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Short-term forecasting GDP with a DSGE model augmented by monthly indicators

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Editorial

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Short-term forecasting GDP with a DSGE model augmented by monthly indicators[1]

Marianna Červená and Martin Schneider
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Abstract

DSGE models are useful tools for evaluating the impact of policy changes but their use for (short-term) forecasting is still at an infant stage. Besides theory based restrictions, the timeliness of data is an important issue. Since DSGE models are based on quarterly data, they are vulnerable to a publication lag of quarterly national accounts. In this paper we propose a framework for a short-term forecasting of GDP based on a medium-scale DSGE model for a small open economy within a currency area that utilizes the timely information available in monthly conjunctural indicators. To this end we adopt a methodology proposed by Giannone, Monti and Reichlin (2009). Using Austrian data we find that the forecasting performance of the DSGE model can be improved considerably by conjunctural indicators while still maintaining the story-telling capability of the model.

Keywords: DSGE models, nowcasting, short-term forecasting, monthly indicators

1 Introduction

In recent years, DSGE models have become a commonly used tool for macroeconomic policy advice. Almost all central banks devote considerable resources to build DSGE models in order to analyze relevant policy issues.[2] These efforts have been mainly motivated by the fact that DSGE models have much sounder theoretical foundations than traditional econometric models. Furthermore, since the work of Smets & Wouters (2003) it is well known that the forecasting performance of DSGE models is comparable with that of unconstrained Bayesian VAR models. Nevertheless, most central banks still rely on traditional macroeconometric models to produce their regular forecasts. Within the Euro area, the only national central bank that uses DSGE models for forecasting is the Bank of Finland. A number of reasons may be deemed responsible. Beside open technical issues that remain to be solved (regarding the structure of models, their validation and the communication of the results, see Tovar (2008)), costly investment in the old forecasting infrastructure and a general skepticism about new technologies are factors that impede their wide-spread use in regular forecasting.

An area, where DSGE models have not been applied until now is short-term forecasting. Here, the reasons are obvious and straightforward. Whilst DSGE models allow for a coherent representation of an economy, they are based on quarterly data which as such are subject to significant publication lags and allow only for a very limited number of forecast updates per year. To be more specific, Quarterly National Accounts data are released with a publication lag of around 40 days after the end of the respective quarter for the flash estimate and 70 days for the first complete release. Moreover, such models are hence not able to exploit the information contained in monthly indicators such as e.g. consumer and business surveys. Instead, a short-term forecast (usually up to two quarters) is typically

[1]First and foremost, we would like to thank Lukas Reiss for his invaluable help in setting up the DSGE model. We also like to thank an anonymous referee for helpful comments.

[2]Some examples are the US Federal Reserve System (SIGMA), the ECB (New Area Wide Model), the Bank of Canada (TOTEM), the Bank of Finland (AINO), the Sveriges Riksbank (RAMSES) and the Norges Bank (NEMO)

produced using a statistical framework. It often serves as a starting point for a medium-term forecast, which in turn is based on a structural model. It is integrated in the medium-term forecast either by residual adjustement (in traditional macroeconometric models) or by manipulating structural shocks (in DSGE models).

The Oesterreichische Nationalbank (OeNB) publishes a regular short-term forecast of Austrian GDP (OeNB's Economic Indicator) that is currently based on two non-structural models (a dynamic factor model and an unobserved components model, see Fenz *et al.* (2005)). Although these models produce reliable forecasts, the OeNB aims to broaden the methodological base of its Economic Indicator. Furthermore, the OeNB is currently directing its modeling resources into the development of a quarterly DSGE model of the Austrian economy (Fenz *et al.* (2010)). Thus it seems rather natural to employ this model also for the short-term forecasting. However, the crucial point is how to integrate monthly conjunctural indicators in the DSGE framework in order to exploit the latest available information for forecasting. Therefore an approach that is capable of bridging a structural model on a quarterly basis with monthly indicators is necessary. Unfortunately, conventional bridging approaches are not able to link a structural quarterly model with a set of monthly indicators while preserving the structure of the model.

Recently, Giannone *et al.* (2009) (GMR) have proposed a methodology that suits our needs and meets the above mentioned criteria. The approach is based on a statistical framework developed in Giannone *et al.* (2008). First, the quarterly state-space representation of a DSGE model is transformed into a monthly representation that is consistent with the dynamics of the original quarterly model. The transformed model is then linked to a set of monthly economic indicators via bridge equations. The Kalman filter is used to estimate states which (compared to the original setup) are now augmented by the information contained in the monthly indicators. Furthermore, the method is able to handle the jagged edge problem and thus makes it possible to continuously update the forecasts from the DSGE model every time new information becomes available. By exploiting additional relevant information, the approach is expected to improve the forecasting performance of the DSGE model. Note however that as the forecasts are now also based on the information contained in monthly indicators, the choice of employed indicators is of crucial importance for the forecasting performance and should not be taken lightly. Giannone *et al.* (2009) have circumvented this problem by using an 'expert guess' sample.

Our contribution to the literature is that we extend the work of GMR along several dimensions. First, we utilize a state-of-the-art DSGE model instead of the toy-model used by GMR. Second, we address the issue of variable selection by proposing three different methodologies for the subsample selection (namely random selection, forward stepwise selection and selection based on an Efroymson-type algorithm).[3] Furthermore, to illustrate the importance of proper variable selection we compare the forecasting performance of the model using different samples of monthly indicators. Third, we demonstrate the ability of the approach to produce regular short-term forecasts in an institutional context and show how to give them a structural interpretation.

The paper is organized as follows. Section 2 describes the DSGE model that will be used for the study. In section 3 we discuss the method of Giannone *et al.* (2009) for transforming the quarterly model into a monthly state space representation bridged with economic indicators. Section 4 describes the problem of variable selection and the pseudo real-time forecasting exercise. In section 5 we demonstrate the ability of the model to produce short-term forecasts of Austrian GDP with a meaningful structural interpretation. Section 6 concludes.

[3]Note that the exhaustive search through a set of indicators assumed to be relevant for the forecasting of GDP is not possible. Consider a relatively small set of candidates for auxiliary variables, say 20 variables. In case a subsample of at most 10 variables which performs the best is to be selected, an exhaustive search would need to test 616665 different models.

2 An open-economy DSGE model for the Austrian economy

In this section we present the DSGE model. In developing the model we had to bear in mind a trade-off between constructing a model that is rich enough to allow for an interesting structural interpretation of the forecasts obtained and keeping it small enough to remain tractable. Furthermore, the transformation of the log-linearized solution of the model from quarterly to monthly frequency requires that the size of the model is not too large.[4] In addition, the state estimates of the quarterly and of the transformed monthly form are identical only when the quarterly states do not exhibit signs of non-stationarity.[5] Note that the model is a simplified version of the model of Fenz *et al.* (2010). It is a DSGE model of a small open economy in a monetary union. The domestic economy is linked to the rest of the union via trade and financial flows. The interest rate is exogenous for the domestic economy. An endogenous risk premium (which depends on the net foreign asset position of the domestic economy) is added to the interest rate and closes the model. The domestic economy is populated by a continuum of households and three types of firms; domestic intermediate goods producers, domestic goods assembling firms and final goods assembling firms. The model includes real (external habit formation) and nominal (Calvo prices and partial price indexation) frictions. The foreign economy is modeled by three exogenous processes for world demand for Austrian exports, world inflation and the world interest rate. The model consists of 15 endogenous variables plus 13 shock processes. It is estimated by the means of ten time series.[6]

