Three Essays in Empirical Macroeconomics

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Introduction

One of the central and most fundamental questions in the field of empirical macroeconomics is which factors explain movements in macroeconomic aggregates such as output, investment, consumption and inflation. This thesis comprises three self-contained chapters that each contribute new insights to this field. Chapter 1 examines the role of shocks to consumer misperceptions in explaining macroeconomic fluctuations. In the backdrop of the European sovereign debt crisis, Chapter 2 investigates whether the co-movement of the fiscal balance and the current account depends on the indebtedness of the government. Chapter 3 identifies monetary policy shocks for the United Kingdom (U.K.) based on a narrative methodology and estimates the effects of monetary policy on the macroeconomy. The remainder of the introduction provides a more detailed description of each chapter.

Chapter 1. The first chapter estimates the importance of shocks to consumer misperceptions ("noise shocks") in explaining U.S. business cycle fluctuations. A central question that has shaped the area of modern empirical macroeconomics at least since the studies of Sims (1980) and Kydland and Prescott (1982) is: What are the sources of macroeconomic fluctuations? Notable contributions building on these studies are Galí (1999) and Smets and Wouters (2007), who investigate the role of conventional demand, supply and markup shocks in a new Keynesian model framework. Beyond these conventional shocks, a number of studies emphasize the idea of expectation-driven cycles (e.g. Beaudry and Portier, 2004, 2006; Lorenzoni, 2009; Eusepi and Preston, 2011; Angeletos and La'O, 2013). This chapter examines the role of consumer optimism and pessimism induced by "noise shocks" as a source for macroeconomic fluctuations relative to other demand and supply shocks. As noise shocks are not directly observed this chapter proposes an imperfect information model that is used for structural estimation.

In particular, this chapter embeds imperfect information as in Lorenzoni (2009) into a Smets and Wouters (2007)-type dynamic stochastic general equilibrium (DSGE) model and estimates the structural model with Bayesian methods. Agents only observe aggregate productivity and a signal about its permanent component contaminated with noise. Based on this information agents form beliefs about the temporary and the permanent component of productivity. Shocks to the signal ("noise shocks") trigger aggregate fluctuations unrelated to fundamental changes in productivity. Noise shocks explain up to 14 percent of output volatility and up to 25 percent of consumption fluctuations. Counterfactual experiments show that nominal rigidities and the specification of the monetary policy rule are crucial for the importance of noise shocks. These features are crucial to resolve conflicting results in previous literature (see Blanchard, L'Huillier, and Lorenzoni, forthcoming; Barsky and Sims, 2012). Bayesian model comparison cannot sharply distinguish between the incomplete and the full information model. However, the baseline imperfect information model is clearly favored compared to a model specification that is closer to Blanchard et al. (forthcoming), which imposes identical productivity autocorrelation parameters. The smoothed signal co-moves positively with consumer sentiment data from the Michigan Survey of Consumer Sentiments.

Chapter 2.[1] This chapter examines whether the co-movement of the fiscal balance and the current account depends on the government debt-to-GDP ratio. The possible consequences of rising public debt stocks in many European countries have received much attention in the recent policy debate. In the euro zone the average government debt-to-GDP ratio increased from 70 percent to 90 percent between 2008 and 2012. Increasing government debt stocks have brought several European governments to the brink of default and Greece to actually default in 2012. Before and during the beginning of the global financial crisis of 2007-09 several southern European countries experienced increasing fiscal deficits and widening current account imbalances. These observations have rekindled the issue of possible causal linkages of the fiscal balance to the current account — a debate that has received much attention since the observation of twin deficits in the U.S. economy in the 1980s. Since 2008-09,

[1] The work in this chapter has been conducted jointly with Ronald Rühmkorf.

despite protracted fiscal deficits, the current accounts of southern European countries have been rebalancing sharply, suggesting that the link between the twin deficits has diminished. This chapter investigates from an empirical and a theoretical perspective whether the co-movement of the two balances changes with increasing government debt.

The first part of the analysis presents the estimation of a dynamic panel threshold model for 15 European countries to quantify the influence of sovereign indebtedness on the relationship between the fiscal balance and the current account. One advantage of this method is that it allows us to estimate a threshold value for sovereign debt (instead of exogenously imposing a threshold). Below the estimated threshold of 72 percent government debt-to-GDP this study finds a significant, positive relationship between the fiscal balance and the current account, whereas above the threshold the *partial* correlation is insignificant with a point estimate around zero. Splitting the sample into observations above and below the estimated threshold, this chapter shows that the correlation of the two balances falls by 0.19 when moving from the low government debt regime to the high government debt regime. The second part of the analysis provides a structural explanation for the empirical evidence based on a small open economy model allowing for the possibility of sovereign default. High government debt-to-GDP ratios raise non-linear sovereign default risk premia due to the increasing probability of government default and lead to a higher uncertainty about future taxes. Therefore, private saving increases while fiscal deficits are expanding, leading to a less pronounced current account deficit. The model-based correlation of the fiscal balance and the current account declines by 0.15 when moving from a low government debt regime to a high government debt regime, which is in line with the empirical evidence.

CHAPTER 3.[2] This chapter identifies monetary policy shocks based on a new, extensive real-time forecast data set and estimates the effects of these shocks on the U.K. macroeconomy. Despite considerable research on the efficacy of monetary policy a key question in monetary economics still remains: to what extent can monetary policy affect inflation and real outcomes? The predominant finding of widely applied structural vector autoregressive (VAR) models is that the peak effect of monetary policy innovations on prices and output is around 0.5 to 1 per cent. A notable

[2]The work in this chapter has been conducted jointly with James Cloyne.

exception is the narrative identification methodology pioneered by Romer and Romer (2004), which finds effects several times larger than previous studies.[3] Despite the attention given to these findings, there are no other applications of the narrative methodology. Moreover, much of the literature has focused on the U.S. economy. This chapter fills both these gaps, providing new narrative-based estimates of the effects of monetary policy in the U.K. economy.

Chapter 3 argues that the U.K. is an ideal country to conduct the narrative approach: There is a wealth of real-time and forecast data available and Bank Rate is the intended policy target rate.[4] In employing the Romer–Romer methodology this chapter constructs a new, extensive real-time forecast database from historical sources. A first stage regression purges the intended policy target rate of systematic policy changes to the policymakers' real-time information set. Based on the new policy shock series this chapter finds moderate effects of monetary policy on the macroeconomy: A 100 basis points increase in the policy rate reduces output by up to 0.6 per cent and inflation by up to 0.8 percentage points after two to three years. Despite controlling for commodity prizes, oil prizes, and exchange rates a conventional, recursive VAR with Bank Rate produces a persistent prize puzzle. The methodology employed in this chapter resolves the prize puzzle of the U.K. and shows that forecasts are crucial for this result. In addition, Chapter 3 provides a range of robustness checks, among these alternative timing assumptions, single equation regressions, different forecast sources, and sub-samples.

Despite addressing three distinct research questions, each of the three chapters in this thesis aims to shed new light on key issues in the field of empirical macroeconomics. In particular, they examine the role of noise shocks as a driver of the business cycle (Chapter 1), the influence of government indebtedness on the co-movement of the fiscal balance and the current account (Chapter 2) and the narrative identification of monetary policy shocks and its effect on macroeconomic aggregates such as output an inflation (Chapter 3).

[3]This approach follows earlier work using a slightly different narrative identification strategy in Romer and Romer (1989).

[4]For the U.S. Romer and Romer (2004) first need to construct an intended policy target series from historical documents as the federal funds rate is a market rate.

Chapter 1

Consumer misperceptions, uncertain fundamentals, and the business cycle

1.1 Introduction

The notion that consumer optimism or pessimism can cause business cycle fluctuations has a long tradition in economics. It dates back at least to Pigou (1927), who believed that "errors of undue optimism or undue pessimism in their business forecasts" caused industrial fluctuations, and Keynes (1936), who assigned a large role to "animal spirits" in explaining business cycle fluctuations. A number of studies revive the idea of expectation-driven cycles (e.g. Beaudry and Portier, 2004, 2006; Eusepi and Preston, 2011; Angeletos and La'O, 2013). Among these, Lorenzoni (2009) presents a calibrated model where noise shocks or "animal spirit" shocks induce business cycle fluctuations.[1] Noise shocks induce fluctuations in consumers' beliefs unrelated to fundamental changes, generating positive co-movement in consumption, output, employment and inflation.

This chapter provides new empirical evidence on the importance of noise shocks as a driving force of the U.S. business cycle and compares the fit to the perfect information model. Imperfect information as in Lorenzoni (2009) is embedded in a new Keynesian model with price and wage rigidity, investment adjustment costs and variable capital utilization building on the models of Smets and Wouters (2007), Justiniano, Primiceri, and Tambalotti (2010), and Fernández-Villaverde (2010). Consumers are rational and *passively learn* about the fundamentals of the economy by observing noisy signals.[2] Specifically, agents learn about the temporary and the permanent

[1] Lorenzoni (2009) calibrates the signal to generate as much demand-side volatility as possible.
[2] A large literature focuses on different variants of learning, among these rational inattention (e.g.

component of productivity by only observing aggregate productivity and a signal about permanent productivity contaminated with noise. Shocks to the signal ("noise shocks") affect consumers' perception about unobserved productivity components triggering aggregate fluctuations.[3] The main results are: Noise shocks account for 14 percent of output fluctuations and 25 percent of consumption fluctuations on impact. After twelve quarters, they still explain ten percent of output and twelve percent of consumption fluctuations.

Blanchard, L'Huillier, and Lorenzoni (forthcoming) show that the consumers' signal extraction problem implies a non-fundamental vector autoregressive (VAR) representation rendering it impossible to identify noise shocks in a VAR. The filtering problem and the identification of noise shocks require the estimation of a structural model. Building on their contribution I employ Bayesian methods to estimate a medium-scale imperfect information new Keynesian model with several shocks using U.S. data. Based on these estimates it takes consumers about eight quarters to disentangle pure noise from fundamental shocks. Furthermore, smoothed estimates of the signal fit remarkably well to data from the Michigan Consumer Sentiment Survey.

Counterfactual experiments show that nominal rigidities and the specification of the Taylor rule crucially affect the importance of noise shocks – a finding that also helps to reconcile conflicting results on the importance of noise shocks as I discuss later. A positive noise shock triggers a perceived wealth effect as consumers mistake noise for an increase in permanent productivity. The higher is the price stickiness, the stronger the response of aggregate demand. Wage stickiness substantially increases consumption fluctuations even in the presence of moderate price stickiness: Sticky wages imply that firms rationally anticipate reduced fluctuations in their real marginal costs. Hence, inflation variability decreases as compared to the flexible wage case. Less variation in inflation reduces the responsiveness of the real interest rate through the Fisher equation and therefore reduces consumers' willingness to postpone consumption to later periods. Thus, due to a weaker intertemporal substitution effect, households increase consumption more under sticky wages than under flexible wages. In addition, the less responsive the central bank sets interest rates to inflation and real activity,

Makowiak and Wiederholt, 2009) and least-squares learning (e.g. Eusepi and Preston, 2011). In the present chapter learning means that rational agents form beliefs about unobserved state variables.

[3] The model features a variety of conventional supply, demand and markup shocks.

the stronger are the effects of noise shocks through less variation in the real interest rate.

This chapter also compares the fit of the incomplete information model with the model where consumers perfectly observe the state of the economy using marginal likelihoods. The resulting Bayes factor is too small to sharply discriminate between both models. This chapter also estimates the imperfect information model assuming identical autocorrelation parameters for the temporary and permanent productivity process as in Blanchard et al. (forthcoming). The joint dynamics of the data are better matched in the model, allowing for different autocorrelation parameters as measured by the Bayes factor. It is noteworthy that the estimation of the restricted case yields a very high degree of nominal rigidity and small Taylor rule coefficients. In line with my counterfactual analysis these estimates contribute to a much stronger effect of noise shocks on real activity.

Closely related empirical literature does not agree on the importance of noise shocks finding that these shocks explain between zero and 75 percent of short-run fluctuations in consumption. The model framework in this chapter nests the specifications in Blanchard et al. (forthcoming) and Barsky and Sims (2012) allowing to identify the factors that drive the importance of noise shocks. Blanchard et al. (forthcoming) employ a maximum likelihood estimation of a highly stylized new Keynesian model with noise shocks. They find that 75 percent of consumption fluctuations on impact and still more than 50 percent after four quarters are due to noise shocks, while productivity shocks account for the remaining fraction. However, their estimation yields virtually fixed prices running counter to microeconomic evidence on price adjustments (e.g. Bils and Klenow, 2004) and macroeconomic evidence from estimated DSGE models (e.g. Smets and Wouters, 2007). In an extended new Keynesian model similar to the one employed in this chapter (but with identical autocorrelation parameters for temporary and permanent productivity and without price and wage indexation) they find that noise shocks explain more than 50 percent of consumption fluctuations on impact and about 25 percent after two years. Noise shocks account for a large fraction of cyclical fluctuations due to high degrees of nominal rigidity and a very low responsiveness to inflation and output of the interest rate rule.[4] By

[4]Estimates for the average price and wage duration are close to two years and the Taylor rule coefficient on inflation is virtually one.

impulse response function matching Barsky and Sims (2012) estimate a DSGE model featuring price rigidity, habit formation, and capital adjustment costs, finding that noise shocks explain virtually no aggregate fluctuations due to general equilibrium effects. Based on counterfactual analysis this chapter confirms that for intermediate degrees of price rigidity and flexible wages noise shocks do not explain a large fraction of consumption volatility, but in combination with wage rigidity noise shocks do account for a sizable fraction of business cycle fluctuations.

Noise-driven business cycles as presented in this chapter crucially differ from the literature on news-driven business cycle models (e.g. Jaimovich and Rebelo, 2009; Schmitt-Grohé and Uribe, 2012). In their frameworks agents have more information than in the imperfect information setup considered in this work as they perfectly observe current and future productivity ("news") shocks.[5] In addition to the aforementioned studies this chapter is also related to Milani (2007) and Eusepi and Preston (2011). These papers provide a learning mechanism where agents deviate from the rational expectations assumption in that agents learn about parameters of the model from historical data. The focus of this work is instead to analyze an incomplete information model which gives rise to a channel leading agents to temporarily deviate from the complete information model equilibrium. Thus, within an imperfect information model, noise shocks generate business cycle fluctuations in a full rational expectations framework.

The outline of this chapter is as follows. Section 1.2 provides the model, formalizes the imperfect information environment and outlines the solution method. Section 1.3 shows the estimation strategy and results. This section also conducts prior predictive analysis and Bayesian model comparisons. Section 1.4 presents impulse response functions and performs forecast error variance decompositions. Section 1.5 provides a sensitivity analysis based on counterfactual experiments. Section 1.6 provides the conclusion.

[5] In principle, information about future changes may be offset by a new observation in the next period, e.g. a positive news shock to be realized in three periods from today may be offset in period two. As news shocks are typically assumed to be i.i.d., systematic/correlated erroneous beliefs cannot arise.

1.2 The model

This section provides a concise overview of the model which builds on the new Keynesian frameworks of Smets and Wouters (2007), Justiniano et al. (2010) and Fernández-Villaverde (2010). The core elements of the model are relatively standard and therefore this section presents a non-technical description of the model. In addition, the imperfect information setup and the solution method to the imperfect information model are introduced.

1.2.1 Model overview

The model economy is structured as follows: A continuum of households each offers differentiated labor services to intermediate firms, a continuum of monopolistically competitive intermediate goods firms and perfectly competitive final good firms that bundle the intermediate goods. The model is closed by a monetary authority that implements an interest rate feedback rule responding to inflation and output growth. Price and wage rigidity is introduced via a Calvo (1983)-mechanism. Prices and wages that cannot be adjusted follow an indexation rule. Households maximize an additively-separable utility function with habits in consumption and they rent the capital stock to firms subject to variable capital utilization and investment adjustment costs. In addition to noise shocks the model features the following structural shocks: temporary and permanent neutral total factor productivity (TFP), investment-specific TFP, monetary policy, price and wage markup shocks. A detailed outline and derivation of the model economy is provided in Appendix 1.A.

To introduce and formalize the imperfect information setup the production function of intermediate goods is presented. A continuum of monopolistically competitive firms indexed by $i \in [0, 1]$ each produces a differentiated good, $Y_t(i)$, using the same technology

$$Y_t(i) = A_t K_t^{\alpha}(i) N_t(i)^{1-\alpha} - \phi z_t^{profits} \,, \tag{1.1}$$

where the fixed cost of production is ϕ. $K_t(i)$ and $N_t(i)$ are, respectively, the firm's capital and labor input. The aggregate level of technology is given by $A_t = X_t Z_t$, where X_t denotes the permanent and Z_t is the temporary component. The growth rate of the permanent component follows an AR(1) process, which implies that the level X_t builds up gradually over time in response to a shock. The stochastic processes are:

$$\frac{X_t}{X_{t-1}} = \left(\frac{X_{t-1}}{X_{t-2}}\right)^{\rho_x} \exp(\epsilon_{x,t}) \ , \qquad \epsilon_{x,t} \sim \mathcal{N}(0, \sigma_x^2) \tag{1.2}$$

$$Z_t = Z_{t-1}^{\rho_z} \exp(\epsilon_{z,t}) \ , \qquad \epsilon_{z,t} \sim \mathcal{N}(0, \sigma_z^2) \ . \tag{1.3}$$

A conventional assumption in the DSGE literature (e.g. Smets and Wouters, 2007) is that rational agents perfectly observe all states and shocks of the economy. This chapter relaxes the assumption that agents perfectly observe the entire state and instead considers a model of passive learning.[6] Agents behave fully rational given their information sets. Following Lorenzoni (2009) agents only observe aggregate productivity A_t, but neither the exact realization of its permanent nor its temporary component. In addition, consumers observe a noisy signal about the permanent component

$$S_t = X_t \exp(\epsilon_{s,t}) \ , \qquad \epsilon_{s,t} \sim \mathcal{N}(0, \sigma_s^2) \ , \tag{1.4}$$

where σ_s measures the precision of the signal. A shock to the signal is defined as a noise shock. The signal conveys information that helps consumers to infer the actual level of permanent productivity. The additional information comprises, for example, consumer sentiment studies, financial market prices, or sector statistics of the economy. How exactly consumers form beliefs about unobserved variables is addressed in Section 1.2.3.

1.2.2 Linearization

The model features a unit root in productivity A_t and thus, consumption, investment, capital, real wages and output fluctuate around a stochastic non-stationary balanced growth path. Therefore, the model is expressed in terms of detrended

[6] The present chapter assumes that agents learn passively, whereas in models of rational inattention agents learn actively as agents dynamically choose which variables they observe subject to an information capacity restriction (e.g. Sims, 2003; Makowiak and Wiederholt, 2009). The setup is also different from least-squares learning (e.g. Milani, 2007; Eusepi and Preston, 2011) that relaxes the rational expectations assumption.

variables denoted with a 'hat', e.g. $\hat{Y}_t = Y_t/A_t$.[7] A complete list of all detrended first-order conditions can be found in Appendix 1.A.6. Using standard methods, I log-linearize the detrended first-order conditions around the zero price and wage inflation steady state. Henceforth, lower case variables denote log-linear deviations from their steady state.

Aggregate productivity equals the sum of permanent and temporary productivity:

$$\hat{\mu}_t^A \quad = \quad \hat{x}_t + z_t \ . \tag{1.5}$$

The permanent and temporary productivity component are, respectively, given by:

$$\begin{aligned} \hat{x}_t &= \rho_x \hat{x}_{t-1} - \rho_x \hat{x}_{t-2} - z_{t-1} + \rho_x \hat{\mu}_{t-2}^A + \epsilon_{x,t} \ , \quad && \epsilon_{x,t} \sim \mathcal{N}(0, \sigma_x^2) && (1.6) \\ z_t &= \rho_z z_{t-1} + \epsilon_{z,t} \ , && \epsilon_{z,t} \sim \mathcal{N}(0, \sigma_z^2) \ . && (1.7) \end{aligned}$$

For identical autocorrelation coefficients $\rho_x = \rho_z$ the variances of both shocks are linearly dependent under the assumption:

$$\rho_x \sigma_x^2 = (1 - \rho_x)^2 \sigma_z^2 \equiv \sigma_A^2 \ , \tag{1.8}$$

where σ_A^2 denotes the variance of aggregate productivity growth $\hat{\mu}_t^A$. The noisy signal $\hat{s}_t$ is correlated with permanent productivity:

$$\hat{s}_t = \hat{x}_t + \epsilon_{s,t} \ , \qquad \epsilon_{s,t} \sim \mathcal{N}(0, \sigma_s^2) \ . \tag{1.9}$$

1.2.3 Information structure

Consumers imperfectly observe the state of the economy and are exposed to non-fundamental noise shocks.[8] Agents observe aggregate productivity and a noisy signal about the permanent component of productivity. The signal represents additional information that improves the consumers' estimate about the true permanent productivity. A noise shock, $\epsilon_{s,t}$, affects private sector beliefs about components of productivity and induces consumers to temporarily over- or underestimate the actual

[7] The variables A_t, X_t and S_t are detrended with lagged productivity A_{t-1}. The growth rate of TFP is denoted by $\mu_t^A = A_t/A_{t-1}$.

[8] Noise shocks are non-fundamental in the sense that they do not actually change productivity.

productivity of the economy triggering perceived wealth effects.

The information structure captures the notion that agents form erroneous beliefs about unobserved fundamentals of the economy and thereby generate short-run fluctuations. Having observed aggregate productivity and the signal, consumers update their beliefs about the permanent and the temporary component via the Kalman filter. As the system of equations is linear and all shocks are Gaussian, using the Kalman filter implies that consumers process information in the most efficient way (see Hamilton, 1994, Chapter 13).

Consumers' beliefs about the unobserved variables follow the law of motion (see Appendix 1.B for a detailed derivation):

$$\begin{pmatrix} \hat{x}_{t|t} \\ \hat{x}_{t-1|t} \\ z_{t|t} \\ \hat{\mu}^A_{t-1|t-1} \end{pmatrix} = A \begin{pmatrix} \hat{x}_{t-1|t-1} \\ \hat{x}_{t-2|t-1} \\ z_{t-1|t-1} \\ \hat{\mu}^A_{t-2|t-2} \end{pmatrix} + B \begin{pmatrix} \hat{\mu}^A_t \\ \hat{s}_t \end{pmatrix} . \tag{1.10}$$

To clarify notation, $\hat{x}_{t-1|t}$ denotes the consumers' belief about the unobserved state $\hat{x}_{t-1}$ at time t or equivalently $\hat{x}_{t-1|t} = \mathbb{E}_t\left[\hat{x}_{t-1}|\mathcal{I}_t\right]$, where $\mathcal{I}_t$ denotes the consumers' information set comprising all observables up to period t.[9] Solving the filtering problem numerically yields the elements of matrix A and B which are non-linear functions of the parameters $\rho_x, \rho_z, \sigma_x, \sigma_z$ and σ_s. The elements of matrix A indicate how much past beliefs affect contemporaneous beliefs. The coefficients in matrix B indicate how much weight consumers give to each observable.

Noise shocks provide interesting dynamics as the shock size interacts non-linearly with its contribution to business cycle fluctuations. At intermediate values of the signal precision agents place some weight on the signal and thus will respond to this information. For imprecise signals (large σ_s) agents place very little weight on the information they convey. In contrast, perfectly observed structural shocks in the model will cause larger effects on macroeconomics variables the higher the standard deviation of each shock.

[9] Lagged productivity growth $\hat{\mu}^A_{t-1|t-1}$ is perfectly observed; however the variable is needed to derive the detrended process for the permanent productivity component $\hat{x}_{t|t}$.

1.2.4 Solution method

Solving DSGE models where agents receive noisy information and learn about unobserved state variables necessitates an adjustment of conventional solution methods. Using conventional solution methods for rational expectations models (see Klein, 2000; Sims, 2002) the full-information log-linearized model is solved by a first-order approximation around the steady state. All agents' behavior is fully rational given their information set. This behavior implies agents optimally form expectations about unobserved states from the set of observables by employing the Kalman filter to solve the signal extraction problem. In the linearized model equilibrium certainty-equivalence applies.[10] Consequently agents behave as if the optimal forecast of an unobserved state is the true state variable. Hence, consumers' beliefs, $(\hat{x}_{t|t}, \hat{x}_{t-1|t}, z_{t|t})$, about the unobserved state variables subsequently replace the respective actual state variables in the log-linearized state space representation under perfect information. Baxter, Graham, and Wright (2011) provide a general overview of solution methods for rational expectation models with various informational frictions.

To illustrate the solution procedure more clearly the full-information model solution in state space representation is given by

$$X_{1,t} = \Pi X_{2,t-1} \;, \tag{1.11}$$

$$X_{2,t} = M X_{2,t-1} + \tilde{R}\epsilon_t \;, \tag{1.12}$$

where $X_{1,t}$ is the vector of control variables, $X_{2,t}$ contains all state variables and $\tilde{R}$ is a matrix that scales the shock vector ϵ_t. The matrices M and Π map lagged state variables to contemporaneous state variables and to control variables, respectively. To solve the imperfect information model the unobserved states are then replaced by their estimated counterparts such that the control variables $X_{1,t}$ are a linear function of the estimated, unobserved states, i.e.

$$X_{1,t} = \Pi X_{2,t-1|t-1} \;, \tag{1.13}$$

where, importantly, the coefficients of the policy function, Π, are identical to those

[10]The literature often explores linearized models of imperfect information (e.g. Lorenzoni, 2009; Nimark, 2013) rather than solving a fully non-linear imperfect information model.

obtained in the complete-information solution. Appendix 1.C provides further details on the solution method.

1.3 Estimation methodology

To address the central question how much noise shocks contribute to U.S. business cycle fluctuations I estimate the model using Bayesian methods and compute variance decompositions. A full information structural estimation technique is required to avoid identification problems that arise due to the consumers' signal extraction problem. Blanchard et al. (forthcoming) show that if agents face a signal extraction problem as considered in the present chapter, the DSGE model exhibits a non-invertible VAR representation in the observables, i.e. there exists no mapping from the reduced form residuals into the structural shocks of the model. Given that the model is not invertible one cannot identify the structural shocks via any identification scheme in a structural VAR. However, these authors as well as Leeper, Walker, and Yang (2009) show that it is possible to use a full-information estimation approach such as maximum likelihood or Bayesian methods in order to identify the structural shocks. This chapter pursues the latter approach and uses prior information about certain parameter values.

First, a prior predictive analysis demonstrates that noise shocks are likely to explain a moderate fraction of consumption and output growth fluctuations, but much less of investment volatility. Second, the results of the posterior distributions are presented. Third, this section compares the fit of various model specifications employing Bayesian model comparison techniques.

1.3.1 Data

The model is estimated using six quarterly U.S. time series for the sample period 1970:1 to 2011:4. The data series are log differences in consumption, investment, real wages, productivity, inflation, and the effective federal funds rate.[11] The steady state growth rate of TFP is set to unity and accordingly all variables prior to estimation

[11] The data sources and the construction of the series in the observation equation are reported in Table 1.6 and Table 1.7 of Appendix 1.D.

are demeaned. The observation equation relates the observed data to the respective counterparts in the model:

$$\mathcal{Y}_t = \begin{pmatrix} \Delta \log(\mathrm{C}_t) \\ \Delta \log(\mathrm{I}_t) \\ \Delta \log(\mathrm{W}_t) \\ \Delta \log(\mathrm{A}_t) \\ \Delta \log(\mathrm{GDPDEF}_t) \\ \mathrm{FFR}_t \end{pmatrix} = \begin{pmatrix} \hat{c}_t - \hat{c}_{t-1} + \hat{a}_{t-1} \\ \hat{i}_t - \hat{i}_{t-1} + \hat{a}_{t-1} \\ \hat{w}_t^r - \hat{w}_{t-1}^r + \hat{a}_{t-1} \\ \hat{a}_t - \hat{a}_{t-1} \\ \pi_t \\ r_t \end{pmatrix}. \tag{1.14}$$

In addition to many likelihood-based estimation studies of DSGE models the observation equation includes neutral TFP growth. The real-time productivity series of Kimball, Fernald, and Basu (2006) is the best available TFP measure as it is adjusted for variations in factor utilization. In particular the series facilitates the estimation of the productivity process parameters, which affect how long consumers take to disentangle actual changes in productivity from pure noise shocks.[12]

1.3.2 Fixed parameters

Prior to estimation a set of parameters is fixed (see Table 1.1). The discount factor β is set to 0.99 as the model is matched to quarterly frequency. The fixed cost of production ϕ is matched to maintain zero profits in steady state. Productivity growth is set to unity ($\mu^A = 1$) as the model is matched to demeaned data. Capital depreciation is 2.5 percent per quarter. The steady state price and wage markup are each set to 12.5 percent.

1.3.3 Prior distributions

Prior distributions are in line with those commonly employed in the literature (see Smets and Wouters, 2007; Justiniano et al., 2010; Fernández-Villaverde, 2010). Table 1.3 displays an overview of the prior choices. Prior means are set to match

[12] Adding output growth would require to add measurement error as the resource constraint would otherwise postulate a linear relationship in the observables (see Schmitt-Grohé and Uribe, 2012). For this reason the model is estimated without output growth.

Table 1.1: Parameters fixed prior to estimation

Parameter	Value	Description/Target
β	0.99	Stochastic discount factor
ϑ	8	Steady state labor hours: 0.35
u	1	Steady state capital capacity utilization
ϕ	0.045	Zero profits in steady state
μ^A	1	Growth rate of productivity
δ	0.025	Annual depreciation rate of 10%
η_p	9	Steady state price markup of 12.5%
η_w	9	Steady state wage markup of 12.5%

estimates from previous studies and the standard errors are selected to cover a wide range of values including those of previous estimates.

The price and wage stickiness parameter are drawn from a beta distribution with a prior mean value that implies an average price and wage duration of 3 quarters and a standard deviation of 0.1. According to the terminology in Del Negro and Schorfheide (2008), who perform a detailed analysis of choosing prior distributions for these two parameters, the prior mean is in the middle of their categories *agnostic* and *high rigidities*. Price and wage indexation also follow a beta distribution with mean 0.7 and standard deviation 0.1. For the Taylor rule coefficients on inflation I select a normal distribution with mean 1.4 and standard deviation 0.125 and on output growth a mean and standard deviation of 0.1.

Autocorrelation parameters follow a diffuse beta distribution which is naturally bounded on the unit interval. Concerning the prior assumption for the standard errors of the structural shocks, I assume an inverse gamma distribution which has positive support with mean 1 and a standard deviation of 5, except for permanent productivity where I choose a smaller mean of 0.5. This choice is motivated by the observation that small shocks to the permanent component induce large level effects. The prior mean for the precision of the signal is 1 percent — a value that also covers the range of estimates in Blanchard et al. (forthcoming). The remaining parameters are drawn from prior distributions comparable to those selected in Smets and Wouters (2007), Justiniano et al. (2010) and Fernández-Villaverde (2010).

1.3.4 Prior predictive analysis

A prior predictive analysis is used to assess how strongly structural shocks affect business cycle fluctuations and in particular to show that consumption and output dynamics are not a priori driven by noise shocks. This method is used to verify the importance of each structural shock in generating business cycle fluctuations based on the theoretical model given the specified priors, before confronting the model with actual data.

Simulating the prior predictive of a model has been employed recently by Leeper, Traum, and Walker (2011) to compare variants of DSGE models in generating fiscal multipliers. In the same spirit the range of variance decompositions implied by the model and the priors is explored. The *ex-ante* predictive distribution for the observables is

$$p(y) = \int_{\Theta} p(\theta)p(y|\theta)d\theta \ , \tag{1.15}$$

where $p(\theta)$ is the prior distribution and $p(y|\theta)$ is the model distribution. The prior distribution of observables $p(y)$ is simulated by drawing from $\theta^{(m)}$, and $y^{(m)} \sim p(y|\theta^{(m)})$ for $m = 1, .., 50000$. Based on simulated values of observables the vector of interest ω, i.e. the forecast error variance decomposition $p(\omega|y, \theta)$, is computed.

To provide a fair comparison and to be consistent with the empirical DSGE literature the standard deviations for all shocks are drawn from the same prior distribution except for the permanent productivity shock which has a smaller mean for the reasons discussed before.[13] Table 1.2 presents the results. Noise shocks explain between zero and ten percent of consumption as well as of output fluctuation and very little of investment growth volatility. Monetary policy and TFP shocks explain the largest fraction of consumption, investment, output and wage fluctuations. Wage markup shocks virtually do not account for business cycle fluctuations as their shock size is relatively small (compared to the estimated value as is shown later). Price markup shocks mostly drive wage and output growth volatility. As expected, investment-specific TFP shocks mostly account for investment dynamics. How much each structural shock actually contributes to the business cycle crucially depends on

[13] Studies that use identical prior distributions for each shock are for example Rabanal and Rubio-Ramírez (2005); Smets and Wouters (2007); Fernández-Villaverde (2010); Leeper et al. (2010); Justiniano et al. (2010).

Table 1.2: Prior predictive probability distribution: variance decomposition

	Temp. TFP	Perm. TFP	Invest.-spec. TFP	Monetary policy	Price markup	Wage markup	Noise
				Consumption growth			
Quarters							
1	14.2 [1.0,36.8]	46.1 [3.3,92.2]	0.1 [0,0.2]	30.2 [0.4,92.3]	5.2 [0,26.8]	0.1 [0,0.2]	4.0 [0.1,9.8]
4	8.8 [0.8,22.1]	58.7 [7.0,93.2]	0.1 [0,0.3]	24.4 [0.2,88.1]	3.9 [0,18.9]	0.1 [0,0.1]	4.0 [0.2,9.2]
12	8.6 [0.8,21.5]	58.4 [6.6,93.2]	0.3 [0,0.7]	24.9 [0.2,88.6]	4.1 [0,20.1]	0.1 [0,0.1]	3.8 [0.2,9.0]
				Investment growth			
Quarters							
1	12.4 [0.6,32.7]	32.3 [0.9,82.7]	11.9 [0.1,59.2]	31.6 [0.6,92.6]	9.7 [0.1,49.5]	0.3 [0,0.6]	1.9 [0,6.4]
4	6.4 [0.5,14.6]	52.5 [3.5,91.5]	10.2 [0.1,52.8]	23.2 [0.2,86.2]	6.3 [0.0,33.3]	0.2 [0,0.4]	1.2 [0,3.2]
12	4.9 [0.5,11.9]	58.6 [5.8,93.8]	8.7 [0.1,45.7]	21.1 [0.2,83.6]	5.6 [0.0,29.3]	0.2 [0,0.3]	0.9 [0,2.3]
				Output growth			
Quarters							
1	12.9 [0.8,34.7]	42.9 [2.6,91.3]	2.7 [0,13.0]	31.0 [0.5,92.4]	6.7 [0,35.3]	0.1 [0,0.3]	3.7 [0.1,9.5]
4	7.8 [0.7,19.7]	57.2 [6.3,92.7]	2.0 [0,8.6]	24.6 [0.3,87.7]	4.9 [0,25.0]	0.1 [0,0.2]	3.5 [0.1,8.5]
12	7.4 [0.7,18.7]	57.6 [6.2,92.8]	1.8 [0,7.9]	24.8 [0.3,88.1]	5.0 [0,25.9]	0.1 [0,0.2]	3.3 [0.1,8.1]
				Wage growth			
Quarters							
1	19.8 [2.1,40.0]	43.2 [3.8,84.1]	0.4 [0,1.0]	4.8 [0,27.7]	29.4 [0.5,90.0]	0.4 [0,1.1]	2.1 [0,6.6]
4	8.5 [1.4,16.8]	67.3 [13.1,93.8]	0.3 [0,0.7]	3.6 [0,19.6]	19.0 [0.2,78.2]	0.2 [0,0.5]	1.1 [0,2.9]
12	6.4 [1.4,14.1]	73.2 [18.0,96.2]	0.4 [0,1.0]	3.4 [0,18.6]	15.7 [0.1,71.6]	0.2 [0,0.4]	0.8 [0,2.0]

Notes: The table reports mean values with 5 and 95 percentiles in brackets.

the estimated standard deviation of the shock.

The importance of noise shocks changes non-linearly with the precision of the signal, as agents put more or less weight on its reliability to be informative about the true fundamentals of the economy. For all other shocks in the model it holds that the higher the standard deviation the stronger the effect of the shock. The range of the 5 and 95 percentile is relatively tight for noise shocks (it ranges from zero to ten percent for consumption fluctuations on impact) and covers a larger range for permanent TFP, monetary policy and price markup shocks.[14] Choosing prior means

[14]The estimated standard deviation of monetary policy shocks is one fourth smaller and for markup shocks it is substantially higher such that their relative importance in a variance decomposition of the model simulated at the posterior mean is different from the findings based on a prior predictive analysis.

for the standard deviations closer to those in the estimated model yields stronger noise-driven business cycles. A priori the model is flexible in the dimension that noise shocks can in principle account for various amounts of business cycle fluctuations. The next section estimates the model and presents variance decompositions based on actual U.S. post-war data.

