hence points into the direction of interpreting current business conditions reported to Q1 in levels rather than changes relative to previous periods.

4.3.1.2 Interpretation of Expected Future Business Conditions

Next, the analysis focuses at the interpretation of firms' expected future business conditions reported to Q2. While the wording of the question refers to an expected *change* in future business conditions, the evidence presented in the following points more into the direction of an interpretation in *levels*, i.e., that firms reporting to expect "more favorable" business conditions expect their future business conditions to be above the trend rather than to increase relative to today's levels.

To begin with, I compare the time series of average expected future business conditions in the next six months (Q2), denoted $\overline{\text{Exp}}_t^{+6m}$, to average realized business conditions (Q1). Panel A of Figure 4.4 plots the log-deviation of average realized and expected future business conditions from the HP-filtered trend with $\lambda = 129,600$.[24] Both time series are highly correlated across all sector-specific surveys. As expected, the time series of average (detrended) business expectations precede the mean levels in realized business conditions. In the manufacturing and services surveys, the correlation between both time series is largest if average business expectations are lagged by five months, which closely

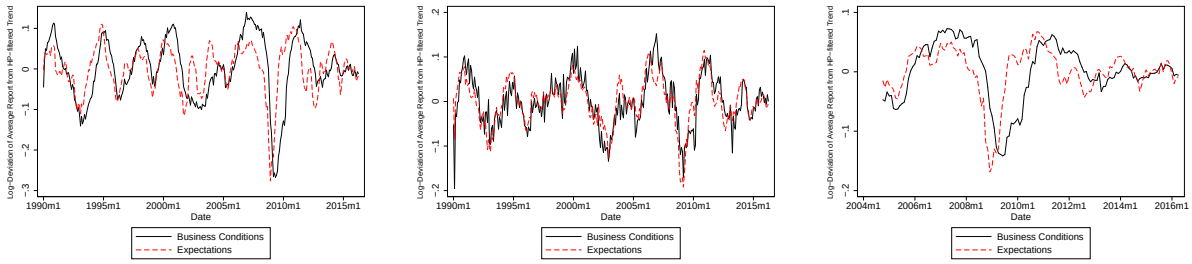
[23]The respective cross-correlograms are presented in Table 4.B.1 in the Appendix. Alternatively, the time series can be detrended using growth rates. As shown in Figure 4.B.1 in the Appendix, the growth rate in revenues closely fits the growth rates in average reported business conditions.

[24]Deviations from the HP-filtered trend are chosen for the sake of comparability to the results presented in Figures 4.3 and 4.6. Figure 4.B.2 in the Appendix plots the time series of average business conditions and expectations without detrending (Panel A). Further, Panel B of Figure 4.B.2 displays the mean reports to Q1 and Q2 after purging for firm fixed effects in order to control for time-invariant firm-specific optimism or pessimism as documented by Bachmann and Elstner (2015) in a related context. The results do not deviate substantially from those using deviations from the HP-filtered trend.

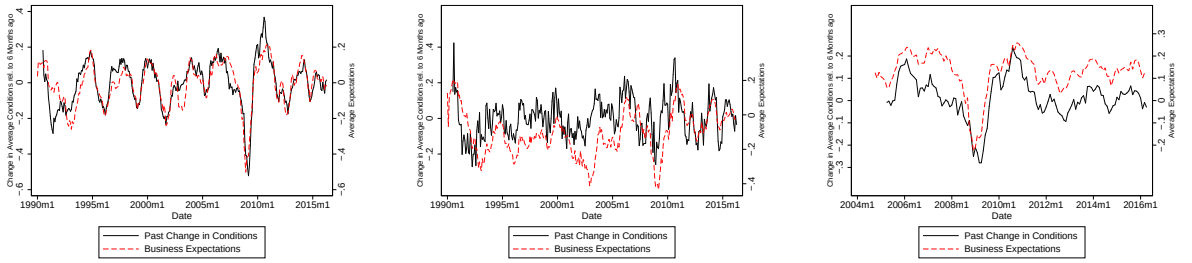
Figure 4.4: Average Business Conditions Relative to Average Business Expectations

Manufacturing Retail & Wholesale Services

Panel A: Mean Expectations vs. Mean Realized Business Conditions



Panel B: Mean Expectations vs. Past Changes in Mean Realized Business Conditions

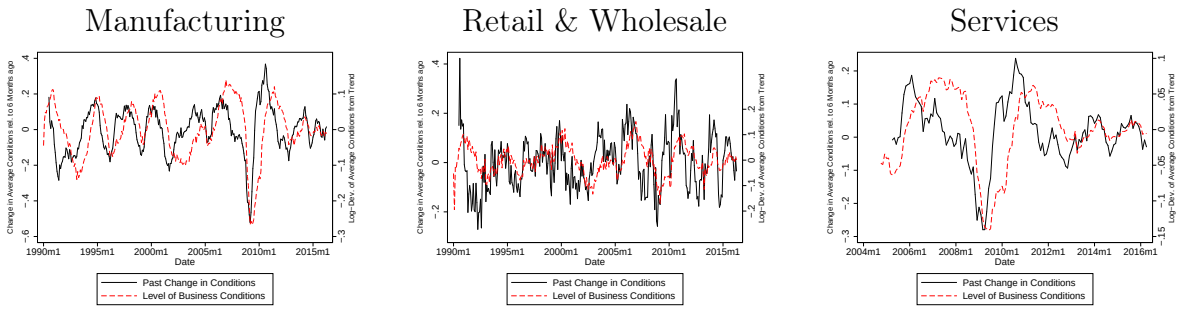


Notes: Panel A plots the time series of seasonally adjusted mean reports on current business conditions (Q1) and expected business conditions for the next six months (Q2) of firms in the respective industry surveys of the IBS. The time series are seasonally adjusted by controlling for month fixed effects. Both time series are detrended using the log-deviation from an HP-filtered trend with smoothing parameter $\lambda = 129,600$ (1,600) for monthly (quarterly) data. Panel B plots mean expected business conditions (right axis) against the change in average realized business conditions (Q1) relative to six months before reporting date t (left axis).

corresponds to the forecast horizon in Q2 ($\rho(\overline{\hat{\text{Exp}}}_t^{+6m}, \overline{\hat{\text{Cond}}}_{t+5}) = 0.81$ in both surveys). In the case of the retail and wholesale survey, the correlation between both time series is strongest at contemporaneity ($\rho(\overline{\hat{\text{Exp}}}_t^{+6m}, \overline{\hat{\text{Cond}}}_t) = 0.82$).

