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European University Institute

Department of Economics

Essays in Applied Macroeconometrics

Sebastian Watzka

Thesis submitted for assessment with a view to obtaining
the degree of Doctor of Economics of the European University Institute

Florence
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Contents

Part I

Introduction

My thesis consists of three independent chapters. Each of them is an empirical study using time series techniques to learn something about the macroeconomy. Hence the title "Essays in Applied Macroeconometrics". Whilst the first chapter is a rather descriptive analysis of the functioning of European bond markets when public news come out, the second and third chapters are guided by business cycle theory and use this theory in the estimation of the models. The next section gives a very brief overview of the thesis.

The first chapter, "Macroeconomic News and the European Bond Market", is an empirical analysis of how the European bond market reacts to macroeconomic announcements and in particular to news in those announcements. The second and third chapters study the causes of the US business cycle and the functioning of the US labor market. The second chapter, "Shocks and Adjustment Costs in an estimated RBC model for the US", takes the simple RBC model and asks which real shocks and which factor adjustment costs matter for the US business cycle in such a model. The third chapter, "Dynamic Beveridge and Phillips curves: A macroeconometric analysis of the US labor market", investigates in more detail the frictions in the US labor market. Although chapters two and three are empirical in nature, they are firmly grounded in dynamic stochastic general equilibrium (DSGE) theory and make heavy use of this theory in the empirical analysis. The rest of this introduction summarizes each chapter in some more detail.

In the first chapter I study the question how European bond markets respond to macroeconomic news. Bond markets are very interesting to study because the price of bonds depends essentially only on the discount rate, or the yield. Using an expectations hypothesis theory of the term-structure the paper argues that because a bond's yield is approximately an average of expected future short rates, the response of the yield tells us something about the market's change in expectations about the future short rates set by the central bank.

The study uses high-frequency intradaily data on 2 and 10-year German government bond yields, which have become pretty good measures of what could constitute a truly European bond, event data on 17 macroeconomic announcements and standard time series regression and GARCH models. I do indeed find strong effects of macroeconomic surprises on the conditional mean and volatility of yield changes. These effects are generally stronger for the short yield. Optimistic surprises about the future prospect of the economy, say a higher than expected Ifo index announcement, generally increase bond yields, suggesting the market expects future short term rates to be set higher by the central bank. The announcements whose surprises matter most are the ECB interest rate decision, the Ifo index announcement, and the US employment and GDP figures. Announcements increase - on impact - the volatility of yield change shocks, but this effect disappears quickly. Somewhat surprisingly I find that *surprises* actually *lower* the conditional volatility in the market. In other words, bigger surprises lead to lower yield change shock volatility. I argue that this could be due to a somewhat *clearer* signal sent by rather big surprises, but this finding deserves more research effort in the future. This finding seems to be rather new to the literature.

The second and third chapters in my doctoral thesis then deal with a macroeconometric analysis of the US business cycle and the labor market in particular. Both papers use DSGE models whose structural parameters are estimated using recently advocated estimation methods. The research is therefore empirically motivated, but contains a very strong structural flavor.

In my second chapter I estimate the structural causes and factor frictions of the US business cycle within a Real Business Cycle (RBC) framework. In particular, I set up a small-scale RBC model that allows for five structural shocks: In addition to the standard technology shock I include a shock to preferences, labor supply, the depreciation rate and a government spending shock. To study the importance of factor market frictions I also allow for capital and labor adjustment costs. The full model is then estimated using Bayesian methods on US post-war data. I then use the estimated model to answer the following questions: which economic shocks drive the US business cycle, which factor market is more rigid, and whether the structure of the US economy has changed in the early 1980s.

The method and the model allow me to answer these questions, though it needs to be admitted that the answer depends critically on the assumed model framework. I then find technology shocks to be indeed very important for most variables. Hours worked, however, is driven almost entirely by the labor supply shock. This somehow suggests that the standard RBC model cannot generate an hours worked time series that resembles the true hours worked time series of the US. It implies instead that an exogenous shock to labor supply alone is responsible for generating the hours worked series. Further, labor adjustment costs are found to matter strongly in the propagation of the shocks. This hints to the existence of substantial real rigidities arising from labor market imperfections. This issue is taken up again in my third paper which I will outline below. Finally, there is some evidence on a structural break in the deep parameters of the model with the shock processes becoming less volatile after 1984.

In the third chapter I look more carefully into the US labor market. From an aggregate perspective I study the effects of monetary policy shocks and technology shocks on the Beveridge curve, i.e. the relation between unemployment and vacancies, and on the Phillips curve, i.e. the relation between unemployment and inflation. The paper first uses a Structural Vector Autoregressive (VAR) model to identify the two structural shocks. Conditional correlation analysis, impulse responses and variance decompositions are then studied with focus on key labor market variables. In particular, I am interested in how and to what extend monetary policy and technology shocks affect unemployment, vacancies, job finding probability series, as well as other standard macroeconomic time series such as output, inflation, and nominal interest rates. Looking at conditional correlations and variance decompositions, I find that it is mainly the monetary policy shock that is responsible for the negative slopes of the Beveridge and Phillips curves, and for accounting for the bulk of variation in labor market variables. Instead the technology shock accounts for most of the variation in output. Looking at impulse response functions I find strong and persistent effects of monetary policy shocks with a general hump-shaped pattern of response of labor market variables.

The second part of the chapter tries to explain these findings within a New Keynesian DSGE model which allows for labor market frictions. The friction in the labor market arises from an assumed search and matching process between unemployed workers and vacancies. The structural parameters of the DSGE model are then estimated by matching as closely as possible the model impulse responses to those from the VAR. Though the model can replicate most impulse responses fairly well, it fails to account for the response of unemployment to the monetary policy shock. Some of the parameter estimates are also crossly at odds with microeconometric evidence, most important of these is the Calvo price-setting parameter. I then argue that the model needs to be changed to correct these failings: It seems vacancies react too strongly following a monetary policy shock - compared to unemployment - thus including some kind of vacancy adjustment costs or sunk costs for job creation might alleviate this problem.

Part II

Chapters

Chapter 1

Macroeconomic News and the European Bond Market

Abstract

Using intradaily data on German government bonds, this paper finds evidence for strong impacts of new information coming from scheduled macroeconomic announcements on conditional means and variances of yield changes. In particular, optimistic surprises about the future path of the economy lead to positive yield changes, and vice versa for pessimistic surprises. On the contrast, we do not find any evidence of pure announcement effects. US announcements have strong impacts on the European bond market.

We also find strong effects of macroeconomic announcements on the conditional volatility of yield change shocks. In particular, volatility is higher during times of announcements. The dynamic pattern of volatility in response to announcements is somewhat unclear: Whilst results for a short bond clearly indicate that volatility is reduced somewhat before the announcement and immediately afterwards, no clear picture emerges from results for a long bond.

Finally, and quite surprisingly, we find *negative* effects of true *surprises* on conditional volatility. This dampening effect of big surprises seems to be a novel finding in the literature.

1.1 Introduction

In this study I use intradaily yield data to analyze how key macroeconomic news affect European financial markets. Market practitioners need to forecast and discount future cash flows adjusted for the riskiness of the cash flow. Default-free government bonds are particularly easy instruments to price as the cash flows are fixed in nominal terms and as they involve no risk of default. They only depend on the discount rate or the yield of the bond. Studying how bond yields respond to macroeconomic news, like employment, inflation or business confidence announcements, therefore corresponds to a study of how the discount rate responds to those news.

This is of interest to macroeconomists for understanding how changes in expectations about the future development of the economy change the expectations of future short-term interest rates. According to the expectations hypothesis of the term-structure of interest rates, yields of bonds with a long time to maturity are approximately an average of expected future short rates, normally supposed to be set by the central bank. Changes of longer bond yields in response to macroeconomic announcement thus reveal changes in investors' expectations about the future path of interest rates set by the central bank. The central bank can use this information to better understand the market's beliefs about its own reaction function. In particular, by comparing the reactions of yield changes to different macroeconomic announcements it is possible to obtain information on the relative weights the markets believe the central bank attaches to the different macroeconomic announcements. Understanding - and influencing - private agents' beliefs about monetary policy is of crucial importance in the conduct of monetary policy.

The question is also of interest to financial econometricians for understanding the functioning of financial markets in general, and the properties of financial time series in particular. Financial time series have often been found to be time dependent, and more precisely, autocorrelated in absolute and squared terms. Studying the reaction of yields to public macroeconomic news allows one to test whether public news can in fact generate this kind of persistence. We find that they cannot: Though volatility is higher during times of announcements, it falls again immediately afterwards.

Using simple regression and GARCH modelling techniques, this paper shows that macroeconomic news can account for some important patterns in the conditional mean and variance of intradaily yield changes of European government bonds. Fundamentals do therefore matter to financial markets. However, for the conditional mean this holds only if we filter out a "surprise" component from the announcement. Optimistic news about the future prospect of the economy then lead to positive yield changes, and vice versa for pessimistic news. The resulting yield change is larger for bonds with a short maturity and smaller for bonds with a long maturity. We also find strong effects of surprises in US announcements on the European bond market.

Results for the conditional variance do reveal some pure announcement effects: In particular, volatility increases when an announcement occurs. A clear dynamic response pattern of volatility to announcements is found for a short 2-year bond: volatility falls in the periods preceding the announcement and immediately afterwards, thus supporting the results of Jones et al (1998). Results for the 10-year bond do, however, not reveal such a clear pattern. Finally, and somewhat surprisingly, we find negative effects on conditional volatility when we include measure of surprises in our variance equation. Thus, *bigger* surprises somewhat counterintuitively *reduce* volatility of the shock series.

We argue that one possible explanation could be that bigger surprises indicate a somewhat clearer picture to market participants, thus reducing uncertainty about the true fundamentals. However, this needs to be addressed in much greater detail in future research.

The chapter is organized as follows: Section 1.2 reviews the literature, section 1.3 sets up a simple model of how news affect the yields of bonds with different maturities, section 1.4 presents the data and some preliminary analysis, section 1.5 then carries out the econometric analysis and section 1.6 concludes.

1.2 Previous Studies

The literature on announcement effects in financial markets is quite extensive and growing rapidly. This section gives a brief review to highlight important concepts, differences and developments and to put this work into perspective.

Early studies, e.g. Ederington and Lee (1993), adopted an event-study approach and selected those time intervals as events during which announcements occurred. They find that the bulk of intradaily price volatility in the US bond market can be accounted for by scheduled macroeconomic announcements. Their approach, however, does not distinguish between those announcements that really surprised the markets and those that did not surprise the markets very much. In other words, because they essentially create a dummy variable which takes on the value 1 during times of announcements, and zero otherwise, they do not capture the surprise component of the relevant announcements. Depending on the specific circumstances, markets might be very surprised if the ECB announces it decided to raise interest rates, or they might not be surprised at all.

In fact, economic theory predicts that prices of financial assets should only adjust to the arrival of "news". Thus, only the unanticipated part or surprise component of an announcement should matter for the response of markets. Fleming and Remolona (1997) were amongst the first to extend the dummy-variable approach to include true surprises. These surprises are usually calculated as the difference of the actual announced values from survey forecasts which are conducted shortly before the announcement. In this study, I will first consider dummy variables and then extend the analysis to surprises.

Studies on the stock market have found it difficult to identify information which could account for the largest stock price movements. In an analysis of the fifty largest one-day price moves in the Standard and Poor's Composite Stock Index since 1946, Cutler, Poterba, and Summers (1989) find that in most cases the information cited by the press as causing the market move "is not particularly important."

Using daily data for the S&P 500, McQueen and Roley (1993) find a stronger relationship between stock prices and news only after controlling for different stages of the business cycle. Intuitively, stock prices depend on both uncertain future cash flows and the discount rate. An upward revision of expected real activity, for example, raises the discount rate which would lower stock prices. But at the same time, the revision might raise expected future cash flows which increases stock prices. The overall effect is thus mixed for stocks. By controlling for the business cycle they condition on the cash flows and focus on the effect of news on equity discount rates. Using US Treasury bills and bonds as proxies they find six out of eight announcements significantly affecting both, the short term bill and the long term bond. The announcements with the biggest impact on both long and short yields are labor market indicators (unemployment rate and non-farm payrolls). In addition, the long yield is strongly impacted by price level indicators (CPI and PPI), whilst the short yield is impacted mainly by Federal Reserve discount rate and money supply changes.

In a recent study on the foreign exchange market, Andersen et al (2003) study the joint response of conditional mean and variance adjustments to macroeconomic news releases using weighted-least squares methods. Using high-frequency intradaily tick data that appeared on the Reuters screen to construct 5-minute returns for various US dollar exchange rates, they find jumps in the conditional mean adjustment occurring immediately in the 5-minute interval following the news announcement and little movement thereafter. The response of the conditional variance is rather more gradual and persistent, and pure announcement effects which are independent of the magnitude of the surprises are found.

Studies for the bond market have shown that bond prices or yields adjust even faster to news than exchange rates. Several studies use high-frequency intradaily tick-by-tick data for US T-bills and bonds spot or futures prices which is easily available. Applying an event-study framework Ederington and Lee (1993) study the response of the T-bond futures market and find that the bulk of the price adjustment occurs within one minute after the announcement, whilst volatility remains considerably higher for another 15 minutes and slightly higher for several hours. They further show that most of the intraday and day-of-the-week volatility patterns is in fact due to the timing of macroeconomic announcements, which in the US usually occur at 8:30 am (Eastern Time) towards the end of the week. The announcement releases with the greatest impact on yields are found to be using a simple dummy series regression (in order of decreasing impact): the employment report, the PPI, the CPI, and durable goods orders.

In their widely quoted paper Fleming and Remolona (1997) study the response of the five-year Treasury note price and trading activity over a one year sample period using tick data and announcement dummies as well as surprise data. They find a long list of announcements significantly impacting on the bond price with the biggest impact coming again from employment and price level as well as consumer confidence indicators. They further show that market conditions of uncertainty as measured by implied volatility derived from options prices frequently increase the price, and in particular, the trading activity response following an announcement possibly indicating a rise in disagreement in traders' beliefs about what constitutes a fair price or simply an increase in speculative trading.

More recently, researchers have tried to capture the conditional volatility effects of news parametrically using various GARCH models. The seminal paper by Jones et al (1998) uses daily data on US Treasury bonds and announcement dummies for employment and PPI to study the volatility pattern on and following an announcement, and in particular whether announcements lead to longer persistence of volatility. They find no persistence of the increased volatility following an announcement at all, but a significantly positive risk premium on announcement days. Further, they find evidence of a "calm-before-the-storm" effect, i.e. volatility being low in anticipation of an announcement. They conclude that volatility persistence is not due to some feature of the trading or information-processing process following announcements, but rather because most news is clustered over time. However, their study is limited by the fact that they only use announcement dummies, i.e. no surprises, and that they consider daily data, not intradaily data. Thus it seems natural to extend their analysis.

Li and Engle (1998) confirm their finding that announcement day shocks have small persistence, but great impacts on volatility in the short run. They extend the analysis by distinguishing between positive and negative news and find strong asymmetric effects at work: positive shocks depress volatility on consecutive days, while negative shocks increase volatility.

Studying the interdependence and spillover effects between euro area and US news impacts on money markets, Ehrmann and Fratzscher (2002) find that "euro area financial markets react more strongly to news in the US than vice versa." Applying EGARCH and weighted-least-squares techniques, they further find evidence of markets going through a learning process about ECB monetary policy, and of nonlinearities in the response to news. Volatility seems to increase less following announcements that are far from their long run average and thus, giving clear implications of the future course of monetary policy.

As these and related issues are of central interest to central banks, several recent policy papers have studied the response of yields or interest rates to macroeconomic news. Fleming and Remolona (1997) set the pace not only for the policy oriented. More recent studies include Brooke et al (1999) for the UK, Fell (2002) studying the response of the bond market to ECB interest rate decisions, Goldberg and Leonard (2003) studying spillover effects of US/euro area announcements using hourly data on German bonds, and Molgaard Pederson and Wormstrup (2001) looking at the response of the euro area yield curve to announcements using daily data on 3-month EURIBOR rates and 2-year and 10-year German government bonds.

This paper analyzes the impact of key macroeconomic announcements on conditional means and variances of German intradaily bond yields with maturities of 2 and 10 years. Because of the near convergence of European bond yields to German yields with the introduction of the Euro, we believe German bond yields are a pretty good approximation to what would constitute a truly European bond yield.

The set of macroeconomic announcements consists of 17 key macroeconomic variables of the Euro Area, Germany and the US. In particular, for the Euro Area we consider announcements of the following seven variables: ECB interest rates, Euro Area money supply, GDP, industrial production, HICP, HICP flash estimates and unemployment data. For Germany the set of variables consists of the following five: CPI, the Ifo index, GDP, industrial production and unemployment. Finally, for the US we consider the following five variables: Fedfunds target rate, employment, GDP, industrial production and CPI. These variables are usually considered to be market movers and found to significantly affect the US bond market. In this study we extend the analysis to see how these announcements affect the European bond market.

1.3 A Simple Model of News and the Yield Curve

This section presents a simple model highlighting in an ad-hoc and highly stylized way how yields of bonds with different maturities respond to different news releases. Using three equations only - a monetary transmission mechanism equation, a central bank reaction function, and an arbitrage equation using the expectations hypothesis - it is shown that announcement surprises have a declining impact over the yield curve, i.e. the biggest impact is found on bonds with the shortest maturity. This is what intuition leads one to expect as the long yield is an average of current and expected future short yields.

However, it needs to be pointed out that for more complex transmission mechanism equations - with more persistent effects of shocks or with a hump-shaped impulse-response function of shocks - the response of the long yield could exceed the response of the short yield. The results of the following model are thus conditional on the assumption that the shocks or surprises are rather transitory.

The model set up is similar to Haldane and Read (2000), but changed in a way to explicitly deal with the effect of news on spot yields, rather than forward rates. In particular, the model consists of the following three equations:

$$x_{t+1} = \alpha x_t + \beta y_{1,t} + \epsilon_{t+1} \tag{1.1}$$

$$y_{1,t} = \delta(x_t - x_t^*) \tag{1.2}$$

$$y_{n,t} = \frac{1}{n}(y_{1,t} + E_t y_{1,t+1} + ... + E_t y_{1,t+n-1}) \tag{1.3}$$

where x_t is a scalar or vector of macro variables, like GDP or income, inflation or unemployment, and $y_{n,t}$ is the yield at time t of a bond with maturity n. The short term interest rate, $y_{1,t}$ is assumed to be set by the central bank. Equation (1.1) can be thought of as the reduced-form of the monetary policy transmission mechanism of the macro variables which are assumed to be covariance stationary, in line with the above discussion on the dynamics of the transmission mechanism. The short rate affects the vector of macro variables with a time lag of one period. The parameter β measures the effect of the short rate on the macro variables. If x_t consists of GDP only, then β should be negative, whilst it should be positive if x_t consists of unemployment only.

The term $(\epsilon_{t+1}|I_t) \sim N(0, \sigma_t^2)$ represents a surprise shock hitting the economy with possibly time-varying conditional variance. The surprise is assumed known to the central bank when policy decisions for period $t+1$ are made, but unknown to the public. Thus, I_t is the public sector's information set, not however that of the central bank. When making decisions for period $t+1$ the public has to form expectations of ϵ_{t+1} conditional on period t information, with the property that $E_t(\epsilon_{t+1}) = 0$ where E_t is the expectations operator with respect to the information set I_t. The public only learns about ϵ_{t+1} after the interest rate decision has been made when it observes x_{t+1} and $y_{1,t}$ and hence can infer ϵ_{t+1} from equation (1.1). At the same time the public learns about x_t^*, the vector of possibly time varying policy targets.

Equation (1.2) defines the reaction function of the central bank which seeks to offset deviations from policy targets by varying the short-run interest rate. The parameter δ should be of opposite sign to β for policy to be shock-absorbing. All parameters are assumed to be common knowledge.

Finally, equation (1.3) is a linearized version of the pure expectations hypothesis: The long yield is an average of expected future short rates, which are supposed to be under the control of the central bank (equation (1.2)). Thus, it immediately follows that the long rate depends on the market's expectation of what the central bank is going to do with the short rate, which again is determined by news about the macroeconomy (see equation (1.1)).

There are two sources of uncertainty in the model: first, uncertainty arising from the public only learning about ϵ_{t+1} after the interest rate decision has been made, and second, uncertainty about current and future policy targets, $\{x_{t+i}^*\}_{i=1}^{\infty}$. The former can be seen as uncertainty arising from the announcements of macroeconomic news, like GDP figures, unemployment numbers, or interest rate decisions, whilst the latter can be regarded as proper reaction function uncertainty arising from imperfect policy credibility.

As this study's concern is the effect of news on the bond market only, this study disregards reaction function uncertainty for the moment and treats x_t^* as known. It further simplifies the analysis to set x_t^* equal to a constant, and without loss of generality, equal to zero, i.e. $x_t^* = \overline{x} = 0$ as there is currently no evidence that the ECB, for instance, is going to change its policy targets in the future.

To see what the model predicts for yield changes, we solve for the 'unexpected' component of the n-period yield, $y_{n,t} - E_{t-1}y_{n,t}$, which can be approximately regarded as the yield change if $E_{t-1}y_{n,t}$ is approximately equal to $y_{n,t-1}$, i.e. if yields have approximately the martingale property. Substituting in for $y_{1,t}$ from equation (1.2) gives

$$x_{t+1} = (\alpha + \beta\delta)x_t + \epsilon_{t+1} \tag{1.4}$$

from which the above stationarity condition is derived. Applying the expectations hypothesis, equation (1.3), and using backward substitution for x_t, then gives the result for the approximate yield change:

$$y_{n,t} - E_{t-1}y_{n,t} = \frac{\delta}{n}\left[\frac{1-(\alpha+\beta\delta)^n}{1-(\alpha+\beta\delta)}\right]\epsilon_t. \tag{1.5}$$

The impact of announcement surprises, ϵ_t, is thus seen to be largest for short yields and declining for yields with longer maturities. A higher persistence parameter α, and lower values (in absolute terms) of β and δ, the parameters determining the relation between the macro variables and the short rate, are further seen to increase the response of longer yields to news. Finally, as expected, the sign of the yield change is the same as the sign of the surprise, i.e. positive (negative) announcement surprises lead to positive (negative) yield changes.

Thus, this simple and highly stylized model gives clear predictions on the impact of news on yield changes across the maturity spectrum. Some further issues should be mentioned in concluding. First, allowing for more general monetary transmission mechanism processes would be one way of generalizing the results. However, the covariance stationarity assumption seems somewhat natural for an assumed AR(1) process. But more general processes are conceivable. Second, the lag structure of the interest rate impact on the macro variables could be changed, and the macro variables could be made dependent on a long term interest rate rather than a short rate. Third, the model could be generalized to accommodate changes in future policy target values and in particular, to allow for uncertainty around these target values on behalf of the public. And finally, this model has nothing to say about the impact of news on the volatility process of yield changes. These and other issues present open questions for research.

1.4 Data and Preliminary Analysis

Having derived some theoretical predictions on the impact of news on yield changes, this section and the next present the empirical part of the paper. The following two subsections describe the yield and announcement data, whilst the last subsection discusses the econometric methodology and uses a simple regression model in a preliminary analysis of the data. Later sections then extend the analysis to account for time varying conditional variances of the error term.

1.4.1 Yield Data

We study the impact of news on intradaily yield changes of 2-year and 10-year German government bonds over the period January 1999 to June 2003. The literature uses both, percentage rates of change of bond prices as well as yield changes to measure changes in the bond market. Appendix 1.7.1 shows the relation between bond price changes and yield changes and why it is appropriate to consider yield changes. To precisely capture the immediate impact of news on the yield change one would need to obtain yield data from just before to just after the news release. Whilst this is done in some studies using tick data, others use daily data which contains more noise, but which can potentially tell more about the long-run effect of the news on the market. This study goes the middle way and uses intradaily data taken at five times a day. Specifically, the yield data consists of Reuters data taken at 9:00, 12:00, 15:00, 18:00 and 21:00. Appendix 1.7.2 plots the two yield series and their intradaily changes over the sample period. As this study is concerned with the response of yields to the release of news, we consider intradaily yield changes, rather than their levels. These intradaily yield changes thus consist of the changes in yield from 9:00 to 12:00, from 12:00 to 15:00, from 15:00 to 18:00, from 18:00 to 21:00 and from 21:00 to 9:00. Though the intervals are not equally spaced because of the long interval from 9pm to 9am when the market is closed, there does not seem to be a straightforward procedure to follow in the literature and precisely because market activity is arguably lower during that period, we believe the fact that the intervals are irregularly spaced does not matter much for the subsequent analysis.

Financial time series are well known for their time dependencies, like autocorrelation, and in particular, ARCH effects (see Bollerslev et al 1992). To consider these effects in the raw series, the sample autocorrelation functions of the yield changes, and the absolute and squared yield changes of both series are shown in figure 1.1.

The figure indicates some autocorrelation for the level of yield changes, and strong autocorrelation for the squared and absolute series of yield changes. Thus, it seems appropriate at this stage to later use ARCH-type of models that will capture this time-varying volatility pattern in the yield changes. Some further points deserve mentioning: First, the autocorrelation of the absolute series seems stronger than that of the squared series. Second, in general, autocorrelation seems to be stronger for the 10-year yield series than for the 2-year yield series, though the autocorrelation for the first two lags is far stronger in the 2-year series. And third, there seems to be an interesting cyclical pattern at work, noticeable for the two absolute yield change series and the squared yield changes of the 10-year series: the autocorrelations at lags 5, 10, 15, and 20 are noteworthy higher than the rest. Lag five corresponds to the yield change of the same interval a day ago. Thus, there seems to be more autocorrelation in the volatility of daily yield changes, than in the volatility of intradaily yield changes.

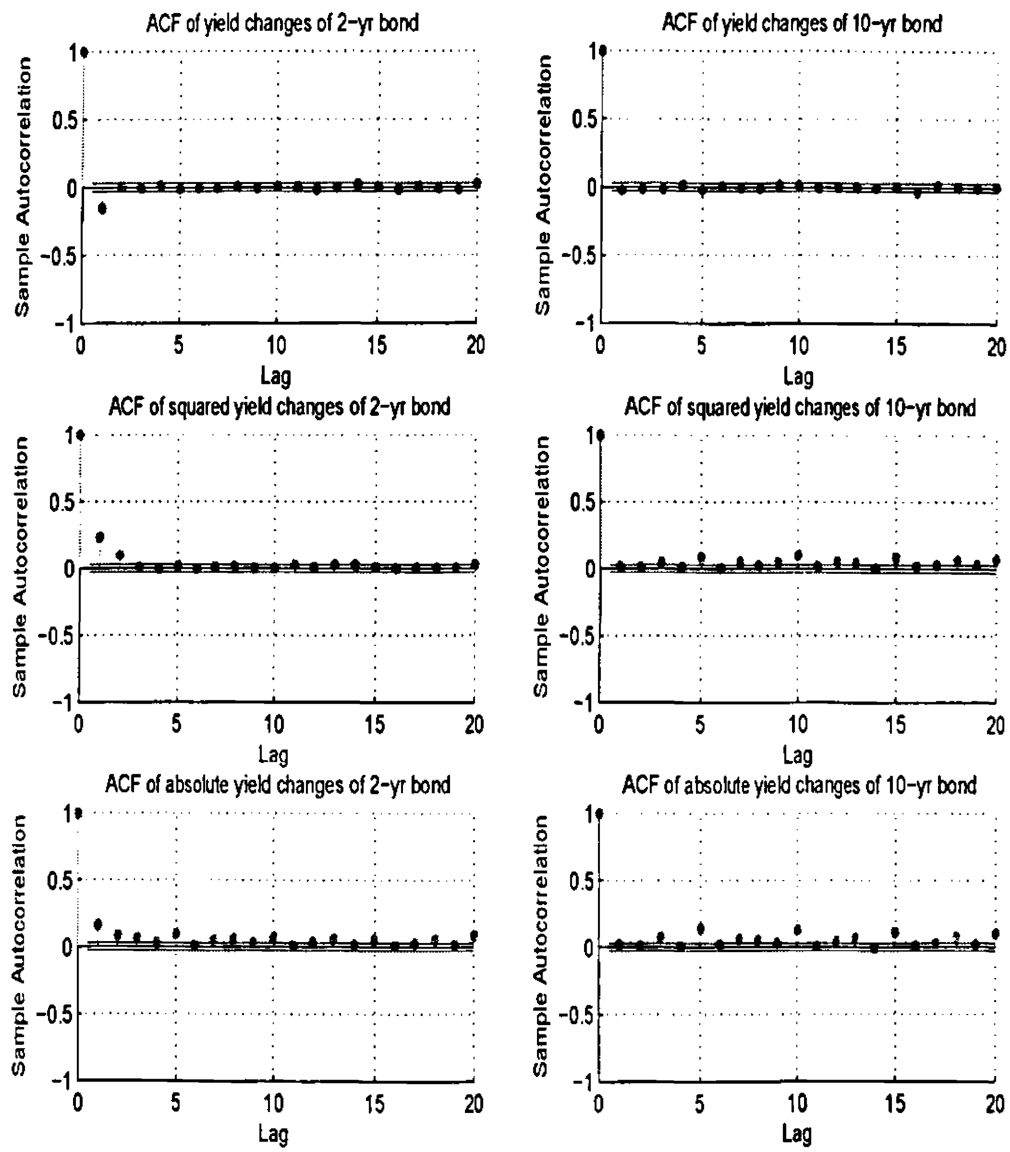

Figure 1.1: Autocorrelation properties of yield changes.

1.4.2 Announcement Data

The set of announcements consists of weekly, monthly and quarterly scheduled announcements of 17 key macroeconomic variables of the Euro Area, Germany and the US over the same time period as the yield series. In particular, the selected announcements are: For the Euro Area: ECB interest rates, Euro Area money supply, GDP, industrial production, HICP, HICP flash estimates and unemployment data. For Germany: CPI, the Ifo index, GDP, industrial production and unemployment. For the US: the Federal Funds target rate, employment, GDP, industrial production and CPI. These announcements are usually regarded as market-movers by market participants and the US announcements have been found significant for the US bond market. Thus it seems natural to include them in the set of announcements.

1.4.3 Preliminary Analysis

To capture surprises, market expectations of announcements are taken from surveys conducted by vendors like Bloomberg and MMS International. Every Friday, Bloomberg and MMS International regularly survey key financial institutions - mainly investment banks - about their forecasts about macroeconomic releases in the following week. The median is then usually taken as the 'market expectation'. The surprise series for each of the three announcements is then calculated by subtracting the median forecast, or market expectation, from the actual announcement. To facilitate comparison of regression parameters for different announcements, the surprises are then standardized by dividing through by their sample standard deviations. Thus, the variance of all standardized surprises is set equal to one. Formally, we have

$$s_{k,t} = \frac{A_{k,t} - F_{t-1}(A_{k,t})}{\widehat{\sigma}_k} \tag{1.6}$$

where $s_{k,t}$ is the standardized surprise of announcement $k = 1..K$, where $A_{k,t}$ and $F_{t-1}(A_{k,t})$ are the value of the actual announcement and its survey forecast as of time $t-1$, respectively, and where $\widehat{\sigma}_k$ is the sample standard deviation of the nonstandardized surprises, i.e. of $A_{k,t} - F_{t-1}(A_{k,t})$.

There were between six and 83 announcements for each of the 17 announcement series, with only six announcements for Euro Area GDP and with 83 announcements for ECB interest rate announcements. In general, there were fewer Euro Area announcements than there were German or US announcements. Using a time series set up with as many as five observations a day, and a sample running from January 1999 to June 2003, gives 5042 observations after deleting any missing values in the series. This means the $s_{k,t}$ series contain very many zeros. In fact, $s_{k,t}$ can only be non-zero on days of an announcement of series k, and then only if the announcement differs from the survey value, i.e. if there was a surprise.

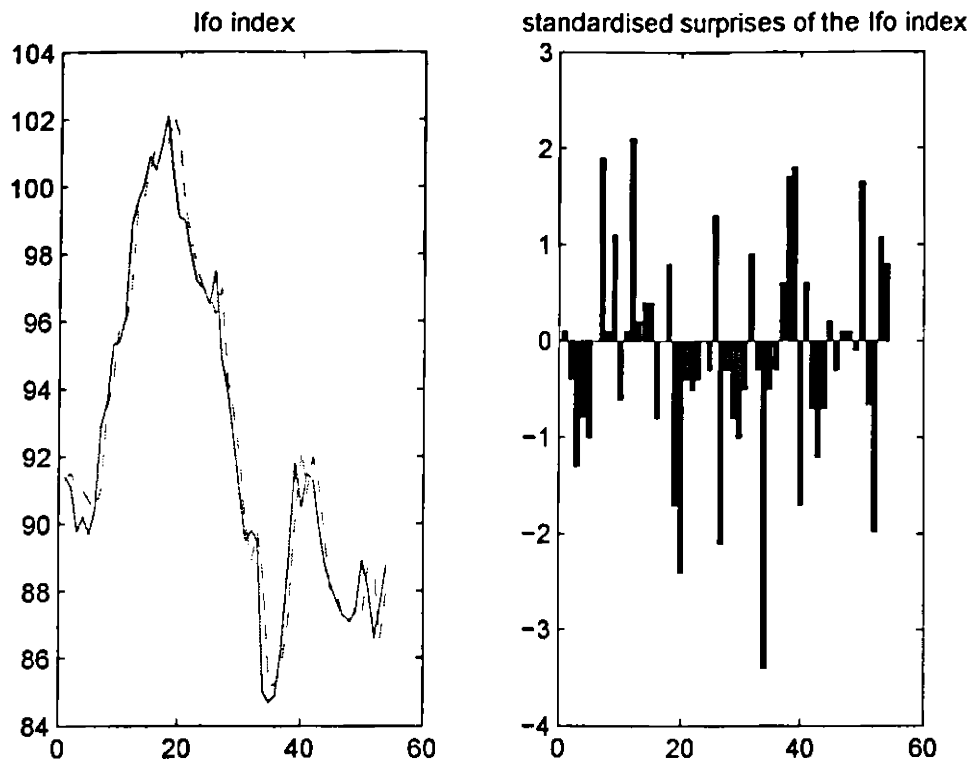

Figure 1.2: The Ifo index as an example. Left panel: solid line: announced valus, dashed line: market forecasts. Right panel: standardized surprises.

