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Evidence for Austria Using Survey Data

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Business Cycle Dynamics and Firm Heterogeneity

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Abstract

We study the (macroeconomic) consistency of individual firm-level business tendency survey responses and take firm-level heterogeneity explicitly into account. Adding firm-level, industry- and region-specific structural characteristics allows controlling for additional microeconomic heterogeneity. The dataset we use are the business tendency survey micro data for Austrian manufacturing covering the time period 1996 to 2012. Our results show that firm-specific information embedded in the qualitative survey questions is relevant to understand aggregate business cycle dynamics. For example, the assessment of firms' order book levels, their current degree of capacity utilisation and their production expectations as well as obstacles in their production activities due to insufficient demand show evidence of a significant effect in explaining a firms' change in current production output. However, we do not find clear results with respect to firm size, nor do we find explanatory power of the industry affiliation of a firm and with respect to regional characteristics. We are able to identify heterogeneity in behaviour for cyclical up- and downswings as well as between large and small firms.

Keywords: *business cycle, business tendency surveys, firm-level expectations, ordered probit*

JEL-Codes: *C33, D22, E32*

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1. Introduction

Business cycle research usually focuses on the macroeconomic level. Most of the theoretical and empirical business cycle literature deals with this ‘aggregated’ view, even though it is microfounded by representative agents. In our analysis of business cycle dynamics and differentials, we depart to some extent from the standard approach and incorporate the micro perspective as well.[1] This allows us on the one hand to verify the consistency of common business cycle characteristics with individual firm-level survey responses. On the other hand, our approach permits us to incorporate firm-heterogeneity, though often neglected in the analysis of ‘aggregated’ business cycle movements, and to check whether heterogeneity plays a significant role in shaping the overall business cycle.

In the macroeconomic context, the aggregated measure usually represents some quantitative indicator of economic activity with its scope for an economy as a whole (e.g. GDP), for a particular sector or industry (e.g. industrial production) or for demand components like consumption. These measures are typically derived from official statistics. The assessment of the current economic environment such as a countries’ stance in the business cycle requires timely and up-to-date information for decision-makers (e.g. policy makers) and for policy-orientated research. But official quantitative data are not only available with a significant time delay and on a low-frequency basis but are also subject to subsequent revisions. This ‘information gap’ leaves room for uncertainty, not just for the future path of the economy but also with respect to its current state. Qualitative indicators, such as information derived from business tendency surveys (BTS), can help to mitigate the problem and close the gap of missing readily available ‘hard’ (i.e. quantitative) data. As a consequence, ‘soft’ (i.e. survey)

[1] In the field of business cycle research, in particular at the theoretical side, ‘micro-foundation’ of the models started to gain attention, for example, in Kydland and Prescott’s (1982) real business cycle (RBC) model. This was following Lucas’ (1976) critique of econometric policy evaluation with the missing notion of rational expectations. A further development (and structurally related to the RBC models) are the so-called dynamic stochastic general-equilibrium (DSGE) models (see e.g. Smets and Wouters, 2003; Christiano et al., 2005).

indicators are widely used to assess current economic developments and/or base short-term economic forecasts on it. Prominent examples of BTS sourced indicators are the Ifo business climate index or the economic sentiment indicators (ESI) provided by the European commission.

It is common to translate the individual survey responses into quantitative measures in form of ‘balance statistics’.[2] These indicators reflect an ‘aggregated’ view (i.e. cross-sectional average) of economic agents’ judgment of their current economic environment and their expectations. The latter play a crucial part in the decision making process of an agent (e.g. firm) and may affect the immediate and future course of their business activity (Erkel-Rousse and Minodier, 2009). Typically, questions in business surveys refer (a) to firm-specific characteristics such as production, sales, inventories, demand conditions, prices and employment, and, (b) to the general macroeconomic environment. Both dimensions are key elements reflecting business conditions and economic activity.

Moreover, the qualitative data should represent a reasonable proxy for the underlying quantitative, but not yet available, business cycle indicators from official statistics. But as Graff and Etter (2004) point out, there exists a trade-off between timeliness and precision of such indicators. BTS data reveal the required information *as early* as possible (usually by the end of the month), whereas official business cycle indicators are supposed to reflect the realisation of the underlying economic process *as close* as possible. The informational content of the survey questions asked aims to cover the broad range of business activities and different phases of a firm’s production process. Following the stylised representation in Oppenländer (1996: 26ff), a firm’s economic processes may be linked on a ‘time-dimension’

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[2] Anderson (1951) proposed the use of a balance statistic to convert qualitative survey data into quantitative measures of respondents’ assessments and expectations. The balance is usually calculated as the difference between (weighted) percentages of positive and negative answers to the respective question of interest. A huge literature is devoted to survey response quantification. Nardo (2003) or Mitchell et al. (2004) provide, among others, an overview of quantification techniques and discuss issues of them.

around its actual production activity: Expectations about future business conditions (e.g. with respect to earnings or production capacity) in accordance with actual demand conditions (e.g. degree of incoming orders, change in the level of inventory) lead production and sales of a firm. The degree of a firm's capacity utilisation, for example, usually runs in-line with output, whereas firms react in adjusting their employment-levels most often past current production decisions. These stylized business cycle regularities with respect to the timing (lead/lag/co-movement) should be evident in the data, irrespective of using quantitative or qualitative business cycle indicators.

Moreover, the indicators should be statistically correlated if both sources (BTS data and official statistics) measure and relate to the same empirical process (for example industrial production). A number of empirical studies have analysed business cycle properties of survey data, its theoretical foundations or its practical use in the analysis of current economic conditions as well as its short-term forecasting ability of economic activity.[3] In a nutshell, BTS data have shown to contain an indispensable source of relevant business cycle information. Though most of these studies resort on 'balance statistics' in their analysis, implicitly assuming that firms are homogeneous entities or difference between them cancel each other out in the aggregate. But this possibly ignores important aspects of observable firm-specific heterogeneity that might be of interest. The cross-sectional behaviour and characteristics of individual firms can help in understanding the behaviour of aggregates (Higson et al., 2002). In a recent study on business cycle dynamics, Müller and Köberl (2015) argue in line with Caballero and Engel (2003) and Clower (1998) that results obtained on the

[3] For example: Hölzl and Schwarz (2014) provide an overview of the methodology and assess the business cycle properties and forecast characteristics of 'aggregated' (i.e. balanced) BTS data for the Austrian economy. Cesaroni (2011) investigates the cyclical behavior of survey indicators such as the degree of plant utilisation, inventories, order book levels, and confidence indices with respect to the Italian business cycle and confirms the predictive ability of these qualitative indicators in forecasting short-term GDP growth. Knetsch (2005) focuses in the case for Germany on inventory fluctuations and the co-movement between the 'aggregated' survey responses and official inventory investment.

micro level (e.g. individual firms) might differ in the interpretation of the same aggregate phenomena and that firm behaviour has to be taken into account before drawing conclusions on the macro level.

In macroeconomics, shocks are generally interpreted as evidence of a common aggregate disturbance which have originated *inter alia* from monetary policy, or technology changes and spread out into the national economy, their regions and industrial sectors (Park and Hewings, 2003). However, shocks specific to a region or industry sector may also influence other regions and industries, for example, through supply-chain or FDI linkages. Therefore, differentials in business cycles at a disaggregated dimension can, among other things, be related to (inter)national, region-specific and/or industry-specific shocks and these cycles may not necessarily coincide with and share the same properties of the aggregated business cycle.

Empirical studies focusing on the regional (i.e. sub-national) or sectoral (i.e. sub-industry) dimension usually assess whether similarity of the industrial mix lead to business cycle synchronisation or whether industry-specific shocks increase business cycle differentials for regions with a high degree of specialisation.[4] But as Basile et al. (2014) have shown, adding the firm-level dimension to the analysis of business cycle dynamics, thus allowing for firm heterogeneity, may change results. Their analysis uses BTS micro data for the Italian economy, and they distinguish between firm-, sectoral-, and regional-specific factors. They find evidence that the industry mix does not provide an explanation for the (regional, i.e. in their case North versus South) business cycles differentials. However, differences in terms of

[4] Fatás (1997), Forni and Reichlin (1997), Clark and van Wincoop (2001) and Barrios et al. (2003) were among the first to highlight and stress the potential importance of the regional dimension. For studies analysing sources of business cycle co-movements and fluctuations on a disaggregated regional and/or sectoral level see e.g. Clark and Shin (1998); Park and Hewings (2003); Reis (2005); Belke and Heine (2006); Afonso and Furceri (2007); Norman and Walker (2007); Holly and Petrella (2008) or Gadea et al. (2011). With respect to Austrian regions see Bierbaumer-Polly (2012) or Bierbaumer-Polly and Mayerhofer (2013). The authors studied the development of (aggregated) business cycles in the Austrian provinces and found that the business cycle patterns differ considerably not just in an interregional comparison but also in terms of the national economy.

enterprise composition (i.e. firm-specific variables such as firm size or export propensity) do account for large parts of these differentials over different phases of the Italian business cycle. The results in Basile et al. (2014) affirm theoretical indications that firm-specific information might help explaining ‘aggregated’ business cycle dynamics and acting, *inter alia*, as mechanism for transmission of shocks.

Other empirical studies using qualitative survey data at an individual firm-level and related to the domain of business cycle analysis are, among others, Kaiser and Spitz (2000); Ehrmann (2005); Nieuwstad (2005); Müller and Köberl (2007, 2008) and Bachmann et al. (2012).

Kaiser and Spitz (2000), for example, show that the inclusion of firm-specific variables such as regional and sectoral affiliation or firm size may substantially reduce the inaccuracy of the standard error of the outcome variable of interest (e.g. sales growth). Ehrmann (2005) has used business survey data to investigate the link between firm size and the monetary transmission mechanism. He finds that business conditions of small firms deteriorate relatively more compared to large ones after a monetary tightening. Nieuwstad (2005) compares the fit of production information (recent output and expectations) derived from manufacturing business sentiment surveys in the Netherlands to official turnover statistics for the respective company. He shows in the case for individual data that about one third of all survey respondents give coherent and unbiased answers to the questions relating to recent production, but also a high share of companies (roughly 20 per-cent) answer completely illogical. At the industry level the fit between the balance statistics and production data increases to more than 50 percent. Accounting for seasonality leads in addition to an increased fit between survey and official data, and, in general, firms are better at assessing the recent past than predicting the near future.

By using micro data from the BTS in the Swiss manufacturing industry, Müller and Köberl (2007) investigate the adjustment process of a firm to a demand shock, where the authors interpret a firms' judgment about its technical capacities in line with the effective change in capacity utilisation from one period to another as a positive, negative, or no demand shock. The results indicate that companies react asymmetrically to the respective shock-type. Adjustments to positive shocks occur in sum about a half year faster than adjustments to negative shocks. In their subsequent study, Müller and Köberl (2008) use their identification scheme of shocks in order to derive a business cycle indicator. Using this measure, the authors show in a nowcasting exercise the good forecasting performance of this indicator for one quarter ahead forecasts of the Swiss real GDP growth. Bachmann et al. (2012) construct monthly uncertainty indices from German and U.S. business survey data in order to analyse the dynamic relationship between uncertainty and economic activity. To measure uncertainty the authors resort on the one hand to ex-ante forecast disagreement. This is based on the cross-sectional (weighted) standard deviation of the survey responses. On the other hand, the cross-sectional standard deviation of ex-post forecast errors, where forecast errors are built on the difference between current production changes and production change expectations in the previous period, is used as another proxy for uncertainty. The results in Bachmann et al. (2012) point to a "wait and see" effect[5] of uncertainty on economic activity, tough smaller in magnitude in the case for Germany compared to the U.S.

In light of the above, our objective and contribution to the empirical literature is threefold: First, by analysing micro BTS data, we are in a position to verify and test the (macro) consistency of the business tendency survey responses of key questions related to the *business cycle dimension*, such as the assessment of current production or order book levels. In doing so, we adhere to economic processes of a firm as sketched out in Oppenländer (1996: 26ff). Second, we take advantage of the micro dataset and take (observable) firm-heterogeneity

[5] The literature (see e.g. Bloom, 2009) describes the "wait and see effect" as a cautious firm behaviour related to an interaction between uncertainty and frictions related to adjustment costs for labor and capital (at least) in the short-run.

explicitly into account in modelling ‘aggregated’ business cycle dynamics. Besides the business cycle dimension (Objective 2), where firm-heterogeneity is implicitly considered due to the use of the individual survey responses, we focus on the *structural dimension* as well. Following Basile et al. (2014), we control for additional heterogeneity by adding firm-level, industry-specific and regional ‘structural’ characteristics to the model. In addition, we test for business cycle differentials along various aspects (e.g. differences between business cycle phases: upswing vs. downswing). Finally, to best of our knowledge, no empirical analysis along the individual firm-level dimension for the Austrian economy has been conducted to investigate ‘macro’ business cycle dynamics from a ‘micro’ perspective.[6] The use of the micro WIFO Business Cycle Survey (Konjunkturtest – KT) data represents a novelty in this respect. The econometric estimations are based on a Correlated Random Effects Ordered Probit Model.

The remainder of this paper is organised as follows. Section 2 describes the micro dataset, outlines the utilised covariates and discusses briefly their expected effects. Section 3 explains the model and sets out our estimation strategy. Section 4 discusses results. The paper ends in concluding remarks.

2. Data and measurements

Our dataset contains individual firm-level survey data as well as industry and regional information. The firm-level dimension is our main data source. We utilise micro data from the monthly WIFO KT, which is a representative monthly business tendency survey (BTS). The time period we cover ranges from the beginning of 1996 up to the end of 2012 (T_m=204 months). The unbalanced panel dataset contains n_m=2,772 firms and in total i_m=115,055

[6] There exist, though, quite a few studies analysing the aggregated Austrian business cycle. Among them are Breuss (1984), Hahn and Walterskirchen (1992), Artis et al. (2004a, 2004b), Scheiblecker (2007) and Bierbaumer-Polly (2010).

observations. Given the month-by-month survey interval, our initial database is based on monthly observations. However, some relevant questions in the survey, like the degree of capacity utilisation, are only asked on a quarterly basis and some firms answer only the quarterly questionnaire.[7] As the quarterly-type indicators may encompass relevant business cycle information and we want to use information on a large number of firms, we constrain our panel data sample to the quarterly frequency (T_q=68 quarters, n_q=2,563 firms, i_q=55,250 observations)[8]. With respect to our industry- and regional-level data we resort to annual employment data taken from the Austrian Social Security Database (ASSD), which is an administrative register and provides data on a highly disaggregated level (e.g. NACE-5-digit on the sectoral level or on municipalities in the regional context).

2.1 A proxy for the 'aggregated' business cycle

First and foremost, we need some proxy measure for the 'aggregated' business cycle derived from the individual firm-level data. The questions asked in the WIFO KT are either related to the current business situation or refer to the respective expectations about the coming development.[9] Out of this set of questions the assessment of a firms' production output, in particular the change in the output level, provides a natural candidate for depicting business cycle information. Similar to Basile et al. (2014), we use the question on "*Our production has been ... in the last 3 months? (a) increased, (b) remained the same, or (c) decreased*" as our

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[7] Until 1996 the WIFO KT was a quarterly survey. In 1996 the frequency changed to a monthly survey. Many of the firms in the survey panel opted to continue to answer the survey on a quarterly basis.

[8] Quarterly questions are contained in the January, April, July and October survey. Given that a high proportion of respondents predominantly participate only in the 'comprehensive' survey, thus every three months, the coverage of firms is by far highest in the first month of a quarter. Therefore, limiting the analysis only to the quarterly frequency should not raise a major concern. It is to note, though, that this approach results in losing information for firms participating on a month-by-month basis. Responses, for example, for February get skipped.

[9] See Appendix Table A1 for an overview of the WIFO KT questionnaire.

dependent variable (y_{it}).[10] We assume that the response to this question captures the current state of a firms' position in the business cycle. Our outcome variable is coded as 1='has increased', 2='remained the same', and 3='has declined'. The informational content of the qualitative assessment of a firm's production output is widely used among business cycle analysts due to its timely availability compared to official quantitative data and its forecasting capability of business cycle movements of some underlying economic activity measure like GDP or industrial production.

Usually, 'balance statistics' (i.e. share of positive answers [$y_{it} = 1$] minus share of negative answers [$y_{it} = 3$]) are derived from the individual firm responses to quantify the informational content embedded in the question asked.[11] A positive value means that the overall tendency of the production output has been increasing. This points to an expansion of economic activity, hence, to an upswing in the business cycle. Contrary, a negative balance value, i.e. relatively more firms indicate decreasing production levels, may be an indication of a business cycle downturn. Given that the export orientated manufacturing sector plays a crucial role for the small and open Austrian economy, it is reasonable to assume, though qualitative in nature, that the assessment of the change in production output provides a good proxy for the national business cycle.[12]

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[10] There exists a slight difference in the question asked related to current production in the Italian survey. The question is read as "*Do you consider the level of production of your company in the current month as high, normal or low?*" and is more related to the judgement of the 'stock', whereas in Austria the question focuses more on the 'flow' (i.e. the change from one period to another). With respect to the business cycle, the former is more concerned with the level of economic activity (boom vs. recession) whereas the later relates to changes in the cycle (expansion vs. contraction). See, for example, Asako et al. (2007) for a discussion on differences among firms concerning their perception of the business cycle.

