Three Empirical Essays in Economics Using Firm Level Panel Data

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Preface

The use of panel data in economic research has become more and more popular over the last 15 years. Especially the greater availability of panel data – particularly in developing countries – and the increase of the computational power of the desktops available have probably played an important role in their rising utilization.[1]

Nonetheless, the large number of methodical advantages of panel data compared to pure cross-section or pure time-series data might have contributed to their increasing importance as well. For example, using panel data provides the greater possibility to tackle problems such as the existence of individual heterogeneity and moreover allows to identify effects which otherwise are not detectable (see Baltagi, 2008, Chapter 1.2). Linked to the former aspect, panel data also provides the possibility to specify more complex behavioral models. There are a number of further advantages not mentioned in this section. However, there is no doubt that panel data helps to improve the quality of economic analysis. Panel data commonly provides a greater degree of information, joint with a greater degree of variability, which results in more degrees of freedom, less collinearity among the variables and higher efficiency, and by this can help to answer a number of research questions which otherwise might not have been able to be addressed.[2]

This dissertation consists of three empirical essays using micro panel data which stem from two important surveys in Germany – the Ifo Business Tendency Survey and the Ifo Innovation Survey for the German manufacturing industry.

The Ifo Business Tendency Survey is conducted monthly since 1949 and serves as base for the well-known Ifo Business Climate Index. Before 1991, only firms from West Germany participated in the survey. Subsequently, the panel was enlarged to Eastern Germany. The firms are asked questions about the development of certain key measures – such as the current business situation, their expectations or their level of production –, which are included monthly in the survey. Furthermore, the firms are asked certain special questions, which are included at a lower frequency or even temporar-

[1]See Hsiao (2003), Chapter 1.1, Nerlove (2002), Chapter 1.
[2]See Baltagi (2008), Chapter 1.2, Hsiao (2003), Chapter 1.1.

ily. Currently, the total number of companies of the manufacturing industry registered for the survey is about 3200. The participation rate is about 92 %, resulting in a coverage ratio of about 35 % of the German manufacturing industry in terms of turnover (see Goldrian, 2004). Overall, besides about 20 identification variables on certain firm characteristics, the dataset provides over 60 other variables on firm specific developments.

The Ifo Innovation Survey is conducted annually since 1979 for West German firms and subsequently was enlarged to East German firms in 1991. The survey consists of two question complexes: A complex of general questions relevant for all firms, regardless of their level of innovative activity, and a complex of more specific questions, relevant particularly for firms which currently are involved in an innovative activity. The several different questions on the innovative activity of the firms are classified inter alia by type of innovation, input of know-how, expenses, technological focus and complexity. Moreover, there exist further standard questions such as questions on innovation goals, innovation impulses and innovation obstacles. The coverage ratio in terms of employees of the manufacturing industry is about 14 % (see Goldrian, 2004). Besides 9 identification variables and about 30 variables on general measures of the firm such as turnover, revenue, number of employees and academic background of the employees, the survey consists of about 700 variables on the innovative activity of the firms – from questions asked since the start of the survey as well as questions which were included in the survey only temporarily.[3]

As the units of observation of the surveys have unique identification variables and are based on the same population, they can be matched to one large dataset. This is another huge advantage as it provides the possibility to address a much bigger range of research questions than usual.[4] The following chapters present examples of how the general advantages of panel data as well as the specific advantages of the two micro panel datasets can be used in economic analysis.

[3]For a more detailed overview about the questionnaires of both surveys, see Becker and Wohlrabe (2008).

[4]Remark: Both datasets as well as a matched version are provided by the Economics & Business Data Center (EBDC), a combined platform for empirical research in business administration and economics of the Ludwig-Maximilian University of Munich (LMU) and the Ifo Institute for Economic Research.

The first chapter analyses the effects of the degree of credit constraints the firms are facing on their innovative activity. One of the biggest issues present in the quite extensive literature on this subject is the lack of direct measures for the degree of credit constraints as well as the innovative activity.[5] Different to the data used by earlier research, the matched data allow to use both a direct measure for the degree of credit constraints as well as a direct measure for the innovative activity. Furthermore, the design of the survey questions and the panel structure of the dataset allow to avoid problems commonly difficult to solve such as the existence of forward looking adjustments in a world of expectations or mutual causation, and moreover to analyse potential asymmetries in the effects of above average and below average credit conditions. As opposed to many other investigations the analysis shows clear evidence for a negative effect of credit constraints on the innovative activity of firms. In addition, it shows that below average financing conditions restrict innovative activity, while above average financing conditions do not foster it. To explain this novel result the usual theory of innovation activity is extended by rigidities with respect to a firm's individual innovation capacity, which leads to a differentiation between a long run and a short run equilibrium in innovative output.

The second chapter takes a similar vein. Specifically, this chapter analyses the effects of innovative activity on the competitiveness of firms. From theory, innovations are one of the main drivers of the competitiveness, the growth of an economy, respectively. Accordingly, a huge literature exists analysing the effects of innovative activity on growth in terms of export shares, sales or employment. By using the datasets described above the essay contributes to this literature in several ways: First, the datasets allow to use direct information on the competitive situation of the company, on the national as well as the international level. Second, they also allow to use direct information on the innovative activity of firms, by this avoiding issues of commonly used indirect measures like the level of investments in R&D or patents. Third, and most importantly, in the analysis one is able to differentiate between product and process innovations, where until now only little research is done. The results show the big importance of innovative activity for the competitive situation of firms. Moreover, the results show that product innovations contribute to

[5] For example, for the degree of the credit constraints the firms are facing there mostly are used some inverse cash flow ratios or other balance sheet measures. For their innovative activity there mostly is used the level of investment in R&D or the number of patents.

an increase of the competitive situation of the firm, while process innovations obviously do not, thereby providing evidence for the superior importance of non-price factors compared to price factors with respect to competitiveness and growth.

The third chapter connects to a quite large body of macroeconomic literature, which analyses the effects of oil price shocks on the macroeconomy. The first section shows that it is difficult to identify negative effects of oil price increases on the level of the German industrial production by using standard structural VAR models. By deriving these results with German data the analysis is in line with an important branch of literature investigating the oil price macroeconomy relationship for the United States. In the second section of the chapter, by using the Ifo micro dataset, an analysis on the micro level is performed, where certain problems such as endogeneity or reverse causality are circumvented. Here one indeed can observe significant negative effects of oil price increases on the level of production in Germany. Based on these results, in a third section information from the micro dataset is processed and subsequently integrated into the macroeconomic models of section one. When doing this one can observe a negative effect of oil price hikes on the level of production also on the macroeconomic level. The last section of the chapter then consists of a counterfactual analysis, which examines, how much the oil price hike in 2007/08 contributed to the subsequent recession in Germany.

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Chapter 1

Financing Conditions, the Concept of Innovation Capacity and the Innovative Activity of Firms

In this chapter a novel survey dataset allows us to use a direct measure for credit constraints as well as a direct measure for the innovative activity of a firm to identify the effects of credit constraints on the innovative behaviour of firms. Furthermore, the design of the survey questions and the panel structure of the dataset allow us to avoid problems commonly difficult to solve such as the existence of forward looking adjustments in a world of expectations or mutual causation, and moreover to analyse potential asymmetries in the effects of above average and below average credit conditions. As opposed to many other analyses we find clear evidence for a negative effect of credit constraints on the innovative activity of firms. In addition, we find that below average credit conditions restrict innovative activity, while above average credit conditions do not foster it. To explain this novel result we extend the usual theory of innovation activity by rigidities with respect to a firm's individual innovation capacity, which leads to a differentiation between a long run and a short run equilibrium in innovative output.

1.1 Introduction

One of the most popular areas of research on credit constraints is their effect on the innovative activity of firms. This field is of great importance as innovative activity is considered as one of the main factors for economic growth and firm performance.

Due to the lack of appropriate data, earlier literature has mostly used indirect measures as indicators for credit constraints and innovative activity (Bhagat and Welch, 1995, Harhoff, 1998, Hall et al., 2001, Bond et al., 2006).[1] However, the results concerning the existence as well as the degree of the effects of credit constraints were far from clear cut. Moreover, the use of the indirect measures was questioned in recent years.[2] Due to better availability of data literature has been published which applies more direct measures (Binz and Czarnitzki, 2008, Atzeni and Piga, 2007, Hottenrott and Peters, 2009, Savignac, 2006). Nonetheless, often a direct measure of only one of the variables of interest – either of the level of credit conditions or of the level of innovative activity – is available. Moreover, by investigating the effects of credit conditions on the innovative activity of firms, it often is impossible to consider problems caused by the existence of forward looking adjustments in a world of expectations, unobserved heterogeneity, or mutual causation.

This essay contributes to the literature by using a novel dataset to solve these issues and moreover to analyse aspects which until now have not been taken into account. First, the dataset provides – unlike other datasets – both direct information on the degree of the credit constraints as well as direct information on the beginning of an innovation activity. This helps to avoid the drawbacks we had until now by using indirect measures. Secondly, the design of the survey questions and the panel structure of the dataset give us the possibility of avoiding issues like unobserved heterogeneity or mutual causation between the dependent variable and its regressors. Third, due to

[1]Most prominent indirect measures are several inverse cash flow ratios of a company as proxies for the degree of the credit constraints the firm is facing and the investment in R&D as proxy for the innovative activity of the firm.

[2]For example, R&D activities are only one input factor to the innovation process and all innovations do not necessarily stem from R&D. Furthermore and more severely, the measure on the degree of credit restrictions is also an indirect one. In this context especially the use of cash flow ratios as proxies for the credit condition of a firm is questioned (see Kaplan and Zingales, 1997, Alti, 2003).

the availability of variables such as the expectations of a firm concerning the future business situation we can also deal with problems usually difficult to solve such as forward looking adjustments in a world of expectations. Finally, the unique possibility to distinguish between “normal”, “good” and “bad” credit conditions allows to analyse if there exist asymmetries in the effects of above average and below average credit conditions.

The results give – unlike those of many other papers – strong evidence that credit constraints restrict innovative activity. Moreover, the results provide evidence for asymmetries in the effects of above average and below average credit conditions. We show that below average credit conditions restrict innovative activity, whereas above average credit conditions do not foster it. This novel result could support hypotheses, which state that a firm’s innovation capacity plays an important role in its innovation behaviour. To strengthen this thesis we expand the usual theory of innovation activity by rigidities with respect to a firm’s individual innovation capacity, which leads to a differentiation between a long run and a short run equilibrium in innovative output.

The remainder of the essay is organized as follows. Section 2 provides the conceptual framework for the analysis. Section 3 presents some information about the survey dataset used in the essay. Section 4 describes our empirical specification and methodology. Section 5 presents the estimation results. Section 6 concludes.

1.2 Conceptual Framework

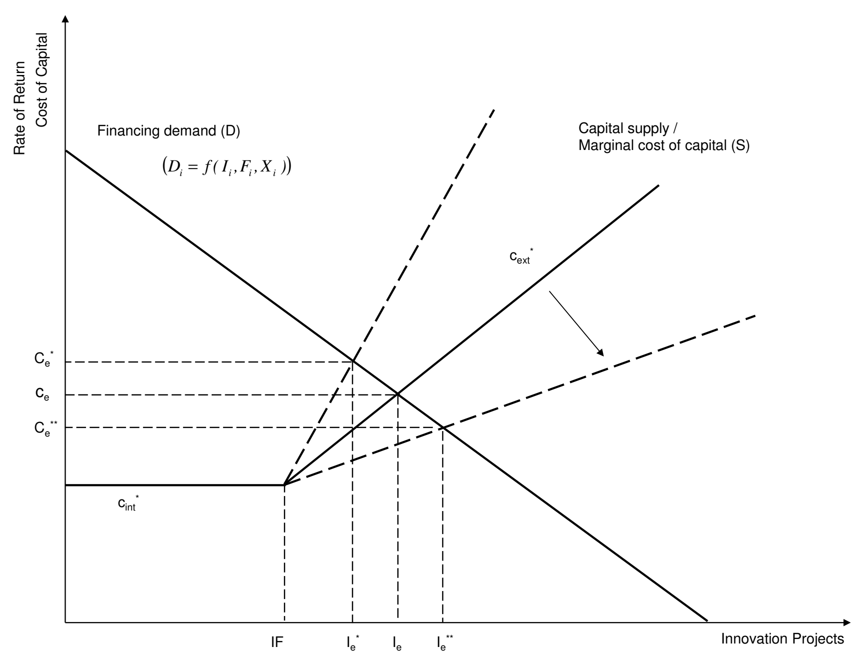
To relate our empirical investigations to theory we use a standard model, which analyses the effects of financing conditions on innovative activity.[3] Subsequently, the model is extended by taking into account rigidities with respect to a firm’s individual innovation capacity.

Figure 1.1 provides the standard model, which hereafter is referred to as “long run equilibrium model”. D_i is the capital demand curve of the firm, representing the marginal revenues of capital depending on the level of innovative

[3] The model inter alia is used by Howe and Mc Fetridge (1976), Carpenter and Petersen (2002), and Hottenrott and Peters (2009).

output. The marginal revenues of capital depend on the level of innovation expenditures I_i, firm-specific characteristics F_i and industry characteristics X_i. The capital demand curve therefore is defined as $D_i = f(I_i, F_i, X_i)$. S_i is the capital supply curve for the company, representing the marginal costs of capital depending on the level of innovative output. As there exist two sources of capital supply – internal as well as external sources – we assume a pecking order. This means that in the first place the firms will use their internal funds IF_i. Afterwards they will start to obtain external financing, with a positive relationship between the amount of capital and marginal costs. The intersection of the supply and the demand curves constitutes the equilibrium innovative output I_e. In this setting, worsening financing conditions, represented by a steeper supply curve, will lead to higher marginal costs in equilibrium and lower innovative output. Vice versa, improving financing conditions, represented by a flatter supply curve, will lead to lower marginal costs in equilibrium and higher innovative output.

Figure 1.1: Conceptual Framework – Long Run Equilibrium

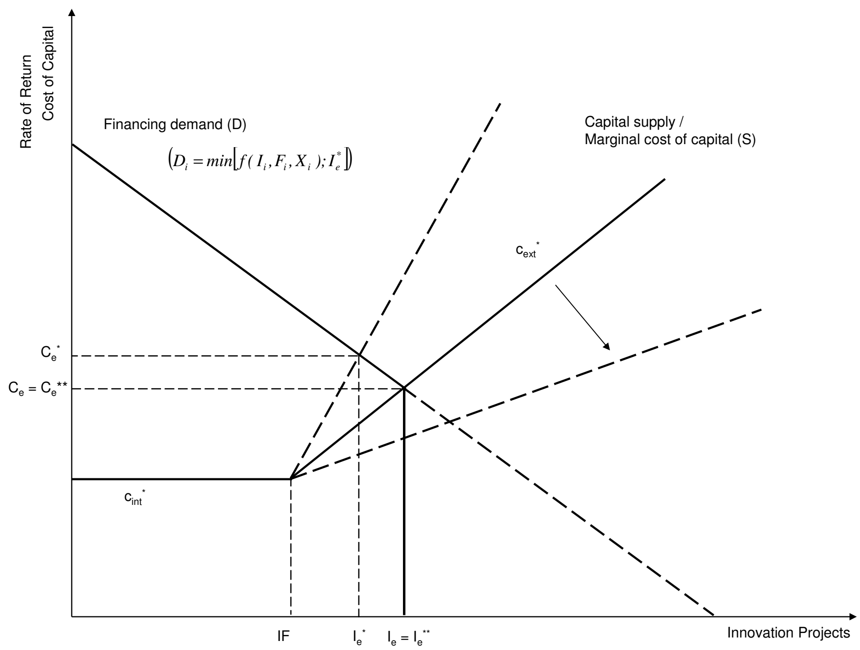


To underpin our novel findings at the empirical level – the existence of asymmetries in the effects of above average and below average financing conditions – we now distinguish between the long run equilibrium provided above and a short run equilibrium derived in the following. By this means we introduce the concept of innovation capacity and short term rigidities with respect to the adjustment of the level of input factors to R&D. The individual innovation capacity is defined as the number of potential innovation projects the firm is able to produce over a certain period. It may be determined by the amount of different input factors to R&D – such as the number of researchers allocated to R&D, their level of know-how or the quality of the technical equipment related to R&D. How much of these input factors a company accumulates depends on the firm's individual capital costs and is determined in the long run equilibrium (see Figure 1.1). In the long run the firm will choose its level of input factors to R&D – and accordingly its innovation capacity – such that it can produce exactly I_e of potential innovation projects. If it produces on average less than I_e potential projects, this is inefficient as additional innovation projects still will yield positive net marginal revenues but cannot be undertaken. If it produces on average more than I_e potential projects, it is inefficient as not all of the available innovation projects can be undertaken due to negative net marginal revenues.

However, by introducing adjustment rigidities with respect to the input factors to R&D, the implications of the model differ from before. Specifically – and in contrast to the long run equilibrium model – the firms now are facing a demand function of $D_i = min[f(I_i, F_i, X_i]); {I_e}^*]$. This means that the demand curve now is kinked at point I_e (see Figure 1.2). By this we take into account that – due to the presence of the adjustment rigidities introduced in the model – in the short run the innovative output cannot be increased above its maximum level (which is determined by the firm's innovative capacity, its long run equilibrium I_e). As one can see, in this framework worsening financing conditions, represented by a steeper supply curve, again lead to less potential innovation projects being undertaken. However, unlike in the long run equilibrium model, improving financing conditions, represented by a flatter supply curve, now have no positive effect on the level of innovative output, as the maximum level of potential innovative projects is limited to I_e.

This leads to the result we obtain from our empirical investigations: a deterioration of financing conditions decreases innovative activity, while an improvement will not foster it (in the short run).

Figure 1.2: Conceptual Framework – Short Run Equilibrium



1.3 Data

To perform our analysis we use data from two sources: the Ifo Innovation Survey and the Ifo Business Tendency Survey for German manufacturing firms.[4] As the surveys include questions which are asked on different frequencies, we will transform all variables that are used to the lowest frequency (annual) if necessary.

The Ifo Innovation Survey is carried out annually. The survey inter alia

[4]Both datasets are provided by the Economics & Business Data Center (EBDC), a combined platform for empirical research in business administration and economics of the Ludwig Maximilian University of Munich (LMU) and the Ifo Institute for Economic Research.

asks the firms,[5] if they have "started or continued" an innovation project in the preceding year. As the survey additionally provides information as to whether the company has "finished" or "stopped" an innovation project, we can correct for years in which the company only continued an innovation project.[6] Innovations are categorized as either product or process innovations. The resulting variables are the variable *"productinnov",* which is coded 1, if a product innovation has started in the corresponding year, and 0 otherwise, and the variable *"processinnov"*, which is coded 1, if a process innovation has started in the corresponding year, and 0 otherwise.

The Ifo Business Tendency Survey is carried out monthly and contains questions asked at different frequencies. One of the questions regards the financing conditions the firms are facing and is included in the survey biannually. The answers are coded as -1 ("favourable financing conditions"), 0 ("normal financing conditions"), and +1 ("reserved financing conditions"). These data are aggregated on an annual basis by taking the averages of the values of the variable for each year. The variable *"credit"* resulting from this can be interpreted as the average financing conditions over the year. It can take values of 1, 0.5, 0, -0.5, or -1, where the limit value of 1 implies that the company reported below average financing conditions at both inquiry dates of the year, and the limit value of -1 implies that the company reported above average financing conditions at both inquiry dates of the year.[7]

[5]Note that each ID-number of the dataset is representing a single production entity for a single product of the firm rather than the whole firm. This aspect is a further advantage of the dataset as it allows a more detailed analysis for multi-product firms. However, for simplicity, in the following we will refer to the particular unit of observation as "firm".