2.1 Households

The economy is populated by a continuum of households, indexed by $h \in [0, 1]$. They maximize their intertemporal utility function which is given by

$$E_t \sum_{s=0}^{\infty} \beta^s e^b_{t+s} \left(ln(C_{h,t+s} - \kappa C_{t+s-1}) - \frac{e^l_{t+s}}{1+\sigma_l} H^{1+\sigma_l}_{h,t+s} \right),$$

where $C_{h,t}$ is the consumption of household h, $H_{h,t}$ are working hours supplied by households h and C_{t-1} denotes the average consumption of the economy in the previous period. β is the subjective discount factor and κ the degree of (external) habit formation. $e^l_t = (1-\rho_l) + \rho_l e^l_{t-1} + \epsilon_{l,t}$ is a negative labor supply (in terms of hours) shock and $e^b_t = (1-\rho_b) + \rho_b e^b_{t-1} + \epsilon_{b,t}$ is a positive consumption shock. The budget constraint for the representative household is given by

$$\begin{aligned} C_{h,t} + I_{h,t} + T_t + \frac{B^f_{h,t}}{R^f_t \tilde{\phi}\left(nfa_t, e^{rp}_t\right) P_t} &= \\ = \frac{B^f_{h,t-1}}{P_t} + W_{h,t}H_{h,t} + (R^k_t Z_{h,t} - \Psi(Z_{h,t}))K_{h,t-1} + D_t + \Gamma_t + \int_0^1 \Psi(Z_{h,t})K_{h,t-1}di, \quad (1) \end{aligned}$$

[4]The transformation requires a computation of a Kronecker product, where the size grows with N^4.

[5]In order to achieve the latter requirement, we have added two shocks that do not have a meaningful economic interpretation, but were only included to ensure the stationarity of the corresponding states. For further details, see section 2.5.

[6]Compared to the model of Fenz *et al.* (2010), we have made the following simplifications to meet the above-mentioned requirements. The permanent technology shock has been dropped. Therefore, the model includes only a stationary technology shock. Wage rigidities have been dropped. Hence the model contains sticky prices only. Exports are not impacted by price competitiveness; the rest of the world is modeled by three exogenous processes instead of a three-equation system.

where I_t is investment, T_t is lump-sum-tax, $B^f_{h,t}$ are foreign bonds held in period t,[7] P_t is the price level, R^f_t is the (gross) foreign interest rate paid on bonds, $\tilde{\phi}\,(nfa_t, e^{rp}_t)$ denotes a risk premium on foreign bond holdings,[8] R^k_t is the rate of return on physical capital, $W_{h,t}$ is the real wage rate, Z_t is capital utilization, $\Psi(Z_t)$ is the cost of utilization of capital ($\Psi(1) = 0$ and $\Psi'(1) = \frac{1}{\beta} - 1 + \tau$), K_t is the stock of physical capital, D_t denote dividend payments and Γ_t is the net inflow from state-contingent securities (as we assume a complete market structure). Households own the capital stock. The law of motion of capital is given by

$$K_{h,t} = (1-\tau)K_{h,t-1} + \left(1 - S\left(e^i_t \frac{I_{h,t}}{I_{h,t-1}}\right)\right) I_{h,t}, \tag{2}$$

where τ is the rate of depreciation, $S(.)$ are investment adjustment costs ($S(1) = S^{'}(1) = 0$ and $S^{''}(1) > 0$) and e^i is a negative investment shock ($E(e^i) = 1$; law of motion: $e^i_t = (1-\rho_i) + \rho_i e^i_{t-1} + \epsilon^i_t$).

The households maximize their utility by choosing the level of consumption, bond holdings, investment and the capital utilization rate subject to (1) and (2). In addition, they optimize wages after receiving a signal indicating that they are allowed to do so (more on that below in the same section). $D_{h,t}$ and $\Gamma_{h,t}$ are taken as given. The complete household problem thus has the following form

$$\Omega_{h,t} = \sum_{s=0}^{\infty} \beta^s \left[\begin{array}{l} e^b_{t+s}\left(\ln(C_{h,t+s} - \kappa C_{t+s-1}) - \frac{e^l_{t+s}}{1+\sigma_l} H^{1+\sigma_l}_{h,t+s}\right) \\ -\Lambda_{t+s} \left(\begin{array}{l} C_{h,t+s} + I_{h,t+s} + T_{t+s} + \frac{B^f_{h,t+s}}{R^f_{t+s}\tilde{\phi}(nfa_{t+s}, e^{rp}_{t+s})P_{t+s}} \\ -\frac{B^f_{h,t+s-1}}{P_{t+s}} - W_{h,t+s}H_{h,t+s} - \left(R^k_{t+s}Z_{h,t+s} - \Psi(Z_{h,t+s})\right) K_{h,t+s-1} \\ -D_{h,t+s} - \Gamma_{h,t+s} - \int_0^1 \Psi(Z_{h,t+s})K_{h,t+s-1}di \end{array} \right) \\ -\Lambda_{t+s}Q_{t+s}\left(K_{h,t+s} - K_{h,t+s-1}(1-\tau) - \left(1 - S\left(e^I_{t+s}\frac{I_{h,t+s}}{\mu^a I_{h,t+s-1}}\right)\right) I_{h,t+s}\right) \end{array} \right], \tag{3}$$

where Q_t is the real price of one unit of capital. Differentiating with respect to $C_{h,t}$, $B^f_{h,t}$, $I_{h,t}$, $Z_{h,t}$ and $K_{h,t}$, gives us the following set of first order conditions:

$$\frac{\partial \Omega_{h,t}}{\partial B^f_{h,t}} = 0: \qquad E_t\left[\beta \frac{\Lambda_{t+1}}{\Lambda_t} \frac{R^f_t \tilde{\phi}\,(nfa_t, e^{rp}_t)\, P_t}{P_{t+1}}\right] = 1 \tag{4}$$

$$\frac{\partial \Omega_{h,t}}{\partial C_{h,t}} = 0: \qquad \Lambda_t = e^b_t (C_{h,t} - \kappa\, C_{t-1})^{-1} \tag{5}$$

$$\frac{\partial \Omega_{h,t}}{\partial K_{h,t}} = 0: \qquad Q_t = E_t \beta \frac{\Lambda_{t+1}}{\Lambda_t}\left[Q_{t+1}(1-\tau) + Z_{h,t+1}R^k_{t+1} - \Psi(Z_{h,t+1})\right] \tag{6}$$

$$\begin{aligned} \frac{\partial \Omega_{h,t}}{\partial I_{h,t}} = 0: \qquad & 1 + Q_t\left(S^{'}\left(e^i_t \frac{I_{h,t}}{\mu^a I_{h,t-1}}\right) e^i_t \frac{I_{h,t}}{\mu^a I_{h,t-1}} - 1 + S\left(e^i_t \frac{I_{h,t}}{\mu^a I_{h,t-1}}\right)\right) \\ & = \beta E_t Q_{t+1} \frac{\Lambda_{t+1}}{\Lambda_t} S^{'}\left(e^i_{t+1}\frac{I_{t+1}}{\mu^a I_{h,t}}\right) e^i_{t+1} \frac{I^2_{h,t+1}}{\mu^a I^2_{h,t}} \end{aligned} \tag{7}$$

$$\frac{\partial \Omega_{h,t}}{\partial Z_{h,t}} = 0: \qquad R^k_t = \Psi^{'}(Z_{h,t}) \tag{8}$$

Equation (4) gives us the consumption Euler equation. The marginal utility of consumption (Λ_t) is defined in equation (5) where we use the fact that all agents consume the same amount of the final

[7] Bonds are zero-coupon bonds, i.e. a bond that pays 1 in period $t+1$ is bought in period t for $\frac{1}{R^f_t \tilde{\phi}(nfa_t, e^{rp})}$.

