A Study of a New-Keynesian DSGE Macro Model: Estimates, Shocks, and Optimal Monetary Policy

By

Erik Hjort

LUND UNIVERSITY
SCHOOL OF ECONOMICS AND MANAGEMENT
Department of Economics
Supervisor: Associate Professor Klas Fregert, Ph.D.

NEKN01 Master Essay I, ECTS 15 Credits
August 29, 2019

A Study of a New-Keynesian DSGE Macro Model: Estimates, Shocks, and Optimal Monetary Policy*

Erik Hjort**

August 29, 2019

This paper estimates and simulates a New-Keynesian small-scale DSGE macro model. The model consists of the hybrid forms of the Phillips curve and the IS curve, and is closed with a Taylor-type feedback rule allowing partial adjustment of the monetary policy instrument. We estimate the three-equation system simultaneously on Swedish data 1995:Q1 to 2014:Q4 with the FIML estimator. The empirical parameter values are then used in simulations of the model to study the impact of shocks and optimize the policy rule by using an objective function. Our estimates indicate that both inflation and output possess a significant forward-looking behavior, and that the policy instrument is adjusted in a gradual manner. A sensitivity analysis of the magnitude of interest rate smoothing suggests a trade-off that the Central Bank faces when exogenous disturbances move the economy. In attempting to gauge preferences of monetary policy, we show that an optimized policy rule that roughly returns the historical rule is characterized by that the monetary authority in descending order stabilizes the volatility of the interest rate, the output gap, and inflation from a target level.

Keywords: New-Keynesian Economics; Rational Expectations; Monetary Policy; Aggregate Shocks; Small-scale DSGE Model.

---

* I am grateful to Klas Fregert for invaluable advice.

** E-mail address: eko14ehj@student.lu.se

Contents

1 Introduction

New-Keynesian models have since long been an important benchmark in monetary economics and monetary policy analysis. These models integrate nominal rigidities from Keynesian economics with the dynamic stochastic general equilibrium (DSGE) methodology from the real business cycle theory. A crucial assumption in the New-Keynesian school of economics is that expectations about future economic conditions plays a key role in the determination of the current state of the economy. Firms operating in an imperfectly competitive market constitutes the supply side of the economy, whereas households making intertemporal choices in consumption comprises the demand side. Both firms and households are assumed to be forward-looking agents that maximizes profits and utility, respectively. The third actor is the Central Bank that conducts monetary policy by adjusting an instrument as a reaction to changed economic conditions.

The New-Keynesian framework has been subject to extensive research over the last two decades. The supply equation builds on the model of nominal rigidities by Calvo (1983), and the model of monopolistic environment by Dixit and Stigliz (1977). The demand equation is drawn from a consumption Euler equation. The conventional in the literature is to model Central Bank behavior with a Taylor-type feedback rule (Taylor, 1993). In its simple form, the supply equation is often referred to as the New-Keynesian Phillips curve and the demand equation as the New-Keynesian IS curve. By bringing together a Phillips curve, an IS curve and a monetary policy rule, a three-equation model is complete.

The microfoundations of the New-Keynesian Phillips curve and the IS curve entails that inflation and output enters the respective equations as pure forward-looking variables. The observed persistence of these variables in the data has, though, lead the literature to motivate the inclusion of backward-looking expectations. The hybrid variants of the behavioral equations allow firms to index their prices (Christiano, Eichenbaum and Evans, 2005), and households can derive utility today from consumption in the past by habit formation (Fuhrer, 2000). In the present paper we relax the assumption of full rationality by adhering to the specification of the hybrid forms of the Phillips and the IS curve.

The majority of the empirically specified monetary policy rules allow some sort of endogenous smoothing (also known as policy inertia, or gradualism, or partial adjustment) of the policy instrument. A common view when estimating such rules is that the Central Bank tend to adjust its instrument in a gradual manner (e.g. Clarida, Galí and Gertler, 1999). To include a policy rule that allows endogenous smoothing in a macroeconomic model has not gone without discussions. Some argue that policy inertia can be optimal (e.g. Sack and Wieland, 2000; Woodford, 1999, 2003b), whilst there are also arguments against specifying endogenous policy smoothing (e.g. Rudebusch, 2002a, 2006; Mavroeidis, 2010). The discussion is not only academically relevant, in 2008 and 2011 the Riksbank Executive Board have talks about interest rate smoothing in monetary policy meetings (Sveriges Riksbank, 2008, 2011), and Bernanke (2004) conveyed in a speech potential advantages of a gradualist approach. This study allows interest rate smoothing but asks the question what the trade-offs might be when exogenous disturbances move the equilibrium of the economy.

This paper estimates and simulates a New-Keynesian small-scale DSGE macro model. We estimate the three-equation system consisting of a Phillips curve, an IS curve, and Taylor-type monetary policy rule simultaneously on Swedish data 1995:Q1 to 2014:Q4 by using the Full Information Maximum Likelihood (FIML) estimator. The empirical parameter values are then used in simulations of the model to study the effect of shocks and optimize the policy rule. The discussion will be related to potential trade-offs the Central Bank face in a policy objective function that serves as a guide in the decision-making. As discussed in Dennis (2006), the weights in a standard objective function used to analyze optimal monetary policy rules reflect how different objectives are a trade-off in response to shocks. The model we study is well-established in the literature and it has been diligently used in studies in monetary economics and monetary policy analysis. Similar types of models are still a benchmark in the literature and underlie more recent research (cf. Baele, Bekaert, Cho, Inghelbrecht and Moreno, 2015; Bikbov and Chernov, 2013). The three-equation system considered has to our knowledge not previously been estimated on Swedish data. The present study is an attempt to fill this gap in the literature. We formulate three key questions. How well does a standard New-Keynesian DSGE model replicate the Swedish data 1995:Q1 to 2014:Q4? What is the effect of exogenous disturbances in the model; is the degree of policy inertia crucial for the impact of a shock? How do we explain the effect of shocks in the model with respect to stabilization preferences of the Central Bank?

The outline of this paper is as follows. In section 2, the model is specified. In Section 3, we discuss the data and its transformations. Section 4 discusses our econometric approach for the empirical analysis and clarifies the numerical simulations of the model. In section 5, we present the parameter estimates and conduct a standard robustness analysis. Section 6 contains the numerical simulations of the model. Section 7 concludes.

2 The Model

The New-Keynesian model we study is largely presented in Walsh (2017), and the complete model has been estimated previously by Lindé (2005). The model consists of one supply equation, one demand equation and a monetary policy rule. The equations are written in log-linearized reduced form in which the variables are measured as deviations from a steady state value.[1] The objective function is not part of the empirical analysis, but for the numerical simulations, why this function is introduced at first in section 6.

2.1 The Hybrid New-Keynesian Phillips Curve

The Hybrid New-Keynesian Phillips curve describes the supply side of the economy. Current inflation depends on expected future inflation, past inflation, and on the contemporaneous output gap.

$$\pi_t = \delta E_t\pi_{t+1} + (1 - \delta)\pi_{t-1} + \lambda\hat{y}_t + \varepsilon_t^{\pi} \qquad 0 < \delta < 1 \qquad \lambda > 0 \tag{1}$$

$\varepsilon_t^{\pi} \sim$ I.I.D. $(0, \sigma_{\pi}^2)$

Where

E_t is the expectational operator conditional on information available at time t.[2]

π_{t+1} is the expected (realized) inflation at time t+1.

$\hat{y}_t$ is the output gap at time t; actual output subtracted with a trend value $\hat{y}_t = (y_t - y_t^*)$.

ε_t^{π} is as a supply shock, assumed to be independently and normally distributed with zero mean and constant variance σ_{π}^2.

We assume model-consistent rational expectations which imply a relationship as follows $E_t\pi_{t+1} = \pi_{t+1} + \varepsilon_t$

The equation states that expectations today of inflation in the next period equals next periods actual inflation plus a random forecast-error today, ε_t. This relationship entails that expected future inflation either turn out slightly higher or lower than the actual inflation in the next period. However, under rational expectations, agents are assumed to be on average correct in their forecasts. Following, we use actual inflation with one lead for $E_t\pi_{t+1}$. The rational expectations assumption holds throughout in the study for all expectations' variables.

---

[1] See the books by Galí (2015), Walsh (2017), and Woodford (2003a) for rigorous treatments of New-Keynesian models including derivation of underpinning microfoundations.

[2] The expectational operator is the mathematical expectations operator.

Expected future inflation enters equation (1) on the assumption that firms have rational expectations and optimizes about the future. The microfoundations that underpins is that firms operate in a monopolistic setting and maximize profits by negotiation about future prices, for example wages (Walsh, 2017). There are several justifications to why past inflation enters the equation. To add lags of endogenous variables at aggregated levels might make the equation become subject to the Lucas Critique (Lucas, 1976). One motivation for past inflation is due as some price-setters index their prices to past inflation (Christiano et al. 2005). Another justification being that some price-setter possess a rule-of-thumb behavior (Galí and Gertler, 1999). Rudd and Whelan (2005) discuss that such interpretations are consistent with a hybrid form of the Phillips Curve, but raises the question if it provides a structural model of inflation that eludes the Lucas Critique.

The hybrid form of the New-Keynesian Phillips curve refers to that past inflation enters equation (1).[3] One interpretation of the written specification is that some share of the price-setters are forward-looking while the others' are backward-looking.[4] Rudd and Whelan (2006) make clear that this constrain also prevent a long-run trade-off between inflation and output. Furthermore, it implies that we will have no statistics of the backward-looking component of inflation in the estimates. If we instead would set $\delta = 1$, the equation becomes the simple forward-looking New-Keynesian Phillips curve. Conversely, if $\delta = 0$ the equation becomes a pure backward-looking Phillips curve.

The parameter λ is the real driving variable that depends crucially on structural parameters which is related to nominal price rigidities. In an original Calvo model, the real driving variable is a real marginal cost (Calvo, 1983).[5] With certain assumptions the relationship between output and real marginal costs reads $mc_t = k\hat{y}_t$ where k is the output elasticity of real marginal costs (Clarida et al. 1999). For a derivation of this relationship, see Walsh (2017), or Woodford (2003a). We suppose that k is constant as in much of the literature. We shall come later to discuss potential empirical issues by this assumption in section 4.

---

[3] Examples of papers that studies equation (1) include Baele et al. (2015), Bekaert, Cho and Moreno (2010), Cho and Moreno (2006), Dennis and Söderström (2006), Fuhrer (2010), Galí, Gertler and Salido-Lopez (2005), Lindé (2005), Rudd and Whelan (2006), and Rudebusch (2002b).

[4] This specification could also be a required condition for identification, see Mavroeidis (2005).

[5] Data of labor share of income is commonly used as proxy for real marginal costs in empirical research. By starting from a Cobb-Douglas production function, Galí and Gertler (1999) shows that $S_t = W_tN_t \ / \ P_tY_t$, and in percent from steady state $mc_t = s_t$. When estimating the Phillips curve with real marginal costs, mc_t enters instead of the output gap $\hat{y}_t$.

2.2 The Hybrid New-Keynesian IS Curve

The Hybrid New-Keynesian IS curve describes the demand side of the economy. Current output depends on expected future output, past output, and on the ex-ante real interest rate.

$$\hat{y}_t = \mu E_t \hat{y}_{t+1} + (1 - \mu)\hat{y}_{t-1} - \sigma[i_t - E_t \pi_{t+1}] + \varepsilon_t^{\hat{y}} \qquad 0 < \mu < 1 \qquad \sigma > 0 \tag{2}$$

$\varepsilon_t^{\hat{y}} \sim$ I.I.D. $(0, \sigma_{\hat{y}}^2)$

Where

$\hat{y}_{t+1}$ is the expected (realized) output at time t+1.

σ is the inverse elasticity of substitution in consumption.[6]

i_t is as a short-term nominal interest rate at time t.

$r_t = [i_t - E_t \pi_{t+1}]$ is the ex-ante real interest rate at time t.

$\varepsilon_t^{\hat{y}}$ is a demand shock, assumed to be independently and normally distributed with zero mean and constant variance $\sigma_{\hat{y}}^2$.

Expected future output enters equation (2) on the assumption that households are forward-looking and derive utility today from consumption in the future. The underlying microfoundations is that households are optimizing by making intertemporal choices in consumption such that they maximize their utility, under the assumption that consumption equals output subtracted by government expenditure (Clarida et al. 1999). The presence of past output is motivated by Fuhrer (2000) who shows that households derive utility today from past consumption due to habits. It has also been found that investment spending, another important component of aggregate demand, experience endogenous inertia due to adjustment costs (Christiano et al. 2005; Edge, 2007).[7]

The benchmark case in New-Keynesian models is that the parameter σ shall to be positive.[8] This is due as of the assumption of a dominating substitution effect; higher real interest rates increase savings and dampen current output. The short-term nominal interest rate is the monetary transmission mechanism in the IS curve.[9] As Woodford (2003a) shows using an equation like (2),

---

[6] Woodford (2003a) denote this parameter as the 'intertemporal elasticity of substitution of aggregate expenditure'.

[7] Example of papers that studies equation (2) include Baele et al. (2015), Cho and Moreno (2006), Dennis and Söderström (2006), Fuhrer and Rudebusch (2004), Lindé (2005), and Rudebusch (2002b).

[8] Using a simple forward-looking IS curve (μ = 1), Estrella and Fuhrer (2002) argue that this relationship is counterfactual. They discuss that the level of consumption decreases with a rise in the real interest rate, but that its change must be expected to increase in period t+1 from period t.

[9] In a recent paper, Rupert and Šustek (2019) argue that the monetary transmission mechanism in New-Keynesian models operates through another channel.

aggregate demand depends on all expected future short-term real interest rates and not only on a current ex-ante short real interest rate. This implies that the monetary authorities' main impact on the economy comes from how the interest rate affect the private sectors' expectations about future interest rates, and not primarily by what relative level the current short-term nominal rate is set to (Woodford, 2003a). In turn, the credibility of monetary policy commitment is crucial, and that discretion likely leads to a non-optimal outcome. A consequence for the conduct of monetary policy is that partial adjustments of the interest rate is desirable (Woodford, 2003a).

2.3 Monetary Policy Rule

To close the model, we assume a Taylor-type monetary policy rule describing how a Central Bank adjusts an instrument as a reaction to changed economic conditions. We suppose that the nominal interest rate is the policy instrument of the Central Bank and they take into consideration the previous period's nominal rate when setting the current level. The rule states that the nominal interest rate is adjusted in response to inflation from its target level and to the output gap.

$$i_t = (1 - \rho)[\phi_\pi \pi_t + \phi_{\hat{y}} \hat{y}_t] + \rho i_{t-1} + \varepsilon_t^i \qquad 0 < \rho < 1 \qquad \phi_\pi > 0 \qquad \phi_{\hat{y}} > 0 \tag{3}$$

$$\varepsilon_t^i \sim \text{I.I.D.}\ (0, \sigma_i^2)$$

Where

i_t is a short-term nominal interest rate.

ρ is a parameter which capture interest rate smoothing.

ϕ_π is the monetary authority's response to inflation from its target level.

$\phi_{\hat{y}}$ is the monetary authority's response to the output gap.

ε_t^i is a monetary policy shock, assumed to be independently and normally distributed with zero mean and constant variance σ_i^2.

As shown by Clarida et al. (1999), a rule like equation (3) can be written as a function of two equations

$$i_t^* = \phi_\pi \pi_t + \phi_{\hat{y}} \hat{y}_t \tag{4}$$

$$i_t = (1 - \rho) i_t^* + \rho i_{t-1} + \varepsilon_t^i \tag{5}$$

Where

i_t^* is the monetary authority's target interest rate.

Equation (4) states that the Central Bank adjusts the desired value of the nominal interest rate as a reaction to deviations of inflation from its target and to the contemporaneous output gap. Equation (5) states that the nominal interest rate is adjusted only gradually to the desired level. A combination of these two equations is the resulting monetary policy rule, equation (3). In this resulting rule, the relative value of the smoothing parameter ρ determines the weight assigned to the lagged nominal interest rate, whilst the weight $(1 - \rho)$ is assigned to the target interest rate (Clarida et al. 1999). By studying equation (4) and (5) we see that this way of specifying interest rate smoothing indicates that it is intentional by the policy makers to reach a desirable state of the economy, as modeled by a target interest rate.

The parameter ϕ_π measures the Central Bank's long-run response to inflation and $\phi_{\hat{y}}$ measures the concern of output stability.[10] If $\phi_\pi > 1$, then the Central Bank stabilizes inflation, and if $\phi_\pi < 1$, the Central Bank accommodates inflation. Whenever $\phi_\pi > 1$, the Taylor-principle is satisfied, which is necessary condition to enable numerical solutions of a New-Keynesian model (e.g. Bullard and Mitra, 2002). We discuss further about equilibrium conditions in section 4.3. Three justifications to interest rate smoothing are policy conservatism and financial market stability (Clarida et al. 1999), and because it levers on expectations (Woodford, 2003b). Rudebusch (2002a) argue, on the other hand, that evidence of policy inertia in Taylor-rules is an illusion and instead propose that it reflects persistent shocks. As Rudebusch (2006) make clear, the question is not whether gradual adjustment of the policy instrument exists, but whether it is endogenous or exogenous.

The Central Bank is assumed to react to the deviation of inflation from its target level. In this study we use two definitions of the inflation target. Recall that the variables are measured as deviations from a steady state value, which in the empirical analysis is defined as de-meaned series. Hence, our first definition of the inflation target is simply the average of the data series of inflation as in, for example, Clarida et al. (1999). In this case, we have a three-equation model containing three variables. When studying a three-equation New-Keynesian model, it is fairly common to close the model with three variables (e.g. Cho and Moreno, 2006; Lindé, 2005; Leeper and Zha, 2001). In the empirical analysis, to take into account the conditions of the Swedish economy, we use yet another definition of the inflation target. The second definition is the 2 percent goal set by the Riksbank as of 1993. In this case, the model instead contains four variables.