[6]To correct the original variable for values indicating only a continuation of an innovation project we proceed as follows. The value of the variable at time t will be converted from 1 to 0 (i.e. the value of 1 of the variable is indicating a continuation rather than the start of an innovation project), if there was a start or continuation of an innovation project in the preceding year (and no finish or stop of an innovation project), and concurrently no finish or stop of an innovation project in the current period (to prevent that a new innovation project was started after finishing or stopping another process within the same year). The possibility that there exist multiple product or process innovations at the same time is mostly prevented by the fact that each ID-number of the dataset represents a single production entity for a single product of the firm rather than the whole firm. However, the estimations using the dataset without the correction provide qualitatively the same results (see Appendix C).

[7]Furthermore, a value of 0.5 indicates that the corresponding firm reported below average financing conditions at one inquiry date of the year and normal financing conditions

Furthermore, the Ifo business tendency service consists of questions on the overall business situation of the firm (*"situat"*) and on the overall expectations of the firm (*"expect"*)[8]. The answers to the question regarding the business situation of the firm are coded as -1 ("bad business situation"), 0 ("normal business situation"), and +1 ("good business situation"). The answers to the question regarding the firms' expectations are coded as -1 ("expectations worsened"), 0 ("expectations remained constant"), and +1 ("expectations increased"). As the questions on the business situation and the expectations of the companies are conducted monthly, the corresponding variables also have to be aggregated on an annual basis. We do this by again taking the averages of the values of the variables for each year. The variables resulting from this can be interpreted as the average business situation over the year and the change in the firm's expectations over the year, respectively.

Finally, the business tendency survey provides information on certain firm characteristics. First of all we can relate to the size of a company in terms of its market power (*"mkp"*), which is defined as the number of employees per firm divided by the number of employees in the firm's branch. In addition, each firm is allocated to one of the following 14 manufacturing subsectors: Food, Beverages and Tobacco; Textiles and Textile Products; Tanning and Dressing of Leather; Cork and Wood Products except Furniture; Pulp, Paper, Publishing and Printing; Refined Petroleum Products; Chemicals and Chemical Products; Rubber and Plastic Products; Other Non-metallic Mineral Products; Basic and Fabricated Metal Products; Machinery and Equipment; Electrical and Optical Equipment; Transport Equipment; Furniture, Manufacture. Furthermore, each firm is allocated to one of the following regions in Germany: East Germany, West Germany, South Germany and North Germany.

at the other inquiry date of the year. Correspondingly, a value of -0.5 indicates that the corresponding firm reported above average financing conditions at one inquiry date of the year and normal financing condition at the other inquiry date of the year. When the variable takes the value 0, the companies mostly have reported normal financing conditions at both inqiry dates. The situation that a company has reported above average financing conditions at one inquiry date of the year and below average financing conditions at the other inquiry date of the year, which also results in a value of the variable of 0, accounts only for a small minority of cases (34 out of 2898 cases, representing 1.17% of the whole sample).

[8]The variable refers to the expectations the firms are facing with respect to the following 6 months.

We use data for the period from 2003 to 2007. The dataset is organized as an unbalanced panel. The total number of observations is about 3,000. A more detailed overview about the questionnaire and the survey variables can be found in Becker and Wohlrabe (2008).

1.4 The Model

1.4.1 Specification

To identify possible effects of credit restrictions on the innovative activity of firms we specify the model as

$$y_{it} = \alpha_{it} + \beta_1 credit_{it} + \beta_2 expect_{it} + \beta_3 situat_{it} + \beta_4 mkp_{it} + \\ + \beta_5 exit_{it} + \beta_6 B_{it} + \beta_7 L_{it} + \beta_8 T_{it} + u_{it}.$$

In our first specification, y_{it} is a dummy variable with value 1, if firm i started an innovation project (product or process innovation) at time t, and 0 otherwise. In our second and third specifications we distinguish between product and process innovations. Specifically, we estimate a second model in which y_{it} is a dummy variable with value 1, if firm i started a product innovation project at time t, and 0 otherwise. Similarly, we estimate a third model in which y_{it} is a dummy variable with value 1, if firm i started a process innovation project at time t, and 0 otherwise.

The variable *"credit"* represents the financing conditions the firm is facing. The higher the value of the variable, the worse the financing conditions over the year. It is worthwhile to note that the innovation question in the survey refers to the start of an innovation activity rather than the achievement of an innovation. From this follows that the variable is included contemporaneously, as it is highly likely that the timing of the financing of an innovation project is assigned closely to the actual beginning of an innovation activity. To identify any asymmetries in the effects of below average and above average financing conditions, we provide alternative specifications where we split the variable *"credit"* into two dummy variables. In particular, we create one dummy variable which is coded 1, if the financing conditions over the year were worse than normal, and 0 otherwise (*"creditdif"*). Likewise, we create a second dummy variable which is coded 1, if the financing conditions over the year were better than normal, and 0 otherwise (*"crediteas"*).

Furthermore, the firms' decisions to start an innovation project very likely are influenced by their expectations. As our dataset includes information about the firms' expectations, we have the almost unique possibility to control for this aspect. Consequently, the variable *"expect"* is introduced, representing the change in expectations of the firm over the year. The higher the value of the variable, the more the expectations of the company improved over the year. As the variable *"credit"*, the variable *"expect"* is included contemporaneously as a firm will take into account the current rather than the past expectations when deciding to start an innovation project. To capture the effects of firm-specific developments we control for the actual business situation of the firm. The business situation of the firm is represented by the variable *"situat"*, which is the higher the better the business situation was over the year. Similarly to the variable *"expect"*, the variable *"situat"* is included contemporaneously as a firm will take into account current rather than past firm developments when deciding to start an innovation project. Beside this, we introduce the variable *"mkp"*, which represents the size of the firm in terms of its relative number of employees compared to the competitors of its branch. This variable might be of potential relevance as previous research provides evidence for a clearly positive relationship between the market power and the level of innovative activity of a firm.

In addition, we control for certain other firm characteristics. To account for a heterogeneous level of innovation activity between firms of different branches we include vector B_{it}, a set of 13 dummy variables which indicate the affiliation of the firm to a specific branch.[9] For similar reasons – heterogeneity in the innovation activity of companies of different regions – we include a further set of dummy variables, represented by vector L_{it}, which consists of 3 dummy variables indicating the region the company is allocated to.[10] Moreover, to take into account possible changes of the innovative behaviour over time due to major technological or structural developments, we introduce vector T_{it}, which consists of 4 time dummies representing the years 2004 to 2007.[11]

[9] The baseline branch is the branch "Machinery and Equipment".

[10] The baseline region is North Germany.

[11] The baseline year is the year 2003.

Finally, we have to address a possible sample selection bias due to attrition,[12] as some companies initially included in the survey were discharged from the survey over time. The main reasons for discharging usually are that the company is no longer interested in taking part in the survey, that the company was taken over by another firm or that the company went bankrupt. If the exit of the companies is not random and there exist some common underlying reasons that the companies left the survey – e.g. bad overall performance – there could be some source of sample selection bias in our estimations. In order to ease this problem we include the dummy variable *"exit"*, which indicates if a firm has left the survey over the period of the analysis, thereby capturing firm-specific common characteristics of those firms which were discharged from the survey (see Smolny, 1996).

1.4.2 The Aspect of Endogeneity

As in most analyses, one major point to address is that of endogeneity in its various forms. This short section deals with this aspect. Specifically, it lists the different potentially relevant types of endogeneity, discusses how they are related to our analysis and how the analysis deals with these different types, if necessary.

The first source of endogeneity is unobserved heterogeneity. In this context one has to note that the design of the questions of interest in the survey is such that by their nature firm fixed effects are eliminated.[13] This leaves α_{it}, representing the firm-specific effects, and our independent variables uncorrelated and leads us in a first regression to the use of a random effects model, thereby avoiding the incidental parameter problem commonly present when applying a fixed effects estimator in this setting (Neyman and Scott, 1948, Hausman et al., 1984).[14]

[12]See Heckman (1979), Smolny (1998).

[13]The survey asks for the financing conditions and the business situation compared to their normal firm-specific levels (normal, better than normal, worse than normal), which by definition eliminates the firm fixed effects with respect to these variables (similarly to a within-transformation). Furthermore, the survey asks for the change in business expectations on an ordinal scale (improvement/deterioration/no change of business situation), which also rules out any firm fixed effects concerning this variable.

[14]The use of the random effects estimator is also supported by the results of a Hausman test (see Appendix A). However, to take into account potential dynamics of the model

The second source of endogeneity possibly relevant is simultaneity between the response variable and our explanatory variables. For example, it might not only be possible that a firm's decision to innovate is influenced by the firm-specific financing conditions, but also that the firm-specific financing conditions are influenced by the firm's decision to innovate. We can control for this by again using the panel structure of our dataset. In particular, we apply a two stage least squares instrumental variable probit estimator, which allows to instrument our potentially endogenous explaining variables by their first lags.

Finally, when estimating our models for the start of process and product innovations separately, we have to consider the possible simultaneity of these two decisions. Specifically, there exists the possibility that the decision of starting a product innovation is made conditional on the decision of starting a process innovation and vice versa. To take into account this potential dependency we additionally apply a bivariate probit estimator when dealing with these variables.

1.5 Results

Table 1.1 provides the results of our random effects probit panel estimator. It shows how the financing conditions the firms are facing relate to the probability of the start of an innovation project (product or process innovation project) in the corresponding year.

First, when including our original measure of the credit situation in Specification 1 we can observe a clearly significant and negative relationship between worsening financing conditions and the probability that a firm will start an innovation project. The worse the financing conditions (the higher the value of our variable *"credit"*), the smaller the probability that the firm will start an innovation project in the corresponding year (see Column 1).

Secondly, when splitting our financing conditions measure into below average (*"creditdif"*) and above average (*"crediteas"*) financing conditions and replac-

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and to picture persistences possibly existent with respect to our dependent variable we provide an additional robustness check by introducing the first lag of our response variable as additional regressor (see Appendix B).

ing our original variable on the financing conditions with these new variables, we can observe some asymmetries. The results, presented in Columns 2-4 of Table 1.1, show that financing conditions which were worse than normal (*"creditdif"*=1) indeed decrease the probability that a firm will start an innovation project, but that in contrast – and against the standard theory – financing conditions which were better than normal (*"crediteas"*=1) apparently do not have a significantly positive effect.

Table 1.1: Credit Constraints and Innovative Activity – Random Effects Probit Model

	Innov – Binary Panel Regression			
	(1)	(2)	(3)	(4)
credit	-0.189 **	-	-	-
	(0.076)			
creditdif	-	-0.223 **	-	-0.214 **
		(0.084)		(0.085)
crediteas	-	-	0.125	0.066
			(0.122)	(0.124)
expect	0.187 *	0.190 *	0.183 *	0.188 *
	(0.107)	(0.106)	(0.107)	(0.107)
situat	0.293 ***	0.295 ***	0.328 ***	0.292 ***
	(0.086)	(0.085)	(0.085)	(0.086)
mkp	1.666 ***	1.698 ***	1.685 ***	1.702 ***
	(0.527)	(0.527)	(0.527)	(0.528)
branch	yes	yes	yes	yes
region	yes	yes	yes	yes
time	yes	yes	yes	yes
exit	yes	yes	yes	yes
Log-Lik.	-1580.86	-1580.43	-1583.44	-1580.29
Observ.	2898	2898	2898	2898

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. Standard errors in parentheses.

As discussed in Section 4, there might exist some potential endogeneity bias due to simultaneity between the dependent variable and its regressors. To prove that our results are not driven by this aspect we perform an instrumental variable estimation, in which we tackle this issue. Specifically, we apply a two stage least squares probit instrumental variable estimator as an additional robustness check. Consequently, our potential endogenous variables – the variables on the financing conditions, the variable on the state of the business and the variable on the change in the expectations of the firm – are instrumented by their first lags. For all these instruments the first stage regressions indicate that they are significant and strong instruments.[15]

The results of the second stage regressions are presented in Table 1.2. In Column 1 we again can observe a clearly negative and significant effect of worsening financing conditions on the innovative activity of firms, which is in line with our previous findings. Furthermore, also the results of the estimations when including the two separate variables for above average and below average financing conditions, presented in Columns 2-4, support and even strengthen the findings of our preceding estimations. As before we find that below average financing conditions restrict innovative activity, whereas above average financing conditions do not foster it. In this context it is worthwhile to note that the coefficients of the IV-estimator for our variables "credit" and "creditdiff" are higher than in our baseline estimations, suggesting an underestimation of the effects of worsening financing conditions on the innovative activity of firms when not taking into account the aspect of mutual causation. By this, our results support findings of previous literature highlighting the reverse causality between credit restrictions and innovative activity (Hajivassiliou and Savignac, 2007, Savignac, 2008).

[15] The results of the first stage regressions are available upon request.

Table 1.2: Credit Constraints and Innovative Activity – Instrumental Variable Probit Model

	Innov – Binary IV Regression			
	(1)	(2)	(3)	(4)
credit	-0.297 **	-	-	-
	(0.134)			
creditdif	-	-0.430 **	-	-0.494 **
		(0.174)		(0.213)
crediteas	-	-	0.002	-0.233
			(0.384)	(0.438)
expect	0.416 **	0.393 **	0.385 **	0.389 **
	(0.345)	(0.166)	(0.165)	(0.166)
situat	0.485	0.157	0.309 **	0.171
	(0.271)	(0.134)	(0.130)	(0.136)
mkp	1.094	0.875	0.778	0.865
	(0.848)	(0.588)	(0.580)	(0.590)
branch	yes	yes	yes	yes
region	yes	yes	yes	yes
time	yes	yes	yes	yes
exit	yes	yes	yes	yes
Log-Lik.	-764.19	-1580.43	-1583.44	-1580.29
Observ.	1489	1489	1489	1489

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. Standard errors in parentheses.

A further feature of our dataset is the possibility to distinguish between product and process innovations. This allows to apply some additional robustness checks by performing our analysis for the two kinds of innovative activity separately. Specifically, we can examine if the previous results hold when distinguishing between process and product innovations. Table 1.3 provides the results of our random effects panel estimator for both kinds of innovative activity. Table 1.4 provides the results of our two stage instrumental variable estimator.[16] As already mentioned in Section 4, when distinguishing between the decision to start a product innovation and the decision to start a process innovation, we have to consider in addition the possible simultaneity of the

[16] Again, also here the first stage regressions indicate our instruments are significant and strong instruments. As before, the results of the first stage regressions are available upon request.

two decisions. Consequently, in Table 1.5 we provide the results when applying a bivariate probit estimator to account for the potential dependency of the two decisions.

Columns 1-4 of each table provide the results regarding the probability to start a product innovation project, Columns 5-8 of each table provide the results regarding the probability to start a process innovation project. However, one can see that for both kinds of innovative activity the outcomes again support our previous findings. All estimations show a clearly significant and negative relationship between worsening financing conditions and the probability that the firm will start a product or process innovation project, respectively. Moreover, the results again show that below average financing conditions have a negative effect on the decisions to start product as well as process innovation projects and that above average financing conditions do not foster them, thereby supporting previous findings and conclusions.

Table 1.3: The Differentiation between Product- and Process Innovations – Random Effects Panel Probit Model

	Productinnov – Binary Panel Regression				Processinnov – Binary Panel Regression			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
credit	-0.229 ***	-	-	-	-0.190 **	-	-	-
	(0.076)				(0.075)			
creditdif	-	-0.244 ***	-	-0.233 ***	-	-0.187 **	-	-0.165 *
		(0.084)		(0.085)		(0.083)		(0.085)
crediteas	-	-	0.145	0.080	-	-	0.213 *	0.166
			(0.122)	(0.123)			(0.121)	(0.122)
expect	0.193 **	0.200 **	0.235 ***	0.196 **	0.298 ***	0.306 ***	0.328 ***	0.299 ***
	(0.085)	(0.084)	(0.084)	(0.085)	(0.084)	(0.084)	(0.083)	(0.084)
situat	0.272 **	0.275 **	0.265 **	0.273 **	0.033	0.036	0.028	0.031
	(0.107)	(0.107)	(0.108)	(0.107)	(0.105)	(0.105)	(0.105)	(0.105)
mkp	0.907 *	0.939 *	0.939 *	0.944 *	1.136 **	1.159 **	1.172 **	1.171 **
	(0.484)	(0.483)	(0.486)	(0.483)	(0.459)	(0.459)	(0.461)	(0.460)
branch	yes	yes	yes	yes	yes	yes	yes	yes
region	yes	yes	yes	yes	yes	yes	yes	yes
time	yes	yes	yes	yes	yes	yes	yes	yes
exit	yes	yes	yes	yes	yes	yes	yes	yes
Log-Lik.	-1501.75	-1502.08	-1501.87	-1505.58	-1376.95	-1377.63	-1378.58	-1376.71
Observ.	2898	2898	2898	2898	2898	2898	2898	2898

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. Standard errors in parentheses.

Table 1.4: The Differentiation between Product- and Process Innovations – Instrumental Variable Probit Model

	Productinnov – Binary IV Regression				Processinnov – Binary IV Regression			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
credit	-0.301 **	-	-	-	-0.425 ***	-	-	-
	(0.146)				(0.157)			
creditdif	-	-0.457 **	-	-0.448 **	-	-0.591 ***	-	-0.669 ***
		(0.177)		(0.217)		(0.190)		(0.234)
crediteas	-	-	0.245	0.033	-	-	0.032	-0.283
			(0.386)	(0.439)			(0.422)	(0.485)
expect	0.155	0.124	0.248 *	0.122	0.162	0.141	0.341 **	0.155
	(0.136)	(0.136)	(0.132)	(0.139)	(0.145)	(0.146)	(0.141)	(0.148)
situat	0.297 **	0.291 *	0.288 *	0.291 *	0.338	0.329 *	0.317 *	0.325 *
	(0.168)	(0.169)	(0.168)	(0.169)	(0.180)	(0.181)	(0.179)	(0.182)
mkp	-0.156	-0.102	-0.151	-0.100	1.062 *	1.140 *	0.999 **	1.136 *
	(0.654)	(0.658)	(0.647)	(0.659)	(0.591)	(0.596)	(0.585)	(0.600)
branch	yes	yes	yes	yes	yes	yes	yes	yes
region	yes	yes	yes	yes	yes	yes	yes	yes
time	yes	yes	yes	yes	yes	yes	yes	yes
exit	yes	yes	yes	yes	yes	yes	yes	yes
Observ.	1489	1489	1489	1489	1489	1489	1489	1489

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. Standard errors in parentheses.

Table 1.5: The Differentiation between Product- and Process Innovations – Binary Bivariate Probit Model

	Productinnov – Binary Bivariate Regression				Procesinnov – Binary Bivariate Regression			
	(1a)	(2a)	(3a)	(4a)	(1b)	(2b)	(3b)	(4b)
credit	-0.202 ***	-	-	-	-0.190 ***	-	-	-
	(0.051)				(0.053)			
creditdif	-	-0.234 ***	-	-0.231 ***	-	-0.222 ***	-	-0.215 ***
		(0.057)		(0.058)		(0.059)		(0.060)
crediteas	-	-	0.092	0.021	-	-	0.114	0.049
			(0.085)	(0.087)			(0.086)	(0.088)
expect	0.149 ***	0.153 ***	0.196 ***	0.151 ***	0.236 ***	0.240 ***	0.278 ***	0.236 ***
	(0.054)	(0.054)	(0.053)	(0.054)	(0.057)	(0.056)	(0.056)	(0.057)
situat	0.228 ***	0.229 ***	0.224 ***	0.229 ***	0.081	0.081	0.078	0.081
	(0.069)	(0.069)	(0.068)	(0.069)	(0.072)	(0.072)	(0.072)	(0.072)
mkp	0.740 **	0.763 **	0.763 **	0.765 **	0.826 ***	0.846 ***	0.849 ***	0.850 ***
	(0.326)	(0.329)	(0.323)	(0.329)	(0.315)	(0.312)	(0.317)	(0.312)
branch	yes	yes	yes	yes	yes	yes	yes	yes
region	yes	yes	yes	yes	yes	yes	yes	yes
time	yes	yes	yes	yes	yes	yes	yes	yes
exit	yes	yes	yes	yes	yes	yes	yes	yes
Log-Lik.	-2760.19	-2759.13	-2768.59	-2758.98	-2760.19	-2759.13	-2768.59	-2758.98
Observ.	2898	2898	2898	2898	2898	2898	2898	2898

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. Standard errors in parentheses.