Then, I examine the interpretation that is closest to the wording of the questions, i.e., that Q1 refers to an expected *change* in future business conditions captured by Q2. As displayed in Panel B of Figure 4.4, the time series of average expectations and the change in average realized business conditions during the last 6 months are strongly correlated in the case of the manufacturing and services surveys. However, average expectations do not appear to precede changes in average business conditions because the correlation between the time series is highest at *contemporaneity* in both cases, i.e., $\rho(\overline{\text{Exp}}_t^{+6m}, (\overline{\text{Cond}}_t - \overline{\text{Cond}}_{t-6})) = 0.85$ and 0.89 in the manufacturing and services survey, respectively. As can be inferred from the cross-correlograms in Table 4.B.2 in the Appendix, the time series correlation between mean expectations regarding the next six months and the subsequently realized change in business conditions during the next six

Figure 4.5: Relationship Between Past Changes and Future Levels in Business Conditions



Notes: Time series of the change in average realized business conditions (Q1) relative to six months before reporting date t (left axis) are plotted against the detrended level of average reported current business conditions (Q1) (right axis). The latter time series is detrended using the log-deviation from an HP-filtered trend with smoothing parameter $\lambda = 129,600$. Both time series are seasonally adjusted by controlling for month fixed effects.

months ($\overline{\text{Cond}}_{t+6} - \overline{\text{Cond}}_t$) is much lower, i.e., $\rho = 0.28$ (manufacturing) and 0.34 (services).

Furthermore, the relationship between Q2 and changes in Q1 is much worse in the subset of retail and wholesale firms. Here, the correlation between both time series is much weaker than in the first scenario. The correlation coefficient is highest at the third lead of business expectations, i.e., once expectations formulated in month t are compared to the change in conditions between three and nine months in the past ($\rho(\overline{\text{Exp}}_t^{+6m}, (\overline{\text{Cond}}_{t-3} - \overline{\text{Cond}}_{t-9})) = 0.54$). On top of this, the correlation between expectations and future realized changes in business conditions even turns negative ($\rho(\overline{\text{Exp}}_t^{+6m}, (\overline{\text{Cond}}_{t+6} - \overline{\text{Cond}}_t)) = -0.13$).

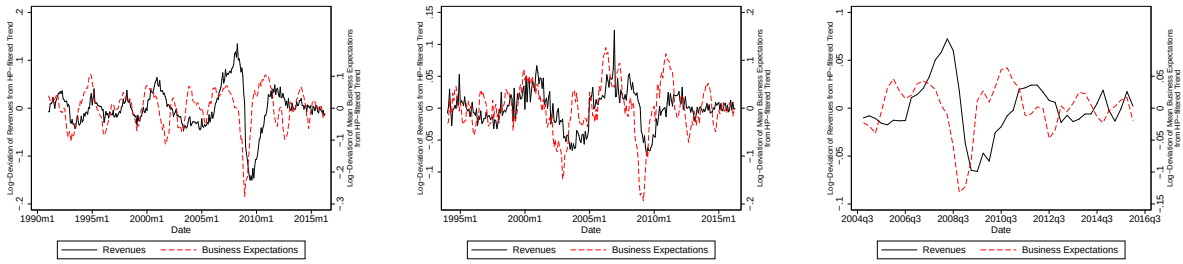
The high correlation between past changes in Q1 and average business expectations documented in Panel B for the case of manufacturing and services firms could be reconciled with the "level"-interpretation of Panel A if past changes in realized conditions were a strong predictor for their future level. Figure 4.5 points into exactly this direction as changes in business conditions of manufacturing and services firms during the previous six months are indeed strongly correlated with the subsequent deviation of business conditions from their trend. Interestingly, this pattern is much weaker in the case of retail and wholesale firms which possibly explains the lower correlation between their average expectations and past changes in realized business conditions.

Relating average expectations about future business conditions to administrative revenue data delivers a comparable picture. Average reported business expectations of firms precede the *level* of administrative revenue data in all sector-specific surveys. Panel A of Figure 4.6 displays the detrended time series $\overline{\hat{\text{Exp}}}_t^{+6m}$ and $\overline{\hat{\text{Revenues}}}_t$. In the case of the retail and wholesale survey, the time series correlation is highest if expectations

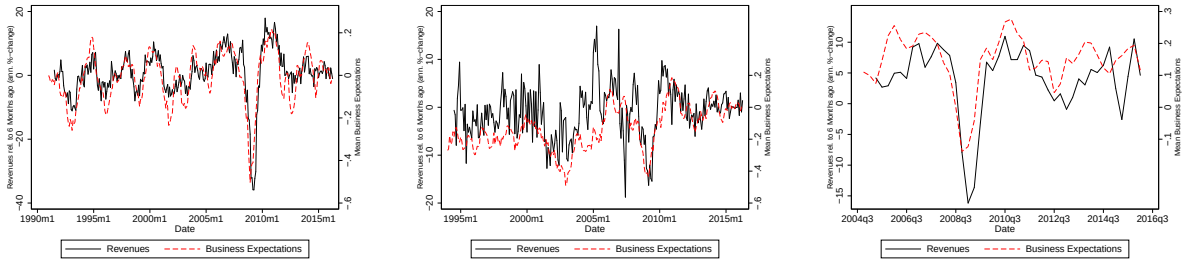
Figure 4.6: Average Business Expectations Relative to Administrative Revenue Data

Manufacturing Retail & Wholesale Services

Panel A: Mean Expectations vs. Level of Revenues



Panel B: Mean Expectations vs. Past Changes in Revenues



Notes: Panel A plots the mean expected business conditions for the next six months as reported to Q2 in the IBS (right axis) against the mean of industry-specific, seasonally adjusted revenue indices weighted by the number of firms in each industry (left axis). Mean business expectations are deseasonalized by purging for month fixed effects. For the subset of services firms, mean business expectations are transferred to quarterly frequency by taking means as revenue data are only available on a quarterly basis. Both time series are detrended using the log-deviation from an HP-filtered trend with smoothing parameter $\lambda = 129,600$ (1,600) for monthly (quarterly) data. Panel B plots mean expected business conditions (right axis) against the annualized change in weighted revenues relative to six months before reporting date t (left axis).