[8] For the definition of net foreign assets, see section 2.4.

good (due to the contingent securities). The law of motion for real value of capital Q_t is given in (6). The investment equation is given by (7). The first order condition for the capital utilization rate is given by (8).

2.2 Domestic firms

Our domestic model economy consists of three types of firms; intermediate goods producing firms, a domestic goods assembling firm and a final goods firm. Intermediate goods firms produce differentiated intermediate goods by using a fixed amount of capital and labor as inputs in a Cobb Douglas production function. Production is subject to a transitory technology shock. The domestic good assembling firm buys these differentiated intermediate goods and transforms them in a homogeneous domestic good. The final good firm combines the domestic and imported good into a final good using CES technology. For the sake of simplicity, assume that there is only one final good in the economy.

2.2.1 Domestic goods assembling firm

The domestic good is assembled by one domestic goods assembling firm which buys differentiated intermediate goods from a continuum of domestic intermediate goods producers and transforms them into a homogeneous domestic good.

$$Y_t = \left[\int_0^1 Y_{j,t}^{\frac{1}{1+\lambda_{p,t}}} dj \right]^{1+\lambda_{p,t}} \tag{9}$$

Y_t denotes the domestic intermediate good, $Y_{j,t}$ the differentiated intermediate goods and $\lambda_{p,t}$ is a time-varying markup subject to a cost-push shock. Following Smets & Wouters (2003) we assume the cost-push to be iid. Cost minimization of the domestic goods assembling firm yields demand for output of firm j $(Y_{j,t})$,

$$Y_{j,t} = \left(\frac{P_{j,t}^d}{P_t^d} \right)^{\frac{-(1+\lambda_{p,t})}{\lambda_{p,t}}} Y_t \tag{10}$$

where P_t^d denotes the price of the differentiated good j. The aggregate price P_t^d of the domestic good is given by

$$P_t^d = \left[\int_0^1 (P_{j,t}^d)^{\frac{-1}{\lambda_{p,t}}} dj \right]^{-\lambda_{p,t}} \tag{11}$$

2.2.2 Domestic intermediate goods producers

There is a continuum $j \in [0,1]$ of intermediate goods producers that transform homogeneous input from labor service firm and capital (rented from households) into differentiated output. The production function is given by:

$$Y_{j,t} = e_t^a \check{K}_{j,t}^{\alpha} H_{j,t}^{1-\alpha} - A_t \Phi \tag{12}$$

where e_t^a is a stationary technology shock, $H_{j,t}$ and $\check{K}_{j,t}$ denote labor and effective capital employed by firm j. Φ are fixed costs of production. The technology shock is given by

$$e_t^a = (1 - \rho_a) + \rho_a e_{t-1}^a + \epsilon_t^a. \tag{13}$$

Physical capital $\bar{K}_j$ is transformed into effective capital $\check{K}_{j,t}$ by choosing the degree of capital utilization Z_t.

$$\int_0^1 \check{K}_{j,t} dj = \int_0^1 Z_{h,t} \bar{K}_j dh \tag{14}$$

The intermediate goods producers solve two optimization problems. On the input side, they minimize their production costs. On the output side, they maximize their profits from selling their differentiated products to the domestic goods assembling firm, subject to Calvo frictions. This approach is standard in the literature and leads to the following two first order conditions derived from the two optimization problems.[9]

The cost-minimizing condition on the input side is given by

$$\frac{\check{K}_{j,t}}{H_{j,t}} = \frac{\alpha}{1-\alpha} \frac{W_t}{R_t^k}, \tag{15}$$

The first order condition on the output side can be written as:

$$\sum_{s=0}^{\infty} \xi_p^s \beta^s \Lambda_{t+s} Y_{j,t+s} \left[\left(\frac{P_{t+s-1}^d}{P_{t-1}^d} \right)^{\gamma_p} \frac{\tilde{P}_{j,t}^d}{P_{t+s}} - (1 + \lambda_{p,t}) MC_{t+s} \right] = 0 \tag{16}$$

Using (11), we can obtain the price of the domestic good P_t^d as a CES aggregate over the prices of adjusters and non-adjusters:

$$P_t^d = \left[\xi_p \left(P_{t-1}^d (\pi_{t-1}^d)^{\gamma_p} \right)^{-\frac{1}{\lambda_{p,t}}} + (1 - \xi_p) \left(\tilde{P}_{j,t}^d \right)^{-\frac{1}{\lambda_{p,t}}} \right]^{-\lambda_{p,t}} \tag{17}$$

2.2.3 Final good assembling firms

For the sake of simplicity we assume that there is only one final good in the domestic economy (F_t) that is used for private consumption, investment, exports and government consumption. This final good is assembled by a continuum of final good assembling firms, which work under perfect competition and use domestically produced and imported commodities as inputs. $F_t = \int_0^1 f(D_{i,t}, M_{i,t}) di$, where $\int_0^1 D_{i,t} di = Y_t$ and $\int_0^1 M_{i,t} di = M_t$. $f()$ is a CES production function of final good assembling firm i

$$f(D_{i,t}, M_{i,t}) = \left[\mu^{\frac{\sigma_m}{1+\sigma_m}} D_{i,t}^{\frac{1}{1+\sigma_m}} + (1 - \mu)^{\frac{\sigma_m}{1+\sigma_m}} (\phi_{i,t} M_{i,t})^{\frac{1}{1+\sigma_m}} \right]^{1+\sigma_m}, \tag{18}$$

[9] See Smets & Wouters (2003) and Fenz *et al.* (2010) for a more detailed elaboration.

where μ is a parameter for a home bias for domestically produced goods, and $\frac{1+\sigma_m}{\sigma_m}$ is the elasticity of substitution between domestically produced and imported intermediate goods. Production of the final good is subject to import adjustment costs $\phi_{i,t}$, which depend on the change of the ratio of imports to domestic goods in period t relative to period $t-1$.

$$\phi_{i,t} = \left[1 - \phi_m \left(e_t^m - \frac{M_{i,t}/D_{i,t}}{M_{t-1}/D_{t-1}}\right)^2\right], \tag{19}$$

with $e_t^m = (1-\rho_m) + \rho_m e_{t-1}^m + \epsilon_t^m$ and $E(e_t^m) = 1$.

2.3 The foreign economy

Austria is linked with the foreign economy via trade and financial flows. The foreign economy is modeled in a parsimonious way by assuming three shock processes for export demand, world prices and the world interest rate. We assume that domestic exports evolve according to world demand and that price competitiveness does not play a role. This helps to simplify the model.

Exports

$$X_t = (1-\rho_x)\bar{X} + \rho_x X_t + \epsilon_t^x; \tag{20}$$

World inflation

$$\Pi_t^f = (1-\rho_{\pi f}) + \rho_{\pi f}\Pi_{t-1}^f + \epsilon_t^{\pi f}; \tag{21}$$

World interest rate

$$R_t^f = (1-\rho_{Rf}) + \rho_{Rf} R_{t-1}^f + \epsilon_t^{Rf}; \tag{22}$$

2.4 Model closure

In addition to the equations presented above, two market clearing conditions and a closure rule are needed to complete the model. The first market clearing condition relates the value of final goods to nominal GDP plus nominal imports

$$\left(C_t + I_t + X_t + G_t\right) P_t = P_t^d Y_t + P_t^M M_t, \tag{23}$$

where government consumption G_t is assumed to be exogenous with steady state value G

$$G_t = (1-\rho_g)\bar{G} + \rho_g G_{t-1} + \epsilon_t^g. \tag{24}$$

The second market clearing condition equals domestic production to demand.

$$Y_t = A_t^{1-\alpha} e_t^a \left(\int_0^1 \check{K}_{j,t}^{\frac{\alpha}{1+\lambda_{p,t}}} H_{j,t}^{\frac{1-\alpha}{1+\lambda_{p,t}}} dj\right)^{1+\lambda_{p,t}} - A_t \Phi. \tag{25}$$

