

Three Essays on Price Setting and Monetary Policy

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Preface

The following three chapters are broadly connected by the general research question of how, under which conditions, and to what extent monetary policy affects macroeconomic variables. Chapters 1 and 2 empirically analyze the price setting behavior of German retail firms and investigate the validity of competing assumptions concerning the pricing mechanism of firms employed by New Keynesian Dynamic Stochastic General Equilibrium (DSGE) models using a novel business survey dataset. In particular, in Chapter 1 we use aggregated survey data to analyze the importance of the frequency of price adjustment, the extensive margin, for overall inflation dynamics and investigate its responsiveness to monetary and business cycle shocks in a structural vector autoregression (SVAR) framework. Chapter 2 exploits the firm-specific nature of the survey data and offers a microeconomic analysis on the determinants of price adjustment at the level of the individual firm. In Chapter 3 an actual analysis of the effects of monetary policy is provided. In particular, we propose a novel sign-restriction setup to identify an unconventional monetary policy shock within an SVAR model under zero lower bound (ZLB) conditions and ask whether and how such a shock affects macroeconomic variables. Although the three chapters are broadly connected by a general research theme all of them are self-contained and can be read independently of each other.

One important aspect in the analysis of real effects of monetary policy measures by means of New Keynesian DSGE models is the particular assumption concerning the price setting behavior of firms. Most standard DSGE models largely rely on nominal frictions to generate real effects of monetary policy. In fact, the idea that nominal imperfections play an important role for short-run economic fluctuations is deeply entrenched in the history of macroeconomics and goes back to

prominent 20th century economists.¹ Early examples of static models of imperfect competition featuring nominal frictions in the form of price adjustment costs include Mankiw (1985) and Akerlof and Yellen (1985).² They show that even small nominal frictions, such as menu costs preventing immediate price adjustment, are sufficient for aggregate shocks to be transmitted to the real economy and can thus cause large fluctuations in real variables such as output or employment. In such a setting, monetary policy actions have the potential to stabilize the economy since monetary shocks are not offset by immediate price adjustment as would be the case under a flexible price regime. The most prominent example of such frictions is the concept of price stickiness implying delayed price adjustment by firms. Early empirical support in favor of the sticky price assumption was provided by the seminal study of Cecchetti (1986) analyzing magazine prices, followed by one-time interview studies conducted by Blinder (1991) for the US and Fabiani et al. (2006) for the Euro area. Moreover, recently, a growing number of studies using large item-level datasets for various sectors, products and countries report further evidence on price setting; see, inter alia, Bils and Klenow (2004) and Dhyne et al. (2006).³

While there exists, therefore, a broad acceptance of the sticky price assumption as an important feature of New Keynesian models, the exact mechanism underlying the price setting process is not yet fully understood. On the one hand, standard dynamic price setting models such as Calvo (1983) or Taylor (1980) assume an exogenous time dependent price setting process implying that each period a fixed fraction of firms sets a new price independently of the economic environment they are faced with. By contrast, the price setting decision is rendered endogenous in menu cost pricing models where the optimal timing of price adjustment is assumed to be the outcome of a maximization problem of the firm, which incurs a fixed cost of changing the price. An early contribution introducing endogenous pricing policies is the (S,s)-framework of Caplin and Spulber (1987), which was subsequently included into DSGE models by, for

¹See Ball and Mankiw (1994) for a convincing overview.

²Other early sticky price models include Rotemberg (1982), Blanchard and Kiyotaki (1987) and Ball and Romer (1989).

³Even though there exists a large degree of heterogeneity across countries, products and datasets, non-sale consumer prices generally adjust infrequently; the median price duration is around 8 months in the US (Klenow and Kryvtsov, 2008; Nakamura and Steinsson, 2008) and around 10 months in the Euro area (Dhyne et al., 2006).

instance, Dotsey et al. (1999), Golosov and Lucas (2007) and Midrigan (2011). Another alternative way to model nominal stickiness with the objective to arrive at realistic predictions concerning monetary policy effects is provided by sticky plan models assuming sluggish adjustment of a whole sequence of future prices instead of individual prices at every period. The distinction between time- and state-dependence generally applies to these models as well. While the sticky information model of Mankiw and Reis (2002) is an example of a time-dependent pricing plan model, in the state-dependent sticky plan model of Burstein (2006) firms' updating of pricing plans is endogenized.

A thorough analysis of the price setting mechanism of firms in order to disentangle and evaluate these competing assumptions is important for at least two reasons. First, different price adjustment assumptions can imply quite divergent predictions concerning the strength and persistence of monetary policy effects. Dotsey et al. (1999) show that prices adjust slower and by smaller amounts in response to a monetary shock in a time-dependent setup compared to the state-dependent case. Corresponding output effects of monetary shocks are thus stronger compared to a state-dependent setting. Moreover, Dotsey and King (2005) show that also qualitatively, state-dependent models generate dynamic responses of output and inflation to monetary shocks that are quite different in comparison to those implied by time-dependent settings. Second, Lombardo and Vestin (2008) show that depending on the price setting mechanism put in place welfare outcomes can differ significantly implying that the maximization problem of a welfare-maximizing central bank is conditional on the respective pricing assumption. In particular, Calvo-type pricing rules imply a larger welfare cost compared with menu cost pricing.

Despite the high relevance of the topic and despite a recently growing theoretical and empirical literature on price setting, benefiting from an improved availability of micro price data, a clear consensus on the validity of different price adjustment schemes is still lacking. In practice, in most New Keynesian DSGE models time-dependent pricing rules are assumed for reasons of model tractability.⁴ Additionally, such a simplification is often rationalized by the notion that during not so volatile low-inflation periods firms do not necessarily respond to such

⁴See, for instance, the model heterogeneous sticky price model by Carvalho (2006) and the discussing therein.

aggregate shocks and may indeed adapt time-dependent pricing rules.⁵

The two essays provided in the first two chapters of this thesis address the above-mentioned issues and therefore contribute to the empirical literature analyzing the price setting behavior of firms to derive implications for sticky price models⁶. One main broad question underlying both chapters is whether time-dependence is indeed a valid description of price setting during a low-inflation period. More precisely, both chapters investigate the price setting behavior of German retail firms using a novel firm-level dataset, which is constructed from a large panel of business surveys by the Ifo Institute for Economic Research. The dataset contains qualitative data not only on prices and price expectations but also on additional firm characteristics indicating the idiosyncratic state of the firm and can therefore be used to answer a range of questions related to price setting.

The overriding question asked in Chapter 1 is whether the assumption of time-dependent pricing is supported by the data for a low-inflation period.⁷ In particular, we contribute to the literature on three main dimensions. First, using aggregated survey price data over the period 1970-2010 we decompose the rate of inflation into the frequency of price adjustment, which we call the extensive margin (EM) and the size of price adjustment (intensive margin, IM) and analyze the importance of the EM for overall inflation dynamics. Such an assessment is instructive with respect to core assumptions of different price setting models; while the extensive margin is inactive in time-dependent models, in state-dependent settings price adjustment may be driven by the size or the fraction of price changes, or both. In the state-dependent model of Dotsey et al. (1999) the relatively fast reaction of prices to shocks is largely caused by movements in the extensive margin. By contrast, the models of Golosov and Lucas (2007) and Midrigan (2011) predict the extensive margin to be rather unresponsive to shocks; inflation dynamics are mainly driven by fluctuations in the intensive margin.

An analysis of the dynamics of the extensive margin therefore allows evaluating the relative importance of the time- versus state-dependent pricing assumption, and may additionally shed some more light on the validity of the divergent fea-

⁵This is in the spirit of the rational inattention model of Mackowiak and Wiederholt (2009) predicting that firms only respond to aggregate shocks, such as an increase in inflation, when aggregate conditions become volatile relative to idiosyncratic conditions.

⁶Please refer to Klenow and Malin (2010) for an extensive survey of the literature.

⁷Chapter 1 is based on joint work with Kai Carstensen.

tures of different state-dependent models. In general, we find that the extensive margin matters for aggregate inflation dynamics, and that its importance is positively correlated with the overall rate of inflation. Importantly, however, for our German sample we do not need inflation rates of more than 5% to obtain such an outcome, which contrasts existing studies for high inflation periods. These findings also hold for price expectations suggesting an important role of state-dependent sticky plan models.

Second, we additionally examine the role of the two components of price adjustment for aggregate inflation dynamics not only at a month-on-month basis but also at lower frequency ranges such as the business cycle frequency. Conducting a spectral decomposition of the time series we show that low-frequency components of the data tend to dominate variations in aggregate inflation and that this is largely driven by the spectral dynamics of the extensive margin. Moreover, at the business cycle frequency the EM accounts for a large share of inflation's variance - even in periods of very low inflation. Third, we estimate an SVAR model with theory-based sign restrictions for the German economy over the period 1991-2009, a period of very low inflation, in order to assess the dynamic responses of the extensive and intensive margin to monetary policy shocks and business cycle disturbances. In particular, we are mainly interested whether the frequency of price adjustment responds to aggregate shocks, which should not be the case according to time-dependent theories. Our results show that even during this low-inflation episode the extensive margin significantly reacts to monetary policy and aggregate demand shocks. Our VAR-based results thus confirm that state-dependence seems to play a non-negligible role for price adjustment in the German retail sector.

All in all, our analysis and corresponding findings thus suggest that the price adjustment decision should be endogenized in theoretical models of price setting. Models that rely on standard time dependent rules may not be able to realistically predict the dynamics of the frequency of price changes and may thus have difficulties to generate reasonable monetary policy effects. In particular, menu cost models that allow for a substantial role of the EM in the transmission of monetary shocks seem to be more in line with the data than those solely emphasizing the IM as the only transmission channel of economic shocks to prices, even for a period of very low inflation.

While Chapter 1 analyzes price setting from an aggregate perspective, Chapter 2 exploits the firm-specific nature of the dataset in an attempt to shed more light on the question of which factors underly the probability of price adjustment. So far, this question has not yet been fully resolved in the empirical literature. The main impediment to clearly measuring the relative importance of different price adjustment determinants is the fact that most studies use quantitative item-level datasets, which do not allow to fully capture the pricing decision at the level of the individual firm. By contrast, using business survey data it is possible to analyze the pricing behavior at the firm-level, which allows an assessment of the importance of the firm-specific economic situation and may thus potentially lead to clearer results. More specifically, we estimate univariate and bivariate ordered probit models relating the probability of both price adjustment and the updating of pricing plans to a set of time- and state-dependent variables. This analysis allows us to address three main questions.

First, given the time series evidence in favor of state-dependence reported in Chapter 1 it will be assessed whether state-dependent variables characterizing the economic environment of the specific firms are indeed important for the price adjustment probability relative to time-dependent factors. In this respect, it is particularly interesting to differentiate between factors characterizing the state of the individual firm and the aggregate economic environment, which is possible using the firm-level data.⁸ Second, using data on price expectations it is furthermore analyzed how firms update plans of future prices. In particular, we ask whether there is evidence of state-dependent setting of pricing plans, which helps to shed more light on the validity of different pricing plan models.

The third question asked in Chapter 2 is concerned with the importance of real rigidities in the form of intermediate input cost changes for price adjustment. This issue is related to the recurring difficulty in the modeling of price setting to appropriately match features observed in the micro data with aggregate outcomes. In standard menu cost models prices are adjusted infrequently but still nominal shocks have no effects on the real economy. On the other hand, models of imperfect information (Mackowiak and Wiederholt, 2009) imply large and persistent real effects of monetary shocks despite of frequent price adjustment.

⁸For instance, Golosov and Lucas (2007) and Mackowiak and Wiederholt (2009) stress the importance of idiosyncratic shocks for price setting relative to aggregate disturbances. In an empirical application for the Swiss manufacturing sector, Lein (2010) reports significant effects of firm-specific factors for the price adjustment probability.

Furthermore, at the macro data level, for instance Christiano et al. (1999) report persistent real effects of monetary policy shocks, which are difficult to reconcile with the extent of price stickiness found at the micro level. Congruously, the slope of the New Keynesian Phillips Curve resulting from Smets and Wouters (2003)-type DSGE models is estimated to be too low to be explained by nominal rigidities alone.⁹ One approach to generate more pronounced non-neutralities with respect to monetary policy has been to additionally incorporate real rigidities in pricing models; a proposal that goes back to Ball and Romer (1990) suggesting real rigidities as a way to boost the extent of non-neutralities with respect to monetary shocks in models of price setting.¹⁰ One important example of real rigidities are sticky intermediate inputs. In models that account for price rigidities at different production stages firms at each stage of processing face sticky input costs preventing them from changing their own prices following a shock to the economy. Thus, intermediate inputs act as “multipliers” for price stickiness (Basu, 1995; Huang and Liu, 2001). In particular, we analyze the role of intermediate input costs for the price adjustment probability and assess the degree of additional rigidity at the retail level, which allows us to shed more light on the validity of the predictions of the corresponding models.

Overall, our findings suggest an important role for state-dependence; cumulative changes of macroeconomic variables since the last individual price adjustment as well as changes in institutional conditions significantly determine the timing of price adjustment. Given the low overall rate of inflation during the sample period considered this result is remarkable and is not consistent with the notion of aggregate conditions being irrelevant for price setting during low-inflation episodes. Moreover, factors characterizing the firm-specific environment such as for instance deteriorations in the actual and expected state of business or changes in the business volume have highly significant effects. This is a new result, which could not have been obtained using quantitative price data. The finding that firm-specific conditions are important determinants for price setting confirms the evidence for state-dependence and additionally points to the relative importance of idiosyncratic shocks for pricing. We furthermore find similar effects for the probability of changing pricing plans; most state-dependent factors are highly

⁹See Mackowiak and Smets (2008) for a discussion and summary.

¹⁰Kuester et al. (2009) propose an alternative way to reconcile Phillips Curve parameter estimates with micro data facts showing that GMM slope estimates are biased downwards (i.e. biased towards implying too much price rigidity) in the presence of autocorrelated cost-push shocks.

significant and economically important. Thus, our results provide evidence in favor of state-dependent sticky plan models à la Burstein (2006). Finally, relating measures of changes in wholesale and manufacturing prices to the timing of price changes in the retail sector we find that indeed, intermediate input cost changes are important determinants for price adjustment, which is in line with the corresponding theoretical models featuring such real rigidities. However, we find that the effect of input cost changes on price adjustment in retail is rather persistent. This suggests that there is some degree of additional rigidity at the retail level, which is not implied by some of the above-mentioned models.

As outlined above, Chapters 1 and 2 are concerned with the conditions necessary for monetary policy to be effective. Since both studies analyze non-crisis sample periods the results obtained are valid for “normal times” when central banks use standard policy measures. Empirically, it is already well documented in the literature how such standard measures affect the economy.¹¹ There is, however, much less evidence on macroeconomic effects of unconventional monetary policy measures during times of economic turmoil and consequent near-zero interest rates. In Chapter 3 we attempt to close this gap and offer new evidence on the real effects of non-standard policy measures at the zero lower bound using post-1995 Japanese data.¹²

The analysis of unconventional monetary policy at the ZLB is a currently relevant topic. In general, following crisis episodes central banks may see themselves forced to cut interest rates to very low levels to provide economic stimulus - with the result that subsequent standard policy actions via the interest rate become infeasible. An obvious example is the recent financial crisis that culminated with the fall of Lehman Brothers inducing major central banks to cut interest rates to historically low levels in order to stabilize the economy. By mid 2009, policy rates in the Euro area, the US, the UK and Japan were close to zero.¹³ Obviously,

¹¹There is a broad consensus that expansionary monetary policy has a delayed and temporary positive effect on inflation and output; see Bernanke and Blinder (1992) and Christiano et al. (1999). However, different identifying assumptions can actually lead to quite diverging results (Uhlig, 2005).

¹²Chapter 3 is based on joint work with Sebastian Watzka.

¹³However, the speed and the severity of the cuts varied across countries. While the Fed specified a range of 0 - 0.25% for the Federal Funds Rate in December 2008 already, the UK bank rate and the main refinancing rate of the ECB were reduced to 0.5% and 1% in spring 2009, respectively. The call rate of the Bank of Japan fluctuated around 0.1% from January 2009. See Lenza et al. (2010) or Meier (2009) for more details.

during periods of economic turmoil stabilizing policy measures are most needed; in these periods central banks usually rely on so-called unconventional policy measures. Examples of such policy measures include an expansion or reshuffling of central bank balance sheets, but also verbal policy commitments to future low interest rates.¹⁴

So far, unconventional monetary policy measures have mainly been evaluated according to their effects on financial variables such as interest rate spreads or long-term yields. We argue, however, that the theoretical impact of expansionary policy measures on for instance long-term yields is not clear; if a central bank intervention is expected to be successful in stimulating the economy, inflation and real rates are in fact likely to rise in the future. Inflationary expectations and long-term nominal yields should thus rise as well. Moreover, even if long-term yields were negatively affected, there is no broad consensus on whether this would indeed be transmitted to the economy via, for instance, portfolio effects. While it is therefore instructive to adopt an agnostic stance with respect to long-term yields and investigate unconventional monetary policy effects on other macroeconomic factors, there are only few corresponding studies.

In Chapter 3 we contribute to the existing literature on the effects of non-standard monetary policy by focusing on its impact on a broader range of aggregate measures such as real output, prices, broader money supply and the exchange rate. We analyze the case of Japan since, in contrast to other industrialized countries, this economy has been at the ZLB for an extended period of time and thus the sample period is sufficiently long for a time series investigation. Since we attempt to analyze the effectiveness of the Quantitative Easing (QE) Policy implemented by the Bank of Japan in 2001, we focus on quantitative easing as opposed to other non-standard policy measures. In particular, we propose a novel theory-based sign restriction SVAR approach to identify unconventional monetary policy shocks when the economy is at the ZLB, remaining as agnostic as possible with regard to real output and financial variables, such as long-term yields and the exchange rate.

The quantitative easing shock we identify leads to a significant decrease in the long-term government bond yield and increases industrial production significantly but only temporarily and with a considerable delay. Compared with a

¹⁴For more details on the different dimensions along which unconventional policy measures can be classified see Bernanke and Reinhart (2004) or Meier (2009).

traditional monetary shock during the pre-1995 period in Japan, the response of industrial production is weaker and much more transient. The effect on prices is also positive but rather mild and highly transient as well. Our results thus suggest that while the Japanese Quantitative Easing experiment was successful at temporarily stimulating real activity, it did not lead to a pronounced increase in prices necessary for the economy to escape from its deflationary spiral. To the extent that the economic situation in Japan during our sample period is comparable to that in other industrialized countries after the financial crisis the results provided in Chapter 3 may be interesting for these countries as well. Since both the crisis in Japan following the stock market crash in the early 1990s as well as the financial crisis in the US and the Euro area are mainly due to a bursting of housing market bubbles, at least the initial situation is similar.

Our results concerning possible transmission channels of quantitative easing are rather limited; while portfolio effects could possibly be brought about by the fall in the long-term yield, neither the exchange rate nor broader money supply, two potentially important variables with regard to policy transmission¹⁵, show a significant reaction to the QE-shock. One possible interpretation of this, in the spirit of Svensson (2003) and Orphanides and Wieland (2000), could be that the Bank of Japan did not do enough to depreciate the exchange rate, which would promote economic activity at the ZLB. A more detailed analysis of potential channels of transmission of unconventional monetary policy at the ZLB is left for future research.

¹⁵See, for instance, Ugai (2007).

Chapter 1

Time- or State-Dependence? An Analysis of Inflation Dynamics Using German Business Survey Data^{*}

1.1 Introduction

The question concerning the exact price setting mechanism underlying the patterns of price adjustment observed in the data has not yet been sufficiently answered by the empirical literature. This paper offers new evidence on the relationship between aggregate inflation dynamics and price setting at the level of the individual firm and attempts to shed more light on the validity of different price setting models. On the one hand, in standard time-dependent models à la Taylor (1980) or Calvo (1983), the timing of price adjustment is exogenous implying that the frequency of price adjustment is invariant over time. On the other hand, state-dependent theories assume the timing of price changes to be the outcome of a maximization problem of firms.¹ Hence, the frequency of price adjustment is endogenous and may vary with economic conditions. Evaluating these two alternative mechanisms to investigate which of them more closely reflects the true underlying price adjustment process is important for at least

^{*}This paper is joint work with Kai Carstensen

¹Examples of such models are Caplin and Spulber (1987), Dotsey et al. (1999), Gertler and Leahy (2008), Golosov and Lucas (2007) and Midrigan (2011).

two reasons. First, an analysis of competing price setting models is relevant for policy-making because of their diverging implications for the transmission of monetary policy. For instance, Dotsey and King (2005) show that prices tend to react faster to monetary policy shocks in state-dependent frameworks as compared to time-dependent models leading to a less persistent effect on real output in the former models. Second, Lombardo and Vestin (2008) show that in general, welfare implications of these diverging price setting mechanisms are different indicating that a welfare-maximizing central bank faces a different maximization problem depending on the assumption concerning price setting behavior.

We argue that both the dynamics of the frequency of price adjustment, which we call the *extensive margin* (EM), as well as its importance for overall inflation variability are highly informative concerning the validity of core assumptions of different price setting models. While the frequency of price changes is fixed in time-dependent models and price responses to a shock therefore occur due to an increase in the average size of price changes (*intensive margin*, IM), in state-dependent models it is either the *size* or the *frequency* of price changes that react, or both. Analyzing the behavior of the extensive and intensive margins of price setting should therefore reveal to which extent the implications of state-dependent pricing theories are supported by the data relative to time-dependence.

Moreover, if state-dependence is important, such an analysis also allows evaluating the divergent features of different state-dependent models. In menu-cost models like Dotsey et al. (1999), the reason for the faster reaction of prices to shocks is due to fluctuations in the frequency of price adjustment. By contrast, in the model of Golosov and Lucas (2007) it is mainly the size of the price changes that react to the shock while the frequency of price adjustment is relatively unaffected. The reason is that the model assumes a large menu cost, such that prices are mostly changed following large idiosyncratic shocks but not as a reaction to small aggregate shocks. Moreover, while generating more pronounced monetary non-neutralities compared to the predictions of Golosov and Lucas (2007), the menu cost model of Midrigan (2011) featuring a leptokurtic price distribution thus allowing for a larger degree of dispersion between price changes predicts a small response of the extensive margin to shocks as well. However, Karadi and Reiff (2011) show that for larger shock sizes or positive trend inflation the extensive margin plays a more important role in the pass-through of shocks in such

a model. In fact, the authors show that after accounting for trend inflation of 2% or assuming somewhat larger shock sizes the extensive margin substantially reacts to shocks and the share of the reaction of inflation caused by fluctuations in the extensive margin gets sizeable.

Related to the above-mentioned time- and state-dependent frameworks are sticky plan models, where firms set entire pricing plans instead of individual prices at every period. The distinction between time- and state-dependence also applies to these models. While sticky information models predict that every period a fixed fraction of firms updates an entire sequence of future prices implying that the frequency of expected future price changes is constant over time², the sticky plan model of Burstein (2006) constitutes an example of state-dependent price updating. In this model firms' updating of pricing plans is constrained by a menu cost - the frequency of changes in pricing plans is thus endogenous and adjusts once accumulated shocks to the economy are large enough.³

Using a novel dataset constructed from a large panel of firm-level business surveys of German retailers over the period 1970-2010 we contribute to the literature in various important ways. First, the dataset allows us to assess the implications of different models of both price setting as well as the updating of pricing plans because our survey dataset contains firm-specific information on both realized price changes and price expectations. We examine the driving forces of aggregate inflation dynamics by, following Klenow and Kryvtsov (2008), decomposing aggregate inflation into the size and the frequency of price adjustment. Overall, we find that not only the intensive margin matters for aggregate inflation dynamics. For periods of relatively high and volatile inflation variations in the extensive margin are important for the variability of the overall rate of inflation as well. For the period 1970-1985, the extensive margin's share of overall inflation variability is about 15%. Importantly, for our German sample we do not need inflation rates of more than 5% to achieve such an outcome,⁴ which

²Examples include Bonomo and Carvalho (2004), Caballero (1989), and Mankiw and Reis (2002, 2006). While in Bonomo and Carvalho (2004) the time-dependent formation of pricing plans is due to the simultaneous occurrence of both menu and information costs, in Mankiw and Reis (2002, 2006) imperfect information is assumed to follow from a fixed cost of observing the state of the economy. See also Mankiw and Reis (2010) for an overview.

³Related to this model are recent contributions by Alvarez et al. (2010) and Bonomo et al. (2010) endogenizing the mechanism underlying the price reviewing process. Including both menu and information costs these models feature a state-dependent updating of pricing plans.

⁴In particular, the average annual rate of consumer price inflation in Germany has been 4.6% for the period 1970-1985.

contrasts existing studies for different countries during high and low inflation periods of Gagnon (2009), Wulfsberg (2009) and Hofstetter (2010). These findings also hold for price expectations suggesting an important role of state-dependent sticky plan models.

Second, we argue that complementary to the existing approach to analyzing the different components of price setting it is important to examine the role of the extensive and intensive margins for aggregate inflation dynamics not only at a month-on-month basis but also at lower frequencies. With sticky prices, the fraction of firms that decide to change their prices due to changes in the economic environment might be relatively stable in the very short run, but as economic shocks accumulate over time, firms may gradually decide to adjust their prices. We therefore explicitly analyze the importance of the extensive margin at different frequency ranges. To the best of our knowledge, a thorough assessment of the role of the extensive margin at, for instance, the business cycle frequency has not been forthcoming. We show that fluctuations in aggregate inflation are dominated by low-frequency components of the data, and that this is largely driven by the dynamics of the extensive margin. Moreover, at lower frequency ranges the EM accounts for a large share of inflation's variance - even in periods of rather low inflation. At the business cycle frequency the EM accounts for between 26% and 32% of inflation's variance for the full sample period.

Third, we further assess the dynamics of the extensive and intensive margin, respectively, using a structural VAR (SVAR) model with theory-based sign restrictions for the German economy over the period 1991-2009. We find that even during this low-inflation episode the extensive margin as well as the frequency of price increases and decreases show a significant reaction following a monetary policy and an aggregate demand shock. This confirms that the predictions of standard time-dependent theories are not supported by the data.

Overall, our results suggest that the price setting decision of firms should be endogenized in theoretical models in order to realistically predict the dynamics of the frequency of price changes - even during periods of low inflation. In particular, menu cost models that allow for a non-negligible role of the extensive margin in the transmission of monetary shocks seem to be more in line with the data than those mainly emphasizing the intensive margin as a channel of transmission of economic shocks to prices. Interestingly, even during a period of very low inflation the frequency of price adjustment significantly reacts to ag-

gregate shocks suggesting that even during such low-volatility periods standard time-dependent price setting rules do not represent a good approximation to their state-dependent counterparts due to their diverging predictions concerning inflation dynamics.

Our study relates to a growing empirical literature analyzing the price-setting behavior of firms using detailed price data. Despite an increasing research effort, so far it has been difficult to find clear evidence in favor of state- versus time-dependence. On the one hand, empirical studies analyzing microdata underlying the CPI and PPI find support for both time- and state-dependent elements. Examples include Bils and Klenow (2004) and Nakamura and Steinsson (2008) for the US and Dhyne et al. (2006) and Vermeulen et al. (2007) for the Euro area. Hoffmann and Kurz-Kim (2006) offer corresponding evidence for German CPI data. On the other hand, however, Eichenbaum et al. (2011) find evidence that in the US the most common prices (*reference prices*) closely comove with costs. In Lein (2010) this evidence for state-dependence is confirmed for Swiss manufacturing firms.

This paper differs from these contributions in that we adopt an aggregate perspective analyzing the dynamics of overall inflation and its components. Our approach is closest to the one followed by, inter alia, Klenow and Kryvtsov (2008), Gagnon (2009), Wulfsberg (2009) and Hofstetter (2010). Using aggregate US CPI data Klenow and Kryvtsov (2008) decompose monthly inflation into the fraction of products with price changes and their average size and find the extensive margin to be rather stable and uncorrelated with inflation, while the intensive margin is highly correlated with inflation and accounts for almost all of inflation's variance. Gagnon (2009) finds similar results for low-inflation episodes using Mexican CPI data; the average frequency (size) of price changes is weakly (strongly) correlated with inflation due to offsetting movements in the frequency of price increases and decreases. When inflation increases to 10-15%, however, both the extensive and intensive margins are important for inflation dynamics. Wulfsberg (2009) and Hofstetter (2010) report similar findings for low- and high-inflation periods using Norwegian CPI data and Colombian newspaper prices, respectively.⁵

⁵Related older empirical studies analyzing price setting for high inflation periods include Lach and Tsiddon (1992) and Baharad and Eden (2004) for Israel and Konieczny and Skrzypacz (2005) for Poland. The datasets used in these studies are however more limited and include mainly food products.

The remainder of the paper is organized as follows. Section 1.2 describes the survey dataset, explains the statistics calculated for the analysis and gives the main price setting facts. In Section 1.3, a spectral assessment of the time series is given followed by a variance decomposition of aggregate inflation. Section 1.4 explains the VAR framework and Section 1.5 reports and discusses the results thereof. Finally, Section 1.6 concludes

1.2 Price Setting Facts from Business Survey Data

1.2.1 Data Description and Discussion

The dataset contains monthly firm-level price data of a large panel of business surveys for the retail sector conducted by the Ifo Institute for Economic Research. Next to the retail sector the business survey also contains information on the wholesale and manufacturing sectors as well as the service and construction sectors, see Becker and Wohlrabe (2008). We focus on the retail sector since the composition of goods in this sector is closest to the CPI, which better allows us to compare our results to existing studies. The firm-specific survey data is available for the period January 1990 to June 2009 covering around 2000 West German retail firms. For the period prior to 1990 and after June 2009 only aggregated time series concerning the percentage of firms that increased or decreased their prices is available⁶. Each retail firm can be allocated to one of the following sectors: automobile, food and beverages, communication and information technology, household products, recreational products and other industrial products. Relative to the CPI missing items are services including housing rents as well as energy goods such as oil products as well as gas and electricity. Amongst other questions, firms are asked whether they changed the price of their products in the last month. The answers are coded as 1 (“increased”), 0 (“not changed”) and -1 (“decreased”).⁷ Moreover, firms are asked about their *expectations* concerning the setting of prices in the future. More specifically, they are asked whether they expect to change the price of their products in the coming three months; answers are again coded as 1 (“expect to increase”), 0 (“expect not to change”) and -1

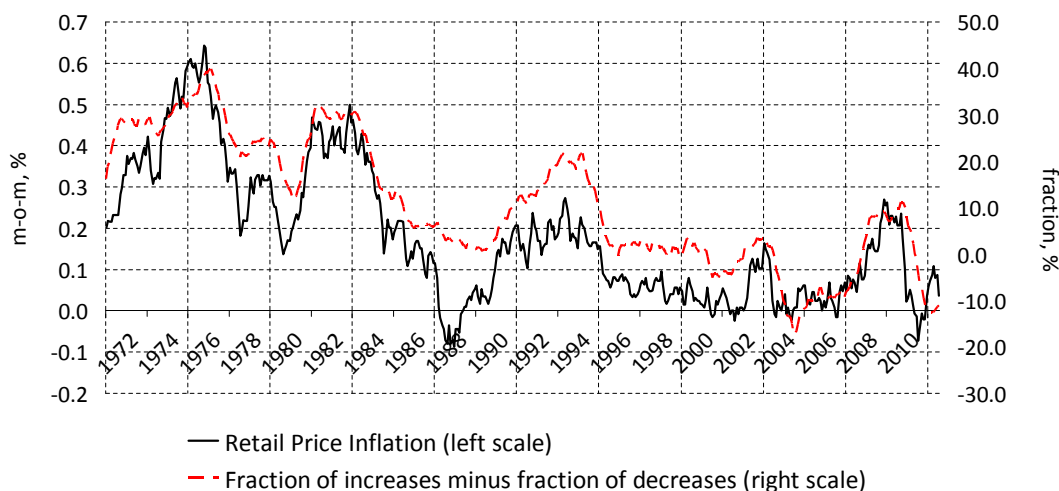
⁶For more details concerning the availability of the different series see Appendix 1.A.1.

⁷For more details on the questionnaires as well as on the respondents see Appendix 1.A.1. and Abberger et al. (2009).

(“expect to decrease”).

Relative to other data sources, the survey dataset offers several advantages. First, in contrast to detailed quantitative price data for specific *products* underlying CPI calculations as used by e.g. Bils and Klenow (2004), Klenow and Kryvtsov (2008) or Dhyne et al. (2006), our dataset contains *firm*-specific information on prices, which better allows us to analyze decisions taken at the firm-level.⁸ Second, the business survey data contain information on firms’ price expectations allowing to assess the validity of different sticky plan models, which is not possible using item-level price data. A third advantage of the dataset at hand is that firms are not asked directly for their pricing strategies as it is the case for the one-time interview studies conducted by, for instance, Blinder (1991) for the US and Fabiani et al. (2006), for the Euro area. To the extent that firms may be unwilling to respond truthfully to questions regarding their pricing strategies, such an interview method could lead to biased responses. However, it should be noted that due to the qualitative nature of the questionnaires, the dataset does not offer information concerning the size of price changes. However, Figure 1.1 reveals that the survey data largely reflect the official retail price inflation.

Figure 1.1: Aggregated Micro Retail Price Data and Retail Price Index



The figure displays the comovement of the fraction of price increases minus the fraction of price decreases in the survey data with the monthly rate of change

⁸Moreover, the data contains idiosyncratic information on key economic measures such as business volume, demand or the expected business development. This allows an assessment of the price setting behavior of firms at the micro level; see Schenkelberg (2011).

of the German retail price index constructed by the Federal Bureau of Statistics.⁹ A further disadvantage of the dataset is that the data contain both single- and multi-product firms and there is no information on how multi-product firms answer the pricing questions. However, this problem is mitigated by the fact that firms are asked to fill in different questionnaires for their respective product groups.¹⁰

A number of authors stress that the macroeconomic implications of price adjustment, especially of consumer prices, is conditional on the particular type of these price changes (Klenow and Malin, 2010; Nakamura and Steinsson, 2008). For instance, the transient nature of price changes due to end-of-season sales implies that the extent of aggregate price adjustment is reduced (Kehoe and Midrigan, 2007). Moreover, sales prices may be independent of macroeconomic conditions (Taylor, 1999) implying that the coexistence of different types of price changes may conceal the true adjustment mechanism underlying regular price setting. Thus, in order to draw unbiased conclusions concerning the price setting behavior of regular prices, sales should be filtered out of the data. Unfortunately, in the business survey, firms are not asked whether a price change results from a “sale” or is a “regular” price change. We thus follow Nakamura and Steinsson (2008) and exclude “V-shaped” price changes using a sale filter. This is, however, only possible for the period 1990-2009 (see Appendix 1.A.1.). It turns out that the occurrence of sales in the data is very limited; our results are insensitive to the exclusion of such temporary price changes. This is in line with Dhyne et al. (2006) reporting that sales-related price changes are less important for the Euro area compared with the US. While we can account for sales in the survey data, it is however not possible to identify price changes related to product substitutions.

1.2.2 Decomposing the Rate of Inflation

Because the survey data does not contain information on the size of price changes, defined as the intensive margin throughout the paper, we construct this statistic from the survey data. As a first step, note that the rate of inflation can be decomposed into the fraction of price changes and the average size of these changes (Klenow and Kryvtsov, 2008):

⁹Both series are displayed as 12-month moving averages.

¹⁰A recent meta-study on the survey provides some further details on how multi-product firms tend to fill in the questionnaires. Please refer to Appendix 1.A.1.

$$\pi_t \approx \pi_t^K \cdot fr_t = IM_t \cdot EM_t, \quad (1.1)$$

where π_t^K denotes the average rate of inflation of those firms changing their prices in period t and fr_t indicates the fraction of price changes in period t . The extensive margin is constructed by aggregating the firm-specific price information:

$$EM_t = \frac{\sum_{i=1}^n y_t^+ + \sum_{i=1}^n y_t^-}{\sum_{i=1}^n y_t^+ + \sum_{i=1}^n y_t^- + \sum_{i=1}^n y_t^0}, \quad (1.2)$$

where y_t^+ , y_t^- and y_t^0 denote price increases, decreases and observations for which the price has not been changed in a certain period. Since the dataset does not contain consistent information concerning the importance of the respective products for the whole sample period we study, we implicitly assume that all products have equal weights.¹¹ Using this aggregated time series, the implied intensive margin can be constructed as:

$$IM_t \approx \frac{\pi_t}{EM_t}, \quad (1.3)$$

where π_t denotes the monthly rate of change of the retail price index for Germany, obtained from the Federal Bureau of Statistics. The extensive margin can be further decomposed into the fraction of price increases and decreases:

$$F_t^+ = \frac{\sum_{i=1}^n y_t^+}{\sum_{i=1}^n y_t^+ + \sum_{i=1}^n y_t^- + \sum_{i=1}^n y_t^0}$$

$$F_t^- = \frac{\sum_{i=1}^n y_t^-}{\sum_{i=1}^n y_t^+ + \sum_{i=1}^n y_t^- + \sum_{i=1}^n y_t^0}.$$

Tables 1.1 and 1.2 contain summary statistics for the components of inflation calculated as described above. In order to be able to relate our results to those found in the literature we also report the main statistics for the US dataset used by Klenow and Kryvtsov (2008) over the period 1988 to 2004. For better comparison Table 1.1 displays the statistics for the German data for this particular period as well. The monthly rate of retail price inflation is 0.09% (or about

¹¹The Ifo survey dataset does contain a variable indicating the weight of the firms, which corresponds to the respective business volume. However, for the retail sector, these weights are only available for the period 1990-2009, so we are not able to construct weighted measures for the full sample period. We have checked, however, that for this subsample the statistics are very similar when we use a weighted extensive margin measure.

1.1% annually). The average monthly frequency of price changes is 24.9% with a standard deviation of 7.7%; the implied average duration of a price spell is thus about 4 months.¹² This is comparable to the US statistics.¹³ The relatively high frequency of price changes stands, however, in contrast to similar measures for the Euro area and Germany. Generally, with an average frequency of only 15%, price adjustments are less frequent in the Euro area compared to the US (Dhyne et al., 2006). For Germany, Hoffmann and Kurz-Kim (2006) report the monthly frequency of price changes to range between 10.1 - 11.3%. However, this difference can be explained by the fact that, in contrast to the survey dataset used for this paper, the CPI data includes categories characterized by a relatively infrequent price adjustment such as electricity and gas as well as rents and other services. The IM averages 0.3% with a standard deviation of 0.8%. It is highly correlated with the rate of retail price inflation, while the EM is relatively uncorrelated with inflation (.94 versus .19). Importantly, this high correlation of the IM and the rate of inflation is not only due to its construction; correlations reported for the US data are very similar.

Table 1.1: Summary Statistics - Comparison with US Data

	German data, 1988 - 2004				US data, 1988 - 2004		
	Mean (%)	StDev (%)	Corr π	Regression on π	Mean (%)	StDev (%)	Corr π
π_t	0.09	0.21			0.27	0.36	
IM_t	0.33	0.88	0.94	3.79***	0.98	1.19	0.99
EM_t	24.88	7.71	0.19	6.86***	26.6	3.2	0.25
Fr_t^+	13.88	7.61	0.42	14.92***	15.0	2.6	0.69
Fr_t^-	11.00	7.01	-0.24	-8.07***	11.5	2.5	-0.41

Notes: German sample runs from 1988:01 to 2004:12 with monthly frequency. The retail price index is obtained from the Federal Bureau of Statistics. The last column in the left panel contains OLS regression coefficients from the following regressions: $x_t = \alpha + \beta\pi_t + u_t$.

Moreover, similarly to the US statistics, we observe a higher correlation with inflation as soon as the frequency of price changes is separated into the frequency

¹²The term implied average duration refers to the inverse of the monthly frequency of price changes: $d = 1/fr$. See e.g. Dhyne et al. (2006) for a discussion of different measures of the duration of price spells.

¹³See Bils and Klenow (2004) and Klenow and Kryvtsov (2008)

of increases and decreases (.42 and -.24). The asymmetry between both statistic's correlations with inflation is documented in the literature as well. Finally, even though the EM is not so correlated with inflation, regression results from a simple OLS regression in column five of the table show that the relation between the extensive margin as well as the frequency of price increases are significantly related to overall inflation.

Table 1.2 displays the summary statistics for the full sample as well as several subsamples. We separate the full sample in three periods. While the first runs from 1970:01 to 1985:12 thus including a period of relatively high and volatile inflation in Germany and Europe, the second starts in 1986:01 and ends in 1998:12, just before the European Monetary Union (EMU) came into force. The last period starts with the beginning of the EMU in 1999:01 and runs until 2010:07. As is shown in the table, when the 1970's and early 80's are included in the sample, both the rate of retail price inflation and the intensive margin are relatively high and more volatile. While the average annualized rate of inflation is about 2.2% for the full period, it reaches 4.1% for the period 1970-1985. Similarly, including this period in the sample leads to a larger average frequency of price changes. On average, 28.9% of the firms change their prices in a given month during the full sample, while during the period 1970-1985 the average frequency is even 33.4%. Moreover, the extensive margin is more strongly correlated with the rate of inflation (.41 and .42 for the periods 1970-2010 and 1970-1985, respectively). Accordingly, the frequency of price increases is much larger during these periods and correlation with the rate of inflation is higher.

By contrast, the fraction of price decreases becomes less important during these periods both in terms of size and comovement with inflation. In the period prior to the EMU, 1986-1998, the average rate of inflation as well as the EM and IM are quite similar to the statistics for the Klenow/Kryvtsov period, while, however, the extensive margin and the frequency of price increases are somewhat more correlated with inflation. Contrarily, during the most recent period, 1999-2010, both the EM and the fraction of price increases are only weakly correlated with inflation.

Table 1.2: Summary Statistics - Different Sample Periods

Variable	1970-2010			1970-1985		
	Mean (%)	StDev (%)	Corr π_t	Mean (%)	StDev (%)	Corr π_t
π_t	0.18	0.31		0.34	0.34	
IM_t	0.55	1.02	0.92	0.97	1.00	0.90
EM_t	28.87	9.98	0.41	33.39	10.63	0.42
Fr_t^+	19.62	11.47	0.55	28.39	10.90	0.45
Fr_t^-	9.24	6.66	-0.32	5.00	3.13	-0.14
Variable	1986-1998			1999-2010		
	Mean (%)	StDev (%)	Corr π_t	Mean (%)	StDev (%)	Corr π_t
π_t	0.09	0.21		0.07	0.26	
IM_t	0.34	0.98	0.93	0.22	0.88	0.97
EM_t	22.51	7.50	0.39	29.76	7.50	0.08
Fr_t^+	14.60	8.17	0.46	13.16	6.82	0.26
Fr_t^-	7.92	4.37	-0.19	16.60	6.31	-0.19

Notes: Samples run from 1970:01 to 2010:07, 1970:01 to 1985:12, 1986:01 to 1998:12 and 1999:01 to 2010:07, respectively. Frequency is monthly. The retail price index is obtained from the Federal Bureau of Statistics.

Accordingly, the asymmetry between the frequency of price increases and decreases is less pronounced. The results displayed in Tables 1.1 and 1.2 are in line with previous studies of the dynamics of inflation and its components during periods of high and low inflation (Gagnon, 2009; Wulfsberg, 2009).

Figure 1.2 plots the evolution of the retail price inflation as well as the extensive and the intensive margin of price adjustment. As expected, the IM reflects the evolution of retail price inflation over time. However, the figure also shows that the EM is not completely stable but seems to comove with the rate of inflation as well. Figure 1.3 displays the frequency of price increases and decreases, respectively, as well as the rate of retail price inflation. The figure clearly shows the comovement between overall inflation and the frequency of price increases.¹⁴ While the fraction of price decreases is small and rather stable until the late 1990's it becomes more volatile and increases considerably from 2002. This surge in the frequency of firms that decrease their prices drives the upward trend in the ex-

¹⁴Both figures display month-on-month changes of the retail price index. The extensive and intensive margins as well as the frequency of price increases and decreases enter as 12-month moving averages.

tensive margin from the late 90's, visible in Figure 1.2. One possible explanation for this pattern might be the wage moderation and associated low-inflation tendencies in Germany resulting from an increasing pressure of the country to retain international competitiveness after the introduction of the monetary union; see e.g. Burda and Hunt (2011). Overall, both figures suggest that the frequency of price changes is not invariant over time as predicted by standard time-dependent theories.

Figure 1.2: Retail Price Inflation, Extensive and Intensive Margins

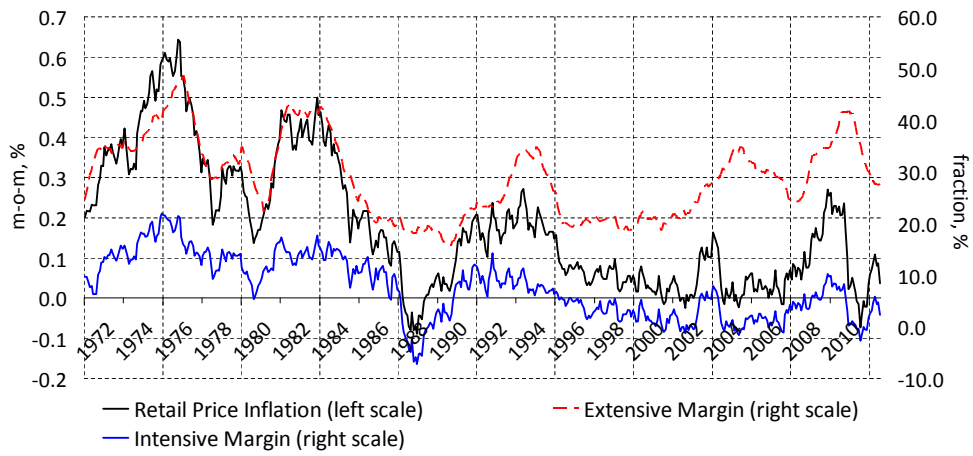
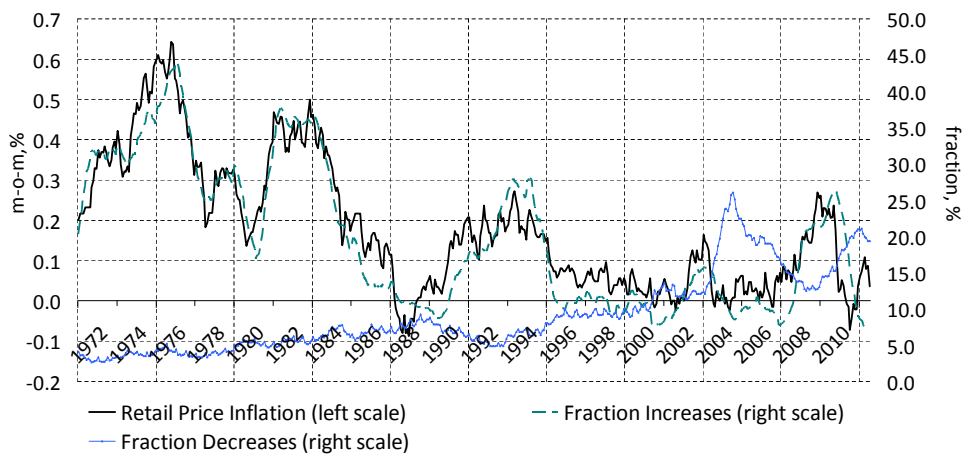


Figure 1.3: Retail Price Inflation, Fraction of Price Increases and Decreases



1.2.3 Price Expectations

Due to the information on firms' expectations included in the business survey dataset, the frequency of changes in price expectations can be calculated analogously to that of price realizations. The calculation of the intensive margin, however, is slightly more complicated and involves additional assumptions. We start by calculating the extensive margin of changes in price expectations as:

$$EM_t^{exp} = \frac{\sum_{i=1}^n y_t^{exp,+} + \sum_{i=1}^n y_t^{exp,-}}{\sum_{i=1}^n y_t^{exp,+} + \sum_{i=1}^n y_t^{exp,-} + \sum_{i=1}^n y_t^{exp0}}. \quad (1.4)$$

Using the formula for the expected value of a product of two random variables, the expected rate of inflation can be expressed as:

$$\begin{aligned} E_t[\pi_{t+j}] &\approx E_t[IM_{t+j} \cdot EM_{t+j}] \\ &= E_t[IM_{t+j}] \cdot E_t[EM_{t+j}] + cov_t[IM_{t+j}, EM_{t+j}]. \end{aligned}$$

From this expression, the intensive margin of price expectations can be calculated as:

$$E_t[IM_{t+j}] \approx \frac{E_t[\pi_{t+j}] - cov_t[IM_{t+j}, EM_{t+j}]}{E_t[EM_{t+j}]} \quad (1.5)$$

The first assumption necessary in order to compute a measure of the size of expected price changes concerns the expectation horizon of the firms. In fact, firms are asked for their expectations over the following *three* months. Because our analysis is based on a monthly frequency, however, we have to control for this. Assuming that the information firms provide over this three-month horizon mainly reflects expectations concerning the middle of this range, i.e. month $t+2$, the extensive margin of expected price changes can be written as $EM_t^{exp} \approx E_t[EM_{t+2}]$.¹⁵ The second assumption concerns the formation of inflation expectations, $E_t[\pi_{t+j}]$. As baseline we construct this measure by assuming perfect foresight in expectation formation, i.e. $E_t[\pi_{t+j}] = \pi_{t+j}$. Relaxing this assumption by considering static expectations, i.e. $E_t[\pi_{t+j}] = \pi_{t-1}$, or by generating inflation forecasts using a simple AR(1) model does not significantly change our results. Finally, the covariance between the IM and EM is approxi-

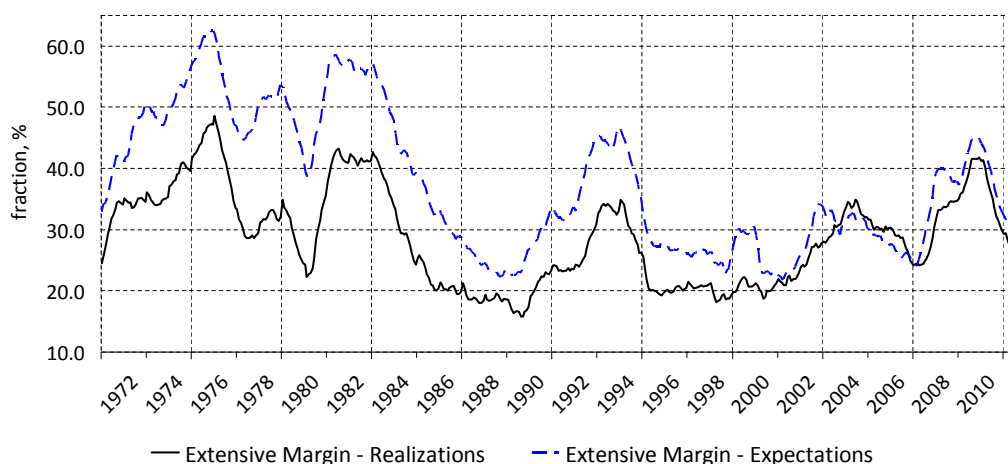
¹⁵Of course, this assumption can be varied by assuming, for instance, that firms truly report expectations concerning the subsequent month only or that they give some sort of average measure for the coming three months. Results are insensitive to varying this assumption.

mated using the statistics based on realized price changes, calculated separately for the respective sample periods. Alternatively, we construct moving covariance measures of the two series; results are robust to using such measures for various window sizes.