1.3.5 Posterior distributions

Following the steps in An and Schorfheide (2007) and Fernández-Villaverde (2010) I estimate the vector of parameters Θ using Bayesian methods. Denote the observed data series by $\{\mathcal{Y}_t\}_{t=1}^T$. Using the Kalman filter I obtain the likehood $\mathcal{L}\left(\{\mathcal{Y}_t\}_{t=1}^T|\Theta\right)$ from the state space representation of the model. The posterior distribution $p\left(\Theta|\{\mathcal{Y}_t\}_{t=1}^T\right)$ is proportional to the likelihood times the prior $p\left(\Theta\right)$:

$$p\left(\Theta|\{\mathcal{Y}_t\}_{t=1}^T\right) \propto \mathcal{L}\left(\{\mathcal{Y}_t\}_{t=1}^T|\Theta\right) p\left(\Theta\right). \tag{1.16}$$

Since no closed-form solution for the posterior distribution exists, I resort to numerical methods. The Chris Sims optimization routine is employed to compute the posterior mode and the Hessian evaluated at the posterior mode. Given the posterior mode, I use the random-walk Metropolis-Hastings algorithm to sample from the posterior density. The scale parameter for the jumping distribution is chosen to match an average acceptance rate of 31 percent. Two chains with $750,000$ draws each are generated of which the last $150,000$ draws of each chain are used to compute posterior statistics, which were sufficient to obtain convergence of the MCMC chains. Further diagnostics and prior versus posterior plots are reported in Appendix 1.F.[15]

Table 1.3 reports the estimated means of the posterior distribution and the 5 and 95 percentiles.[16] The posterior mean value for the precision of noise shocks is 0.31%, indicating a much higher signal precision than the estimate in Blanchard et al. (forthcoming). Their estimate is five times larger ($\sigma_s = 1.47\%$) and lies outside the 5 and 95 percentile of the posterior distribution of this study. Nonetheless the

[15] This appendix also includes the fit of the observables to actual data and check plots for the maximization of the posterior mode. In addition the identification checks of Iskrev (2010) confirm that given the vector of observables all parameters are identifiable at the prior mean.

[16] The estimation is carried out in an adapted code of Dynare 4.3.3. to incorporate the solution method as described in Section 1.2.4.

estimated signal precision in this study remains sufficiently noisy indicating substantial misperceptions of consumers about the true underlying productivity processes. Calvo parameter estimates imply an average price and wage duration of ten and three quarters, respectively. Previous literature provides estimates for price stickiness typically ranging from 0.66 to 0.87 and for wage stickiness around 0.68 to 0.70 (see Smets and Wouters, 2007; Justiniano et al., 2010; Fernández-Villaverde, 2010). The Taylor rule coefficient for inflation is 1.14 and for output growth the estimate is 0.21. The persistence of nominal interest rates is 0.8. The estimated Taylor rule coefficients are very similar to previous estimates in the literature (e.g. Fernández-Villaverde, 2010).

The autocorrelation parameter of the productivity processes, $\rho_x = 0.97$, implies that the permanent component increases gradually and the temporary component decreases slowly ($\rho_z = 0.92$). As expected, the standard deviation for permanent productivity is much smaller than for temporary productivity ($\sigma_x = 0.15\%$ and $\sigma_z = 0.77\%$). In line with Smets and Wouters (2007) the standard deviation for the wage markup shock is relatively large. This finding has triggered an extensive literature about what accounts for the finding that wage markup shocks explain about 50% of real GDP fluctuations.[17]

The remaining parameters for habits in consumption, adjustment costs in investment and utilization costs are close to previous estimates. The capital share $\alpha = 0.1$ is below the estimate of other papers, among these Justiniano, Primiceri, and Tambalotti (2013) find $\alpha = 0.16$. The inverse Frisch elasticity of $\varphi = 1.18$ is comparable with preceding findings in the literature (e.g. Fernández-Villaverde, 2010).

[17] Justiniano et al. (2013) use two different measures of wage inflation and estimate a medium-scale model with measurement error in wages growth to account for high frequency movements in the series and find that this strongly reduces the variation in worker's quarter-on-quarter monopoly power. Wage markup shocks are observationally equivalent to labor supply shocks (not included in the model) and therefore difficult to interpret (see also the discussion in Chari et al., 2009). The work by Galí, Smets, and Wouters (2011) extends the model to include involuntary unemployment, which overcomes the identification problem outlined in Chari et al. (2009) when using unemployment data. In order to keep the model tractable and to trace out the importance of noise shocks relative to other shocks – be it preference or markup shocks – the inclusion of unemployment is left for further research.

Table 1.3: Prior and posterior distribution of incomplete information model

		Prior			Posterior		
Parameter	Description	Distr.	Mean	Std	Mean	5%	95%
h_c	Habit persistence	$\mathcal{B}$	0.6	0.1	0.82	0.78	0.85
κ	Investment adj. costs	$\mathcal{N}$	6	2	8.99	6.68	11.27
α	Capital share	$\mathcal{B}$	0.3	0.1	0.10	0.05	0.14
φ	Inverse Frisch elasticity	$\mathcal{G}$	2	0.75	1.18	0.42	1.90
δ_2	Capital utilization costs	$\mathcal{N}$	0.2	0.1	0.13	0.05	0.21
θ_p	Price stickiness	$\mathcal{B}$	0.7	0.1	0.90	0.87	0.93
θ_w	Wage stickiness	$\mathcal{B}$	0.7	0.1	0.66	0.55	0.79
χ_p	Price indexation	$\mathcal{B}$	0.7	0.2	0.81	0.67	0.96
χ_w	Wage indexation	$\mathcal{B}$	0.7	0.2	0.59	0.37	0.83
γ_{dy}	Taylor rule: output growth	$\mathcal{N}$	0.1	0.1	0.21	0.08	0.33
γ_π	Taylor rule: inflation	$\mathcal{N}$	1.4	0.125	1.14	1.04	1.24
γ_R	Interest rate smoothing	$\mathcal{B}$	0.7	0.1	0.80	0.77	0.83
ρ_{is}	Inv.-specific TFP	$\mathcal{B}$	0.8	0.1	0.66	0.55	0.77
ρ_x	Perm. neutral TFP	$\mathcal{B}$	0.8	0.1	0.97	0.95	0.99
ρ_z	Temp. neutral TFP	$\mathcal{B}$	0.8	0.1	0.92	0.89	0.95
ρ_p	Price markup	$\mathcal{B}$	0.7	0.1	0.55	0.38	0.74
ρ_w	Wage markup	$\mathcal{B}$	0.7	0.1	0.92	0.88	0.97
ρ_{plag}	Lagged price markup	$\mathcal{B}$	0.5	0.1	0.49	0.39	0.60
ρ_{wlag}	Lagged wage markup	$\mathcal{B}$	0.5	0.1	0.58	0.48	0.67
$100\sigma_s$	Noise shock	$\mathcal{IG}$	1	5	0.31	0.2	0.41
$100\sigma_x$	Perm. TFP	$\mathcal{IG}$	0.5	5	0.15	0.11	0.19
$100\sigma_z$	Temp. TFP	$\mathcal{IG}$	1	5	0.77	0.7	0.84
$100\sigma_m$	Monetary policy	$\mathcal{IG}$	1	5	0.26	0.24	0.28
$100\sigma_{is}$	Investment-spec. TFP	$\mathcal{IG}$	1	5	9.46	6.37	12.63
$100\sigma_p$	Price markup	$\mathcal{IG}$	1	5	3.34	2.32	4.32
$100\sigma_w$	Wage markup	$\mathcal{IG}$	1	5	13.28	4.44	24.17

Notes: The estimated incomplete information model $\mathcal{M}_1$. $\mathcal{B}$ is beta distribution, $\mathcal{G}$ is gamma distribution, $\mathcal{IG}$ is inverse gamma distribution, $\mathcal{N}$ is normal distribution.

1.3.6 Model comparisons

Bayesian estimation techniques are well-suited to compare various model specifications (see Fernández-Villaverde and Francisco Rubio-Ramirez, 2004; An and

Schorfheide, 2007). Previous results of this chapter were based on the assumption that agents in the economy imperfectly observe the state of the economy. The imperfect information model $\mathcal{M}_1$ is compared to the model with perfect information $\mathcal{M}_2$, i.e. the permanent and the temporary productivity process are perfectly observed and, hence, the signal is superfluous. A meaningful comparison of marginal likelihoods requires the estimation with the same vector of observables for each model. For this reason the precision of the signal is set to zero ($\sigma_s = 0$), such that the signal perfectly reveals the true state of the economy.

The posterior odds ratio is the product of the prior odds ratio times the marginal likelihoods of both models $\mathcal{M}_1$ and $\mathcal{M}_2$:

$$\frac{p\left(\mathcal{M}_1|\{\mathcal{Y}_t\}_{t=1}^T\right)}{p\left(\mathcal{M}_2|\{\mathcal{Y}_t\}_{t=1}^T\right)} = \frac{p(\mathcal{M}_1)}{p(\mathcal{M}_2)} \frac{p\left(\{\mathcal{Y}_t\}_{t=1}^T|\mathcal{M}_1\right)}{p\left(\{\mathcal{Y}_t\}_{t=1}^T|\mathcal{M}_2\right)} \,. \tag{1.17}$$

The ratio of the marginal likelihoods, the Bayes factor, is used to compare the fit of models. The Bayes factor takes into account the number of estimated parameters and, thus, favors a parsimonious model specification.

The marginal likelihood for the imperfect information model is -922.1 and that for the perfect information model is -916.2. Hence, the model with perfect information is $e^{5.9}$ times more likely to be the data generating process than the model with imperfect information. On grounds of the Bayes factor it is difficult to judge this as decisive evidence in favor of the complete information model. Marginal likelihoods are very sensitive to small changes in the model specification and typically the differences in the marginal likelihoods are much larger. For example, Rabanal and Rubio-Ramírez (2005) and An and Schorfheide (2007) compare various specifications of a new Keynesian model and interpret a Bayes factor of the magnitude e^5 not as conclusive evidence as it is too small.

To ensure better comparability to previous literature I estimate the imperfect information model under the assumption that $\rho_x \equiv \rho_z$ ($\mathcal{M}_3$).[18] Comparing the restricted imperfect information model to the one that allows for different coefficients in the productivity processes I find that the unrestricted model explains the data much better. The Bayes factor implies that the baseline specification is $e^{58.7}$ times more likely than the special case with identical parameters for the productivity processes.

[18]The estimation results are shown in Appendix 1.E.

Table 1.4: Log marginal densities

Specification	$p\left(\{\mathcal{Y}_t\}_{t=1}^{T} \vert \mathcal{M}_i\right)$	Bayes factor
Imperfect info model $\mathcal{M}_1$	-922.1	1
Perfect info model $\mathcal{M}_2$	-916.2	exp(5.9)
Imperf. info model ($\rho_x = \rho_z$) $\mathcal{M}_3$	-981.2	exp(58.7)

Notes: The marginal density of the data conditional of the model is computed with the modified harmonic mean estimation as defined by Geweke (1999).

The restricted model forces $\rho_x \equiv \rho_z (= 0.95)$ and the estimated signal is less precise as σ_s increases from 0.31% to 0.51%. It is noteworthy that the estimated Taylor rule parameters change substantially: The inflation coefficient is at the bound to the indeterminacy region ($\gamma_\pi = 1.001$) and the reaction to output growth becomes weaker ($\gamma_{dy} = 0.08$). In fact, these estimates are very similar to Blanchard et al. (forthcoming) who assume that $\rho_x = \rho_z$ and who find ($\gamma_\pi = 1.01$ and $\gamma_y = 0.02$) that noise shocks account for a much higher fraction of consumption and output fluctuations. Later, Section 1.5 investigates the sensitivity of noise shock induced business cycles for various specifications of the Taylor rule and nominal rigidities.

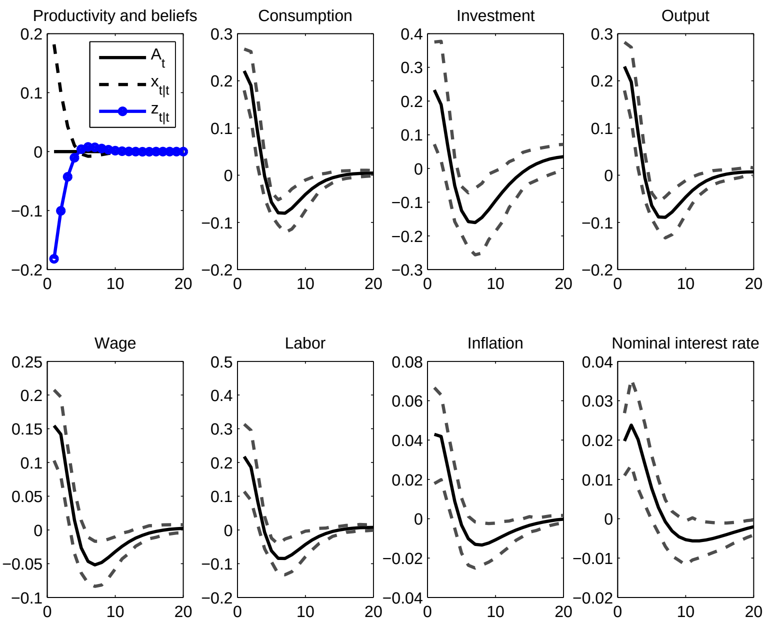
1.4 Results

1.4.1 Impulse responses

Figure 1.1 depicts the impulse response functions to a one standard deviation noise shock with parameter values at their posterior mean together with 90 percent confidence bands. The upper left panel shows the evolution of beliefs about permanent ($x_{t|t}$) and temporary ($z_{t|t}$) productivity. When a positive noise shock materializes, consumers believe that permanent productivity has increased. However, as they have not yet observed a change in aggregate productivity, they believe that a negative temporary productivity shock offsets the permanent shock. It takes about eight quarters until agents have learned that the productive capacity of the economy has actually not changed. The signal shock itself is not persistent, but the beliefs about the unobserved states are erroneous for a few quarters as it takes time until consumers have disentangled fundamental shocks from noise shocks.

The perceived wealth effect induced by noise shocks increases consumption, investment and output like a conventional demand shock. To clear the labor market hours worked increase and real wages temporarily rise. Monetary policy reduces inflationary pressures by increasing interest rates. Nominal rigidities and the Taylor rule affect the real interest rate response and, thus, crucially affect the strength of the intertemporal substitution effect.

Figure 1.1: Impulse responses to a noise shock



Notes: Impulse responses to a one standard deviation noise shock with parameters at their posterior mean value. Dashed gray lines indicate 90 percent confidence bands. All variables are measured in percentage deviations from steady state (x-axis). A time unit is a quarter (y-axis).

The dynamics after an expansionary monetary policy shock are similar to those induced by a noise shock as both are demand shocks (see Figure 1.4 in Appendix 1.E). Importantly, both shocks are not observationally equivalent, which would complicate the identification of shocks. Two crucial differences emerge: First, noise shocks cause strong hump-shapes and macroeconomic variables overshoot a few quarters after the shock. Second, a positive noise shock induces an economic expansion accompanied by an increase in the nominal interest rate to reduce inflation, whereas a surprise increase in the nominal interest rate decreases demand and, therefore, has contractionary effects on the observed variables. These differences in the conditional moments ensure that both shocks are separately identified in the estimation.

1.4.2 Business cycle contribution of noise shocks

The forecast error variance decomposition evaluates the quantitative importance of noise shocks relative to conventional sources such as supply, demand, and markup shocks in explaining business cycles. Table 1.5 reports the conditional forecast error variance decomposition for output, consumption, investment and wage growth. Noise shocks explain 25 percent of consumption growth fluctuations on impact and still account for about 15 percent after four quarters and 12 percent in the longer term.[19] Eventually wage markup and permanent productivity shocks explain the highest fraction of consumption volatility. As noise shocks do not fundamentally change macroeconomic conditions and rational agents learn the true nature of shocks roughly within two years, it is natural that the importance of noise shocks vanishes over time. Nonetheless, noise shocks account for substantial short-term dynamics. Monetary policy shocks virtually do not affect consumption and output growth. The latter is mostly driven by neutral and investment-specific TFP shocks as well as by wage markup shocks in consensus with Smets and Wouters (2007). The impact effect of noise shocks on output growth is 14 percent and around 10 percent at the four to twelve quarter horizon. Wage growth is mainly driven by both markup shocks.

Justiniano et al. (2010) estimate a similar new Keynesian model with perfect information finding that preference shocks explain more than 50 percent of consumption fluctuations. Preference shocks affect the economy via the intertemporal Euler equation. Noise shocks have similar features but offer a different interpretation about business cycle episodes. While ad-hoc preference shocks are difficult to interpret, noise shocks emerge naturally in a model of imperfect information and square well with the notion that consumer sentiments partially drive cyclical fluctuations. In line with my findings neutral TFP shocks are the second most important driver of consumption fluctuations in their study. More than 60 percent of output fluctuations are

[19] As noted earlier the precision of the signal interacts non-linearly with the shock size. Noise shocks explain the largest fraction of consumption fluctuations at intermediate degrees of the signal precision (see Figure 1.5 in Appendix 1.E).

Table 1.5: Forecast error variance decomposition

	Temp. TFP	Perm. TFP	Invest.-spec. TFP	Monetary policy	Price markup	Wage markup	Noise
			Consumption growth				
Quarters							
1	9.6	9.1	0.2	6.6	7.4	42.4	24.9
4	5.2	47.8	0.2	4.0	4.0	23.3	15.5
12	3.9	58.0	0.2	3.4	3.5	18.8	12.1
			Investment growth				
Quarters							
1	0.9	0.4	84.9	2.4	4.4	6.2	0.7
4	1.3	2.9	80.0	2.7	4.1	8.0	0.9
12	1.6	3.4	77.8	2.7	4.1	9.5	0.8
			Output growth				
Quarters							
1	4.9	5.1	38.7	5.0	6.7	25.5	14.2
4	3.8	35.0	21.8	4.0	4.7	19.2	11.5
12	3.1	44.4	17.7	3.7	4.4	17.1	9.6
			Wage growth				
Quarters							
1	1.7	2.3	0.2	1.0	24.4	63.6	6.8
4	1.7	24.1	0.4	1.1	18.6	47.1	6.9
12	1.5	36.9	0.4	1.0	15.4	39.1	5.7

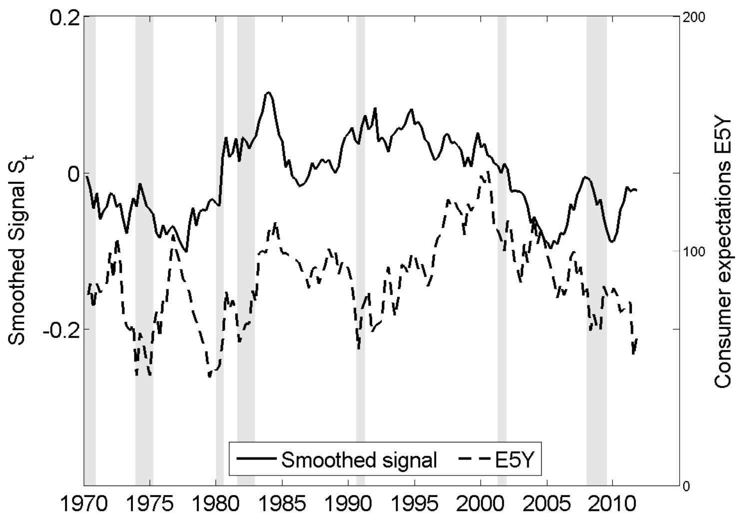
Notes: Forecast error variance decomposition with parameter values at posterior mean.

driven by neutral and investment-specific TFP shocks, also comparable to Justiniano et al. (2010) who report 75 percent. Investment fluctuations are mainly driven by investment-specific TFP shocks and price markup shocks. They find more than 80 percent is accounted for by investment-specific shocks as compared to 78 percent for a twelve quarter horizon in the present study. Finally, in accordance with Justiniano et al. (2010) price and wage markup shocks explain the bulk of variation in wage growth.

1.4.3 Business cycle episodes of consumers' signal

The noisy signal in the model is correlated with trend productivity to capture that consumers and firms typically have more information about the state of the economy than only aggregate productivity data. To draw a retroperspective history of U.S. business cycles smoothed estimates of the signal are backed out based on the Kalman filter. Figure 1.2 shows the smoothed signal in comparison with consumer survey data from the Michigan Consumer Sentiment Survey. The following observations stand out: The smoothed signal and consumer expectations co-move positively (the correlation is 0.24). During most of the NBER recessions consumer sentiment and the signal simultaneously decline. The smoothed signal and consumer sentiment are relatively low during the productivity decline in the 1970s. The drop in trend productivity growth that was recognized in the early 2000s is reflected in a substantial decline in both series. Finally, the Great Recession is exactly matched by a fall in the smoothed signal.

Figure 1.2: Smoothed signal and consumer sentiment data



Notes: Smoothed signal based on Kalman filter and Michigan Consumer Sentiment Survey: business conditions expected during the next five years. Grey areas indicate NBER recessions. The left y-axis is measured in percentage deviations from steady state. The right y-axis is normalized to 100.

The signal process is not a priori modeled to match with actual consumer survey data. Against this background the smoothed signal fits remarkably well to consumer sentiment data. However, the modeling as to how exactly consumers form beliefs to map survey data into the model is left for future research.

1.5 Robustness

This section builds up further intuition regarding the propagation of noise shocks and assesses their role in driving macroeconomic fluctuations. The higher the degree of price and wage rigidity, the stronger the effect of noise shocks. In addition, the weaker nominal interest rates react to inflation and output growth the more do noise shocks affect real macroeconomic variables. Finally, the findings are related to those from previous literature showing which factors cause the (seemingly) conflicting results of Blanchard et al. (forthcoming) and Barsky and Sims (2012).

1.5.1 Interaction of nominal rigidities and noise shocks

Counterfactual experiments explore the importance of noise shocks in interaction with price and wage rigidity. Based on these experiments this section reports variance decompositions of noise shocks based on parameter values at their posterior mean for different degrees of nominal rigidity and various Taylor rule coefficients.

The left panel of Figure 1.3 reports the fraction of consumption fluctuations accounted for by noise shocks across all admissible values of price and wage rigidity.[20] First, consider the extreme case of fixed prices ($\theta_p = 1$) while keeping wages flexible. The consumers' Euler equation plays the key role in the transmission of noise shocks. In this fixed price case, inflation does not change and thus the only source of movements in the nominal interest rate is through output changes. Consequently, the real interest rate response is muted, which implies almost perfect consumption smoothing.[21] Hence, if prices are fixed, quantities fully adjust to the temporary wealth effect inducing a strong response in consumption, investment and output (by

[20] The estimated values for price and wage stickiness are 0.90 and 0.66, respectively, which implies that noise shocks account for 25 percent of consumption fluctuations.

[21] In the fixed-price model the intertemporal substitution effect is very small; for $\gamma_{dy} = 0$ the channel is shut off and thus the model turns into a partial equilibrium model as the intertemporal price, i.e. the real interest rate, is constant.

the full amount of expected long-run movement in productivity). In this case noise shocks explain almost 60 percent of consumption volatility.

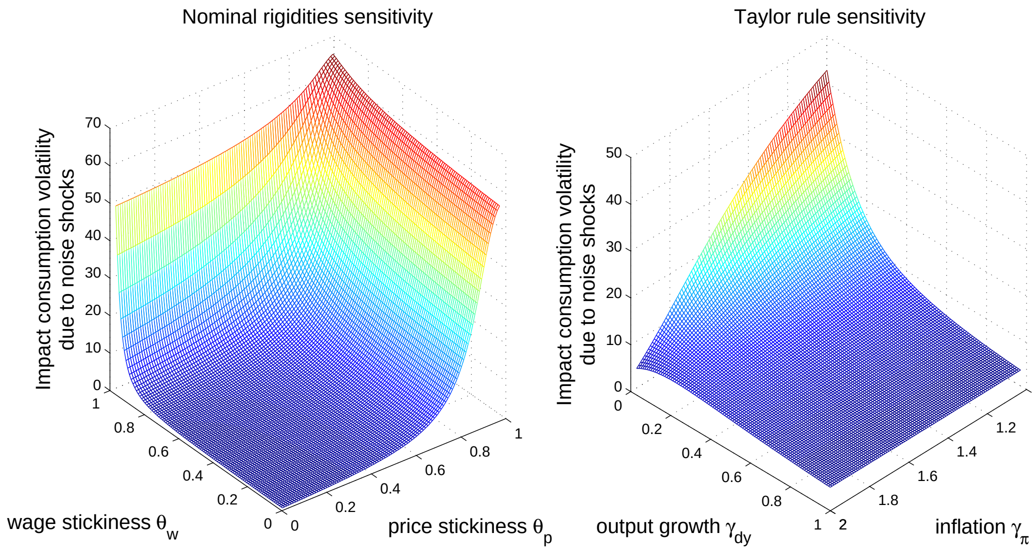
Allowing for sticky prices strengthens the intertemporal substitution effect which substantially alters the importance of noise shocks in explaining business cycles. Setting the frequency of price adjustment to an average price duration of 2.5 to 5 quarters ($\theta_p \in [0.6, 0.8]$), mutes the propagation of noise shocks with regard to consumption as compared to the fixed price case. As inflation and consequently the nominal interest rate increases, the real interest rate also rises. Thus, consumers prefer to postpone consumption to later periods, but eventually learn that the fundamentals of the economy have actually not changed leading to a weaker response in consumption and in output.

Adding nominal wage rigidity revives the role of noise shocks in explaining consumption volatility as compared to flexible wages. Figure 1.3 illustrates that the higher is wage stickiness the more do noise shocks account for consumption fluctuations. The driving force is that sticky wages dampen the effect on real marginal costs, which leads to less variability in inflation. Thus the intertemporal substitution effect is smaller the more rigid are wages leading to a stronger consumption increase. Hence, sticky nominal wages amplify the role of noise shocks as a driving force of consumption and output fluctuations. The extreme case of fixed prices and fixed wages implies that noise shocks account for close to 70 percent of consumption fluctuations.

1.5.2 Interaction of Taylor rule and noise shocks

The responsiveness of the nominal interest rate to inflation and output growth also crucially changes the transmission of noise shocks on consumption and output. In the same spirit as before I vary the inflation coefficient on the interval $\gamma_\pi \in [1.01, 2]$ as well as the coefficient on output growth $\gamma_{dy} \in [0, 1]$. The fraction of consumption fluctuations accounted for by different specifications of the monetary policy rule are presented in the right panel of Figure 1.3. The main result is that the importance of noise shocks relative to all other structural shocks increases substantially the closer the inflation coefficient is to unity and the smaller the output growth coefficient. The reason is that the stronger the response to inflation, the more does the real interest rate increase. Thus, consumers will postpone consumption to future periods, but then observe no actual fundamental productivity increases in later periods. Even for

Figure 1.3: Interaction of nominal rigidities and monetary policy rule with noise shocks



Notes: Fraction of impact consumption volatility attributed to noise shocks with parameters at posterior mean and where price and wage stickiness (left panel) and the Taylor rule coefficients on inflation and output growth (right panel) are varied. The axis for the inflation coefficient is reversed.

very low inflation coefficients ($\gamma_\pi = 1.01$) noise shocks might still not substantially contribute to consumption volatility if interest rates were to respond strongly to output ($\gamma_{dy} \geq 0.5$). Large coefficients on output growth will again raise the real interest rate providing a channel that leads agents to postpone consumption. If noise shocks were a major driver of the business cycle and the central bank wanted to mute consumption volatility, it should respond in particular to output fluctuations and react strongly to inflation.

1.5.3 Comparison to previous literature

The sensitivity analysis helps to reconcile the broad range of results regarding the importance of noise shocks found in previous literature. Blanchard et al. (forthcoming) find that noise shocks explain up to 75 percent of consumption fluctuations in a basic new Keynesian model with virtually fixed prices — a finding that is also confirmed in the extended new Keynesian model in this chapter (with fixed prices). In contrast, Barsky and Sims (2012) find that noise shocks do not contribute to consumption and output fluctuations. Without wage rigidity and at intermediate degrees of price stickiness as in the model of Barsky and Sims (2012) I also find that noise shocks play a negligible role in contributing to business cycle fluctuations. Both models disregard wage rigidity, which substantially amplifies the transmission of noise shocks as I show in the robustness analysis. The estimation in this chapter finds that U.S. data square well with a noisy signal and intermediate values of price and wage stickiness, implying that noise shocks explain a sizeable fraction of U.S. business cycles.

In their DSGE exercise Blanchard et al. (forthcoming) estimate that noise shocks explain up to 50 percent of consumption fluctuations, double the size as compared to the results of this chapter. These authors find that interest rates respond very mildly to output ($\gamma_y = 0.02$) and to inflation ($\gamma_\pi = 1.01$). Their estimated Calvo parameters imply average price and wage durations of about eight quarters. The parameter values of high rigidity and low responsiveness of monetary policy generate much stronger effects of noise shocks as shown in the previous robustness section.

Estimating the imperfect information model that forces the autocorrelation parameter for the temporary and the permanent productivity process to be identical yields estimates ($\rho_x = 0.95, \theta_p = 0.92, \theta_w = 0.79, \gamma_y = 0.08$ and $\gamma_\pi = 1.001$) that are closer to Blanchard et al. (forthcoming), who impose this assumption. Jointly estimating the precision of the signal, nominal rigdities and the interest rate rule in combination with a flexible structure for the productivity processes ($\rho_x \neq \rho_z$) provides a general framework capable of accounting for a broad range for outcomes of noise-driven business cycles. The formal model comparison in Section 1.3.6 reveals that the model with different productivity parameters provides a much better fit to explain the joint behavior of U.S. data than the model that imposes identical productivity parameters.

1.6 Conclusion

Large-scale DSGE models such as Smets and Wouters (2007) widely applied by central bankers and policymakers typically feature structural shocks that induce fundamental changes in the economy. This chapter contributes to the literature providing new empirical evidence on the importance of noise shocks in generating cyclical fluctuations in an estimated new Keynesian model. The model framework nests all of the frictions employed in previous empirical literature (i.e. Blanchard et al., forthcoming; Barsky and Sims, 2012) and adds a more flexible structure for the productivity processes. Noise shocks contribute to 25 percent of consumption fluctuations and 14 percent of output volatility on impact. These findings are about half the size than those documented in Blanchard et al. (forthcoming).

Nominal frictions and the Taylor rule play a crucial role in determining the importance of noise shocks for consumption fluctuations. Sticky prices and wages dampen the response in the real interest rate such that consumption increases strongly in response to a noise shock. Additionally, the weaker the central bank's reaction to inflation and output growth the stronger the real effects of noise shocks. Counterfactual experiments confirm the result in Barsky and Sims (2012) that for intermediate degrees of price stickiness and flexible wages noise shocks explain virtually no consumption fluctuations. For high degrees of nominal rigidities and very low Taylor rule coefficients noise shocks explain more than 50 percent of consumption fluctuations in line with Blanchard et al. (forthcoming).

Bayesian model comparison reveals that the complete and incomplete information explain the joint behavior of U.S. data almost equally well - rendering it impossible to empirically prefer one model over the other. However, the model with different persistence parameters for the temporary and the permanent productivity component is clearly favored to the model with identical persistence parameters for both processes.

The smoothed signal fits remarkably well to consumer survey data. Further research aiming to align consumer sentiment studies and heterogeneous beliefs with DSGE models is likely to prove very interesting. In particular using real-time consumer sentiment data to facilitate the estimation of DSGE models would be an interesting avenue for further research.

Appendix to Chapter 1

1.A Model appendix

The core of the model builds on conventional medium-scale DSGE models such as Smets and Wouters (2007), Justiniano et al. (2010) and Fernández-Villaverde (2010).[22]

1.A.1 Households

The economy is inhabited by a continuum of households indexed by $h \in [0,1]$. Preferences are additively separable in consumption and labor supply

$$U(C_t(h), N_t(h)) = \log\left(C_t(h) - h_c C_{t-1}(h)\right) - \vartheta \frac{N_t(h)^{1+\varphi}}{1+\varphi}\ , \tag{1.18}$$

where $C_t(h)$ denotes household h's consumption and $N_t(h)$ the amount of hours worked. The parameter h_c denotes habit persistence in consumption, ϑ determines labor supply in steady state and φ is the inverse Frisch elasticity of labor supply.

Each household h supplies a different type of labor $N_t(h)$ and has some monopoly power in the labor market, posting the nominal wage $W_t(h)$ at which it is willing to supply specialized labor services to firms that demand them (see Erceg, Henderson, and Levin, 2000). Households have access to a complete set of state-contingent Arrow-Debreu securities to fully insure against idiosyncratic income risk that derives from the limited ability to adjust wages in each period.[23] Let $D_{t+1}(h)$ denote the payoff in period $t+1$ of the portfolio of state-contingent securities held by household h at the end of period t and let $Q_{t,t+1}$ denote the stochastic discount factor. The budget constraint of household h is given by

$$P_t C_t(h) + P_t I_t(h) + \mathbb{E}_t\left\{Q_{t,t+1} D_{t+1}(h)\right\} - D_t(h) \tag{1.19}$$

$$= W_t(h) N_t(h) + \left(R_t^k u_t(h) - \frac{1}{\mu_t^{IS}} P_t a(u_t(h))\right) K_{t-1}(h) + T_t(h) + \Upsilon_t(h)\ , \tag{1.20}$$

[22] An excellent textbook treatment of the new Keynesian framework is Galí (2008).

[23] With complete markets, consumption and the marginal utility of consumption are equalized across households and states at all times in equilibrium (given identical endowments).

where $I_t(h)$ is investment, $K_t(h)$ is the capital stock, $T_t(h)$ are lump-sum payments and $\Upsilon_t(h)$ are the profits of firms. The utilization rate of capital, $u_t(h)$, transforms physical capital into effective capital rented to firms at real rate r_t^k. The cost of physical capital utilization is a quadratic function $a(u_t(h)) = \delta_1(u_t(h) - 1) + \frac{\delta_2}{2}(u_t(h) - 1)^2$ where in steady state, $u = 1, a(1) = 0$ with curvature $\frac{a''(1)}{a'(1)} = \frac{\delta_2}{\delta_1}$. Households own and invest in capital facing investment adjustment costs as in Christiano et al. (2005). The law of motion for capital is:

$$K_t(h) = (1-\delta)K_{t-1}(h) + \mu_t^{IS}\left(1 - S\left(\frac{I_t}{I_{t-1}}\right)\right)I_t(h) \ . \tag{1.21}$$

Investment adjustment costs are specified as in Christiano, Eichenbaum, and Evans (2005): $S(I_t/I_{t-1}) = \frac{\kappa}{2}\left(\frac{I_t}{I_{t-1}} - \mu^I\right)^2$ which are introduced to dampen the volatility of investment over the business cycle. The parameter $\kappa \geq 0$ measures the curvature of investment adjustment costs and μ^I is the long-run growth rate of investment. In steady state it holds that $S = S' = 0$ and $S'' > 0$. The exogenous investment-specific technological shock μ_t^{IS} measures the variation in the efficiency at which the final good can be transformed into physical capital and follows an AR(1) process:

$$\log\left(\mu_t^{IS}\right) = \rho_{is}\log\left(\mu_{t-1}^{IS}\right) + \epsilon_{is,t} \qquad \epsilon_{is,t} \sim \mathcal{N}(0, \sigma_{is}^2) \ . \tag{1.22}$$

A representative household h maximizes the expected discounted lifetime utility with respect to $C_t(h), u_t(h), K_t(h), I_t(h), W_t(h), N_t(h)$ and $D_{t+1}(h)$ subject to the budget constraint (1.19) and a standard no-Ponzi scheme condition. Households have identical first-order conditions as consumers have access to complete financial markets where they insure their idiosyncratic income risk.