---

[10] Example of papers that studies equation (3) include Lindé (2005), Lubik and Schorfheide (2004), and Rudebusch (2002a). Baele et al. (2015), Cho and Moreno (2006), Clarida et al. (2000), and Mavroeidis (2010) studies a version instead assuming that the Central Bank responds to expected future inflation.

The theory that underpins equation (1) and (2) entails that we shall define inflation as a quarterly annualized change $\pi_t = 400(\ln P_t - \ln P_{t-1})$, with P_t denoting the price index.[11] The first definition of the inflation target is then straightforward to calculate as the mean of this series. The second definition of the inflation target we use, which is the goal set by the Riksbank, is defined over an annual change (a year-on-year growth rate). Using quarterly data, we define inflation in the policy rule (3) as $\pi_t^a = 100(\ln P_t - \ln P_{t-3})$ with the 'a' denoting an annual change. Then we subtract the 2 percent target from each observation of this series. The two definitions of inflation are related but not the same; a quarterly annualized change is typically more volatile than an annual change. From here on, we use the notation π_t for the first definition of the inflation target with the associated calculation of inflation, whereas $\bar{\pi}_t$ is used for the second definition. The data with its transformations is described in detail in section 3.

2.4 A New-Keynesian Macro Model

By bringing together equation (1), (2) and (3) we have a system of three equations. The complete New-Keynesian model is

$$\begin{aligned}
\pi_t &= \delta E_t\pi_{t+1} + (1-\delta)\pi_{t-1} + \lambda\hat{y}_t + \varepsilon_t^{\pi} && , \quad \varepsilon_t^{\pi} \sim \text{I.I.D.}\,(0, \sigma_{\pi}^2)\ , \quad 0 < \delta < 1 \qquad \lambda > 0 \\
\hat{y}_t &= \mu E_t\hat{y}_{t+1} + (1-\mu)\hat{y}_{t-1} - \sigma[i_t - E_t\pi_{t+1}] + \varepsilon_t^{\hat{y}} && , \quad \varepsilon_t^{\hat{y}} \sim \text{I.I.D.}\,(0, \sigma_{\hat{y}}^2)\ , \quad 0 < \mu < 1 \qquad \sigma > 0 \\
i_t &= (1-\rho)[\phi_{\pi}\pi_t + \phi_{\hat{y}}\hat{y}_t] + \rho i_{t-1} + \varepsilon_t^{i} && , \quad \varepsilon_t^{i} \sim \text{I.I.D.}\,(0, \sigma_{i}^2)\ , \quad 0 < \rho < 1 \qquad \phi_{\pi} > 0 \quad \phi_{\hat{y}} > 0
\end{aligned} \tag{6}$$

The model can be expressed in matrix form

$$\begin{bmatrix} 1 & -\lambda & 0 \\ 0 & 1 & \sigma \\ -(1-\rho)\phi_{\pi} & -(1-\rho)\phi_{\hat{y}} & 1 \end{bmatrix} \begin{bmatrix} \pi_t \\ \hat{y}_t \\ i_t \end{bmatrix} = \begin{bmatrix} \delta & 0 & 0 \\ \sigma & \mu & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} E_t\pi_{t+1} \\ E_t\hat{y}_{t+1} \\ E_t i_{t+1} \end{bmatrix} + \begin{bmatrix} (1-\delta) & 0 & 0 \\ 0 & (1-\mu) & 0 \\ 0 & 0 & \rho \end{bmatrix} \begin{bmatrix} \pi_{t-1} \\ \hat{y}_{t-1} \\ i_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_t^{\pi} \\ \varepsilon_t^{\hat{y}} \\ \varepsilon_t^{i} \end{bmatrix}$$

And in compact notation

$$AX_t = BE_tX_{t+1} + CX_{t-1} + \varepsilon_t$$

$$\varepsilon_t \sim (0, D)$$

---

[11] Or simply a quarterly change in equation (1) $\pi_t = (\ln P_t - \ln P_{t-1})$ as in, for example, Galí and Gertler (1999).

Where

A, B and C are the defined (3 x 3) matrices containing the model parameters. $X_t = (\pi_t \;\; \hat{y}_t \;\; i_t)'$ is the variables. ε_t is the column vector of the shocks in which the 0 is a (3 x 1) mean zero column vector and the D denoting the diagonal of the variances of the shocks in an error variance-covariance matrix.

This simple three-equation model describes the economy with three variables ($\pi_t \; \hat{y}_t \; i_t$) and three exogenous shocks ($\varepsilon_t^{\pi} \; \varepsilon_t^{\hat{y}} \; \varepsilon_t^{i}$). The compact matrix notation of a New-Keynesian model like system (6) is sometimes used to derive equilibrium solutions (see Cho and Moreno, 2003, 2006, and references therein). The individual shocks are assumed to be I.I.D. However, it makes reasons to estimate model-equations simultaneously if the shocks are contemporaneously correlated (Dennis, 2006). If the shocks in estimates turns out to be correlated, then our simultaneous-equation method is more efficient than single-equation methods. This is because the FIML estimator uses all (full) information of a specified system of equations. We shall come later to discuss our empirical approach in section 4.

This type of model is interpreted in different ways in the literature. Our interpretation of the justifications of the parameters is that they are microfounded, which is one of reasons that makes us consider the model as a DSGE model. Also, by writing the system in compact matrix notation, and as the model is solved numerically, we make clear that we consider it as a three-variable model. Baele et al. (2015) considers a similar type of model as an example of a small-scale DSGE macro model, whereas Bikbov and Chernov (2013) instead interpret a version as a purely empirical specification.[12] Moreover, the model contains no explicit open-economy variables. The standard procedure to open up for international trade is to augment the equations with a real exchange rate, see an example of a model in Froyen and Guender (2018). There are in particular two reasons why we do not extend the model. The first argument is based on some results of previous research, and the second is with respect to the chosen estimation method.

An augmented exchange rate in the Phillips curve would allow for imported inflation. This has though been found to have limited empirical relevance. Allsopp, Kara and Nelson (2006) estimate a New-Keynesian Phillips Curve augmented with a real exchange rate, this parameter is though rejected. The IS curve could be valid in an open economy context provided that the elasticity of

---

[12] By similar types of models we refer to that Baele et al. (2015), and Bikbov and Chernov (2013) studies the model under the assumption that the Central Bank reacts to expected future inflation.

substitution σ captures the net-trade channel of monetary policy (Kara and Nelson, 2004), and if the shock $\varepsilon_t^{\hat{y}}$ include external shocks (Neiss and Nelson, 2003). By abstracting from exchange rates, Neiss and Nelson (2003) calibrates the parameter σ to a higher value. Stracca (2010) adds a real exchange rate in the IS curve, the results are mixed. Finally, in larger models using Swedish data, a response parameter to the real exchange rate in a policy rule has been found to be relatively small (Adolfson, Laséen, Lindé and Villiani, 2008).

The FIML estimator is sensitive to misspecifications of a model (e.g. White, 1982; Galí et al. 2005; Mavroeidis, 2005). Also, we would like to keep the textbook theory relevant for the studied model. Our focus in the empirical section is to see if a standard model can well reproduce the Swedish data. This facilitates the comparisons of our parameter estimates with existing studies. Furthermore, even though a small model, there are arguments to why policy-relevance might benefit from resisting to add more parameters and, or, variables. We have emphasized that the model is well-established and that it has been widely used in studies on monetary policy analysis. Chari, Kehoe and McGrattan (2009) discuss that developments of New-Keynesian models that include new types of shocks, for example shocks to exogenous spending and to the risk premium, unlikely are structural. They argue that the literature has added parameters to DSGE models which lack microfoundations so that shocks no longer are structural, and that this leads to New-Keynesian models not being useful for monetary policy analysis.

3 The Data

The sample covers the period 1995:Q1 to 2014:Q4.[13] All data are retrieved from Statistics Sweden and the Riksbank. The variables are de-meaned prior to estimates, which in the empirical section is our definition of the variables measured as deviations from a steady state value. The data with its transformations is described variable-by-variable below.

The quarterly data for output is retrieved seasonally adjusted from Statistics Sweden. Both nominal and real gross domestic product (GDP) data are collected as the nominal data is needed to calculate the GDP deflator. Starting with the output gap, real output is detrended with the HP-filter choosing a smoothing parameter of 1600 for quarterly data (Hodrick and Prescott, 1997). Denoting the log real output y_t and the trend estimate y_t^* we define the output gap as $\hat{y}_t = 100(y_t - y_t^*)$. The HP-filter could produce imprecise end-point estimates of the trend, why the first 12 and last 12 estimates are excluded as proposed in Sørensen and Whitta-Jacobsen (2010). One lag and one lead are used in the tests, and so output is detrended for the period 1992:Q1 to 2017:Q4.

Three different price indices are used as measures of inflation for robustness checks. All data for inflation is retrieved from Statistics Sweden. The first is the GDP deflator. Denoting the nominal GDP as Y_t the GDP deflator is computed as $P_t = 100(Y_t/Y_{t,\,2017})$, where $Y_{t,\,2017}$ is real output at 2017 chained prices and P_t is the price index. We use the quarterly annualized change as definition of inflation $\pi_t = 400(\ln P_t - \ln P_{t-1})$. The two other measures of inflation are the consumer price index (CPI), and the consumer price index with fixed rate (CPIF). Neither CPI nor CPIF is seasonally adjusted and the data are retrieved at monthly frequency. We compute the quarterly averages of the monthly data over the associated three months. Then, we seasonally adjust the series in Eviews by using Census X-13. Finally, we use the definition of inflation as above and calculate the quarterly annualized change.

As mentioned in section 2.1, we estimate the model with two definitions of the inflation target in the policy rule. We use the same measures of inflation, but with another definition. In this case, we define inflation as an annual change $\pi_t^a = 100(\ln P_t - \ln P_{t-3})$, with the 'a' denoting an annual change. After this calculation, we proceed by subtracting the target of 2 percent $\bar{\pi}_t = (\pi_t^a - \pi^*)$, with $\pi^* =$ 2.0 percentage points. The final step is to de-mean the remainder. However, recall that this definition only holds for the policy rule. The definition of a quarterly annualized change of inflation

---

[13] Note that, as we use one lead and one lag of inflation and output, the actual test period is 1995:Q2 to 2014:Q3.

is used in the estimates of equation (1) and (2) independently of the assumption on how the Central Bank react to inflation.

The nominal interest rate is the policy rate of the Riksbank, the repo rate. The quarterly average of daily data expressed as units of percent per year are retrieved from the Riksbank. One could also consider a short-term interbank rate, for example a 3-month Stockholm Interbank Offered Rate (STIBOR), in the IS-curve.[14] Using an interbank rate in the IS curve might be a more theory-consistent choice with the interpretation that households hold bonds. However, the repo rate is throughout used in the empirical analysis since the model is interpreted and treated as a DSGE model.

---

[14] The correlation between the repo rate and the 3-month STIBOR between 1995:Q1 to 2014:Q4 are 98 percent, quarterly averages. We experimented by using a 3-month STIBOR instead of the repo rate in the estimates; it made no significant difference.

4 Methodology

The model is estimated as a simultaneous-equations system by using the FIML estimator.[15] Two classic econometric methods to estimate equations with forward-looking variables are generalized method of moments (GMM), and maximum likelihood (ML). Lately, Bayesian techniques has become increasingly common. After the model parameters are estimated, the model is numerically simulated. We continue by discussing motivations in the choice of the FIML estimator. Thereafter we discuss some of limitations in the study. Finally, we briefly describe the numerical simulations.

4.1 Econometric Approach

Two classic econometric estimators widely used to estimate rational expectations equations are GMM and ML. The two methods treat forward-looking variables in different ways. In short, GMM expresses the forward-looking variable as a function of instruments, whereas ML produces model-consistent forecasts of the forward-looking variable (Jondeau and Le Bihan, 2003). One could estimate a model by a single-equation approach or by a joint-estimation approach; see Beyer, Farmer, Henry and Marcellino (2005) for a side-by-side comparison of single-equation estimates versus system-equation estimates of a New-Keynesian model. The two econometric methods and the two approaches have its advantages and disadvantages, some of which are discussed briefly.

The GMM estimator is oftentimes employed for its simplicity and because one need not have to make any distributional assumptions of the residuals. The ML estimator take into account the structure of the real driving variable, referring to the Phillips Curve, whilst the GMM estimator does not (Jondeau and Le Bihan, 2003). Common argument against GMM is that the use of instrumental variables could produce spurious estimates of the forward-looking parameter as the estimator is sensitive to the choice of instruments. We discuss this below with reference to previous literature that have conducted Monte-Carlo simulations. Some arguments against ML include that the estimator assume normality and non-serially correlated residuals.

It has been shown with Monte-Carlo simulations that the GMM estimator could produce spurious estimates of forward-looking parameters in New-Keynesian equations. Lindé (2005) finds that GMM estimates biases the parameter δ in equation (1) so that it supports a backward-looking Phillips curve, even though the true Phillips curve could be forward-looking. Jondeau and Le Bihan (2003), Mavroeidis (2005), and Rudd and Whelan (2005) finds the opposite; that GMM biases δ so

---

[15] The empirical analysis is carried out in the econometric software Eviews.

that it supports a forward-looking curve when the true Phillips curve is backward-looking. In a study of the IS curve, Fuhrer and Rudebusch (2004) finds that GMM overestimates μ in equation (2) towards 0.5 when it actually is below this threshold. They find that the ML estimates are unbiased in the experiment. Also, we consider a small sample period; it has been shown that GMM could produce a small-sample parameter bias (Fuhrer, Moore and Schuh, 1995).

The equations are estimated on the assumption of multivariate normality and serially independent residuals. Phillips (1982) argue that FIML estimates could be consistent despite non-normality. Nonetheless, we evaluate the robustness of the parameter estimates with standard residual diagnostic tests. If it proves that the distributional assumptions are violated, we conduct standard tests to improve our statistical inference. The standard tests considered are a stability test and an extension of the model in which the equations are augmented with additional lags of the endogenous variables.

The model is estimated with a system-equation approach.[16] Our motivation for this is twofold. First, as discussed, by this we allow contemporaneous correlations between the individual shocks to be taken into account with in the estimates. Second, as Beyer et al. (2005) shows, a system-equation approach compared to single-equation approaches yields more efficient estimates, as is shown by inter alia lower standard errors in relation to parameters values. Potentially, this might be a result from allowing the correlations between the shocks. A possible problem of a system-equation approach compared to single-equation approaches is that the FIML estimator are sensitive to the structure of the model, as mentioned previously. This is one of reasons that makes us consider a standard model.

4.2 Empirical Limitations

We discuss three of limitations which here are important in the bridge between the theory and the empirical analysis. These limitations relate to the choice of data, model specification, and the choice of detrending method for output.

A more theory-consistent real driving variable of the economy in the supply equation is a real marginal cost rather than an output gap. The literature is not concordant whether it is crucial to use measures of one or the other in empirical analysis. We assume that the estimates of the parameter λ would not have different 'signs' depending on whether we use a measure for a real

---

[16] ML is referred to single-equation methods and FIML to system-equation methods.

marginal cost rather than the output gap. This assumption would be consistent with the results in Lindé (2005), who consider both variables in separate estimates. The assumption would not be consistent with Galí and Gertler (1999), who obtains a positive value of the parameter λ only when using a measure of a real marginal cost. When the output gap is used in the estimates, they find this parameter to be negative.

The real interest rate is downward-trending during the sample period which could have an impact on the estimates. One could empirically test the IS curve including a natural real interest rate in the IS-curve, as in Stracca (2010).[17] We experimented with this approach by detrending the series of the real interest rate with the HP-filter and using the trend as a measure of the natural interest rate. The results are no different from the estimates of model (6), and are thus not reported in the results section.

There are several methods to detrend output, for instance by the HP-filter or by a Kalman-filter. It has been found that various methods could produce considerable different estimates of the trend (see Canova, 1998). This is though not to say that one method is preferred to another. With regard to previous empirical research on New-Keynesian models, several studies have considered different methods of measuring the output gap as robustness checks. For example, Cho and Moreno (2006) uses three different measures of the output gap for the U.S., linearly detrended output, quadratically detrended output and a measure by the Congressional Budget Office. They find that the model parameters are roughly the same across those three methods, or measures, of the output gap. We choose to limit to the use of linearly detrended output.

4.3 Numerical Simulations

After we have estimated the parameters, the model is numerically simulated.[18] The simulations are carried out to solve the model with a unique stationary equilibrium, and in an attempt to gauge preferences of the Central Bank. The model is one with rational expectations; it is a stochastic- and not a deterministic model. As Fair (1984) make clear, to simulate and to solve a stochastic macroeconomic model is the same thing; we use the terms interchangeable. We proceed by describing the intensions with the simulations and how it relates to the empirical analysis.

---

[17] The ex-ante real interest rate becomes $r_t = [i_t - \pi_{t+1} - \bar{r}_t]$, with $\bar{r}_t$ being the natural real interest rate. This specification is common in theoretical models, see Galí (2015), and Walsh (2017).

[18] The simulations are carried out using Dynare in MATLAB. Dynare is a software platform compatible with MATLAB that is used to analyze economic models. Read more on https://www.dynare.org

The simulation is numerical, on theoretical moments, whereas the estimates are on real data. The relationship between those two sections is as follows. In the empirical section, the model is estimated on real data. The parameter values we obtain with the associated standard deviations of the shocks, and also the correlations between the shocks, are then set in the simulations of the model. Provided that some conditions need to be satisfied to be able to solve the model, some amendments might have to be made. This is discussed in conjunction with the empirical analysis. A stepwise-procedure to study macroeconomic models (model specification, estimates and analysis) is well explained in Fair (1984), and for example Dees, Pesaran, Smith and Smith (2010) have a similar approach in applied research.