For Austria as a small member country of the European Monetary Union, the Euro area interest rate can be treated as exogenous. Therefore, we cannot use a monetary policy rule to stabilize the model. Instead, we use a risk premium on foreign bond holdings to close the model. The risk-adjusted interest rate is given by $R_t^f \tilde{\phi}\left(nfa_t, e_t^{RP}\right)$. $\tilde{\phi}$ denotes a risk premium on foreign bond holdings $B_{i,t}^f$ similar to Adolfson *et al.* (2007), which is a function of net foreign assets (nfa). $\tilde{\phi}$ has the following functional form:

$$\tilde{\phi}\left(nfa_t, e_t^{RP}\right) = \exp\left(-\phi_a nfa_t + e_t^{RP}\right) \tag{26}$$

When a country is a net borrower, the risk-adjusted interest rate increases. This dampens consumption and investment and brings the net foreign asset position back to zero. When a country is a net lender, it receives a lower interest rate on its savings, which boosts domestic demand. The net foreign asset position of the domestic economy is determined by the trade balance. In the steady state, net foreign assets equal zero. A non-zero net foreign asset position has to be mirrored by foreign bond holdings. Foreign bond holdings evolve according to

$$\frac{B_t^f}{R_t^f \tilde{\phi}\left(nfa_t, e^{RP}\right)} = B_{t-1}^f + P_t X_t - P_T^M M_t. \tag{27}$$

2.5 The log-linear model

The log-linearized version of the model can be found in the appendix. For details on the log-linearization, see Fenz *et al.* (2010). A few issues are worth being mentioned. As mentioned in the beginning of this section, we had to introduce two shocks to ensure stationarity of the state estimates. The first is a shock to net foreign assets e_{nfa}, which are determined by cumulating net exports. Although both exports and imports are stationary, net foreign assets exhibit a unit root. This causes a severe problem, since the transformation from quarterly to monthly frequency assumes stationary states. Hence, the quarterly and the monthly state space form exhibit different dynamics at the monthly compared to the quarterly frequency. This is particularly inconvenient, since the net foreign asset position impacts on both consumption and investment via the risk premium. With an additional shock, the log-linearized equation for net foreign assets becomes

$$\beta\widehat{nfa}_t = \widehat{nfa}_{t-1} + \bar{x}_y(\widehat{e}_{yf,t} - \widehat{m}_t) + \widehat{p}_{d,t} + \widehat{e}_t^{nfa}. \tag{28}$$

The second shock is a shock to relative prices. Since relative prices are cumulated inflation differences, they may also depart from stationarity for a couple of periods, yielding different dynamics of the quarterly and the monthly model.

$$\widehat{p}_{d,t} = \widehat{p}_{d,t-1} + \widehat{\pi}_{d,t} - \widehat{\pi}_t - \widehat{e}_t^{pio} \tag{29}$$

This non-stationarity is taken up by the relative price shock.

2.6 Estimation

As common in the literature, we calibrate a subset of parameters. The bulk of calibrated parameters refers to the steady state values. We set the discount factor β to 0.99, which corresponds to an annual steady state interest rate of 4%. The capital share in the production function (α), is set to 0.31. In addition we have calibrated some parameters, which are difficult to identify. ϕ, the share of fixed costs in production, is set to 0.3. $\tilde{\phi}_a$, the parameter of the risk premium function, is set to 0.007. σ_c is calibrated to 1.5. Regarding the price-setting mechanism, the share of non-adjusters ξ_p and the degree of price-indexation γ_p can not be identified simultaneously. Hence we have calibrated ξ_p to 0.65 and estimated γ_p. We have estimated the model using ten time series for the period 1987Q1 to 2009Q2 (see figure 1) using Bayesian techniques.[10] For output, consumption, investment, exports, imports, hours worked and the real wage we took logs and computed deviations from an HP trend. For domestic and foreign inflation we computed growth rates to the previous period and subtracted a linear trend from them. The (quarterly) interest rate is in levels. We use inverse gamma distributions for shock variances (which have to be greater zero), beta distributions for shock autocorrelations (which are bounded between zero and one) and normal distributions for the remaining parametes. We took 250,000 draws of the Metropolis-Hasting algorithm. Tables 7 and 8 and Figure 2 present the prior and posterior distributions. Figure 2 reveals that some of the parameters cannot be properly identified, since the posterior distributions equal the prior distributions. This is the case for $\sigma_{RP}, \rho_{\pi_f}$, ρ_{RP} and γ_p. Most of the remaining estimation parameters values are reasonable and in line with the literature.

2.7 Variance decomposition and impulse responses

In this subsection we present some properties of the estimated model. Table 9 presents the forecast error variance decomposition of GDP and inflation. GDP is to a large extent driven by foreign demand, proxied by exports. Exports explain more than half of the variation of the GDP. Furthermore, important shocks for GDP are the shock to import adjustment costs and the government spending shock. In the short run, these three shocks explain about 90% of GDP. In the long run, the technology shock is gaining some importance, but demand shocks remain the main driving force of GDP. Inflation of final goods (π) is mostly driven by export demand and imported inflation. Foreign inflation and the shock to import inflation explain about 1/3 of the variance of inflation. Those results are more or less in line with the results of Breuss & Rabitsch (2009) and Breuss & Fornero (2009), who also find an import role of both foreign and domestic demand shocks for Austria. This is a key distinguishing feature of our model compared to similar models for the Euro area (e.g. Christoffel *et al.* (2008)), where GDP is to a larger extent driven by other types of shocks (especially interest rate and risk premium).

Figures 4 to 7 present the impulse response functions of the model to a number of selected shocks. Namely, a technology shock, a consumption preference shock, a price markup shock and an export shock. A positive *technology shock* increases the productivity of the inputs into the production process. This gives firms an incentive to increase investment. Since both consumption and investment adjust sluggishly, labor demand as well as capacity utilization decrease initially. Accordingly, real wages fall. Domestic demand reaches its maximum after one and a half year, leading to small increases of hours worked and the capacity utilization. The fall in the domestic price level increases price competitiveness of domestic production relative to imports and causes imports to fall. In addition, it causes the (nominal) net foreign asset position to deteriorate, resulting in an increase of the risk premium. This drives domestic demand back to the steady state. The *consumption preference shock* changes the preferences of the consumer towards more consumption and less work. The decline of hours worked

[10]For the purpose of variable selection we estimate the model recursively for shorter time spans.

has to be compensated by an increase in capacity utilization. The increase in consumption is to a large extent offset by a fall in investment. Consequently, GDP rises only marginally on impact and declines afterwards, since the capital stock falls. A *markup shock* drives a wedge between the prices of domestic firms and their marginal costs. This leads to an immediate increase of prices. Due to declining real wages, labor supply decreases. The fall of the value of the firm (Tobin's q) causes investment to decline. Since the markup shock is assumed to be i.i.d, its effect on the economy vanishes rather quickly. A positive *export shock* causes prices, real wages as well as the return to capital to increase. This causes firms to increase investment and households to work more. In addition, capacity utilization goes up. Investment reaches its peak after three and a half years and returns to the steady state afterwards. Consumption shows a much weaker and smoother reaction. GDP reaches its maximum on impact and declines afterwards. Compared to similar models such as Smets & Wouters (2003) or the New Area Wide Model of the ECB (Christoffel *et al.* (2008)), our model shows similar responses for the majority of shocks.