1.A.2 Optimal wage setting

Differentiated labor services are bundled to a homogeneous labor good N_t according to a Dixit-Stiglitz aggregator

$$N_t = \left[\int_0^1 N_t(h)^{\frac{\eta_{w,t}-1}{\eta_{w,t}}} dh\right]^{\frac{\eta_{w,t}}{\eta_{w,t}-1}} \ , \tag{1.23}$$

where $\eta_{w,t}$ denotes the intratemporal elasticity of substitution across different varieties of labor types. The time-varying gross markup $\mu_{w,t} = \frac{\eta_{w,t}}{\eta_{w,t}-1}$ follows an exogenous ARMA(1,1) process

$$\log\left(\frac{\mu_{w,t}}{\mu_w}\right) = \rho_w \log\left(\frac{\mu_{w,t-1}}{\mu_w}\right) + \epsilon_{w,t} - \rho_{wlag}\epsilon_{w,t-1} \ , \qquad \epsilon_{w,t} \sim \mathcal{N}(0, \sigma_w^2) \ , \quad (1.24)$$

where $\epsilon_{w,t}$ is a wage markup shock. The optimal bundling of differentiated labor services based on cost minimization yields the labor demand schedule:

$$N_t(h) = \left(\frac{W_t(h)}{W_t}\right)^{-\eta_{w,t}} N_t \ . \qquad (1.25)$$

The aggregate wage index W_t is a composite of all labor type specific wage rates:

$$W_t = \left[\int_0^1 W_t(h)^{1-\eta_{w,t}} dh\right]^{\frac{1}{1-\eta_{w,t}}} . \qquad (1.26)$$

The fraction $(1-\theta_w)$ of households can adjust their posted nominal wage. Wage inflation and infrequent wage adjustments induce relative wage distortions that facilitate an inefficient allocation of labor. Each period optimizing households choose their wage $W_t^\star(h) = W_t(h)$ for their labor type in order to maximize the expected discounted lifetime utility subject to the labor demand schedule. The wage of the remaining fraction of households θ_w is indexed to past inflation. A household that is not allowed to change wages for τ periods has a normalized wage of $\prod_{s=1}^{\tau} \frac{\Pi_{t+s-1}^{\chi_w}}{\Pi_{t+s}} W_t(h)$, where the indexation parameter is $\chi_w \in [0,1]$. The relevant terms of the optimization problem are:

$$\max_{W_t^\star(h)} \mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta\theta_w)^\tau \left[-\vartheta \frac{N_{t+\tau}(h)^{1+\varphi}}{1+\varphi} + \lambda_{t+\tau} \prod_{s=1}^{\tau} \frac{\Pi_{t+s-1}^{\chi_w}}{\Pi_{t+s}} \frac{W_t(h)}{P_{t+\tau}} N_{t+\tau}(h)\right] \quad \text{s.t.} \quad (1.27)$$

$$N_{t+\tau}(h) = \left(\prod_{s=1}^{\tau} \frac{\Pi_{t+s-1}^{\chi_w}}{\Pi_{t+s}} \frac{W_t(h)}{W_t}\right)^{-\eta_{w_{t+\tau}}} N_{t+\tau} \ . \qquad (1.28)$$

Given the assumption of complete markets (assuming identical initial conditions) and separable utility in labor (see Erceg et al., 2000), I consider a symmetric equilibrium where $C_t(h) = C_t, \lambda_t(h) = \lambda_t, u_t(h) = u_t, K_t(h) = K_t, I_t(h) = I_t$ and $W_t^\star(h) = W_t^\star$.

1.A.3 Final good producers

Perfectly competitive final good producers bundle intermediate goods $Y_t(i)$ to a final good Y_t following a Dixit-Stiglitz aggregation technology:

$$Y_t = \left[\int_0^1 Y_t(i)^{\frac{\eta_{p,t}-1}{\eta_{p,t}}} di \right]^{\frac{\eta_{p,t}}{\eta_{p,t}-1}} . \tag{1.29}$$

The time-varying intratemporal elasticity of substitution across different varieties of consumption goods is denoted $\eta_{p,t}$. The time-varying gross price markup $\mu_{p,t} = \frac{\eta_{p,t}}{\eta_{p,t}-1}$ follows an exogenous ARMA(1,1) stochastic process

$$\log\left(\frac{\mu_{p,t}}{\mu_p}\right) = \rho_p \log\left(\frac{\mu_{p,t-1}}{\mu_p}\right) + \epsilon_{p,t} - \rho_{plag}\epsilon_{p,t-1} , \qquad \epsilon_{p,t} \sim \mathcal{N}(0, \sigma_p^2) , \tag{1.30}$$

where $\epsilon_{p,t}$ is a price markup shock. Profit maximization yields the input demand schedule for intermediate goods:

$$Y_t(i) = \left(\frac{P_t(i)}{P_t}\right)^{-\eta_{p,t}} Y_t^d . \tag{1.31}$$

The minimum costs of a bundle of intermediate goods that provides one unit of composite good amounts to the aggregate price index:

$$P_t = \left[\int_0^1 P_t(i)^{1-\eta_{p,t}} di \right]^{\frac{1}{1-\eta_{p,t}}} . \tag{1.32}$$

1.A.4 Intermediate goods producers

A continuum of monopolistically competitive firms is indexed by $i \in [0, 1]$, where each firm produces a differentiated good using the same technology

$$Y_t(i) = A_t K_t^{\alpha}(i) N_t(i)^{1-\alpha} - \phi z_t^{profits} , \tag{1.33}$$

where the fixed cost of production is ϕ. The aggregate level of technology is $A_t = X_t Z_t$, where X_t and Z_t denote the permanent and the temporary component, respectively. The growth rate of the permanent component follows an AR(1) process, which implies that the level X_t builds up gradually over time. The stochastic processes are:

$$\frac{X_t}{X_{t-1}} = \left(\frac{X_{t-1}}{X_{t-2}}\right)^{\rho_x} \exp(\epsilon_{x,t}) , \qquad \epsilon_{x,t} \sim \mathcal{N}(0,\sigma_x^2) \tag{1.34}$$

$$Z_t = Z_{t-1}^{\rho_z} \exp(\epsilon_{z,t}) , \qquad \epsilon_{z,t} \sim \mathcal{N}(0,\sigma_z^2) . \tag{1.35}$$

In addition, consumers observe a noisy signal about the permanent component

$$S_t = X_t \exp(\epsilon_{s,t}) , \qquad \epsilon_{s,t} \sim \mathcal{N}(0,\sigma_s^2) , \tag{1.36}$$

where σ_s measures the signal precision and $\epsilon_{s,t}$ is a noise shock.

Firms set prices in a staggered fashion à la Calvo (1983), i.e. firms can re-optimize prices with probability $(1-\theta_p)$ each period and, therefore, take into account that they may not be able to adjust prices in the next period. Prices of those firms that cannot change prices are indexed to past inflation for which the degree of indexation is governed by $\chi_p \in [0,1]$. Firms set prices $P^\star = P(i)$ to maximize expected profits subject to the demand schedule (1.31)

$$\max_{P_t^\star} \mathbb{E}_t \sum_{\tau=0}^{\infty} \theta_p^\tau Q_{t,t+\tau} Y_{t+\tau}(i) \left(\prod_{s=1}^{\tau} \Pi_{t+s-1}^{\chi_p} \frac{P_t(i)}{P_{t+\tau}} - MC_{t+\tau}(i) \right) \qquad \text{s.t.} \tag{1.37}$$

$$Y_{t+\tau}(i) = \left(\prod_{s=1}^{\tau} \Pi_{t+s-1}^{\chi_p} \frac{P_t(i)}{P_{t+\tau}} \right)^{-\eta_{p_t}} Y_{t+\tau}^d , \tag{1.38}$$

where $Q_{t,t+s}$ is the households' stochastic discount factor as defined before and $MC_t(i)$ is firm i's real marginal cost.

1.A.5 Monetary policy and aggregation

The central bank operates a Taylor rule where the nominal interest rate R_t responds to changes in inflation and output growth as well as the lagged interest rate

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\gamma_R} \left[\left(\frac{\Pi_t}{\Pi}\right)^{\gamma_\pi} \left(\frac{\frac{y_t^d}{y_{t-1}^d}}{\mu^y} \right)^{\gamma_{dy}} \right]^{1-\gamma_R} \exp(\epsilon_{m,t}) , \epsilon_{m,t} \sim \mathcal{N}(0,\sigma_m^2) . \tag{1.39}$$

Aggregate demand in the economy is:

$$Y_t^d = C_t + I_t + \left(\mu_t^{IS}\right)^{-1} a(u_t) K_{t-1} \ . \tag{1.40}$$

1.A.6 Detrended model equilibrium conditions

$$\hat{\lambda}_t = \left(\hat{C}_t - h_c \hat{C}_{t-1} \frac{1}{\mu_t^A}\right)^{-1} - \beta h_c \mathbb{E}_t \left(\hat{C}_{t+1}\mu_{t+1}^A - h_c \hat{C}_t\right)^{-1} \tag{1.41}$$

$$\hat{\lambda}_t = \beta \mathbb{E}_t \frac{\hat{\lambda}_{t+1}}{\mu_{t+1}^A} \frac{R_t}{\pi_{t+1}} \tag{1.42}$$

$$q_t^k \mu_{t+1}^A = \beta \mathbb{E}_t \frac{\hat{\lambda}_{t+1}}{\hat{\lambda}_t} \left((1-\delta) q_{t+1}^k + r_{t+1}^k u_{t+1}\right) \tag{1.43}$$

$$- \beta \mathbb{E}_t \frac{\hat{\lambda}_{t+1}}{\hat{\lambda}_t} \frac{1}{\mu_{t+1}^{IS}} \left(\delta_1 (u_{t+1} - 1) + \frac{\delta_2}{2} (u_{t+1} - 1)^2\right) \tag{1.44}$$

$$1 = q_t^k \mu_t^{IS} \left[1 - \frac{\kappa}{2}\left(\frac{\hat{I}_t}{\hat{I}_{t-1}} \mu_t^A - \mu^I\right)^2 - \kappa \left(\frac{\hat{I}_t}{\hat{I}_{t-1}} \mu_t^A - \mu^I\right) \frac{\hat{I}_t}{\hat{I}_{t-1}} \mu_t^A\right] \tag{1.45}$$

$$+ \beta \mathbb{E}_t q_{t+1}^k \frac{\hat{\lambda}_{t+1}}{\hat{\lambda}_t} \frac{1}{\mu_{t+1}^A} \mu_{t+1}^{IS} \kappa \left(\frac{\hat{I}_{t+1}}{\hat{I}_t} \mu_{t+1}^A - \mu^I\right) \left(\frac{\hat{I}_t}{\hat{I}_{t-1}} \mu_t^A\right)^2 \tag{1.46}$$

$$r_t^k = \frac{1}{\mu_t^{IS}} \left(\delta_1 + \delta_2 \left(u_t - 1\right)\right)$$

$$g_t^1 = \hat{\lambda}_t mc_t \hat{y}_t^d + \beta \theta_p \mathbb{E}_t \left(\frac{\Pi_t^{\chi_p}}{\Pi_{t+1}}\right)^{-\eta_{p,t+1}} g_{t+1}^1 \tag{1.47}$$

$$g_t^2 = \hat{\lambda}_t \Pi_t^* \hat{y}_t^d + \beta \theta_p \mathbb{E}_t \left(\frac{\Pi_t^{\chi_p}}{\Pi_{t+1}}\right)^{1-\eta_{p,t+1}} \frac{\Pi_t^*}{\Pi_{t+1}^*} g_{t+1}^2 \tag{1.48}$$

$$\eta_{p,t} g_t^1 = \left(\eta_{p,t} - 1\right) g_t^2 \tag{1.49}$$

$$f_t = \frac{\eta - 1}{\eta} \left(\hat{W}_t^*\right)^{1-\eta_{w,t}} \hat{\lambda}_t \left(\hat{W}_t\right)^{\eta_{w,t}} l_t^d \tag{1.50}$$

$$+ \beta \theta_w \mathbb{E}_t \left(\frac{\Pi_t^{\chi_w}}{\Pi_{t+1}}\right)^{1-\eta_{w,t+1}} \left(\frac{\hat{W}_{t+1}^*}{\hat{W}_t^*} \mu_{t+1}^A\right)^{\eta_{w,t+1}-1} f_{t+1} \tag{1.51}$$

$$f_t = \vartheta \left(\frac{\hat{W}_t}{\hat{W}_t^*}\right)^{\eta_{w,t}(1+\varphi)} \left(l_t^d\right)^{1+\varphi} \tag{1.52}$$

$$+ \beta \theta_w \mathbb{E}_t \left(\frac{\Pi_t^{\chi_w}}{\Pi_{t+1}}\right)^{-\eta_{w,t+1}(1+\varphi)} \left(\frac{\hat{W}_{t+1}^*}{\hat{W}_t^*} \mu_{t+1}^A\right)^{\eta_{w,t+1}(1+\varphi)} f_{t+1} \tag{1.53}$$

$$\frac{u_t \hat{k}_{t-1}}{l_t^d} = \frac{\alpha}{1-\alpha}\frac{\hat{w}_t}{r_t^k}\mu_t^A \tag{1.54}$$

$$mc_t = \left(\frac{1}{1-\alpha}\right)^{1-\alpha}\left(\frac{1}{\alpha}\right)^{\alpha}\hat{w}_t^{1-\alpha}\left(r_t^k\right)^{\alpha} \tag{1.55}$$

$$1 = \theta_p\left(\frac{\Pi_{t-1}^{\chi_p}}{\Pi_t}\right)^{1-\eta_{p,t}} + (1-\theta_p)\left(\Pi_t^*\right)^{1-\eta_{p,t}} \tag{1.56}$$

$$1 = \theta_w\left(\frac{\Pi_{t-1}^{\chi_w}}{\Pi_t}\right)^{1-\eta_{w,t}}\left(\frac{\hat{w}_{t-1}}{\hat{w}_t}\frac{1}{\mu_t^A}\right)^{1-\eta_{w,t}} + (1-\theta_w)\left(\Pi_t^{*w}\right)^{1-\eta_{w,t}} \tag{1.57}$$

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\gamma_R}\left(\left(\frac{\Pi_t}{\Pi}\right)^{\gamma_\Pi}\left(\frac{\frac{\hat{y}_t^d}{\hat{y}_{t-1}^d}\mu_t^A}{\mu^y}\right)^{\gamma_Y}\right)^{1-\gamma_R}\exp\left(\varepsilon_{m,t}\right) \tag{1.58}$$

$$\hat{y}_t^d = \frac{\left(\mu_t^A\right)^{-\alpha}\left(u_t\hat{k}_{t-1}\right)^{\alpha}\left(l_t^d\right)^{1-\alpha} - \phi}{\upsilon_t^p} \tag{1.59}$$

$$\hat{y}_t^d = \hat{c}_t + \hat{I}_t + \left(\mu_t^{IS}\right)^{-1}\left(\delta_1\left(u_t-1\right) + \frac{\delta_2}{2}\left(u_t-1\right)^2\right)\hat{k}_{t-1}\left(\mu_t^A\right)^{-1} \tag{1.60}$$

$$l_t = \upsilon_t^w l_t^d \tag{1.61}$$

$$\upsilon_t^p = \theta_p\left(\frac{\Pi_{t-1}^{\chi_p}}{\Pi_t}\right)^{-\eta_{p,t}}\upsilon_{t-1}^p + (1-\theta_p)\left(\Pi_t^*\right)^{-\eta_{p,t}} \tag{1.62}$$

$$\upsilon_t^w = \theta_w\left(\frac{\Pi_{t-1}^{\chi_w}}{\Pi_t}\right)^{-\eta_{w,t}}\left(\frac{\hat{w}_{t-1}}{\hat{w}_t}\frac{1}{\mu_t^A}\right)^{-\eta_{w,t}}\upsilon_{t-1}^w + (1-\theta_w)\left(\Pi_t^{*w}\right)^{-\eta_{w,t}} \tag{1.63}$$

$$0 = \hat{k}_t - (1-\delta)\hat{k}_{t-1}\frac{1}{\mu_t^A} - \mu_t^{IS}\left(1 - \frac{\kappa}{2}\left(\frac{\hat{I}_t}{\hat{I}_{t-1}}\mu_t^A - \mu^I\right)^2\right)\hat{I}_t \tag{1.64}$$

Exogenous processes are specified in the main text and in Appendix 1.A.

1.B Consumers' Kalman filter

Define the matrices:

$$C = \begin{bmatrix} \rho_x & -\rho_x & -1 & \rho_x \\ 1 & 0 & 0 & 0 \\ 0 & 0 & \rho_z & 0 \\ 1 & 0 & 1 & 0 \end{bmatrix}, \Sigma_1 = \begin{bmatrix} \sigma_x^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_z^2 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$D = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix}, \Sigma_2 = \begin{bmatrix} 0 & 0 \\ 0 & \sigma_s^2 \end{bmatrix}.$$

The process for $\xi_t = \left(\hat{x}_t, \hat{x}_{t-1}, z_t, \hat{\mu}^A_{t-1}\right)$ is described compactly as

$$\xi_t = C\xi_{t-1} + R\epsilon_t \ , \tag{1.65}$$

and the observation equation for consumers is

$$y_t = \left(\hat{\mu}^A_t, \hat{s}_t\right)' = D\xi_t + S\epsilon_t \ , \tag{1.66}$$

where y_t is the vector of observables, ϵ_t contains all structural shocks, $\mathbb{E}_t\left[R\epsilon_t\epsilon_t'R'\right] = \Sigma_1$ and $\mathbb{E}_t\left[S\epsilon_t\epsilon_t'S'\right] = \Sigma_2$. Let $P = \mathrm{Var}_{t-1}\left[\xi_t\right]$. The value of P is found by solving the following equation:

$$P = C\left[P - PD'(DPD' + \Sigma_2)^{-1}DP\right]C' + \Sigma_1. \tag{1.67}$$

According to the updating equation of a linear projection (see Hamilton (1994), equation 13.2.15) the evolution of the unobserved state is:

$$\begin{aligned} \xi_{t|t} &= \xi_{t|t-1} + PD(DPD' + \Sigma_2)^{-1}(y_t - D\xi_{t|t-1}) && (1.68) \\ &= (I - BD)\xi_{t|t-1} + PD(DPD' + \Sigma_2)^{-1}y_t && (1.69) \\ &= A\xi_{t-1|t-1} + BDC\xi_{t-1} + B(DR + S)\epsilon_t \ . && (1.70) \end{aligned}$$

The last step uses $\xi_{t|t-1} = C\xi_{t-1|t-1}, B = PD(DPD' + \Sigma_2)^{-1}$ and $A = (I - BD)\,C$. Equation (1.10) in the main text follows the notation based on matrices A and B.

1.C Model solution

The solution to the full information log-linearized model can be obtained using standard methods, e.g. Klein (2000). The vector of control variables is $X_{1,t}$ and the vector of state variables is denoted by $X_{2,t}$. The full information model solution is given in recursive form by the policy (Π) and transition (M) function respectively

$$\begin{aligned} X_{1,t} &= \Pi X_{2,t-1} \ , & (1.71) \\ X_{2,t} &= M X_{2,t-1} + \tilde{R}\epsilon_t \ , & (1.72) \end{aligned}$$

where $X_{2,t} = \begin{bmatrix} \hat{x}_t & \hat{x}_{t-1} & z_t & \mathbf{X}_t^{obs} \end{bmatrix}'$, $\epsilon_t = [\epsilon_{x,t} \ \ \epsilon_{z,t} \ \ \epsilon_{s,t} \ \ \epsilon_{m,t} \ \ \epsilon_{p,t} \ \ \epsilon_{w,t} \ \ \epsilon_{is,t}]'$, and $\mathbf{X}_t^{obs}$ is the vector of observed states. Introducing imperfect information necessitates an adjustment of solution methods as proposed in Baxter et al. (2011). Agents cannot directly observe the components of productivity, i.e. $\hat{x}_t$ and z_t. Define the vector of unobserved states as $\xi_t = \begin{bmatrix} \hat{x}_t & \hat{x}_{t-1} & z_t & \hat{\mu}_{t-1}^A \end{bmatrix}'$, which is a subset of all state variables $X_{2,t}$.[24] Agents form contemporaneous estimates about the states, i.e. $\xi_{t|t}$, stemming from solving the Kalman filtering problem (Appendix 1.B contains a detailed derivation). The following system describes the evolution of the actual states and the beliefs of the agents

$$\begin{bmatrix} \xi_t \\ \xi_{t|t} \end{bmatrix} = \begin{bmatrix} N_{11} & 0 \\ N_{21} & N_{22} \end{bmatrix} \begin{bmatrix} \xi_{t-1} \\ \xi_{t-1|t-1} \end{bmatrix} + \begin{bmatrix} R \\ B(DR+S) \end{bmatrix} \epsilon_t \ ,$$

where $N_{11} = C$. Solving the consumers' Kalman filtering problem yields a recursive solution for the contemporaneous beliefs (see equation (1.70)), i.e.

$$\xi_{t|t} = A\xi_{t-1|t-1} + By_t = A\xi_{t-1|t-1} + BDC\xi_{t-1} + B(DR+S)\epsilon_t \ , \qquad (1.73)$$

such that $N_{21} = BC$ and $N_{22} = A$. The matrices A, B, C and D were already introduced in the filtering problem described in Appendix 1.B. Given the contemporaneous estimates about the unobserved states $\xi_{t-1|t-1}$ and the linearity of the model,

[24]Note that $\hat{\mu}_{t-1}^A$ is perfectly observed, but it is required to pin down $\hat{x}_t$.

certainty equivalence[25] applies (see Baxter et al., 2011) and hence

$$X_{1,t} = \Pi X_{2,t-1|t-1} \; , \tag{1.74}$$

where $X_{2,t-1|t-1} = \left[\xi_{t-1|t-1} \;\; \mathbf{x}^{obs}_{i,t-1}\right]'$ and $\mathbf{x}^{obs}_{i,t-1}$ represents all observable lagged state variables.[26]

[25]Certainty equivalence implies that even though consumers know that they imperfectly observe the fundamentals of the economy, their decisions are as if they knew the true value of the unobserved state variable (i.e. under full information).

[26]For example, Pearlman et al. (1986), Pearlman (1992), Svensson and Woodford (2004) and Lorenzoni (2009) also use certainty equivalence in a linear model with partial information.

1.D Data appendix

Table 1.6: Data sources

Label	Description	Source
GDP	Gross domestic product	BEA (Table 1.1.5, Line 1)
GDPQ	Real gross domestic product	BEA (Table 1.1.6, Line 1)
GCND	Pers. cons. expend. on nondurable goods	BEA (Table 1.1.5, Line 4)
GCS	Pers. cons. expend. on services	BEA (Table 1.1.5, Line 5)
NRI	Real nonresidential investment	BEA (Table 1.1.6, Line 8)
RI	Real residential investment	BEA (Table 1.1.6, Line 11)
P16	Civilian non-institutional pop. over 16	BLS (LNU00000000Q)
E16	Civilian employment (S.A.)	BLS (LNS12000000)
TFP	Real-time utilization adj. TFP	Fernald (2012)
LBCPU	Hourly non-farm business compensation	BLS (PRS85006103)
FYFF	Effective federal funds rate	St. Louis FRED
E5Y	Business conditions expected during the next five years	Michigan Consumer Sentiment Survey Table 16

Table 1.7: Data construction

Label	Description	Construction
GDPDEF	GDP deflator	GDPQ/GDP
C	Real per-capita consumption	(GCND+GCS)/P16/GDPDEF
Y	Real per-capita output	GDPQ/P16
I	Real per-capita investment	(NRI+RI)/P16
W	Real wages	LBCPU/GDPDEF
FFR	Effective federal funds rate	Quarterly average of FYFF
TFP	Real-time utilization adj. TFP	TFP

Notes: The data set constructed with U.S. data is transformed to match the model equivalents specified in the observation equation (1.14) in the main text.

1.E Further estimation results

Table 1.8: Prior and posterior distribution of complete information model

		Prior			Posterior		
Parameter	Description	Distr.	Mean	Std	Mean	5%	95%
h_c	Habit persistence	$\mathcal{B}$	0.6	0.1	0.82	0.79	0.86
κ	Investment adj. costs	$\mathcal{N}$	6	2	9.07	6.68	11.26
α	Capital share	$\mathcal{B}$	0.25	0.1	0.10	0.05	0.15
φ	Inverse Frisch elasticity	$\mathcal{G}$	2	0.75	1.19	0.38	1.95
δ_2	Capital utilization costs	$\mathcal{N}$	0.15	0.05	0.14	0.05	0.22
θ_p	Price stickiness	$\mathcal{B}$	0.66	0.1	0.90	0.86	0.93
θ_w	Wage stickiness	$\mathcal{B}$	0.66	0.1	0.67	0.55	0.79
χ_p	Price indexation	$\mathcal{B}$	0.7	0.15	0.81	0.67	0.96
χ_w	Wage indexation	$\mathcal{B}$	0.7	0.15	0.59	0.38	0.83
γ_{dy}	Taylor rule: output growth	$\mathcal{N}$	0.1	0.1	0.22	0.09	0.35
γ_π	Taylor rule: inflation	$\mathcal{N}$	1.4	0.125	1.18	1.07	1.30
γ_R	Interest rate smoothing	$\mathcal{B}$	0.7	0.1	0.80	0.77	0.83
ρ_{is}	Inv.-specific TFP	$\mathcal{B}$	0.8	0.1	0.66	0.56	0.77
ρ_x	Perm. neutral TFP	$\mathcal{B}$	0.8	0.1	0.96	0.95	0.98
ρ_z	Temp. neutral TFP	$\mathcal{B}$	0.8	0.1	0.93	0.90	0.96
ρ_p	Price markup	$\mathcal{B}$	0.7	0.1	0.56	0.38	0.74
ρ_w	Wage markup	$\mathcal{B}$	0.7	0.1	0.91	0.86	0.96
ρ_{plag}	Lagged price markup	$\mathcal{B}$	0.5	0.1	0.49	0.39	0.60
ρ_{wlag}	Lagged wage markup	$\mathcal{B}$	0.5	0.1	0.57	0.47	0.66
$100\sigma_x$	Perm. TFP	$\mathcal{IG}$	0.5	5	0.17	0.13	0.23
$100\sigma_z$	Temp. TFP	$\mathcal{IG}$	1	5	0.73	0.66	0.80
$100\sigma_m$	Monetary policy	$\mathcal{IG}$	1	5	0.26	0.24	0.28
$100\sigma_{is}$	Investment-spec. TFP	$\mathcal{IG}$	1	5	9.50	6.32	12.64
$100\sigma_p$	Price markup	$\mathcal{IG}$	1	5	3.22	2.13	4.22
$100\sigma_w$	Wage markup	$\mathcal{IG}$	1	5	14.56	4.90	28.32

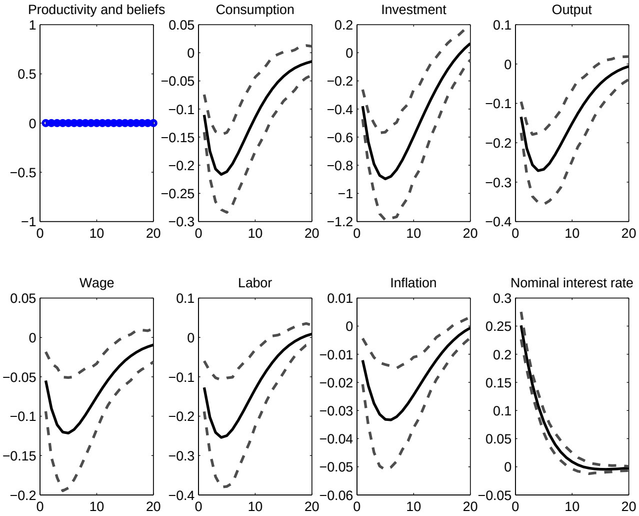
Notes: The complete information model $\mathcal{M}_2$ is estimated with a precise signal, i.e. $\sigma_s = 0$. $\mathcal{B}$ is beta distribution, $\mathcal{G}$ is gamma distribution, $\mathcal{IG}$ is inverse gamma distribution, $\mathcal{N}$ is normal distribution.

Table 1.9: Prior and posterior distribution of incomplete information model with identical productivity parameters

Parameter	Description	Prior			Posterior		
		Distr.	Mean	Std	Mean	5%	95%
h_c	Habit persistence	$\mathcal{B}$	0.6	0.1	0.59	0.54	0.64
κ	Investment adj. costs	$\mathcal{N}$	6	2	7.02	4.58	9.44
α	Capital share	$\mathcal{B}$	0.3	0.1	0.14	0.06	0.24
φ	Inverse Frisch elasticity	$\mathcal{G}$	2	0.75	1.45	0.58	2.21
δ_2	Capital utilization costs	$\mathcal{N}$	0.2	0.1	0.08	0.00	0.18
θ_p	Price stickiness	$\mathcal{B}$	0.7	0.1	0.91	0.89	0.94
θ_w	Wage stickiness	$\mathcal{B}$	0.7	0.1	0.78	0.67	0.87
χ_p	Price indexation	$\mathcal{B}$	0.7	0.2	0.88	0.80	0.97
χ_w	Wage indexation	$\mathcal{B}$	0.7	0.2	0.47	0.23	0.74
γ_{dy}	Taylor rule: output growth	$\mathcal{N}$	0.1	0.1	0.08	-0.01	0.18
γ_π	Taylor rule: inflation	$\mathcal{N}$	1.4	0.125	1.001	1.000	1.005
γ_R	Interest rate smoothing	$\mathcal{B}$	0.7	0.1	0.67	0.62	0.71
ρ_{is}	Inv.-specific TFP	$\mathcal{B}$	0.8	0.1	0.70	0.58	0.80
$\rho_x = \rho_z$	Neutral TFP	$\mathcal{B}$	0.8	0.1	0.95	0.93	0.97
ρ_p	Price markup	$\mathcal{B}$	0.7	0.1	0.41	0.28	0.53
ρ_w	Wage markup	$\mathcal{B}$	0.7	0.1	0.90	0.85	0.94
ρ_{plag}	Lagged price markup	$\mathcal{B}$	0.5	0.1	0.46	0.36	0.56
ρ_{wlag}	Lagged wage markup	$\mathcal{B}$	0.5	0.1	0.61	0.52	0.71
$100\sigma_s$	Noise shock	$\mathcal{IG}$	1	5	0.51	0.25	0.77
$100\sigma_a$	Neutral TFP	$\mathcal{IG}$	1	5	1.03	0.93	1.13
$100\sigma_m$	Monetary policy	$\mathcal{IG}$	1	5	0.3	0.28	0.33
$100\sigma_{is}$	Investment-spec. TFP	$\mathcal{IG}$	1	5	6.89	3.97	9.5
$100\sigma_p$	Price markup	$\mathcal{IG}$	1	5	3.92	2.88	4.86
$100\sigma_w$	Wage markup	$\mathcal{IG}$	1	5	32.3	9.93	53.69

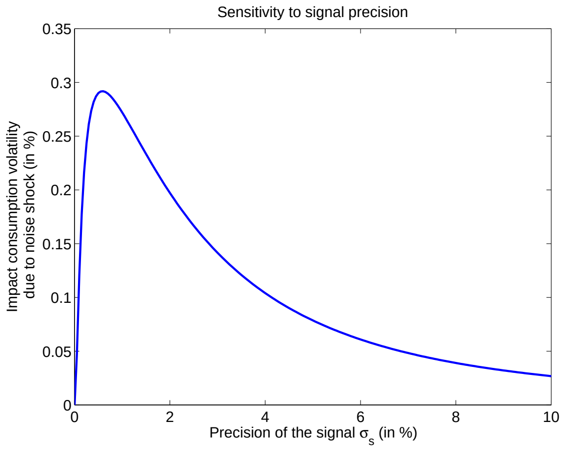
Notes: The incomplete information model $\mathcal{M}_3$ is estimated based on $\rho_z = \rho_x$. $\mathcal{B}$ is beta distribution, $\mathcal{G}$ is gamma distribution, $\mathcal{IG}$ is inverse gamma distribution, $\mathcal{N}$ is normal distribution.

Figure 1.4: Impulse responses to a monetary policy shock



Notes: Impulse responses to a one standard deviation monetary policy shock with parameters at their posterior mean value. The dashed lines are 90 percent confidence bands. All variables are measured in percentage deviations from steady state (x-axis). A time unit is a quarter (y-axis).

Figure 1.5: Sensitivity to signal precision

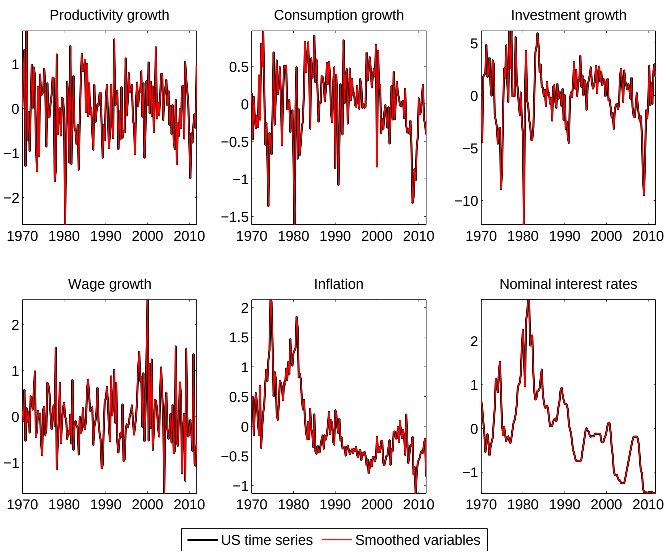


Notes: Fraction of impact consumption volatility attributed to noise shocks with parameters at posterior mean and varying the signal precision between zero and ten percent.