1.6 Summary and Conclusion

In this essay we have analysed the effects of financing conditions on the innovative activity of firms. In contrast to other literature we could use direct measures for the innovative activity of the firms as well as for the financing conditions the firms are facing, by this means avoiding problems of indirect measures commonly applied as proxies for these two variables. Moreover, the dataset provided the possibility to control for the business expectations of a firm – due to the existence of forward-looking adjustments in a world of expectations an important determinant of the innovative activity of the firm. In addition, the characteristics of the dataset and the design of the survey questions allowed us to avoid endogeneity issues caused by unobserved heterogeneity or mutual causation, which commonly are present in the literature. Finally, the possibility to differentiate between "worse than average" and "better than average" financing conditions allowed us to analyse potential asymmetries in the effects of below average and above average financing conditions.

The results provided – as opposed to many other papers – strong evidence that worsening financing conditions restrict the innovative activity of firms. More interestingly, the results showed asymmetries in the effects of below average and above average financing conditions. We found that below average financing conditions restrict innovative activity, whereas above average financing conditions do not foster it. The novel second result on the existence of asymmetries has interesting implications. It gives strong evidence for considerations raised in more recent literature that the individual innovation capacity of a firm plays an important role for its innovative activity. To additionally support our findings we have extended the usual theory of innovation activity by rigidities with respect to a firm's individual innovation capacity, which leads to a differentiation between a long run and a short run equilibrium in innovative output.

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Appendix

A Results of the Hausman Test

Table 1.6: Hausman Test – Baseline Specification with Dependent Variable "Innov"

	(b) (fixed effects)	(B) (random effects)	(b-B) (difference)	(sqrt(diag($V_b - V_B$))) (s.e.)
credit	-0.019	-0.043	0.024	0.018
expect	-0.006	0.040	-0.046	0.029
situat	0.058	0.066	-0.008	0.023
d_2004	-0.033	-0.030	-0.002	0.014
d_2005	-0.033	-0.021	-0.012	0.015
d_2006	-0.025	-0.036	0.011	0.018
d_2007	-0.030	-0.047	0.017	0.021

b = consistent under H0 and Ha; obtained from linear fixed effects panel estimator.
B = inconsistent under Ha, efficient under H0; obtained from linear random effects panel estimator.

Test: H0: difference in coefficients not systematic

$$\chi^2(8) = (b - B)'[(V_b - V_B)^{(-1)}](b - B) = 6.44$$
$$Prob > \chi^2 = 0.5978$$

Table 1.7: Hausman Test – Baseline Specification with Dependent Variable "Productinnov"

	(b) (fixed effects)	(B) (random effects)	(b-B) (difference)	(sqrt(diag($V_b - V_B$))) (s.e.)
credit	-0.023	-0.049	0.025	0.019
expect	0.010	0.054	-0.043	0.027
situat	0.027	0.041	-0.014	0.025
d_2004	-0.009	-0.010	0.001	0.013
d_2005	-0.002	-0.005	0.003	0.014
d_2006	-0.008	-0.025	0.017	0.018
d_2007	-0.014	-0.036	0.022	0.020

b = consistent under H0 and Ha; obtained from linear fixed effects panel estimator.
B = inconsistent under Ha, efficient under H0; obtained from linear random effects panel estimator.

Test: H0: difference in coefficients not systematic

$$\chi^2(8) = (b - B)'[(V_b - V_B)^{(-1)}](b - B) = 7.05$$
$$Prob > \chi^2 = 0.5311$$

Table 1.8: Hausman Test – Baseline Specification with Dependent Variable “Processinnov”

	(b) (fixed effects)	(B) (random effects)	(b-B) (difference)	(sqrt(diag($V_b - V_B$))) (s.e.)
credit	0.009	-0.039	0.048	0.018
expect	-0.026	0.004	-0.030	0.030
situat	0.040	0.058	-0.019	0.023
d_2004	-0.042	-0.045	0.003	0.012
d_2005	-0.043	-0.032	-0.011	0.014
d_2006	-0.030	-0.046	0.016	0.018
d_2007	-0.038	-0.068	0.030	0.017

b = consistent under H0 and Ha; obtained from linear fixed effects panel estimator.
B = inconsistent under Ha, efficient under H0; obtained from linear random effects panel estimator.

Test: H0: difference in coefficients not systematic

$$\chi^2(8) = (b-B)'[(V_b - V_B)^{(-1)}](b-B) = 12.40$$
$$Prob > \chi^2 = 0.1342$$

B Robustness Check – First Lag of Dependent Variable as Additional Regressor

Table 1.9: Robustness Check – Lag of Dependent Variable Included as Additional Regressor

	Innov		Productinnov		Processinnov	
	(1)	(2)	(3)	(4)	(5)	(6)
credit	-0.185 **		-0.202 **	-	-0.212 **	-
	(0.086)		(0.090)		(0.106)	
creditdif	-	-0.234 **	-	-0.240 **	-	-0.200 *
		(0.095)		(0.099)		(0.117)
crediteas	-	0.025	-	0.013	-	0.168
		(0.140)		(0.144)		(0.164)
expect	0.154	0.153	0.189	0.188	0.120	0.115
	(0.116)	(0.116)	(0.122)	(0.122)	(0.145)	(0.145)
situat	0.349 ***	0.345 ***	0.251 **	0.251 **	0.484 ***	0.481 ***
	(0.095)	(0.095)	(0.097)	(0.097)	(0.119)	(0.119)
mkp	1.539 ***	1.569 ***	0.925 *	0.963 *	0.820	0.851
	(0.589)	(0.589)	(0.576)	(0.574)	(0.692)	(0.692)
branch	yes	yes	yes	yes	yes	yes
region	yes	yes	yes	yes	yes	yes
time	yes	yes	yes	yes	yes	yes
exit	yes	yes	yes	yes	yes	yes
Log-Lik.	-1013.20	-1012.28	-971.63	-971.09	-860.25	-859.92
Observ.	1999	1999	1999	1999	1999	1999

Random effects probit model. + First lag of the dependent variable.
***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. Standard errors in parentheses.

C Robustness Check – Dataset without Corrections

Table 1.10: Robustness Check – Use of the Initial Dataset without Corrections

	Innov		Productinnov		Processinnov	
	(1)	(2)	(3)	(4)	(5)	(6)
credit	-0.199 **	-	-0.236 ***	-	-0.188 **	-
	(0.084)		(0.085)		(0.083)	
creditdif	-	-0.199 **	-	-0.221 **	-	-0.160 *
		(0.095)		(0.095)		(0.094)
crediteas	-	0.119	-	0.165	-	0.189
		(0.138)		(0.137)		(0.136)
expect	0.295 **	0.294 **	0.360 ***	0.360 ***	0.045	0.042
	(0.120)	(0.120)	(0.122)	(0.122)	(0.118)	(0.118)
situat	0.254 ***	0.253 ***	0.155	0.155	0.386	0.388
	(0.096)	(0.096)	(0.096)	(0.096)	(0.095) ***	(0.095) ***
mkp	-0.338	-0.322	-0.213	-0.197	0.038	0.053
	(0.614)	(0.613)	(0.598)	(0.597)	(0.585)	(0.584)
branch	yes	yes	yes	yes	yes	yes
region	yes	yes	yes	yes	yes	yes
time	yes	yes	yes	yes	yes	yes
exit	yes	yes	yes	yes	yes	yes
Log-Lik.	-1544.69	-1544.46	-1481.58	-1481.36	-1396.41	-1395.99
Observ.	2898	2898	2898	2898	2898	2898

Random effects probit model. ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$.
Standard errors in parentheses.

Chapter 2

Product and Process Innovations and Growth – New Evidence from Firm Level Panel Data

In theory, innovations are one of the main drivers of the competitiveness, the growth of an economy, respectively. Accordingly, a huge literature exists analysing the effects of innovative activity on growth in terms of export shares, sales or employment. We contribute to this literature in several ways: First, from a novel survey data set we are able to use direct information on the competitive situation of the company, at the national as well as the international level. Secondly, we are also able to use direct information on the innovative activity of firms, by this avoiding issues of commonly applied indirect measures like the level of investments in R&D or patents. Thirdly, and most importantly, in our analysis we are able to differentiate between product and process innovations, where until now only little research has been done. The results show the major importance of innovative activity for the competitive situation of firms. Moreover, the results show that product innovations contribute to an improvement in the competitive situation of firms, while process innovations obviously do not, thereby providing evidence for the superior importance of non-price factors compared to price factors with respect to competitiveness and growth.

2.1 Introduction

At the micro level, competitiveness is generally defined as the ability of a company to grow. In earlier literature, mainly price factors – e.g. cost reductions – were considered as determining the competitiveness of a firm. This view was questioned by the publication of Kaldor (1978) along with the so called Kaldor paradox. The Kaldor paradox describes the empirical finding that countries which experience a significant increase in their labour costs often concurrently experience an increase in their export shares. In light of this, by using several measures for the growth of the companies, a huge body of literature appeared, which considered non-price factors – especially in terms of innovations – as important determinants of the competitiveness of firms. In this framework, most prominent and vital branches of research discuss the influence of innovative activity on export shares (see e.g. Sterlacchini, 1999, Roper and Love, 2002, Bleaney and Wakelin, 2002) or on the level of employment (see e.g. Piva and Vivarelli, 2005, Bogliacino and Pianta, 2010, or Chennels and Van Reenen, 2002, for an overview).

In this essay we analyse the effects of innovative activity on the competitveness, the growth of a firm, respectively. By doing so we are able to use a novel measure of the competitiveness of the firm, obtained from a direct question included in a large business survey in Germany. In addition, different to many other analyses we are able to use a direct measure of the innovative activity of firms as well, thereby avoiding issues of indirect measures commonly applied, such as the level of investments in R&D or patents (see Griliches, 1979, Hall et al., 2001, Becheikh et al., 2006). This allows for the first time to analyse directly the relationship between innovative activity and competitiveness. Moreover, from the data available we can differentiate between the introduction of a product innovation and the introduction of a process innovation, allowing for a more detailed analysis and avoiding certain issues when targeting the aspect of non-price factors in terms of innovative activity. Specifically, when analysing the effects of non-price factors in terms of innovative activity, one has to consider that certain innovation projects could also target cost reduction in the production process. As the dataset allows the discrimination between product innovations, which by definition target non-price competition – e.g. product differentiation – and process innovations, which by definition target price competition – e.g. cost reduction – we can take this aspect into account.

The results highlight the major importance of innovations for growth. By using a direct measure of the competitive situation of a firm as well as for the innovative activity of a firm we find a clearly significant and positive effect of innovative activity – at the national as well as at the international level. More importantly, when distinguishing between product and process innovations we find that only the introduction of product innovations significantly contributes to an improvement in the competitive situation of the firm, while we cannot observe this for the introduction of process innovations. This result provides evidence that non-price factors indeed play a superior role for competitiveness and growth compared with price factors.

Consequently, the remainder of the essay is organized as follows. Section 2 provides some information about the dataset. Section 3 describes our empirical specification. Section 4 presents the estimation results. Section 5 concludes.

2.2 The Survey Data

To perform our analysis we use data from two sources: the Ifo Innovation Survey and the Ifo Business Tendency Survey for German manufacturing firms.[1] In these datasets, the unit of observation for multi product firms represents a single production entity for a single product of the firm rather than the whole firm, thereby enabling a more detailed analysis than usual. However, for the sake of simplicity, in the following we will refer to a unit of observation as a "firm". As the surveys include questions which are asked on different frequencies, we will transform all variables used to the lowest frequency (annual) if necessary.

2.2.1 Data from the Ifo Innovation Survey

The data on the innovative activity of the firm stem from the Ifo Innovation Survey, which is conducted annually. Specifically, the survey asks at the be-

[1]Both datasets are provided by the Economics & Business Data Center (EBDC), a combined platform for empirical research in business administration and economics of the Ludwig Maximilian University of Munich (LMU) and the Ifo Institute for Economic Research.

ginning of each year, whether the firm has introduced an innovation in the preceding year. Innovations are categorized in product and process innovations. The resulting variables are the variable *"prodinnov"*, which is coded 1, if a product innovation was introduced in the preceding year, and 0 otherwise, and the variable *"procinnov"*, which is coded 1, if a process innovation was introduced in the preceding year, and 0 otherwise.[2]

Table 2.1 provides some descriptive statistics, which will be of importance in the following for some robustness checks. The first two rows present the frequencies of the outcomes of the variables *"prodinnov"* and *"procinnov"* described above. The last 4 rows present the joint frequencies of the variables *"prodinnov"* and *"procinnov"*. In particular, row 3 provides the frequency for the situation in which product and process innovations were introduced contemporarily (*"prod- and procinnov"*). Row 4 and row 5 provide the frequencies for the situation in which only a product innovation (*"prodinnov only"*), and the situation in which only a process innovation (*"procinnov only"*) was introduced. Row 6 shows the frequency for the situation in which no innovation at all was introduced (*"noinnov"*).

Table 2.1: Descriptive Statistics – Innovation Variables

		yes (1)	no (0)	total
Unconditional	prodinnov	3131	4266	7397
Frequencies		(42.33 %)	(57.67 %)	(100.00 %)
	procinnov	2248	5149	7397
		(30.39 %)	(69.61 %)	(100.00 %)
Conditional	prod- and procinnov	1788	5609	7397
(Joint)		(24.17 %)	(75.83 %)	(100.00 %)
Frequencies	prodinnov only	1343	6054	7397
		(18.16 %)	(81.84 %)	(100.00 %)
	procinnov only	460	6937	7397
		(6.22 %)	(93.78 %)	(100.00 %)
	noinnov	3806	3591	7397
		(51.45 %)	(48.55 %)	(100.00 %)
		7397	-	
		(100.00 %)		

[2]The possibility that there exist multiple product or process innovations at the same time is mostly prevented by the fact that each ID-number of the dataset represents a single production entity for a single product of the firm rather than the whole firm.

2.2.2 Data from the Ifo Business Tendency Survey

The data on the competitive situation of the firm stem from the monthly Ifo business tendency service and are included in the survey quarterly. The survey asks about the change in the competitive situation of the firm at the national level as well as at the European level (excluding the domestic market). For the remainder of the essay we will refer to the latter as the "international level". The answers are coded as +1 ("competitive situation improved over the last 3 months"), 0 ("competitive situation remained constant over the last 3 months"), and -1 ("competitive situation worsened over the last 3 months"). These data are aggregated on a yearly basis by taking the averages of the values of the variables over the year. The variables resulting from this can be interpreted as measures of the change in the competitive situation of the firm at the national level over the year (*"compet-nat"*) and of the change in the competitive situation of the firm at the international level over the year (*"compet-int"*). They can take values between +1 and -1, where the limit value of +1 indicates that the firm reported an improvement of the competitive situation at the national/international level in every quarter of the year. Correspondingly, the limit value of -1 indicates that the firm reported a worsening in the competitive situation at the national/international level in every quarter of the year.

Furthermore, the Ifo business tendency service consists of a question on the overall business situation of the firm. The answers to this question are coded as -1 ("unfavourable business situation"), 0 ("normal business situation"), and +1 ("good business situation"). Similarly to the question on the competitive situation of the firm, the question on the business situation of the firm is asked several times during the year (every month). Accordingly, this variable also has to be aggregated on a yearly basis. We do this again by taking the average of the values of the variable of the single months. The resulting variable *"situat"* can be interpreted as the average business situation over the year. In addition, to control for the overall demand situation of the firm, we use survey questions asking for the change of the demand situation as well as the order situation of the company. The answers to these question are coded as -1 ("worse"), 0 ("equal"), and +1 ("better"). As both variables are asked by the survey on a monthly basis we transform them on a yearly basis in the way already described. The resulting variables can be interpreted as measures of the change in the demand situation of the firm over the year (*"demand"*) and the change in the number of orders of the firm over the year (*"orders"*), respectively.

Finally, the business tendency survey provides information on certain firm characteristics. First of all, we can relate to the size of a company in terms of its number of employees. Specifically, this is done by generating the variable *"size"*, which is the natural logarithm of the number of employees of the firm. In addition, each firm is allocated to one of the following 14 manufacturing subsectors: Food, Beverages and Tobacco; Textiles and Textile Products; Tanning and Dressing of Leather; Cork and Wood Products except Furniture; Pulp, Paper, Publishing and Printing; Refined Petroleum Products; Chemicals and Chemical Products; Rubber and Plastic Products; Other Non-metallic Mineral Products; Basic and Fabricated Metal Products; Machinery and Equipment; Electrical and Optical Equipment; Transport Equipment; Furniture, Manufacture. Furthermore, each firm is allocated to one of the following regions in Germany: East Germany, West Germany, South Germany and North Germany.

We use data for the period from 1994 to 2007. The dataset is organized as an unbalanced panel, and the total number of observations is about 7400. A detailed overview of the questionnaire and the survey variables can be found in Becker and Wohlrabe (2008).

2.3 Empirical Specification

To analyse the possible effects of innovative activity on the competitive situation of the firms we specify the baseline model as

$$y_{it} = \alpha_{it} + \beta_1 innov_{it} + \beta_2 situat_{it} + \beta_3 demand_{it} + \beta_4 orders_{it} +$$

$$+ \beta_5 size_{it} + \beta_6 exit_{it} + \beta_7 B_{it} + \beta_8 L_{it} + \beta_9 T_{it} + u_{it},$$

where y_{it} is the variable representing the competitive situation of firm i at time t.

In a first specification, our explanatory variable of interest is the variable *"innov"*. This variable is a dummy variable, which equals 1, if firm i has introduced a product or process innovation at time t, and 0 otherwise. In a second specification we distinguish between product and process innovations. Specifically, we replace the variable *"innov"* by two variables, where one variable represents the introduction of a product innovation, and the other variable represents the introduction of a process innovation. Accordingly, we include the dummy variable *"prodinnov"*, which equals 1, if firm i has introduced a product innovation at time t, and 0 otherwise, and the dummy variable *"procinnov"*, which equals 1, if firm i has introduced a process innovation at time t, and 0 otherwise. It is important to note that these innovation variables are included in the model contemporaneously. This is reasonable as technological adoption and progress at the national as well as the international level are so fast in most industries that innovations will be imitated very immediately or will even be obsolete within one year, as claimed in Lachenmaier and Woessmann (2006). Consequently, the introduction of an innovation will influence the competitive situation in the current year, but not the one in the following year.

Furthermore, we include the variable *"situat"* to control for the overall business situation of the firm. By introducing this variable we aim to capture both the overall macroeconomic developments and firm-specific developments, which could influence the judgement of the firm concerning its current competitive situation. The higher the value of the variable, the better was the business situation over the year. As with the innovation variables, the variable *"situat"* is included contemporaneously. This is reasonable as the judgement concerning the change of the competitive situation of the firm naturally is linked to the current rather than to the past business situation of the firm. Moreover, we include two measures for the demand situation of the firm. Specifically, we include our variable *"demand"*, which captures the current demand situation of the firm, and our variable *"orders"*, which captures the future prospects of the demand situation of the firm. As the variable on the business situation of the firm, the two demand variables are included contemporaneously for the same reasons. Finally, we include the variable *"size"*, which represents the size of the firm in terms of its number of employees, expressed in natural logarithms. By this we take into account potential different developments of bigger and smaller firms with respect to their competitive situation.