[11] Usual assumptions of the balance method are that the cut-points between the different possible answer categories are equally spaced (i.e. symmetric around zero) and that the cut-points are equal across respondents as well as across time (Henzel and Wollmershäuser, 2005).

[12] For balances, Hölzl and Schwarz (2014) have demonstrated that aggregated indices of the WIFO KT provide a reliable tool for monitoring the current economic situation. In particular, the authors show a high correlation of sector-wide balance indices (i.e. including manufacturing, construction and services) with overall economic activity. The contemporaneous cross-correlation coefficient for the period 1997-2013 for the balance indicator reflecting current economic conditions (including the assessment of current production levels) is greater than +0.6, with its highest value (>+0.7) reaching at about one quarter lead.

There have been numerous studies on the quantification of qualitative survey data, i.e. the way in which survey responses are linked to and anticipate official data (see, for example, Geil and Zimmermann, 1996; Nardo, 2003; or Vermeulen, 2014, for a discussion). Prominent quantification techniques found are the Carlson and Parkin (1975) 'probability approach' and the Pesaran (1984) 'regression approach'. In following Cunningham et al. (1998) who give a micro-foundation to the Carlson-Parkin method, our empirical firm-level model (as outlined in Section 3) is in the spirit of the 'probability approach'.[13]

2.2 Firm-level covariates/controls

The WIFO KT micro database contains the full set of individual firm responses of the questions asked in the BTS, as well as some structural firm characteristics. We assume that the first depicting a broad range of economic processes and business activities of a firm and, as such, containing appropriate firm-level covariates to analyse and verify 'aggregated' business cycle dynamics. The latter, on the other hand, can be used to control for structural elements of the surveyed firms, allowing for additional firm-heterogeneity in the analysis.

Our selection of the firm-level covariates as explanatory determinants for the current production activity of a firm and, in the aggregate, of the economy as a whole, is guided by economic processes of a firm and its temporal link to the business cycle (Oppenländer, 1996: 26ff). Covering current business cycle dynamics we use information on (*i*) order book levels, (*ii*) main factors limiting production[14], (*iii*) stock of finished products, (*iv*) selling prices, and (*v*) degree of capacity utilisation. For the set of forward looking questions, i.e. related to

[13] Note, though, that the balance statistic approach is just a special case (i.e. with time invariant parameters) of the Carlson-Parkin method.

[14] In the question related to factors limiting the current production, the respondents are asked to choose between six categories (none, insufficient demand, shortage of labour force, shortage of material and/or equipment, financial constraints, others).

expected changes in the coming months, we resort to expectations on (*vi*) production output, (*vii*) selling prices, and (*viii*) employment along with firms' (*ix*) overall business sentiment.

Table 1 provides an overview of the list of explanatory variables along its classification of the economic process and its business cycle timing with respect to a firm's current production output. Further, the expected sign of the correlation between the qualitative indicator and production output (irrespective if measured with survey data or official statistics) is shown.

Table 1: Firm-level covariates (business cycle dimension)

Question	**Economic Process** [1)]	**Timing** [2)]	**Correlation** [3)]
Production (change), next 3 months	Expectations	lead	+
Selling prices (change), next 3 months	Expectations	lead	+
Firm's employment (change), next months	Expectations	lead	+
Firm's business sentiment (level), next 6 months	Sentiment	lead	+
Total order books (level), current	Demand	lead	+
Factors limiting productions [4)]	Demand/Supply/Finance	lead/co	-
Stocks of finished products (level), current	Demand/Production	co	-
Selling prices (change), past 3 months	Demand/Production	co	+
Capacity utilisation (level)	Production	co	+

Notes: 1) Classification according to Oppenländer (1996: 27). 2) The timing notation indicates the expected temporal pattern with respect to the current production activity of a firm: lead=leading; co=contemporaneously. 3) The "+" and "-" sign indicates the expected change of current production output based on an increase of the respective survey indicator. Its also an indication of the pro-/countercyclicality of the indicator. 4) We test for two (out of six) categories: insufficient demand and financial constraints.

As has been verified in numerous empirical studies and used in applied business cycle analysis, firms' expectations on their short-term economic prospects (e.g. with respect to production, employment, or their selling prices) provide leading information for the assessment of current economic activity. To take advantage of this leading behaviour we utilise the firm-level covariates related to expectations one period lagged (i.e. expectations at time t_{q-1} are used in explaining change in current production at time t_q). Similarly, we lag the survey responses related to order book levels also by one quarter, given that changes in demand conditions do not immediately soak up in changing production levels.

With respect to the structural characteristics of the surveyed firms, we resort on the one hand to the natural logarithm of firm size (number of employees) and its squared term. On the other hand, we utilise industry classification of a firm. The role of firm size has been emphasised in the literature related to monetary policy and credit markets. Firm size is widely considered a proxy, though far away from perfect, for capital market access (Carreira and Silva, 2010). Results show that small firms with little collateral and lower value of assets should be more affected by a monetary tightening than large ones and the strength of (small) firms' reaction to a monetary shock depends on the stance of the business cycle (see e.g. Gertler and Gilchrist, 1994; Perez-Quiros and Timmermann, 2000; or Ehrmann, 2005). With respect to regional business cycle differentials Basile et al. (2014) find that firm size has a positive and significant effect on the probability of having a high level of production in the North vs. South and that this effect is greater in business cycle upswings. To test the effect of small vs. large, we add a dummy large and set its value equal one for firms with an employment threshold of greater or equal to 100 employees.

In contrast to the firm size effect, and against existing empirical evidence, Basile et al. (2014) do not find a significant effect of the industry mix in explaining differences in regional business cycle dynamics. To employ industry information in our analysis we extract the NACE-2-digit code and create industry-sector dummies for each of the sectors available. Using the NACE classification, we further supplement the firm-level data with an industry classification based on main industrial groupings (MIGs; i.e. intermediate goods, capital goods, and consumer goods)[15].

[15] See http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Main_industrial_grouping_(MIG).

2.3 Industry covariates/controls

Industry covariates and controls are used to take industry-specifics into account. First, we employ a measure of mobility barriers and follow Hölzl (2013) by using an indicator of excess labour turnover. Excess labour turnover is defined as

$$EXLT_g = \frac{JC_t + JD_t - |JC_t - JD_t|}{0.5 \times (E_t + E_{t-1})} \tag{2-1}$$

where JC_t and JD_t denote job creation and destruction in two-digit industry g (with $g = 1, \dots, G$) during time *t* and *t-1*, respectively, and E represents employment levels in this sector. $EXLT_g$ measures excessive employment turnover that is not related to changes in the level of employment and, thus, does not account for the variability of employment growth but for the volatility of job generation and job destruction. As such, it is a proxy for mobility barriers like sunk costs, especially for mobility barriers that relate to firm specific human capital and firm specific organizational capital. Industries with a low value of $EXLT_g$ exhibit a high degree of labour hoarding and can be thought as industries that face higher (implicit) labour adjustment costs, as labour hoarding is closely associated with organisational and firm-specific capital embedded in a firm's workforce (Oi, 1962). Over the course of the business cycle firms in industries that exhibit low values of $EXLT_g$ will not adjust their workforce and production capacity as much as firms in sectors where labour hoarding is less prevalent. Thus, labour hoarding may affect the probability of firms' indicating increased production output from one period to another.

Furthermore, we add to our set of industry data the average employment growth in the period between 1996 and 2012 as well as the number of employees (taken as median averaged across the years 1996 to 2012) in each industry. This is done to control for differences in growth rates across industries. Firms in growing industries are expected to be more likely to indicate an expansion of their production levels than firms in declining industries.

2.4 Regional covariates/controls

For the regional aspects we augment the dataset with a sector concentration index. Depending on the type of (macro-)economic shock, the degree of specialisation of a region, among other things, can impact on a firms' production output during the business cycle. Firms in regions characterised by a high concentration of only few sectors might react differently compared to firms operating in regions which are broadly diversified with respect to the industry structure. Frenken et al. (2007) state that portfolio theory, with its claim that variety reduces risk, might help in investigating the effect of a region's sectoral composition on the firms' business cycle movement, which in turn feeds back to the aggregated output.

We calculate a related variety (RV) measure for each NUTS-3 region based on annual employment data. Regions with a sectoral composition of related industries are more prone to aggregated demand shocks; however, knowledge spillovers (Jacobs externalities) between firms within the regions are more likely among related sectors. In following Frenken et al. (2007), we derive a specialisation indicator as the weighted sum of entropy statistics at the 4-digit level within each 2-digit industrial sector. It is given by

$$P_g = \sum_{i \in S_g} p_i \tag{2-2}$$

$$H_g = \sum_{i \in S_g} \frac{p_i}{P_g} log_2 \left(\frac{1}{p_i/P_g} \right) \tag{2-3}$$

$$RV = \sum_{g=1}^{G} P_g H_g \tag{2-4}$$

where all the NACE-4-digit sectors i are assigned to a particular 2-digit sector S_g (with $g = 1, \dots, G$), the 2-digit sector shares P_g are the sum of all 4-digit shares p_i, and H_g represents the weighted entropy within each of the 2-digit sectors. We test the related variety measure either based on all sectors (RV_{all}) or restricted to only manufacturing sectors (RV_{manuf}).

Besides the RV measure, we also control for employment concentration (EC) in a region at the NACE 4-digit level by deriving a Herfindahl-Hirschman Index (HHI). It is formally defined as

$$EC^{HHI} = \sum_{g=1}^{G} p_i^2 \qquad (2\text{-}5)$$

where p_i is the employment share of a 4-digit sector on total industry employment, with $i \in S_g$. We again calculate one version for all industrial sectors (EC_{all}^{HHI}) and one for the manufacturing sectors (EC_{manuf}^{HHI}) only.

Basile et al. (2014) argue that local characteristics such as the local judicial system (i.e. the institutional environment in which firms operate), financial development of the region (i.e. the degree of credit market development), or production decision of neighbouring firms (i.e. local demand externalities) may represent regional unobserved structural factors which impact on a firm's production output over the course of the business cycle. Similar to Basile et al. (2014), we construct a local externality measure, $locEXT_{rt}$, for each NUTS-3 region which should capture local technological and demand externalities. We proxy local externality by

$$locEXT_{rt} = BAL_{rt}^{y_{it}} \times EMPD_{rt} \qquad (2\text{-}6)$$

where $BAL_{rt}^{y_{it}}$ indicates the balance statistic of the question related to the change in production output and $EMPD_{rt}$ represents employment density in the region derived as total employment divided by the size (i.e. square kilometre) of the respective region. In our analysis, we take the average of $locEXT_{rt}$ between 1996 and 1998 to proxy for local externalities.

In order to identify differences in business cycle dynamics between urban and rural geographical areas, we add a respective dummy. Our classification is based on a typology set out by Eurostat which defines regions within the European Union as either 'predominantly urban', 'intermediate, close to a city' or 'predominantly rural' according to some population densities criteria. Based on the zip-code of a firm, we take the respective NUTS-3 code assigned to the zip-code and map the NUTS-3 region to the urban/rural typology accordingly. Our dummy variable 'urban' takes on the value one for the first two types of regions, zero otherwise.

Summary statistics of the firm-level variables are reported in Table 2.[16] The median size of a firm in our sample is 85 and 47% of the firms are 'large' ones (according to our threshold). Half of the firms are classified as belonging to industries mainly producing intermediate goods, and nearly 60% of the firms are located in 'urban' regions. With respect to the business cycle related categorical covariates, the descriptive shows that the middle category is by far the most chosen one. Moreover, large firms tend to indicate a positive change in production output more often compared to small firms, and, similarly they exhibit a higher degree of capacity utilisation. Large firms are also more optimistic in their production and employment expectations and suffer not as often from insufficient demand as small firms do (16% vs. 22%). The degree of capacity utilisation is higher in industries specialising in investment goods and lower for consumer goods industries. Out of the responses to factors limiting current production, two thirds of the firms indicate no production obstacles, almost 20% face insufficient demand and only less than 1% are confronted with financial constraints (mostly small firms).

3. Empirical model

Our outcome variable of interest, hence our proxy for the 'aggregated' business cycle, is represented by firms' assessments of their most recent changes in production output. We denote this variable, which is limited and ordinal in nature, as y_{it}. The observed outcome in y_{it} represents an underlying latent value of the change in the production level of the surveyed firm (y_{it}^*).

[16] Table A2 and A3 (Appendix) provide an overview of the sectoral and regional specific control variables in conjunction with its NACE-2-digit and NUTS-3 breakdown, respectively.

Table 2: Descriptive statistics – Firm-level covariates/controls

Distribution - Continuous covariates		No. of obs.	Min	Q (25%)	Median	Q (75%)	Q (90%)	Max	Mean	SD	Skewness
Time-varying (x_{it})											
Firm size		55,250	1	30	85	230	520	10,000	231.5	557.8	8.9
Capacity utilisation [1]		55,250	30	75	85	95	100	100	81.8	15.1	-1.1

Percentage of firms - Categorial covariates / controls		Total	Modalities: *Firm size* large	*Firm size* small	*MIG-classification* interm.	*MIG-classification* investment	*MIG-classification* consumer	*Regional* urban	*Regional* rural	*Business Cycle Phase* up	*Business Cycle Phase* down
Time-varying (x_{it} | Current)											
Current level of production	+	27.1	30.3	24.2	27.1	28.5	25.7	27.4	26.8	29.9	23.6
	=	55.1	54.5	55.6	54.9	54.8	55.8	55.0	55.2	54.6	55.8
	–	17.8	15.2	20.2	18.0	16.7	18.5	17.6	18.0	15.5	20.6
Order book levels [2]	>	27.1	30.2	24.4	26.6	30.2	25.5	27.0	27.3	28.9	25.0
	=	50.9	50.5	51.2	51.0	47.4	53.9	50.8	50.9	50.3	51.6
	<	22.0	19.3	24.4	22.4	22.4	20.7	22.1	21.8	20.8	23.4
Factors limiting production	none	65.2	68.5	63.3	65.5	61.0	68.1	65.0	65.5	65.0	65.4
	insufficient demand	19.1	15.9	21.8	19.5	16.9	19.9	19.2	18.9	18.4	19.9
	shortage of labour force	5.8	5.1	6.4	5.0	6.5	4.2	6.2	5.3	5.7	6.0
	shortage of material and/or equipment	5.2	6.5	4.1	5.2	7.8	2.9	5.1	5.3	6.0	4.2
	financial constraints	0.9	0.3	1.4	0.6	1.5	1.0	0.9	0.9	0.9	0.9
	others	3.9	3.8	3.9	4.1	3.3	3.9	3.6	4.2	4.0	3.7
Stock finished products	>	18.5	19.0	18.0	21.0	15.9	15.4	17.7	19.4	17.6	19.5
	=	75.9	75.5	76.3	72.8	78.5	80.1	76.6	75.1	76.0	75.8
	<	5.6	5.4	5.8	6.2	5.6	4.5	5.7	5.5	6.3	4.8
Selling prices	+	12.1	13.0	11.3	13.5	9.5	11.3	11.3	13.1	12.4	11.7
	=	69.9	67.9	71.7	65.2	75.6	74.9	69.7	70.2	69.6	70.3
	–	18.0	19.1	17.1	21.3	14.8	13.8	19.0	16.7	18.0	18.0
Capacity utilisation	up to 50%	6.9	2.7	10.6	6.8	4.8	9.1	6.5	7.5	6.5	7.4
	50-75%	23.8	20.2	26.9	23.3	19.5	28.6	24.4	22.9	23.0	24.8
	75-90%	43.1	44.6	41.7	43.4	41.8	43.4	43.5	42.5	43.6	42.4
	90-100%	26.2	32.6	20.7	26.5	34.0	18.9	25.6	27.1	27.0	25.4
Time-varying (x_{it} | Expectations)											
Production expectations [2]	+	20.5	23.1	18.2	20.1	21.6	20.2	20.4	20.6	20.8	20.1
	=	66.8	65.7	67.9	67.5	64.6	67.4	67.1	66.4	67.2	66.3
	–	12.7	11.2	14.0	12.4	13.8	12.4	12.5	13.0	11.9	13.6