1.F Estimation diagnostics

1.F.1 Fit of the model

Figure 1.6: U.S. data and smoothed observables



1.F.2 Posterior mode check

Figure 1.7: Check plots for posterior mode maximization (1/3)

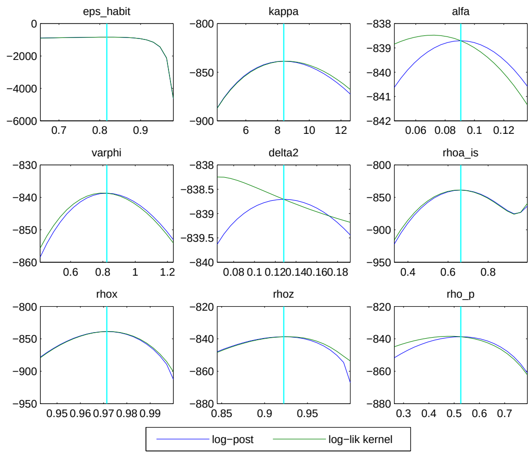


Figure 1.8: Check plots for posterior mode maximization (2/3)

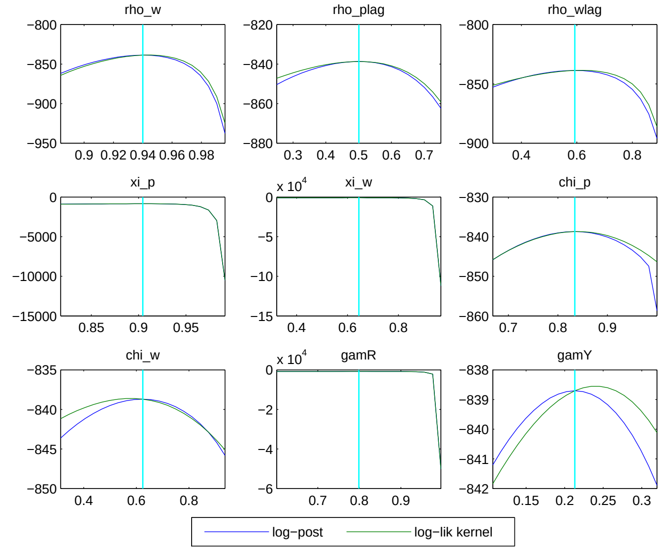
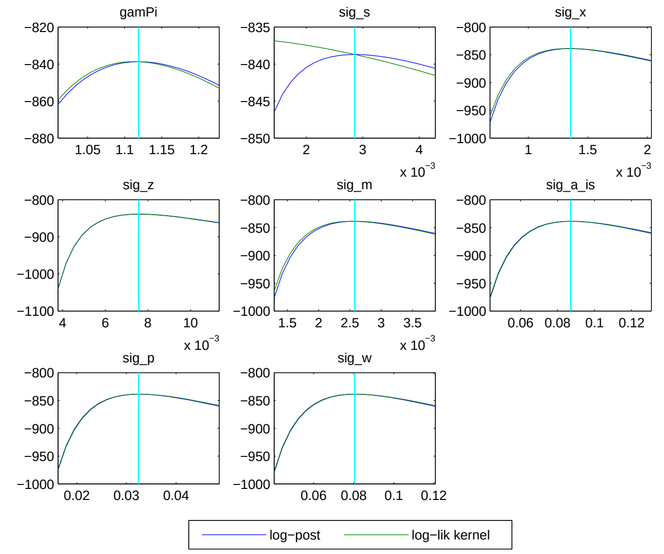
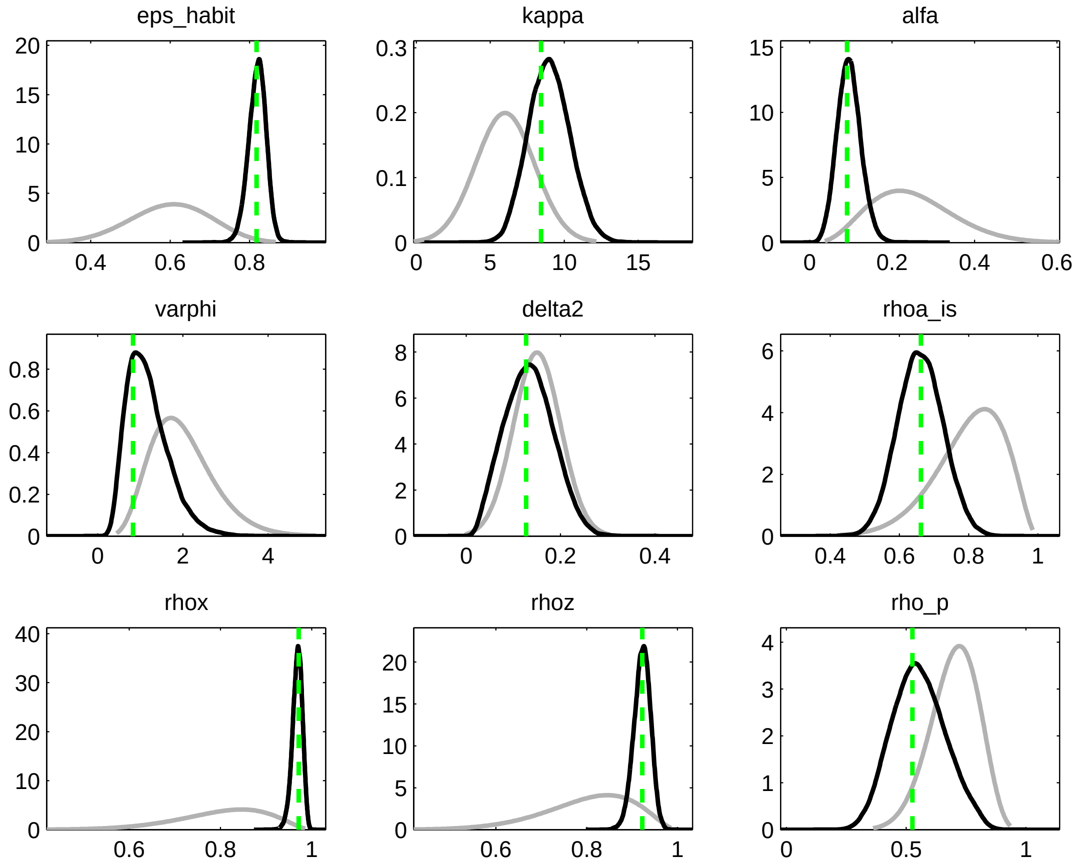


Figure 1.9: Check plots for posterior mode maximization (3/3)



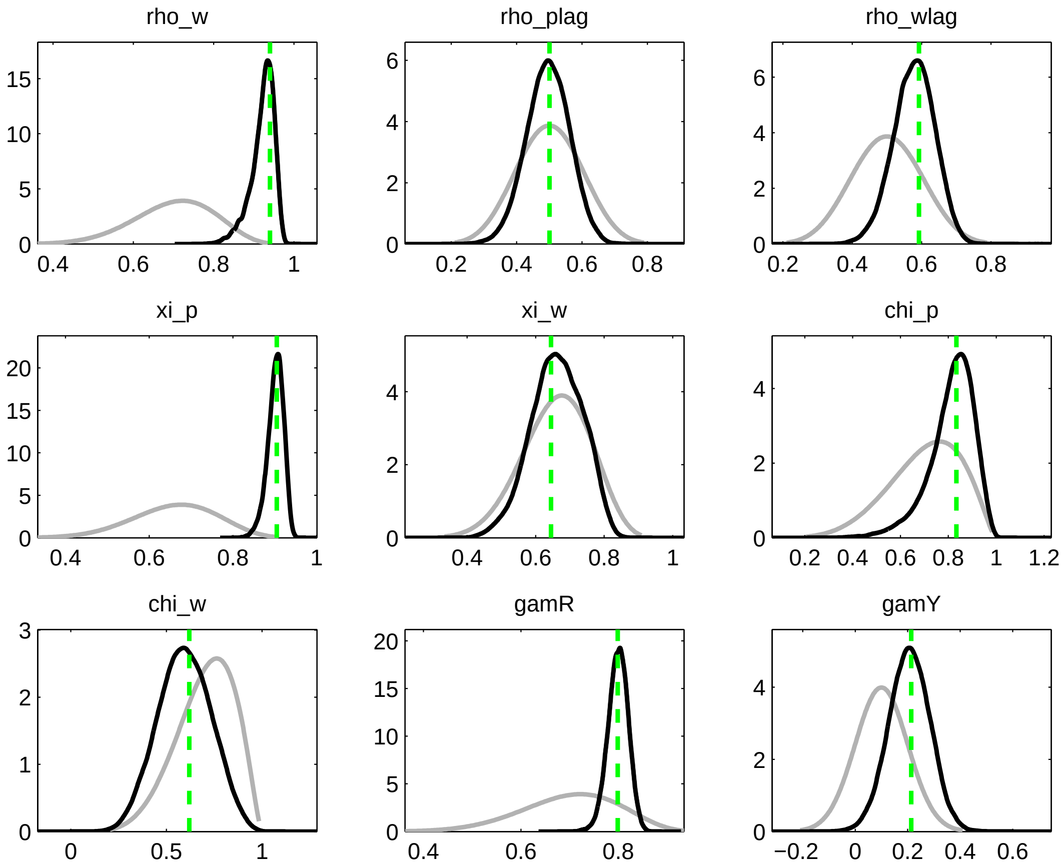
1.F.3 Prior and posterior distributions

Figure 1.10: Prior versus posterior distribution $\mathcal{M}_1$ (1/6)



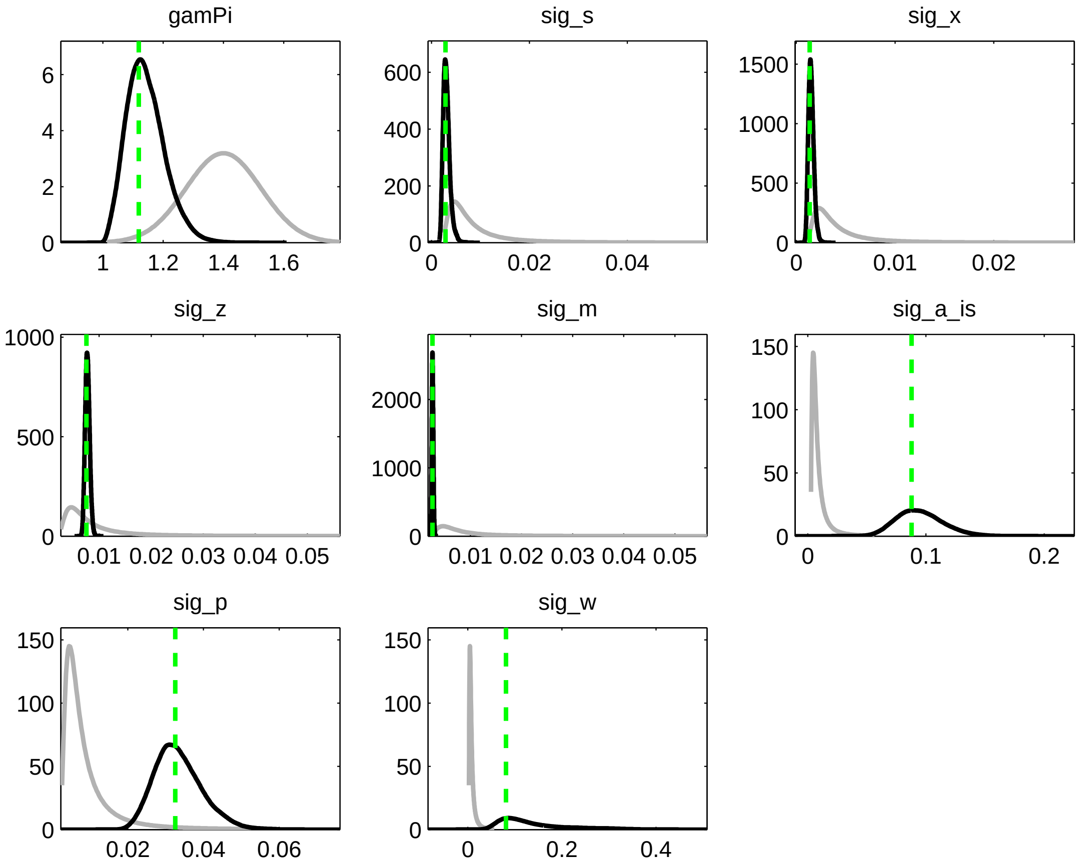
Notes: Prior versus posterior distribution of baseline incomplete information model $\mathcal{M}_1$.

Figure 1.11: Prior versus posterior distribution $\mathcal{M}_1$ (2/6)



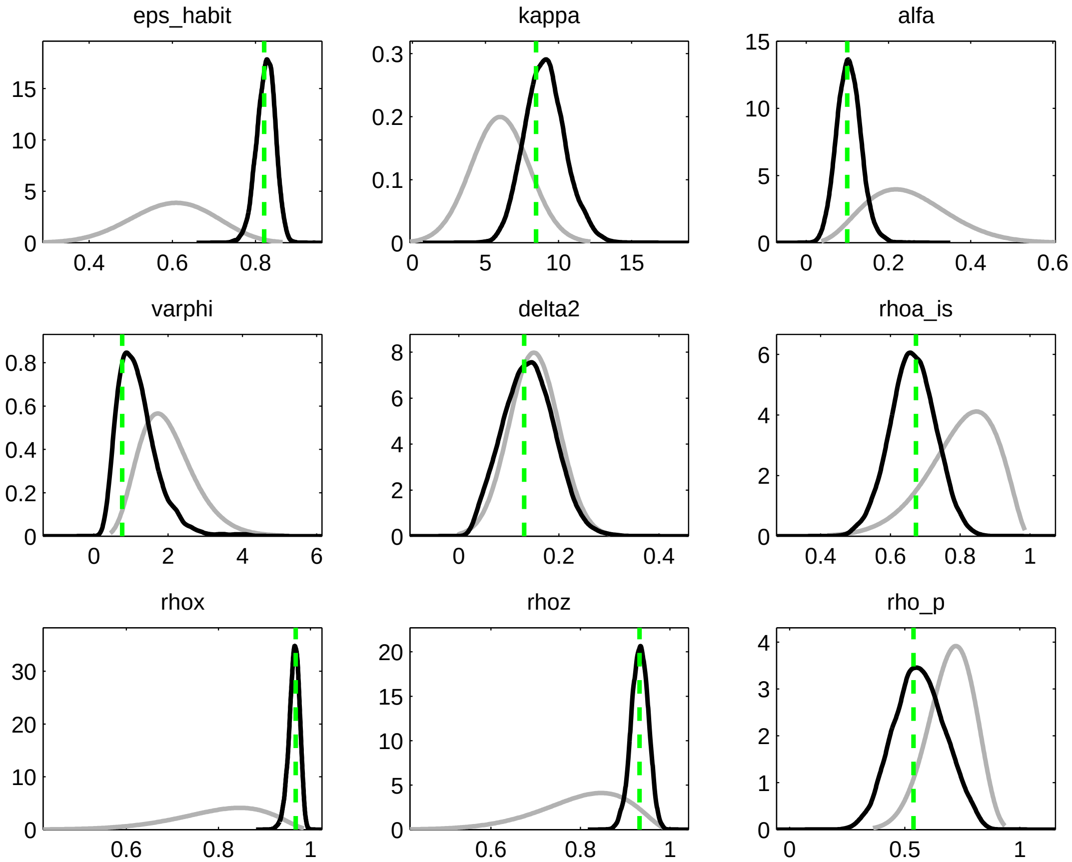
Notes: Prior versus posterior distribution of baseline incomplete information model $\mathcal{M}_1$.

Figure 1.12: Prior versus posterior distribution $\mathcal{M}_1$ (3/6)



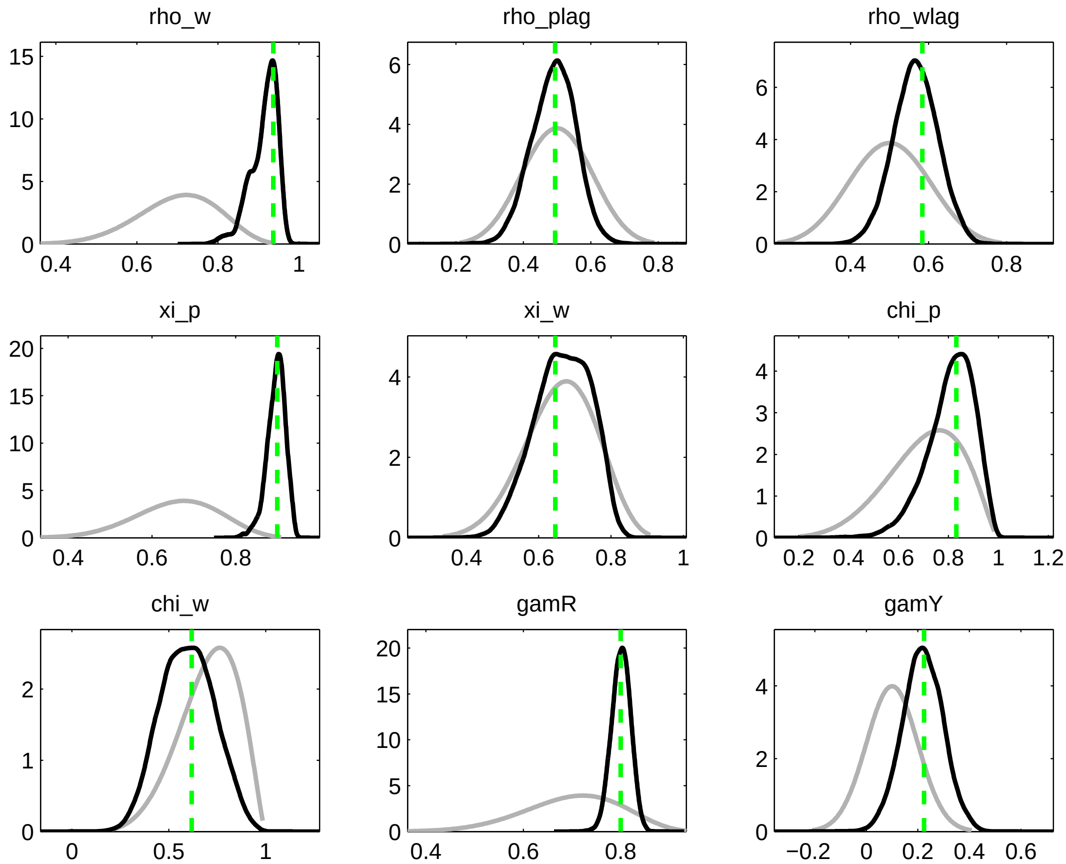
Notes: Prior versus posterior distribution of baseline incomplete information model $\mathcal{M}_1$.

Figure 1.13: Prior versus posterior distribution $\mathcal{M}_2$ (4/6)



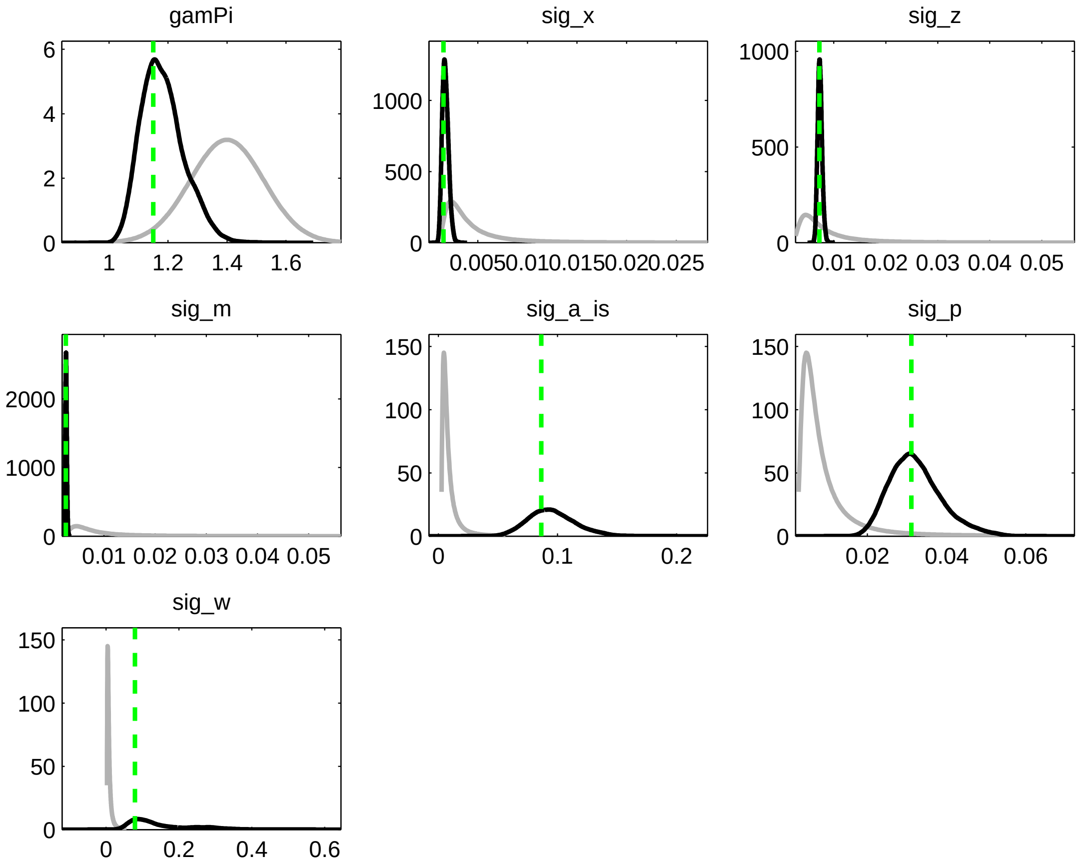
Notes: Prior versus posterior distribution of perfect information model $\mathcal{M}_2$.

Figure 1.14: Prior versus posterior distribution $\mathcal{M}_2$ (5/6)



Notes: Prior versus posterior distribution of perfect information model $\mathcal{M}_2$.

Figure 1.15: Prior versus posterior distribution $\mathcal{M}_2$ (6/6)



Notes: Prior versus posterior distribution of perfect information model $\mathcal{M}_2$.

Chapter 2

Sovereign default risk and state-dependent twin deficits

2.1 Introduction

The notion of 'twin deficits' is based on the observation that the fiscal deficit and the current account deficit increased in tandem during the 1980s in the U.S. economy. In several European countries twin deficits also occurred in the years before and during the global financial crisis, reviving the debate about whether increasing fiscal deficits cause larger current account imbalances. In particular southern European countries have experienced large increases in current account imbalances and widening fiscal deficits. Since 2008-09 current accounts in these countries are rebalancing despite protracted fiscal deficits, suggesting that the link between the twin deficits has diminished. Fiscal deficits were partially the result of large fiscal stimulus packages that were intended to foster economic growth. These large fiscal deficits increased public debt stocks, bringing several European governments to the brink of default and Greece to actually default in 2012. In light of the European sovereign debt crisis, we examine whether public indebtedness affects the co-movement of the fiscal balance and the current account. First, we provide empirical evidence showing that the co-movement of the two balances depends on the government debt-to-GDP ratio. Second, we examine whether a small open economy model with the possibility of sovereign default can explain our empirical evidence.

In the first part of the analysis we estimate the government debt-to-GDP threshold to separate our sample into a low and a high debt regime. For that purpose we estimate a dynamic panel threshold model for 15 European countries to quantify the influence of sovereign indebtedness on the relationship between the fiscal balance and the current account.[1] One advantage of the dynamic panel estimation procedure is that we estimate the threshold rather than exogenously imposing it. Based on our estimation strategy we find that the government debt-to-GDP threshold is 72 percent. Splitting our sample into observations above and below the estimated threshold, we find that the correlation of the two balances falls by 0.19 when moving from the low government debt regime to the high government debt regime. In the second part of our analysis we provide a theoretical explanation for the empirical evidence. We allow for the possibility of sovereign default in a non-linear small open economy model. High government debt-to-GDP ratios lead to increasing risk premia as observed in troubled European countries. Facing higher uncertainty about future taxes, households increase saving rather than accumulate debt to smooth consumption during an economic downturn. Private saving increases while fiscal deficits are expanding, leading to a less pronounced current account deficit. The model-based correlation of the fiscal balance and the current account declines by 0.15 when moving from a low government debt regime to a high government debt regime, which is in line with our empirical evidence.

From a theoretical point of view the relationship between the fiscal balance and the current account is ambiguous. The national income accounting identity states that the current account equals the flow of national savings of the private and the public sector net of investment. A fiscal deficit (i.e. negative public saving) leads, ceteris paribus, to a lower current account. Therefore the accounting identity implies a perfect, positive correlation of the twin deficits. However, given fixed investment, the endogenous private saving decision also affects the current account and thus the relationship between the twin deficits. Households internalize the government budget constraint and increase private saving as they expect that higher government debt leads to higher future taxes – a point emphasized by proponents of the Ricardian equivalence. If household saving increases sufficiently, it is possible that the current account remains unaffected implying no co-movement of fiscal deficits and current account deficits.

[1] Our baseline empirical specification follows Nickel and Vansteenkiste (2008) who estimate a dynamic threshold model employing non-dynamic panel techniques based on Hansen (1999). We apply the recently developed methodology of Kremer, Bick, and Nautz (2013) that allows for the estimation of a dynamic panel threshold model, correcting for the potential bias from using an endogenous regressor.

In our theoretical model we try to account for a key feature of the recent European debt crisis, which is the possibility of sovereign default. We assume that the government borrows from international investors and partially defaults when the amount of government debt exceeds the fiscal limit. Following Bi (2012) the fiscal limit is the maximum debt repayment capacity of the government, i.e. the present discounted value of all possible future fiscal surpluses. International investors demand non-linear sovereign default risk premia when public debt approaches unsustainable levels. Labor taxes increase with the public debt stock. Optimizing households receive transfers from the government and they consume, work and trade assets on international financial markets.

The model is calibrated to match data for Greece, which is one of the countries that experienced large external imbalances and high sovereign spreads in recent years. A negative productivity shock at low government debt-to-GDP ratios leads to an increase in taxes and the fiscal balance temporarily moves into deficit. To smooth consumption households increase borrowing. This implies a strong, positive correlation between the fiscal balance and the current account. A negative productivity shock at high government debt levels affects households via expected labor taxes: First, emerging sovereign risk premia destabilize the fiscal balance, triggering government debt accumulation and increasing expected labor taxes. Second, a government default reduces public debt and, thus, also taxes. As a consequence households expect a larger dispersion of tax rates as government debt approaches high levels. These effects induce optimizing households to increase their saving, which partially offsets current account deficits that result from increasing fiscal deficits. Based on non-linear model simulations with productivity shocks and transfer spending shocks at a low and at a high government debt-to-GDP ratio we show that the correlation of the twins changes by a comparable magnitude as in our empirical analysis.

Current account imbalances and their co-movement with fiscal deficits have received much attention in the literature. The first intertemporal current account model is studied in Sachs (1981) and is extended by Obstfeld and Rogoff (1995). Building on these theoretical foundations, the studies of Glick and Rogoff (1995), Corsetti and Müller (2008) and Bussière, Fratzscher, and Müller (2010) provide evidence that productivity shocks are the main driver of current account dynamics. Corsetti and Müller (2006) show that further important drivers of the co-movement of the twin deficits are the persistence of government spending and the openness of the economy.

Most empirical studies (e.g. Chinn and Prasad, 2003; Chinn and Ito, 2007; Gruber and Kamin, 2007; Lane and Milesi-Ferretti, 2012) find a significant positive relationship in the medium-term between the fiscal balance and the current account using panel methods.[2] This chapter contributes new estimates using the estimation strategy outlined in Kremer et al. (2013) finding a positive and significant coefficient for the fiscal balance below the government debt threshold, but above the threshold the estimate is slightly negative and insignificant. Our estimated threshold of 72 percent is robust to alternative specifications of the empirical model.[3]

In closed economy frameworks Sutherland (1997) and Perotti (1999) show that the consumption response of the private sector can depend on the government debt-to-GDP ratio. In these models a fiscal deficit leads to an increase in consumption at low debt levels, while a fiscal deficit leads to a decrease in consumption at high debt levels. In difference to our framework these models do not allow for a government default.

Increasing government debt-to-GDP ratios have received much attention in the recent policy debate and the academic literature in the course of the European sovereign debt crisis due to surging sovereign interest rates and sovereign default. This work provides a theoretical framework that includes key features of the recent crisis and shows that optimizing households internalize growing government debt stocks, which leads to state-dependent dynamics.

This chapter is structured as follows. Section 2.2 reports our empirical results. Section 2.3 outlines our theoretical model, derives the state-dependent fiscal limit and discusses the non-linear solution method. Section 2.4 presents model simulations which demonstrate that the co-movement of the twins is state-dependent. Section 2.5 provides the conclusion.

[2] A notable exception is Kim and Roubini (2008), who find evidence in favor of a 'twin divergence' rather than a 'twin deficit' for the U.S. based on VAR methods.

[3] Our estimated threshold is slightly higher than the estimate of Baum et al. (2013), who employ a threshold model to examine non-linear effects of debt and real GDP growth rates.

2.2 Empirical evidence

In the first part of our analysis, we provide empirical evidence on the co-movement of the fiscal balance and the current account and how the relationship of the two balances changes at different government debt-to-GDP ratios. Building on Nickel and Vansteenkiste (2008) who estimate a similar dynamic panel threshold model with non-dynamic panel methods, we apply the methodology of Kremer et al. (2013) to avoid a possible endogeneity bias. Following this procedure we estimate the government debt-to-GDP threshold. We show that the correlation of the fiscal balance and the current account for the low and the high government debt regime are significantly different from each other.

2.2.1 Estimation strategy

We apply the following dynamic panel threshold model to estimate the relationship of the fiscal balance and the current account depending on the government debt-to-GDP ratio:

$$\begin{aligned} CA_{it} &= \mu_i + \chi CA_{i,t-1} \\ &+ \beta_1 FB_{it} I(\tfrac{Debt_{it}}{GDP_{it}} \leq \boldsymbol{\gamma}) + \beta_2 FB_{it} I(\tfrac{Debt_{it}}{GDP_{it}} > \boldsymbol{\gamma}) + \alpha' x_{it} + u_{it}, \end{aligned} \tag{2.2.1}$$

where the current account (CA) and the fiscal balance (FB) are measured in percent of GDP.[4] The threshold level (γ) splits the threshold variable (the government debt-to-GDP ratio) into two regimes. The set of control variables is denoted by x_{it}. The indicator function $I(\cdot)$ indicates the regime defined by the threshold variable q_{it} and the threshold level γ. Following previous literature (e.g. Bussière et al., 2006) we include the lagged current account as a regressor in the baseline specification.

As in Caner and Hansen (2004), we first estimate a reduced form regression for the endogenous variable on a set of instruments, in our case higher lags of the dependent variable. We use the predicted values of the lagged dependent variable $\widehat{CA}_{i,t-1}$ to replace $CA_{i,t-1}$. Second, we repeatedly estimate equation (2.2.1) via least squares for all n threshold candidates to obtain the sum of squared residuals $S_n(\gamma)$. The

[4]Following previous literature (e.g. Chinn and Prasad, 2003; Gruber and Kamin, 2007) we assume that the fiscal balance is not endogenous to the current account. It seems unlikely that European policymakers systematically adjust the fiscal balance to changes in the current account.

estimated threshold is selected as the one that minimizes the sum of squared residuals:

$$\hat{\gamma} = \underset{\gamma}{\operatorname{argmin}}\, S_n(\gamma). \tag{2.2.2}$$

The confidence interval for the estimated threshold level $\hat{\gamma}$ according to Caner and Hansen (2004) is given by

$$\hat{\Gamma} = \{\gamma : LR_n(\gamma) \leq C\}, \tag{2.2.3}$$

where C denotes the 95% percentile of the asymptotic distribution of the likelihood ratio statistic $LR_n(\gamma)$. Given the estimate of the threshold $\hat{\gamma}$, the slope coefficients of equation (2.2.1) are estimated using the generalized method of moments (GMM). Further details on the estimation strategy can be found in Appendix 2.B.

2.2.2 Estimation results

The data set is an unbalanced panel of 15 European countries from 1980 to 2010.[5] Table 2.1 provides the main results of our baseline estimation. The series of threshold candidates ranges from 29.2 percent to 101.6 percent of government debt-to-GDP.[6] The threshold estimate of the government debt-to-GDP ratio is 71.8 percent. This threshold value splits the sample into 260 observations below and 93 observations above the threshold. The 95 percent confidence interval of the threshold ranges from 69.4 percent to 75.0 percent.

The estimated coefficients for the fiscal balance differ significantly across both regimes. The fiscal balance is positively correlated (0.16) with the current account if government debt is below the threshold. However, in the high government debt regime, there is virtually no relationship (-0.04) between the fiscal balance and the current account. Thus, a one percent increase in the fiscal deficit is associated with a current account deterioration of 0.16 percent in the low government debt regime, while the same increase in the fiscal deficit has virtually no influence on the current account in the high government debt regime.

[5] Detailed information about the data set is given in Appendix 2.A.

[6] We follow Hansen (1999) and trim the series of threshold candidates by excluding those that lie in the highest and in the lowest 5% quantile to avoid that the threshold sorts too few observations in one of the regimes.

A number of previous studies (see Chinn and Prasad, 2003; Chinn and Ito, 2007; Gruber and Kamin, 2007; Bussière, Fratzscher, and Müller, 2010; Lane and Milesi-Ferretti, 2012) estimate the relationship of the fiscal balance and the current account without applying a threshold model. These studies find a positive relationship between these two balances ranging from 0.06 to 0.3. Our fiscal balance estimate for the low government debt regime is in line with these previous estimates. The estimated coefficient of the lagged current account is positive (0.59) and highly significant. This estimate reflects the high persistence of current account dynamics and, thus, the importance of estimating a dynamic model of the current account.

Table 2.1: Estimation results

Variable	Coefficient	Std. dev.
Current account ($t-1$)	0.59***	(0.16)
Fiscal balance (Debt/GDP $\leq \hat{\gamma}$)	0.16**	(0.07)
Fiscal balance (Debt/GDP $> \hat{\gamma}$)	-0.04	(0.05)
Terms of trade	0.05***	(0.02)
Openness	-0.01	(0.01)
Relative income to U.S.	0.01	(0.04)
Output gap (in % of potential GDP)	-0.28***	(0.11)
Change of total investment (in % of GDP)	-0.14	(0.08)
Labor productivity	0.04	(0.03)
Real effective exchange rate	-0.06***	(0.02)
Dependency ratio (% of working-age pop.)	0.16**	(0.08)
Threshold estimate (in % of GDP)	$\hat{\gamma} = 71.8$	
95% confidence region	$[69.4 - 75.0]$	
Total number of observations	353	

Dependent Variable: Current account (t). */**/*** indicate significance at the 10/5/1 percent level. Standard errors in brackets. The threshold of 71.8% splits the sample into 260 observations below and 93 observations above the threshold. The current account and the fiscal balance are measured in percent of GDP.

The point estimates of the control variables are consistent with previous studies and in line with implications of theoretical open economy models. The estimated threshold of 71.8 percent is robust to a range of alternative specifications of the panel model. A detailed discussion of the results, several robustness checks and a detailed discussion of the related empirical literature can be found in Appendix 2.B.

The estimation yields evidence for significant differences in the regime-dependent fiscal balance coefficients indicating that the co-movement of the fiscal balance and the current account is state-dependent. The estimated regime-dependent coefficients (β_i) are *partial* correlations. In our theoretical analysis (in Section 2.3) we examine the model-implied correlation of the two balances at a low and at a high government debt level. The correlation of the twins implied by the model cannot be directly compared to the estimated *partial* correlations of the panel threshold model. Table 2.2 reports the correlation of the two balances in the data for observations below and above the estimated government debt-to-GDP threshold. For observations below the threshold of 71.8 percent the correlation of the fiscal balance and the current account is 0.57, whereas the correlation is 0.38 for observations above the threshold. Therefore, the difference amounts to 0.19. The confidence intervals for the correlations in both debt regimes indicate that these values are significantly different at a 10 percent significance level. The change in the correlation (0.22) of the two balances is robust to considering the lower (69.4%) and the upper (75.0%) bound of the confidence region.

Table 2.2: Regime-dependent correlations of fiscal balance and current account

Threshold: γ_i	corr(FB,CA) $< \gamma_i$	corr(FB,CA) $> \gamma_i$	Δ corr(FB,CA)
71.8	0.57 [0.50, 0.64]	0.38 [0.26, 0.49]	0.19
69.4	0.58 [0.51, 0.64]	0.35 [0.25, 0.47]	0.22
75.0	0.56 [0.50, 0.63]	0.33 [0.21, 0.46]	0.22

Notes: The left column states the estimated threshold value $\hat{\gamma}$ of 71.8 percent and its confidence bounds of 69.4 and 75.0 percent debt-to-GDP. The second and third column report the correlations of the fiscal balance (FB) and the current account (CA) below and above the threshold value. The 90 percent confidence interval of the correlations is reported in brackets. Δ corr(FB,CA) denotes the difference between the correlation in the low debt regime and the correlation in the high debt regime.

In the backdrop of the current account identity our empirical findings suggest that households' behavior responds differently to fiscal deficits at low government debt-to-GDP ratios compared to high ratios: The higher the government debt-to-GDP ratio, the stronger households compensate a fiscal deficit by increasing saving, offsetting the effect of a fiscal deficit on the current account. This finding is robust to considering the correlations as well as the regime-dependent *partial* correlation estimates. The behavior of households at high government debt-to-GDP ratios is consistent with the implications of the Ricardian equivalence hypothesis. In the next section we examine the occurrence of twin deficits in a structural model to provide a theoretical explanation for the observed change in the correlation of the 'twins'.

2.3 The Model

In our theoretical analysis, we consider a small open economy model with defaultable public debt and private asset holdings that are both held by foreign investors. Households borrow and lend at a time-invariant world interest rate facing portfolio adjustment costs. The government raises distortionary labor taxes, pays transfers to households and invests in unproductive government expenditures. The government can default on its outstanding debt. Risk-neutral foreign investors require an endogenous default risk premium when government debt approaches the 'effective fiscal limit'. Following Bi (2012) the effective fiscal limit is a random draw from the model-implied state-dependent distribution of the fiscal limit. A sovereign default occurs when the government debt stock exceeds the effective fiscal limit.

2.3.1 Households

Consider an economy populated by an infinite number of identical households that choose consumption c_t, leisure L_t, and debt d_t^H to maximize

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u\left(c_t, L_t\right) \ , \tag{2.3.1}$$

where $\beta \in (0,1)$ is the discount factor, subject to the budget constraint

$$c_t = W_t \left(1-\tau_t\right)\left(1-L_t\right) + z_t + d_t^H - (1+r)d_{t-1}^H - \frac{\psi}{2}\left(d_t^H - d^H\right)^2 \ , \tag{2.3.2}$$

and a no-Ponzi scheme condition. The budget constraint includes consumption c_t, after tax income $W_t\left(1-\tau_t\right)\left(1-L_t\right)$, government transfers z_t to the households and operations in international financial markets. Households trade a riskless bond d_t^H (positive values of d_t^H denote debt) at a constant world interest rate r. Following

Schmitt-Grohé and Uribe (2003) we assume quadratic portfolio adjustment costs that are weighted by the parameter $\psi > 0$, where d^H denotes the steady state net foreign asset position of households. We set the discount factor β equal to one over the gross world interest rate:

$$\beta(1+r) = 1 \; . \tag{2.3.3}$$

We assume Greenwood, Hercowitz, and Huffman (1988) preferences

$$u(c, L) = \frac{\left(c_t - \chi\frac{(1-L_t)^\omega}{\omega}\right)^{1-\sigma} - 1}{1-\sigma} \; , \tag{2.3.4}$$

where the Frisch elasticity of labor supply is $1/(\omega - 1)$ and $\chi > 0$ determines the relative disutility of labor. The degree of relative risk aversion is measured by $\sigma > 0$. As pointed out by Schmitt-Grohé and Uribe (2003) as well as by Mendoza and Yue (2012), these preferences simplify the supply side of the model and help to explain international business cycle facts.[7] The households' first-order conditions are

$$\left(c_t - \frac{\chi(1-L_t)^\omega}{\omega}\right)^{-\sigma} = \lambda_t \tag{2.3.5}$$

$$1 - L_t = \left[\frac{W_t(1-\tau_t)}{\chi}\right]^{\frac{1}{\omega-1}} \tag{2.3.6}$$

$$\lambda_t\left(1 - \psi(d_t^H - d^H)\right) = \beta(1+r)\mathbb{E}_t\lambda_{t+1} \; , \tag{2.3.7}$$

where λ_t is the Lagrange multiplier of the budget constraint.