In addition, we control for certain other firm characteristics. To account for heterogeneous developments of the particular branches we include vector

B_{it}, a set of 13 dummy variables which indicate the affiliation of the firm to a specific branch.[3] For similar reasons – heterogeneous developments of different regions – we include a further set of dummy variables, represented by vector L_{it}, which consists of 3 dummy variables indicating the region the company is allocated to.[4] Lastly, we introduce vector T_{it}, which consists of 13 time dummies representing the years 1995 to 2007, to pay attention to possible changes of innovative behaviour over time due to major technological or structural developments.[5]

Finally, we have to address a potential sample selection bias due to attrition,[6] as some companies initially included in the surveys were discharged over time. Main reasons for discharging usually are that the company is no longer interested in taking part in the survey, that the company was taken over by another firm or that the company went bankrupt. If the exit of the companies is not random and there exist some common underlying reasons that the companies left the survey – e.g. bad overall performance – there could be some source of sample selection bias in our estimations. In order to ease this problem we include the dummy variable *"exit"*, which indicates whether a firm has left the survey over the period of the analysis, thereby capturing firm-specific common characteristics of the firms which were discharged from the survey (see Smolny, 1996).

In a first analysis we use a linear panel estimator. In this context one has to note that the design of the questions in our survey is such that by their nature firm fixed effects are eliminated.[7] This leaves α_{it}, representing the firm-specific effects, and our independent variables uncorrelated and leads us in a first regression to the use of a random effects model. However, to take into account potential dynamics of the model and to picture persistences

[3]The baseline branch is the sector "Machinery and Equipment".

[4]The baseline region is North Germany.

[5]The baseline year is the year 1994.

[6]See Heckman (1979), Smolny (1998).

[7]The survey asks for the business situation of the firm compared to its normal firm-specific level, which by definition eliminates the firm fixed effects with respect to this variable. Furthermore, the survey asks for the change of the demand and the order situation of the firm on an ordinal scale, which also rules out any firm fixed effects concerning these variables. Similarly, our innovation variable, representing the timing of the introduction of an innovation (and measured on a nominal scale), is also not affected by firm-specific characteristics.

possibly existent with respect to our dependent variable we provide an additional robustness check by introducing the first lag of our response variable as additional regressor (see Appendix A).

In a second analysis we try to rule out the possibility that our results are driven by a potential endogeneity bias due to simultaneity between the dependent variable and its regressors. For example, it might be possible not only that the introduction of an innovation influences the competitive situation of the firms, but also that the competitive situation influences the timing of the introduction of an innovation. Similarly, the business as well as the demand situation might have an effect on the judgement of the firm about its current competitive situation, but the competitive situation highly likely also influences the business and the demand situation of the firm. We can control for this issue by using the panel structure of our dataset. Specifically, we can apply a random effects instrumental variable panel estimator, which allows us to instrument our explanatory variables by their first lags and so to take into account the potential simultaneity problem.

In this context it also might be of interest, in what direction, if any, the coefficients of the variables of concern – our innovation variables – are biased without considering the endogeneity issue due to mutual causation. For example, one might argue that an increase in innovative activity will improve competitiveness, and vice versa, improved competitiveness will have a positive effect on decision of the company to innovate. This could be the case if the improved competitive situation enables the firms to perform additional innovation projects which otherwise would not have been undertaken, and will lead to an overestimation of the effects of innovations on competitiveness when using standard estimators. Others then might argue that an increase in the innovative activity will improve competitiveness, but that improved competitiveness will have a negative effect on the decision of the firm to innovate. This could be the case if the marginal return from new innovations decreases with the level of competitiveness, thereby decreasing the incentive of the firms to decide further innovations, and will lead to an underestimation of the effects of innovations on competitiveness when using standard estimators.

Finally, as an additional robustness check we apply a random effects panel tobit estimator to take into account that our dependent variable is censored at an upper bound of 1 and a lower bound of -1.

2.4 The Estimation Results

2.4.1 Baseline Regressions

Table 2.2 provides the results of our baseline estimations using a linear random effects panel estimator. It shows how innovative activity influences the competitive situation of a firm.

Table 2.2: Competitive Situation on the National Level – Baseline Regressions

	Linear Panel Regression			
	(1)	(2)	(3)	(4)
innov	0.032 ***	0.030 ***	-	-
	(0.008)	(0.008)		
prodinnov	-	-	0.039 ***	0.036 ***
			(0.009)	(0.009)
procinnov	-	-	-0.001	-0.001
			(0.009)	(0.009)
situat	0.147 ***	0.143 ***	0.147 ***	0.143 ***
	(0.011)	(0.010)	(0.011)	(0.010)
demand	0.259 ***	0.261 ***	0.258 ***	0.261 ***
	(0.022)	(0.022)	(0.022)	(0.022)
orders	0.088 ***	0.083 ***	0.087 ***	0.082 ***
	(0.021)	(0.021)	(0.021)	(0.021)
size	0.004	0.004	0.004	0.003
	(0.004)	(0.003)	(0.004)	(0.003)
branch	yes	no	yes	no
region	yes	no	yes	no
time	yes	no	yes	no
exit	yes	no	yes	no
Observ.	7397	7397	7397	7397

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. Standard errors in parentheses.

Columns 1 and 2 provide the results when analysing the effects of the introduction of any innovation – process or product. As one can see in Column 1, the introduction of an innovation leads to a clearly significant improvement in the competitive situation of the firm. The estimation results shown in Column 2 indicate that this finding is not caused by the introduction of the several dummy variables.

More interestingly, Columns 3 and 4 provide the results of our estimations when differentiating between the introduction of a product innovation and the introduction of a process innovation. As one can see in Column 3, the positive effect of innovative activity on the competitive situation of the firms identified in our preceding estimations seems only to be driven by the introduction of product innovations. While the effect of an introduction of a product innovation is clearly significant and positive, the effect of the introduction of a process innovation is greatly insignificant and de facto close to zero. Again, the empirical outcomes are not caused by the introduction of the dummy variables, as shown in Column 4.[8]

2.4.2 Robustness Checks

As already stated in Section 3, there exists the possibility of endogeneity between the dependent variable and its regressors due to mutual causation. To control for this potential issue we perform a robustness check by applying a linear random effects instrumental variable panel estimator. Specifically, we instrument the potential endogenous variables *"innov"*, *"prodinnov"*, *"procinnov"*, *"situat"*, *"demand"* and *"orders"* by their first lags. For all these instruments the first stage regressions indicate that they are significant and strong instruments.[9] The results of the second stage regressions, presented in Columns 1-3 of Table 2.3, support the findings of our preceding estimations. Column 1 again provides evidence that an introduction of any innovation, product or process, improves the competitive situation of the company significantly. Columns 2 and 3 then show that the preceding result

[8]Furthermore, it is worth to mention that the coefficient of the dummy variable *"exit"* is not significantly different from zero and excluding the variable barely alters the results (results available upon request). This indicates that the problem of attrition is not present in this dataset for our specification.

[9]Results of the first stage regressions are available upon request.

is driven only by the positive and significant effect of product innovations. Note that the coefficients regarding the effect of innovative activity on competitiveness compared with the ones of the standard estimations increase, considering an underestimation of the effects without taking into account the endogeneity due to reverse causality. This obviously implies some negative causal effect of an improvement in competitiveness on the decision of the firms to innovate. As already stated, such an outcome could be explained by diminishing marginal returns from innovations with the improvement of the firms' competitiveness, their market power obtained by innovations, respectively, which decreases the incentive of the firms to implement further innovations.

Table 2.3: Competitive Situation on the National Level – Robustness Checks (1)

	Linear IV Panel Regression			Panel Tobit Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
innov	0.093 ***	-	-	0.035 ***	-	-
	(0.016)			(0.008)		
prodinnov	-	0.079 ***	0.070 ***	-	0.041 ***	0.038 ***
		(0.018)	(0.017)		(0.009)	(0.009)
procinnov	-	0.010	0.016	-	0.000	0.000
		(0.022)	(0.021)		(0.009)	(0.009)
situat	0.099 ***	0.091 ***	0.096 ***	0.152 ***	0.152 ***	0.147 ***
	(0.015)	(0.014)	(0.014)	(0.009)	(0.009)	(0.009)
demand	0.373 ***	0.411 ***	0.417 ***	0.273 ***	0.274 ***	0.276 ***
	(0.050)	(0.044)	(0.044)	(0.019)	(0.019)	(0.019)
orders	0.130 **	0.114 **	0.109 **	0.090 ***	0.090 ***	0.084 ***
	(0.053)	(0.047)	(0.046)	(0.019)	(0.019)	(0.019)
size	0.002	0.004	0.002	0.004	0.004	0.004
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
branch	yes	yes	no	yes	yes	no
region	yes	yes	no	yes	yes	no
time	yes	yes	no	yes	yes	no
exit	yes	yes	no	yes	yes	no
Observ.	5099	5099	5099	7397	7397	7397

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. Standard errors in parentheses.

Moreover, we have to take into account that our dependent variable is censored at an upper bound of 1 and a lower bound of -1. We do this by applying a random effects panel tobit estimator as an additional robustness check. However, the corresponding results presented in Columns 4-6 of Table 2.3 are in line with our previous findings. Specifically, the coefficients estimated differ only slightly from our baseline estimation results of the linear random effects panel estimator (see Table 2.2).

Until now, we have analysed solely the effects of innovative activity on the domestic competitiveness of firms. However, as outlined in Section 2 of this chapter, the survey data also provides the possibility of performing an analysis of the effects of innovative activity on the international competitiveness. We use this possibility to apply an additional robustness check. Specifically, we now regress the variable measuring the change of the competitive situation at the international level on our innovation measures and our control variables. The analysis is performed by again applying a linear random effects panel estimator as baseline estimator, a linear random effects instrumental variable estimator to tackle the aspect of endogeneity and a random effects tobit panel estimator to take into account that our dependent variable is censored at an upper bound of 1 and a lower bound of -1.

The results of the corresponding estimations are provided in Table 2.4. From this table, one can see that the implications of our previous analyses at the national level also hold at the international level. We can observe evidence that innovative activity improves the competitive situation of the firms also at the international level (see Columns 1, 3 and 5), and that this improvement again is caused solely by the introduction of product innovations (see Columns 2, 4 and 6). Moreover, and more interestingly, the results do not change significantly even at the quantitative level. For all estimators, the coefficients of the estimations for the effects of innovative activity on the national competitiveness (see Tables 2.2 and 2.3) and for the effects of innovative activity on the international competitiveness (see Table 2.4) differ only slightly, implying that domestic and international competitiveness are affected by innovative activity in the same way and to the same extent.

Table 2.4: Competitive Situation on the International Level – Robustness Checks (2)

	Linear Panel Regression		Linear IV Panel Regression		Panel Tobit Regression	
	(1)	(2)	(3)	(4)	(5)	(6)
innov	0.026 ***	-	0.098 ***	-	0.029 ***	-
	(0.010)		(0.022)		(0.010)	
prodinnov	-	0.033 ***	-	0.130 ***	-	0.036 ***
		(0.011)		(0.030)		(0.011)
procinnov	-	0.006	-	-0.043	-	0.007
		(0.010)		(0.035)		(0.010)
situat	0.094 ***	0.094 ***	0.097 ***	0.103 ***	0.098 ***	0.097 ***
	(0.012)	(0.012)	(0.020)	(0.021)	(0.011)	(0.011)
demand	0.155 ***	0.154 ***	0.260 ***	0.256 ***	0.164 ***	0.163 ***
	(0.024)	(0.024)	(0.070)	(0.073)	(0.023)	(0.023)
orders	0.100 ***	0.100 ***	0.229 ***	0.226 ***	0.109 ***	0.109 ***
	(0.023)	(0.023)	(0.074)	(0.076)	(0.022)	(0.022)
size	0.016 ***	0.015 ***	0.008	0.008	0.018 ***	0.017 ***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
branch	yes	yes	yes	yes	yes	yes
region	yes	yes	yes	yes	yes	yes
time	yes	yes	yes	yes	yes	yes
exit	yes	yes	yes	yes	yes	yes
Observ.	5723	5723	3974	3974	5723	5723

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. Standard errors in parentheses.

Finally we apply a robustness check concerning the model specification. Until now, we only took into account the effects of the introduction of product and process innovations in isolation, neglecting possible interaction effects regarding these two innovative activities. Potential interaction effects might be of importance as concurrent introductions of product and process innovations could generate externalities and by this could enhance or dampen the effects of the particular innovations. Moreover, from rows 3-6 of Table 2.1, which present the joint frequency distribution of the outcomes of the innovation variables, one can see that such concurrent introductions of product and process innovations took place quite often. Specifically, a concurrent introduction of product and process innovations occurred in 24.17 % of cases, while an introduction of a product innovation without the concurrent introduction of a process innovation took place in only 18.16 % of cases. An introduction of a process innovation without the concurrent introduction of a product innovation even took place in only 6.22 % of cases. Consequently, we additionally introduce the interaction variable *"prod*proc"*, which is coded

1, if the introduction of product and process innovations took place contemporarily, and 0 otherwise.

Tables 2.5 and 2.6 present the results for the effects of innovative activity on the competitiveness of firms when introducing the variable *"prod*proc"*. Table 2.5 thereby is referring to the competitiveness of the firms at the national level. Table 2.6 is referring to the competitiveness of the firms at the international level. However, one again can observe that the results don't change significantly from our previous findings. Moreover, the coefficients of the interaction effects are mainly insignificant, by this giving no support to the thesis of positive or negative externalities or interaction effects of the concurrent introduction of product and process innovations.

Table 2.5: Competitive Situation on the National Level – Robustness Checks (3)

	Linear Panel Regression		Linear IV Panel Regression		Panel Tobit Regression	
	(1)	(2)	(3)	(4)	(5)	(6)
prodinnov	0.041 ***	0.038 ***	0.106 ***	0.104 ***	0.043 ***	0.041 ***
	(0.011)	(0.011)	(0.024)	(0.024)	(0.011)	(0.011)
procinnov	0.003	0.004	0.082 *	0.112 **	0.005	0.006
	(0.015)	(0.014)	(0.045)	(0.046)	(0.015)	(0.015)
prod*proc	-0.007	-0.008	-0.103 **	-0.135 **	-0.008	-0.009
	(0.019)	(0.018)	(0.052)	0.054	(0.019)	0.019
situat	0.147 ***	0.143 ***	0.100 ***	0.108 ***	0.152 ***	0.147 ***
	(0.011)	(0.010)	(0.016)	(0.016)	(0.009)	(0.009)
demand	0.258 ***	0.261 ***	0.370 ***	0.364 ***	0.273 ***	0.276 ***
	(0.022)	(0.022)	(0.050)	(0.051)	(0.019)	(0.019)
orders	0.087 ***	0.082 ***	0.133 **	0.135 ***	0.090 ***	0.084 ***
	(0.021)	(0.021)	(0.053)	(0.054)	(0.019)	(0.019)
size	0.004	0.004	0.002	0.001	0.004	0.004
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
branch	yes	no	yes	no	yes	no
region	yes	no	yes	no	yes	no
time	yes	no	yes	no	yes	no
exit	yes	no	yes	no	yes	no
Observ.	7397	7397	5099	5099	7397	7397

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. Standard errors in parentheses.

Table 2.6: Competitive Situation on the International Level – Robustness Checks (4)

	Linear Panel Regression		Linear IV Panel Regression		Panel Tobit Regression	
	(1)	(2)	(3)	(4)	(5)	(6)
prodinnov	0.027 **	0.028 **	0.129 ***	0.142 ***	0.029 **	0.032 **
	(0.012)	0.012	(0.027)	(0.024)	(0.012)	(0.012)
procinnov	-0.009	-0.012	-0.023	-0.026	-0.010	-0.013
	(0.019)	(0.019)	(0.050)	(0.047)	0.018	(0.018)
prod*proc	0.023	0.042 ***	-0.020	-0.022	0.025	0.028
	(0.022)	(0.012)	(0.057)	(0.054)	0.022	(0.022)
situat	0.094 ***	0.098 ***	0.086 ***	0.089 ***	0.097 ***	0.101 ***
	(0.012)	(0.011)	(0.017)	(0.016)	(0.011)	(0.010)
demand	0.154 ***	0.151 ***	0.300 ***	0.306 ***	0.163 ***	0.160 ***
	(0.024)	(0.024)	(0.058)	(0.055)	(0.023)	(0.022)
orders	0.100 ***	0.101 ***	0.224 ***	0.220 ***	0.109 ***	0.110 ***
	(0.023)	(0.023)	(0.061)	(0.058)	(0.022)	(0.022)
size	0.015 ***	0.016 ***	0.009 **	0.009 **	0.017 ***	0.017 ***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
branch	yes	no	yes	no	yes	no
region	yes	no	yes	no	yes	no
time	yes	no	yes	no	yes	no
exit	yes	no	yes	no	yes	no
Observ.	5723	5723	3974	3974	5723	5723

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. Standard errors in parentheses.

2.5 Conclusion

This essay has analysed the effects of innovative activity on the competitiveness of firms. In this framework we were able to use a direct measure of the competitive situation of the firms, at the national and the international level, as well as a direct measure of the innovative activity of the firms, thereby avoiding issues of indirect measures commonly applied. Moreover, the possibility of differentiating between the introduction of a product innovation and the introduction of a process innovation allowed us to perform a more detailed analysis and so to contribute to the discussion of the importance of price and non-price factors for the competitive situation of firms.

The results of the analysis have highlighted the great relevance of innovative activity as determinant of economic growth. Moreover, the analysis has shown that only product innovations significantly foster the competitive situation of a firm, while process innovations obviously do not. This finding also contributes to the discussion about the Kaldor Paradox and related literature, which highlights the superior role of non-price factors compared to price factors for the competitiveness of firms.

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Appendix

A Robustness Check – First Lag of Dependent Variable as Additional Regressor

Table 2.7: Competitive Situation on the National Level – Lag of Dependent Variable Included as Additional Regressor

	Linear Panel Regression			
	(1)	(2)	(3)	(4)
innov	0.023 ***	0.024 ***	-	-
	(0.008)	(0.008)		
prodinnov	-	-	0.026 ***	0.026 ***
			(0.010)	(0.010)
procinnov	-	-	-0.001	-0.002
			(0.010)	(0.010)
situat	0.102 ***	0.101 ***	0.102 ***	0.101 ***
	(0.011)	(0.011)	(0.010)	(0.011)
demand	0.236 ***	0.241 ***	0.236 ***	0.242 ***
	(0.026)	(0.026)	(0.023)	(0.026)
orders	0.104 ***	0.099 ***	0.103 ***	0.098 ***
	(0.025)	(0.025)	(0.023)	(0.025)
size	0.006 *	0.005	0.006 *	0.005
	(0.003)	(0.003)	(0.003)	(0.003)
branch	yes	no	yes	no
region	yes	no	yes	no
time	yes	no	yes	no
exit	yes	no	yes	no
Observ.	5046	5046	5046	5046

+ first lag of dependent variable; ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$.
Standard errors in parentheses.