precede revenues by six months ($\rho(\overline{\hat{\text{Revenues}}}_t, \overline{\hat{\text{Exp}}}^{+6m}_{t-6}) = 0.71$). In the case of the manufacturing (services) survey, the time series correlation is highest if average business expectations are lagged by eight months (three quarters), i.e., $\rho(\overline{\hat{\text{Revenues}}}_t, \overline{\hat{\text{Exp}}}^{+6m}_{t-8}) = 0.63$ ($\rho(\overline{\hat{\text{Revenues}}}_t, \overline{\hat{\text{Exp}}}^{+6m}_{t-9}) = 0.75$). The finding that expectations preceded revenues by more than six months in the latter two cases is in line with the observation in Section 4.3.1.1 that the level of realized business conditions preceded the time series of revenues by three months in the manufacturing and services surveys.

In contrast, expectations do not precede future changes in revenues to a degree that is comparable to the "level"-interpretation. For the case of the manufacturing and services survey, average expectations are again highly correlated with past changes in revenues, see Panel B of Figure 4.6 and the cross-correlograms summarized in Table 4.B.3 in the Appendix. The correlation between the time series approaches its maximum at the second lag of expectations in the subset of manufacturing firms, i.e., $\rho(\overline{\text{Exp}}^{+6m}_{t-2}, \Delta\overline{\text{Revenues}}_{t,t-6}) =$

0.82. Similarly, the correlation between both series is highest if expectations are lagged by one quarter in the services survey, i.e., $\rho(\overline{\text{Exp}}_{t-3}^{+6m}, \Delta\overline{\text{Revenues}}_{t,t-6}) = 0.84$. Comparable to the evidence from Panel B of Figure 4.4, the relationship between expectations and changes in revenues is much weaker for the case of retail and wholesale firms. Here, the correlation is largest if expectations are related to the change in revenues between seven and one months prior to the date when expectations are reported to the IBS, i.e., $\rho(\overline{\text{Exp}}_{t}^{+6m}, \Delta\overline{\text{Revenues}}_{t-1,t-7}) = 0.47$.

Taken together, the evidence presented in this section appears to be more consistent with the "level"-interpretation of Q2. In this case, Q2 captures the expected level of future business conditions being above/below the trend instead of the expected future change in conditions relative to the level in the reporting month. With the exception of the retail and wholesale survey, the latter interpretation cannot be ruled out with certainty, however, as expectations stated in Q2 appear to reflect past changes in business conditions and revenues to a comparable degree.

4.3.2 Relationship Between Survey Questions: Panel Regressions

The evidence based on aggregate time series presented in the previous section showed that it is reasonable to interpret firms' assessments of their current business conditions in levels. In contrast, the picture is less clear regarding the interpretation of firms' expectations about their business conditions in the next six months. The evidence points into the direction of interpreting expected conditions along the same lines as current conditions, while the analysis could not rule out that Q2 captures the expected future changes in Q1. In order to shed more light on the interpretation of the two main questions in the IBS, this section takes a step forward by exploiting the panel dimension of the micro data.

For this purpose, I compare the degree to which firms' expectations about business conditions during the next six months either reflect the *level* of ex post realized future business conditions or represent the ex post realized *change* in future business conditions compared to the reporting month. Specifically, I perform several regressions of the following form

$$\text{Exp}_{i,t}^{+6m} = \beta_{\mathbf{1}}' \, \mathbf{Cond}_{i,t+l} + \beta_{\mathbf{2}}' \, \mathbf{\Delta Cond}_{i,(t+l,t+l-6)} + \alpha_i + \varepsilon_{i,t}, \tag{4.1}$$

where $\text{Exp}_{i,t}^{+6m}$ denotes firm i's expectations for the next 6 months reported in month t to Q2. The column vector $\mathbf{Cond}_{i,t+l}$ subsumes business conditions reported to Q1 l months after reporting month t. In turn, the column vector $\mathbf{\Delta Cond}_{i,(t+l,t+l-6)}$ refers to the six-month change in business conditions at different points in time. I also add firm fixed effects α_i to control for time-invariant patterns in the expectation formation process of

firms.[25] The vectors $\beta_{\mathbf{1}}$ and $\beta_{\mathbf{2}}$ entail the coefficients of interest that capture the degree to which expectations reflect future levels or changes of business conditions.

First, the level of business conditions realized six months after reporting date t is strongly reflected in previously stated expectations. Column (1) of Table 4.3 displays the results from regressing $\text{Exp}_{i,t}^{+6m}$ on $\text{Cond}_{i,t+6}$ along with firm fixed effects. As standard deviations of $\text{Exp}_{i,t}^{+6m}$ and $\text{Cond}_{i,t+6}$ are of comparable size, the estimated coefficient $\hat{\beta}_1$ can be interpreted such that a one standard deviation increase in the level of ex post realized business conditions in $t+6$ is *ceteris paribus* associated with an appreciation of expectations by 0.18 standard deviations in the panel of manufacturing, 0.16 standard deviations for retailers and wholesalers as well as 0.13 standard deviations for firms in services.

As displayed in Column (2), the inclusion of the current level of business conditions does not substantially alter the degree to which ex post realized business conditions in $t+6$ are captured by expectations in the subset of manufacturing firms and services companies. Hence, firms incorporate at least some information about the future level of business conditions into their expectations that is not captured by their current business condition. This effect is also prevalent in the retail and wholesale sector although the coefficient capturing the effect of $\text{Cond}_{i,t+6}$ drops to 0.09 after controlling for $\text{Cond}_{i,t}$.[26]

Second, firms' expectations are less strongly associated with the ex post realized change in business conditions during the next six months ($\Delta\text{Cond}_{i,(t+6,t)}$). The results summarized in Column (3) show that future changes in conditions are much less strongly reflected in expectations compared to the future level in realized business conditions documented above. In the case of manufacturing firms, $\hat{\beta}_2$ is only slightly positive and an increase in $\Delta\text{Cond}_{i,(t+6,t)}$ by one standard deviation is associated with an appreciation in $\text{Exp}_{i,t}^{+6m}$ by 0.014 standard deviations, only. This relationship is also relatively small ($\hat{\beta}_2 = 0.045$) in the subset of services firms and even turns negative in the case of retail and wholesale firms ($\hat{\beta}_2 = -0.10$).