Figure 1.4 shows the extensive margin constructed from realized and expected price changes, respectively. The frequency of expected price changes is almost always higher than the frequency of realized price adjustments; since in any given month firms indicate expectations for the coming three months while price realizations are reported monthly this pattern is not surprising. Moreover, the figure shows that after certain events the extensive margin of price expectations increases more strongly than the extensive margin of price realizations indicating that firms' expectations might be somewhat more responsive to economic conditions compared to actual price changes. Recent examples are the boom after the German reunification between 1991 and 1993, the introduction of the monetary union and the Euro in 1999 and 2002, respectively, as well as a period of relatively strong growth in Germany around 2006.

Overall, however, the figure shows that the comovement between the two series is rather strong and there seems to be a general convergence over time. Moreover, even though they differ in magnitude, spikes in the two series almost always coincide suggesting that, following a shock to the economy, not only pricing plans but also actual prices change.

Figure 1.4: Extensive Margin - Realized and Expected Price Changes



This descriptive finding is not in line with sticky plan models that imply a reaction of pricing plans but not of realized prices in a given period. Table 1.3 shows summary statistics for price expectations.

Table 1.3: Summary Statistics - Price Expectations

Variable	1970-2010			1970-1985		
	Mean (%)	StDev (%)	Corr. $E_t[\pi_{t+2}]$	Mean (%)	StDev (%)	Corr. $E_t[\pi_{t+2}]$
$E_t[\pi_{t+2}]$	0.18	0.31		0.33	0.34	
IM_t^{exp}	0.34	0.81	0.93	0.65	0.73	0.95
EM_t^{exp}	37.39	13.02	0.46	47.36	11.60	0.33
$Fr_t^{+,exp}$	30.78	15.44	0.49	44.17	12.15	0.35
$Fr_t^{-,exp}$	6.60	4.93	-0.32	3.20	1.83	-0.28
Variable	1986-1998			1999-2010		
	Mean (%)	StDev (%)	Corr. $E_t[\pi_{t+2}]$	Mean (%)	StDev (%)	Corr. $E_t[\pi_{t+2}]$
$E_t[\pi_{t+2}]$	0.09	0.21		0.07	0.26	
IM_t^{exp}	0.20	0.75	0.95	0.19	0.85	0.97
EM_t^{exp}	30.36	9.77	0.36	31.41	8.49	0.15
$Fr_t^{+,exp}$	24.40	10.55	0.37	19.29	9.03	0.18
$Fr_t^{-,exp}$	5.96	2.87	-0.14	12.12	4.99	-0.07

Notes: Samples run from 1970:01 to 2010:05, 1970:01 to 1985:12, 1986:01 to 1998:12 and 1999:01 to 2010:05, respectively. Frequency is monthly. The retail price index is obtained from the Federal Bureau of Statistics.

Compared to the statistics calculated from price realizations (Tables 1.1 and 1.2), the moments of the expected rate of inflation and the expected size of price changes as well as their correlation are quite similar. However, the mean of the extensive margin is larger reflecting that a change in price plans occurs more often than actual prices changes. Furthermore, the frequency of expected price increases is much larger than that of expected price decreases (30.8% and 6.7 % for the period 1970-2010); this asymmetry is not that pronounced for price realizations. Thus, apparently, firms expect to increase their price more often than they actually do. Related, the correlation between the expected rate of inflation and the extensive margin as well as the frequency of price increases, respectively, is higher than for price realizations.

Apart from these differences, the general tendency of the EM showing a higher correlation with the rate of inflation during periods of relatively high inflation

is also present for price expectations. The correlation between the frequency of expected price changes and the expected rate of inflation is 0.15 for the “low-inflation” period 1999-2010, while it is 0.46, 0.33 and 0.36 for the full period and for the periods 1970-85 and 1986-98, respectively. Moreover, the average value of the EM is much higher during the period 1970-85 (47.4%) suggesting that during periods of high expected inflation a much larger share of firms expects to change prices in the future. Thus, firms seem to adjust pricing plans in line with economic developments, which accords with state-dependent sticky plan models.

1.3 The Importance of the EM and IM for Aggregate Inflation Dynamics

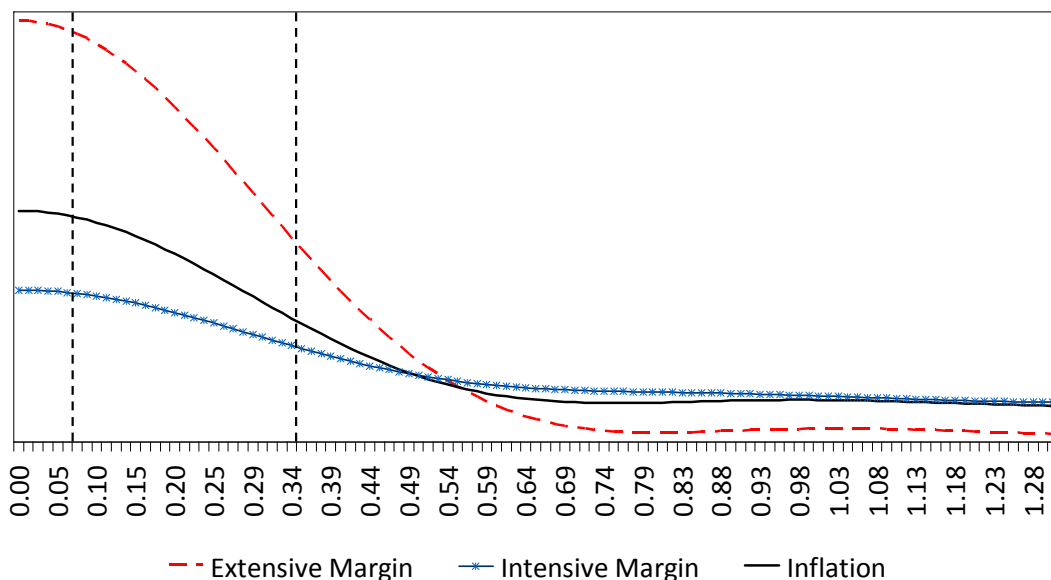
1.3.1 Spectral Analysis

Before turning to an assessment of the relative importance of the extensive and intensive margins for aggregate inflation dynamics, we employ univariate spectral analysis for the three time series in order to determine the cycle component dominant for the variability of the respective series. For instance, Dhyne et al. (2006) find a considerable degree of price stickiness for the Euro area implying that the frequency of price changes does not adjust immediately. We therefore argue that the unimportance of variations in the EM for aggregate inflation dynamics during low-inflation regimes reported by e.g. Klenow and Kryvtsov (2008) and Gagnon (2009) may be due to the fact that the analysis is done at the monthly frequency even though the extensive margin is relatively stable at high frequencies.

Using spectral analysis, the series of interest can be converted from the time domain into the frequency domain using a Fourier transform. This allows estimating the relative importance of different frequencies in terms of their explanatory power for variations in the respective time series. In particular, the spectral density function of a time series y_t with the j th autocovariance function γ_j can be expressed as $S_y(\omega) = \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \gamma_j e^{-ij\omega}$ (Hamilton, 1994), where the spectrum is a periodic function of ω . According to Granger (1966), the “typical spectral shape” of an economic time series has its spectral mass concentrated at low frequencies and is declining exponentially as the frequency increases. This implies that seasonally adjusted economic time series are dominated by long run trends

and by business cycle frequencies relative to short-term fluctuations. The spectral density functions of the rate of inflation, the extensive and intensive margins are shown in Figure 1.5. The functions are obtained by using the standard estimator $\hat{S}_y(\omega) = \frac{1}{2\pi} \left(\omega_0 \hat{\gamma}_0 + 2 \sum_{j=1}^{M_T} \omega_j \hat{\gamma}_j \cos(\omega_j) \right)$, which yields precise estimates by downweighting the autocovariance for larger lags (Lütkepohl and Krätzig, 2004). The frequencies, given as a fraction of π , can be converted back to the number of months of the cycle duration by the formula $d = \frac{2\pi}{\omega}$. The spectral shape of the rate of retail price inflation resembles the “typical shape” as defined by Granger (1966) in that the density function is highest at low frequencies and declines smoothly with increasing frequency.

Figure 1.5: Spectral Densities of the Rate of Inflation, the IM and EM



Notes: The spectral densities are constructed using the following estimator: $\hat{S}_y(\omega) = \frac{1}{2\pi} \left(\omega_0 \hat{\gamma}_0 + 2 \sum_{j=1}^{M_T} \omega_j \hat{\gamma}_j \cos(\omega_j) \right)$. We use a standard Bartlett window procedure with window size 10.

The figure reveals the driving force behind this observation; while the spectral density function of the intensive margin is relatively flat over the range of frequencies, the spectral shape of the extensive margin is much more concentrated at very low frequencies. The vertical lines in the figure mark the frequencies corresponding to one and a half and eight years, which accords with the NBER business cycle definition. For all three series the business cycle interval contains the main mass of the spectral density; this pattern is clearest for the extensive

margin. This implies that, following changes in the economic environment, in the very short run it is mainly the *size* of the price changes that reacts, while the fraction of firms that additionally decide to adjust prices only changes gradually if shocks to the economy accumulate.

In line with these observations, our time series of interest are smoothed using a symmetric two-sided band-pass filter suggested by Baxter and King (1999) to isolate the low-frequency components.¹⁶ This allows to analyze the patterns of comovement between the rate of inflation and the extensive and intensive margins at the business cycle frequency.

Table 1.4: Cross Correlations with Inflation - $Corr(x_t, \pi_{t+k})$

k (+ /-)	EM_t		IM_t		Fr_t^+		Fr_t^-	
	lag	lead	lag	lead	lag	lead	lag	lead
0	0.658	0.658	0.826	0.826	0.739	0.739	-0.242	-0.242
1	0.680	0.618	0.791	0.816	0.762	0.693	-0.245	-0.126
2	0.688	0.565	0.727	0.775	0.769	0.634	-0.244	-0.144
3	0.680	0.502	0.638	0.707	0.759	0.564	-0.238	-0.164
4	0.668	0.430	0.531	0.617	0.732	0.486	-0.225	-0.186
5	0.622	0.353	0.412	0.512	0.690	0.402	-0.206	-0.207
6	0.576	0.273	0.288	0.398	0.635	0.317	-0.180	-0.226

Notes: The cross-correlations are calculated using the filtered series. We use a symmetric two-sided Baxter-King filter filtering frequencies corresponding to 18-96 months with 36 lags and leads. Sample period is 1970:01-2007:07.

Table 1.4 shows cross correlations constructed from the filtered series. As far as contemporaneous correlations are concerned, as expected, the extensive margin is more strongly correlated with inflation at the business cycle frequency ($Corr(EM_t, \pi_t) = .66$). Furthermore, the correlation with lagged values of the rate of inflation is even higher suggesting stickiness in the response of the frequency of price changes to changes in the rate of aggregate inflation. In line with state-dependent models, the frequency of price changes reacts gradually as changes in aggregate inflation accumulate. Accordingly, the correlation between the rate of inflation and the frequency of price increases and decreases, respectively, is much larger at the business cycle frequency. The frequency of increases

¹⁶In particular, the series are produced using the Baxter-King filter with 36 leads and lags. The filter weights are chosen to obtain an optimal approximation to the 18-96 month band-pass filter.

is highly correlated with the rate of inflation ($Corr(Fr_t^+, \pi_t) = .74$), while the correlation between decreases and inflation is less pronounced ($Corr(Fr_t^-, \pi_t) = -.24$). This asymmetry is also documented in Klenow and Kryvtsov (2008) and Gagnon (2009) at the monthly frequency. By contrast, the intensive margin is somewhat less correlated with the rate of inflation at the business cycle frequency ($Corr(IM_t, \pi_t) = .83$).

1.3.2 Dynamic Correlations

In order to further analyze the underlying comovement between the extensive and intensive margin with the rate of retail price inflation at different frequencies, we employ the concept of dynamic correlation proposed by Croux et al. (2001). This measure is calculated directly in the frequency domain and allows therefore to capture the correlation between two series of interest at any cycle duration. Thus, relative to calculating the static correlation of two series at a certain frequency band, this dynamic procedure offers additional insights. Dynamic correlation between two variables can be defined as:

$$\rho_{xy}(\omega) = \frac{C_{xy}(\omega)}{\sqrt{S_x(\omega)S_y(\omega)}},$$

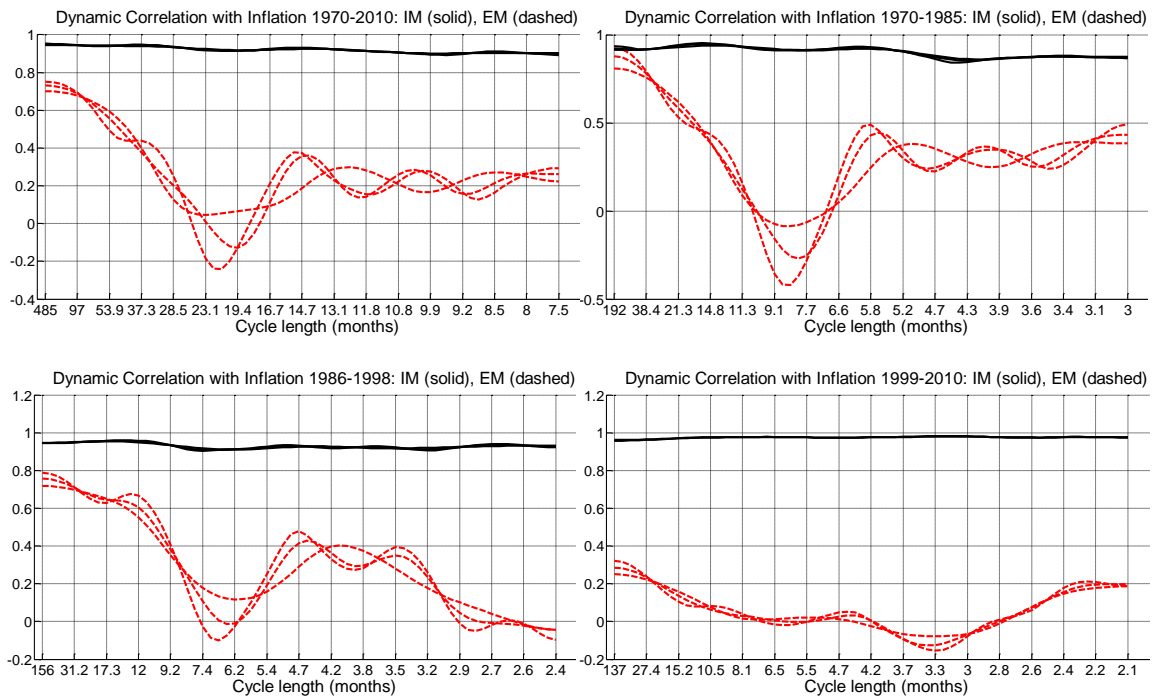
where $S_x(\omega)$ and $S_y(\omega)$ are the spectral density functions of x and y as defined in the last subsection and $-\pi \leq \omega < \pi$ denotes the frequency. $C_{xy}(\omega)$ is the co-spectrum of x and y , which can be interpreted as that part of the covariance between the two variables that is due to cycles with frequency ω (Hamilton, 1994).

Figure 1.6 shows the respective dynamic correlations of the extensive and intensive margin with the rate of retail price inflation.¹⁷ As expected, the figure clearly shows that the correlation between the intensive margin and inflation is high and stable across frequencies. Because we want to evaluate whether state-dependence is present in the data, we are however mostly interested in the comovement of the EM with inflation. In line with the spectral densities of the respective variables shown above, the dynamic correlation between the EM and inflation increases with cycle duration. In particular, for the full sample period, correlation is above

¹⁷The correlations calculated using the filtered series given in Table 1.3 are not equal to a simple average of the dynamic correlations over the corresponding frequencies. However, the order of magnitude of the different measures is still comparable. See Croux et al. (2001) for more details.

.70 at cycle durations of more than 96 months (eight years). Furthermore, in line with the summary statistics for the different subsamples given in the last section, the dynamic correlation between the EM and inflation is higher for periods of higher overall inflation. While for the period 1970-1985 correlation between the EM and inflation is almost as large as that between the IM and inflation (around 0.90) for very low frequencies, the comovement between the two series is substantially reduced for the period 1999-2010. While the dynamic correlation still increases with cycle duration, its absolute value is smaller staying below .40 at any frequency. The descriptive evidence offered by the figure is thus in line with the static cross-correlations of the Baxter-King filtered series given above in that it suggests that the EM is not stable over time. Instead, in a higher and more variable inflation regime, the EM shows an increased responsiveness with respect to overall inflation dynamics.

Figure 1.6: Dynamic Correlation with Inflation



Notes: The figure displays measures of dynamic correlations according to $\rho_{xy}(\omega) = C_{xy}(\omega) / \sqrt{S_x(\omega)S_y(\omega)}$. Samples run from 1970:01 to 2010:07, 1970:01-1985:12, 1986:01-1998:12 and 1999:01-2010:07. We use a Bartlett window with smoothing parameters 8, 10 and 12.

1.3.3 Variance Decomposition

In order to assess the relative importance of the frequency and size of price adjustment for aggregate inflation dynamics, following Klenow and Kryvtsov (2008), the variance of retail price inflation is decomposed into terms involving the variance of the intensive and extensive margin, respectively:

$$\begin{aligned} \text{var}(\pi_t) &= \underbrace{\text{var}(IM_t) \cdot \overline{EM}^2}_{\text{"IM term"}} \\ &+ \underbrace{\text{var}(EM_t) \cdot \overline{IM}^2 + 2 \cdot \overline{IM} \cdot \overline{EM} \cdot \text{cov}(EM_t, IM_t)}_{\text{"EM terms"}} + O_t. \end{aligned} \quad (1.6)$$

In this expression, O_t are higher order terms that are functions of the extensive margin. The IM term involves the variance of the intensive margin, while the EM terms contain the variance of the extensive margin as well as the covariance of the EM and IM. Standard time-dependent theories imply that the extensive margin is inactive, so the intensive margin terms account for all of inflation's variance. By contrast, some state-dependent models predict the EM terms to account for a relatively large fraction of overall inflation variability.¹⁸ However, as has been mentioned before, some state-dependent menu-cost models as, for instance, the model of Golosov and Lucas (2007) including large idiosyncratic shocks, predict the IM term to be more important relative to the EM component. For the US Klenow and Kryvtsov (2008) report that the IM term explains almost all variations in the rate of inflation, while the EM terms are small (95% versus 5%). Similarly, for the Mexican CPI dataset Gagnon (2009) finds that the EM terms are relatively unimportant during periods of low inflation, while the IM term accounts for about 90% of inflation's variance. Only if the rate of inflation increases to 10 - 15% does the IM term fall to about 35% implying a larger role for the frequency of price changes.

Tables 1.5 and 1.6 show the results of the variance decomposition for our dataset for price realizations and expectations, respectively. Using the unfiltered data, in accordance with the previous literature for low-inflation periods, the IM term represents a rather large fraction of the variance of retail price inflation for both realized price changes and expectations for the Klenow/Kryvtsov-period 1988-

¹⁸Thus, Klenow and Kryvtsov (2008) label the respective components "time-dependent term" (TDP term) and "state-dependent terms" (SDP terms).

2004 and for the EMU sample 1999-2010 (100.0% and 99.9% for price realizations and 102.8% for expectations). Correspondingly, the EM terms are unimportant for the variance of inflation (0.6% and 2.6% as well as 1.6%, respectively).

However, the EM terms become more important once we regard periods of relatively high inflation. For the period 1970-1985, the EM terms account for more than 15% of inflation's variance for price realizations, while for price expectations it is 10%.

Table 1.5: Variance Decomposition - Price Realizations

Share of Inflation Variance (%)			
Unfiltered Data			
	IM Term	EM Terms	HO Terms
1970-2010	0.898	0.100	0.002
1970-1985	0.955	0.153	-0.108
1986-1998	1.057	0.064	-0.121
1999-2007	0.999	0.006	-0.004
1988-2004	1.000	0.026	-0.025
Baxter-King Filter, 1.5-8 years			
	IM Term	EM Terms	HO Terms
1970-2007	0.804	0.264	-0.067
1970-1985	0.629	0.696	-0.324
1986-1998	1.029	0.125	-0.153
1999-2007	1.136	-0.012	-0.124
1988-2004	0.913	0.098	-0.011
Baxter-King Filter, 3-8 years			
	IM Term	EM Terms	HO Terms
1970-2007	0.660	0.323	0.017
1970-1985	0.412	0.777	-0.189
1986-1998	1.105	0.126	-0.231
1999-2007	0.799	0.060	0.141
1988-2004	0.880	0.128	-0.009

Notes: Samples run from 1970:01 to 2007:07, 1970:01-1985:12, 1986:01-1998:12, 1999:01-2007:07 and 1988:01-2004:12. See equation (1.6) for a definition of the IM, EM and HO terms. For the filtered series, we use a symmetric two-sided Baxter-King filter with frequencies corresponding to 18-96 and 36-96 months, respectively, with 36 lags and leads.

Thus, it is mainly the higher-inflation episode during the 1970's and early 80's that drives the relatively high share of the EM terms for the full sample period (10.0% and 10.2% for realized and expected price changes, respectively).

The descriptive evidence offered above suggests that the comovement between the overall rate of inflation and the frequency of price adjustment becomes important at lower frequencies. Thus, we would expect the share of the EM terms to become even larger once analyzed at the appropriate cycle length. Therefore, we conduct the variance decomposition additionally using the Baxter-King filtered series to isolate the business cycle component of the respective time series.¹⁹

Tables 1.5 and 1.6 reveal that the EM terms become more important at the business cycle frequency. For instance, isolating the components with cycle duration of 1.5-8 years, the percentage of inflation's variance explained by the EM terms rises to about 10% over the Klenow-Kryvtsov-sample for price realizations. For the full sample period, the EM terms now account for about 26.4% and 23.2% for price realizations and expectations, respectively, while for the period 1970-1985 the shares rise to even about 69.6% for price realizations and 35.3% for expectations. Relative to the small percentages for the unfiltered series, those shares are clearly substantial. For cycle durations of between 3 and 8 years, this increase in the importance of the extensive margin for overall inflation dynamics is even more pronounced. Over the full sample period, the shares of the EM terms increase to 32.3% and 33.9% for price realizations and expectations, respectively, while the importance of the IM term is reduced (66.0% and 77.1%, respectively). For price realizations, the EM terms are even dominant vis-à-vis the IM term over the higher-inflation period 1970-1985 (77.7% versus 41.2%).

¹⁹We use a symmetric two-sided Baxter-King filter with frequencies corresponding to 18-96 and 36-96 months, respectively, with 36 lags and leads. Because the Baxter-King filter applies a weighted moving average procedure with weights summing to zero (Baxter and King, 1999), to calculate the variance shares, we add back the mean of the time series over the respective sample periods.

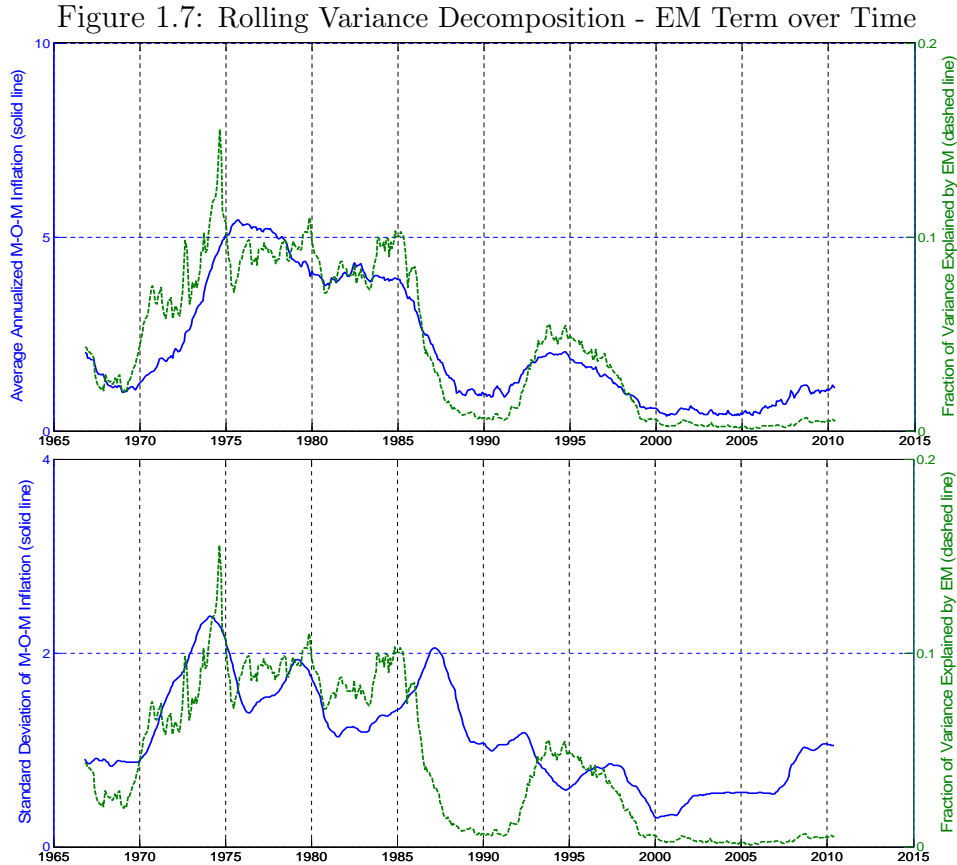
Table 1.6: Variance Decomposition - Price Expectations

Share of Inflation Variance (%)			
Unfiltered Data			
	IM Term	EM Terms	HO Terms
1970-2010	0.963	0.102	-0.065
1970-1085	1.045	0.100	-0.146
1986-1998	1.131	0.046	-0.177
1999-2007	1.028	0.016	-0.043
Baxter-King Filter, 1.5-8 years			
	IM Term	EM Terms	HO Terms
1970-2007	0.978	0.232	-0.210
1970-1085	0.884	0.353	-0.237
1986-1998	1.010	0.083	-0.093
1999-2007	1.275	0.142	-0.417
Baxter-King Filter, 3-8 years			
	IM Term	EM Terms	HO Terms
1970-2007	0.771	0.339	-0.110
1970-1085	0.604	0.512	-0.116
1986-1998	0.901	0.191	-0.092
1999-2007	1.047	0.157	-0.205

Notes: Samples: 1970:01 to 2007:05, 1970:01-1985:12, 1986:01-1998:12, and 1999:01-2007:05. See equation (1.6) for a definition of the IM, EM and HO terms. For the filtered series, we use a symmetric two-sided Baxter-King filter with frequencies corresponding to 18-96 and 36-96 months, respectively, with 36 lags and leads.

Figure 1.7 visualizes the increasing importance of the EM terms for periods of higher inflation. Both panels of the figure display results of a rolling variance decomposition, where the EM shares for each month have been calculated on the basis of the respective previous 72 months. For instance, the share of the EM term in January 1980 reflects its importance over the period January 1974 to December 1979. In the upper panel the shares of the EM terms are related to the respective average annualized rate of retail price inflation at every point in time. The two lines in the figure show a clear comovement of the two series. This reflects the finding that with decreasing rates of inflation the extensive margin

becomes less important for overall inflation dynamics and vice versa. Finally, the lower panel of Figure 1.7 shows that the role of the extensive margin for overall inflation variability is positively related to inflation volatility, too. The figure again displays the rolling variance shares of the extensive margin together with the standard deviation of the month-on-month rate of inflation.



Notes: The green dashed lines display a rolling measure of the extensive margin term constructed according to equation (1.6). The blue solid lines show a moving average of the annualized rate of retail price inflation (upper panel) as well as the standard deviation of month-on-month retail price inflation (lower panel).

A number of interesting conclusions emerge from the above exercises. First, the results presented above for the German data are in line with Gagnon (2009), who finds a much more pronounced role of the extensive margin for inflation dynamics for high-inflation episodes. This result is remarkable because even for the episode 1970-1985, the average annualized rate of inflation is low (about 4%) compared to the Mexican high-inflation episodes, where CPI inflation reached

41% in 1995. Thus, while for the Mexican sample annual inflation needs to be at 10-15% for the EM terms to become important, we find this pattern also for substantially lower inflation rates. Second, we find much higher shares of the EM terms at lower frequencies suggesting that, even during periods of low inflation, the frequency of price changes is not invariant over time as standard time-dependent models predict. Instead, the fraction of firms that decide to adjust prices changes gradually over time. This is consistent with menu-cost models implying that firms adjust prices once the costs of having implemented a non-optimal price due to accumulated change in the economic environment exceeds the adjustment cost; see e.g. Cecchetti (1986). Third, results are quite similar for price expectations implying that pricing plans are adjusted gradually over time, too. Time-dependent sticky plan models in the spirit of Mankiw and Reis (2002) imply that the frequency of firms that update their price expectations is invariant. Our results show, however, that the extensive margin of expected price changes is important for inflation dynamics at the business cycle frequency. These results accord with state-dependent sticky plan models in the spirit of Burstein (2006) or Alvarez et al. (2010) postulating a menu-cost of changing plans of future prices.

1.4 A VAR Model for Germany

1.4.1 The Basic VAR Model

In this section we analyze the effects of a monetary policy shock and business cycle disturbances on the respective components of inflation; we are of course mostly interested in the response of the frequency of price adjustment. We estimate the following reduced-form VAR model:

$$Y_t = c + A(L)Y_{t-1} + u_t, \quad (1.7)$$

where Y_t is a vector of endogenous variables, c is a vector of intercepts, $A(L)$ is a matrix of autoregressive coefficients of the lagged values of Y_t and u_t is a vector of error terms. In our benchmark regression we include the following five variables:

$$Y_t = [IP_t, PPI_t, EM_t, IM_t, R_t]. \quad (1.8)$$

As equation (1.8) above shows, the vector Y_t of endogenous variables contains the German industrial production IP_t , the producer price index PPI_t , the extensive margin (EM_t) and intensive margin (IM_t) of retail price inflation and the three-month Euribor R_t .²⁰ By including both the extensive and intensive margin of price adjustment in our VAR model instead of a measure of the overall retail price development we are able to analyze the effects of aggregate shocks on both components separately.²¹

Except for the Euribor, all variables are seasonally adjusted. German industrial production and the producer price index are included as log-levels, which according to Sims et al. (1990) leads to consistent parameter estimates, see also Hamilton (1994). The extensive and intensive margin and the Euribor enter in percentages. All variables are linearly detrended prior to estimation. In the benchmark case, six lags of the endogenous variables are included in the estimation, which seems to be sufficient to capture the dynamics of the model.²²

We estimate the model by employing Bayesian methods using monthly data over the period 1991:01-2009:06. The sample period only starts in 1991 in order to exclude any shocks resulting from the German reunification that could possibly be confused with a monetary policy shock. The ongoing convergence process in the early and mid-90's towards stage three of the monetary union may justify that our sample period starts several years before the official start of the EMU (Surico, 2003). In any case, our results are robust to the inclusion of dummy variables indicating the introduction of the Euro or the start of the European Monetary Union in 2002 and 1999, respectively; see Appendix 1.A.2.²³

²⁰Our results are robust to including the oil price as an additional variable to account for changes in world economic conditions (Smets and Peersman, 2001). Moreover, including M1 as a measure of monetary aggregate does not alter the main results. Regression results of these modified specifications are available upon request.

²¹Strictly speaking, however, this approach can only be considered an approximation. In fact, retail price inflation is given by the *product* of the two components, which we include separately in our linear VAR model. In order to better account for this we additionally estimate an alternative specification, where we linearize equation (1.1) as follows: $\pi_t \approx \pi_t^K \cdot fr_t = IM_t \cdot EM_t = EM_t(IM_t - 1) + EM_t$. We accordingly include these two modified terms in our alternative specification in order to assess whether the response of the extensive margin to shocks is sensitive to this modification. Results from this alternative estimation are in fact very similar to the benchmark results.

²²While different lag length criteria lead to different suggestions concerning the number of lags to include, all of them tend to propose shorter lag lengths. Nevertheless, to ensure that the model captures the dynamics of the system one should ideally include at least 12 lags, which, however, may lead to degrees of freedom problem given our relatively short sample period. Overall, our results are largely robust to varying the lag length.

²³Additionally, we estimated the model for the period prior to the German reunification;

1.4.2 Alternative Specification: Increases versus Decreases

We additionally estimate a further specification that includes the fraction of price increases and decreases, respectively, instead of the extensive margin. Thus, the overall fraction of price changes is split up into these two separate components. This allows us to analyze the respective responses of these measures to a monetary shock and thus to learn more about the driving forces underlying the reaction of the extensive margin. The modified specification is given by:

$$Y_t = [IP_t, PPI_t, FRI_t, FRD_t, IM_t, R_t], \quad (1.9)$$

where FRI_t and FRD_t denote the fraction of price increases and decreases, respectively. Again, all variables are linearly detrended and, except for the Euribor, seasonally adjusted. As before, industrial production and the PPI enter in log-levels, while the fraction of price increases and decreases, respectively, the IM and the Euribor enter in percentages. As in the benchmark model, we include six lags of the endogenous variables.

1.4.3 Identification of Structural Shocks

Following Uhlig (2005), Canova and De Nicolò (2002) and Peersman (2005) we impose sign restrictions on the impulse response functions to identify the structural shocks of interest. This approach allows us to explicitly incorporate common assumptions regarding the impulse responses in our VAR system and to avoid well-known puzzles as, for instance, the “price puzzle” (Uhlig, 2005). Furthermore, we do not have to rely on Cholesky or Blanchard-Quah decompositions; according to e.g. Faust (1998) contemporaneous zero-restrictions may not hold in reality, while long-run restrictions may lead to biased results in small samples (Faust and Leeper, 1997).

We implement the sign restriction approach by drawing the VAR parameters from the Normal-Wishart posterior distribution and construct an impulse vector for each draw. As a next step, we calculate the corresponding impulse responses

1973-1989. While the qualitative results concerning the extensive margin are robust, we encounter, however, a price puzzle. Moreover, Chow breakpoint tests indicate structural instability in the early 1980’s at the 5% level. We therefore only report results for the period 1991-2009, where structural stability seems to be given. Regression results for different sample periods as well as results of the Chow breakpoint tests are available upon request.

for all variables over the specified horizon.²⁴ In particular, the reduced-form innovations u_t with variance-covariance matrix $\Sigma = E(u_t u_t')$ are related to the structural shocks ϵ_t according to $\epsilon_t = B^{-1}u_t$, with $B = W\Sigma^{1/2}Q$. $W\Sigma^{1/2}$ is the Cholesky factor obtained from the Bayesian estimation of the VAR model for each of the 1000 draws, and Q is an orthogonal matrix with $QQ' = I$. To generate Q , we draw a random matrix U from an $N(0,1)$ density and decompose this matrix using a QR decomposition. This procedure follows Rubio-Ramirez et al. (2006) and has been applied in the existing literature, see Enders et al. (2011) and Hristov et al. (2011). Alternatively, one could generate the Q matrix by using a Givens transform based on rotations of Given matrices (Canova and De Nicolo, 2002). Fry and Pagan (2007) show, however, that these two approaches generally lead to the same structural shocks.

For each of the Cholesky factors we draw U until we find a matrix that implies impulse responses to the structural shocks according with the imposed sign restrictions.²⁵ For the specification given in equation (1.8), for instance, the impulse response functions r_{ijt}^k of variable $j = 1, \dots, 5$ to shock $i = 1, 2, 3$ at horizon $t = 1, \dots, 60$ constructed using model $k = 1, \dots, 1000$ (where k indexes the different values of Q) are then summarized by computing the median over k of r_{ijt}^k .

With regard to the statistic summarizing the information obtained from our estimation, Fry and Pagan (2007) show that reporting the median of the impulse responses may be a problematic approach because this measure in effect summarizes responses that are generated by different models. Hence, since two shocks may be generated by two different models Q , they need not be orthogonal. This of course leads to problems in the interpretation of the structural shocks and the corresponding impulse responses. We thus follow Fry and Pagan (2007) and construct impulse responses for each shock that are implied by a single model Q . In particular, we choose the model that generates impulse responses that are closest to the median over k of r_{ijt}^k . To find this model and construct the shocks accordingly, we first standardize the impulse responses r_{ijt}^k by subtracting off their median and divide by their standard deviation over all 1000 models. We

²⁴Estimation was performed on the basis of Fabio Canova's SVAR Matlab codes, which can be downloaded from his website <http://www.crei.cat/people/canova/>.

²⁵Enders et al. (2011) propose to allow for small deviations from the sign restrictions when searching for admissible impulse responses to avoid discarding responses that mildly violate only few of the restrictions. While this is useful in case the number of restricted variables and identified shocks is large as in Enders et al. (2011), it does not seem to be necessary for our relatively small specification. We therefore stick to our restrictions and thus avoid imposing additional assumptions concerning the value of the deviation.

then construct a vector ϕ^k for each value Q^k . Having grouped our standardized impulse responses, we are then interested in the model Q that minimizes $\phi^{k'} \phi^k$. Since we include the extensive and intensive margin in percentages in our model, we are interested in the cumulative impulse responses of these variables to the identified shocks. Therefore, when constructing the “close-to-median” impulse response functions we consider cumulative impulse responses for these variables in the minimization problem given above.

Next to a monetary policy shock we additionally identify two business cycle shocks. In particular, we are interested in a positive aggregate demand and a positive aggregate supply disturbance. We require our structural shocks to be orthogonal; it is shown in Mountford and Uhlig (2009) how the identification scheme of Uhlig (2005) can be extended to simultaneously identify several shocks.²⁶ In the baseline specification, restrictions are binding for twelve months following the shock; a similar restriction horizon is used by Scholl and Uhlig (2006).

A summary of the restrictions considered in the benchmark case is provided in Table 1.7. As can be seen in the upper panel of the table, identification is achieved by imposing the standard assumptions that a contractionary monetary policy shock has a non-positive effect on industrial production, on the producer price index and on the monetary aggregate as well as a non-negative effect on the short term interest rate. These restrictions are implied by a wide range of DSGE models; see for instance Canova et al. (2007). Moreover, they have been applied in VAR analyses by, for instance, Canova and De Nicolo (2002) and Peersman (2005). Because we are mainly interested in the response of the intensive and extensive margin to the monetary shock, we do not restrict these variables. For the second specification that differentiates price increases and decreases we use a similar identification scheme, shown in the lower panel of Table 1.7. Again, the two components of the extensive margin as well as the intensive margin are left unrestricted in order to be able to analyze the reaction of these variables to the identified shock.

²⁶In particular, in order to prevent that any remaining disturbances enter our identified shocks we impose corresponding reverse restrictions on the two unidentified innovations within our VAR system.

Table 1.7: Identifying sign restrictions

Variable	Response to			Restriction
	monetary shock	demand shock	supply shock	Horizon
Industrial Production	≤ 0	≥ 0	≥ 0	$K = 12$
PPI	≤ 0	≥ 0	≤ 0	$K = 12$
Extensive Margin				
Intensive Margin				
Euribor	≥ 0	≥ 0	≤ 0	$K = 12$
Industrial Production	≤ 0	≥ 0	≥ 0	$K = 12$
PPI	≤ 0	≥ 0	≤ 0	$K = 12$
Fraction Increases				
Fraction Decreases				
Intensive Margin				
Euribor	≥ 0	≥ 0	≤ 0	$K = 12$

Notes: The table displays sign restrictions on the responses of the variables in the model after a monetary, demand and supply shock, respectively. $K = 12$ indicates that the restriction horizon is twelve months.

1.5 Results of the SVAR Model

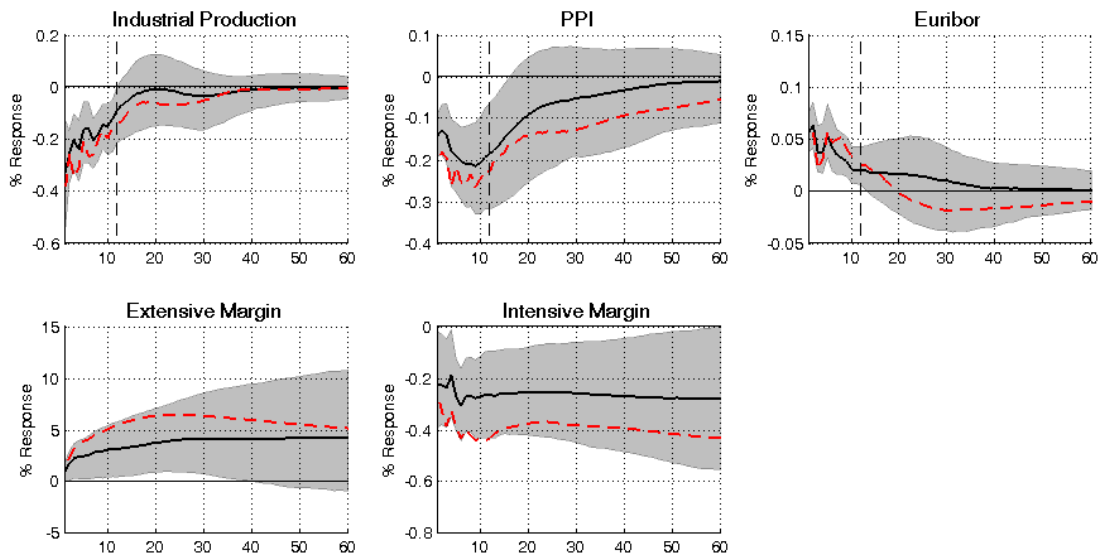
1.5.1 The Benchmark Specification

Figure 1.8 displays impulse responses of the variables included in the SVAR to a contractionary monetary policy shock that is identified according to the identification scheme described in the last section. In the figure, the inner solid lines denote the median impulse responses identified from a Bayesian vector-autoregression with 1000 draws using sign restrictions, while the shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the impulse responses.²⁷ The dashed vertical lines mark the end of the restriction horizon, which is 12 months for the benchmark regression. The red dashed lines additionally show the impulse responses generated by the one model that is closest to the median over all 1000 draws. It can be seen that generally, the impulse responses generated by this “close-to-median” model are quite similar to the median over all models, so our results are robust to this adjustment. Since the signs of the responses of industrial production, the producer price index as well as the Euri-

²⁷Under the assumption of normality, these percentiles correspond to one-standard error bands, see Uhlig (2005). Reporting one-standard error confidence bands is a standard approach in the literature.

bor have been restricted, there is no need to extensively interpret the direction of these adjustments. As preset, industrial production falls as a reaction to the shock. Similarly, the producer price index falls by about 0.25% and stays below benchmark for about two years. As specified, the Euribor increases and remains above baseline somewhat longer than restricted. To evaluate the response of the size and frequency of price adjustment separately, we leave the extensive and intensive margins unrestricted. Figure 1.8 shows that the extensive margin increases significantly following the shock and reaches its maximum cumulative response of around 4 percentage points after two years. The direction of the response is as expected; the fraction of firms that decides to adjust prices rises. The increase is temporary; after around three years the cumulative response becomes insignificant.

Figure 1.8: Impulse Responses to a Monetary Shock

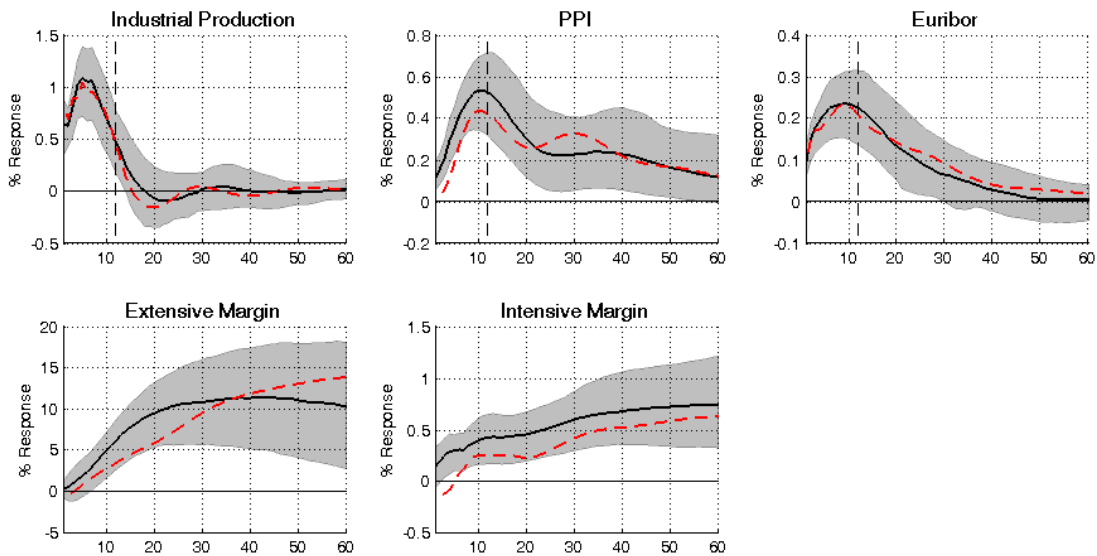


Notes: The black lines denote the median of the impulse responses following a contractionary monetary shock, the red dotted lines indicate the “close-to-median” model, and the shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses. Impulse responses are identified from a BVAR (1000 draws) using sign restrictions with a restriction horizon of 12 months. The impulse responses of industrial production, the PPI and the Euribor are changes in (log) levels of the variables, impulse responses of the IM and EM are cumulative responses.

As expected, the average size of price adjustment, the intensive margin, decreases following a contractionary monetary shock; the maximum cumulative response amounts to around -0.25 percentage points after about three years.

Figures 1.9 and 1.10 show the impulse responses to business cycle disturbances that have been explicitly identified to disentangle the monetary shock from aggregate supply and demand shocks. Moreover, the response of the extensive margin to shocks to the real economy are of course interesting in itself indicating whether the frequency of price adjustment responds to aggregate economic shocks next to monetary policy shocks. Figure 1.9 reveals that the extensive margin clearly responds to a positive demand shock; the cumulative response is significant and strong amounting to more than 10 percentage points after about two and a half years. Moreover, as expected, the intensive margin increases as well. By contrast, a positive supply shock does not have a significant effect on the extensive margin, while the response of the intensive margin is weak and significant for a few periods only, as Figure 1.10 shows.

Figure 1.9: Impulse Responses to a Demand Shock

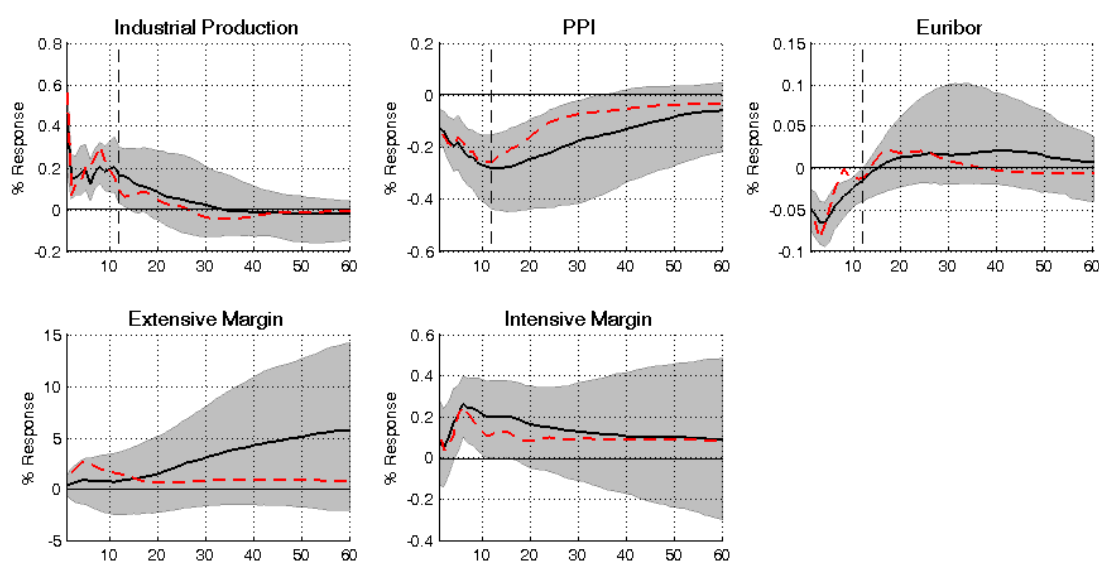


Notes: The black lines denote the median of the impulse responses following a positive demand shock, the red dotted lines indicate the "close-to-median" model, and the shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses. Impulse responses are identified from a BVAR (1000 draws) using sign restrictions with a restriction horizon of 12 months. The impulse responses of industrial production, the PPI and the Euribor are changes in (log) levels of the variables, impulse responses of the IM and EM are cumulative responses.

Overall, however, the significant and relatively strong reaction of the extensive margin to a monetary policy shock as well as to an aggregate demand disturbance clearly contradicts the implications of time-dependent models that the frequency

of price changes is inactive and does not react to economic conditions. Instead, the results are in line with the predictions of the menu-cost model of Dotsey et al. (1999) that the frequency of price adjustment does respond to monetary shocks and that it varies with the business cycle. Moreover, similar results are found by Karadi and Reiff (2011) calibrating the state-dependent model of Midrigan (2011) accounting for larger shock sizes.