Table 2 (cont.): Descriptive statistics – Firm-level covariates/controls

Percentage of firms - Categorial covariates / controls		**Total**	**Modalities**									
			Firm size		***MIG-classification***			***Regional***		***Business Cycle Phase***	
			large	**small**	**interm.**	**investment**	**consumer**	**urban**	**rural**	**up**	**down**
Time-varying (x_{it} | Expectations) cont.											
Selling price expectations [2]	+	12.9	13.4	12.4	14.0	10.6	12.5	12.7	13.1	12.5	13.3
	=	75.3	73.2	77.2	72.3	78.8	78.6	75.0	75.7	75.4	75.1
	–	11.8	13.5	10.4	13.7	10.7	8.9	12.3	11.2	12.1	11.6
Employment expectations [2]	+	10.8	13.1	8.8	9.6	16.1	8.7	10.8	10.9	10.8	10.9
	=	72.8	69.8	75.5	74.2	67.1	75.0	72.6	73.1	72.8	72.9
	–	16.4	17.0	15.8	16.2	16.8	16.3	16.7	16.0	16.4	16.3
Business sentiment [2]	>	12.8	13.0	12.5	12.6	14.4	11.7	12.9	12.6	13.3	12.1
	=	71.0	72.8	69.3	69.9	71.1	73.1	70.8	71.2	71.2	70.7
	<	16.3	14.1	18.2	17.5	14.5	15.2	16.3	16.2	15.5	17.2
Time-constant (x_i)											
MIG-classification	intermediate	52.8	53.4	52.3	-	-	-	50.3	56.2	-	-
	investment	22.1	24.3	20.2	-	-	-	23.7	20.0	-	-
	consumer	25.1	22.3	27.5	-	-	-	26.0	23.8	-	-
Province-classification	Vienna	10.5	9.9	10.9	9.0	9.3	14.6	18.2	0.1	-	-
	Lower-Austria	21.5	21.5	21.6	23.3	22.4	17.2	21.0	22.3	-	-
	Burgenland	22.7	24.4	21.2	21.3	26.5	22.1	23.1	22.1	-	-
	Styria	6.6	4.4	8.5	5.9	7.7	7.0	7.3	5.6	-	-
	Carinthia	6.8	6.7	6.8	6.5	4.7	9.3	4.1	10.4	-	-
	Upper Austria	7.3	6.9	7.6	5.7	7.6	10.3	9.7	3.9	-	-
	Salzburg	8.2	7.2	9.1	9.1	7.5	7.0	6.2	10.9	-	-
	Tyrol	13.5	16.3	11.1	16.8	12.4	7.6	9.9	18.5	-	-
	Vorarlberg	3.0	2.6	3.3	2.5	1.9	4.9	0.5	6.3	-	-
Modalities											
Firm size	small	52.6	-	-	-	-	-	-	-	-	-
	large	47.4	-	-	-	-	-	-	-	-	-
MIG-classification	intermediate	52.8	-	-	-	-	-	-	-	-	-
	investment	22.1	-	-	-	-	-	-	-	-	-
	consumer	25.1	-	-	-	-	-	-	-	-	-
Urban/rural-classification	urban	57.4	-	-	-	-	-	-	-	-	-
	rural	42.6	-	-	-	-	-	-	-	-	-
Business Cycle Phase	up	49.6	-	-	-	-	-	-	-	-	-
	down	50.4	-	-	-	-	-	-	-	-	-

Source: Own calculations.
Notes: 1) The indicator of "Capacity utilisation" is actually a censored categorial variable (ranging from 30 up to 100 per-cent, on a 10 per-cent scale). But it is treated like a continuous variable in the analysis. 2) Covariates are used in the analysis as one period lagged (t-1).

In a baseline setting, the cumulative probabilities of the discrete outcome y_i are related to a set of exogenous variables x:[17]

$$\Pr(y_i \leq j|x) = F\left(\kappa_j - x'\beta\right) j = 1, \dots, J \tag{3-1}$$

The κ_j are the unknown threshold parameters which split the range of the latent variable into J categories, the β are the unknown coefficients and the function F represents, in our application, a cumulative standard normal distribution, $\phi(\bullet)$. The assumption of normality provides the path for the class of an ordered probit model. To ensure well-defined probabilities, it is required that $\kappa_j > \kappa_{j-1}$, $\kappa_J = \infty$ and $\kappa_0 = -\infty$.

Considering the underlying latent variable y_i^*, which is linearly related to observable and unobservable factors, it can be written as

$$y_i = j \text{ if and only if } \kappa_{j-1} \leq y_i^* = x'\beta + u < \kappa_j \tag{3-2}$$

For the unobservable factors, a zero mean and constant variance (i.e. $\sigma^2 = 1$) assumption is necessary for identification purpose. In addition, the baseline model assumes that the thresholds are the same for all individuals. As such, an increase in any of the x will shift the cumulated distribution to the right or left but with no change in the slope of the distribution.

The conditional cell probabilities that a firm reports a particular outcome j can be expressed as:

$$\Pr(y_i = j|x) = F\left(\kappa_j - x'\beta\right) - F\left(\kappa_{j-1} - x'\beta\right) \tag{3-3}$$

In our three-categories setting ($J = 3$) this is read as:

$$\Pr(y_i = 1|x_{it}) = F(-x_i'\beta_1) \tag{3-4}$$

$$\Pr(y_i = 2|x_{it}) = F(-x_i'\beta_2) - F(-x_i'\beta_1) \tag{3-5}$$

$$\Pr(y_i = 3|x_{it}) = 1 - F(-x_i'\beta_2) \tag{3-6}$$

[17] Formal exposition following Boes and Winkelmann (2006) and Pfarr et al. (2011).

A wide range of estimators exists if the model is linear. However, in the non-linear case, like estimating a model for ordered categorical variables (as we do), no straightforward method exists. In business cycle analysis or in micro-econometrics the (panel) probit model has been widely used in regressions for qualitative data.

The baseline model is read as[18]

$$y_{it}^{*} = \eta_t + \beta' x_{it} + c_i + u_{it}, \quad i = 1, \dots, N, \quad t = 1, \dots, T \qquad (3\text{-}7)$$

$$Var(\nu_{it}) = \sigma_c^2 + \sigma_u^2 = \sigma_c^2 + 1$$

$$Corr(\nu_{it}, \nu_{st}) = \rho = \frac{\sigma_c^2}{\sigma_c^2 + 1}$$

where c_i is an unobserved effect representing individual (i.e. firm) heterogeneity; x_{it} are either time-constant or time-varying observed individual characteristics; the $\{u_{it}: t = 1, \dots, T\}$ are idiosyncratic errors and the composite error at time t is $\nu_{it} = c_i + u_{it}$, which is usually serially correlated and could also be heteroskedastic; the η_t represents separate period intercepts and are handled with time-dummies. The covariates and the idiosyncratic errors are assumed to exhibit strict exogeneity, i.e. $Cov(x_{is}, u_{it}) = 0$ with $s, t = 1, \dots, T$.

With respect to the unobserved individual heterogeneity, $Cov(x_{it}, c_i) = 0$ with $t = 1, \dots, T$ is imposed, which represents a 'random effects' type of assumption. In the random effects estimation the composite error ν_{it} is assumed to be uncorrelated not only with x_{it} but also with x_i. However, an endogeneity problem may arise if the 'random effects' type of assumption (i.e. no correlation between the explanatory variables, x_{it}, and the individual-specific effects c_i) is violated. The estimation of the model will lead to inconsistent.

To relax this issue we estimate a so-called correlated random effects (CRE) model by including averages of the time-varying variables as additional explanatory variables

[18] In the estimation we correct (i.e. cluster) the standard errors for correlations across the multiple observations we have for each firm.

(Wooldridge, 2002). The CRE model allows modeling the c_i in the following way: $c_i = \omega + \bar{x}_i\xi + a_i$, with conditional normality $a_i|x_i \sim Normal(0, \sigma_a^2)$. Allowing for correlation between c_i and x_{it} by adding time averages of the time-varying variables refers to a Mundlak-Chamberlain type transformation (see Mundlak, 1978; and Chamberlain, 1982). The main benefits of the CRE estimator are that it controls for unobserved time-constant heterogeneity as with fixed effects, and by including time-averages we can measure the effects of time-constant covariates.

Estimation procedures for ordered categories usually assume that the estimated coefficients of the explanatory variables do not vary between the categories (Long, 1997), thus, having the same thresholds across individuals (i.e. firms). This is commonly known as the parallel-trend assumption. In our estimation we stick to this rather strong assumption.[19]

The estimation of the CRE ordered probit model is done using maximum likelihood.[20] The likelihood for each unit is approximated by Gauss-Hermite quadrature (Butler and Moffitt, 1982). The quantities of interest in the estimation are marginal effects given that the size of the estimated coefficients[21] of the covariates does not have any direct interpretation per se – despite the fact that the sign of the β_js and the marginal effects are the same. The marginal (or partial) effect at a particular point ($\tilde{x}_j$) of a continuous covariate x_j is given by[22]

$$\left.\frac{\partial E[y|x,c]}{\partial x_j}\right|_{x_j=\tilde{x}_j} = \left.\frac{\partial F[x\beta+c]}{\partial x_j}\right|_{x_j=\tilde{x}_j} = f(\tilde{x}\beta + c)\beta \tag{3-8}$$

[19] An alternative is the class of generalised ordered probit models which relax this assumption and let the coefficients of the variables to vary across categories allowing for heterogeneous effects of some explaining factors (Boes, 2007; Boes and Winkelmann, 2006). Basile et al. (2014) have applied a variant of the generalised specification to check for robustness of their results, but found no significant differences to the results based on the restricted model (i.e. with homogeneous and exogenous thresholds).

[20] Various approaches have been suggested in the literature to estimate ordinal discrete choice panel-data models. The most widely used ones are the maximum likelihood (ML) estimation or the generalised method of moments (GMM) technique. See, for example, Greene (2004) or Bertschek and Lechner (1998) for some discussion of the ML and GMM approach with respect to panel probit models.

[21] The estimated coefficients represent $\beta/_\sigma$, so their magnitudes are in units of the standard-deviation of the errors.

[22] Note that the relative marginal effects do not depend on the covariates, i.e. $\frac{\partial F[x\beta+c]}{\partial x_j} \Big/ \frac{\partial F[x\beta+c]}{\partial x_k} = \frac{f(x\beta+c)\beta_j}{f(x\beta+c)\beta_k} = \frac{\beta_j}{\beta_k}$.

where f represents a $\phi(\bullet)$ standard normal probability distribution function (pdf). If we assume for the unobserved individual heterogeneity c_i that $E(c_i) = \mu_c$, the partial effect at the average (PEA) is $PEA_{x_j}(x) = \theta_j(x, \mu_c) = \frac{\partial F(x,\mu_c)}{\partial x_j} = \beta_j \phi(x\beta)$.[23] As conventionally done, the $\widetilde{x_j}$ is set to the mean value ($\overline{x_j}$) of the respective covariate. For assessing and comparing the goodness-of-fit of our models, we resort similar to Basile et al. (2014) to the widely used McFadden (1973) Pseudo-R^2, AIC, BIC as well as on R^2 measures proposed by Aldrich and Nelson (1984) and Maddala (1983).[24]

4. Estimation procedure and results

4.1 Deriving a proxy for the 'aggregated' business cycle

In a first step, we specify our baseline CRE ordered probit model with only quarterly time-dummies, which correspond to quarterly fixed effects (equation (4-1)). For each period a time-dummy (η_t) is used and the marginal effects on these dummies indicate for each of the three possible responses (i.e. 1=increased, 2=remained unchanged, 3=decreased) the probability that production output has changed accordingly. The term $c_i + u_{it}$ represents the composite error as outlined in equation (3-7).

$$y_{it}^* = \eta_t + c_i + u_{it}, \quad \text{with } i = 1, \dots, N;\ t = 1, \dots, T \tag{4-1}$$

The marginal effects[25] of the η_t for $y_{it} = 1$ are shown in Figure 1.

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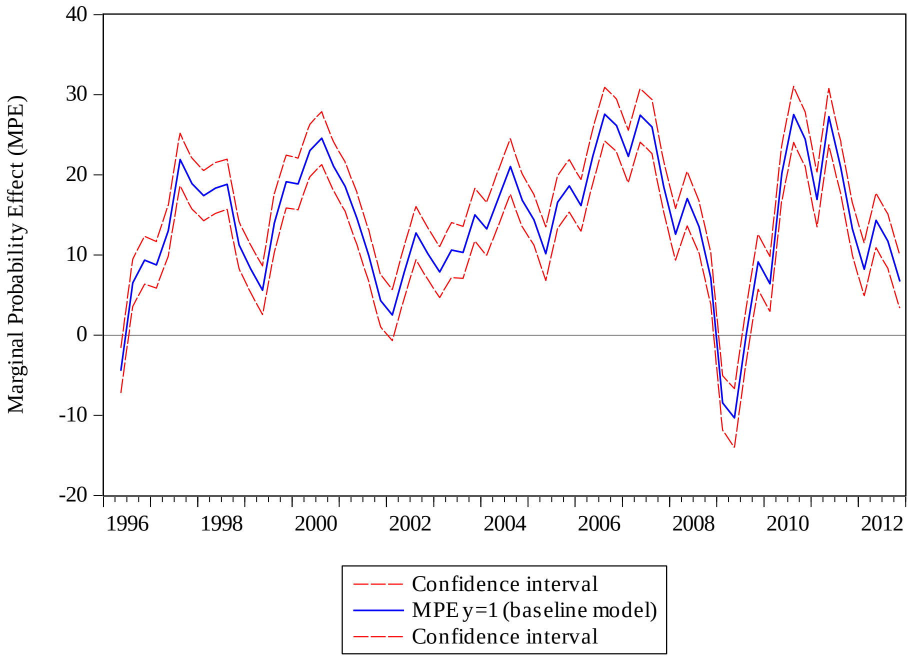
[23] Besides the PEA we can also obtain the average partial effect (APE) which is derived by averaging across the distribution of the unobserved heterogeneity c_i, i.e. $APE_{x_j}(x) = E_{c_i}[\theta_j(x, c_i)]$. Note that both partial effects are different quantities and can produce different estimates. The PEA is an estimate of the marginal effect for a particular entity (e.g. person, firm) at chosen covariate values (e.g. at their means), whereas the APE is an estimate of a population-averaged marginal effect.

[24] Table D1 in the Annex provides an overview of the model comparison results for the various nested model variants. In the main text we refer to the Pseudo-R^2 measure proposed by McFadden (1973).

[25] The estimated marginal probability effects at time t for a particular covariate for the possible outcomes ($y_{it} \in \{1,2,3\}$) sum up to 0. If a firm is more likely to report outcome $y_{it} = 1$, the likelihood of indicating one of the other outcomes has to decrease. As such, the marginal effects have to balance each other out. Figure B1 in the Appendix provides the respective figure.

Figure 1: Marginal probability effects of time-dummies



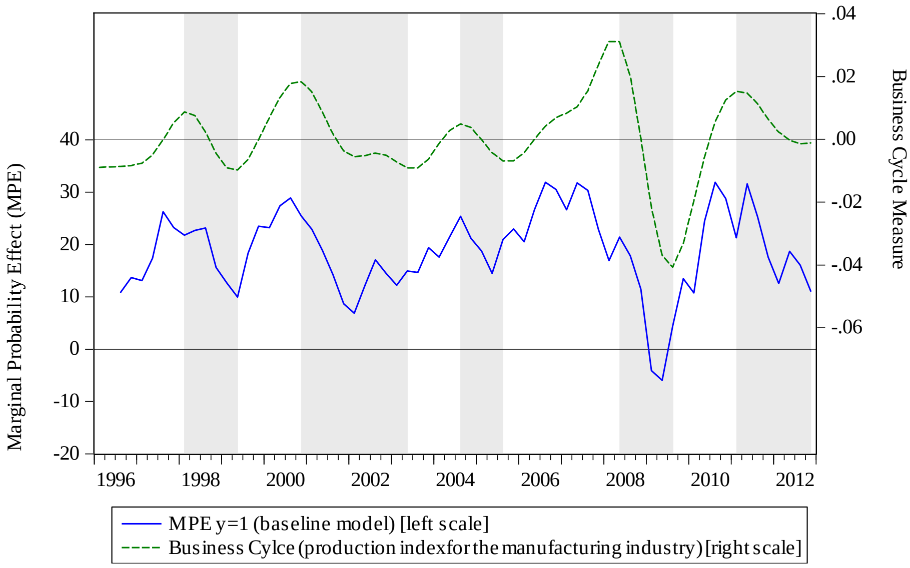
Source: Own calculations.

The estimates, plotted along the time-dimension, show expected business cycle dynamics with its characteristic pattern of up- and downswings in time.[26] In the period we cover (1996 to 2012), a firm's probability of having an increasing level of production ($y_{it} = 1$) goes up during the period from 1996 to mid 1997, followed by a downward trend until mid 1999 and then changes to an increasing trend up to the 2nd quarter of 2000. After 2000 the probability of a firm expanding its production level has been decreasing again until the beginning of 2002, when it switched again into an upward trend until early of 2007, with an exception from the end of 2004 until the beginning of 2005. During the years of the financial crisis 2008/09 a sharp decline in the marginal effect can be observed. The lowest probability is recorded for the 2nd quarter of 2009. From there on, the probability that a firm indicates an increase in its

[26] The estimation of equation (4-1) has been performed on the dataset constrained to the quarterly interval (i_q=55,250 obs.). For robustness we also compared these estimates to the one obtained using the monthly interval (i_m=115,055 obs.). The results for the marginal effects on the quarterly time-dummies are very similar. Figure B2 in the Appendix provides the respective figure.

production level went up again up to the first half of 2011 and switched again into a decreasing trend until the end of our sample period.

Figure 2: Marginal probability effects of time-dummies vs. manufacturing business cycle



Source: Own calculations.