Including the change in business conditions during the previous six months to model (4.1) does not substantially alter the degree to which future changes in business conditions between $t+6$ and t are captured by expectations, see Column (4). Past changes in conditions are reflected more strongly in the expectations of manufacturing firms as

[25] For example, firm fixed effects control for persistence in optimism or pessimism of firms as documented by Bachmann and Elstner (2015). The results do not differ once firm fixed effects are omitted from the estimation as documented in Table 4.B.4 in the Appendix. Moreover, the results are robust to the inclusion of time fixed effects as shown in Table 4.B.5. While time fixed effects control for the general business cycle in business expectations, they also reduce the dimension of information reflected by the other independent variables. The implications for the understanding of firms' expectation formation process are discussed in Chapter 1.

[26] This pattern is most likely due to heterogeneity in the forecast horizons of firms in the different sector-specific surveys of the IBS. See Chapter 1 for a detailed analysis of this issue.

Table 4.3: Relationship Between Survey Questions: Panel Regressions

	Expected Business Conditons for the Next 6 Months							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Manufacturing							
Conditions_{t+6}	0.18***	0.13***			0.19***			
	(0.0060)	(0.0054)			(0.0075)			
Conditions_{t}		0.10***				0.018***		
		(0.0053)				(0.0053)		
$(\text{Conditions}_{t+6} - \text{Conditions}_{t})$			0.014***	0.069***	-0.050***			
			(0.0040)	(0.0046)	(0.0066)			
$(\text{Conditions}_{t} - \text{Conditions}_{t-6})$				0.15***	0.082***			
				(0.0054)	(0.0049)			
$\overline{\text{Conditions}}_{t+1,t+6}$						0.26***		0.28***
						(0.0084)		(0.0084)
$\overline{\text{Conditions}}_{t+1,t+6} - \text{Conditions}_{t}$							0.042***	-0.018***
							(0.0056)	(0.0053)
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.221	0.230	0.193	0.216	0.235	0.240	0.194	0.240
Observations	687178	687178	687178	687178	687178	687178	687178	687178
	Panel B: Retail & Wholesale							
Conditions_{t+6}	0.16***	0.085***			0.36***			
	(0.0057)	(0.0038)			(0.0092)			
Conditions_{t}		0.28***				0.22***		
		(0.0067)				(0.0063)		
$(\text{Conditions}_{t+6} - \text{Conditions}_{t})$			-0.10***	-0.046***	-0.28***			
			(0.0038)	(0.0037)	(0.0080)			
$(\text{Conditions}_{t} - \text{Conditions}_{t-6})$				0.13***	0.0051			
				(0.0044)	(0.0043)			
$\overline{\text{Conditions}}_{t+1,t+6}$						0.24***		0.46***
						(0.0072)		(0.0097)
$\overline{\text{Conditions}}_{t+1,t+6} - \text{Conditions}_{t}$							-0.13***	-0.22***
							(0.0056)	(0.0063)
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.322	0.384	0.314	0.332	0.384	0.397	0.314	0.397
Observations	243723	243723	243723	243723	243723	243723	243723	243723
	Panel C: Services							
Conditions_{t+6}	0.13***	0.12***			0.12***			
	(0.010)	(0.0094)			(0.013)			
Conditions_{t}		0.029***				-0.041***		
		(0.0089)				(0.0080)		
$(\text{Conditions}_{t+6} - \text{Conditions}_{t})$			0.045***	0.080***	0.0027			
			(0.0060)	(0.0074)	(0.010)			
$(\text{Conditions}_{t} - \text{Conditions}_{t-6})$				0.083***	0.041***			
				(0.0090)	(0.0075)			
$\overline{\text{Conditions}}_{t+1,t+6}$						0.27***		0.23***
						(0.016)		(0.017)
$\overline{\text{Conditions}}_{t+1,t+6} - \text{Conditions}_{t}$							0.087***	0.041***
							(0.0085)	(0.0080)
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.323	0.323	0.314	0.320	0.324	0.333	0.316	0.333
Observations	187379	187379	187379	187379	187379	187379	187379	187379

Notes: The dependent variable is the business expectation for the next six months as reported to Q2 of the IBS. Conditions_t and Conditions_{t+6} are realized business conditons stated to Q1 at the reporting month t as well as six months thereafter. Accordingly, $(\text{Conditions}_{t+6} - \text{Conditions}_t)$ and $(\text{Conditions}_t - \text{Conditions}_{t-6})$ capture the difference between realized business conditions at the respective dates. $\overline{\text{Conditions}}_{t+1,t+6}$ is the mean of ex post realized business conditions in the following six months. Standard errors are (two-way) clustered at the firm and date levels. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

well as retailers and wholesalers than the ex post realized changes in future conditions. In the case of services firms, both changes are reflected to a comparable degree. This observation is in line with the results of Section 4.3.1.2 that average business expectations are strongly correlated with past rather than future changes in business conditions.

Furthermore, a horse race between both interpretations clearly favors both variables being driven by the same latent variable. As documented in Column (5) of Table 4.3, the coefficient that captures the degree to which $\text{Cond}_{i,t+6}$ is reflected in expectations is largely unaffected by the inclusion of future and past changes ($\Delta\text{Cond}_{i,(t+6,t)}$ and $\Delta\text{Cond}_{i,(t,t-6)}$) in the case of manufacturing and services firms and even increases strongly in size in the sample of retail and wholesale firms. In contrast, the weight on $\Delta\text{Cond}_{i,(t+6,t)}$ gets either negative (manufacturing and retail/wholesale) or insignificant (services), while the impact of past changes strongly decreases across all sector-specific surveys.