Table 2.8: Competitive Situation on the International Level – Lag of Dependent Variable Included as Additional Regressor

	Linear Panel Regression			
	(1)	(2)	(3)	(4)
innov	0.021 **	0.025 **	-	-
	(0.008)	(0.010)		
prodinnov	-	-	0.027 **	0.035 ***
			(0.011)	(0.011)
procinnov	-	-	-0.001	-0.005
			(0.011)	(0.011)
situat	0.071 ***	0.073 ***	0.071 ***	0.073 ***
	(0.012)	(0.012)	(0.012)	(0.012)
demand	0.171 ***	0.172 ***	0.171 ***	0.172 ***
	(0.027)	(0.028)	(0.028)	(0.028)
orders	0.108 ***	0.107 ***	0.107 ***	0.107 ***
	(0.026)	(0.026)	(0.026)	(0.026)
size	0.014	0.014	0.014	0.013
	(0.004)	(0.004)	(0.004)	(0.004)
branch	yes	no	yes	no
region	yes	no	yes	no
time	yes	no	yes	no
exit	yes	no	yes	no
Observ.	3825	3825	3825	3825

+ first lag of dependent variable; ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$.
Standard errors in parentheses.

Chapter 3

How Strongly Did the 2007/08 Oil Price Hike Contribute to the Subsequent Recession?

In this chapter we challenge the view that the oil price has lost its influence on economic activity after the mid-1980s. While we concede that typical VAR models put forward in the literature fail to identify oil price shocks that significantly affect aggregate production, we obtain clearly negative output and positive producer price effects of oil price hikes in a firm level analysis for which we exploit a unique microeconomic dataset for Germany. Inspired by this finding, we aggregate the firm level information into a single indicator that signals in which periods the German economy was in a supply regime, i.e., in a situation when prices and production moved in opposite directions. Concentrating an otherwise standard VAR based search on these periods, we are able to identify an oil price shock that affects the German production even on the aggregate level. In a counterfactual analysis we show that the 2007/08 oil price hike contributed notably to the subsequent recession in Germany even though it was by far not the main driver.

3.1 Introduction

Conventional wisdom says that the worldwide recession of the years 2008/09 was driven by the downturn of the real estate market in the United States and the following crisis of the banking sector, which peaked with the bankruptcy of Lehman Brothers in September 2008. However, some voices argue that other reasons significantly contributed to the recession as well. The preceding oil price hike reaching 145 USD per barrel at the beginning of July 2008[1] is an often cited candidate. Hamilton (2009) even argues that in the absence of the high oil price perhaps no recession had occurred. This statement is controversial. Recent literature suggests that the effects of oil price changes on the economy decreased or even vanished over the last 30 years. Specifically, many authors find that a structural break in the oil price-macroeconomy relationship occurred during the first half of the 1980's. For the time thereafter it seems difficult to identify effects of the oil price on the macroeconomy by using standard VAR approaches (Herrera and Pesavento, 2007, Hooker, 2002). For the G-7 countries Blanchard and Gali (2008) conclude that the oil price has lost its influence on the production level since 1983. They argue that this finding can be explained by more flexible labor markets, more credible monetary policy and a smaller share of oil in the production process.

As a major drawback, many of the results in the literature are based on the assumption that oil price changes are caused by only one single structural shock which is thus very general and difficult to interpret. Kilian (2008) tackles this problem by decomposing oil price changes into demand and supply driven shocks. By comparing seven major industrialized economies he shows that exogenous oil supply shocks can trigger economic downswings, yet the magnitude of the effects differs from country to country. More recently, Kilian (2009) decomposes oil price surprises into three components, namely, world economic demand, world supply of oil and precautionary demand for oil, which captures market concerns about the availability of future oil supply. His central conclusion is that only supply driven oil price shocks and precautionary demand shocks have negative effects on macroeconomic aggregates, while a mainly demand driven shock itself does not affect the economy. Concerning the last recession, from the results of Kilian (2009) one could conclude that the oil price increase during 2008 did not contribute

[1]See US Energy Information Administration (EIA).

to the crisis, since the preceding oil price increase was mainly caused by world demand. In contrast, Hamilton (2009) argues that the oil price increase in 2008, although being driven by increasing world demand, affected most countries much like a supply driven shock because the additional world demand mainly was originated by one single country, China, and that this single country took so much of the oil supply that the other countries experienced this as a supply shock. A further issue pointed out by Hamilton (1996, 2003) is the possible existence of asymmetries in the effects of oil price shocks. He argues that oil price hikes give rise to recessions, whereas oil price decreases do not affect macroeconomic activity to the same magnitude. Moreover, oil price increases may be much less harmful to the macroeconomy if they simply correct preceding decreases.

Against this background, this essay has two aims. First, it contributes to the economic debate whether the oil price has lost its influence on aggregate activity since the mid-1980s as argued by Hooker (2002), Herrera and Pesavento (2007), and Blanchard and Gali (2008). Second, it re-assesses how important the 2007/08 oil price hike was as a cause for the subsequent recession, thereby adding to the research of Hamilton (2009) and Kilian (2009). The idea of the essay is to augment an otherwise standard macroeconomic VAR model with information from the firm level and use this to identify an oil price shock that leads to a slump in production and an increase in the general price level, and can thus be termed a "classical" oil supply shock. We concentrate on the German economy as for the German manufacturing sector there exists a unique firm level dataset which allows us to implement our combined macro-micro perspective.

We start our analysis by applying various VAR approaches suggested in the literature to identify oil price shocks hitting the German economy. It turns out that it is hardly possible to detect any recessionary tendencies after such a shock. This finding is in line with the results of an important branch of literature on the subject and seems to confirm that the oil price has lost its influence on the macroeconomy. However, the identification of an oil supply shock is difficult and quite controversial, see Kilian and Murphy (2010). In particular, to convincingly disentangle oil supply from, say, world demand shocks, it is necessary to control for all exogenous demand shifts that affect the oil price. Since the relationship between world demand and oil prices is anything but certain, this amounts to a challenging task. By exploiting a novel microeconomic panel dataset that comprises monthly business survey results for the German manufacturing sector we can alleviate this issue. Controlling for demand developments on the firm level we obtain significant and intuitive direct effects of oil price changes on production and prices. In addition, we find that demand side effects are strong and may thus obscure the negative effects of oil price hikes in aggregate models. Inspired by these results, we aggregate the firm level data into an indicator that signals whether the German economy was in what we call a supply regime, i.e., in a situation when prices and production moved into opposite directions. We then take up our VAR analysis but this time concentrate on supply regime periods. It turns out that this is sufficient to identify an oil supply shock with intuitive and statistically significant effects even on the aggregate level. In a counterfactual analysis we show that these effects are also economically significant.

The remainder of the essay is structured as follows. Section 2 provides an analysis on the macro level using different approaches from the literature to examine the effects of oil prices changes on German production. In Section 3 we estimate the effect of oil price changes on production and prices at the firm level. In Section 4 we augment an otherwise standard VAR model with the supply regime indicator and find a significantly negative effect of oil price hikes that is robust to a large number of model variations. In Section 5 we ask whether the German economy would have avoided the recent recession if the preceding oil price hikes had not occurred. Section 6 concludes.

3.2 Standard Approaches to Identify the Effects of Oil Price Shocks on the German Economy

In this section we apply several standard approaches put forward in the literature to identify the effects of oil price shocks on the German economy. In the first step we modify the VAR model for Germany of Peersman and Smets (2003) in a way that allows us to study the effects of oil price changes. The main drawback of this baseline model is that it only allows for a single, and thus very general, oil price shock. In the second step, we therefore integrate a model of the world oil market in the line of Kilian (2009) – which identifies one supply-specific and two demand-specific oil price shocks – with the German VAR model. To ensure that the results do not depend on a single identification strategy, we use both a Cholesky decomposition as in Kilian (2009) and the sign restriction approach suggested by Peersman and Van Robays (2009).

3.2.1 The Baseline Model

Our baseline model is a variant of the well-known VAR model for Germany of Peersman and Smets (2003). Unlike them, we specify it with monthly variables and include the nominal oil price instead of a world commodity price index. The model is

$$Y_t = B(L)X_t + A(L)Y_{t-1} + u_t, \tag{3.1}$$

where Y_t denotes the vector of endogenous variables and consists of the nominal WTI oil price in euros[2], the German industrial production, the German producer price index, the three-month Euribor[3] and an indicator for German price competitiveness.[4] The vector X_t defines the exogenous variables, which are included to control for changes in world demand. It contains US industrial production and the effective Fed funds rate.

We estimate the VAR model in levels using monthly data over the period from January 1980 to February 2009. The sample is chosen to be consistent with our subsequent analysis of a microeconomic dataset which is only available for this time period. As proposed by Peersman and Smets (2003) the VAR features a constant and a time trend, and all variables are seasonally adjusted

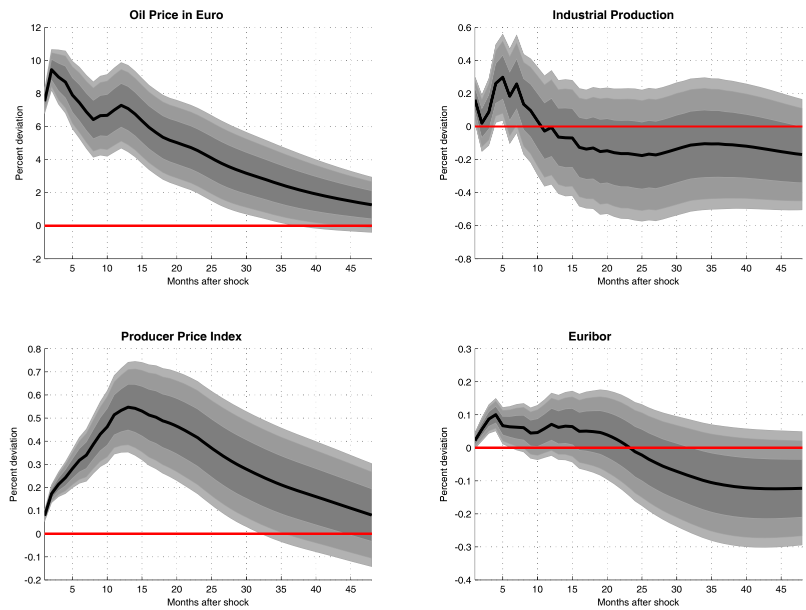
[2] We use the nominal rather than the real oil price for the following reason. Deflating the oil price with a German price index leads to an endogeneity problem, as the price index is affected by domestic variables which violates our assumption of a recursive structure in the following Cholesky decomposition, see Fukunaga, Hirakata and Sudo (2010) and the references therein for a discussion.

[3] Before 1999 we use the Fibor as short term interest rate instead of the Euribor.

[4] The indicator for price competitiveness is taken from the Deutsche Bundesbank. It is based on exchange rates and consumer price indices against 23 selected industrial countries and thus can be interpreted as a real effective exchange rate.

and expressed in natural logarithms, except for the nominal interest rate. The model is estimated as a subset VAR, i.e., we impose the restriction that the oil price only depends on its own lags, a constant, a time trend and the variables summarized in X_t. The VAR model contains 12 lags.[5]

Figure 3.1: Impulse Responses to an Oil Price Shock in the Baseline Model (68-, 90- and 95 Percent Confidence Intervals)



The oil price shock is identified by applying the Cholesky decomposition, where the oil price is placed first to allow it to influence all German variables contemporaneously. For the remaining variables we choose the following ordering: industrial production, producer price index, Euribor and price competitiveness.[6]

The estimated impulse responses together with 68, 90 and 95 percent confi-

[5]The qualitative results do not depend on the choice of the lag order.

[6]Changing the ordering of the unrestricted variables in the Cholesky decomposition does not greatly alter our results.

dence bands computed by means of the Hall bootstrap procedure are shown in Figure 3.1. After an oil price shock, which brings about a price increase for oil of roughly 8 percent on impact, we observe a significant positive reaction of the producer prices. The impulse response function has a hump shape pattern and reaches its peak after 12 months. The nominal interest rate rises as well. However, the response is weak and becomes insignificant after 6 months. Surprisingly, industrial production expands in the first 6 months after the shock even if not highly significantly so. Only after one year the reaction becomes negative, but it remains insignificant. Hence, we obtain the counterintuitive result that an oil price hike has expansionary short-term effects and only mildly contractionary medium-term effects.

3.2.2 The Kilian Type VAR Model with Cholesky Decomposition

The main drawback of the baseline model is that it only allows for a single oil price shock which may be a mixture of oil demand and oil supply shocks. Hence, the counterintuitive result obtained before might be the consequence of an incomplete identification scheme.[7] Kilian (2009) addresses this problem by decomposing oil price changes into three components, namely, shocks to world economic demand, to world oil supply and to oil-specific demand. The latter captures shifts in market concerns about the availability of future oil supply and is therefore also called precautionary demand for oil. To implement this, we add the Kilian (2009) three-equation oil market model to a VAR model of the German economy in a way similar to Fukunaga et al. (2010). Specifically, the resulting VAR model has the form

$$\begin{pmatrix} Y_{1,t} \\ Y_{2,t} \end{pmatrix} = \begin{pmatrix} A_{11}(L) & 0 \\ A_{21}(L) & A_{22}(L) \end{pmatrix} \begin{pmatrix} Y_{1,t} \\ Y_{2,t} \end{pmatrix} + \begin{pmatrix} u_{1,t} \\ u_{2,t} \end{pmatrix}, \tag{3.2}$$

[7] Additionally, the linear relationship between oil price changes and output could be criticized. Hamilton (1996, 2003) proposes nonlinear transformations of oil price increases, called net oil price increases, to better capture asymmetric effects of oil price shocks. However, if one replaces the nominal oil price by net oil price increases, the results of the VAR model do not change considerably. In particular, we still do not obtain recessionary tendencies after an oil price shock.

where $Y_{1,t}$ defines the vector of global oil market variables and consists of the world oil production, global industrial production and the nominal WTI oil price in US dollars.[8] Here we denominate the oil price in US dollars rather than in euros to be in line with Fukunaga et al. (2010) and Peersman and Van Robays (2009). The vector $Y_{2,t}$ denotes the domestic macroeconomic block and contains the industrial production, the producer price index, the three-month Euribor and the indicator for price competitiveness as in the baseline model.

We estimate this Kilian-type VAR model using monthly data over the period from January 1980 to February 2009.[9] The VAR features a constant and 12 lags. All variables are seasonally adjusted, expressed in logs and transformed to first differences, except for the nominal interest rate.[10] For the identification of the structural shocks to the global oil market we follow the recursiveness assumption by Kilian (2009). To identify oil supply shocks as innovations to global oil production, it is assumed that there exist no contemporaneous reactions of global oil production to global demand shocks and oil-specific demand shocks. This assumption is consistent with the consensus view in the literature that the short-run elasticity of oil supply is low. To disentangle the remaining two shocks, it is imposed that the oil-specific demand shock does not affect global industrial production on impact. For the domestic variables we allow that they respond contemporaneously to all oil market shocks. Moreover, we impose a lower triangular structure for the domestic macroeconomic block with the following ordering: industrial production, producer price index, Euribor and price competitiveness.

The cumulative (level) responses of the oil market variables and the German variables are shown in Figures 3.2 to 3.4. A negative oil supply shock leads to a permanent decline in oil production but has only a small and transitory

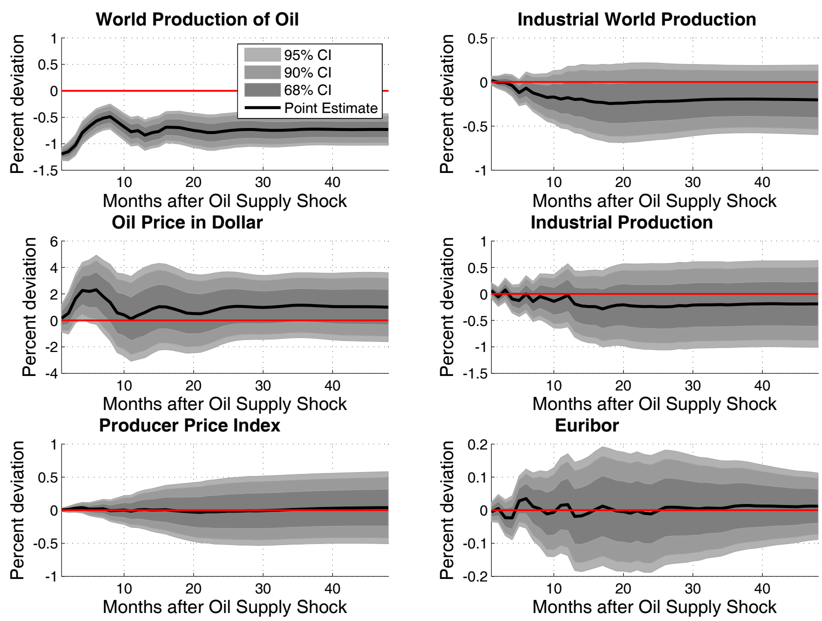
[8]Global industrial production is proxied by the industrial production of the OECD countries plus the six major non-member economies. The oil price is given in nominal instead of real terms because of the endogeneity problem discussed in Footnote 2. By using these two variables, we follow Fukunaga, Hirakata and Sudo (2010).

[9]Estimating the oil market block with monthly data from January 1973 to December 2008 replicates the results of Fukunaga, Hirakata and Sudo (2010). However, our estimation sample starts 1980 to be consistent with the micro data approach reported below.

[10]Unlike Peersman and Smets (2003), both Kilian (2009) and Fukunaga et al. (2010) estimate their VAR models in first differences. To facilitate comparison with their results, we follow their specification.

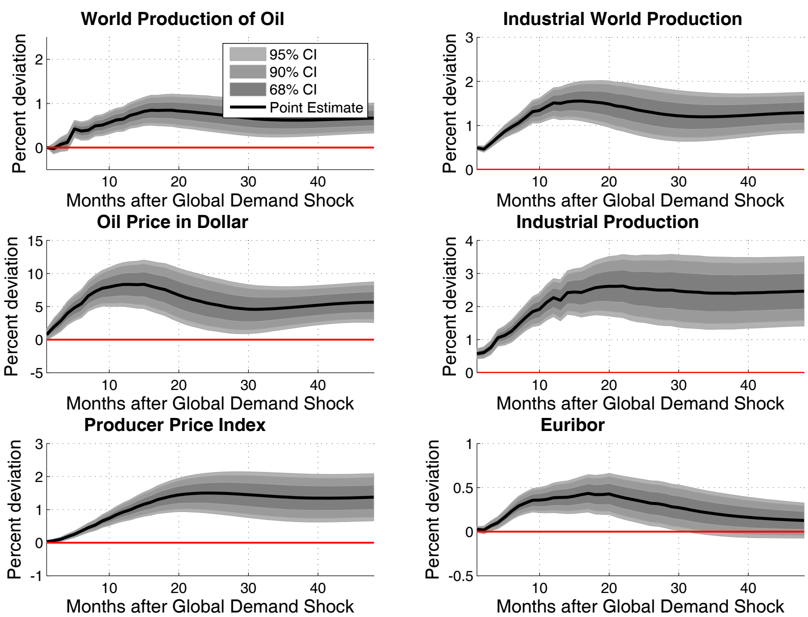
effect on the oil price. The German variables are largely unaffected. Hence, we obtain the same counterintuitive result as in the baseline model. This time it is even more surprising, as the Kilian-type model is intended to carefully identify a classical oil supply shock.

Figure 3.2: Cumulative Responses to an Oil Supply Shock in the Recursive Kilian Model (68-, 90- and 95 Percent Confidence Intervals)



The global demand shock immediately shifts global industrial production upwards by 0.5 percent. The effect peaks after 18 months at 1.5 percent and remains significant for more than four years. As a consequence of this strong and long-lasting increase in world demand, both oil supply and oil prices significantly increase for a sustained period of time. Given the export orientation of the German economy, German production reacts more strongly than world production and peaks after 20 months. At the same time, domestic prices increase and the central bank responds with an interest rate hike.