As an example, figure 1.2 shows the actually announced values together with their market forecasts and corresponding standardized surprises of the Ifo index. The solid line in the left diagram shows the actual announcements of the Ifo index, whilst the dashed line shows the market forecasts as measured by the median of the Bloomberg survey. In general, the forecasts are pretty close to the actual value, however, there were seemingly somewhat more negative surprises over the sample period than positive surprises, as shown in the right diagram which plots the standardized surprises. Ehrmann and Fratzscher (2002) test for the properties of survey data and find, however, little evidence of bias or inefficiency.

One important shortcoming of our approach, and of most studies in the literature, is that we do not consider information about the market uncertainty around the market forecast. Essentially, it seems natural to believe the market's response to a surprise is different (presumably bigger) when the market was pretty sure about its forecast beforehand. On the other hand, if the market has not been pretty sure about its forecast, one would expect the market's response to the same surprise to be different (presumably somewhat smaller). It would, in fact, be possible to test for such effects because

Bloomberg and other vendors do actually publish individual market participants' forecasts, however it was not possible to retrieve this data.

Another important point concerns the timing of the releases. Having set up the yield changes according to the changes over the various intervals, the announcement surprises need to be matched to the corresponding interval when the announcement took place. ECB interest rate decisions were announced at 9:00 at the beginning of the sample period, but the ECB soon changed the time of announcement to 13:45 when a press statement is communicated before the ECB press conference. Euro Area money supply announcements are made at 10:00 and all other Euro Area announcements are made at 12:00. All German announcements other than the Ifo index are made at 8:00. The Ifo index is announced at 10:00. Unfortunately, I only have data on unemployment announcements made by the Deutsche Bundesbank, not those made by the Bundesagentur für Arbeit, which is the one more closely looked at in the press. All US announcements, with the exceptions of the Federal Funds target rate and the industrial production figures, are announced at 8:30 Eastern Time which corresponds to 14:30 Central European Time. The Fedfunds target rate is announced at 14:30 Eastern Time which corresponds to 20:30 CET. Finally, US industrial production figures are announced at 9:15 Eastern Time corresponding to 15:15 Central European Time. One needs to be very careful in matching these announcements to the corresponding yield changes.

Finally, before moving to more formal econometric analysis, we plot figures of the standard deviations of the yield changes at the various time intervals conditional on whether there has been an announcement on that particular day or not. Figure 1.3 shows the results. Though this is purely descriptive, it reveals the higher volatility of yield changes on days with at least one announcement compared to days without any announcement. The difference between the no-announcement lines and the announcement lines is biggest at the time interval from 12 to 15, exactly that interval during which the US data is announced and during which the US market opens. This suggests at least some influence of the US economy and financial markets on European bond markets. Full histograms of yield changes conditional on announcement and no-announcement days are shown in appendix 1.7.3.

1.5 Econometric analysis

This section explains the econometric methodology and the results. All calculations were carried out in Eviews and Matlab. Section 1.5.1 uses simple regression models to estimate the effects of macroeconomic announcements and their surprises on yield changes. Regression analysis tells us how the market's beliefs about future short term interest rates set by the central bank are affected by the different kinds of announcement surprises. We first use a "dummy" approach in which we only include dummy

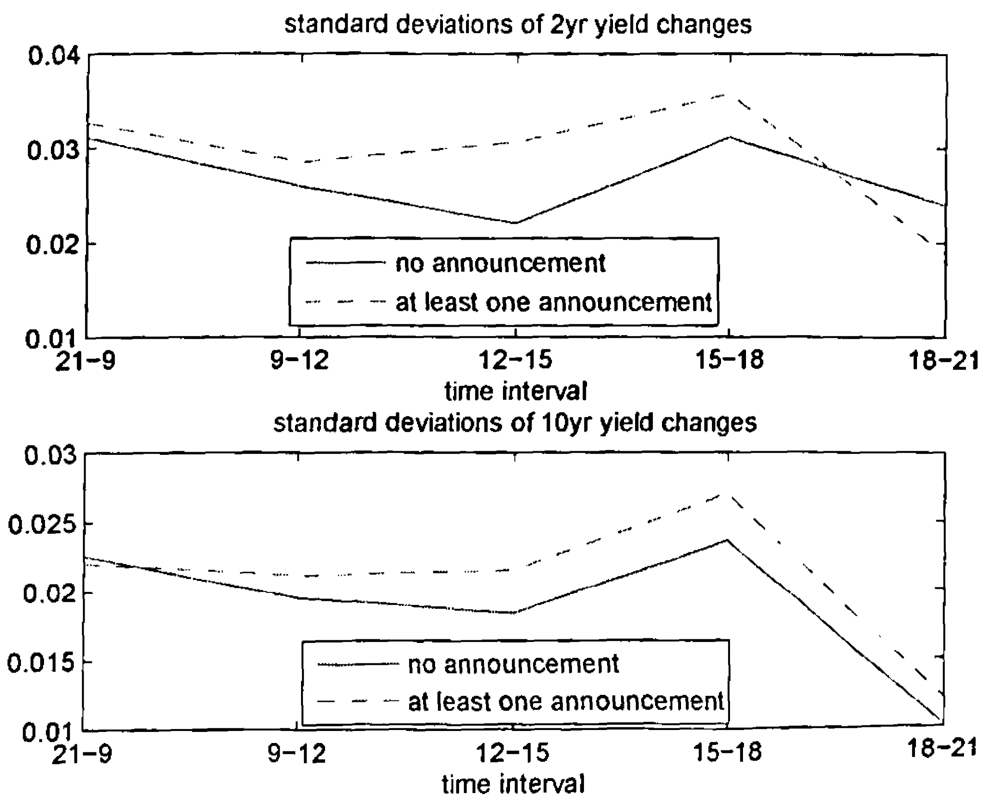

Figure 1.3: Standard deviations of yield changes conditional on whether an announcement has occurred or not.

variables for the specific announcements as exogenous regressors. As mentioned in the introduction, economic theory predicts that financial markets should only respond to true "news", that is the surprise component of any announcement. The pure fact that an announcement is going to occur would not matter, if markets knew exactly what the announcement was going to be. From a theoretical point of view it thus seems necessary to extend the regression analysis to a "surprise" approach in which we regress yield changes on the surprise components of the individual announcements as discussed above. The empirical results strongly support the rational markets "surprise" hypothesis: Whilst none of the announcement dummies are found to significantly affect yield changes, quite a few of the announcement surprises do have significant effects.

Section 1.5.2 then extends the analysis to jointly model the conditional mean and variance of yield changes as functions of announcement dummies and announcement surprises. To this end we make use of the standard, and widely used, univariate GARCH(1,1) model. The theoretical motivation for modelling the conditional volatility of yield changes is that we not only want to see how the market's beliefs about future short term interest rates changes, but also how the market's uncertainty around these beliefs changes with the arrival of news. We take the view that volatility in financial markets indicates to some extend increased uncertainty about true fundamentals. The econometric motivation arises from diagnostic checks of the residuals from the regression analysis. Squared residuals are strongly correlated, thus pointing towards ARCH-effects in the residuals.

1.5.1 Regression models and the conditional mean of yield changes

We begin our regression analysis with a standard "dummy"- regression model in which we regress the yield change on lagged yield changes and on announcement dummies that take the value 1 if an announcement has been made and zero otherwise. Formally, we write the model as:

$$\Delta y_t = \alpha_0 + \sum_{l=1}^{L} \alpha_l \Delta y_{t-l} + \sum_{k=1}^{K} \beta_k d_{k,t} + \sum_{m=1}^{M} \delta_m \widetilde{d}_{m,t} + u_t \tag{1.7}$$

where Δy_t is the intradaily yield change and where $d_{k,t}$ is the dummy variable that takes on the value 1 if an announcement is made of the macroeconomic series k at time t, and takes the value zero otherwise. The auxiliary dummy variables $\widetilde{d}_{m,t}$ capture the fact that at least one announcement has occurred in a particular interval and also time of the day effects independent from whether any macroeconomic announcement has occurred.

The results of the dummy regression model (1.7) are given in table 1. A lag length of one was chosen to eliminate any autocorrelation in the residuals. The key result from table 1 is that hardly any announcement dummy is found significantly different from zero. The only announcement that is estimated to have a significant effect on yield changes - irrespective of whether it did actually surprise the market - is the US employment report announcement which leads to fairly big negative changes in European yields. In other words, the pure knowledge that the Bureau of Labor Statistics is going to announce its employment report is enough for European bond yields to fall, thus indicating the market expects lower future short term interest rates in the Euro Area. Other than that, we also find systematically positive yield changes for the time interval dummy from 12:00 to 15:00, the time when the US market opens, again suggesting strong dependencies of the European bond market on the US market.

The main conclusion from the "dummy" regression is, however, that essentially none of the macroeconomic announcements is found to significantly affect yield changes when they enter as dummy variables. The pure fact that an announcement is going to happen does not lead to much systematic movement in the European bond market.

Table 1: OLS with dummies	2-year yield change		10-year yield change	
	coefficient	p-value	coefficient	p-value
constant	-0.265	0.766	-0.038	0.570
lag 1	**-0.132**	**0.000**	**-0.032**	**0.024**
ECB_d	0.663	0.270	0.449	0.317
FED_d	-0.299	0.6839	0.255	0.641
EURM3_d	0.103	0.877	0.145	0.769
EURGDP_d	-0.564	0.638	-0.300	0.737
EURIP_d	-0.340	0.664	0.165	0.777
EURHICP_d	0.242	0.722	0.472	0.352
EURHICPFLASH_d	-0.525	0.565	0.216	0.751
EURUNE_d	-0.152	0.830	0.293	0.579
DECPI_d	0.559	0.423	0.346	0.505
DEIFO_d	0.405	0.530	0.405	0.400
DEGDP_d	-0.007	0.994	0.751	0.247
DEIP_d	-0.349	0.600	0.055	0.911
DEUNE_d	-0.051	0.941	0.354	0.487
USEMP_d	**-1.175**	**0.076**	-0.800	0.105
USGDP_d	0.009	0.991	0.651	0.273
USIP_d	-0.182	0.792	0.395	0.443
USCPI_d	0.345	0.589	0.496	0.297
Announcement Dummy	-0.024	0.966	-0.428	0.304
Dummy_21_9	-0.105	0.425	0.156	0.112
Dummy_9_12	-0.099	0.436	0.046	0.628
Dummy_12_15	**0.257**	**0.054**	0.142	0.152
Dummy_15_18	-0.022	0.860	-0.012	0.901
R-squared		0.023		0.006
F-statistic		5.105		1.285
p-value (F-statistic)		0.000		0.164

Note 1: Yield changes are measured in basis points.
Note 2: Definitions of variables in appendix 1.7.4.
Note 3: Numbers in bold indicate significance at the 10 percent level.

As mentioned above, economic theory only predicts that "surprises" should matter to financial markets. Thus, even if we do not find any evidence for pure announcement effects, we can not conclude that macroeconomic announcements do not matter in general for the European bond market. Instead we should study how the bond market reacts to the arrival of news, or put differently, surprises. We thus specify the following "surprises" regressions model:

$$\Delta y_t = \alpha_0 + \sum_{l=1}^{L} \alpha_l \Delta y_{t-l} + \sum_{k=1}^{K} \beta_k s_{k,t} + \sum_{m=1}^{M} \delta_m \widetilde{d}_{m,t} + u_t \tag{1.8}$$

where $s_{k,t}$ is the standardized surprise of the macroeconomic series k at time t and where $\widetilde{d}_{m,t}$ are dummy variables as discussed above. The parameters of interest are the β_k's, measuring the response of the yield to news.

Table 2 shows the results, again using a lag length of one. Contrary to the above findings, quite a few of the announcement surprises are found to be significantly different from zero. In particular, interest rate decisions by both, the ECB and the Fed, have strong effects on 2-year yield changes of European government bonds. An increase in the ECB target rate of 100 basis points leads to an increase in 2-year yields of 15.9 basis points. Equally, an increase in the Fedfunds target rate of 100 basis points leads to an increase in 2-year yields of 7.4 basis points. The other coefficient estimates can be interpreted in a similar way. Interestingly, with the exception of the German unemployment rate, all significant regressors enter with the right sign, i.e. optimistic news about the future growth path of the economy lead to yield increases, and pessimistic news to yield decreases.

This can be explained by a the simple model of the expectations hypothesis of section 1.3. The long yield is a weighted average of the expected future short rates. If market participants are surprised by optimistic views about the future path of the economy, it seems likely that they revise their expectations about future short term interest rates set by the central bank upwards. This will lead to higher long term yields and therefore a positive yield change. By observing the market's reaction to news, the central bank can thus learn about the importance the market attaches to the various indicators about the future growth prospects of the economy. Because the market will, however, try to best forecast the path of future short term policy rates, the central bank can actually infer from the market's response to these news how much weight the market believes the central bank attaches to the various economic indicators. Thus, the central bank can learn about the market's perception of its own reaction function.

In particular, we find that for the 2-year yield change, surprises in the Ifo index are found to have the biggest impact, whilst for the 10-year yield change, surprises in the US employment rate and the US industrial production index are found to have roughly the same effect as surprises in the Ifo index. Interestingly, surprises in all US announcements have strong and statistically significant effects on the European bond market, reflecting both the high degree of integration of world financial markets and the importance of US future economic prospects for short term policy rates in the Euro Area. The time dummy for the interval from 12:00 to 15:00 is also estimated significantly for the 2-year yield change. It is exactly that time when US financial markets open.

Generally, the response of the 2-year yield is larger than the response of the 10-year yield, thus in line with the economic model presented above. Finally, the R^2 is very low in both regressions. Though this is fairly typical in these "news" regressions, it is not quite clear why this is the case. Including more lags of the endogenous variable does not increase the R^2 very much either. Rigobon and Sack (2006) argue that it has to do with the fact that news are difficult to measure and in fact rather noisy using the approach adopted in this paper. The discrete nature of the news variables in this approach, and in particular, the fact that for each announcement series there are only a few surprises does, however, make it appear quite plausible that the R^2 is estimated to be very small indeed.

Table 2: OLS with surprises	2-year yield change		10-year yield change	
	coefficient	p-value	coefficient	p-value
constant	-0.032	0.710	-0.040	0.543
lag 1	**-0.133**	**0.000**	**-0.030**	**0.034**
ECB_s	**0.159**	**0.000**	-0.020	0.492
FED_s	**0.074**	**0.057**	0.003	0.912
EURM3_s	**0.118**	**0.003**	0.045	0.118
EURGDP_s	0.034	0.377	**0.053**	**0.067**
EURIP_s	0.051	0.189	0.015	0.602
EURHICP_s	0.007	0.859	-0.003	0.910
EURHICPFLASH_s	0.008	0.838	-0.003	0.922
EURUNE_s	-0.010	0.805	0.008	0.769
DECPI_s	-0.022	0.573	-0.014	0.625
DEIFO_s	**0.193**	**0.000**	**0.104**	**0.000**
DEGDP_s	0.046	0.235	0.020	0.499
DEIP_s	0.025	0.529	0.023	0.429
DEUNE_s	0.010	0.806	**0.067**	**0.022**
USEMP_s	**0.150**	**0.000**	**0.111**	**0.000**
USGDP_s	**0.083**	**0.032**	**0.053**	**0.068**
USIP_s	**0.072**	**0.064**	**0.102**	**0.000**
USCPI_s	**0.084**	**0.031**	**0.079**	**0.007**
Announcement dummy	0.033	0.804	-0.112	0.253
Dummy_21_9	-0.091	0.470	**0.172**	**0.067**
Dummy_9_12	-0.063	0.606	0.051	0.576
Dummy_12_15	**0.239**	**0.057**	0.121	0.198
Dummy_15_18	-0.027	0.826	-0.006	0.950
R-squared		0.036		0.015
F-statistic		8.117		3.290
p-value		0.000		0.000

Note 1: Yield changes are measured in basis points

Note 2: Definitions of variables in appendix 1.7.4.

Note 3: Numbers in bold indicate significance at the 10 percent level.

The lag length was chosen based on a mixture of information criterion considerations, autocorrelation properties of the residuals and parsimony. Other lagged dependent variables were found to be both, insignificant and not changing the results. Though the residuals of the models are not autocorrelated, further diagnostic tests indicated that strong ARCH effects exist. Appendix 1.7.5 (table 5.1) shows detailed results of the Q-test and the LM-test for ARCH effects in the residuals.

The p-value of the Q-statistic for squared residuals of the 2-year yield model is zero for all lags from 1 to 36. The LM-test gives the same result. For the model of the 10-year yield change, only the p-values of the Q-statistic and the LM-statistic for the first lag is nonzero. All other tests indicate strong ARCH effects. Furthermore, both residual series are highly non-normal.

The next section sets up a GARCH modelling framework to properly model these features of the data and to obtain estimates of the impact of news on the conditional volatility of the yield changes.

1.5.2 GARCH models and the conditional variance of yield changes

It seems quite natural to believe that macroeconomic news not only lead to systematic changes in the level of yields, but that they also affect yield change volatility. Announcements might increase volatility because of the increased uncertainty around the time of the announcement and the subsequent realization of the news. But it also conceivable that they reduce volatility because of a clarifying effect of the news. Market participants' uncertainty about the fundamental yield might therefore either rise or fall with a news announcement. For this reason and because of the above diagnostic finding of ARCH-effects in the residuals, we now use GARCH models to explain yield changes.

The following two subsections apply the standard and very widely used GARCH(1,1) model of Bollerslev (1986) to our European yield change series and extend them by including dummy variables and surprise regressors to capture the effect of news in both the conditional mean and variance equations. We keep the conditional mean equation unchanged and modify the equation for the conditional variance. In the following subsection we use an announcement dummy variable in an approach similar to the above "dummy" regression model and compare our results to those of Jones et al (1998) who use daily data for the US. The subsequent subsection then uses our measures of surprises to see how true surprises affect conditional volatility in European bond markets.

The GARCH "lead-lag dummy" model

The GARCH (1.1) "lead-lag dummy" model consists of equations (1.9) to (1.11). Equation (1.9) is similar to equation (1.8), i.e. the conditional mean is modelled as a linear regression containing lagged dependent variables and surprise regressors as well as dummies. The disturbance is assumed to be normally distributed with zero mean and conditional variance equal to σ_t^2 (equation (1.10)). We model the conditional variance as an extended GARCH (1,1) process (equation (1.11)). In particular, to study the dynamic response pattern of yield change volatility we also include lagged and lead series of an announcement dummy variable in addition to the standard ARCH (u_{t-1}^2) and GARCH (σ_{t-1}^2) terms. The announcement dummy, d_t, takes on the value 1 if any announcement was made during an interval and zero otherwise. We can formally write the GARCH "lead-lag dummy" model as:

$$\Delta y_t = \alpha_0 + \sum_{l=1}^{L} \alpha_l \Delta y_{t-l} + \sum_{k=1}^{K} \beta_k s_{k,t} + \sum_{m=1}^{M} \delta_m \widetilde{d}_{m,t} + u_t \qquad (1.9)$$

$$u_t|\Omega_{t-1} \sim N(0, \sigma_t^2) \qquad (1.10)$$

$$\sigma_t^2 = \phi_0 + \phi_1 u_{t-1}^2 + \theta_1 \sigma_{t-1}^2 + \sum_{j=-2}^{2} \gamma_j d_{t+j} + \sum_{m=1}^{M} \delta'_m \widetilde{d}_{m,t} \qquad (1.11)$$

Results of the GARCH "lead-lad dummy" model are shown in tables 3.1 and 3.2 respectively. The results for the conditional mean equation are pretty similar to those for the "surprise" regression model above with some minor exceptions. For the 2-year yield change these are: The Fedfunds rate surprise ceases to be significant, instead the Flash estimate of the Euro Area HICP index is highly significant, but enters with a negative sign. This is somewhat troubling because the parameter is precisely estimated and it is counterintuitive that a higher than expect inflation rate should reduce long-term bond yields. Higher than expected inflation rates should revise market's forecasts for future short-term policy rates upwards, thus given the term-structure equation (equation (1.3)) we would expect an increase in longer term yields too. This seems not to have been the case for the Euro Area in the sample period studied. Finally, US industrial production figures are not estimated significantly different from zero. For the 10-year yield change the exceptions are: Euro Area GDP surprises cease to be significant, German unemployment ceases to be significant, but it entered with the wrong sign in the "surprise" regression model. And finally, surprises of the Ifo index and almost all US surprises are again found to significantly impact on the yield changes of European bonds.

Table 3.1: GARCH(1,1) with "lead-lag" dummies	2-year yield change		10-year yield change	
conditional mean equation	coefficient	p-value	coefficient	p-value
constant	-0.019	0.774	-0.023	0.544
lag 1	**-0.151**	**0.000**	-0.016	0.207
ECB_s	**0.174**	**0.000**	-0.022	0.351
FED_s	0.064	0.540	0.001	0.981
EURM3_s	**0.101**	**0.031**	0.044	0.182
EURGDP_s	0.059	0.348	0.053	0.488
EURIP_s	0.043	0.700	0.016	0.797
EURHICP_s	-0.003	0.958	-0.007	0.887
EURHICPFLASH_s	**-0.139**	**0.000**	-0.005	0.952
EURUNE_s	-0.014	0.672	-0.008	0.730
DECPI_s	-0.019	0.645	-0.012	0.720
DEIFO_s	**0.186**	**0.000**	**0.107**	**0.000**
DEGDP_s	0.043	0.748	0.021	0.863
DEIP_s	0.028	0.703	0.026	0.530
DEUNE_s	-0.009	0.845	0.062	0.211
USEMP_s	**0.137**	**0.000**	**0.117**	**0.001**
USGDP_s	**0.091**	**0.011**	**0.053**	**0.092**
USIP_s	0.072	0.363	**0.104**	**0.019**
USCPI_s	**0.098**	**0.000**	**0.078**	**0.000**
Announcement dummy	-0.049	0.745	-0.105	0.347
Dummy_21_9	-0.083	0.446	0.134	0.115
Dummy_9_12	-0.077	0.451	0.034	0.647
Dummy_12_15	**0.201**	**0.054**	0.105	0.169
Dummy_15_18	**-0.305**	**0.004**	-0.052	0.501

Note 1: Yield changes are measured in basis points

Note 2: Definitions of variables in appendix 1.7.4.

Note 3: Numbers in bold indicate significance at the 10 percent level.

Turning now to the conditional variance equation we find the following results: The constant, the ARCH and the GARCH terms all enter with high levels of significance. Most of the dummy variables significantly affect the conditional volatility of yield change shocks. We also find strong time effects. When we condition on announcements, conditional volatility is highest in the late afternoon period from 15:00 to 18:00 and overnight from 21:00 to 9:00 though the latter is presumably a result of the much longer length of that interval. Turning to the announcement dummy variable, which captures any announcement, no matter what macroeconomic series, nor whether the market was truly surprised, we again find strong positive effects on conditional volatility during the interval when the announcement takes place. Volatility of the 2-year yield change shock then falls quickly subsequently, but remains significantly higher for the 10-year yield change shock. We find some evidence of the "calm before the storm" effect of Jones et al (1998) with the 2-year yield volatility being significantly reduced two intervals, i.e. between three to six hours before the announcement. This effect does, however, disappear in the interval immediately preceding the announcement interval. Interestingly, though the time effects on conditional volatility are of rather similar magnitude for both yield change series, the announcement effect is much stronger for the 2-year series. In particular, the marked pattern found in Jones et al (1998) of reduced volatility just before the announcement, the rise in volatility during the announcement period, and the subsequent quick fall in volatility can only be found for the 2-year yield change series. Though we can partially replicate the findings of Jones et al (1998) we should keep in mind that our study differs in at least three dimensions: We use European yield data, we make use of low-intra-daily frequency data, and we include a much larger set of announcements. Finally, our results are in line with the results of Andersson et al (2006) which use higher-frequency data on German bond futures and a larger set of announcements. However, they only consider dummy variables in the conditional variance equations. We next extend their analysis to include measures of true surprises. This will be discussed next.

Table 3.2: GARCH(1,1) with "lead-lag" dummies	2-year yield change		10-year yield change	
conditional variance equation	coefficient	p-value	coefficient	p-value
constant	**0.936**	**0.000**	**-0.256**	**0.000**
ARCH	**0.219**	**0.000**	**0.050**	**0.000**
GARCH	**0.181**	**0.000**	**0.211**	**0.000**
Announcement dummy lead (2)	**-1.068**	**0.000**	0.042	0.608
Announcement dummy lead (1)	0.226	0.206	0.039	0.738
Announcement dummy	**3.470**	**0.000**	**0.976**	**0.000**
Announcement dummy lag (1)	**-0.745**	**0.029**	**0.625**	**0.011**
Announcement dummy lag (2)	**-0.487**	**0.016**	0.001	0.996
Dummy_21_9	**5.800**	**0.000**	**5.022**	**0.000**
Dummy_9_12	**2.601**	**0.000**	**2.799**	**0.000**
Dummy_12_15	**2.377**	**0.000**	**2.924**	**0.000**
Dummy_15_18	**6.885**	**0.000**	**4.952**	**0.000**
R-squared		0.030		0.015
F-statistic		4.475		2.108
p-value		0.000		0.000
Log likelihood		-11904.78		-10416.11

Note 1: Yield changes are measured in basis points.
Note 2: Definitions of variables in appendix 1.7.4.
Note 3: Numbers in bold indicate significance at the 10 percent level.

The GARCH "surprise" model

Having established the response of the conditional volatility of yield change shocks to a rather typical announcement, we now extend the analysis in two interesting directions: First, we study the different effects of the different kinds of announcements and second, we only consider true surprises. By the same economic argument as above, everything that has already been expected by market participants should not affect pricing behavior, thus the conditional mean and volatility should be a function of measures of surprises only, not actually of announcement dummies. This strictly holds only if investors are supposed to be risk-neutral, as otherwise changes in the uncertainty about news would most likely also affect pricing behavior. We make this assumption mainly because of the unavailability of the data mentioned above, but it should be tested for empirically.

The GARCH (1,1) "surprise" model consists of equations (1.12) to (1.14). Equation (1.12) is the same as equations (1.8) and (1.9). The disturbance is again assumed to be normally distributed with zero mean and conditional variance equal to σ_t^2 (equation (1.13)). We now model the conditional variance as a GARCH (1,1) process with the squared surprise series as additional exogenous variables (equation (1.14)). In other words, the surprise regressors not only enter the conditional mean equation, but also the conditional variance equation. We include *squared* values of the surprises, because it seems natural to believe that positive and negative surprises should have symmetric effects on the conditional variance. Assuming otherwise would constrain them to have asymmetric effects. In other words positive surprises would increase volatility and negative surprises would necessarily reduce volatility, and vice versa. Though this obviously is a possibility, it is not clear why it should be the case. If anything it seems more appropriate to distinguish news according to whether they are perceived as "good" or "bad" news, but this extension is beyond the scope of this paper.

We formally write the GARCH "surprise" model as:

$$\Delta y_t = \alpha_0 + \sum_{l=1}^{L} \alpha_l \Delta y_{t-l} + \sum_{k=1}^{K} \beta_k s_{k,t} + \sum_{m=1}^{M} \delta_m \widetilde{d}_{m,t} + u_t \tag{1.12}$$

$$u_t | \Omega_{t-1} \sim N(0, \sigma_t^2) \tag{1.13}$$

$$\sigma_t^2 = \phi_0 + \phi_1 u_{t-1}^2 + \theta_1 \sigma_{t-1}^2 + \sum_{k=1}^{K} \gamma_k s_{k,t}^2 + \sum_{m=1}^{M} \delta'_m \widetilde{d}_{m,t} \tag{1.14}$$

Results of the GARCH "surprise" model are shown in tables 4.1 and 4.2. Table 4.1 is very similar to table 3.1. With the exception of surprises in the Flash estimate of the Euro Area HICP all variables that were found significant above are again estimated to significantly impact on the conditional yield in the GARCH "surprise" model. All significant estimates are in line with our small term-structure model that optimistic news about the future economy should lead to yield increases. For instance, a one-standard deviation positive surprise in the Ifo-index raises 2-year yields by 0.18 basis points. The Ifo-index is indeed found to have the strongest impact on European bond markets, followed by ECB rate decisions for the 2-year yield and two US announcements for the 10-year yield. In fact, US announcements are again found to be very important for the long yield, suggesting that US macroeconomic announcements are believed by market participants to be a good indicator for European medium to long term interest rates, and to some extend for European short run yields.

Table 4.1: GARCH(1,1) with squared surprises in variance equation	2-year yield change		10-year yield change	
conditional mean equation	coefficient	p-value	coefficient	p-value
constant	-0.042	0.853	-0.044	0.804
lag 1	**-0.138**	**0.000**	-0.026	0.246
ECB_s	**0.168**	**0.000**	-0.021	0.552
FED_s	0.078	0.377	-0.003	0.844
EURM3_s	**0.116**	**0.007**	0.041	0.161
EURGDP_s	0.041	0.893	0.046	0.685
EURIP_s	0.052	0.608	0.020	0.719
EURHICP_s	-0.006	0.942	-0.010	0.845
EURHICPFLASH_s	-0.008	0.892	-0.005	0.949
EURUNE_s	-0.008	0.835	-0.009	0.822
DECPI_s	-0.017	0.563	-0.013	0.598
DEIFO_s	**0.183**	**0.000**	**0.106**	**0.006**
DEGDP_s	0.051	0.724	0.018	0.859
DEIP_s	0.019	0.640	0.025	0.331
DEUNE_s	0.001	0.980	0.063	0.173
USEMP_s	**0.145**	**0.000**	**0.116**	**0.000**
USGDP_s	**0.084**	**0.015**	**0.053**	**0.047**
USIP_s	0.063	0.136	**0.103**	**0.000**
USCPI_s	0.081	0.217	**0.078**	**0.069**
Announcement dummy	0.027	0.891	-0.101	0.407
Dummy_21_9	-0.069	0.792	0.164	0.409
Dummy_9_12	-0.057	0.831	0.048	0.811
Dummy_12_15	0.224	0.418	0.120	0.556
Dummy_15_18	-0.056	0.827	-0.009	0.961

Note 1: Yield changes are measured in basis points

Note 2: Definitions of variables in appendix 1.7.4.

Note 3: Numbers in bold indicate significance at the 10 percent level.

Turning to the results for the conditional variance equation, we again find strong ARCH and GARCH effects. The unexpected, but very interesting finding of the conditional variance estimation is that almost all squared surprises, and in any case all those found to significantly impact on the conditional variance, are found to do so by *reducing* conditional volatility. For the 2-year yield, for instance, surprises in US industrial production figures are found to have a strong negative effect on the conditional volatility of yield change shocks. In other words, the bigger the surprise, the smaller is the volatility of the shock to the yield change. Using absolute values of surprises rather than squared values leads to very similar results (see appendix 1.7.6 for detailed results). Thus this is indeed a very robust finding. The results also show that far more of the surprises have significant effects on conditional variance rather than on the conditional mean. In fact, quite many of the squared surprises are found to significantly impact on conditional volatility.

But it does indeed seem somewhat counterintuitive that bigger surprises should actually lower volatility. In particular, whilst the "dummy" GARCH model suggests that announcements do actually on impact increase the volatility of yield change shocks.

they instead are found insignificant once we control for true surprises. This question should be studied in more detail than what is possible in this study. One possible answer could be that bigger surprises give a somewhat *clearer* picture to market participants as to where the economy is heading. Thus investors' uncertainty about the fundamentals might actually be decreasing in the size of the surprise. This might then reduce volatility in the market.