Lastly, I demonstrate that expectations are even more strongly associated with the average level of business conditions *during* the next six months compared to the level *in* six months. Regressing business expectations on average reported conditions between $t+1$ and $t+6$, denoted $\overline{\text{Cond}}_{i,t+1,t+6}$, delivers larger coefficients compared to the specification using $\text{Cond}_{i,t+6}$ only. As displayed in Column (6), a one standard deviation increase in the average level of ex post realized business conditions during the next six months is *ceteris paribus* associated with an appreciation of expectations by 0.26 standard deviations in the panel of manufacturing, 0.24 standard deviations for retail and wholesale firms, and 0.27 standard deviations in the case of service companies. In turn, the change in average future business conditions relative to the level in t ($\overline{\text{Cond}}_{i,t+1,t+6} - \text{Cond}_{i,t+6}$) is much less strongly reflected in firms' expectations as can be inferred from Columns (7) and (8).

Taking together, the evidence presented in this section strongly speaks in favor of interpreting business expectations in levels rather than changes of business conditions. Despite of the potentially misleading wording of the question, it is very unlikely that Q2 captures the expected change in Q1. In contrast, it is more likely that firms refer to the current and expected level of their revenues when answering Q1 and Q2.

4.4 Conclusion

This chapter describes how two major obstacles that have prevented panel data research based on the universe of firms in the IBS can be removed: heterogeneities (1) across different sector-specific surveys of the IBS in the level of the observational units (product vs. firm) as well as (2) in the industry classification systems used in the micro data. For this purpose, I aggregate the survey responses of the most important sector-specific surveys covering manufacturing, retail/wholesale, and services to the firm-level and transfer the

sector identifiers contained in the micro data to the official German industry classification systems *WZ 03* and *WZ 08*.

The harmonized firm-level dataset expands the scope for economic research based on the micro data of the IBS which has up to date mainly been restricted to the analysis of manufacturing firms. The value added of the harmonization procedure is largest for the micro data in the retail and wholesale survey as it adjusts for a break in the methodology in the survey in 2006. This adjustment permits to jointly analyze firms' survey responses in the time periods before and after the break. For example, the analysis of Chapter 1 makes use of this opportunity in order to study the formation of firms' expectations regarding their own future business conditions across firms in all main sectors of the economy. Moreover, we are able to examine anticipation effects of retail firms to an increase in German value added taxes in 2007 based on data before and after the methodological break.

In addition, the transfer of the sector identification variables to the standard industry classification systems *WZ 03* and *WZ 08* is useful for at least two reasons. On the one hand, fixed effects can be applied along the same level of industry aggregation in order to flexibly control for industry-specific variation of any kind. On the other hand, the harmonized IBS data can be merged to industry-level data from other sources which are usually coded according to the classification systems *WZ 03* and *WZ 08*. Based on this, Chapter 3 matches firms in the IBS to data on the distribution of wages in their industry and location in order to identify the degree to which firms are affected by the introduction of statutory minimum wages in Germany in 2015. Moreover, Chapter 2 examines the relationship between market volatility and the information content of firms' expectations in the IBS based on industry-level revenue data from administrative sources.

Furthermore, the harmonized firm-level dataset can be used to shed light on the interpretation of the most widely used variables in the IBS, i.e., firms' assessments about their current business conditions as well as their expectations for the next six months. The chapter provides new insights on this issue based on the analysis of average time series of both questions in relation to industry-level revenue data as well as applying panel regressions at the firm-level. The results speak in favor of interpreting firms' reported business conditions and expectations as their assessment of current and expected future levels of revenues. In contrast, it is very unlikely that business expectations capture the expected change in reported current business conditions despite of the potentially misleading wording of the questions. Empirical studies that examine the relationship of firms' expected and realized business conditions should hence interpret the respective survey questions as referring to the similar dimension of the same latent variable.

Appendices to Chapter 4

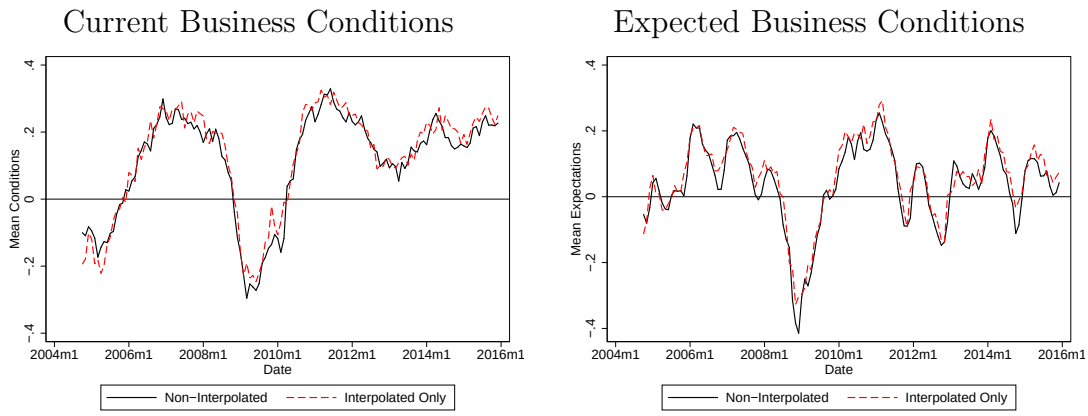
4.A Additional Descriptive Statistics

Table 4.A.1: Attrition: Survival Rates Depending on Starting Dates

Start Date t	Firms @ t	Fraction of Firms Surviving (in %) For At Least...						
		6m	1yr	2yrs	5yrs	10yrs	15yrs	20yrs
1992m1	6603	98.6	95.3	89.5	70.2	49.0	33.9	24.0
1995m1	6914	94.8	90.4	81.2	61.8	42.0	29.2	20.5
1998m1	5855	94.9	89.9	81.7	63.9	43.9	31.2	
2001m1	5062	95.7	91.8	83.7	66.2	46.5	31.1	
2004m1	4573	95.5	91.5	84.9	68.1	48.2		
2007m1	7526	94.8	90.1	83.5	67.2			
2010m1	8452	96.1	92.3	85.9	66.6			
2013m1	8503	95.5	90.9	82.2				

Notes: This table summarizes the survival rates of firms, i.e., the fraction of firms that is still contained in the sample after a specific period of time elapsed since several predefined starting dates t.