2.3.2 Production

The production function of output is linear in labor:

$$y_t = A_t\left(1 - L_t\right) \; . \tag{2.3.8}$$

[7] Greenwood et al. (1988) preferences remove the wealth effect, which helps to avoid counterfactual increases in labor when total factor productivity falls.

The process of total factor productivity (TFP), A_t, follows an AR(1) process:

$$\ln\left(\frac{A_t}{A}\right) = \rho_A \ln\left(\frac{A_{t-1}}{A}\right) + \epsilon_{A,t} \ , \qquad \epsilon_{A,t} \sim \mathcal{N}\left(0, \sigma^2_{\epsilon_A}\right) \ , \tag{2.3.9}$$

where A denotes steady state productivity.

Wages are determined on a competitive labor market. Thus, the wage equals the marginal product of labor which in our case equals TFP:

$$W_t = A_t \ . \tag{2.3.10}$$

2.3.3 Government

The government receives tax revenues $\tau_t W_t (1 - L_t)$ through distortionary labor taxation and issues new public debt b_t at a given price q_t. It finances government spending g_t and transfers z_t. In addition, the government can default on the fraction $\triangle_t$ of its outstanding debt and pays back the remaining debt from last period $b^d_t = (1 - \triangle_t)\, b_{t-1}$. Hence, the government budget constraint is:

$$\tau_t A_t (1 - L_t) + b_t q_t = b^d_t + g_t + z_t \ . \tag{2.3.11}$$

We assume that the tax rate τ_t adjusts linearly to the public debt stock:

$$\tau_t - \tau = \gamma_b \left(b^d_t - b\right) . \tag{2.3.12}$$

Government spending is a stationary process that responds systematically to changes in productivity. The parameter γ_g measures the elasticity of government spending g_t with respect to productivity:

$$\log\left(\frac{g_t}{g}\right) = \gamma_g \log\left(\frac{A_t}{A}\right) \ . \tag{2.3.13}$$

Transfers follow a Markov switching process with a stationary and a non-stationary regime as in Davig and Leeper (2011):

$$z_t = \begin{cases} (1-\rho_z) z + \rho_z z_{t-1} + \epsilon_{z,t} & \text{for } S_{Z,t} = 1 \\ \mu z_{t-1} + \epsilon_{z,t} & \text{for } S_{Z,t} = 2 \ , \end{cases} \tag{2.3.14}$$

where $|\rho_z| < 1$, $\mu > 1$ and $\epsilon_{z,t} \sim \mathcal{N}\left(0, \sigma^2_{\epsilon_z}\right)$. Transfers follow a stationary path when $S_{Z,t} = 1$ and an explosive path when $S_{Z,t} = 2$, where the regimes, $S_{Z,t}$, follow a Markov chain with transition matrix

$$\begin{pmatrix} p^{MS} & 1-p^{MS} \\ 1-p^{MS} & p^{MS} \end{pmatrix}. \tag{2.3.15}$$

With probability p^{MS} government transfers stay in one of the regimes. For example, in case of a high probability p^{MS} transfers are likely to grow for many periods in the non-stationary regime leading to government debt accumulation. The process switches from one regime to the other with probability $1 - p^{MS}$, such that transfers are ultimately stabilized (as $\rho_z < 1$).

2.3.4 Foreign investors

Domestic households and the domestic government borrow and lend from foreign investors. Unlike the households, the government can default on a fraction of its outstanding debt stock. Foreign investors have access to an international credit market where they can borrow or lend unlimited amounts at a constant world interest rate $r > 0$.

Foreign investors act in competitive markets and choose loans b_t in each period to maximize expected profits ϕ_t, taking prices as given. Risk-neutral investors price bonds such that they break even in expected value:

$$\phi_t = -b_t q_t + \mathbb{E}_t\left[\frac{(1-\Delta_{t+1})}{1+r} b_t\right] . \tag{2.3.16}$$

Consequently the equilibrium government bond price q_t reflects the risk of default that investors face:

$$q_t = \mathbb{E}_t\left[\frac{(1-\Delta_{t+1})}{1+r}\right] . \tag{2.3.17}$$

As international investors are risk neutral and are fully compensated for the default risk they are indifferent between holding household debt and government bonds.

2.3.5 Current account

In our model household and government liabilities are held vis-à-vis the rest of the world. Borrowing and lending of the private and public sector affect the current account as follows:

$$
\begin{aligned}
CA_t^{private} &= -d_t^H + d_{t-1}^H \;, && (2.3.18)\\
CA_t^{public} &= -b_t q_t + b_{t-1} q_{t-1} \;. && (2.3.19)
\end{aligned}
$$

The private sector current account equals the change in households' saving. The public current account is identical to the fiscal balance as the entire public debt stock is held abroad. The sum of both sub-balances amounts to the aggregate current account CA_t.[8]

2.3.6 Laffer curve and fiscal limit

The proportional labor tax induces a distortion in the economy as it influences the households' labor decision, which in turn affects government tax revenues. Distortionary labor taxation gives rise to a Laffer curve and, hence, to a revenue-maximizing tax rate. With Greenwood et al. (1988) preferences tax revenues amount to:

$$
T_t = \tau_t W_t \left(1 - L_t\right) = \tau_t W_t \left[\frac{W_t(1-\tau_t)}{\chi}\right]^{\frac{1}{\omega-1}} \;. \tag{2.3.20}
$$

The maximum amount of tax revenues, $T_t^{\max}$, is generated at the revenue-maximizing tax rate which is at the peak of the Laffer curve. The revenue-maximizing tax rate, $\tau_t^{\max}$, is derived as follows:

$$
\begin{aligned}
\frac{\partial T_t}{\partial \tau_t} &= W_t \left[\frac{W_t(1-\tau_t)}{\chi}\right]^{\frac{1}{\omega-1}} + \tau_t W_t \frac{1}{\omega-1} \left[\frac{W_t(1-\tau_t)}{\chi}\right]^{\frac{1}{\omega-1}-1} \left(-\frac{W_t}{\chi}\right) = 0\\
\Leftrightarrow \;\; & \tau_t^{\max} = \frac{\omega-1}{\omega} \;.
\end{aligned}
$$

Although the revenue-maximizing tax rate only depends on the Frisch elasticity of

[8] Note that positive values of d_t^H and b_t^d mean that households and the government have external liabilities. An increase of d_t^H or b_t^d implies a negative current account.

labor supply, the maximum amount of tax revenues also depends on the state of the economy (in our case TFP).

Next, we use the revenue-maximizing tax rate to derive the fiscal limit which is a state-dependent distribution. Following Bi (2012) the state-dependent fiscal limit $\mathcal{B}^*(A_t, z_t, S_{Z,t})$ is the maximum level of debt that the government is able to service, i.e. the present discounted value of all possible future fiscal surpluses.[9] The fiscal limit depends on the exogenous states A_t, z_t and $S_{Z,t}$ as well as their future realizations ($j \geq 1$) and the parameters of the model:

$$\mathcal{B}^*(A_t, z_t, S_{Z,t}) = \sum_{j=0}^{\infty} \beta^{t+j} \left(T_{t+j}^{\max} - g_{t+j} - z_{t+j} \right) \ .$$

We derive the fiscal limit from the perspective of risk-neutral foreign investors, who price the bonds, and thus we set the stochastic discount factor to β. To simulate the fiscal limit $\mathcal{B}^*(A_t, z_t, S_{Z,t})$ for given initial conditions $(A_t, z_t, S_{Z,t})$ we randomly draw future shocks A_{t+j}, z_{t+j} and $S_{Z,t+j}$ for $j = 1, 2, .., N$.[10] Based on $m = 1, 2, ..., M$ simulations of $\mathcal{B}_m^*(A_t, z_t, S_{Z,t})$, we approximate the state-dependent fiscal limit $\mathcal{B}^*(A_t, z_t, S_{Z,t})$ by a normal distribution for each state of the economy.

It is often challenging for investors to determine whether a government is actually willing to increase taxes or to cut spending to avoid a default. Possible resistance by the population against austerity measures might also influence political decisions. Hence, international investors face a high degree of uncertainty that surrounds political processes in countries with high government debt-to-GDP ratios when pricing government bonds. In our model the political uncertainty is reflected by randomly drawing an *effective fiscal limit*, which follows a state-dependent distribution. As in Bi (2012) the government defaults when the public debt stock b_{t-1} exceeds the *effective fiscal limit* b_t^*.[11]

Sturzenegger and Zettelmeyer (2008) show that international investors can usually negotiate a repayment of a large share of the original claim after a default. Therefore, we assume that the government does not default on its entire debt stock, but on the

[9] As Bi (2012) we do not consider the expected value of the fiscal limit, but all possible realizations and thus the fiscal limit is a distribution.

[10] We simulate $N = 200$ periods and repeat this calculation $M = 100000$ $(m = 1, 2, ...M)$ times. At longer horizons the discounted value of government fiscal surpluses is virtually zero.

[11] In contrast, Eaton and Gersovitz (1981) and Arellano (2008) provide a model of sovereign default where the government has an incentive to default despite being able to repay its debt.

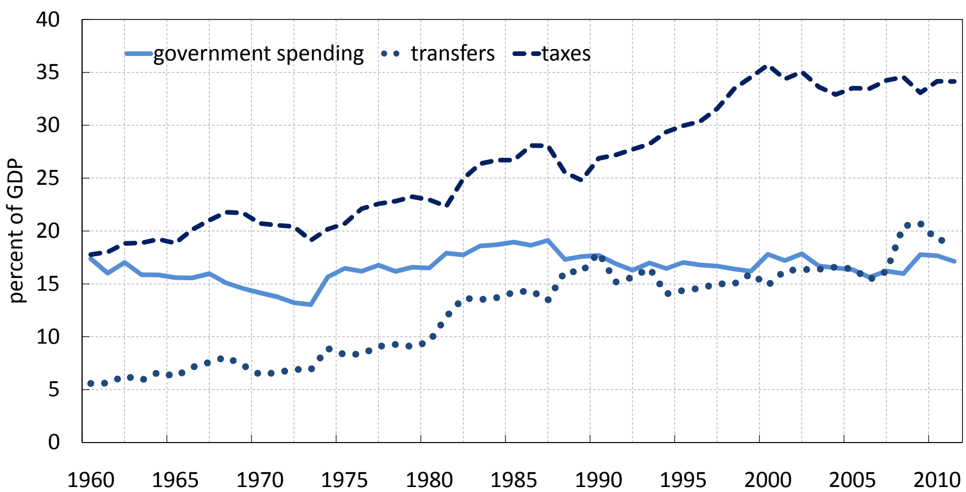
fraction $\delta \in [0, 1]$ which reflects the size of the 'haircut'. Hence, the default scheme is:

$$\Delta_t = \begin{cases} 0 & \text{if } b_{t-1} < b_t^* \sim \mathcal{B}^*(A_t, z_t, S_{Z,t}) \\ \delta & \text{if } b_{t-1} \geq b_t^* \sim \mathcal{B}^*(A_t, z_t, S_{Z,t}) \,. \end{cases} \tag{2.3.21}$$

2.3.7 Calibration

We calibrate the model to match annual data for Greece from 1960 to 2010. The case of Greece is particularly interesting for our analysis as the country currently has the highest debt stock in Europe, experiences surging sovereign interest rates and has large external imbalances.[12] Table 2.3 summarizes the calibration of the model. In line with previous literature we pick conventional values for the discount factor, the coefficient of relative risk aversion, the Frisch elasticity and the disutility of labor. Portfolio adjustment costs are chosen to match the standard deviation of the trade balance to output ratio following Schmitt-Grohé and Uribe (2003). The steady state level of TFP is normalized to 1.

Figure 2.1: Government spending, transfers and taxes in Greece



Source: OECD Economic Outlook No. 86 (2009).

[12]State-dependent twin deficits also occur when calibrating the model to another country with a different fiscal limit. As we show in the next section households saving increases in the proximity of the respective fiscal limit.

Figure 2.1 shows that the ratio of government spending relative to GDP in Greece remained stable over the last decades. Average government spending is 16.57 percent of GDP and average lump-sum transfers amount to 12.27 percent of GDP. The elasticity of government spending with respect to real GDP per worker, γ_g, is estimated in a linear regression for the full sample. The estimation yields a value of -0.07. The estimated response of taxes to an increase of the debt-to-GDP ratio is 0.42 in a linear regression. The government therefore raises taxes by about 1 percentage point in response to an increase of government debt by 2.5 percent of GDP.

Table 2.3: Model calibration to Greek economy

Parameter		Value	Target/Source
Discount factor	β	0.95	Annual interest rate: 5.26%
Relative risk aversion	σ	2	Schmitt-Grohé and Uribe (2003)
Frisch elasticity	$1/(1-\omega)$	0.9	Kimball and Shapiro (2008)
Disutility of labor	χ	3.173	Steady state labor supply: 25%
Portfolio adjustment costs	Ψ	0.005	Std(trade balance/GDP): 7.3%
Steady state TFP	A	1	TFP normalized to one
Government spending/GDP	g/y	16.57%	OECD EO No. 86 (2009)
Transfer/GDP	z/y	12.27%	OECD EO No. 86 (2009)
Gov. spending elasticity	γ_g	-0.07	Own estimate
Tax reaction coefficient	γ_b	0.42	Own estimate
Government debt/GDP	b/y	60%	Bank of Greece (2013)
Household debt/GDP	d^H/y	60%	Avg. external priv. debt/GDP
Tax rate	τ	31.84%	Avg. government debt/GDP
Default rate	δ	15%	Bi (2012), EU Commission
Productivity persistence	ρ_A	0.53	Own estimate
Std. dev. of prod. shock	σ_{ϵ_A}	0.027	Own estimate
Transfer spending persistence	ρ_z	0.9	Bi et al. (2013)
Explosive transfer growth	μ	1.01	Bi et al. (2013)
Markov switching probability	p^{MS}	0.9	Bi et al. (2013)
Std. dev. of transfer shock	σ_{ϵ_z}	0.07	Own estimate
	Average fiscal limit:		
Mean (% of GDP)	$\mathcal{B}^*$	156%	MCMC simulation
Std. dev. (% of GDP)	$\sigma_{\mathcal{B}^*}$	21%	MCMC simulation

We set the steady state of total external debt-to-GDP ratio to 120 percent to match average total external liabilities of Greece from 1995 to 2010. About half of total gross external debt are public sector liabilities.[13] Thus, in our calibration, half of total external debt is public external debt and the other half is private sector external debt. As total external liabilities are 120 percent of GDP, we set both the private and public external debt-to-GDP ratio to 60 percent of GDP. To match the average government debt-to-GDP ratio of 60 percent we set the steady state tax rate to 31.84 percent.

We consider various sources to calibrate the size of the haircut in our model for the case of Greece. The European Commission (2011) forecast in autumn 2011 published before the debt restructuring in 2012 reports a government debt-to-GDP ratio of 198.3 percent at the end of 2012. The most recent forecast release in spring 2013 of the European Commission (2013) for the government debt-to-GDP ratio after the debt restructuring is 161.6 percent, suggesting that the haircut is estimated to effectively lower public debt by 18 percent at the end of 2012. Considering the empirical evidence of previous debt restructurings, Bi (2012) computes historical haircuts indicating an average size of 13 percent (excluding default events below a haircut of 3 percent). A haircut of this size is also in line with estimates in Sturzenegger and Zettelmeyer (2008), Panizza (2008) and Moody's (2011). Therefore, we choose a conservative value of 15 percent for the default fraction.[14]

We estimate the exogenous processes for productivity and transfers using HP-filtered data. The log of productivity as measured by real GDP per worker has a persistence of 0.53 and a standard deviation of 0.027 of the shock. Figure 2.1 illustrates that transfer payments from the government to households continuously increased in Greece over the last decades. Following Bi, Leeper, and Leith (2013) we set the Markov switching probability p^{MS} of the transfer process to 0.9. This implies that on average the transfer process stays in each regime for ten years. The parameter of the explosive transfer growth μ is set to 1.01 to match the growth of transfers in Greece since 1960 and ρ_z is set to 0.9. The estimated standard deviation

[13]Based on data from the Bank of Greece 56 percent of total external debt is government debt. To our knowledge disaggregated data for the pre-1995 period is not available.

[14]In March 2012 Greece implemented a 53.5 percent haircut to the nominal value of debt held by the private sector, which roughly held half of the total debt stock suggesting a haircut of around 25 percent. Later in 2012 the Troika (ECB, IMF and European Commission) had to recapitalize the Greek banking system, which was holding around one-third of government debt, effectively reducing the net impact of the debt restructuring. However, assuming a higher default fraction does not alter the mechanism of the model and only changes the maximum risk premia that the international investors demand from the government.

of the transfer shock is 0.07 in a least squares regression.

Based on the calibration we determine the resulting average mean and standard deviation across all fiscal limits. The mean of all fiscal limits is 156 percent of steady state output and the standard deviation is 21 percent as a fraction of steady state GDP. The next section addresses how the fiscal limit changes with the state of the economy.

2.3.8 Laffer curve and fiscal limit for Greece

The revenue maximizing tax rate only depends on the Frisch elasticity. Figure 2.2 shows the Laffer curve for three different values of the Frisch elasticity. Based on the calibration of our model the revenue-maximizing tax rate is 52.6 percent. This tax rate is close to the revenue maximizing labor tax rate of about 60 percent for Greece estimated by Trabandt and Uhlig (2011).

Figure 2.2: Sensitivity of Laffer curve to the Frisch elasticity of labor supply

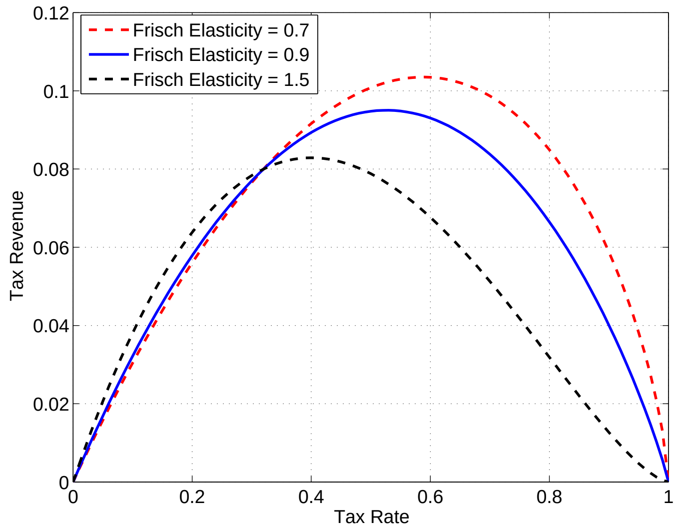
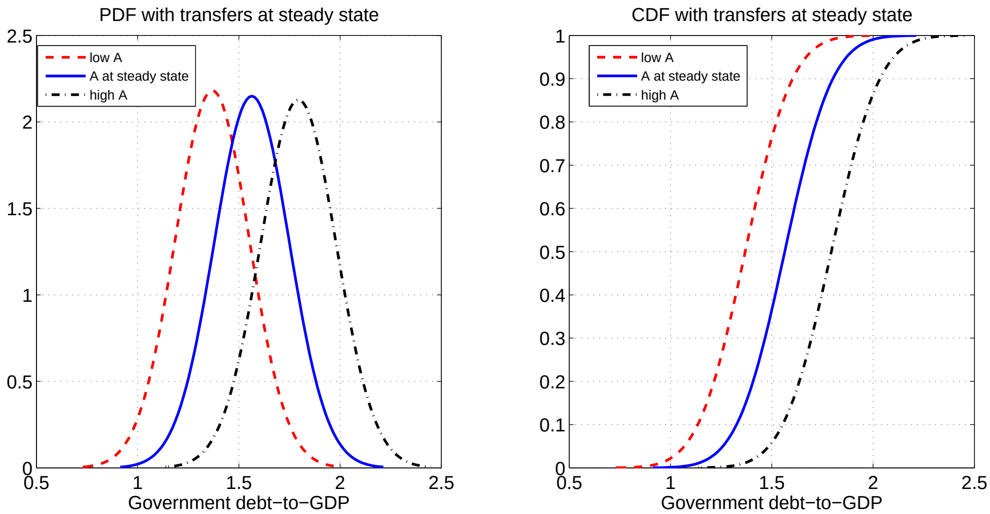


Figure 2.3 displays the distribution of the fiscal limit based on the calibrated model. The fiscal limit depends on the state of the economy. The left panel depicts the probability density function for different productivity states, while the right panel shows the cumulative density function. As the fiscal limit shifts with the state of the

Figure 2.3: State-dependent distribution of the fiscal limit



Notes: State-dependent distributions of the fiscal limit for different TFP states and transfers in steady state of the stationary regime. Each distribution is approximated by a normal distribution. The left panel shows the probability density functions and the right panel shows the cumulative density functions.

economy, the default probability is also state-dependent. In a recession, i.e. in a low productivity state, the average fiscal limit is much lower compared to an economy that is in a high productivity state. During an economic downturn tax revenues are smaller and productivity is likely to stay at low levels due to its persistence. These two effects lower average future fiscal surpluses, shifting the mean of the fiscal limit to lower government debt-to-GDP ratios. The mean of the fiscal limit is at 163 percent of GDP for an intermediate TFP state, 146 percent of GDP for the lowest TFP state and 183 percent of GDP for the highest TFP state when transfers are at the mean and in the stationary regime.[15] For low TFP states sovereign risk premia occur around 130 percent government debt-to-GDP. This value is close to actual data for

[15]The fiscal limit also shifts with different states of transfer spending and the Markov switching process between stable and explosive transfer growth. The mean of the fiscal limit is at 140 percent of GDP when transfers are in the highest state and at 189 percent of GDP when transfers are in the lowest state with productivity at steady state and in the stationary transfer regime. A shift from the stable to the explosive transfer regime leads to a shift of the mean of the fiscal limit from 163 percent of debt to GDP to 150 percent of debt to GDP with productivity and transfers at their steady state.

Greece as sovereign bond spreads have increased dramatically since April 2010 when government debt-to-GDP was 131 percent. Since 2008 the country is also in a severe recession, which is reflected by a low TFP state in the model.

2.3.9 Solution method

The model features non-linearities due to the possibility of government default and the regime switching of government transfers. For our calibration the fiscal limit is far away from the steady state. For these reasons we use a global solution method to solve the model. The complete set of model equilibrium conditions is listed in Appendix 2.C. We express the model by two first-order difference equations to solve for two policy functions. In particular, the first equilibrium condition is the households' first-order condition (2.3.7) and the second equilibrium condition is the government budget constraint (2.3.11) combined with the first-order condition of foreign investors (2.3.17):

$$\lambda(\Psi_t)\left(1-\psi((f^{d^H}(\Psi_t)-d^H)\right)=\beta\,(1+r)\,\mathbb{E}_t\lambda(\Psi_{t+1}) \tag{2.3.22}$$

$$\frac{b_t^d+g_t+z_t-\tau(\Psi_t)A_t(1-L(\Psi_t))}{f^b(\Psi_t)}=\mathbb{E}_t\left\{\frac{(1-\Delta(f^b(\Psi_t),f^{d^H}(\Psi_t),A_{t+1},z_{t+1},S_{Z,t+1})}{1+r}\right\} \tag{2.3.23}$$

where $\Psi_t=\left\{b_t^d,d_{t-1}^H,A_t,z_t,S_{Z,t}\right\}$ is the state vector of the economy. To solve the model we employ the non-linear algorithm described in Coleman (1991) and Davig (2004). This procedures discretizes the state space Ψ_t and finds a fixed point in the policy rules $b_t=f^b(\Psi_t)$ and $d_t^H=f^{d^H}(\psi_t)$ for each grid point in the state space. Further details on the solution method are in Appendix 2.D.

2.4 Model results

First, we show that the correlation of the fiscal balance and the current account changes with the government debt-to-GDP ratio. Then, we provide intuition for the change of the correlation examining policy rules. Finally, to illustrate the state-dependent model dynamics, we present impulse responses to productivity shocks at a low and at a high government debt-to-GDP ratio.

2.4.1 State-dependence of twin deficits

Table 2.4 presents the correlations between the fiscal balance and the current account at a low and at a high government debt-to-GDP ratio.[16] The correlation of the two balances declines as government debt-to-GDP levels increase, in line with our empirical results in Section 2.2. The model with both shocks implies a perfect correlation of the fiscal balance and the current account for public debt-to-GDP at 60 percent. The correlation of the twins declines to 0.85 at a government debt-to-GDP ratio of 140 percent. Therefore the change in the correlation is 0.15 when moving from the low government debt regime to the high debt regime. At low government debt levels government and household debt co-move almost one-for-one ($corr(CA^{private}, FB) = 0.99$). However, at high government debt-to-GDP levels the correlation is much lower ($corr(CA^{private}, FB) = 0.04$).

To compare our model-implied correlation with actual data we report the state-dependent correlation of the fiscal balance and the current account calculated in Section 2.2 for 15 European countries. Table 2.4 reports the absolute change (0.19) in the correlations of the twins between the high and low government debt regime in the data. The model-implied change in the correlation (0.15) is close to the one found in the data.

To shed light on the relative importance of each shock Table 2.4 also reports correlations conditional on each shock. Even though the correlation of the fiscal balance and the current account conditional on transfer shocks is high (0.86) in the low debt regime, it is negative (-0.36) in the high debt regime. In line with Corsetti and Müller (2008) we find that the unconditional correlation of the two balances in the model is dominated by TFP shocks.

2.4.2 Model dynamics

To highlight the key transmission mechanisms we discuss the properties of two policy functions: sovereign interest rates and households' saving. International investors demand risk premia when government debt approaches the fiscal limit and

[16] The reported statistics for the model are an average over 500 simulations of eight years each. We only include simulations without default episodes. We choose a short simulation period to avoid a possible bias in the reported results by excluding too many draws that result in a government default that implies a large current account surplus.

Table 2.4: State-dependent correlations of fiscal balance and current account

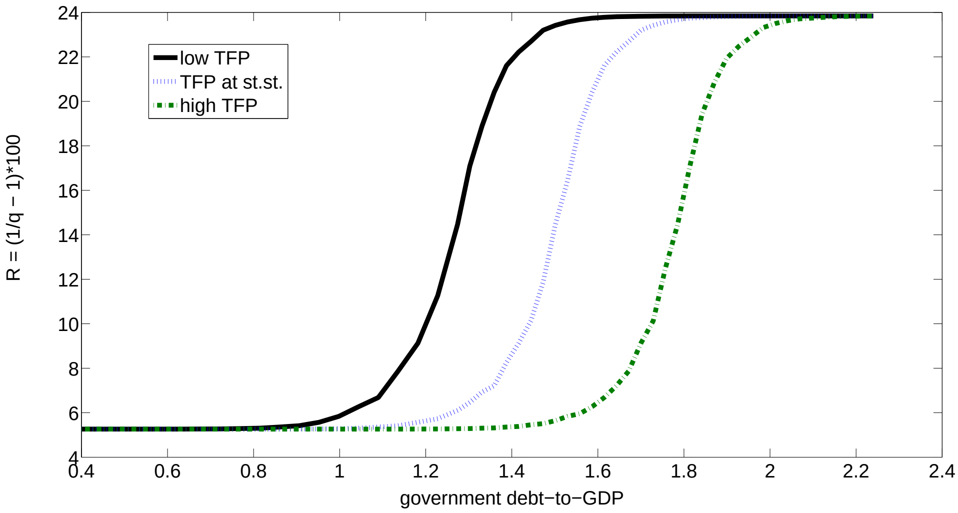
Low vs. high government debt-to-GDP: Δ corr(FB,CA)	
Data	0.19
Model	0.15
Low government debt-to-GDP: 60 percent	
Both shocks	1.00
TFP shocks	1.00
Transfer shocks	0.86
High government debt-to-GDP: 140 percent	
Both shocks	0.85
TFP shocks	0.86
Transfer shocks	-0.36

Notes: Correlations of fiscal balance (FB) and current account (CA), both in percent of GDP. The low government debt level is the steady state value of the model. Δ corr(FB,CA) denotes the difference between the correlation of the low debt regime and the correlation of the high debt regime. All simulations are based on the stationary transfer regime.

the probability of default increases (see Figure 2.4). Up to a government debt-to-GDP ratio of around 100 percent foreign investors do not demand sovereign default risk premia as they expect no risk of a government default in the next period independent of today's productivity state. Hence, sovereign bond yields equal the risk-free rate. Sovereign interest rates increase up to 24 percent for high government debt levels. Since international investors are risk neutral they demand risk premia that offset the expected loss due to the possible government default.

The government debt level at which investors demand risk premia depends on the state of the economy as the latter affects the fiscal limit. For example, if the economy is in a recession, i.e. in a low TFP state, tax revenues are low and the fiscal limit is shifted to the left. Hence, in a recession the probability of sovereign default is much higher as compared to an economy in a high productivity state. Consequently, at the lowest productivity state default risk premia begin to emerge at around 100 percent of government debt-to-GDP, whereas at the highest TFP state risk premia emerge at around 160 percent of government debt-to-GDP.

Figure 2.4: Sovereign interest rates at different government debt-to-GDP ratios

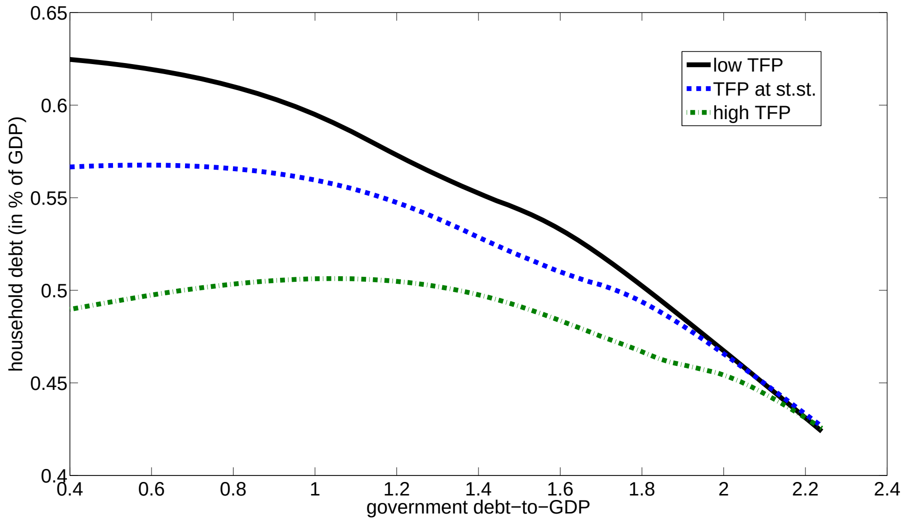


Notes: Household debt and transfer spending are both set to steady state and transfer spending is in the stationary regime. Horizontal axis: ratio of government debt-to-GDP. Vertical axis: in percentage points.

Households trade assets with foreign investors to smooth consumption and to insure against expected tax changes due to the risk of government default. The saving decision at different productivity states depends non-linearly on the public debt stock (see Figure 2.5). When government debt-to-GDP is around 60 percent (steady state) households accumulate debt relative to steady state household debt to smooth consumption at a low TFP state. However, around 140 percent government debt-to-GDP ratio households save relative to steady state household debt in all TFP states as public debt increases.

The households' saving decision is influenced by the level of government debt due to the possibility of government default in the proximity of the fiscal limit. A more costly roll-over of government debt increases the fiscal deficit and leads to higher expected future labor taxes. However, households benefit from a realized government default as a default leads to lower government debt and, thus, to lower distortionary taxes.[17] The distortion caused by labor tax increases with higher government debt levels. To insure against higher expected future labor taxes households save relative to steady state household debt when government debt is high even when faced with negative TFP shocks.

Figure 2.5: Households' saving decision at different government debt-to-GDP ratios



Notes: Transfer spending is at steady state and in the stable process. Horizontal axis: ratio of government debt-to-GDP. Vertical axis: households' choice of debt in percent of GDP when the households' debt stock in the last period is at steady state.

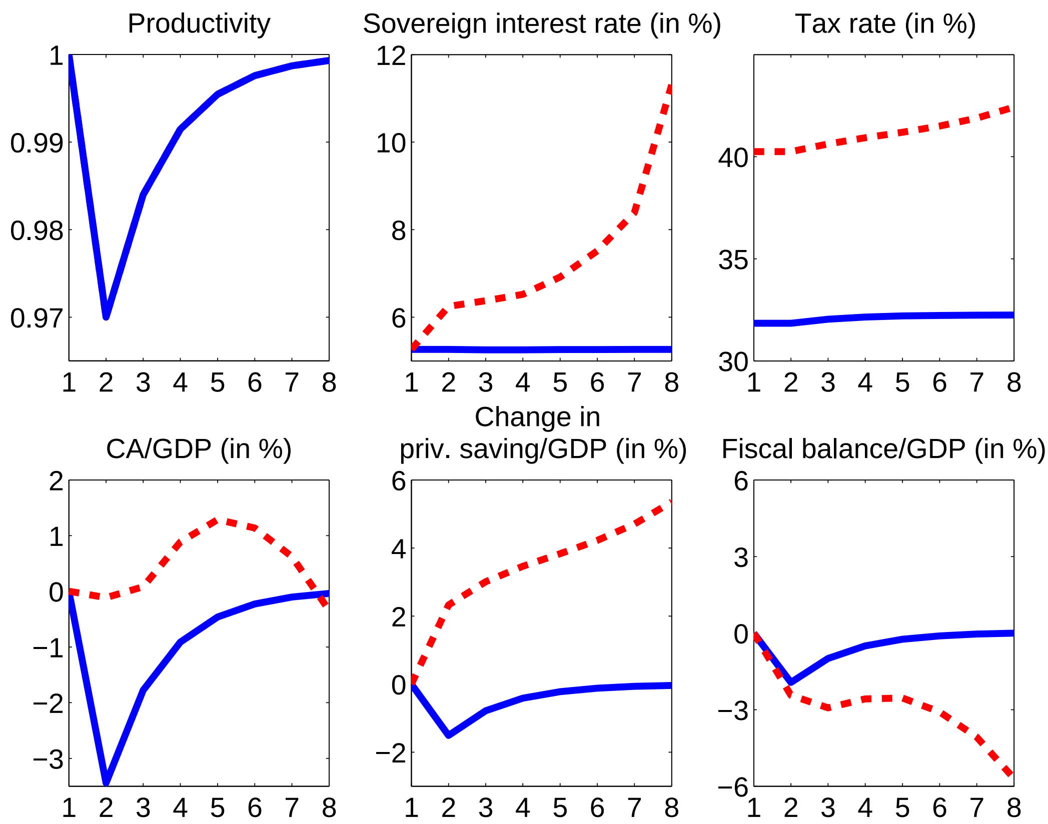
2.4.3 Impulse response functions

We simulate the model conditional on a negative productivity shock at different government debt-to-GDP ratios to assess the state-dependent dynamics. A negative TFP shock captures the economic downturn of Greece which is in a recession since 2008. The shock destabilizes the fiscal sector leading to sovereign interest rate spreads at high public debt levels.

[17]Introducing an exogenous cost of default as in Arellano (2008) would lead to a stronger increase of household saving at high government debt as households would try to insure against this cost. This would lead to a stronger reduction of the correlation of the twins.

Figure 2.6 displays the effects of a negative TFP shock at a low (60%) and a high (140%) government debt-to-GDP ratio. At a low government debt-to-GDP ratio higher tax rates and lower output leads households to increase debt to smooth consumption. Households therefore increase private debt, i.e. the change in private saving is negative. Hence, the change in private saving and the fiscal balance co-move positively and the aggregate current account turns negative. Thus, the correlation of the fiscal balance and the current account is unity.

Figure 2.6: Simulation of negative TFP shock at low vs. high government debt



Notes: Impulse responses to a 3 percent negative productivity shock. We initialize the simulation at 60% government debt-to-GDP (blue solid line) and 140% government debt-to-GDP (red dashed line). Household debt is set to its ergodic mean. A time unit is one year.