Table 4.2: GARCH(1,1) with squared surprises in variance equation	2-year yield change		10-year yield change	
conditional variance equation	coefficient	p-value	coefficient	p-value
constant	**4.641**	**0.000**	**2.525**	**0.000**
ARCH	**0.116**	**0.000**	**0.086**	**0.000**
GARCH	**0.577**	**0.000**	**0.570**	**0.000**
ECB_s_squared	0.006	0.275	0.003	0.360
FED_s_squared	**-0.010**	**0.067**	-0.003	0.338
EURM3_s_squared	**-0.016**	**0.000**	**-0.007**	**0.039**
EURGDP_s_squared	-0.001	0.866	-0.001	0.483
EURIP_s_squared	**-0.007**	**0.030**	**-0.003**	**0.000**
EURHICP_s_squared	**-0.009**	**0.000**	**-0.004**	**0.000**
EURHICPFLASH_s_squared	0.001	0.709	**-0.003**	**0.000**
EURUNE_s_squared	-0.003	0.640	-0.000	0.919
DECPI_s_squared	-0.006	0.317	-0.003	0.541
DEIFO_s_squared	**-0.010**	**0.057**	-0.002	0.517
DEGDP_s_squared	**-0.003**	**0.000**	**-0.002**	**0.000**
DEIP_s_squared	**-0.017**	**0.000**	**-0.006**	**0.042**
DEUNE_s_squared	-0.003	0.823	-0.000	0.946
USEMP_s_squared	-0.008	0.212	**-0.007**	**0.074**
USGDP_s_squared	**-0.009**	**0.000**	-0.003	0.208
USIP_s_squared	**-0.022**	**0.000**	-0.008	0.160
USCPI_s_squared	0.003	0.676	0.002	0.470
Announcement dummy	-0.158	0.814	-0.115	0.674
Dummy_21_9	-0.463	0.593	-0.283	0.670
Dummy_9_12	-0.498	0.505	-0.438	0.388
Dummy_12_15	-0.323	0.687	-0.316	0.539
Dummy_15_18	-0.238	0.723	-0.314	0.533
R-squared		0.036		0.015
F-statistic		3.846		1.560
p-value		0.000		0.008
Log likelihood		-12366.9		-10889.07

Note 1: Yield changes are measured in basis points.
Note 2: Definitions of variables in appendix 1.7.4.
Note 3: Numbers in bold indicate significance at the 10 percent level.

Finally, a glance at the diagnostic tests (see appendix 1.7.5, table 5.2) reveals that the ARCH-effects do indeed disappear when modelling 2-year yield changes with the above GARCH(1,1) model, not however when using that same model for modelling 10-year yield changes. Strong ARCH-effects do remain in the residuals of the latter and do not disappear when adding more ARCH or GARCH terms in the conditional variance equation. Thus, we should be somewhat sceptical on the results for the 10-year yield change series whilst we can be quite confident in those for the 2-year yield.

1.6 Conclusion

The results of this paper suggest that news on macroeconomic fundamentals do matter for European bond markets. Using the widely used GARCH(1,1) model we find that quite a few surprises affect the conditional mean of yield changes. Most important are surprises of the following announcements: the ECB interest rate decision, the Ifo index, and the four US announcements studied (in particular the US employment report and GDP figures). Surprises in these announcements result in bigger responses of the 2-year yield than of the 10-year yield. The GARCH(1,1) model of course also allows us to investigate the effects of macroeconomic announcements on the conditional volatility of yield change shocks. We find strong announcement effects, with volatility rising when an announcement occurs, but somewhat surprisingly we find a negative impact of surprises on volatility. In other words, bigger surprises tend to reduce the volatility of the shocks. This point deserves more research efforts in the future. We argue that one possibility for this finding could be that bigger surprises - say a much bigger than expected interest rate increase by the ECB, perhaps together with a strong and clear press release - can better signal the path of future short term interest rates that the central bank is most likely to follow. Investors' uncertainty about future short term interest rates would then be reduced, despite the fact that the surprise was indeed very big. This could then lower the volatility of yield change shocks.

1.7 Appendix

1.7.1 Relation between bond price and yield

We have

$$\begin{aligned} P_{t,n} &= \frac{1}{[1+y_{t,n}]^n} \\ P_{t+1,n-1} &= \frac{1}{[1+y_{t+1,n-1}]^{n-1}} \end{aligned}$$

We want to write the percentage change in the bond price in terms of yield changes

$$\log\left[\frac{P_{t+1,n-1}}{P_{t,n}}\right] = ?$$

$$\begin{aligned} \log\left[\frac{P_{t+1,n-1}}{P_{t,n}}\right] &= \log\left[\frac{[1+y_{t,n}]^n}{[1+y_{t+1,n-1}]^{n-1}}\right] \\ &= n\log(1+y_{t,n}) - (n-1)\log(1+y_{t+1,n-1}). \end{aligned}$$

For small values of $y_{t,n}$ and $y_{t+1,n-1}$ we use the approximation

$$\log(1+x) = x$$

and obtain

$$\begin{aligned} \log\left[\frac{P_{t+1,n-1}}{P_{t,n}}\right] &= ny_{t,n} - (n-1)y_{t+1,n-1} \\ &= -n\Delta y_{t+1,n-1} + y_{t+1,n-1}. \end{aligned} \tag{1.15}$$

where we have additionally used the fact that for large values of n, $y_{t,n}$ is approximately equal to $y_{t+1,n-1}$. In words, for bonds with very long maturities, say e.g. 12 years, the difference between today's yield and tomorrow's yield with a remaining maturity of 12 years less one day is arguably negligible.

The key result of equation 1.15 is of course that the rate of change of the bond price is inversely related to the yield change. This makes sense, because we know that if the bond price rises, the yield simultaneously falls.

1.7.2 Yield and yield change data

Figure 1.4: Intradaily yield data of German 2 and 10 year government bonds.

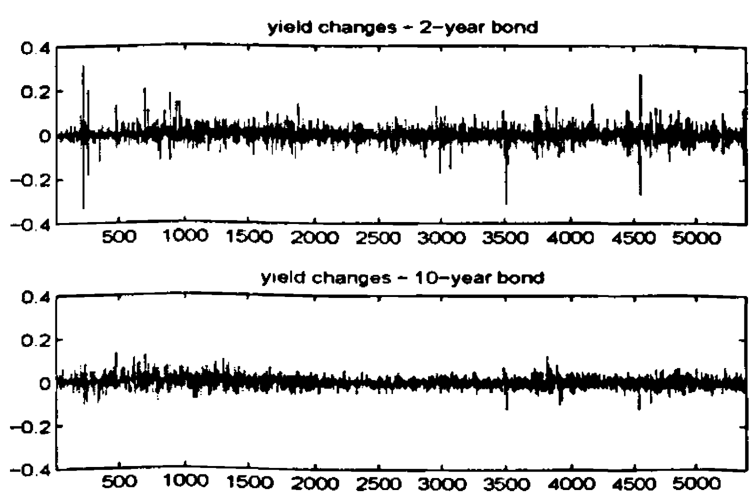

Figure 1.5: Intradaily yield change data of German 2 and 10 year government bonds.

1.7.3 Histograms of yield changes on no-announcement days versus announcement days

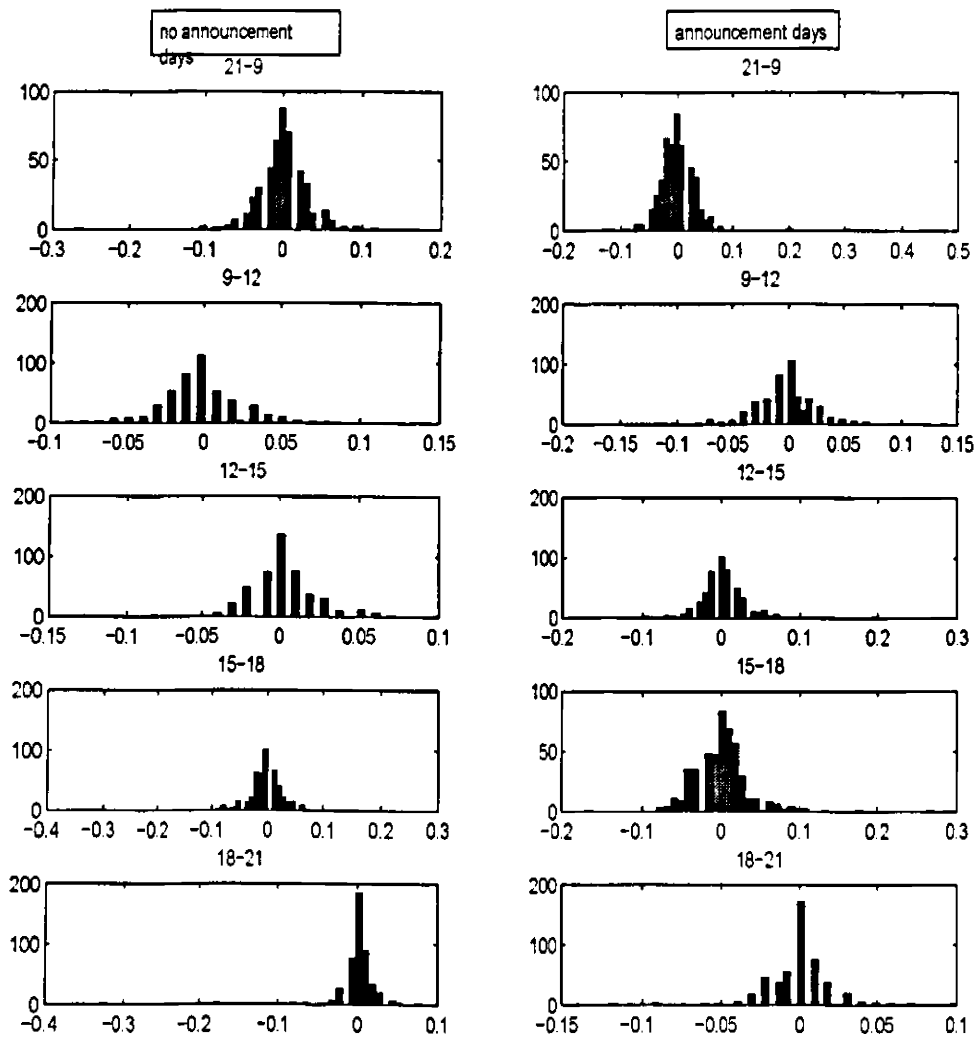

Figure 1.6: Histograms of 2-year yield changes conditional on whether an announcement has occurred or not.

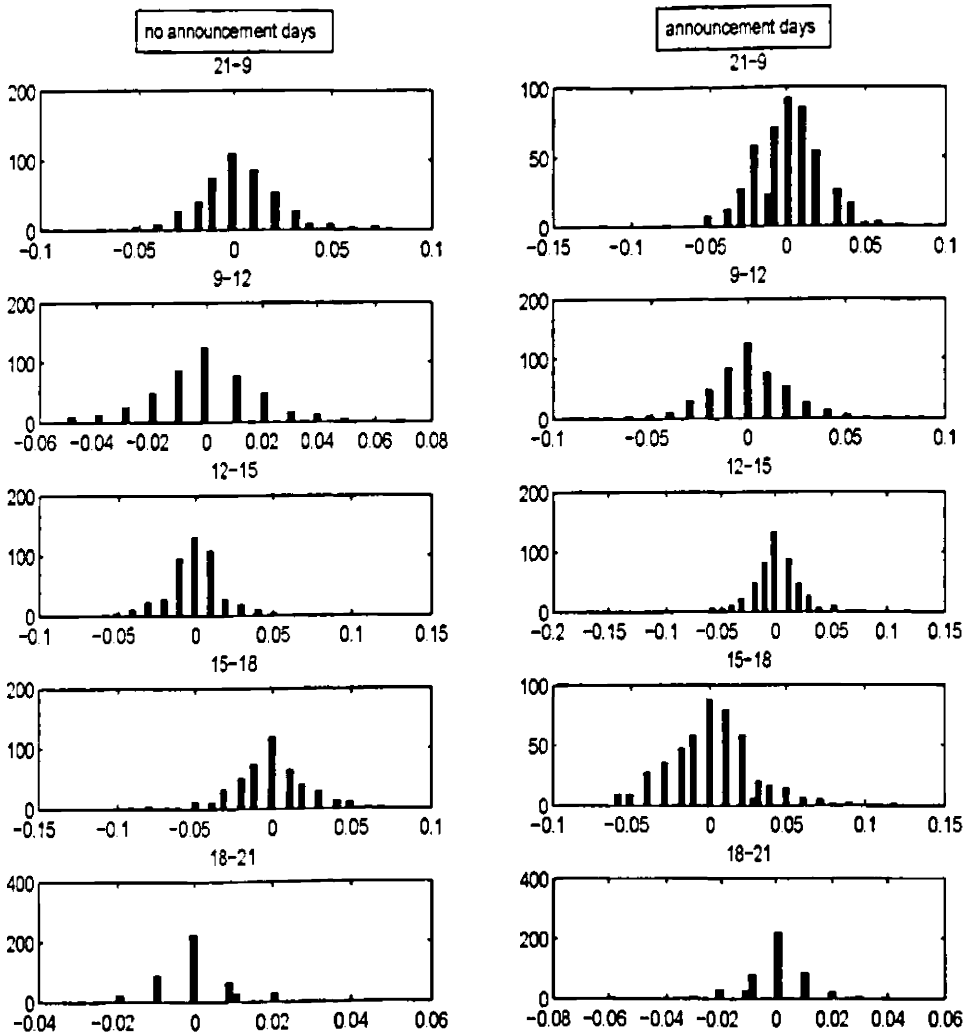

Figure 1.7: Histograms of 10-year yield changes conditional on whether an announcement has occurred or not.

1.7.4 Definition of variables

ECB	ECB interest rate
FED	Federal Reserve interest rate
EURM3	Euro Area money supply
EURGDP	Euro Area GDP
EURIP	Euro Area industrial production
EURHICP	Euro Area Harmonised Index of Consumer Prices
EURHICPFLASH	Flash estimate of EURHICP
EURUNE	Euro Area unemployment rate
DECPI	German Consumer Price Index
DEIFO	Ifo indicator
DEGDP	German GDP
DEIP	German industrial production
DEUNE	German unemployment rate
USEMP	US employment
USGDP	US GDP
USIP	US industrial production
USCPI	US Consumer Price Index
Announcement dummy	Dummy that takes the value 1 if any announcement occurs
Dummy_21_9	Time dummy that takes the value 1 in the interval from 21:00 to 9:00
Dummy_9_12	Time dummy that takes the value 1 in the interval from 9:00 to 12:00
Dummy_12_15	Time dummy that takes the value 1 in the interval from 12:00 to 15:00
Dummy_15_18	Time dummy that takes the value 1 in the interval from 15:00 to 18:00

1.7.5 Model diagnostics for the regression and GARCH models with surprises: test statistics for ARCH-effects and descriptive statistics using squared residuals.

Table 5.1: "Surprise" regression model

Table 5.1	2-year yield change				10-year yield change			
lag	Q-stat	p-value	LM-stat	p-value	Q-stat	p-value	LM-stat	p-value
1	44.26	0.00	44.23	0.00	1.25	0.26	1.25	0.26
5	112.76	0.00	103.47	0.00	43.48	0.00	41.90	0.00
10	113.85	0.00	103.66	0.00	112.87	0.00	95.74	0.00
20	141.11	0.00	121.15	0.00	230.67	0.00	151.36	0.00
30	151.41	0.00	128.02	0.00	325.08	0.00	182.95	0.00
skewness	-0.414				0.119			
kurtosis	17.131				6.211			
JB (p-value)	0.000				0.000			

Table 5.2: "Surprise" GARCH model

Table 5.2	2-year yield change				10-year yield change			
lag	Q-stat	p-value	LM-stat	p-value	Q-stat	p-value	LM-stat	p-value
1	1.63	0.20	1.63	0.20	3.03	0.08	3.02	0.08
5	5.02	0.41	5.06	0.41	25.13	0.00	25.24	0.00
10	5.16	0.88	5.20	0.88	75.68	0.00	76.06	0.00
20	35.92	0.02	34.53	0.02	160.53	0.00	138.82	0.00
30	50.92	0.01	47.47	0.02	230.51	0.00	169.05	0.00
skewness	-0.275				0.092			
kurtosis	15.992				6.229			
JB (p-value)	0.000				0.000			

1.7.6 GARCH model with absolute surprises in variance equation

Table 6.1: GARCH(1,1) with absolute surprises in variance equation	2-year yield change		10-year yield change	
conditional mean equation	coefficient	p-value	coefficient	p-value
constant	-0.050	0.820	-0.048	0.773
lag 1	**-0.148**	**0.000**	-0.029	0.173
ECB_s	**0.168**	**0.000**	-0.018	0.589
FED_s	**0.077**	**0.064**	-0.007	0.587
EURM3_s	**0.116**	**0.008**	0.037	0.235
EURGDP_s	0.042	0.907	**0.048**	**0.079**
EURIP_s	0.049	0.412	0.023	0.507
EURHICP_s	-0.006	0.912	-0.012	0.734
EURHICPFLASH_s	-0.020	0.734	0.012	0.752
EURUNE_s	-0.012	0.716	-0.011	0.709
DECPI_s	-0.016	0.598	-0.011	0.684
DEIFO_s	**0.199**	**0.000**	**0.105**	**0.005**
DEGDP_s	0.050	0.406	0.020	0.791
DEIP_s	0.017	0.497	0.026	0.231
DEUNE_s	-0.006	0.850	0.059	0.199
USEMP_s	**0.143**	**0.000**	**0.117**	**0.005**
USGDP_s	**0.075**	**0.042**	**0.051**	**0.093**
USIP_s	**0.099**	**0.007**	**0.102**	**0.000**
USCPI_s	**0.080**	**0.048**	**0.074**	**0.008**
Announcement dummy	-0.004	0.981	-0.086	0.460
Dummy_21_9	-0.049	0.846	0.187	0.319
Dummy_9_12	-0.053	0.834	0.032	0.862
Dummy_12_15	0.185	0.489	0.079	0.679
Dummy_15_18	-0.073	0.770	-0.005	0.977

Note 1: Yield changes are measured in basis points

Note 2: Definitions of variables in appendix 4.

Note 3: Numbers in bold indicate significance at the 10 percent level.

Table 6.2: GARCH(1,1) with absolute surprises in variance equation	2-year yield change		10-year yield change	
conditional variance equation	coefficient	p-value	coefficient	p-value
constant	**4.712**	**0.000**	**2.529**	**0.000**
ARCH	**0.117**	**0.000**	**0.076**	**0.000**
GARCH	**0.586**	**0.000**	**0.572**	**0.000**
ECB_s_absolute	0.158	0.144	0.063	0.299
FED_s_absolute	**-0.391**	**0.005**	-0.121	0.143
EURM3_s_absolute	**-0.216**	**0.072**	-0.049	0.456
EURGDP_s_absolute	0.022	0.926	-0.067	0.772
EURIP_s_absolute	**-0.285**	**0.000**	**-0.123**	**0.000**
EURHICP_s_absolute	**-0.283**	**0.000**	**-0.137**	**0.000**
EURHICPFLASH_s_absolute	0.043	0.595	-0.065	0.350
EURUNE_s_absolute	-0.135	0.259	-0.038	0.567
DECPI_s_absolute	-0.129	0.317	-0.035	0.713
DEIFO_s_absolute	-0.184	0.150	-0.050	0.416
DEGDP_s_absolute	-0.173	0.506	**-0.094**	**0.000**
DEIP_s_absolute	**-0.381**	**0.000**	**-0.137**	**0.003**
DEUNE_s_absolute	-0.128	0.434	0.022	0.729
USEMP_s_absolute	-0.121	0.300	-0.000	1.000
USGDP_s_absolute	-0.200	0.165	-0.027	0.728
USIP_s_absolute	**-0.366**	**0.000**	-0.094	0.212
USCPI_s_absolute	0.063	0.565	0.052	0.228
Announcement dummy	-0.321	0.646	-0.117	0.674
Dummy_21_9	-1.230	0.146	-0.478	0.449
Dummy_9_12	-1.060	0.127	-0.773	0.098
Dummy_12_15	-0.460	0.561	-0.434	0.361
Dummy_15_18	-0.411	0.532	-0.584	0.210
R-squared		0.035		0.015
F-statistic		3.776		1.534
p-value		0.000		0.010
Log likelihood		-12323.3		-10841.54

Note 1: Yield changes are measured in basis points.

Note 2: Definitions of variables in appendix 4.

Note 3: Numbers in bold indicate significance at the 10 percent level.

Bibliography

Andersen, Torben G.; Bollerslev, Tim; Diebold, Francix X. and Clara Vega, (2003): "Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange", American Economic Review, Vol.93 No1, p.38-62.

Andersson, Magnus, Lars Jul Hansen and Szabolcs Sebestyen, (2006): "Which News Moves the Euro Area Bond Market?", ECB Working Paper 631.

Bollerslev, Tim (1986): "Generalized Autoregressive Conditional Heteroskedasticity", Journal of Econometrics, 31:207-27.

Bollerslev, Tim (1990): "Modelling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized ARCH Model", Review of Economics and Statistics, 72:3, 498-505.

Bollerslev, Tim; Chou, Ray Y. and Kenneth F. Kroner (1992): "ARCH modeling in finance: A review of the theory and empirical evidence"; Journal of Econometrics, 52:5-59.

Brooke, Martin; Danton, Graeme and Richhild Moessner, (1999); Bank of England Quarterly Bulletin.

Cutler, David M.; Poterba, James M., and Lawrence H. Summers, (1989): "What Moves Stock Prices?"; Journal of Portfolio Management, 15:4-12.

Ederington, Louis H., and Jae Ha Lee, (1993); "How Markets Process Information: News Releases and Volatility"; Journal of Finance, 48:4, 1161-1191.

Ehrmann, Michael, and Marcel Fratzscher, (2002); "Interdependence between the Euro Area and the US: What Role for EMU?"; ECB Working Paper No. 200.

Fell, John, (2002); "How does the bond market react to ECB interest rate changes?"; ECB Capital Markets Economic Perspectives, No.2.

Fleming, Michael J. and Eli M. Remolona, (1997); "What Moves the Bond Market?"; FRBNY Policy Review.

Goldberg, Linda and Deborah Leonard, (2003); "What Moves Sovereign Bond Markets? The Effects of Economic News on US and German Yields"; FRBNY Current Issues in Economics and Finance.

Gravelle, Toni and Richhild Moessner, (2001); "Reactions of Canadian Interest Rates to Macroeconomic Announcements: Implications for Monetary Policy Transparency"; Bank of Canada Working Paper 2001-5.

Haldane, Andrew G., and Vicky Read, (2000); "Monetary policy surprises and the yield curve"; Bank of England Working Paper 106.

Jones, Charles M., Lamont, Owen and Robin L. Lumsdaine, (1998); "Macroeconomic news and bond market volatility"; Journal of Financial Economics, 47:315-337.

Li, Li and Robert F. Engle, (1998); "Macroeconomic Announcements and Volatility of Treasury Futures"; UCSD Discussion Paper 98-27.

McQueen, Grant and V. Vance Roley, (1993); "Stock Prices, News, and Business Conditions"; The Review of Financial Studies, 6:3, 683-707.

Molgaard Pederson, Anders and Jesper Wormstrup, (2001); "Macroeconomic Data Releases and the Yield Curve for the Euro Area"; Danmarks Nationalbank Monetary Review 3rd Quarter.

Nelson, Danial B., (1991); "Conditional Heteroskedasticity in Asset Returns: A New Approach"; Econometrica, 59:2, 347-70.

Rigobon, Roberto and Brian Sack, (2006); "Noisy Macroeconomic Announcements, Monetary Policy, and Asset Prices"; Working Paper.

Chapter 2

Shocks and Adjustment Costs in an estimated RBC model for the US

Abstract

Real Business Cycle (RBC) models advocate the importance of technology shocks for business cycle fluctuations. This paper uses US data on GDP, consumption, investment, and hours worked, to estimate a simple RBC model that also allows for other real, but non-technology shocks. The model in addition allows for capital and labor adjustment costs. It then addresses the following three questions: Which real shocks drive the US business cycle? How important are adjustment costs to business cycle fluctuations? Has there been a change in the structural parameters around 1984?

The empirical findings show first, that technology shocks are indeed the most important shocks in explaining variation in US GDP. However, shocks to preferences, labor supply, and government spending are important as well. In particular, short run variation in consumption is driven mainly by preference shocks. Government spending shocks have strong effects on short run investment decisions, and most importantly, labor supply is mainly determined by the labor supply shock. Second, labor adjustment costs are found to play a key role in the propagation mechanism of the model. And third, there is some evidence of a break in the structural parameters around 1984.

2.1 Introduction

Standard Real Business Cycle (RBC) models usually assume technology shocks as single key driving process of the economy. Thus, they not only abstract from nominal shocks like monetary policy shocks, but often also from other real shocks, such as shocks to preferences, government spending, or the depreciation rate. This paper instead takes the standard RBC model and extends it by adding various shocks, as well as capital and labor adjustment costs as suggested by Cogley and Nason (1995). Using this model, it addresses three important questions: Which real shocks drive the US business cycle? How important are capital and labor adjustment costs in the propagation mechanism?

And has there been a break in the structural parameters of the model around 1984, after which US time series have been found in the literature to have lower volatilities?

To answer these questions, the RBC model is estimated using Bayesian methods on quarterly US data on GDP, consumption, investment and hours worked over the period 1963:1 to 2004:3. The empirical findings indicate that technology shocks are indeed the most important shocks in explaining variation in US GDP and investment. Consumption and hours worked are, however, also strongly affected by other shocks. In particular, variation in hours worked is strongly affected by shocks to the marginal rate of substitution between goods and leisure, and short run consumption is driven mainly by preference shocks. In addition, government spending has some effects on short run variations of investment.

The parameter estimates are generally in line with those usually found in the business cycle literature. An exception to this is the labor adjustment cost parameter which is estimated significantly higher than in other studies (see e.g. Shapiro (1986)). Labor adjustment costs are thus found to have an important impact in the propagation mechanism of the model. Capital adjustment costs, on the other hand, seem not to matter very much.

Finally, I study the properties of the shock processes and whether these have changed over time. To this end, I run a smoothing algorithm to obtain optimal predictions of the hidden shock processes. The visual descriptions nicely show the impact of important historical events like the oil price hikes in the 1970s. I then test for parameter stability over the two sub-samples, and find that parameters are generally stable. The only exceptions are slight changes in the adjustment cost parameters. Labor adjustment costs seem to have risen somewhat after 1984, whilst capital adjustment costs are no longer statistically significant. Finally, there is some evidence of smaller shock variances after 1984.

The remainder of the paper is organized as follows: The next section briefly discusses some of the related literature on the causes of business cycle fluctuations and the different estimation approaches and how this paper fits in. Section 3 sets up the economic model and its approximate solution, whilst section 4 discusses details of the estimation procedure. The results are then presented in section 5, and the last section concludes.

2.2 Literature Review

2.2.1 The importance of real shocks

Prescott (1986) attributes "more than half the fluctuations in the postwar period, with a best point estimate near 75 percent" to technology shocks. Using a somewhat more explicit and generalized argument, Aiyagari (1994) finds that "under several standard assumptions (..) the contribution of technology shocks must be large (at least 78 percent)."

More recently, Ireland (2004a) finds that technology shocks account for more than half the fluctuations in output one quarter ahead, and around 85% of variation in output at the infinite horizon. He also finds strong effects of technology shocks on consumption and investment variation at all horizons, whilst they matter for hours worked variations only at the short horizon of one quarter where they explain around 97%. Just eight quarters ahead, they account for less than 6% of hours variation.

Altig et al (2002) use a New Keynesian framework to study the effects of both, technology shocks and monetary policy shocks. They find that only about 3-8% of output variation can be accounted for by monetary policy shocks, whilst technology shocks account for roughly 45%. This is, however, somewhat at odds with the finding by Shapiro and Watson (1988) that aggregate demand effects contribute around 20% to output fluctuations. Blanchard and Quah (1989) also find important effects of aggregate demand effects in the short run.

Focusing more specifically on the labor market, Chang and Schorfheide (2003) find that shocks to labor supply account for about 30% of variation in hours and about 15% of output fluctuations. They obtain much higher results of the effect on hours when using a home-production model. Then, labor supply shocks are found to explain 66% of hours variation, though they admit the model might be misspecified. Looking at transitory technology shocks of the kind studied by Prescott (1986) and Ireland (2004a), their results show that these account for between 26 and 51% of hours variation and between 36 and 41% of variation in output.

Summing up, it seems that transitory technology shocks can account for between 36% to just above 78% of output variation, and between 6 to 51% of hours variation. Labor supply shocks account for about 15% of output fluctuations, and around 30% of variation in hours worked. Consumption and investment are also strongly affected by transitory technology shocks.

2.2.2 Different approaches to estimation

The rather wide intervals of the above estimates indicate the uncertainty around these figures quite well. Differences in estimates occur for many reasons, one is because of using different methods. When studying the causes of business cycle fluctuations, there are essentially three different ways to proceed: Kydland and Prescott (1982, 1996) propose the "computational experiment" where an economic model is first set up, parameters then calibrated to match certain first moments of the data, and the model's success finally judged in terms of its ability to match various second moments of the data. This method underlies the work of Prescott (1986) and Aiyagari (1994).

Instead, Sims (1980) and others have advocated the use of Vector Autoregressive models on which a minimum set of restrictions is imposed using economic theory to uncover the structural parameters. Shapiro and Watson (1988) and Blanchard and Quah (1989) use this approach and make use of the identifying assumption that only supply shocks can affect output in the long run. Chang and Schorfheide (2003) carry out some of their estimations in a structural VAR and identify the structural parameters by assuming that productivity and hours worked move in opposite directions in response to a labor supply shock.

Finally, more recently, and partly as a response to criticisms to the first two approaches, researchers have been estimating complete structural models of the business cycle. This has been suggested already by Hansen and Sargent (1980) and early examples were Altug (1989), Christiano and Eichenbaum (1992), and Leaper and Sims (1994). More recently, and mentioning only a selected few, Kim (2000) has estimated a model of monetary policy using Maximum Likelihood, Christiano et al (2005) have used minimum distance estimation to study the effects of monetary policy, Schorfheide (2000) has shown how different models can be compared in a Bayesian setting, and Smets and Wouters (2002) have estimated a fully specified DSGE model for the Euro area. The above results of Altig et al (2002), Ireland (2004a), and some of the results of Chang and Schorfheide (2003) were obtained using this approach.

The strength of this approach over the use of structural VARs is that parameters, as well as shocks, have a clear economic meaning. Because the structural parameters are estimated directly, there is no identification problem between reduced form and structural parameters. Another way of saying this is that this method allows to directly write down a full probabilistic description of the data given the structural parameters. Whilst Smets and Wouters (2002) have shown that forecasts obtained from their estimated DSGE model are superior to those obtained from an unrestricted VAR, this is also true for more standard Bayesian VARs as suggested by Doan, Litterman and Sims (1984) which are less densely specified, and thus reduce sampling uncertainty of the estimates.

The risk of the structural approach to estimation is, however, that the model to be estimated is usually a drastic simplification of reality, and therefore always misspecified. Though this has also been documented for structural VARs (see Cooley and Dwyer (1998) and Chari et al (2004)), it poses a much bigger risk for estimation using fully specified DSGE models. In principle though, as shown in Schorfheide (2000), the Bayesian approach allows for model comparison of nested as well as unnested models. Another closely related problem is, that because the restrictions imposed on the estimation by the underlying economic model are highly nonlinear, it is difficult to figure out how exactly they affect the estimation. DelNegro et al (2004) document the nature of misspecification of the New Keynesian model against an alternative unrestricted VAR. They find that even though the degree of misspecification in large-scale DSGE models is rather small, it still cannot be ignored.

2.2.3 Multiple shocks and factor adjustment costs

In this paper, I follow the structural approach to estimation and estimate a fully specified and micro-founded RBC model. In particular, I carry out Bayesian estimation as suggested by DeJong et al (2000), Schorfheide (2000), Smets and Wouters (2002), and others. To study the three questions mentioned in the introduction, I use an extended version of the model suggested by Cogley and Nason (1995). They show that the propagation mechanism of standard RBC models is very weak, and thus argue that introducing capital and labor adjustment costs would improve the autocorrelation and impulse response properties of the variables. This paper extends their model by adding five transitory economic shocks. These are then a technology shock, two shocks to preferences, a shock to the depreciation rate, and a shock to government spending.

In their multiple shock approach, Ingram et al (1994) argue that the importance of any particular shock is essentially indeterminate because shocks are correlated. The method employed in this paper forces the correlation to be zero in the estimation, and therefore does not suffer from this criticism.

The paper contributes to the literature by adding to the results of Ireland (2004a,b) and DeJong et al (2000b). Using Maximum Likelihood estimation, Peter Ireland considers the role of technology shocks in the standard RBC model (2004a), and extends the study to allow for three more non-technology shocks within a New Keynesian framework (2004b). DeJong et al (2000b) use Bayesian methods to study the role of technology shocks and shocks to investment in a model of variable capital utilization.

This paper instead studies the importance of various other real shocks within an RBC model that in addition also allows for adjustment costs as in Cogley and Nason (1995). We thus confine ourselves to the rather well known RBC model and study the structure of the US economy from an RBC perspective. In particular, by including other real shocks we are in a position to judge which economic shocks are important if the true model was in fact the RBC model. Second, by modelling factor adjustment costs explicitly, we not only obtain more realistic impulse response dynamics, but can also evaluate the relative importance of these costs within an aggregate model of the economy. And thirdly, by estimating the model over the two subsamples we can test for changes in the structural parameters. Even though we do not include monetary policy in the analysis, we can still test for whether there have been changes in government spending shock parameters or other shock process parameters.

2.3 A multiple shock RBC model with adjustment costs

The economic model used in the empirical analysis is a *real* model of the economy and features capital and labor adjustment costs and five transitory shocks. It is adapted from Cogley and Nason (1995) by treating all shocks as transitory, and adds three more shocks to the technology and government spending shocks. Two preference shocks are introduced following Bencivenga (1992). One is a shock to the intertemporal elasticity of substitution between consumption over time, and the other one a shock to the intratemporal rate of substitution between goods and leisure at any point in time. Finally, a shock to the depreciation rate is introduced following Ingram et al (1994).