After studying the impact of shocks in the model, we study objectives of monetary policy. A policy objective function is oftentimes used in attempts to solve for an optimal monetary policy rule. To solve for an optimal rule by minimizing the objective function is not our primarily goal, rather, our attempt concern measuring relative weights in the function that return an optimized policy rule close to the historical (empirically estimated) rule. To do this, we use the analytical tool that is commonly used when solving for optimal simple rules. The policy objective function is introduced in section 6.2.

4.3.1 Impulse-Response Functions

We study the impact of shocks with impulse-response functions, which is the standard in DSGE modelling. The numerical simulation solves the model and return theoretical moments which serves as basis for the impulse-response functions.[19] As Galí (2018) discuss, much of the focus of New-Keynesian DSGE models lie in the analysis of equilibrium solutions by which stationary fluctuations is driven by shocks. A prerequisite to be able to solve the model is that Blanchard and Kahn (1980) conditions are satisfied, which is the conditions considered in this paper. The conditions are that a rational expectations model have a unique stationary solution only if the number of eigenvalues in modulus is the same as the number of forward-looking variables (see Walsh, 2017, pp. 91-93). If these conditions are not satisfied, the equilibrium is indeterminate and give rise to 'sunspot fluctuations' (see e.g. Galí, 2018; Lubik and Schorfheide, 2004). If the conditions are satisfied, the equilibrium solution is determinate and the simulation returns theoretical moments; amongst others: standard deviations of the variables, autocorrelations, and variance decompositions. The simulation also computes a Taylor approximation with decision and

---

[19] There are different methodologies to generate shocks in a model, of which two examples are a DSGE model or by defining a VaR model. There are also different ways to identify a shock, see Christiano et al. (1999) for an extensive study on this topic.

transition functions of the model which underlie the generation of the impulse-response functions (see Adjemian et al. 2011, pp. 46)

Together with the impulse-response functions, we report conditional variance decompositions. Conditional variance decompositions are the same as forecast error variance decompositions, which show how the movement of a variable in a model is proportionally determined by different shocks at a given period (Enders, 2014). The conditional variance decompositions are plotted in figures in which the vertical axis represents either of the three variables whose movement following a shock, at a given horizon, is determined proportionally by the three shocks.

We specify steady state values of the variables π_t, $\hat{y}_t$ and i_t. We assume that the variables initially are in steady state $\pi_t = \hat{y}_t = i_t = 0$ for $t = 0$, and that the shocks occur at period one $t = 1$. All the shocks and the conditional variance decompositions are viewed over a horizon of 50 periods in which one period represent a quarter of time. The unit on the vertical axis in the impulse-response functions is percentage points. The shocks are interpreted as positive in terms of absolute values.

5 Empirical Results

In this section we present the estimates of the New-Keynesian macro model. We begin with a discussion of our parameter estimates. Thereafter we extract the shocks from one of the parameter sets and examine the robustness of the estimates.

5.1 FIML Estimates of the New-Keynesian Macro Model

Table 1. FIML Estimates of the New-Keynesian Macro Model with Three Measures of Inflation and Two Different Definitions of the Inflation Target in the Monetary Policy Rule

Parameters	Set (1)	Set (2)	Set (3)	Set (4)	Set (5)	Set (6)
δ	0.4967***	0.5091***	0.5101***	0.4967***	0.5092***	0.5100***
	(0.1183)	(0.0738)	(0.0946)	(0.1183)	(0.0738)	(0.0946)
λ	0.0464	0.1213	0.0574	0.0464	0.1231	0.0577
	(0.1940)	(0.0986)	(0.1009)	(0.1939)	(0.0986)	(0.1009)
μ	0.4995***	0.5211***	0.5201***	0.4995***	0.5214***	0.5202***
	(0.0443)	(0.0481)	(0.0441)	(0.0443)	(0.0481)	(0.0441)
σ	-0.0030	-0.0287	-0.0530*	-0.0032	-0.0290	-0.0530*
	(0.0231)	(0.0266)	(0.0287)	(0.0230)	(0.0266)	(0.0288)
ρ	0.9174***	0.9245***	0.9170***	0.9112***	0.9112***	0.9030***
	(0.0204)	(0.0192)	(0.0204)	(0.0210)	(0.0196)	(0.0203)
ϕ_{π}	0.0064	1.0784**	0.1049	0.6033	1.4389**	1.7848***
	(0.2369)	(0.4580)	(0.3723)	(0.5693)	(0.6008)	(0.6906)
$\phi_{\hat{y}}$	2.0753***	1.6774***	2.0401***	1.8910***	1.4743***	1.7234***
	(0.5357)	(0.4837)	(0.5277)	(0.4875)	(0.4255)	(0.3929)
σ_{π}	2.9681	1.5140	1.5524	2.9681	1.5139	1.5524
$\sigma_{\hat{y}}$	0.5600	0.5541	0.5438	0.5600	0.5541	0.5438
σ_{i}	0.3546	0.3335	0.3544	0.3523	0.3403	0.3405

NOTES: The estimates are carried out using the FIML estimator. The columns are sets of parameters. Set (1) π_t = GDP deflator, π_t in the policy rule. Set (2) π_t = CPI, π_t in the policy rule. Set (3) π_t = CPIF, π_t in the policy rule. Set (4) π_t = GDP deflator, $\bar{\pi}_t$ in the policy rule. Set (5) π_t = CPI, $\bar{\pi}_t$ in the policy rule. Set (6) π_t = CPIF, $\bar{\pi}_t$ in the policy rule. Robust standard errors in parentheses. The optimization method is BHHH with max 1000 iterations. The residual covariance is diagonal and the information matrix is Hessian. The sample period is 1995:Q1 to 2014:Q4. Asterisk denotes $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

The general picture is that the forward-looking behavior in both the Phillips and the IS curve is important for the dynamics of contemporaneous inflation and output. The forward-looking parameters δ and μ are throughout significant and the variation across the parameter sets are low. When using CPI or CPIF, both parameters are consistently above the important value 0.5, whilst with the GDP deflator the estimates are below 0.5. Baele et al. (2015) mentions, on the other hand, that low standard errors of these parameters are evidence in advantage to backward-looking processes. Our estimates reveal that the standard errors are fairly low for both these parameters. The value of δ and μ are similar to FIML estimates on U.S. data, see Cho and Moreno (2006). The degree of forward-looking behavior in the Phillips curve is typically lower than when estimating the equation separately with GMM; for estimates on U.S. data, see Galí et al. (2005) and Lindé (2005), and on Swedish data, see Holmberg (2006). It is also lower compared with some studies that conduct system-equation GMM estimates (cf. Beyer et al. 2005; Bekaert et al. 2010). Fuhrer (2010) obtains a value of δ on 0.51 using ML and Bayesian techniques. Moreover, the value of μ is by and large in line with some of the literature that estimates the IS curve separately, see Fuhrer and Rudebusch (2004) for estimates on U.S. data using ML, and Goodhart and Hofmann (2005) for the G7 countries using the GMM estimator.

The parameter for the real driving variable in the Phillips curve λ is theoretically correctly signed but not significant in any of the cases. The finding is not too uncommon in the literature, for example Fuhrer (2010) also obtains a non-significant λ. The parameter value is relatively high as an estimate when using CPI. Cho and Moreno (2006) obtains a value of 0.0011, though not significant. Lindé (2005) find λ to be 0.048, however, with additional lags of inflation. The parameter value is though fairly consistent with Baele et al. (2015) who obtains 0.102 using U.S. survey-based expectations data of inflation and output.

The parameter σ is wrongly signed in all the sets and even significant at the 10 percent level using CPIF. This is empirical evidence in that the Central Bank cannot affect aggregate demand by this mechanism in the IS curve. The parameter value using CPI is fairly close to the estimate which Goodhart and Hoffmann (2005) obtains for Canada, -0.038. Stracca (2010) also obtains a negative σ in several of cases in tests of the IS curve when utilizing data for 22 countries, and concludes that the results might be because of off-setting income effects. Dees et al (2010) finds a theory-counterfactual empirical relationship between expected future output and the elasticity of substitution. Estimating a New-Keynesian Model for 33 countries, they find that for 10 out of 14 countries when μ is positive and significant, then σ is negative.

The different sets show that the estimates of response parameters in the policy rule are sensitive to the measure and the definition of inflation, and also to the assumption on how the Central Bank react to inflation. When using the GDP deflator, the parameter ϕ_π is low independent of the assumption on how the monetary authorities react on inflation. The estimate seems to suffer by parameter uncertainty, that might take the form of a high standard error in relation to the parameter value. When using CPI or CPIF this parameter might have lower uncertainty, and also satisfies the Taylor-principle $\phi_\pi > 1$ in three out of four cases. Notably, this principle is satisfied whenever the coefficient significant, otherwise not. This satisfied condition implies that the model has a unique stationary equilibrium and can be solved, which is a necessary condition to fulfill in the subsequent simulations. The Central Bank reacts more strongly to inflation when responding to deviations of the two percent target from the annual inflation rate instead of to the deviation of an average target from the quarterly annualized inflation rate: compare set (4) with set (1), set (5) with set (2), and set (6) with set (3). Our results indicate that the Central Bank has a relatively high concern to output stabilization, a result that to a degree stand in contrast to some of the empirical literature. The degree of interest rate smoothing is high, consistent with Adolfson et al. (2008) that uses Swedish data, and Mavroeidis (2010) that utilize U.S. data.

By comparing the statistics across the different sets, we see that using CPI instead of the GDP deflator as measure of inflation improves the fit of the model. Statistically, this is particularly true for the Phillips curve as the standard deviation of the shocks σ_{π} are high when using the GDP deflator. It appears that even when using CPI or CPIF the standard deviation is fairly high, suggesting that the hybrid New-Keynesian Phillips curve do not so well explain the inflation dynamics for Sweden, consistent with Holmberg (2006). Some studies that estimate similar models with U.S. data obtains lower values of σ_{π}. Lindé (2005) obtains a value of 0.7957 though with some additional lags, and Cho and Moreno (2006) finds a corresponding value of 0.4585. Bekaert et al. (2010) obtains a value of 1.249 in a study of a five-equation model. The statistics of the IS curve show small variations across the different sets, apart from the parameter σ.[20] In contrast to the supply shocks, the standard deviation of the demand shocks is fairly low which is an indication that the IS curve has a better empirical fit. The standard deviation of the policy shocks is relatively low and do not vary significantly across the sets.

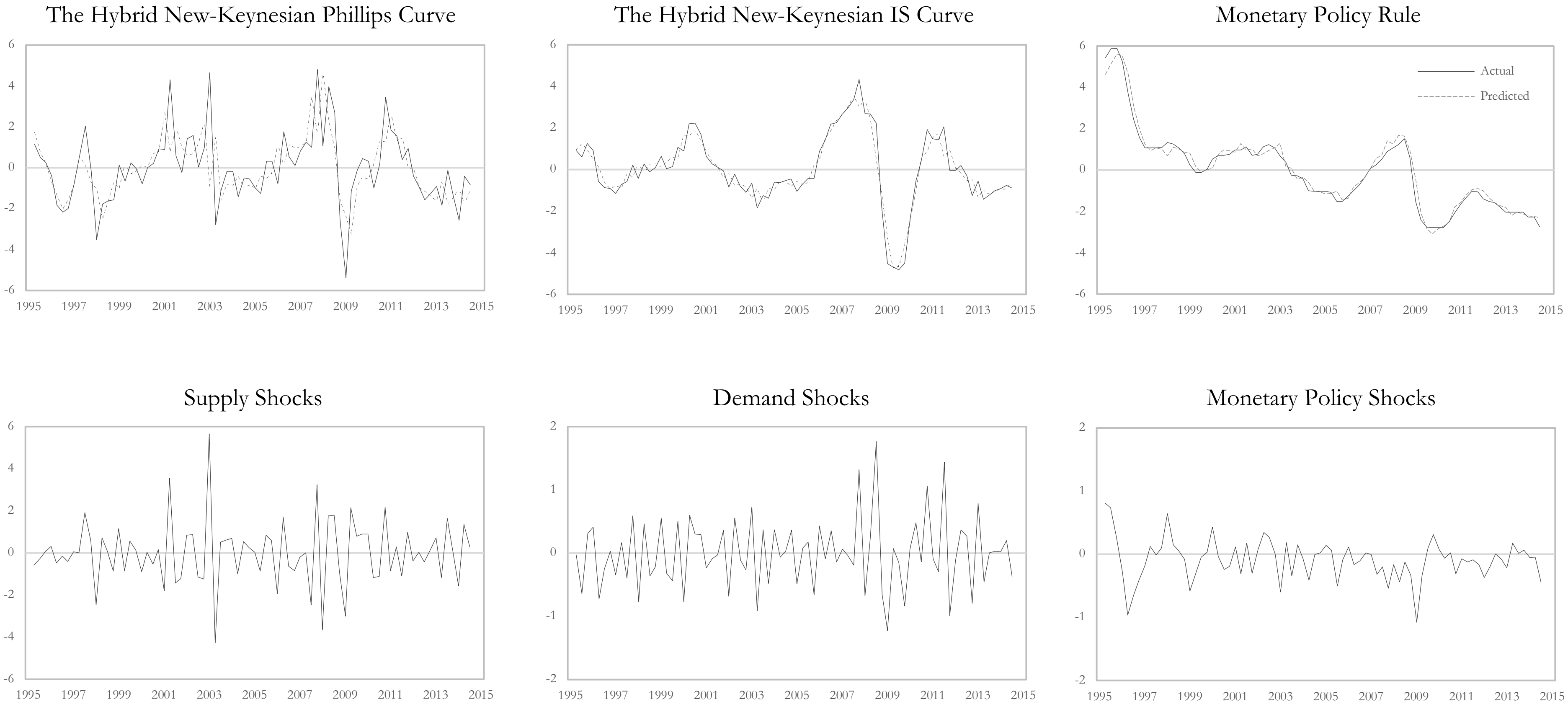
For the remainder of the study we continue with parameter set (2). In this set, the Taylor-principle is satisfied, the model contains three variables, and the equations exhibit a relatively good empirical fit. Figure 1 plots the actual and one-time ahead predicted values of the model-equations with the associated shocks. As can be seen by the reported statistics in the notes, the Phillips curve has a fairly low explanatory power, whilst the IS curve and the monetary policy rule has high. This point was mentioned when discussing the standard deviations of the shocks. The Phillips curve do not too well capture the high peaks and low throughs of inflation, most visible around 2003 and during the financial crisis in 2007-2009.

---

[20] We tested the model with CPI instead using the ex-post real interest rate $r_t = [i_t - \pi_t]$ in the IS curve. Interestingly, the parameter σ is then positive and significant at the five percent level.

The Durbin-Watson statistics indicates that the Phillips and the IS curve suffers from negative autocorrelation (Durbin Watson Statistics > 2.0) whilst the monetary policy rule has positive (Durbin Watson Statistics < 2.0). The downward-skewness of the policy shocks are clearly visible graphically; the predicted values of the rule are lagging behind the actual repo rate. We proceed by examining the properties of the shocks in more detail.

Figure 1. Actual and Predicted Values with the Associated Shocks of the New-Keynesian Macro Model; Parameter Set (2)



The Hybrid New-Keynesian Phillips Curve

The Hybrid New-Keynesian IS Curve

Monetary Policy Rule

Supply Shocks

Demand Shocks

Monetary Policy Shocks

Notes: Actual and predicted values with the associated shocks.
Adjusted R^2: Phillips Curve 0.24; IS Curve 0.90; Monetary Policy Rule 0.97.
Durbin Watson Statistics: Phillips Curve 3.02; IS Curve 2.83; Monetary Policy Rule 1.07.
The variables are de-meaned prior to the estimates.

5.2 Robustness Analysis

The FIML estimator is consistent under multivariate normality and non-serially correlated residuals. We extract the shocks of parameter set (2) from table 1 and conduct residual diagnostic tests to examine the validity of our estimates. Following our results, we discuss potential remedies and conduct standard tests to improve our statistical inference.

Table 2. Residual Diagnostics of the New-Keynesian Macro Model; Parameter Set (2)

Panel 1. Correlations	$\varepsilon_t^{\pi}\,\varepsilon_t^{\hat{y}}$	$\varepsilon_t^{\pi}\,\varepsilon_t^{i}$	$\varepsilon_t^{\hat{y}}\,\varepsilon_t^{i}$			
Contemporaneous Correlations	0.4046	-0.1966	-0.1044			
Panel 2. Autocorrelations, Lag = i	$\varepsilon_t^{\pi}\,\varepsilon_{t-i}^{\pi}$	Pval. ε_t^{π}	$\varepsilon_t^{\hat{y}}\,\varepsilon_{t-i}^{\hat{y}}$	Pval. $\varepsilon_t^{\hat{y}}$	$\varepsilon_t^{i}\,\varepsilon_{t-i}^{i}$	Pval. ε_t^{i}
1	-0.5114	0.0000	-0.4191	0.0000	0.3640	0.0010
2	-0.0900	0.0000	-0.0700	0.0010	0.0521	0.0040
3	0.1460	0.0000	0.2830	0.0000	-0.2395	0.0020
4	0.0531	0.0000	-0.1543	0.0000	-0.2830	0.0000
Panel 3. Empirical Distribution Normality Tests	Val. ε_t^{π}	Pval. ε_t^{π}	Val. $\varepsilon_t^{\hat{y}}$	Pval. $\varepsilon_t^{\hat{y}}$	Val. ε_t^{i}	Pval. ε_t^{i}
Lilliefors (D)	0.1069	0.0276	0.0691	> 0.1	0.0903	> 0.1
Cramer-von Mises (W2)	0.1447	0.0272	0.0507	0.4962	0.1299	0.0429
Watson (U2)	0.1436	0.0191	0.0449	0.5343	0.1292	0.0317
Anderson-Darling (A2)	0.9282	0.0176	0.4317	0.2981	0.8442	0.0284

NOTES: Panel 1 shows the contemporaneous correlations between the shocks. Panel 2 reports the autocorrelation of the shocks with probability values from the Ljung-Box Q-test. Panel 3 is various empirical distribution tests of normality.