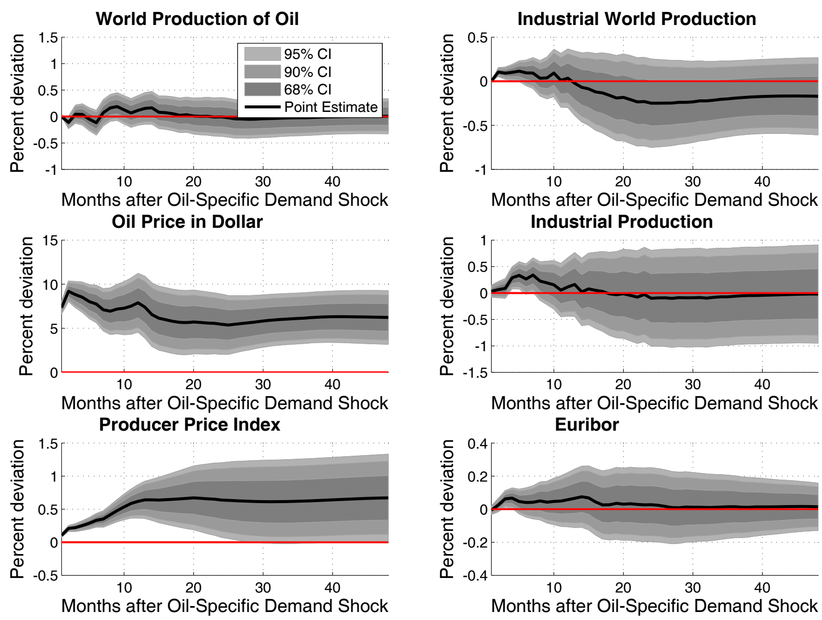
Figure 3.3: Cumulative Responses to a Global Demand Shock in the Recursive Kilian Model (68-, 90- and 95 Percent Confidence Intervals)



The oil-specific demand shock possesses a large and persistent effect on the oil price but not on oil production or world demand. Therefore, it only transmits to German producer prices which increase significantly. The influence on German industrial production is small and very short-lived.

We conclude that identifying oil price shocks by means of the Kilian approach does not alter the counterintuitive result of the baseline model that supply determined oil price shocks do not affect German economic activity. Instead we find that global demand shocks are of prime importance. That they raise both global oil prices and industrial production might explain the finding of the baseline model that a general – and thus difficult to interpret – oil price hike temporarily increases German production.

Figure 3.4: Cumulative Responses to an Oil-Specific Demand Shock in the Recursive Kilian Model (68-, 90- and 95 Percent Confidence Intervals)



3.2.3 The Kilian Type VAR Model with Sign Restrictions

In more recent papers, Baumeister, Peersman and Van Robays (2009) and Peersman and Van Robays (2009) try to relax the recursive identification assumptions imposed by Kilian (2009). They use the method of sign restrictions proposed by Peersman (2005) and Uhlig (2005) to disentangle the structural shocks affecting the oil price. More specifically, to identify an oil supply shock, a world demand shock and an oil-specific demand shock they restrict the impulse responses of global industrial production, global oil production and the oil price. In contrast to the Cholesky decomposition, this identification approach uses soft restrictions in the sense that no zero restrictions are placed on the contemporaneous impact matrix. Our baseline sign restrictions are fully consistent with the restrictions used in the analysis of Peersman and Van Robays (2009) and are summarized in Table 3.1.

Table 3.1: Sign Restrictions (Restriction Period of 6 Months)

	Oil Supply Shock	Global Demand Shock	Oil-specific Demand Shock
Oil Production	≤ 0	≥ 0	≥ 0
Global Production	≤ 0	≥ 0	≤ 0
Oil Price	≥ 0	≥ 0	≥ 0

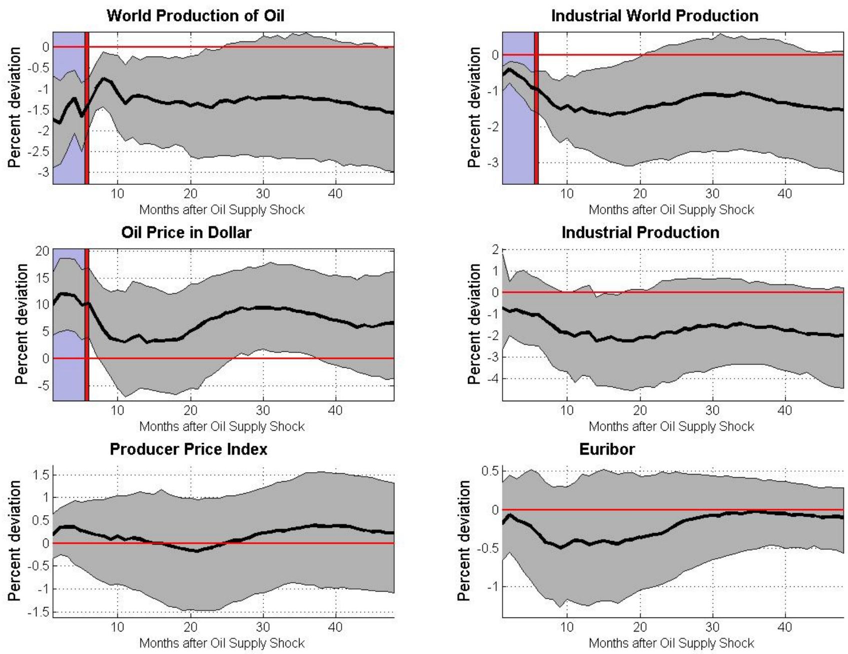
These restrictions imply that a contractionary oil supply shock raises the price of oil and reduces the global production of industrial goods and oil. A positive global demand shock raises oil production, global industrial production and the price of oil. A positive oil-specific demand shock triggers a contraction of world output while the price and the supply of oil increase. Unlike Peersman and Van Robays (2009) we do not impose restrictions on any of the response functions for a whole year. We prefer a shorter restriction period of 6 months, as the results of the recursive identification scheme above suggest that a restriction period of 12 months might be a too strong assumption.[11]

Figures 3.5 to 3.7 depict the cumulated (level) impulse responses of the oil market and domestic variables together with the 16th and 84th percentile error bands.[12] All responses have been normalized to an increase in the price of oil by 10 percent. The effects of a negative oil supply shock identified with sign restrictions are grossly comparable to those identified above with the Cholesky decomposition. As the major difference, the shock now leads to a significant contraction in world output. This translates into German industrial production, albeit not significantly so. Moreover, as before the German producer price index does not react at all. Hence, it is questionable whether this is really an oil supply shock. Concerning the other two shocks,

[11]This point is supported by the finding that the sign restriction algorithm takes a very long time (several weeks) in order to find the given number of admissible draws for a restriction period of 12 months.

[12]Again, the VAR-system is estimated by using monthly data over the period from January 1980 to February 2009. The VAR features a constant and all variables are seasonally adjusted, expressed in logs and transformed to first differences, except for the nominal interest rate. Note that the error bands are calculated with a Bayesian method of inference and not by the Hall bootstrap procedure. We report 68 percent confidence intervals as usual in the literature on Bayesian VAR models.

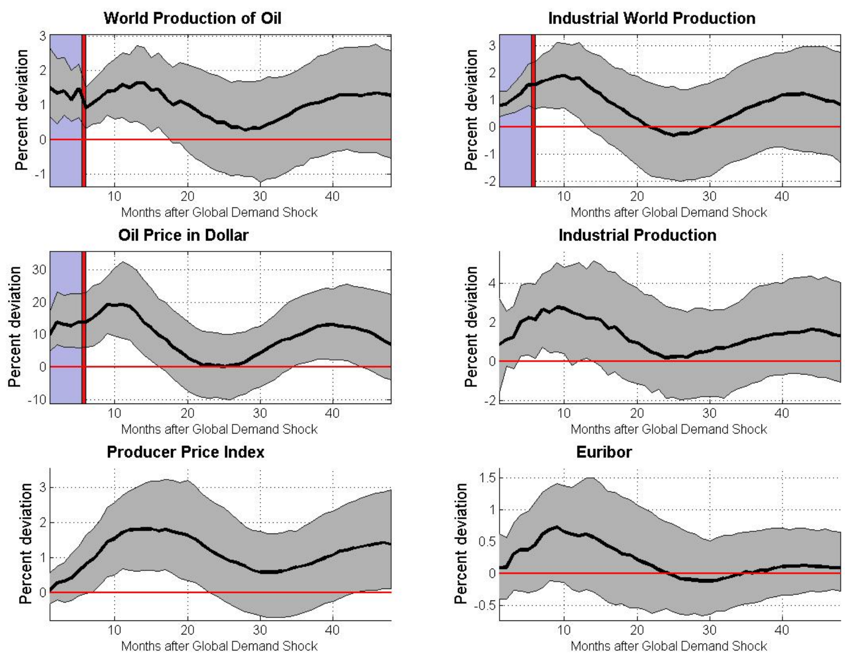
Figure 3.5: Cumulative Responses to an Oil Supply Shock Using Sign Restrictions (68 Percent Confidence Intervals)



the qualitative results do not seem to depend strongly on the identification scheme. For example, a global demand shock leads to a gradual increase in German production and prices which is qualitatively and in magnitude similar to the results reported above, while the dynamic patterns change somewhat.

Overall, we find that the sign restriction approach does not allow to convincingly identify an oil supply shock which simultaneously shifts German production down and producer prices up. Besides this, in a recent paper Kilian and Murphy (2010) cast doubts on the empirical results based solely on sign restrictions. In their view the results are biased due to the fact that the eventual impulse response functions are constructed as the medians of all admissible solutions to the sign restriction problem and many of them imply implausible magnitudes for the instantaneous impact on oil market variables, especially the short run elasticity of oil supply. This finally leads

Figure 3.6: Cumulative Responses to a Global Demand Shock Using Sign Restrictions (68 Percent Confidence Intervals)

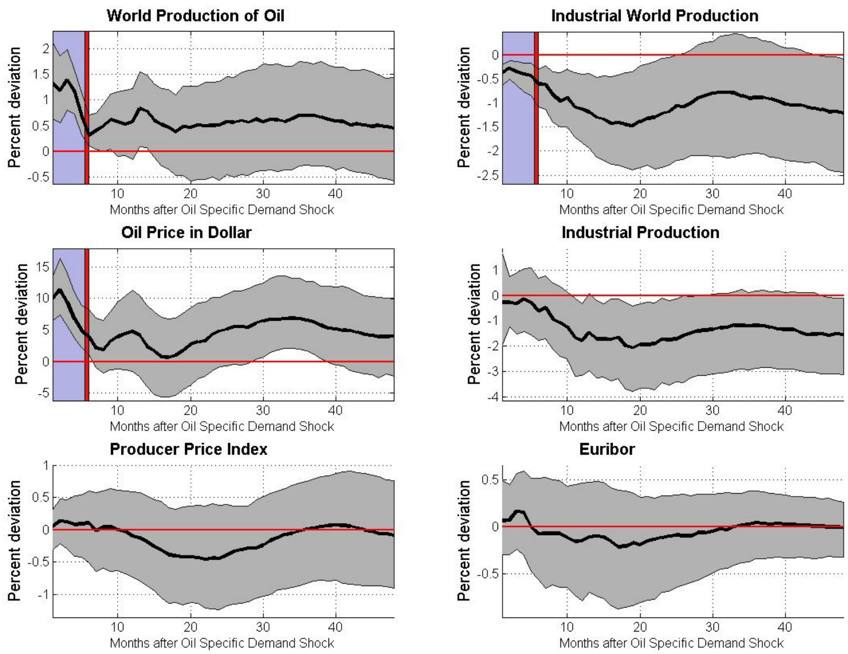


to an overestimation of the relevance of oil supply shocks.[13]

Taking all the previous results together we have to conclude that the VAR models proposed in the literature have difficulties to identify oil price shocks in a satisfactory way. In particular, the German output reactions are small and lack statistical significance. Does this mean that oil price shocks do not matter for economic activity? Given the importance attached to these shocks in the public and professional debate, this interpretation appears premature. It seems much more likely that the VAR models were not successful in disentangling supply and demand side developments. Therefore, in the remainder of the essay we proceed as follows. In a first step, we examine the direct

[13]We find that this is relevant also for our dataset. Once we impose an upper bound for the absolute short term elasticity of industrial production to an oil supply shock, the significance of the impulse response is reduced further. Detailed results are available upon request.

Figure 3.7: Cumulative Responses to an Oil-Specific Demand Shock Using Sign Restrictions (68 Percent Confidence Intervals)



effects of oil price changes on output and price setting at the firm level. This should help us to understand whether there are any noticeable contractionary effects of oil price hikes. The advantage of using firm-level data is that we can control for demand-side developments that otherwise may contaminate the results. However, we cannot derive general equilibrium results from a microeconometric analysis as feedback effects are neglected. Therefore, in a second step, we derive an indicator from the firm-level data that signals whether the firms are, on average, in a "supply regime" (output and prices move in opposite directions) as opposed to a "demand regime" (output and prices move in the same direction). We then use this indicator to identify oil price shocks within a VAR model of the German macroeconomy.

3.3 The Effects of Oil Price Shocks on the Firm Level

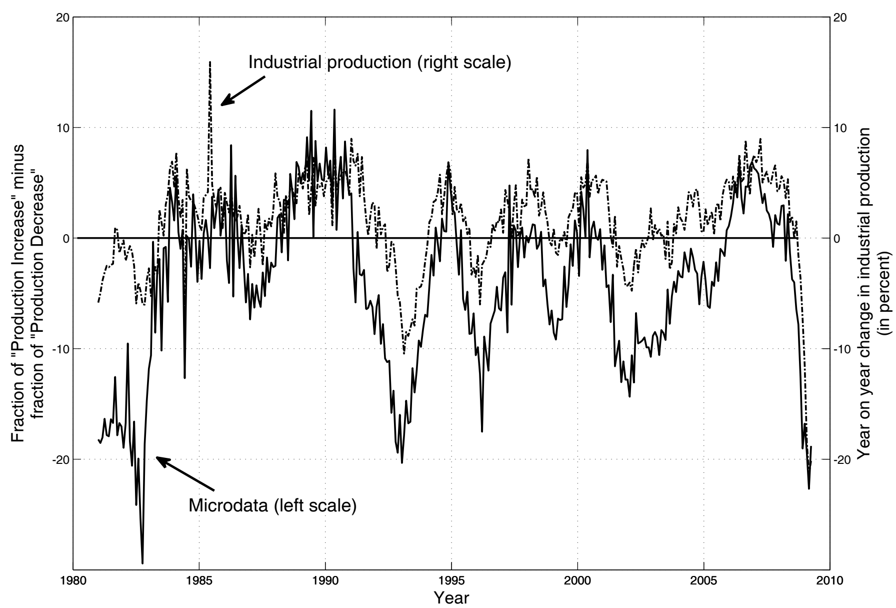
For an average individual firm, a hike in the oil price has ceteris paribus a direct cost effect that should unambiguously lead to a reduction in output and an increase of sales prices. On the aggregate level, this effect might be masked if, for example, the oil price hike reflects an increase in world demand. While an appropriate identification scheme should be able to separate out such demand-side shocks, the results of the VAR models analysed in the previous section indicated that this task is difficult to achieve without recourse to additional information.

Lescaroux (2011) argues that an analysis on the slightly more disaggregate sectoral level yields the expected result that an increase in oil prices depresses production. However, even at the sectoral level, the identification problem is not easily solved unless one is willing to impose an exogeneity restriction on the oil price (as done by Lescaroux, 2011). Therefore, in the following we use firm level survey data which allow us to control for demand developments that are exogenous to the firm. To this end, we estimate a production function and a price setting function for the average German industrial firm and introduce the aggregate oil price as one of the explanatory variables. It turns out that the oil price has a significantly negative effect on production and a significantly positive effect on prices. After a brief description of the data set we explain our estimation strategy and present our results.

3.3.1 The Survey Data

To measure firm-level production and pricing in the German industry, we use the monthly business tendency survey of the Ifo Institute (for a description of the survey see Appendix A). Specifically, we consider two survey questions. The question "Compared to the previous month, our domestic level of production has decreased/remained unchanged/increased." characterizes the change in production (*production*). The question "Compared to the previous month, our domestic sales prices have been increased/remained unchanged/decreased." is used to assess the change in prices (*price*). For these and all comparable questions, the answers are coded as -1 ("decreased"), 0 ("unchanged"), and +1 ("increased"). Note that we analyse qualitative answers, i.e., firms report the direction but not the size of the changes. However, aggregating the firm-level data by subtracting the percentage of price decreases from the percentage of price increases for each month leads to time series that resemble macroeconomic conditions quite well, see Figures 3.8 and 3.9. The correlation of the aggregated survey production series and the German industrial production is about 0.75, the correlation of the aggregated survey sales price series and the German producer price index is about 0.5.

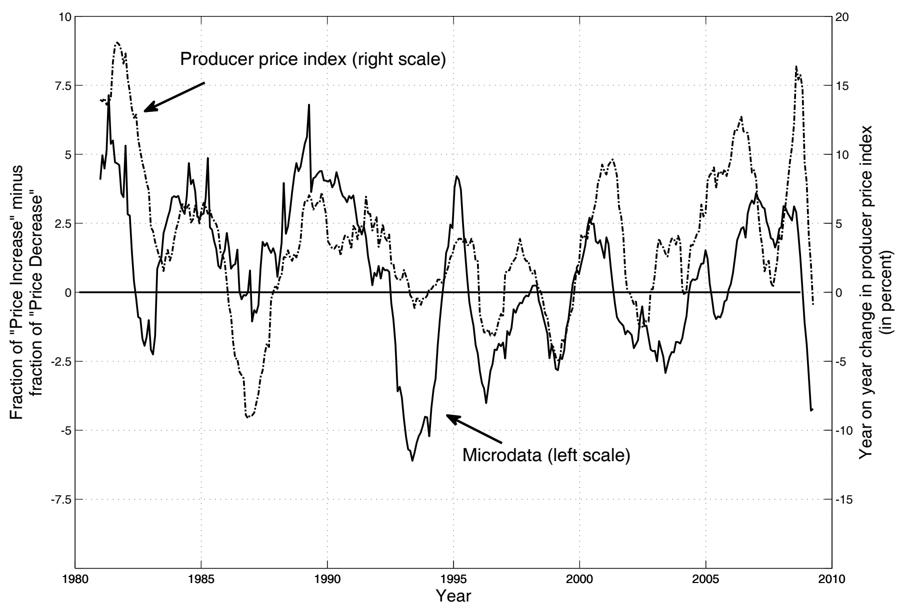
Figure 3.8: Aggregated Micro Production Data and Industrial Production



To account for firm-specific demand developments we consider two additional survey questions: the change in demand a firm faces (*demand*) and the change in incoming orders (*orders*). Further firm-specific information is included by using size and sector dummies. Concerning the size of a firm, we know whether the number of employees is below 50, between 50 and 199, between 200 and 499, between 500 and 999, or equal or above 1000. From this, five dummy variables are constructed that can also be interpreted as proxies for labor input in the production function. To control for sectoral differences, we add dummy variables that categorize the firms in one of the 14 industrial sectors listed in Appendix A. To account for geographical effects a dummy variable for Eastern Germany is included.

We use data of the period from January 1980 to February 2009.[14] The dataset is organized as an unbalanced panel of around 11,000 firms of the manufacturing industry, which have participated at least 48 times in the survey.