The detailed model setup is as follows: The representative household maximizes expected utility which is given by

$$E_t \sum\nolimits_{s=0}^{\infty} \beta^{t+s} U(c_{t+s}, h_{t+s}) \tag{2.1}$$

where c_t and h_t are consumption and hours worked, and β is the subjective time discount factor. Period utility is given by:

$$U(c_t, h_t) = \varepsilon_t^p \left(\frac{c_t^{1-\gamma^c}}{1-\gamma^c} - \chi \frac{\varepsilon_t^h h_t^{1+\gamma^h}}{1+\gamma^h} \right). \tag{2.2}$$

where γ_c is the coefficient of relative risk aversion, or equivalently the inverse of the elasticity of substitution of consumption, and where γ_h is the inverse of the elasticity of work with respect to the wage. χ determines the average amount of time allocated to work. The shock to the intertemporal elasticity of substitution of consumption is given by ε_t^p, and the shock to the intratemporal elasticity of substitution between goods and leisure is ε_t^h. In the following, I will refer to ε_t^p as a preference shock and to ε_t^h as a labor supply shock.

The household earns his income by renting capital and labor services out to firms. Each period, the household decides how much of his income he should consume and how much he should invest in new capital. The household's budget constraint then writes as:

$$p_t c_t + p_t^I i_t = w_t h_t + r_t k_t \tag{2.3}$$

where p_t is the price of consumption goods, which we normalize to one, where p_t^I is the relative price of investment, w_t and r_t are the real wage and the rental rate of capital, and where i_t and k_t are investment and the capital stock, respectively.

Firms are maximizing expected discounted profits which are given by:

$$E_t \sum_{s=0}^{\infty} \rho_{t+s} \left[y_{t+s} - w_{t+s} h_{t+s} - r_{t+s} k_{t+s} \right] \tag{2.4}$$

where y_t is output, w_t and r_t are the real wage and the rental rate of capital, respectively, and where ρ_t is the stochastic discount factor defined as $\rho_{t+s} = \beta^s \frac{U_c(c_{t+s}, h_{t+s})}{U_c(c_t, h_t)}$.

When changing either of the factors of production, firms incur adjustment costs. This, of course, makes the firm's problem dynamic in nature. Following Cogley and Nason (1995), adjustment costs are introduced in the production function as follows:

$$\ln(y_t) = \ln[a_t f(k_t, h_t)] - \frac{\varphi_k}{2} \left[\frac{\Delta k_t}{k_{t-1}} \right]^2 - \frac{\varphi_h}{2} \left[\frac{\Delta h_t}{h_{t-1}} \right]^2 \tag{2.5}$$

where a_t is the technology shock, and where φ_k and φ_h are the two adjustment cost parameters. Because of the loglinear structure, they can be regarded as being equal to the marginal cost, in terms of percent of output, following a one percent increase in the factors of production, labor or capital. The function $f(k_t, h_t)$ is assumed to be of standard Cobb-Douglas style:

$$f(k_t, h_t) = k_t^{\alpha} h_t^{1-\alpha} \tag{2.6}$$

where α is the capital share of income.

The capital accumulation equation is given as follows:

$$k_{t+1} = (1 - \delta_t) k_t + i_t \tag{2.7}$$

where i_t is investment and where δ_t is the depreciation rate which is stochastic and unknown at $t-1$, but known at time t.

The government is assumed to only use up resources, and thus government spending enters only in the market clearing condition:

$$y_t = c_t + i_t + g_t \tag{2.8}$$

with government spending, g_t, being another stochastic process.

The model is closed by specifying stochastic processes for each of the economic shocks.[1] A common, though not entirely innocuous assumption to make is to specify independent processes for each shock. In particular, it is assumed that each shock follows an independent univariate AR(1). To be precise, let $z_t = [a_t\ \varepsilon_t^p\ \varepsilon_t^h\ \delta_t\ g_t]'$, then the shocks are assumed to follow:

$$z_t = \Phi z_{t-1} + \eta_t \tag{2.9}$$

where Φ is diagonal and η_t is a normally distributed zero-mean white noise process with with diagonal covariance matrix Σ. In particular, we have

$$\Phi = \begin{bmatrix} \rho_a & 0 & 0 & 0 & 0 \\ 0 & \rho_{e^p} & 0 & 0 & 0 \\ 0 & 0 & \rho_{e^h} & 0 & 0 \\ 0 & 0 & 0 & \rho_\delta & 0 \\ 0 & 0 & 0 & 0 & \rho_g \end{bmatrix}, \qquad \Sigma = \begin{bmatrix} \sigma_a^2 & 0 & 0 & 0 & 0 \\ 0 & \sigma_{e^p}^2 & 0 & 0 & 0 \\ 0 & 0 & \sigma_{e^h}^2 & 0 & 0 \\ 0 & 0 & 0 & \sigma_\delta^2 & 0 \\ 0 & 0 & 0 & 0 & \sigma_g^2 \end{bmatrix}. \tag{2.10}$$

The representative household chooses consumption and hours worked to maximize (2.1) subject to (2.3). The representative firm chooses capital and labor to maximize (2.4). Because the solution to the competitive equilibrium problem is the same as the one to the social planner problem, we in fact solve the social planner problem because it is easier to solve. The social planner maximizes expected utility subject to the capital accumulation equation using the relevant technology of production:

$$max \quad E_t \sum_{s=0}^{\infty} \beta^{t+s} U(c_{t+s}, h_{t+s}) \tag{2.11}$$

subject to

$$k_{t+1} = (1 - \delta_t)k_t + y_t - c_t \tag{2.12}$$

with

$$y_t = a_t f(k_t, h_t) exp\left(-\frac{\varphi_k}{2}\left(\frac{\Delta k_t}{k_{t-1}}\right)^2 - \frac{\varphi_h}{2}\left(\frac{\Delta h_t}{h_{t-1}}\right)^2\right) \tag{2.13}$$

[1]It should be noted that the concept of shocks made in the business cycle literature differs from the one in the time series literature, which usually assumes shocks to be the white noise processes driving the variables in the system. Here, the shocks are themselves the variables. In what follows, I use the term "innovations" to refer to the white noise processes governing the economic "shock" processes.

The first order optimality conditions are given in the appendix. For completeness I briefly state the loglinearized equations here. The hat indicates percentage deviations from steady state:

$$\hat{w}_t \approx \gamma_h \hat{h}_t + \gamma_c \hat{c}_t + \hat{\varepsilon}_t^h \tag{2.14}$$

$$0 \approx \gamma_c E_t(\hat{c}_t - \hat{c}_{t+1}) + E_t(\hat{\varepsilon}_{t+1}^p - \hat{\varepsilon}_t^p) + (1-\beta)E_t r_{t+1} - \beta\bar{\delta}E_t(\delta_{t+1}) \tag{2.15}$$

$$\hat{w}_t \approx \hat{y}_t - \hat{h}_t - \frac{\varphi_h}{1-\alpha}(\hat{h}_t - \hat{h}_{t-1}) + \frac{1}{1+\bar{r}}\frac{\varphi_h}{1-\alpha}E_t(\hat{h}_{t+1} - \hat{h}_t) \tag{2.16}$$

$$\hat{r}_t \approx \hat{y}_t - \hat{k}_t - \frac{\varphi_k}{\alpha}(\hat{k}_t - \hat{k}_{t-1}) + \frac{1}{1+\bar{r}}\frac{\varphi_k}{\alpha}E_t(\hat{k}_{t+1} - \hat{k}_t) \tag{2.17}$$

It can nicely be seen how the labor supply shock enters into the household's first order condition with respect to hours worked, and how the preference shock enters into the Euler equation. In case of zero adjustment costs, the firm's optimality conditions reduce to the standard ones.

The structural parameters to be estimated can then be collected in a vector, θ, which can therefore be written as:

$$\theta = [\alpha\ \beta\ \bar{\delta}\ \chi\ \varphi_h\ \varphi_k\ \gamma_c\ \gamma_h\ \rho_a\ \rho_{\varepsilon^p}\ \rho_{\varepsilon^h}\ \rho_\delta\ \rho_g\ \sigma_a\ \sigma_{\varepsilon^p}\ \sigma_{\varepsilon^h}\ \sigma_\delta\ \sigma_g]' \tag{2.18}$$

For every θ within the economically relevant parameter space, Θ, the model can now be solved for the decision rules by applying for instance the solution algorithm proposed by Paul Klein (2000). In particular, if we write the loglinearized model as:

$$A(\theta)E_t x_{t+1} = B(\theta)x_t, \tag{2.19}$$

where $x_t = [s_t'\ u_t']'$ contains the state variables, s_t, and the control variables, u_t, of the system, then the solution in terms of the decision rules is given by:

$$s_t = F(\theta)s_{t-1} + J\eta_t \tag{2.20}$$

$$u_t = P(\theta)s_t \tag{2.21}$$

where the functional dependence of the A, B, F and P matrices on θ is made explicit. The vector of innovations to the shocks, η_t, is assumed to be white noise with covariance matrix, Σ, as given in (2.10). The matrix J is block diagonal with zeros everywhere apart from ones along the lower-right part of the main diagonal picking the specific shock processes. The next section will discuss this system and its probabilistic representation in more detail.

2.4 Econometric Method

Bayesian estimation of the structural parameters of the model is carried out by combining the likelihood function of the solution system given in (2.20) and (2.21) with a prior density over the parameter space. As the solution system is already in state-space form, the Kalman filter can be used to recursively calculate the likelihood function. The posterior density is then maximized numerically to obtain an estimate of the posterior mode with covariance matrix of the estimate taken to be the inverse hessian evaluated at the maximum. In addition, a Markov-Chain Monte Carlo (MCMC) method, as suggested by Schorfheide (2000) and Otrok (2001), is then used to obtain estimates of the full posterior density. The next two subsections discuss in more detail how the likelihood function of the solution system is calculated and how the MCMC algorithm is used to sample from the posterior.

2.4.1 Likelihood Function

In calculating the likelihood function of the system (2.16) and (2.17) one has some freedom as to the choice of variables in the state and control vectors, s_t and u_t, respectively. Thus, one has some freedom as to the choice of variables one is going to use in the estimation, and for which one therefore will obtain a probabilistic representation. Because I want to study the effects of the shocks on the main economic time series, it seems sensible to choose u_t to contain output, consumption, investment, and hours worked. The state vector should be kept small and I therefore choose s_t to contain the endogenous state variables, k_t and h_{t-1}, as well as all the five exogenous shocks. Thus, the state and control vectors of (2.20) and (2.21) are written as follows:

$$s_t = \begin{bmatrix} \hat{k}_t \\ \hat{h}_{t-1} \\ \hat{a}_t \\ \hat{\varepsilon}_t^p \\ \hat{\varepsilon}_t^h \\ \hat{\delta}_t \\ \hat{g}_t \end{bmatrix}, \qquad u_t = \begin{bmatrix} \hat{y}_t \\ \hat{c}_t \\ \hat{i}_t \\ \hat{h}_t \end{bmatrix}. \tag{2.22}$$

In principle, I could add another variable to the control vector because there are five shocks in the model and, as argued for instance by Fernandez-Villaverde and Rubio-Ramirez (2004), the model would still be nonsingular when using five variables in the estimation. I decide not to do mainly because of the difficulties in obtaining data on real wages and the real interest rate that would be of similar standard in terms of quality as the other time series. Measurement errors could be introduced here by adding zero-mean white noise errors to the observation equation (2.21) as originally done by Altug (1989), and more recently by Ireland (2004a) who adds serially correlated measurement errors that are assumed to follow a VAR(1). I refrain from adding measurement errors mainly because it is perfectly valid to estimate the model based on four variables only, and second, because adding measurement errors is always somewhat adhoc - even though they would be justified when using real wage or real interest data. Adding serially correlated measurement errors seems even more adhoc, though it would most likely capture important dynamics in the data. However, I prefer to estimate the model with all uncertainty arising from structural shocks that can be given a clear economic interpretation.

The likelihood function of the data is then calculated by applying the Kalman filter. Derivation and properties of the Kalman filter can be found in e.g. Harvey (1989). Here.

I will only sketch how the likelihood function is calculated as a by-product from running the filter. If we denote the joint data density of the system (2.20) and (2.21) by $p(Y_T;\theta)$ with $Y_T = \{u_T, u_{T-1}, \ldots, u_1\}$ containing the observed data, then the likelihood function of the data given the parameter vector θ can be found by factoring the joint density as:

$$L(\theta; Y_T) = p(Y_T;\theta) = \prod_{t=1}^{T} p(u_t|Y_{t-1};\theta) \tag{2.23}$$

where $p(u_t|Y_{t-1};\theta)$ is the density of u_t conditional on information at $t-1$. Assuming η_t is normally distributed, u_t is conditionally normal with mean given by:

$$\hat{u}_{t|t-1} = P\hat{s}_{t|t-1} \tag{2.24}$$

where $\hat{s}_{t|t-1}$ is the optimal forecast of the state vector s_t conditional on information at $t-1$. The covariance matrix of u_t conditional on $t-1$ is

$$\Omega_t = PE_{t-1}(s_t - \hat{s}_{t|t-1})(s_t - \hat{s}_{t|t-1})'P'. \tag{2.25}$$

Finally, the loglikelihood function of the data, Y_T, evaluated at θ can be written as

$$\log L = -\frac{n_u T}{2}\log 2\pi - \frac{1}{2}\sum_{t=1}^{T}\log|\Omega_t(\theta)| \tag{2.26}$$

$$-\frac{1}{2}\sum_{t=1}^{T}(u_t - \hat{u}_{t|t-1}(\theta))'\Omega_t^{-1}(\theta)(u_t - \hat{u}_{t|t-1}(\theta)) \tag{2.27}$$

where n_u is the number of variables in u_t. Because the state vector is largely unknown, we need to use the Kalman filter to find its optimal forecasts, $\hat{s}_{t|t-1}$ and the forecasts' updates given new information at time t. Details of how the optimal forecasts and updates are derived are given in the appendix.

In Bayesian estimation interest focuses on the posterior density. The posterior is obtained by multiplying the likelihood with the prior density. The prior density is taken over the economically relevant parameter space of structural parameters, Θ. At each θ we have

$$p(\theta|Y_T) = p(\theta)L(\theta;Y_T) \tag{2.28}$$

where $p(\theta)$ is the prior, and $p(\theta|Y_T)$ the posterior density, respectively. The posterior is then either maximized and the mode is taken as estimate, with the inverse Hessian of the posterior evaluated at the estimated mode used as approximate covariance matrix. Or else, Markov-Chain Monte Carlo (MCMC) methods are used to generate draws from the posterior. The next section discusses briefly how MCMC algorithms, and in particular, the Metropolis-Hastings algorithm, can be used to generate draws from $p(\theta|Y_T)$.

2.4.2 Bayesian Inference

The objective of the MCMC algorithm is to generate samples that mimic samples drawn from the posterior $p(\theta|Y_T)$. The Metropolis-Hastings algorithm used here belongs to the class of acceptance-rejection sampling algorithms where proposal draws are taken from a generating density, and the draws are either accepted or rejected based on a certain acceptance probability. It is a "Markov-Chain" Monte Carlo algorithm because each proposal is drawn from a density that depends only on the previous draw. In particular, each proposal draw in the algorithm is generated as follows:

$$\tilde{\theta}^{(i)} = \theta^{(i-1)} + \epsilon_i \qquad \epsilon_i \sim N(0, cV). \tag{2.29}$$

Thus, the proposal draws are generated by a random walk process. A draw is then either accepted, i.e. $\theta^{(i)} = \tilde{\theta}^{(i)}$, or else the previous draw is taken as new draw, and $\theta^{(i)} = \theta^{(i-1)}$. Whether a draw is accepted or not depends on the acceptance probability, $\alpha(\tilde{\theta}^{(i)}, \theta^{(i-1)})$, which for the Metropolis-Hastings algorithm is given by:

$$\alpha(\tilde{\theta}^{(i)}, \theta^{(i-1)}) = \min\left[\frac{p(\tilde{\theta}^{(i)}|Y_T)}{p(\theta^{(i-1)}|Y_T)}, 1\right]. \tag{2.30}$$

The acceptance probability for the Metropolis algorithm is thus given by the ratio of the posteriors evaluated at the proposal and at the previous draw. If a proposal draw gives higher posterior density than the previous draw, then this new draw is taken with certainty. If not, then the proposal draw is taken with probability given by (2.30), which in that case will necessarily be smaller than one.

Important issues in MCMC sampling are the choice of generating density, the number of draws, and in particular, the related issue of convergence. The generating density should in general be close to the posterior, though this is, of course, unknown. Choosing a multivariate normal density is usually a good idea. The covariance matrix, V, will then be important. I follow Schorfheide (2000) and take the inverse Hessian obtained from posterior maximization as covariance matrix in the MCMC algorithm.

2.5 Estimation and Results

This section discusses the dataset, the use of prior information, and the estimation results obtained from maximization of the posterior and from the MCMC algorithm.

2.5.1 Data

The data used in the estimation is quarterly US data from 1963:1 to 2004:3. The sample contains therefore 167 observations. Nominal output, consumption, and investment data is taken from the National Incomes and Products Accounts from the BEA website. The data is converted to real data by dividing with corresponding price deflators. Output is taken to be GDP, consumption is the sum of nondurables consumption plus consumption of services, and investment is taken to be nonresidential investment. Per capita data is obtained by dividing through by the working age population which is taken from the OECD database. Hours worked data is also taken from the OECD and calculated as follows: Hours worked per employee in the business sector is multiplied by the total number of employees. The total number of hours worked in the economy is then divided by the working age population. These transformations are also used by Chang and Schorfheide (2003) and make the data used in the estimation comparable to those used in their model.

The solution of the model is given in terms of variables measured as percentage deviations from steady state. Thus, some method needs to be used to approximate the unknown steady state. Following Otrok (2001), I detrend the data by first taking logs of the data, and then applying the Hodrick-Prescott filter with standard smoothing parameter for quarterly data of 1600. The detrended data used in the estimation is shown in the appendix. It should be noted that there are many other detrending procedures used in the literature. Linear detrending is used by Smets and Wouters (2002), whilst Ireland (2004a) and Chang and Schorfheide (2003) detrend within the model. This latter detrending procedure has become popular recently, because it allows using information about the cointegration properties of the data (see also Kapetanios et al (2005)).[2]

2.5.2 Prior Information

The prior information used in the estimation is based on priors used, as well as on estimation results found in other studies. The uncertainty around the prior information is hoped to reflect the different views within the economics profession about reality. Assuming prior information to be independent for each parameter, we can factor the prior as

$$p(\theta) = p(\theta_1)p(\theta_2)\dots p(\theta_{n_\theta}) \tag{2.31}$$

where n_θ is the number of parameters to be estimated. The parameter vector θ in (2.18) contains 18 parameters. Following standard practise in the literature, some of them are fixed in the estimation. In particular, there is both, strong evidence in the data, and strong arguments in the literature (e.g. Prescott (1986)), that the capital share of output should be 0.36, and that the subjective time discount factor should be equal to 0.99 per quarter. The steady-state depreciation rate is set to 0.025, and the weight parameter χ is set to guarantee that households allocate one-third of their time to working. The government spending ratio is set to 20% which has been the post-war average in the US.

All remaining 14 parameters are then estimated. In particular, rewriting θ to only include those parameters that are estimated, we have

$$\theta = [\varphi_h \; \varphi_k \; \gamma_c \; \gamma_h \; \rho_a \; \rho_{\varepsilon^p} \; \rho_{\varepsilon^h} \; \rho_\delta \; \rho_g \; \sigma_a \; \sigma_{\varepsilon^p} \; \sigma_{\varepsilon^h} \; \sigma_\delta \; \sigma_g]', \tag{2.32}$$

where the important adjustment costs parameters are given by φ_h and φ_k.

[2]This is an interesting issue that will be taken up in future work.

Because there is not much information on the size of adjustment costs in RBC models[3], I will use rather uninformative priors. Information about the adjustment cost parameters comes from Cogley and Nason (1995) who refer to estimates by Shapiro (1986). In particular, the prior mean of φ_h is taken to be 0.36 which is the value chosen by Cogley and Nason, who, however, mention that this might probably overstate the size of aggregate labor adjustment costs. The prior mean of the capital adjustment cost parameter is taken to be 2.2 which is also based on Shapiro (1986). As to the uncertainty around these parameters, I assume them to be normally distributed with standard deviation equal to 1.50 each, and truncated at zero. Thus, I use a very weak prior on them, reflecting the uncertainty around them.

The prior density of the utility function parameters is taken to be the same as in DeJong et al (2000). They use normal priors with mean for the coefficient of relative risk aversion, γ_c, equal to 1.50, and with mean for the inverse of the elasticity of substitution in labor supply, γ_h, equal to 0.60. They use prior standard deviations of 0.25 and 0.10, for the two parameters respectively, giving 95% prior coverage intervals of (1.0,2.0) for γ_c and of (0.4,0.8) for γ_h.

As for the persistence parameters of the shock processes, I follow Smets and Wouters (2002) by assuming them to be beta distributed with mean equal to 0.85 and standard deviation 0.10. The beta distribution nicely covers the range between zero and one.

The most difficult parameters to find information on are the standard deviations of the shock innovations. Prescott (1986) calibrates σ_a to be 0.763. This seems rather large when compared to Ireland's (2004a) finding of it being only 0.0050. Smets and Wouters assume most of the standard deviations of their shock innovations to be between 0.10 and 1.00, with $\sigma_a = 0.40$. I go for a compromise and choose them to have mean 0.10. Following Smets and Wouters, I assume them to follow an inverse gamma distribution with degree of freedom (d.o.f.) parameter set to 2. This guarantees a wide support and an infinite standard error. A summary of all prior information is shown in table 2.1.

2.5.3 Parameter Estimates

Table 2.2 contains the parameter estimates obtained from maximizing the posterior. The standard errors are the square roots of the diagonal elements of the approximate inverse hessian of the posterior at the maximizing vector. It should be noted, that posteriors tend to be asymptotically normal, and thus, these two parameters, in principle, determine the posterior density. The MCMC algorithm should, in principle at least, deliver exact finite sample estimates. Asymptotically though, the results from the posterior maximization procedure should be similar to those from the MCMC algorithm. All posterior densities are plotted in appendix 2.7.4. By and large, it does indeed seem to be the case that the asymptotic results are fairly good approximations to the results from the MCMC algorithm. Thus this section presents the results from the posterior

[3] There probably is more information than I grant, but because there is no unified handling of adjustment costs in the literature, it is not possible for me to find any definitive sources.

Table 2.1: Prior information

Parameter	Prior density			
	type	mean	st. dev.	source
φ_h	Normal	0.36	1.50	Shapiro (1986)
φ_k	Normal	2.20	1.50	Shapiro (1986)
γ_c	Normal	1.50	0.25	DeJong et al (2000)
γ_h	Normal	0.60	0.10	DeJong et al (2000)
ρ_a	Beta	0.85	0.10	Smets and Wouters (2003)
ρ_{ε^p}	Beta	0.85	0.10	S&W
ρ_{ε^h}	Beta	0.85	0.10	S&W
ρ_δ	Beta	0.85	0.10	S&W
ρ_g	Beta	0.85	0.10	S&W
σ_a	inv. Gamma	0.10	2 (d.o.f)	various sources
σ_{ε^p}	inv. Gamma	0.10	2 (d.o.f)	v.s.
σ_{ε^h}	inv. Gamma	0.10	2 (d.o.f)	v.s.
σ_δ	inv. Gamma	0.10	2 (d.o.f)	v.s.
σ_g	inv. Gamma	0.10	2 (d.o.f)	v.s.

maximization procedure, highlighting where necessary any differences from the MCMC results.[4].

The estimates of the posterior maximization are most correctly interpreted in a Bayesian way by claiming that posteriors are normally distributed and taking the mode and diagonal values of the inverse Hessian as mean and variance parameter of this posterior. Posterior probabilities of parameters lying in certain regions can then be calculated. Alternatively, one can try to visually investigate the posteriors obtained from the MCMC-routine (see appendix 2.7.4). In precise Bayesian terms we would summarize the information in table 2.2 by stating that the probability that each single parameter is equal to or less than zero is less than five percent.

The following sections discuss the model estimates more precisely and for ease of argument takes on a classical interpretation of the parameters.

All parameters are estimated significantly different from zero. In general, the parameter estimates seem quite reasonable. This section discusses utility function and shock processes parameters. Adjustment costs are discussed in the next subsection.

The coefficient of relative risk aversion is estimated to be 1.83 which is quite high, but in line with some of the studies mentioned in Prescott (1986). Households' intertemporal substitution of consumption is therefore found to be rather low. The inverse of the elasticity of substitution of work is found to be very close to the prior mean of 0.6. The

[4]The MCMC algorithm was run with one million draws.

Table 2.2: Posterior mode estimates

Parameter	Estimates from posterior maximization	
	mode	st. err.
φ_h	3.1650	0.8641
φ_k	2.5009	1.1514
γ_c	1.8317	0.2394
γ_h	0.6587	0.0957
ρ_a	0.9338	0.0155
ρ_{ε^p}	0.7614	0.0761
ρ_{ε^h}	0.9492	0.0224
ρ_δ	0.7800	0.0956
ρ_g	0.7722	0.0708
σ_a	0.0070	0.0004
σ_{ε^p}	0.0058	0.0007
σ_{ε^h}	0.0149	0.0017
σ_δ	0.0221	0.0105
σ_g	0.0289	0.0017

standard error is only a little smaller than the prior density, thus the data does not provide much new information about this parameter.

Looking at the histograms obtained from the MCMC algorithm (see appendix 2.7.4, figure 2.7) we find the asymptotic standard errors of the utility function estimates to be much bigger than the (finite sample) standard errors resulting from the MCMC algorithm. The MCMC estimates are fairly precise, in any case more precise than the prior information, and located near the mean of the prior distributions.

Technology shocks are found to be very persistent, with ρ_a being 0.93. This is very close to Prescott's value of 0.95, though smaller than the near-unit root of 0.9983 found by Ireland (2004a). Using Euro area data, Smets and Wouters (2002) find ρ_a to be 0.83. Chang and Schorfheide (2003) find it to be 0.745. The standard error of my estimate is somewhat smaller than the one of Smets and Wouters, but it is bigger than the one found by Ireland. DeJong et al (2000) estimate ρ_a to be 0.97 with a standard error of 0.014. This is very close to my results.

It is more difficult to compare the other persistence parameters with the literature, basically because researchers have only recently started estimating multiple shock models. Comparing my estimates to those of Smets and Wouters for the Euro area, my preference shock process is less persistent than theirs, with my estimated ρ_ε being 0.76, and their MCMC estimate being 0.89. The standard error of my estimate is slightly less than four times the size of the Smets and Wouters one. My estimate of the persistence of the hours shock is virtually identical to theirs: my estimate is 0.95, they find it to be 0.96 when maximizing the posterior, and 0.98 when using MCMC. Their standard error of the former estimate is 0.019, my estimate is 0.022. Chang and Schorfheide (2003) find the persistence parameter of the hours shock to be 0.865 with standard error 0.034. The hours shock process and the technology shock process are the most persistent processes in my results. The persistence parameter of the depreciation rate shock is rather low, only being 0.78. The standard error is rather big, close to the 0.1 assumed in the prior. Only the government persistence parameter is found not to be in line with existing studies. Government spending is usually found to be rather persistent, but not in my results. Smets and Wouters find ρ_g to be 0.96, I find it to be only 0.77.

Again looking at the results from the MCMC algorithm (appendix 2.7.4, figure 2.8) we find the results from the two different estimation methods to be roughly similar. A noticeable exception is the persistence parameter of the labor supply shock which is estimated much smaller under the MCMC algorithm.

The standard deviation of technology shock innovations is estimated to be 0.007 with standard error 0.0004. This compares very well with Ireland's estimate of 0.005 and standard error 0.0003. Chang and Schorfheide (2003) find $\sigma_a = 0.009$ with standard error 0.001. DeJong et al (2000) estimate it much smaller. They find $\sigma_a = 1.4e-5$ with standard error 5.8e-6. Smets and Wouters (2002), using Euro Area, data estimate the standard deviation of the technology shock to be 0.006, i.e. very close the estimate of this study using US data. In general, my estimates of the standard deviations of the shock innovations are of a similar magnitude as those of Smets and Wouters. They do, however, find a much smaller standard deviation of their government spending shock innovations. Interestingly, the most volatile innovation in Smets and Wouters (2002) is the innovation to the labor supply shock process. Though the volatilities of the innovations to the government spending and depreciation rate shocks are the most volatile in this paper, we do also find that the innovations to the labor supply shock process are of a magnitude bigger than those to the technology and prefernce shock processes. Our estimate of the standard deviation of the labor supply shock process, indeed, compares well with the one from Chang and Schorfheide (2003). They find it to be 0.021, with standard error 0.007. My estimate is 0.015 with standard error 0.002.

Finally, the results of the MCMC algorithm for the standard deviations of the shock innovations (see appendix 2.7.4, figure 2.9) are found to be very similar to the asymptotic ones.

To sum up, all my estimates are significantly different from zero, and very much in line with existing studies. The intertemporal elasticity of substitution of households is found to be rather small. The shock processes are found to be persistent, though away from unit roots. Comparing my estimates of the standard deviations with the literature is more difficult, but to the extent that a comparison is possible, they are found to be well in line. Finally, the results from the MCMC algorithm are quite similar to the asymptotic ones obtained from posterior maximization, with the only big exceptions being the utility function parameters.

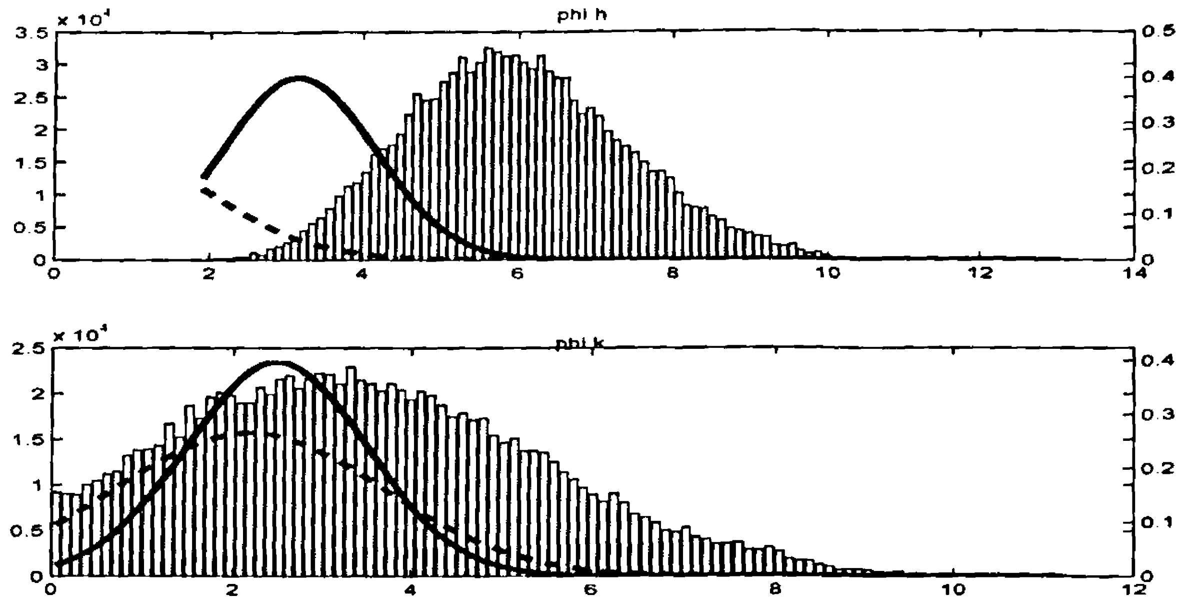

Figure 2.1: Adjustment cost parameters. Dashed line: Prior, solid line: Asymptotic Posterior, histogram: MCMC results.

2.5.4 How important are adjustment costs?

Most importantly though, the estimates of the adjustment cost parameters are both significantly different from zero. The evidence is less strong for the capital adjustment cost parameter which is only marginally bigger than the prior mean, but with a somewhat smaller standard error than prior standard deviation. But there is strong evidence that aggregate labor adjustment costs matter for the internal propagation mechanism of the model, and in particular, for the economic model to match the data as good as possible. The importance of the labor adjustment cost parameter is shown in figure 2.1 by comparing the prior with the posterior densities. The dashed line gives the prior density, the solid line the posterior based on asymptotic results and normality assumptions, and the histogram the results from the MCMC algorithm. As mentioned above, posteriors tend to be asymptotically normal, so given the rather long sample we would expect the asymptotic posteriors to be reasonable approximations to the finite sample posteriors. Though this is indeed found to be the case for the capital adjustment cost parameter, it does not hold for labor adjustment cost parameter where the MCMC posterior is quite a bit to the right of the asymptotic posterior indicating an even higher value for labor adjustment costs.

As seen in the top panel of figure 2.1 both posteriors are far away from zero, and thus clearly significantly different from zero. Instead the bottom panel of figure 1 shows the posteriors of the capital adjustment cost parameter to be very close to the prior, and in particular, much closer to the zero point. These results indicate that labor adjustment costs play an important role in explaining major US macroeconomic time series through an RBC model.

2.5.5 What real shocks drive the US business cycle?

Forecast Error Variance Decompositions are used to study the relative importance of each of the five shocks on variation in the four data series. Interest focuses on short run variation one quarter ahead, on variation at the business cycle frequencies of four and ten quarters, and at long run variation 10 and 25 years ahead. The results are presented in appendix 2.7.5.