Figure 1.10: Impulse Responses to a Supply Shock



Notes: The black lines denote the median of the impulse responses following a positive supply shock, the red dotted lines indicate the “close-to-median” model, and the shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses. Impulse responses are identified from a BVAR (1000 draws) using sign restrictions with a restriction horizon of 12 months. The impulse responses of industrial production, the PPI and the Euribor are changes in (log) levels of the variables, impulse responses of the IM and EM are cumulative responses.

At this point, however, it is worth addressing a seemingly surprising feature of the results presented. The empirical results from the SVAR reported above suggest that the frequency of price changes is responsive to monetary shocks as well as aggregate demand disturbances. Since this evidence is obtained for the period 1991 - 2009, a period of relatively low and not so volatile inflation, these findings are somewhat surprising given the descriptive evidence offered in Section 1.3 suggesting that the EM is important for inflation dynamics mainly during high-inflation periods prior to 1990. However, these different findings can be reconciled by noting that while the evidence offered in Section 1.3 is concerned

with the overall comovement of the frequency of price adjustment with inflation, the SVAR analysis given in the second part of the paper specifically focuses on the dynamics of the EM *conditional* on specific shocks to the economy. Thus, it might well be the case that while the extensive margin reacts to a contractionary monetary shock or an aggregate demand disturbance during this low-inflation episode, it still is rather unimportant for overall inflation dynamics relative to periods of higher inflation.

1.5.2 Fraction of Increases and Decreases

Figures 1.11 to 1.13 show impulse responses of the modified specification of the VAR model given in equation (1.9). Instead of the extensive margin, the model now includes the frequency of price increases and decreases separately. The sign restrictions are defined as before with the latter variables as well as the intensive margin remaining unrestricted. As expected, Figure 1.11 reveals that the cumulative response of the fraction of price decreases is significantly positive following a contractionary monetary policy shock. The cumulative response of the frequency of price increases falls with a delay but the response is, however, insignificant. Thus, as expected, the significantly positive reaction of the overall frequency of price changes following the monetary shock is due to a rise in the share of firms that decrease their price following the contractionary shock that offsets the negative reaction of the frequency of price increases in the short-run.²⁸ By contrast, in the case of a positive demand shock both the fraction of firms increasing and the fraction of those decreasing their prices drive the overall response of the EM; while the fraction of price increases rises significantly after around six months, the fraction of decreases falls around eight months after the shock. Finally, in the case of a supply shock, neither of the two components of the extensive margin reacts, which explains the insignificant reaction of the overall frequency of price changes.

²⁸Arguably, with positive trend inflation, the fall in the frequency of price increases should be larger than the rise in the frequency of price decreases. However, we control for a time trend in our VAR model.

Figure 1.11: Impulse Responses to a Monetary Shock - Fraction of Increases and Decreases

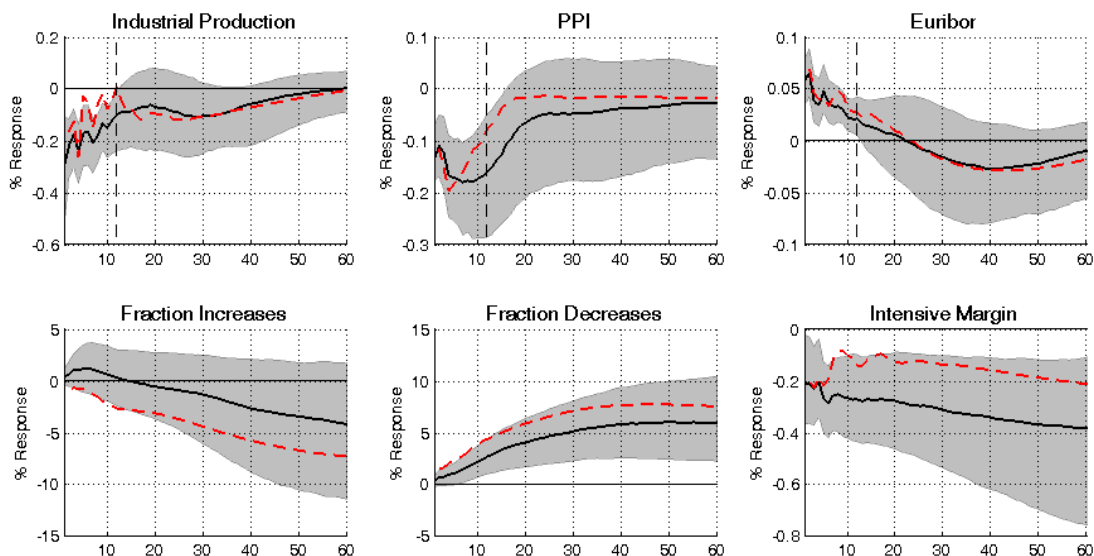
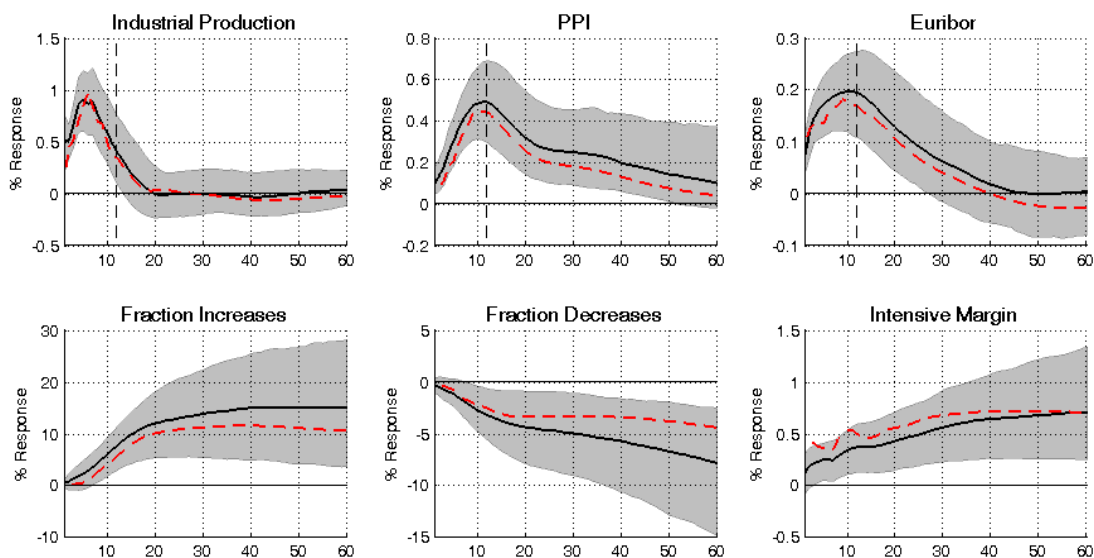
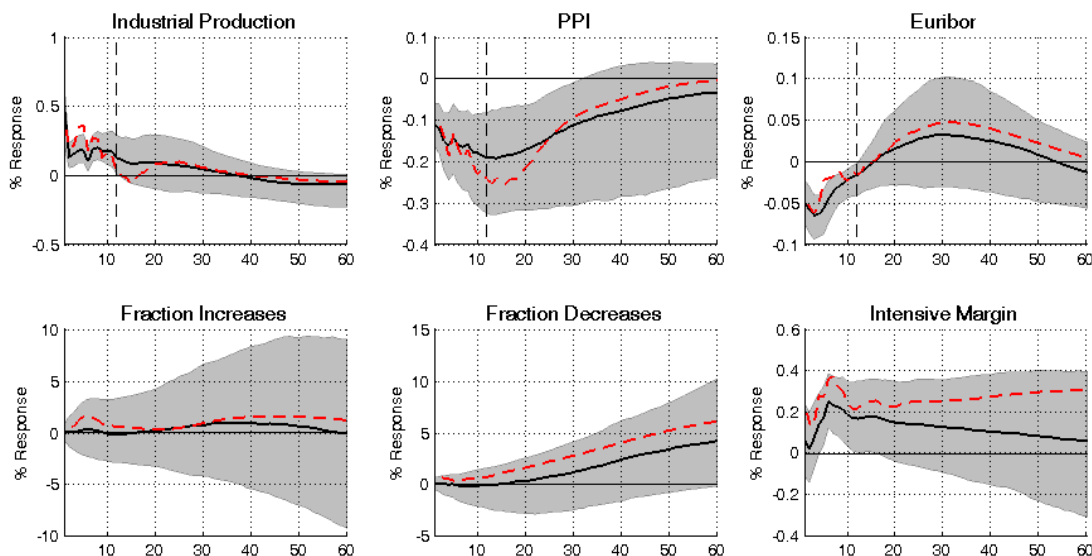


Figure 1.12: Impulse Responses to a Demand Shock - Fraction of Increases and Decreases



Notes: The black lines denote the median of the impulse responses following a contractionary monetary shock and positive demand shock, respectively. The red dotted lines indicate the “close-to-median” model, and the shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses. Impulse responses are identified from a BVAR (1000 draws) using sign restrictions with a restriction horizon of 12 months. The impulse responses of industrial production, the PPI and the Euribor are changes in (log) levels of the variables, impulse responses of the IM, FRI and FRD are cumulative responses.

Figure 1.13: Impulse Responses to a Supply Shock - Fraction of Increases and Decreases



Notes: The black lines denote the median of the impulse responses following a positive supply shock, the red dotted lines indicate the “close-to-median” model, and the shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses. Impulse responses are identified from a BVAR (1000 draws) using sign restrictions with a restriction horizon of 12 months. The impulse responses of industrial production, the PPI and the Euribor are changes in (log) levels of the variables, impulse responses of the IM, FRI and FRD are cumulative responses.

1.5.3 The Importance of the Identified Shocks

In this section we assess the explanatory power of our structural shocks for the two components of inflation, where we are of course mainly interested in the effects on the extensive margin. In particular, we construct the forecast error variance decomposition of the structural shocks as well as a historical decomposition of the variables included in the model. To make sure that our identified shocks are indeed orthogonal and that forecast error variance shares add up to one, both measures are based on the one draw generating impulse responses closest to the median over all draws; see Section 1.4.3.²⁹ We already showed in the last subsection that the impulse responses generated by the “close-to-median model” are very similar to the median over all admissible impulse responses.

²⁹In fact, it is the sum of the variance shares of our three identified shocks and the two unidentified disturbances, capturing all remaining shocks, which equals one. Naturally, the sum of the variance share of these further shocks equals one minus the sum of the shares of the identified shocks.

Table 1.8: Forecast Error Variance Decomposition

Variable	Horizon	Shock to			Sum
		Demand	Supply	Monetary Policy	
Extensive Margin	12 mth.	22	21	29	72
	24 mth.	38	13	18	69
	36 mth.	32	11	15	58
	48 mth.	27	10	12	49
	60 mth.	24	9	11	44
Intensive Margin	12 mth.	15	3	44	62
	24 mth.	15	4	39	58
	36 mth.	15	4	39	58
	48 mth.	14	4	38	56
	60 mth.	14	4	37	55

Notes: The table displays variance shares of a demand, supply and monetary policy shock, respectively as well as the sum of all identified shocks over a 1-5 year forecast horizon. Entries are in percent.

The forecast error variance decomposition is calculated in order to investigate the quantitative importance of the identified shocks for the variables in the model. We are of course mainly interested in the importance of the shocks for the two components of inflation, most notably of the extensive margin. Table 1.8 summarizes the forecast error variance shares of the extensive and intensive margin resulting from the identified structural shocks at the 1-5 year forecast horizon. The last column shows that the three shocks explain between around 45% and 70% of the variations in these variables. Since our shocks are solely identified on the basis of sign restrictions and we only explicitly identify three shocks, the relatively large share of variation explained by other, non-identified shocks is not surprising. Compared to other studies within the sign-restriction literature the sum of the shares of all identified shocks is of comparable magnitude.³⁰

For the extensive margin both the aggregate demand shock and the monetary shock are most important with variance shares ranging from around 10% to 40%. While the demand shock seems to explain more of the variations in the EM over the medium horizon, the variance share of the monetary policy shock is highest for a short horizon. The aggregate supply shock plays a somewhat less important

³⁰See, for instance, Straub and Peersman (2006).

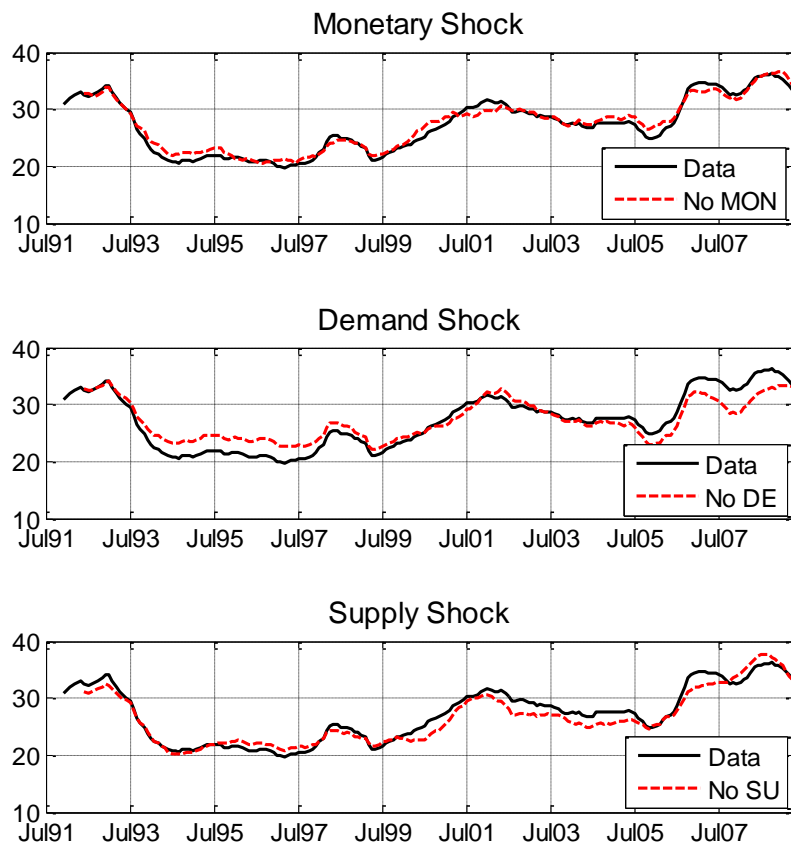
role. This is in line with results from the impulse response analysis showing a mostly insignificant response of the EM to a supply shock. Overall, the three identified shocks explain up to 72% of the variations in the extensive margin. Thus, quantitatively, aggregate economic shocks seem to be important for the dynamics of the frequency of price adjustment.

Moreover, Table 1.8 shows variance share for the intensive margin. While for this variable the supply shock plays a rather unimportant role, the monetary policy shock affects variations in this variable to a rather large extent with variance shares of around 40%. The demand shock seems to be somewhat more important for the intensive margin compared to the supply shock.

Moreover, we conduct a historical decomposition of the data in order to evaluate the relative importance of the shocks for our variables of interest at different points in time. Figures 1.14 and 1.15 show both the actual development of the extensive and intensive margin, respectively, as well as their counterfactual evolution sequentially setting the three shocks to zero. The counterfactual series are constructed simply by subtracting the contribution of the QE-shock from the actual time series.³¹ The figures show that while the extensive margin would have been higher without the monetary policy shock from around 1993 to 1997, around the year 2000 and again in the period 2004-2006, the intensive margin would have been lower without the shock during these periods. Since these periods are associated with a rather contractionary monetary policy stance, these findings are in line with the impulse response analysis implying a positive reaction of the extensive margin to a contractionary monetary policy shock and a negative response of the intensive margin to such a disturbance. Furthermore, Figure 1.14 confirms the relatively important role of aggregate demand shocks for the extensive margin; without the negative demand disturbances in the mid 90's the extensive margin would have been higher, while it would have been somewhat lower around the period 2005-2007 when the economy was characterized by a positive business cycle environment. Finally, Figure 1.15 shows the relatively larger impact of the supply shock on the intensive margin.

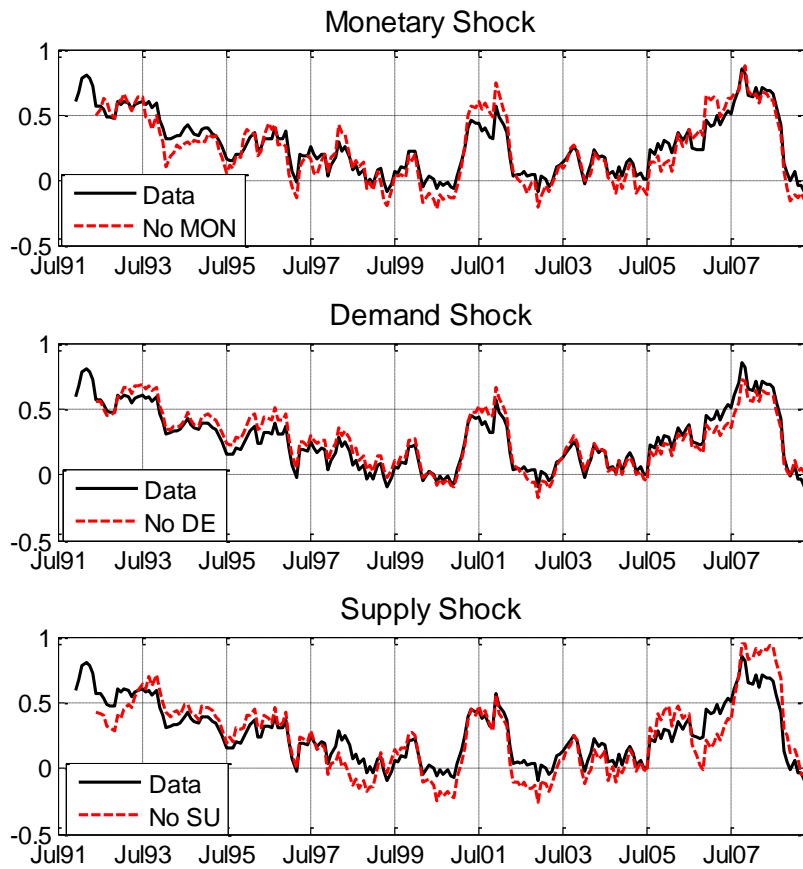
³¹The decomposition of the data was performed using the Matlab code of Kilian (2009), which can be downloaded online at <http://www.aeaweb.org/articles.php?doi=10.1257/aer.99.3.1053>. Of course, the counterfactual development of the two variables are based on our VAR model only and should therefore be interpreted with caution.

Figure 1.14: Historical Decomposition: Actual and Counterfactual Evolution of the Extensive Margin



Notes: The black solid lines indicate the actual extensive margin series, while the red dashed lines denote the counterfactual evolution of the extensive margin without a monetary, a demand and a supply shock, respectively. All series are displayed as 12-month moving averages, entries are in percent.

Figure 1.15: Historical Decomposition: Actual and Counterfactual Evolution of the Intensive Margin



Notes: The black solid lines indicate the actual intensive margin series, while the red dashed lines denote the counterfactual evolution of the extensive margin without a monetary, a demand and a supply shock, respectively. All series are displayed as 12-month moving averages, entries are in percent.

1.6 Conclusion

The question concerning the exact mechanism underlying sticky prices is not yet sufficiently answered in the empirical literature on price setting. We attempt to shed new light on this issue and provide evidence on the relationship between aggregate inflation dynamics and the extensive margin of price adjustment within the German retail sector in order to evaluate the predictions of different price setting models. This is done using a novel firm-level dataset constructed from a large panel of business surveys of German retail firms over the period 1970-2010. The dataset includes information on realized price changes as well as price expectations allowing to analyze the frequency of both price adjustment and the updating of pricing plans.

Following Klenow and Kryvtsov (2008) we decompose the variance of inflation into terms involving the extensive and intensive margin, respectively. We find that for periods of relatively high and volatile inflation, such as the period 1970-1985, not only the intensive margin matters for aggregate inflation dynamics but variations in the extensive margin are important for the variability of the overall rate of inflation as well. In contrast to existing evidence for Mexico, Columbia and Norway reported by Gagnon (2009), Hofstetter (2010) and Wulfsberg (2009), respectively, for Germany we do not need annual inflation rates of more than 5% to observe these results. Moreover, our findings suggest that at the business cycle frequency the extensive margin comoves much more strongly with the rate of inflation and accounts for a large share of inflation's variance - even in periods of very low inflation. This is a new result and is clearly at odds with standard time-dependent pricing models implying an inactive role of the extensive margin. Furthermore, estimating a structural VAR model with theory-based sign restrictions for the German economy over the period 1991-2009, we find that the extensive margin as well as the frequency of price increases and decreases, respectively, show a significant reaction following contractionary monetary policy shocks and aggregate demand shocks. Moreover, quantitatively, our identified shocks clearly affect the evolution of the frequency of price adjustment. Thus, the extensive margin responds to economic conditions, which provides further evidence in favor of state-dependent pricing.

The results outlined in this paper have important implications for the modeling of price stickiness. Overall, our findings suggest that the timing of price changes should be endogenized in models of price setting if they are to realistically pre-

dict both the dynamics of the frequency and magnitude of price changes. More specifically, the results imply that models predicting an important role for the extensive margin for overall inflation dynamics and thus for the transmission of a monetary shock are more in line with the data than models mainly emphasizing the intensive margin such as standard time-dependent models or, similarly, the state-dependent framework of Golosov and Lucas (2007) - even for relatively low-inflation regimes. Thus, even during such “quiet times” the time-dependent price setting assumption does not seem to be appropriate in order to realistically predict the dynamics of different inflation components. Models predicting a relatively important role of the extensive margin include the framework of Dotsey et al. (1999) and, if shocks are assumed to be sufficiently large or trend inflation is included (Karadi and Reiff, 2011), the model of Midrigan (2011) featuring a leptokurtic price distribution. Moreover, the finding that also the extensive margin of price updating is important for overall inflation variability is in line with sticky plan models containing state-dependent elements such as Burstein (2006) or Alvarez et al. (2010).

To the extent that these respective classes of models lead to diverging predictions concerning the speed and persistence of monetary policy transmission as well as the nature of the welfare maximization problem of central banks, these results have interesting policy implications.

1.A Appendix

1.A.1 Data

Business Survey Data

Since 1949 the Ifo Institute for Economic Research has been analyzing economic developments in Germany using monthly business surveys. In the questionnaires firms are asked about the development of certain key measures such as the number of orders and business volume, the perceived state of business as well as the development of prices; see Becker and Wohlrabe (2008) for more details on the variables contained in the survey. A distinct feature of the survey data is that it contains firm-specific information on expectations concerning the future business development as well as future prices. While the data is mainly used for the construction and analysis of business tendency indicators, the fact that the survey contains economic measures characterizing the idiosyncratic state of the firms allows to analyze a variety of other issues as well. As has been emphasized in the main text, in this paper we only analyze data concerning the retail sector. In 2003, the average number of retail firms surveyed each month was 900, while the average response rate was about 70%. The participating firms' share of total revenues generated in the retail sector was about 10%.

For the questions asked in this paper, we only use information on the price development as well as on price expectations for firms within the retail sector. As far as price realizations are concerned, firms are asked to answer the following question:

Development in reporting month:

Relative to the previous month, our sales prices were (1) increased, (2) not changed, (3) decreased

Concerning their price expectations, firms are asked the following question:

Plans and Expectations:

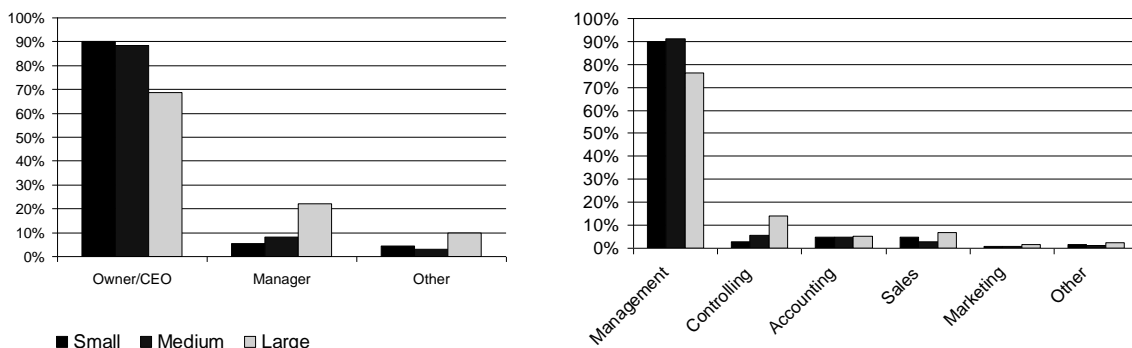
In the next three months we expect our sales prices to (1) increase, (2) not change, (3) decrease

It is explained in the main text how we account for the fact that expectations are reported for the next *three* months.

In order to judge the extent to which the business surveys capture the price developments actually realized by the firms, it is important to know who actually answers the questionnaires. According to Abberger et al. (2009), for small and medium-sized firms, in almost 90% of the cases the surveys are answered by the firm owner, the CEO or another member of the company's board. In the case of large firms, almost 70% of the surveys are answered by the latter group while in about 20% of the cases the questions are answered by department managers (see Figure 1A.1, left panel). Moreover, as can be seen in the right panel in figure, if firms are asked in which department of the company the questionnaires are filled out, about 90% of small and medium-sized firms report "management". For large firms, the questionnaires are answered within the management department in almost 80% of the cases. Thus, overall, the questionnaires are answered at a very high level of expertise suggesting that they reliably report actual price developments.

A final issue concerns the price development reported by multi-product firms. Arguably, the inclusion of multi-product firms in the survey may lead to an upward bias of the frequency of price changes. For instance, in an extreme case, a firm may report a price change even though only the price of one major product has been adjusted. In the survey, this problem is mitigated because multi-product firms are asked to fill out several questionnaires for different product groups. To the extent that firms still have to cluster several sub-products within the same reporting category, about half of the respondents report the average price development of all their products (43.3%) or give information on prices of their most important products in terms of business volume (44.6%). Only 10% report the price development of their main product, while 3.7% use other practices in reporting their price development (Abberger et al., 2009).

Figure 1A.1: Position of the person and department in charge of answering the questionnaires



Left panel, question asked : *Which position does the person in charge of answering the questionnaire have in your company?* Right panel, question asked: *In which department of your company is the survey usually answered?* Since firms may report several departments, percentages don't always add up to 100.

Data Availability

Table 1A.1: Availability of Business Survey and Retail Price Data

Data	Period of availability	Source
Disaggregated survey data, West	1990:01 - 2009:06	Ifo Institute
Disaggregated survey data, East	1998:01 - 2009:06	Ifo Institute
Aggregated survey data, West	1960:01 - 2006:01	Ifo Institute
Aggregated survey data, West&East	1991:01 - 2010:07	Ifo Institute
Retail price index, 1995=100	1950:01 - 1990:12	Federal Bureau of Statistics
Retail price index, 2005=100	1991:01 - 2010:07	Federal Bureau of Statistics

Accounting for Sales

The survey dataset does not contain information on whether a price change is related to temporary sales. We account for the existence of temporary sales in the data by using a “sales filter” proposed in the literature. In particular, we identify such price changes by looking for “V-shaped” patterns in the data using a “sale filter” similar to the one proposed by Nakamura and Steinsson (2008). In particular, we label a price change “sale” if there is a one-time price decrease that

is followed by a price increase. We define different windows for the time it takes for a decrease to be followed by an increase; in particular, we consider one to three months, labeled as window 1, 2 and 3, respectively. Once price changes related to sales are identified by the filter, they are removed by assigning these observations to the group of “no changes”. Observations indicating a price decrease (-1) due to a sale are thus replaced by (0).

As pointed out in Nakamura and Steinsson (2008), this approach has several disadvantages relative to a direct identification of sales. First, clearance sales are not defined as sales using the filter; the measure adopted here may thus underestimate the true frequency of sales. Second, since we work with monthly data, very short-lived sales that are followed by price increases in the same month are not observable in the data and can thus not be identified by the filtering procedure. For instance, a firm that decreases its price at the beginning of the month, and increases it again two weeks later would probably not report these price changes when answering the questionnaire. Third, Nakamura and Steinsson (2008) mention the possibility for the sales filter to confuse sales with “regular” price changes in categories with very volatile price changes such as gasoline. However, since the share of these products in our dataset is very small, this is unlikely to cause any bias. An additional problem for the survey data, however, results from the fact that we do not have idiosyncratic information on the size of price changes. Thus, we do not observe whether prices actually return to the original price or stay low relative to before the sale and are thus not able to distinguish asymmetric and symmetric V-shaped patterns as is done in Nakamura and Steinsson (2008). An additional problem is that we can only account for sales during the period 1990-2009 but not for the full sample period, since we only have aggregate price series for the years prior to 1990.

Table 1A.1 displays the mean frequencies, standard deviations as well as the correlation with the overall rate of retail price inflation of price changes for the original data as well as for the filtered data using the sales filter with different window sizes. As can be seen in the table, removing sales from the data does not cause changes in the statistics related to the extensive margin. The mean frequency of price changes only decreases slightly from 27.32% for the original data to 26.7%, 26.2% and 25.86% for the filtered data using window 1, 2 and 3, respectively. Similarly, the standard deviations for the different series are almost the same decreasing only slightly for the filtered data. Thus, the occurrence of

sales as identified by the procedure described above is not a frequent phenomenon in our data as compared to the US data reported in, for instance, Nakamura and Steinsson (2008). Moreover, using the filter does not influence the correlation with the rate of inflation indicating that the exclusion of sales does not alter the macroeconomic interpretation of the results.

Table 1A.2: Summary Statistics for the Extensive Margin- Excluding Sales

Variable	Mean (%)	Std. dev. (%)	Corr. with π_t
Original data	27.32	7.26	0.18
Sale filter, window 1	26.70	7.09	0.17
Sale filter, window 2	26.20	7.02	0.18
Sale filter, window 3	25.86	7.08	0.19

Notes: Sample runs from 1990:01 to 2009:06 with monthly frequency. The retail price index is obtained from the Federal Bureau of Statistics. Lines 2-4 show results from filtered data, where observations coded as price decreases (-1) identified as “sale” are replaced by “no change” (0).

1.A.2 Robustness Checks

The first robustness check involves specifying the restriction horizon K . In order to check the sensitivity of the impulse responses to variations of the restriction length, we estimate the SVAR additionally choosing different values for K . Figure 1A.2 shows the impulse responses of the variables of interest, the EM and IM, to the monetary policy shock identified under different restriction horizons. While the first row displays results for $K=9$, the second and third rows show impulse responses under $K=12$ and $K=15$, respectively. Figure 1A.2 reveals that for $K=9$ the response of the extensive margin to the monetary shock is insignificant, while the intensive margin decreases significantly.³² In contrast, for shocks affecting the economy for 15 months, the extensive margin shows a significant reaction that is more persistent compared to the case of $K=12$, as can be seen in the third row of the figure.³³ This suggests that the reaction of the frequency of price changes to a monetary shock is stronger, the more persistent its effects are on the economy. By contrast, the response of the intensive margin is similar in all cases. As far as the reaction to the demand and supply shocks are concerned, Figures 1A.3 and 1A.4 show that the impulse responses of the EM and IM to these shocks are very similar for the different restriction horizon; both the response of the EM and IM to the demand shock are significantly positive, while responses to the supply shock are largely insignificant.

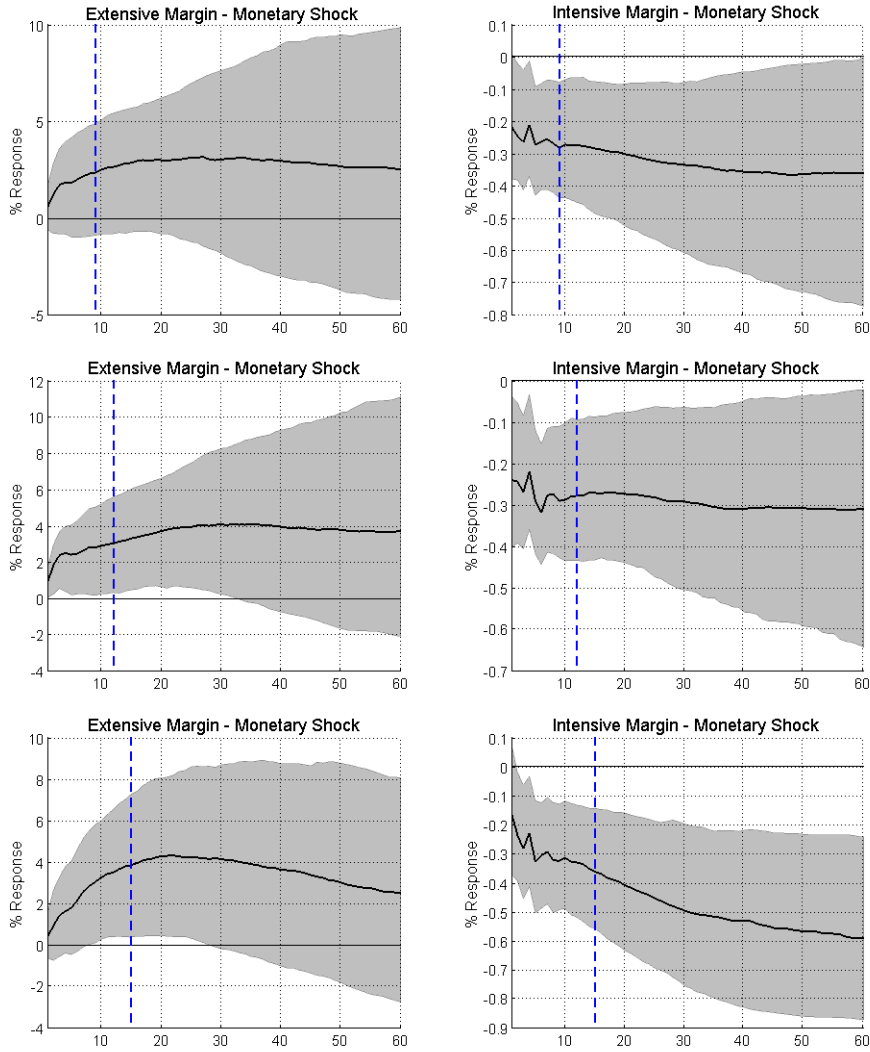
Furthermore, we check whether our results are sensitive to the inclusion of a step dummy, which takes on the value one from the start of the EMU in 1999. Figure 1A.5 shows that the responses of the extensive and intensive margin to our three structural shocks are very similar for this specification compared to the benchmark specification.³⁴

³²Similar results are obtained for a restriction horizon of six months or eight months.

³³Results are very similar for even longer restriction horizons of 18 or 24 months.

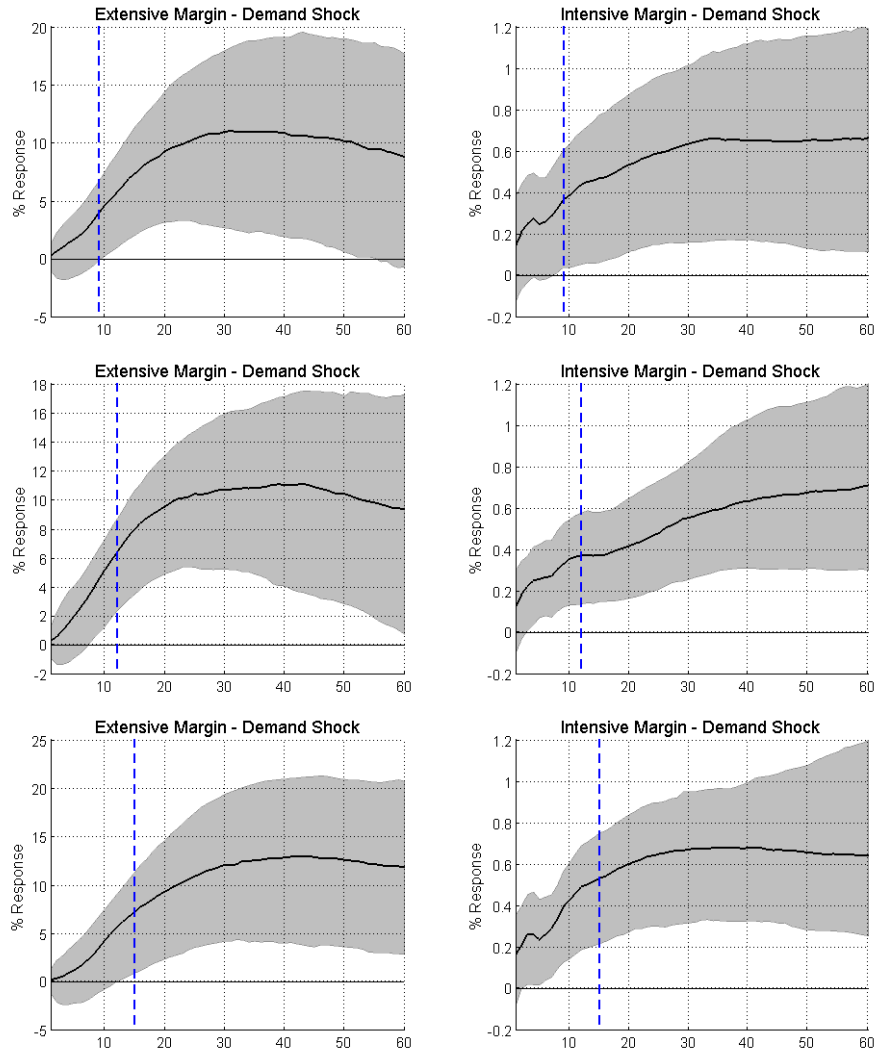
³⁴Moreover, results are qualitatively similar when we include a dummy indicating the actual introduction of the Euro in 2002 instead.

Figure 1A.2: VAR Model with Sign Restrictions: Varying the Restriction Horizon, Monetary Shock



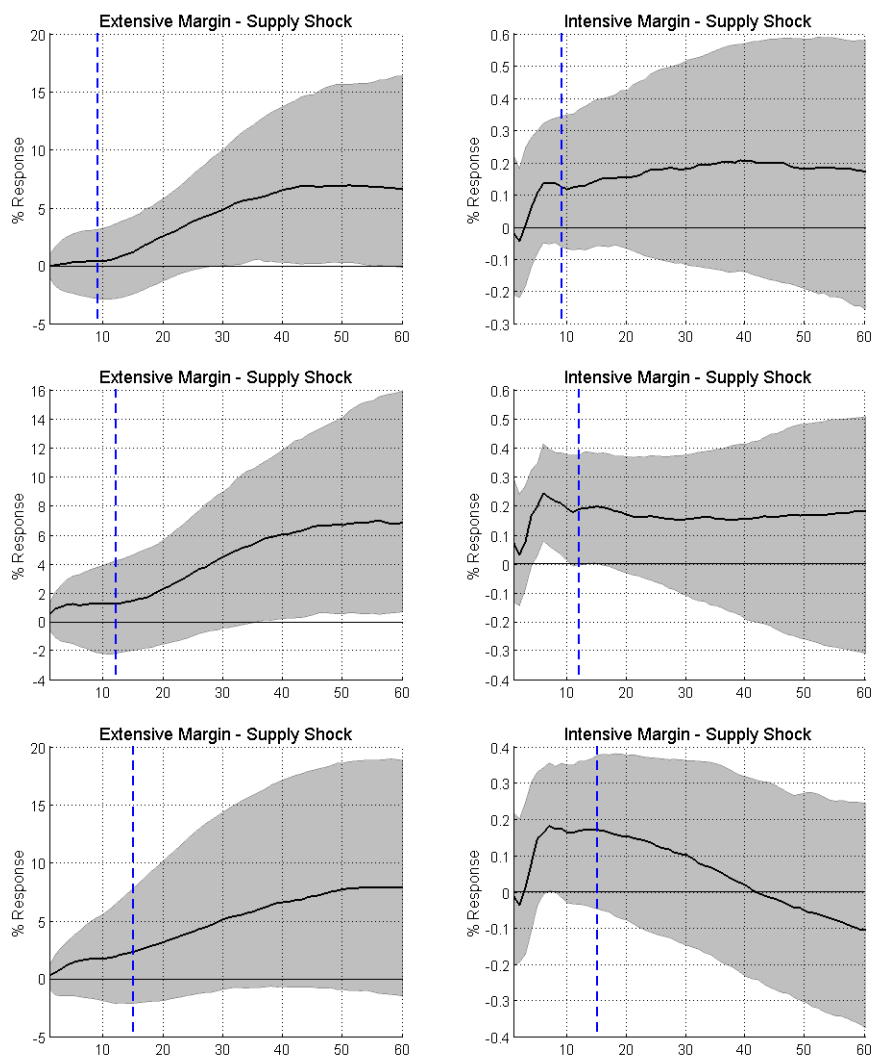
Notes: The inner solid lines denote the median of the impulse responses following a contractionary monetary policy shock. The shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses. The vertical dotted lines denote the respective restriction horizons. All impulse response functions are identified from a Bayesian vector autoregression with 1000 draws using sign restrictions. Rows one, two and three display impulse responses to a monetary shock identified with a restriction horizon of 9 months, 12 months and 15 months, respectively.

Figure 1A.3: VAR Model with Sign Restrictions: Varying the Restriction Horizon, Demand Shock



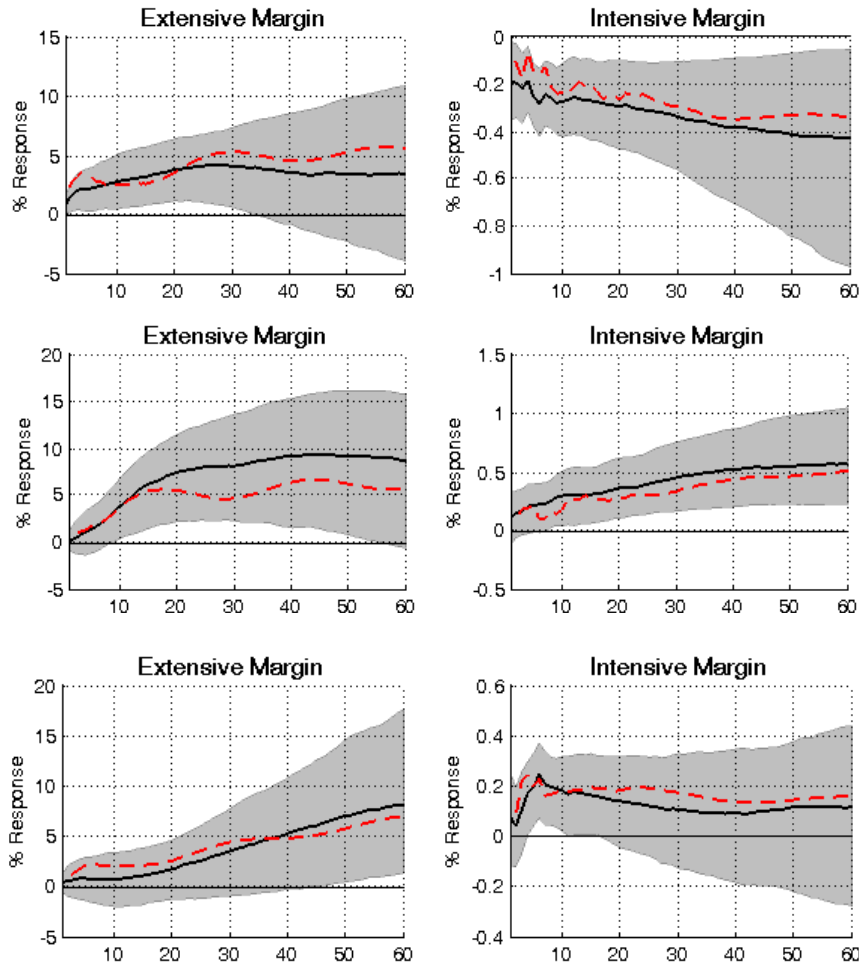
Notes: The inner solid lines denote the median of the impulse responses following a positive demand shock. The shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses. The vertical dotted lines denote the respective restriction horizons. All impulse response functions are identified from a Bayesian vector autoregression with 1000 draws using sign restrictions. Rows one, two and three display impulse responses to a monetary shock identified with a restriction horizon of 9 months, 12 months and 15 months, respectively.

Figure 1A.4: VAR Model with Sign Restrictions: Varying the Restriction Horizon, Supply Shock



Notes: The inner solid lines denote the median of the impulse responses following a positive supply shock. The shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses. The vertical dotted lines denote the respective restriction horizons. All impulse response functions are identified from a Bayesian vector autoregression with 1000 draws using sign restrictions. Rows one, two and three display impulse responses to a monetary shock identified with a restriction horizon of 9 months, 12 months and 15 months, respectively.

Figure 1A.5: VAR Model with Sign Restrictions: Monetary, Demand and Supply Shocks Including EURO Dummy



Notes: The inner solid lines denote the median of the impulse responses following the respective shocks, the red dotted lines indicate the “close-to-median” model, and the shaded areas indicate the the 16% and 84% percentiles of the posterior distribution of the responses. The vertical dotted lines denote the respective restriction horizons. All impulse response functions are identified from a Bayesian vector autoregression with 1000 draws using sign restrictions. Rows one, two and three display impulse responses to a monetary, demand and supply shock, respectively, including a dummy variable indicating the start of the EMU.

Chapter 2

The Determinants of Sticky Prices and Sticky Plans: Evidence from Business Survey Data

2.1 Introduction

The appropriate modeling of price stickiness has long been a major concern within the New-Keynesian literature. In standard time-dependent models firms regularly adjust prices independently of the economic environment (Taylor, 1980; Calvo, 1983). As a consequence, for instance, in the Calvo model only the size of price adjustment varies with economic conditions while the frequency of price setting is constant. In contrast, state-dependent theories assume the timing of price changes to be the outcome of a maximization problem of firms. According to these models, both the size and the frequency of price adjustment vary with aggregate economic conditions and, depending on the respective model, firm-specific variables such as input costs or the individual demand situation.¹ Understanding the exact mechanism underlying the price adjustment decision of firms is important because competing models predict divergent effects of monetary policy and may lead to distinct welfare implications; see Dotsey et al. (1999)

¹See the menu-cost models of Caplin and Spulber (1987), Dotsey et al. (1999), Gertler and Leahy (2008), Golosov and Lucas (2007) and Midrigan (2011). It is, however, also possible to endogenize the price adjustment probability without assuming a menu cost. For instance, Bonomo and Carvalho (2004), assuming a combination of both information and price adjustment costs, derive endogenous time-dependent pricing rules where the length between price changes varies endogenously.

and Lombardo and Vestin (2008).

This paper adds to this discussion by using a new dataset compiled by the Ifo Institute for Economic Research consisting of a large panel of monthly firm-level business surveys from January 1991 to January 2006. We estimate univariate and bivariate ordered probit models to assess the relative importance of time- and state-dependent variables for the probability of both the adjustment of prices and pricing plans.

In the last years, an increasing empirical literature on price stickiness at the micro level emerged. However, results from these studies concerning the determinants of price adjustment still remain rather inconclusive. Examples of corresponding studies include Cecchetti (1986) using data on magazine prices as well as Bils and Klenow (2004), Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008) analyzing larger sets of price data on a broad range of goods collected by national statistical offices to calculate the consumer-/ producer price index (CPI/PPI) for the US. Studies for Euro area countries include Rumler et al. (2011), Aucremanne and Dhyne (2005) and Stahl (2010); Dhyne et al. (2006) and Vermeulen et al. (2007) summarize results for the Euro area as a whole. Overall, the results from these studies concerning the price adjustment process are rather mixed; while generally time-dependent elements seem to be important for a firm's pricing decision, state-dependent factors such as the inflationary regime, institutional changes or variations in costs also affect price adjustment at the micro level. One reason for the lacking consensus concerning the determinants of price adjustment may be that it is generally difficult to fully capture the price setting decision process at the level of the firm using these quantitative datasets. Corresponding studies have to proxy the idiosyncratic state of the firms by using, for instance, accumulated inflation rates since the last price adjustment (Aucremanne and Dhyne, 2005). By contrast, business survey data better allow to analyze pricing behavior at the level of the individual firm leading to potentially clearer results concerning the price adjustment process. So far, business survey data has rarely been used to analyze price setting; recent exceptions are Lein (2010) and Loupiaz and Sevestre (2010) for the Swiss and French industrial sector, respectively.² For Germany, corresponding business survey evidence has so far not been forthcoming.

²A related approach has been the conduct of one-time interview studies asking firms explicitly for the timing of and reasons for price adjustment, see Blinder (1991) for the US and Fabiani et al. (2006) for the Euro area.

We contribute to the existing literature on various important dimensions. First, we are indeed able to analyze the determinants of price setting at the level of the individual firm. As stressed above, relative to an assessment at the item-level such an analysis has the advantage of explicitly capturing the individual business environment of firms since the data allow matching changes in prices to several other firm characteristics. Thus, arguably, a firm-level assessment entails more direct implications for micro-founded macro models. In particular, we analyze whether variables such as changes in the overall state of business, the business volume, or the expected business development are important for a firm's price adjustment decision. The effect of these regressors are particularly interesting because recent price setting models stress the importance of firm-specific shocks for the price setting process (Golosov and Lucas, 2007; Mackowiak and Wiederholt, 2009). Furthermore, we control for the aggregate environment of the firm by including a set of macroeconomic and institutional variables in the model. Overall, our regression results suggest an important role for state-dependence; macroeconomic and institutional factors such as the sectoral rate of inflation, accumulated since the last price change, as well as increases in the VAT rate and the introduction of the Euro are significantly related to the probability of price adjustment. Given the low overall rate of inflation during the sample period considered this result is remarkable. Moreover, factors characterizing the firm-specific environment as well as changes in intermediate input costs have highly significant effects; this is a new result in the literature, which could not have been obtained using most quantitative datasets. Hence, our findings do not support standard time-dependent pricing models predicting an exogenously given probability of price adjustment.