3 A framework to incorporate monthly indicators

Based on a statistical framework of Giannone *et al.* (2008), Giannone *et al.* (2009) have proposed a methodology to incorporate monthly indicators into quarterly structural (DSGE) models. The framework builds on a state space representation of a DSGE model by first transforming the state space representation from a quarterly into a monthly frequency. The transformation is performed in such a way that the dynamics of the transformed model are consistent with those of the original quarterly model. The model is then augmented by a bridge equation which links the model's observable variables with a set of monthly economic indicators. The indicators provide up-to-date information on the current state of the economy which is not included in the observable model variables due to publication lags. Given the additional information available, such a framework (utilized properly) should therefore lead to improved short-term forecasts. Moreover, the framework allows for mixed frequency data [11] and is capable of handling unbalanced data samples. These features are achieved by the use of the Kalman filter.

Giannone *et al.* (2009) consider a class of DSGE models with the following state space representation

$$\begin{aligned} S_{t_q} &= \mathcal{T}_\theta S_{t_{q-1}} + \mathcal{B}_\theta \epsilon_{t_q} \\ Y_{t_q} &= \mathcal{M}_\theta(L) S_{t_q}, \end{aligned} \tag{30}$$

where S_{t_q} are state variables, Y_{t_q} are observables which are assumed to be stationary, ϵ_{t_q} are the orthonormal shocks and time is indexed in quarters t_q. Note that B_θ, $\mathcal{M}_\theta(L)$ and $\mathcal{T}_\theta$ are uniquely determined by the vector of model parameters θ. Furthermore, the model and the parameter vector are considered to be given.

First, the model needs to be transformed from a quarterly into a monthly representation. The transformation will enable us to use monthly observables when available (e.g. inflation and interest rates) and later to introduce a bridge equation linking the original system with a set of monthly conjunctural indicators. Define the vector of monthly states as S_{t_m} and the vector of monthly observables as Y_{t_m}.[12] Assuming that some observable variables used for the estimation or for the forecasting are available

[11] Variables available in quarterly frequency are latent in first two months of the quarter.

[12] Note that the monthly observables must be constructed such that the observations at the end of each quarter (March, June, September and December) correspond to the observations with quarterly frequency. This can be achieved by computing three-month moving averages of the data series. For further details see e.g. Giannone *et al.* (2009) or Angelini *et al.* (2008).

on a monthly and some on a quarterly basis, Giannone *et al.* (2009) derive the corresponding monthly representation of the solution as

$$\begin{aligned} S_{t_m} &= \mathcal{T}_m S_{t_{m-1}} + \mathcal{B}_m \epsilon_{m,t_m} \\ Y_{t_m} &= \mathcal{M}_m(L) S_{t_m} + V_{t_m}, \end{aligned} \tag{31}$$

where

$$\mathcal{T}_m = \mathcal{T}_\theta^{1/3} \tag{32}$$

$$vec(\mathcal{B}_m \mathcal{B}_m') = (\mathcal{I} + \mathcal{T}_m \otimes \mathcal{T}_m + \mathcal{T}_m^2 \otimes \mathcal{T}_m^2)^{-1} vec(\mathcal{B}_\theta \mathcal{B}_\theta'). \tag{33}$$

Second, a mechanism for incorporating auxiliary variables into the monthly model is introduced. Denote the auxiliary variables as X, where X_{t_q} is a $k \times 1$ vector, and use the quarterly observations on both Y and X to estimate the parameters (μ, Λ and the variance-covariance matrix of shocks $E(e_{t_q} e_{t_q}') = R$) of the bridge equation[13]

$$X_{t_q} = \mu + \Lambda Y_{t_q} + e_{t_q}. \tag{34}$$

Since the monthly data are transformed as to correspond to the quarterly equivalent at the end of each quarter, the following equation bridges the set of monthly conjunctural indicators with the model observables in the monthly model

$$X_{t_m} = \mu + \Lambda Y_{t_m} + e_{t_m}, \tag{35}$$

where e_{t_m} is such that $var(e_{i,t_m}) = R_{ii}$ if X_{i,t_m} is available and infinity otherwise.

Finally, equation (35) is used to augment the monthly system. Equation system (36) below constitutes a new state space representation that uses monthly observable variables if available and furthermore exploits the information provided by the set of monthly economic indicators

$$\begin{aligned} S_{t_m} &= \mathcal{T}_m S_{t_{m-1}} + \mathcal{B}_m \epsilon_{m,t_m} \\ Y_{t_m} &= \mathcal{M}_m(L) S_{t_m} + V_{t_m} \\ X_{t_m} - \mu &= \Lambda \mathcal{M}_m(L) S_{t_m} + e_{t_m}. \end{aligned} \tag{36}$$

4 Variable selection and forecasting performance

As we will see later, the selection of a proper set of monthly conjunctural indicators is of crucial importance for the forecasting performance of the model. In order to choose systematically from a vast number of available monthly economic indicator we propose three different subset selection algorithms which can be used individually or, in order to achieve better results, in combination with each other. To be more specific, the algorithms employed are *random selection*, *forward stepwise selection* and *forward stepwise selection with deletion (Efroymson-type algorithm)*. In this paper we apply all of the proposed algorithms on a set of 192 pre-selected indicator candidates (see below) and report a number of selected indicator subsets and their forecasting performance.

Unsurprisingly, different algorithms yield a different subset of monthly auxiliary indicators. In order to evaluate the performance of each of the models as close to the real-time situation as possible, we

[13]Standard OLS is used for the estimation of the parameters.

perform a pseudo-forecasting exercise for each of the subsets. We store the root mean square error (RMSE) for each of the subsets and compare the results with the RMSE of the monthly model without auxiliary variables and the quarterly model.[14] Finally, we adopt the best performing subset of auxiliary variables (in the mean square error sense, but verify the results also by the Diebold-Mariano test) and compare its performance with a number of different benchmarks. Namely, we evaluate the performance against a naive forecast, a time-series benchmark model and the OeNB's Economic Indicator.

4.1 Data

Due to the progress in computer technology and the enormous resources put into the construction of statistics, there are hundreds of monthly indicators available that could potentially help to improve GDP forecasts. Since it is neither feasible nor desirable to use all variables in the forecasting framework, it is necessary to select a subset of accessible indicators that would perform the best. Moreover, subset selection is a time-consuming and computer power demanding process which limits the number of variables that we can start the exercise with. Therefore we begin by creating a pre-selected set of variables that we regard as the most likely candidates for improving the forecasting performance for Austrian GDP.

Based on a survey of the literature on short-term forecasting of GDP[15], we have agreed on a set 48 variables that we deemed the most relevant. Austrian, German and Eurozone indicators together with a number of indicators on the economic climate in the U.S. were included. The data set contains variables such as economic sentiment indicators, purchasing manager's indices, ECB reference rates, stock market price indices, money supply, car registrations, vacancies, unemployment rates, industrial production, commodity prices, unemployment, trade, etc. Furthermore, the pre-selected data set has been augmented by introducing leads up to 3 months ahead for each of the variables, leading to a set of 192 candidates.

The complete list of indicators together with their release dates can be found in Appendix B. In Table 4 we provide a short list of model variables and auxiliary variables grouped according to their release dates. Note that there are 27 different release dates spread throughout the quarter; i.e. depending on the set of selected indicators we update the data set at most 27 times and therefore obtain at most 27 different forecasts per quarter. Most monthly indicators are published relatively soon after the end of the corresponding month, whereas almost all the model variables are published only at the quarterly frequency and with significant time lags (with the only exception being the inflation rate). Overall, we use data that range from January 1987 to August 2009 with the majority of series being available from the beginning of the period (only a number of series have a shorter availability). Furthermore, we have stationarized and standardized all auxiliary variables.[16]

[14]Note that the quarterly model is the original DSGE model where we supply the quarterly data according to the release dates and perform the pseudo-forecasting exercise. The monthly model without auxiliary variables is the quarterly model transformed according to GMR without bridging the system with auxiliary variables equation. Furthermore, as the inflation rate and the interest rate are the only variables that are available at the monthly frequency the monthly and quarterly models will differ only because of the information contained in these two variables. All other model variables are latent during first two months of each quarter and have to be estimated by the Kalman filter.