At high government debt levels the negative productivity shock of the same size causes labor and tax revenues to decline, government spending to increase and the fiscal balance turns negative. Growing government debt brings the stock of sovereign debt close to the fiscal limit, leading to a surge of sovereign risk premia. Households increase saving as they expect that further increases of government debt and tax rates are very likely. The change in private saving therefore turns positive and outweighs the negative contribution of the fiscal balance such that the current account moves into surplus. Due to the endogenous reaction of household saving, the correlation between the fiscal balance and the current account is much lower at high government debt-to-GDP than at a low ratio. In addition, the simulation reflects a situation where increasing risk premia destabilize the government debt-to-GDP ratio as observed during the current European sovereign debt crisis. Without a strong reduction of government expenditures or higher tax revenues the government debt stock is not sustainable resulting in a default in accordance with the actual debt restructuring of Greece in 2012.

2.4.4 Discussion of results

In line with the empirical results our model provides an explanation for the decline in the correlation of the fiscal balance and the current account as the government debt-to-GDP ratio increases. The households' optimal saving decision changes with the government debt-to-GDP ratio and, thus, explains the change of the correlation. The current account identity implies that a fiscal deficit leads, ceteris paribus, to a lower current account. However at high government debt-to-GDP ratios the endogenous saving decision of optimizing households counteracts widening fiscal deficits. In particular, as illustrated by the impulse responses to a negative TFP shock, private saving increases at high government debt, but falls at low government debt-to-GDP ratios. Hence, the correlation of the 'twins' is state-dependent and at high government debt households' saving behavior alleviates the fall in the current account. The change in the model-based correlation of the fiscal balance and the current account is 0.15, which is in line with the change in the empirical correlation of the twins.

2.5 Conclusion

In the first part of this chapter, we estimate a government debt-to-GDP threshold based on a dynamic panel threshold model following Kremer et al. (2013) for a sample of 15 European countries. One advantage of the dynamic panel estimation procedure is that we estimate the threshold rather than exogenously imposing it. We contribute to the twin deficits debate by showing that the correlation of the fiscal balance and the current account depends on the government debt-to-GDP ratio. Based on the estimated threshold of 72 percent we distinguish between a low and a high government debt regime. For each regime we calculate the correlation of the fiscal balance and the current account and find that the state-dependent correlation falls by 0.19 when moving from observations below the threshold to those that are above the threshold.

In the second part of this chapter, we examine a small open economy model allowing for sovereign default to show that the correlation of the twin deficits depends on the level of government debt in line with the observed empirical findings. At high government debt-to-GDP ratios the looming sovereign default risk increases sovereign interest rates, which deteriorate the fiscal balance. Rising sovereign debt levels lead to higher labor taxes, inducing households to increase saving. Also, precautionary saving increases as the dispersion of future expected taxes rises the closer the government debt stock moves to the fiscal limit. Non-linear model simulations reveal that the households' saving channel partially offsets fiscal deficits at high government debt-to-GDP ratios, inducing a decline in the correlation of the fiscal balance and the current account. The decline in the correlation of 0.15 is close to the change of the correlation in the empirical analysis.

The results of this chapter suggest that households' saving has an offsetting effect on substantial and persistent fiscal deficits due to high sovereign risk premia. At high government debt-to-GDP ratios households save more than at times when the economy has a low government debt-to-GDP ratio. Therefore, our evidence — in line with recent data for southern European countries — points to a potential rebalancing of the current account as households increase saving, because of large fiscal deficits that prevail due to high borrowing costs.

The recent global financial crisis and the European sovereign debt crisis with their severe macroeconomic effects have shown that state-dependent dynamics can be important. Households and investors, but also central banks and governments face a higher uncertainty about the economy and 'rare' events such as the occurrence of sovereign default are perceived to be much more likely. This chapter considers one aspect of state-dependence and shows that the size of the government debt-to-GDP ratio affects non-linear default risk premia and the co-movement of the fiscal balance and the current account. Further areas in which state-dependent dynamics are likely to play a crucial role are the size of fiscal multipliers and the effectiveness of austerity programs.

Appendix to Chapter 2

2.A Data description

Table 2.5: List of variables and definitions

Variable	Source	Description
Current account	IMF WEO	Current account balance (in % of GDP)
Fiscal balance	IMF WEO	Fiscal balance (in % of GDP). Net lending is calculated as revenue minus total expenditure.
Government debt	IMF WEO	Government debt (in % of GDP). Gross debt consists of all liabilities that require payment or payments of interest and/or principal by the debtor to the creditor.
Terms of trade	IMF IFS	Export price index divided by import price index
Openness	OECD	Absolute value of exports plus absolute value of imports (in % of GDP)
Relative income	IMF WEO	GDP per capita (PPP) relative to U.S. GDP per capita (PPP)
Output gap	IMF WEO	Output gap (in % of potential GDP)
Change of total invest.	IMF WEO	Change of total investment (in % of GDP)
Labor productivity	OECD	Labor productivity of the total economy
REER	BIS	Weighted average of bilateral exchange rates adjusted by relative consumer prices
Dependency ratio	WDI	Age dependency ratio (in % of working-age population)

Data sources: IMF WEO: IMF World Economic Outlook (Oct 2012), IMF IFS: IMF International Financial Statistics (May 2012), OECD: OECD Economic Outlook No. 92 (Dec 2012), BIS: Bank for International Settlements effective exchange rate indices: narrow indices (Jan 2013), World Bank WDI: World Bank Development Indicators (Jan 2013).

Table 2.6: Summary statistics of dataset

Country	T	mean(CA/GDP)	mean(FB/GDP)	mean($Debt/GDP$)
Austria	23	0.46	-2.75	63.1
Belgium	20	3.33	-2.70	109.4
Germany	16	2.47	-2.79	64.5
Denmark	13	2.68	1.24	51.7
Spain	31	-2.95	-3.41	46.6
Finland	31	1.41	1.01	33.9
France	31	0.12	-3.34	48.7
Great Britain	31	-1.41	-3.16	44.5
Greece	23	-6.01	-8.20	97.8
Ireland	31	-1.84	-4.52	68.7
Italy	22	-0.41	-5.83	108.1
The Netherlands	16	5.29	-1.73	58.2
Norway	31	6.31	7.25	41.3
Portugal	16	-4.84	-2.01	61.3
Sweden	18	5.11	-1.06	55.7

Notes: T: Maximum number of time periods available, CA/GDP: Current account in percent of GDP, FB/GDP: Fiscal balance in percent of GDP, $Debt/GDP$: Government debt in percent of GDP.

2.B Empirical estimation

2.B.1 Data

The data set is an unbalanced panel of 15 European countries from 1980 to 2010.[18] We include a broad set of control variables that potentially affect the current account. In particular, along with the fiscal balance the baseline specification includes the terms of trade, openness, relative income to the U.S. economy, output gap (in percent of potential GDP), the change in total investment (in percent of GDP), labor productivity (of the total economy), the real effective exchange rate and the dependency ratio (in percent of working-age population). Detailed information about the data set is given in Appendix 2.A.

2.B.2 Methodology

We estimate a dynamic panel threshold model of the form

$$y_{it} = \mu_i + \chi y_{i,t-1} + \beta_1 z_{it} I(q_{it} \leq \boldsymbol{\gamma}) + \beta_2 z_{it} I(q_{it} > \boldsymbol{\gamma}) + \alpha' x_{it} + u_{it}, \qquad (2.B.1)$$

where subscript $i = 1, ..., N$ represents the country and subscript $t = 1, ..., T$ denotes the time period. y_{it} is the dependent variable, μ_i is the country specific fixed effect and $y_{i,t-1}$ is an endogenous regressor. z_{it} is a vector of explanatory regressors, $I(\cdot)$ is an indicator function indicating the regime defined by the threshold variable q_{it}, and γ is the threshold level. Thus, the impact of z_{it} on y_{it} can potentially vary depending on whether the threshold variable q_{it} is below or above the threshold. The threshold level γ splits the sample into two regimes, allowing for the estimation of the regime-dependent impact of z_{it} as measured by the coefficients β_1 and β_2. Furthermore, x_{it} contains a set of explanatory regressors which are independent of the threshold. The error term u_{it} is independent and identically distributed with mean zero and finite variance.

Our estimation strategy follows Kremer et al. (2013) who overcome several econometric challenges. In particular, they combine the estimation methods of non-dynamic

[18] The sample includes the following countries: Austria, Belgium, Denmark, Finland, France, Germany, Great Britain, Greece, Ireland, Italy, The Netherlands, Norway, Portugal, Spain and Sweden.

panel threshold models in Hansen (1999) with the estimation strategy in Caner and Hansen (2004) that applies to cross-sectional threshold models with endogenous regressors. Hansen (1999) provides a method to estimate threshold effects in non-dynamic panel models where all regressors have to be exogenous. To eliminate the fixed effects mean differencing is applied. However, in a dynamic panel model as considered in equation (2.B.1) mean differencing potentially leads to inconsistent estimates as the lagged dependent variable will always be correlated with the mean of the individual errors and, thus, with all transformed individual errors (see Arellano, 2003, p. 17). Caner and Hansen (2004) develop an estimator and an inference theory for models with endogenous regressors and an exogenous threshold variable. Their theory applies to cross-sectional data and therefore needs to be extended to the estimation of panel data. For the endogenous regressor an instrumental variable estimation is applied. Building on these two papers, Kremer et al. (2013) provide a new, dynamic version of Hansen's panel threshold model. As in Caner and Hansen (2004) their procedure eliminates fixed effects with the forward orthogonal deviations transformation suggested by Arellano and Bover (1995). Subtracting the average of all future available observations of a variable avoids serial correlation of the transformed errors.

For our empirical exercise we apply the dynamic panel threshold model to estimate the relationship of the fiscal balance and the current account depending on the ratio of government debt-to-GDP:

$$\begin{aligned} CA_{it} &= \mu_i + \chi CA_{i,t-1} \qquad (2.B.2) \\ &+ \beta_1 FB_{it} I(\tfrac{Debt_{it}}{GDP_{it}} \leq \boldsymbol{\gamma}) + \beta_2 FB_{it} I(\tfrac{Debt_{it}}{GDP_{it}} > \boldsymbol{\gamma}) + \alpha' x_{it} + u_{it}, \end{aligned}$$

where the current account (CA) and the fiscal balance (FB) are measured in percent of GDP. The threshold variable is the ratio of government debt-to-GDP. The set of control variables x_{it} includes the variables described above.

Following previous literature (e.g. Bussière et al., 2006), we include the lagged current account as a regressor in the baseline specification. We instrument for $CA_{i,t-1}$ using lagged variables ($CA_{i,t-3}$, $CA_{i,t-4}$ and $CA_{i,t-5}$). Employing few lags prevents overfitting the predicted variable and reduces a possible bias of the coefficient estimates. However, as there is a trade-off between bias and efficiency in small samples, using only few lags comes at the cost of loosing efficiency. To assess the importance of the number of lags included we repeat the estimation using all of the available lags and find that the results are very close to the baseline results (see Appendix 2.B.6).

2.B.3 Further empirical results

The first column of Table 2.7 reports the results of our baseline specification. The key results are discussed in Section 2.2.2 in the main text.

The terms of trade have a significant, positive coefficient (0.05). An increase in the terms of trade reflects that the prices of the export goods increase relative to the prices of the import goods. The positive coefficient is consistent with a positive relationship between national savings and a terms of trade improvement. The partial correlation of openness (defined as imports plus exports in percent of GDP) with the current account is very small and insignificant (-0.01). The estimated coefficient of the relative income to the U.S. has a positive sign (0.01) which might reflect higher investment and borrowing in poorer countries due to either a catch-up effect or higher expected future income. The coefficient is, however, insignificant which is not surprising given that the considered countries all have an income level comparable to the one of the U.S. economy. The output gap co-moves negatively (-0.28) with the current account. A country experiencing an economic expansion would therefore, ceteris paribus, experience a deterioration of the current account which indicates that the positive impact of higher saving is overcompensated by higher investment inflows. As expected from the current account identity a change of investment is associated with a decline (-0.14) of the current account. The coefficient for labor productivity is insignificant (0.04), while the coefficient of the real effective exchange rate is negative (-0.06). The significant positive coefficient (0.16) of the dependency ratio could be explained by lower investment in countries which have a larger share of the population out of the labor force.

We also estimate a non-dynamic panel model (see right column of Table 2.7) to compare our results to previous studies. The threshold estimate in the non-dynamic model is slightly higher than in the dynamic model. While we confirm our previous finding that the partial correlation of the fiscal balance and the current account is lower at high government debt levels, we find that both estimated coefficients are larger compared to the estimates of the dynamic model. These results also highlight

Table 2.7: Estimation results

Variable	Dynamic panel	Non-dynamic panel
Current account ($t-1$)	0.59***	
	(0.16)	
Fiscal balance (Debt/GDP $\leq \hat{\gamma}$)	0.16**	0.43***
	(0.07)	(0.06)
Fiscal balance (Debt/GDP $> \hat{\gamma}$)	-0.04	-0.01
	(0.05)	(0.06)
Terms of trade	0.05***	0.09***
	(0.02)	(0.02)
Openness	-0.01	-0.01
	(0.01)	(0.02)
Relative income to U.S.	0.01	0.08
	(0.04)	(0.06)
Output gap	-0.28***	-0.67***
(in % of potential GDP)	(0.11)	(0.07)
Change of total investment	-0.14	0.12
(in % of GDP)	(0.08)	(0.08)
Labor productivity	0.04	0.09***
	(0.03)	(0.03)
Real effective exchange rate	-0.06***	-0.10***
	(0.02)	(0.02)
Dependency ratio	0.16**	0.37***
(% of working-age pop.)	(0.08)	(0.09)
Threshold estimate (in % of GDP)	$\hat{\gamma} = 71.8$	$\hat{\gamma} = 75.0$
95 % confidence region	[69.4 – 75.0]	[69.4 – 91.05]
Total number of observations	353	353

Dependent Variable: Current account (t). */**/*** indicate significance at the 10/5/1 percent level. Standard errors in brackets. The threshold of 71.8% (75.0%) splits the sample into 260 (271) obs. below and 93 (82) obs. above the threshold. The current account and the fiscal balance are measured in percent of GDP.

the importance of including the lagged current account in our baseline estimation. Compared to the non-dynamic panel the high persistence of the current account and the lower regime-dependent estimates in the dynamic panel model suggest that our baseline specification corrects for a potential bias due to omitting an endogenous regressor.

2.B.4 Robustness

We estimate a range of alternative specifications to confirm and extend our baseline estimation results. First, we estimate the model for the period 1980 to 2007, excluding the period from 2008 to 2010. The financial crisis with its strong influence on average debt levels, fiscal balances and current accounts could potentially affect our estimation results. Second, we re-estimate the model excluding countries with very high or low government debt-to-GDP ratios.

Excluding the financial crisis period we estimate the same government debt-to-GDP threshold of 71.8 percent (see first column of Table 2.8). The coefficients for the control variables are close to those of our baseline results. The exclusion of the financial crisis period slightly affects the estimate of the fiscal balance: The estimate below the threshold increases from 0.16 to 0.30 and at the same time becomes statistically more significant. The estimate at a high government debt-to-GDP ratio decreases from -0.04 to -0.21. Thus, the difference between the state-dependent coefficients of the fiscal balance becomes larger when excluding the financial crisis episode. In comparison to the baseline results household saving therefore compensates a fiscal deficit less in the low debt regime. The exclusion of the crisis period confirms our baseline results: households become more Ricardian at high government debt levels, increasingly compensating the impact of fiscal deficits on the current account by higher household saving.

In a second robustness check we exclude the country with the lowest and several countries with a high average government debt-to-GDP ratio from our sample (see Table 2.8). These countries might influence the estimation results as a majority of their observations are assigned to only one of the two debt regimes. Finland is the country with the lowest average government debt-to-GDP ratio, while there are three countries with relatively high average debt-to-GDP ratios: Belgium, Greece and Italy. We exclude one country at a time. Excluding Belgium (the country with the highest average debt-to-GDP ratio) yields the same estimated threshold of 71.8 percent and the exclusion is inconsequential for the estimation results. Excluding Italy or Finland also yields the same estimated thresholds and similar coefficient estimates as in the baseline estimation. The threshold estimate is slightly larger when excluding Greece, but the point estimates are very similar to the results of the complete sample.

Table 2.8: Robustness

Variable	Subperiod 1980-2007	Excluding Belgium	Excluding Italy	Excluding Greece	Excluding Finland
CA $(t-1)$	0.44***	0.56***	0.59***	0.62***	0.50***
	(0.16)	(0.16)	(0.15)	(0.16)	(0.17)
Fiscal balance	0.30***	0.17**	0.20**	0.17**	0.23***
(Debt/GDP $\leq \hat{\gamma}$)	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)
Fiscal balance	-0.21**	-0.03	0.03	-0.01	0.08
(Debt/GDP $> \hat{\gamma}$)	(0.09)	(0.05)	(0.07)	(0.07)	(0.07)
Terms of trade	0.05***	0.05***	0.04***	0.05***	0.05**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Openness	0.004	0.005	0.001	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Relative income	-0.01	0.004	-0.01	0.02	0.04
to U.S.	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
Output gap	-0.49***	-0.30***	-0.32***	-0.27**	-0.38***
(in % of pot. GDP)	(0.12)	(0.11)	(0.11)	(0.11)	(0.12)
Change of total inv.	-0.13	-0.13	-0.17**	-0.17**	-0.20**
(in % of GDP)	(0.11)	(0.09)	(0.07)	(0.08)	(0.09)
Labor productivity	0.07**	0.03	0.04*	0.04	0.05*
	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
Real effective	-0.07***	-0.06***	-0.04**	-0.05***	-0.04*
exchange rate	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Dependency ratio (in %	0.25***	0.19**	0.22**	0.19**	0.22**
of working-age pop.)	(0.09)	(0.09)	(0.10)	(0.10)	(0.09)
Threshold (% of GDP)	$\hat{\gamma} = 71.8$	$\hat{\gamma} = 71.8$	$\hat{\gamma} = 71.8$	$\hat{\gamma} = 86.9$	$\hat{\gamma} = 71.8$
95 % confidence region	[69.4-74.1]	[69.4-75.0]	[69.4-75.0]	[82.3-91.05]	[69.4-88.0]
Total number of obs.	308	333	331	330	322

Dependent Variable: Current account (t). */**/*** indicate significance at the 10/5/1 percent level. Standard errors in brackets. The current account and the fiscal balance are measured in percent of GDP.

2.B.5 Discussion of related empirical literature

A number of papers estimate the medium-term relationship between the fiscal balance and the current account estimating panel models without threshold. Chinn and Prasad (2003) estimate a static panel for a large set of 88 countries for the sample ranging from 1971 to 1995 and find a significant point estimate for the fiscal balance coefficient of 0.3. Chinn and Ito (2007) report a point estimate of around 0.15 for both a sample of 89 countries as well as for a sub-sample of industrialized countries from 1971 to 2004. Gruber and Kamin (2007) report a value of 0.11 using a longer time span but fewer countries (61) than Chinn and Prasad (2003). The panel estimation of 21 OECD countries in Bussière et al. (2010) yields a significant, positive point estimate of 0.14. Bussière et al. (2006) employ various estimators (LSDV, IV and GMM) to a dynamic panel and find a positive relationship between the fiscal balance and the current account ranging from 0.06 to 0.25. The estimation is based on data for 21 OECD countries for a sample from 1980 to 2003. Their paper also finds a highly significant coefficient for the lagged current account. Lane and Milesi-Ferretti (2012) estimate a static panel for 65 economies for a large sample ranging from 1969 to 2008 finding a highly significant positive fiscal balance coefficient of 0.24. Based on these studies there exists compelling evidence for a small, positive relationship of the fiscal balance and the current account. Studies that estimate a dynamic model find a high persistence of the lagged current account comparable to our estimation results. Estimating our dynamic panel model without a threshold we also find that there is a positive relationship between the current account and the fiscal balance.

In a related study Röhn (2010) finds for a panel of 16 OECD countries that increasing private saving offsets a deficit financed rise in public spending the higher the level of public debt. This implies that consumers become more Ricardian with growing levels of public debt. The findings of Röhn (2010) are consistent with the fact that the correlation of the fiscal balance and the current account declines with rising government debt levels as increasing household saving offsets the negative effect of government deficits on the current account at high public debt levels.

Our results corroborate those of Nickel and Vansteenkiste (2008) who find that the relationship between the fiscal balance and the current account depends on the government debt-to-GDP ratio. Using a sample of eleven Euro area countries for the years 1981 to 2005 they obtain a significant positive coefficient of 0.36 for the estimate of the fiscal balance for the low debt regime. For the high debt regime the estimate is -0.61 but it is not statistically different from zero. They also estimate a sample of 22 industrialized countries and obtain an estimate for the fiscal balance coefficient of 0.45 (significant) and -0.11 (not significant) for the low and high debt regime, respectively. In difference to the estimation strategy used in our study, the results of Nickel and Vansteenkiste (2008) are based on the estimation and inference theory for non-dynamic panels by Hansen (1999).[19] Due to the high persistence of the current account the estimates of Nickel and Vansteenkiste (2008) are potentially biased. Applying the dynamic version of Hansen's model proposed by Kremer et al. (2013), we avoid this problem. We obtain consistent estimates that are smaller than those of Nickel and Vansteenkiste (2008), but we confirm the regime-dependent influence of government debt-to-GDP ratios on the correlation of the fiscal balance and the current account.

[19]These authors use a different sample of countries and analyze a shorter time span.

2.B.6 Additional estimation results

Table 2.9: Estimation results using all available lags

Variable	Coefficient	Std. Error
Current account ($t-1$)	0.56***	(0.09)
Fiscal balance (Debt/GDP $\leq$ 71.8%)	0.17***	(0.05)
Fiscal balance (Debt/GDP $>$ 71.8%)	-0.04	(0.04)
Terms of trade	0.05***	(0.01)
Openness	−0.01	(0.01)
Relative income to U.S.	0.01	(0.04)
Output gap (in % of potential GDP)	−0.30***	(0.07)
Change of total investment (in % of GDP)	−0.12*	(0.07)
Labor productivity	0.04*	(0.02)
Real effective exchange rate	−0.06***	(0.02)
Dependency ratio (% of working-age pop.)	0.17**	(0.07)
Threshold estimate (in % of GDP)	$\hat{\gamma} = 71.8$	
99 % confidence region	[69.4 − 88.0]	
Total number of observations	353	

Dependent Variable: Current account (t). */**/*** indicate significance at the 10/5/1 percent level. Standard errors in brackets. The threshold of 71.8% splits the sample into 260 observations below and 93 observations above the threshold. The current account and the fiscal balance are measured in percent of GDP. We use the largest available number of lags for the current account as instruments for the lagged current account.

2.C Non-linear model equilibrium conditions

$$
\begin{aligned}
(1-L_t) &= \left[\frac{A_t(1-\tau_t)}{\chi}\right]^{\frac{1}{\omega-1}} && \text{(2.C.1)}\\
\lambda_t &= \left(c_t - \frac{\chi(1-L_t)^{\omega}}{\omega}\right)^{-\sigma} && \text{(2.C.2)}\\
\lambda_t\left(1-\psi(d_t^H - d^H)\right) &= \beta(1+r)\mathbb{E}_t(\lambda_{t+1}) && \text{(2.C.3)}\\
c_t + \frac{\psi}{2}\left(d_t^H - d^H\right)^2 &= A_t\left(1-\tau_t\right)\left(1-L_t\right) + z_t + d_t^H - (1+r)d_{t-1}^H && \text{(2.C.4)}\\
y_t &= A_t\left(1-L_t\right) && \text{(2.C.5)}\\
\tau_t A_t\left(1-L_t\right) + b_t q_t &= \left(1-\triangle_t\right)b_{t-1} + g_t + z_t && \text{(2.C.6)}\\
b_t^d &= \left(1-\triangle_t\right)b_{t-1} && \text{(2.C.7)}\\
q_t &= \mathbb{E}_t\left[\frac{(1-\Delta_{t+1})}{1+r}\right] && \text{(2.C.8)}\\
T_t &= \tau_t A_t\left[\frac{A_t(1-\tau_t)}{\chi}\right]^{\frac{1}{\omega-1}} && \text{(2.C.9)}\\
\tau_t - \tau &= \gamma_b\left(b_t^d - b\right) && \text{(2.C.10)}\\
z_t &= \begin{cases}(1-\rho_z)z + \rho_z z_{t-1} + \epsilon_{z,t} & \text{for } S_{Z,t}=1\\ \mu z_{t-1} + \epsilon_{z,t} & \text{for } S_{Z,t}=2\end{cases} && \text{(2.C.11)}\\
\log\left(\frac{A_t}{A}\right) &= \rho_A\log\left(\frac{A_{t-1}}{A}\right) + \epsilon_{A,t} && \text{(2.C.12)}\\
\log\left(\frac{g_t}{g}\right) &= \gamma_g\log\left(\frac{A_t}{A}\right) && \text{(2.C.13)}
\end{aligned}
$$

2.D Non-linear computational method

1. *Policy rules.* To solve the non-linear model we use the monotone map method that is described in Coleman (1991) and Davig (2004). First, we discretize the state space for each state variable, i.e. $\Psi_t = \left\{b_t^d, d_{t-1}^H, A_t, z_t, S_{Z,t}\right\}$. Second, we solve a simplified version of the model without default ($\delta = 0$) with a first-order approximation and use these policy functions to generate an initial set of decision rules denoted by $b_t^d = f_j^b(\Psi_t)$ and $d_t^H = f_j^d(\Psi_t)$. These rules are substituted into the two core equations of the model (the Euler equations (2.3.22) and (2.3.23)). Numerical integration is used to evaluate expectations about future variables. Solving this system for the state variables at each grid point yields updated values for the decision rules, i.e. $b_t^d = f_{j+1}^b(\Psi_t)$ and $d_t^H = f_{j+1}^d(\Psi_t)$ which we use as a new guess to substitute into (2.3.22) and (2.3.23). We repeatedly update the decision rules until the decision rules converge at every grid point in the state space i.e. $|f_j^b(\Psi_t) - f_{j+1}^b(\Psi_t)| < \epsilon$ and $|f_j^d(\Psi_t) - f_{j+1}^d(\Psi_t)| < \epsilon$, where $\epsilon = 10^{-6}$. We obtain a solution of the non-linear model on our grid points. Using the decision rules $f^b(\Psi_t)$ and $f^{d^H}(\Psi_t)$ of the model, we can solve for the remaining variables.

2. *Simulation results.* Given the policy rules we simulate the model economy. We initialize the simulation in the ergodic mean for all variables and then feed in various shock sequences for our exogenous processes. Given these shock sequences, we evaluate the evolution of the endogenous states using linear interpolation. In each period we randomly draw the effective fiscal limit from the state-dependent distribution of the fiscal limit. The government defaults on the fraction δ when its debt stock exceeds the effective fiscal limit.

Chapter 3

The macroeconomic effects of monetary policy: a new measure for the United Kingdom

3.1 Introduction

The efficacy of monetary policy has often been the subject of heated debate and despite considerable research in the academic literature there remains disagreement about its effect on the macroeconomy. A range of empirical estimates have emerged in the literature and the effects on prices and output tend to be between 0.5 and 1 per cent. A notable exception — the so-called narrative method pioneered by Romer and Romer (2004) (RR) — has found large effects.[1] To our knowledge, and despite the attention given to these results, there are no other applications of this methodology to identify monetary policy shocks. In addition, much of the research has focused on the United States and results for other countries such as the United Kingdom are sparse. This chapter fills both these gaps, providing new narrative-based estimates of the effect of monetary policy in the United Kingdom.

We focus on the effect of changes in the central bank's policy interest rate rather than on unconventional measures. Whilst the effect of unconventional measures is clearly an important topic in its own right, it seems likely that interest rates will remain a key policy instrument once economies are able to move away from the zero

[1] This approach follows earlier work using a slightly different narrative identification strategy in Romer and Romer (1989). Narrative approaches have also been employed to identify tax shocks (Romer and Romer, 2010; Cloyne, 2013) and government spending shocks (Ramey and Shapiro, 1998; Ramey, 2011).

lower bound. Furthermore, looking at changes in policy interest rates is important for understanding the effects of monetary policy in the past and to be comparable with the existing literature. The effect of interest rates on the macroeconomy therefore remains of considerable interest, both to macroeconomists and policymakers.

Identifying the effects of changes in monetary policy requires confronting at least three econometric issues. First, monetary policy instruments, interest rates, and other macroeconomic variables are determined simultaneously as policymakers respond to macroeconomic fluctuations and intend their decisions to affect the economy. Second, policymakers are likely to react to expected future economic conditions as well as current and past information. Third, policymakers base their decisions on real-time data, not ex-post data often used in other empirical studies.

A major advantage of the Romer and Romer (2004) approach is that we can directly tackle all three of these empirical challenges. First we need to disentangle cyclical movements in short-term market interest rates from policymakers' intended changes in the policy target rate. A major advantage of employing the approach to the United Kingdom (U.K.) is that the Bank of England's policy rate — Bank Rate[2] — *is* the intended policy target rate. We therefore do not need to construct the implied policy target rate from central bank minutes as in RR. As a second step, the target rate series is purged of discretionary policy changes that were responding to the changes in macroeconomic variables within the policymakers' information set. This information set may include real-time data and forecasts that determine the policy reaction to anticipated economic conditions. We therefore use historical sources to reconstruct a proxy for the information set on which policy decisions were made. Specifically we construct an extensive new data set of historical Bank of England forecasts, private sector forecasts and real-time data.

In general many studies in the literature rely on ex-post data which were not the data actually available to policymakers at the time of their decision. Orphanides (2001) has shown that this can significantly affect estimates of the response of monetary policy to macroeconomic variables. Since our data are real-time, we naturally address this concern.

We perform a first stage regression to purge the intended policy target rate of

[2]Previously Bank Rate was also referred to as Minimum Lending Rate / Repo Rate / Official Bank Rate.

systematic policy changes, producing a new policy shock series. We then use this new shock measure in a range of second stage regressions to analyse the effects of a shock to monetary policy.

Based on our new shock measure, we find that a 100 basis points increase in the policy target rate leads to a peak decline in output of 0.6 per cent[3] and a 0.8 percentage point fall in inflation. These magnitudes are more in line with evidence from conventional vector autoregressive (VAR) models. However, unlike many VAR-based studies, and in keeping with RR for the U.S. economy, we find a negative, significant and theoretically plausible response for inflation and prices. Investigating this issue further we find that including forecast data in our methodology is crucial for delivering a negative response of prices and inflation.[4]

Commonly employed VAR studies, among these Christiano, Eichenbaum, and Evans (1996, 1999), are often based on a recursiveness assumption with the policy instrument (typically interest rates) ordered last. Intuitively, this identification strategy allows all variables to contemporaneously affect interest rates, but interest rates have a lagged effect on the other macroeconomic variables. In response to a 100 basis point contractionary monetary policy shock, these studies typically find an effect on output of around 0.5 to 1 per cent at the peak and similar for inflation.[5] However, there is often a sizable short-term increase in prices in response to a monetary tightening — the "price puzzle", first documented in Sims (1992) — which has lead some to question the result. Using the common recursive VAR approach, we also find a large price puzzle for the U.K. economy. The price puzzle remains even after controlling for commodity prices, oil prices and exchange rates.

Bernanke, Boivin, and Eliasz (2005) argue that typical VARs use too narrow information sets. These authors use factor augmented VARs (FAVARs) to exploit a wide range of U.S. data, finding a peak decline in GDP of 0.6 per cent and of prices by 0.7 per cent. Mumtaz, Zabczyk, and Ellis (2011) estimate a FAVAR model for

[3]As measured by monthly industrial production. For quarterly GDP the peak effect is -0.4 per cent.

[4]Castelnuovo and Surico (2010) show that including forecast data can resolve the U.S. price puzzle in VARs. They argue this is necessary in periods of indeterminacy, where policy did not respect the Taylor Principle.

[5]For the U.S. economy Christiano et al. (1999) find a decline in industrial production of 0.7 per cent and a peak decline in prices of 0.6 per cent. For the U.K. economy Dedola and Lippi (2005) find a drop in industrial production of 0.5 per cent and an insignificant price response.

the U.K., finding a maximum GDP decrease of 0.5 per cent and a price level decline of up to 2 per cent.[6] An advantage of our approach is that forecasts can be seen as summary statistics of the policymakers' information set. Consequently, this approach does not require the large data sets, many of which are only available at a quarterly frequency.

Another strand of the literature, following Uhlig (2005), has proposed using sign-restrictions on the impact responses. Specifically, a contractionary monetary policy shock is assumed to lower prices and output on impact. For a 100 bps monetary contraction, Uhlig (2005) finds a GDP peak decrease of 0.8 per cent and a maximum price decline of 0.4 per cent for the U.S. economy. The results in Mountford (2005) for the U.K. economy are moderate with a maximum GDP drop of 0.6 per cent and a decline in the GDP deflator of 0.15 per cent. One disadvantage of this approach is that the impulse responses are only set-identified. In our approach, we are also agnostic about the direction of the effects of monetary policy.

In contrast to the more moderate effects discussed above, Romer and Romer (2004) find that a 100 basis point monetary tightening in the U.S. has a peak effect on output ranging from around -1.6 to -4.6 per cent and nearly -6.0 per cent on the level of producer prices. Coibion (2012) has recently argued that these effects may be overstated, but still finds effects of several percentage points. As noted, these results are large and the magnitudes naturally raise two questions. First, is there something inherent in this 'narrative' approach that produces large effects? Second — and more fundamentally — are the effects of monetary policy large or small? It is therefore interesting that our narrative-based effects for the U.K. are less pronounced than the larger effects found by RR for the U.S. economy.

The remainder of this chapter is structured as follows. Section 3.2 addresses the econometric challenges in more detail and presents our new real-time database. Section 3.3 estimates our new shock measures and investigates its properties. Section 3.4 presents our baseline results. Section 3.5 shows that our results are robust to a variety of different specifications. This section also shows that forecast data are important for our results and examines sub-samples. Section 3.6 concludes.

[6] The GDP effect is similar across the two sub-samples. The price response, however, is considerably smaller in the 1975-1991 sample at around -0.5 per cent at the peak.

3.2 Methodology

3.2.1 Identification and the first stage regression

In estimating the effects of monetary policy the researcher needs to overcome at least three econometric challenges. First, interest rates and other macroeconomic variables (e.g. output, inflation) are determined simultaneously, generating an identification problem. Second, policymakers are likely not only to react to the current state of the economy, but also to anticipated future macroeconomic conditions. Third, policymakers base their decision on real-time data, whereas many studies employ final revised data.

More formally, we aim to isolate shocks m_t from the systematic movements in the intended policy variable S_t in the following equation:

$$S_t = f(\Omega_t) + m_t \; . \tag{3.2.1}$$

The systematic component of S_t is driven by the policymakers' response to data in their information set Ω_t, where $f(\cdot)$ is a function capturing the systematic reaction and the shock term m_t reflects unexpected shifts in monetary policy.

The VAR literature has mainly tackled the simultaneity problem of interest rates and macroeconomic fluctuations. Often this literature has imposed a timing restriction: macroeconomic variables do not contemporaneously (within the period) react to interest rates (e.g. Christiano et al., 1996, 1999). The equation of the VAR that describes interest rates is therefore directly related to equation (3.2.1) above. Other papers in the literature have used sign-restrictions — following Uhlig (2005) — to identify m_t. This method assumes that a contractionary monetary policy shock is one that, for example, raises interest rates but lowers output and inflation on impact. There are potentially many impact matrices that satisfy these restrictions and, as such, the resulting impulse response functions are only set-identified.

Two further issues are often overlooked in commons approaches. First, forward-looking policymakers may well include forecasts in their information set Ω_t and central banks devote a great deal of resources forecasting the future path of the economy. Moreover, since contemporaneous estimates of the state of the economy are rarely available in real-time, the policymakers' forecasts also include a forecast of the current period. It is worth noting that, in practice, the forecasts may be based on additional information and judgements not readily available to the econometrician.[7]

Second, since monetary policy responds to information available to policymakers at the time of the decision, any regression designed to recover the policy shocks m_t should be based on the real-time data rather than ex-post revised data. As noted, key papers in the existing literature, among these Christiano et al. (1999) and Uhlig (2005), have employed ex-post data. Orphanides (2001, 2003) and Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008) show that estimated monetary policy reaction functions based on ex-post revised data are considerably different when using real-time data.[8]

We apply the Romer and Romer (2004) approach to identify monetary policy shocks m_t. Following the literature we refer to this as a narrative approach because it makes careful use of historical documents to construct the intended policy target rate and the information set of the policymakers prior to their decisions. The first stage of this approach requires constructing a measure of the intended policy target rate (S_t) at *each policy decision.* RR construct the target rate from minutes of the *Federal Open Market Committee* meetings. One advantage of the U.K. monetary framework is that the policy rate — Bank Rate — is the intended policy target. Batini and Nelson (2009), in their extensive history of U.K. monetary policy, argue that short-term interest rates have consistently been used as the policy instrument, even in the periods where the government publicly emphasised money supply or exchange rates.