Second, we analyze information on firms' expectations concerning future prices with the aim to shed more light on the validity of different pricing plan models. In these models firms set entire plans prescribing the development of a sequence of future prices instead of individual prices at every period. The distinction between time- and state-dependence also applies to these models. In sticky information models delayed price adjustment is the consequence of information costs preventing a continuous updating of price plans (Mankiw and Reis, 2002, 2006).³ These models thus imply that the frequency of expected future price changes is constant over time. Contrarily, the state-dependent sticky plan model

³See also Mankiw and Reis (2010) for an overview.

of Burstein (2006) assumes that firms' updating of pricing plans is constrained by a menu cost - the frequency of price updating is thus endogenous and adjusts once accumulated changes in the economic environment are large enough. While, so far, empirical evidence on the mechanism underlying the formation of pricing plans has not been forthcoming for the Euro area, the dataset at hand allows to analyze these issues at a firm-specific level. In particular, we interpret expectations of the firms concerning their price development over the coming three months as plans of future prices, which may be updated in any given month. We are thus able to relate the probability of a change in pricing plans to both time- and state-dependent variables and find that most state-dependent factors are highly significant and economically important. Thus, our results provide evidence in favor of state-dependent sticky plan models.

Third, because the price data can be linked to input costs on a product group-specific basis, we are able to use a measure of the frequency of input price changes as a proxy for input cost shocks. This allows an explicit analysis of the transmission of such shocks through different production stages. The question of whether the retail sector or preceding stages of production are dominant for the timing of price adjustment can have important implications for modeling price stickiness, see Nakamura (2008) for a discussion. In price setting models that explicitly include a production structure, intermediate inputs raise the degree of price stickiness because the pricing decisions of different firms become strategic complements and thus stickiness "adds up" through the production chain (Basu, 1995; Huang and Liu, 2001; Nakamura and Steinsson, 2010). In these models prices of primary goods quickly adjust to macroeconomic shocks, while prices of goods at later stages of processing show a sluggish response to aggregate shocks but respond immediately to input price changes.

In fact, intermediate inputs can be classified as real rigidities, which have long been emphasized in the theoretical literature on price setting next to nominal frictions. For instance, Ball and Romer (1990) present a model featuring real rigidities and argue that small nominal frictions are usually not enough to generate realistic non-neutralities.

We argue that analyzing the degree of additional rigidity at the retail level helps to evaluate the importance of such real rigidities in price setting and allows us to shed more light on the validity of the predictions of the corresponding models. In particular, measures of changes in wholesale and manufacturing prices are

related to the timing of price changes in the retail sector. Our results generally promote pricing models with intermediate inputs where stickiness accumulates through the production chain; changes in input costs are indeed among the most important determinants for price adjustment. In line with empirical results of Nakamura (2008) for the US the effect of input cost changes on price adjustment in retail is rather persistent. This suggests that there is some degree of additional rigidity at the retail level, which is not accounted for by some of the above-mentioned models.

The remainder of the paper is organized as follows. In Section 2.2, the empirical strategy is outlined including a description of the business survey data, the empirical specification as well as the estimated price setting equations. Section 2.3 reports the main results and discusses the findings from a number of sensitivity tests. Finally, Section 2.4 concludes.

2.2 Empirical Strategy

2.2.1 Description and Discussion of the Business Survey Dataset

The dataset consists of a large panel of business surveys for the retail sector conducted by the Ifo Institute for Economic Research. The surveys are mainly used for the construction and analysis of business tendency indicators. In 2003 the average number of retail firms surveyed each month was 900, while the average response rate was about 70%. The participating firms' share of total revenues generated in the retail sector was about 10%. For more details on the survey data see Becker and Wohlrabe (2008) and Appendix 2.A.1.

The econometric sample constructed from this dataset covers about 930 retail firms. Because some of the firms responded to several questionnaires for different product groups, the observation unit is firm-products leading to a total of 2,017 observation units. The sample runs from January 1991 to January 2006.⁴ As firms take part in the survey on a voluntary basis, not every firm responded every month resulting in an unbalanced dataset. To obtain a workable sample, we follow Gopinath and Rigobon (2008) and drop observation units with fewer

⁴Even though the micro survey data is available from 1990:01 the econometric sample constructed from the data starts in 1991:01 since the data for the sector-specific rate of inflation is not available prior to this date. Moreover, the sample only includes observations up to 2006:01 to avoid a break due to a significant change of the questionnaires afterwards.

than six data points. Because at the observation unit level the time elapsed since the last price adjustment is unknown before the first price change the data has been left-censored by dropping all observation units prior to the first price change for the respective firms. This is a standard approach in the literature; see for instance Lein (2010). Moreover, in order to be able to correctly calculate the cumulative changes in the macroeconomic variables since the last price adjustment observations following (preceding) the missing observations are dropped until the next (previous) price change.⁵ After these manipulations the sample contains a total of about 78,000 observations. Each retail firm can be allocated to one of the following sectors: motor vehicles, food and beverages, communication and information technology, household products, recreational products and other industrial products.

Amongst other questions, firms are asked whether they changed the price of their products in the last month (denoted $price_{it}$ for firm i in period t). The answers are coded as 1 (“increased”), 0 (“not changed”) and -1 (“decreased”). Moreover, firms are asked whether they *expect* to change their prices in the coming three months; possible answers are again “increase”, “decrease” and “no changes” ($eprice_{it}$). Further questions considered in the analysis include variables concerning the state of the firm. For instance, firms are asked how they appraise the current state of business ($state_{it}$). Moreover, there are questions related to their business volume ($volume_{it}$) versus the previous month as well as their expectations concerning their orders for the next three months relative to the same month in the previous year ($orders_{it}$). Finally, firms are asked about their expectations concerning the overall business development in the coming six months ($develp_{it}$).

As has been mentioned before, relative to other datasets, the survey dataset provides several advantages with respect to analyzing price setting at the firm level. More conceptually, a further advantage of the data is that firms are not asked directly on their pricing strategies as in one-time interview studies conducted by, for instance, Blinder (1991) for the US and Fabiani et al. (2006), for the Euro area. Such an interview method may lead to biased responses as firms might be unwilling to respond truthfully to questions regarding their pricing strategies.

⁵Results are robust to only dropping the observations following the missing data point until the next price change. Moreover, the main results still hold if missing observations are replaced by 0. This implies the assumption that firms did in fact not change their price in the months they did not report. While this assumption seems reasonable for a dataset that is dominated by observation 0 (“no price change”) for the price variable, it is of course rather strong.

Moreover, in contrast to the one-time interviews firms are asked every month, which better reveals their pricing behavior over time.

Despite these advantages it should be kept in mind that due to the qualitative nature of the questionnaires the data do not contain information concerning the size of price changes. Thus, all price changes are implicitly assumed to be equally sized in this analysis. A further limitation is that the survey data contains both single- and multi-product firms without providing any information on how the latter firms answer the question concerning their prices. This problem is mitigated by the fact that firms are asked to fill in different questionnaires for their respective product groups. Nevertheless, firms still have to cluster the price development of several sub-products within the same category resulting in a certain degree of aggregation of individual prices. However, a recent meta-study on the survey provides details on how multi-product firms tend to fill in the questionnaires; approximately half of the firms indicate the average price development of all of their products, while the other half report prices of their most important commodities. See Appendix 2.A.1 for more details.

A final issue concerns price changes related to temporary sales, which can not easily be identified in our survey dataset since firms are not asked for the reasons of changing their price. To the extent that sales prices may be independent of macroeconomic conditions (Taylor, 1999) the presence of such price changes may potentially conceal the true adjustment mechanism underlying regular price setting. Therefore, following Nakamura and Steinsson (2008), we identified "V-shaped" price changes in the data using a sale filter for the period 1990-2009. Apparently, however, the occurrence of sales in the data is relatively limited. Thus, our results are robust to the exclusion of these temporary price changes, which is not surprising given the relatively lower importance of sales for the Euro area compared to the US as documented in Dhyne et al. (2006).

2.2.2 Descriptive Statistics

Table 2.1 shows conditional and unconditional probabilities of observing a price increase, decrease and no change as well as the respective measures for price expectations. The conditional probabilities can be written as $p^{ij}(P_t) = Prob(P_t = i | x_t = j)$ and $p^{ij}(E_t[P_{t+k}]) = Prob(E_t[P_{t+k}] = i | x_t = j)$ with $i \in (-1, 0, 1)$ and $j \in (-1, 0, 1)$. P_t denotes the reported price realization in a given month, while $E_t[P_{t+k}]$ indicates the reported change in price expectations. Since firms report

their price expectations for the coming *three* months, $k \in (1, 2, 3)$.⁶ x_t denotes the realization of the respective firm-characteristic in the same month. The unconditional probability of observing a price change in a given month is 26%, which is somewhat higher compared to the average frequency of price changes reported for the Euro area (Dhyne et al., 2006). This difference can be explained by the fact that, in contrast to the CPI dataset analyzed by Dhyne et al. (2006), the survey data contain information on retail prices only. Missing items relative to the CPI are, for instance, services including housing rents, which are typically characterized by a particularly low price adjustment frequency.

The table shows that price increases are more likely than price decreases; the unconditional probabilities are 15% and 11%, which is not surprising given a positive inflation environment. For price expectations this asymmetry is somewhat more pronounced (25% versus 8%). Furthermore, the table shows the respective probabilities conditional on observing changes in the other firm-specific variables introduced above. In most of the cases, improvements in the variables describing the state of the firm lead to a higher probability of observing a price increase compared to the probability of a price decrease, while in the case of deteriorations of the firm-specific factors, the probability of a price decrease is higher. This pattern is to be expected if the firm-specific condition depends positively on the demand situation facing the firm.⁷ For instance, the probability of observing a price increase in case of an improvement in the perceived state of business is much larger than that of a “good” state of business and a price decrease (24% versus 5%). A similar pattern can be observed for the other variables.

⁶More precisely, firms are asked to report their *overall* expectations for the next three months. It is thus not clear whether they refer to month $t + 1$, $t + 2$ or $t + 3$, or to some sort of average over the three months when reporting their expectations. See also Section 2.2.4.

⁷However, it is of course not clear ex ante whether considerations related to the demand situation on the one hand or supply-side factors on the other hand are dominant when firms answer questions related to their specific state of business.

Table 2.1: Conditional and Unconditional Probabilities

	Price			Expected price		
	<i>unconditional probabilities</i>					
Increase	0.15			0.25		
No change	0.74			0.66		
Decrease	0.11			0.08		
	<i>conditional probabilities</i>					
	<i>state</i>			<i>state</i>		
<i>price/eprice</i>	good	normal	bad	good	normal	bad
Increase	0.24	0.16	0.11	0.37	0.26	0.20
No change	0.70	0.77	0.70	0.59	0.69	0.65
Decrease	0.05	0.08	0.19	0.04	0.05	0.15
	<i>volume</i>			<i>volume</i>		
<i>price/eprice</i>	higher	as high	lower	higher	as high	lower
Increase	0.22	0.14	0.12	0.34	0.24	0.21
No change	0.71	0.79	0.71	0.61	0.71	0.66
Decrease	0.07	0.07	0.17	0.05	0.06	0.13
	<i>orders</i>			<i>orders</i>		
<i>price/eprice</i>	higher	as high	lower	higher	as high	lower
Increase	0.28	0.15	0.12	0.44	0.25	0.20
No change	0.64	0.77	0.68	0.51	0.70	0.61
Decrease	0.09	0.08	0.20	0.05	0.05	0.18
	<i>develp</i>			<i>develp</i>		
<i>price/eprice</i>	better	as good	worse	better	as good	worse
Increase	0.25	0.14	0.13	0.40	0.24	0.22
No change	0.66	0.77	0.67	0.55	0.71	0.58
Decrease	0.09	0.08	0.21	0.05	0.05	0.20

The left panel presents conditional and unconditional probabilities of observing a price increase, decrease and no price change. The right panel reports probabilities for an increase, decrease or no change in price expectations for the coming three months. Sample period: 1991:01-2006:01.

However, for deteriorations in some of the firm-specific variables this tendency is not as pronounced as for improvements. For instance, a price decrease is only slightly more likely than a price increase if the state of business is “bad” (19% versus 11%). This can be explained by the notion that firms may respond differently to negative shocks as compared to positive shocks. For instance, Lein (2010) report asymmetries in the price response of Swiss manufacturing firms to negative and positive disturbances, respectively.

Adjustment probabilities conditional on improvements of the firm-specific variables show a largely similar pattern for price expectations. For deteriorations of these measures the probability of observing an expected price increases is somewhat higher than that of an expected decrease. This surprising pattern is due to the fact that information on price expectations for the coming *three* months are matched with firm-specific variables reported for the current month only.

Given a positive inflation regime it might well be possible that firms expect a price increase in at least one of the coming three months even if the firm-specific economic outlook is unfavorable in the current month.

Table 2.2 offers some insights on the correlation between realized price changes and price expectations reporting the probability of observing a price change conditional on changes in expectations of future prices. As the table shows, there is a clear positive relation between the two variables; conditional on observing an increase in the expected future price, the probability of a realized price increase is high (39% versus 5% for a price decrease). Similarly, the combination of a decrease in both price realizations and expectations is more likely than observing both a decrease in expected prices and an increase in the realized price. The lower three panels of Table 2.2 show the probabilities of observing a price change conditional on lags of price expectations. Since firms are asked to report their expectations concerning the coming *three* months, probabilities for lags one, two and three are reported.

Table 2.2: Conditional Probabilities of Price Change Given Price Expectations

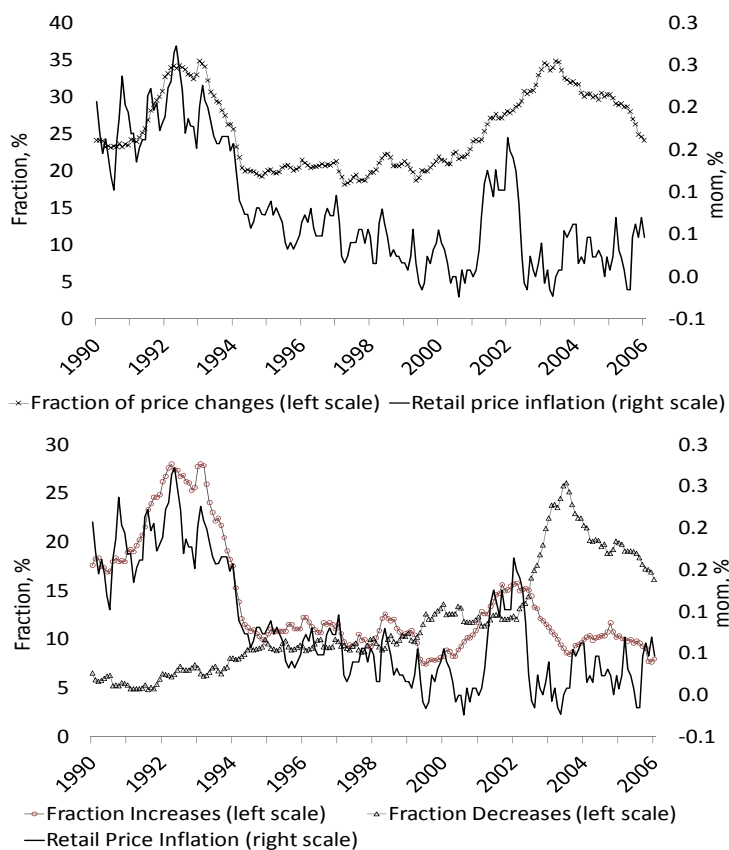
	Expected price (t)		
Price (t)	Increase	No change	Decrease
Increase	0.39	0.08	0.04
No change	0.56	0.84	0.43
Decrease	0.05	0.08	0.53
	Expected price (t-1)		
Price (t)	Increase	No change	Decrease
Increase	0.42	0.06	0.04
No change	0.54	0.85	0.42
Decrease	0.04	0.08	0.55
	Expected price (t-2)		
Price (t)	Increase	No change	Decrease
Increase	0.40	0.07	0.06
No change	0.55	0.85	0.43
Decrease	0.04	0.09	0.52
	Expected price (t-3)		
Price (t)	Increase	No change	Decrease
Increase	0.37	0.08	0.08
No change	0.58	0.83	0.46
Decrease	0.05	0.09	0.46

Probabilities of observing a price increase, decrease and no price change conditional on price expectations in a given month as well as one, two and three months ago, respectively. Sample period: 1991:01-2006:01.

The conditional probabilities reported in the table suggest that in most of the cases firms act as previously expected. Conditional on having expected a price increase, the probabilities of actually observing a realized price increase one, two and three periods later are high (around 40%). A similar pattern can be observed for expected price decreases. This suggests that changes in price expectations can indeed be interpreted as the setting of price plans by firms.

Figure 2.1 provides some aggregated statistics calculated from the micro data. The upper panel of the figure plots the frequency of price changes calculated from the business survey data as well as the rate of monthly retail price inflation.⁸ The figure reveals that the frequency of price adjustment is not completely stable but seems to comove with the rate of inflation over time.

Figure 2.1: Frequency of Price Changes and Retail Price Inflation



⁸Both panels of the figure display month-on-month changes of the retail price index. The frequency of price changes as well as the frequency of price increases and decreases enter as 12-month moving averages.

The lower panel of the figure displays the frequency of price increases and decreases, respectively, as well as the rate of retail price inflation. The figure clearly shows the comovement between the rate of inflation and the frequency of price increases. While the fraction of price decreases is small and rather stable until the late 1990's it becomes more volatile and increases considerably from 2002. This surge in the frequency of firms that decrease their prices drives the upward trend in the overall price adjustment frequency from the late 90's.⁹ Thus, both figures suggest that the frequency of price changes is not invariant over time as predicted by time-dependent theories but that it seems to depend on the overall inflation environment. Given the moderate overall inflation environment, this observation is remarkable.

2.2.3 Econometric Model

The dependent price variables $price_{it}$ and $eprice_{it}$ have three discrete outcomes: -1 for an (expected) price decrease, 0 if there is no price change (if no price change is expected) and +1 for an (expected) price increase. A latent variable specification is assumed to underly the data generating process with an unobserved quantitative price variable y_{it}^* depending on a set of explanatory variables:

$$y_{it}^* = \mathbf{x}_{it}'\boldsymbol{\beta} + u_{it}. \quad (2.1)$$

Following the target-threshold approach suggested by Cecchetti (1986) a menu cost interpretation is applied to this specification. In particular, a fixed cost of price adjustment is assumed that prevents firms from changing prices every period. We assume the following observation rule for the observed discrete price variable y_{it} :

$$y_{it} = \begin{cases} -1 & \text{if } y_{it}^* \leq \alpha_1 \\ 0 & \text{if } \alpha_1 \leq y_{it}^* \leq \alpha_2 \\ 1 & \text{if } \alpha_2 < y_{it}^* \end{cases} \quad (2.2)$$

where α_1 and α_2 are thresholds assumed to be invariant across time and units of observation. Thus, according to this model, the price is increased as soon as the latent price variable y_{it}^* exceeds threshold α_2 , the price is decreased if y_{it}^* is below

⁹One possible explanation for this pattern might be the wage moderation and associated deflationary tendencies in Germany resulting from an increasing pressure of the country to retain international competitiveness after the introduction of the monetary union; see e.g. Burda and Hunt (2011).

threshold α_1 and the price remains unchanged if the unobserved price variable stays within the cutoff-points. In this model the difference between the thresholds can be interpreted to relate to the menu cost concept; the higher the fixed cost of changing the price, the larger is the difference between the cutoff-points and the underlying latent variable has to take on more extreme values in order for a price change to occur. The model is estimated by means of an ordered probit specification. Since the latent variable can be interpreted as deviation of the actual price from the desired optimal price, this ordinal interpretation of the dependent variable applies here. For instance, a high sectoral rate of inflation implies that the realized price is likely to be below the optimal price. Thus, adjustment decision 1 (price increase) is preferred to 0 (no price change), which in turn is preferred to -1 (price decrease).¹⁰ Additionally, a bivariate specification is estimated to control for a possible correlation between the price setting decision and the updating of pricing plans. A specification that controls for this correlation leads to a more efficient estimation relative to simple univariate specifications (Cameron and Trivedi, 2007). In particular, since both dependent variables have three outcome possibilities, a bivariate ordered probit model is estimated. The probability model can be derived from the following latent variable specification:

$$\begin{aligned} y_{1it}^* &= \mathbf{x}'_{1it}\beta_1 + \epsilon_{1it} \\ y_{2it}^* &= \mathbf{x}'_{2it}\beta_2 + \gamma y_{1it}^* + \epsilon_{2it}, \end{aligned} \tag{2.3}$$

where β_1 and β_2 are vectors of unknown parameters and γ is an unknown scalar. ϵ_{1i} and ϵ_{2i} are error terms that are assumed to be distributed bivariate standard normal with correlation ρ . The observation rules for the dependent variables y_{1it} and y_{2it} are analogous to equation (2.2) (Cameron and Trivedi, 2007).¹¹ In order to identify the parameters of the model given in equation (2.3) we normalize the coefficient of one of the time-dependent variables in the vector \mathbf{x}'_{1it} , $Taylor6_{it}$, to one.¹² Furthermore, we estimate a seemingly unrelated specification with two

¹⁰However, to account for possible asymmetries between the data-generating processes underlying price increases and decreases, respectively, we additionally estimate the model separately for these respective outcomes using conditional logit and panel probit specifications. Results are discussed in Section 2.3.5.

¹¹Estimation was performed using the Stata code provided by Zurab Sajaia, which can be downloaded at <http://ideas.repec.org/c/boc/bocode/s456920.html>.

¹²In our case the choice of an appropriate exclusion restriction is somewhat arbitrary. Ar-

sets of regressors for the respective independent variables, where we consider different time-dependent variables for the two cases.¹³ See the next subsection and Section 2.3.5 for more details and a discussion of corresponding results.

For the benchmark case, both models are estimated without the explicit inclusion of individual-specific effects. First, to account for observable heterogeneity, sector-specific dummy variables are included to the set of regressors. Moreover, due to the firm-specific nature of the dataset at hand, arguably, a large extent of firm heterogeneity is already captured by some of the regressors (Lein, 2010). To mitigate the remaining problem of unobserved heterogeneity, we employ the Mundlak-Chamberlain approach of correlated random effects assuming that the individual-specific effects to be related to observed characteristics in the model. To implement this approach for our model, we add a vector of firm-specific means of the individual-specific variables to the set of regressors, which yields consistent estimates also in the case of a pooled model (Mundlak, 1978). In effect, we therefore assume the latent variable specification to take on the following form: $y_{it}^* = \mathbf{x}'_{it}\boldsymbol{\beta} + \bar{x}'_i a + u_{it}$, where \bar{x}'_i are the firm-specific time averages of the regressors. It should be noted that most of the results are robust if we explicitly include random effects and estimate the model using a correlated random effects (CRE) panel probit specification, where we however have to estimate separate regressions for price increases and decreases. Furthermore, our findings are robust to excluding the time averages. Additionally, we estimate a fixed effects specification within a linear panel model. The results of all of these sensitivity tests are discussed in Section 2.3.5.

2.2.4 Price Setting Equations

In equation (2.1) \mathbf{x}'_{it} represents a mix of time- and state-dependent variables. In particular, we estimate the following three specifications:

guably, both dependent variables are potentially affected by all of the explanatory variables, which are described in more detail below. It is thus reassuring that our results are robust to varying the exclusion restriction; corresponding regression results are available upon request.

¹³More specifically, in such a model γ is assumed to be zero, while the error terms are still distributed bivariate standard normal with correlation ρ . See Sajaia (2008).

$$\begin{aligned}
(1) \quad y_{it}^* &= \beta_1 firm_{it} + \beta_2 macro_{it} + \beta_3 D_{it}^I + \beta_3 taylor_{it} + \beta_4 D_{it}^{seas} \\
&+ \beta_5 D_{it}^s + u_{it} \\
(2) \quad y_{it}^* &= \beta_1 firm_{it} + \beta_2 macro_{it} + \beta_3 D_{it}^I + \beta_3 taylor_{it} + \beta_4 D_{it}^{seas} \\
&+ \beta_5 D_{it}^s + \beta_6 P_{it} + u_{it} \\
(3) \quad y_{it}^* &= \beta_1 firm_{it} + \beta_2 macro_{it} + \beta_3 D_{it}^I + \beta_3 taylor_{it} + \beta_4 D_{it}^{seas} \\
&+ \beta_5 D_{it}^s + \beta_6 P_{it} + \beta_7 lP_{it} + u_{it}.
\end{aligned}$$

Estimating specification (1) it will be analyzed whether, next to time dependent variables, measures reflecting the state of the firm as well as macroeconomic and institutional factors have a significant effect on the probability of price adjustment. $firm_{it}$ denotes a vector of the firm-specific variables described in the previous section.¹⁴ Because of potential asymmetries between the effects of improvements and deteriorations in the respective variables, two different dummies indicating improvements and deteriorations (indicated by + and -, respectively) are constructed of all of them. Moreover, a vector of macroeconomic variables, indicated by $macro_{it}$, is included in the model. In standard menu cost models the likelihood of price adjustment depends on the distance of the actual to the optimal price. Because the optimal price itself varies with the state of the economy, this distance depends on changes in macroeconomic factors, accumulated since the last price change. Hence, cumulative values of all macroeconomic variables since the last price adjustment are considered. To account for possible endogeneity problems associated with these variables the model is estimated by including the first individual observation of the dependent variable as an additional regressor, as has been suggested by Wooldridge (2005) and applied by Loupias and Sevestre (2010).¹⁵

¹⁴Endogeneity does not seem to be a problem when using the firm-specific variables as regressors; results are robust to including these variables in first lags as well as to using an instrumental variables estimation. See Section 2.3.5 for details.

¹⁵Card and Sullivan (1988) show that regressors which are state-dependent in the sense that they depend on the duration of the dependent variable may be endogenous and thus lead to biased estimation. Our cumulative variables depend on the duration of the dependent price variable and are therefore examples of such variates.

According to, for instance, Dotsey et al. (1999), an increase in inflation leads to a decline in relative prices of individual firms which should increase the probability of repricing. Thus, the respective cumulative sectoral rate of inflation since the last price change is included to the set of regressors.¹⁶ We include values that are lagged by one period to avoid possible endogeneity problems that may result at this degree of disaggregation. The importance of sectoral inflation for price setting is well established in the literature. In fact, the effect of the sectoral rate of inflation can be interpreted as an indicator of the transmission of shocks to prices between firms (Gautier, 2008). As shown in Section 2.3.5, where results of some robustness checks are provided, however, results are qualitatively similar if the cumulative rate of consumer price inflation rate is used instead of the measures of sectoral inflation.

Furthermore, a measure of cumulative changes in the oil price is included to account for changes in raw material costs related to global demand or supply shocks. Moreover, cumulative changes in the Euro/USD exchange rate are considered to capture changes in foreign demand and costs related to variations in import prices. The vector of macroeconomic variables can thus be characterized by the following expression: $macro_{it} = [\Delta^{cum} P_{it}^j, \Delta^{cum} P_{it}^{oil}, \Delta^{cum} E_{it}^{\text{€}/\$}]'$, where P_{it}^j indicates the price level for sector j , P_{it}^{oil} is the oil price and $E_{it}^{\text{€}/\$}$ stands for the Euro/USD exchange rate. Arguably, this set of macroeconomic variables only constitutes a certain selection of relevant factors and may not cover the entire macroeconomic environment facing the firms. To take account of this possibility we additionally estimate the model including time-specific effects instead of the vector $macro_{it}$. More details and regression results are presented in Section 2.3.5. Furthermore, a set of dummy variables, D_{it}^I , controlling for important institutional events is added. Events that might influence the decision to adjust prices are the introduction of the Euro in 2002 as well as the increases in the value added tax in 1993 and 1998. The dummies are equal to one in the month of the change as well as in the previous and following three months.

We furthermore add a set of time-dependent variables to specification (1). To investigate whether firms in the dataset employ Taylor-type pricing, following Lein (2010), Taylor dummies are constructed ($taylor_{it}$) indicating that the last price change occurred a fixed period ago. According to standard time-dependent models, these variables should be the main determinants of price adjustment.

¹⁶The inflation rates for the respective retail sectors are obtained from the Federal Bureau of Statistics and are matched with the survey data according to the WZ08 2-digit classification.

Studies on the frequency of price changes as, for instance, Hoffmann and Kurz-Kim (2006) for Germany show that there are spikes in hazard rates at six, 12, 18 and 24 months. Therefore, dummy variables are defined accordingly as $taylor6_{it}$, $taylor12_{it}$, $taylor18_{it}$ and $taylor24_{it}$. Arguably, the same Taylor dummies are relevant also for the probability to observe an *expected* price change in the future, since firms may conceivably plan the setting of future prices on the basis of the current information. However, if firms actually practice Taylor-type pricing in a strict sense, one would expect them to account for the additional time between the reporting month and the period they expect the price change to happen when updating their pricing plans. We account for this possibility by constructing an additional set of Taylor dummies, relevant for specifications with the expected price change probability as dependent variable. The construction of these modified dummies is of course complicated by the fact that firms are not asked to report their expectations for the subsequent month, but for the coming three months altogether. Hence, it is not clear to which of these three months they actually refer to when reporting their expectations. We therefore construct three additional sets of Taylor dummies assuming, respectively, that firms in fact consider period $t+1$, $t+2$ or $t+3$ when reporting their expectations. For instance, if we assume that firms in fact report price expectations for the coming month, period $t+1$, the corresponding Taylor dummies indicate that the last price change was five, 11, 17 and 23 months ago. These modified Taylor dummies are indicated by $taylor6_{it}^{t+i}$, $taylor12_{it}^{t+i}$, $taylor18_{it}^{t+i}$ and $taylor24_{it}^{t+i}$, where $i \in (1, 2, 3)$ indicates the respective assumption concerning the expectation horizon of firms. The results for these modified specifications are discussed in the section on robustness, Section 2.3.5.

Furthermore, seasonal dummies are constructed to examine whether the probability of repricing according to fixed time intervals is increased (D_{it}^{seas}). Finally, we account for observable differences between sectors by including sector-specific dummy variables, indicated by D_{it}^s .

In order to shed more light on how price changes are transmitted through the chain of production, variables indicating the frequency of input price changes are included in the specification (P_{it} in specifications (2) and (3)). Moreover, adding lags of these variables allows to analyze the length of the adjustment process to input price changes (lP_{it}). Given the qualitative nature of our dataset, we have to rely on the extensive margin of input price changes as a proxy for

input price shocks. Both wholesale and manufacturing price developments are considered, because retail firms use products of both sectors as inputs.¹⁷ For the construction of the input price measure, business survey data for the wholesale and manufacturing sector is used. Within these sectors, firms are asked similar questions regarding their price development as compared to the retail sector.¹⁸ As far as data for the wholesale sector is concerned, as both datasets are classified according to the same internal classification scheme of the Ifo institute, wholesale price data could exactly be matched to the retail data on a product group-specific basis. The measure of the frequency of price changes in the wholesale sector was constructed by subtracting the share of price decreases within a particular three-digit product category from the fraction of price increases in this sector for every month in every year. Thus, for every product category, the input cost measure was constructed according to:

$$F_{jt}^{ws,+} = \frac{\sum_{i=1}^{n_j} y_{ijt}^{ws,+} - \sum_{i=1}^{n_j} y_{ijt}^{ws,-}}{\sum_{i=1}^{n_j} y_{ijt}^{ws,+} + \sum_{i=1}^{n_j} y_{ijt}^{ws,-} + \sum_{i=1}^{n_j} y_{ijt}^{ws,0}},$$

where $F_{jt}^{ws,+}$ denotes the frequency of the share of price increases minus the share of price decreases of a particular product-group j within the wholesale sector, $y_{ijt}^{ws,+}$ and $y_{ijt}^{ws,-}$ indicate a price increase and a price decrease of firm i belonging to sector j at time t , respectively. $y_{ijt}^{ws,0}$ indicates that the price was not changed. These series for the different product groups could then be matched to every retail firm belonging to the same category. Such an exact match was possible for about 67% of the retail firms.

For manufacturing prices, unfortunately, a sector-specific match of input prices was not possible because this dataset has been coded differently. To construct a measure of the price development, therefore, a weighted average of the share of price increases net of the share of price decreases of all sectors was constructed for every time period: $F_t^{m,+} = \sum_{j=1}^J \omega_j F_{jt}^{m,+}$. In this expression, $F_t^{m,+}$ denotes the weighted average of net price increases within the manufacturing sector at period t , and $F_{jt}^{m,+}$ indicates the frequency of net price increases within each particular manufacturing sector. ω_j indicates the respective weight for each sector.¹⁹

¹⁷Because according to the input-output table of the Federal Bureau of Statistics retail products make up for only about 1% of all inputs used by the wholesale sector, assuming the wholesale price variable to be exogenous in the retail price equation seems reasonable.

¹⁸See Becker and Wohlrabe (2008).

¹⁹The respective weights are chosen according to their respective usage within the retail sector given in the official input-output table of the Federal Bureau of Statistics.

2.3 Results

2.3.1 Time- vs. State-Dependence

Results for the baseline price setting specification (1) and the model including intermediate input costs (2) for price changes are shown in Table 2.3. The table reports marginal effects for the outcomes 1 (price increase) and -1 (price decrease) as well as robust standard errors. First, results for specification (1), shown in the two left panels in Table 2.3, show that the time-dependent variables have significant effects on the probability of price adjustment. For instance, a firm that raised its price exactly four quarters ago faces a 1.1% higher probability of a price increase in a given period. Moreover, if it changed its price two years ago, on average, a firm is 2.7% more likely to decrease its price in the current period. Furthermore, all seasonal dummies are significant. For example, compared to the benchmark season spring, a price increase is 2.3% more likely during winter and 1.7% less likely during summer. Evidence that Taylor and seasonal dummies are indeed of some relevance for the timing of price adjustment has been reported before by, for instance, Lein (2010) and Dhyne et al. (2006). Our results thus confirm that some time-dependent elements seem to be present in the data.

Next to the time-dependent variables, however, we find that most of the firm-specific measures show highly significant effects and have the expected signs. A deterioration in the state of business decreases the probability of observing a price increase by 5.5%, while it increases the likelihood of a price decrease by 5.2%. Similarly, decreases in the expected business development and in orders decrease (increase) the probability of a price increase (decrease); quantitatively, the effects are around 3-4%. Moreover, as expected, improvements in the state of business and increases in the business volume increase (decrease) the likelihood of a price increase (decrease). The direction of the effect of a decrease in business volume is rather surprising leading to a higher likelihood of a price increase (and vice versa). Results from specification (2) show, however, that the effect of this variable is not robust to the inclusion of further variables, see the discussion below. Furthermore, the signs of the marginal effects for increases in orders and improvements in the expected business development are surprising; however, the effect of the former dummy is insignificant, while the marginal effect of the latter is rather small. Overall, the statistically and economically significant effects of the firm-specific variables lead to the tentative conclusion that state-dependence

is important for the pricing behavior of German retail firms and, more specifically, that the idiosyncratic business environment of the firm matters. This is a new result for Germany, which could not have been obtained by analyzing most micro price datasets.

Table 2.3: Ordered Probit Regressions - Dependent Variable: *price*

	(1) - increase		(1) - decrease		(2) - increase		(2) - decrease	
	ME	St.Err.	ME	St.Err.	ME	St.Err.	ME	St.Err.
state ⁻	-0.055***	0.003	0.052***	0.003	-0.029***	0.004	0.023***	0.003
volume ⁻	0.017***	0.003	-0.016***	0.003	-0.006	0.004	0.005	0.003
orders ⁻	-0.034***	0.003	0.032***	0.003	-0.040***	0.004	0.032***	0.004
develp ⁻	-0.031***	0.003	0.029***	0.003	-0.041***	0.005	0.034***	0.004
state ⁺	0.032***	0.005	-0.027***	0.004	0.007	0.006	-0.006	0.005
volume ⁺	0.047***	0.004	-0.040***	0.003	0.034***	0.005	-0.026***	0.003
orders ⁺	-0.008	0.006	0.007	0.006	-0.048***	0.007	0.042***	0.007
develp ⁺	-0.018***	0.005	0.017***	0.005	-0.049***	0.006	0.043***	0.006
inflation	0.026***	0.004	-0.024***	0.003	0.019***	0.005	-0.015***	0.004
oil	0.053***	0.010	-0.049***	0.009	0.052***	0.013	-0.042***	0.010
exchrates	0.019	0.014	-0.018	0.013	0.042**	0.019	-0.033**	0.015
EUR	0.036***	0.007	-0.030***	0.006	0.029***	0.009	-0.021***	0.007
VAT	0.082***	0.005	-0.063***	0.003	0.076***	0.007	-0.052***	0.004
price_ws					0.407***	0.007	-0.323***	0.005
price_m					0.028***	0.007	-0.022***	0.005
taylor6	-0.026***	0.003	-0.025***	0.003	-0.013***	0.003	-0.010***	0.003
taylor12	0.011***	0.003	-0.010***	0.003	0.018***	0.004	-0.014***	0.003
taylor18	-0.043***	0.003	0.042***	0.003	-0.019***	0.003	0.035***	0.004
taylor24	-0.029***	0.003	0.027***	0.003	-0.019***	0.004	0.015***	0.003
winter	0.023***	0.004	-0.020***	0.003	-0.002	0.005	0.001	0.004
summer	-0.017***	0.003	0.016***	0.003	-0.003	0.005	0.002	0.004
fall	-0.033***	0.003	0.032***	0.003	-0.007	0.005	0.006	0.004
Log-Lik.	-64339.486				-42144.969			
Obs.	71218				46611			

*** p<0.01, ** p<0.05, *p<0.1. The table reports marginal effects (ME) and robust standard errors (St.Err.). MEs are calculated for outcomes “price increase” and “price decrease”, respectively, setting all variables at their mean. For binary regressors, the effect is for discrete change from 0 to 1. We additionally include but don’t report firm-specific averages of the individual-specific variables, the first individual observation of the dependent variable and sectoral dummies.

The effects of the cumulative macroeconomic variables as well as the institutional dummies further reinforce the evidence in favor of state-dependence. The effects of cumulative changes of the sectoral rates of inflation as well as the oil price are highly significant and show the expected signs. For instance, an increase in sectoral inflation, accumulated since the last price adjustment, by one percent raises the probability of a price increase; the marginal effect is 0.026. Moreover, a unit increase in the cumulative change of the oil price leads to a higher (lower) likelihood of a price increase (decrease). Furthermore, a depreciation of the

Euro/USD exchange rate increases the likelihood of observing a price increase, which is in line with economic theory since a lower value of the Euro may increase export demand and raises import prices. However, the effect is insignificant. This is, in fact, not too surprising given the extensive empirical evidence documenting an imperfect pass-through of exchange rate fluctuations on domestic prices, see for instance Devereux and Yetman (2010) and Campa and Goldberg (2008).

Additionally, changes in the institutional environment significantly affect the timing of price adjustment; the dummy indicating increases in the VAT rate has a particularly high effect raising (lowering) the probability of a price increase (decrease) by 8.2% (6.3%). Similarly, the introduction of the Euro led more firms to increase their prices, while the fraction of firms decreasing prices was significantly reduced; the effects are 3.6% and 3.0%, respectively.

Table 2.3 also shows regression results of specification (2) that includes changes in intermediate input costs; see the two right panels of the table. Both measures are highly significant and have the expected effects. An increase in the measure of manufacturing price changes increases the likelihood of a price increase and reduces the chance to observe a price decrease; the marginal effects are 0.028 and 0.022, respectively. An increase in the sector-specific measure of the wholesale price adjustment frequency is particularly effective with marginal effects amounting to 0.407 and 0.323 for a price increase and decrease, respectively. This provides evidence in favor of cost-based pricing, which is in line with results reported by Fabiani et al. (2006) for the Euro area and Eichenbaum et al. (2011) for the US. Most of the firm-specific and macroeconomic variables are robust to the inclusion of the intermediate input cost measures.

While the Taylor dummies are robust, too, interestingly, the seasonal dummies are now insignificant. Thus, in specifications (1) these variables capture part of the variations in intermediate input costs suggesting that seasonality observed after estimating specification (1) might in fact not be due to time-dependent pricing behavior.

Overall, these results suggest that while Taylor pricing seems to be relevant for the repricing decision of retail firms, a pure time-dependent representation of pricing is rejected. Most of the factors characterizing both the idiosyncratic and aggregate state of the firms are highly significant and have economically important effects on the price setting decision. Moreover, seasonality is only present in the data as long as intermediate input costs are not accounted for.

This finding reveals that empirical results reported in the literature might be misleading as long as the specification does not control for such state-dependent factors.

2.3.2 Assessing Sticky Plan Models

In order to shed more light on the plausibility of state-dependent sticky plan models, specifications (1) and (2) are estimated with price expectations as dependent variable; results are reported in Table 2.4. To our knowledge, an explicit analysis of pricing plans using survey data has not been forthcoming. Overall, the explanatory variables show quite similar effects on the probability of a change in price plans compared to an actual price adjustment; all firm-specific variables as well as most of the macroeconomic and institutional factors significantly affect the decision to update pricing plans. As for price realizations, deteriorations in the state of business, the expected business development as well as decreases in the number of orders significantly decrease (increase) the probability of observing an expected price increase (decrease). Quantitatively, the effects are similar as well ranging from 2-6%. Increases in the business volume and in orders as well as an improvement in the state of business lead to a higher (lower) likelihood of a positive (negative) change in price expectations.

Moreover, while the introduction of the Euro does not seem to play a role for the updating of pricing plans, the VAT dummy enters significantly. Furthermore, cumulative changes in the sectoral rate of inflation and the exchange rate are significant and have the expected sign. Surprisingly, though, an increase in the cumulative rate of change in the price of oil leads to a *lower* probability of observing an increase in expected price changes. Conceivably, however, in case an oil price increase is due to a contractionary shock to the supply of oil, current and expected negative effects on economic activity could offset upward pressures on expected future prices leading to the observed negative effects on the probability of observing an expected price increase. Indeed, using aggregated data Carstensen et al. (2011) find that a negative oil supply shock leads to a somewhat delayed decline of German GDP and other demand-related variables such as consumption and investment.²⁰

²⁰However, Carstensen et al. (2011) also report that an increase in the price of oil can also be related to a positive innovation to aggregate demand or a positive oil-specific demand shock and that the type of shock matters for the response of the aggregate variables, see also Kilian (2009). The explanation for the observed negative relationship between expected price changes

Table 2.4: Ordered Probit Regressions - Dependent Variable: *expected price*

	(1) - increase		(1) - decrease		(2)- increase		(2) - decrease	
	ME	St.Err.	ME	St.Err.	ME	St.Err.	ME	St.Err.
state ⁻	-0.058***	0.004	0.035***	0.002	-0.043***	0.005	0.024***	0.003
volume ⁻	0.035***	0.004	-0.020***	0.002	0.023***	0.005	-0.012***	0.003
orders ⁻	-0.054***	0.004	0.033***	0.002	-0.064***	0.005	0.036***	0.003
develp ⁻	-0.059***	0.004	0.037***	0.003	-0.066***	0.005	0.038***	0.003
state ⁺	0.015***	0.006	-0.009***	0.003	-0.012*	0.007	0.007*	0.004
volume ⁺	0.052***	0.004	-0.030***	0.002	0.039***	0.005	-0.021***	0.003
orders ⁺	0.035***	0.007	-0.019***	0.004	-0.007	0.009	0.004	0.005
develp ⁺	-0.020***	0.006	0.013***	0.004	-0.054***	0.007	0.032***	0.005
inflation	0.020***	0.004	-0.012***	0.002	0.012**	0.005	-0.006**	0.003
oil	-0.054***	0.012	0.033***	0.007	-0.062***	0.016	0.034***	0.009
exchrates	0.034*	0.017	-0.020*	0.010	0.126***	0.023	-0.069***	0.012
EUR	0.007	0.008	-0.004	0.004	0.008	0.010	-0.004	0.005
VAT	0.082***	0.006	-0.042***	0.003	0.090***	0.007	-0.042***	0.003
price_ws					0.306***	0.007	-0.167***	0.004
price_m					0.066***	0.008	-0.036***	0.004
taylor6	0.007**	0.003	-0.004**	0.002	0.012**	0.005	-0.006**	0.002
taylor12	0.029***	0.004	-0.017***	0.002	0.040***	0.005	-0.022***	0.002
taylor18	-0.018***	0.004	0.011***	0.002	-0.007	0.005	-0.004	0.003
taylor24	-0.006*	0.004	0.004*	0.002	0.012**	0.005	-0.007**	0.003
winter	0.090***	0.004	-0.049***	0.002	0.065***	0.006	-0.033***	0.003
summer	0.082***	0.004	-0.045***	0.002	0.117***	0.006	-0.057***	0.003
fall	0.035***	0.004	-0.020***	0.002	0.067***	0.006	-0.034***	0.003
Log-Lik.	-62635.530				-42174.987			
Obs.	71218				46611			

*** p<0.01, ** p<0.05, *p<0.1. The table reports marginal effects (ME) and robust standard errors (St.Err.). MEs are calculated for outcomes “price increase” and “price decrease”, respectively, setting all variables at their mean. For binary regressors, the effect is for discrete change from 0 to 1. We additionally include but don’t report firm-specific averages of the individual-specific variables, the first individual observation of the dependent variable and sectoral dummies.

Finally, results from specification (2) show that intermediate input price changes are important determinants of changing pricing plans, even though the marginal effects are not as high as for price realizations.

In order to control for a possible correlation between the processes underlying price adjustment and the updating of pricing plans, a bivariate ordered probit model has been estimated allowing for more efficient estimation. Table 2.5 shows marginal effects of the regressors for two outcome possibilities; (1, 1): price increase and expected price increase and (-1, -1): price decrease and expected price decrease.²¹ Results from the Wald test performed to test the independence

and oil price changes given above is thus conditional on the assumption that the oil price rise results from a supply shock.

²¹The outcomes (1, 0), (-1, 0), (0, 1) and (0, -1) are similar compared to the results of the univariate specifications. The outcomes (1, -1) and (-1, 1) rely on a limited number of

of equations hypothesis ($\rho = 0$) indicates that a bivariate specification leads to a more efficient estimation.

Table 2.5: Prices and Pricing Plans - Bivariate Ordered Probit Regression

	(2) - increase, increase		(2) - decrease, decrease	
	ME	St.Err.	ME	St.Err.
state ⁻	-0.034***	0.003	0.007***	0.001
volume ⁻	0.011***	0.003	-0.002***	0.001
orders ⁻	-0.037***	0.003	0.008***	0.001
develp ⁻	-0.038***	0.003	0.009***	0.001
state ⁺	0.003	0.004	-0.001	0.001
volume ⁺	0.036***	0.003	-0.007***	0.001
orders ⁺	-0.010**	0.005	0.003**	0.001
develp ⁺	-0.030***	0.004	0.008***	0.001
inflation	0.012***	0.003	-0.003***	0.001
oil	-0.006	0.010	0.000	0.002
exchrates	0.039***	0.015	-0.008**	0.003
EUR	0.022***	0.007	-0.004***	0.001
VAT	0.079***	0.005	-0.012***	0.001
price_ws	0.228***	0.005	-0.051***	0.001
price_m	0.060***	0.005	-0.012***	0.001
taylor12	0.028***	0.003	-0.028***	0.001
taylor18	-0.024***	0.003	0.005***	0.001
taylor24	-0.004	0.003	0.001*	0.001
winter	0.033***	0.004	-0.006***	0.001
summer	0.051***	0.004	-0.009***	0.001
fall	0.027***	0.004	-0.005***	0.001
Log-Lik.	-81859			
Obs.	46611			
Wald test of independence	Prob> chi2 = 0.000			

*** p<0.01, ** p<0.05, *p<0.1. The table reports marginal effects (ME) and robust standard errors (St.Err.). MEs are calculated for outcomes (1,1) - “price increase” and “expected price increase” and (-1,-1) - “price decrease” and “expected price decrease”. All variables are set at their mean. For binary regressors, the effect is for discrete change from 0 to 1. We additionally include but don’t report firm-specific averages of the individual-specific variables, the first individual observation of the dependent variable and sectoral dummies. The coefficient of *taylor6* has been normalized to one in the *price_{it}* equation.

Overall, the main results of the univariate specifications given in Table 2.3 are robust to a bivariate estimation. With the exception of the effect of an improvement in the state of business, which is now insignificant, all firm-specific variables affect the probability of a price increase and an expected price increase (and vice versa) similarly as in the univariate model. Moreover, sectoral inflation, the exchange rate and both institutional dummies are significant and correctly signed. The oil price variable is now insignificant; while it positively affects the probability of a price increase it has no effect on the chance of observing both an observations and are economically somewhat hard to predict.

actual and expected price increase. But importantly, the measures of intermediate input costs as well as the institutional dummies are highly significant and have relatively large marginal effects. Thus, these findings confirm that a pure time-dependent characterization may not entirely capture the process underlying the formation of pricing plans.²²

2.3.3 Goodness of Fit Comparison

As the previous subsections show, next to time-dependent variables, state-dependent factors are significant determinants for the timing not only of price adjustment but also of the updating of pricing plans. For a further evaluation of these different price setting assumptions, it is additionally interesting whether a pure “state-dependent” specification is able to outperform an econometric model containing only time-dependent elements. To shed more light on the explanatory power of these different sets of variables, we report different goodness of fit measures, see Tables 2.6 and 2.7.

Table 2.6: Goodness of Fit Statistics - Likelihood Ratio Test

		Realized price changes (in current month)				
		Unrestricted:	Restriction:			
		BL Model (2)	no TDP	no SDP	No Macro	No Firm-spec.
LR Test	statistic		212.550	4342.370	28.240	1019.880
	p-value		0.000	0.000	0.000	0.000
	Akaike	83689.28	83887.83	87991.65	83711.52	84683.16
		Expected price changes (for coming three months)				
		Unrestricted:	Restriction:			
		BL Model (2)	no TDP	no SDP	No Macro	No Firm-spec.
LR Test	statistic		683.060	3033.360	36.000	1354.090
	p-value		0.000	0.000	0.000	0.000
	Akaike	83034.02	83703.07	86027.38	83064.02	84362.11

The table shows results of likelihood ratio tests evaluating the null hypothesis that the unconstrained and constrained maxima of the log-likelihood function are the same as well as corresponding Akaike statistics. Abbreviations: *BL Model* - Baseline Model, *no TDP* - excluding time-dependent variables, *no SDP* - excluding state-dependent variables, *no macro* - no cumulative macro variables, *no firm-spec.* - no idiosyncratic variables.

²²As discussed in Section 2.3.5, most of the results are insensitive to estimating a seemingly unrelated bivariate ordered probit specification, where we include two different sets of Taylor dummies in the two respective equations.