[15]To name some among many, references include e.q. Ruenstler & Sedillot (2003), Schneider & Spitzer (2004), Boivin & Giannoni (2006), Golinelli & Parigi (2007), Barhoumi (2008), Giannone *et al.* (2008) and Schumacher & Breitung (2008).

[16]Note that it is important that all the series used for estimation of the DSGE model as well as all auxiliary variables must be stationary. Should this condition be violated, one would not obtain equivalent dynamics with monthly and quarterly versions of the model. This in turn would lead to distorted GDP forecasts.

4.2 Design of the pseudo real-time forecasting exercise

For the pseudo real-time forecasting exercise, we simulate the data flow for both the observable variables of the model and a given subset of auxiliary indicators. For each of the $T = 20$ last quarters (i.e. 2004Q3 to 2009Q2) and each of the $R = 27$ release dates within a quarter, we construct the data set that was available at that point of time. We re-estimate all economic relations (including the DSGE model) for every quarter. Since we do not have access to a real-time database, we use the latest available vintages of the variables. For each of these release dates within the last T quarters, we forecast the model variables for the current quarter and up to 4 quarters ahead. To assess the forecasting performance of a given set of auxiliary variables, we compute the root mean squared error of real GDP growth for $h = 0, \ldots, 4$ quarters ahead forecasts for all $r = 1, \ldots, 27$ data vintages within a quarter.

4.3 Three algorithms for subset selections

In this subsection we discuss the three methodologies that are used throughout the paper. We employ random selection, forward stepwise selection and forward stepwise selection with deletion (Efroymson-type algorithm) to select the best-performing subset of auxiliary variables from our data set.

The first approach is *random selection.* We choose the variables to be included in the sample by randomly drawing the size as well as the composition of the subset. We assume a uniform probability distribution and therefore every variable faces equal probability of being included in the sample. The main disadvantage of this approach is that it fails to explore the variable space in a systematic manner. On the other hand, it does not run the danger of being trapped in a certain region of the variable space. This fact makes it a good candidate for producing a sample that can be used as a starting point for an Efroymson-type algorithm.

The second approach we use is *forward stepwise selection.* It starts from an empty set and systematically searches through a sub-space of the total variable space. We use each of the candidate variables as a sole auxiliary variable and run the pseudo real-time forecasting exercise. We take the variable which produces the minimum RMSE for GDP. Then we select a second variable from the remaining candidates. We proceed until the forecasting performance deteriorates.[17] This method has the advantage that it permits searching the variables space without prohibitive computing costs. On the other hand there is no guarantee that the subset of p variables that exhibits the best forecasting performance should contain the subset of $(p - 1)$ variables that exhibits the best forecasting performance. Hence the procedure might get trapped in a certain region of the variable space and might fail to find the best subset.

Third, we use *forward selection with deletion* (Efroymson-type algorithm, see Miller (2002)) which is performed after each iteration of the forward selection algorithm. After a new variable has been added, we check whether it is possible to delete any of the already included variables without deteriorating the forecasting performance of the model. The algorithm stops if no variable can be included or deleted without worsening of the results. This method works very well together with the random selection or a number of pure forward selection iterations as a starting point. It usually performs better than pure forward selection, especially in the case of highly correlated variables. The method is computationally more demanding since it performs forward selection and checks for deletion in each iteration.

[17] It is a well-known result that the forecasting performance of a model as a function of the number of predictors shows a convex shape. Schneider & Spitzer (2004) and Boivin & Ng (2006) have shown that for factor models - after a certain threshold - the forecasting performance deteriorates when more data series are included.

4.4 Results of subset selection

In this section we present the results of variable selection procedure. In order to demonstrate the impact of the composition of the subset on the forecasting performance, we offer the results of the pseudo-forecasting exercise for a number of subsets obtained by the use of different strategies. First, we introduce an 'expert-guess' subset, which was selected according to the experience of the authors with short-term forecasting ('DSGE-Exp'). The second subset consisting of 17 indicators was determined by pure forward selection ('DSGE-Fw17'). We found that the forecasting performance deteriorated rather quickly for samples with 18 variables and more. The third subset was determined by the combination of random selection and the Efroymson algorithm, yielding a subsample with seven variables ('DSGE-Efr7'). For the fourth subset, a combination of forward selection (up to 21 variables) and the Efroymson algorithm was utilized ('DSGE-Efr21'). Table 3 in Appendix B lists the composition of the subsets.[18]

In Table 1 we report the average RMSE of the GDP growth rate forecasts for all models. The RMSE is reported for the nowcast of the current quarter and for forecasts up to 4 periods ahead. We find a similar forecasting performance of the quarterly and the monthly model because of the limited additional information in the monthly model (only inflation and interest rates). Adding auxiliary variables to the monthly DSGE model clearly improves the forecasting performance for the current quarter. The percentage gain in RMSE ranges from 13% ('DSGE-Exp') to 66% ('DSGE-Efr21'). For longer forecasting horizons, there is almost no gain of adding monthly indicators to the DSGE model. This is an obvious result, since the indicators are available only contemporaneously.

	'DSGE-Q'	**'DSGE-M'**	**'DSGE-Exp'**	**'DSGE-Fw17'**	**'DSGE-Efr7'**	**'DSGE-Efr21'**
Q0	0.780	0.790	0.682	0.489	0.392	0.362
Q1	0.884	0.885	0.838	0.842	0.811	0.854
Q2	0.917	0.918	0.863	0.855	0.813	0.864
Q3	0.928	0.920	0.881	0.828	0.888	0.873
Q4	0.877	0.877	0.879	0.873	0.903	0.879

Table 1: RMSE for GDP growth for different sets of auxiliary variables

The next step is to look at the forecasting performance for the different release dates of monthly indicators. Therefore we simulate the real-time data flow within a quarter. Figure 8 reveals that for our preferred subset of auxiliary variables ('DSGE-Efr21'), the forecasting performance clearly improves throughout the quarter, whereas for the expert guess subsample there is almost no improvement as new data come in.

4.5 Comparison with benchmark time series models

We compare the best performing model('DSGE-Efr21') with two benchmark models, namely a naive forecast and a time-series forecast. For the naive forecast, we take the last observed quarterly GDP growth rate as the estimate for future growth. For the time-series forecast, we have found that a simple AR(1) forecast works best in predicting Austrian GDP. We find that our DSGE model outperforms the benchmark models for the forecast of the current quarter only. For all other horizons, the benchmarks perform better. We perform a Diebold-Mariano test to check for equal forecast accuracy for the forecast of the current quarter. The null hypothesis is that the DSGE model does not perform better than the respective benchmark model for the current quarter. We can reject that hypothesis at the 5% level

[18]The description of the variables can be also found in the same appendix. The number specified after the name of the variable stands for the lead in months.

for both benchmark models, indicating that the virtue in forecast accuracy for the current quarter is significant.