Contrasting the time-pattern of the marginal probability effects of the $\eta_t|y_{it} = 1$ with some aggregated measure of economic activity in the manufacturing sector such as an overall production index or value added measure, it can be seen, that the temporal dynamics (i.e. business cycle movements) are rather similar (Figure 2). For instance, the business cycle component[27] of the quarterly (seasonal adjusted) production index for the Austrian industrial sector has a contemporaneous correlation with the 'time-series' of the marginal effects ($\eta_t|y_{it} = 1$) of +0.67.[28] However, the highest correlation is found at one quarter lead of the marginal probability effects series with a value of +0.79, indicating a leading behaviour over

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[27] The business cycle component has been extracted using the Baxter-King band-pass filter (Baxter and King, 1999) with parameter settings: business cycle frequency between 6 and 32 quarters and filter length of 5 quarters.

[28] Using as reference series the business cycle component of the quarterly value added measure in the manufacturing industry, the correlation reduces marginally to +0.64.

the course of the (manufacturing) business cycle.[29] This result is in line with findings in Hölzl and Schwarz (2014) where the authors employ balances of the BTS data in their analysis of business cycle dynamics. Figure 2 also displays the dating of the business cycle phases (i.e. expansions and recessions).[30] We will use the dating of the cycle later on to investigate business cycle differentials of firms' responses taking into account cyclical asymmetries commonly found in the empirical literature (see e.g. Clements and Krolzig, 2003; Coakley and Fuertes, 2006; Anas et al., 2008).

The estimation of the model with only time-fixed effects controls for time-specific unobserved heterogeneity. However, it leaves a lot of unobservables in the error term. In order to explicitly control for observables and get our estimates of the marginal probability effects more robust, we augment the specification of the model along various dimensions. In detail, we split our estimation procedure in three steps. First of all, representing the core-dimension, we analyse the marginal effects using our set of firm-level covariates/controls. Next, we add the industry as well as regional aspect to the empirical model and attain our full model specification. Finally, we analyse business cycle differences taking business cycle phases (up- vs. downswing), firm size (large vs. small), and firm location (urban vs. rural) into account.

[29] The lead comes as no surprise, given that the BK-filtered business cycle component reflects levels whereas the underlying qualitative outcome variable of current production refers more or less to period-on-period changes. The latter can be seen as 'first difference filter' of the data and as such are prone to substantial shifts in the timing relationships of variables (Baxter and King, 1999).

[30] For dating the business cycle phases we resort to the widely used non-parametric Bry and Boschan (1971) algorithm. According to our dating procedure the business cycle in the manufacturing industry is characterized in the years from 1996 to 2012 by the following phases: 1996:Q1-1998:Q1 (up), 1998:Q2-1999:Q2 (down), 1999:Q3-2000:Q4 (up), 2001:Q1-2003:Q2 (down), 2003:Q3-2004:Q3 (up), 2004:Q4-2005:Q3 (down), 2005:Q4-2008:Q2 (up), 2008:Q3-2009:Q3 (down), 2009:Q4-2011:Q1 (up), and 2011:Q2-2012:Q4 (down).

4.2 Firm-level extension

As shown in Basile et al. (2014), firm specific characteristics play an important role in explaining business cycle differentials. Utilising survey data allows incorporating such information in the model, though constrained due to the particular questions asked. As outlined in the data description section, our set of individual firm-level data contains explanatory variables which are either related to the business cycle dimension (as listed in Table 1) or reflecting structural characteristics (i.e. firm size and industry affiliation). We augment our baseline model specification such that

$$y_{it}^{*} = \eta_t + \delta_s + \Psi_{\mathrm{it}}'\beta + \overline{\Psi_{\mathrm{i}}'}\gamma + c_i + u_{it} \tag{4-2}$$

with $i = 1, \dots, N;\ t = 1, \dots, T;$

where Ψ_{it} denotes the set of time-varying firm-level covariates, $\overline{\Psi}_{\mathrm{i}}$ their respective means according to the Mundlak-Chamberlain CRE approach. As noted in Basile et al. (2014), the marginal effects on the firm-specific covariate represent a ‘shock’-effect (i.e. deviations from the individual averages), whereas the calculated individual averages a ‘level’-effect (i.e. differences between individuals).[31] δ_s represents dummies for the industry affiliation of the firm and is used to control for time-invariant industry fixed effects; these dummies are either coded with respect to the NACE-2-digit breakdown (22 in total; δ_s^{NACE}), or representing one of the three main industrial groupings (δ_s^{MIG}).

Business cycle dimension

The estimation results of the firm-level model with respect to the business cycle covariates (Table 3, top panel) read as follows: All the ‘shock’ estimates of the marginal probability

[31] The estimates of the ‘shock’-effect can be used in the interpretation as kind of performance (short-run) measure, whereas the ‘level’-effect provides more of a structural (long-run) meaning.

effects (mpe) of the firm-level covariates are statistically significant and show apart from one variable (selling price expectations) the expected sign. In the discussion of the results, we focus primarily on the estimates related to increased production output ($y_{it} = 1$).

The mpe on the lagged **order book levels** indicate a strong link between a firms' change in production output and their assessment of their order books, evaluated one quarter in advance.[32] Firms which indicated a more than sufficient backlog of orders tend to have on average a 12% higher probability of having an increasing level of production in the next quarter compared to firms which judged their order book levels in the quarter before as rather low.[33] Moreover, firms which tend to have above average levels of order backlogs with respect to other firms have a 49% higher likelihood of reporting increased production levels. The magnitude of both estimates provides, as expected, a strong indication of firm-specific demand-side effects on the production activities of a firm.

With respect to firms' limiting factors to current production, in particular, related to **shortage of demand**, the mpe displays the expected negative sign.[34] Firms confronted with lack of demand exhibit a probability of increasing their production output, which is 15% lower compared to firms with basically no production obstacles. Interestingly, the 'level' effect exhibits a positive sign with a magnitude of 0.03 (but not statistically significant in this model variant), meaning that firms which on average are more often constrained by shortage of

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[32] Note that incorporating some variables one-period lagged results in loosing data for the first quarter in our sample. The number of observations reduces from i_q=55,250 to i_{q*}=44,683.

[33] Using contemporaneous information on the order book levels provides an even stronger effect of more than sufficient backlogs of order on the probability of a firm having an increasing level of production. The marginal effect on this covariate for $y_{it} = 1$ is 0.56, indicating a more than 50% higher probability of a high level of production (see Table B1 in the Annex for results). There exists a high correlation of a firms' assessment of their change in current production output and their order book levels ($corr_{t0}$=+0.96, $corr_{t-1}$=+0.80). Figure B3 in the Appendix provides the respective figure. Note that the magnitudes of the marginal effects on the other firm-level covariates reduce, but are still predominantly statistically significant.

[34] We have also tested the explanatory power of the WIFO KT question on the limiting factor due to 'financial constraints'. But the results turned out to be not statistically significant; neither could the goodness-of-fit of the overall model be improved. As such we decided to take out this variant from the firm-level model specification and focus in this respect on the answer option 'shortage of demand'.

demand still have a higher probability of increasing current production levels. If the structural effect would be interpreted as indicating 'firm quality', a negative sign of this 'structural' marginal effect would be more plausible. However, if firms report shortage of demand as a limiting factor when the business cycle is down, the structural effect is not related to 'firm quality'. It is then an indicator of whether the firm's demand strongly moves in line with the business cycle.

A firm's assessment of its current inventory level is according to our findings countercyclical related to changes in production output of the firm. The mpe on the covariate **stocks of finished products** is statistically significant and has a negative sign on the response category related to 'too large'. This means, in the short run, firms exhibiting too large inventory levels most likely respond, *ceteris paribus,* to favourable demand-conditions with a cut-back in their current production output and satisfy demand from their stocks. The probability of increasing production output is about 10% lower compared to firms which exhibit a rather low stock of finished products. However, in the long run, firms which tend to assess their inventory level most of the time as too high (compared to other firms) have a 13% higher likelihood of reporting increased production levels. On the one hand, this may indicate that these firms are predominantly faced with high demand for their products and expecting that this will continue in the near future, as such continuing to increase production output may be a rational choice of the firm. But the positive mpe of this structural effect may also be seen as a sign of an 'insufficient' inventory management in place where these firms are not able to adjust their stocks of finished products to an optimal level. However, favouring our first reasoning, empirical evidence shows that inventory management (as part of good business practices) has improved over the last decades, contributing to reduced output volatility (Ahmed et al., 2004; McCarthy and Zakrajsek, 2007).

Table 3: Marginal probability effects: Firm-level

Covariates / controls	y=1		y=2		y=3	
	MPE	SE	MPE	SE	MPE	SE
Business cycle dimension						
Firm-level (Current)						
t-1.Order books.>	0.1153***	(0.007141)	-0.0455***	(0.003375)	-0.0699***	(0.004594)
t-1.Order books.=	0.0371***	(0.004922)	-0.0082***	(0.001060)	-0.0290***	(0.004125)
t-1.Order books.> [bar]	0.4876***	(0.026212)	-0.1827***	(0.012141)	-0.3049***	(0.017014)
t-1.Order books.= [bar]	0.2182***	(0.020442)	-0.0818***	(0.008211)	-0.1364***	(0.013038)
Limit.Factor: Insufficient demand	-0.1455***	(0.006760)	0.0545***	(0.003267)	0.0910***	(0.004493)
Limit.Factor: Insufficient demand [bar]	0.0282	(0.018081)	-0.0106	(0.006804)	-0.0176	(0.011293)
Stock finished products.>	-0.0975***	(0.012950)	0.0389***	(0.006729)	0.0586***	(0.006809)
Stock finished products.=	-0.0524***	(0.011534)	0.0259***	(0.006570)	0.0265***	(0.005027)
Stock finished products.> [bar]	0.1260***	(0.030779)	-0.0472***	(0.011634)	-0.0788***	(0.019328)
Stock finished products.= [bar]	0.0744***	(0.028318)	-0.0279***	(0.010638)	-0.0465***	(0.017750)
Selling prices.+	0.1046***	(0.009271)	-0.0353***	(0.004074)	-0.0693***	(0.006182)
Selling prices.=	0.0629***	(0.005831)	-0.0152***	(0.001285)	-0.0477***	(0.005169)
Selling prices.+ [bar]	-0.0078	(0.034235)	0.0029	(0.012818)	0.0049	(0.021418)
Selling prices.= [bar]	-0.0182	(0.021402)	0.0068	(0.008010)	0.0114	(0.013397)
Capacity utilisation	0.0109***	(0.000327)	-0.0041***	(0.000202)	-0.0068***	(0.000227)
Capacity utilisation [bar]	-0.0090***	(0.000445)	0.0034***	(0.000225)	0.0056***	(0.000273)
Firm-level (Expectations)						
t-1.Production expectations.+	0.2206***	(0.008567)	-0.0734***	(0.005123)	-0.1472***	(0.007485)
t-1.Production expectations.=	0.0893***	(0.005244)	-0.0011	(0.002499)	-0.0883***	(0.006892)
t-1.Production expectations.+ [bar]	0.0528*	(0.031588)	-0.0198*	(0.011860)	-0.0330*	(0.019759)
t-1.Production expectations.= [bar]	-0.0321	(0.024679)	0.0120	(0.009259)	0.0201	(0.015435)
t-1.Selling price expectations.+	-0.0347***	(0.009143)	0.0138***	(0.003780)	0.0209***	(0.005470)
t-1.Selling price expectations.=	-0.0244***	(0.007329)	0.0102***	(0.003349)	0.0142***	(0.004005)
t-1.Selling price expectations.+ [bar]	-0.0540	(0.034160)	0.0203	(0.012890)	0.0338	(0.021300)
t-1.Selling price expectations.= [bar]	-0.0330	(0.027485)	0.0124	(0.010339)	0.0206	(0.017160)
t-1.Employment expectations.+	0.0563***	(0.009428)	-0.0241***	(0.004313)	-0.0322***	(0.005333)
t-1.Employment expectations.=	0.0112*	(0.006066)	-0.0038*	(0.001935)	-0.0075*	(0.004140)
t-1.Employment expectations.+ [bar]	0.0342	(0.027488)	-0.0128	(0.010344)	-0.0214	(0.017159)
t-1.Employment expectations.= [bar]	0.0453**	(0.018429)	-0.0170**	(0.006980)	-0.0283**	(0.011488)
t-1.Business sentiment.>	0.0494***	(0.008907)	-0.0198***	(0.003803)	-0.0296***	(0.005287)
t-1.Business sentiment.=	0.0163***	(0.005710)	-0.0054***	(0.001752)	-0.0109***	(0.003980)
t-1.Business sentiment.> [bar]	-0.0447	(0.028139)	0.0167	(0.010565)	0.0279	(0.017599)
t-1.Business sentiment.= [bar]	-0.0235	(0.020681)	0.0088	(0.007762)	0.0147	(0.012929)
Structural dimension						
Firm-level						
Firmsize	-0.0449***	(0.009204)	0.0168***	(0.003536)	0.0281***	(0.005744)
Firmsize^2	-	-	-	-	-	-
Firmsize [bar]	0.0481***	(0.009508)	-0.0180***	(0.003679)	-0.0301***	(0.005914)
Firmsize^2 [bar]	-	-	-	-	-	-
Nace08-Sector.14	-0.0452**	(0.019415)	0.0170**	(0.007247)	0.0283**	(0.012205)
Nace08-Sector.15	-0.0342*	(0.020417)	0.0128*	(0.007660)	0.0214*	(0.012778)
Nace08-Sector.17	-0.0252*	(0.013268)	0.0094*	(0.004974)	0.0157*	(0.008311)
Nace08-Sector.20	-0.0242*	(0.012915)	0.0091*	(0.004856)	0.0151*	(0.008075)
Nace08-Sector.28	-0.0259**	(0.011234)	0.0097**	(0.004234)	0.0162**	(0.007021)
Nace08-Sector.31	-0.0236*	(0.013041)	0.0088*	(0.004898)	0.0147*	(0.008157)
N	44,683					
Pseudo R^2	0.215					
cut1	-3.3791***	(0.160257)				
cut2	-1.3277***	(0.158918)				

Source: Own calculations.

Notes: *** indicates statistically significance at 1%, ** indicates statistically significance at 5%; * indicates statistically significance at 10% level. MPE referts to the marginal probability effect. SD (in parentheses) represents clustered standard errors. Cut1 and cut2 are the estimated thresholds marking the delimination between the different answer categories in our 3-point categorial outcome variable. The MPE of the variables with a [bar] denote 'level' (long-run) effects, while the other variables listed refer to the 'shock' (short-run) effects. Time-dummies as well as none-significant industry-dummies have been omitted in the output table. The squared term on "Firm size" is used in the model estimation, but we preclude the calculation of the MPE for the squared term given its dependency on the linear term.

Our results for **selling prices** (current quarter) and **selling price expectations** (lagged one quarter), though both statistically significant for the 'shock' effect, provide mixed evidence with respect to its link to firms' production output. On the one hand, firms indicating an upward tendency in their most recent selling prices have an about 10% higher probability of an increased production output compared to firms which are confronted with stagnating or even decreasing prices of their products. Firms in a position of charging higher prices are most likely confronted with more favourable demand for their products and, in turn, this higher demand may materialise in higher production. Similar reasoning may be assumed for price expectations, i.e. firms which have expected higher product prices in the coming month should be those firms which, on average, keep up and expand their production output. However, according to our results the sign of the mpe related to price expectations (lagged one quarter) is negative and points to the contrary. The probability that a firm expanding its output in the face of positive price expectations is 3% lower compared to firms which have expected a reduction in their product selling prices. One rationale behind this finding can be found in the firm innovation literature. Harrison et al. (2014) point out that the productivity effect of process innovation let firms to produce the same or even an increased amount of output with fewer inputs, thus, leading to lower unit costs. Over shorter time periods fixed capacity costs could lead to such an effect if firms expect that increased production leads via a fixed cost channel to lower unit costs. In turn, this kind of cost reduction allows the (innovative) firm to lower its product selling price, resulting in higher production, sales and higher employment.[35] By and large, our findings on price expectations and their impact on a firm's current production decisions are far from clear-cut, as it is not clear whether the demand channel (higher demand leads to higher prices) or a supply channel (capacity costs

[35] Note that the magnitude of the reduced 'cost/price effect' depends on various factors, such as the size of the reduction, the price elasticity of demand or the degree of competition among the firms (Peters et al., 2014).

and innovation lead to changes in the supply and to lower prices) applies. In the BTS firms are asked "*How do you expect your selling prices to change over the next 3 months?*", but there is no information about the 'channel' (e.g. either demand-/supply-side) that guides the price-setting expectations set of the firms.

The estimate for **capacity utilisation** signifies that if a firm enhances its operating grade by one unit (e.g. from 80 to 81 per-cent), the probability that output raises as well increases by 1%. But firms which operate most of the time above average capacity utilisation, i.e. near or on their full production capacity, have as expected a reduced possibility (by minus one percent) to increase their production levels compared to firms confronted with sparse capacity utilisation.

Moreover, firms' **production expectation** derived one quarter in the past provides an early and robust signal of changes in the production output in the next quarter to come. The estimates of the mpe are both positive and statistically significant. The 'shock' effect indicates that if a firm expects an increase in its production level in the coming months, the probability that the production output one-quarter ahead will go up is 22% higher compared to firms expecting their future production output to decline. The structural estimate (i.e. the 'level' effect) of the marginal effect provides a positive magnitude of 9%. Firms which are in general optimistic with respect to their future production possibilities tend to assess their current production activities higher than less optimistic firms. This suggests that these firms are not only more optimistic but also that they have higher growth rates than firms that are less optimistic about their production over the next months.