We see from panel 1 that the shocks to some degree are contemporaneously correlated which make reasons to use a system-equation approach, suggesting that the parameter estimates are more efficient than if we instead would estimate the equations separately. The supply and policy shocks suffer heavily from autocorrelation, as could be inferred by the probability values in the Ljung-Box Q-test. Serially correlated shocks are fairly common when estimating standard New-Keynesian models (cf. Cho and Moreno, 2006). We cannot reject the null of normality of the demand shocks at conventional levels, whilst we reject the null of the supply and the monetary policy shocks.

In calibration, and in derivation of analytical solutions, it is at times assumed that some shocks follow an AR(1) process and decay at some persistence $0 \leq \rho < 1$ (see Clarida et al. 1999; Galí, 2015). It could be interesting to find out if the shocks might be appropriately modelled with an AR(1) process, conditional on our parameter estimates from the FIML estimator. By regressing the shocks on its own lags using the ordinary least squares (OLS) estimator we examine if an AR(1) is significant, and if the residual diagnostics turn to the better. It can be seen from panel 2 that both the demand and the supply shocks exhibit negative persistence up to the second lag. This is not a concern from an econometrical aspect as an AR(1) process allows persistence of the form $-1 \leq \rho \leq 1$. Also, as discussed by Fuhrer (2010), a time series could be considered persistent if the absolute value of its serial correlation is high. Even though the null of normality for the supply shocks cannot be rejected, these are also tested.

Table 3. OLS AR(1) Estimates of the Shocks with Associated Residual Diagnostics; Parameter Set (2)

Panel 1. OLS Estimates of eq. (7)	ρ^{π}	σ_{π}	$\rho^{\hat{y}}$	$\sigma_{\hat{y}}$	ρ^{i}	σ_{i}
$\varepsilon_t^{\pi}\ \varepsilon_t^{\hat{y}}\ \varepsilon_t^{i}$	-0.5106^{***} (0.1075)	1.3002	-0.4218^{***} (0.0851)	0.5027	0.4254^{***} (0.0891)	0.2860
Panel 2. Correlations	$\hat{u}_t^{\pi}\ \hat{u}_t^{\hat{y}}$	$\hat{u}_t^{\pi}\ \hat{u}_t^{i}$	$\hat{u}_t^{\hat{y}}\ \hat{u}_t^{i}$			
Contemporaneous Correlations	0.3522	-0.0721	-0.1348			
Panel 3. Autocorrelations, Lag = i	$\hat{u}_t^{\pi}\ \hat{u}_{t-i}^{\pi}$	Pval. $\hat{u}_t^{\pi}$	$\hat{u}_t^{\hat{y}}\ \hat{u}_{t-i}^{\hat{y}}$	Pval. $\hat{u}_t^{\hat{y}}$	$\hat{u}_t^{i}\ \hat{u}_{t-i}^{i}$	Pval. $\hat{u}_t^{i}$
1	-0.2400	0.0320	-0.1271	0.2561	-0.0831	0.4602
2	-0.3971	0.0000	-0.1687	0.1662	-0.0151	0.7541
3	0.2353	0.0000	0.2914	0.0143	-0.1194	0.6302
4	0.0624	0.0000	-0.1342	0.0178	-0.1812	0.3478
Panel 4. Empirical Distribution Normality Tests	Val. $\hat{u}_t^{\pi}$	Pval. $\hat{u}_t^{\pi}$	Val. $\hat{u}_t^{\hat{y}}$	Pval. $\hat{u}_t^{\hat{y}}$	Val. $\hat{u}_t^{i}$	Pval. $\hat{u}_t^{i}$
Lilliefors (D)	0.0784	> 0.1	0.0755	> 0.1	0.1118	0.0185
Cramer-von Mises (W2)	0.0873	0.1653	0.1130	0.0729	0.1109	0.0779
Watson (U2)	0.0848	0.1488	0.1018	0.0827	0.0955	0.0901
Anderson-Darling (A2)	0.5382	0.1626	0.9167	0.0187	0.5889	0.1205

NOTES: Panel 1 shows the OLS results from regressing the shocks on its own lagged values. Robust standard errors in parentheses. Panel 2 shows the contemporaneous correlations between the innovations. Panel 3 reports the autocorrelation of the innovations with probability values from the Ljung-Box Q-test. Panel 4 is various empirical distribution tests of normality of the innovations. Asterisk denotes $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

The parameter estimates are of the processes

$$\begin{aligned} \varepsilon_t^{\pi} &= \rho^{\pi}\varepsilon_{t-1}^{\pi} + \hat{u}_t^{\pi}\ ,\ -1 \leq \rho^{\pi} \leq 1\ ,\ \hat{u}_t^{\pi} \sim \text{I.I.D.}\ (0, \sigma_{\pi}^2) \\ \varepsilon_t^{\hat{y}} &= \rho^{\hat{y}}\varepsilon_{t-1}^{\hat{y}} + \hat{u}_t^{\hat{y}}\ ,\ -1 \leq \rho^{\hat{y}} \leq 1\ ,\ \hat{u}_t^{\hat{y}} \sim \text{I.I.D.}\ (0, \sigma_{\hat{y}}^2) \\ \varepsilon_t^{i} &= \rho^{i}\varepsilon_{t-1}^{i} + \hat{u}_t^{i}\ ,\ -1 \leq \rho^{i} \leq 1\ ,\ \hat{u}_t^{i} \sim \text{I.I.D.}\ (0, \sigma_{i}^2) \end{aligned} \tag{7}$$

Equation (7) is referred to as shock processes in which the ρ are persistence parameters and the $\hat{u}_t$ are innovations.

We see that all the persistence parameters are significant at the 1 percent level; consequently, the standard deviations of the shocks (here innovations) falls. Panel 3 reveals that the demand shocks still suffers from serial correlation whereas the policy shocks now pass the test. We cannot reject the null of normality for any of the shocks at conventional levels, indicating that adding AR(1) terms might have been a fruitful strategy to improve the residual diagnostics to the better. Even though a significant persistence parameter, the demand shocks approaches non-normality compared with the case in table 2. If we would have specified AR(1) terms for the shocks in the first place, using another estimator, the parameter estimates would most likely change. These estimates are carried out to find if the residual diagnostics turn to the better, and if it is enough with an AR(1) to pass the diagnostic tests, given the parameter values from our FIML estimates.

It is not possible to simply add AR(1) terms in FIML estimates; the estimator assumes multivariate normality of the residuals. One remedy to improve the inference could be extensions of the model, another might be to consider other types of tests. At this stage we consider two standard procedures. The first is to extend the model with additional lags of the endogenous variables. The main focus is to reach normality, and so lags are added to the Phillips curve and the policy rule, but not to the IS curve. Our second test is a stability test of the model conducted by restricting the sample period. Regarding the model-extension we limit to the case of adding one more lag of inflation in the Phillips curve, and one lag of the nominal interest rate in the policy rule. Following Lindé (2005) we restrict the augmented parameters to unity. The augmented model reads[21]

$$
\begin{aligned}
&\pi_t = \delta E_t \pi_{t+1} + (1 - \delta)[\beta_\pi \pi_{t-1} + (1 - \beta_\pi)\pi_{t-2}] + \lambda \hat{y}_t + \varepsilon_t^{\pi} && 0 < \delta < 1 \quad 0 < \beta_\pi < 1 \quad \lambda > 0 \\
&\hat{y}_t = \mu E_t \hat{y}_{t+1} + (1 - \mu)\hat{y}_{t-1} - \sigma[i_t - E_t \pi_{t+1}] + \varepsilon_t^{\hat{y}} && 0 < \mu < 1 \quad \sigma > 0 \\
&i_t = (1 - \rho_1 - \rho_2)[\phi_\pi \pi_t + \phi_{\hat{y}} \hat{y}_t] + \rho_1 i_{t-1} + \rho_2 i_{t-2} + \varepsilon_t^{i} && \phi_\pi > 0 \quad \phi_{\hat{y}} > 0
\end{aligned}
\tag{8}
$$

Again assuming I.I.D. shocks

$\varepsilon_t^{\pi} \sim$ I.I.D. $(0, \sigma_\pi^2)$

$\varepsilon_t^{\hat{y}} \sim$ I.I.D. $(0, \sigma_{\hat{y}}^2)$

$\varepsilon_t^{i} \sim$ I.I.D. $(0, \sigma_i^2)$

The FIML estimates of the augmented model with associated residual statistics are shown on page 25.

---

[21] Representation of an estimated model like (8), with the additional lags in the IS curve and in the policy rule, can be seen on page 395 in Walsh (2017).

Regarding the stability test, the first observation is 1997:Q2, taking into consideration a discussion by Svensson (2015) that the inflation-targeting regime for the Riksbank was established by this year. The last observation is chosen from a trial-and error process. A potential trade-off is considered between reaching normality and decreasing the serial correlations by some marginal versus including adequate number of observations for a reasonable statistical inference. The FIML estimates with associated residual diagnostics are reported in section 2A in the appendix.

Table 4. FIML Estimates of the Augmented Model, system (8)

Parameters	δ	β_π	λ	μ	σ	ρ_1	ρ_2	ϕ_π	$\phi_{\hat{y}}$
Values	0.4921***	0.9176***	0.1271	0.5244***	-0.0331	1.3474***	-0.4243***	0.8751**	0.7651**
Std. Errors	(0.0811)	(0.1879)	(0.0996)	(0.0485)	(0.0274)	(0.0938)	(0.0896)	(0.3617)	(0.3413)

NOTES: The estimates are carried out using the FIML estimator. Robust standard errors in parentheses. The optimization method is BHHH with max 1000 iterations. The residual covariance is diagonal and the information matrix is Hessian. The standard deviations of the shocks are σ_π, $\sigma_{\hat{y}}$ and σ_i = {1.5308, 0.5575, 0.2850}, respectively. π_t = CPI, π_t in the policy rule. The sample period is 1995:Q1 to 2014:Q4. Asterisk denotes $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table 5. Residual Diagnostics of the Augmented Model, system (8)

Panel 1. Correlations	$\varepsilon_t^\pi\,\varepsilon_t^{\hat{y}}$	$\varepsilon_t^\pi\,\varepsilon_t^i$	$\varepsilon_t^{\hat{y}}\,\varepsilon_t^i$			
Contemporaneous Correlations	0.4003	-0.1096	-0.0481			
Panel 2. Autocorrelations, Lag = i	$\varepsilon_t^\pi\,\varepsilon_{t-i}^\pi$	Pval. ε_t^π	$\varepsilon_t^{\hat{y}}\,\varepsilon_{t-i}^{\hat{y}}$	Pval. $\varepsilon_t^{\hat{y}}$	$\varepsilon_t^i\,\varepsilon_{t-i}^i$	Pval. ε_t^i
1	-0.4800	0.0000	-0.4150	0.0000	0.0660	0.5550
2	-0.1220	0.0000	-0.0660	0.0010	-0.0690	0.6930
3	0.1500	0.0000	0.2850	0.0000	-0.0950	0.6880
4	0.0660	0.0000	-0.1520	0.0000	-0.0790	0.7370
Panel 3. Empirical Distribution Normality Tests	Val. ε_t^π	Pval. ε_t^π	Val. $\varepsilon_t^{\hat{y}}$	Pval. $\varepsilon_t^{\hat{y}}$	Val. ε_t^i	Pval. ε_t^i
Lilliefors (D)	0.0744	0.0963	0.0638	> 0.1	0.9861	0.0376
Cramer-von Mises (W2)	0.1195	0.0634	0.0508	0.4952	0.1455	0.0265
Watson (U2)	0.1236	0.0361	0.0453	0.5292	0.1283	0.0324
Anderson-Darling (A2)	0.8313	0.0299	0.4495	0.2698	0.8199	0.0327

NOTES: Panel 1 shows the contemporaneous correlations between the shocks. Panel 2 reports the autocorrelation of the shocks with probability values from the Ljung-Box Q-test. Panel 3 is various empirical distribution tests of normality.

The forward-looking parameter in the Phillips curve falls as a result of adding one more lag of inflation, in line with what is found in Lindé (2005). The estimate of the first lag of inflation is high and results in a weight on the second lag of only 0.0824. Even though a significant parameter, the augmented model returns a higher standard deviation of the supply shocks compared with the original model. The standard errors of the parameters δ and λ are also higher. At the same time, the shocks are still serially correlated, whilst now performing better in the normality tests.

Concluding that, in this case, the empirical strategy to add more lags of inflation seems to yield mixed results to improve the fit of the Phillips curve.

The parameters in the policy rule changes radically when adding one more lag of the interest rate. The estimate of the parameter of the additional lag is significant at the 1 percent level and, at the same time, the response parameters to inflation and output falls. Our estimates of the policy rule seem to resemble some concerns raised by Mavroeidis (2010), arguing that apparent high interest rate smoothing makes it hard to identify how a Central Bank actually responds to inflation and output. Mavroeidis (2010) finds that corresponding parameters to ϕ_π and $\phi_{\hat{y}}$ in a similar rule are unstable partly because of the specified endogenous smoothing of the interest rate, which makes it a formidable challenge to draw conclusions whether the principle $\phi_\pi > 1$ is satisfied or not. Our estimates of the policy rule in the original model, the augmented model, and in the stability test indicates that the only parameter that seem to be stable is ρ. Moreover, the standard deviation of the policy shocks falls in this test, and so does the standard errors of the parameters. Previous evident serial correlation of the policy shocks is now non-existent according to the probability value in the Ljung-Box Q-test, whilst the various normality tests returns similar statistics as with the original model. All in all, the statistical inference speaks in favor of adding one more lag of the interest rate in the policy rule for a better empirical fit; though at the expense of no longer satisfying the Taylor-principle.

In summary, the general picture is that to add a second lag of inflation and the interest rate to the Phillips curve and to the policy rule, respectively, only marginally makes the residual diagnostics to the better. Our diagnostic resembles the concerns in Cho and Moreno (2006), that the inference of the parameter estimates suffers because of serially correlated residuals in small-sample studies. To improve the residual diagnostics, one of considerations could be to extend the model with more parameters and, or, variables. The five-equation model considered in Bekaert et al. (2010) with processes of natural output and a time-varying inflation target, is one example of an extension. Another example is a four-equation model studied in Rupert and Šustek (2019), that includes endogenous capital. We shall leave empirical analysis of other New-Keynesian models on Swedish data a topic for future research.

6 Model Simulations

Thus far we have studied real data for an empirical analysis. In this section our analysis concern numerical simulations. We return to our original model (6). The parameter values of set (2) in table 1 are used in the simulations of the model to study the effect of shocks, and to optimize the monetary policy rule. We proceed by discussing the impact of shocks modeled by impulse-response functions. Then we discuss the implications of optimal monetary policy.

6.1 Supply, Demand and Monetary Policy Shocks

We study the sensitivity of the impulse-response functions to the degree of interest rate smoothing in the policy rule. It could be seen as a structural policy sensitivity analysis in the sense that the level of smoothing might vary across different regimes. For the U.S., Clarida et al. (1999) finds that the value of the interest rate smoothing parameter varies from 0.68 under Pre-Volcker, to 0.79 under Volcker-Greenspan. We vary ρ by a magnitude of 0.1.[22] Given that ρ is estimated to 0.9245 with the imposed restriction $0 < \rho < 1$, we set $\rho = \{0.9245\ 0.8245\ 0.7245\}$, respectively. The other parameters in the model are held fixed at their estimated values contained in set (2) in table 1, with an exception to the elasticity of substitution in consumption σ. A negative σ violates the Blanchard-Kahn conditions which implies that the model cannot be solved under those circumstances. We instead suppose that σ is positive.[23] Even though this is not robust when using the ex-post real interest rate in the estimates, the parameter is positive when using the ex-ante rate (see footnote 20). The parameters in the model are, hence, set to $(\delta, \lambda, \mu, \sigma, \phi_\pi, \phi_{\hat{y}}) = \{0.5091\ 0.1213\ 0.5211\ 0.0287\ 1.0785\ 1.6774\}$.

The magnitude of the shocks are the estimated standard deviations of parameter set (2) found in table 1, $\sigma_\pi, \sigma_{\hat{y}}$ and $\sigma_i = \{1.5140\ 0.5541\ 0.3335\}$. The shocks are to some degree correlated; in this case, the simulation calculates the variance decomposition as if estimating a vector autoregression (VaR) model by a Cholesky decomposition of the covariance matrix of the shocks (Adjemian et al. 2011, pp. 46-47). The contemporaneous correlations between the shocks are from table 2, panel A, $(\varepsilon_t^\pi, \varepsilon_t^{\hat{y}})$, $(\varepsilon_t^\pi, \varepsilon_t^i)$ and $(\varepsilon_t^{\hat{y}}, \varepsilon_t^i) = \{0.4046\ {-0.1966}\ {-0.1044}\}$.[24] The standard deviations and the

---

[22] Other parameters in a monetary policy rule most likely change when ρ changes in estimates. The system is complex; to be able to focus at one question at hand only ρ is varied.