Armed with a series for the intended policy rate we then estimate a first stage regression addressing the econometric challenges discussed above. The precise regression estimated is

$$\begin{aligned}\Delta i_m &= \alpha + \beta i_{t-1} + \sum_{i=-1}^{2} \gamma_i \hat{y}^F_{m,i} + \sum_{i=-1}^{2} \varphi_i \pi^F_{m,i} \\ &+ \sum_{i=-1}^{2} \delta_i (\hat{y}^F_{m,i} - \hat{y}^F_{m-1,i}) + \sum_{i=-1}^{2} \vartheta_i (\pi^F_{m,i} - \pi^F_{m-1,i}) + \sum_{i=1}^{3} \rho_i u_{t-i} + \epsilon_m \ ,\end{aligned} \tag{3.2.2}$$

[7]If the policymakers' forecasts were produced by the same VAR specification, including forecasts may be unnecessary. However, we show forecasts make an important difference to the results, suggesting that common VARs miss key information determining the policy decision.

[8]Ex-post data for some variables, such as real output growth, often turn out to differ substantially from real-time estimates, as shown in Appendix 3.A.

where the dependent variable is measured at a meeting-by-meeting frequency as indicated by subscript m. The subscript i denotes the quarter of the forecast relative to the meeting date and the subscript $t-1$ refer to information from the previous month, not information at the previous meeting. In particular we follow RR and regress the change in the intended policy target (Δi_m) around the policy decision (in practice, between two meetings) on the one and two quarter ahead forecasts of real GDP growth ($\hat{y}^F_{m,i}$) and inflation ($\pi^F_{m,i}$) as well as the real-time backdata of the previous period and the forecast for the current period.[9] We also include revisions in the forecasts relative to the previous round of forecasts (e.g. $\hat{y}^F_{m,i} - \hat{y}^F_{m-1,i}$). In addition, we control for recent economic conditions by including interest rates of the previous month (i_{t-1}) and the unemployment rates of the previous three months (u_{t-i}). The residual ϵ_m is our new monetary policy shock measure.[10]

It is also worth noting that in collecting forecast data for the U.K. economy we are directly constructing a real-time data set to capture the information set of policymakers at each period in time — addressing the issue raised by Orphanides (2001) and others.

To include forecasts in a regression such as equation (3.2.1) they need to be orthogonal to ϵ_m. To achieve this, we carefully exploit the timing of forecast releases to ensure they do not already include the effects of the relevant (subsequent) policy change. We therefore aim to capture the information set of policymakers *prior* to the policy decision. In our baseline specification for estimating the macroeconomic effects of changes ϵ_m, we employ the Cholesky decomposition used in RR and Coibion (2012). These authors assume that the shocks affect the macroeconomy with a one month lag and, for comparability, we initially follow these papers. However, since the forecasts are carefully constructed to be orthogonal to ϵ_m, our method should also allow us to estimate the contemporaneous effect of changes in ϵ_m on other macroeconomic variables and we explore this issue in the robustness section.

Using forecast data to identify ϵ_m also has a further advantage. In principle the researcher may need to include a large number of time series in the VAR as many variables could enter the information set Ω. This is the motivation behind the data-rich FAVAR approach of Bernanke et al. (2005). Forecasts are particularly useful,

[9] The subscript m denotes the meeting date when interest rates are set. The subscript i denotes the quarter of the forecast relative to the meeting date.

[10] Later we transform the residual into a monthly shock series denoted m_t.

however, because they neatly summarize a wider range of macroeconomic information, as well as the anticipated movements in the macroeconomy.

The estimated residuals of the first stage regression are our new exogenous monetary policy shock measure. Our definition of a monetary policy 'shock' therefore captures an unpredictable surprise that is not taken in response to information about current and future economic developments.[11] As such, the 'shock' reflects an unpredictable surprise movement in the target variable and could represent a variety of factors including deliberately induced policy surprises, over- and under-reactions or temporary shifts in the preferences of policymakers.[12] This new meeting-by-meeting measure of monetary policy shocks is converted to a monthly series and, in second stage regressions, is used to estimate the effect of monetary policy on the macroeconomy.

3.2.2 Data construction

As noted above, the official Bank Rate series serves as our intended policy target rate. This is available from the Bank of England website.

Since 1997 the Bank of England has operational independence in setting interest rates to meet an inflation target. To capture the information set of policymakers the natural starting point is to use official Bank of England forecasts for inflation and output growth. Since the Bank of England actually began inflation targeting in 1993, forecasts are available in the quarterly *Inflation Report* (IR) and the forecasts themselves provide quarterly projections for several years ahead.[13]

The Bank of England publishes two sets of forecasts. One set is conditioned on a constant interest rate path which *ex-post* includes the effect of the Monetary Policy Committee's (MPC) Bank Rate decision. The other set is conditioned on a path

[11] Given that the relevant endogeneity of the target rate is with respect to variables in the policymakers' information set, the relevant forecasts are those of the policymakers. It may still be the case that endogenous policy changes are surprises relative to the forecasts of the private sector. We address this issue in the robustness section.

[12] An alternative approach used in the literature uses forward-looking financial market data to construct monetary policy shocks as in Kuttner (2001); Faust, Swanson, and Wright (2004); Bernanke and Kuttner (2005); Gürkaynak, Sack, and Swanson (2005); Barakchian and Crowe (2010) and Wingender (2011) who use Federal Funds future contracts.

[13] Until 2003 the inflation target was defined in terms of the retail prices index excluding mortgage interest payments (RPIX) — first as a band, then as a point target of 2.5 per cent at an annual rate after 1997. After 2003 the inflation target was specified in terms of the consumer prices index (CPI), with a target of 2 per cent annual rate.

for Bank Rate implied by market interest rates *prior* to the meeting. As discussed above, a crucial assumption to ensure identification is that forecasts do not contain information about contemporaneous movements in the interest rate (in other words, they do not take into account of the new policy decision and thus are uncorrelated with the error term ϵ_m). If the forecasts already included the effect of the policy change the regression results would be biased. We therefore use the latter set of forecasts and we assign these data to the relevant meeting of the MPC.[14]

Before 1997 monetary policy decisions were made by the U.K. Treasury. Official Treasury forecasts were produced but only two per year are publicly available and the published forecast is not detailed enough for our purposes. Furthermore, monetary policy was not set at a regular meeting but was changed periodically as deemed necessary. To tackle this problem we also collect forecasts produced by the *National Institute for Economic and Social Research* (NIESR).[15]

Unlike forecasts from other professional bodies, NIESR forecasts are available for a long time period, at a quarterly frequency and for a large number of possible variables of interest. In addition, NIESR is Britain's longest established independent economic research institute, which is widely respected and close to the U.K. policy debate.

We collect NIESR forecasts for our full sample, even for periods when we have Bank of England forecasts. The reason for doing so is twofold. First, we can confirm that the NIESR and Bank of England Inflation Report forecasts are highly correlated (at least for the two quarters ahead we use).[16] Second, we are able to re-estimate our results using only NIESR forecasts for the full sample. Later we show this makes little difference to the results. NIESR forecasts therefore appear to be good proxies for official forecasts. Moreover, new releases of NIESR forecasts have received much attention in the media (e.g. the Financial Times) indicating that these are likely to be known to the private sector and policymakers.

To address the possible endogeneity of forecasts to the policy change we collect all the forecast embargo dates and finalisation dates from the historical hard-copies. We

[14] In addition, MPC minutes are published shortly after the Bank Rate decision, providing further insights into the decision making process.

[15] Although in the baseline analysis we use Bank of England forecasts from 1993 to 1997 where available, regarding them as a closer proxy for Treasury forecasts.

[16] The correlation between NIESR and Bank of England's forecasts for inflation as well as real GDP growth are at around 0.7 for up to two quarter ahead forecasts in the overlapping sample period (1993Q1-2007Q4).

also consult historical editions of the Financial Times archive to confirm the forecast release date. We are therefore able to ensure that a forecast did not already contain the effects of the relevant policy change.

All data pre-1991 have been manually digitised from the hard-copies of the National Institute Economic Review. To illustrate the data source Figure 3.1 provides an extract from the NIESR February 1983 issue of the National Institute Economic Review. For example, we transform GDP forecasts in column 'GDP Index 1975=100' into quarterly growth rates of GDP.

Figure 3.1: Extract from National Institute Economic Review (Vol. 103)

Table 15. Estimates and forecasts of the gross domestic product

The forecast figures are not intended to be more precise than the general statements in the text

£ million, 1975 prices, seasonally adjusted

	GDP[a]		Consumers' expenditure	General government current spending	Gross fixed investment	Exports of goods and services	Stockbuilding	Residual[b]	Total final expenditure[a]	Imports of goods and services	Adjustment to factor cost
	Index, 1975=100	At factor cost									
1981	104.5	98,561	71,871	24,306	18,774	32,329	−1,871	−706	144,703	34,040	12,102
1982	105.0	99,080	72,645	24,601	19,307	32,451	−835	−1,241	146,928	35,336	12,513
1983	*106.5*	*100,430*	*72,109*	*24,750*	*19,679*	*33,451*	*3*	*−1,077*	*148,915*	*36,263*	*12,222*
1984	*108.2*	*102,098*	*72,156*	*24,900*	*19,778*	*34,618*	*1,024*	*−1,095*	*151,380*	*36,963*	*12,319*
1981 I	104.3	24,599	18,040	6,055	4,690	7,850	−642	−561	35,432	7,673	3,160
II	104.0	24,528	17,926	6,052	4,667	8,028	−694	−266	35,713	8,249	2,936
III	104.7	24,693	17,934	6,127	4,663	8,131	−226	247	36,876	9,240	2,943
IV	104.9	24,740	17,971	6,072	4,754	8,320	−309	−127	36,681	8,878	3,063
1982 I	104.6	24,670	17,927	6,147	4,908	8,010	−49	−428	36,515	8,687	3,158
II	104.9	24,740	17,998	6,113	4,702	8,250	14	−353	36,724	9,075	2,909
III	105.3	24,835	18,242	6,191	4,865	7,923	−300	−193	36,728	8,827	3,066
IV Estimate	105.3	24,835	18,478	6,150	4,832	8,268	−500	−266	36,962	8,747	3,380
1983 I Forecast	*105.8*	*24,949*	*18,147*	*6,175*	*4,864*	*8,231*	*−204*	*−268*	*36,945*	*8,942*	*3,054*
II	*106.3*	*25,070*	*18,026*	*6,175*	*4,921*	*8,310*	*7*	*−269*	*37,170*	*9,046*	*3,054*
III	*106.6*	*25,147*	*17,978*	*6,200*	*4,947*	*8,414*	*53*	*−270*	*37,322*	*9,120*	*3,055*
IV	*107.1*	*25,264*	*17,958*	*6,200*	*4,948*	*8,496*	*147*	*−271*	*37,478*	*9,154*	*3,059*
1984 I	*107.7*	*25,394*	*17,923*	*6,225*	*4,953*	*8,561*	*197*	*−272*	*37,588*	*9,133*	*3,060*
II	*108.3*	*25,537*	*18,041*	*6,225*	*4,954*	*8,628*	*259*	*−274*	*37,834*	*9,217*	*3,080*
III	*108.2*	*25,521*	*18,028*	*6,225*	*4,927*	*8,691*	*265*	*−274*	*37,862*	*9,263*	*3,079*
IV	*108.7*	*25,647*	*18,164*	*6,225*	*4,943*	*8,738*	*303*	*−275*	*38,097*	*9,350*	*3,100*
Percentage changes											
1982/81	0.5	0.5	1.1	1.2	2.8	0.4			1.5	3.8	3.4
1983/82	*1.4*	*1.4*	*−0.7*	*0.6*	*1.9*	*3.1*			*1.4*	*2.6*	*−2.3*
1984/83	*1.7*	*1.7*	*0.1*	*0.6*	*0.5*	*3.5*			*1.7*	*1.9*	*0.8*
1982IV/81IV	0.4	0.4	2.8	1.3	1.6	−0.6			0.8	−1.5	10.3
1983IV/82IV	*1.7*	*1.7*	*−2.8*	*0.8*	*2.4*	*2.8*			*1.4*	*4.7*	*−9.5*
1984IV/83IV	*1.5*	*1.5*	*1.1*	*0.4*	*−0.1*	*2.9*			*1.7*	*2.1*	*1.3*

Source: *Economic Trends*, NIESR estimates.
(a) Output measure.
(b) The discrepancy between output and expenditure estimates of GDP.

We use forecast data for real GDP growth and inflation from our new data set. The relevant inflation index varied over our sample. We therefore use the consumer prices deflator (1975-87), retail prices index (RPI) (1987-92), retail prices index excluding mortgages (1993-2003), and the harmonised consumer prices index (2003-07).

As noted above, we use the forecast for the current period (real-time estimates of the current period were rarely available to policymakers) and the forecasts for the two quarters ahead. We collect the relevant real-time backdata, which may also differ from the final revised series. These are available either from the forecast publications themselves or the Bank of England's real-time data set. Our new data set contains 170 potential variables at quarterly frequency from 1975:1 to 2007:4, although not all variables are used in this study. We exclude the most recent years after 2007 when interest rates were maintained close to the zero lower bound. This is a rich data set, which should also prove useful for future research (for details see Table 3.6 in Appendix 3.A).

Since our first stage regression is conducted at a decision-by-decision frequency, the new real-time forecast data set is carefully matched to relevant Bank Rate decisions. In the first part of our sample Bank Rate is changed infrequently, whereas meetings are held on a monthly basis after 1997. Table 3.1 illustrates the construction of our data set using both sources — Bank of England forecasts and NIESR forecasts. The first column lists the date of the Bank Rate decision and the second column specifies the contemporaneous quarter. Forecasts are denoted by $\mathcal{F}^{\text{Source}[\text{Forecast quarter, Forecast year}]}_{\text{Publication date}}$, where we distinguish between the source (IR/NIESR), the quarter and the year the forecast was produced for, and the forecast publication date.[17]

A complication we face is that we do not have new forecasts for every Bank Rate decision as policy meetings take place at higher frequency: there are more Bank Rate decisions than forecast releases. This is also true, although to a lesser degree, in RR. There are a few possible ways to deal with this issue. One option is to only consider Bank Rate changes after a new quarterly release of forecasts (and exclude all other changes). However, this procedure reduces the number of observations substantially. Alternatively we could assign the latest available forecast to that meeting, while still controlling for developments between the last forecast and the policy decision, for

[17]As noted, Bank of England forecasts are officially published *after* the Bank Rate decision they were prepared for. For example, the Bank Rate decision on 6th May 1997 was based on Bank of England forecasts published on 13th May 1997. We assign the 1997Q2 forecast to the contemporaneous quarter, i.e. $\hat{y}_{m,i}$, since it is conditioned on the market path about interest rates prior to the policy announcement. NIESR forecasts released after the policy decision would be endogenous. Therefore, NIESR forecasts are assigned to the Bank Rate decision that is *subsequently* implemented.

Table 3.1: Assignment of forecasts to Bank Rate decisions

Bank Rate	Current quarter	$\hat{y}^F_{m,t-1}$	$\hat{y}^F_{m,t}$	$\hat{y}^F_{m,t+1}$	$\hat{y}^F_{m,t} - \hat{y}^F_{m-1,t}$
15/03/83	Q1 83	$\mathcal{F}^{N[Q4,82]}_{24-02-83}$	$\mathcal{F}^{N[Q1,83]}_{24-02-83}$	$\mathcal{F}^{N[Q2,83]}_{24-02-83}$	$\mathcal{F}^{N[Q1,83]}_{24-02-83} - \mathcal{F}^{N[Q1,83]}_{30-11-82}$
⋮					
06/05/97	Q2 97	$\mathcal{F}^{IR[Q1,97]}_{13-05-97}$	$\mathcal{F}^{IR[Q2,97]}_{13-05-97}$	$\mathcal{F}^{IR[Q3,97]}_{13-05-97}$	$\mathcal{F}^{IR[Q2,97]}_{13-05-97} - \mathcal{F}^{IR[Q2,97]}_{12-02-97}$
06/06/97	Q2 97	$\mathcal{F}^{IR[Q1,97]}_{13-05-97}$	$\mathcal{F}^{IR[Q2,97]}_{13-05-97}$	$\mathcal{F}^{IR[Q3,97]}_{13-05-97}$	$\mathcal{F}^{IR[Q2,97]}_{13-05-97} - \mathcal{F}^{IR[Q2,97]}_{12-02-97}$
10/07/97	Q3 97	$\mathcal{F}^{IR[Q2,97]}_{13-05-97}$	$\mathcal{F}^{IR[Q3,97]}_{13-05-97}$	$\mathcal{F}^{IR[Q4,97]}_{13-05-97}$	$\mathcal{F}^{IR[Q3,97]}_{13-05-97} - \mathcal{F}^{IR[Q3,97]}_{12-02-97}$

Notes: Forecasts are $\mathcal{F}^j_m, m =$ Publication date, $j =$ Source[Forecast quarter, Forecast year], where we distinguish between the source (IR/NIESR), the quarter and the year the forecast was prepared for (t), and the forecast publication date (m). The remaining variables are matched following the same procedure indicated in this table.

example by including unemployment data.

A further issue arises in the earlier sample when we have a new forecast and no change in policy but we do not know whether there was a meeting to decide to leave the rate unchanged. We could either treat the forecast release itself as a decision to keep the rate fixed in the face of new economic developments, or we could disregard these cases.

Having carefully considered these options our preferred specification is to keep all Bank Rate decisions and assign the latest available forecast to that decision. However, we disregard the cases where new forecasts are available but we do not observe a Bank Rate change (since we cannot be sure these are genuine monetary policy *decisions*). This approach maintains a large number of observations and is closest to the implementation in RR.

3.3 The new shock measure

3.3.1 Stage 1: stripping out the systematic component

After assigning the real-time forecast data to Bank Rate decisions, we isolate innovations to Bank Rate that are orthogonal to the real-time information set of policymakers that we consider. We include all Bank Rate changes between 1975 and 2007 except those taking place at very high frequency (i.e. within the same two weeks). The sample covers 235 Bank Rate decisions.

Table 3.2 reports the results from estimating equation (3.2.2). The estimation results indicate that U.K. monetary policy was conducted countercyclically over the sample. Summing up the coefficients on the real GDP growth forecasts yields 0.17 for the *level* and 0.23 for the *change* in the growth forecast. Thus, a one percentage point increase in the real GDP growth forecast from one forecast release to the next leads to an increase in Bank Rate of 40 basis points. The effect on Bank Rate is comparable to the U.S. results of RR, who find a response of 29 basis points in the intended target rate. The response to a one percentage point increase in the inflation rate forecast leads to a rise in Bank Rate of 33 basis points, of which 3 basis points are due to the absolute change in inflation forecasts and 30 basis points are due to the change relative to the last forecast release. The policy target rate in the U.K. reacts stronger (30 basis points) than the intended Federal Funds rate in the U.S. (which increases by 7 basis points) to a one percentage point change in inflation rate forecasts. A one percentage point increase in the unemployment rate in each of the past three months keeping everything else equal reduces the policy target rate by around 5 basis points in the U.K. economy. The same effect is found in the U.S. study in response to a one percentage point increase in the unemployment rate forecast of the current quarter.

In summary, the point estimates for the U.K. and those for the U.S. in RR, although not identical, are qualitatively similar. The results in Table 3.2 also appear to have reasonable and expected signs and magnitudes. Importantly, having stripped out the systematic component of policy, the residual of equation (3.2.2) is our new measure of monetary policy changes orthogonal to the information set of policymakers.

3.3.2 Properties of the new shock series

We now transform the first stage residuals into a monthly series of monetary policy shocks that we use to estimate the macroeconomic effects of changes in monetary policy. Note that the residuals from the first stage regression are dated according to the policy decision (given that we have the exact date of the decision). We therefore transform the residuals into a monthly series as follows. In a month without a Bank

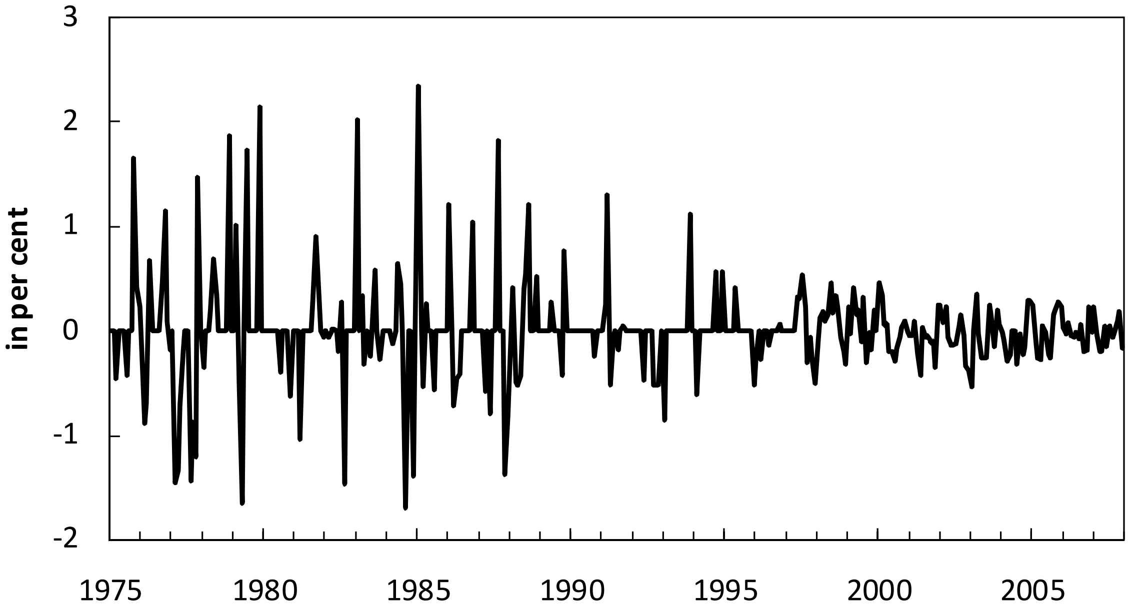
Table 3.2: Determinants of the change in Bank Rate

Variable	Coefficient	Standard error
Constant (α)	-0.231	0.288
Initial Bank Rate (i_{t-1})	-0.006	0.027
Forecasted output growth ($\hat{y}^F_{m,i}$),		
Quarters ahead:		
-1	0.009	0.036
0	0.073*	0.042
1	0.066	0.049
2	0.019	0.061
Forecasted inflation ($\hat{\pi}^F_{m,i}$),		
Quarters ahead:		
-1	0.114*	0.067
0	-0.167	0.107
1	-0.025	0.108
2	0.110	0.077
Change in forecasted output growth ($\hat{y}^F_{m,i} - \hat{y}^F_{m-1,i}$),		
Quarters ahead:		
-1	0.062**	0.031
0	0.060*	0.034
1	0.027	0.042
2	0.080	0.050
Change in forecasted inflation ($\pi^F_{m,i} - \pi^F_{m-1,i}$),		
Quarters ahead:		
-1	0.057	0.118
0	0.386**	0.187
1	-0.243	0.174
2	0.102	0.103
Change in unemployment rate (u_{t-i}),		
Months:		
-1	-1.067**	0.511
-2	0.488	0.821
-3	0.534	0.507

Dependent variable: Change in policy target rate Δi_m. $^{*}/^{**}/^{***}$ indicate significance at 10/5/1 per cent level. $R^2 = 0.28$, D.W. = 1.86, F-Statistic = 4.22, N = 235. Sample covers all Bank Rate changes over the period 1975M3 to 2007M12 that are at least two weeks apart. The regression is based on: $\Delta i_m = \alpha + \beta i_{t-1} + \sum_{i=-1}^{2} \gamma_i \hat{y}^F_{m,i} + \sum_{i=-1}^{2} \varphi_i \pi^F_{m,i} + \sum_{i=-1}^{2} \delta_i (\hat{y}^F_{m,i} - \hat{y}^F_{m-1,i}) + \sum_{i=-1}^{2} \vartheta_i (\pi^F_{m,i} - \pi^F_{m-1,i}) + \sum_{i=1}^{3} \rho_i u_{t-i} + \epsilon_m$.

Rate decision we set the observation to zero. Otherwise we assign the shock to the respective month in which the policy change occurred. For months with multiple policy changes, we sum the shocks. Figure 3.2 displays our new monthly series of exogenous monetary policy shocks. As above, we denote the monthly shock series by m_t.[18]

Figure 3.2: New monthly U.K. monetary policy shock series



The shock series is more volatile in the first half of the sample until 1993. This observation fits well with the view that there was a regime change around 1993. Since October 1992 the Bank of England explicitly targets inflation. The policy making process also has become more transparent due to regular publications of the Inflation Report (since 1993) and MPC Minutes (since 1997). It is therefore interesting that we find a decrease in the shock volatility. Since the independence of the Bank of England in 1997 we find no large surprise monetary policy shocks.[19] In the robustness section we examine results for the post-92 sub-sample.

[18]We find no evidence of serial correlation in the residuals based on the ACF/PACF correlogram at a 1% significance level.

[19]Larger shocks in the first part of the sample also might reflect that the average level of Bank Rate was higher than in the second part of the sample. See also Figure 3.10 in Appendix 3.B for a comparison of the exogenous Bank Rate path compared to the average Bank Rate.

3.3.3 Predictability of the monetary shock series

Our constructed monthly shock series should, in principle, be unpredictable from movements in ex-post revised data. Before proceeding, it is worth confirming this using a series of Granger causality tests. Specifically, we regress the monetary shocks m_t on a set of lagged macroeconomic variables including industrial production, unemployment rate and inflation:

$$m_t = c + \sum_{i=1}^{I} \beta_i x_{t-i} + u_t \ . \tag{3.3.3}$$

The null hypothesis is that our shock series is not predictable from lags of these macroeconomic variables. Table 3.3 reports F-statistics and P-values from estimating equation (3.3.3). We cannot statistically reject the hypothesis of unpredictability,

Table 3.3: Predictability of monetary policy shocks

Variable	F-statistics	P-values
Change in industrial production	1.31	0.21
Monthly inflation rate	0.79	0.67
Unemployment rate	1.05	0.40

Notes: The table reports F-statistics and P-values for the null hypothesis that all coefficients β_i are equal to zero. In each regression we include twelve monthly lags ($I = 12$).

with P-values in Table 3.3 all above 20 per cent. These tests suggest that our shock measure is indeed not predictable.[20]

In contrast to our U.K. results, Coibion (2012) finds that the monetary shock series for the U.S. is predictable in the full sample. The U.S. series only becomes unpredictable after excluding the period in which the Federal Reserve abandoned targeting the Federal Funds rate. However, our results are consistent with the reading of U.K. monetary history by Batini and Nelson (2009): despite historical episodes during which U.K. policymakers emphasised the role of monetary aggregates and exchange rates, short-term interest rates remained a key policy instrument.

[20] The shock series is also not predictable at a 10 per cent significance level when including the contemporaneous value of x_t, as in Coibion (2012).

3.4 The effects of monetary policy

Armed with our new measure of monetary policy shocks, we estimate the effects on output, inflation and unemployment for the sample from 1975M3 to 2007M12. First, we estimate a vector autoregressive (VAR) model following Romer and Romer (2004) and Coibion (2012). In practice VARs are widely used in empirical macroeconomics. As noted in Coibion, Gorodnichenko, Kueng, and Silvia (2012), including the lagged dependent variable and controlling for other shocks may yield more precise estimates in shorter samples. We also include our monetary shock as an endogenous variable in the VAR to control for the possibility of any residual endogeneity of the shock measure with respect to the ex-post revised data. Later we estimate single equation regressions used in RR and confirm our main results.

3.4.1 Empirical specification

In our baseline specification we follow Christiano et al. (1999) and Coibion (2012) using five macroeconomic variables: the log of output as measured by industrial production (seasonally adjusted) (y_t), the unemployment rate (u_t), the 12m rate of the retail prices index excluding mortgage interest payments (π_t), a log commodity price index (seasonally adjusted) ($comp_t$), and our new measure of monetary policy shocks. Data definitions are given in Appendix 3.A. We estimate the effects of monetary policy based on the following VAR:

$$\boldsymbol{X}_t = \boldsymbol{A_0} + \boldsymbol{A_1 t} + \boldsymbol{B(L)}\boldsymbol{X}_{t-1} + \boldsymbol{\epsilon}_t \ , \tag{3.4.4}$$

where $\boldsymbol{B(L)}$ is a lag polynomial with P lags. The vector of observables is $\boldsymbol{X}_t = [y_t, \pi_t, comp_t, u_t, cum.shock_t]'$.

Since conventional VARs are based on interest rates in levels (Bank Rate for the U.K.) we follow Romer and Romer (2004) and Coibion (2012), cumulate our new shock series ($cum.shock_t = \sum_{i=0}^{t} m_i$) and order this series last in the VAR. This ordering is equivalent to assuming that the other variables in the VAR do not react within the month to a change in policy.[21] The data are monthly and we estimate the VAR with $P = 24$ lags. The VAR in RR includes 36 lags and their single equation

[21] Estimating a monthly VAR as we do, the assumption is less restrictive when compared with quarterly VARs but, as noted earlier, we relax this assumption later.

regressions are based on including lags of at least two years. We prefer to include two years of lags to estimate fewer parameters. We also experimented with different values for P and show that the results are robust (as shown in the Appendix). All figures below report impulse responses together with 68 and 95 per cent bootstrapped confidence intervals using 2,000 replications.[22]

3.4.2 Results

Figure 3.3 presents the main result of this chapter. In response to a 100 basis points (bps) increase in the monetary policy target rate, the inflation rate falls by up to -0.77 percentage points.[23] Industrial production has a peak decline of -0.57 per cent and the unemployment rate peaks at 0.19 percentage points. Inflation does not react strongly on impact, but declines sharply 18 months after the shock, reaching its peak effect after 33 months. The drop in industrial production peaks two years after the shock. Unemployment begins to rise significantly 12 months after the shock. The signs of all variables are consistent with the responses of a variety of theoretical models (e.g. Smets and Wouters, 2007) and accord well with economic intuition.

Our results are smaller than the narrative estimates found by RR for the U.S. economy. This is true even considering the more muted effects found by Coibion (2012) who investigates the robustness of the RR shock series. Our findings therefore suggest the effects of monetary policy in the U.K. are of the order of magnitude found by other VAR-based methods in the literature.

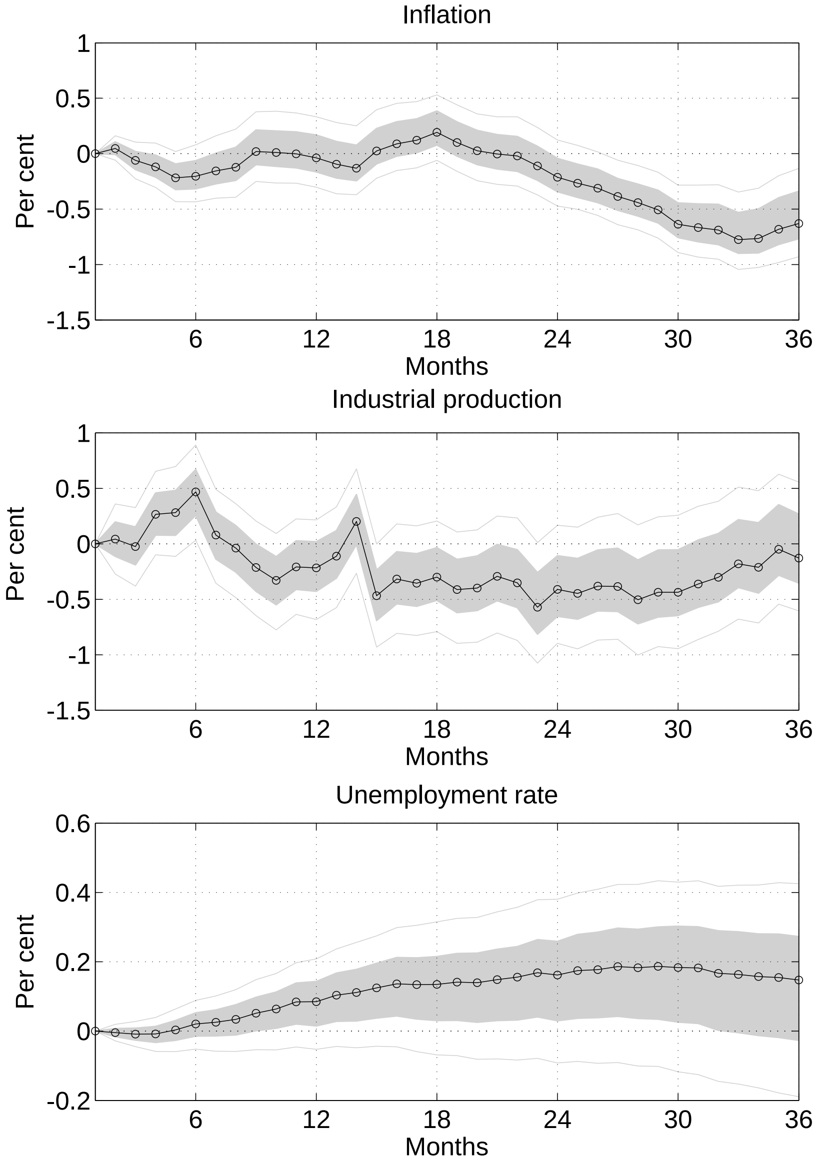
For the U.K. Dedola and Lippi (2005) also report a fall of around 0.5 per cent in industrial production. Mountford (2005) and Mumtaz et al. (2011) find that GDP falls by 0.6 and 0.5 per cent respectively. However, there is more disparity in the estimated response of inflation. For example, in Dedola and Lippi (2005), the price level rises following a monetary contraction. Below we also show a 'price puzzle' exists using the recursive identification methodology in a conventional VAR with Bank Rate as the policy variable (rather than our shock). Using the new shock series in our approach resolves this puzzle.

Most studies conducted for the U.S. and other countries also find that real activity

[22] The bootstrapped confidence intervals are robust to a higher number of repetition, e.g. 10,000.

[23] The shock returns to zero after about 24 months. The results are robust to using the alternative price measures RPI and CPI as presented in Figure 3.11 in Appendix 3.B.

Figure 3.3: The macroeconomic effects of a monetary policy shock



Notes: Impulse responses to a 100 bps increase in policy target rate. VAR with industrial production, inflation rate (RPIX12m), unemployment rate, commodity prices and our shock measure. P=24. Sample: 1975-2007. Confidence bands indicate 68 and 95 per cent intervals.

as measured by industrial production or total output declines between 0.5 and 1 per cent to a 100 bps increase in the interest rate. A concise overview of selected studies can be found in Table 3.4.