Technology shocks are found to have strong effects on all variables except for hours worked. Though technology shocks have strong impacts on consumption, investment, and output at all horizons, there seem to be some differences with increasing forecast horizon. In particular, the effect of technology shocks on output variation falls with increasing forecast horizon, whilst it is increasing for the other two variables.

The other important shock to virtually all variables is the shock to hours worked, or the labor supply shock. The importance of the shock rises with the forecast horizon. Variation in hours worked is essentially only driven by labor supply shocks. Even though unconditional correlation between hours worked and the real wage, or average productivity, have not been calculated yet, it seems from these results that it is rather the labor supply curve that is shifting, than the labor demand, or marginal product of labor schedule. Together, the technology shock and the labor supply shock account for about 90% of all long run variation in the variables. If one interprets these shocks as "supply side shocks", then this result gives supportive evidence to the SVAR literature making use of the Blanchard-Quah identifying assumption that only supply side shocks matter in the long run.

Consumption is strongly driven in the short run by preference shocks that change the marginal rate of substitution between consuming today and tomorrow. A positive shock to preferences makes consuming today and taking leisure today essentially cheaper, and therefore increases current consumption and leisure.

Government spending shocks are found very important for investment at essentially all business cycle frequencies. It matters particularly strongly for investment variations up to two years horizon, but still has some effects in the very long run.

To trace out the latent shock processes over time, I run a smoothing algorithm which calculates optimal estimates of the state vector, s_t, using all sample information. In other words, we want to calculate $\hat{s}_{t|T}$. Details of how the algorithm works are found in Harvey (1989). Essentially, it involves running the Kalman filter forwards and backwards. The results are plotted in figure 2.2.

It is interesting to see that positive shocks to the depreciation rate, that is higher depreciation rates than in the steady state, coincide with the oil price crises of 1973 and 1979. Petrol intensive capital will most likely have depreciated faster after the oil price hikes. On the other hand, it is somewhat surprising that the technology shocks are positive during that time period. One would imagine that oil price shocks act as negative technology shocks. Here, they are seen to have lagged effects only. It also interesting to see the spikes in government spending occurring in 1968, during the Vietnam war. Another spike occurred just recently, around 2002, maybe because of the recent increase in US defence spending as response to September 11, 2001. These results should however be treated with great care, as no confidence bounds for the smoothed series are yet available.

Finally, I calculated standard deviations of the shock processes for two different sample periods. It has been documented in the literature (see e.g. McConnell and Perez-Quiros (2000)) that there occurred a reduction in volatility in US GDP growth rates around the first quarter in 1984. There is an ongoing debate about whether the lower volatility since then has been due to policy factors (better monetary or fiscal policy), or whether it is the result of unusually quiescent macroeconomic shocks (Stock and Watson (2003)). Obviously, the simple RBC model that I have been using cannot answer any questions about monetary policy, but it can help to study whether real shocks themselves, one of them being government spending shocks, have become less volatile. The estimated standard deviations are given below:

Sample period	Standard deviations of latent shock processes				
	technology	preference	hours	depreciation	government
pre-1984	0.0123	0.0094	0.0284	0.0072	0.0439
post-1984	0.0064	0.0052	0.0171	0.0043	0.0331

Though no statistical inference can be made, from just looking at the point estimates it seems that there has been some reduction in volatility coming from the shock processes directly. In particular, it seems that volatility in technology shocks has been much lower since 1984. The reduction in volatility is proportionally lowest for government spending shocks, suggesting that government policy is not responsible for the reduced volatility in post-1984 US macroeconomic time series data.

2.5.6 Has there been a structural break in 1984?

Because it seems there have been some changes around 1984, we now estimate the parameters for the two subsamples separately. The results are found in appendix 2.7.6. Inspecting them, we find that the labor adjustment cost parameter has risen from 2.9 to 3.9. This increase is just about bigger than one standard error, thus it is not entirely clear what inference should be drawn. We might regard it, however, as evidence in favor of an increase in aggregate labor adjustment costs after 1984.

The capital adjustment cost parameter has, if anything, become less significant for the post-1984 sample. This information is shown in figures 2.3 and 2.4 which show the posteriors of the adjustment cost parameters for the two subsamples, together with their priors. Figure 2.3 shows the shift to the right of the posterior of the labor adjustment cost parameter, as well as the slight decrease in dispersion. Figure 2.4, instead, shows that the means of the two posteriors for the capital adjustment cost parameter are virtually unchanged, whilst the dispersion around the post-1984 estimate has increased visibly. The 95% coverage interval now does not exclude the zero anymore.

With regard to the rest of the parameters, there seem to be some changes in the persistence and standard deviation parameters. The utility function parameters have

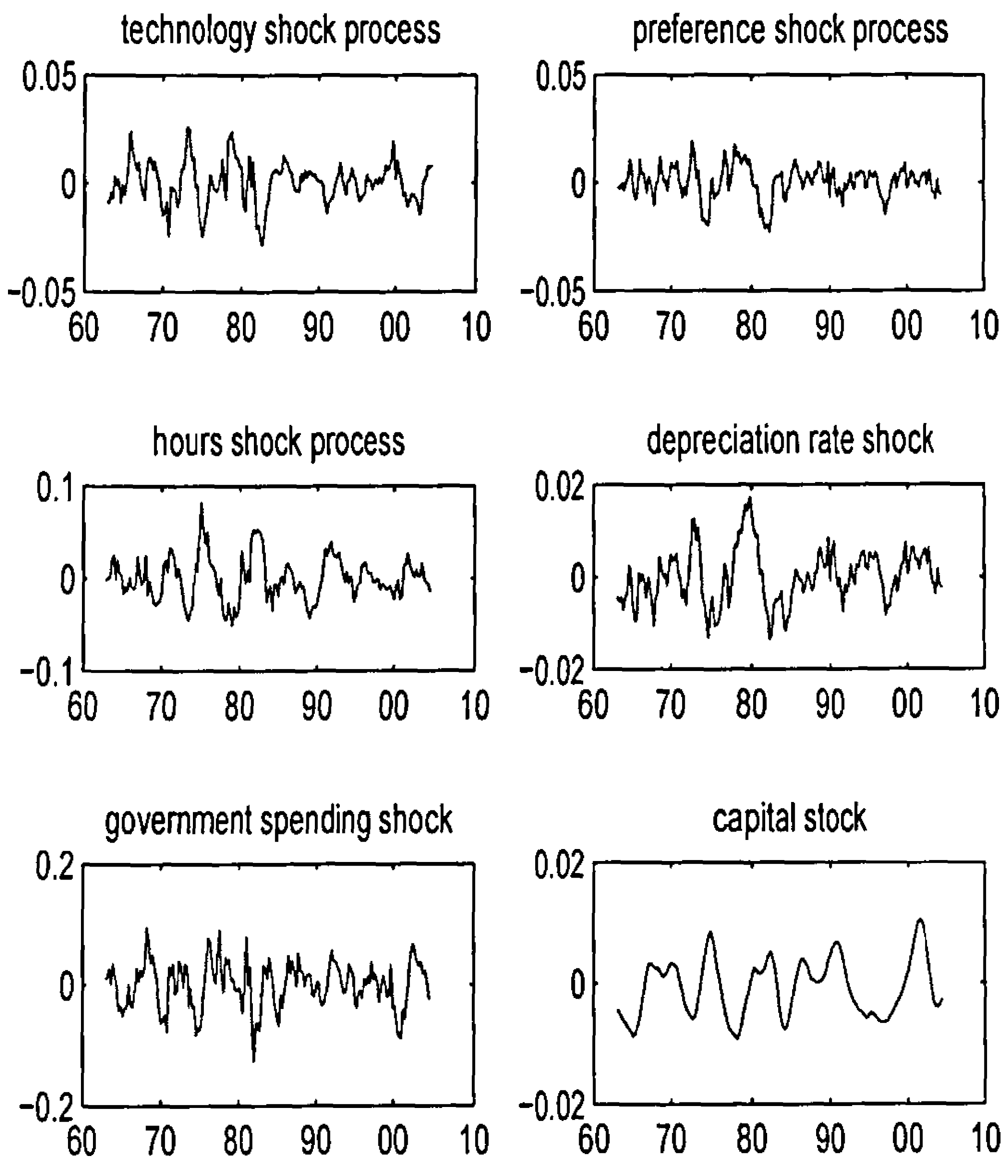

Figure 2.2: The latent shock processes.

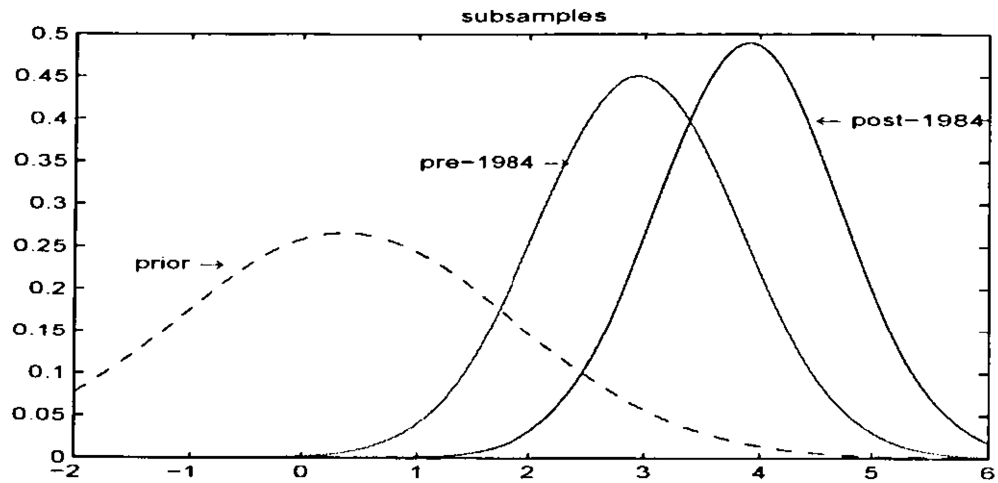

Figure 2.3: Labor adjustments costs for the two subsamples.

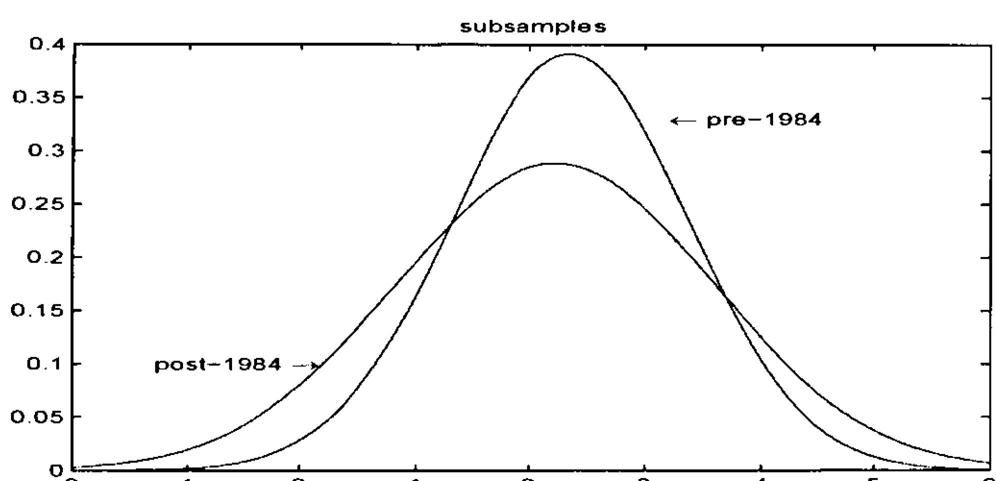

Figure 2.4: Capital adjustments costs for the two subsamples.

not changed very much. Interestingly, in each of the subsamples, ρ_{ε_p} is now close to one, suggesting that the preference shock process follows a unit-root. This is not the case for the full sample, as the above results have shown. The persistence parameter of the hours shocks seems to have decreased significantly after 1984. Given an unchanged variance of the innovations to the hours shock, this would have reduced the variance of the hours shock series. This is in fact what we see in the above table. Equally, there has been a reduction in the standard deviations of the technology shock and the government spending shock. Given the very small standard errors of the two shock processes, these reductions are likely to be significant and thus in line with the evidence presented by Stock and Watson (2003) who argue that the lower volatility in US GDP after 1984 is mainly due to less volatile innovations to the shock processes, in other words sheer luck. The only standard deviation parameter that is estimated bigger in the post-1984 sample is the one of the depreciation rate process.

To sum up, there is some evidence that a break in some of the structural parameters has occurred in the first quarter of 1984. In particular, it seems that aggregate labor adjustment costs have risen after 1984, and that capital adjustment costs have become insignificant. Further, there is some evidence of changes in the parameters of the shock processes. In particular, the standard deviation of innovations to technology and government shocks seem to be somewhat smaller after 1984. This points towards the conclusion of Stock and Watson (2003) who argue that it is pure luck that US time series exhibit less volatility after 1984.

2.6 Conclusion

This paper has used the standard RBC model extended for labor and capital adjustment costs, and five shocks, to study three questions: What drives the US business cycle? How important are adjustment costs? And has there been a change around 1984?

Although the model is, as any model, a strong simplification and therefore misspecification of reality, mainly because it is missing out monetary policy effects, and also because the government is not treated appropriately, it does show results that have clear economic meanings. First, the US business cycle is mainly driven by technology and hours shocks. Preference shocks matter for consumption in the short run, and government spending shocks play a key role for variation in investment. Second, aggregate labor adjustment costs are found to play a key role, whilst capital adjustment costs seem not to matter very much. Third, there is some evidence of a structural break around 1984. In particular, labor adjustment costs seem to have risen and the technology shock process become less volatile. However, this needs to be tested for more carefully.

The importance of labor adjustment costs suggests empirical research should focus on the labor market. Estimating RBC models with frictions in the labor market will therefore become increasingly important in future work. Finally, any realistic model of the business cycle should take into account of monetary policy effects.

2.7 Appendix

2.7.1 First-order conditions

The first-order optimality conditions of the economic model are standard, with the exception that the firm's conditions are a little bit more awkward to write down because of the loglinear nature of the production function. For completeness, I briefly state all conditions here:

The household satisfies the following optimality conditions:

$$1 = E_t\left[\beta(1 + r_{t+1} - \delta_{t+1})\left(\frac{c_t}{c_{t+1}}\right)^{\gamma_c}\left(\frac{\varepsilon^p_{t+1}}{\varepsilon^p_t}\right)\right] \tag{2.33}$$

$$w_t = \chi\varepsilon^h_t h_t^{\gamma_h} c_t^{\gamma_c}. \tag{2.34}$$

The firm's first optimality conditions are derived as follows. Writing the production function (2.5) for the time being as

$$y_t = a_t f(k_t, h_t) - \frac{\tilde{\varphi}_k}{2}\left[\frac{\Delta k_t}{k_{t-1}}\right]^2 - \frac{\tilde{\varphi}_h}{2}\left[\frac{\Delta h_t}{h_{t-1}}\right]^2, \tag{2.35}$$

and using the fact that $\frac{\partial \ln y_t}{\partial(\Delta j_t/j_{t-1})} = \frac{1}{y_t}\frac{\partial y_t}{\partial(\Delta j_t/j_{t-1})}$ allows me to substitute back for $\tilde{\varphi}_j = \varphi_j y_t$ for $j = k, h$ such that we can finally write

$$y_t = a_t f(k_t, h_t)\left[1 - \frac{\varphi_k}{2}\left(\frac{\Delta k_t}{k_{t-1}}\right)^2 - \frac{\varphi_h}{2}\left(\frac{\Delta h_t}{h_{t-1}}\right)^2\right]^{-1}. \tag{2.36}$$

The first-order conditions are then given by:

$$r_t = \alpha\frac{y_t}{k_t} - y_t\Psi_t^{-1}\alpha_k\frac{\Delta k_t}{k_{t-1}}\frac{1}{k_{t-1}} + E_t\left[\frac{1}{1+r_{t+1}}y_{t+1}\Psi_{t+1}^{-1}\alpha_k\frac{\Delta k_{t+1}}{k_t}\frac{1}{k_t}\right] \tag{2.37}$$

$$w_t = \alpha\frac{y_t}{k_t} - y_t\Psi_t^{-1}\alpha_k\frac{\Delta k_t}{k_{t-1}}\frac{1}{k_{t-1}} + E_t\left[\frac{1}{1+r_{t+1}}y_{t+1}\Psi_{t+1}^{-1}\alpha_k\frac{\Delta k_{t+1}}{k_t}\frac{1}{k_t}\right] \tag{2.38}$$

where $\Psi = \left[1 - \frac{\varphi_k}{2}\left(\frac{\Delta k_t}{k_{t-1}}\right)^2 - \frac{\varphi_h}{2}\left(\frac{\Delta h_t}{h_{t-1}}\right)^2\right]$.

Equations (2.33), (2.34), (2.37), and (2.38) can then be loglinearized to obtain equations (2.14) to (2.17) of section 2.3.

Finally, the loglinearized version of (2.7) is given by

$$\hat{k}_{t+1} \approx (1-\bar{\delta})\hat{k}_t - \bar{\delta}\hat{\delta}_t + \bar{\delta}\hat{i}_t. \tag{2.39}$$

The rest of the system is standard.

2.7.2 Kalman filter equations

Let's rewrite the state space system (2.20) and (2.21) here for ease of text flow:

$$
\begin{aligned}
s_t &= F(\theta)s_{t-1} + J\eta_t && (2.40)\\
u_t &= P(\theta)s_t && (2.41)
\end{aligned}
$$

where we assume η_t is distributed normal $(0, \Sigma)$ as in (2.10).

Denoting $E_{t-1}(s_t - \hat{s}_{t|t-1})(s_t - \hat{s}_{t|t-1})'$ now by $\Lambda_{t|t-1}$ the updating makes use of the well-known property of normal variates[5] that if

$$
\begin{bmatrix} s_t \\ u_t \end{bmatrix} \sim N\left(\begin{bmatrix} F\hat{s}_{t|t-1} \\ P\hat{s}_{t|t-1} \end{bmatrix}, \begin{bmatrix} \Lambda_{t|t-1} & \Lambda_{t|t-1}P' \\ P\Lambda_{t|t-1} & P\Lambda_{t|t-1}P' \end{bmatrix} \right), \tag{2.42}
$$

where $\hat{s}_{t+1|t}$ is the optimal forecast of the state vector as of time $t-1$, then the conditional density of s_t given u_t is normal with mean and covariance matrix given by:

$$
\begin{aligned}
\hat{s}_{t|t} &= \hat{s}_{t|t-1} + \Lambda_{t|t-1}P'\Omega_t^{-1}(u_t - P\hat{s}_{t|t-1}) && (2.43)\\
\Lambda_{t|t} &= \Lambda_{t|t-1} - \Lambda_{t|t-1}P'\Omega_t^{-1}P\Lambda_{t|t-1} && (2.44)
\end{aligned}
$$

and where $\Omega_t = P\Lambda_{t|t-1}P'$.

The optimal forecast of the state vector and its covariance matrix follow directly from (2.40)

$$
\begin{aligned}
\hat{s}_{t|t-1} &= F\hat{s}_{t-1|t-1} && (2.45)\\
\Lambda_{t|t-1} &= F\Lambda_{t-1|t-1}F' + J\Sigma J' && (2.46)
\end{aligned}
$$

The Kalman filter then iterates on the prediction equations (2.45), (2.46), and on the updating equations (2.43), (2.44) to obtain $\hat{s}_{t|t-1}$ and $\Lambda_{t|t-1}$ for $t = 1, \ldots, T$ from which $\hat{u}_{t|t-1}$ and Ω_t can be calculated using (2.24) and (2.25).

[5] For an easy derivation see e.g. Hamilton (1994), pp.100-102.

2.7.3 The detrended data set

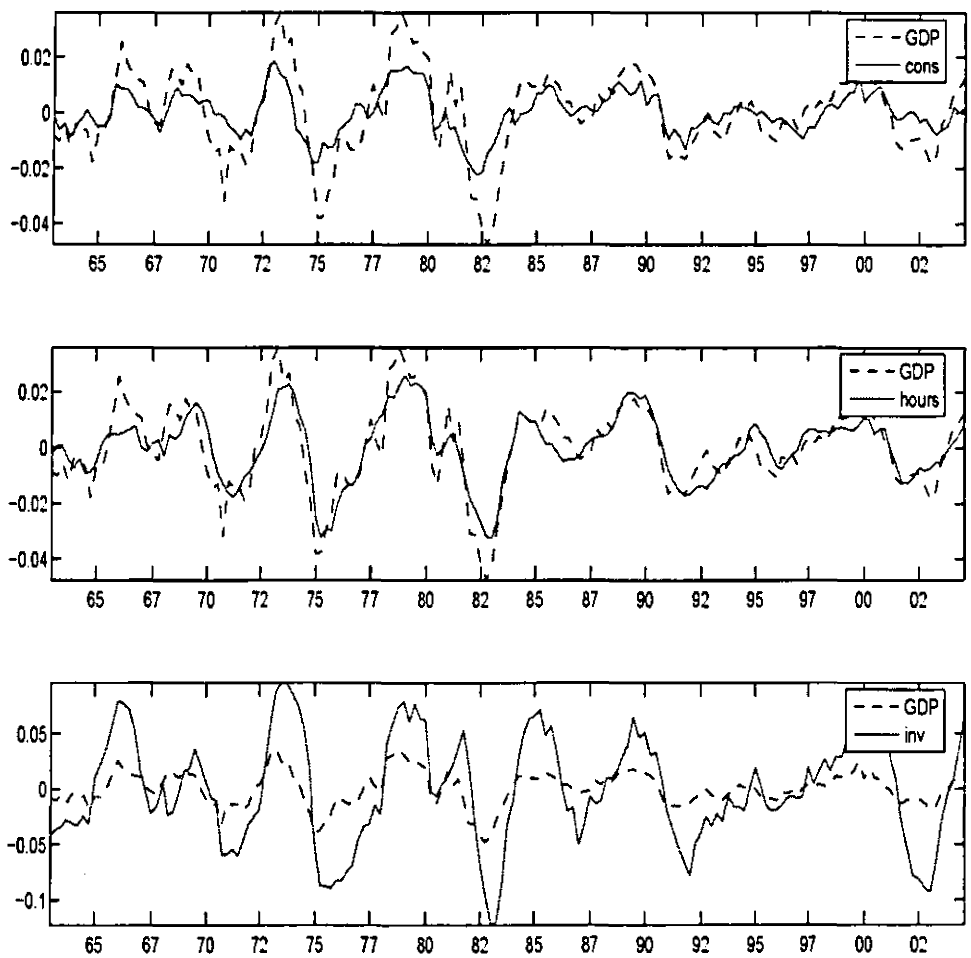

Figure 2.5: The detrended data series. Source: BEA and OECD.

2.7.4 Plots of prior and posterior densities

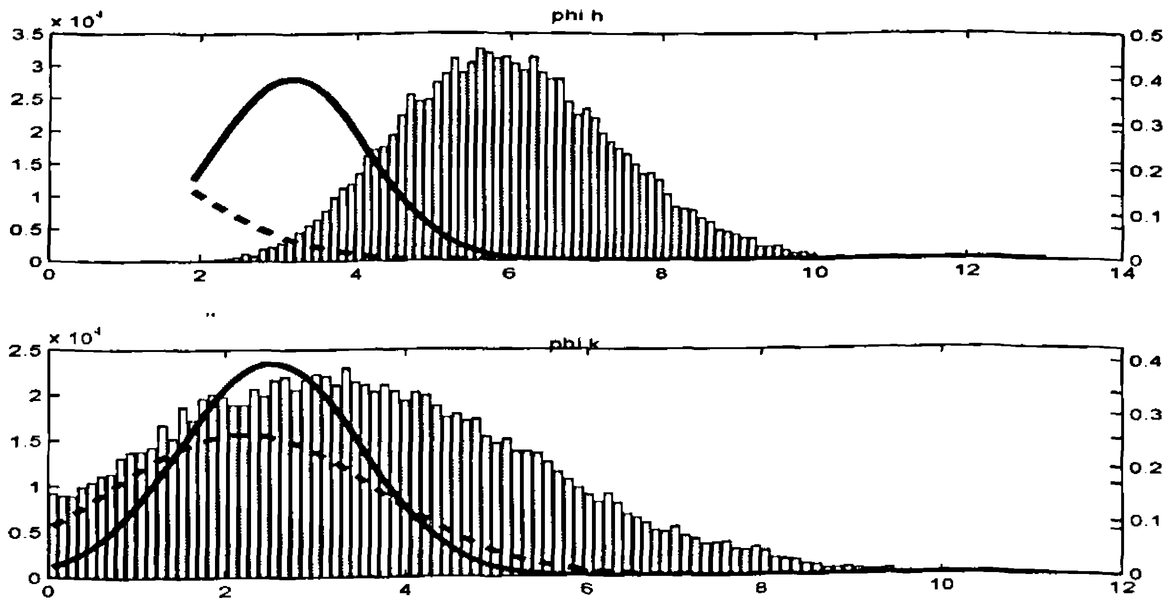

Figure 2.6: Adjustment cost parameters. Dashed line: Prior, solid line: Asymptotic Posterior, histogram: MCMC results.

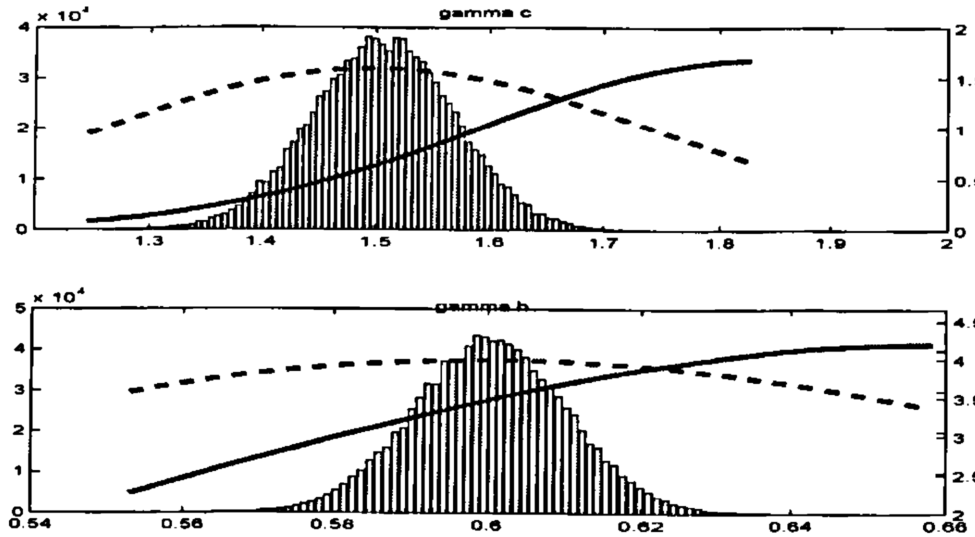

Figure 2.7: Utility function parameters. Dashed line: Prior, solid line: Asymptotic Posterior, histogram: MCMC results.

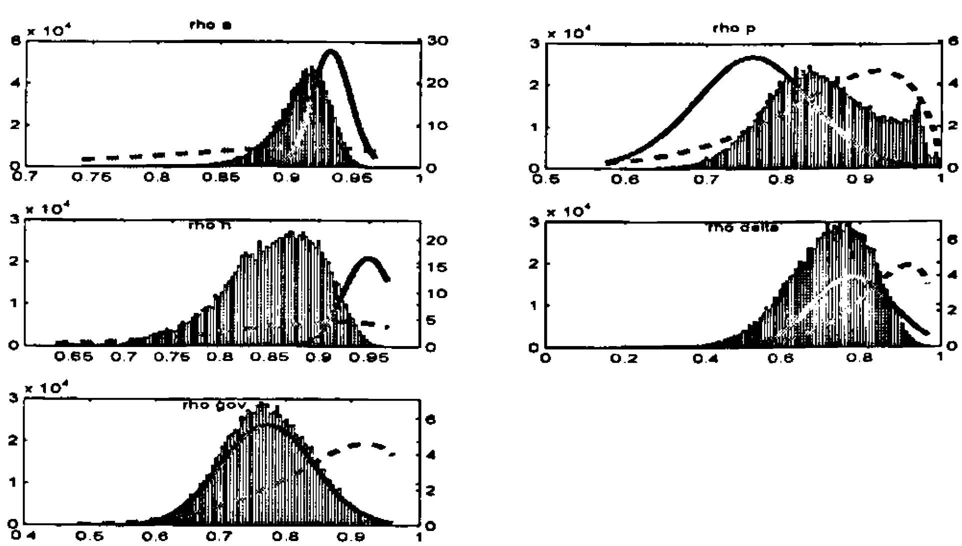

Figure 2.8: Shock persistence parameters. Dashed line: Prior, solid line: Asymptotic Posterior, histogram: MCMC results.

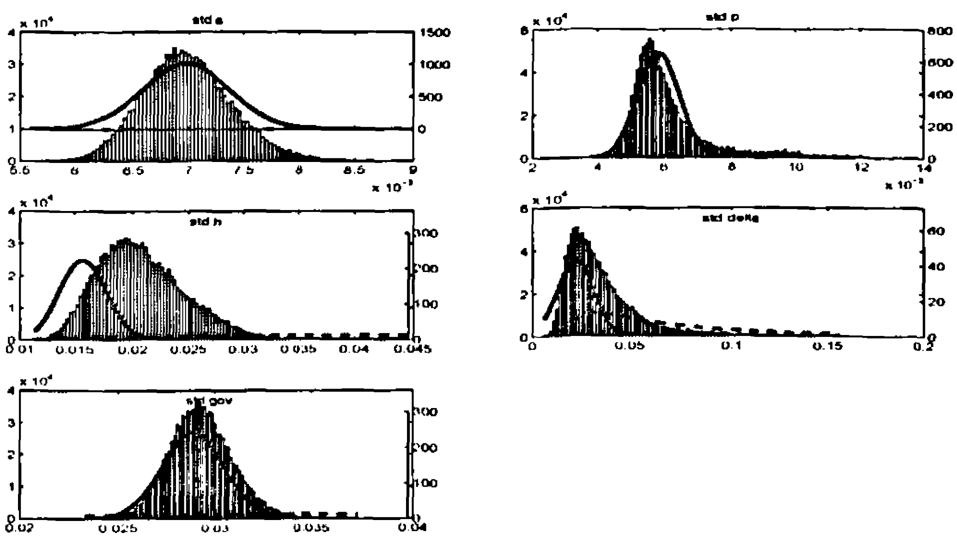

Figure 2.9: Standard deviation parameters of shock innovations. Dashed line: Prior, solid line: Asymptotic Posterior, histogram: MCMC results.

2.7.5 Forecast Error Variance Decompositions

quarters	shock	consumption	hours	investment	output
1	technology	0.3053	0.0407	0.5285	0.9051
	preference	0.4321	0.1044	0.0741	0.0103
	hours	0.2306	0.8460	0.0186	0.0837
	depreciation	0.0097	0.0018	0.0015	0.0002
	government	0.0223	0.0071	0.3773	0.0007
4	technology	0.4033	0.0366	0.5746	0.7650
	preference	0.2632	0.0656	0.0710	0.0187
	hours	0.3024	0.8910	0.1239	0.2143
	depreciation	0.0040	0.0007	0.0024	0.0018
	government	0.0271	0.0060	0.2281	0.0002
10	technology	0.4789	0.0277	0.5816	0.6708
	preference	0.1239	0.0338	0.0488	0.0152
	hours	0.3606	0.9331	0.2355	0.3098
	depreciation	0.0085	0.0004	0.0026	0.0033
	government	0.0280	0.0050	0.1315	0.0009
40	technology	0.5096	0.0310	0.5573	0.5917
	preference	0.0410	0.0218	0.0302	0.0095
	hours	0.4109	0.9388	0.3298	0.3894
	depreciation	0.0166	0.0025	0.0029	0.0056
	government	0.0218	0.0058	0.0798	0.0038
100	technology	0.5041	0.0683	0.5490	0.5722
	preferences	0.0288	0.0214	0.0284	0.0089
	hours	0.4314	0.8994	0.3446	0.4071
	depreciation	0.0165	0.0039	0.0034	0.0067
	government	0.0192	0.0069	0.0747	0.0051

2.7.6 Results of subsample estimations

Pre-1984 sample

Parameter	Estimates from posterior maximization	
	mode	st. err.
φ_h	2.9427	0.8851
φ_k	2.3397	1.0197
γ_c	1.4533	0.2371
γ_h	0.6411	0.0926
ρ_a	0.9210	0.0289
ρ_{ε^p}	0.9899	0.0070
ρ_{ε^h}	0.9398	0.0247
ρ_δ	0.8789	0.0791
ρ_g	0.8300	0.1314
σ_a	0.0089	0.0006
σ_{ε^p}	0.0196	0.0085
σ_{ε^h}	0.0170	0.0022
σ_δ	0.0290	0.0135
σ_g	0.0343	0.0030

Post-1984 sample

Parameter	Estimates from posterior maximization	
	mode	st. err.
φ_h	3.9089	0.8146
φ_k	2.2125	1.3830
γ_c	1.2514	0.2277
γ_h	0.6270	0.0970
ρ_a	0.9446	0.0151
ρ_{ε^p}	0.9993	0.0009
ρ_{ε^h}	0.8116	0.0798
ρ_δ	0.8056	0.0818
ρ_g	0.8362	0.0515
σ_a	0.0049	0.0004
σ_{ε^p}	0.0236	0.0104
σ_{ε^h}	0.0129	0.0022
σ_δ	0.0608	0.0283
σ_g	0.0231	0.0016

Bibliography

Aiyagari, S. Rao, (1994): "On the Contribution of Technology Shocks to Business Cycles", Federal Reserve Bank of Minneapolis Quarterly Review, 18(1), 22-34.