	'Naive'	'Time Series'	'DSGE-Efr 21'
Q0	0.831	0.841	0.362
Q1	0.799	0.802	0.854
Q2	0.791	0.785	0.864
Q3	0.784	0.773	0.873
Q4	0.789	0.743	0.879

Table 2: RMSE for GDP growth for different models

4.6 Comparison with the OeNB's Economic Indicator

Finally, we compare the forecasting performance of our model with the OeNB's Economic Indicator (EI). The EI is a regular short-term GDP forecast, which is published at a quarterly frequency beginning from the first quarter of 2003. It is based on a combination of the forecasts of an unobserved component model and a dynamic factor model, supplemented by expert judgement (Fenz *et al.* (2005)). It is usually published around the 10th day of each quarter. The forecasting horizon consists of the previous and the currrent quarter.[19] In order to make the competition as fair as possible, we compare the EI's forecast for the current quarter[20] with the corresponding vintage (i.e. vintage 5) of our pseudo real-time forecasting exercise. However, some caveats of this comparison have to be mentioned. One problem that remains is the fact that our pseudo real-time exercise is based on the final release of GDP, whereas the EI is compiled on the basis of the first releases of the GDP series. This clearly penalizes the EI, since we compute the RMSE based on final data. This is especially crucial, since the final GDP series used in our exercise is more volatile than the series that was available for most of the time when the EI was compiled. This is due to the fact that the idiosyncratic component of the seasonally adjusted series, that has been removed in previous vintages, is now included in the series. Another critical point is that the sample included the sharp downturn in GDP in the first quarter of 2009 (-2.7%), which was poorly predicted by all forecasting models. Bearing these caveats in mind, we find that our DSGE model (RMSE=0.508) performs slightly better than the EI (RMSE=0.613), although the difference is not significant (p-value of the Diebold-Mariano test=0.197).

5 A structural interpretation of the forecast

In this section we demonstrate the usability of the model to produce forecasts with a meaningful structural interpretation. We therefore use the currently available GDP data (up to the second quarter of 2009) and produce forecasts for twelve quarters. We begin by interpreting the variance decomposition of the main model variables for the last historical quarters and for the projection horizon. Figure 10 shows the variance decomposition of the detrended growth rates of GDP, consumption, imports and for inflation. For the sake of clarity, we have aggregated the twelve shocks to four groups. Wherease we have one technology shock only, there are four domestic demand shocks (consumption preference, government spending and investment), four price shocks (price markup, labour supply, foreign inflation, shock to relative prices), two interest rate shocks (foreign interet rate, risk premium) and two foreign shocks (export demand and import adjustment costs). The downturn in GDP was mainly driven by

[19]Note that quarterly GDP is published with a delay of 70 days.

[20]This corresponds to a forecasting horizon of two quarters, since GDP for the previous quarter has also to be projected

foreign shocks, especially by the export shock. In addition, the Austrian economy faced a series of negative technology shocks. These shocks are identified by a negative comovement of GDP and real wages. Due to strong increases of agreed wages, real wages rose strongly in the course of 2008. Further negative contributions come from price shocks (i.e. price markup shock and labor supply shock). Similar to the technology shock, price shocks are identified by a negative comovement of output and prices. What distinguishes the two types of shocks is the behavior of hours worked. A positive price shock dampens both output and hours worked, whereas a technology shock drives them into the opposite direction. Due to the introduction of short-time employment schemes ('Kurzarbeit'), hours worked fell less then output. Private consumption was surprisingly strong in the second quarter of 2009, mainly driven by policy measures such as the car scrapping scheme and from low interest rates. Thus policy interventions show up as positive contributions from demand and interest rate shocks. In the first two quarters of the forecasting horizon, private consumption growth will decline, mainly driven by the vanishing contributions from those two shock categories. From the beginning of 2010 onwards, private consumption growth converges to its steady state growth rate (figure 12). Investment activity is declining since the second quarter of 2008, driven by negative contributions of foreign and technology shocks. It is projected to further decline until the second quarter of 2010, since the positive impact of the interest rate decreases fades out. The steep decline of inflation (to the previous quarter) was driven by the shortfall of export demand. It was counteracted by a series of negative technology shocks that pushed up inflation. Since the positive impact of the technology shock fades out, inflation continues to fall before it picks up again in the course of 2010. Figure 11 shows the evolution of the shock innovations and shock processes in the last eight historical quarters. Over the forecasting horizon, the shock innovations are zero. The shock processes gradually return to zero, depending on the shock persistence.

Augmenting this forecast with monthly indicators (figure 13) mainly changes the picture in the first quarter of the projection horizon (2009Q3). The majority of the selected monthly indicators points upwards. The augmented model hence suggests a stronger recovery in the third quarter of 2009. The variance decomposition (figure 10) shows that this is mainly due to a stronger recovery of exports than implied by the dynamics of the DSGE model only. For the following quarters, there is almost no difference in the growth forecast.

6 Conclusion

In this paper we have utilized the methodological framework proposed by Giannone *et al.* (2009) to produce short-term forecasts for the Austrian economy. First, we have built and estimated a medium-scale DSGE model which was then transformed and augmented by a set of monthly economic indicators. The selection of a set of appropriate monthly conjunctural indicators from the bulk of available information is a crucial part of the forecasting exercise. In order to address the issue we have proposed three different methodologies for variable selection. Namely, random selection, forward stepwise selection and Efroymson-type algorithm. The results of a pseudo-forecasting exercise (that simulates the real-time data flow) suggest that the best performance is obtained when an Efroymson-type algorithm is employed after a number of iterations of pure forward stepwise selection.

Augmented by an appropriate set of monthly indicators, the DSGE model clearly outperforms the benchmark models in the very short run. For the forecast of the current quarter, the RMSE is by more than fifty percent lower compared with the DSGE model without auxiliary variables and with the benchmarks. From the second forecasting quarter onwards, there is no extra information that can be utilized to improve the forecasts.

The results suggest that the approach of GMR in combination with a state-of-the-art DSGE model and a properly selected set of indicators provides a promising technique to bridge the gap between the two workhorse forecasting models used in central banks, namely structural (DSGE) models and short-term forecasting tools based on monthly indicators. It allows to produce forecasts with a meaningful structural interpretation that can take advantage of the latest conjunctural information.

Appendices

A Transformation of the state-space representation to the monthly frequency

In this section we derive the parameters of the monthly state space form. In section A.1 we derive the parameters of the monthly state space form of GMR. In section section A.2 we show the additional steps that are necessary to derive these parameters from the DYNARE state space form.

A.1 Derivation of the parameters of the monthly state space form

Recall from section 3 the quarterly state space form

$$\begin{aligned} S_{t_q} &= \mathcal{T}_\theta S_{t_q-1} + \mathcal{B}_\theta \epsilon_{t_q} \\ Y_{t_q} &= \mathcal{M}_\theta(L) S_{t_q}, \end{aligned}$$

Transformed to the monthly frequency, this system becomes

$$\begin{aligned} S_{t_m} &= \mathcal{T}_m S_{t_{m-1}} + \mathcal{B}_m \epsilon_{m,t_m} \\ Y_{t_m} &= \mathcal{M}_m(L) S_{t_m} + V_{t_m}, \end{aligned}$$

where

$$\begin{aligned} \mathcal{T}_m &= \mathcal{T}_\theta^{1/3} \\ vec(\mathcal{B}_m \mathcal{B}_m') &= (\mathcal{I} + \mathcal{T}_m \otimes \mathcal{T}_m + \mathcal{T}_m^2 \otimes \mathcal{T}_m^2)^{-1} vec(\mathcal{B}_\theta \mathcal{B}_\theta'). \end{aligned}$$

Where the transformation of $\mathcal{T}_m$ is obvious, we show the derivation of $\mathcal{B}_m$. We can derive the parameters of the monthly state space form $S_{t_m} = T_m S_{t_m-1} + B_m \varepsilon_{t_m}$ from the parameters of the quarterly state space form $S_{t_q} = T_\theta S_{t_q-1} + B_\theta \varepsilon_{t_q}$. We begin by iterating the monthly state space form

$$S_{t_m} = T_m^3 S_{t_m-3} + B_m \varepsilon_{t_m} + T_m B_m \varepsilon_{t_m-1} + T_m^2 B_m \varepsilon_{t_m-2}$$