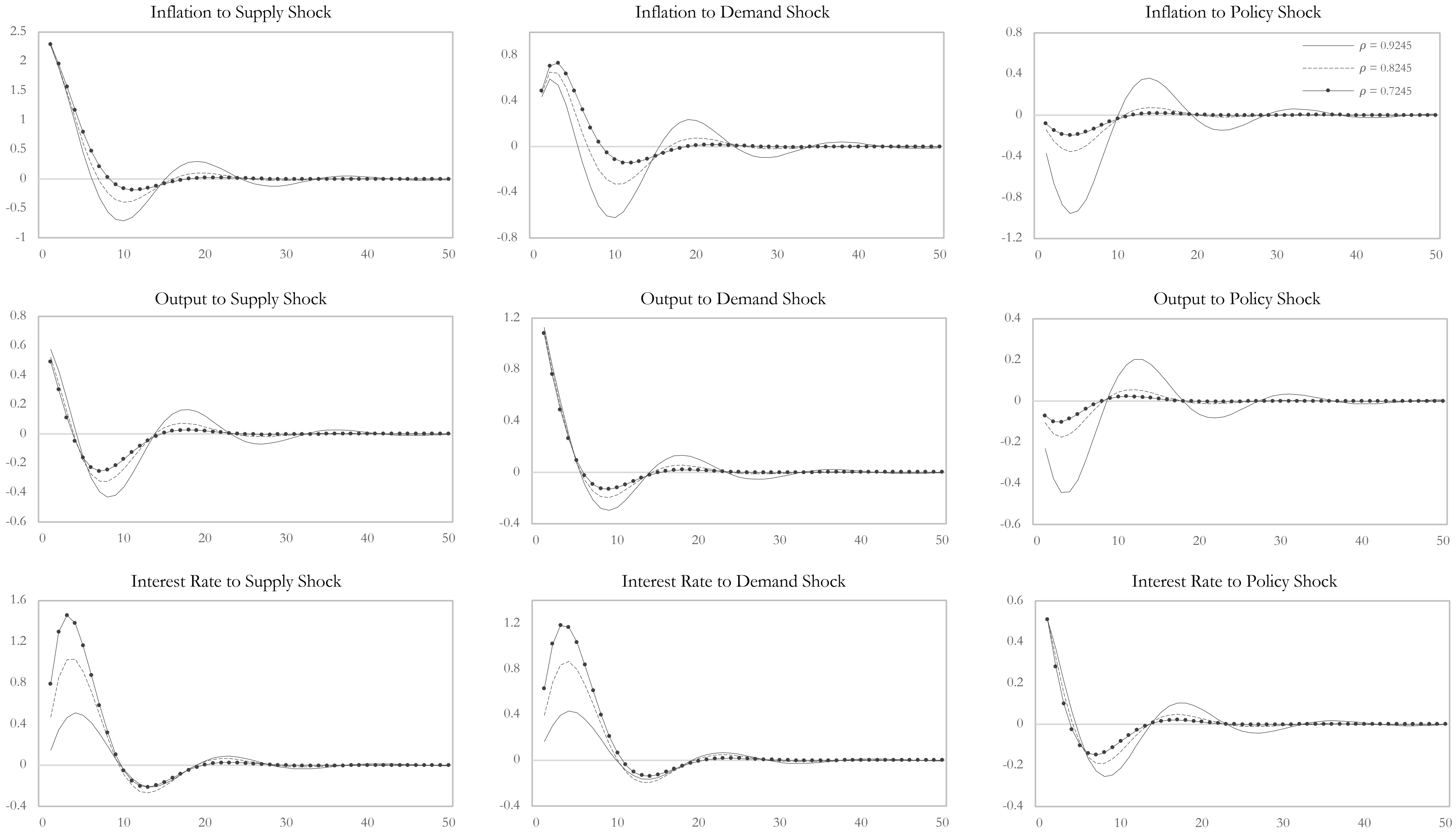
[23] An alternative procedure could have been to constrain the parameter σ to a positive value prior to the estimates in the first place. Baele et al. (2015) impose a positive constrain of this parameter because unconstrained ML estimates of the IS curve often result in a negative, small, or non-significant σ.

[24] The shape of the impulse-response functions when abstracting from setting the correlations of the shocks in the model makes no significant difference. One exception is the immediate response of output to a supply shock; this is discussed in the forthcoming analysis.

correlations between the shocks are held fixed when varying ρ. The conditional variance decompositions belong to the setting when $\rho = 0.9245$.

In the appendix we report impulse-response functions when the other parameters in the model are varied one-by-one.

Figure 2. Impulse-Response Functions of the New-Keynesian Macro Model; Sensitivity Analysis of ρ



Inflation to Supply Shock

Inflation to Demand Shock

Inflation to Policy Shock

Output to Supply Shock

Output to Demand Shock

Output to Policy Shock

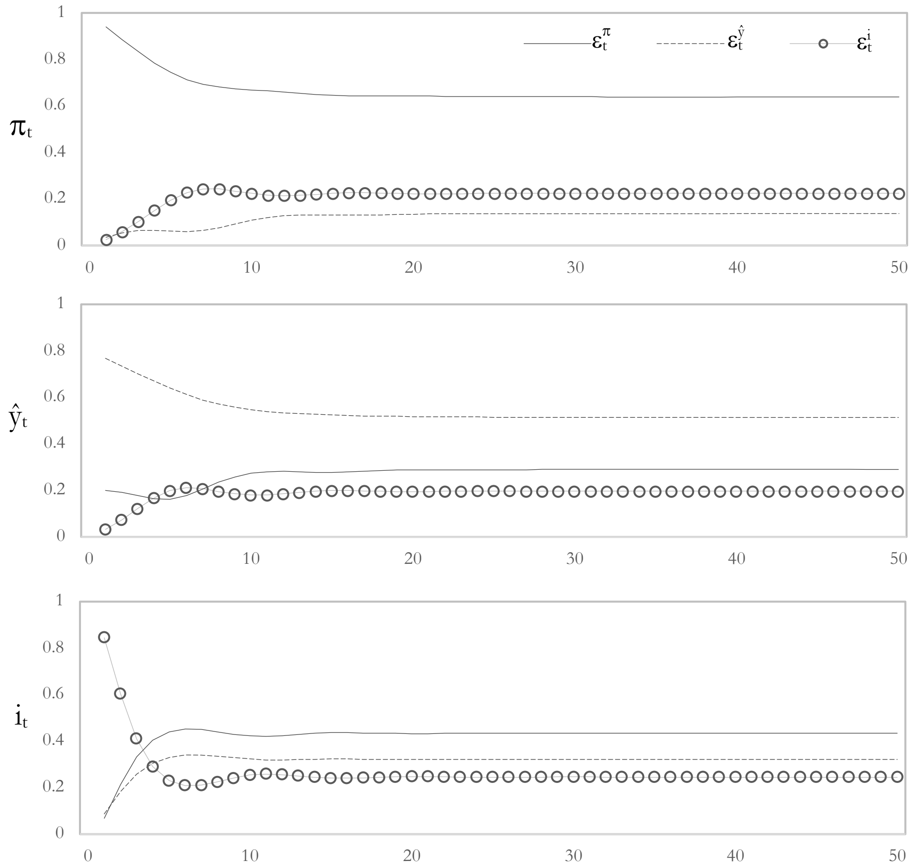
Interest Rate to Supply Shock

Interest Rate to Demand Shock

Interest Rate to Policy Shock

Notes: Solid line $\rho = 0.9245$; dashed line $\rho = 0.8245$; circle-marked line $\rho = 0.7245$.
The other parameters in the model are set to $(\delta, \lambda, \mu, \sigma, \phi_{\pi}, \phi_{\hat{y}}) = \{0.5091\ 0.1213\ 0.5211\ 0.0287\ 1.0785\ 1.6774\}$

Figure 3. Conditional Variance Decompositions (ρ = 0.9245)



NOTES: Figure 3 shows the conditional variance decompositions of the shocks for the setting when ρ = 0.9245. Solid line is supply shock; dashed line is demand shock; circle-marked line is policy shock.

A positive exogenous supply shock immediately raise inflation, output and the nominal interest rate. Supply shocks are commonly referred to as cost push shocks in the New-Keynesian framework. A classic example of such a shock is an oil shock. Higher oil prices put upward pressure on the overall price level, leading an oil-import dependent country to spend a higher proportion of income on oil-imports. By economic intuition output shall fall and not go up as an immediate reaction. The immediate jump of output is due as of the correlation between supply and demand shocks. We see that a supply shock has a large impact on inflation; a one standard deviation shock leads to an increase of inflation by around 2.3 percent. Inflation quickly falls after the shock following a hike in the nominal rate by an inflation-fighting Central Bank ($\phi_\pi > 1$). The higher the concern the Central Bank has on inflation and output stabilization, the quicker (in time) inflation and output fall below steady state after a supply shock, that is, the functions shifts to the left (see figure 5A and 6A in the appendix). Apart from the immediate jump in output, which is solely because of the correlations between the shocks, the immediate responses of the three variables to a supply shock is in line with the theory, and with applied research (e.g. Bekaert et al. 2010; Cho and Moreno, 2006; Dees et al. 2010).

An exogenous demand shock immediately increases all three variables, consistent with the theory. Demand shocks in a New-Keynesian model like the one we study could be related to disturbances to the private sectors' preferences or to government spending (e.g. Mavroeidis, 2010). The magnitude of the initial jump of a demand shock on its own variable is lower than for case of a supply shock, partly as a result of the lower standard deviation. The demand shocks last for about 6 to 7 years (24 to 28 quarters), which is in line with some of the literature (Bekaert et al. 2010; Cho and Moreno, 2006; Dees et al. 2010).

A contractionary exogenous monetary policy shock immediately leads to lower inflation and output, whilst the nominal rate goes up. An example of an exogenous monetary policy shock could be an implementation error (Lubik and Schorfheide, 2004). The main effect of inflation and output following a policy shock is after around 5 quarters, consistent with Christiano et al. (2005), see figure 1 in their paper. The interest rate quickly falls below the steady state after the disturbance. Moreover, the main effect of output to a policy shock is in periods after which the effect is the highest on the interest rate itself, as in Christiano et al. (2005). They discuss that such effects reflect significant propagation mechanisms in a model.

Following a policy shock, we see that the major effect on inflation happens in the periods after which the effect is the highest on output.[25] This finding is consistent with Christiano et al. (2001) that studies a VAR model. Woodford (2003a) emphasize that this is evidence of which a simple New-Keynesian Phillips curve is too forward-looking. Woodford (2003a) discuss that if the simple New-Keynesian Phillips curve holds, the peaks and throughs of a policy shock on inflation should precede the ones on output and not lag behind.[26] This point is also mentioned in Walsh (2017), emphasizing that a rise in the real driving variable in the future that can be forecasted should immediately result in higher inflation today. With the assumption of model-consistent, rational expectations, the theory suggests that the path after a policy shock may well be forecastable (Woodford, 2003a).

The conditional variance decompositions show that the most important shocks as the explanation of the movement of the variables at short horizons is shocks to its own variables. This is consistent

---

[25] In figure 2 following a policy shock, for $\rho = 0.9245$, the lowest through of output and inflation is at period 4 and period 5, respectively. The highest peak is at period 12 and period 14, respectively.

[26] Abstract from the shock and set $\delta = 1$ in equation (1) $\pi_t = \delta E_t \pi_{t+1} + \lambda \hat{y}_t$. Replace δ with a discount factor, β, and iterate forward to obtain $\pi_t = \beta E_t \pi_{t+1} + \lambda \hat{y}_t = \lambda \sum_{i=0}^{\infty} \beta^i E_t \hat{y}_{t+i}$

with what should be expected in the VaR literature (Enders, 2014).[27] We see that both the supply and the demand shocks explain the majority of the movement of its own variables also at longer horizons, whilst the movement of the nominal rate is more dominated by demand rather than policy shocks. The compositions are by and large robust with some of the countries studied in Dees et al. (2010), even though they study an IS curve augmented with a real exchange rate. They find that the exchange rate shock explains only around 10 percent of the variation of the variables throughout. Furthermore, the policy shock accounts for a relatively small share of variation of inflation, slightly above 20 percent at longer horizons. Christiano et al. (2005) also finds that monetary policy shocks do not account for a substantial fraction of the variance of inflation. They also find that policy shocks account for a relatively high share of the variation of real variables, therein output. Our findings stand in contrast to this, figure 3 show that a policy shock explain slightly below 20 percent of the variation of output at peak levels. The analysis though conforms with the discussion in Christiano et al. (1999), that the consensus in the literature seem to be that a policy shock explains only modestly the variation of output.

The impulse-response functions are of a cyclical shape. Dees et al. (2010) also studies cyclical impulse-response functions.[28] They discuss that some of the cyclicality might be due to complex eigenvalues of the solution of the model. The model is to some extent an empirical specification with the inclusion of endogenous persistence of the variables. Endogenous persistence makes a contribution to shocks have a long-lived effect on the variables (Salemi, 2006). In theoretical models, the shape of impulse-responses is commonly of a more monotonic form (see Galí, 2015; Walsh, 2017; Woodford, 2003a). Even though a small model, the impact of a shock is a dynamic process and the return to steady state take some time. Some of the factors that affect the shape of the functions are the parameter values, the standard deviations of and the correlations between the shocks, and the endogenous persistence of the three variables (in addition to figure 2, see also figure 1A and 3A in the appendix). In our case, a higher ρ results in higher variability of some functions whilst lower for others. Higher standard deviation of the shocks leads to a higher cyclicality, and so does the correlations between the shocks; the shape differs only minorly though. We experimented by varying the standard deviations and also abstracting from the correlations, none of whose functions are reported.

---

[27] The inference of conditional variance decompositions could suffer if shocks are non-orthogonal; from the estimates we have seen that the shocks are correlated. Dees et al. (2010) also allows correlations between some shocks in analysis of forecast error variance decompositions.

[28] Examples of other papers that studies cyclical impulse-response functions include Baele et al. (2015), Christiano et al. (2005), Dennis (2006), Dennis and Söderström (2006), Fuhrer (1997), and Fuhrer and Moore (1995).

Higher degree of interest rate smoothing amplifies the effect of a policy shock on inflation and output. At the same time, higher (lower) smoothing leads to a smaller (larger) response of the nominal interest rate to supply and demand shocks.[29] The analysis is consistent with Cho and Moreno (2003). Provided our assumption that the Central Bank chooses the degree of ρ to set the nominal rate, the sensitivity analysis shows a trade-off that the Central Bank faces. On the one hand a lower ρ directly dampens the variability of inflation and output after a policy shock, and, on the other, a lower ρ directly amplify the variability of the nominal interest rate following supply and demand shocks, which indirectly propagates through the economic system and affect the variability of inflation and output.

6.2 Optimal Monetary Policy

In this section we introduce the policy objective function. We are interested in to gauge preferences of the Central Bank that makes the simulation return a policy rule close to the historical rule. As discussed in Dennis (2006), the weights in an objective function used to analyze optimal monetary policy reflect how different objectives are a trade-off in response to shocks. This means that our attempt concern measuring preferences of policy that return an optimized rule in which the impact of shocks matches our impulse-response functions in figure 2.

6.2.1 A Policy Objective Function

A policy objective function specifies the monetary authorities' goals of monetary policy. We assume an objective of policy as proposed by Woodford (2003a).[30] The function contains targets to stabilize the unconditional variance of inflation from a target level, the output gap, and the level of the nominal interest rate.[31]

$$E[\mathcal{L}_t] = \text{Var}(\pi_t) + \lambda_1\text{Var}(\hat{y}_t) + \lambda_2\text{Var}(i_t) \qquad \lambda_1 \geq 0 \qquad \lambda_2 \geq 0 \tag{9}$$

Where

$E[\mathcal{L}_t]$ is the expected loss.

λ_1 is the monetary authority's preference to output stability relative to inflation stability.

λ_2 is the monetary authority's preference to interest rate stability relative to inflation stability.

---

[29] This finding is consistent with a discussion being held in Clarida et al. (1999), see result 11 in their paper.

[30] See chapter 6 in Woodford (2003a) for a theoretic treatment of this policy objective function.

[31] The variables are in deviations from a target value. The theoretical version of the function oftentimes has the following appearance $E[\mathcal{L}_t] = (\pi_t - \pi^*)^2 + \lambda_1(\hat{y}_t - y^*)^2 + \lambda_2(i_t - i^*)^2 \quad \lambda_1 \geq 0 \quad \lambda_2 \geq 0$

The parameters λ_1 and λ_2 are interpreted as the weights that the Central Bank assign to stabilization of the output gap and the level of the interest rate with respect to stabilization of inflation from a target value.[32] Svensson (1999) refer $(\lambda_1, \lambda_2) = \{0\ 0\}$ to as strict inflation targeting and either, or both, $(\lambda_1, \lambda_2) = \{> 0\}$ as flexible inflation targeting. The loss-function is defined over an infinite-horizon. We bring together the New-Keynesian macro model (6) with the objective function (9).

$$\begin{aligned}
\pi_t &= \delta E_t\pi_{t+1} + (1 - \delta)\pi_{t-1} + \lambda\hat{y}_t + \varepsilon_t^{\pi} && 0 < \delta < 1 \quad \lambda > 0 \\
\hat{y}_t &= \mu E_t\hat{y}_{t+1} + (1 - \mu)\hat{y}_{t-1} - \sigma[i_t - E_t\pi_{t+1}] + \varepsilon_t^{\hat{y}} && 0 < \mu < 1 \quad \sigma > 0 \\
i_t &= (1 - \rho)[\phi_\pi\pi_t + \phi_{\hat{y}}\hat{y}_t] + \rho i_{t-1} + \varepsilon_t^{i} && 0 < \rho < 1 \quad \phi_\pi > 0 \quad \phi_{\hat{y}} > 0
\end{aligned} \tag{6}$$

$$\underset{(\phi_\pi,\, \phi_{\hat{y}})}{\text{Min}} \quad E[\mathcal{L}_t] = \text{Var}(\pi_t) + \lambda_1\text{Var}(\hat{y}_t) + \lambda_2\text{Var}(i_t) \qquad \lambda_1 \geq 0 \quad \lambda_2 \geq 0 \tag{9}$$

Model settings are

Parameters $(\delta, \lambda, \mu, \sigma, \rho) = \{0.5091\ 0.1213\ 0.5211\ 0.0287\ 0.9245\}$

Standard deviations of the shocks $(\sigma_\pi, \sigma_{\hat{y}}, \sigma_i) = \{1.5140\ 0.5541\ 0.3335\}$

Correlations between the shocks $(\varepsilon_t^{\pi}, \varepsilon_t^{\hat{y}})$, $(\varepsilon_t^{\pi}, \varepsilon_t^{i})$ and $(\varepsilon_t^{\hat{y}}, \varepsilon_t^{i}) = \{0.4046\ {-0.1966}\ {-0.1044}\}$

Starting values of the parameters to be optimized[33] $(\phi_\pi, \phi_{\hat{y}}) = \{1.0785\ 1.6774\}$

Parameter bounds are set to $(\phi_\pi, \phi_{\hat{y}}) = \{0 \leq \phi_\pi, \phi_{\hat{y}} \leq 5\}$

The policymakers are assumed to optimize subject to the constraints embodied in the model-economy. The constraints are the behavioral equations consisting of the Phillips and the IS curve, whereas the parameters to be optimized are ϕ_π and $\phi_{\hat{y}}$. The objective function serves a guide to the Central Bank in the decision-making. The parameter ρ is also assumed to be chosen by the Central Bank, however, this parameter is for simplicity fixed in this problem. This means that ρ is set together with the other parameters of the Phillips and the IS curve.[34] Our concern is to provide values of λ_1 and λ_2, whereas ϕ_π and $\phi_{\hat{y}}$ are optimized.