Altig, David, Lawrence J. Christiano, Martin Eichenbaum and Jesper Linde, (2002): "Technology Shocks and Aggregate Fluctuations", Manuscript.

Altug, Sumru (1989): "Time-to-Build and Aggregate Fluctuations: Some New Evidence", International Economic Review, 30(4), 889-920.

Bencivenga, Valerie R. (1992): "An Econometric Study of Hours and Output Variation with Preference Shocks", International Economic Review, 33(2), 449-471.

Blanchard, Olivier J. and Danny Quah, (1989): "The Dynamic Effects of Aggregate Demand and Supply Disturbances", American Economic Review, 79(4), 655-673.

Chang, Yongsung, and Frank Schorfheide (2003): "Labor-supply shifts and economic fluctuations", Journal of Monetary Economics, 50, 1751-1768.

Chari, V.V., Patrick J. Kehoe, and Ellen R. McGrattan (2004): "A Critique of Structural VARs using Real Business Cycle Theory", Federal Reserve Bank of Minneapolis, Working Paper 631.

Christiano, Lawrence J. and Martin Eichenbaum (1992): "Current Real-Business-Cycle Theories and Aggregate Labor-Market Fluctuations", American Economic Review, 82(3), 430-450.

Christiano, Lawrence J., Martin Eichenbaum and Charles L. Evans (2005): "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy", Journal of Political Econome, 113(1), 1-45.

Cogley, Timothy and James M. Nason (1995): "Output Dynamics in Real-Business Cycle Models", American Economic Review, 85(3), 492-511.

Cooley, Thomas F. and Mark Dwyer (1998): "Business cycle analysis without much theory: A look at structural VARs", Journal of Econometrics, 83, 57-88.

DeJong, David N., Beth F. Ingram and Charles H. Whiteman (2000a), "A Bayesian approach to dynamic macroeconomics", Journal of Econometrics, 98, 203-223.

DeJong, David N., Beth F. Ingram and Charles H. Whiteman (2000b), "Keynesian Impulses versus Solow Residuals: Identifying Sources of Business Cycle Fluctuations", Journal of Applied Econometrics, 15, 311-329.

DelNegro, Marco , Frank Schorfheide, Frank Smets and Raf Wouters (2004): "On the Fit and Forecasting Performance of New-Keynesian Models", Manuscript.

Doan, T.R., R. Litterman and C.A. Sims (1984): "Forecasting and conditional projection using realistic prior distributions", Econometric Review, 3, 1-100.

Fernandez-Villaverde, Jesus and Juan Francisco Rubio-Ramirez (2004): 'Comparing dynamic equilibrium models to data: a Bayesian approach'", Journal of Econometrics, 123, 153-187.

Hamilton, James (1994): "Time Series Analysis", Princeton University Press, Princeton, New Jersey.

Hansen, Lars Peter and Thomas J. Sargent (1980): "Formulating and Estimating Dynamic Linear Rational Expectations Models", Journal of Economic Dynamics and Control, 2, 7-46.

Harvey, Andrew C. (1989): "Forecasting, structural time series models and the Kalman filter", Cambridge University Press, Cambridge, UK.

Ingram, Beth Fisher, Narayana R. Kocherlakota and N.E. Savin (1994): "Explaining business cycles: A multiple-shock approach", Journal of Monetary Economics, 34, 415-428.

Ireland, Peter N. (2004a): "A Method for taking Models to the Data", Journal of Economic Dynamics and Control.

Ireland, Peter N. (2004b): "Technology Shocks in the New Keynesian Model", Review of Economics and Statistics, 86(4), 923-936.

Kapetanios, G., A. Pagan and A. Scott, (2005): "Making a Match: Combining Theory and Evidence in Policy-Oriented Macroeconomic Modelling", CAMA Working Paper Series.

Kim, Jinill, (2000): "Constructing and estimating a realistic optimizing model of monetary policy", Journal of Monetary Economics, 45, 329-359.

Klein, Paul (2000): "Using the generalized Schur form to solve a multivariate linear rational expectations model", Journal of Economic Dynamics and Control, 24, 1405-1423.

Kydland, Finn E. and E. Prescott, (1982): "Time to Build and Aggregate Fluctuations", Econometrica, 50(6), 1345-1370.

Kydland, Finn E. and Edward C. Prescott (1996): "The Computational Experiment: An Econometric Tool", Journal of Economic Perspectives, 10(1), 69-85.

Leaper, Eric M. and Christopher A. Sims (1994): "Toward a Modern Macroeconomic Model Usable for Policy Analysis", In Fischer, S. and J.J. Rotemberg (Eds.), NBER Macroeconomics Annual, MIT Press, Cambridge, MA.

McConnell, Margaret M. and Gabriel Perez-Quiros (2000): "Output Fluctuations in the United States: What Has Changed Since the Early 1980's?", American Economic Review, 90(5), 1464-1476.

Otrok, Christopher (2001): "On measuring the welfare cost of business cycle", Journal of Monetary Economics, 47, 61-92.

Prescott, Edward C., (1986): "Theory Ahead of Business Cycle Measurement", Federal Reserve Bank of Minneapolis Quarterly Review.

Schorfheide, Frank (2000): "Loss-Function-Based Evaluation of DSGE Models", Journal of Applied Econometrics, 15, 645-670.

Shapiro, Matthew D. (1986): "The Dynamic Demand for Capital and Labor", Quarterly Journal of Economics, 101(3), 513-42.

Shapiro, Matthew D., and Mark W. Watson, (1988): "Sources of Business Cycle Fluctuations", NBER Working Paper No. 2589.

Sims, Christopher A. (1980): "Macroeconomics and Reality", Econometrica, 48(1), 1-48.

Smets, Frank and Raf Wouters, (2002): "An Estimated Stochastic Dynamic General Equlibrium Model of the Euro Area", European Central Bank, Working Paper 171.

Stock, James H. and Mark W. Watson (2003): "Has the Business Cycle Changed? Evidence and Explanations", Manuscript.

Chapter 3

Dynamic Beveridge and Phillips curves: A macroeconometric analysis of the US labor market

Abstract

This paper addresses the question how monetary policy shocks and technology shocks affect the US labor market. Focus is on the dynamics of conditional Beveridge and Phillips curves.

Conditional correlations reveal that it is mainly the monetary shock that generates the negative slopes of the Beveridge and Phillips curves. The technology shock instead seems to be shifting the two curves. The business cycle of the labor market thus seems to be a monetary phenomenon. Looking at variance decompositions we find that although output is mainly affected by the technology shock, labor market variables are mainly affected by monetary shocks.

Finally, a New Keynesian DSGE model with a non-Walrasian labor market is estimated using impulse response matching techniques. Though most impulse responses can be replicated fairly well, some parameter estimates are crossly at odds with the microeconometric evidence. Moreover, the model fails to explain unemployment behavior in response to the monetary shock, the very variable the model aims to explain.

3.1 Introduction

Policy discussion on the economy often centers around unemployment issues. This is true in most of the European countries, which have been experiencing persistently high unemployment rates over the last couple of decades, and it is true for the USA where cyclical unemployment variations have usually played a key role in election outcomes. It is therefore surprising that standard macroeconomic models until recently have usually ignored unemployment. This is also true for the fully-specified New Keynesian models of Smets and Wouters (2002) and Christiano, Eichenbaum and Evans (2005) (henceforth CEE)).[1]

Only recently a strand of the literature has finally begun to include equilibrium unemployment theory in DSGE models through a matching model of the labor market (see Merz (1995) and Andolfatto (1996) for an RBC model framework, and Trigari (2004), Walsh (2003), Christoffel et al (2005), or Braun (2005) for a New Keynesian framework). Whilst the first set of papers were calibrated to match unconditional first and second moments, the second set of papers used more formal estimation techniques. In particular, Trigari and Braun use impulse response matching techniques, whilst Christoffel et al use Bayesian estimation techniques. Somewhat surprisingly though, and to the best of my knowledge, none of the papers actually tries to explain unemployment in the estimation.

This is somewhat discomforting given the importance attributed to unemployment in the political debate. Policy makers surely want to know how much impact their decisions will have on the unemployment rate. This paper tries to answer that question from two different perspectives: First, a very general time series model is used with as few assumptions as possible. In particular, we make use of structural VAR analysis to just identify monetary policy shocks and technology shocks. Second, a tightly parameterized DSGE model with a matching labor market is then used to rationalize the empirical findings. In particular, the model's parameters are estimated and the model is evaluated by its ability to match the impulse responses from the VAR.

The key findings can be summarized as follows: Conditional correlation analysis reveals that the strong negative relationship between unemployment and vacancies, the Beveridge curve, found in the data is mainly the result of monetary policy shocks. Monetary easing sends the economy into boom, profits rise as do vacancies and unemployment falls. In effect, this leads to a clockwise move along the downward sloping Beveridge curve. Technology shocks also add to some extent, though less significantly, to the negative slope of the Beveridge curve. In effect, output rises, unemployment falls and vacancies rise.

The Phillips curve, however, is entirely driven by monetary shocks. Inflation rises sluggishly after an interest rate cut, whilst unemployment falls significantly. Technology shocks instead have very limited effects on inflation and unemployment. If anything, then technology shocks affects them in the same direction. These findings should not be very surprising, given that most economists believe monetary policy matters more for business cycles than do technology shocks.

Looking at impulse responses, these findings are supported. Monetary shocks have strong and significant impacts on the US labor market. In particular, an interest rate

[1] A noteworthy exception is Gali (1995, 1996) who incorporates involuntary unemployment in a DSGE modelling framework.

cut reduces unemployment and increases vacancies simultaneously (Beveridge curve). The responses are hump-shaped with a maximum impact after around 2 years, before fading out to steady-state levels. Though the technology shock is found to have the same qualitative effects on unemployment and vacancies, those effects are generally not significantly different from zero.

The monetary shock also affects the dynamics of the Phillips curve. Whilst unemployment follows an immediate hump-shaped pattern, inflation first falls (the price puzzle) before it begins to rise very sluggishly with a maximum reached only after 3 years. The absolute correlation between unemployment and inflation is biggest when inflation is shifted forward 2 to 3 quarters. The responses of inflation and unemployment to technology shocks move - if anything - in the same direction: both unemployment and inflation fall. Thus, technology shocks fail to explain the Phillips curve.

Finally, variance decompositions support the claim that the US labor market is mainly driven by monetary policy shocks. Around 20 percent of the variation in unemployment and vacancies at business cycle frequencies is explained by the monetary shock.

After having presented and discussed the results from the SVAR, the paper takes these results as empirical facts and tries to explain them within a fully specified New Keynesian DSGE model which contains only a small number of structural parameters. The key feature of the DSGE model is a non-Walrasian labor market with search frictions. Unemployment thus exists in equilibrium and can be given a meaningful interpretation in the model. The model's structural parameters are estimated via the impulse-response matching method of, amongst others, Rotemberg and Woodford (1998) and CEE. The key findings are, first, some parameter estimates are strongly at odds with the microeconometric evidence. Second, even though the model generally succeeds in matching the impulse responses, it fails to explain the response of unemployment to the monetary policy shock. And third, the estimated model shows virtually no response to the technology shock.

This paper builds on recent work by Braun(2005) and Trigari (2003, 2004) who study and evaluate the effects of monetary policy shocks within a DSGE setting. We extent their analyzes by jointly identifying a monetary policy shock and a permanent technology shock within the model. We highlight the effects of those shocks on the US labor market by including all key labor market variables - including unemployment - in the analysis. We first employ a structural VAR analysis to empirically evaluate conditional correlations, dynamic responses, and variance decompositions. We then try to explain those findings within a New Keynesian model framework that includes a matching model of the labor market.

The structure of the paper is as follows: The next section reviews key stylized facts of the US labor market. Section 3 then discusses our structural VAR analysis. We explain the identifying assumptions, estimation method, and report key results. Section 4 sets up the economic model trying to rationalize the empirical results. The model is then estimated using impulse response matching techniques in section 5. Finally, section 6 concludes.

3.2 Stylized US labor market facts

Standard discussions of key US labor market characteristics usually focus on the behavior of employment and aggregate or per capita hours worked over the cycle (see Kydland (1995), or Gali (1995)). This is natural given the exclusion of unemployment as an independent variable from early DSGE models. Aggregate hours worked is highly procyclical with a contemporaneous correlation coefficient with real GNP of 0.9. Roughly two-thirds of variation in aggregate hours is due to employment variation, the other one-third due to variation in hours per worker (see Kydland (1995)).

This paper instead focuses on unemployment, vacancies, and inflation, with emphasis on unemployment. We therefore plot unemployment against real GDP, vacancies and inflation. Figure 3.1 reveals the typical negative correlation between unemployment and GDP known as Okun's law. The unemployment series is of lower frequency than the cyclical GDP series.

More importantly for this paper, the second panel shows the almost perfect negative correlation between unemployment and vacancies as measured by the help-wanted index. This negative relationship between unemployment and vacancies is known as the Beveridge curve. Both series have been rising somewhat during the 70s, but otherwise look rather stationary. One of the aims of this paper is to recover the different economic sources causing this relationship.

The last panel shows the relationship between unemployment and inflation, generally known as Phillips curve. Though there are clear periods during which the two series move in opposite directions (e.g. the 50s and 60s, as well as from the 80s to the present), there has been a long period during the 70s during which the unemployment rate has been lagging behind inflation but otherwise moving in the same direction. This period has become known as stagflation during which inflation and unemployment remain at very high levels. A second objective of the paper is to explain the causes of the generally negative, but sometimes positive relationship between unemployment and inflation.

The same information is shown in figure 3.2 which presents the Beveridge and Phillips curves in typical scatterplots. As expected there is a strong negative relationship between unemployment and vacancies. During a boom, more vacancies are posted and unemployment is low, the opposite holds during recessions. Interestingly, the figure also highlights important shifts of the Beveridge curve. In particular during the 70s the curve has been shifting outwards with unemployment and vacancies rising simultaneously.

The lower panel of figure 3.2 shows a plot of the Phillips curve. The relationship is by far less strong than the Beveridge curve. Again we notice the outward shift of the Phillips

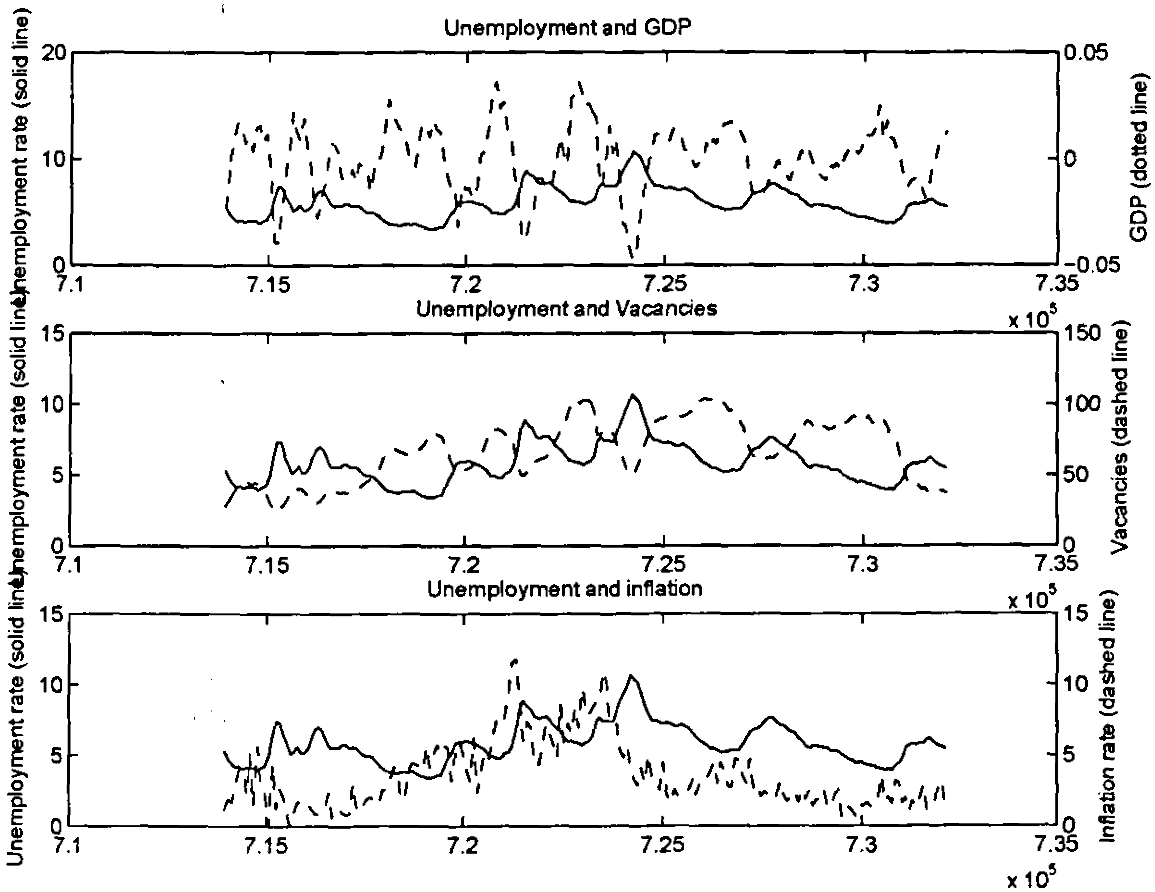

Figure 3.1: Unemployment, Vacancies, and Inflation

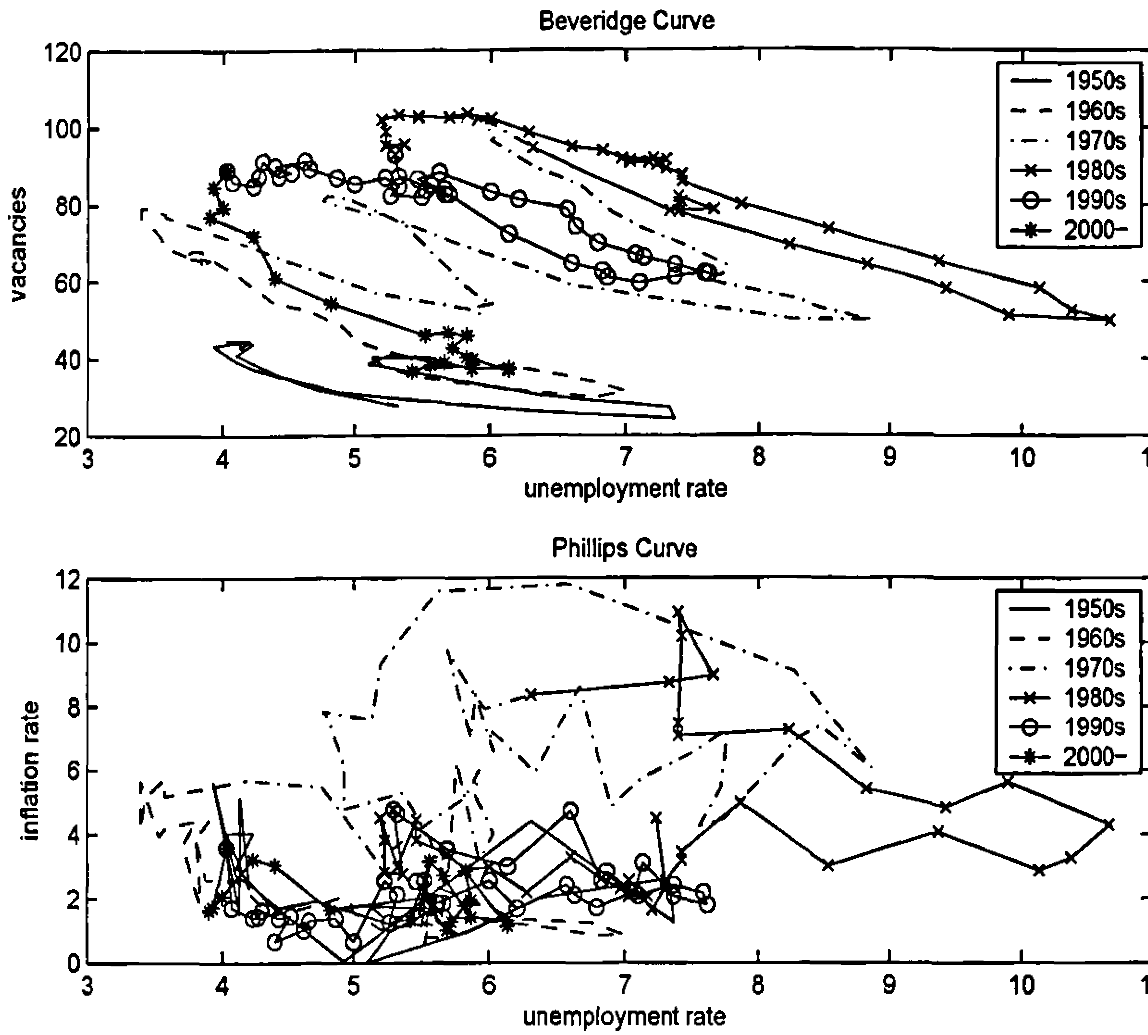

Figure 3.2: The US Beveridge and Phillips Curves

curve during the 70s, and the disinflation and increase in unemployment in the early 80s. Looking ahead, it will therefore be necessary in the statistical analysis to estimate truly structural relationships that will remain unchanged during policy interventions.

Table 3.1 summarizes the findings using HP-filtered data with a smoothing parameter of 10^5 which is the value suggested in Shimer (2005). Unemployment is countercyclical, and strongly negatively correlated with vacancies (the correlation coefficient is -0.904) which are themselves procyclical. Unemployment and inflation is only weakly negatively correlated with a correlation coefficient of -0.211.

To investigate the causal effects of the above results, the next section sets up a structural VAR model which imposes just enough restrictions as necessary to just-identify the two shocks of interest: the monetary policy shock and the technology shock.

Table 3.1: Crosscorrelations

	GDP	Unemployment	Vacancies	Inflation
GDP	1.000	-0.737	0.792	0.119
Unemployment	—	1.000	-0.904	-0.211
Vacancies	—	—	1.000	0.167
Inflation	—	—	—	1.000

3.3 Structural VAR Analysis: Macroeconomic Shocks and the US labor market

This section uses a SVAR methodology to analyze the determinants of US Beveridge and Phillips curves. We first discuss the SVAR model, its identifying assumptions and the estimation procedure. We then study the impacts of the two identified shocks, a monetary shock and a technology shock, on the economy. To this end we calculate conditional correlations, impulse responses and variance decompositions.

3.3.1 The SVAR model

This section discusses the SVAR model, its identifying assumptions and the estimation procedure. We identify two structural shocks: a monetary policy shock and a technology shock. To achieve identification we make use of a recursiveness assumption and a long run a restriction. In particular, we follow CEE in assuming that the only variable responding on impact to a monetary policy shock is the Federal Funds rate. All other variables in the VAR respond with a lag only. The long-run restriction follows Gali (1999) and implies that the only shock allowed to have a permanent effect on labor productivity is the technology shock.

In effect, we make use of the same set of identifying assumptions used in Altig, Christiano, Eichenbaum and Linde (2005) (henceforth ACEL). We differ from ACEL by focussing explicitly on the labor market. Related studies using a SVAR methodology to study the US labor market are Braun et al (2005), Fujita (2005), Michelacci and Lopez-Salido (2004) and Ravn (2005).

Braun et al (2005) use sign restrictions on non-labor market variables to identify four shocks and their effects on the labor market variables. Fujita (2005) uses a trivariate VAR using sign restrictions to identify an aggregate shock. Michelacci and Lopez-Salido (2004) use different trivariate SVAR models to disentangle a neutral technology shock and an embodied technology shock. They do not, however, estimate the two shocks jointly. Ravn (2005) jointly identifies a technology shock and a government spending shock and finds that his theoretical DSGE model can successfully account for the responses of the output variables, but not for those of the labor market variables.

This paper differs from the ones just mentioned because it tries to jointly estimate the responses to a monetary policy shock and a technology shock by using two identification assumptions that have become fairly accepted amongst economists. We believe our identifying assumptions are more credible because they are firmly grounded in economic theory. No arbitrary assumptions on the length of sign restrictions need to be made. We do take notice, however, of recent criticisms of long-run restrictions in the literature.[2]

We now develop some notation and discuss the identifying assumptions in some detail. The time series used in the SVAR estimation are labor productivity, hours worked, a measure of the real wage, inflation, unemployment and vacancy rates, the job finding probability as measured by Shimer (2005) and the federal funds rate. The vector Y_t can thus be written as:

$$Y_t = \begin{bmatrix} \Delta a_t \\ h_t \\ w_t \\ \pi_t \\ u_t \\ v_t \\ f_t \\ ff_t \end{bmatrix} = \begin{bmatrix} \Delta a_t \\ Y_{1,t} \\ ff_t \end{bmatrix} \tag{3.1}$$

where a_t is labor productivity measured as $\ln(GDP_t/h_t)$, h_t is the log of hours worked per capita, π_t is the inflation rate, u_t is the log of the unemployment rate, v_t is the log of the vacancy rate obtained by dividing the help-wanted index by a measure of working age population, f_t is Shimer's job finding probability and ff_t is the federal funds rate. $Y_{1,t} = [h_t, w_t, \pi_t, u_t, v_t, f_t]'$ is used to present the VAR in a compact form in the subsequent analysis. To conform with the economic model h_t, u_t and v_t are expressed in per capita terms by dividing through by a measure of working age population. The real wage series is real compensation per hour taken from the BLS. All series are publicly available and taken from the BEA, BLS and St. Louis Fed. The job finding probability is taken from Robert Shimer (2005) and measures the probability that any individual unemployed worker finds a job. Shimer argues that it is the job finding rate that matters for the business cycle, rather than the job separation rate. We therefore do not include the job separation rate within the VAR and do not model endogenous job separation in the DSGE model.

All variables other than labor productivity are included in levels. A linear trend is fitted to the real wage series before the system is estimated (see also ACEL). Unit roots are not explicitly taken into account. This can be justified by the results of Sims, Stock and Watson (1990). It should also be noted that the only theoretically nonstationary variable in Y_t is the real wage and if we are to take our DSGE model seriously we should treat all other variables as stationary, at least from a DSGE modelling perspective. The sample period runs from 1959Q1 to 2001Q4 and corresponds to the sample used in ACEL.

[2]For a recent assessment see Christiano, Eichenbaum and Vigfusson (2006) and Erceg, Guerrieri and Gust (2004). For a critique of SVAR with long-run restrictions see Erceg, Guerrieri and Gust (2004) and Chari, Kehoe and McGrattan (2005), and somewhat older see Faust and Leeper (1997).

We now write the structural VAR as follows:

$$A(L)Y_t = \varepsilon_t \tag{3.2}$$

where $A(L) = A_0 + A_1L + A_2L^2 + ... + A_pL^p$.[3] Write a generic element of $A(L)$ as $\alpha(L)_{i,j}$, and let the structural shocks be given by:

$$\varepsilon_t = \begin{bmatrix} \varepsilon_t^a \\ \varepsilon_t^Y \\ \varepsilon_t^{ff} \end{bmatrix} \tag{3.3}$$

where ε_t^a is the technology shock, ε_t^Y the vector of shocks corresponding to $Y_{1,t}$, and ε_t^{ff} the monetary policy shock. We are now ready to explain our identifying assumptions.

Identifying the monetary policy shock

The monetary policy shock is identified by assuming that only the interest rate responds on impact to a monetary policy shock. In other words, all other variables in the system respond with a lag to a monetary policy shock.

Thus, we can impose the following recursive, block-triangular structure on the A_0 matrix:

$$A_0 = \begin{bmatrix} \alpha_{1,1}^0 & \alpha_{1,2}^0 & 0 \\ \alpha_{2,1}^0 & \alpha_{2,2}^0 & 0 \\ \alpha_{3,1}^0 & \alpha_{3,2}^0 & \alpha_{3,3}^0 \end{bmatrix} \tag{3.4}$$

Writing out (3) line by line, the interest rate equation reads as follows:

$$\alpha_{3,3}^0 ff_t = -\sum_{j=0}^{p} \alpha_{3,1}^j \Delta a_{t-j} - \sum_{j=0}^{p} \alpha_{3,2}^j Y_{1,t-j} - \sum_{j=1}^{p} \alpha_{3,3}^j ff_{t-j} + \varepsilon_t^{ff} \tag{3.5}$$

and can be estimated by OLS because the monetary policy shock is assumed to be orthogonal to the regressors. Running OLS then naturally sets the sample correlation to zero. The other equations read as:

$$\alpha_{1,1}^0 \Delta a_t = -\sum_{j=1}^{p} \alpha_{1,1}^j \Delta a_{t-j} - \sum_{j=0}^{p} \alpha_{1,2}^j Y_{1,t-j} - \sum_{j=1}^{p} \alpha_{1,3}^j ff_{t-j} + \varepsilon_t^a \tag{3.6}$$

$$\alpha_{2,2}^0 Y_{1,t} = -\sum_{j=0}^{p} \alpha_{2,1}^j \Delta a_{t-j} - \sum_{j=1}^{p} \alpha_{2,2}^p Y_{1,t-j} - \sum_{j=1}^{p} \alpha_{2,3}^j ff_{t-j} + \varepsilon_t^Y \tag{3.7}$$

[3] In the actual estimation we follow the literature and include $p = 4$ lags in the VAR.

Identifying the technology shock

To identify the technology shock we follow Gali (1999) who draws upon work by Shapiro and Watson (1988) and Blanchard and Quah (1989) in assuming that the technology shock is the only shock that has a permanent effect on labor productivity.

We write the SVAR in its structural moving average representation:

$$Y_t = C(L)\epsilon_t \tag{3.8}$$

The identifying assumption translates into zero entries in the last columns of the first row of the long-run impact matrix, C(1),

$$C(1) = \begin{bmatrix} c_{1,1}(1) & 0 & 0 \\ c_{2,1}(1) & c_{2,2}(1) & c_{2,3}(1) \\ c_{3,1}(1) & c_{3,2}(1) & c_{3,3}(1) \end{bmatrix} \tag{3.9}$$

The restrictions on the long-run impact matrix then translate into corresponding restrictions on $A(1) = C(1)^{-1}$. Assuming that $C(1)$ is indeed invertible, we can then write the matrix $A(1)$ as follows[4]

$$A(1) = \begin{bmatrix} \alpha_{1,1}(1) & 0 & 0 \\ \alpha_{2,1}(1) & \alpha_{2,2}(1) & \alpha_{2,3}(1) \\ \alpha_{3,1}(1) & \alpha_{3,2}(1) & \alpha_{3,3}(1) \end{bmatrix} \tag{3.10}$$

To impose those restrictions we follow Shapiro and Watson (1988) and rewrite the matrix lag polynomial $A(L)$ as follows:[5]

$$A(L) = A(1) + (1 - L)\tilde{A}(L) \tag{3.11}$$

Rewriting (3.2) using (3.11) we therefore obtain

$$A(1)Y_t + (1 - L)\tilde{A}(L)Y_t = \varepsilon_t \tag{3.12}$$

where $\tilde{A}(L) = \tilde{A}_0 + \tilde{A}_1 L + \tilde{A}_2 L^2 + \cdots + \tilde{A}_{p-1}L^{p-1}$.

[4]For a more detailed discussion see Shapiro and Watson (1988). Note also that Shapiro and Watson were the first to find a fall in hours worked on impact of a technology shock (see their figure 2.) This seems to have gone unnoticed since.

[5]A constructive proof goes as follows:

$$A(L) = A_0 + A_1 L + A_2 L^2 + \cdots + A_p L^p$$

Writing out (9) we obtain:

$$A_0 + A_1 L + A_2 L^2 + \cdots + A_p L^p = A_0 + A_1 + A_2 + \cdots + A_p + (1-L)\tilde{A}_0 + (1-L)\tilde{A}_1 L + \cdots + (1-L)\tilde{A}_{p-1} L^{p-1}$$

Imposing this condition on equation (3.6) we obtain:

$$\alpha_{1,1}^0 \Delta a_t = -\sum_{j=1}^{p} \alpha_{1,1}^j \Delta a_{t-j} - \sum_{j=0}^{p-1} \tilde{\alpha}_{1,2}^j \Delta Y_{1,t-j} - \sum_{j=1}^{p-1} \tilde{\alpha}_{1,3}^j \Delta ff_{t-j} + \varepsilon_t^a \tag{3.13}$$

Now because $\alpha_{2,1}^0 \neq 0$, $\Delta Y_{1,t}$ will be correlated with ε_t^a because of equation (3.7). We therefore cannot use OLS to estimate (3.6), but instead need to refer to Instrumental Variables (IV) estimation choosing as instruments a constant, Δa_{t-j}, $Y_{1,t-j}$, and ff_{t-j}, for $j = 1, 2, \dots, p$.

Finally, we need to estimate the block of equations (3.7). Because Δa_t is correlated with ε_t^Y (because of equation (3.6)), and because $\alpha_{2,1}^0 \neq 0$ leads to simultaneity of the variables in $Y_{1,t}$, we again need to refer to IV estimation. This is done using the same set of instruments as before plus the residuals from equation (3.13) and those from the recursive system (3.7). The residuals from (3.13) are by their structural nature uncorrelated with ε_t^Y and because of (3.6) correlated with the regressor Δa_t. Thus they qualify as instruments. By construction the sample correlation between the structural shocks is then set to zero.