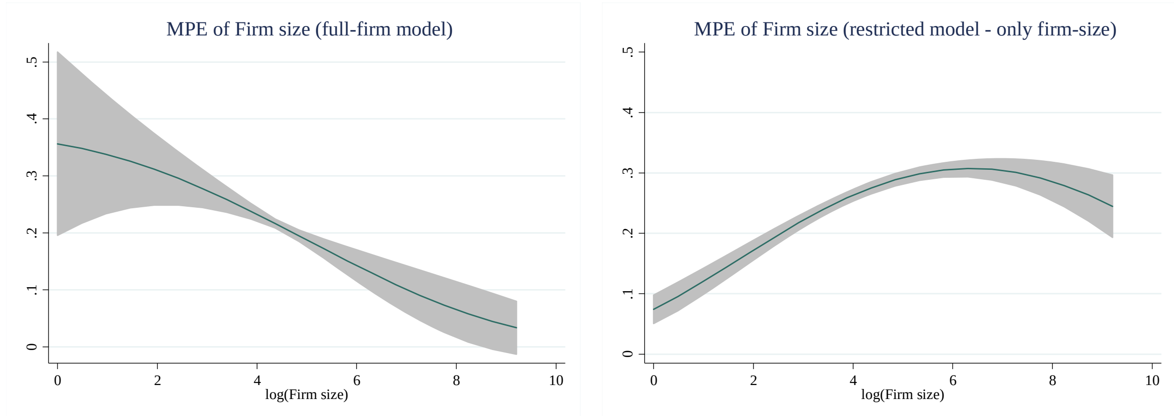
Next, the estimate for **employment expectations** lagged one-quarter shows that firms planning to increase their employment levels in the near future are also those with a higher probability of positive changes in their immediate production output (by about 6% compared to firms which expect to reduce their workforce). Thus, confirming the leading property of this firm-level labour market related BTS question. However, we do not find a statistically significant structural effect. That is to say that firms which on average are more optimistic with respect to their demand for labour do not exhibit a higher probability of increasing current production levels.

Finally, the estimation results for the business cycle covariate reflecting firms **overall business sentiment**, which can be seen as a proxy of future demand or business conditions and, thus, exhibiting the most forward looking and broad measure in the context of the BTS (Nerlove, 1983; Oppenländer, 1996: 307), reveal for the 'shock' effect a positive and statistically significant coefficient. This indicates that if a firm expecting favourable business conditions in the next two quarters to come, the probability that production output increases in the next quarter as well is 5% higher compared to more pessimistic firms.

Structural dimension

The results with respect to the 'structural' covariates in the firm-level model can be summarised as follows (see Table 4 – bottom panel): The marginal probability of the 'shock' effect on the **firm-size** covariate exhibits a negative sign with 0.05 in magnitude, i.e. as (log) firm size increases by one unit the predicted probability of increasing production output reduces by about 5%. We would have expected the opposite sign, given for example the arguments and empirical evidence found in the literature on the transmission of monetary shocks (Dedola and Lippi, 2005). Firm size has been identified as a determinant for different reactions, and, in particular, larger firms tend to be more prone to these shocks. Larger firms should also face lower borrowing constraints (Basile et al., 2014). As such it is assumed that large firms are in a better position to smooth production activities and change their output. The positive firm size effect should diminish and turn negative at some point, indicating an inverted U-shaped relationship. We have modelled this potential none-linearity by including the squared term of firm size in the estimation. But we do not calculate the marginal effect for the none-linear term, given the interdependency between both terms. Instead, we obtain the predictions for the marginal effect of firm size not just for the mean value, but also evaluated over a broad range of values. Figure 3 (left graph) provides the respective distribution of the mpe for the full firm-level model. The downward sloping shape confirms the negative sign of the mpe (calculated at the mean). However, an estimation of a restricted model variant with just using the firm-specific structural variables besides the quarterly dummies reveals a distribution of the marginal firm size effects which has the expected shape (Figure 3 – right graph). Moreover the point estimate for firm size has in this case the expected positive sign (though not statistically significant).

Figure 3: Marginal probability effects of (log) firm size: Full model vs. restricted



Source: Own calculations.

It seems that some of the business cycle related covariates in the full model carry firm size correlated information and pick-up parts of the firm size effect. Descriptive statistics support this argument. We have seen that there are distinct differences in the responses modalities between large and small firms (e.g. large firms tend to be more optimistic or face stronger demand).

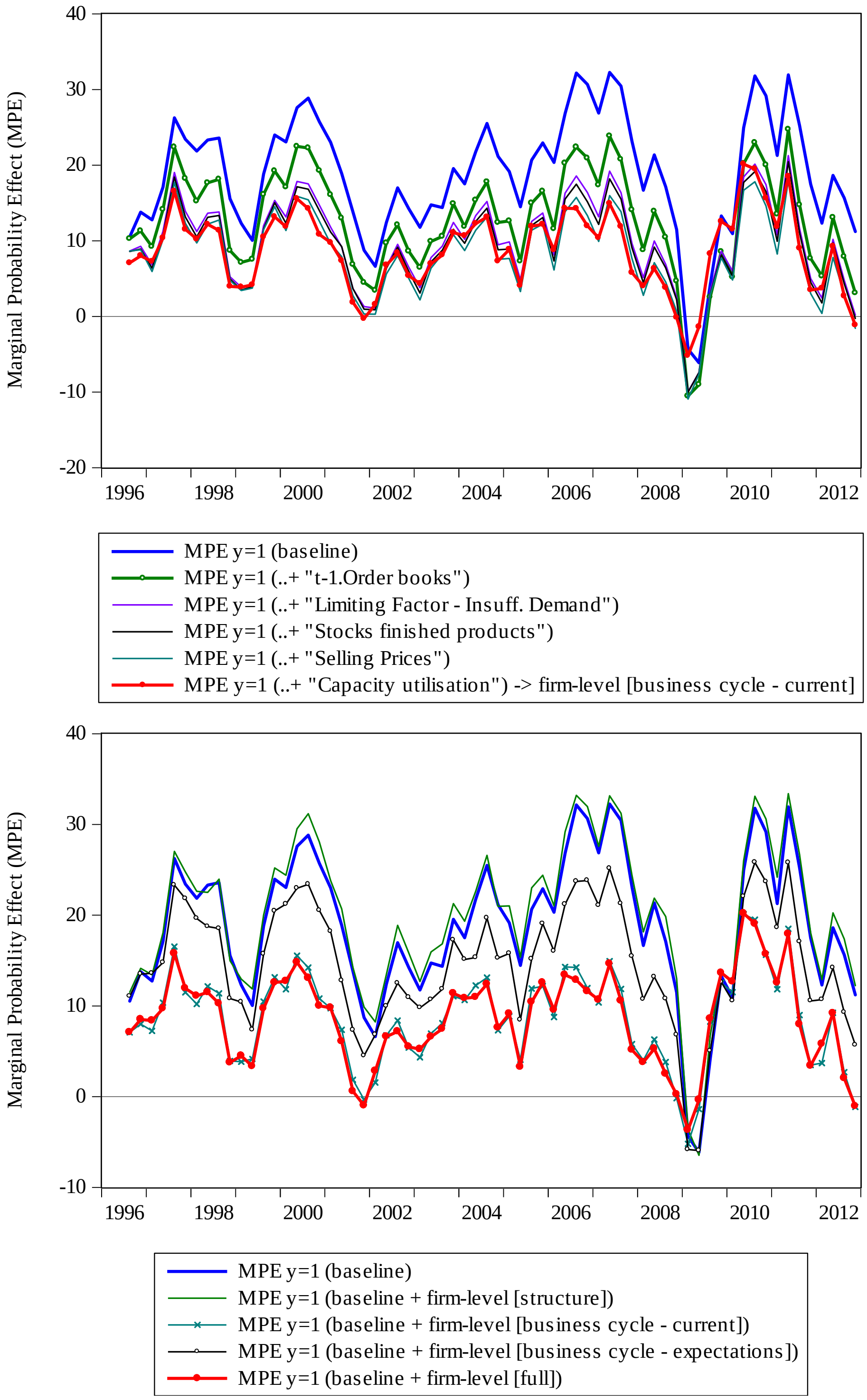
The marginal effect of the firm-size variable averaged across each firm exhibits also a statistically significant coefficient (mpe=0.05), but contrary to the ‘shock’ effect, with a positive sign. Larger firms (on average) tend to have a 5% higher probability of expanding their production output compared to (on average) smaller firms. This indicates also that smaller firms have a persistently lower propensity to assess their production level as increasing, and, at the aggregate level, we should observe a level difference in the business cycle assessment between small and large firms.

Finally, the estimates for the controls related to the **industry affiliation** of a firm (irrespective if we model it with δ_s^{NACE} or δ_s^{MIG}) show predominantly statistically insignificant results. This rather low explanatory power of the industry mix is in line with findings in Basile et al. (2014) and suggests that firm heterogeneity dominates industry heterogeneity when it comes to the variance of firm-level answers in business tendency surveys.

<u>Explanatory power of the firm-level covariates</u>

Our results so far indicate that the demand-side covariates (current order book levels and limited demand conditions), the degree of capacity utilisation as well as the expected direction of future production levels have the highest explanatory power with respect to a firm’s current production output. The full ‘firm-level’ model also exhibits the highest goodness-of-fit value in the Pseudo-R^2 measure (0.215). The biggest improvement is achieved once the model is augmented with the information on the order book levels (lagged on period). This is also confirmed by looking on the respective changes in the quarterly time-dummies η_t (see Figure 4 – top panel).

Figure 4: Marginal probability effects: Model variants and full ‘firm-level’ model



Source: Own calculations.

Adding order book level information and the covariate on limiting factors due to shortage of demand to the model takes out some of the unobserved factors impacting on our ‘proxy’ for the overall business cycle. The estimates of η_t are reduced considerably. The inclusion of the other business cycle related variables reflect the 'current' environment impact on η_t only to some lesser extent.

Furthermore, contrasting the estimates of the quarterly time-dummies in the full 'firm-level' model specification with some interim model specifications (see Figure 4 – lower panel), we see that only controlling for firm size and sector affiliation (i.e. for the 'structural' element) does not reduce the marginal probability effects of the quarterly time-dummies ($\eta_t | y_{it} = 1$) obtained from the baseline model. Adding the set of business cycle covariates related to 'expectations' picks up some of the unobserved factors, but not as much as in the case of the covariates reflecting 'current' business activities. For the latter, the magnitudes of the temporal dynamics over the course of the business cycle are almost identical to the results obtained from the full 'firm-level' model. Hence, business cycle information embedded in this type of questions exhibits the highest explanatory power in our model setup.

4.3 Industry-/Regional-level extension

Having controlled for observable firm-specific heterogeneity, we finally augment our model with our available industry and regional variables. Our full model specification is outlined as follows:

$$y_{it}^* = \eta_t + \delta_s^{MIG} + \varphi_s + \vartheta_r + \Psi_{\mathrm{it}}'\beta + \overline{\Psi_{\mathrm{i}}'}\gamma + c_i + u_{it} \tag{4-3}$$

with $i = 1, \ldots, N;\ t = 1, \ldots, T;$

where φ_s denotes the additional set of industry-specific covariates (at the NACE-2-digit breakdown) and ϑ_r represents our region-specific characteristics (at the NUTS-3 level). The estimation results of our complete model are shown in Table 4.

Table 4: Marginal probability effects: Full model specification

Covariates / controls	y=1		y=2		y=3	
	MPE	SE	MPE	SE	MPE	SE
Business cycle dimension						
Firm-level (Current)						
t-1.Order books.>	0.1152***	(0.007122)	-0.0450***	(0.003331)	-0.0702***	(0.004606)
t-1.Order books.=	0.0371***	(0.004909)	-0.0080***	(0.001033)	-0.0291***	(0.004137)
t-1.Order books.> [bar]	0.4898***	(0.025908)	-0.1817***	(0.011875)	-0.3081***	(0.016963)
t-1.Order books.= [bar]	0.2226***	(0.019892)	-0.0826***	(0.007929)	-0.1400***	(0.012803)
Limit.Factor: Insufficient demand	-0.1449***	(0.006763)	0.0537***	(0.003209)	0.0911***	(0.004524)
Limit.Factor: Insufficient demand [bar]	0.0293*	(0.017589)	-0.0109*	(0.006548)	-0.0185*	(0.011059)
Stock finished products.>	-0.0970***	(0.012935)	0.0383***	(0.006668)	0.0586***	(0.006852)
Stock finished products.=	-0.0520***	(0.011520)	0.0255***	(0.006520)	0.0265***	(0.005060)
Stock finished products.> [bar]	0.1269***	(0.030272)	-0.0471***	(0.011332)	-0.0798***	(0.019124)
Stock finished products.= [bar]	0.0773***	(0.027764)	-0.0287***	(0.010328)	-0.0486***	(0.017510)
Selling prices.+	0.1042***	(0.009248)	-0.0347***	(0.004024)	-0.0694***	(0.006199)
Selling prices.=	0.0627***	(0.005814)	-0.0149***	(0.001249)	-0.0477***	(0.005179)
Selling prices.+ [bar]	-0.0100	(0.033550)	0.0037	(0.012431)	0.0063	(0.021120)
Selling prices.= [bar]	-0.0241	(0.020949)	0.0090	(0.007755)	0.0152	(0.013204)
Capacity utilisation	0.0109***	(0.000326)	-0.0040***	(0.000199)	-0.0068***	(0.000226)
Capacity utilisation [bar]	-0.0090***	(0.000428)	0.0033***	(0.000217)	0.0056***	(0.000265)
Firm-level (Expectations)						
t-1.Production expectations.+	0.2202***	(0.008546)	-0.0725***	(0.005074)	-0.1477***	(0.007494)
t-1.Production expectations.=	0.0890***	(0.005224)	-0.0006	(0.002489)	-0.0885***	(0.006904)
t-1.Production expectations.+ [bar]	0.0545*	(0.031410)	-0.0202*	(0.011679)	-0.0343*	(0.019764)
t-1.Production expectations.= [bar]	-0.0319	(0.024364)	0.0118	(0.009054)	0.0201	(0.015325)
t-1.Selling price expectations.+	-0.0346***	(0.009123)	0.0136***	(0.003730)	0.0210***	(0.005499)
t-1.Selling price expectations.=	-0.0243***	(0.007310)	0.0101***	(0.003311)	0.0142***	(0.004023)
t-1.Selling price expectations.+ [bar]	-0.0661**	(0.033670)	0.0245*	(0.012622)	0.0416**	(0.021092)
t-1.Selling price expectations.= [bar]	-0.0364	(0.026979)	0.0135	(0.010052)	0.0229	(0.016944)
t-1.Employment expectations.+	0.0561***	(0.009404)	-0.0238***	(0.004266)	-0.0323***	(0.005352)
t-1.Employment expectations.=	0.0112*	(0.006051)	-0.0037*	(0.001907)	-0.0075*	(0.004153)
t-1.Employment expectations.+ [bar]	0.0311	(0.027606)	-0.0116	(0.010276)	-0.0196	(0.017342)
t-1.Employment expectations.= [bar]	0.0450**	(0.018123)	-0.0167**	(0.006790)	-0.0283**	(0.011371)
t-1.Business sentiment.>	0.0493***	(0.008889)	-0.0196***	(0.003763)	-0.0297***	(0.005311)
t-1.Business sentiment.=	0.0163***	(0.005697)	-0.0053***	(0.001721)	-0.0110***	(0.003999)
t-1.Business sentiment.> [bar]	-0.0474*	(0.028097)	0.0176*	(0.010450)	0.0298*	(0.017675)
t-1.Business sentiment.= [bar]	-0.0232	(0.020406)	0.0086	(0.007577)	0.0146	(0.012838)
Structural dimension						
Firm-level						
Firmsize	-0.0445***	(0.009206)	0.0165***	(0.003503)	0.0280***	(0.005777)
Firmsize^2	-	-	-	-	-	-
Firmsize [bar]	0.0475***	(0.009501)	-0.0176***	(0.003639)	-0.0299***	(0.005942)
Firmsize^2 [bar]	-	-	-	-	-	-
Industry-level						
Excess labour turnover	0.0063***	(0.002401)	-0.0023***	(0.000893)	-0.0040***	(0.001513)
Employment growth (avg. 96-12)	0.0040**	(0.001851)	-0.0015**	(0.000686)	-0.0025**	(0.001168)
No. of employees (median, avg. 96-12)	0.0006	(0.000737)	-0.0002	(0.000274)	-0.0004	(0.000463)
Regional-level						
Employment concentration	0.0214	(0.456232)	-0.0079	(0.169203)	-0.0135	(0.287029)
Employment concentration [bar]	0.0429	(0.486822)	-0.0159	(0.180612)	-0.0270	(0.306212)
Sector concentration	-0.0030	(0.048996)	0.0011	(0.018175)	0.0019	(0.030822)
Sector concentration [bar]	-0.0053	(0.049990)	0.0020	(0.018540)	0.0033	(0.031451)
Local externalities	0.0002	(0.000292)	-0.0001	(0.000108)	-0.0001	(0.000184)
N	44,683					
Pseudo R^2	0.215					
cut1	-3.4745***	(0.189084)				
cut2	-1.4239***	(0.187732)				

Source: Own calculations.