---

[32] Example of papers that studies function (9) include Giannoni and Woodford (2003), Rudebusch (2006), Taylor and Williams (2011), and Woodford (1999, 2003b). Example of paper that studies an objective function in which instead the change in the interest rate, from a period to another, enters (9) include Dennis (2006), Levin and Williams (2003), Rudebusch (2001), Rudebusch and Svensson (1999), and Söderström, Söderlind and Vredin (2002).

[33] It makes no difference in the simulations if these parameters instead were to be set to some arbitrary values.

[34] The Dynare codes are provided in the appendix.

Instead of attempting to find some values of the parameters in the policy rule that minimizes function (9), our primarily goal is to find values of λ_1 and λ_2 that roughly returns our empirical estimates of ϕ_π and $\phi_{\hat{y}}$. Put differently, instead of trying values of λ_1 and λ_2 so that the expected loss is minimized, we provide 'guesses' of these parameters in an attempt to make the simulation return ϕ_π and $\phi_{\hat{y}}$ fairly close to the historical rule. By this approach we use the method, or analytical tool, commonly employed to compute optimal policy rules to gauge preferences of the Central Bank by using our empirical model-statistics.

A precise match of those parameters in simulations without any form of grid search is a formidable challenge. In previous empirical research, estimates of λ_1 and λ_2 has widely varied. For example, Dennis (2006) uses U.S. data and finds $(\lambda_1, \lambda_2) = \{3.141\ 37.168\}$ for the Pre-Volcker period between 1966:Q1 to 1979:Q3, and $(\lambda_1, \lambda_2) = \{2.941\ 4.517\}$ for the Volcker-Greenspan period between 1982:Q1 to 2000:Q2. Rudebusch and Svensson (1999) uses $(\lambda_1, \lambda_2) = \{1.0\ 0.5\}$ as 'typical' benchmark weights. In calibration, Söderström et al. (2002) finds that values of $(\lambda_1, \lambda_2) = \{\lambda_1 \leq 0.10\ 0.5 \leq \lambda_2 \leq 2.0\}$ matches U.S. data between 1987:Q4 to 1999:Q4, and Giannoni and Woodford (2003) set $(\lambda_1, \lambda_2) = \{0.048\ 0.236\}$ in their study. Rudebusch (2006) discuss that a value assigned to interest rate smoothing of $(\lambda_2) = \{1.0\}$ would be implausibly high given the emphasis of Central Banks on the importance of stabilization of inflation and output.

Provided the wide variety of λ_1 and λ_2 in the literature, and our intention of using the function, we instead 'calibrate' these parameters. We try different values of λ_1 and λ_2 that are found in previous empirical research and also values that are often set in the academic literature. However, as we in this case attempt to match theoretical moments with empirical parameter values, particularly high or low values are not considered.

6.2.2 Optimal Rule under Commitment

Table 6. Simulations of Optimal Simple Rule under Commitment

Configuration	Parameters		Standard Deviations			Policy Objectives		
Number	ϕ_π	$\phi_{\hat{y}}$	(π_t)	$(\hat{y}_t)$	(i_t)	λ_1	λ_2	$E[\mathcal{L}_t]$
1	3.4071	1.0112	3.4431	2.0590	2.6451	0	1	18.8506
2	5.0000	5.0000	2.9639	1.6960	3.6962	1	0	11.6604
3	3.3672	1.5731	3.3955	1.9920	2.7180	0.5	1	20.8997
4	4.5852	3.2118	3.0545	1.8078	3.3547	1	0.5	18.2248
5	2.5024	0.7776	3.8199	2.1930	2.2429	0.1	2	25.1342
6	1.7945	1.4557	4.1033	2.1855	2.0678	2.7	4.6	49.4016
7	4.4922	5.0000	3.0388	1.6945	3.5612	4	0.5	27.0604
8	1.7379	0.8377	4.3058	2.3411	1.9125	1	5	42.3090
9	3.3407	2.0897	3.3613	1.9353	2.7897	1	1	22.8257
10	4.6316	2.4467	3.0742	1.8660	3.2697	0.5	0.5	16.5360

NOTES: The first column denotes the sets of the different combinations of preference weights with the associated expected loss. The second column reports the returned optimized parameters in the policy rule. The third column shows theoretical standard deviations in percentage points. The fourth column is the assumed objectives of monetary policy.

The general picture is that, in our model, various combinations of 'typical' preference weights suggests a monetary policy rule with larger responses to economic conditions than what is observed in the historical rule. This is a fairly common result in the literature (Dennis, 2006; Rudebusch, 2001; Rudebusch and Svensson, 1999; Rotemberg and Woodford, 1997). The findings imply that in an optimal rule, under certainty equivalence, the policy rate is more vigorously varied in response to inflation from a target and to the output gap, as compared with the historical rule. This is in turn often linked to probable data and parameter uncertainties that the monetary authorities' face (see e.g. Rudebush, 2001). The configuration number 2 has the lowest expected loss; however, this combination leads ϕ_π and $\phi_{\hat{y}}$ reaching their upper bounds of the imposed restrictions, which means that the simulation suggests 'unreasonably' high values of those parameters. The economic interpretation of this finding is that some weight on interest rate stabilization is non-negligible in the objective function. An absent concern about output stabilization, configuration number 1, results in a high ϕ_π compared to the empirical estimate.

The configuration number 6, taken from Dennis (2006), seems to be the combination of weights considered that largely make the simulation returns an optimized policy rule close to the historical rule. Dennis (2006) estimate preference parameters on U.S. data by using a pure backward-looking model, as formulated by Rudebusch and Svensson (1999). We instead study a hybrid model that allows both backward-looking and forward-looking private-sector expectations, and assume that the Riksbank's objective include stabilizing the level in the interest rate (see footnote 32). In section

5.2 we found that the estimates with one additional lag of inflation in the Phillips Curve resulted in mixed improvements of the residual diagnostics. Also, as discussed in Levin and Williams (2003), various models that competes about the formation of expectations can be robust in a general case provided that the objective function include substantial weight on both inflation and output stabilization. We have seen that a positive weight on output stabilization is non-negligible in the objective function. This combination of λ_1 and λ_2 leads to a higher ϕ_π than in the historical rule and a slightly lower $\phi_{\hat{y}}$. To judge the importance of these differentials for the impact of shocks in the model, see figure 3A and 4A in the appendix that contain sensitivity analysis of those parameters. With these preferences, the Central Bank act as to stabilize the interest rate, the output gap and inflation from a target, in that order.

The analysis is affected by, for example, the relatively high standard deviation of the supply shocks. This contributes to higher theoretical standard deviations of the variables compared to the observed standard deviations of the variables on real data.[35] In turn, the high theoretical standard deviations have an impact on how different combinations of λ_1 and λ_2 leads to some values of the optimized parameters ϕ_π and $\phi_{\hat{y}}$. However, we motivate the relevance of the analysis that all three variables appear to be explicitly stabilized, as follows.[36] A concern about both inflation and output stabilization is by and large the conventional case in studies on optimal policy; it could be put in relation to the aim of the Riksbank's monetary policy.[37] An argument in the academic literature to motivate stabilization of the interest rate in some form is if the private sector has rational expectations (e.g. Levin, Wieland, Williams, 1999; Sack and Wieland, 2000; Williams, 2003; Woodford, 1999, 2003b). In this study we show by using Swedish data that both inflation and output possess a significant forward-looking behavior.

---

[35] The standard deviations of the variables on real data is: CPI inflation 1.7535 percentage points; output gap 1.7130 percentage points; policy rate 2.0144 percentage points.

[36] There are arguments that $(\lambda_2) = \{0\}$, see for example Svensson (2003).

[37] Available online under 'The tasks of the Riksbank': https://www.riksbank.se/en-gb/about-the-riksbank/the-tasks-of-the-riksbank

6 Conclusions

In this paper we have estimated and simulated a New-Keynesian small-scale DSGE macro model. The three-equation system consisting of a Phillips curve, an IS curve and a Taylor-type monetary policy rule was estimated simultaneously on Swedish data 1995:Q1 to 2014:Q4 by using the FIML estimator. The empirical parameter values were then used in simulations of the model to generate impulse-response functions and to optimize the monetary policy rule. In the introduction we addressed three key questions. How well a standard New-Keynesian DSGE model can replicate the Swedish data between 1995:Q1 to 2014:Q4; what the effect of exogenous disturbances is in the model; and how to explain the effect of shocks with respect to stabilization preferences of the Central Bank. Our empirical analysis suggested that both inflation and output possess a significant forward-looking behavior, and that Central Bank behavior is characterized by a substantial degree of policy inertia. However, the residual diagnostic indicated that the shocks suffered from non-normality and serial correlation, which made it difficult to draw critical conclusions.

The empirical parameter values were used in simulations of the model. We found that higher level of interest rate smoothing amplifies the effect of a policy shock on inflation and output. It was also shown that higher degree of interest rate smoothing leads to a smaller response of the interest rate to supply and demand shocks. The parameterization on a match between the historical rule with Central Bank preferences suggested that the monetary authority in descending order stabilizes the volatility of the policy rate, the output gap and inflation from a target. We motivated our analysis by referring to the aim of the Riksbank's monetary policy and by providing justifications from the academic literature.

We have discussed that extensions of the model could improve the statistics if misspecified, some of which extensions resulting in larger models have been mentioned. At the same time, it has been emphasized that one motivation in the choice of model has been to keep the textbook theory relevant. Additional literature on development of New-Keynesian models is desirable; development with sound theoretical underpinnings which also could promote estimates fulfill critical distributional assumptions.

References

Adjemian, S., Bastani, H., Juillard, M., Karamé, F., Maih, J., Mihoubi, F., Perendia, G., Pfeifer, J., Ratto, M., Villemot, S. (2011). Dynare: Reference Manual, Version 4. Dynare Working Papers, 1, CEPREMAP.

Adolfson, M., Laséen, S., Lindé, J., Villiani, M. (2008). Evaluating an estimated new Keynesian small open economy model. *Journal of Economic Dynamics and Control.* Vol. 32, pp. 2690-2721.

Allsopp, C., Kara, A., Nelson, E. (2006). United Kingdom inflation targeting and the exchange rate. *The Economics Journal.* Vol. 116, F232–F244.

Baele, L., Bekaert, G., Cho, S., Inghelbrecht, K., Moreno, A. (2015). Macroeconomic regimes. *Journal of Monetary Economics*. Vol. 70, pp. 51-71.

Bekaert, G., Cho, S., Moreno, A. (2010). New Keynesian Macroeconomics and the Term Structure. *Journal of Money, Credit and Banking*. Vol. 42, pp. 33-62.

Bernanke, B.S. (2004). Gradualism. Speech 540. Board of Governors of the Federal Reserve System.

Beyer, A., Farmer, R.E.A., Henry, J., Marcellino, M. (2005). Factor Analysis in a New-Keynesian Model. ECB Working Paper Series. No. 510, August 2005.

Bikbov, R., Chernov, M. (2013). Monetary policy regimes and the term structure of interest rates. *Journal of Econometrics*. Vol. 174, pp. 27-43.

Blanchard, O.J., Kahn, C.M. (1980). The Solution of Linear Difference Models under Rational Expectations. *Econometrica*. Vol. 48, pp. 1305-1311.

Bullard, J., Mitra, K. (2002). Learning about monetary policy rules. *Journal of Monetary Economics*. Vol. 49, pp. 1105–1129.

Calvo, G.A. (1983). Staggered Prices in a utility-maximizing framework. *Journal of Monetary Economics*. Vol. 12, pp. 383-398.

Canova, F. (1998). Detrending and business cycle facts. *Journal of Monetary Economics*. Vol. 41, pp. 475-512.

Chari, V.V., Kehoe, P.J., McGrattan, E.R. (2009). New Keynesian Models: Not Yet Useful for Policy Analysis. *American Economic Journal: Macroeconomics*. Vol. 1, pp. 242-266.

Cho, S., Moreno, A. (2003). A Structural Estimation and Interpretation of the New Keynesian Macro Model. Faculty Working Papers 14/03. University of Navarra.

Cho, S., Moreno, A. (2006). A Small-Sample Study of the New-Keynesian Macro Model. *Journal of Money, Credit and Banking*. Vol. 38, pp. 1461-1481.

Christiano, L.J., Eichenbaum, M., Evans, C.L. (1999). Monetary Policy Shocks: What have we learned and to what end? *Handbook of Macroeconomics*. Edt. 1. Vol. 1, pp. 65-148.

Christiano, L.J., Eichenbaum, M., Evans, C.L. (2001). Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy. NBER Working Paper. No. 8403.

Christiano, L.J., Eichenbaum, M., Evans, C.L. (2005). Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy. *Journal of Political Economy*. Vol. 113, pp. 1-45.

Clarida, R., Galí, J., Gertler, M.J. (1999). The Science of Monetary Policy: A New Keynesian Perspective. *Journal of Economic Literature*. Vol. 37, pp. 1661–1707.

Clarida, R., Galí, J., Gertler, M.J. (2000). Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory. *The Quarterly Journal of Economics*. Vol. 115, pp. 147–180.

Dees, S., Pesaran, M.H., Smith, L.V., Smith, R.P. (2010). Supply, Demand and Monetary Policy Shocks in a Multi-Country New Keynesian Model. ECB Working Paper Series. No. 1239.

Dennis, R. (2006). The Policy Preferences of the U.S. Federal Reserve. *Journal of Applied Econometrics*. Vol. 21, pp. 55-77.

Dennis, R., Söderström, U. (2006). How Important is Precommitment for Monetary Policy? *Journal of Money, Credit and Banking*. Vol. 38, pp. 847-872.

Dixit, A.K., Stiglitz, J.E. (1977). Monopolistic Competition and Optimum Product Diversity. *American Economic Review*. Vol. 67, pp. 297-308.

Edge, R.M. (2007). Time-to-build, time-to-plan, habit-persistence, and the liquidity effect. *Journal of Monetary Economics*. Vol. 54, pp. 1644-1669.

Enders, W. (2014). *Applied Econometric Time Series*. Fourth edition. John Wiley and Sons.

Estrella, A., Fuhrer, J.C. (2002). Dynamic Inconsistencies: Counterfactual Implications of a Class of Rational-Expectations Models. *American Economic Review*. Vol. 92, pp. 1013-1028.

Fair, R.C. (1984). *Specification, Estimation, and Analysis of Macroeconomic Models*. Harvard University Press.

Fuhrer, J.C. (1997). The (Un)Importance of Forward-Looking Behavior in Price Specifications. *Journal of Money, Credit and Banking*. Vol, 29. pp. 338-350.

Fuhrer, J.C. (2000). Habit Formation in Consumption and Its Implications for Monetary-Policy Models. *The American Economic Review*. Vol. 90, pp. 367-390.

Fuhrer, J.C. (2010). *Handbook of Monetary Economics*. Chapter 9 – Inflation Persistence. Vol. 3, pp. 423–486.

Fuhrer, J.C. Moore, G. (1995). Inflation Persistence. *The Quarterly Journal of Economics*. Vol. 110, pp. 127-159.

Fuhrer, J.C., Rudebusch, G.D. (2004). Estimating the Euler equation for output. *Journal of Monetary Economics*. Vol. 51, pp. 1133–1153.

Fuhrer, J.C., Moore, G.R., Schuh, S.D. (1995). Estimating the linear-quadratic inventory model maximum likelihood versus generalized method of moments. *Journal of Monetary Economics*. Vol. 35, pp. 115-157.

Froyen, R.T., Guender, A.V. (2018). The real exchange rate in Taylor rules: A Re-Assessment. *Economic Modelling*. Vol. 71, pp. 140-151.

Galí, J. (2015). *Monetary Policy, Inflation, and the Business Cycle: An Introduction to the New Keynesian Framework and its Applications*. Second Edition. Princeton University Press.

Galí, J. (2018). The State of New Keynesian Economics: A Partial Assessment. *Journal of Economic Perspectives*. Vol. 32, pp. 87-112.

Galí, J., Gertler, M. (1999). Inflation dynamics: A Structural econometric analysis. *Journal of Monetary Economics*. Vol. 44, pp. 195-222

Galí, J., Gertler, M., Salido-Lopez, D. (2005). Robustness of the Estimates of the Hybrid New Keynesian Phillips Curve. *Journal of Monetary Economics*. Vol. 52, pp. 1107-1118.