Having discussed our two identifying assumptions and explained the estimation procedure, we next turn to analyze the results from the VAR. We first look at conditional correlations and then study impulse responses and variance decompositions. All estimations were done in Matlab. [6]

3.3.2 Correlation Analysis

To study the effect of the two shocks on the Beveridge and Phillips curves, we calculate conditional correlations by simulating counterfactual data from the estimated VAR. In particular, we use the estimated VAR and the structural shocks and feed in only one of the shocks at a time. In effect, we simulate artificial data as follows:

And equating coefficients gives the recursive system:

$$\begin{aligned}
\tilde{A}_0 &= A_0 - A_0 - A_1 - \cdots - A_p \\
\tilde{A}_0 &= -\sum_{i=1}^{p} A_i \\
\tilde{A}_1 - \tilde{A}_0 &= A_1 \\
\tilde{A}_1 &= -\sum_{i=2}^{p} A_i \\
&\dots \\
\tilde{A}_j &= -\sum_{i=j+1}^{p} A_i \\
&\dots \\
\tilde{A}_{p-1} &= -A_p
\end{aligned}$$

[6]Heavy use was made of Larry Christiano's Matlab files.

$$\hat{y}_t = \hat{A}_0^{-1}\left(\hat{\epsilon}_t - \hat{A}_1\hat{y}_{t-1} - \cdots - \hat{A}_p\hat{y}_{t-p}\right) \tag{3.14}$$

where $\hat{\epsilon}_t$ has only one non-zero element, namely the estimated structural shock which we use to simulate the data. Figure 3.3 shows unconditional and conditional scatter plots of actual and simulated data.

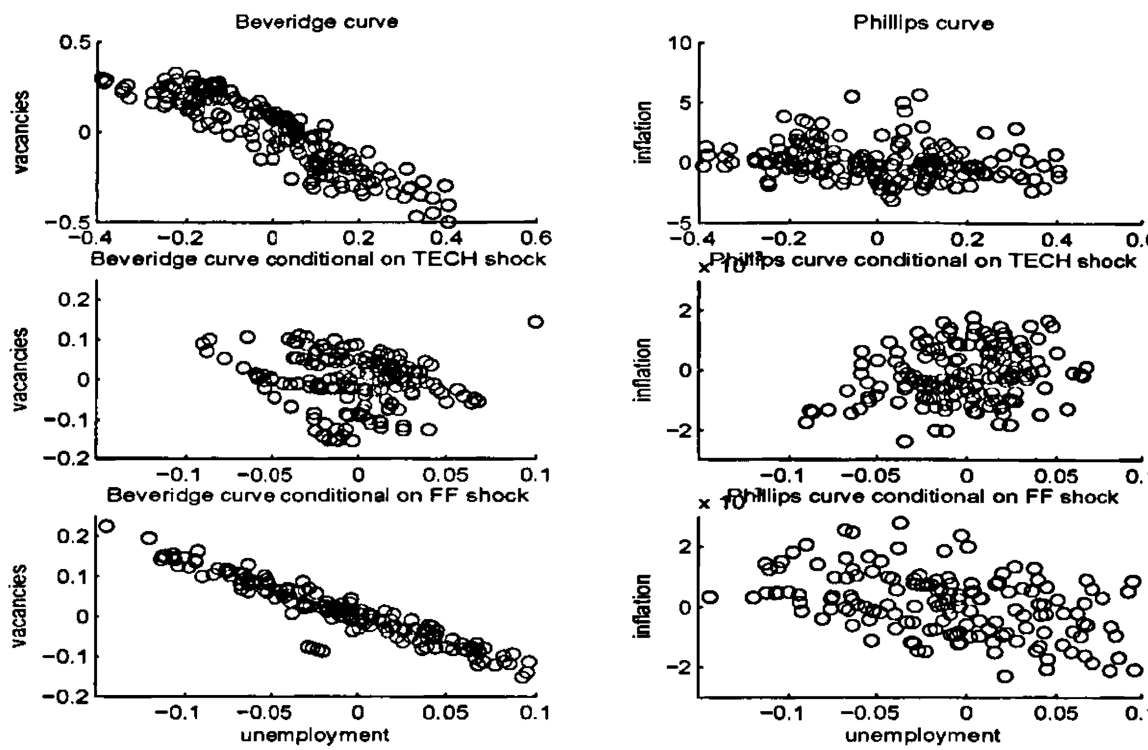

Figure 3.3: Scatterplots

The top panels reveal the strong negative Beveridge curve relationship and the much weaker Phillips curve relationship mentioned in section 3.2. Interestingly the technology shock does not add very much to either of the curves. Instead it even seems to induce a positive correlation in the Phillips curve. In other words, the technology shock seems to be shifting both curves rather than leading to moves along them.

This is dramatically different for the federal funds rate shock (here FF): The federal funds shock induces a strong negative relationship between vacancies and unemployment and is thus mainly responsible for the unconditional Beveridge curve. A cut in the federal funds rate sends the economy into a boom, raising aggregate demand and vacancies and lowering unemployment. At the same time, the rise in aggregate demand increases inflation. This induces the much weaker negative correlation between unemployment and inflation seen in the bottom right panel of figure 3.3.

Having presented scatterplots of counterfactual data generated by feeding in only one shock at a time, we now calculate conditional cross autocorrelation function. In

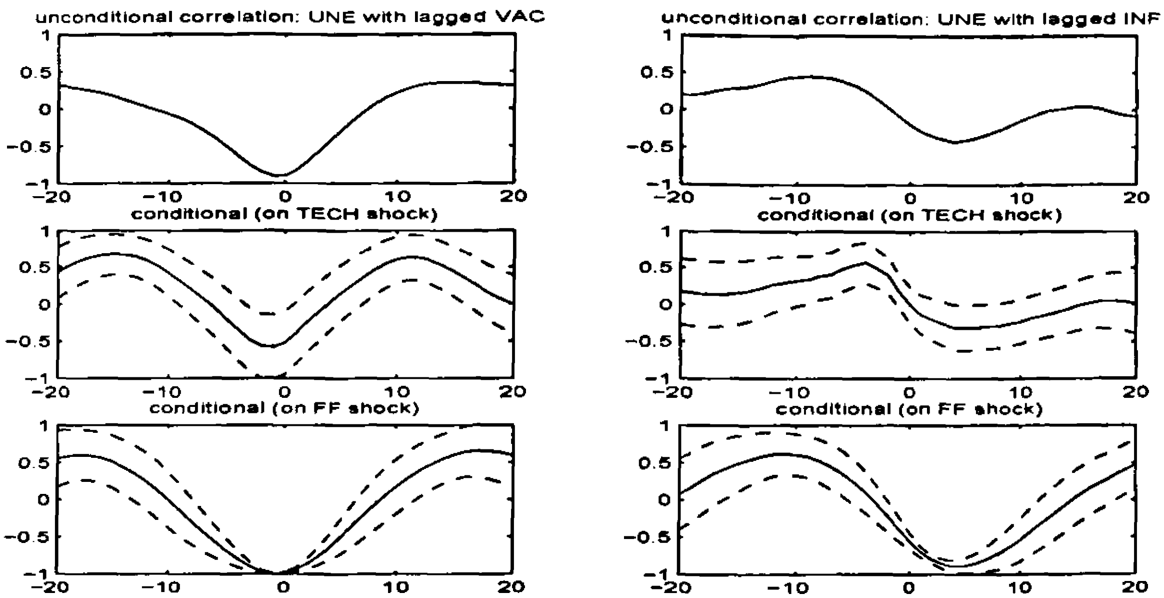

Figure 3.4: Dynamic Crosscorrelations and 95 percent confidence intervals

other words, we are interested in the co-movement of unemployment with lagged and led vacancies and inflation conditional on either of the two shocks. Figure 3.4 shows the results. The left panel shows the expected results: unemployment and vacancies are strongly negatively correlated and the effect is strongest at contemporaneous lags.

Inflation instead seems to be leading unemployment somewhat (see top right panel showing unconditional correlations). The contemporaneous effect of the technology shock on the Phillips curve is not significantly different from zero. However, the federal funds rate shock does reveal a strong negative correlation between unemployment and led inflation. Inflation seems to be leading unemployment by around 4 quarters. This is interesting given the sluggish nature of inflation which might one lead to expect inflation was lagging. But the delayed effects of business cycle fluctuations on unemployment seem to be stronger than those on inflation.

3.3.3 Impulse Responses

This section discusses the dynamic impacts of the two shocks in greater detail by looking at impulse response functions. Figures 3.5 and 3.6 show point estimates of the impulse responses together with their 95 percent confidence intervals.[7]

A cut in the Federal Funds rate by one standard deviation, or around 60 basis points, increases output by a maximum impact of 0.4 percent after around 6 quarters. All variables other than the real wage react statistically different from zero. The responses of the labor market variables virtually mirror each other; unemployment and vacancies,

[7]Confidence intervals were computed as in ACEL. They bootstrap 1,000 impulse responses, calculate standard deviations and assume pointwise normality of the impulse response functions.

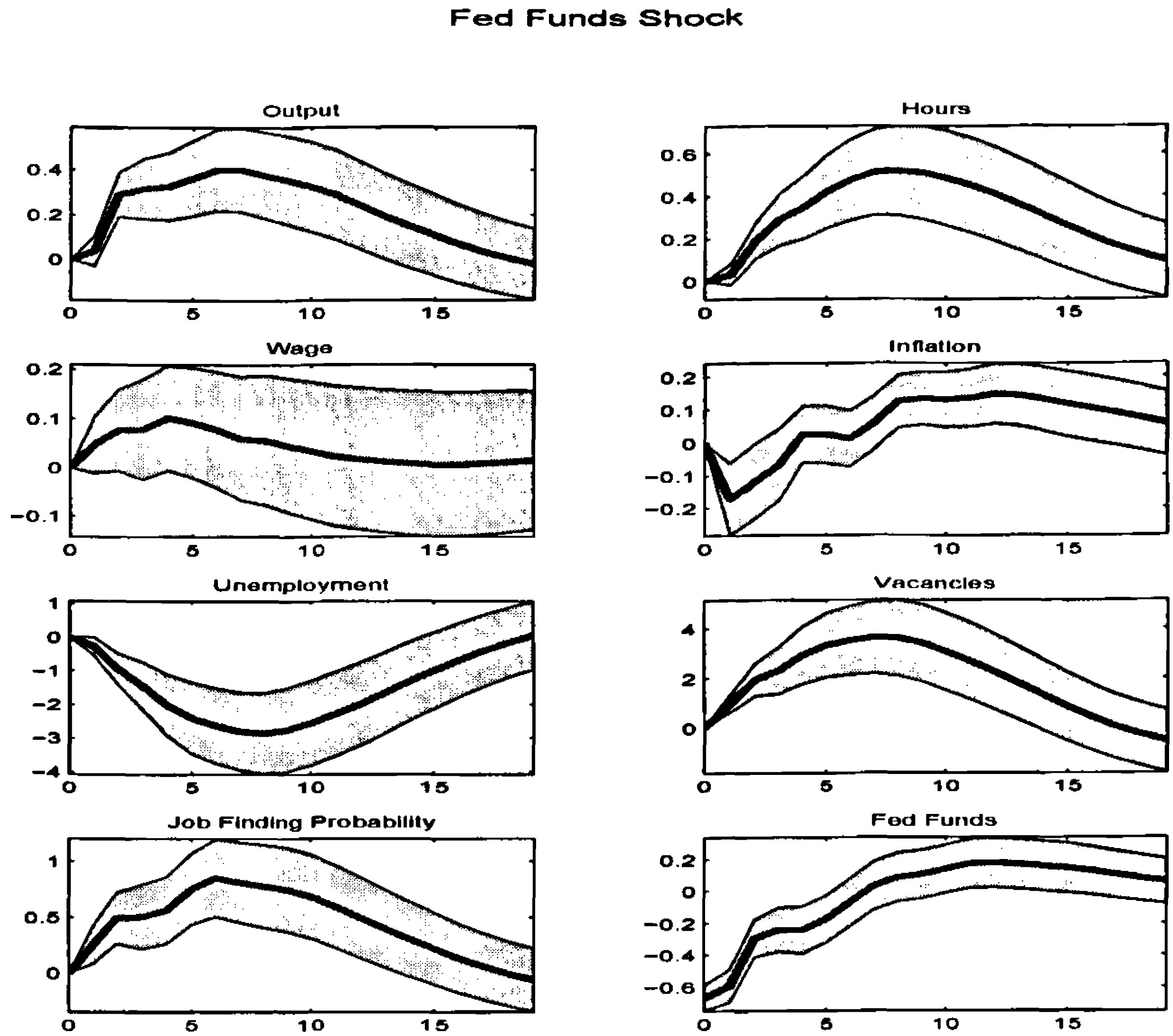

Figure 3.5: Impulse Responses to monetary shock and 95 percent confidence intervals

however, falling, respectively, rising much stronger than hours worked. In particular, unemployment responds in a reversed hump-shaped manner and reaches a minimum of -3 percent from steady state after around 8 quarters. The response of vacancies mirrors the one for unemployment. The economic model will help us clarifying what is going on in the economy. Looking ahead it seems likely that after a nominal interest rate cut - and because prices adjust only slowly - the real rate will fall. Current consumption and investment become relatively cheap which increases demand for output. Thus, output rises leading to a fall in unemployment and a rise in hours worked and vacancies. Inflation instead responds much more sluggishly to the rate cute, initially even falling. It rises to a maximum only after around 12 quarters. It will be difficult for the economic model to capture this sluggishness in inflation.

The effects of the technology shock on the economy are less clear. In general, most responses are not significantly different from zero. There are, however, some exceptions:

Output rises by assumption. Hours worked rise on impact, before dipping somewhat during quarters 2 to 4. They then start rising again reaching a maximum of 0.4 percent above steady state at quarter 5. Hours remain significantly positive up to around quarter 15. The evidence presented here is therefore more in line with the results of Christiano, Eichenbaum and Vigfusson (2003) rather than with those of Gali (1999).

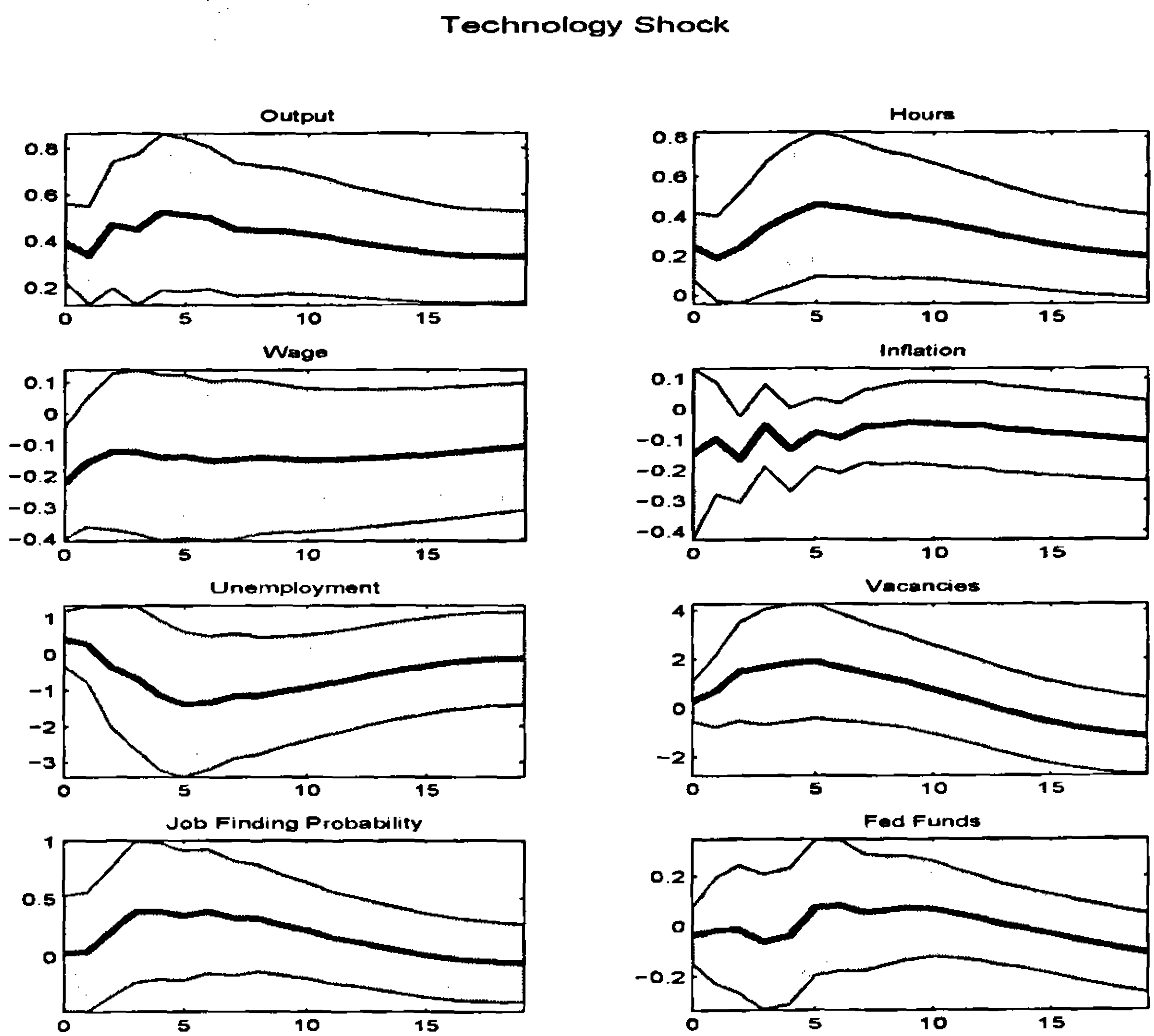

Figure 3.6: Impulse Responses to technology shock and 95 percent confidence intervals

The responses of the other variables are qualitatively similar to those of the monetary policy shock, with the only exception that inflation - if anything - seems to be falling. Again, technology shocks by themselves cannot explain the Phillips curve. This needs to be interpreted with care, however, because most impulse responses to the technology shock are not significantly different from zero.

Table 3.2: Variance decomposition

Variance due to Technology Shock				
quarters	1	5	10	20
Output	0.424	0.287	0.300	0.340
Hours	0.303	0.142	0.188	0.195
Wage	0.188	0.074	0.068	0.071
Inflation	0.026	0.058	0.061	0.062
Unemployment	0.032	0.019	0.041	0.038
Vacancies	0.009	0.054	0.058	0.050
Job finding	0.000	0.029	0.042	0.037
Fed Funds	0.003	0.002	0.006	0.012
Variance due to Monetary Policy Shock				
Output	0	0.087	0.146	0.133
Hours	0	0.079	0.200	0.223
Wage	0	0.015	0.014	0.009
Inflation	0	0.036	0.051	0.084
Unemployment	0	0.065	0.184	0.200
Vacancies	0	0.111	0.228	0.210
Job finding	0	0.071	0.178	0.188
Fed Funds	0.878	0.323	0.216	0.210

3.3.4 Variance Decompositions

Finally, we present variance decompositions showing how much of the variation in a particular variable is due to either of the two shocks. Table 3.2 summarizes the results: Output is mainly affected by technology shocks - their effect however following a U-shaped pattern with the forecast horizon. Most labor market variables, however, are affected stronger by the monetary policy shock. In particular, around 20 percent of variation in unemployment and vacancies at business cycle frequencies is explained by the monetary policy shock.

Summing up, the evidence suggests it is necessary to include a monetary policy shock in economic models of the labor market. The well-known Beveridge and Phillips curves are mainly caused by monetary policy shocks. Even though technology shocks seem to matter for output fluctuations, mainly monetary policy shocks cause variation in labor market variables at the business cycle frequency.

The next section develops an economic model that will help to understand the workings of the economy underlying the empirical findings.

3.4 Modelling unemployment, vacancies and inflation

To jointly model the responses of unemployment, vacancies and inflation to monetary policy and technology shocks we incorporate a matching model of the labor market into an otherwise standard New Keynesian DSGE model in which monetary shocks have real effects because of price rigidities. The model setup is similar to the one in Trigari (2003).

To make the economic model consistent with the identifying assumptions of the VAR we need to make two important extensions: First, the monetary policy shock in the VAR is identified by assuming that the only variable reacting on impact to a monetary policy shock is the nominal interest rate itself. All other variables respond with a lag. Thus, the economic model needs to reflect this timing assumption. It is imposed within the model by forcing agents to base their period-t decisions on information of the technology shock up to period t, but on information of the monetary policy shock up to period t-1 only. In other words, all conditional expectations in the model are written as $E(x_{t+s}|\Omega_t)$ where $\Omega_t = \{\epsilon^z_{t-i}, \epsilon^m_{t-i-1}; i = 0, \dots, \infty\}$.

Second, because the technology shock is identified as the only shock having a permanent effect on labor productivity in the long run, we follow Ireland (2004) and implement this assumption within the economic model by assuming the technology process follows a random walk with possibly autocorrelated error term.

The economy consists of four types of agents: households, two types of firms, and a central bank. The decision problems of the agents will be discussed in the following sections.

We briefly outline the structure of the economy first: Households consume, search for jobs, bargain if matched with a firm and work or are unemployed. The production sector consists of two types of firms: perfectly competitive intermediate goods firms, and monopolistically competitive final goods retail firms. Matching and production takes place in the intermediate goods sector. Firms post vacancies, bargain if matched with an unemployed worker and produce the intermediate good under a standard Cobb-Douglas production function. Retail sector firms then buy the intermediate good, differentiate it and sell it in a monopolistically competitive product market. Price rigidities are introduced through a Calvo price setting mechanism. Because of the distinction between intermediate goods firms and final goods firms we can separate the matching and production decision from the price-setting decision. Finally, the central bank sets the nominal interest rate according to a Taylor-type monetary policy rule.

3.4.1 Households

The economy consists of many households. These households all have the same utility functions and differ only to the extent that some of them are employed whilst others are unemployed. Because this would make households heterogeneous with respect to their wealth positions (because of their different employment histories), we assume households pool all their income and thereby insure each other against idiosyncratic income risk.

We now describe the preferences of our representative household:

The infinitely-lived representative household receives utility over consumption and leisure. In particular, we assume the household maximizes the following utility function over consumption, leisure, and bond holdings:

$$E_t = \sum_{s=t}^{\infty} \beta^s \Big[\log(c_t - \rho_h c_{t-1}) - \kappa_h \frac{h_t^{1+\phi}}{1+\phi} \Big] \tag{3.15}$$

subject to a series of intertemporal budget constraints:

$$c_t + \frac{b_{t+1}}{i_t p_t} \leq w_t h_t + \frac{b_t}{p_t}. \tag{3.16}$$

Here, c_t, h_t and b_t are consumption, hours worked, and bond holdings, and $0 < \rho_h < 1$ governs the degree of habit persistence in consumption. i_t and p_t are the gross nominal interest rate paid on bonds and the aggregate price level, respectively. Consumption and the real value of bond holdings must not exceed labor income and financial wealth held in the form of bonds in the current period.

The representative household chooses consumption, leisure and bond holdings to maximize (3.15) subject to (3.16). The solution to this problem must satisfy a standard Euler equation where special care needs to be taken because of the nonstandard way that conditional exoectations are modelled (see the above definition of the information set):

$$\lambda_t = \beta E_t [r_t \lambda_{t+1}] \tag{3.17}$$

where λ_t is the marginal utility of consumption in and where r_t is the gross real interest rate from period t to t+1:

$$r_t = \frac{p_t}{p_{t+1}} i_t \tag{3.18}$$

3.4.2 Firms

There are two types of firms in the economy: intermediate goods producing firms and final goods producing retailers. Intermediate goods producing firms operate in perfectly competitive factor and goods markets. They post vacancies which are then stochastically matched with unemployed workers. Intermediate goods producing firms bargain with the unemployed over the wage. Finally, they sell the produced good to final goods producing retailers. These retailers buy the intermediate good, differentiate it, and sell it in a monopolistic market. Because of their monopoly power, they can set their goods prices. Price rigidities are introduced through a Calvo price setting scheme. This section describes the optimization problems of the two types of firms in more detail.

Intermediate goods firms, matching and production

There are infinitely many intermediate goods firms, each producing with a production function of the following type:

$$f(h_t) = z_t h_t^{\alpha} \tag{3.19}$$

where z_t is a technology factor that is common to all firms. Because our identifying assumption in the SVAR implies that the technology shock is the only shock that has a permanent effect on labor productivity, we assume technology follows a random walk with

$$z_t = z_{t-1} + \epsilon_t^z \tag{3.20}$$

and autocorrelated error term

$$\epsilon_t^z = \rho_{\epsilon_z} \epsilon_{t-1}^z + \eta_t. \tag{3.21}$$

The technology shock is then given by η_t.

Production however only takes place when a firm advertising a job vacancy is actually matched with an unemployed worker. The matching function is assumed to be of the following Cobb-Douglas type with constant returns:

$$m_t = \sigma_m u_t^{\sigma} v_t^{1-\sigma} \tag{3.22}$$

where σ between 0 and 1 and where σ_m is a scale parameter reflecting the efficiency of the matching process. If matched, firm and worker bargain over wage and hours and start producing the following period. Each period a matched job breaks up with exogenous probability ρ. Employment n_t thus evolves according to the following dynamic equation:

$$n_t = (1-\rho)n_{t-1} + m_{t-1} \tag{3.23}$$

which says that the number of matched workers at the beginning of period t, n_t, is given by the fraction of matches in $t-1$ that survives to the next period, $(1-\rho)n_{t-1}$, plus the newly-formed matches, m_{t-1}. The labor force being normalized to one, the unemployment rate at the beginning of any given period is $1 - n_t$.

Bellman equations

We next discuss the Bellman equations describing the values of a job, a vacancy, an employed worker and an unemployed worker, respectively. It is helpful to first develop some notation: Let θ_t be defined as labor market tightness and accordingly be defined as $\theta_t = \frac{v_t}{u_t}$. The job finding probability of an unemployed worker is given by $s_t = \frac{m_t}{u_t} = \sigma_m \theta_t^{1-\sigma}$ and is thus an increasing function of labor market tightness. The worker finding probability of a vacant job is given by $q_t = \frac{m_t}{v_t} = \sigma_m \theta_t^{-\sigma}$ and is decreasing with labor market tightness.

The value of a job (in terms of current consumption units) is then given by J_t:

$$J_t = x_t f(h_t) - w_t h_t + E_t \beta_{t+1}(1-\rho) J_{t+1} \tag{3.24}$$

where x_t is the relative price of the intermediate good and w_t is the wage rate. The value of the job consists of current period profits, $x_t f(h_t) - w_t h_t$, plus the expected, appropriately discounted value of the job as of next period. This can be explained as follows: Next period, with probability $1-\rho$ the match continues. In this case, the firm obtains a future payoff J_{t+1}. With probability ρ, instead, the match is discontinued in $t+1$ and the firm obtains a future payoff of zero. Finally, the expected future value of the job is discounted with the factor β_{t+1}, where $\beta_{t+1} = \beta\frac{\lambda_{t+1}}{\lambda_t}$. The use of this discount factor effectively evaluates profits in terms of the values attached to them by the households, who ultimately own the firms.

The other three Bellman equations can be explained similarly. The value of a vacancy is given by V_t:

$$V_t = -\frac{\kappa}{\lambda_t} + E_t\beta_{t+1}[q_t(1-\rho)J_{t+1} + (1-q_t)V_{t+1}] \tag{3.25}$$

where κ is the utility cost of entertaining an open vacancy. Dividing the utility cost by the marginal utility of consumption λ_t effectively transforms the utility cost of the vacancy into costs expressed in units of consumption goods. The vacancy is matched with a worker and is not severed with probability $q_t(1-\rho)$ and remains open with probability $1-q_t$.

The value of employment and unemployment is denoted by W_t and U_t respectively. The flow value of employment is given by the wage bill, $w_t h_t$, minus the utility cost of working expressed in units of consumption goods $\frac{\kappa_h}{\lambda_t}\frac{h_t^{1+\phi}}{1+\phi}$. The worker remains employed in the next period with probability $1-\rho$ and becomes unemployed with probability ρ.

$$W_t = w_t h_t - \kappa_h \frac{h_t^{1+\phi}}{1+\phi} + E_t\beta_{t+1}[(1-\rho)W_{t+1} + \rho U_{t+1}] \tag{3.26}$$

Finally, the unemployed worker receives flow benefits of b and finds a job that is not severed with probability $s_t(1-\rho)$ and remains unemployed otherwise. The value of unemployment, U_t, is therefore given by:

$$U_t = b + E_t\beta_{t+1}[s_t(1-\rho)W_{t+1} + (1-s_t(1-\rho))U_{t+1}] \tag{3.27}$$

Solving the matching model

To solve the matching model for the equilibrium value functions, two further assumptions are needed:

We first assume that in equilibrium free entry ensures that the value of vacancies is zero, i.e. $V_t = 0$. Equation (3.25) then reduces to:

$$\kappa = E_t\beta_{t+1}[q_t(1-\rho)J_{t+1}] \tag{3.28}$$

which we can solve forward to establish that in equilibrium the expected cost of a vacancy, $\frac{\kappa}{q_t}$ is equal to the expected discounted stream of future profits,

$$\frac{\kappa}{q_t} = E_t \Sigma_{s=1}^{\infty} \beta_{t+s} (1-\rho)^s \tilde{\pi}_{t+s} \tag{3.29}$$

where $\tilde{\pi}_t$ are the profits of the firm.

Second, we assume that a matched pair of firm and worker share the joint surplus of the match according to the Nash bargaining solution. The Nash bargaining solution splits the joint surplus of the match according to the bargaining weight parameter η. In particular, if we define the joint surplus as $S_t = E_t - U_t + J_t$, the bargaining rule chooses the wage rate such that:

$$W_t - U_t = \eta S_t \tag{3.30}$$

$$J_t = (1-\eta) S_t \tag{3.31}$$

The system can then be rearranged to obtain a "wage equation". Importantly, the wage rate in this model does not adjust to equate the marginal product of labor with the marginal rate of substitution as in a competitive labor market model. Instead, although the equilibrium wage rate turns out to depend on these magnitudes, it also depends on labor market tightness, the flow cost of a vacancy and on the benefit level of unemployment.

The Nash bargaining solution has recently received much criticism from a number of authors (see e.g. Shimer (2005) and Hall (2005)). Shimer studies the effect of labor productivity shocks on labor market tightness within the RBC model. He argues that the Nash bargaining solution creates a too flexible real wage rate that absorbs a firm's incentive to create vacancies in response to a rise in labor productivity. Profits will rise and additional vacancies will be created. But because this leads to a rise in the job finding probability, it increases the value of being unemployed which is the outside option of the worker in the Nash bargaining solution. Wages will therefore rise, reducing profits and therefore firms' incentives to open new vacancies. Labor market tightness, $\theta = \frac{v_t}{u_t}$ is thus not very responsive to labor productivity shocks. Comparing unconditional volatilities, Shimer then argues that this is very different in US data where labor market tightness is found to be much more volatile than average labor productivity. He concludes that the matching model does a bad job in explaining the data. Note, however, that Shimer compares his model's results to unconditional average labor productivity, when in fact he should compare it to average labor productivity conditional on a technology shock.

When estimating the above New Keynesian matching model I seem to find exactly the opposite result: The model matches most empirical impulse responses surprisingly well. However, it fails to explain the very variable we wanted to explain, namely unemployment. The reason for this seems not to be a qualitatively different response pattern in the model, but simply the fact that in the model vacancies react much stronger to monetary policy shocks than unemployment. This is not so in the data. Vacancies then seem to overreact, generating a too high labor market tightness.

Final goods firms and price setting

Final goods firms buy the intermediate good at price, x_t, differentiate it at zero cost and sell it to consumers in a monopolistically competitive market. The demand facing each monopolist is given by:

$$y_{it} = \left(\frac{p_{it}}{p_t}\right)^{-\epsilon} y_t \tag{3.32}$$

I follow Calvo (1983) and assume that there is a fixed given probability, $1-\varphi$, which is the same for all firms, with which a firm can reset its price in any given period. The average duration a price is kept fixed is therefore given by $\frac{1}{1-\varphi}$. I further assume that firms that cannot re-optimize their price simply index to lagged inflation:

$$p_{it} = \pi_{t-1} p_{i,t-1}. \tag{3.33}$$

Final goods firms choose their price to maximize expected profits where expectations now take into account that the firm might not be allowed to reset its prices for a certain length of time. In particular, the probability that a firm is not allowed to adjust its price for l periods is given by φ^l. The firm then chooses $p_{i,t}$ to maximize:

$$E_t \Sigma_{s=0}^{\infty} \beta_{t+s} \varphi^s \left(\frac{p_{i,t}}{p_{t+s}} \mu_{t,s} - x_{t+s}\right) y_{i,t+s} \tag{3.34}$$

subject to the demand function (3.32) and to

$$\mu_{t,s} = \pi_t \pi_{t+1} \dots \pi_{t+s-1}. \tag{3.35}$$

The solution to this problem gives the optimal price set by the final goods firm. In essence, this price is a complicated function of future expected marginal costs of the firm. The aggregate price level can be shown to be:

$$p_t = \pi_{t-1}\left(\varphi p_{t-1}^{1-\epsilon} + (1-\varphi) p_{i,t}^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}} \tag{3.36}$$

3.4.3 Central Bank

The nominal interest rate is assumed to be set by the central bank. In particular, I assume the following somewhat generalized Taylor rule:

$$i_t = \rho_i i_{t-1} + (1-\rho_i)\gamma_\pi E_t \pi_{t+1} + (1-\rho_i)\gamma_y y_t + (1-\rho_i)\gamma_g g_t + \epsilon_t^m. \tag{3.37}$$

where ρ_i measures the degree of interest rate smoothing, and where the parameters γ_π, γ_y and γ_g measure the response of the central bank to deviations in expected inflation.

to output deviations and to the growth rate of output, $g_t = \frac{y_t}{y_{t-1}}$. All variables in the Taylor rule are already in log-deviation from steady state. The Taylor rule can be regarded as somewhat generalized because of the inclusion of the growth rate of output (see also Ireland (2004b). Empirically, it is not clear whether the central bank reacts only to deviations from potential output - with all the problems of measurement of this variable - or to a measure of the actual growth of output. Thus, equation (3.37) also contains the growth rate of output. Finally, the monetary policy shock is given by ϵ_t^m.