Figure 3.9: Aggregated Micro Sales Price Data and Producer Price Level



3.3.2 Modeling the Firm Level Effects of Oil Price Shocks

To identify the direct firm-level effects of oil price changes, we specify the following production and price setting functions which can be understood as

[14]The firm-level dataset is available to researchers with a delay.

general reduced form equations. We add various control variables to ensure that the effects are not spurious.

The production function is

$$y_{it} = oil_{it}\beta_1 + MACRO_{it}^{Ger}\beta_2 + MACRO_{it}^{US}\beta_3 + DEMAND_{it}\beta_4 + DFIRM_{it}\beta_5 + DMONTH_{it}\beta_6 + DEVENT_{it}\beta_7 + u_{it}, \quad (3.3)$$

where the production volume, y_{it}, is a latent quantitative variable that relates to the qualitative survey variable, $production_{it}$, by the observation rule

$$production_{it} = \begin{cases} -1, & \text{if } y_{it} \leq \alpha_1 \\ 0, & \text{if } \alpha_1 < y_{it} \leq \alpha_2 \\ +1, & \text{if } \alpha_2 < y_{it} \end{cases} \quad (3.4)$$

with threshold values α_1 and α_2. The variable of main interest, oil_{it}, is defined as the firm-specific percentage change of the WTI oil price in euros between month t and the last time firm i changed its production volume. We use this cumulative difference because firms do not report production changes every month. By regressing on this cumulative variable we face the problem of potential endogeneity due to its state dependency. To alleviate this issue we follow the recommendations of Wooldridge (2005) and add the first individual observation of the dependent variable as an additional regressor to the model. To be consistent with the baseline VAR model, we also include the remaining German and US macroeconomic variables, denoted as $MACRO_{it}^{Ger}$ and $MACRO_{it}^{US}$, respectively.[15] Like the oil price, all these variables are defined as percentage changes since the last revision of the production volume except for the interest rates for which the changes are given in percentage points.

By $DEMAND_{it}$ we denote a vector of variables that control for the demand situation faced by an individual firm which is assumed to be predetermined in the month of a survey. Specifically, we use the survey variables representing the change in demand (*demand*) and the change in orders (*orders*). For

[15] The German variables are industrial production, the producer price index, the three month Euribor, and the indicator of price competitiveness. The US variables are industrial production and the Fed funds rate.

both of them, there again exist three answer categories: -1=decrease, 0=unchanged, 1=increase. As these variables have an ordered outcome and the interpretation of coefficients estimated for such variables is not very convenient, we split each of them into two dummy variables. One dummy equals 1 if there is an increase and 0 otherwise and the other equals 1 if there is a decrease and 0 otherwise. We label them with the suffixes *up* and *down*, respectively.[16]

To address the problem of unobserved firm heterogeneity concerning our firm-specific variables we include the vector $DFIRM_{it}$ of firm-specific control variables. These include averages of each firm-specific variable as proposed by Mundlak (1978) and Chamberlain (1984). By introducing these averages we try to capture unobserved individual effects associated with the firm-specific variables and therefore to alleviate the issue of unobserved heterogeneity. In addition, we use a set of dummy variables controlling for the firm size, the sectoral classification as described above, and the geographical allocation (Western versus Eastern Germany).[17]

Finally, we control for specific time patterns. First, seasonal effects are accounted for by including dummies for each month of the year ($DMONTH_{it}$).[18] Second, we also control for important institutional events that could have influenced the behavior of the firms ($DEVENT_{it}$). The events considered are the physical introduction of the euro in 2002 and the changes in the level of the value added tax in 1983, 1993, 1998 and 2007. These dummies are equal to one for the month the change happened and for the past and following three months, as some firms may have reacted in advance or with a delay.

Because of the latent structure of the left-hand side variable, we estimate the parameters of the production function by means of an ordered probit model. To avoid distortions of the estimated standard errors we cluster the data on the firm level. To control for the decrease of observations in our

[16]Furthermore, to tackle the potential problem of endogeneity between our firm-specific variables and our dependent variable we additionally apply a robustness check by including these variables as first lags in an alternative specification.

[17]The baseline dummy for the firm size is the dummy representing a firm size in terms of the number of employees of equal or above 1000. The baseline sectoral classification is the machinery industry. The baseline geographical allocation is Western Germany.

[18]The baseline month is December.

panel data over time we weight the observations with respect to the number of observations of the corresponding time period.[19] Furthermore, to provide an additional robustness check with respect to the panel structure of our dataset we also apply a linear fixed effects panel estimator.

Missing observations are handled as follows. In all estimations reported below we use a dataset from which incomplete spells are dropped, because the calculation of cumulative differences requires spells that start and end with a production change. As a robustness check, we repeated all estimations by replacing missing observations with zeros which seems natural because the "no change" answer strongly dominates in the sample. The results remained qualitatively unchanged which suggests that concentrating on complete spells does not create a selection bias.

As a second equation we specify the price setting function of the firms. The dependent variable, *price*, is again qualitative. The right-hand side of the price setting equation is the same as in (3.3) as it is highly likely that a reduced form equation for the price setting equation contains the same explanatory variables as the reduced form equation for the production function. The macroeconomic variables are defined as the cumulative differences since the last price change. For the price setting decision, this approach reflects a possible menu cost behavior of the firms (see Loupias and Sevestre, 2010). We again create spells of consecutive observations, which start and end with a price change. Finally, to account for the lower trend inflation for the time after 1990, we include a dummy variable for this period.[20]

[19]The decrease of observations over time reflects the change in the economic structure in Germany (decreasing importance of the industrial sector) rather than problems of the survey to acquire participants. However, we also present an estimation without the time weights as robustness check.

[20]Before 1990 average inflation was more that 1 percentage point higher than thereafter. This can also be seen in the price setting behavior of the firms if one computes the fractions of companies stating that they have raised or lowered their prices.

3.3.3 Results

The estimation results for the production function are shown in the Columns 1-5 of Table 3.2.[21] According to our baseline result in Column 1, an oil price hike significantly decreases the probability that a firm raises its production (and, vice versa, significantly increases the probability that a firms lowers its production). Columns 2-5 display several variations of the model and the estimation method to check for the robustness of this result. First, we use an ordered probit estimator without time-weights, i.e., we neglect that the number of firms in the panel decreases over time (Column 2). Second, we drop the time dummies representing institutional events like value added tax reforms or the introduction of the euro because one could argue that there is some arbitrariness in choosing these events and not others (Column 3). Third, we lag the firm-specific variables by one month to minimize any potential endogeneity problem (Column 4). Finally, we apply a fixed effects panel estimator to take into account the panel structure of our dataset (Column 5). In all cases the effect of the oil price is negative, highly significant, and of similar magnitude.

Furthermore, an increase in firm-specific demand, as measured by *demandup* and *ordersup*, leads to an increase in production, while a decrease in demand, as measured by *demanddown* and *ordersdown*, triggers a slightly asymmetric decrease in production. These effects are much stronger than the effects of our macroeconomic variables which suggests that the demand situation plays a central role for the production decision of a firm. Therefore, it is important to control for firm-specific demand if one wants to identify the direct effects of oil price increases. Otherwise, the positive correlation of oil prices and world demand in boom periods may bias the estimated oil price coefficient.

The results for the price setting function of the firms are displayed in the Columns 6-10 of Table 3.2. The baseline result in Column 6 shows that an oil price hike significantly increases the probability that a firm raises its prices. This result is robust to the same variations in the model and the estimation method as described for the production function, see Columns 7-10. Moreover, the effects of the firm-specific demand variables are again

[21] Detailed results are available from the authors upon request. It turns out that the dummies controlling for the sector, the company size, the value added tax reforms, the implementation of the euro, and for seasonality are mostly significant.

Table 3.2: Results of the Firm-Level Production and Price Setting Equations

		Production equation					Price setting equation				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
OIL		-0.011***	-0.013***	-0.012 ***	-0.009 ***	-0.031 ***	0.013 ***	0.014 ***	0.012 ***	0.016 ***	0.017 ***
		(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)
$MACRO^{Ger}$	indprod	0.168***	0.173 ***	0.188 ***	0.346 ***	0.474 ***	0.077 ***	0.083 ***	0.118 ***	0.108 ***	0.258 ***
		(0.011)	(0.010)	(0.011)	(0.014)	(0.024)	(0.013)	(0.011)	(0.012)	(0.012)	(0.022)
	ppi	0.036***	0.041***	0.036 ***	0.002	0.093 ***	0.154 ***	0.157 ***	0.169 ***	0.127 ***	0.321 ***
		(0.009)	(0.009)	(0.009)	(0.011)	(0.022)	(0.010)	(0.010)	(0.011)	(0.010)	(0.020)
	euribor	0.002***	0.002***	0.002 ***	0.003 ***	0.004 ***	0.004 ***	0.003 ***	0.004 ***	0.004 ***	0.009 ***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
	compet	-0.007	0.000	-0.019	0.031**	0.010	-0.002	-0.022*	-0.032**	0.053 ***	-0.044*
		(0.013)	(0.013)	(0.013)	(0.015)	(0.030)	(0.013)	(0.012)	(0.012)	(0.013)	(0.025)
$DEMAND$	demandup	0.219***	0.224***	0.219 ***	0.054 ***	0.409 ***	0.021 ***	0.021 ***	0.021 ***	0.002 ***	0.037 ***
		(0.004)	(0.004)	(0.004)	(0.002)	-(0.353)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
	demanddown	-0.111***	-0.113 ***	-0.111 ***	-0.056 ***	-0.353 ***	-0.039 ***	-0.038 ***	-0.039 ***	-0.033 ***	-0.075 ***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
	ordersup	0.084***	0.076 ***	0.084 ***	0.075 ***	0.161 ***	0.036 ***	0.033 ***	0.036 ***	0.028 ***	0.058 ***
		(0.003)	(0.003)	(0.003)	(0.002)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
	ordersdown	-0.089***	-0.087 ***	-0.089 ***	-0.086 ***	-0.244 ***	-0.048 ***	-0.046 ***	-0.049 ***	-0.039 ***	-0.090 ***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
$MACRO^{US}$		yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
$DFIRM$		yes	yes	yes	yes	no	yes	yes	yes	yes	no
$DMONTH$		yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
$DEVENT$		yes	yes	no	yes	yes	yes	yes	no	yes	yes
Log-Lik.		-639668.29	-646312.67	-640093.28	-754601.83	-	-501228.23	-485935.99	-501586.74	-496610.50	-
Observ.		873657	873657	873657	866387	873657	701961	701961	701961	694956	701961

Columns (1)&(6): ordered probit, time weighted, clustered standard errors. Columns (2)&(7): ordered probit, not time weighted, clustered standard errors. Columns (3)&(8): ordered probit, time weighted, clustered standard errors, without dummies for institutional events. Columns (4)&(9): ordered probit, time weighted, clustered standard errors, firm-specific variables included in lags. Columns (5)&(10): linear fixed effects panel estimator. Columns (1)-(3) and (6)-(8): first observation of depended variable added as explanatory variable (see Wooldridge, 2005). Variable notations: indprod = industrial production; ppi = producer price index; compet = indicator for price competitiveness. All results expressed as marginal effects. Robust standard errors in parentheses. ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$.

statistically significant, quantitatively important, and of the expected sign.

To sum up, controlling for the firm-specific demand situation we find significant effects of oil price changes on the firm level in the German industrial sector: firms cut their production volume and increase their sales prices. Hence, from this perspective oil price changes can be interpreted as classical supply shocks.

3.4 Using a Supply Regime Indicator to Identify Oil Supply Shocks

The preceding analysis yielded conflicting results regarding the recessionary impact of oil price hikes. On the one hand, using VAR models it turned out to be difficult to convincingly identify negative oil supply shocks that significantly reduce aggregate output. On the other hand, using firm level data there was strong evidence that an average firm reacts to an increase in oil prices by cutting down on production. While it is certainly not possible to derive general equilibrium conclusions from a microeconometric production equation as feedback effects are not modeled, this approach nevertheless seems to deliver information that is not already contained in typical VAR models. Therefore, it could be beneficial to combine the firm level information with an otherwise standard VAR model in order to improve the identification of an oil supply shock to the German economy.

Our approach to use the firm level information is as follows. We calculate the fraction of firms in a given month which report that they move output and prices in opposite directions. If the fraction is large, we conclude that the economy is in a "supply regime". Assuming that oil supply shocks generate output and price reactions of opposite sign, it seems sensible to concentrate the VAR based search for oil supply shocks on these periods. We implement this by assuming that the effect of an oil price shock depends on how deeply the economy is in a supply regime. It turns out that this is sufficient to generate impulse responses that coincide with both our theoretical expectations and the microeconomic evidence presented above. It should be noted that the definition of what we call a supply regime is not directly related to the development of oil prices because there can be many reasons why prices and output move into opposite directions. Hence, not only oil price shocks can give rise to supply regimes but all sorts of cost push and technology shocks. This implies that we do not force the VAR to deliver the expected results but simply confine the search to more promising periods. Whether oil price shocks play any role in these periods is left unconstrained.

In the following, the construction of the indicator is described in detail. Subsequently, the indicator is introduced as an interaction variable into an otherwise standard VAR model to analyse how oil price shocks affect the German economy during supply regimes. Finally, some robustness checks are provided.

3.4.1 Construction of the Supply Regime Indicator

The economy-wide supply regime indicator shall condense the firm level survey information to detect time periods where disproportionately many firms move their production and prices in opposite directions. To this end, for each firm a supply regime indicator S_{it}^{firm} is constructed by subtracting the price response from the production response. Since both production and price responses are coded as -1 (decreased), 0 (unchanged) and $+1$ (increased), the new variable can have 5 different outcomes, see Table 3.3.

Table 3.3: Possible Outcomes for the Firm-Specific Supply Regime Indicator

	Price Increased	Price Unchanged	Price Decreased
Production Increased	0	$+1$	$+2$
Production Unchanged	-1	0	$+1$
Production Decreased	-2	-1	0

The outcome -2 indicates that the firm is in a contractionary supply regime as it increases its price and decreases its production level, while a value of $+2$ indicates an expansionary supply regime where the price is reduced and the production volume is raised. Intermediate cases are coded with -1, 0, and $+1$. Note that what might be called a demand regime – price and production move in the same direction – is coded as 0.

To calculate an economy-wide supply regime indicator we simply take the cross-sectional average of the firm-specific indicator at each month,

$$S_t = \frac{1}{N_t} \sum_{i=1}^{N} S_{it}^{\text{firm}} * 100 \tag{3.5}$$

and center the resulting time series at zero. The upper panel of Figure 3.10 depicts the economy-wide indicator together with the month on month growth rate of the WTI oil price in euros. To enhance readability, both series are smoothed by means of a centered 12-month moving average. The supply regime indicator is particularly negative at the beginning of the 1980s after the second oil price shock, in late 2001 following the the 9/11 terrorist attacks, and in the second half of 2008 after the strong oil price increases. However, there is no clear stable relationship between the indicator and the movements of the oil price. This implies that the indicator carries information not already contained in the oil price.

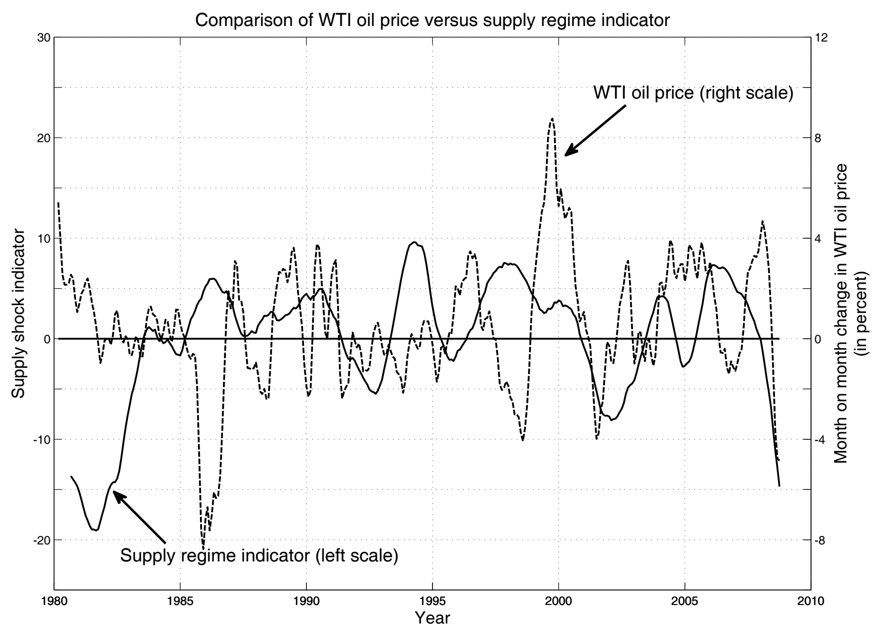
3.4.2 Identification of Oil Price Shocks during Supply Regimes

To concentrate the VAR based search for oil price shocks on supply regimes, we use an interaction variable approach. To this end, we normalize the absolute value of the economy-wide supply regime indicator such that it takes values between 0 and 1. Let us denote this variable by I_t. It takes on values near 1 if many firms move their output and prices into opposite directions which signals that the economy is in a supply regime. We then multiply I_t with the WTI oil price in euros, oil_t, which yields the interaction $Ioil_t = I_t oil_t$. This is introduced into our baseline VAR model as follows:

$$Y_t = B(L)X_t + A(L)Y_{t-1} + C(L)Ioil_{t-1} + u_t, \tag{3.6}$$

where as before $Y(t)$ denotes the vector of endogenous variables (the WTI oil price in euros, the industrial production, the producer price index, the three-month Euribor and the indicator for price competitiveness) and X_t comprises the exogenous variables (US industrial production and the effective Fed funds

Figure 3.10: Economy-Wide Supply Regime Indicator



rate). The vector of lag polynomials $C(L)$ corresponds to the interaction and can be interpreted as follows. During deep (positive or negative) supply regimes the indicator is near one. In this case, the total effect of the oil price on the left-hand side variables is the sum of the lag polynomial $C(L)$ and the respective coefficients related to the oil price in the lag polynomial $B(L)$. Put differently, if the oil price is ordered first in vector Y_t, we add the first column of each matrix in $A(L)$ to the corresponding vector of $C(L)$. In the other extreme, e.g. during strong demand regime periods, the indicator is 0 and $C(L)$ can thus be neglected. In average times, the indicator is between 0 and 1 and downweights the coefficients in $C(L)$.

The interaction setup can be interpreted in two different ways. We prefer to think of it as a tool to disentangle oil supply from other shocks to oil prices, notably demand shocks. This is possible if oil supply shocks dominate other oil shocks during supply regimes. Hence, we do not identify world demand or oil-specific demand shocks. Moreover, we neither argue that oil supply shocks were absent during non-supply regime periods nor that other oil price shocks were absent during supply periods. All we say is that oil supply shocks dominate and are thus easy to identify during supply regime periods, i.e., during periods in which many firms move prices and output in opposite directions. Hence, the respective column in $A(L)$ characterizes the average impact of a very general oil price shock during non-supply regime periods while $C(L)$ contains the additional effect during supply regimes that is presumed to be due to an oil supply shock. Their sum is thus the total effect that can be attributed to oil supply shocks.

Alternatively, the interaction dummy setup can be thought of as a way to detect non-linear relationships in the transmission of oil price shocks to the German economy. In contrast to Hamilton (1996, 2003), who proposes non-linear transformations of oil price increases, our approach then poses that a general oil price shock may have different effects during supply regime periods and other times, no matter whether it is positive or negative. As a robustness check, we also restrict our indicator variable to contractionary supply regime periods, i.e., to periods when many firms reduce output and raise prices. As described below, this does not change the results markedly.