Table 3.4: The effects of monetary policy shocks in previous studies

Authors	Country	Method	Peak Effects (in %)	
			Output	Prices/Inflation
Romer and Romer (2004)	U.S.	narrative	-1.6 to -4.6 (IP)	-5.9 (PPI Level)
Coibion (2012)	U.S.	narrative	-2.6 (IP)	-2.9 (CPI)
Dedola and Lippi (2005)	U.K.	VAR	-0.5 (IP)	0.2 (CPI Level)
Mountford (2005)	U.K.	sign-restriction	-0.6 (GDP)	-0.15 (GDP Defl.)
Mumtaz et al. (2011)	U.K.	FAVAR	-1.0/-2.0 (IP, 75-91/92-05) -0.5/-0.5 (GDP,75-91/92-05)	-0.3/-2 on CPI (75-91/92-05)
Bernanke and Mihov (1998)	U.S.	VAR	-0.6 to -1 (GDP)	-0.7 to -1.6 (GDP Defl.)
Christiano et al. (1999)	U.S.	VAR	-0.7 (IP)	-0.6
Bernanke et al. (2005)	U.S.	FAVAR	-0.6	-0.7
Uhlig (2005)	U.S.	sign-restriction	-0.8 to 0.8	-0.4

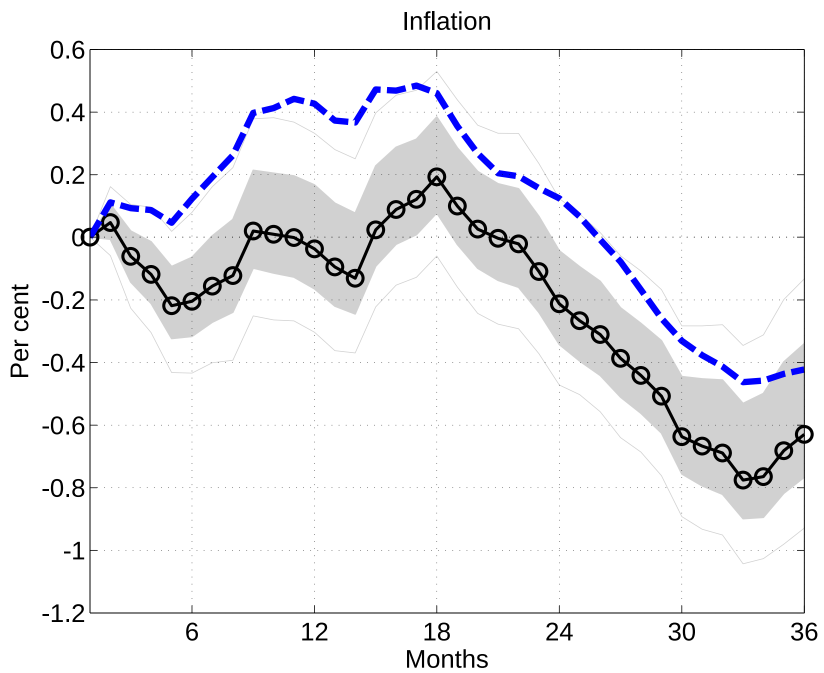
Notes: The results from previous studies listed in the table are from impulse responses displayed in these papers. We computed implied peak effects to a 100 bps increase in the interest rate. In brackets we report the specific output and price measure, where IP denotes industrial production.

3.4.3 The price puzzle

Conventional VARs which employ observed interest rates and the recursive identification strategy of Christiano et al. (1999) often generate a substantial and persistent price puzzle — a monetary policy tightening is followed by an increase in the price level and/or inflation rate. This observation, first documented in Sims (1992) and dubbed the 'price puzzle' by Eichenbaum (1992), has raised doubts about the recursive identification scheme, being at odds with conventional intuition and theory. A large literature has proposed various methods to resolve this puzzle, such as expanding the VAR with oil prices and commodity prices or to use FAVARs. The motivation behind these approaches is that conventional VARs do not contain enough observables to capture the information actually available to policymakers and driving the changes in interest rates.

For the U.K. economy, we also find that a VAR with Bank Rate as the policy instrument (rather than our shock) and employing the recursive identification assumption produces a large and persistent price and inflation puzzle.[24] As a robustness check we add a variety of variables to this VAR including commodity prices, oil prices, money supply and various exchange rate measures. However, adding these variables does not solve the U.K. price puzzle. Figure 3.4 shows the inflation response to a 100 bps increase in Bank Rate in a conventional VAR (dashed line) and compares it to the response based on our new shock series. Using the standard recursive method, the inflation response is positive for around two years and lies outside of the 95 per cent confidence intervals of our baseline results.

Figure 3.4: Response of inflation in VAR with the new shock measure vs. a conventional, recursive VAR with Bank Rate



Notes: Impulse responses to a 100 bps increase in policy target rate. VAR with industrial production, inflation rate (RPIX12m), unemployment rate, commodity prices and shock measure. P=24. Sample: 1975-2007. The circled line is the inflation response based on the new shock measure together with the respective confidence bands. The dashed line is the inflation response based on a conventional, recursive VAR with Bank Rate. Confidence bands indicate 68 and 95 per cent intervals.

[24] In our procedure, we replace Bank Rate in the VAR specification with our new monetary shock measure.

Romer and Romer (2004) also document a large price puzzle for the U.S. using the conventional recursive VAR methodology and show that their new shock measure solves this issue. It therefore seems a robust feature of both the U.S. and U.K. that applying the narrative identification strategy resolves the puzzling results in conventional VAR studies.

3.5 Robustness and extensions

3.5.1 Comparison to the Romer–Romer results

Earlier we estimated the effects of our new shock series using a VAR but in principle we should also be able to estimate a single equation auto-regressive distributed lag model. In this section we compare the effects of monetary policy shocks on the price level and on industrial production estimating single equation regressions as in Romer and Romer (2004). We regress each macroeconomic variable (x_t) on its lags and lags of the policy shock m_t directly estimated from the first stage:

$$\Delta x_t = c + \sum_{i=1}^{P} \beta_i \Delta x_{t-i} + \sum_{j=1}^{Q} \gamma_j m_{t-j} + \epsilon_t \,. \tag{3.5.5}$$

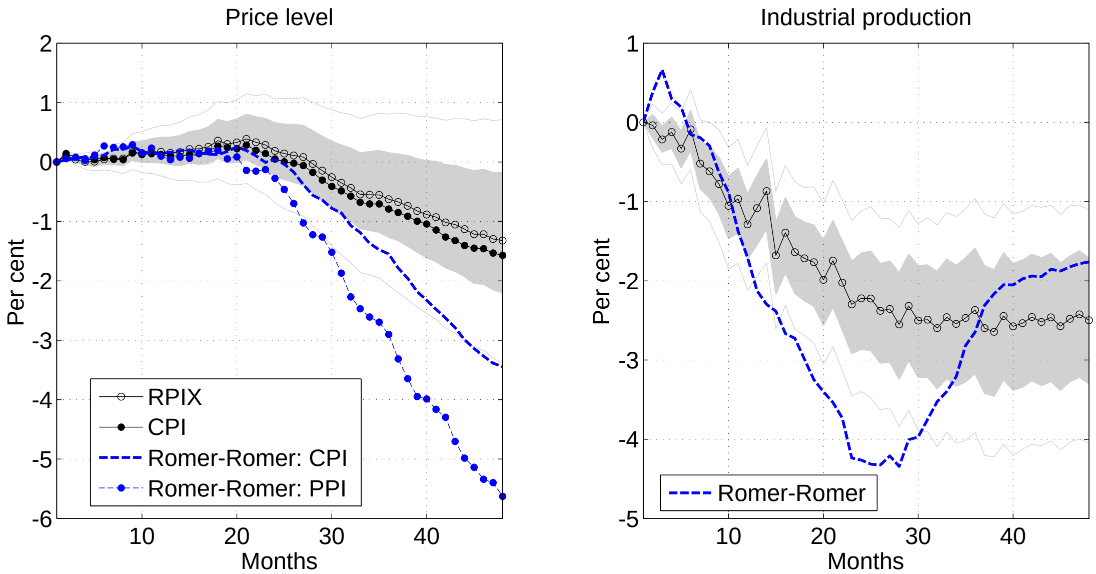
To follow Romer and Romer (2004) we assume that the shock does not contemporaneously affect the macroeconomic variable x_t. To ensure comparability we also set $P = 24$ and $Q = 36$ for industrial production and $P = 24$ and $Q = 48$ for the price level. Figure 3.5 presents the impulse responses of the price level as measured by RPIX and CPI as well as industrial production to a permanent 100 bps increase of the policy shock. The 68 and 95 per cent confidence bands are again bootstrapped (2,000 repetitions).

Both price measures decline significantly by up to 1.5 per cent after four years in response to a 100 bps monetary tightening. Strikingly, compared to the peak effect documented in Romer and Romer (2004) the U.K. price responses are smaller by up to a factor of three. Although the effect is smaller, the dynamics are similar: a protracted price response to a policy target rate increase which is flat and insignificant for almost two years.

Industrial production immediately drops after the shock and reaches its minimum at -2.5 per cent about 30 months after the shock. Again this is less pronounced than the U.S. results, where industrial production responds by up to -4.3 per cent. It is noteworthy that the RR study for the U.S. finds a small output puzzle in the first five months after the shock, which is not a feature of our results for the U.K. economy.

The single equation results, in keeping with RR, suggest larger – but qualitatively similar – effects compared to our VAR results. However, these larger effects partly reflect the way the impulse responses are computed. In the baseline VAR the shock decays endogenously while in this section it is implicitly modelled as a permanent change.[25]

Figure 3.5: Single equation regressions



Notes: Impulse responses to a 100 bps increase in policy target rate. Confidence bands indicate 68 and 95 per cent intervals.

[25] Although it is not necessarily a permanent change in monetary policy as there may be offsetting changes to Bank Rate in later periods. Note that these are slightly different exercises and the responses are also affected by the implied Bank Rate path which is more persistent in the single equation regression than in the VAR.

3.5.2 Alternative timing assumptions

So far we have followed the previous literature (Christiano et al., 1996, 1999; Romer and Romer, 2004; Coibion, 2012) imposing that the policy change does not contemporaneously affect macroeconomic variables. We relax this assumption for the following reason. The regressors in the first stage regression capture the real-time information set of policymakers prior to the policy rate decision. As discussed, we carefully ensure that the forecasts do not include the consequences of the policy change. If we have correctly captured the information set that policymakers used to form their decision, our shock measure m_t should be contemporaneously exogenous. Rather than assuming movements in policy do not contemporaneously affect other variables in the second stage VAR, we should, in principle, be able to relax this assumption.

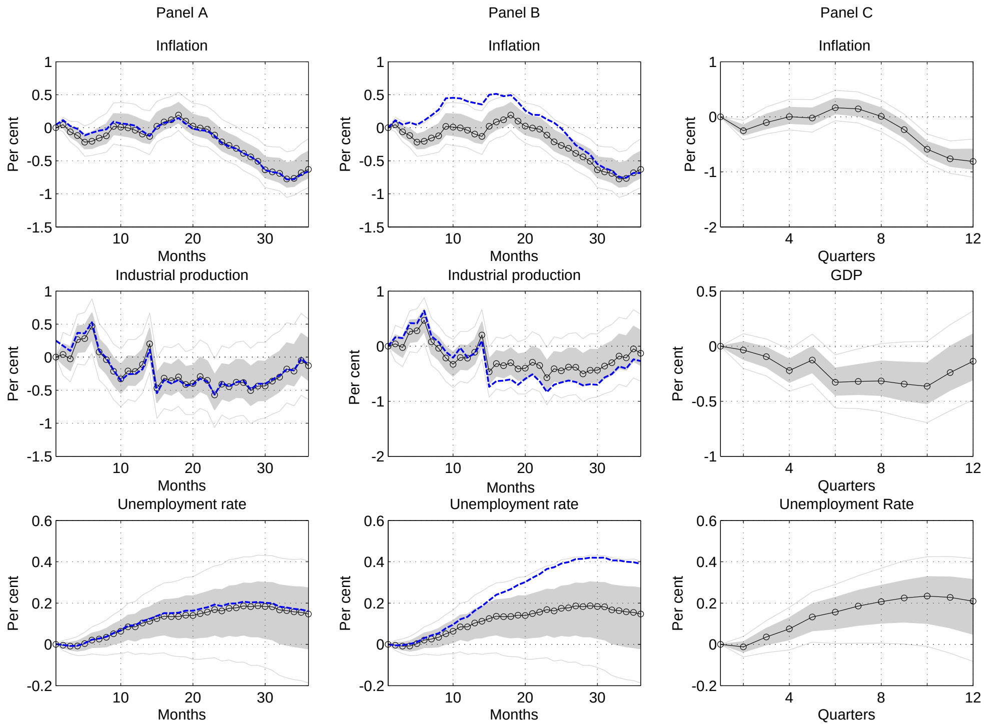
We therefore estimate our baseline VAR with the shock measure ordered first in the recursive ordering. This implies that contemporaneous macroeconomic fluctuations do not affect the policy decision other than via the forecasts. This seems reasonable given the discussion above. We can now identify the contemporaneous effects of our monetary shocks.

Panel A of Figure 3.6 presents the results based on this new identification assumption (blue dashed line). Our results are virtually identical, suggesting that the effects of monetary policy are indeed very protracted, building up slowly over time.

3.5.3 Do the forecasts matter?

Previously we argued that forecasts provide summary statistics of the policymakers' information set. Forecasts also allow us to control for policy reactions designed to offset future business cycle movements. If policy did not respond to forecasted conditions, or if the VAR already contains sufficient information to make their inclusion redundant, excluding the forecasts from our first stage regression would not alter our baseline results. To examine this possibility we estimate the first stage regression only including lagged real-time variables. Panel B in Figure 3.6 shows the results of this exercise. With forecasts excluded we find a substantial and pronounced price puzzle, the unemployment response doubles and the industrial production response is slightly stronger. These findings suggest that policymakers do respond

Figure 3.6: Robustness to timing assumptions, excluding forecasts and quarterly GDP data



Notes: Impulse responses to a 100 bps increase in policy target rate (dashed line) of alternative specification compared to baseline specification (circled line) with corresponding 68 and 95 per cent confidence intervals. The baseline specification uses industrial production, RPIX12m inflation, unemployment rate, commodity prices, and our shock measure. Panel A: non-recursive VAR allowing for contemporaneous effect (dashed line). Panel B: first stage regression with only lagged variables (dashed line). Panel C: quarterly VAR with GDP.

to anticipated movements in the macroeconomy and that this information is not adequately summarised by conventional macroeconomic variables used in VARs.

As a further experiment, we estimate the first stage regression excluding real-time backdata and forecasts of the current period.[26] Interestingly, the dynamics are very similar to our baseline results in Section 4. It is therefore the inclusion of the forecasts that seems key for removing the price puzzle.

In a related contribution, Castelnuovo and Surico (2010) provide compelling evidence that the omission of expected inflation in a VAR can account for the price

[26]In practise, we estimate equation (3.2.2) with the forecast horizon $i = 1, 2$ instead of $i = -1, 0, 1, 2$.

puzzle in indeterminate monetary regimes. In essence excluding forecasts causes omitted variable bias and the empirical evidence for the U.K. economy in this section is in line with their finding. That said, we find a price puzzle after 1993 as well using a conventional recursive VAR with Bank Rate, in a regime widely regarded as satisfying the Taylor Principle.

3.5.4 Quarterly VAR with GDP

In earlier sections we used industrial production as our measure of output. This is useful because it is available monthly and correlates strongly with GDP. To provide an estimate of how strongly monetary policy shocks affect the total economy, as measured by GDP, we estimate a quarterly VAR with National Accounts data.[27] In line with our baseline results the peak decline in inflation is 0.81 percentage points and the unemployment rate significantly build up to 0.23 percentage points (see Panel C in Figure 3.6). GDP significantly falls below zero to a minimum of -0.36 per cent. The effect on GDP is roughly half the size of industrial production. A smaller peak effect on GDP as compared to industrial production is in line with the U.K. result of Mumtaz et al. (2011).[28]

3.5.5 Expanding the first stage: money supply and exchange rates

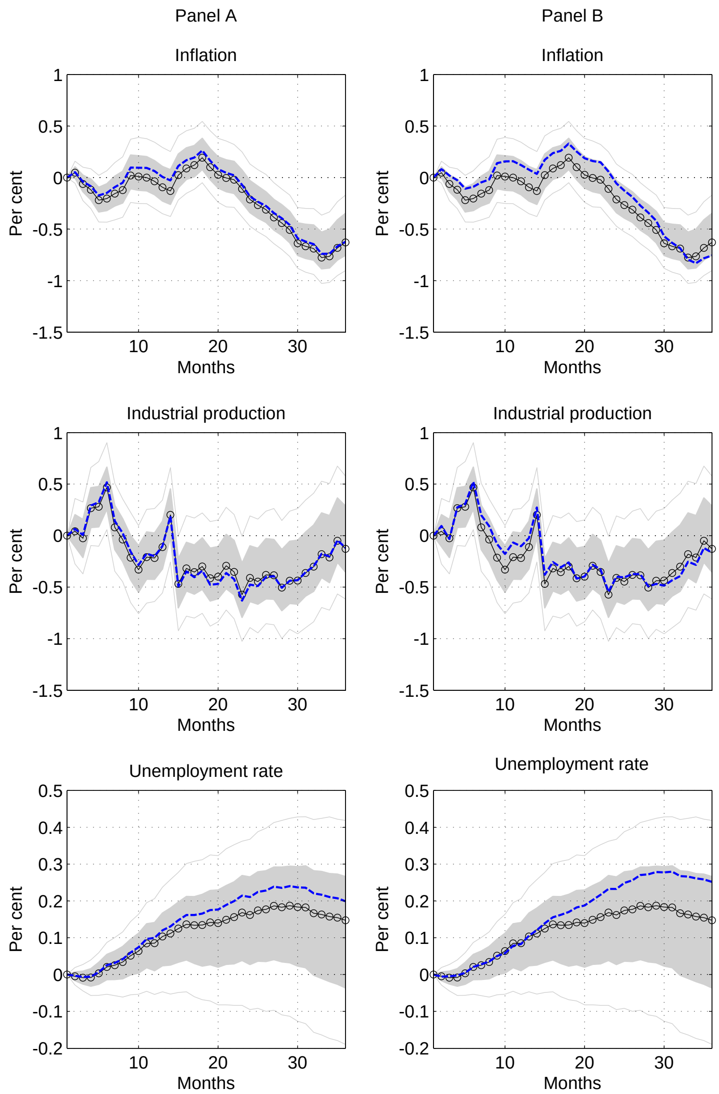
Although inflation targeting has been the stable policy regime since 1993, there have been a number of other experiments since 1975. Monetary targeting was emphasised in the early 1980s and stricter control of the money supply had begun in the late 1970s. In addition, during the latter half of the 1980s the U.K. began shadowing the Deutsche Mark as a forerunner to the U.K. joining the European Exchange Rate Mechanism, which it then was forced to leave in 1992.

Batini and Nelson (2009) argue that short-term interest rates have consistently been used as the policy instrument even throughout these earlier periods of U.K. monetary policy. Nonetheless, to examine whether these extra objectives affected the

[27]We include GDP, RPIX, unemployment rate and our shock measure cumulated to a quarterly series.

[28]It is worth noting that we also find a price puzzle using quarterly data in a conventional recursive VAR with Bank Rate.

Figure 3.7: Robustness to including extra first stage regressors and using NIESR forecasts



Notes: Impulse responses to a 100 bps increase in policy target rate (dashed line) of alternative specification compared to baseline specification (circled line) with corresponding 68 and 95 per cent confidence intervals. The baseline specification uses industrial production, RPIX12m inflation, unemployment rate, commodity prices, and our shock measure. Panel A: first stage regression includes lagged money supply M0, US Dollar-Sterling exchange rate, DM (Euro)-Sterling exchange rate (dashed line). Panel B: using only NIESR forecasts (dashed line) in first stage regression.

setting of the policy target rate, we expand the variables in the first stage regression to include lagged money supply (M0) as well as the US Dollar-Sterling exchange rate and the Deutsche Mark/Euro-Sterling exchange rate.[29] Panel A of Figure 3.7 shows that our baseline results are largely unaffected by the inclusions of these extra variables.

3.5.6 Private sector forecasts

A possible concern is whether NIESR forecasts (for periods where official forecasts were unavailable) are suitable substitutes for official forecasts. Ideally we would like to have used official forecasts for the full sample, but these were unavailable further back. Previously we noted that NIESR and Bank of England forecasts are highly correlated at short forecast horizons. Moreover, if private sector forecasts are a good proxy for official forecasts we should expect very similar results using NIESR forecasts in our first stage regression for the full sample. To investigate the validity of employing private forecasts, we estimate the first stage regression using only NIESR data (blue dashed line). Panel B in Figure 3.7 shows that the impulse responses based on NIESR data for the full sample are almost identical and lie well within the 95 per cent confidence bands of our baseline results (solid line). The results are virtually unchanged suggesting that NIESR forecasts are a valid proxy for the policymakers' information set.

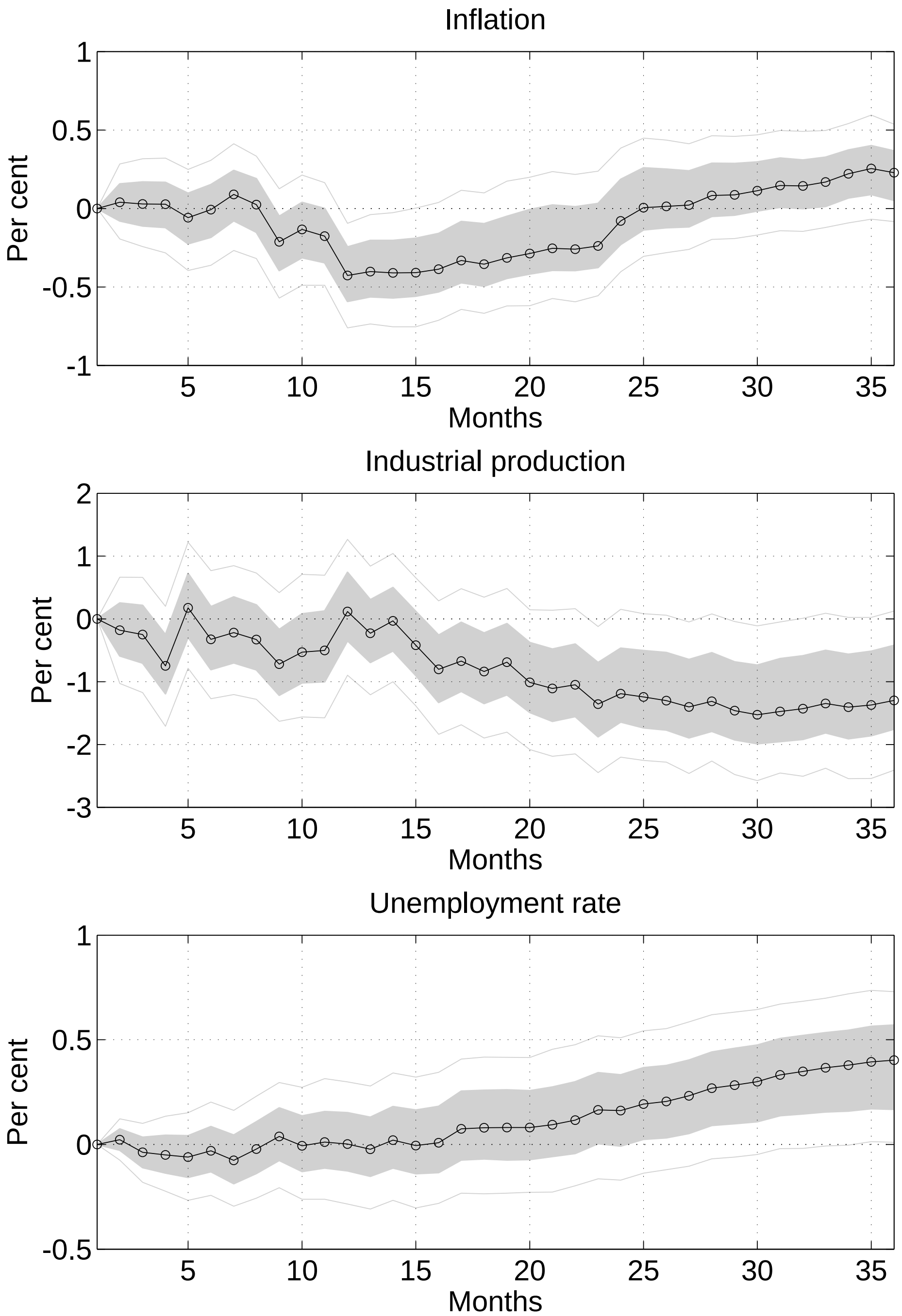
3.5.7 Monetary policy since the inflation targeting regime

Since October 1992 the U.K. has operated an inflation targeting regime. Earlier we showed that the volatility of our monetary policy shock series is much smaller after the early 1990s. In this subsection we examine the effects of monetary policy for the post-1992 sample.

Figure 3.8 shows that in response to a 100 bps increase in the policy target rate, the inflation rate falls by up to 0.43 percentage points. Industrial production exhibits a peak decline of 1.53 per cent and a rise in unemployment rate of 0.40 percentage

[29] Clarida, Galí, and Gertler (1998) estimate policy rules for several countries, among these for the U.K. economy, and include the Sterling-Deutsche Mark exchange rate as a relevant regressor.

Figure 3.8: The effects of monetary policy under inflation targeting



Notes: Impulse responses to a 100 bps increase in policy target rate. VAR with industrial production, inflation rate (RPIX12m), unemployment rate, commodity prices and our shock measure. P=12. Sample: 1993-2007. Confidence bands indicate 68 and 95 per cent intervals.

points.[30] The following differences stand out when comparing the results to the full sample findings. Inflation begins to fall nine months after the shock, rather than 18 months in our baseline results. Furthermore, after two years the effect on inflation returns back to zero. Similar to before, the real effects on unemployment and industrial production begin to materialize about 15 to 18 months after the increase in policy target rate. The real effects in a quarterly VAR are similar to our previous results. For the post-92 sample the peak effect of GDP is -0.3 per cent and is only slightly smaller than for the full sample (see Figure 3.6).

Quantitatively the response of industrial production is around two and a half times larger in the post-1992 sample, with unemployment twice as large, but the inflation response is half the magnitude. Consistent with Mumtaz et al. (2011) we find a more pronounced effect of industrial production in response to a monetary policy shock after 1992. However, our results — and those of Mumtaz et al. (2011) — suggest moderate GDP effects that are similar pre- and post-1992. Although our peak effect on inflation is smaller than their results, they do also find that a fall in inflation is quicker in the more recent sub-sample. One interpretation of the faster response for inflation might be that inflation targeting regimes are tougher at controlling inflation in the aftermath of an expansionary shock to monetary policy. The faster fall in prices may also reflect changes in price and wage setting behaviour since the 1980s.

3.6 Conclusion

Identifying exogenous variation in monetary policy is challenging. This chapter tackles this issue for the U.K. by applying the identification strategy of Romer and Romer (2004). While numerous studies employ more conventional VAR methodologies, to our knowledge, there has been no other application of this so-called narrative strategy to corroborate the large effects found for the U.S. economy. Moreover, there is comparatively little evidence of the macroeconomic effects of monetary policy for the U.K. economy.

The U.K. is an excellent country to conduct this new study: the Bank of England's policy rate *is* the intended target rate and there is a wealth of U.K. real-time and

[30] In comparison, the recursive VAR with Bank Rate yields a persistent price puzzle with a peak effect of 0.5 percentage points.

forecast data available. We construct a new, extensive real-time forecast database and carefully match these data to relevant Bank Rate decision. We therefore reconstruct the policymakers' information set prior to the policy change, allowing us to identify monetary policy shocks from a first stage regression.

Armed with our new shock measure we find moderate effects of monetary policy on the macroeconomy. A 100 basis point tightening leads to a maximum decline in output of 0.6 per cent and a fall in inflation of 0.8 percentage points after two to three years. Monetary policy changes have a protracted effect on the economy, with little initial impact. Our results also suggest that GDP responds less than industrial production — around 0.4 per cent at peak in response to a contractionary monetary policy shock.

Our findings are more in line with conventional VAR evidence than with the large effects Romer and Romer (2004) and Coibion (2012) find for the U.S. economy. That said, in keeping with RR, we are able to resolve the price puzzle for the U.K. — a key challenge of common recursive identification approaches. We show that the narrative approach employed here, in particular the use of forecast data, is crucial for this result.

The effect of changes in monetary policy continues to be keenly debated, both in academic and policy circles. In addition, it seems likely that interest rates will remain a key instrument of monetary policy as economies recover from the Great Recession. Our new estimates therefore contribute to this ongoing debate. By conducting the narrative approach this chapter provides a rich new data set as well as a monetary policy shock measure of the U.K. economy. We hope both will provide exciting scope for future research.

Appendix to Chapter 3

3.A Data appendix

Table 3.5: Data sources

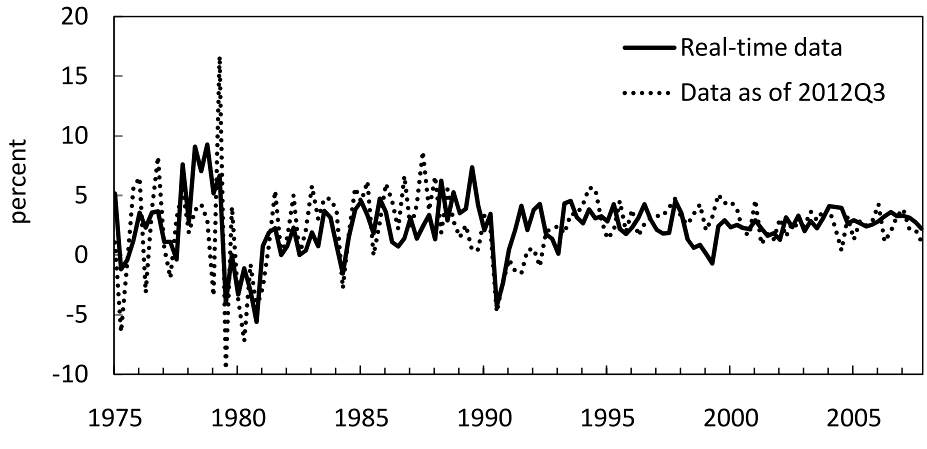
Variable	**Source**	**Description**	**Series**
Output	ONS	GDP seasonally adjusted (S.A.)	ABMI
Industrial production	ONS	Covers manufacturing, mining and quarrying and energy supply (S.A.)	CKYW
Inflation (RPIX)	ONS	Annual change in Retail Price Index excluding mortgage interest payments	CHMK
Inflation (RPI)	ONS	Annual change in Retail Price Index	CHAW
Inflation (CPI)	ONS	Annual change in Consumer Price Index	D7BT
Interest rates	Bank of England	Bank Rate / Minimum Lending Rate / Repo Rate / Official Bank Rate	"Official Bank Rate history"
Unemployment rate	ONS	Unemployment rate (Age 16 and over). Claimant count and ILO measure (S.A.)	MGSX
Money supply M0	Bank of England	Monthly average amount outstanding of total sterling notes and coin in circulation, excluding backing assets for commercial banknote issue in Scotland and Northern Ireland (S.A.)	LPMAVAB
Exchange rates Sterling/USD	Bank of England	Spot exchange rate, USD into Sterling (monthly average)	XUMAUSS
Exchange rates Sterling/Euro	Bundesbank	Spot exchange rate Euro into Sterling (monthly average)	BBK01.WT5627
Exchange rates Sterling/DM	Bundesbank	Spot exchange rate DM into Sterling (monthly average)	BBK01.WT5005
Effective exchange rates	Bank of England	IMF-based effective exchange rate index (1975-2006), thereafter effective exchange rate index. (monthly average, S.A.).	XUMABK82, XUMAGBG
Commodity price index	IMF	IMF Commodity price index converted to Sterling (S.A.)	

Table 3.6: Variables of real-time forecasts data set

Variable	Source	Description	Available period
Real GDP growth	IR	Annualised quarterly real GDP growth rates (S.A.)	1997-08
RPIX	IR	Annual RPIX inflation rate	1993-03
HCPI	IR	Annual HCPI inflation rate	2003-08
Real GDP growth	NIESR	Annualised quarterly real GDP growth rates (S.A.)	1975-08
RPI/RPIX	NIESR	Annual RPIX inflation rate	1987-08
HCPI	NIESR	Annual HCPI inflation rate	1999-08
GDP Deflator	NIESR	Annualised quarterly GDP deflator	1987-08
Consumer price defl.	NIESR	Annualised quarterly consumer price deflator	1975-89
Effective exchange rate	NIESR	Annualised quarterly exchange rate growth rate	1975-08
Unemployment rate	NIESR	Annual unemployment rate (ILO rate after 98Q3) (S.A.)	1987-08
Trade Balance/GDP	NIESR	Trade balance-GDP ratio (S.A.)	1992-08

Notes: If available we collected up to eight quarters forecasts and eight quarters backdata amounting to 17 observations for each variable including the real-time estimate of the contemporaneous quarter.

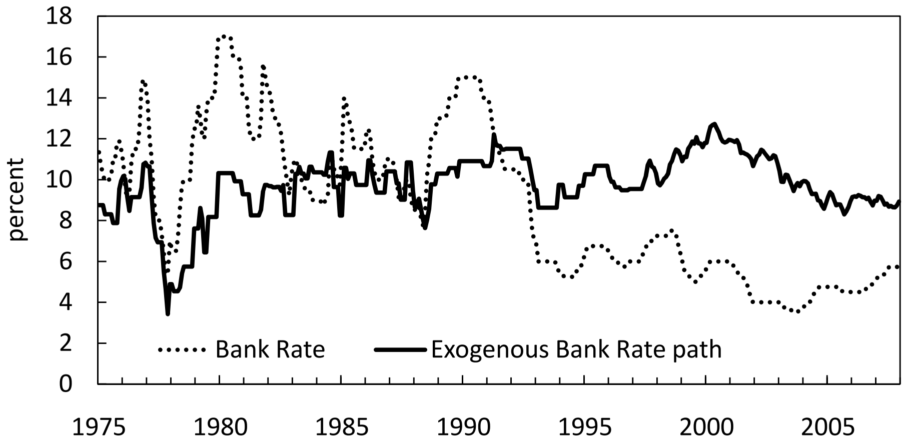
Figure 3.9: Real-time and revised data for annualised real GDP growth



Notes: Real-time data is the nowcast based on NIESR (1975-1993) and Inflation Report (1993-2007).

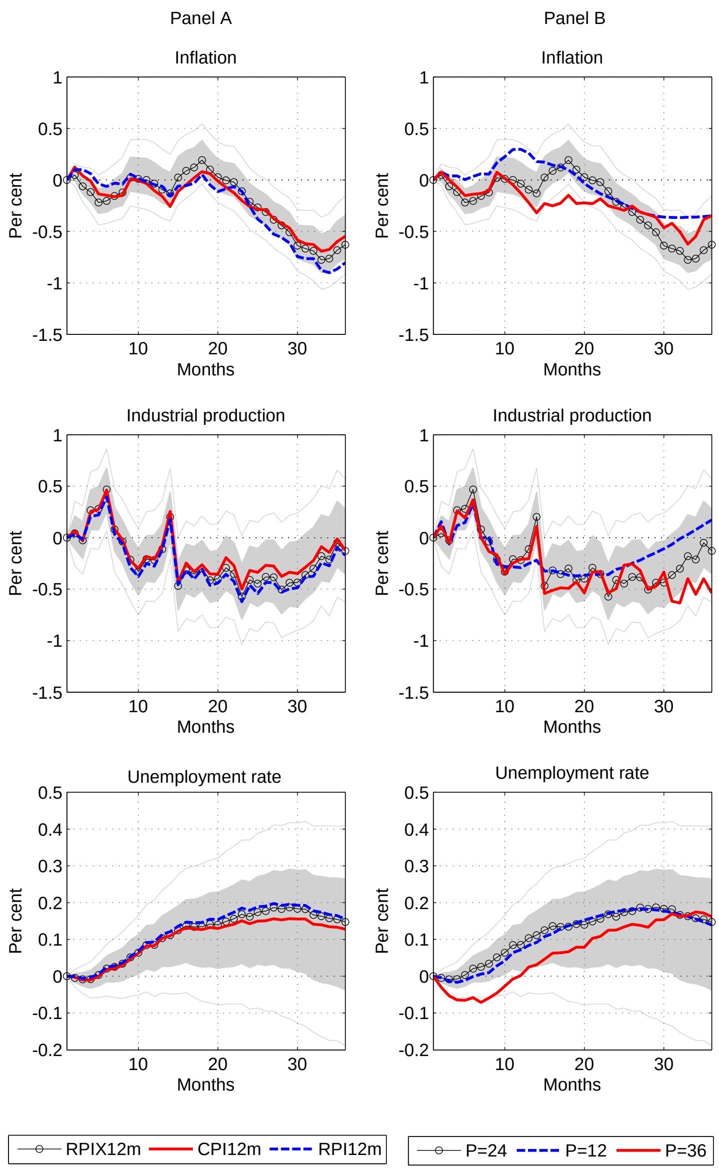
3.B Further results

Figure 3.10: Cumulated shock series and actual Bank Rate



Notes: Exogenous Bank Rate path is the cumulated shock series adjusted for the average Bank Rate.

Figure 3.11: Robustness to alternative price measures and lag length



Notes: Impulse responses to a 100 bps increase in policy target rate (dashed line) of alternative specification compared to baseline specification (circled line) with corresponding 68 and 95 per cent confidence intervals. The baseline specification uses industrial production, RPIX12m inflation, unemployment rate, commodity prices, and our shock measure. Panel A compares the dynamics for various inflation measures (RPI and CPI) to the baseline VAR with RPIX. Panel B provides the baseline VAR results compared to including 12 and 36 lags.

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