3.4.4 Equilibrium

The model is closed by an economy wide market clearing assumption:

$$y_t = c_t \tag{3.38}$$

and a market clearing condition in the intermediate goods sector:

$$y_t = n_t(1-\rho)f(h_t) \tag{3.39}$$

where $n_t(1-\rho)$ is the number of intermediate goods firms actually producing in t.

The system of equilibrium conditions can be written in log-linearized form can be written as

$$A(\theta)E_t\begin{bmatrix} s_{t+1} \\ c_{t+1} \end{bmatrix} = B(\theta)\begin{bmatrix} s_t \\ c_t \end{bmatrix} \tag{3.40}$$

where s_t contains all the state variables of the model (with the exogenous state variables listed last), where c_t contains all the control variables, and where θ is the vector of all structural parameters of the model. The model can then be solved using any of the available algorithms to yield the following state space representation

$$c_t = F(\theta)s_t \tag{3.41}$$

$$s_{t+1} = P(\theta)s_t + J\begin{bmatrix} \epsilon_t^m \\ \eta_t \end{bmatrix} \tag{3.42}$$

where the matrices $F(\theta)$ and $P(\theta)$ are nonlinear functions of the structural parameters and where the matrix $J = [0; I_2]'$ contains a zero block in its top block and a two-by-two identity matrix in its bottom block picking the exogenous shocks.

3.5 Estimation and Results

Various methods have been suggested over the last decade or so to estimate the structural parameters of economic models. Essentially, there are three strands in this growing literature that aims to estimate fully specified DSGE models using sound econometric methods, instead of simply calibrating those models to unconditional first and sometimes second moments of the data. In effect, all these methods estimate the structural parameters by optimizing some kind of criterion function that depends on the model, the model parameters, as well as on the data.

Maximum Likelihood methods derive the likelihood function of the linearized and solved DSGE model which can typically be written in state-space form and then picks as point estimates the vector that maximizes the likelihood function. The inverse of the Hessian at the maximizing vector then serves as estimated asymptotic covariance matrix. Ireland (2004b) shows how to estimate a New Keynesian model with MLE methods and Ireland (2004a) estimates a RBC model with VAR(1) measurement error structure also using MLE.

Bayesian methods combine the likelihood function with a prior density over the structural parameters to derive the posterior density. The posterior density is either taken to be the normal with mean taken to be the posterior mode and covariance matrix the inverse Hessian at the posterior mode. Though this is often valid asymptotically, Markov-Chain Monte Carlo methods are usually used to derive a better approximation of the full posterior which should be valid also in small samples.

Finally, limited information methods have also been used to estimate the structural parameters of DSGE models. Rotemberg and Woodford (1998) and CEE, for instance, propose to use minimum distance estimation to minimize some distance function between empirical impulse response functions and theoretical impulse responses coming from the economic model. The advantage of the limited information approach is that the researcher only needs to model that part of the economy which he is ultimately interested in. The remaining parts of the economy need not be specified and in this sense, the researcher can remain agnostic with respect to the rest of the data generating process under the null hypothesis.

Because in this paper we are only interested in the effects of monetary policy and technology shocks, we make use of the limited information approach and match DSGE model impulse responses with the empirical ones from the SVAR model. This allows us to focus on the two key shocks, the variables' responses, and the ability of our economic model to match the data, without having to specify - and thereby to possibly misspecify the model - other economic shocks. In fact, the particular limited information method that I apply in this paper can be regarded as rather conservative, as it makes use of SVAR analysis with fairly generally accepted identifying assumptions[8] and of an economic model that consists of a baseline New Keynesian model with a micro-founded non-Walrasian labor market model that has also recently become accepted in the business cycle literature.

Following Rotemberg and Woodford and CEE, the model's structural parameters are therefore estimated by minimizing a weighted distance metric between the empirical

[8]Of course, every identifying assumption could (and should) be questioned, but the literature suggests that the identifying assumption of the fedfunds shock is widely accepted, whilst the evidence on the technology shock seems slightly in favor of the assumption (compare with the debate on hours worked by Gali and others.

impulse responses from the SVAR and those from the New Keynesian DSGE model.[9] Specifically, if θ is the vector of parameters that we wish to estimate, our minimization procedure chooses $\hat{\theta}$ to minimize the following function:

$$\hat{\theta} = \text{argmin}_{\theta \in \Theta} \quad (\hat{\Psi}_T - \Psi(\theta))' W_T (\hat{\Psi}_T - \Psi(\theta)) \tag{3.43}$$

where $\hat{\Psi}_T$ contains the impulse responses from the two identified shocks from the SVAR[10], $\Psi(\theta)$ is the stacked vector of all model impulse responses, and where W_T is a diagonal weighting matrix containing the inverses of the variances of the various impulse responses along the diagonal. In effect, the more precisely we estimate a certain impulse response, the more weight will that impulse response get in the estimation. In principle, any positive definite weighting matrix W_T with $\text{plim}W_T = W$ would deliver consistent estimates of θ. We choose W_T to be diagonal because of its intuitive appeal that $\hat{\theta}$ will be chosen such that the model impulse responses will be as close to the empirical impulse responses as possible. However, other (and maybe more efficient) choices of W_T are possible (see Meier and Müller for a discussion).

Referring to results by Newey and McFadden (1994) and following the discussion in Meier and Müller (2005), we are now in a position to derive the asymptotic distribution of our estimator of θ. Essentially, because $\hat{\theta}$ can be regarded as a classical minimum distance estimator in the words of Newey and McFadden, and if certain regularity conditions are satisfied, we know that $\hat{\theta}$ is a consistent estimator of θ. Moreover, Newey and McFadden show that $\hat{\theta}$ is asymptotically normal if properly standardized:

$$\sqrt{T}(\hat{\theta} - \theta) \xrightarrow{d} N\Big(0, (G'WG)^{-1}(G'W\Sigma WG)(G'WG)^{-1}\Big) \tag{3.44}$$

where $G = \nabla_\theta \Psi(\theta)$ denotes the Jacobian matrix of the impulse response functions generated from the model, $W = \text{plim}W_T$, and Σ is the asymptotic covariance matrix of $\sqrt{T}(\hat{\Psi}_T - \Psi)$. Let $A\hat{v}ar(\hat{\Psi}_T)$ denote our bootstrap estimate for the asymptotic variance of $\hat{\Psi}_T$, so that $A\hat{v}ar(\hat{\Psi}_T) = \hat{\Sigma}/T$. All matrices in (3.44) can be estimated consistently. Specifically, estimates of W and Σ are obtained as by-products of our bootstrapping procedure, and G can be obtained from numerical differentiation. Our estimate of the asymptotic covariance matrix of $\hat{\theta}$ then reads as

$$A\hat{v}ar(\hat{\theta}) = \left(\hat{G}'W_T\hat{G}\right)^{-1} (\hat{G}'W_T A\hat{v}ar(\hat{\Psi}_T) W_T \hat{G}\Big) \left(\hat{G}'W_T\hat{G}\right)^{-1}, \tag{3.45}$$

allowing us to report asymptotic standard errors for our estimates.

The vector of structural parameters of the economic model is given by $\theta = \{\beta, \epsilon, \alpha, \phi, \rho_h, \varphi, \rho, \sigma, \eta, \rho_i, \gamma_\pi, \gamma_y, \gamma_g, \rho_{\epsilon_t}\}$. Because some of these parameters are fairly uncontroversial in the literature and can be calibrated from first moments of the data, we choose

[9] All calculations carried out in this section were again done in Matlab.

[10] We use a total of 313 impulse responses. Thus, the dimensions of $\hat{\Psi}_T$ and $\Psi(\theta)$ are both 313 times 1.

Table 3.3: Calibrated Parameters

β	0.99
ϵ	11.00
α	0.66

Table 3.4: Steady state values

h	0.33 (steady state hours worked)
n	0.8 (steady state employment rate)
q	0.7 (steady state probability that firm fills vacancy)
s	0.25 (steady state probability that unemployed finds job)
z	1 (steady state technology level)

not to estimate them. These are the discount factor of the household, β, which is set to 0.99, implying a quarterly real interest rate of approximately 1%; the elasticity of substitution among alternative differentiated goods, ϵ, is set to 11, implying a mark-up of 10 percent; and the α coefficient in the production function is taken to be 0.6667. Table 3 summarizes this information.

The remaining parameters, $\tilde{\theta} = \{\phi, \rho_h, \varphi, \rho, \sigma, \eta, \rho_i, \gamma_\pi, \gamma_y, \gamma_g, \rho_{\epsilon_z}\}$ are then estimated. Before we estimate these parameters of interest, we also need to determine steady state values for some variables. We follow the literature and set the average time spent working to one third and the steady state employment rate to 0.8. Following Trigari (2003), the steady state probability that a firm fills a vacancy is set to 0.7 and the steady state probability that an unemployed worker finds a job to 0.25. Steady state technology level is set to 1. Table 3.4 summarizes this information.

The resulting parameter estimates and their estimated asymptotic standard errors are shown in table 3.5. I discuss utility function parameters first. The inverse of the intertemporal elasticity of labor supply, ϕ, is estimated to be 12.110 which is fairly large, implying a very small labor supply elasticity of just 8 percent. This is an interesting finding because it is entirely in line with microeconometric estimates of this elasticity being close to 0 and in any case not higher than 0.5. Instead, most macroeconometric studies estimate this elasticity to be much higher.[11] However, the standard error is big, thus not much can be said about the actual value of the true parameter. The rather large standard error of the estimate of ϕ seems to be a rather common finding in the literature.[12]

[11]Compare this with Smets and Wouters (2002) who estimate ϕ close to 1.

[12]Smets and Wouters (2002) mention in passing that "this parameter is not very precisely estimated." (p.24)

Table 3.5: Estimation Results

parameter	estimate	standard error
ϕ	12.110	11.744
ρ_h	0.832	0.063
φ	0.986	0.008
ρ	0.487	0.086
σ	0.837	0.028
η	0.000	0.016
ρ_i	0.865	0.068
γ_π	1.005	0.446
γ_y	0.031	0.123
γ_g	0.795	0.741
ρ_{ϵ_z}	0.000	0.164

Habit persistence is estimated to be very strong with ρ_h equal to 0.832 and a small standard error of 0.063. This compares with the smaller values found in the literature: Smets and Wouters (2003) estimate habit persistence to be 0.552 using Euro area data, CEE estimate it to be 0.65 and Boldrin, Christiano and Fisher (2001) estimate it to be 0.7. Though the obtained estimate in this paper is indeed high, there seems to be some controversy as to the true value of the parameter in the literature. Interestingly, the habit persistence parameter is estimated much more precisely than the elasticity of labor substitution parameter. This is also the case in Smets and Wouters (2002).

Price stickiness is estimated to be very high. The estimate for $\varphi = 0.986$ implies an implausible high average duration of prices, $\frac{1}{1-\varphi}$, of 71 quarters or almost 18 years. This strongly contrasts with microeconometric evidence finding average price durations not longer than 4-6 quarters (see Bils and Klenov, 2004). The standard error is very small, thus it seems this parameter is crucial in generating the right degree of nominal rigidity that is found in the data. This comes at the cost of microeconomic evidence, but also suggests that stronger nominal rigidities need to be introduced to capture the persistence in the data. It strongly points at misspecification of the economic model.

The matching function parameters are also somewhat at odds with microeconometric evidence. The quarterly worker separation rate, ρ, is estimated to be 48 percent which contrasts with evidence of Davis, Haltiwanger and Schuh (1996) which estimates it at about 8 percent. The elasticity of new matches with respect to the number of searching workers, σ, is estimated to be 0.84, which is again much higher than the 0.4 estimate of Blanchard and Diamond (1989). Worker bargaining power, η, is estimated to very small, with a value close to zero. This is similar to the calibrated value of Cooley and Quadrini (1999). As argued in Trigari (2003) this value is key to the sluggish response of the real wage to the monetary policy shock.

The parameters characterizing monetary policy are somewhat more in line with the literature. The smoothing coefficient, ρ_i, is estimated to be 0.865 which compares well with the estimate of Clarida, Gali and Gertler of 0.9. The other reaction function parameter estimates compare fairly well with the estimates of Ireland (2004b) who also estimates a somewhat "generalized" Taylor curve. The Fed's response to inflation, γ_π, is estimated quite a bit below the value suggested in Taylor (1993), but between the two baseline estimates of Clarida, Gali and Gertler who estimate it to be 0.83 for the pre-Volcker period and 2.15 for the Volcker-Greenspan period. The standard error is pretty large, probably also reflecting the fact that our sample covers the entire post-war period, i.e. also the pre-Volcker era during which monetary policy in the US is believed to having been rather accommodating (see e.g. Clarida, Gali and Gertler (2000) and Lubik and Schorfheide (2004)).[13] My estimate of the response coefficient to output deviations, γ_y, is 0.03 with a fairly big standard error. Ireland (2004) estimates this parameter at the same value with much greater precision using Maximum Likelihood methods. The estimated response coefficient to the growth rate of output, γ_g, is 0.79 which is big compared to Ireland's estimate of 0.25. However, the standard error is again quite large, thus not much can be said about whether these parameters do actually differ.

Finally, the technology persistence parameter, ρ_{ϵ_z}, is estimated at zero, but again the standard error is big implying a small positive value for ρ_{ϵ_z} is not at all unlikely.

To judge the ability of the estimated economic model to explain the empirical impulse response functions, figures 3.7 and 3.8 show the estimated model impulse responses together with those from the VAR and the 95 percent confidence intervals.

The model does a fairly good job in explaining most variables, however three exceptions stand out. First, the model cannot explain the response of unemployment to a monetary policy shock. The impulse response implied by the economic model is indistinguishable from the zero line and is outside the confidence interval for almost the entire business cycle frequency. Second, the hours worked series shows a noticeable increase only at the first quarter. Otherwise the response is again indistinguishable from the zero line, and in any case not within the confidence interval. And thirdly, the response of the real wage to the technology shock is far outside the confidence interval.

Apart from these specific problems, it generally seems to be the case that the estimated model's responses to the technology shock show virtually no transitional dynamics at all. There are essentially two reasons why this should be the case: First, the economic model does not generate enough transitional dynamics itself, and second, the SVAR impulse responses to the technology shock are usually not very informative about the sign and the shape of the true impulse responses. The two reasons taken together imply that the estimation procedure emphasizes the responses to the monetary policy shock over the technology shock (i.e. the weighting matrix W_T puts more weight on the impulse responses to the monetary shock (because of those impulse responses being more precisely estimated)), and by doing this is picking parameter values which imply almost no transitional dynamics to the technology shock.

Finally, the inability of the model to replicate the empirical impulse response of the unemployment variable to the monetary shock should be discussed somewhat more. This

[13]This hypothesis could be tested for by estimating the model separately for the two subsamples and comparing parameter estimates over the different samples.

paper has tried to include key labor market variables in the estimation of a structural model of the US labor market. Unemployment is one of the key macroeconomic variables and commonly referred to in the political discussion. It should be included in any empirical model of the business cycle that is going to be used in policy making.

It does seem, however, that the model presented in this paper does not achieve its goal of explaining the response of unemployment to the monetary policy shock. In particular, the model does not generate the right *relative* volatilities of unemployment and vacancies. The estimation procedure then needs to *trade off* the importance of matching either of these two. It seems that it is "easier" for the model (given the data) to match vacancies, than unemployment.

A natural candidate to obtain a smaller response of vacancies to shocks is through vacancy adjustment costs (see Braun (2005)) or somewhat more rigorously through sunk costs of creating a vacancy (see Fujita and Ramey (2005)). Such costs could be included in an extended version of the model.

3.6 Conclusion

This paper considered the dynamic effects of monetary policy and technology shocks on key US labor market variables. This was achieved through a structural VAR model where the two shocks were identified jointly through both a short-run recursive restriction and a long-run restriction. The results indicate strong effects of monetary policy shocks on the US labor market. Unemployment, vacancies and the job finding probability all respond in a hump-shaped pattern and all responses are significantly different from zero. Instead the responses to the technology shock are rather sluggish and persistent and in any case not significantly different from zero. The strong effects of monetary policy shocks are also found in variance decompositions and correlation analysis. Beveridge and Phillips curves are clearly monetary phenomena.

Thus, the empirical results of the paper emphasize the importance of including labor market variables in DSGE models of the business cycle, and in particular, highlight the importance of monetary shocks for explaining the business cycle as opposed to technology shocks as advocated by the Real Business Cycle literature.

The paper then tried to explain the dynamic behavior of the US economy through a New Keynesian model with a matching model of the labor market. Though, generally speaking, many impulse responses can be replicated fairly well, there are at least three important problems: First, some parameter estimates are crossly at odds with microeconometric evidence. Second, the model cannot explain the behavior of unemployment following a monetary shock. And thirdly, the estimated model shows virtually no transitional dynamics in response to a technology shock.

These problems suggest the economic model should be changed or extended to better accommodate the empirical results. Introducing vacancy adjustment costs or sunk costs for the creation of vacancies seems to be a possibility to dampen the response of vacancies to monetary shocks, thus probably helping to better explain unemployment. Similarly, introducing capital stock dynamics should change the transitional dynamics in response to a technology shock.

Finally, we should be careful in drawing overly confident inference from our SVAR analysis. The debate about the problems of using long-run restrictions to identify shocks should make us somewhat sceptical about the conclusions we draw on the responses to the technology shock. But given that the responses to the technology shock are not estimated precisely at all, not much can be said about them anyway. However, it is conceivable that a more efficient estimation method would deliver more precise estimates of the impulse responses. In addition, the stationarity properties of the data have not been examined, thus unit roots might cause problems for the estimation and inference. Accounting for possible cointegrating relationships might lead to more efficient estimates.

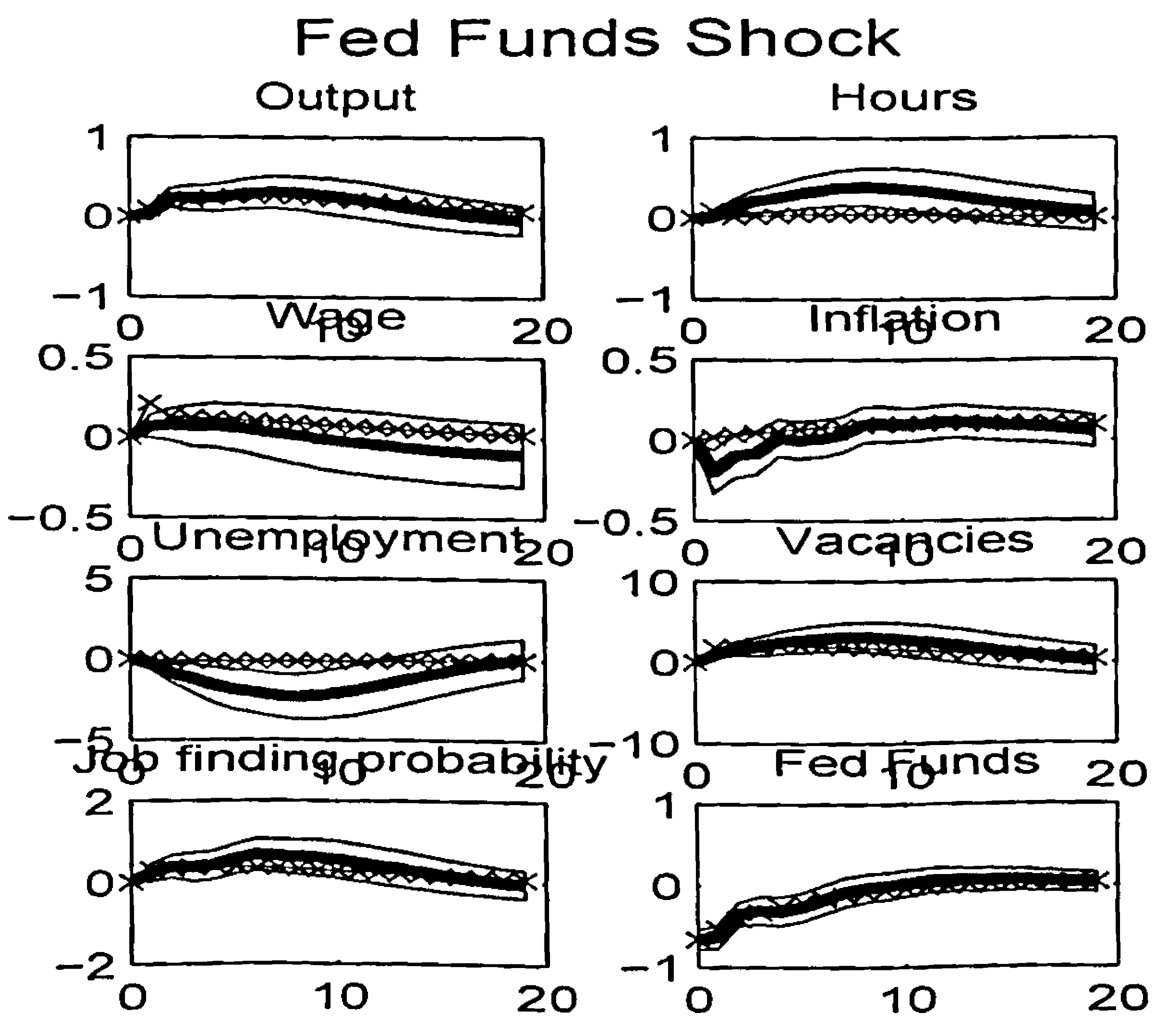

Figure 3.7: Fedfunds shock: estimated impulse responses (crosses) and impulse responses from VAR (solid line)

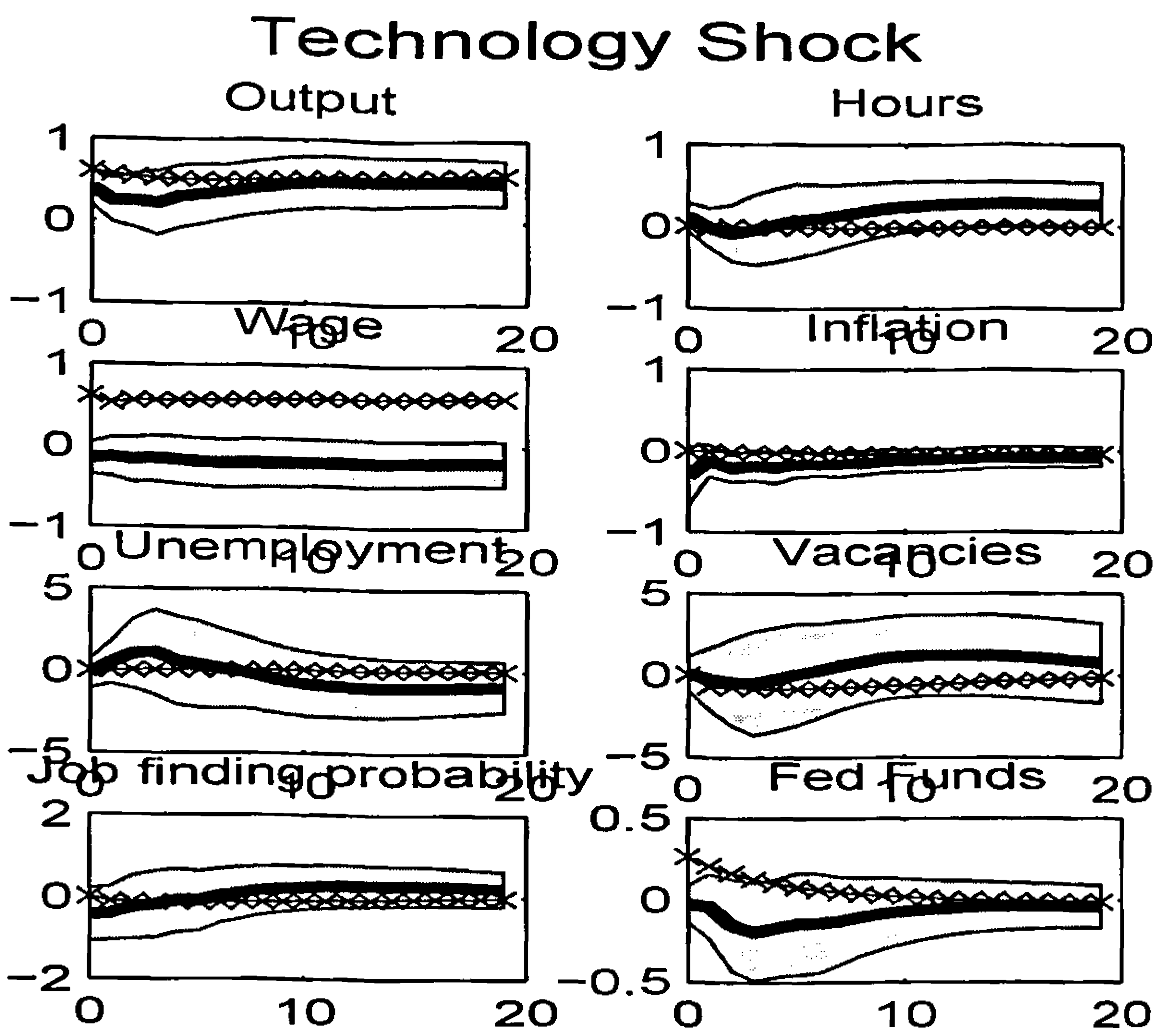

Figure 3.8: Technology shock: estimated impulse responses (crosses) and impulse responses from VAR (solid line)

Bibliography

Altig, David, Lawrence J. Christiano, Martin Eichenbaum and Jesper Linde (2005): "Firm Specific Capital, Nominal Regidities and the Business Cycle", NBER Working Paper 11034.

Andolfatto, David (1996): "Business Cycles and Labor-Market Search", American Economic Review, Vol. 86, No. 1, 112-132.

Bils, Mark and Peter J. Klenow (2004): "Some Evidence on the Importance of Sticky Prices", Journal of Political Economy, vol. 112, no. 5, 947-985.

Blanchard, Olivier J. and Peter Diamond (1989): "The Beveridge Curve", Brookings Papers on Economic Activity, Vol. 1989, No. 1, 1-76.

Blanchard, Olivier J. and Danny Quah (1989): "The Dynamic Effects of Aggregate Demand and Supply Disturbances", American Economic Review, 79(4), 655-673.

Boldrin, Michele, Lawrence J. Christiano and Jonas D. Fisher (2001): "Habit Persistence, Asset Returns, and the Business Cycle", American Economic Review 91 (March): 149-66.

Braun, Helge (2005): "(Un)Employment Dynamics: The Case of Monetary Policy Shocks", Preliminary Version.

Braun, Helge, Reinout De Bock, and Riccardo DiCecio (2006): "Aggregate Shocks and Labor Market Fluctuations", Federal Reserve Bank of St. Louis Working Paper 2006-004A.

Calvo, Guillermo A. (1983): "Staggered Prices in a Utility-Maximizing Framework", Journal of Monetary Economics, 12, 383-398.

Chari, V.V., Patrick J. Kehoe, and Ellen R. McGrattan (2004): "A Critique of Structural VARs using Real Business Cycle Theory", Federal Reserve Bank of Minneapolis, Working Paper 631.

Christiano, Lawrence J., Martin Eichenbaum and Charles L. Evans (2005): "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy", Journal of Political Econome, 113(1), 1-45.

Christiano, Lawrence J., Martin Eichenbaum and Robert Vigfusson (2003): "What Happens After A Technology Shock", International Finance Discussion Papers, Number 768.

Christiano, Lawrence J., Martin Eichenbaum and Robert Vigfusson (2005): "Assessing Structural VARs", Preliminary.

Christoffel, Kai, Keith Kuester and Tobias Linzert (2005): "The Impact of Labor Markets on the Transmission of Monetary Policy in an Estimated DSGE Model"

Clardia, Richard, Jordi Gali and Mark Gertler (2000): "Monetary Policy Rules and Macroeconomic Stability: Evidence and some Theory", Quarterly Journal of Economics, 147-180.

Cooley, Thomas and Vincenzo Quadrini (1999): "A Neoclassical Model of the Phillips Curve", Journal of Monetary Economics, 4, 165-193.

Davis, Steven, John Haltiwanger and Scott Schuh (1996): "Job Creation and Destruction", MIT Press.

Erceg, Christopher J., Luca Guerrieri and Christopher Gust (2004): "Can Long-Run Restrictions Identify Technology Shocks", International Finance Discussion Papers, Number 792.

Faust, Jon and Eric M. Leeper (1997): "When Do Long-Run Identifying Restrictions Give Reliable Results?", Journal of Business and Economic Statistics, Vol. 15, No. 3, 345-353.

Fujita, Shigeru (2004): "Vacancy Persistence", Federal Reserve Bank of Philadelphia, Working Paper No. 04-23.

Fujita, Shigeru and Garey Ramey (2005): "The Dynamic Beveridge Curve", Federal Reserve Bank of Philadelphia, Working Paper No. 05-22.

Gali, Jordi (1995): "Real Business Cycles With Involuntary Unemployment", C. V. Starr Center for Applied Economics, NYU, Working Paper 95-12.

Gali, Jordi (1996): "Unemployment in dynamic general equilibrium economies", European Economic 40, 839-845.

Gali, Jordi (1999): "Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?", American Economic Review, Vol. 89, No. 1, 249-271.

Hall, Robert E. (2005): "Employment Fluctuations with Equilibrium Wage Stickiness", American Economic Review, Vol. 95, No. 1, 50-65.

Ireland, Peter N. (2004a): "A Method for taking Models to the Data", Journal of Economic Dynamics and Control.

Ireland, Peter N. (2004b): "Technology Shocks in the New Keynesian Model", Review of Economics and Statistics, 86(4), 923-936.

Kydland, Finn E. (1995): "Business Cycles and Aggregate Labor Market Fluctuations", in Thomas F. Cooley, "Frontiers of Business Cycle Research", Princeton University Press.

Lubik, Thomas A. and Frank Schorfheide (2004): "Testing for Indeterminacy: An Application to U.S. Monetary Policy", American Economic Review, Vol. 94, No. 1, 190-217.

McConnell, Margaret M. and Gabriel Perez-Quiros (2000): "Output Fluctuations in the United States: What Has Changed Since the Early 1980's?", American Economic Review, 90(5), 1464-1476.

Meier, Andre and Gernot J. Müller (2005): "Fleshing Out The Monetary Transmission Mechanism: Output Composition And The Role Of Financial Frictions", European Central Bank Working Paper 500.

Merz, Monika (1995): "Search in the labor market and the real business cycle", Journal of Monetary Economics 36, 269-300.

Michelacci, Claudio and Jose David Lopez-Salido (2004): "Technology Shocks and Job Flows", CEPR Discussion Paper No. 4426.

Newey, Whitney K. and Daniel McFadden (1994): "Large Sample Estimation and Hypothesis Testing", Handbook of Econometrics, Ch. 36.

Ravn, Morten O. (2005): "Labor Market Matching, Labor Market Participation and Aggregate Business Cycles: Theory and Structural Evidence for the US", Working Paper.

Rotemberg, Julio J. and Michael Woodford (1998): "An Optimization-Based Econometric Framework for the Evaluation of Monetary Policy: Expanded Version", NBER Technical Working Paper Series No. 233.

Shapiro, Matthew D., and Mark W. Watson (1988):"Sources of Business Cycle Fluctuations", NBER Working Paper No. 2589.

Shimer, Robert (2005): "The Cyclical Behavior of Equilibrium Unemployment and Vacancies", American Economic Review, Vol. 95, No. 1, 25-49.

Sims, Christopher A., James H. Stock and Mark W. Watson (1990): "Inference in Linear Time Series Models with some Unit Roots", Econometrica, Vol. 58, No. 1, 113-144.

Smets, Frank and Raf Wouters (2002): "An Estimated Stochastic Dynamic General Equlibrium Model of the Euro Area", European Central Bank, Working Paper 171.

Taylor, John B. (1993): "Discretion versus policy rules in practice", Carnegie-Rochester Conference Series on Public Policy 39, 195-214.

Trigari, Antonella (2003): "Labor Market Search, Wage Bargaining and Inflation Dynamics"

Trigari, Antonella (2004): "Equilibrium Unemployment, Job Flows and Inflation Dynamics", ECB Working Paper 304.

Walsh, Carl E. (2003): "Labour market search and monetary shocks", in Sumru Altug, Jagjit S. Chadha and Charles Nolan (eds.), "Dynamic Macroeconomic Analysis: Theory and Policy in General Equilibrium", Cambridge University Press.

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