Notes: *** indicates statistically significance at 1%, ** indicates statistically significance at 5%; * indicates statistically significance at 10% level. MPE referts to the marginal probability effect. SD (in parentheses) represents clustered standard errors. Cut1 and cut2 are the estimated thresholds marking the delimination between the different answer categories in our 3-point categorial outcome variable. The MPE of the variables with a [bar] denote 'level' (long-run) effects, while the other variables listed refer to the 'shock' (short-run) effects. Time-dummies have been omitted in the output table. Industry dummies have been dropped from the estimation due to the inclusion of the industry-level variables (otherwise colliniarty is present). The squared term on "Firmsize" is used in the model estimation, but we preclude the calculation of the MPE for the squared term given its dependency on the linear term.

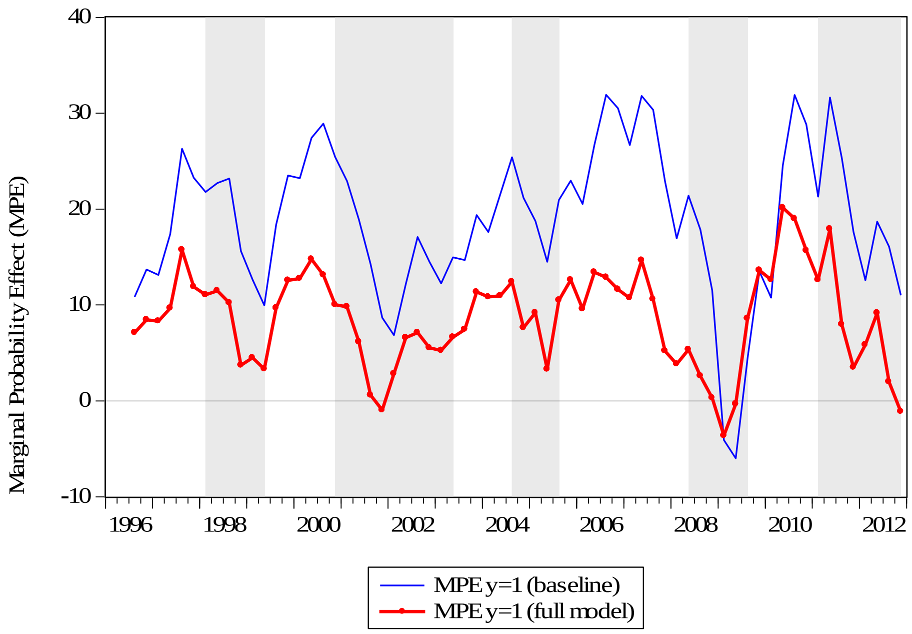
Including our industry as well as regional variables leaves the sign, magnitude and statistically significance of the firm-level covariates basically unchanged. With respect to the industry-level, our variable for sunk costs (proxied by the indicator of **excess labour turnover**) turns out to be statistically significant with a positive marginal probability effect of 0.01. This says that firms operating in an industry which is characterised by a high degree of labour turnover have a higher likelihood of increasing production (around 1%) compared to firms in where labour hoarding is dominating. The marginal effect of **employment growth** is also statistically significant (at the 5%-level) and positive but small in magnitude. Firms in high growth industries (measured by means of employment growth) have on average a higher probability of increasing production output as firms in low growth industries.

Controlling for regional aspects does not help improving the fit of the model, nor does it provide statistically significant marginal probability effects on our NUTS-3 related measures of specialisation (as measured with **related variety**), **employment concentration** and **local externalities**. With regard to business cycles Austrian regions do not have an impact on firm's assessment of their production levels. This stands quite in contrast to the findings by Basile et al. (2014) for Italian manufacturing, who find significant marginal effects on regional characteristics like local externalities or local financial backwardness in explaining North-South differences in the business cycle.

In our analysis, the inclusion of industry and regional information in the model only increased marginally the Pseudo-R^2 measure, and the estimates of the quarterly time-dummies η_t are nearly identical to the results obtained from the 'firm-level' model.

Figure 5 plots the estimates of η_t from the baseline specification (equation (4-1)) as well as from the full model specification (equation (4-3)). The full set of covariates controls for a large part of the unobserved factors embedded in the baseline specification. The estimated marginal probability effects of η_t are on average approximately half the size in the full model specification compared to the baseline. Adding firm-level, industry- and region-specific information allows controlling for additional microeconomic heterogeneity, whilst keeping the overall business cycle dynamics rather similar (contemporaneous correlation between both η_t 'time-series' is +0.75).[36]

Figure 5: Marginal probability effects: Baseline vs. full model specification



Source: Own calculations.

Interestingly, the differences between both estimates are widening up in the business cycle boom years prior the outbreak of the financial crisis and becoming negligibly small in the immediate year of the crisis and half way through the business cycle upswing in the years thereafter. It indicates that the global macroeconomic shock of the financial crisis has hit all firms in a quite similar way and that firm-level heterogeneity has not played a major role in shaping the overall business cycle during the crisis. However, in the years prior the crisis and after the crisis the evidence suggests that firm-level heterogeneity and shocks matter for shaping aggregate business cycle dynamics.

[36] The correlation with respect to the overall business cycle measure of industrial production is to some extent lower in the case of the full model specification. However, the highest correlation is found at two quarters lead (+0.6) compared to one quarter (+0.79) in the baseline setting.

4.4 Extension: firm heterogeneity and business cycle differentials

Our results so far indicate that mainly firm-level business cycle elements as well as to some degree industry-level specifics provide statistically significant marginal probability effects with the expected sign. In a final step, we analyse the effect of the introduced firm heterogeneity in our model on (i) differences along the business cycle (upswing vs. downswing), (ii) differences between large and small firms[37], and (iii) differences between geographical areas (urban vs. rural). In doing so we interact each time-varying firm-level covariate with the respective dummy (either D_{it}^{up}, D_{it}^{large}, or D_{it}^{urban}). Tables C1 to C3 in the Annex provide detailed results.

With respect to the **business cycle phases** we obtain statistically significant marginal effects on the interaction term ($D_{it}^{up} \times \Psi_{\mathrm{it}}$) for production and selling price expectations as well as for capacity utilisation. For example, in upswings of the business cycle firms are more optimistic in terms of their production expectations for the coming months. The probability of an increase in their output level is 3% higher as compared to downturns in the business cycle. Similar results with respect to production expectations are derived for differences between **large and small firms** ($D_{it}^{large} \times \Psi_{\mathrm{it}}$). For large firms expecting an increase in their production level in the coming months, the probability that the increase in the production output will materialise is 7% higher compared to small firms. Moreover, large firms tend to be more negatively affected by demand shocks (mpe is minus 3%) and exhibit a lower probability (mpe is minus 5%) of raising their selling prices in phases where the firm increases its production output ($y_{it} = 1$).

[37] We classify an observation as 'large' firm if the stated number of employees in the respective question is greater or equal to 100. According to our chosen threshold, about 47% of the observations represent large firms.

Using the regional classification of **urban vs. rural** for analysing differences in the business cycle dynamics, we find no clear indication of statistical significant marginal effects on the interaction terms ($D_{it}^{urban} \times \Psi_{\mathrm{it}}$). This confirms our results for the regional controls, ϑ_r, in the full model specification, where these controls have all been found to be not statistically significant. This leads us to conclude that the regional dimension does not help in explaining differences in business cycle dynamics across firms in Austria.

5. Conclusions

In macroeconomics the business cycle is usually analysed from an ‘aggregated’ point of view, either using broad measures of economic activity obtained from official statistics or utilising timely available qualitative data from business tendency surveys (or a combination of both) at a fairly aggregated level. The latter are typically used as ‘balance statistics’, reflecting cross-sectional averages of economic agents’ judgement of their current business conditions and their expectations. The set of survey questions asked aims to cover a broad range of economic activities and expectations at the firm level that are related to the actual (production) activity of the firm. Thus business tendency survey data contains also firm-specific information that is usually ignored in business cycle research. Aggregating survey responses to balances leads to robust aggregate indicators but masks potentially aspects of individual firm behaviour, which may help to understand better the behaviour of aggregate indicators. The research presented in this paper is a first step into this direction. We used business tendency survey micro data to study the (macro) consistency of firm-level answers with regard to current assessments and expectations as well as the impact of structural characteristics and persistent firm heterogeneity on the answering patterns. As dependent variable we used the assessment of the change in production during the past three months, a variable that is very closely correlated to indicators of industrial production or value added and, thus, of special interest in business cycle analysis for forecasting.

Our results show that the answers by firms to different questions within the business tendency survey are largely consistent at the microeconomic level. This is especially visible for the assessment for order book levels, their current degree of capacity utilisation and their production expectations. Strict ccontemporaneous consistency has been verified for the stock of finished products, capacity utilisation and assessments of limiting factors of production (as well as for current order book levels, a result not reported here). Even more important for business cycle research is our result of temporal consistency covering successive (quarterly) waves of the survey, as this provides evidence for the usefulness of asking for short-term expectations. Order books as well as production expectations measured one quarter ahead show a very high association with the current assessment of production changes and provide explanatory power. This result strongly suggests that part of business cycle developments unfolds over time. Looking at these results over time also allows differentiating between unexpected and expected business cycle movements. The findings show that during the immediate years of the financial crisis in 2008/09 firm-level heterogeneity did not add much to the explanation of the business cycle shock, suggesting that this crisis was largely unexpected by Austrian manufacturing firms. But overall our econometric results show that firm-level covariates have explanatory power to help to predict changes in firms' production output. Heterogeneity across firms plays an important role and both short-run and long-run effects can be identified in the data. However, in contrast to the firm-level assessments and expectations, structural characteristics related to the firm (firm size), the industry the firm is operating in or the region it is located do not play a crucial role in shaping the answers. These variables do not affect our results, although we can observe important differences between small and large firms that industry-specifics affects the behaviour of firms. With respect to persistent firm-level differences we find that firms which exhibit a long-run above average to the questions regarding order book levels, the stock of finished products and to a lesser extend also to employment expectations have in general also a higher probability to assess the change in production levels above average. These results confirm that the findings on persistent heterogeneity in the microeconomic literature on productivity (e.g. Syverson, 2011) carry also over to business tendency surveys. Thus our analysis of business cycle dynamics from a ‘micro’ perspective not only provides explanatory power in the short-run but gives information on important long-run heterogeneity.

Overall, our findings show that using business tendency survey micro data, in particular the information set reflecting business cycle conditions (current and expectations), allows to study overall business cycle dynamics in a consistent way and that the answers to business tendency surveys – also at the firm-level – capture primarily the business cycle phenomenon and are not driven primarily by structural characteristics. Taking firm-level heterogeneity into account could be fruitful for forecasting, as it could be one avenue to get clearer grip on the ‘balanced’ results of business tendency surveys. Further research is needed to provide tools for business cycle analysis whether there is the possibility to construct indices on subsets of firms reflecting (observable) heterogeneity at the firm-level.

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Appendix

Table A1: Questionnaire of the monthly WIFO KT (manufacturing sector)

Question [1)]	**Interval** [2)]	**Categories** [3)]
According to harmonised questionnaire		
Production, past 3 months	monthly	+ / = / -
Production, next 3 months	monthly	+ / = / -
Total order books, current	monthly	> / = / <
Export order books, current	monthly	> / = / <
Stocks of finished products	monthly	> / = / <
Selling prices, next 3 months	monthly	+ / = / -
Firm's employment, next months	monthly	+ / = / -
Factors limiting productions	quarterly	4)
Production capacity, current	quarterly	> / = / <
Months of production secured	quarterly	5)
Order books, past 3 months	quarterly	+ / = / -
Export order books, next 3 months	quarterly	+ / = / -
Capacity utilisation	quarterly	6)
Competitive position, domestic market	quarterly	+ / = / -
Competitive position, EU markets	quarterly	+ / = / -
Competitive position, extra-EU markets	quarterly	+ / = / -
Supplementary questions by WIFO		
Selling prices, past 3 months	quarterly	+ / = / -
Firm's business sentiment, current	quarterly	> / = / <
Firm's business sentiment, next 6 months	quarterly	> / = / <
Firm's assessment of their business conditions, coming months	quarterly	7)
Overall economic sentiment, current	quarterly	> / = / <
Overall economic sentiment, next 6 months	quarterly	> / = / <
Firm's total employment	quarterly	8)

Source: based on DG-ECFIN (2007) and WIFO BTS questionnaire.
Notes: 1) Firms are asked in their response to abstract from seasonal variations. 2) Quarterly questions are contained in the January, April, July and October survey. 3) "+ / = / -" relate to change: increased, remain unchanged, decreased; "> / = / <" relate to level: above normal, normal, below normal. 4) Respondents are requested to select one out of the following factors: none, insufficient demand, shortage of labour force, shortage of material and/or equipment, financial constraints, or other factors. 5) Quantitative question in number of months. 6) Quantitative question in percentage of full capacity; ranging from 30 up to 100 per-cent, on a 10 per-cent scale. 7) Categories: reasonable assessable, hardly assessable, to some degree uncertain, or uncertain as never before. 8) Quantitative question in number of employees.

Table A2: Descriptive statistics – Industry dimension (NACE-2-digit breakdown)

Section	Description	MIG-classification [2]	No. of obs. freq.	No. of obs. %		Covariates / controls [3] excess labour turnover	Covariates / controls [3] employment growth in % (avg. 96-12)	Covariates / controls [3] median no. of employees (avg. 96-12)
10	Manufacture of food products	intermediate / consumer	3,418	6.2		0.0734	-0.3	5.2
11	Manufacture of beverages	consumer	1,576	2.9		0.0532	-1.2	3.9
12	Manufacture of tobacco products [1]	consumer	-	-				
13	Manufacture of textiles	intermediate / consumer	2,352	4.3		0.0553	-4.0	3.1
14	Manufacture of wearing apparel	consumer	1,269	2.3		0.0488	-6.2	2.0
15	Manufacture of leather and related products	consumer	694	1.3		0.0587	-2.1	2.5
16	Manufacture of wood and of products of wood/cork, except furniture; manuf. of articles of straw / plaiting materials	intermediate	4,738	8.6		0.0719	-0.2	3.9
17	Manufacture of paper and paper products	intermediate	2,645	4.8		0.0374	-0.7	9.6
18	Printing and reproduction of recorded media	consumer	1,466	2.7		0.0678	-2.3	5.1
19	Manufacture of coke and refined petroleum products [1]	-	-	-				
20	Manufacture of chemicals and chemical products	intermediate	2,714	4.9		0.0480	-0.3	4.6
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	consumer	644	1.2		0.0333	2.9	4.1
22	Manufacture of rubber and plastic products	intermediate	3,304	6.0		0.0556	0.8	8.1
23	Manufacture of other non-metallic mineral products	intermediate	3,982	7.2		0.0616	0.1	4.1
24	Manufacture of basic metals	intermediate	3,099	5.6		0.0362	0.1	22.0
25	Manufacture of fabricated metal products, except machinery and equipment	intermediate / capital	6,614	12.0		0.0682	1.2	4.9
26	Manufacture of computer, electronic and optical products	intermediate / capital / consumer	1,702	3.1		0.0694	-0.5	4.5
27	Manufacture of electrical equipment	intermediate	2,705	4.9		0.0602	0.8	6.8
28	Manufacture of machinery and equipment n.e.c.	capital	6,687	12.1		0.0511	1.7	7.1
29	Manufacture of motor vehicles, trailers and semi-trailers	capital	1,206	2.2		0.0480	0.9	8.1
30	Manufacture of other transport equipment	capital / consumer	296	0.5		0.0318	0.6	6.7
31	Manufacture of furniture	consumer	2,371	4.3		0.0728	-2.3	4.1
32	Other manufacturing	capital / consumer	1,350	2.4		0.0720	-1.5	3.0
33	Repair and installation of machinery and equipment	capital	418	0.8		0.0674	6.6	3.6
		Total	55,250	100.0	*Min*	0.0318	-6.2	2.0
					Max	0.0734	6.6	22.0
					Mean	0.0565	-0.3	5.8
					SD	0.0134	2.5	4.1

Source: Own calculations.

Notes: 1) Section 12 and 19 have been omitted in the analysis due to missing firms allocated to that section. 2) MIG-classification based on NACE-3-digit breakdown. 3) See Section 2 for detailed data description.