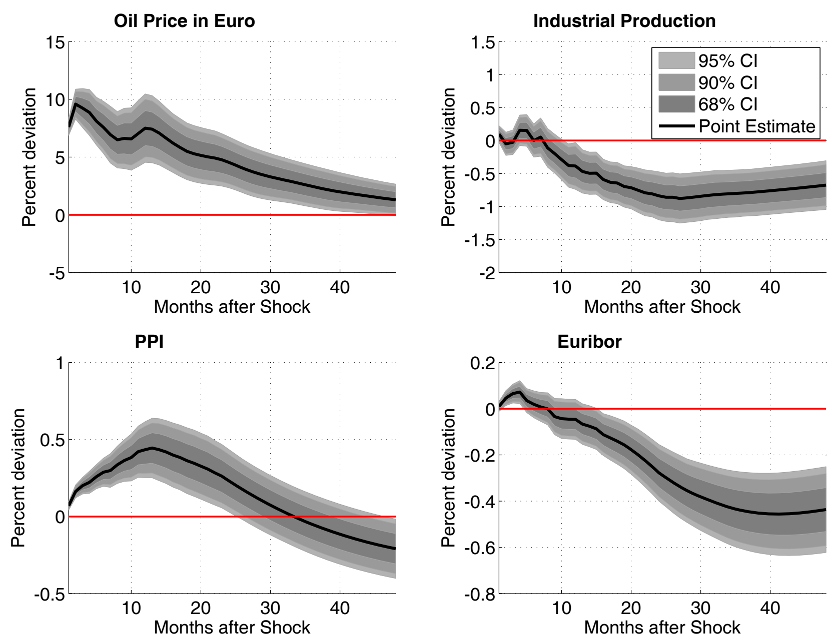
The interaction VAR model is estimated in levels using monthly data over the period from January 1980 to February 2009. It features a constant and a linear trend.[22] All variables are seasonally adjusted and expressed in natural logarithms, except for the nominal interest rate. The model is estimated as a subset VAR where the oil price defines the only subset variable. The covariance matrix is orthogonalized by means of a Cholesky decomposition, where the oil price is placed on the first position. For the remaining variables we choose the same ordering as in Section 2.

Figure 3.11 displays the impulse responses during a supply regime. The oil price shock triggers a very persistent increase in the oil price which peaks at nearly 10 percent after one month. Producer prices jump upwards on impact and rise further for more than one year. Industrial production does not change significantly during the first few months but it starts falling within the first year and remains below zero for an extended period of time. This is

[22]We do not include the supply regime indicator I_t in levels as its interpretation is not straightforward. However, if we do so as recommended by, e.g., Brambor et al. (2005) for interaction models, the impulse responses remain largely unchanged.

very different to the standard VAR model without interaction term analysed above. Probably as a reaction to rising prices, the nominal interest rate goes slightly up on impact and is lowered only after industrial production has started to decrease. The results indicate that it is possible to identify oil price shocks which lead to a slump in production and a rise in prices.

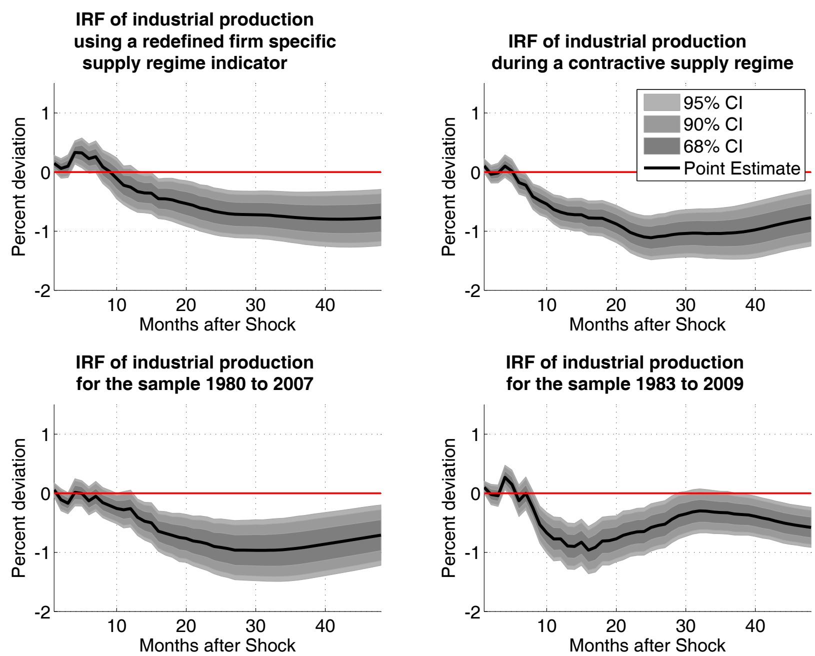
Figure 3.11: Impulse Response Functions to an Oil Price Shock during a Supply Regime (68-, 90- and 95 Percent Confidence Intervals)



3.4.3 Robustness Checks

In this section we provide a number of robustness checks. As the first check, we redefine the firm specific supply regime indicator by assigning to it a -2 if the firm increases its price and decreases its production level, a $+2$ if the firm decreases its price and increases its production level, and a 0 else. This means that, unlike before, all intermediate cases, where one of the two variables changes and the other one is constant, are coded as 0. Thereby, possible misallocations of periods as supply regimes that are in fact demand regimes are circumvented and the indicator becomes more selective. All other steps remain unchanged. The resulting impulse responses are very similar to the baseline interaction VAR with the only exception that the short-term response of industrial production becomes significant, see Figure 3.12 (upper left panel).[23]

Figure 3.12: Impulse Response Functions to an Oil Price Shock (68-, 90- and 95 Percent Confidence Intervals) – Robustness Check 1



Following Hamilton (1996, 2003), who stresses the importance of oil price increases as opposed to decreases, we also consider to select only contractive supply periods, i.e., periods in which unusually many firms reduce output and raise prices. To this end, we set all values of I_t to zero for which the economy-wide supply regime indicator is positive. This means that we concentrate only on periods where our indicator provides evidence for a negative supply regime. This may have two advantages: First, the motivation for the

[23]Detailed results are available from the authors upon request.

essay was the question whether and how the 2008 oil price contributed to the subsequent recession. Second, by identifying periods where the indicator features very positive values, we encounter the potential problem of not being able to distinguish between a cost shock (such as an oil price shock) and a positive technology shock. Assuming that economic contractions are rather not caused by negative technology shocks, this problem is mitigated during negative supply regimes. The impulse response of industrial production extracted from negative supply periods only is displayed in the upper right panel of Figure 3.12. It is very similar to the one extracted from both positive and negative supply periods. The same holds for all other impulse responses. Only the confidence bands are now tighter. This could reflect that it is easier to identify contractionary as opposed to expansionary oil supply shocks, which is in accordance with the findings of Hamilton (1996, 2003).

To examine whether our results are driven by influential observations at the beginning and the end of the sample, we report estimation results based on either the period from January 1980 to December 2007 or the period from January 1983 to December 2009. The first sample excludes the recent recession and the preceding oil price hike in 2008, the second sample excludes the effects of the second oil price crisis that – according to our indicator – led to a contractive supply regime during 1980-82, see Figure 3.11. The resulting impulse responses are provided in the lower panels of Figure 3.12 and show that our previous findings remain largely unaltered. However, excluding the first three years of the sample has the effect that the output response becomes less persistent. Nevertheless, unlike Blanchard and Gali (2008), we still find strongly significant effects for the sample starting in the mid-1980s.

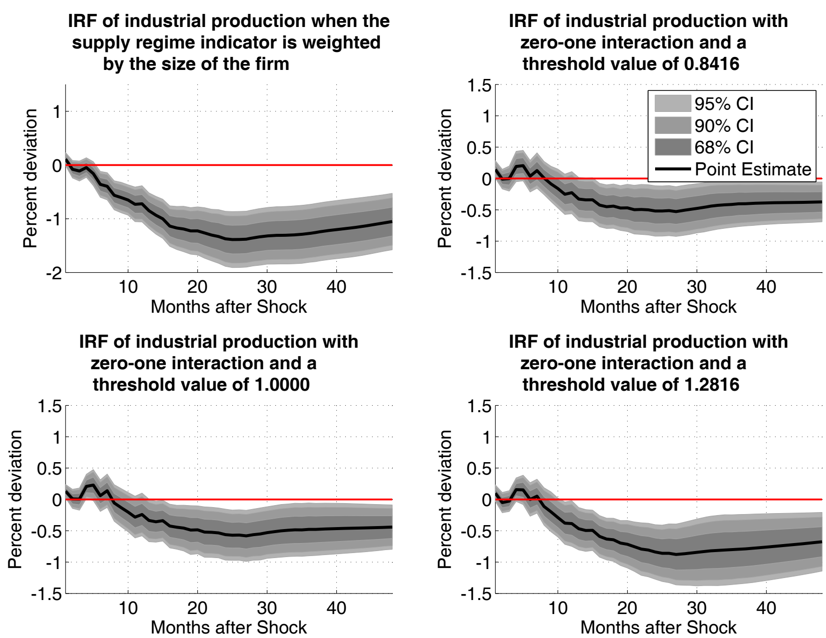
Furthermore, one could argue that neglecting the firm size when calculating our economy-wide supply regime indicator as an unweighted average across all firms could distort the results. This is possible if, e.g., large firms are better hedged against oil price risks and thus react more mildly than smaller firms such that an unweighted average would be too volatile. To the extent that this leads to a wrong identification of the supply regime periods, our baseline results could be biased. Therefore, in a next step we use an indicator that is constructed as a cross-sectional average weighted by firm size. Firm size is measured as the fraction of employees in firm i of the total number of employees at time t ($empfrac_{it}$). The weighted economy-wide supply regime indicator is then constructed from the firm-specific supply regime variables

S_{it}^{firm} – defined as the firm's production response minus its price response – as

$$\tilde{S}_t = \sum_i empfrac_{it} S_{it}^{\text{firm}} * 100. \tag{3.7}$$

After centering this variable, we proceed in the same way as in the baseline interaction VAR. It turns out that accounting for the firm size does not change our findings to a large extent. In particular the impulse response of production remains largely unchanged, see the upper left panel of Figure 3.13.

Figure 3.13: Impulse Response Functions to an Oil Price Shock (68-, 90- and 95 Percent Confidence Intervals) – Robustness Check 2



As a final robustness check, we use a zero-one instead of a continuous interaction. To this end, we construct a dummy variable D_t that is assigned a value of 1 if in a certain month the economy-wide supply regime indicator lies outside the range $[-v, v]$. To limit the arbitrariness of a specific threshold value v we report the results for three different choices, namely $v = 0.8416\sigma$, $v = 1.000\sigma$, and $v = 1.2816\sigma$, where σ is the sample standard deviation of the supply regime indicator. Under normality, these thresholds correspond to the 20, 16, and 10 percent quantiles, respectively. We then replace $Ioil_t$ in (3.6) with $Doil_t = D_t oil_t$ and leave everything else unchanged. The resulting impulse responses of industrial production after an oil supply shock are displayed in the upper right and the two lower panels of Figure 3.13. It turns out that the downswing in production is the larger the more observations are placed in the non-supply regime. This is the expected result as on the flip side this means that the reaction becomes (absolutely) stronger the smaller and, thus, the more extreme the sample is from which the oil supply shock is identified. Still, the exercise demonstrates that our identification strategy does not depend very strongly on how the dummy is defined. In addition, the difference to the continuous interaction approach is not substantial.

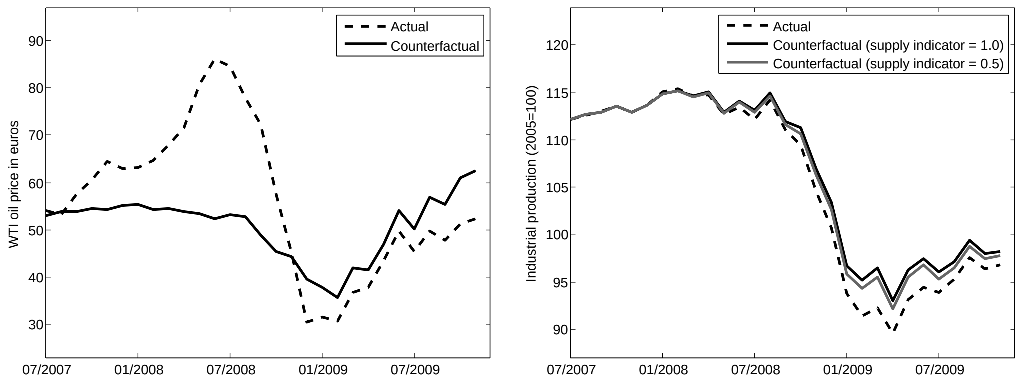
3.5 How Strongly Did the 2007/08 Oil Price Hike Contribute to the Recession in Germany?

In the preceding section we have shown that there exists a clear relationship between oil price changes and real economic activity. Now we examine how strongly the oil price hike in 2007/08 contributed to the recent recession in Germany. To this end, we set all oil price shocks from July 2007 to February 2009 to zero and calculate the counterfactual development of the variables endogenous to our VAR model. We find that both the initial increase and the subsequent decline in oil prices would not have occurred, see Figure 3.14 (left panel). Without the shocks, the oil price would have stayed between 50 and 60 euros per barrel until mid-2008 instead of rising up to almost 90 euros. Being partly driven by the US business cycle it would have dropped to 40 euros during the US recession and recovered to 60 euros by December 2009.[24]

The effect on German industrial production can be inferred from the right

[24] Note that our estimation sample ends in February 2009, hence this is an out-of-sample forecast and must be taken with great caution.

Figure 3.14: Counterfactual Analysis for Industrial Production



panel of Figure 3.14. Even without the oil price shocks, there would have been a huge drop in German production because in the counterfactual experiment we leave the US industrial production and the Fed funds rate plunge as actually observed, which in turn drives Germany into a recession. Nevertheless, the oil price has a non-negligible effect on German production. The extent of this effect depends on the development of the supply regime indicator which took values between 0.5 and 1.0 since August 2008. As we did not model this variable, we assume that an endogenized counterfactual indicator would have been within this range. Specifically, we perform two counterfactual experiments taking as given over the whole simulation period an indicator value of either 0.5 or 1.0. It turns out that without the oil price shocks, average production in 2009 would have been between 1.9 and 2.7 percent higher for supply regime indicator values of 0.5 and 1.0, respectively.

At first sight, a direct oil price effect on German output in the range of 2.5 percent appears to be small given a total drop in production of more than 15 percent from 2008 to 2009. However, the average annual growth rate of German production between 1991 and 2007 was as small as 1.2 percent and thus only half of the oil price effect. In addition, one has to bear in mind that the experiment leaves US industrial production and the Fed funds rate as actually observed because they are exogenous to our VAR model. To the extent that the oil price hike had a contractive effect on the US business cycle, the transmission to German production would have been stronger. Hence, our results can be interpreted as a lower bound for the unknown total effect.

3.6 Conclusion

In this essay we have shown that the oil price still has an economically and statistically significant effect on aggregate production in Germany. Thereby, we challenged the view put forward in an important branch of the literature that oil price increases have lost their influence on the macroeconomy since the mid-1980s. We arrived at this conclusion in three steps.

First, when estimating standard VAR models often used to assess the impact of oil price shocks on macro variables, we replicated the neutrality result of the literature. It is however debatable whether this finding really reflects the unimportance of oil products for the economy or whether it must be attributed to the difficulty to identify an oil price shock that is not contaminated by demand developments. This is important because demand shocks move output and oil prices simultaneously in the same direction and may thus obscure the negative effect of independent oil price shocks on output. Therefore, in a second step, we analysed the effect of oil price changes on output and prices at the firm level using a unique survey dataset for German manufacturing firms. The microeconomic approach has the advantage that problems of endogeneity and reverse causality are circumvented. Moreover, the data allow to control for demand shifts faced by the firms. Estimating reduced form production and pricing functions yielded the result that oil price hikes lower production and increase prices. From this we concluded that oil price shocks should be easier to identify on the macro level if we concentrate on supply regime periods, i.e., on periods in which output and prices move into opposite directions.

In a third step, we implemented this idea by constructing a survey based indicator that signals how deeply the German economy is in a so-defined supply regime. We augmented an otherwise standard VAR model for the aggregate economy with this indicator and obtained the same result as on the micro level, namely, that positive oil price shocks lead to rising prices and declining output. In a counterfactual analysis we showed that oil price changes are not only statistically significant but also quantitatively relevant: Without the 2007/08 oil price hike, German industrial production in 2009 would have been around 2.5 percent higher than actually observed. Given an average annual growth rate of 1.2 percent this is a notable effect. At the same time, this result is not in conflict with the view that the oil price was not the major driver of the 2009 recession which witnesses a total drop in production of more than 15 percent.

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Appendix

A The Ifo Business Tendency Survey

The micro data stem from the Ifo Business Tendency Survey for the German manufacturing industry. The survey is conducted monthly since 1949 and serves as base for the well-known Ifo Business Climate Index. However, due to longitudinal consistency problems and availability of the micro data in a processable form we only use the data since 1980. Before 1991, only firms from West Germany participated in the survey. Subsequently, the panel was enlarged to Eastern Germany. Currently, the total number of companies registered for the survey is about 3200. The participation rate is about 92 %, resulting in a coverage ratio of about 35 % of the German manufacturing industry in terms of turnover (Goldrian, 2004). The firms are asked about the development of certain key measures. These measures are classified in groups concerning the current situation (business situation, volume of orders), tendencies in the past month (demand, production level, domestic sales prices, volume of orders), expectations for the next 3 months (production level, domestic sales prices, exports and employment) and expectations for the next 6 months (business situation). The enterprises can give one of three categorical answers ("1" positive, "2" neutral, "3" negative) per standard question.

For our analysis, the information on the production development, the price development, the order development and the demand development is central. In order to better understand the information the data set contains, this section provides some details on the questionnaire design of the central variables. As far as production realizations are concerned, firms are asked to answer the following question: "*Compared to the previous month, our domestic level of production has decreased/remained unchanged/increased*". Concerning the price realizations the firms are asked to answer the question "*Compared to the previous month, our domestic sales prices have been decreased/remained unchanged/increased*". Regarding the demand situation, firms are asked to answer the following question: "*Compared to the previous month, our demand situation has improved/remained unchanged/worsened*". Concerning the order situation the firms are asked to answer the question "*Compared to the previous month, our overall level of orders has decreased/remained unchanged/increased*".

Furthermore, each firm is allocated to one of the following 14 manufacturing subsectors: Food, Beverages and Tobacco; Textiles and Textile Products; Tanning and Dressing of Leather; Cork and Wood Products except Furniture; Pulp, Paper, Publishing and Printing; Refined Petroleum Products; Chemicals and Chemical Products; Rubber and Plastic Products; Other Nonmetallic Mineral Products; Basic and Fabricated Metal Products; Machinery and Equipment; Electrical and Optical Equipment; Transport Equipment; Furniture, Manufacture. Finally, the data set provides a size classification of the firms, categorizing the firms into 5 different size classes. The exact classification is as follows: "1" firm with less than 50 employees, "2" firm with 50-199 employees, "3" firm with 200-499 employees, "4" firm with 500-999 employees, "5" 1000 or more employees.

A more detailed overview about the questionnaire can be found in Becker and Wohlrabe (2008).

Eidesstattliche Versicherung

Ich versichere hiermit eidesstattlich, dass ich die vorliegende Arbeit selbständig und ohne fremde Hilfe verfasst habe. Die aus fremden Quellen direkt oder indirekt übernommenen Gedanken sowie mir gegebene Anregungen sind als solche kenntlich gemacht. Die Arbeit wurde bisher keiner anderen Prüfungsbehörde vorgelegt und auch noch nicht veröffentlicht.

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