Giannoni, M.P., Woodford, M. (2003). How Forward-Looking Is Optimal Monetary Policy? *Journal of Money, Credit and Banking*. Vol. 35, pp. 1425-1469.

Goodhart, C., Hofmann, B. (2005). The IS curve and the transmission of monetary policy: is there a puzzle? *Applied Economics*. Vol. 37, pp. 29-36.

Hodrick, R.J., Prescott, E.C. (1997). Postwar U.S. Business Cycles: An Empirical Investigation. *Journal of Money, Credit and Banking*. Vol. 29, pp. 1-16.

Holmberg, K. (2006). Derivation and Estimation of a New Keynesian Phillips Curve in a Small Open Economy. Sveriges Riksbank Working Paper Series No. 197.

Jondeau, E., H. Le Bihan (2003). ML vs. GMM estimates of hybrid macroeconomic models with an application to the 'New Phillips Curve'. Banque de France Working Paper No. 103.

Kara, A., Nelson, E. (2004). International Evidence on the Stability of the Optimizing IS Equation. *Oxford Bulletin of Economics and Statistics.* Vol. 66, pp. 687-712.

Leeper, E.M., and Zha, T. (2001). Assessing Simple Policy Rules: A View from a Complete Macro Model. Federal Reserve Bank of Atlanta. Working Paper 2000-19.

Levin, A.T., Williams, J.C. (2003). Robust monetary policy with competing reference models. *Journal of Monetary Economics.* Vol. 50, pp. 945-975.

Levin, A.T., Wieland, V., Williams, J. (1999). Robustness of Simple Monetary Policy Rules under Model Uncertainty. In: Monetary Policy rules, Taylor, J.B. (Ed.). University of Chicago Press, pp. 263–299.

Lindé, J. (2005). Estimating New-Keynesian Phillips curves: A full information maximum likelihood approach. *Journal of Monetary Economics.* Vol. 52, pp. 1135–1149.

Lubik, T.A., Schorfheide, F. (2004). Testing for Indeterminacy: An Application to U.S. Monetary Policy. *American Economic Review.* Vol. 94, pp. 190-217.

Lucas, R.E. (1976). Econometric Policy Evaluation: A Critique. Carnegie-Rochester Conference Series on Public Policy. Vol. 1, pp. 19-46.

Mavroeidis, S. (2005). Identification Issues in Forward Looking Models Estimated by GMM with an Application to the Phillips Curve. *Journal of Money, Credit and Banking*, Vol. 37, pp. 421-448.

Mavroeidis, S. (2010). Monetary Policy Rules and Macroeconomic Stability: Some Evidence. *American Economic Review.* Vol. 100, pp. 491-503.

Neiss, K.S., Nelson, E. (2003). The real interest rate gap as an inflation indicator. *Macroeconomic Dynamics.* Vol. 7, pp. 239–262.

Phillips, P.C.B. (1982). On the Consistency of Nonlinear FIML. *Econometrica.* Vol. 50, pp. 1307-1324.

Rotemberg, J., Woodford, M. (1997). An Optimization-Based Econometric Framework for the Evaluation of Monetary Policy. NBER *Macroeconomic Annual.* Vol. 12, pp. 297-361.

Rudd, J., Whelan, K. (2005). New tests of the new-Keynesian Phillips curve. *Journal of Monetary Economics*. Vol. 52, pp. 1167–1181.

Rudd, J., Whelan, K. (2006). Can Rational Expectations Sticky-Price Models Explain Inflation Dynamics? *The American Economic Review*. Vol. 96, pp. 303-320.

Rudebusch, G.D. (2001). Is the Fed too Timid? Monetary Policy in an Uncertain World. *The Review of Economics and Statistics*. Vol. 83, pp. 203-217.

Rudebusch, G.D. (2002a). Term structure evidence on interest rate smoothing and monetary policy inertia. *Journal of Monetary Economics*. Vol. 49, pp. 1161-1187.

Rudebusch, G.D. (2002b). Assessing Nominal Income Rules for Monetary Policy with Model and Data Uncertainty. *The Economic Journal*. Vol. 112, pp. 402-432.

Rudebusch, G.D. (2006). Monetary Policy Inertia: Fact or Fiction? *International Journal of Central Banking*. Vol. 2, pp. 86-135.

Rudebusch, G.D., Svensson, L.E.O. (1999). Policy Rules for Inflation Targeting. In *Monetary Policy Rules*. Taylor J.B. (Ed.). Chicago: University of Chicago Press.

Rupert, P., Šustek, R. (2019). On the mechanics of New-Keynesian models. *Journal of Monetary Economics*. Vol. 102, pp. 53-69.

Sack, B., Wieland, V. (2000). Interest-rate smoothing and optimal monetary policy: a review of recent empirical evidence. *Journal of Economics and Business*. Vol. 52, pp. 205-228.

Salemi, M.K. (2006). Econometric Policy Evaluation and Inverse Control. *Journal of Money, Credit and Banking*. Vol. 38, pp. 1737-1764.

Sørensen, P.B., Whitta-Jacobsen, H.J. (2010). *Introducing Advanced Macroeconomics: Growth and Business Cycles*. McGraw-Hill Higher Education. 2nd Edition.

Stracca, L. (2010). Is the New Keynesian IS Curve Structual? ECB Working Paper Series. No. 1236, August 2010.

Svensson, L.E.O. (1999). Inflation Targeting: Some Extensions. *The Scandinavian Journal of Economics*. Vol. 101, pp. 337-361.

Svensson, L.E.O. (2003). What is Wrong with Taylor Rules? Using Judgement in Monetary Policy through Targeting Rules. *Journal of Economic Literature*. Vol. 41, pp. 426-477.

Svensson, L.E.O. (2015). The Possible Unemployment Cost of Average Inflation below a Credible Target. *American Economic Journal: Macroeconomics*. Vol. 7, pp. 258-296.

Sveriges Riksbank (2008). Minutes of the Executive Board's monetary policy meeting. No. 24, 3 December 2008.

Sveriges Riksbank (2011). Minutes of the Executive Board's monetary policy meeting. No. 6, 19 December 2011.

Söderström, U., Söderlind, P., Vredin, A. (2002). Can a Calibrated New-Keynesian Model of Monetary Policy Fit the Facts? Sveriges Riksbank Working Paper Series No. 140.

Taylor, J.B. (1993). Discretion versus policy rules in practice. *Carnegie-Rochester Conference Series on Public Policy*. Vol. 39, pp. 195-214 North-Holland.

Taylor, J.B., Williams, J.C. (2011). *Handbook of Monetary Economics*. Chapter 15 – Simple and Robust Rules for Monetary Policy. Vol. 3, pp. 829-859.

Walsh, C.E. (2017). *Monetary Theory and Policy*. Fourth edition. The MIT Press.

White, H. (1982). Maximum Likelihood Estimation of Misspecified Models. *Econometrica*. Vol. 50, pp. 1-25.

Williams, J.C. (2003). Simple Rules for Monetary Policy. *Economic Review*. 2003, pp. 1-12.

Woodford, M. (1999). Optimal Monetary Policy Inertia. The Manchester School Supplement. Vol. 67.

Woodford, M. (2003a). *Interest and Prices: Foundations of a Theory of Monetary Policy*. Princeton University Press.

Woodford, M. (2003b). Optimal Interest-Rate Smoothing. *Review of Economic Studies*. Vol. 70, pp. 861-886.

Appendix

1A. Macroeconomic Data

Table 1A. Macroeconomic Data

Variable	Description	Source
Nominal GDP	Current prices SEK. Expenditure approach. Quarterly data. Seasonally adjusted.	Statistics Sweden
Real GDP	2017 Chained prices SEK. Expenditure approach. Quarterly data. Seasonally adjusted.	
CPI	Consumer price index, total. 1980 = 100. Monthly data. Not seasonally adjusted.	Statistics Sweden
CPIF	Consumer price index fixed rate, total. 1987 = 100. Monthly data. Not seasonally adjusted.	
Repo rate	Units of percent per year. Quarterly data.	The Riksbank

NOTES: The sample period is 1995:Q1 to 2014:Q4.

2A. Stability Test

Table 2A. FIML Estimates of the New-Keynesian Macro Model, 1997:Q2 to 2009:Q4

Parameters	δ	λ	μ	σ	ρ	ϕ_π	$\phi_{\hat{y}}$
Values	0.5081^{***}	0.1268	0.5314^{***}	-0.0773^{*}	0.8842^{***}	0.4498^{*}	1.1694^{***}
Std. Error	(0.0942)	(0.1236)	(0.0578)	(0.0407)	(0.0421)	(0.2827)	(0.4184)

NOTES: The estimates are carried out using the FIML estimator. Robust standard errors in parentheses. The optimization method is BHHH with max 1000 iterations. The residual covariance is diagonal and the information matrix is Hessian. The standard deviations of the shocks are σ_π, $\sigma_{\hat{y}}$ and $\sigma_i = \{1.7663, 0.5519, 0.3096\}$. π_t = CPI, π_t in the policy rule. The sample period is 1997:Q2 to 2009:Q4. Asterisk denotes $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table 3A. Residual Diagnostics of the New-Keynesian Macro Model, 1997:Q2 to 2009:Q4

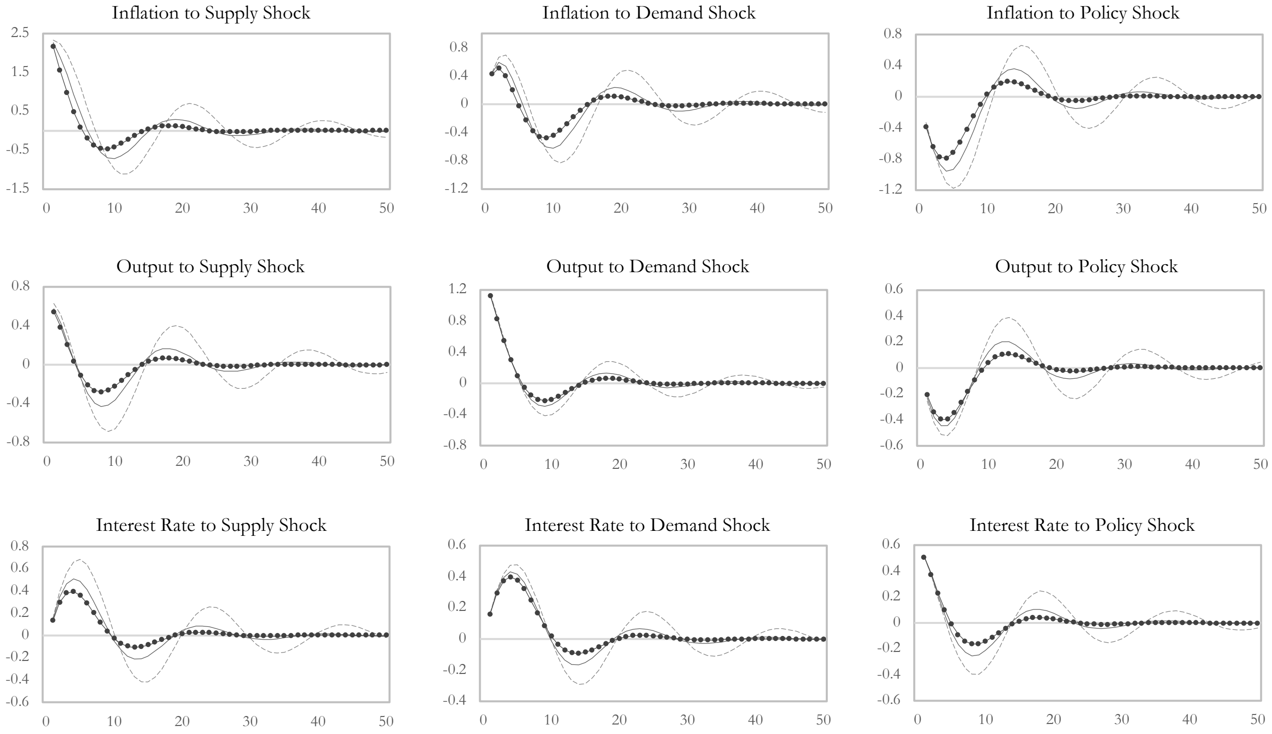
Panel 1. Correlations	$\varepsilon_t^\pi\ \varepsilon_t^{\hat{y}}$	$\varepsilon_t^\pi\ \varepsilon_t^i$	$\varepsilon_t^{\hat{y}}\ \varepsilon_t^i$			
Contemporaneous Correlations	0.4701	-0.1419	-0.1341			
Panel 2. Autocorrelations, Lag = i	$\varepsilon_t^\pi\ \varepsilon_{t-i}^\pi$	Pval. ε_t^π	$\varepsilon_t^{\hat{y}}\ \varepsilon_{t-i}^{\hat{y}}$	Pval. $\varepsilon_t^{\hat{y}}$	$\varepsilon_t^i\ \varepsilon_{t-i}^i$	Pval. ε_t^i
1	-0.5180	0.0000	-0.3660	0.0070	0.2840	0.0370
2	-0.0740	0.0010	-0.0430	0.0250	0.0380	0.1090
3	0.1420	0.0010	0.2500	0.0120	-0.0700	0.1950
4	0.1110	0.0020	-0.1360	0.0180	-0.0620	0.2950
Panel 3. Empirical Distribution Normality Tests	Val. ε_t^π	Pval. ε_t^π	Val. $\varepsilon_t^{\hat{y}}$	Pval. $\varepsilon_t^{\hat{y}}$	Val. ε_t^i	Pval. ε_t^i
Lilliefors (D)	0.1267	0.0396	0.1101	> 0.1	0.0859	> 0.1
Cramer-von Mises (W2)	0.1056	0.0912	0.0923	0.1395	0.0659	0.3153
Watson (U2)	0.1052	0.0724	0.0922	0.1152	0.0588	0.3507
Anderson-Darling (A2)	0.6308	0.0948	0.6462	0.0867	0.4423	0.2682

NOTES: Panel 1 shows the contemporaneous correlations between the shocks. Panel 2 reports the autocorrelation of the shocks with probability values from the Ljung-Box Q-test. Panel 3 is various empirical distribution tests of normality.

3A. Impulse-Response Functions of the New-Keynesian Macro Model with Sensitivity Analysis

Solid line is invariably impulse-response functions with the same parameter set. The magnitude of the shocks are the estimated standard deviations from table 1. The correlations between the shocks are from panel A in table 2. The sensitivity analysis with dashed and circle-marked line are one-by-one changes of parameter values. The parameters are varied either both higher and lower, higher only, or lower only, depending on the Blanchard-Kahn conditions.

Figure 1A. Impulse-Response Functions of the Model; Sensitivity Analysis of δ

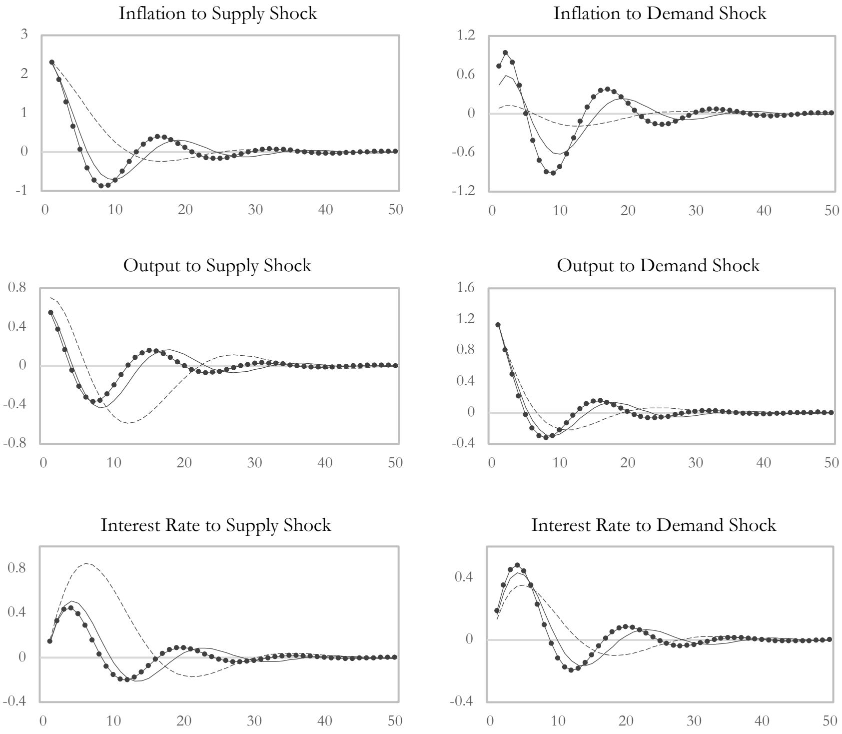


NOTES: Solid line $\delta = 0.5091$; dashed line $\delta = 0.4591$; circle-marked line $\delta = 0.5591$.
The other parameters in the model are set to $(\lambda, \mu, \sigma, \rho, \phi_\pi, \phi_{\hat{y}}) = \{0.1213\ 0.5211\ 0.0287\ 0.9245\ 1.0785\ 1.6774\}$