Table A3: Descriptive statistics – Regional dimension (NUTS-3 breakdown)

Code	Regionname	Province	Urban/Rural [1]	No. of obs.			Covariates / controls [2]				
							specialisation		employment concentration		local
				freq.	%		manuf.	all industries	manuf.	all industries	externalities
AT111	Mittelburgenland	Burgenland	rural	272	0.5		1.046	1.337	0.109	0.026	2.736
AT112	Nordburgenland	Burgenland	rural	828	1.5		1.543	1.771	0.034	0.020	2.786
AT113	Südburgenland	Burgenland	rural	504	0.9		1.025	1.517	0.060	0.019	1.832
AT121	Mostviertel-Eisenwurzen	Lower Austria	rural	1,920	3.5		1.820	1.882	0.033	0.014	1.413
AT122	Niederösterreich-Süd	Lower Austria	urban	2,687	4.9		2.050	1.864	0.022	0.014	1.207
AT123	Sankt Pölten	Lower Austria	rural	1,298	2.4		1.699	1.624	0.034	0.058	2.234
AT124	Waldviertel	Lower Austria	rural	1,642	3.0		1.486	1.627	0.049	0.016	1.802
AT125	Weinviertel	Lower Austria	rural	375	0.7		1.401	1.525	0.061	0.028	0.474
AT126	Wiener Umland/Nordteil	Lower Austria	urban	1,409	2.6		1.922	2.004	0.033	0.014	-0.087
AT127	Wiener Umland/Südteil	Lower Austria	urban	2,481	4.5		1.830	1.895	0.027	0.014	8.622
AT130	Wien	Vienna	urban	5,987	10.8		1.834	1.769	0.032	0.022	-37.339
AT211	Klagenfurt-Villach	Carinthia	urban	1,976	3.6		1.677	1.808	0.040	0.027	-3.420
AT212	Oberkärnten	Carinthia	rural	870	1.6		1.235	1.357	0.062	0.028	0.458
AT213	Unterkärnten	Carinthia	rural	1,710	3.1		1.645	1.654	0.037	0.015	2.306
AT221	Graz	Styria	urban	1,792	3.2		1.243	1.457	0.085	0.037	1.682
AT222	Liezen	Styria	rural	584	1.1		1.113	1.213	0.080	0.031	-0.263
AT223	Östliche Obersteiermark	Styria	urban	1,306	2.4		1.493	1.441	0.077	0.027	2.472
AT224	Oststeiermark	Styria	rural	1,371	2.5		1.496	1.463	0.046	0.023	2.731
AT225	West- und Südsteiermark	Styria	rural	1,208	2.2		1.434	1.582	0.047	0.018	-1.526
AT226	Westliche Obersteiermark	Styria	rural	1,096	2.0		1.284	1.334	0.046	0.020	2.888
AT311	Innviertel	Upper Austria	rural	2,950	5.3		1.734	1.704	0.031	0.014	1.089
AT312	Linz-Wels	Upper Austria	urban	4,751	8.6		1.921	1.744	0.032	0.022	11.821
AT313	Mühlviertel	Upper Austria	rural	964	1.7		1.270	1.385	0.067	0.023	1.132
AT314	Steyr-Kirchdorf	Upper Austria	rural	1,390	2.5		1.389	1.517	0.097	0.029	7.747
AT315	Traunviertel	Upper Austria	urban	2,716	4.9		1.666	1.674	0.034	0.015	-2.349
AT321	Lungau	Salzburg	rural	196	0.4		0.597	1.003	0.096	0.047	-0.257
AT322	Pinzgau-Pongau	Salzburg	rural	987	1.8		1.114	1.201	0.047	0.060	-0.754
AT323	Salzburg und Umgebung	Salzburg	urban	2,320	4.2		1.839	1.945	0.025	0.016	3.164
AT331	Außerfern	Tyrol	rural	215	0.4		0.263	0.662	0.220	0.068	1.889
AT332	Innsbruck	Tyrol	urban	1,273	2.3		1.336	1.615	0.089	0.026	-0.154
AT333	Osttirol	Tyrol	rural	192	0.4		0.742	1.103	0.230	0.047	1.267
AT334	Tiroler Oberland	Tyrol	rural	277	0.5		0.988	1.015	0.077	0.082	-0.074
AT335	Tiroler Unterland	Tyrol	rural	1,782	3.2		1.471	1.355	0.050	0.039	3.647
AT341	Bludenz-Bregenzer Wald	Vorarlberg	rural	895	1.6		1.192	1.035	0.078	0.054	-0.128
AT342	Rheintal-Bodenseegebiet	Vorarlberg	urban	3,026	5.5		1.867	1.607	0.041	0.025	14.179
			Total	55,250	100.0	*Min*	0.263	0.662	0.022	0.014	-37.339
						Max	2.050	2.004	0.230	0.082	14.179
						Mean	1.419	1.505	0.064	0.030	1.006
						SD	0.401	0.306	0.047	0.017	7.565

Source: Own calculations.

Notes: 1) Urban/rural-classification based on a typology set out by Eurostat. 2) See Section 2 for detailed data description.

Table B1: Marginal probability effects: full ‘firm-level’ model (Order book level not lagged!)

Covariates / controls	y=1		y=2		y=3	
	MPE	**SE**	**MPE**	**SE**	**MPE**	**SE**
Business cycle dimension						
Firm-level (Current)						
Order books.>	0.5607***	(0.009762)	-0.1939***	(0.010081)	-0.3668***	(0.009719)
Order books.=	0.1264***	(0.003248)	0.1636***	(0.009877)	-0.2901***	(0.009840)
Order books.> [bar]	0.2114***	(0.029017)	-0.1040***	(0.014545)	-0.1074***	(0.015126)
Order books.= [bar]	0.0836***	(0.022096)	-0.0411***	(0.010886)	-0.0425***	(0.011345)
Limit.Factor: Insufficient demand	-0.0806***	(0.006021)	0.0397***	(0.003240)	0.0410***	(0.003227)
Limit.Factor: Insufficient demand [bar]	-0.0152	(0.017006)	0.0075	(0.008362)	0.0077	(0.008650)
Stock finished products.>	-0.0385***	(0.011737)	0.0189***	(0.006358)	0.0196***	(0.005519)
Stock finished products.=	-0.0165	(0.010283)	0.0090	(0.005918)	0.0075*	(0.004375)
Stock finished products.> [bar]	0.0503*	(0.029451)	-0.0248*	(0.014502)	-0.0256*	(0.014986)
Stock finished products.= [bar]	0.0298	(0.027592)	-0.0146	(0.013575)	-0.0151	(0.014031)
Selling prices.+	0.0460***	(0.008227)	-0.0214***	(0.004092)	-0.0246***	(0.004375)
Selling prices.=	0.0307***	(0.005372)	-0.0131***	(0.002053)	-0.0176***	(0.003427)
Selling prices.+ [bar]	0.0167	(0.032841)	-0.0082	(0.016195)	-0.0085	(0.016649)
Selling prices.= [bar]	-0.0028	(0.020482)	0.0014	(0.010072)	0.0014	(0.010410)
Capacity utilisation	0.0067***	(0.000272)	-0.0033***	(0.000176)	-0.0034***	(0.000160)
Capacity utilisation [bar]	-0.0048***	(0.000393)	0.0023***	(0.000218)	0.0024***	(0.000198)
Firm-level (Expectations)						
t-1.Production expectations.+	0.1657***	(0.008314)	-0.0741***	(0.005009)	-0.0916***	(0.006133)
t-1.Production expectations.=	0.0689***	(0.004795)	-0.0122***	(0.001872)	-0.0567***	(0.005437)
t-1.Production expectations.+ [bar]	0.0651**	(0.030341)	-0.0320**	(0.014980)	-0.0331**	(0.015421)
t-1.Production expectations.= [bar]	-0.0229	(0.023221)	0.0112	(0.011423)	0.0116	(0.011807)
t-1.Selling price expectations.+	-0.0135	(0.008435)	0.0069	(0.004338)	0.0066	(0.004118)
t-1.Selling price expectations.=	-0.0116*	(0.006645)	0.0060*	(0.003556)	0.0056*	(0.003097)
t-1.Selling price expectations.+ [bar]	-0.0359	(0.033222)	0.0177	(0.016416)	0.0182	(0.016822)
t-1.Selling price expectations.= [bar]	-0.0225	(0.026860)	0.0111	(0.013247)	0.0114	(0.013622)
t-1.Employment expectations.+	0.0861***	(0.009063)	-0.0460***	(0.005536)	-0.0401***	(0.004137)
t-1.Employment expectations.=	0.0295***	(0.005043)	-0.0119***	(0.001808)	-0.0176***	(0.003347)
t-1.Employment expectations.+ [bar]	0.0063	(0.026654)	-0.0031	(0.013118)	-0.0032	(0.013536)
t-1.Employment expectations.= [bar]	0.0198	(0.017561)	-0.0097	(0.008665)	-0.0101	(0.008906)
t-1.Business sentiment.>	-0.0132*	(0.007834)	0.0064*	(0.003756)	0.0068*	(0.004098)
t-1.Business sentiment.=	-0.0042	(0.005527)	0.0021	(0.002826)	0.0021	(0.002702)
t-1.Business sentiment.> [bar]	-0.0277	(0.026616)	0.0136	(0.013109)	0.0141	(0.013519)
t-1.Business sentiment.= [bar]	-0.0189	(0.019873)	0.0093	(0.009783)	0.0096	(0.010098)
Structural dimension						
Firm-level						
Firm size	-0.0171**	(0.008406)	0.0084**	(0.004159)	0.0087**	(0.004262)
Firm size^2						
Firm size [bar]	0.0184**	(0.008728)	-0.0090**	(0.004328)	-0.0093**	(0.004416)
Firm size^2 [bar]						
N	44,683					
Pseudo R^2	0.349					
cut1	-3.9626***	(0.174704)				
cut2	-1.4933***	(0.171215)				

Source: Own calculations.

Notes: *** indicates statistically significance at 1%, ** indicates statistically significance at 5%; * indicates statistically significance at 10% level. MPE referts to the marginal probability effect. SD (in parentheses) represents clustered standard errors. Cut1 and cut2 are the estimated thresholds marking the delimination between the different answer categories in our 3-point categorial outcome variable. The MPE of the variables with a [bar] denote 'level' effects. Time-dummies as well as the industry-dummies have been omitted in the output table.

Table C1: Marginal probability effects on the interaction-term: up vs. down business cycle phase

Covariates / controls	y=1		y=2		y=3	
	MPE	SE	MPE	SE	MPE	SE
Business cycle dimension						
Firm-level (Current)						
UP * t-1.Order books.>	0.0032	(0.011354)	-0.0012	(0.004233)	-0.0020	(0.007121)
UP * t-1.Order books.=	0.0141	(0.009775)	-0.0052	(0.003648)	-0.0088	(0.006131)
UP * t-1.Order books.> [bar]	-0.0085	(0.036812)	0.0032	(0.013724)	0.0053	(0.023088)
UP * t-1.Order books.= [bar]	-0.0986***	(0.030470)	0.0368***	(0.011411)	0.0618***	(0.019124)
UP * Limit.Factor: Insufficient demand	0.0075	(0.010275)	-0.0028	(0.003831)	-0.0047	(0.006445)
UP * Limit.Factor: Insufficient demand [bar]	-0.0049	(0.027129)	0.0018	(0.010114)	0.0031	(0.017015)
UP * Stock finished products.>	-0.0065	(0.019192)	0.0024	(0.007156)	0.0041	(0.012037)
UP * Stock finished products.=	0.0040	(0.017011)	-0.0015	(0.006342)	-0.0025	(0.010669)
UP * Stock finished products.> [bar]	0.0151	(0.042466)	-0.0056	(0.015833)	-0.0095	(0.026634)
UP * Stock finished products.= [bar]	0.0020	(0.039583)	-0.0007	(0.014757)	-0.0012	(0.024826)
UP * Selling prices.+	0.0104	(0.014968)	-0.0039	(0.005582)	-0.0065	(0.009387)
UP * Selling prices.=	0.0222**	(0.010778)	-0.0083**	(0.004027)	-0.0139**	(0.006761)
UP * Selling prices.+ [bar]	-0.0387	(0.048697)	0.0144	(0.018161)	0.0243	(0.030542)
UP * Selling prices.= [bar]	-0.0125	(0.031452)	0.0047	(0.011727)	0.0078	(0.019726)
UP * Capacity utilisation	-0.0012***	(0.000368)	0.0005***	(0.000138)	0.0008***	(0.000231)
UP * Capacity utilisation [bar]	0.0019***	(0.000534)	-0.0007***	(0.000200)	-0.0012***	(0.000335)
Firm-level (Expectations)						
UP * t-1.Production expectations.+	0.0322**	(0.014819)	-0.0120**	(0.005539)	-0.0202**	(0.009295)
UP * t-1.Production expectations.=	0.0284**	(0.012308)	-0.0106**	(0.004601)	-0.0178**	(0.007720)
UP * t-1.Production expectations.+ [bar]	-0.0189	(0.045868)	0.0070	(0.017102)	0.0118	(0.028768)
UP * t-1.Production expectations.= [bar]	0.0504	(0.037958)	-0.0188	(0.014162)	-0.0316	(0.023809)
UP * t-1.Selling price expectations.+	-0.0349**	(0.016547)	0.0130**	(0.006181)	0.0219**	(0.010381)
UP * t-1.Selling price expectations.=	-0.0346***	(0.012824)	0.0129***	(0.004797)	0.0217***	(0.008046)
UP * t-1.Selling price expectations.+ [bar]	0.0391	(0.049921)	-0.0146	(0.018616)	-0.0245	(0.031311)
UP * t-1.Selling price expectations.= [bar]	0.0174	(0.038338)	-0.0065	(0.014294)	-0.0109	(0.024046)
UP * t-1.Employment expectations.+	0.0084	(0.016538)	-0.0031	(0.006166)	-0.0053	(0.010373)
UP * t-1.Employment expectations.=	0.0032	(0.011149)	-0.0012	(0.004157)	-0.0020	(0.006992)
UP * t-1.Employment expectations.+ [bar]	-0.0039	(0.041759)	0.0014	(0.015568)	0.0024	(0.026191)
UP * t-1.Employment expectations.= [bar]	-0.0228	(0.028371)	0.0085	(0.010580)	0.0143	(0.017794)
UP * t-1.Business sentiment.>	-0.0013	(0.015403)	0.0005	(0.005742)	0.0008	(0.009661)
UP * t-1.Business sentiment.=	-0.0108	(0.011254)	0.0040	(0.004198)	0.0067	(0.007059)
UP * t-1.Business sentiment.> [bar]	0.0308	(0.040882)	-0.0115	(0.015245)	-0.0193	(0.025642)
UP * t-1.Business sentiment.= [bar]	0.0299	(0.031237)	-0.0111	(0.011650)	-0.0187	(0.019593)
Structural dimension						
Firm-level						
UP * Firm size	0.0075	(0.013336)	-0.0028	(0.004973)	-0.0047	(0.008364)
UP * Firm size [bar]	-0.0026	(0.013604)	0.0010	(0.005072)	0.0016	(0.008532)
N	44,683					
Pseudo R^2	0.215					
cut1	-3.5129***	(0.132638)				
cut2	-1.4613***	(0.131821)				

Source: Own calculations.

Notes: Only results for the interaction term are shown, the other covariates have been dropped from the output (the sign and magnitude of these marginal effects have not changed compared to the results presented in Table 3). "UP *" denotes the interaction term reflecting the difference in the marginal effect compared to the baseline (i.e. business cycle phase of downswing). For general notes see Table 3.