Figure 4.A.1: Effect of Linear Interpolation of Missing Data



Notes: Time series of average reports on current business conditions as stated to Q1 in the IBS and average values of interpolated business conditions if missing answers are linearly interpolated as long as the gap in the data is not longer than two consecutive months.

4.B Interpretation of Current and Expected Business Conditions: Supplementary Material

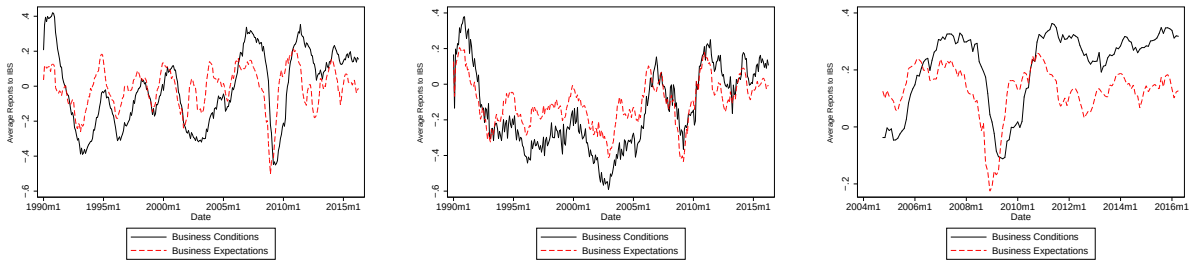
Figure 4.B.1: Average Business Conditions Relative to Administrative Revenue Data: Detrending Using Growth Rates

Notes: Times series of seasonally adjusted mean reports on current business conditions as stated to Q1 in the IBS (right axis) and the mean of industry-specific, seasonally adjusted revenue indices weighted by the number of firms in each industry (left axis). Mean business conditions are deseasonalized by purging for month fixed effects and and detrended using the change relative to twelve months before. For the subset of services firms, mean business conditions are transferred to quarterly frequency by taking means as revenue data are only available on a quarterly basis.

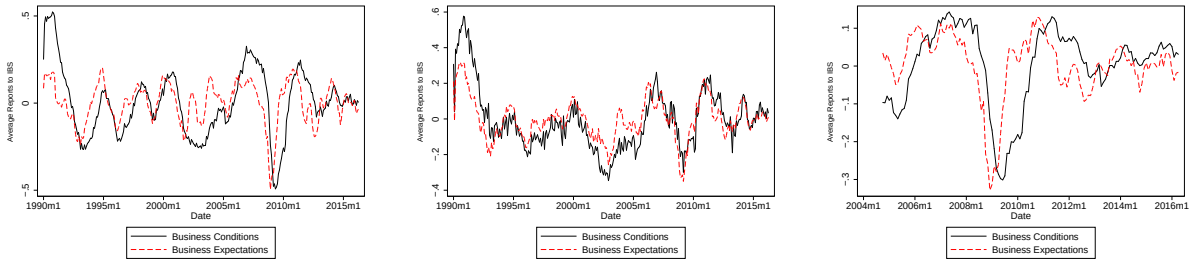
Figure 4.B.2: Average Business Conditions Relative to Average Business Expectations: Alternative Specifications

Manufacturing Retail & Wholesale Services

Panel A: Mean Expectations vs. Mean Business Conditions



Panel B: Mean Expectations vs. Mean Business Conditions - Purged for Firm FE



Notes: Panel A plots the time series of seasonally adjusted mean reports on current business conditions (Q1) and expected business conditions for the next six months (Q2) of firms in the respective sector-specific surveys of the IBS. The time series are seasonally adjusted by controlling for month fixed effects, but not detrended as in Figure 4.4. Panel B plots the same time series after additionally purging for firm fixed effects.

Table 4.B.1: Cross-Correlogram: Average Current Conditions vs. Revenue Data

Lag/Lead l in Months	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6
	Panel A: Manufacturing												
$\rho(\overline{\hat{\text{Revenues}}}_{t+l}, \overline{\hat{\text{Cond}}}_t)$	0.254	0.364	0.471	0.567	0.656	0.731	0.783	0.822	0.845	**0.849**	0.837	0.815	0.779
$\rho(\frac{\overline{\text{Rev.}}_{t+l} - \overline{\text{Rev.}}_{t+l-6}}{\overline{\text{Rev.}}_{t+l-6}}, \overline{\text{Cond}}_t)$	0.697	0.714	**0.717**	0.701	0.679	0.644	0.588	0.52	0.443	0.358	0.264	0.172	0.086
	Panel B: Retail and Wholesale												
$\rho(\overline{\hat{\text{Revenues}}}_{t+l}, \overline{\hat{\text{Cond}}}_t)$	0.404	0.475	0.518	0.558	0.621	0.669	**0.724**	0.677	0.716	0.715	0.685	0.667	0.68
$\rho(\frac{\overline{\text{Rev.}}_{t+l} - \overline{\text{Rev.}}_{t+l-6}}{\overline{\text{Rev.}}_{t+l-6}}, \overline{\text{Cond}}_t)$	**0.385**	0.367	0.375	0.339	0.333	0.331	0.317	0.259	0.261	0.241	0.19	0.158	0.133
	Panel C: Services												
$\rho(\overline{\hat{\text{Revenues}}}_{t+l}, \overline{\hat{\text{Cond}}}_t)$	0.173			0.509			0.763			**0.842**			0.808
$\rho(\frac{\overline{\text{Rev.}}_{t+l} - \overline{\text{Rev.}}_{t+l-6}}{\overline{\text{Rev.}}_{t+l-6}}, \overline{\text{Cond}}_t)$	0.687			**0.700**			0.577			0.321			0.049

Notes: Cross-correlogram of the time series of average (seasonally adjusted) business conditions (Q1) and revenues. In the first row, both time series are detrended by means of an HP-filter with smoothing parameter $\lambda = 129,600$ (1600) for monthly (quarterly) data. In the second row, average business conditions are contrasted to the growth rate in revenues relative to six months before.