In Table 2.6 we report results of likelihood ratio tests, which are conducted to check whether there are significant differences in terms of the explanatory power of a range of restricted models relative to our benchmark specification (2), which serves as the unrestricted model. In particular, the table reports results for four restricted models; specifications excluding the time- and state-dependent variables, respectively, a model excluding the cumulative macro variables, and a specification excluding the firm-specific variables. As can be seen in Table 2.6, the LR tests detect significant differences relative to the unrestricted model in all four cases; the null hypothesis that the constrained and unconstrained maxima of the log-likelihood functions are the same are rejected at the 1% confidence level. Thus, including both time- and state-dependent factors leads to a significant improvement in the explanatory power of the model. However, the Akaike criterion, reported in the last row of each panel in the table, shows that the inclusion of the state-dependent factors improves the model's goodness of fit to a larger extent compared to including the time-dependent factors. The lower panel shows that all of these results also hold for specifications with the probability of observing an expected price change as dependent variable.

For the application at hand, employing the LR Test entails the problem that the respective models need to be nested. To be able to use the test, when estimating the restricted models we therefore need to discard all observation units with missing data points for certain variables, which were not considered for the benchmark model.²³ Discarding observations which in principle could be used for estimation of the restricted model may lead to misleading results. We therefore report as simple alternative goodness of fit measures the percent correctly predicted by the different models. In particular, we compute the overall percent correctly predicted as well as the predicted probabilities of the three respective outcomes $y_{it} = 1$, $y_{it} = -1$ and $y_{it} = 0$, given the explanatory variables. It could well be the case that for certain specifications it is easy for the model to predict one outcome but harder to predict another, which could lead to misleading results (Wooldridge, 2002). It is assumed that the model predicts y_{it} to be 1, for instance, if the predicted probability for outcome $y_{it} = 1$ is highest relative to the probabilities for $y_{it} = 0$ and $y_{it} = -1$. The percentage of times the predicted

²³More specifically, for estimation of the full model we can only use 46611 observations, while for a model including only time-dependent variables, for instance, 71218 observations are available. This is due to fact the available survey data only allows us to match the intermediate input cost measures to certain product-groups and we consequently loose data points. See Section 2.2.4 for more details.

y_{it} is equal to the actual outcome is the overall percent correctly predicted.²⁴ Table 2.7 shows that, for realized price changes, the “full model” including all state- and time-dependent variables predicts the actual outcomes correctly in 57.2% of the cases. This is clearly superior compared to a model excluding all state-dependent regressors, indicated by “TDP model” in column four of the table (53.0%). By contrast, a “state-dependent” model (“SDP Model”) excluding Taylor as well as seasonal dummies performs much better. In fact, the percent correctly predicted by the SDP model of 56.9% is quite close to the performance of the full model. This suggests that the addition of time-dependent variables does not improve the model’s fit to a large extent confirming the results of the LR test. The difference between the full and the TDP model in terms of correctly predicting price increases is even larger (23.8% versus 34.0%) indicating that the purely time-dependent specification is especially inappropriate for analyzing the frequency of price increases. An obvious reason could be that firms substantially take into account changes in intermediate input costs and accumulated inflation rates when deciding on price increases, which is a robust result reported in the last subsection.

Table 2.7: Goodness of Fit Statistics - Percent Correctly Predicted

		Realized price changes (in current month)				
		BL Model (2)	TDP Model	SDP Model	No Macro	No Firm-spec.
PCP	overall	57.24%	53.02%	56.92%	55.35%	57.21%
	$y_{it} = 1$	33.98%	23.81%	34.00%	39.33%	33.67%
	$y_{it} = -1$	17.43%	16.26%	15.77%	23.33%	16.49%
	$y_{it} = 0$	84.76%	85.46%	84.80%	79.32%	85.23%
		Expected price changes (for coming three months)				
		BL Model (2)	TDP Model	SDP Model	No Macro	No Firm-spec.
PCP	overall	56.42%	54.66%	56.06%	55.35%	56.41%
	$y_{it} = 1$	43.86%	31.30%	42.36%	43.46%	30.57%
	$y_{it} = -1$	8.04%	0.00%	8.94%	11.01%	3.23%
	$y_{it} = 0$	78.77%	84.12%	78.81%	76.84%	85.78%

The table shows the percent correctly predicted for all outcomes (*overall*), and for outcomes increases ($y_{it} = 1$), decreases ($y_{it} = -1$) and no changes ($y_{it} = 0$) in actual prices and price expectations, respectively.

²⁴The overall percent correctly predicted should be equal to a weighted average of the corresponding values for the different outcomes, where the weights equal the respective fractions of the three outcomes (Wooldridge, 2002). We have checked that this is indeed the case.

Contrarily, in terms of predicting outcome 1, price increases, the SDP model does as well as the full model. The table furthermore reveals that a similar pattern can also be observed for expected price changes. In general, all models reported in the lower panel of the table have a hard time predicting price decreases compared to the models with the actual price change probability as dependent variable, which might be related to the fact that expected price decreases are much less common than expected price increases (see Section 2.2.2.).

A further comparison of the percent correctly predicted of specification (2) and a model that excludes macroeconomic variables and sector-specific input price variables (see column 6 in the table) reveals that an inclusion of these aggregate measures leads to an improvement in performance. In contrast, a model excluding the firm-specific variables (see column 7) does almost as well as the full model in terms of the overall percent correctly predicted. Thus, while the firm-specific variables significantly change the repricing probability and contribute to a clear improvement in the fit of the model, they are not as important for the overall performance of the model as the set of cumulative macro factors and the input cost measures.²⁵ This finding is not in line with some of the existing studies on price setting using item-level data; these studies generally report a not so pronounced role of aggregate measures for pricing, see for instance Hoffmann and Kurz-Kim (2006). These diverging results might be related to the fact that we analyze pricing decisions at the *firm-level*, which, to the extent that firms report some sort of average price development for their products, implies a certain level of aggregation. Apparently, at this level of aggregation macroeconomic factors are more relevant compared to price adjustment at the item-level.

2.3.4 Intermediate Inputs

Regression results of specification (2) show that intermediate input prices are generally important determinants for price adjustment of retail firms. In specification (3) six lags of the respective input price measures have been added in order to analyze the speed of price adjustment to changes in the extensive margin of input price changes; results are shown in Table 2.8.

²⁵This finding contrasts the Akaike statistics reported in Table 2.6, which are higher for models without firm-specific variables. These differences could be due to the fact that, to run the LR tests and obtain the corresponding Akaike statistics, we had to delete a substantial number of observations, so the Akaike statistics may be misleading. By contrast, to construct the percent correctly predicted we could use all observations available.

Table 2.8: Ordered Probit Regressions - Lagged Intermediate Input Costs

	(3) Increase		(3) Decrease	
	ME	St.Err.	ME	St.Err.
firm-specific	robust		robust	
inflation	0.003	0.006	-0.002	0.005
oil	0.083***	0.014	-0.065***	0.011
exchrate	0.058***	0.019	-0.045***	0.015
EUR	0.008	0.010	-0.006	0.008
VAT	0.062***	0.007	-0.042***	0.004
price_ws	0.219***	0.011	-0.170***	0.009
price_m	0.009	0.013	0.007	0.010
price_ws (-1)	0.142***	0.012	-0.110***	0.009
price_ws (-2)	-0.032***	0.012	0.025***	0.009
price_ws (-3)	0.005	0.012	-0.004	0.009
price_ws (-4)	-0.038***	0.011	0.030***	0.009
price_ws (-5)	-0.040***	0.012	0.031***	0.009
price_ws (-6)	0.053***	0.011	-0.041***	0.008
price_m (-1)	0.097***	0.015	-0.075***	0.011
price_m (-2)	-0.030**	0.015	0.023**	0.012
price_m (-3)	-0.107***	0.015	0.083***	0.012
price_m (-4)	-0.050***	0.015	0.039***	0.012
price_m (-5)	0.063***	0.014	-0.049***	0.011
price_m (-6)	0.096***	0.013	-0.074***	0.010
taylor	robust		robust	
season	not sign.		not sign.	
Log-Lik.	-33295.870			
Obs.	38100			

*** p<0.01, ** p<0.05, *p<0.1. The table reports marginal effects (ME) and robust standard errors (St.Err.). MEs are calculated for outcomes “price increase” and “price decrease”, respectively, setting all variables at their mean. For binary regressors, the effect is for discrete change from 0 to 1. We additionally include but don’t report the firm-specific variables, firm-specific averages of the individual-specific variables, the first individual observation of the dependent variable, sectoral dummies, seasonal dummies as well as Taylor dummies for six, 12, 18 and 24 months.

As far as the product group-specific wholesale price measure is concerned, almost all lags are significant and have economically important effects. This suggests that on average, retail firms do not react immediately to a wholesale price change but that the adjustment process is only complete after several months. Adding up the marginal effects for the contemporaneous measures as well as the significant lags yields cumulative marginal effects of a unit increase in the wholesale price measure on the probability of observing a price increase and decrease of 0.30 and -0.24, respectively. Similarly, adjustment to manufacturing price changes seems to be sluggish; all lags of the manufacturing price index are significant. The accumulated effect is about 0.07 and -0.05 for price increases and decreases, respectively.

Thus, while intermediate input prices are important determinants of price ad-

justment in retail, changes in input costs are not fully reflected in the repricing probability on impact but affect the price adjustment decision within the retail sector for several months following the change. This suggests that there is some additional rigidity at the retail level, which is not in line with the predictions of some of the corresponding price setting models as for instance Basu (1995) and Nakamura and Steinsson (2010). In contrast, the regression results shown in Table 2.8 are in line with the empirical evidence for the US reported by Nakamura (2008) showing that price stickiness at the retail level is dominant for the timing of retail price changes.

2.3.5 Robustness Checks

In order to check for robustness of the results, several variations of specification (2) for both the probability of actual price changes as well as the updating of pricing plans are estimated. The corresponding results can be found in Tables 2.9 - 2.15 in Appendix 2.A.2.

The first robustness check is concerned with the construction of the Taylor dummies for the specifications considering the probability of observing an expected price change as dependent variable. It has been argued above that, strictly speaking, one should account for the additional time elapsed between the reporting month and the period the firm actually expects the price change to happen. We constructed modified Taylor dummies accordingly for the following three different assumptions: that firms refer to the coming month ($t + 1$), to the period $t + 2$ and to the period $t + 3$, respectively, when reporting their expectations for the coming quarter. Table 2.9 shows that our results are rather insensitive to including these different sets of Taylor dummies instead of the benchmark Taylor variables. A notable exception, however, is the sectoral rate of inflation, which is now insignificant. Table 2.10 shows the results of a seemingly unrelated bivariate ordered probit estimation, where we include two different sets of dummy variables in the two respective equations for *price* and *eprice*. While for the *price* equation we consider the baseline Taylor dummies, we include the modified Taylor dummies in the *eprice* equation assuming that firms actually report their expectations exactly two periods in advance ($t + 2$).²⁶ Compared to the benchmark bivariate ordered probit model the results are very similar. As for the

²⁶Results are very similar when consider the Tylor dummies assuming that firms refer to period $t + 1$ and $t + 3$, respectively, when reporting their price expectations.

benchmark model, the effect of the rate of inflation is significant reflecting that this variable seems to be important for realized price changes, while its relevance for expected price changes seems to be questionable.

Moreover, we check whether our results for both price realizations and expectations are robust to changing the estimation method, see Tables 2.11 and 2.12 in Appendix 2.A.2 for actual price changes and changes in pricing plans, respectively. To control for possible asymmetries between the respective data generating processes of price increases and decreases we estimate separate logit specifications for outcomes $y_{it} = 1$ and $y_{it} = -1$. The main results are largely in line with those based on the ordered probit estimation suggesting that using a symmetric specification is a valid approach.²⁷ For actual price changes, important exceptions are changes in the oil price for price increases as well as, for price decreases, the rate of inflation and the Euro dummy. While changes in the rate of inflation are important for the probability of a price increase, the variable is insignificant for price decreases, which is plausible in an environment of positive inflation. Similarly, as one would expect, the introduction of the Euro was important only for price increases. As far as the effects of oil price changes are concerned, it has already been discussed above that it is not clear whether such changes are due to demand or supply shocks, with potentially diverging results. Moreover, in general, the importance of raw material price changes are questionable for the retail sector, so the sensitivity of this result is not too surprising. Moreover, we estimate the model using a panel probit specification with correlated random effects (CRE); again, the main conclusions are robust to this variation. For pricing plans, Table 2.12 shows that while the effects of the sectoral rate of inflation, increases in the state of business as well as, for price decreases, the manufacturing price measure are not robust when using the panel probit specification, the effects of all other variables are insensitive.

Furthermore, specification (2) is estimated using a linear regression model allowing for an easy implementation of individual-specific effects that capture unobserved heterogeneity. While the more structural nonlinear index models like ordered probit lead to more efficient estimators if the distributional assumptions are correct, estimators obtained by using the linear model are always consistent (Angrist and Pischke, 2008). The main results are unaffected by using this esti-

²⁷Taylor dummies indicating that the last price change was six and 18 months ago, respectively, are not shown in the tables for reasons of space; results are very similar compared to the benchmark findings.

mation method. Moreover, the marginal effects calculated for the ordered probit coefficients show a similar order of magnitude as the coefficients from the linear model further reinforcing the validity of the key conclusions stated above. Finally, a linear specification allows us to easily apply an instrumental variables estimation. In the tables we provide results of a two stage least square instrumental variables estimation with the dummies indicating changes in the business volume, expected orders and the expected business development assumed to be endogenous. As instruments we consider first lags of the endogenous regressors.²⁸ The results show that the qualitative effects of most firm-specific variables are robust to estimating an IV specification.

Further robustness checks are concerned with the choice of explanatory variables included in the model; see Tables 2.13 and 2.14. Results are largely insensitive to the inclusion of a measure of cumulative changes in the aggregate rate of CPI inflation instead of the respective sectoral rates, the exclusion of the firm-specific means of the individual-specific variables, and the inclusion of month-on-month changes of the macroeconomic variables instead of cumulative changes. To account for possible endogeneity of the firm-specific variables, in an alternative specification these measures enter in first lags. The coefficients of these variables are still highly significant suggesting that endogeneity problems associated with these variables are unlikely.

As a final robustness check we substitute the variables measuring the macroeconomic situation of the firms as well as the institutional dummies by time-specific effects. Table 2.15 shows that the vast majority of the other variables are robust to including time-specific effects. Results of a Wald test indicate that the time dummies are jointly significant at the 1% level. Furthermore, most of the time effects are individually significant.

²⁸Results of the first stage regression indicate that these measures are significant and represent strong instruments.

2.4 Conclusion

This paper contributes to the empirical literature on price stickiness by analyzing the determinants of price setting and the updating of pricing plans of German retail firms using a new business survey dataset. The dataset allows an analysis at the level of the individual firm, so compared to an assessment of item-level micro price data we are able to capture the decision problem at the firm-level. The main objectives of the analysis have been to assess the relative importance of time- versus state-dependent factors as determinants of the timing of price and pricing plan adjustment and to shed more light on the relevance of real rigidities in the form of intermediate input costs for the pricing decision of retail firms.

Regressing the price adjustment probability not only on time-dependent and macroeconomic variables but also on factors characterizing the individual-specific condition of firms we find that next to time-dependent variables such as Taylor dummies, most state-dependent factors significantly change the repricing probability. Cumulative changes in the sectoral rate of inflation and the oil price as well as the introduction of the Euro or changes in the VAT rate determine the timing of price adjustment; pricing decisions of firms thus seem to respond to economic shocks. Moreover, most of the variables describing the specific state of the firm turn out to be highly significant. For instance, on average, a decrease in the overall state of business reported by a firm leads to a 5.5% lower chance of observing a price increase. Similarly, deteriorations in the expected number of orders or the expected business development significantly induce firms to decrease their prices, while, for instance, increases in the business volume lead to a higher chance to observe a price increase. The finding that these idiosyncratic variables are important is a new result for the retail sector, which could not have been obtained using quantitative price data at the item-level.

Overall, the results suggest that standard time-dependent models à la Calvo (1983) or Taylor (1980) may not be sufficient to describe the price adjustment process - even for a period of relatively low inflation. Instead, our results may be interpreted as evidence in favor of menu cost models, which endogenize the price setting process by assuming a fixed cost of price adjustment such as, for instance Dotsey et al. (1999) or Golosov and Lucas (2007). It is important to note, however, that while these features of the data are in line with the assumptions of menu cost models, some of the results do also accord with implications of models assuming endogenous time-dependent pricing rules such as Bonomo and

Carvalho (2004). In this model, information on aggregate shocks is assumed to be costless and these shocks may thus influence the price adjustment probability. However, the significant effects of the idiosyncratic variables are more difficult to reconcile with such a model.

Moreover, the survey dataset allows matching the probability to observe a pricing plan adjustment to the time- and state-dependent explanatory variables discussed above. We find that changes in price expectations are driven by similar factors compared to changes in actual prices. Most of the firm-specific variables, macroeconomic measures as well as the VAT dummy are highly significant and economically important. However, relative to actual price changes, the sectoral rate of inflation is not as important for the adjustment of pricing plans, while the exchange rate now plays a significant role. A further difference is the effect of the introduction of the Euro, which is not important for the updating of future pricing plans. Overall, however, the results do not support time-dependent pricing plan models; rather, our findings are in line with state-dependent pricing plan models of, for instance, Burstein (2006).

Finally, with respect to the importance of intermediate variables, regression results show first, that input price variability is indeed an important determinant of price adjustment in retail. Explicitly modeling the transmission of price changes through the chain of production is thus a valid approach. More generally, this also suggests that real rigidities - at least in the form of sluggish intermediate input costs - are important for the timing of price adjustment. However, our findings indicate that it takes time for retail prices to adjust to input cost changes suggesting that there is additional rigidity at the retail level, which is not in line with some of the predictions of the corresponding models.

2.A Appendix

2.A.1 Business Survey Data

Since 1949 the Ifo Institute for Economic Research has been analyzing economic developments in Germany using monthly business surveys; see Becker and Wohlrabe (2008) for more details on the variables contained in the survey. In the questionnaires firms are asked about the development of certain key measures such as the number of orders and business volume, the perceived state of business as well as the development of prices. A distinct feature of the survey data is that it contains firm-specific information on expectations concerning the future business development as well as future prices. While the data is mainly used for the construction and analysis of business tendency indicators, the fact that the survey contains economic measures characterizing the specific state of the individual firms allows to analyze a variety of other issues as well. As has been emphasized in the main text, in this paper we only analyze data concerning the retail sector. In 2003, the average number of retail firms surveyed each month was 900, while the average response rate was about 70%. The participating firms' share of total revenues generated in the retail sector was about 10%. The following list gives an overview of the precise wording of the questions asked for the variables used in this paper.

Development in reporting month:

Q1: Relative to the previous month, our sales prices were (1) increased, (2) not changed, (3) decreased

Q2: We currently assess our state of business as (1) good, (2) satisfactory, (3) bad

Q3: Relative to the previous month, our business volume was (1) increased, (2) not changed, (3) decreased

Plans and expectations:

Q4: In the next three months we expect our sales prices to (1) increase, (2) not change, (3) decrease

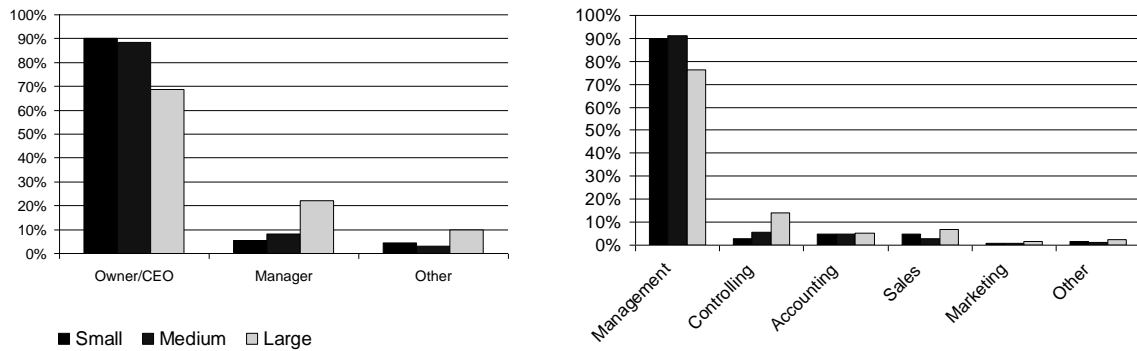
Q5: In the next three months we expect the number of orders to (1) increase, (2) not change, (3) decrease

Q6: In the next six months we expect our business development to be (1) more favorable, (2) not changed, (3) less favorable

In order to judge to what extent the business surveys capture the price developments actually realized by the firms, it is important to know who actually answers the questionnaires. According to Abberger et al. (2009), for small and medium-sized firms, in almost 90% of the cases the surveys are answered by the firm owner, the CEO or another member of the company's board. In the case of large firms, almost 70% of the survey are answered by the latter group while in about 20% of the cases the questions are answered by department managers (see Figure 2A.1). Moreover, as can be seen in the figure, if firms are asked in which department of the company the questionnaires are filled out, about 90% of small and medium-sized firms report "management". For large firms, the questionnaires are answered within the management department in almost 80% of the cases. Thus, overall, the questionnaires are answered at a very high level of expertise suggesting that they reliably reflect actual price developments.

A final issue concerns the price development reported by multi-product firms. Arguably, the inclusion of multi-product firms in the survey may lead to an upward bias of the frequency of price changes. For instance, in an extreme case a firm may report a price change even though only the price of one major product has been adjusted. In the survey, this problem is mitigated because multi-product firms are asked to fill out several questionnaires for different product groups. To the extent that firms still have to cluster several sub-products within the same reporting category, about half of the respondents report the average price development of all their products (43.3%) or give information on prices of their most important products in terms of business volume (44.6%). Only 10% report the price development of their main product, while 3.7% use other practices in reporting their price development (Abberger et al., 2009).

Figure 2A.1: Position of the person and department in charge of answering the questionnaires



Left panel, question asked : *Which position does the person in charge of answering the questionnaire have in your company?* Right panel, question asked: *In which department of your company is the survey usually answered?* Since firms may report several departments, percentages don't always add up to 100.

2.A.2 Robustness Checks

Table 2.9: Robustness Check: Ordered Probit, Different Taylor Dummies. Dependent Variable: *eprice*

	Expectation for $t + 1$		Expectation for $t + 2$		Expectation for $t + 3$	
	Incr.	Decr.	Incr.	Decr.	Incr.	Decr.
state ⁻	-0.044*** (0.005)	0.024*** (0.003)	-0.041*** (0.005)	0.022*** (0.003)	-0.0412*** (0.005)	0.0222*** (0.003)
volume ⁻	0.027*** (0.005)	-0.014*** (0.002)	0.026*** (0.005)	-0.014*** (0.002)	0.0252*** (0.005)	-0.0132*** (0.002)
orders ⁻	-0.053*** (0.005)	0.029*** (0.003)	-0.051*** (0.005)	0.028*** (0.003)	-0.0512*** (0.005)	0.0282*** (0.003)
develp ⁻	-0.053*** (0.005)	0.030*** (0.003)	-0.052*** (0.005)	0.029*** (0.003)	-0.0522*** (0.005)	0.0292*** (0.003)
state ⁺	-0.002 (0.007)	0.001 (0.004)	-0.001 (0.007)	0.001 (0.004)	-0.002 (0.007)	0.001 (0.004)
volume ⁺	0.042*** (0.005)	-0.022*** (0.003)	0.043*** (0.005)	-0.022*** (0.003)	0.0442*** (0.005)	-0.0232*** (0.003)
orders ⁺	0.012 (0.009)	-0.006 (0.005)	0.012 (0.009)	-0.006 (0.005)	0.013 (0.009)	-0.007 (0.005)
develp ⁺	-0.032*** (0.007)	0.018*** (0.004)	-0.031*** (0.007)	0.017*** (0.004)	-0.0322*** (0.007)	0.0182*** (0.004)
inflation	0.007 (0.005)	-0.004 (0.003)	0.004 (0.005)	-0.002 (0.003)	0.004 (0.005)	-0.002 (0.003)
oil	-0.101*** (0.016)	0.054*** (0.009)	-0.110*** (0.016)	0.059*** (0.009)	-0.114*** (0.017)	0.061*** (0.009)
exchrates	0.075*** (0.023)	-0.040*** (0.012)	0.079*** (0.023)	-0.042*** (0.012)	0.076*** (0.023)	-0.041*** (0.012)
EUR	0.015 (0.010)	-0.008 (0.005)	0.019* (0.010)	-0.010* (0.005)	0.019 (0.010)	-0.010 (0.005)
VAT	0.094*** (0.007)	-0.043*** (0.003)	0.195*** (0.007)	-0.043*** (0.003)	0.096*** (0.007)	-0.044*** (0.003)
price_ws	0.197*** (0.008)	-0.105*** (0.004)	0.195*** (0.008)	-0.104*** (0.004)	0.199*** (0.008)	-0.107*** (0.004)
price_m	0.082*** (0.008)	-0.044*** (0.004)	0.076*** (0.008)	-0.041*** (0.004)	0.080*** (0.008)	-0.043*** (0.004)
taylor6 ^{t+i}	-0.002 (0.005)	0.001 (0.003)	-0.020*** (0.005)	0.011*** (0.003)	-0.021*** (0.005)	0.011*** (0.003)
taylor12 ^{t+i}	0.026*** (0.005)	-0.014*** (0.003)	0.021*** (0.005)	-0.011*** (0.003)	0.013*** (0.005)	-0.007*** (0.003)
taylor18 ^{t+i}	-0.038*** (0.005)	0.021*** (0.003)	-0.054*** (0.005)	0.030*** (0.003)	-0.034*** (0.005)	0.019*** (0.003)
taylor24 ^{t+i}	-0.022*** (0.005)	0.012*** (0.003)	-0.029*** (0.005)	0.016*** (0.003)	-0.033*** (0.005)	0.018*** (0.003)
winter	0.080*** (0.006)	-0.040*** (0.003)	0.075*** (0.006)	-0.037*** (0.003)	0.075*** (0.006)	-0.037*** (0.003)
summer	0.126*** (0.006)	-0.059*** (0.002)	0.119*** (0.006)	-0.056*** (0.002)	0.119*** (0.006)	-0.056*** (0.002)
fall	0.068*** (0.006)	-0.034*** (0.003)	0.066*** (0.006)	-0.033*** (0.003)	0.066*** (0.006)	-0.033*** (0.003)
Log.-Lik.	-41516.232		-41442.689		-41481.265	
Obs.	46611		46611		46611	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The table reports marginal effects (ME), which are calculated for outcomes “price increase” and “price decrease”, respectively, setting all variables at their mean. For binary regressors, the effect is for discrete change from 0 to 1. We additionally include but don’t report firm-specific averages of the individual-specific variables, the first individual observation of the dependent variable and sectoral dummies. We include the modified Taylor dummies accounting for the additional time elapsed between the reporting month and the period of the expected price change.

Table 2.10: Robustness Check: Bivariate Ordered Probit, Different Taylor Dummies.

	Expectation for $t + 2$			
	increase, increase		decrease, decrease	
	ME	St.Err.	ME	St.Err.
state ⁻	-0.024***	0.002	0.010***	0.001
volume ⁻	0.006***	0.002	-0.003***	0.001
orders ⁻	-0.027***	0.003	0.012***	0.001
develp ⁻	-0.028***	0.003	0.013***	0.001
state ⁺	0.005	0.003	-0.002	0.001
volume ⁺	0.028***	0.003	-0.011***	0.001
orders ⁺	-0.010**	0.004	0.003**	0.002
develp ⁺	-0.023***	0.003	0.010***	0.002
inflation	0.008***	0.003	-0.003***	0.001
oil	-0.010	0.008	0.009	0.003
exchrates	0.027**	0.011	-0.013**	0.005
EUR	0.021***	0.006	-0.007***	0.002
VAT	0.064***	0.004	-0.019***	0.001
price_ws	0.188***	0.004	-0.073***	0.002
price_m	0.040***	0.004	-0.017***	0.002
taylor66 ^{t+2}	-0.006***	0.001	0.003***	0.001
taylor126 ^{t+2}	0.004***	0.001	-0.002***	0.001
taylor186 ^{t+2}	-0.015***	0.001	0.008***	0.001
taylor246 ^{t+2}	-0.007***	0.001	0.004***	0.001
taylor6	-0.007***	0.002	0.002***	0.001
taylor12	0.004**	0.002	-0.001**	0.001
taylor18	-0.018***	0.002	0.006***	0.001
taylor24	-0.010***	0.002	0.003***	0.001
winter	0.024***	0.003	-0.011***	0.001
summer	0.033***	0.003	-0.016***	0.001
fall	0.015***	0.003	-0.008***	0.001
Log.-Lik.	-81823.010			
Obs.	46611			
Wald test of independence	Prob> chi2 = 0.000			

*** p<0.01, ** p<0.05, *p<0.1. The table reports marginal effects (ME) and robust standard errors (St.Err.). MEs are calculated for outcomes (1,1) - “price increase” and “expected price increase” and (-1,-1) - “price decrease” and “expected price decrease”. All variables are set at their mean. For binary regressors, the effect is for discrete change from 0 to 1. We additionally include but don’t report firm-specific averages of the individual-specific variables, the first individual observation of the dependent variable and sectoral dummies. We perform a seemingly unrelated estimation with two different sets of regressors for the respective equations. For the *eprice*-equation, modified Taylor dummies are included assuming that firms in fact report expectations for month $t + 2$.

Table 2.11: Robustness Check: Different Estimation Methods. Dependent Variable: *price*

	Conditional Logit		Panel Probit - CRE		Linear Regression		
	Incr.	Decr.	Incr.	Decr.	Pooled	FE	IV Reg
state ⁻	-0.025*** (0.005)	0.031*** (0.004)	-0.032*** (0.006)	0.024*** (0.004)	-0.064*** (0.007)	-0.047*** (0.007)	-0.049* (0.026)
volume ⁻	-0.003 (0.005)	0.002 (0.004)	0.000 (0.006)	0.018*** (0.004)	-0.002 (0.007)	-0.018*** (0.007)	0.149** (0.070)
orders ⁻	-0.022*** (0.005)	0.035*** (0.004)	-0.013** (0.006)	0.027*** (0.004)	-0.069*** (0.007)	-0.036*** (0.007)	-0.167*** (0.021)
develp ⁻	-0.015** (0.006)	0.044*** (0.005)	-0.010 (0.006)	0.026*** (0.004)	-0.069*** (0.007)	-0.032*** (0.007)	-0.130*** (0.020)
state ⁺	0.025*** (0.007)	0.009 (0.006)	0.021*** (0.007)	0.002 (0.005)	0.032*** (0.010)	0.024** (0.009)	0.651** (0.028)
volume ⁺	0.028*** (0.006)	-0.037*** (0.004)	0.019*** (0.006)	-0.013*** (0.004)	0.071*** (0.008)	0.028*** (0.007)	0.023 (0.100)
orders ⁺	-0.015* (0.008)	0.044*** (0.008)	-0.003 (0.009)	0.022*** (0.007)	-0.035*** (0.011)	-0.017 (0.012)	-0.183 (0.030)
develp ⁺	-0.014** (0.007)	0.053*** (0.007)	-0.005 (0.008)	0.020*** (0.006)	-0.055*** (0.010)	-0.022** (0.010)	-0.169*** (0.033)
inflation	0.024*** (0.005)	0.002 (0.004)	0.019*** (0.005)	0.002 (0.004)	0.022*** (0.007)	0.013** (0.006)	0.019** (0.008)
oil	-0.280*** (0.023)	-0.253*** (0.018)	-0.198*** (0.030)	-0.093*** (0.019)	0.090*** (0.030)	0.007 (0.030)	0.167*** (0.034)
exchrates	-0.022 (0.031)	-0.011 (0.022)	-0.037 (0.037)	0.027 (0.025)	0.048 (0.011)	-0.012 (0.041)	0.108** (0.044)
EUR	0.060*** (0.012)	-0.004 (0.007)	0.069*** (0.012)	-0.007 (0.006)	0.061*** (0.013)	0.066*** (0.013)	0.082*** (0.015)
VAT	0.089*** (0.008)	-0.039*** (0.004)	0.094*** (0.009)	-0.025*** (0.004)	0.120*** (0.010)	0.096*** (0.009)	0.108*** (0.010)
pr_ws	0.315*** (0.008)	-0.212** (0.006)	0.362*** (0.013)	-0.175*** (0.010)	0.552*** (0.011)	0.552*** (0.012)	0.540*** (0.012)
pr_man	0.121*** (0.008)	0.013*** (0.006)	0.101*** (0.009)	-0.008 (0.005)	0.071*** (0.011)	0.061*** (0.010)	0.049*** (0.012)
taylor12	0.122*** (0.005)	0.074** (0.004)	0.087*** (0.005)	0.052*** (0.004)	0.021*** (0.006)	0.006 (0.006)	0.015** (0.007)
taylor24	0.051*** (0.005)	0.060** (0.004)	0.027*** (0.005)	0.043*** (0.004)	-0.027*** (0.007)	-0.043*** (0.006)	-0.045*** (0.007)
winter	0.031*** (0.006)	0.019** (0.005)	0.054*** (0.007)	0.024*** (0.004)	0.005 (0.008)	0.012** (0.007)	-0.002 (0.009)
summer	0.016** (0.006)	0.007 (0.005)	0.034*** (0.007)	0.011*** (0.004)	0.005 (0.008)	0.010 (0.007)	-0.006 (0.014)
fall	-0.013** (0.006)	-0.003 (0.005)	-0.010 (0.006)	-0.005 (0.004)	-0.014 (0.008)	-0.004 (0.008)	0.016 (0.031)
Log-Lik.	-22221	-18184	-19640	-15664			
Obs.	46611	46611	46611	46611	46611	46611	46611

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Columns 2 and 3 report marginal effects from a pooled logit regression for price increases and decreases, respectively. Columns 4 and 5 report marginal effects from a panel probit regression with correlated random effects. Marginal effects are computed by setting all variables at their mean. For binary regressors, the effect is for discrete change from 0 to 1. Column 6 reports coefficients from a linear regression. Column 7 reports coefficients from a linear panel regression with fixed effects. Column 8 reports coefficients from a linear instrumental variables regression using a 2SLS estimator with volume⁻, orders⁻, develp⁻, volume⁺, orders⁺ and develp⁺ as endogenous variables instrumented by their respective first lags.

Table 2.12: Robustness Check: Different Estimation Methods. Dependent Variable: *expected price*

	Conditional Logit		Panel Probit - CRE		Linear Regression		
	Incr.	Decr.	Incr.	Decr.	Pooled	FE	IV Reg
state ⁻	-0.050*** (0.006)	0.023*** (0.003)	-0.060*** (0.006)	0.011*** (0.002)	-0.069*** (0.007)	-0.063*** (0.007)	-0.051** (0.026)
volume ⁻	0.037*** (0.006)	-0.005* (0.003)	0.026*** (0.006)	0.003 (0.002)	0.043*** (0.007)	0.020*** (0.007)	0.186*** (0.069)
orders ⁻	-0.043*** (0.006)	0.039*** (0.004)	-0.053*** (0.007)	0.021*** (0.003)	-0.082*** (0.008)	-0.077*** (0.007)	-0.154*** (0.021)
develp ⁻	-0.009 (0.006)	0.060*** (0.004)	-0.001 (0.007)	0.026*** (0.003)	-0.083*** (0.008)	-0.056*** (0.007)	-0.181*** (0.020)
state ⁺	0.008 (0.008)	0.018*** (0.005)	0.009 (0.008)	0.002 (0.002)	-0.009 (0.010)	0.013 (0.009)	0.030 (0.028)
volume ⁺	0.041*** (0.006)	-0.022*** (0.003)	0.005 (0.007)	-0.005*** (0.002)	0.066*** (0.008)	0.015** (0.007)	0.041 (0.100)
orders ⁺	0.041*** (0.010)	0.031*** (0.007)	0.032*** (0.011)	0.010*** (0.004)	0.013 (0.012)	0.028 (0.012)	0.001 (0.029)
develp ⁺	-0.005 (0.009)	0.049*** (0.006)	0.009 (0.009)	0.005* (0.003)	-0.050*** (0.010)	0.004 (0.010)	-0.122*** (0.032)
inflation	0.015*** (0.005)	0.006* (0.003)	0.007 (0.006)	0.003** (0.002)	0.012* (0.007)	0.003 (0.006)	0.004 (0.008)
oil	-0.448*** (0.028)	-0.139*** (0.013)	-0.356*** (0.032)	-0.013 (0.008)	-0.115*** (0.030)	-0.157*** (0.029)	-0.071** (0.033)
exchrates	0.051 (0.035)	-0.040** (0.016)	0.035 (0.042)	-0.016 (0.012)	0.110*** (0.042)	0.092** (0.040)	0.195*** (0.043)
EUR	0.035*** (0.012)	0.014** (0.006)	0.057*** (0.013)	0.001 (0.003)	0.019 (0.014)	0.045*** (0.013)	0.041*** (0.015)
VAT	0.106*** (0.008)	-0.027*** (0.003)	0.111*** (0.009)	-0.013*** (0.002)	0.130*** (0.010)	0.109*** (0.009)	0.119*** (0.010)
pr_ws	0.206*** (0.010)	-0.081*** (0.005)	0.202*** (0.012)	-0.015*** (0.003)	0.285*** (0.011)	0.213*** (0.012)	0.283*** (0.011)
pr_m	0.157*** (0.009)	-0.005 (0.005)	0.146*** (0.010)	-0.031*** (0.004)	0.135*** (0.011)	0.134*** (0.010)	0.103*** (0.012)
taylor12	0.096*** (0.005)	0.015*** (0.003)	0.072*** (0.006)	-0.004*** (0.001)	0.065*** (0.006)	0.071*** (0.006)	0.068*** (0.007)
taylor24	0.049*** (0.006)	0.011*** (0.003)	0.026*** (0.006)	-0.005*** (0.001)	0.022*** (0.007)	0.033*** (0.006)	0.027*** (0.007)
winter	0.043*** (0.007)	-0.050*** (0.003)	0.068*** (0.007)	-0.021*** (0.002)	0.105*** (0.008)	0.107*** (0.007)	0.098*** (0.008)
summer	0.103*** (0.007)	-0.064*** (0.003)	0.133*** (0.008)	-0.030*** (0.003)	0.176*** (0.008)	0.177*** (0.007)	0.179*** (0.014)
fall	0.119*** (0.007)	-0.002 (0.003)	0.142*** (0.008)	-0.001 (0.002)	0.098*** (0.008)	0.103*** (0.007)	0.121*** (0.031)
Log.-Lik.	-26053	-15147	-22392	-11882			
Obs.	46611	46611	46611	46611	46611	46611	46611

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Columns 2 and 3 report marginal effects from a pooled logit regression for price increases and decreases, respectively. Columns 4 and 5 report marginal effects from a panel probit regression with correlated random effects. Marginal effects are computed by setting all variables at their mean. For binary regressors, the effect is for discrete change from 0 to 1. Column 6 reports coefficients from a linear regression. Column 7 reports coefficients from a linear panel regression with fixed effects. Column 8 reports coefficients from a linear instrumental variables regression using a 2SLS estimator with volume⁻, orders⁻, develp⁻, volume⁺, orders⁺ and develp⁺ as endogenous variables instrumented by their respective first lags.

Table 2.13: Robustness Check: Ordered Probit Regressions, Variations in Set of Regressors. Dependent Variable: *price*

	(3a)		(3b)		(3c)		(3d)	
	Incr.	Decr.	Incr.	Decr.	Incr.	Decr.	Incr.	Decr.
statebus ⁻	-0.040*** (0.004)	0.033*** (0.003)	-0.036*** (0.004)	0.029*** (0.003)	-0.014*** (0.004)	0.012*** (0.003)	-0.030*** (0.004)	0.025*** (0.003)
busvol ⁻	-0.001 (0.004)	0.001 (0.003)	-0.001 (0.004)	0.001 (0.003)	0.027 (0.004)	-0.021 (0.003)	-0.005*** (0.004)	0.004*** (0.003)
orders ⁻	-0.039*** (0.004)	0.032*** (0.004)	-0.040*** (0.004)	0.033*** (0.003)	-0.037*** (0.004)	0.030*** (0.004)	-0.030*** (0.004)	0.024*** (0.004)
busdev ⁻	-0.030*** (0.004)	0.025*** (0.004)	-0.040*** (0.004)	0.033*** (0.004)	-0.033*** (0.005)	0.027*** (0.004)	-0.033*** (0.005)	0.028*** (0.004)
statebus ⁺	0.017*** (0.006)	-0.014*** (0.005)	0.021*** (0.006)	-0.016*** (0.005)	0.008 (0.006)	-0.006 (0.005)	0.012** (0.006)	-0.010** (0.005)
busvol ⁺	0.039*** (0.005)	-0.031*** (0.003)	0.042*** (0.005)	-0.032*** (0.003)	0.027*** (0.005)	-0.021*** (0.003)	0.035*** (0.005)	-0.027*** (0.003)
orders ⁺	-0.029*** (0.007)	0.025*** (0.007)	-0.019*** (0.007)	0.015** (0.006)	-0.016** (0.008)	0.013** (0.007)	-0.029*** (0.007)	0.025*** (0.007)
busdev ⁺	-0.038*** (0.006)	0.033*** (0.006)	-0.030*** (0.006)	0.025*** (0.005)	-0.036*** (0.006)	0.031*** (0.006)	-0.040*** (0.006)	0.035*** (0.006)
inflation	0.366*** (0.046)	-0.299*** (0.038)	0.017*** (0.005)	-0.013*** (0.004)	0.292*** (0.041)	-0.233*** (0.033)	0.044*** (0.006)	-0.035*** (0.005)
oil	-0.003 (0.016)	0.003 (0.014)	0.052*** (0.013)	-0.041*** (0.011)	0.046*** (0.015)	-0.037*** (0.012)	0.004** (0.002)	-0.003** (0.002)
exchrates	-0.017 (0.020)	-0.014 (0.017)	0.022 (0.019)	-0.017 (0.015)	0.030 (0.019)	-0.024 (0.015)	-0.001* (0.001)	0.001* (0.001)
EUR	0.046*** (0.009)	-0.034*** (0.006)	0.037*** (0.009)	-0.027*** (0.006)	0.035*** (0.009)	-0.026*** (0.006)	0.037*** (0.009)	-0.027*** (0.006)
VAT	0.079*** (0.006)	-0.056*** (0.004)	0.078*** (0.007)	-0.053*** (0.004)	0.077*** (0.007)	-0.053*** (0.004)	0.074*** (0.007)	-0.051*** (0.004)
pr_ws	0.338*** (0.007)	-0.276*** (0.005)	0.333*** (0.007)	-0.263*** (0.006)	0.321*** (0.007)	-0.257*** (0.006)	0.315*** (0.007)	-0.251*** (0.006)
pr_man	0.050*** (0.007)	-0.041*** (0.006)	0.043*** (0.007)	-0.034*** (0.005)	0.043*** (0.007)	-0.034*** (0.005)	0.048*** (0.006)	-0.038*** (0.005)
taylor12	0.017*** (0.004)	-0.014*** (0.003)	0.022*** (0.004)	-0.017*** (0.003)	0.021*** (0.004)	-0.016*** (0.003)	0.019*** (0.004)	-0.015*** (0.003)
taylor24	-0.015*** (0.004)	0.012*** (0.003)	-0.015*** (0.004)	0.012*** (0.003)	-0.017*** (0.004)	0.014*** (0.003)	-0.016*** (0.004)	0.013*** (0.003)
winter	0.009* (0.005)	-0.007* (0.004)	0.003 (0.005)	-0.002 (0.004)	0.003 (0.005)	-0.002 (0.004)	0.002 (0.005)	-0.002 (0.004)
summer	-0.001 (0.005)	0.001 (0.004)	-0.003 (0.005)	0.002 (0.004)	0.003 (0.005)	-0.002 (0.004)	0.005 (0.005)	-0.004 (0.004)
fall	-0.002 (0.005)	0.002 (0.004)	-0.008 (0.005)	0.006 (0.004)	0.003 (0.005)	-0.002 (0.004)	-0.008* (0.005)	0.006* (0.004)
Log.-Lik.	-46571		-41882		-4182		-40953	
Obs.	50904		46611		45683		45683	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, *p<0.1. The table reports marginal effects for the outcomes “price increase” and “price decrease”, respectively, setting all variables at their mean. For binary regressors, the effect is for discrete change from 0 to 1. We additionally include but don’t report firm-specific averages of the individual-specific variables, the first individual observation of the dependent variable, sectoral dummies as well as Taylor dummies for six and 18 months, respectively. (3a): including the cumulative rate of change of the aggregate rate of CPI inflation, (3b): excluding firm-specific means of idiosyncratic variables, (3c): idiosyncratic variables enter in first lags, (3d): macroeconomic variables included as month-on-month changes.

Table 2.14: Robustness Check: Ordered Probit Regressions, Variations in Set of Regressors. Dependent Variable: *expected price*

	(3a)		(3b)		(3c)		(3d)	
	Incr.	Decr.	Incr.	Decr.	Incr.	Decr.	Incr.	Decr.
state ⁻	-0.048*** (0.005)	0.026*** (0.003)	-0.044*** (0.004)	0.024*** (0.002)	-0.027*** (0.005)	0.015*** (0.003)	-0.048*** (0.005)	0.026*** (0.003)
volume ⁻	-0.028*** (0.005)	-0.015*** (0.002)	0.028*** (0.005)	-0.015*** (0.002)	0.032*** (0.005)	-0.018*** (0.003)	0.027*** (0.005)	-0.014*** (0.002)
orders ⁻	-0.062*** (0.005)	0.034*** (0.003)	-0.062*** (0.005)	0.034*** (0.003)	-0.048*** (0.005)	0.028*** (0.003)	-0.061*** (0.005)	0.034*** (0.003)
develp ⁻	-0.053*** (0.005)	0.030*** (0.003)	-0.066*** (0.005)	0.037*** (0.003)	-0.057*** (0.005)	0.034*** (0.003)	-0.054*** (0.005)	0.030*** (0.003)
state ⁺	0.005 (0.007)	0.003 (0.003)	-0.004 (0.007)	0.002 (0.004)	-0.017** (0.007)	0.010** (0.004)	-0.006 (0.007)	0.003 (0.004)
volume ⁺	0.044*** (0.005)	-0.023*** (0.003)	0.049*** (0.005)	-0.025*** (0.003)	0.034*** (0.005)	-0.019*** (0.003)	0.044*** (0.005)	-0.023*** (0.003)
orders ⁺	0.005 (0.009)	-0.003*** (0.005)	0.015* (0.008)	-0.008* (0.004)	-0.031*** (0.009)	0.018*** (0.005)	0.005 (0.009)	-0.003 (0.005)
develp ⁺	-0.032*** (0.007)	0.018*** (0.004)	-0.026*** (0.007)	0.014*** (0.004)	-0.051*** (0.007)	0.031*** (0.005)	-0.033*** (0.007)	0.019*** (0.004)
inflation	0.469*** (0.049)	-0.253*** (0.027)	0.009* (0.005)	-0.005* (0.003)	1.261*** (0.119)	-0.713*** (0.068)	0.011** (0.005)	-0.006** (0.003)
oil	-0.112 (0.017)	0.061*** (0.010)	-0.083*** (0.016)	0.044*** (0.009)	-0.083*** (0.016)	0.047*** (0.009)	-0.010*** (0.002)	0.005*** (0.001)
exchrates	0.078*** (0.022)	-0.042 (0.012)	0.081*** (0.023)	-0.043*** (0.012)	0.118*** (0.023)	-0.067*** (0.013)	-0.002** (0.001)	0.001** (0.000)
EUR	0.021** (0.010)	-0.011** (0.005)	0.014 (0.010)	-0.007 (0.005)	0.000 (0.010)	0.000 (0.006)	0.020** (0.010)	-0.011** (0.005)
VAT	0.096*** (0.007)	-0.044*** (0.003)	0.094*** (0.007)	-0.043*** (0.003)	0.085*** (0.007)	-0.042*** (0.003)	0.094*** (0.007)	-0.043*** (0.003)
price_ws	0.200*** (0.007)	-0.276*** (0.005)	0.208*** (0.008)	-0.111*** (0.004)	0.340*** (0.007)	-0.192*** (0.004)	0.198*** (0.008)	-0.107*** (0.004)
pr_m	0.097*** (0.007)	-0.041*** (0.006)	0.090*** (0.008)	-0.048*** (0.004)	0.067*** (0.008)	-0.038*** (0.004)	0.088*** (0.007)	-0.048*** (0.004)
taylor12	0.049*** (0.004)	-0.026*** (0.003)	0.046*** (0.005)	-0.024*** (0.002)	0.044*** (0.005)	-0.024*** (0.003)	0.049*** (0.004)	-0.026*** (0.002)
taylor24	0.014*** (0.004)	0.007*** (0.002)	0.017*** (0.005)	-0.009*** (0.003)	0.015*** (0.005)	-0.008*** (0.003)	0.013*** (0.005)	-0.007*** (0.002)
winter	0.072*** (0.005)	-0.035* (0.003)	0.071*** (0.006)	-0.035*** (0.003)	0.057*** (0.006)	-0.031*** (0.003)	0.078*** (0.005)	-0.039*** (0.003)
summer	0.122*** (0.006)	-0.058 (0.002)	0.119*** (0.006)	-0.056*** (0.002)	0.120*** (0.006)	-0.060*** (0.003)	0.125*** (0.006)	-0.059*** (0.002)
fall	0.069*** (0.006)	-0.034 (0.003)	0.069*** (0.006)	-0.034*** (0.003)	0.069*** (0.006)	-0.031*** (0.003)	0.067*** (0.006)	-0.034*** (0.003)
Log.-Lik.	-45426		-41540		-40800		-45450	
Obs.	50904		46611		45683		50904	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, *p<0.1. The table reports marginal effects for the outcomes “expected price increase” and “expected price decrease”, respectively, setting all variables at their mean. For binary regressors, the effect is for discrete change from 0 to 1. We additionally include but don’t report firm-specific averages of the individual-specific variables, the first individual observation of the dependent variable, sectoral dummies as well as Taylor dummies for six and 18 months, respectively. (3a): including the cumulative rate of change of the aggregate rate of CPI inflation, (3b): excluding firm-specific means of idiosyncratic variables, (3c): idiosyncratic variables enter in first lags, (3d): macroeconomic variables included as month-on-month changes.