The New-Keynesian Macro Model

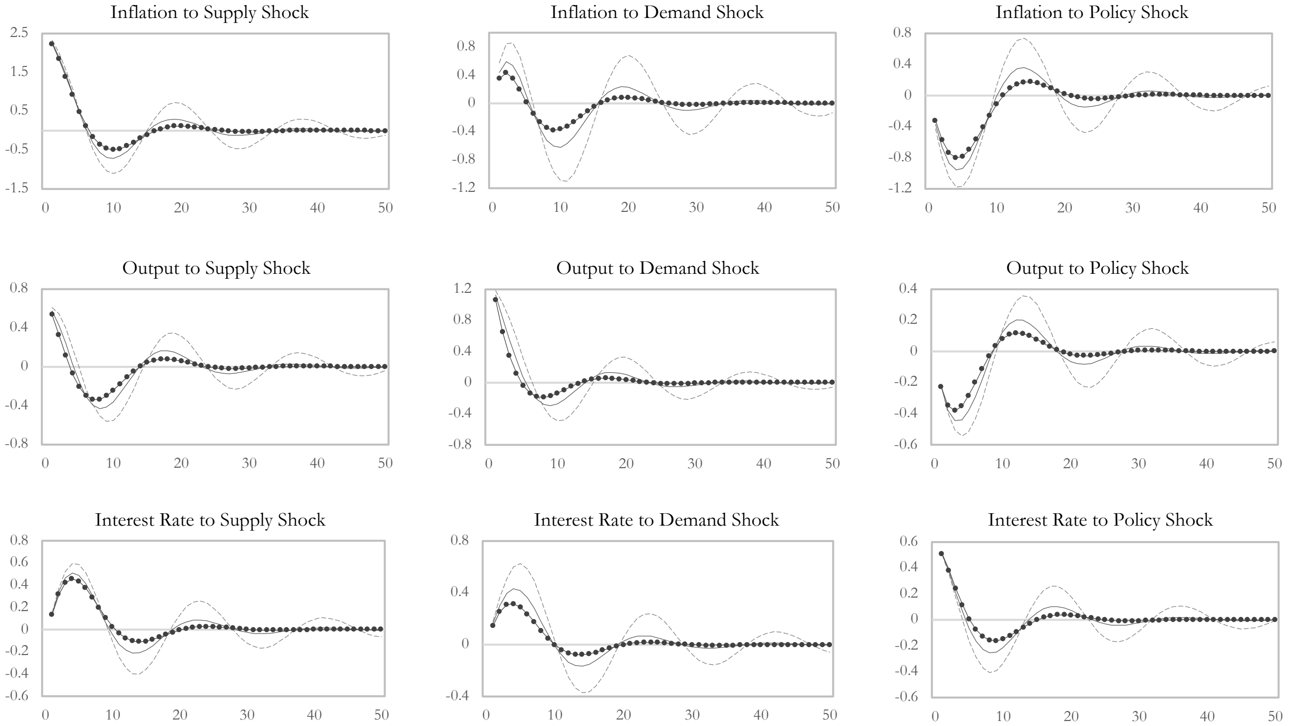
$$\begin{aligned}
\pi_t &= \delta E_t\pi_{t+1} + (1-\delta)\pi_{t-1} + \lambda\hat{y}_t + \varepsilon_t^{\pi} && 0<\delta<1 \quad \lambda>0 \\
\hat{y}_t &= \mu E_t\hat{y}_{t+1} + (1-\mu)\hat{y}_{t-1} - \sigma[i_t - E_t\pi_{t+1}] + \varepsilon_t^{\hat{y}} && 0<\mu<1 \quad \sigma>0 \\
i_t &= (1-\rho)[\phi_\pi\pi_t + \phi_{\hat{y}}\hat{y}_t] + \rho i_{t-1} + \varepsilon_t^{i} && 0<\rho<1 \quad \phi_\pi>0 \quad \phi_{\hat{y}}>0
\end{aligned} \tag{6}$$

Figure 2A. Impulse-Response Functions of the Model; Sensitivity Analysis of λ



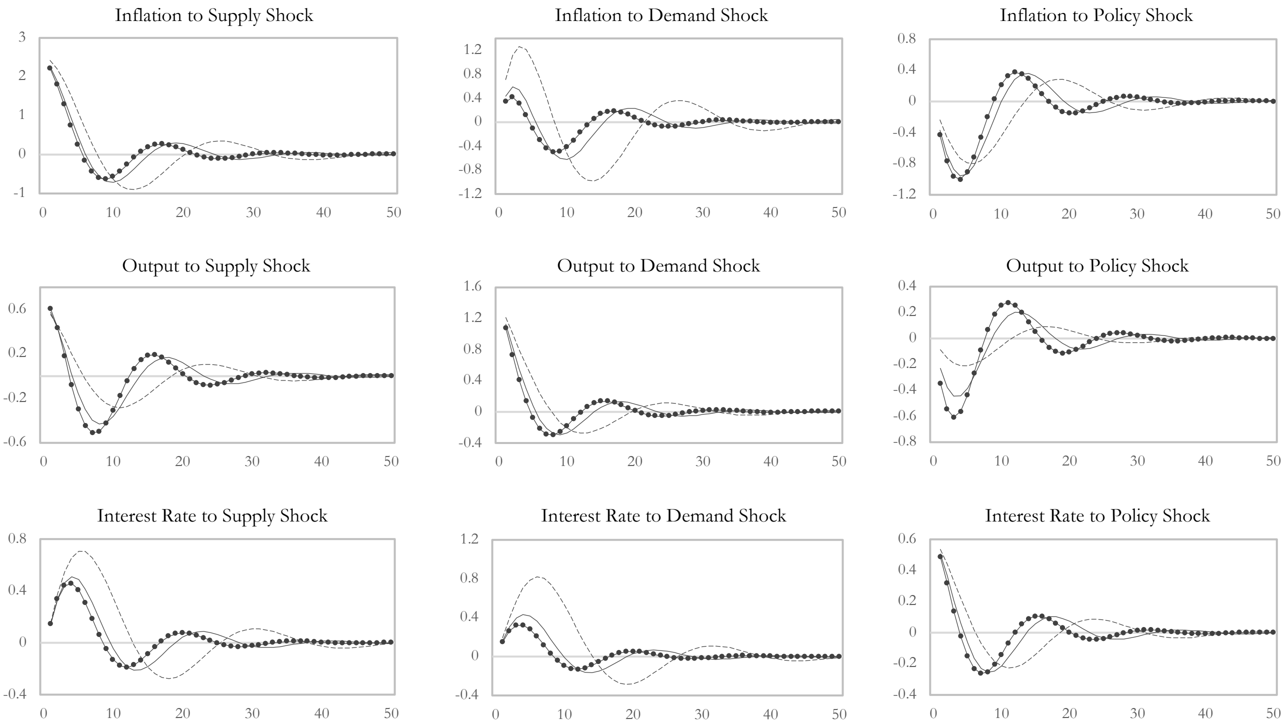
NOTES: Solid line λ = 0.1213; dashed line λ = 0.0213; circle-marked line λ = 0.2213.
The other parameters in the model are set to (δ, μ, σ, ρ, ϕ_π, $\phi_{\tilde{y}}$) = {0.5091 0.5211 0.0287 0.9245 1.0785 1.6774}

Figure 3A. Impulse-Response Functions of the Model; Sensitivity Analysis of μ



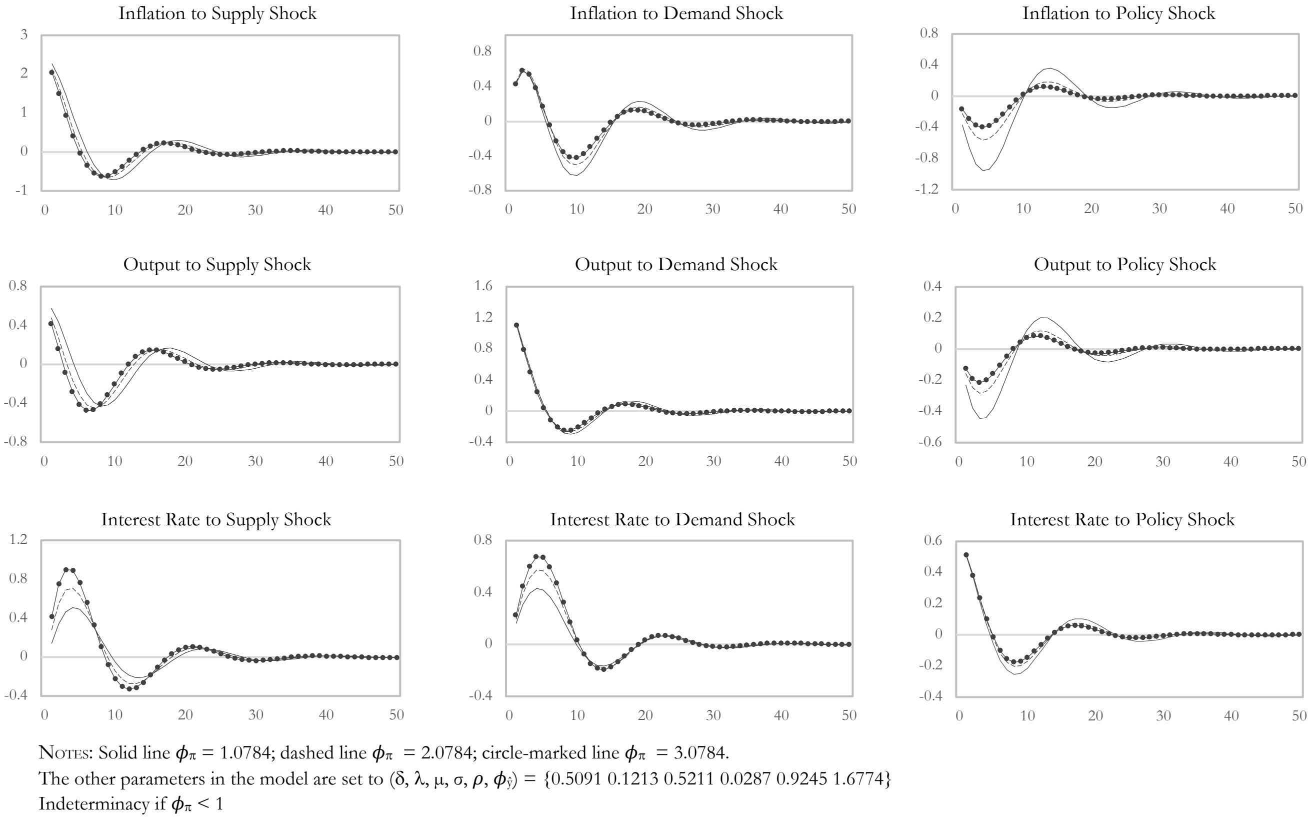
NOTES: Solid line μ = 0.5211; dashed line μ = 0.4711; circle-marked line μ = 0.5711.
The other parameters in the model are set to (δ, λ, σ, ρ, ϕ_π, $\phi_{\tilde{y}}$) = {0.5091 0.1213 0.0287 0.9245 1.0785 1.6774}

Figure 4A. Impulse-Response Functions of the Model; Sensitivity Analysis of σ



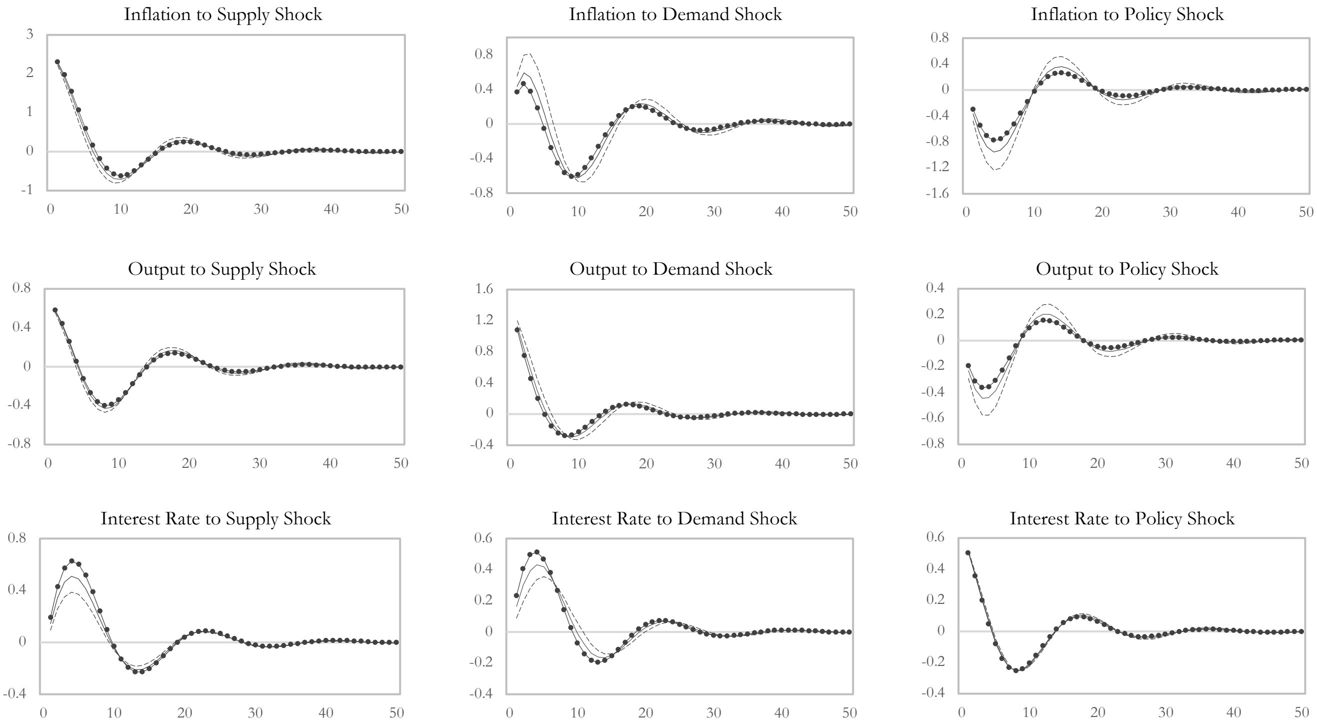
NOTES: Solid line $\sigma = 0.0287$; dashed line $\sigma = 0.0087$; circle-marked line $\sigma = 0.0487$.
The other parameters in the model are set to $(\delta, \lambda, \mu, \rho, \phi_\pi, \phi_{\hat{y}}) = \{0.5091\ 0.1213\ 0.5211\ 0.9245\ 1.0785\ 1.6774\}$
Indeterminacy if $\sigma < 0$

Figure 5A. Impulse-Response Functions of the Model; Sensitivity Analysis of ϕ_π



NOTES: Solid line $\phi_\pi = 1.0784$; dashed line $\phi_\pi = 2.0784$; circle-marked line $\phi_\pi = 3.0784$.
The other parameters in the model are set to $(\delta, \lambda, \mu, \sigma, \rho, \phi_{\hat{y}}) = \{0.5091\ 0.1213\ 0.5211\ 0.0287\ 0.9245\ 1.6774\}$
Indeterminacy if $\phi_\pi < 1$

Figure 6A. Impulse-Response Functions of the Model; Sensitivity Analysis of $\phi_{\hat{y}}$



NOTES: Solid line $\phi_{\hat{y}}$ = 1.6774; dashed line $\phi_{\hat{y}}$ = 0.6774; circle-marked line $\phi_{\hat{y}}$ = 2.6774.
The other parameters in the model are set to (δ, λ, μ, σ, *ρ*, ϕ_π) = {0.5091 0.1213 0.5211 0.0287 0.9245 1.0785}

4A. Dynare Codes

Code 1A. Impulse-Response Functions of the New-Keynesian Macro Model

```
[Code by Erik Hjort, April 23, 2019]

Var pi, y, r;

Varexo shock_supply, shock_demand, shock_policy;

Parameters delta,lambda,mu,sigma,rho,phi_pi,phi_y,sigma_supply,sigma_demand,sigma_policy;

delta=0.5091; lambda=0.1213; mu=0.5211; sigma=0.0287; rho=0.9245; phi_pi=1.0784;
phi_y=1.6774; sigma_supply=1.5140; sigma_demand=0.5541; sigma_policy=0.3335;

Model(linear);

pi=delta*pi(+1)+(1-delta)*pi(-1)+lambda*y+shock_supply;
y=mu*y(+1)+(1-mu)*y(-1)-sigma*(r-pi(+1))+shock_demand;
r=rho*r(-1)+(1-rho)*(phi_pi*pi+phi_y*y)+shock_policy;

End;

Initval; y=0; r=0; pi=0; End;
Endval; y=0; r=0; pi=0; End;

Shocks;
var shock_supply=sigma_supply;
var shock_demand=sigma_demand;
var shock_policy=sigma_policy;
corr shock_supply, shock_demand = 0.4046;
corr shock_supply, shock_policy = -0.1966;
corr shock_demand, shock_policy = -0.1044;

End;

Stoch_simul(irf=50,conditional_variance_decomposition=[1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,
16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,
47,48,49,50]);
```

Code 2A. Optimal Simple Rule under Commitment

```
[Code by Erik Hjort, May 8, 2019]

Var pi, y, r;

Varexo shock_supply, shock_demand, shock_policy;

Parameters delta,lambda,mu,sigma,rho,phi_pi,phi_y,sigma_supply,sigma_demand,sigma_policy;

delta=0.5091; lambda=0.1213; mu=0.5211; sigma=0.0287; rho=0.9245; phi_pi=1.0784;
phi_y=1.6774; sigma_supply=1.5140; sigma_demand=0.5541; sigma_policy=0.3335;

Model(linear);

pi=delta*pi(+1)+(1-delta)*pi(-1)+lambda*y+shock_supply;
y=mu*y(+1)+(1-mu)*y(-1)-sigma*(r-pi(+1))+shock_demand;
r=rho*r(-1)+(1-rho)*(phi_pi*pi+phi_y*y)+shock_policy;

End;

Shocks;
var shock_supply=sigma_supply;
var shock_demand=sigma_demand;
var shock_policy=sigma_policy;
corr shock_supply, shock_demand = 0.4046;
corr shock_supply, shock_policy = -0.1966;
corr shock_demand, shock_policy = -0.1044;

End;

lambda1 = 0.00;
lambda2 = 1.00;

Optim_weights;
pi 1;
y lambda1;
r lambda2;

End;

Osr_params phi_pi phi_y;

Osr_params_bounds;
phi_pi, 0.0, 5.0;
phi_y, 0.0, 5.0;

End;

Osr(opt_algo=9);
```