Table C2: Marginal probability effects on the interaction-term: large vs. small firms

Covariates / controls	y=1		y=2		y=3	
	MPE	**SE**	**MPE**	**SE**	**MPE**	**SE**
Business cycle dimension						
Firm-level (Current)						
LARGE * t-1.Order books.>	0.0214*	(0.011371)	-0.0080*	(0.004295)	-0.0134*	(0.007103)
LARGE * t-1.Order books.=	0.0133	(0.009840)	-0.0050	(0.003706)	-0.0083	(0.006146)
LARGE * t-1.Order books.> [bar]	-0.0797**	(0.037586)	0.0299**	(0.014205)	0.0498**	(0.023498)
LARGE * t-1.Order books.= [bar]	-0.0220	(0.031313)	0.0083	(0.011768)	0.0137	(0.019556)
LARGE * Limit.Factor: Insuff. demand	-0.0324***	(0.010405)	0.0122***	(0.003965)	0.0203***	(0.006510)
LARGE * Limit.Factor: Insuff. demand [bar]	0.0123	(0.028039)	-0.0046	(0.010524)	-0.0077	(0.017519)
LARGE * Stock finished products.>	-0.0258	(0.018966)	0.0097	(0.007145)	0.0161	(0.011846)
LARGE * Stock finished products.=	-0.0233	(0.016739)	0.0088	(0.006307)	0.0146	(0.010454)
LARGE * Stock finished products.> [bar]	-0.0494	(0.044806)	0.0186	(0.016854)	0.0309	(0.027990)
LARGE * Stock finished products.= [bar]	-0.0581	(0.041726)	0.0218	(0.015691)	0.0363	(0.026091)
LARGE * Selling prices.+	-0.0486***	(0.014946)	0.0183***	(0.005711)	0.0304***	(0.009343)
LARGE * Selling prices.=	-0.0285***	(0.010779)	0.0107***	(0.004095)	0.0178***	(0.006736)
LARGE * Selling prices.+ [bar]	-0.0219	(0.049347)	0.0082	(0.018534)	0.0137	(0.030819)
LARGE * Selling prices.= [bar]	0.0371	(0.031797)	-0.0139	(0.011953)	-0.0232	(0.019873)
LARGE * Capacity utilisation	0.0001	(0.000381)	-0.0000	(0.000143)	-0.0001	(0.000238)
LARGE * Capacity utilisation [bar]	-0.0007	(0.000565)	0.0003	(0.000213)	0.0004	(0.000353)
Firm-level (Expectations)						
LARGE * t-1.Production expectations.+	0.0673***	(0.014871)	-0.0253***	(0.005770)	-0.0421***	(0.009309)
LARGE * t-1.Production expectations.=	0.0198	(0.012361)	-0.0074	(0.004661)	-0.0124	(0.007722)
LARGE * t-1.Production expect.+ [bar]	0.0897*	(0.046713)	-0.0337*	(0.017650)	-0.0561*	(0.029183)
LARGE * t-1.Production expect.= [bar]	0.0112	(0.039005)	-0.0042	(0.014649)	-0.0070	(0.024358)
LARGE * t-1.Selling price expectations.+	-0.0276*	(0.016578)	0.0104*	(0.006254)	0.0172*	(0.010356)
LARGE * t-1.Selling price expectations.=	-0.0432***	(0.012851)	0.0162***	(0.004915)	0.0270***	(0.008035)
LARGE * t-1.Selling price expect.+ [bar]	0.0614	(0.050761)	-0.0231	(0.019117)	-0.0384	(0.031696)
LARGE * t-1.Selling price expect.= [bar]	0.0135	(0.038572)	-0.0051	(0.014491)	-0.0084	(0.024083)
LARGE * t-1.Employment expectations.+	-0.0115	(0.016581)	0.0043	(0.006230)	0.0072	(0.010357)
LARGE * t-1.Employment expectations.=	-0.0112	(0.011114)	0.0042	(0.004179)	0.0070	(0.006943)
LARGE * t-1.Employment expect.+ [bar]	-0.0524	(0.042118)	0.0197	(0.015855)	0.0327	(0.026307)
LARGE * t-1.Employment expect.= [bar]	-0.0373	(0.028681)	0.0140	(0.010797)	0.0233	(0.017917)
LARGE * t-1.Business sentiment.>	0.0027	(0.015401)	-0.0010	(0.005783)	-0.0017	(0.009618)
LARGE * t-1.Business sentiment.=	0.0056	(0.011293)	-0.0021	(0.004242)	-0.0035	(0.007053)
LARGE * t-1.Business sentiment.> [bar]	-0.1125***	(0.041733)	0.0422***	(0.015881)	0.0702***	(0.026059)
LARGE * t-1.Business sentiment.= [bar]	-0.0250	(0.032252)	0.0094	(0.012130)	0.0156	(0.020135)
Structural dimension						
Firm-level						
LARGE * Firm size	0.0287	(0.023340)	-0.0108	(0.008955)	-0.0179	(0.014406)
LARGE * Firm size [bar]	-0.0280	(0.021427)	0.0105	(0.008022)	0.0175	(0.013431)
N	44,683					
Pseudo R^2	0.217					
cut1	-3.6374***	(0.135007)				
cut2	-1.5803***	(0.134228)				

Source: Own calculations.

Notes: Only results for the interaction term are shown, the other covariates have been dropped from the output (the sign and magnitude of these marginal effects have not changed compared to the results presented in Table 3). "LARGE *" denotes the interaction term reflecting the difference in the marginal effect compared to the baseline (i.e. small firms). For general notes see Table 3.

Table C3: Marginal probability effects on the interaction-term: urban vs. rural regions

Covariates / controls	y=1 MPE	y=1 SE	y=2 MPE	y=2 SE	y=3 MPE	y=3 SE
Business cycle dimension						
Firm-level (Current)						
URBAN * t-1.Order books.>	-0.0180	(0.011451)	0.0067	(0.004276)	0.0113	(0.007181)
URBAN * t-1.Order books.=	-0.0088	(0.009876)	0.0033	(0.003685)	0.0055	(0.006193)
URBAN * t-1.Order books.> [bar]	-0.0265	(0.037583)	0.0099	(0.014023)	0.0166	(0.023564)
URBAN * t-1.Order books.= [bar]	0.0130	(0.031223)	-0.0048	(0.011646)	-0.0081	(0.019578)
URBAN * Limit.Fact.: Insuff. demand	0.0067	(0.010369)	-0.0025	(0.003868)	-0.0042	(0.006502)
URBAN * Limit.Fact.: Insuff. demand [bar]	-0.0143	(0.028280)	0.0053	(0.010548)	0.0090	(0.017734)
URBAN * Stock finished products.>	0.0243	(0.019125)	-0.0091	(0.007139)	-0.0153	(0.011993)
URBAN * Stock finished products.=	0.0412**	(0.016906)	-0.0154**	(0.006324)	-0.0258**	(0.010603)
URBAN * Stock finished products.> [bar]	0.0087	(0.044432)	-0.0033	(0.016570)	-0.0055	(0.027863)
URBAN * Stock finished products.= [bar]	-0.0066	(0.041568)	0.0025	(0.015505)	0.0041	(0.026063)
URBAN * Selling prices.+	-0.0055	(0.015051)	0.0020	(0.005614)	0.0034	(0.009438)
URBAN * Selling prices.=	0.0010	(0.010939)	-0.0004	(0.004080)	-0.0006	(0.006859)
URBAN * Selling prices.+ [bar]	0.0112	(0.050127)	-0.0042	(0.018699)	-0.0070	(0.031429)
URBAN * Selling prices.= [bar]	-0.0002	(0.032594)	0.0001	(0.012157)	0.0001	(0.020437)
URBAN * Capacity utilisation	0.0004	(0.000371)	-0.0001	(0.000138)	-0.0002	(0.000232)
URBAN * Capacity utilisation [bar]	-0.0005	(0.000537)	0.0002	(0.000201)	0.0003	(0.000337)
Firm-level (Expectations)						
URBAN * t-1.Production expectations.+	0.0240	(0.014922)	-0.0090	(0.005572)	-0.0151	(0.009357)
URBAN * t-1.Production expectations.=	0.0162	(0.012401)	-0.0060	(0.004629)	-0.0102	(0.007776)
URBAN * t-1.Production expect.+ [bar]	0.1185**	(0.047310)	-0.0442**	(0.017673)	-0.0743**	(0.029699)
URBAN * t-1.Production expect.= [bar]	0.0987**	(0.039258)	-0.0368**	(0.014679)	-0.0619**	(0.024630)
URBAN * t-1.Selling price expectations.+	0.0030	(0.016686)	-0.0011	(0.006224)	-0.0019	(0.010462)
URBAN * t-1.Selling price expectations.=	-0.0017	(0.012938)	0.0006	(0.004826)	0.0011	(0.008112)
URBAN * t-1.Selling price expect.+ [bar]	-0.0267	(0.051270)	0.0100	(0.019128)	0.0168	(0.032145)
URBAN * t-1.Selling price expect.= [bar]	-0.0046	(0.039521)	0.0017	(0.014742)	0.0029	(0.024780)
URBAN * t-1.Employment expectations.+	0.0252	(0.016647)	-0.0094	(0.006216)	-0.0158	(0.010439)
URBAN * t-1.Employment expectations.=	0.0082	(0.011244)	-0.0030	(0.004195)	-0.0051	(0.007050)
URBAN * t-1.Employment expect.+ [bar]	-0.0187	(0.043414)	0.0070	(0.016195)	0.0117	(0.027220)
URBAN * t-1.Employment expect.= [bar]	-0.0511*	(0.029564)	0.0191*	(0.011042)	0.0320*	(0.018540)
URBAN * t-1.Business sentiment.>	0.0124	(0.015542)	-0.0046	(0.005799)	-0.0078	(0.009745)
URBAN * t-1.Business sentiment.=	-0.0037	(0.011379)	0.0014	(0.004244)	0.0023	(0.007135)
URBAN * t-1.Business sentiment.> [bar]	-0.0764*	(0.041652)	0.0285*	(0.015542)	0.0479*	(0.026139)
URBAN * t-1.Business sentiment.= [bar]	-0.0346	(0.031968)	0.0129	(0.011924)	0.0217	(0.020052)
Structural dimension						
Firm-level						
URBAN * Firm size	0.0110	(0.013557)	-0.0041	(0.005059)	-0.0069	(0.008500)
URBAN * Firm size [bar]	-0.0079	(0.013839)	0.0029	(0.005162)	0.0049	(0.008678)
N	44,683					
Pseudo R^2	0.216					
cut1	-3.2491***	(0.169137)				
cut2	-1.1962***	(0.168552)				

Source: Own calculations.
Notes: Only results for the interaction term are shown, the other covariates have been dropped from the output (the sign and magnitude of these marginal effects have not changed compared to the results presented in Table 3). "URBAN *" denotes the interaction term reflecting the difference in the marginal effect compared to the baseline (i.e. rural regions). For general notes see Table 3.

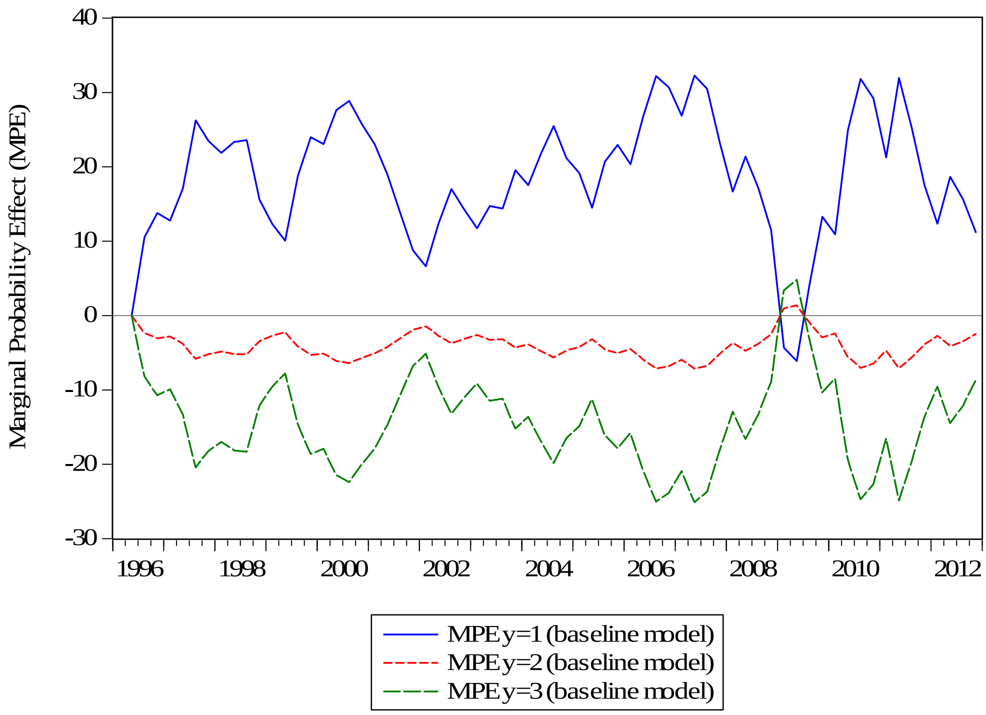
Table D1: Model evaluation – "goodness-of-fit" results

Model (i_{q*}=44,683 no. of. obs.)	**R^2_{McF}**	**R^2_{AN}**	**R^2_{M}**	**AIC**	**BIC**
q-dummies [baseline]	0.025	0.030	0.031	86,012	86,604
q + firm-level [structure]	0.033	0.033	0.034	85,314	85,958
q + firm-level [business cycle - current]	0.192	0.119	0.126	71,338	72,070
q + firm-level [business cycle - expectations]	0.104	0.085	0.088	79,076	79,807
q + firm-level	**0.215**	**0.163**	**0.177**	**69,359**	**70,447**
q + firm-level [structure] + industry controls	0.034	0.035	0.035	85,171	85,842
q + firm-level [structure] + regional controls	0.033	0.034	0.035	85,302	85,990
full model: firm-level + industry + regional	**0.215**	**0.161**	**0.175**	**69,362**	**70,355**
firm-level + UP*	0.215	0.298	0.346	69,381	70,618
firm-level + LARGE*	0.216	0.299	0.347	69,309	70,545
firm-level + URBAN*	0.215	0.298	0.345	69,403	70,640

Source: Own calculations.

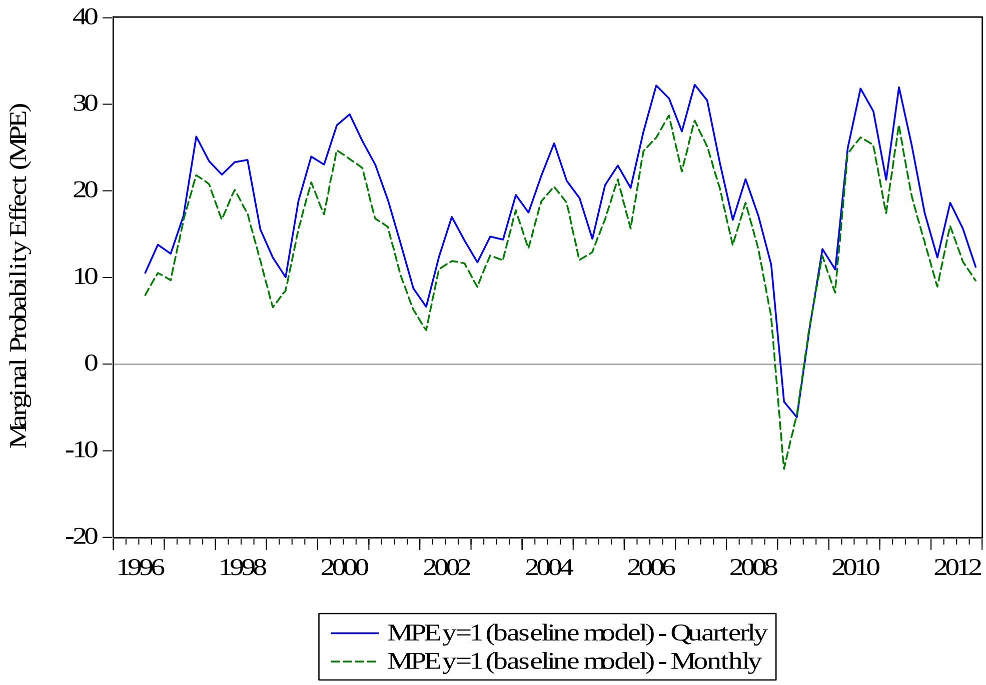
Notes: Pseudo-R^2 measures: McF.. McFadden, AN..Aldrich-Nelson, M..Maddala; Variable notation: q..q-dummies; UP*..interaction with "business cycle upswing" dummy; LARGE*..interaction with "large firm" dummy; URBAN*..interaction with "urban location" dummy.

Figure B1: Marginal probability effects of time-dummies ($y_{it} \in \{1,2,3\}$)



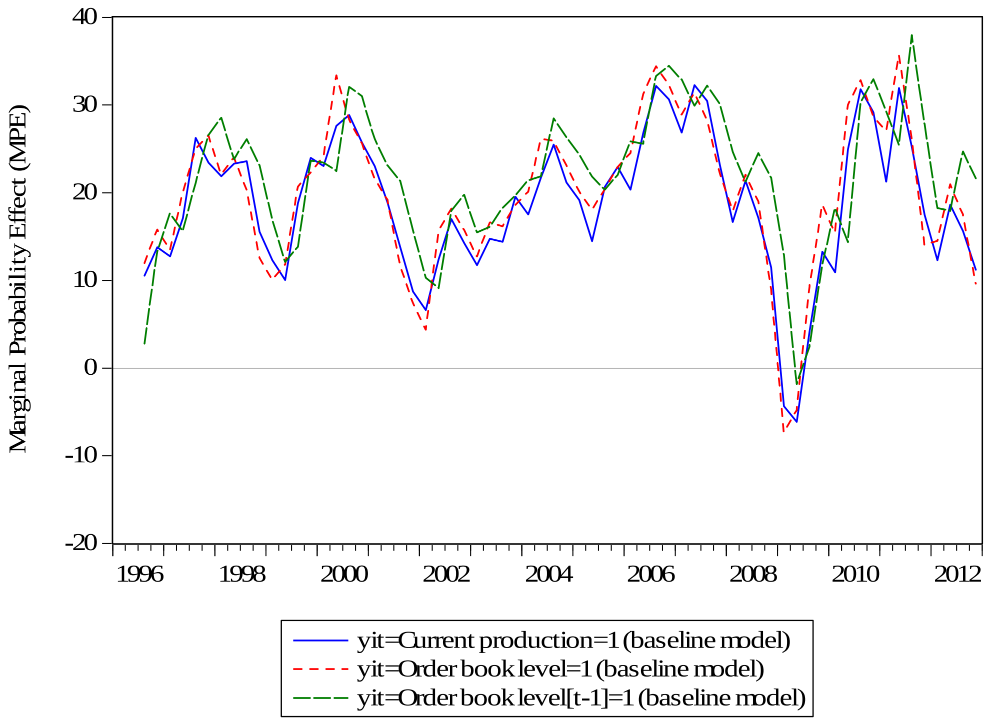
Source: Own calculations.

Figure B2: Marginal probability effects of time-dummies – quarterly vs. monthly interval



Source: Own calculations.

Figure B3: Marginal probability effects of time-dummies – y_{it} vs. order book levels



Source: Own calculations.