Table 2.15: Robustness Check: Ordered Probit Regressions, Including Time-Specific Effects instead of Macro Variables

	Dependent: <i>price</i>				Dependent: <i>expected price</i>			
	Increase		Decrease		Increase		Decrease	
	ME	St.Err.	ME	St.Err.	ME	St.Err.	ME	St.Err.
state ⁻	-0.026***	-0.004	0.021***	-0.003	-0.028***	0.005	0.015***	0.003
volume ⁻	-0.038***	-0.005	0.031***	-0.004	-0.016***	0.005	0.009***	0.003
orders ⁻	-0.030***	-0.004	0.025***	-0.004	-0.051***	0.005	0.027***	0.003
devel ⁻	-0.032***	-0.004	0.026***	-0.004	-0.057***	0.005	0.031***	0.003
state ⁺	0.011*	-0.006	-0.009*	-0.005	-0.021***	0.007	0.011***	0.004
volume ⁺	0.002	-0.005	-0.002	-0.004	0.018***	0.006	-0.009***	0.003
orders ⁺	-0.039***	-0.007	0.034***	-0.007	0.001	0.009	-0.001	0.004
devel ⁺	-0.036***	-0.006	0.032***	-0.006	-0.032***	0.007	0.018***	0.004
price_ws	0.284***	-0.008	-0.229***	-0.006	0.160***	0.008	-0.083***	0.004
price_m	0.109***	-0.041	-0.088***	-0.033	-0.208	0.174	0.109	0.091
taylor12	0.014***	-0.004	-0.011***	-0.003	0.037***	0.005	-0.019***	0.002
taylor24	0.000	-0.004	0.000	-0.003	0.037***	0.005	-0.019***	0.002
summer	-0.079	-0.048	0.070	-0.047	0.227***	0.072	-0.096***	0.025
winter	0.095**	-0.044	-0.068**	-0.028	0.293***	0.054	-0.115***	0.016
fall	0.086*	-0.049	-0.063*	-0.032	0.192***	0.056	-0.082***	0.019
Log-Lik.	-45352.474				-44431.587			
Obs.	50904				50904			
Wald Test Joint Sign.	Prob > chi2 = 0.0000							

*** p<0.01, ** p<0.05, *p<0.1. The table reports marginal effects (ME) and robust standard errors (St.Err.). MEs are calculated for outcomes “price increase” and “price decrease” and “expected price increase” and “expected price decrease”, respectively, setting all variables at their mean. For binary regressors, the effect is for discrete change from 0 to 1. We additionally include but don’t report time-fixed effects, firm-specific averages of the individual-specific variables, the first individual observation of the dependent variable, sectoral dummies as well as Taylor dummies for six and 18 months.

Chapter 3

Real Effects of Quantitative Easing at the Zero Lower Bound: Structural VAR-Based Evidence from Japan^{*}

3.1 Introduction

So far, unconventional monetary policy measures have mainly been evaluated on the basis of their effects on financial variables such as interest rates or interest rate spreads. There are only few empirical studies analyzing the effectiveness of monetary policy during “exceptional times” with respect to real activity and other macroeconomic variables. We attempt to close this gap by studying the real effects of Quantitative Easing (QE) in a structural VAR (SVAR) model when the short-term interest rate is constrained by the zero lower bound (ZLB). We use monthly Japanese data for the period 1995-2010 - a period during which the Bank of Japan’s target rate, the overnight call rate, has been very close to zero. We propose a novel sign restriction setup based on corresponding DSGE models to identify our structural shocks. Estimating the model, we find that a QE-shock which raises reserves by about 7% leads to a significant drop in long-term interest rates and significantly increases industrial production by 0.4% after about 20 months. The same shock has a rather weak and similarly transient effect on prices. Our results thus provide mixed evidence on the successfulness of QE in Japan suggesting that whilst real economic activity does seem to pick

^{*}This paper is joint work with Sebastian Watzka

up temporarily after a QE-shock, it does not seem to affect prices in such a way that Japan could exit its deflationary period. However, compared to a traditional monetary policy shock during “normal times”, identified for the pre-1995 period when monetary policy was not constrained by the ZLB, the QE-shock only has a very limited potential to favorably affect *both* output and prices. With regard to possible monetary transmission channels at the ZLB, our results can only offer preliminary conclusions. While the long-term yield decreases significantly, which could potentially lead to portfolio rebalancing effects, the exchange rate does not react to the shock during our full sample period. Moreover, broader money supply does not react to the QE-shock suggesting a limited scope for policy transmission via direct quantity effects at the ZLB.

Our study adds to the existing literature in various important ways. First, focusing specifically on post-1995 Japanese data where the policy rate of the Bank of Japan was very close to zero allows us to identify a monetary policy shock at the ZLB. In particular, we identify a shock that raises reserves held at the Bank of Japan, which was the main monetary instrument during the ZLB period we consider. We call such a shock unconventional monetary policy shock or QE-shock for short. Thus, we mainly focus on the effects of quantitative easing as opposed to other non-standard measures.¹ Second, including a set of standard macro variables in our VAR allows us to analyze the effects of such a QE-shock on a broader set of variables than usually studied in the literature on unconventional monetary policy effects. In particular, we assess the effects of a QE-shock on real economic activity and on prices, but also investigate its effects on the long-term government bond yield, the exchange rate and money supply. Third, using a sign restriction approach to identify the QE-shock allows us to remain relatively agnostic about whether, how, and when real activity and the long-term interest rate respond to the shock. In particular, in contrast to most of the existing literature, we do not have to restrict the long-term yield nor the exchange rate in order to credibly identify an unconventional monetary shock, which allows us to let the data speak concerning the effects on these variables. Short-term policy rates in the US, the Euro area, the UK and other industrialized

¹The literature generally defines as unconventional such monetary measures adopted by central banks that differ from a traditional interest rate setting decision. Examples of other monetary alternatives include alterations of the composition of the central banks balance sheet (“qualitative easing”) or changing interest-rate expectations by policy commitments. For more details on the different dimensions along which unconventional policy measures can be classified see Bernanke and Reinhart (2004) or Meier (2009).

economies are currently very low and therefore possibly also constrained by the ZLB. To the extent the economic circumstances are similar in these countries, our results may thus also shed light on the effects of the currently implemented quantitative easing measures adopted by other central banks.

The effects of monetary policy shocks when monetary policy is not constrained by the ZLB has been well documented in the literature. There is a broad consensus that expansionary monetary policy, by lowering the policy interest rate, temporarily affects inflation and output positively.² There is much less empirical evidence on the real effects of monetary policy shocks at the ZLB. One obvious reason might be that most economies until very recently have not been in such a situation and that sample periods to use in estimation would thus be notoriously short. However, at least since 2000, when the Fed lowered the Federal Funds rate to very low levels in response to the bursting of the IT-bubble, there has been an important theoretical discussion on how to avoid liquidity traps and how to escape them once an economy found itself in the trap.³ This literature identifies at least two possible transmission channels of monetary policy at the ZLB, summarized for instance by Bernanke and Reinhart (2004). First, an increase in reserves induces investors to rebalance their portfolios as a consequence of decreasing marginal returns to liquidity resulting from the money increase in the investor's portfolio. Consequently, investors tend to reduce money holding and increase purchases of other assets, such as equities, thereby raising prices of these assets. This portfolio channel is in the spirit of the monetarist analysis of Meltzer (1995), see also Hetzel (2003, 2004) for a discussion. Second, unconventional monetary policy may work by altering expectations concerning the future policy path potentially leading to changing inflation expectations, a channel that is stressed by, *inter alia*, Eggertsson and Woodford (2003).

The recent financial crisis and consequent central bank interest rate cuts have led to renewed interest in the effects of non-standard monetary policies. Examples of recent theoretical models analyzing unconventional policy measures within DSGE frameworks with financial frictions include Nakov (2008), DelNegro et al. (2010), Gertler and Karadi (2011) and Gertler and Kiyotaki (2010). Calibrating the model to the subprime crisis period in the US, for instance Gertler and Karadi

²See Christiano et al. (1999). But note that different identifying restrictions can in fact lead to quite different results; see Uhlig (2005) and Lanne and Lütkepohl (2008).

³See e.g. Bernanke (2002), Bernanke et al. (2004), Bernanke and Reinhart (2004), Krugman (1998) or Svensson (2003).

(2011) find that unconventional monetary policy measures in the form of central bank credit intermediation can have considerable effects on output, inflation and interest rate spreads, especially at the zero lower bound.

While these theoretical contributions thus emphasize real effects of such policy measures, recent empirical studies tend to merely focus on the effect unconventional policies have on financial variables such as long-term interest rates or interest rate spreads. With regard to the effects of quantitative easing on a broader set of macroeconomic variables, these studies are rather silent. Examples of corresponding studies include Gagnon et al. (2011), Hamilton and Wu (2011) and Stroebel and Taylor (2009) for the US, Meier (2009) for the UK, ECB (2010) for the Euro area, Kimura and Small (2006) and Oda and Ueda (2007) for Japan. Analyzing the effects of monetary expansions, most notably in the form of large-scale central bank purchases of government bonds, these studies generally find negative effects on yield spreads of such non-standard policies. In particular, the yields of various assets do tend to decline thereby narrowing the spread to the corresponding risk-free rate. However, these effects are generally found to be very small.

It is important to note, however, that the theoretical impact of such expansionary policy measures on long-term yields is not clear. Theoretical studies such as Doh (2010) refer to portfolio shifts and explain the expansionary effect of such a policy decision by arguing that the purchase of long-term bonds by the central bank will naturally lower long-term bond yields. This lower yield on government bonds then feeds through to other asset markets making long-term financing for investment and durable goods cheaper thereby stimulating aggregate demand. This argument is partly supported by the empirical evidence of the above mentioned studies. However, theoretically it is not clear that long-term yields are indeed supposed to fall in response to QE measures. Indeed, if market participants believe the central bank intervention is successful in stimulating the economy by increasing aggregate demand, inflation and real rates are likely to rise in the future. Inflationary expectations should thus rise and long-term nominal yields should in fact rise as well. Moreover, even if long-term yields were negatively affected by such a policy, there is no broad consensus on whether the portfolio rebalancing channel described above would actually function successfully.⁴

⁴For instance, Eggertsson and Woodford (2003) argue that unconventional policy can only work through changing expectations concerning the future policy outlook and thus inflation rates.

We therefore argue that it is important to remain agnostic about the behavior of long-term yields following expansionary QE-policy shocks. In addition, and importantly, we supplement previous studies by focusing on the effects unconventional policies have on the real economy and on prices. These variables are of ultimate interest to the central bank and general public and of course important for welfare considerations.

So far, the corresponding empirical evidence of unconventional policies on these variables is rather scarce and a consensus on the effectiveness of these measures has not yet been reached. Examples of VAR studies on the monetary transmission in Japan include Miyao (2000, 2002), Fujiwara (2006) and Inoue and Okimoto (2008). While Miyao (2002), however, studies the effects of monetary policy during normal times when monetary policy was not constrained by the ZLB, Miyao (2002), Fujiwara (2006) and Inoue and Okimoto (2008) analyze sample periods at most up to 2003. Hence, these studies are not particularly informative concerning the macroeconomic effects of QEP at the zero lower bound. More recent VAR studies using a sign-restriction approach to identify unconventional monetary shocks at near-zero interest rates for different countries and sample periods include Baumeister and Benati (2010), Peersman (2011) and Kamada and Sugo (2006). While Baumeister and Benati (2010) find some significant real effects of quantitative easing in different countries including Japan for the Great Recession period 2007-09, results reported by Kamada and Sugo (2006) for Japan over the period 1978-2005 are less optimistic. Both studies rely, however, on relatively restrictive identification schemes restricting financial variables such as interest rate spreads or the exchange rate. Peersman (2011) finds that unconventional shocks can in principle affect macroeconomic variables in the Euro area; the responses of output and prices are, however, much more delayed compared to standard policy measures during normal times. Importantly, in this study only those non-standard shocks are identified that actually have an effect on the supply of credit. Using a Bayesian shrinkage VAR model, Lenza et al. (2010) report some significant effects of unconventional monetary shocks on macroeconomic variables such as industrial production, the number of loans granted, unemployment and inflation in the Euro area by means of a counterfactual analysis. However, their exercise implies that only those policy measures are analyzed that actually had an effect on interest rate spreads, which is in the spirit of Peersman (2011). We prefer to remain more agnostic with respect to

the effects of unconventional monetary policy on such financial variables. Further empirical studies on macroeconomic effects of unconventional monetary policy that are less closely related to this paper include Chung et al. (2011) and Bowman et al. (2011). Chung et al. (2011), using a set of structural and time series models estimated for the US, find that asset purchases by the Fed have been successful at mitigating the macroeconomic costs of the ZLB in the US. Finally, Bowman et al. (2011) investigate the “bank lending channel”, emphasized by for instance Kashyap and Stein (2000), of unconventional monetary policy by analyzing Japanese bank-level data and find a significant but rather small effect of QE policies on bank lending.

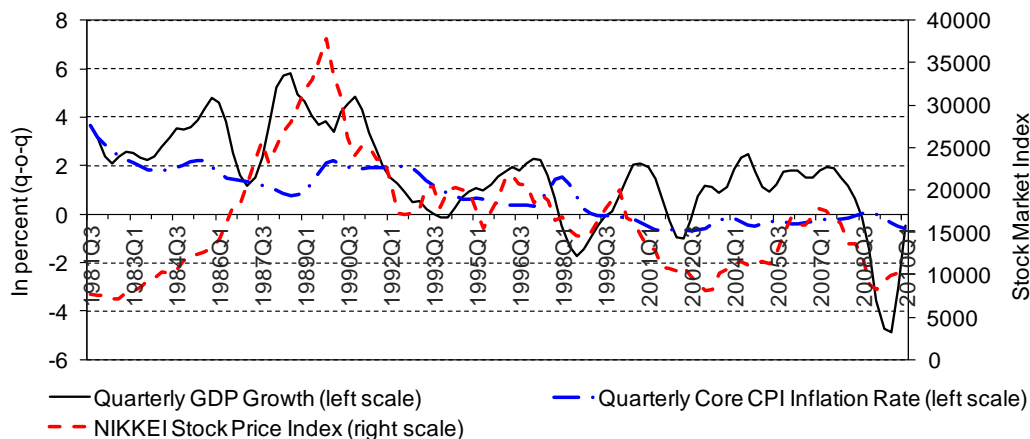
The remainder of the paper is organized as follows: Section 3.2 gives a brief overview of key features of the monetary policy decisions implemented by the Bank of Japan since the stock market crash in the early 90s. Section 3.3 describes the setup of our SVAR model as well as the identification strategy for the unconventional monetary shock. Results are presented and discussed in Section 3.4. Finally, Section 3.5 concludes.

3.2 Monetary Policy in Japan Since the Early 1990s

This section briefly sketches key macroeconomic and monetary policy developments in Japan since the early 1990s. For a thorough discussion please refer to Benati and Goodhart (2010), Ugai (2007) and Mikitani and Posen (2000).

The bursting of the Japanese stock market bubble and the accompanying period of economic distress can be seen in Figure 3.1. The figure displays four-quarter moving averages of the quarterly GDP growth rate as well as the quarterly rate of core consumer price inflation (left scale) along with the quarterly average of the NIKKEI stock index (right scale). The stock market was rising dramatically until around 1990. This went together with an increase in industrial production under fairly low and constant rates of inflation. Realizing that the elevated stock and land prices seemed out of touch with fundamentals the Bank of Japan did in fact continuously increase the call rate. Optimism turned into pessimism around 1990/91 and both stock and land prices started falling rapidly. At the same time, GDP growth decreased; whilst annual GDP grew in the period 1985-91 by an average rate of 3.9% per year, it slowed down to only 0.8% post-1991.

Figure 3.1: Quarterly GDP Growth, Consumer Price Inflation and NIKKEI Stock Index



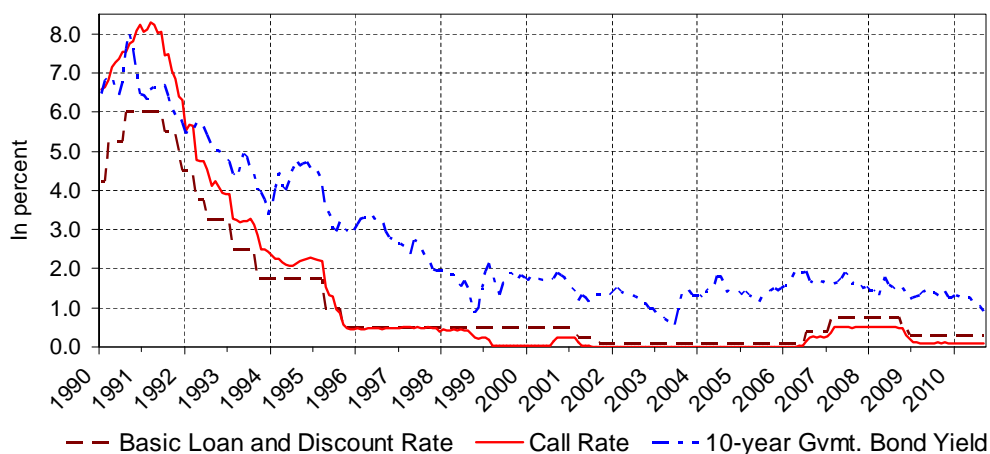
Meanwhile, despite a small spike in the rate of inflation due to the VAT increase in 1997, inflation subsequently decreased reaching negative rates in 1999 and trending below zero from 2000. As a consequence of decreasing growth rates, the usually low Japanese unemployment rate increased sharply. This of course is the numerical basis for the well-known label “Japan’s lost decade”.⁵ In response to these developments, in 1999 the Bank of Japan officially introduced its so-called Zero Interest Rate policy (ZIRP) involving a decrease of the call rate to 0.03% (see Figure 3.2). It also tried to steer market expectations by adding commitments to its policy statements indicating that it would keep the call rate low for a longer time period. Figure 3.2 shows that this is indeed what happened; the call rate stayed below 0.5% until around 2007/2008, while most of the time it was very close to zero. Along with the policy rate other interest rates such as long-term yields decreased during that time; the figure shows that for instance the 10-year government bond yield fell steadily from around 6-8% in the early 1990’s to below 2% in 1998.

Following the bursting of the IT-stock market bubbles the Bank of Japan introduced a more aggressive policy program. From March 2001 until March 2006 it implemented the so-called “Quantitative Easing Policy” (QEP) which consisted of three main elements: (i) the operating target was changed from the call rate to the outstanding current account balances (CABs) held by banks at the Bank of Japan, (ii) to commit itself to continue providing ample liquidity to banks

⁵See e.g. Hayashi and Prescott (2002).

until inflation stabilized at zero percent or a slight increase, and (iii) to increase the amount of outright purchases of long-term Japanese government bonds. In particular, in March 2001 the Bank of Japan set the target for CABs to ¥5tn, higher than the required reserve level. The target was then raised further to ¥35tn in 2004. To meet the respective targets the Bank of Japan purchased ¥400bn worth of long-term government bonds per month at the beginning of QEP; the amount of bonds purchased was later extended to ¥1200bn per month (Benati and Goodhart, 2010).

Figure 3.2: Bank of Japan Short- and Long-Term Interest Rates



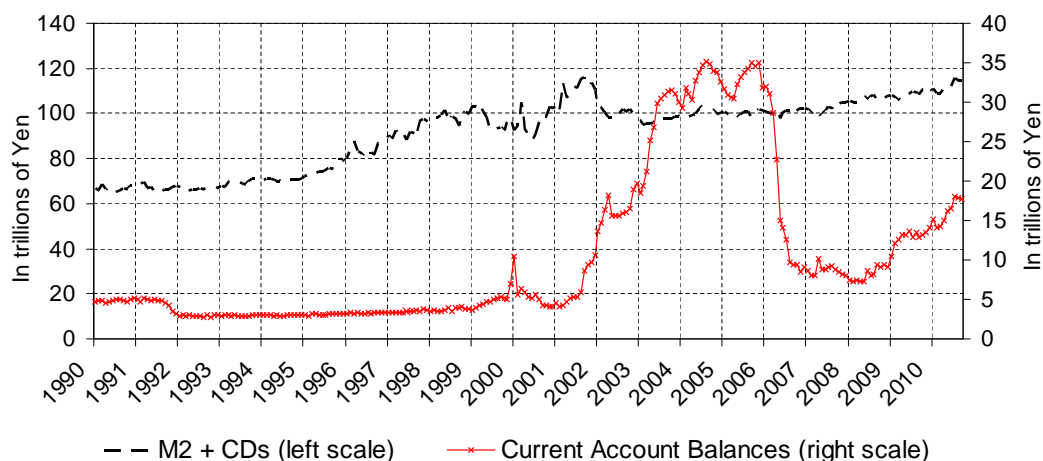
From 2003 onwards the central bank additionally purchased other assets such as equities or asset-backed securities.⁶ The monetary development and the effect of the Bank of Japan’s QEP measures can be seen in Figure 3.3. We plot that part of the monetary base that is the CAB holdings of banks at the Bank of Japan. The figure shows the enormous increase in reserves during the QEP period and later again when the recent financial crisis hit. At the same time we see a short-lived decline in the broader monetary aggregate M2 plus Certificates of Deposits (CDs) with a subsequent stagnation. Thus, apparently, broader measures of the money stock did not increase with the base money expansions confirming the breakdown of the money multiplier during the QEP period in Japan already documented in the literature (Benati and Goodhart, 2010; Kuttner, 2004).

Having these macroeconomic and monetary developments in mind we next want to present our identification strategy based on the reasonable assumption that

⁶See the survey by Ugai (2007) or Benati and Goodhart (2010) for more details.

the Bank of Japan since 1995 did not conduct its monetary policy through the call rate anymore - which was constrained by the ZLB - but by changing the reserve holdings of banks at the Bank of Japan.

Figure 3.3: Monetary Aggregates in Japan



3.3 Identification of Structural Shocks in a Sign Restriction VAR

3.3.1 Specification of the VAR Model

To analyze the effects of monetary policy on economic activity and the price level at the ZLB, the following reduced-form VAR model is estimated:

$$Y_t = c + A(L)Y_{t-1} + u_t, \quad (3.1)$$

where c is a vector of intercepts. Y_t is a vector of endogenous variables, $A(L)$ is a matrix of autoregressive coefficients of the lagged values of Y_t and u_t is a vector of residuals. In this model, the reduced-form error terms are related to the uncorrelated structural errors ϵ_t according to:

$$\epsilon_t = B^{-1}u_t. \quad (3.2)$$

It is explained in the next subsection how we identify and construct the structural shocks.

In our benchmark regression we include the following five macroeconomic variables in the VAR-system:

$$Y_t = [CPI_t, IP_t, RES_t, LTY_t, EXR_t]. \quad (3.3)$$

where CPI_t denotes the core consumer price index and IP_t indicates the Japanese industrial production index. Moreover, we include reserves (RES_t), the 10-year yield of Japanese government bonds (LTY_t) and the real effective exchange rate of the Yen against other currencies (EXR_t) in the set of regressors. The exchange rate is included in the model because its role in the transmission of unconventional policy has been stressed within the theoretical literature on monetary policy at the ZLB (Orphanides and Wieland, 2000; Coenen and Wieland, 2003; McCallum, 2000). These models usually imply a real depreciation of the domestic currency following a base money injection due to portfolio rebalancing effects. A detailed description of the data is given in Appendix 3.A.1.

The VAR model is estimated by means of Bayesian methods using monthly data over the period March 1995 to September 2010. The start of the sample is motivated by the fact that the Bank of Japan first decreased the call rate to values of around 1% in spring 1995 and subsequently lowered the policy rate to 0.5% in the course of the year 1995.⁷ In the benchmark case, six lags of the endogenous variables are included in the estimation, which seems to be sufficient to capture the dynamics of the model.⁸ Except for the long-term yield, all variables are seasonally adjusted and included as log-levels, which, according to Sims et al. (1990) leads to consistent parameter estimates. We linearly detrend all variables prior to estimation. Overall, the model seems to be sufficiently stable; Figure 3A.14 in Appendix 3.A.4 shows that residual autocorrelation does not seem to be a problem, while results of a Residual Autocorrelation LM Test, reported in Table 3A.1, show that the null hypothesis of no residual autocorrelation cannot be rejected for most lag lengths.

With respect to the Bank of Japan's monetary instrument we argue above that Japan has been at the ZLB during the whole sample period under consideration.

⁷As discussed in Section 3.4.4, quantitatively, our main results are insensitive to changing the sample start. Moreover, we additionally estimate the model for the QEP period only, see again Section 3.4.4.

⁸While different lag length criteria lead to different suggestions concerning the number of lags to include, all of them tend to propose an even shorter lag length. Our main results are, however, robust to varying the lag length; see Section 3.4.4.

In the course of 1995, the call rate has been reduced to 0.5% severely reducing its importance as a policy instrument. Because the call rate has at the same time been more or less constant over our sample period we do not include this variable in our VAR.⁹ Instead, we treat as monetary policy instrument bank reserves held at the Bank of Japan. Specifically, we choose the outstanding current account balances of banks held at the Bank of Japan as our measure of reserves. As a robustness check, we estimate an alternative specification including excess reserved held at the Bank of Japan as policy instrument instead of the total volume of bank reserves. As discussed in Section 3.4.4, our results are insensitive to this modification.

Additionally, we estimate a further specification including a measure of Japanese money supply, M2 + CDs. It has been argued that a base money expansion implemented by the Bank of Japan should lead to an increase in broader money supply, M2 + CDs in the case of Japan, and thus to an increase in output and prices due to direct quantity effects (Ugai, 2007; Hetzel, 2004). However, Figure 3.3 suggests a breakdown of the money multiplier during the ZLB period; during the period of massive quantitative easing in the early 2000's M2 + CDs did in fact not increase with the monetary base. This is in line with Kuttner (2004) reporting evidence against a strong relationship between base money and broader money supply during the ZLB episode in Japan. Naturally, in such a situation there is limited scope for direct quantity effects of a monetary expansion, even if in principle a stable link between money supply and output exists.¹⁰

It is thus interesting to more formally investigate to what extent M2 + CDs responds to a structural QE-shock in our model. Our final specification thus additionally includes the log of M2 + CDs ($M2_t$), again seasonally adjusted and linearly detrended:

$$Y_t = [CPI_t, IP_t, RES_t, LTY_t, EXR_t, M2_t]. \quad (3.4)$$

⁹However, we have checked that our results are insensitive to including the call rate in the model.

¹⁰In fact, the question concerning the stability of the relationship between money stock and real activity and prices in Japan during the period of the ZLB is not fully resolved yet; see Miyao (2005), Benati and Goodhart (2010) and the discussion in Ugai (2007).

3.3.2 Identification of Structural Shocks

As in Uhlig (2005), Canova and De Nicrolo (2002) and Peersman (2005) identification of the structural shocks is achieved by imposing sign restrictions on the impulse response functions. Additionally, following Peersman (2011) we impose zero restrictions on selected entries of the contemporaneous coefficient matrix. Using zero restrictions on some designated impact responses next to sign restrictions allows us to improve identification of the structural shocks and thus to enhance the interpretation of the respective impulse response functions by exploiting additional economic information (Kilian and Murphy, 2010).

Next to the unconventional monetary shock we additionally identify two traditional disturbances; a positive demand and a positive supply shock. These shocks are identified in order to prevent that disturbances related to business cycle fluctuations enter the identified unconventional monetary shock. Moreover, identification of these two additional shocks helps to analyze the importance of our shock of interest, the QE shock, relative to these aggregate economic shocks.¹¹ We naturally require the business cycle shocks to be orthogonal to the monetary shock. Mountford and Uhlig (2009) show how the identification setup in Uhlig (2005) can be extended to identify more than one shock; our identification strategy follows their approach. In particular, in order to prevent that any remaining disturbances enter our identified shocks we impose corresponding reverse restrictions on the two unidentified innovations within our VAR system. In contrast to identification strategies based on Cholesky or Blanchard-Quah decompositions, the sign restriction approach explicitly incorporates assumptions that are often used implicitly allowing a more transparent procedure. Moreover, we avoid to impose zero restrictions on long-run impulse responses, which may be problematic both regarding the economic interpretation (Faust, 1998) as well as from a statistical perspective (Faust and Leeper, 1997).

The sign restriction approach is implemented by taking draws for the VAR parameters from the Normal-Wishart posterior, constructing an impulse vector for each draw and calculating the corresponding impulse responses for all variables over the specified horizon.¹² In particular, the reduced-form innovations u_t relate to the structural shocks according to equation (3.2) above with $B = W\Sigma^{1/2}Q$,

¹¹The relative magnitude of the respective shocks is analyzed in Section 3.4.3 by means of a forecast error variance decomposition.

¹²Estimation was performed on the basis of Fabio Canova's SVAR Matlab codes, which can be downloaded from his website <http://www.crei.cat/people/canova/>.

where $W\Sigma^{1/2}$ is the Cholesky factor obtained from the Bayesian estimation of the VAR model for each of the 1000 draws, and Q is an orthogonal matrix with $QQ' = I$. In this application, using the Cholesky decomposition merely serves as an auxiliary tool and is only one of several ways to obtain a triangular matrix. To generate Q , we draw a random matrix U from an $N(0,1)$ density and decompose this matrix using a QR decomposition.¹³ For each of the 1000 Cholesky factors we search over possible U matrices until we find a matrix generating responses to the respective shocks that are in line with the sign restrictions we impose. Additionally, as has been mentioned above, zero restrictions are imposed on selected elements of the coefficient matrix B . This is implemented by specifying the corresponding entries in the random matrix U to be zero. The impulse response functions r_{ijt}^k of variable $i = 1, \dots, 5$ to shock $j = 1, 2, 3$ at horizon $t = 1, \dots, 60$ constructed using model $k = 1, \dots, 1000$ (where k indexes the different values of Q) are then summarized by computing the median over k of r_{ijt}^k .

It is important to note, however, that solely relying on the median of all admissible impulse responses may be questionable, especially if several shocks are identified at the same time (Fry and Pagan, 2007). First, since the median *over* k summarizes information obtained from different models, the reported structural impulse response functions may be hard to interpret. Second, and related, since two shocks may be generated from two different models, the structural disturbances are not necessarily orthogonal. We account for these issues by following Fry and Pagan (2007) and additionally reporting impulse responses generated by *one* model Q ; the model that leads to impulse responses that are as close to the median over k of r_{ijt}^k as possible. This model is found by first standardizing the impulse responses r_{ijt}^k by subtracting their median and divide by their standard deviation over the 1000 models satisfying the sign restrictions. The standardized impulse responses are then grouped into a vector ϕ^k for each value Q . We subsequently choose the model that minimizes $\phi^{k'}\phi^k$:

$$Q^* = \underset{Q}{\operatorname{argmin}} \sum_{i=1}^5 \sum_{j=1}^3 \sum_{t=0}^{60} \left(\frac{r_{ijt}^k - \operatorname{med}(r_{ijt})}{\operatorname{std}(r_{ijt})} \right)^2.$$

¹³This procedure follows Rubio-Ramirez et al. (2006) and has been used in the VAR literature, see e.g. Enders et al. (2011) and Hristov et al. (2011). An alternative approach to generate an orthogonal matrix Q would be to use a Givens transform based on rotations of Given matrices used by, for instance, Canova and De Nicolo (2002). The two approaches are discussed in Fry and Pagan (2007), who show that they generally lead to the same Q and thus to the same shocks.

We report and discuss the corresponding impulse responses in our section on robustness (Section 3.4.4).

3.3.3 Demand, Supply and Monetary Shocks at the ZLB in the Theoretical Literature

As has been stressed above, the existing VAR literature on the transmission of unconventional monetary policy is rather scarce and thus a broad consensus concerning the identification of a QE-shock at the ZLB is yet to be reached. Moreover, it is not clear *ex ante* whether the usual identifying restrictions for aggregate demand and supply shocks are still valid if the interest rate is close to zero. In particular, the main impediment to disentangling the monetary shock from business cycle disturbances at the ZLB is the fact that the interest rate cannot be restricted, as is usually done in more traditional setups in order to identify a monetary shock during normal times. In fact, as mentioned before, we do not even include the call rate in the model. Nevertheless, we show below that it is still possible to derive a clear identification setup using a mix of zero and sign restrictions that are implied by theoretical models. Thus, as a first step, we take a closer look at the theoretical DSGE literature concerned with the modeling of the ZLB before deriving our identifying restrictions.

One approach within the theoretical literature on monetary policy at the ZLB has been to calibrate (McCallum, 2000; Orphanides and Wieland, 2000) or estimate (Coenen and Wieland, 2003) open-economy macro models that consider the case of zero interest rates. Allowing the quantity of base money to affect output and inflation even if the interest rate is zero, these models imply that liquidity injections lead to an increase in output and inflation, given that these policy measures are sufficiently aggressive. The particular channel that these models rely on is the portfolio rebalancing effect along the lines of Meltzer (1995, 2001) and Mishkin (2001) implying a rebalancing of investors' portfolios following a base money injection. More specifically, these models put emphasis on the role of assets denominated in foreign currency; the real exchange rate depreciation resulting from such a surge in demand for these assets in turn helps to increase output and prices. Relative to this class of macro models, more microfoundation is provided by a growing DSGE literature aiming at a characterization of optimal monetary policy in a situation of zero interest rates including Eggertsson

and Woodford (2003), Jung et al. (2005), Eggertsson (2006) and Nakov (2008). This stream of the literature stresses changing expectations of future monetary policy as the main channel of transmission of base money injections instead of direct quantity effects. Thus, if a base money injection is successful in that it leads to lower expected interest rates in the future and increases inflationary expectations as of today, it may increase output and inflation. While these different approaches focus on diverging channels underlying the effect of quantitative easing, the outcome is similar: a rise in the reserve component of the monetary base in a situation of zero interest rates should lead to a non-negative effect on output and prices. Moreover, these results are in line with recent DSGE models of DelNegro et al. (2010) and Gertler and Karadi (2011) analyzing central bank credit interventions within a framework with financial frictions. These studies find that such unconventional policies can mitigate negative effects of a financial crisis on output and inflation at the zero lower bound.

As far as the business cycle shocks are concerned, for our benchmark identification scheme we make use of results of Yano (2009), who presents an estimated New Keynesian DSGE model for the Japanese economy under ZLB conditions which offers more insights into the reaction of macro variables following business cycle shocks at the ZLB. In particular, the model implies that prices and output move in the same direction following a demand shock and in opposite directions after a supply shock. This model therefore implies similar reactions of the variables to these two shocks at the ZLB compared to normal times.

The responses of the variables to business cycle shocks implied by the model of Yano (2009) are not undisputed, however. Eggertsson (2010) provides a DSGE model in which the ZLB is the outcome of a negative preference shock moving the economy away from the zero-inflation natural rate steady state and into the ZLB. Again, in this model a positive aggregate demand shock increases output and inflation. However, in contrast to the responses implied by the model of Yano (2009) an aggregate supply shock also leads output and inflation to move in the same direction; in the case of a positive supply shock *both* inflation and industrial production decrease. More specifically, a positive supply shock boosts deflationary expectations due to falling prices, which puts upward pressure on the real rate of interest. During normal times monetary policy would react to this by lowering the nominal interest rate in order to offset the increase in the real rate. Since at the ZLB such a cut in the nominal interest rate is not possible, the

result of such a shock is a decline in consumption and thus a decrease in aggregate demand.¹⁴ In fact, this unusual transmission mechanism of shocks at the ZLB has been recognized by a number of authors accounting for these special effects in their models. For instance, Christiano et al. (2009) report quantitatively large government spending multipliers at the ZLB compared to normal times, where the difference results from real interest rate increases which cannot be offset by monetary policy actions. Similarly, Corsetti et al. (2010) show that the effect of expected spending reversals following fiscal stimulus is complicated by the interplay of deflationary expectations and increases in the real interest rate at the ZLB as compared to normal times.

3.3.4 Identifying Sign Restrictions

Using the implications of these theoretical models we now present our identifying set of sign restrictions. As far as identification of the business cycle shocks is concerned we will take into account the diverging predictions of the DSGE models of Yano (2009) and Eggertsson (2010), respectively, by implementing restrictions implied by the former in our benchmark identification, while the restrictions in line with the latter model are used in an alternative identification scheme.

Benchmark Identification

We first describe our benchmark identification scheme for the benchmark specification. Sign restrictions are binding for twelve months following the shock,¹⁵ while the zero restriction is imposed on impact only. Table 3.1 summarizes the restrictions considered for the benchmark model. Restrictions on the sign of the impulse response functions are indicated in the columns “sign” in the table, while zero restrictions are given in the column “impact”. The latter restrictions are employed only for identification of the QE-shock. As Table 3.1 shows, to identify an aggregate demand shock we restrict output and prices to move in the same direction; both variables are assumed to increase following a positive demand shock. For an aggregate supply shock we impose that output and prices move in opposite directions. These assumptions allow us to disentangle these two shocks.

¹⁴While in Eggertsson (2010) the focus is on fiscal shocks or, more specifically, on the adverse consequences of tax reductions at the ZLB, the results of the model similarly apply to other shocks that tend to enhance deflationary expectations such as a positive supply shock. See Appendix 3.A.2 for more details on the model.

¹⁵A similar restriction horizon is used by e.g. Scholl and Uhlig (2006).

As has been explained above, our restrictions are in line with the predictions of DSGE models explicitly modeling the zero lower bound, such as Yano (2009). Moreover, similar restrictions are implied by standard DSGE models (Straub and Peersman, 2006; Canova and Paustian, 2010) and are also imposed in more traditional VAR studies (Peersman, 2005; Canova et al., 2007).

The unconventional monetary shock is identified by restricting reserves to increase following the shock; this is our key assumption for the identification of a reserves shock. Furthermore, we assume a lagged impact of the unconventional monetary shock on consumer prices; the contemporaneous coefficient of this variable is restrained to zero.

Table 3.1: Identifying Sign Restrictions - Benchmark Identification

Variable	Demand shock	Supply shock	QE-shock		horizon
	sign	sign	impact	sign	
CPI	> 0	< 0	0	≥ 0	$K = 12$
Ind. production	> 0	> 0			$K = 12$
Reserves				> 0	$K = 12$
Long-term yield					
Exch. rate					
M2					

Notes: The table displays sign restrictions on the responses of the variables in the model after a demand, supply and QE-shock, respectively. $K = 12$ indicates that the restriction horizon is twelve months.

The assumption that nominal shocks do not have a contemporaneous impact on real variables and consumer prices has traditionally been used in VAR studies analyzing the effects of monetary policy; see for instance Bernanke and Blinder (1992) and Christiano et al. (1999). Additionally, similar restrictions have recently been employed within a sign-restriction setup for the identification of unconventional monetary shocks in the Euro area; Peersman (2011) uses a mix of zero impact and sign restrictions within his SVAR analysis. Furthermore, on the theoretical side, these restrictions are in line with for instance Coenen and Wieland (2003) showing that liquidity injections in a situation of zero interest rates only affect output and prices with a lag. For these reasons, we consider imposing such zero restrictions on the impact matrix a rather conservative approach, especially since we are using monthly data. In contrast to the above-mentioned studies, however, we do not restrict the impact coefficient of industrial production in order to be as agnostic as possible with regard to real

effects of quantitative easing. Next to the zero restriction on CPI we additionally assume a non-negative response of the consumer price level to the QE-shock. As outlined above, this is in line with a wide range of theoretical models incorporating the ZLB (Coenen and Wieland, 2003; Eggertsson and Woodford, 2003; Eggertsson, 2006).¹⁶ However, since the Bank of Japan adopted the QE policies also with the objective to tackle the deflation problem in Japan it is additionally interesting to assess the effects of a QE-shock on the CPI without restricting the response in the first place. We thus offer an alternative restriction setup which is more agnostic with regard to the reaction of prices, see Section 3.4.4.

Because the central question assessed in this paper is concerned with the effectiveness of unconventional monetary policy measures on the real economy, which is the ultimate concern of central banks facing a liquidity trap situation, we leave the dynamic response of industrial production to a QE-shock unrestricted. Moreover, we do not restrict the 10-year government bond yield. As discussed in the Introduction, the effects of quantitative easing on long-term yields are theoretically not clear; observing *rising* yields following a base money expansion may be possible as a consequence of increasing inflation expectations or increasing risk premia. We also abstain from restricting the exchange rate in order to let the data speak concerning its effect of the QE-shock and thus its role in the transmission of unconventional policy. Hence, using the above identification scheme allows us to let the data speak concerning the effects of an unconventional monetary shock on the real economy, long-term interest rates and the exchange rate, which stands in contrast to existing studies on the macroeconomic effects of quantitative easing. Crucially, the contemporaneous zero restriction following a QE-shock imposed on consumer prices is sufficient to disentangle the unconventional monetary shock from the business cycle disturbances (Peersman, 2011). The set of identifying restrictions for our alternative specification given in equation (3.4) is very similar; the restrictions imposed on the CPI, industrial production and reserves are the same as those used for the benchmark specification above. We do not restrict our measure of money supply to additionally analyze the role of the money multiplier at the zero lower bound.

¹⁶Theoretically, there is no reason for this asymmetric restriction approach concerning output and prices, both with regard to the zero and sign restrictions. We pursue this strategy with the objective of being as unrestrictive as possible with respect to real variables, which is in the spirit of Uhlig (2005). However, we confirm that our results are robust to also imposing a zero restriction on the impact coefficient of industrial production; see Section 3.4.4.

Alternative Identification Scheme

In order to check whether our results concerning the QE-shock are still valid when we account for the somewhat diverging effects of a positive supply shock at the ZLB predicted by Eggertsson (2010) we attempt to implement these restrictions in an alternative setup, summarized in Table 3.2. Since both the demand and supply shocks should now induce output and prices to move in the same direction, we cannot easily differentiate between the two shocks. In particular, simply assuming the signs on prices and output to be positive and negative after a positive demand and a positive supply shock, respectively, would be meaningless. The reason is that we have to allow for sign reversal while searching over the impulse response functions since shocks can be positive or negative.

Table 3.2: Identifying Sign Restrictions - Alternative Identification à la Eggertsson (2010)

Variable:	Demand shock	Supply shock	QE-shock		horizon
	sign	sign	impact	sign	
CPI	> 0	< 0	0	≥ 0	$K = 12$
Ind. production	> 0	< 0			$K = 12$
Reserves				> 0	$K = 12$
Long-term yield					
Exch. rate					
Further restriction:	sign	sign	impact	sign	horizon
$ \frac{IP}{CPI} $	> 1	< 1			$K = 1$

Notes: The table displays sign restrictions on the responses of the variables in the model after a demand, supply and QE-shock, respectively. $K = 12$ indicates that the restriction horizon is twelve months. $\frac{IP}{CPI}$ denotes the ratio of the response of industrial production to the response of the CPI.

To deal with this problem we propose another way to disentangle shocks using the different slope properties of the aggregate supply and demand equations in the model. In particular, as shown in Eggertsson (2010), for standard parameter values used for calibration of the model, the AD-curve will always be steeper than the AS-curve.¹⁷ A positive demand shock thus leads to a proportionately

¹⁷It is pointed out in Eggertsson (2010) that as the number of period the economy is trapped at the ZLB increases, the AD-curve becomes flatter, while the slope of the AS-curve increases. At a certain critical point both curves would be parallel such that no solution exists. It is, however, assumed in his model that the ZLB episode is short enough such that this situation is avoided. See Eggertsson (2010) or Appendix 3.A.2 for more details on the model and corresponding assumptions.

larger impact on the value of the output gap versus inflation than a positive supply shock in this model. In line with these model features, we restrict the ratio of the responses of these variables to be larger than one in absolute value for the demand shock, and less than one for the supply shock. In fact, since we estimate the model in levels, we restrict the ratio of the response of industrial production to the response of the CPI instead of the output gap and inflation. Additionally, a positive demand shock is assumed to lead to a positive reaction of both output and prices, while a positive supply shock is restricted to lower these variables. Equations (3.5) to (3.8) summarize the conditions for positive and negative demand and supply shocks, respectively:

$$\epsilon^{DE,+} \quad \text{with} \quad \{CPI > 0, \quad IP > 0, \quad |IP/CPI| > 1\} \quad (3.5)$$

$$\epsilon^{DE,-} \quad \text{with} \quad \{CPI < 0, \quad IP < 0, \quad |IP/CPI| > 1\} \quad (3.6)$$

$$\epsilon^{SU,+} \quad \text{with} \quad \{CPI < 0, \quad IP < 0, \quad |IP/CPI| < 1\} \quad (3.7)$$

$$\epsilon^{SU,-} \quad \text{with} \quad \{CPI > 0, \quad IP > 0, \quad |IP/CPI| < 1\}, \quad (3.8)$$

where $\epsilon^{DE,+}$ and $\epsilon^{DE,-}$ indicate a positive and negative demand shock, and $\epsilon^{SU,+}$ and $\epsilon^{SU,-}$ denote a positive and negative supply shock, respectively. Thus, for instance a positive demand shock is now identified by the simultaneous occurrence of an increase in industrial production, a rise in the CPI and the ratio of the two responses being larger than one in absolute value, while a negative demand shock is assumed to decrease output and prices and still leads to a ratio of the respective responses which is larger than one. Thus, a negative demand shock is clearly disentangled from a positive supply shock featuring negative restrictions on output and prices as well, but which is identified by the ratio of the respective responses being smaller than one in absolute value. The QE-shock is identified as before and can again be disentangled from the other shocks by imposing the zero restriction on the CPI.

As far as the restriction horizon is concerned, we choose again 12 months for the restrictions regarding the QE-shock and the positivity/negativity constraints on output and prices for the business cycle shocks. By contrast, we restrict the ratio of the responses only for the first period after the shock in order to remain as conservative as possible with regard to these non-standard restrictions. However, we have checked that estimating the model varying the restriction horizon for the ratio of the responses does not change our main results.

3.4 Results

3.4.1 Impulse Response Analysis for the Benchmark Identification Scheme

Benchmark Specification

Figures 3.4, 3.5 and 3.6 show the impulse responses to the three shocks based on the benchmark specification and identification scheme explained above. Figure 3.4 shows the responses to our unconventional monetary policy shock. In the figure, the solid black lines denote the median impulse responses from a Bayesian vector autoregression with 1000 draws, while the shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the impulse responses.¹⁸

The response of reserves has been restricted to increase following the shock, so the immediate positive reaction is not surprising by construction. In particular, reserves rise by up to 7% and stay significantly above the zero line for much longer than preset; about two years. As restricted, CPI does not react on impact. Thereafter, the response is clearly positive. Note that while we imposed the reaction of the price level to be non-negative, this does not imply that we imposed a strictly positive reaction of this variable. It can be seen, however, that the response is rather weak fluctuating around 0.05%. The mild and transient response of the price level to the QE-shock implies that the rate of inflation may also react only temporarily and weakly. Nevertheless, the effect is significant for somewhat longer than restricted; about 20 months.

Crucially, the main variable of interest, industrial production, has been left unrestricted. It can be seen in the figure that an expansionary QE-shock leads to a significant increase of industrial production by about 0.4%; the effect is significant after 20 months. The figure shows that this response is highly transient and becomes insignificant already after around six months. Thus, our VAR-based results suggest that an unconventional monetary policy shock can in fact increase economic activity for some time; however, with a delay of around one and a half years and only temporarily. Somewhat surprisingly, we observe an insignificant negative reaction of industrial production during the first few months following the shock. This is, however, consistent with Lenza et al. (2010) reporting a negative effect on industrial production and unemployment in the first months after

¹⁸Under the assumption of normality, these percentiles correspond to one-standard error bands, see Uhlig (2005). Reporting one-standard error confidence bands is a standard approach in the sign-restriction literature.

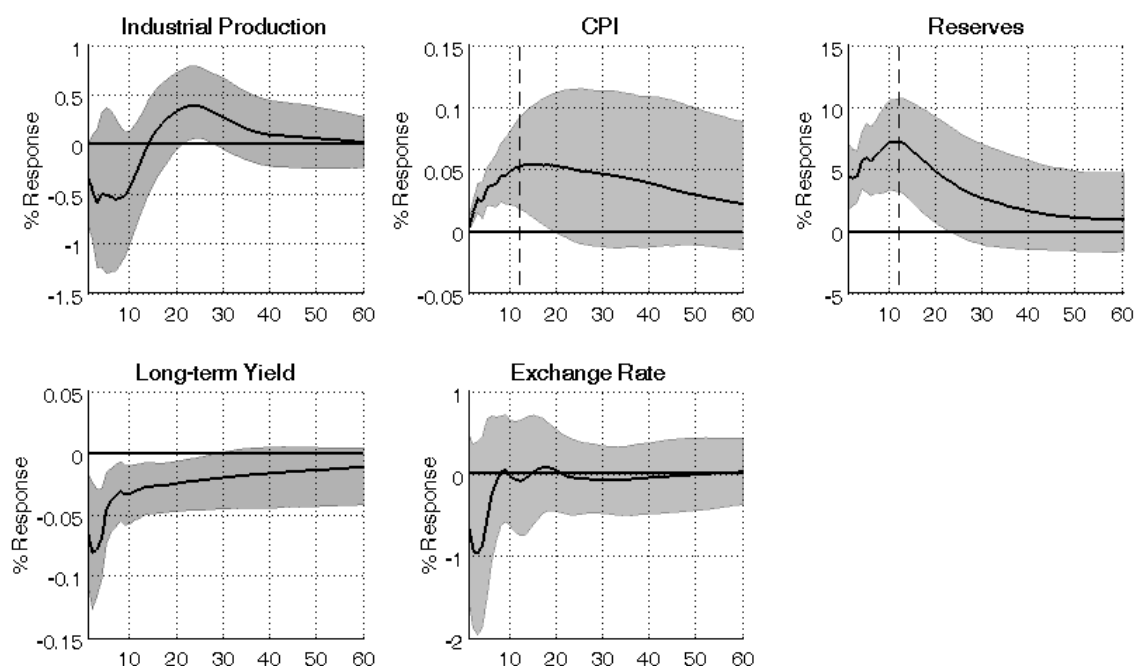
an unconventional policy shock for the Euro area. They rationalize this pattern by the notion that variables related to real activity usually react with a delay to monetary policy shocks, and that there often is a positive contemporaneous correlation between output and interest rates in the data. Since we observe falling long-term interest rates after a QE-shock this explanation may be applicable for our empirical model as well.