Table 4.B.2: Cross-Correlogram: Average Current Conditions vs. Average Expectations

Lag/Lead l in Months	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7
	Panel A: Manufacturing												
$\rho(\overline{\hat{\text{Cond}}}_{t+l}, \overline{\hat{\text{Exp}}}_t^{+6m})$	-0.043	0.075	0.2	0.323	0.45	0.567	0.654	0.724	0.775	0.8	**0.807**	0.796	0.772
$\rho((\overline{\text{Cond}}_{t+l} - \overline{\text{Cond}}_{t+l-6}), \overline{\text{Exp}}_t^{+6m})$	0.588	0.666	0.736	0.789	0.83	**0.845**	0.816	0.755	0.665	0.552	0.418	0.276	0.151
	Panel B: Retail and Wholesale												
$\rho(\overline{\hat{\text{Cond}}}_{t+l}, \overline{\hat{\text{Exp}}}_t^{+6m})$	0.359	0.465	0.567	0.632	0.728	**0.818**	0.78	0.796	0.792	0.748	0.693	0.643	0.596
$\rho((\overline{\text{Cond}}_{t+l} - \overline{\text{Cond}}_{t+l-6}), \overline{\text{Exp}}_t^{+6m})$	0.496	0.527	**0.539**	0.509	0.504	0.489	0.392	0.299	0.209	0.118	-0.007	-0.125	-0.151
	Panel C: Services												
$\rho(\overline{\hat{\text{Cond}}}_{t+l}, \overline{\hat{\text{Exp}}}_t^{+6m})$	-0.101	0.021	0.15	0.277	0.416	0.54	0.632	0.71	0.767	0.799	**0.813**	0.811	0.8
$\rho((\overline{\text{Cond}}_{t+l} - \overline{\text{Cond}}_{t+l-6}), \overline{\text{Exp}}_t^{+6m})$	0.513	0.613	0.706	0.777	0.849	**0.883**	0.867	0.812	0.724	0.615	0.476	0.335	0.219

Notes: Cross-correlogram of the time series of average (seasonally adjusted) business conditions (Q1) and business expectations for the next six months (Q2). In the first row, both time series are detrended by means of an HP-filter with smoothing parameter $\lambda = 129,600$. In the second row, average business expectations are contrasted to the difference in average business conditions relative to six months before.

Table 4.B.3: Cross-Correlogram: Average Business Expectations vs. Revenue Data

Lag/Lead l in Months	-3	-2	-1	0	1	2	3	4	5	6	7	8	9
	Panel A: Manufacturing												
$\rho(\widehat{\overline{\text{Revenues}}}_{t+l}, \widehat{\overline{\text{Exp}}}_t^{+6m})$	-0.205	-0.085	0.035	0.154	0.27	0.371	0.454	0.519	0.574	0.608	0.625	**0.631**	0.625
$\rho(\frac{\overline{\text{Rev.}}_{t+l} - \overline{\text{Rev.}}_{t+l-6}}{\overline{\text{Rev.}}_{t+l-6}}, \overline{\text{Exp}}_t^{+6m})$	0.58	0.668	0.739	0.79	0.814	**0.819**	0.796	0.738	0.669	0.58	0.477	0.373	0.275
	Panel B: Retail and Wholesale												
$\rho(\widehat{\overline{\text{Revenues}}}_{t+l}, \widehat{\overline{\text{Exp}}}_t^{+6m})$	0.246	0.315	0.385	0.455	0.505	0.565	0.626	0.651	0.685	**0.706**	0.694	0.693	0.664
$\rho(\frac{\overline{\text{Rev.}}_{t+l} - \overline{\text{Rev.}}_{t+l-6}}{\overline{\text{Rev.}}_{t+l-6}}, \overline{\text{Exp}}_t^{+6m})$	0.437	0.443	**0.465**	0.459	0.453	0.457	0.444	0.404	0.371	0.328	0.275	0.221	0.143
	Panel C: Services												
$\rho(\widehat{\overline{\text{Revenues}}}_{t+l}, \widehat{\overline{\text{Exp}}}_t^{+6m})$	-0.399			0.008			0.381			0.635			**0.747**
$\rho(\frac{\overline{\text{Rev.}}_{t+l} - \overline{\text{Rev.}}_{t+l-6}}{\overline{\text{Rev.}}_{t+l-6}}, \overline{\text{Exp}}_t^{+6m})$	0.399			0.737			**0.842**			0.707			0.443

Notes: Cross-correlogram of the time series of average (seasonally adjusted) business expectations for the next six months (Q2) and revenues. In the first row, both time series are detrended by means of an HP-filter with smoothing parameter $\lambda = 129,600$ (1600) for monthly (quarterly) data. In the second row, average business expectations are contrasted to the growth rate in revenues relative to six months before.

Table 4.B.4: Relationship Between Survey Questions: Panel Regressions Without Fixed Effects