Indeed, in contrast to some previous studies we do not restrict the response of the long-term government bond yield since its reaction following a QE-shock is theoretically unclear. In fact, Figure 3.4 shows a significantly negative initial reaction of this variable; the 10-year government bond yield falls by about 0.07 percentage points on impact. The negative effect lasts for around two years. Hence, even though the effects are quantitatively not very large, our result can in fact be interpreted as evidence for the view that QE works by lowering long-term rates. Importantly, this result has been obtained by using an agnostic approach with respect to the long-term yield. Finally, we included the real effective exchange rate in our model in order to investigate whether this variable is important for the transmission of unconventional monetary policy. The figure shows, however, that adding this variable does not help us in shedding more light on the specifics of the transmission mechanism. In fact, the response of the exchange rate is insignificant over the entire horizon.

All in all, the results presented in Figure 3.4 suggest that a quantitative easing strategy in a situation of near-zero interest rates has the potential to stimulate real economic activity, at least temporarily and with a delay. However, our results also show that the Bank of Japan's second main goal motivating such a policy, namely to increase the price level in order to boost the rate of inflation and to eventually bring an end to Japan's deflationary episode, is difficult to achieve by such measures. Hence, our benchmark results provide mixed evidence for the overall effects of unconventional monetary shocks on the economy.

Moreover, the finding that the responses of industrial production and prices are rather mild and transient when leaving the long-term yield and the exchange rate unrestricted suggests that it is important to agnostically analyze the responses of such financial variables. A fall in long-term yields alone cannot guarantee a pronounced increase in economic activity nor a strong rise in the price level. Similarly, restricting the exchange rate does not seem to be a sensible approach for the identification of a QE-shock at the ZLB.

Figure 3.4: Impulse Responses to a QE-Shock - Benchmark Identification and Model



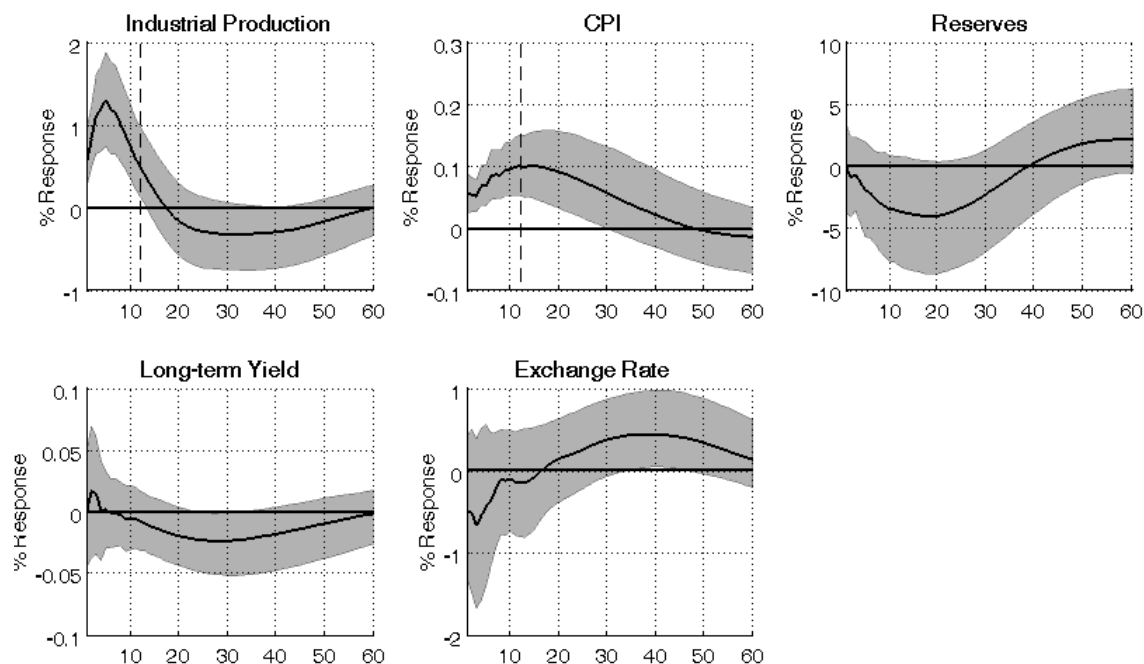
Responses over a 60-month horizon to a QE-shock as identified in Table 3.1. Solid lines denote the median impulse responses from a BVAR (1000 draws), shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses. Vertical lines indicate the restriction horizon.

The impulse response functions for the demand and supply shocks are shown in Figures 3.5 and 3.6, respectively. These two shocks are mainly identified for the purpose of controlling for other business cycle disturbances in the estimation and to compare the quantitative effects of the QE shock with these other structural shocks (See Section 3.4.3). Because most variables have been restricted we only briefly discuss the results here.

Following a demand shock, industrial production and the CPI are restricted to rise. Hence the initial increase in these variables is not surprising. However, note that CPI rises significantly over a much longer period than restricted. Industrial production does also stay significantly positive for somewhat longer than the restriction horizon. Turning to the responses of reserves and long-term yields to the demand shock, we find both variables falling; however, the effects are insignificant. The exchange rate shows a significant positive reaction after two to three years; in fact, this results in in line with existing VAR-based evidence reported by Clarida and Gali (1994) and Farrant and Peersman (2006). However,

compared to their results obtained for non-ZLB sample periods, the reaction of the exchange rate to a business cycle shocks at the ZLB is much more delayed.

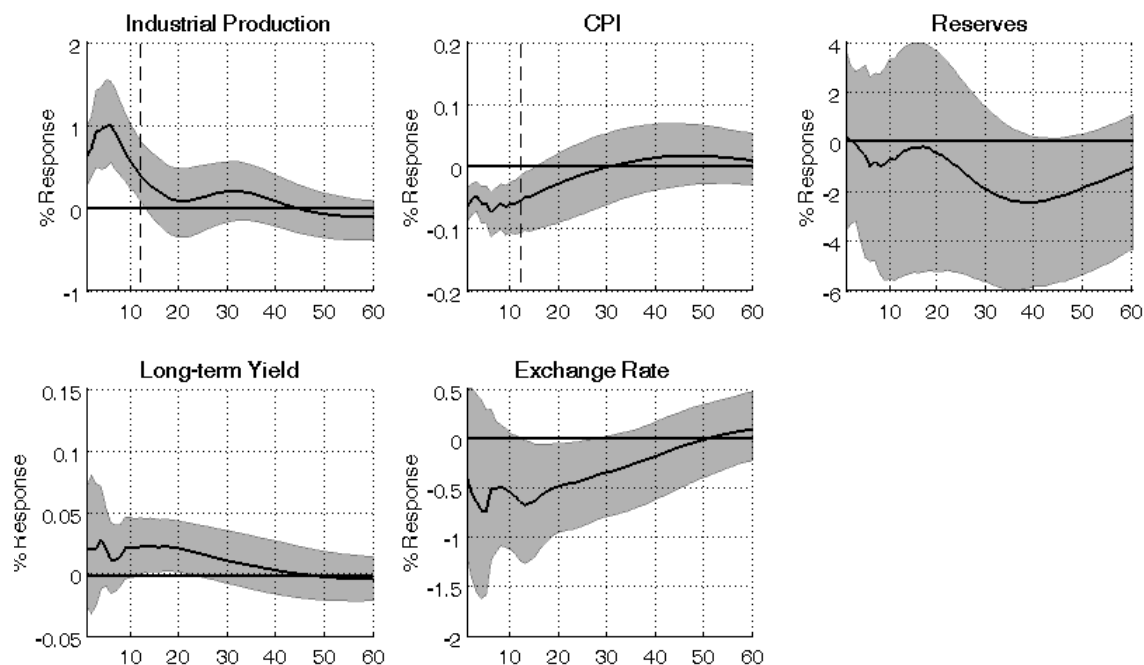
Figure 3.5: Impulse Responses to a Demand Shock - Benchmark Identification and Model



Responses over a 60-month horizon to a demand shock as identified in Table 3.1. Solid lines denote the median impulse responses from a BVAR (1000 draws), shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses. Vertical lines indicate the restriction horizon.

Figure 3.6 finally shows the impulse response functions following a supply shock. Again, the initial increase in industrial production and decrease in CPI are by construction, and again, the responses last somewhat longer than preset. The figure furthermore shows a significant depreciation of the Japanese currency following a positive supply shock. As for the demand shock, the latter result accords with existing empirical results; for instance Farrant and Peersman (2006) report decreasing relative prices and a currency depreciation following a relative supply shock.

Figure 3.6: Impulse Responses to a Supply Shock - Benchmark Identification and Model

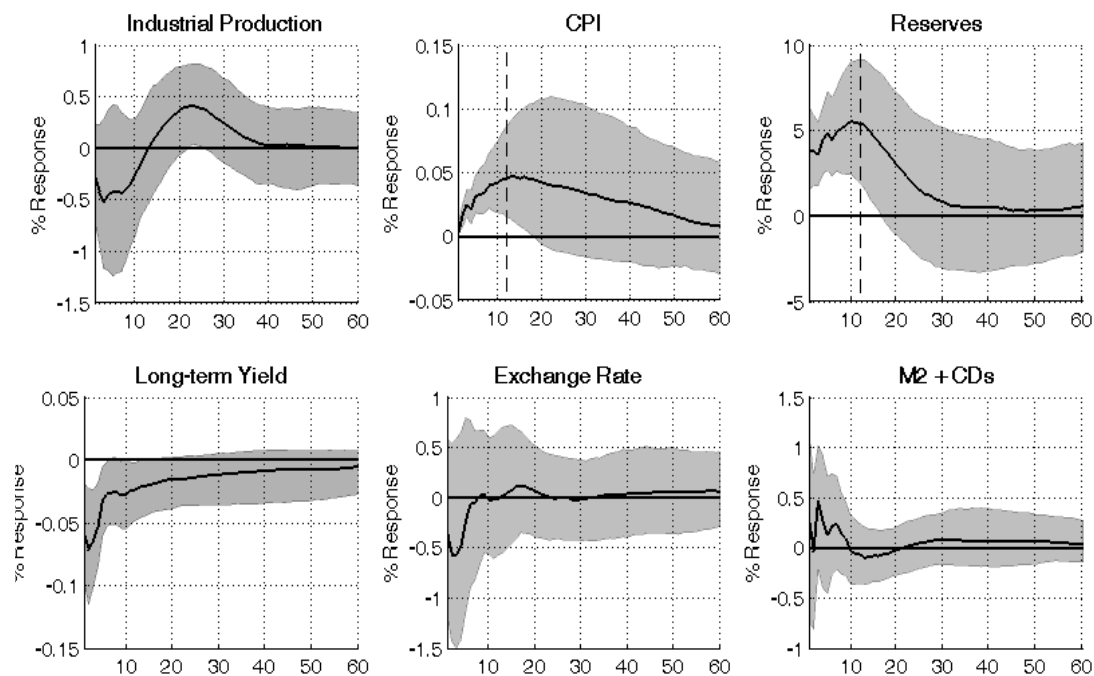


Responses over a 60-month horizon to a supply shock as identified in Table 3.1. Solid lines denote the median impulse responses from a BVAR (1000 draws), shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses. Vertical lines indicate the restriction horizon.

Alternative Specification - The Importance of the Money Multiplier

We now focus on the responses to the QE-shock only and discuss the results of the additional specification given in equation (3.4). Figure 3.7 shows the impulse responses to the QE-shock resulting from the specification including the measure of broader money supply, $M2 + CDs$. Estimating this extended model serves as a robustness test, but may also shed some more light on whether the response of this variable can help explaining the transmission mechanism of the QE-shock. In particular, while $M2 + CDs$ did generally not increase with base money expansions, as documented above, it is interesting to investigate its reaction to our QE-shock more structurally. As can be seen in the figures, the qualitative results do not change after including money supply as an additional variable. Industrial production still rises by up to 0.4%; however, error bands are somewhat wider.

Figure 3.7: Impulse Responses to a QE-Shock - Including M2



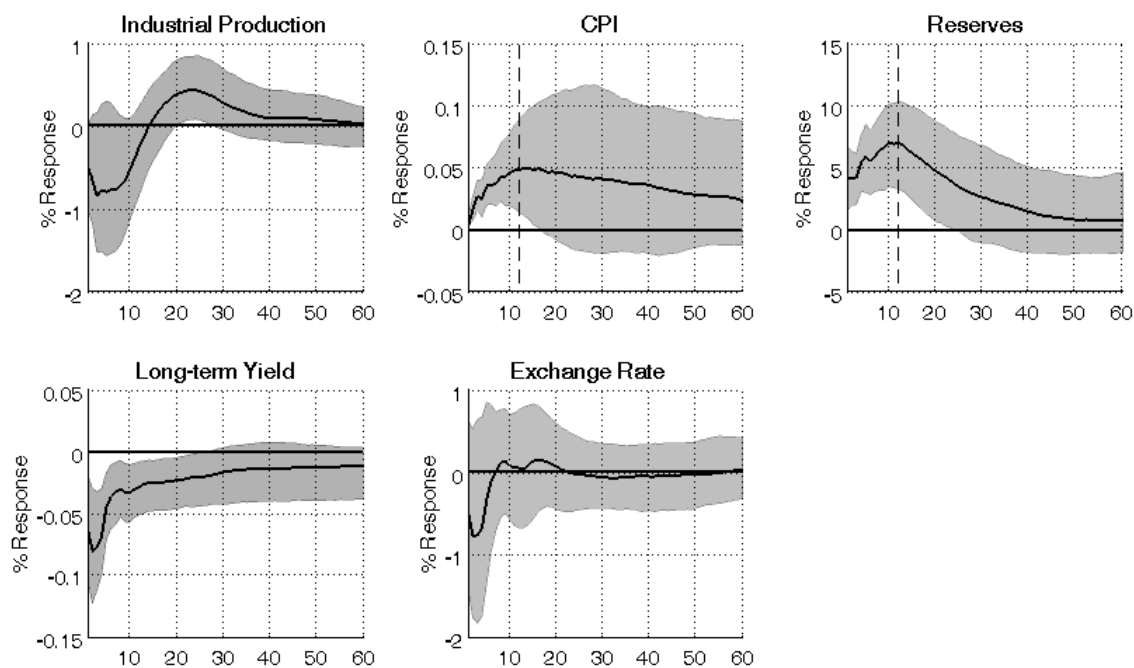
Responses over a 60-month horizon to a QE-shock as identified in Table 3.1. Solid lines denote the median impulse responses from a BVAR (1000 draws), shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses. Vertical lines indicate the restriction horizon.

As in the benchmark case, the response of the consumer price index becomes insignificant after a while. The responses of the other variables are very similar to those in the benchmark case. Thus, our extended specification does not change our main conclusion that while it may be possible to temporarily increase production by quantitative easing measures, both production and prices only show a highly transient reaction to such a policy shock. Moreover, the response of the long-term yield is robust to this extended specification confirming that long-term rates do in fact fall after such an unconventional shock. However, while M2 + CDs increases slightly following a QE-shock, the response is insignificant confirming that in fact broader money supply did not react to QE measures implemented by the Bank of Japan during our sample period. This suggests that monetary policy transmission via direct quantity effects is difficult for our sample period, which confirms existing empirical results; see Kuttner (2004).

3.4.2 Alternative Identification à la Eggertsson (2010)

We next turn to our empirical results for the alternative sign restriction scheme given in Table 3.2. These restrictions differ from the benchmark setup only in the identification of the demand and supply shocks. Because the theoretical predictions from the DSGE-model of Eggertsson (2010) imply sign restrictions that render demand and supply shocks indistinguishable, we need to impose an additional restriction on the relative magnitudes of the output and price responses. Results for the three shocks are given in Figures 3.8, 3.9 and 3.10.

Figure 3.8: Impulse Responses to a QE-Shock - Identification Scheme à la Eggertsson (2010)



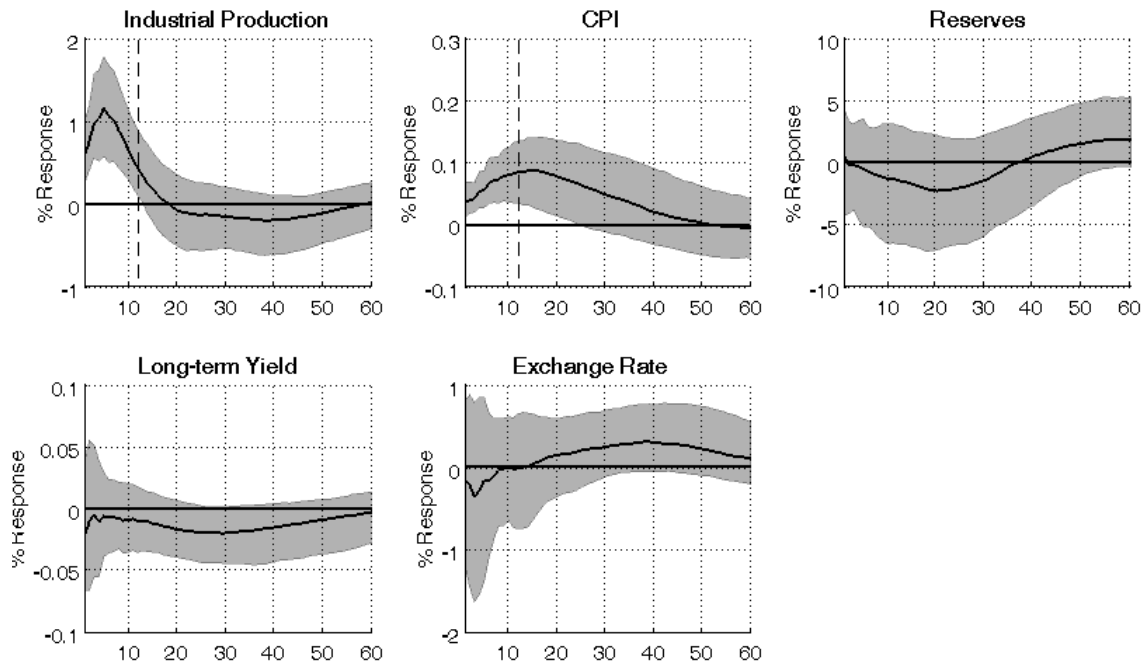
Responses over a 60-month horizon to a QE-shock as identified in Table 3.2. Solid lines denote the median impulse responses from a BVAR (1000 draws), shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses. Vertical lines indicate the restriction horizon.

Figure 3.8 shows the impulse responses to the QE-shock using our alternative identification scheme. As expected, the results are very similar to those from our benchmark identification. Moreover, interestingly, results for the demand shock are very similar to the benchmark results, as can be seen in Figure 3.9. It can be

seen that after a demand shock, again, the initial increase in industrial production and CPI is by construction. And again, the price level remains significantly positive for only slightly longer than the restricted horizon. Similarly, reserves do not react significantly in this case.

More interestingly, turning to the impulse responses to the supply shock under the alternative identification scheme, we naturally find some differences. Figure 3.10 shows the effects of the supply shock under this identification: industrial production and CPI are restricted to fall following a positive supply shock.

Figure 3.9: Impulse Responses to a Demand Shock - Identification Scheme à la Eggertsson (2010)



Responses over a 60-month horizon to a demand shock as identified in Table 3.2. Solid lines denote the median impulse responses from a BVAR (1000 draws), shaded areas the 16% and 84% percentiles of the posterior distribution of the responses. Vertical lines indicate the restriction horizon.

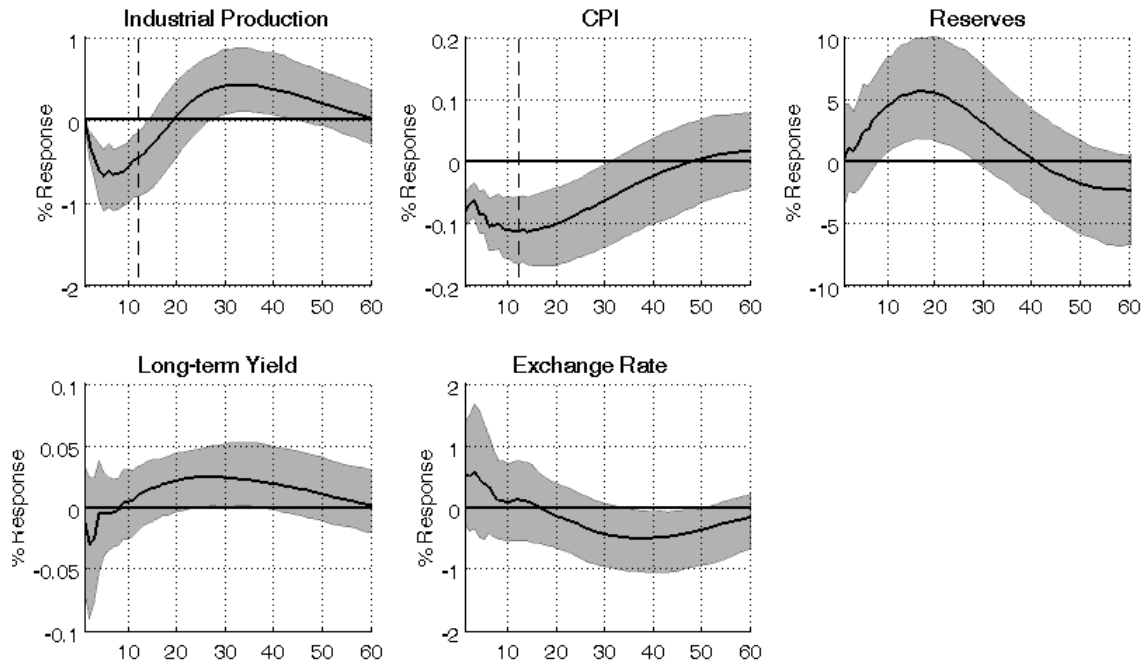
The crucial identifying restriction regarding the relative magnitudes of the responses of production and prices can be seen by comparing the absolute size of the response of production to the demand and supply shocks in the very first period after the shock. Industrial production is restricted to respond stronger than CPI following the demand shock, but less strong than CPI following the

supply shock in the first period following the respective shock.

Figure 3.10 shows, however, that the negative response of industrial production becomes stronger relative to the response of the CPI soon after the first period. The initial fall of industrial production, which was specified within the restriction setup, is partly offset by an increase in production after about two and a half years. The responses of most of the other variables are as expected; CPI remains significantly negative for almost three years, while reserves significantly rise after around six months.

The significant increase in reserves may reflect an expansionary reaction of the central bank following a positive supply shock that puts further downward pressure on prices. Finally, as for the benchmark identification of a supply shock, we see a delayed depreciation of the exchange rate.

Figure 3.10: Impulse Responses to a Supply Shock - Identification Scheme à la Eggertsson (2010)



Responses over a 60-month horizon to a supply shock as identified in Table 3.2. Solid lines denote the median impulse responses from a BVAR (1000 draws), shaded areas the 16% and 84% percentiles of the posterior distribution of the responses. Vertical lines indicate the restriction horizon.

3.4.3 Discussion of the Results

In this section we qualify and discuss the effects of our QE-shock. First, we assess its explanatory power relative to the other structural shocks by means of a forecast error variance decomposition as well as a historical decomposition of the data. Second, the effects of the QE-shock at the ZLB are compared to the effects of a traditional monetary policy shock identified for “normal times” when policy was not constrained by the ZLB.

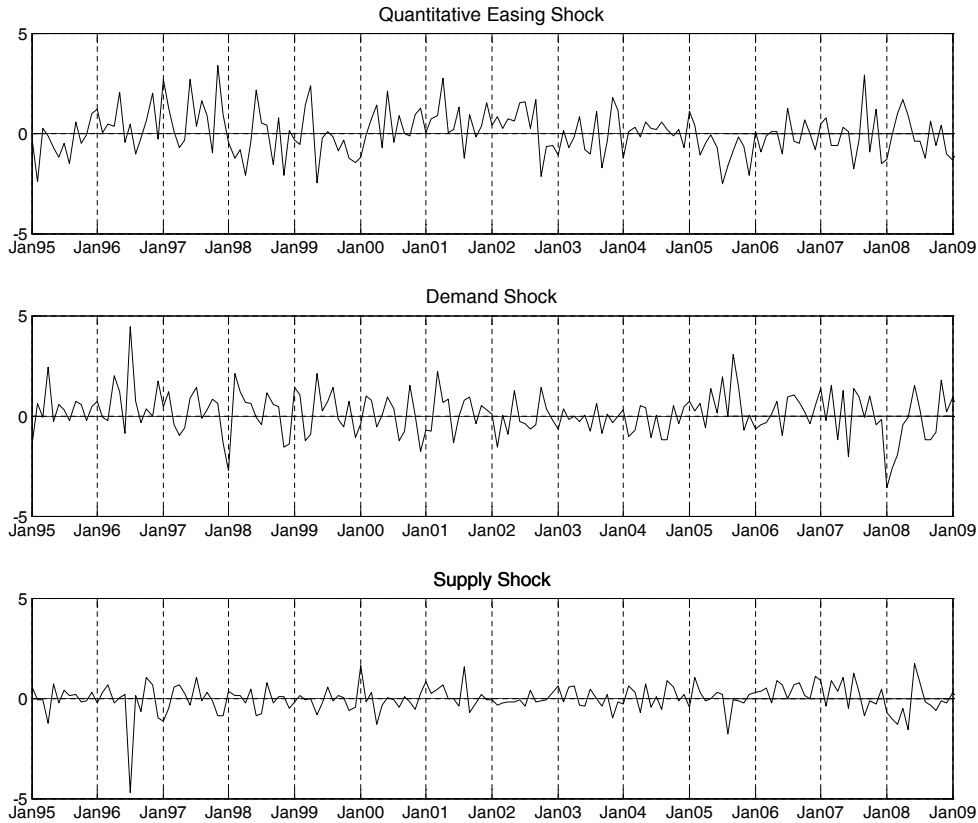
Explanatory Power of the Structural Shocks

In this section we assess the relative quantitative importance of the three structural shocks by means of a forecast error variance decomposition as well as a counterfactual analysis. We report results for both the benchmark identification scheme and the alternative setup based on assumptions in Eggertsson (2010). Since we identified the demand and supply shocks mainly to evaluate the importance of the QE-shock relative to business cycle disturbances, we have to check whether the corresponding results are sensitive to this alteration in the identification setup. All measures reported in this section are based on the “close-to-median” model constructed according to Fry and Pagan (2007) (see Section 3.3.2). We thus make sure that our identified shocks are orthogonal and that forecast error variance shares add up to one.¹⁹

Figure 3.11 plots the monthly evolution of our three structural shocks, identified according to the benchmark identification scheme, over time. The figure shows that our QE-shock reflects the monetary expansion resulting from the QE policies from 2001 to 2006. Moreover, monetary policy was expansionary in the late 90’s, a period associated with a declining policy rate and increasing movements in CABs toward the end of the decade; see also Figure 3.3.

¹⁹In fact, it is the sum of the variance shares of our three identified shocks and the two unidentified disturbances, capturing all remaining shocks, which equals one. Naturally, the sum of the variance share of these further unidentified shocks equals one minus the sum of the shares of the identified shocks.

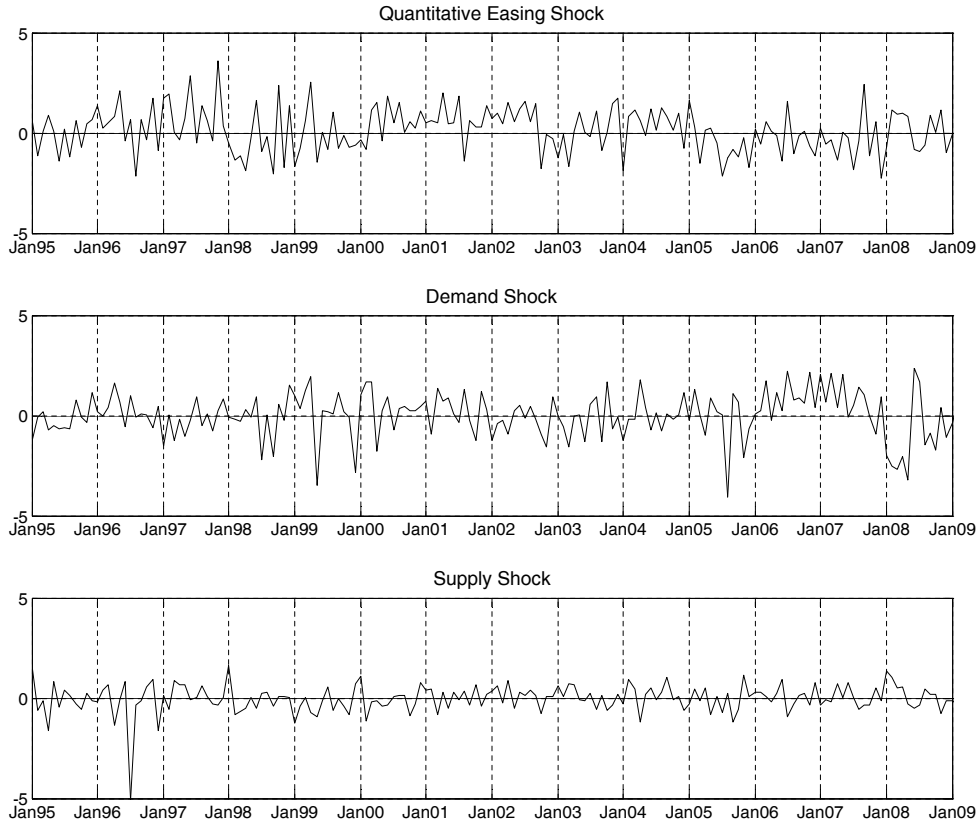
Figure 3.11: Evolution of the Structural Shocks - Benchmark Identification



The figure displays the monthly evolution of the QE-shock, the demand and the supply shock, respectively. The structural shocks are identified according to the benchmark identification scheme given in Table 3.1.

The observation that our model generates substantially positive unconventional shocks already in the 90's in fact confirms the validity of analyzing a sample that includes this period. It can also be seen that the end of the official QE-policies in 2006 is captured by our model; the figure shows negative QE-shocks during this time. As can be seen in the lower two panels the increase in output in 2006/2007 and the subsequent slump during and after the financial crisis in 2008/2009 are associated with positive and negative business cycle disturbances, respectively. Figure 3.12 shows the shock series resulting from the alternative identification scheme. As expected, the QE-shock evolves similarly to the benchmark shock series. Naturally, however, the respective development of the demand and supply shocks differs somewhat from the benchmark case. In general, positive and negative

Figure 3.12: Evolution of the Structural Shocks - Alternative Identification à la Egertsson



The figure displays the monthly evolution of the QE-shock, the demand and the supply shock, respectively. The structural shocks are identified according to the alternative identification scheme given in Table 3.2.

In order to get a better understanding of the relative importance of our identified shocks in terms of their predictive ability over a longer time horizon, we calculate the forecast error variance decomposition, which gives the estimated shares of the variability of each variable due to the respective shocks. Our main interest is of course focused on the variance shares of the QE-shock because they can be interpreted as measures of the explanatory power of unconventional policy shocks for variations in the macroeconomic variables included in the model. Table 3.3 displays the forecast error variance shares of the endogenous variables for each of the three shocks identified according to the benchmark setup at the 12 to 60-month forecast horizon.

Table 3.3: Forecast Error Variance Decomposition - Benchmark Identification

variable	horizon	QE	DE	SU	SUM	variable	horizon	QE	DE	SU	SUM
<i>IP</i>	12 mth.	18	33	22	73	<i>CPI</i>	12 mth.	3	29	31	63
	24 mth.	21	27	21	69		24 mth.	5	38	13	56
	36 mth.	26	21	17	64		36 mth.	8	32	8	48
	48 mth.	21	17	15	53		48 mth.	11	27	9	47
	60 mth.	18	15	13	46		60 mth.	10	23	12	45
<i>RES</i>	12 mth.	16	15	0	31	<i>LTY</i>	12 mth.	30	18	6	54
	24 mth.	42	5	1	48		24 mth.	35	22	13	70
	36 mth.	40	3	1	44		36 mth.	29	27	12	68
	48 mth.	35	3	1	39		48 mth.	26	24	10	60
	60 mth.	27	4	1	32		60 mth.	24	22	10	56
<i>EXR</i>	12 mth.	27	2	20	49						
	24 mth.	19	3	26	48						
	36 mth.	13	4	26	43						
	48 mth.	9	5	19	33						
	60 mth.	7	5	15	27						

Notes: The table displays variance shares of the QE-shock, the demand- and the supply-shock as identified according to the benchmark scheme. Entries are in percent. *IP* = industrial production, *CPI* = consumer price index, *RES* = reserves, *LTY* = long-term yield, *EXR* = exchange rate.

The last columns of the respective panels show the sum of the variance shares of the variables due to all three identified shocks. It can be seen that the three identified shocks do not explain more than 73% of the variations in the respective variables; especially at longer horizons the explanatory power of the shocks diminish. A relatively large part of the variations in the respective variables is due to all remaining unidentified shocks. These relatively low total variance shares for some variables are not unusual in sign restriction applications; see e.g. Straub and Peersman (2006). It can be seen, however, that the QE-shock explains a non-negligible part of the variations in industrial production, our main variable of interest; variance shares range from 18% to 26% at the 36-month horizon. With regard to CPI, the unconventional shock explains around 5% to 10% of the fluctuations confirming the relatively minor role for this variable already reported above.

For both variables the demand shock is a much more important source of variation with variance shares of around 20 - 40%. As expected, the supply shock is particularly important for the CPI over a shorter horizon. Moreover, this shock is relatively important for fluctuations in industrial production. Interestingly, the long-term yield is largely affected by the QE-shock, which accounts for up

to 35% of variations in this variable. Unsurprisingly, variations in current account balances are largely due to the QE-shock we identify, while the business cycle shocks are of minor importance. The variance shares of the exchange rate are quite high for the one- and two-year horizon; however, the impulse response analysis revealed that the effects on this variable are insignificant.

Comparing the variance shares calculated for our alternative identification scheme, displayed in Table 3.4, reveals that these results are largely invariant to the identification setup with regard to the business cycle shocks.

Table 3.4: Forecast Error Variance Decomposition - Alternative Identification à la Eggertsson

variable	horizon	QE	DE	SU	SUM	variable	horizon	QE	DE	SU	SUM
<i>IP</i>	12 mth.	19	63	3	85	<i>CPI</i>	12 mth.	3	9	17	29
	24 mth.	15	44	4	63		24 mth.	9	15	37	61
	36 mth.	18	31	4	53		36 mth.	12	18	40	70
	48 mth.	13	23	5	41		48 mth.	16	18	38	72
	60 mth.	12	20	5	37		60 mth.	19	18	38	75
<i>RES</i>	12 mth.	29	5	30	64	<i>LTY</i>	12 mth.	59	1	5	65
	24 mth.	32	2	10	44		24 mth.	54	2	13	69
	36 mth.	22	2	6	30		36 mth.	47	5	16	68
	48 mth.	18	2	5	25		48 mth.	45	6	17	68
	60 mth.	16	2	6	24		60 mth.	45	6	16	67
<i>EXR</i>	12 mth.	19	8	20	47						
	24 mth.	14	6	16	36						
	36 mth.	11	5	13	29						
	48 mth.	9	4	12	25						
	60 mth.	8	5	12	25						

Notes: The table displays variance shares of the QE-shock, the demand- and the supply-shock as identified according to the alternative scheme. Entries are in percent. *IP* = industrial production, *CPI* = consumer price index, *RES* = reserves, *LTY* = long-term yield, *EXR* = exchange rate.

The variance shares of the QE-shock are of comparable magnitude for most of the variables included in the model, with one exception being the long-term yield, which is now affected more strongly by the QE-shock, while the demand shock plays a rather unimportant role. As far as the variance shares of the business cycle shocks are concerned, it can be seen that the demand shock now plays a more substantial role for variations in industrial production, while the supply shock is rather unimportant. This is partly by construction; we specified the demand shock to have a larger impact on this variable than the supply shock.

However, while we imposed this restriction for one period only, the variance shares show this pattern also for longer horizons. Vice versa, the supply shock is more important for CPI than the demand shock; however, in line with the findings of the impulse response analysis the difference is not as pronounced.

All in all, these findings suggest that while the QE-shock affects output and prices in a non-negligible way, business cycle shocks such as, most notably, aggregate demand shocks constitute a much more important source of the variability of these variables.

As a final exercise we conduct a historical decomposition of the data in order to evaluate the relative importance of the QE-shock for the variables in the model at different points in time. In particular, we use the decomposition of the data to calculate the counterfactual development of the variables setting the QE-shock to zero. We only report this measure for the benchmark identification because we are only interested in the effects of the QE-shock here. As one would expect, these results are very similar for the alternative identification scheme.²⁰

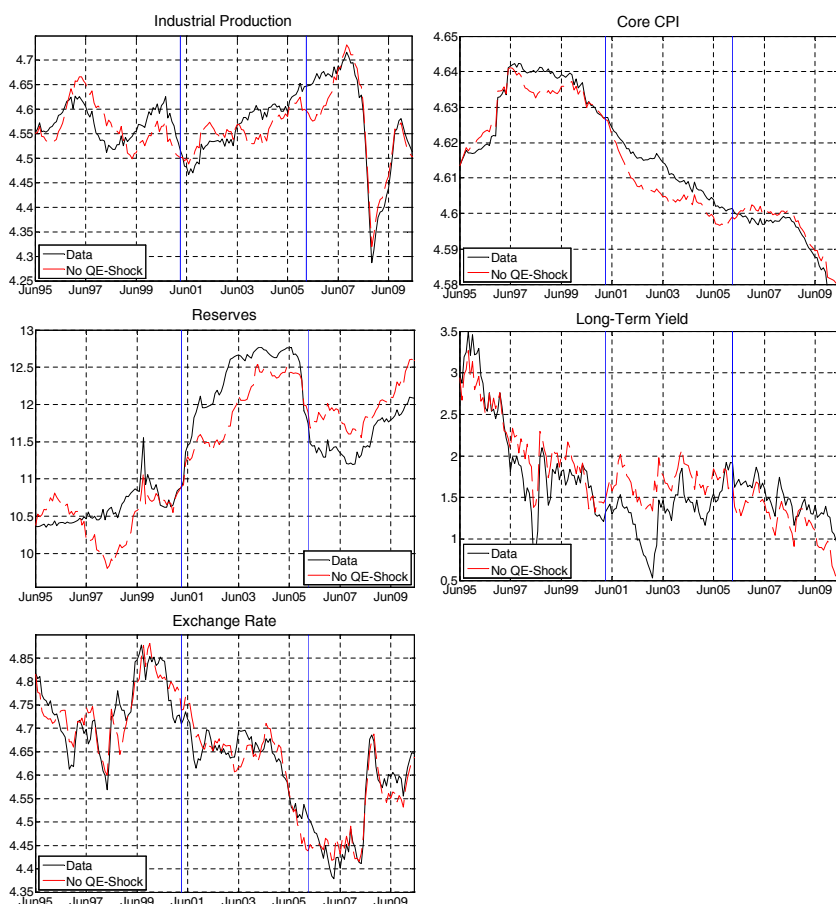
The counterfactual series are constructed simply by subtracting the contribution of the QE-shock from the actual time series.²¹ Figure 3.13 shows both the actual development of the five variables included in the benchmark SVAR model as well as the respective counterfactual evolution. It can be seen in the figure that industrial production would have been somewhat lower if no QE-shock had occurred during the period 1999-2001 and from 2003-2007. Quantitative easing measures, to the extent they are captured by our QE-shock, thus affected the evolution of output positively, but with a considerable delay. Similarly, the core CPI would have been somewhat lower if no QE-shock had occurred exactly during the QEP-period as well as from June 1997 to the end of 1999, when the monetary stance was expansionary as well. The contemporaneity of the effect on CPI is, of course, by construction; however, it can be seen that the effect does not fade right away. Furthermore, Figure 3.13 reveals that indeed our QE-shock identified according to the benchmark setup explained above contributed positively to the level of current account balances from 1997-1999 and during the QEP period. Our shock thus captures a substantial part of the reserves expansions implemented by the Bank of Japan within the QEP. Moreover, it

²⁰The decomposition of the data was performed using the Matlab code of Kilian (2009), which can be downloaded online at <http://www.aeaweb.org/articles.php?doi=10.1257/aer.99.3.1053>.

²¹Of course, the counterfactual development of the respective variables is solely based on our simple VAR model and should therefore be interpreted with caution.

can also be seen that the long-term yield would have been substantially higher during the QEP period without the QE-shock we identify.

Figure 3.13: Actual and Counterfactual Evolution of the Variables



The figure displays the actual and counterfactual evolution of industrial production, CPI, reserves and the long-term yield under the assumption that no QE-shock occurred. Series for industrial production, CPI, reserves and the exchange rate are in log-levels, the long-term yield series is in percent. The blue vertical lines indicate the QEP period 2001:03-2006:03.

To summarize, this counterfactual exercise nicely shows that our QE-shock indeed captures part of the increase in current account balances, not only during the QEP period but also during the late 1990's, and that this shocks affects the behavior of industrial production, the CPI and long-term yields, especially during and after the QEP period. In line with the insignificant effect of the QE-shock on the exchange rate, this variable's development does not seem to depend on the QE-shock; its counterfactual evolution mostly matches its actual behavior.

Comparison with a Traditional Monetary Shock pre-1995

In order to put into perspective the effects of the QE-shock it is instructive to compare the unconventional policy shock, identified under ZLB conditions, with a traditional monetary shock during “normal times”. We therefore additionally estimate a VAR model for the Japanese economy for the pre-1995 period, including the following variables:

$$Y_t = [CPI_t, IP_t, CRATE_t, M0_t, EXR_t], \quad (3.9)$$

where CPI_t , IP_t and EXR_t denote the core consumer price index, the industrial production index and the real effective exchange rate; these variables have been used in the benchmark specification as well. Additionally, we include the call rate, which has been the main operating target of the Bank of Japan in the pre-1995 period ($CRATE_t$)²². We furthermore consider the monetary base ($M0_t$), which has also been included in the “traditional” VAR model of Miyao (2002).²³ We again estimate the model in log-levels after seasonally adjusting CPI_t , IP_t , EXR_t and $M0_t$. As for the benchmark estimation, we linearly detrend the variables prior to estimation and include six lags of the endogenous variables. Again, our results are robust to changing the lag length. We estimate the model for the period January 1975 to December 1994; Chow breakpoint tests confirm our sample choice.²⁴

We again identify the monetary shock using sign restrictions, which are summarized in Table 3.5. As can be seen in the table, we impose the standard assumptions that an expansionary monetary policy shock has a non-negative effect on consumer prices, on the monetary base as well as a non-positive effect on the policy interest rate. Similar restriction schemes have been used in existing VAR analyses, see Uhlig (2005), Canova et al. (2007) and Peersman (2005). As in Uhlig (2005), we adopt an agnostic stance with respect to industrial produc-

²²See Miyao (2002) and Ugai (2007), among many other references. We follow Miyao (2002) and link the monthly average of the uncollateralized overnight call rate, which is considered the main policy instrument but only available from July 1985, with the collateralized call rate. To link the two series, as in Miyao (2002), we add the mean difference between the two series to the collateralized rate

²³We include this variable because it has been used in the VAR literature for Japan, and because it is available from 1975. Our main results are robust if we include the reserve component of the monetary base, which is, however, only available from 1981.

²⁴In fact, two tests reject the hypothesis of parameter stability at the 1% confidence level, when the break date is exogenously specified as January 1995. See Table 3A.2 in Appendix 3.A.4

tion in order to be able to compare the real effects of our QE-shock under ZLB conditions reported above with the effects of a traditional shock during “normal times”.

Table 3.5: Identifying Sign Restrictions - Traditional Shock Pre-1995

Variable	Demand shock	Supply shock	Monetary shock	horizon
CPI	≥ 0	≤ 0	≥ 0	$K = 12$
Ind. production	≥ 0	≥ 0		$K = 12$
Call rate	≥ 0	≤ 0	≤ 0	$K = 12$
Monetary base			≥ 0	$K = 12$
Exch. rate				

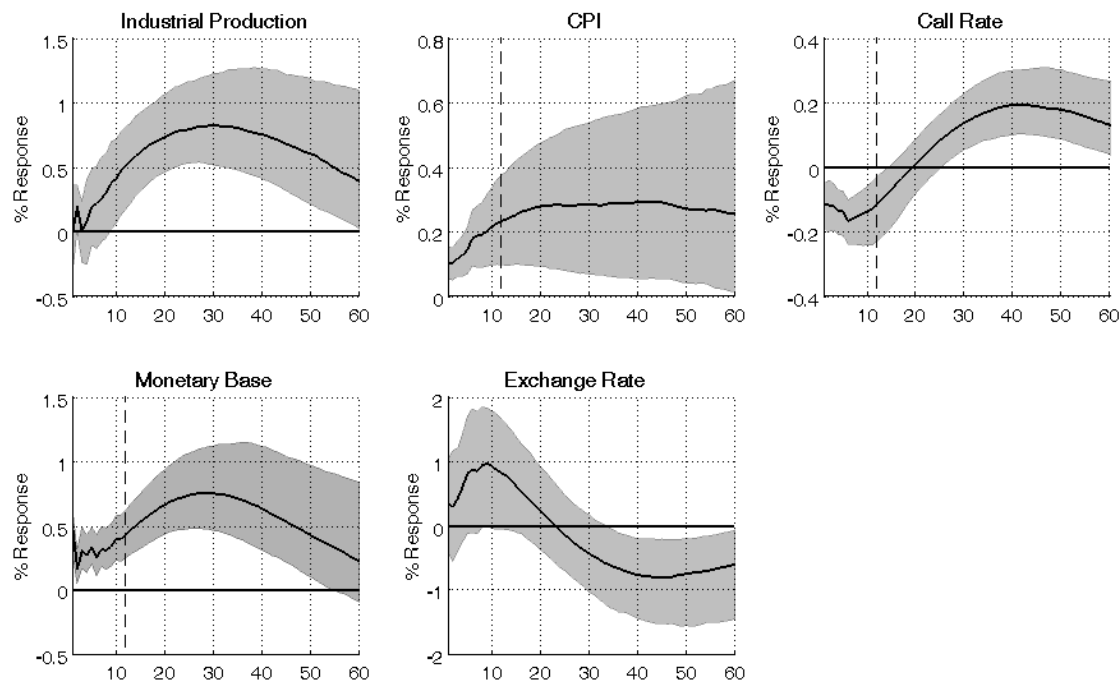
Notes: The table displays sign restrictions on the responses of the variables in the model after a demand, supply and traditional monetary shock, respectively. $K = 12$ indicates that the restriction horizon is twelve months.

Figure 3.14 displays the impulse responses of the variables included in specification (3.9) to the traditional expansionary monetary policy shock as identified in Table 3.5. Again, the black lines show the median impulse responses from a BVAR with 1000 draws, while the shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses.

The responses of the monetary base, the call rate and the CPI have been restricted for 12 months following the shock, so the direction of the responses is by construction. It can be seen, however, that compared to the reaction to a QE-shock at the ZLB the response of the CPI is much stronger amounting to 0.3% after about one and a half year. The shape of the price response following the traditional expansionary policy shock is in line with existing VAR evidence for Japan (Miyao, 2002) and elsewhere (Christiano et al., 1999; Peersman, 2005) during normal times; CPI increases gradually and shows a rather persistent reaction. With regard to the policy instrument, the initial decline in the call rate is later offset by an increase in this variable; a phenomenon that is found in other VAR applications as well.²⁵ The figure furthermore shows a prolonged increase in the monetary base following the shock, which lasts much longer than preset.

²⁵For instance, Uhlig (2005) rationalizes this observation by the notion that monetary policy shocks may indeed reflect exogenous shocks to the policy reaction function, which the central bank later tries to offset by reversing its course.

Figure 3.14: Impulse Responses to a Traditional Monetary Shock



Responses over a 60-month horizon to a traditional monetary shock as identified in Table 3.5. Solid lines denote the median impulse responses from a BVAR (1000 draws), shaded areas the 16% and 84% percentiles of the posterior distribution of the responses. Vertical lines indicate the restriction horizon.

As expected, the exchange rate decreases due to the shock indicating a significant but delayed depreciation of the currency. Most interestingly, the response of industrial production, which has been left unrestricted, appears to be rather strong and persistent compared to its reaction to the unconventional shock at the ZLB. Figure 3.14 shows a hump-shaped response of industrial production, which becomes significantly positive after around six months. The response is somewhat stronger compared to the rather mild reaction of output following a QE-shock amounting to almost 1% after around two years. In fact, the shape of the output response resembles traditional VAR evidence reported by Christiano et al. (1999) and Peersman (2005).

The main conclusion emerging from assessing the effects of a traditional expansionary interest rate innovation during normal times is that compared to such a policy shock our QE-shock only has a very limited potential to favorably affect important macroeconomic variables if the economy is at the ZLB. Compared to

the effects of the traditional policy shock, the responses of prices and output are rather weak and last only temporarily.

3.4.4 Robustness

Close-to-Median Model

The first robustness check is concerned with the median as a way to summarize the information obtained from the sign-restriction approach to generating impulse responses. Figures 3A.2 to 3A.4 in Appendix 3.A.3 replicate the median impulse responses along with the 68% confidence intervals to the respective shocks. The red dashed lines additionally show the impulse responses generated by the one model that is closest to the median over all 1000 models; see Section 3.3.2. It can be seen that generally, the impulse responses generated by this “close-to-median model” are very similar to the median over all models.

Further Variations in the Identification Scheme

We check sensitivity of our results to two further variations in the identification scheme with regard to identification of the QE-shock.²⁶ First, we additionally impose an impact zero restriction on industrial production; this setup is summarized in Table 3.6. As has been mentioned above, both consumer prices and output are usually assumed to react with a lag to monetary shocks - we only left the response of industrial production unrestricted in the benchmark scheme to be agnostic concerning the real effects of unconventional monetary policy. Imposing this additional zero restriction, however, results in a more conservative identification scheme. As can be seen in Figure 3A.5 in Appendix 3.A.3, our results are largely insensitive to this alteration. In fact, the effect of the QE-shock on industrial production is even somewhat more pronounced compared to the benchmark case.

The second alteration with regard to the restriction setup is concerned with the effect on consumer prices. Arguably, since one of the objectives of the Bank of Japan conducting the QEP was to affect prices and to resolve the deflationary spiral, it is instructive to additionally adopt a more agnostic stance with regard to the effects on this variable. In order to better analyze the actual effect of our

²⁶We stick to our benchmark identification setup for the demand and supply shock, see Table 3.1. However, the corresponding results for the QE-shock are very similar when we identify the business cycle shocks according to the Eggertsson (2010)-setup.