	Expected Business Conditons for the Next 6 Months							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Manufacturing							
Conditions_{t+6}	0.22***	0.15***			0.24***			
	(0.0052)	(0.0048)			(0.0067)			
Conditions_{t}		0.12***				0.020***		
		(0.0051)				(0.0053)		
$(\text{Conditions}_{t+6} - \text{Conditions}_{t})$			0.017***	0.073***	-0.079***			
			(0.0040)	(0.0045)	(0.0065)			
$(\text{Conditions}_{t} - \text{Conditions}_{t-6})$				0.16***	0.068***			
				(0.0052)	(0.0051)			
$\overline{\text{Conditions}}_{t+1,t+6}$						0.28***		0.30***
						(0.0072)		(0.0069)
$\overline{\text{Conditions}}_{t+1,t+6} - \text{Conditions}_{t}$							0.047***	-0.020***
							(0.0055)	(0.0053)
Firm FE								
R^2	0.059	0.071	0.000	0.025	0.075	0.083	0.001	0.083
Observations	687418	687418	687418	687418	687418	687418	687418	687418
	Panel B: Retail & Wholesale							
Conditions_{t+6}	0.28***	0.12***			0.45***			
	(0.0072)	(0.0045)			(0.010)			
Conditions_{t}		0.32***				0.22***		
		(0.0070)				(0.0063)		
$(\text{Conditions}_{t+6} - \text{Conditions}_{t})$			-0.098***	-0.042***	-0.33***			
			(0.0039)	(0.0038)	(0.0084)			
$(\text{Conditions}_{t} - \text{Conditions}_{t-6})$				0.14***	-0.022***			
				(0.0044)	(0.0046)			
$\overline{\text{Conditions}}_{t+1,t+6}$						0.27***		0.50***
						(0.0078)		(0.010)
$\overline{\text{Conditions}}_{t+1,t+6} - \text{Conditions}_{t}$							-0.13***	-0.22***
							(0.0057)	(0.0063)
Firm FE								
R^2	0.101	0.196	0.012	0.032	0.196	0.214	0.011	0.214
Observations	243891	243891	243891	243891	243891	243891	243891	243891
	Panel C: Services							
Conditions_{t+6}	0.21***	0.17***			0.24***			
	(0.0095)	(0.0079)			(0.013)			
Conditions_{t}		0.073***				-0.031***		
		(0.0084)				(0.0082)		
$(\text{Conditions}_{t+6} - \text{Conditions}_{t})$			0.046***	0.082***	-0.070***			
			(0.0059)	(0.0071)	(0.011)			
$(\text{Conditions}_{t} - \text{Conditions}_{t-6})$				0.089***	0.0045			
				(0.0087)	(0.0082)			
$\overline{\text{Conditions}}_{t+1,t+6}$						0.31***		0.28***
						(0.013)		(0.013)
$\overline{\text{Conditions}}_{t+1,t+6} - \text{Conditions}_{t}$							0.090***	0.031***
							(0.0085)	(0.0082)
Firm FE								
R^2	0.052	0.056	0.002	0.009	0.056	0.071	0.004	0.071
Observations	187595	187595	187595	187595	187595	187595	187595	187595

Notes: The dependent variable is the business expectation for the next six months as reported to Q2 of the IBS. Conditions_t and Conditions_{t+6} are realized business conditons stated to Q1 at the reporting month t as well as six months thereafter. Accordingly, $(\text{Conditions}_{t+6} - \text{Conditions}_t)$ and $(\text{Conditions}_t - \text{Conditions}_{t-6})$ capture the difference between realized business conditions at the respective dates. $\overline{\text{Conditions}}_{t+1,t+6}$ is the mean of ex post realized business conditions in the following six months. Standard errors are (two-way) clustered at the firm and date levels. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.B.5: Relationship Between Survey Questions: Panel Regressions Incl. Firm and Date Fixed Effects

	Expected Business Conditons for the Next 6 Months							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Manufacturing				
Conditions_{t+6}	0.14***	0.10***			0.17***			
	(0.0034)	(0.0030)			(0.0058)			
Conditions_{t}		0.097***				0.029***		
		(0.0042)				(0.0042)		
$(\text{Conditions}_{t+6} - \text{Conditions}_{t})$			0.0035	0.050***	-0.059***			
			(0.0027)	(0.0027)	(0.0051)			
$(\text{Conditions}_{t} - \text{Conditions}_{t-6})$				0.12***	0.057***			
				(0.0030)	(0.0033)			
$\overline{\text{Conditions}}_{t+1,t+6}$						0.22***		0.25***
						(0.0050)		(0.0058)
$\overline{\text{Conditions}}_{t+1,t+6} - \text{Conditions}_{t}$							0.025***	-0.029***
							(0.0037)	(0.0042)
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
Date FE	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.254	0.261	0.238	0.251	0.264	0.269	0.239	0.269
Observations	687178	687178	687178	687178	687178	687178	687178	687178
				Panel B: Retail & Wholesale				
Conditions_{t+6}	0.13***	0.074***			0.34***			
	(0.0042)	(0.0033)			(0.0086)			
Conditions_{t}		0.26***				0.21***		
		(0.0063)				(0.0060)		
$(\text{Conditions}_{t+6} - \text{Conditions}_{t})$			-0.096***	-0.045***	-0.26***			
			(0.0034)	(0.0032)	(0.0076)			
$(\text{Conditions}_{t} - \text{Conditions}_{t-6})$				0.12***	0.0018			
				(0.0034)	(0.0039)			
$\overline{\text{Conditions}}_{t+1,t+6}$						0.22***		0.44***
						(0.0065)		(0.0090)
$\overline{\text{Conditions}}_{t+1,t+6} - \text{Conditions}_{t}$							-0.13***	-0.21***
							(0.0051)	(0.0060)
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
Date FE	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.350	0.402	0.349	0.363	0.402	0.412	0.348	0.412
Observations	243723	243723	243723	243723	243723	243723	243723	243723
				Panel C: Services				
Conditions_{t+6}	0.10***	0.096***			0.10***			
	(0.0060)	(0.0055)			(0.010)			
Conditions_{t}		0.024***				-0.032***		
		(0.0074)				(0.0071)		
$(\text{Conditions}_{t+6} - \text{Conditions}_{t})$			0.035***	0.062***	-0.0022			
			(0.0043)	(0.0043)	(0.0083)			
$(\text{Conditions}_{t} - \text{Conditions}_{t-6})$				0.061***	0.027***			
				(0.0055)	(0.0055)			
$\overline{\text{Conditions}}_{t+1,t+6}$						0.22***		0.19***
						(0.010)		(0.012)
$\overline{\text{Conditions}}_{t+1,t+6} - \text{Conditions}_{t}$							0.071***	0.032***
							(0.0064)	(0.0071)
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
Date FE	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.348	0.349	0.343	0.346	0.349	0.356	0.345	0.356
Observations	187379	187379	187379	187379	187379	187379	187379	187379

Notes: The dependent variable is the business expectation for the next six months as reported to Q2 of the IBS. Conditions_t and Conditions_{t+6} are realized business conditons stated to Q1 at the reporting month t as well as six months thereafter. Accordingly, $(\text{Conditions}_{t+6} - \text{Conditions}_t)$ and $(\text{Conditions}_t - \text{Conditions}_{t-6})$ capture the difference between realized business conditions at the respective dates. $\overline{\text{Conditions}}_{t+1,t+6}$ is the mean of ex post realized business conditions in the following six months. Standard errors are (two-way) clustered at the firm and date levels. Level of significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

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