QE-shock on the CPI we implement a further identification scheme leaving the response of the CPI unrestricted, except for the zero restriction.²⁷ To make sure to clearly identify an unconventional monetary shock without this restriction we assume a non-positive reaction of the long-term yield following the shock.²⁸ This third alternative identification scheme is summarized in Table 3.7.

As shown in Figure 3A.6, qualitatively, our results are insensitive to this alteration. Interestingly, consumer prices show a significantly positive reaction to the shock during the first eight months. This indicates that in general, imposing the non-negativity constraint as in the benchmark identification scheme is not at odds with the data. However, as for the benchmark case the effect is rather weak and highly transient confirming that prices are hardly affected by an unconventional policy shock.

Table 3.6: Identifying Sign Restrictions - Alternative Identification II

Variable	Demand shock	Supply shock	QE-shock		horizon
	sign	sign	impact	sign	
CPI	> 0	< 0	0	≥ 0	$K = 12$
Ind. production	> 0	> 0	0		$K = 12$
Reserves				> 0	$K = 12$
Long-term yield					
Exch. rate					

Table 3.7: Identifying Sign Restrictions - Alternative Identification III

Variable	Demand shock	Supply shock	QE-shock		horizon
	sign	sign	impact	sign	
CPI	> 0	< 0	0		$K = 12$
Ind. production	> 0	> 0			$K = 12$
Reserves				> 0	$K = 12$
Long-term yield				≤ 0	$K = 12$
Exch. rate					

²⁷We still need the zero restriction in order to be able to clearly identify the three shocks.

²⁸The validity of this restriction is of course confirmed by our benchmark results reported above. Moreover, restricting long-term interest rates to identify unconventional monetary shocks is a common approach in the sign-restriction literature, see Baumeister and Benati (2010) and Peersman (2011).

Changing the Sample Period

As we argue above, already since the mid 90's the call rate was increasingly losing its central role as a policy instrument; instead, the Bank of Japan began to conduct policy via current account balances (see Section 3.2). However, Figure 3.3 nevertheless suggests a break in the CAB series around the period the quantitative easing policy was implemented.²⁹ In order to check whether our results are robust to accounting for the change in this series, we additionally estimate our benchmark specification for a shorter sample period ranging from March 2000 to March 2007. Thus, we only estimate the model for the QEP period as well as the preceding and subsequent 12 months. We extend the sample in this way to be able to use a sufficient number of observations for the estimation³⁰, but also because the amount of CABs was already varied to a relatively large extent by the Bank of Japan prior to the official start of the QEP in 2001, and the measures were possibly not fully terminated right after the official end of these policies. Figure 3.3 confirms this showing spikes in the CAB series already around 1999/2000 and again in 2007. Figure 3A.7 shows that our main results are qualitatively similar for this smaller sample; however, the quantitative effects on industrial production and CPI are somewhat smaller. Interestingly, analyzing this smaller sample, the exchange rate now increases significantly after the QE-shock by around 0.7%. This suggests that apparently, during this period taken by itself, the QE-measures lead to an appreciation of the currency after around six months. This somewhat surprising finding is may be reconciled by noting that a currency appreciation could of course also result from secondary effects. An increase in industrial production as well as a generally more favorable economic outlook resulting from QE measures may increase aggregate demand for domestic goods thereby raising relative prices. Importantly, however, apart from the reaction of the exchange rate, which has been insignificant in the benchmark estimation, the results for the other variables are insensitive to changing the sample period.

As a further way to account for the break in the data around the start of the QEP,

²⁹In fact, Chow breakpoint tests do not concordantly reject the null hypothesis of parameter stability. As Table 3A.2 in Appendix 3.A.3 shows, for 2001:03 as break date, the Chow forecast test does not reject the Null at the 1% confidence level, while the other two tests only reject the Null at the 5% level. Parameter instability is somewhat clearer for break date 2000:03.

³⁰Starting the sample at a later date leads to issues related to an insufficient number of free parameters. In order to further save degrees of freedom, we only include three lags in the model, which is suggested by most lag length criteria.

we estimate the model using our full sample period but additionally including a step dummy indicating the start of the QE program in March 2001. Figure 3A.8 shows that our results are largely insensitive to this alteration even though the identified shock is now somewhat smaller raising reserves only by around 5%-6%.

Further Robustness Checks

A further sensitivity test involves specifying the restriction horizon K . As noted by, for instance, Uhlig (2005), it is difficult to base the choice of the appropriate restriction horizon on economic theory resulting in some degree of arbitrariness in specifying this parameter. We therefore check the sensitivity of our results to this choice by estimating the benchmark model for different restriction horizons. Figure 3A.9 in Appendix 3.A.3 shows the impulse response functions for our variables of interest, CPI and industrial production, for a lower restriction horizon compared to the benchmark model of six months, $K = 6$, and for a longer horizon of 18 months, $K = 18$, (displayed in the first and the third row, respectively). The benchmark case, $K = 12$ is given in the second row. The dashed vertical lines again indicate the respective restriction horizon. It can be seen in the figure 3A.9 that our qualitative results are very similar. However, error bands are wider for a restriction horizon of six months.³¹ By contrast, the response of industrial production lasts somewhat longer for $K = 18$, while the effect on CPI is slightly stronger in this case.³²

Furthermore, qualitatively, our results are robust to changing the number of lags included in the VAR model to 4, 9 or 12; see Figure 3A.10 in Appendix 3.A.3. The figure reveals, however, some quantitative differences; for longer lag lengths the effect on the CPI becomes stronger. Similarly, Figure 3A.11 in Appendix 3.A.3 shows that starting the sample period for instance at 1994:01 when the Bank of Japan first lowered the call rate to values of around 2% does not alter our main findings. Furthermore, starting the sample in January 1996 or January 1997 leads to qualitatively similar results.³³ These results are displayed in Figure 3A.11.

Moreover, we replace the variable representing the main monetary instrument during the QEP; instead of CABs we now include excess reserves as main mon-

³¹Similar results are obtained for a restriction horizon of nine months or eight months.

³²Again, results are very similar for even longer restriction horizons of, say, 24 months.

³³Given that for instance Inoue and Okimoto (2008) find evidence for a break in the Japanese economic system around 1996 this result is particularly reassuring.

etary instrument. Arguably, reserve holdings in excess of reserve requirements may be considered a more direct measure of expansionary monetary policy. Figure 3A.12 shows that the QE-shock we identify in this specification raises excess reserves by around 25%. The effects on the other variables are very similar to our benchmark model; while the increase in industrial production is somewhat less pronounced, the effects on the CPI and the long-term yield are qualitatively and quantitatively similar.

Finally, we include a dummy indicating the VAT increase in April 1997; the dummy variable takes on the value one in the period of the increase and in the three subsequent months. Figure 3A.13 shows that the results for the QE-shock are insensitive to accounting for this fiscal policy measure.

3.5 Conclusion

The primary objective of this paper has been to assess the macroeconomic effects of QE measures adopted by the Bank of Japan during a prolonged zero lower bound episode. We suggest to use results from the theoretical literature to derive identifying restrictions for our SVAR model. In particular, we propose a set of sign restrictions based on predictions of DSGE models explicitly taking into account the ZLB, which clearly identify an unconventional shock without imposing restrictions on real activity, interest rates, yield spreads or the exchange rate. Given that a broad consensus is still missing as to how to identify monetary shocks at the ZLB, we used two different identification strategies. Our results, which are robust to various alterations in the specification and identification setup, show that a QE-shock does positively and significantly affect industrial production; however, the response is rather delayed and highly transient. After around two years industrial production has risen by about 0.4% following an unconventional shock; a shock that at the same time leads to an increase in reserves by about 7%. Moreover, the shock has a significant effect on core CPI, which is, however, quite weak and of transient nature as well. Overall, therefore, our empirical results tend to suggest that unconventional policy actions can, with a considerable delay, positively affect real economic activity even when the economy is at the zero lower bound. However, the QE-shock we identify only has a rather weak and temporary effect on output and prices. Compared to a traditional monetary policy shock, which is identified for the pre-1995 period when monetary policy was *not* constrained by the ZLB, the effects of the QE-shock on the macroeconomic variables included in the model are rather negligible.

To the extent that economic conditions are similar in other advanced economies where monetary policy is possibly constrained by the ZLB as well, these results may be interesting also with regard to the effects of unconventional policy actions in these other countries.

Concerning possible transmission channels of unconventional monetary policy our empirical results only allow limited conclusions. We report a clear and significant decrease in long-term yields, which could potentially induce portfolio shifts in the spirit of Meltzer (1995). On the other hand, we do not find any significant negative effect on the exchange rate suggesting that potential portfolio rebalancing effects - at least in terms of shifts towards assets denominated in foreign currency - have not been effective in depreciating the Japanese currency.

Moreover, our results suggest a negligible role of broader monetary aggregates; M2 + CDs do not react significantly to the QE-shock indicating limited scope for a monetary base expansion to affect output and prices via direct quantity effects, even if a stable relation between money supply, prices and output existed.

One possible interpretation of these findings, along the lines of Svensson (2003), could be that the Bank of Japan simply did not do enough to depreciate the exchange rate thereby fostering economic activity. Related, Hetzel (2003, 2004) argues that the base money expansion implemented by the Bank of Japan was limited to reserves demanded by banks and the public; only a more pronounced expansion beyond the amount demanded by the public would in effect lead to substantial effects on output and prices.

However, given the limited ability of our SVAR model to analyze an even larger set of variables, a more detailed assessment of the particular transmission channels at work following unconventional policy shocks is difficult. A further investigation of this issue, possibly within a more extended empirical model, is left for future research.

3.A Appendix

3.A.1 Data

Monetary variables

For our ZLB model, we include a measure of reserve holdings, the long-term interest rate, as well as a measure of the Japanese money stock. To estimate the effects of the traditional shock, we include the call rate and the monetary base M0. More specifically, as a measure of reserves, we include the average outstanding current account balances (CABs) held by financial institutions at the Bank of Japan. This is the part of the monetary base that can be referred to as reserves held at the central bank. As broader money supply, we consider the most commonly used measure of money stock in Japan, which is M2 + CDs. As a measure of long-term rates we include the 10-year government bond yield. The call rate series is constructed from the respective monthly average of the uncollateralized and the collateralized overnight call rate. All these series have been obtained from the Bank of Japan's statistics website. The measures of the monetary aggregates and the reserves variables are seasonally adjusted by X12-ARIMA.

Prices and Exchange Rate

We include the core consumer price index, which measures the development of consumer prices excluding energy and food. Base year is 2005. The core CPI has been obtained from Datastream. Moreover, we include a narrow index of the real effective exchange rate of the Yen against other currencies as published on the Bank for International Settlements' (BIS) website. Both series are seasonally adjusted by X12-ARIMA.

Industrial Production

We include a measure of the Japanese industrial production as a generally used indicator of economic activity. Base year is 2005. The series has been obtained from Datastream and is seasonally adjusted by X12-ARIMA.

3.A.2 Foundations for the Alternative Identification Scheme - The Model of Eggertsson (2010)

This section shortly summarizes important aspects of the model of Eggertsson (2010), which is an example of a standard New Keynesian DSGE model with monopolistic competition and nominal frictions in the form of a standard Calvo-type price setting rule.³⁴ The model explicitly accounts for the zero lower bound, which arises as the result of a negative preference shock leading to an output collapse. After such a shock, the economy is assumed to stay at the ZLB with probability μ and to revert back to steady state with probability $1 - \mu$.

Monetary policy in this model follows a Taylor rule, which incorporates the possibility of the zero lower bound: $i_t = \max(0, r_t^e + \phi_\pi \pi_t + \phi_y \hat{Y}_t)$, where r_t^e is an exogenous shock, \hat{Y}_t denotes the output gap, π indicates the rate of inflation, and ϕ_π and ϕ_y are the Taylor rule coefficients. It is then shown that monetary policy is implemented according to:

$$\begin{aligned} i_t &= r_H^e \quad \text{for } t \geq T^e \\ i_t &= 0 \quad \text{for } 0 < t < T^e, \end{aligned}$$

where r_H^e denotes the policy shock in the non-recession case and T^e denotes the stochastic date where the shock returns back to steady state. With these assumptions in place, Eggertsson (2010) arrives at the following AD and AS equations describing the output gap and inflation for $t < T^e$:

$$AD \quad \hat{Y}_L = \mu \hat{Y}_L + \sigma \mu \pi_L + \sigma r_L^e \quad (3.10)$$

$$AS \quad \pi_L = \kappa \hat{Y}_L + \beta \mu \pi_L, \quad (3.11)$$

where r_L^e denotes the negative preference shock in the recession state, indicated by L , and the coefficients are $\sigma, \kappa > 0$ and $0 < \beta < 1$. Eggertsson (2010) outlines these two equations in a graph, which is replicated in the left panel of Figure 3A.1. The blue dashed lines indicate the multiperiod recession case, in which the ZLB lasts longer than one period; $\mu > 0$. This is the case we refer to in our identification scheme implemented above. As was discussed above, the AD curve is now upward sloping. At the ZLB, any changes in expected

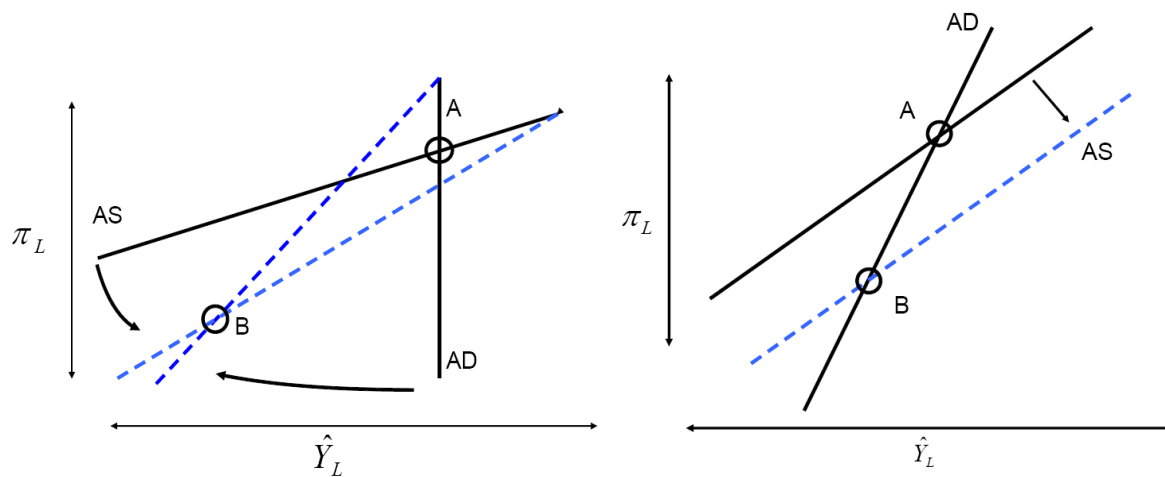
³⁴Since the focus of his study is on the effects of fiscal policy, the model features a more explicit depiction of the public sector, i.e. taxes and government spending relative to standard models.

inflation and resulting swings in the real interest rate cannot be offset by the nominal interest rate. Thus, for instance expected deflation ($\mu\pi_L < 0$) leads future consumption to be cheaper than current consumption, which results in a contraction of consumption and thus output. With regard to the AS curve for the multiperiod ZLB case, its slope is now steeper than for the one-period recession case; expected deflation leads firms to lower prices by more for a given decrease in demand.

One crucial point for the correct implementation of our alternative identification scheme given above relates to the necessary conditions for the AD curve to be steeper than the AS curve. As noted in footnote 20 in Eggertsson (2010), the dynamics of the model amplify the longer the ZLB period lasts. As can be seen in equations (3.10) and (3.11), as μ increases the AD curve becomes flatter and the AS curve steeper resulting in a lower intersection point in the left panel of Figure 3A.1. At a critical value $1 > \bar{\mu} > 0$, called the “deflationary black hole” in Eggertsson (2010), both curves are parallel and no solution exists. Throughout the paper, Eggertsson (2010) assumes $\mu < \bar{\mu}$ for a well-defined solution to exist. Thus, if one accepts the assumption the μ is below this critical value or, in other words, the ZLB does not last “forever”, our restriction setup is a valid identification scheme.

Finally, the right panel of Figure 3A.1 shows the effect of a positive aggregate supply shock shifting down the AS curve. In fact, Eggertsson (2010) focuses on shocks related to tax cuts; however, the crucial point about such a tax shock leading to the distinct dynamics at the ZLB is that it works via aggregate supply thus influencing expectations about future deflation. Thus, similar dynamics would be at work for any supply shock; in our analysis above we do not explicitly discuss the nature of the supply shock. As can be seen in Figure 3A.1, for the ZLB case (for $\mu > 0$) the positive supply shock now decreases both inflation and output.

Figure 3A.1: The Effect of a Multiperiod Recession in Eggertsson (2010)

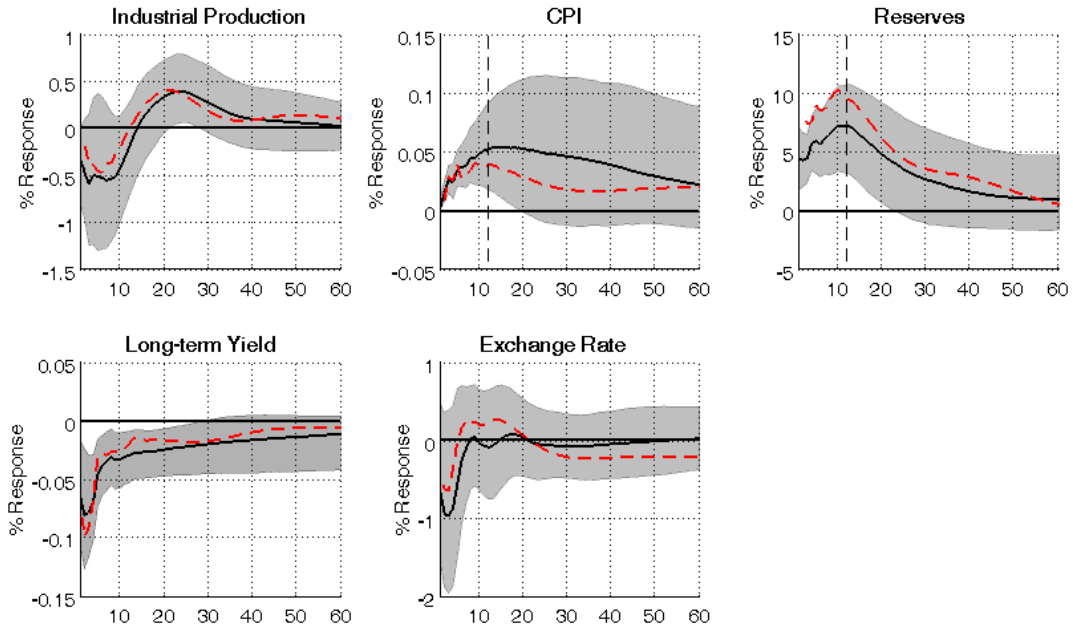


Source of the Figure:

Eggertsson, G. B. (2010). *What Fiscal Policy is effective at zero interest rates?* In NBER Macro- conomics Annual 2010, Volume 25, NBER Chapters, National Bureau of Economic Research, Inc.

3.A.3 Robustness of the Results

Figure 3A.2: Impulse Responses to a QE-Shock - Close-to-Median Model



Responses to a QE-shock. Solid lines denote the median impulse responses from a BVAR (1000 draws), shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses. The red dotted lines display the response generated by the close-to-median model.

Figure 3A.3: Impulse Responses to a Demand Shock - Close-to-Median Model

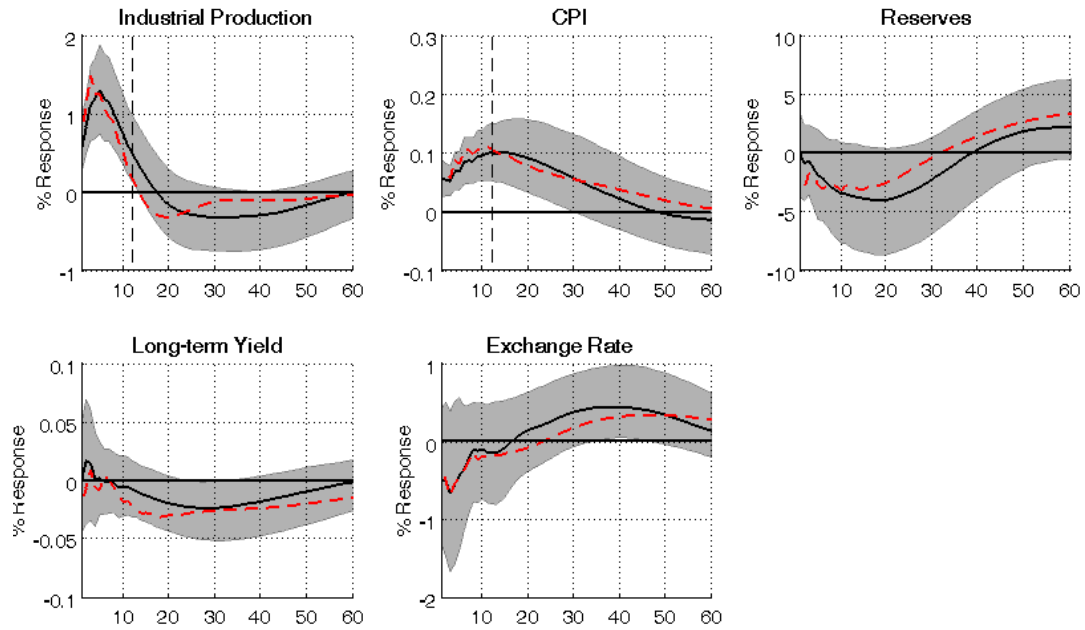
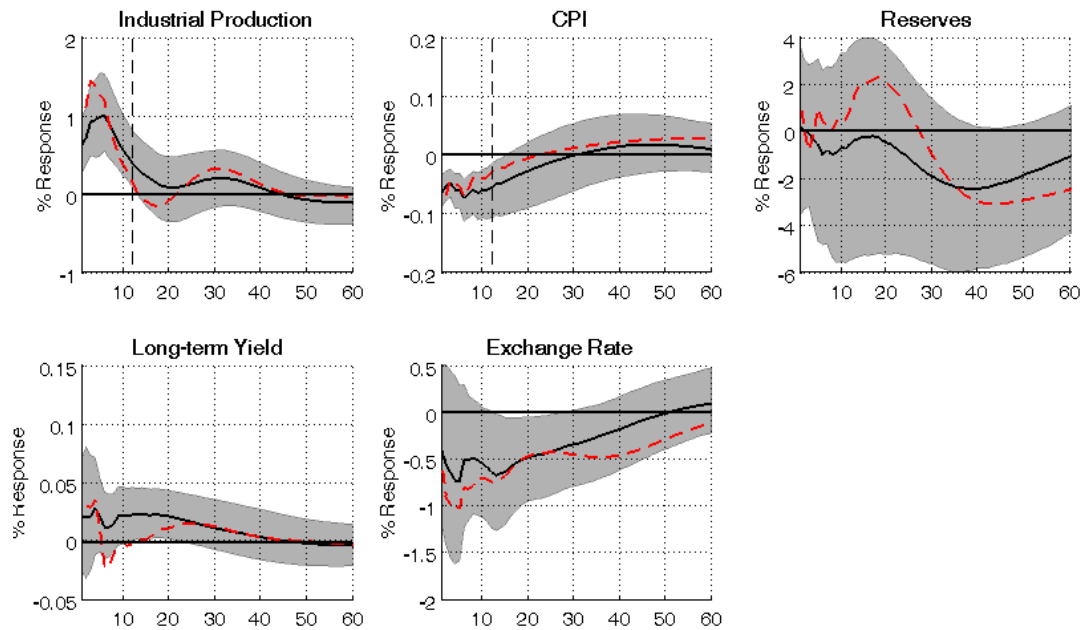


Figure 3A.4: Impulse Responses to a Supply Shock - Close-to-Median Model



Responses to a demand shock (Figure 3A.3) and a supply shock (Figure 3A.4). Solid lines denote the median impulse responses from a BVAR (1000 draws), shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses. The red dotted lines display the response generated by the close-to-median model.

Figure 3A.5: Impulse Responses to a QE-Shock - Alternative Restriction Setup II

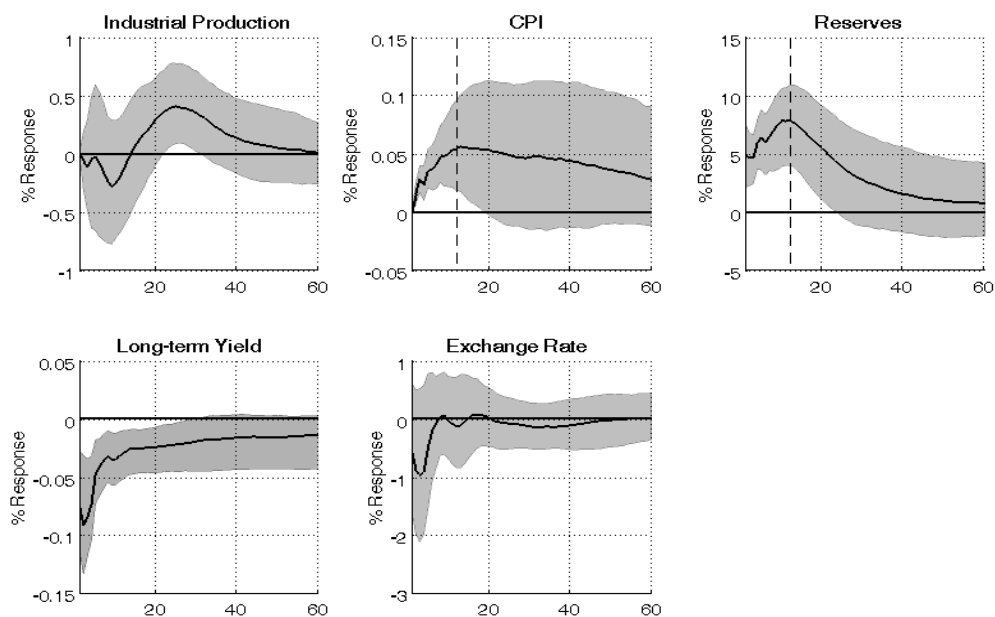
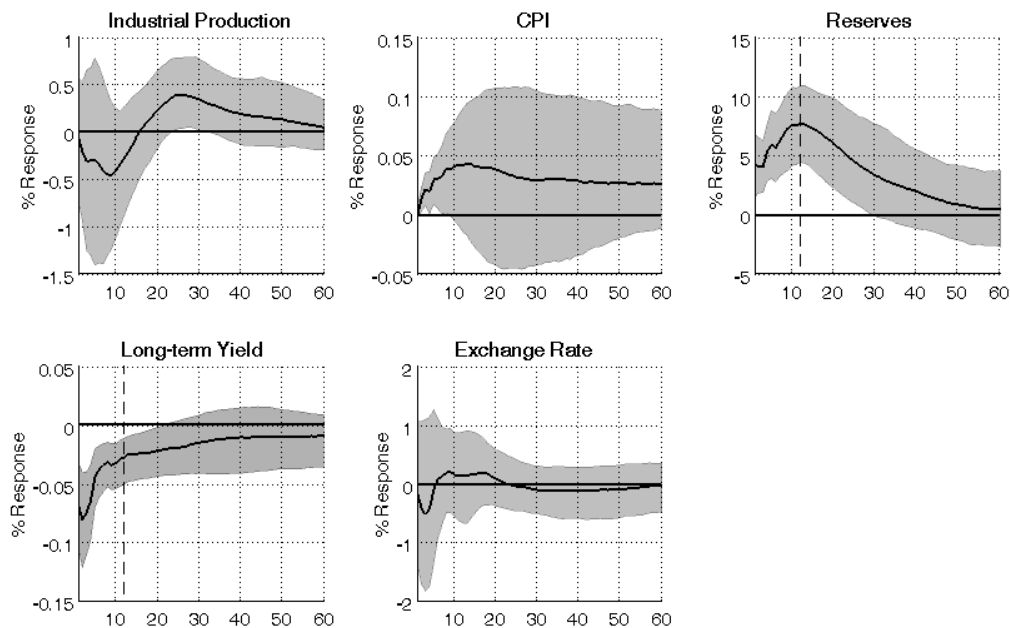


Figure 3A.6: Impulse Responses to a QE-Shock - Alternative Restriction Setup III



Responses to a QE-shock with zero restriction on IP (Figure 3A.5) and restrictions on LTY (Figure 3A.6). Solid lines denote median impulse responses from a BVAR (1000 draws), shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses.

Figure 3A.7: Impulse Responses to a QE-Shock - Shorter Sample Period

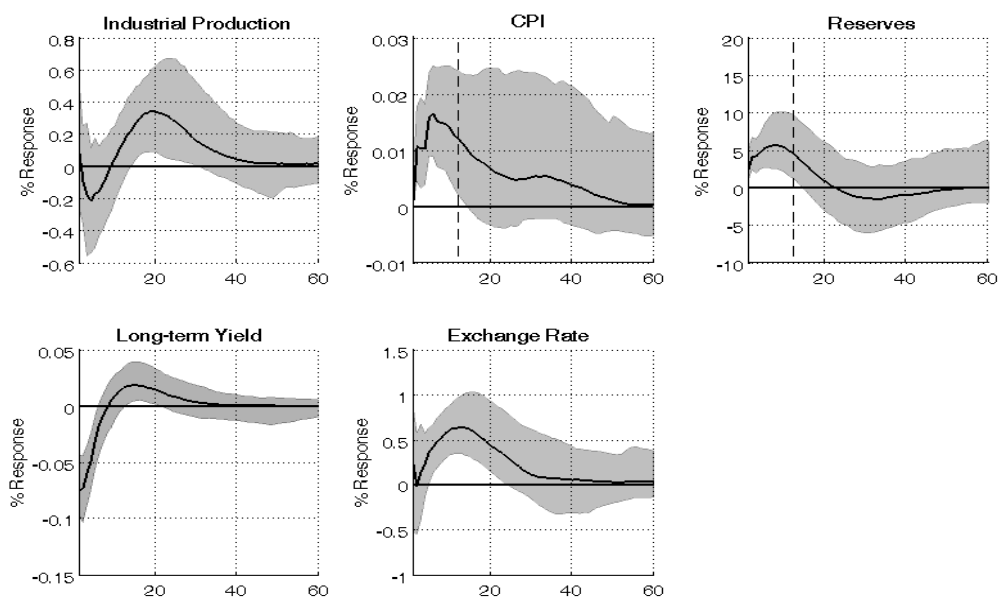
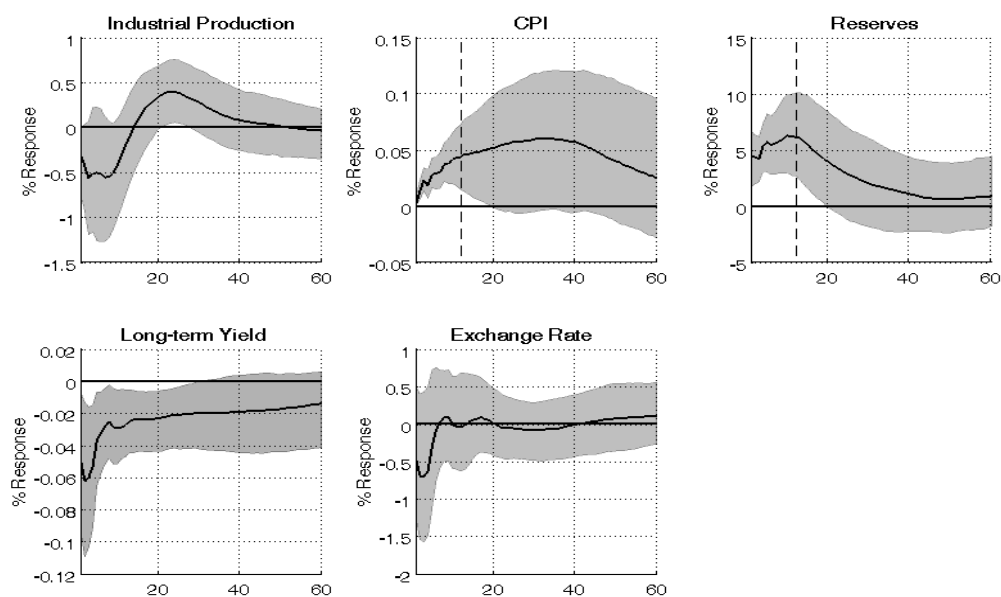
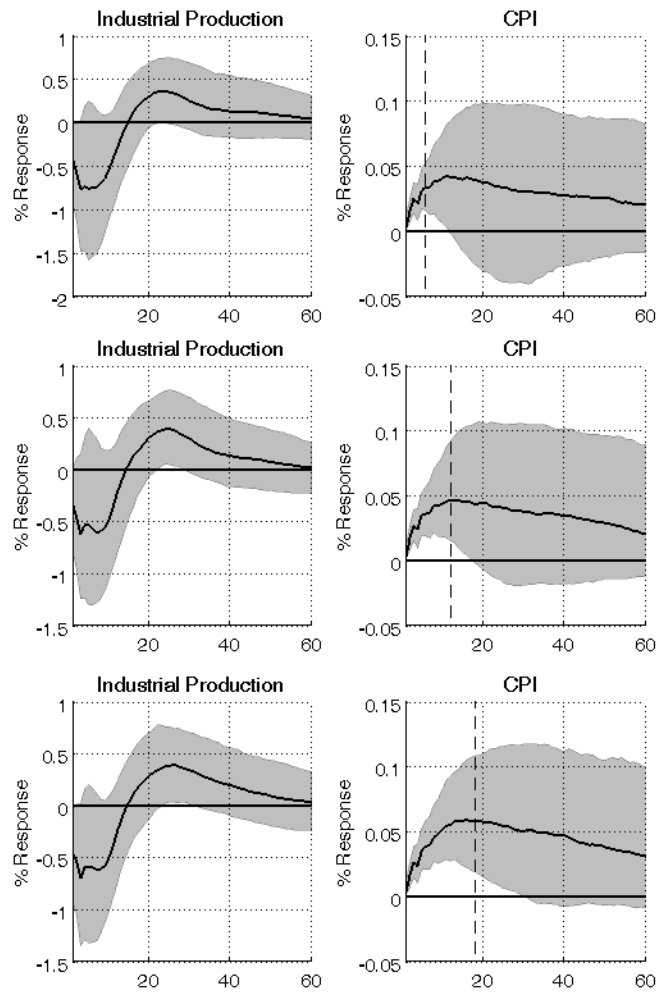


Figure 3A.8: Impulse Responses to a QE-Shock - Including a QEP-dummy



Responses to a QE-shock. Figure 3A.7: sample period is 2000:03-2007:03. Figure 3A.8: full sample including QEP dummy. Solid lines denote median impulse responses from a BVAR (1000 draws), shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses.

Figure 3A.9: Impulse Responses to a QE-Shock - Varying the Restriction Horizon



The figure displays responses of industrial production and the CPI to a QE-shock for different restriction horizons. Solid lines denote the median impulse responses from a BVAR (1000 draws), shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses. The dashed vertical lines indicate the respective restriction horizon.

Figure 3A.10: Impulse Responses to a QE-Shock - Different Lag Lengths

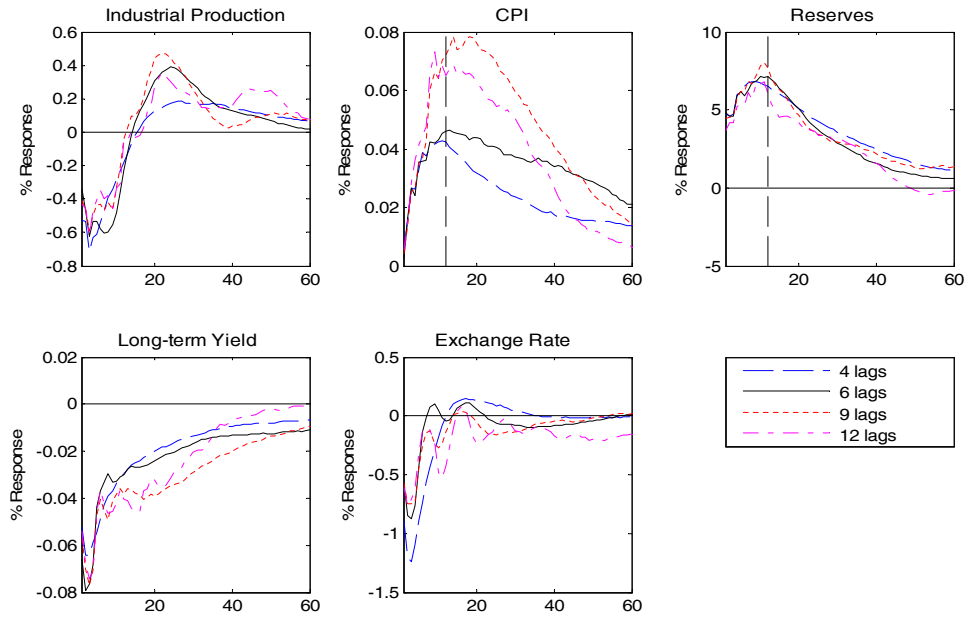
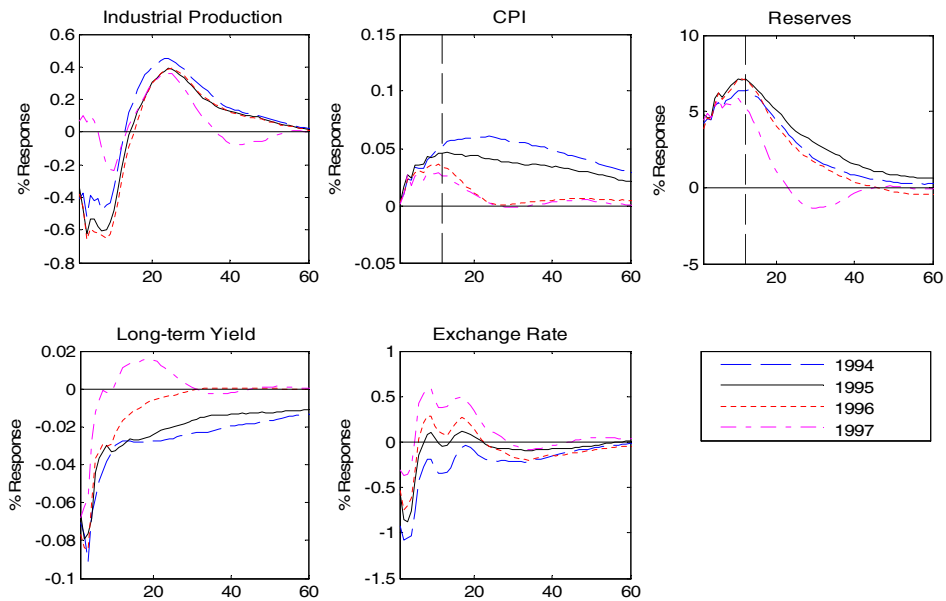
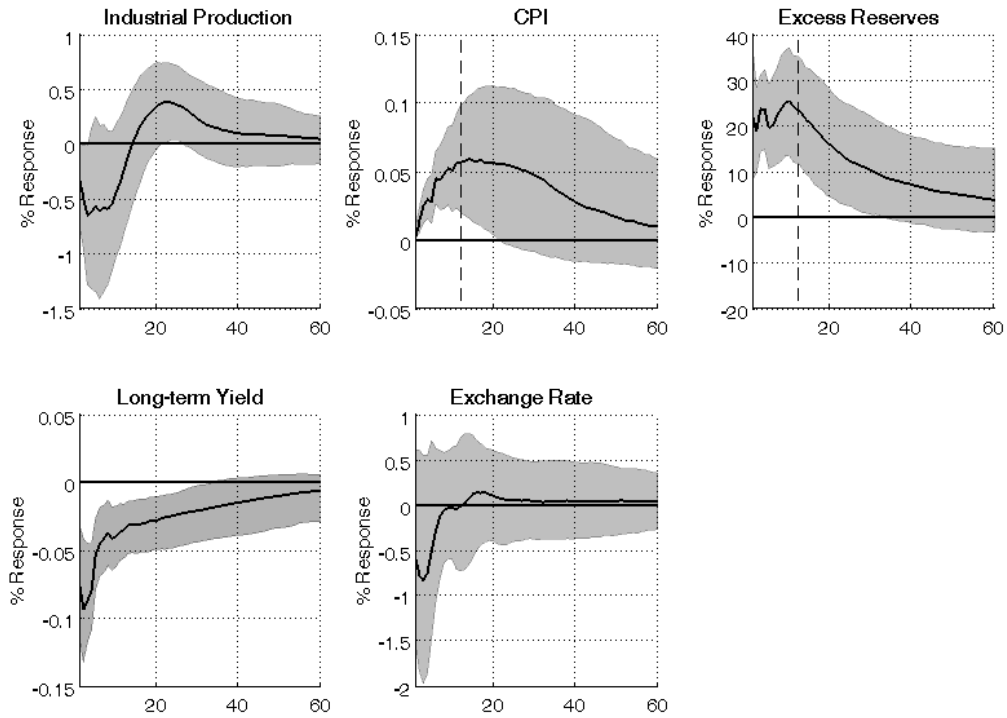


Figure 3A.11: Impulse Responses to a QE-Shock - Different Sample Periods



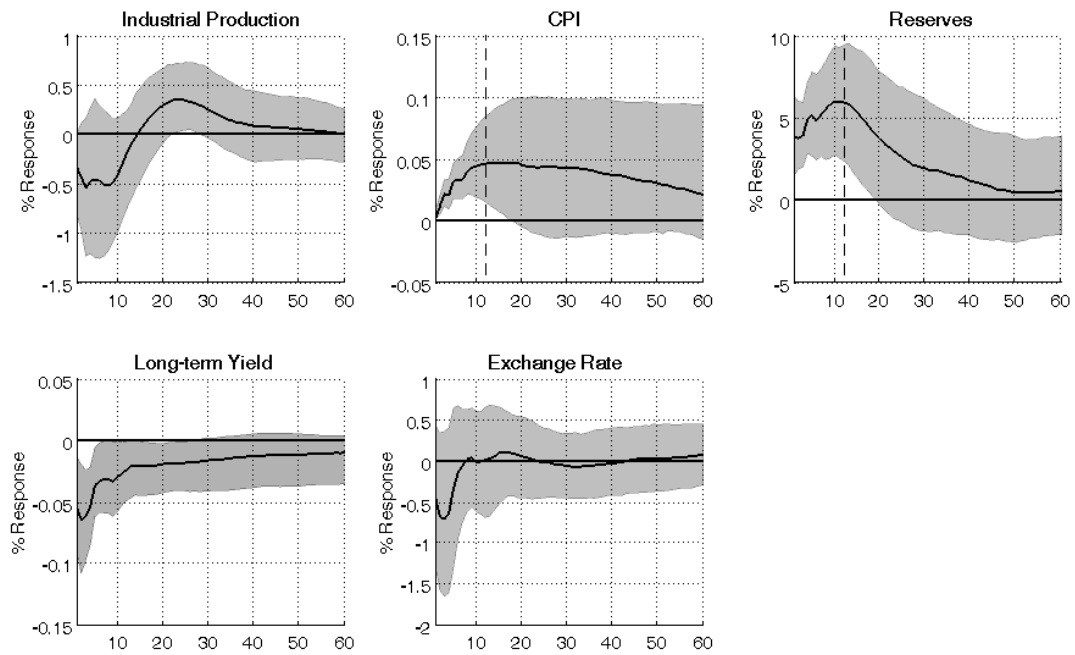
Both figures show responses to a QE-shock. The lines denote the median impulse responses from a BVAR (1000 draws) for the respective sample periods and lag lengths. The respective sample periods start in January of each year (Figure 3A.11). Error bands are omitted.

Figure 3A.12: Impulse Responses to a QE-Shock - Changing Policy Instrument



Responses to a QE-shock. The specification includes excess reserves as policy instrument instead of current account balances. The solid lines denote the median impulse responses from a BVAR (1000 draws), the shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses.

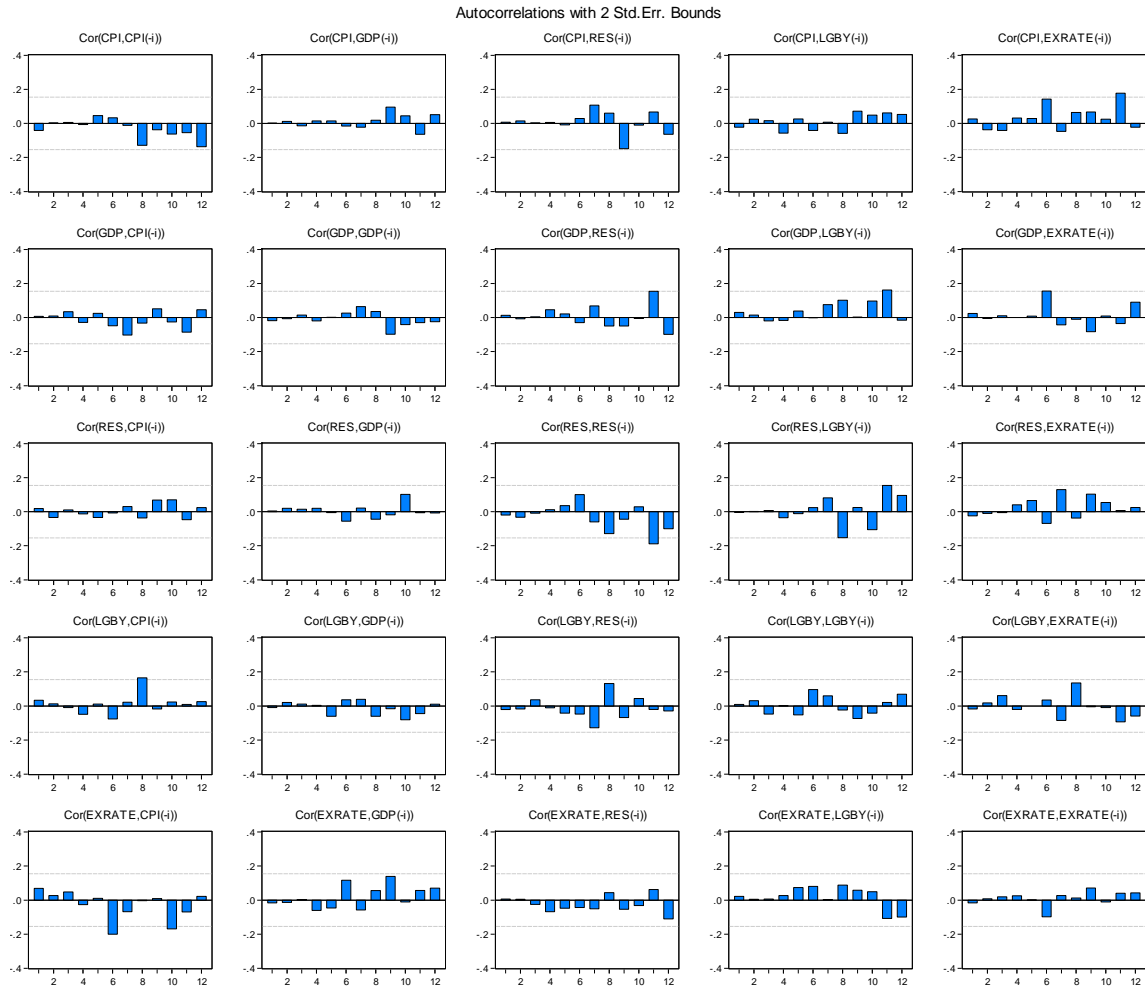
Figure 3A.13: Impulse Responses to a QE-Shock - Accounting for VAT Change



Responses to a QE-shock. The specification includes a dummy variable accounting for the increase in the VAT rate in April 1997. The solid lines denote the median impulse responses from a BVAR (1000 draws), the shaded areas indicate the 16% and 84% percentiles of the posterior distribution of the responses.

3.A.4 Stability of the VAR Model

Figure 3A.14: Estimated Autocorrelations of the Residuals



The figure displays estimated residual autocorrelations of the reduced-form VAR model for lag lengths 1 to 12. The horizontal lines depict 2 standard-error bounds.

Table 3A.1: VAR Residual Serial Correlation LM Test

Lags	LM-statistic	p-value
1	33.25362	0.1248
2	17.98747	0.8429
3	19.23321	0.7858
4	23.56596	0.5446
5	22.99284	0.5780
6	30.08349	0.2212
7	21.70059	0.6530
8	32.03714	0.1569
9	22.93013	0.5816
10	15.97500	0.9156
11	38.84599	0.0382
12	19.94261	0.7498

Notes: The table displays test statistics and p-values from a serial autocorrelation LM test for lag lengths 1 - 12. The approximate distribution is chi-square with 16 degrees of freedom.

Table 3A.2: Chow Breakpoint Tests

Break Date: 2000 M3*		Break Date: 2001 M3*		Break Date: 1995 M1**	
Chow BP Test		Chow BP Test		Chow SS Test	
Test Statistic	505.823	Test Statistic	423.276	Test Statistic	1086.226
P-value	0.002	P-value	0.019	P-value	0.000
Chow SS Test		Chow SS Test		Chow SS Test	
Test Statistic	395.464	Test Statistic	342.831	Test Statistic	353.654
P-value	0.001	P-value	0.036	P-value	0.000
Chow Forecast Test		Chow Forecast Test		Chow Forecast Test	
Test Statistic	1.182	Test Statistic	0.892	Test Statistic	1.232
P-value	0.659	P-value	0.945	P-value	0.108

Notes: The table shows Chow break-point (BP), sample-split (SS) and forecast tests reporting bootstrapped p-values with 1000 replications; see Candelon and Lutkepohl (2001).*: Specification according to equation (3.3), sample is 1995:03-2010:09. **: Specification according to equation (3.9), sample is 1975:01-2010:09.

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Eidesstattliche Versicherung

Ich versichere hiermit eidesstattlich, dass ich die vorliegende Arbeit selbstständig 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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