At the end of each quarter, $S_{t_q} = S_{t_m}$. Hence

$$T_\theta S_{t_q-1} + B_\theta \varepsilon_{t_q} = T_m^3 S_{t_m-3} + B_m \varepsilon_{t_m} + T_m B_m \varepsilon_{t_m-1} + T_m^2 B_m \varepsilon_{t_m-2}$$

Taking into account that $T_\theta = T_m^3$ gives us

$$B_\theta \varepsilon_{t_q} = B_m \varepsilon_{t_m} + T_m B_m \varepsilon_{t_m-1} + T_m^2 B_m \varepsilon_{t_m-2}$$

In the next step, we multiply each side of the equation by its prime. The shocks ε_{t_q} and ε_{t_m} are assumed to follow orthonormal white noise processes. This implies that $E(\varepsilon_{t_q}\varepsilon'_{t_q}) = I$ $(E(\varepsilon_{t_m}\varepsilon'_{t_m}) = I)$ and $E(\varepsilon_{t_m}\varepsilon'_{t_m-k}) = 0 \;\forall\; k$.

$$B_\theta B'_\theta = B_m B'_m + T_m B_m B'_m T'_m + T^2_m B_m B'_m T^{2'}_m$$

Now we use the following rule for matrix vectorization (see e.g. Dhrymes (2000), p.120):

$$D = ABC \Rightarrow vec(D) = (C' \otimes A)vec(B)$$

$$vec(B_\theta B'_\theta) = \left(I + T_m \otimes T_m + T^2_m \otimes T^2_m\right) vec(B_m B'_m)$$

$$vec(B_m B'_m) = \left(I + T_m \otimes T_m + T^2_m \otimes T^2_m\right)^{-1} vec(B_\theta B'_\theta)$$

We solve this equation for B_m by decomposing the matrix $B_m B'_m$ into its eigenvectors, such that $B_m B'_m = VDV'$, where V is the matrix of eigenvectors and D a diagonal matrix with the corresponding eigenvalues. If $B_m B'_m$ has deficient rank (i.e. the number of shocks is smaller than the number of states), we drop the eigenvectors with zero eigenvalues.[21]

A.2 Transformation of DYNARE decision rules

We use DYNARE to solve and estimate our DSGE model at the quarterly frequency. The first-order approximation of the solution is known as the decision rule and has the following form

$$\mathcal{Y}_{t_q} = A_q \mathcal{Y}_{t_q-1} + B_q u_{t_q}, \tag{37}$$

where $\mathcal{Y}_{t,q}$ is a vector of endogenous model variables and $u_{t,q}$ is an error term. A_q and B_q are coefficient matrices derived from the structural parameters of the model. [22] DYNARE distinguishes between four categories of variables according to their timing in the following order

$$\mathcal{Y}_{t_q} = \begin{bmatrix} \mathcal{Y}_{t_q,ST} \\ \mathcal{Y}_{t_q,PD} \\ \mathcal{Y}_{t_q,PF} \\ \mathcal{Y}_{t_q,FW} \end{bmatrix}, \tag{38}$$

[21]This decomposition is not unique, since B_m can be multiplied by any orthonormal matrix J, such that $B_m JJ' B'_m = B_m B'_m$

[22]In DYNARE, A_q is stored in the variable oo_.dr.ghx and B_g in oo_.dr.ghu

where $\mathcal{Y}_{t_q,ST}$ are static variables (i.e. they appear only at the current period), $\mathcal{Y}_{t,PD}$ are purely predetermined variables (i.e. they appear only at the current and lagged periods), $\mathcal{Y}_{t,PF}$ are variables that are both predetermined and forward-looking (i.e. they appear at the current, future and lagged periods) and $\mathcal{Y}_{t,FW}$ are purely forward-looking variables (i.e. they appear only at the current and future periods). In this form, the decision rule is not suitable for transformation to the monthly frequency. Therefore, some manipulations have to be carried out. First, we split up the DYNARE decision rule (37) into two parts

$$S_{t_q} = A_{s,q} S_{t_q-1} + B_{s,q} u_{t_q} \tag{39}$$

$$Y_{t_q} = A_{y,q} S_{t_q-1} + B_{y,q} u_{t_q}, \tag{40}$$

with $S_{t_q} = \begin{bmatrix} \mathcal{Y}_{t,ST} \\ \mathcal{Y}_{t,FW} \end{bmatrix}$ being the vector of state variables and and $Yt = \begin{bmatrix} \mathcal{Y}_{t,PD} \\ \mathcal{Y}_{t,PF} \end{bmatrix}$ being the vector of other endogenous variables. $A_{s,q}$, $A_{y,q}$, $B_{s,q}$ and $B_{y,q}$ are the respective rows of A_q and B_q. Now we transform (39) to the monthly frequency

$$S_{t_m} = A_{s,m} S_{t_m-1} + B_{s,m} u_{t_m} \tag{41}$$

with $A_{s,m} = A_{s,q}^{1/3}$ and $vec(B_{s_m} B'_{s_m}) = (\mathcal{I} + A_{s,m} \otimes A_{s,m} + A_{s,m}^2 \otimes A_{s,m}^2)^{-1} vec(B_{s,q} B'_{s,q})$. Since the other endogenous variables Y_{t_q} depend on lagged states S_{t_q-1} instead of contemporaneous states S_{t_q} as in (31), we have to shift this equation such that Y_{t_q} depends on the current states. We insert $S_{t_q-1} = A_{s,q}^{-1} \left(S_{t_q} - B_{s,q} u_{t_q} \right)$ into (40) and obtain

$$Y_{t_q} = A_{y,q} A_{s,q}^{-1} S_{t_q} + \left(B_{y,q} - A_{y,q} A_{s,q}^{-1} B_{s,q} \right) u_{t_q} \tag{42}$$

This contemporaneous relationship holds on both the quarterly and monthly level. By changing time subscripts from q to m we get

$$Y_{t_m} = A_{y,q} A_{s,q}^{-1} S_{t_m} + \left(B_{y,q} - A_{y,q} A_{s,q}^{-1} B_{s,q} \right) u_{t_m} \tag{43}$$

As the next step, we re-express Y_{t_m} in terms of lagged monthly states S_{t_m-1} by plugging in the monthly state equation (41) into (43). This gives us

$$Y_{t_m} = A_{y,q} A_{s,q}^{-1} A_{s_m} S_{t_m-1} + \left(A_{y,q} A_{s,q}^{-1} B_{s,m} + B_{y,q} - A_{y,q} A_{s,q}^{-1} B_{s,q} \right) u_{t_m} \tag{44}$$

Finally, we stack the system such that all model variables are treated as states to get rid of the measurement errors in the the observation equation. Instead, we introduce an observation equation that just links the observables to the data by the means of a selection matrix C_m. Our monthly state space form thus becomes

$$S_{t_m} = A_m S_{t_m-1} + B_m u_{t_m} \tag{45}$$

$$Y_{t_m} = C_m S_{t_m}, \tag{46}$$

with

$$\begin{aligned}
A_m &= \begin{bmatrix} A_{s_m} \\ A_{y,q} A_{s,q}^{-1} A_{s_m} \end{bmatrix} \\
B_m &= \begin{bmatrix} B_{s,m} \\ B_{y,q} + A_{y,q} A_{s,q}^{-1} (B_{s,m} - B_{s,q}) \end{bmatrix} \\
A_{s_m} &= A_{s_q}^{1/3} \\
vec(B_{s_m} B'_{s_m}) &= (\mathcal{I} + A_{s,m} \otimes A_{s,m} + A_{s,m}^2 \otimes A_{s,m}^2)^{-1} vec(B_{s,q} B'_{s,q}),
\end{aligned}$$

which is now identical to the monthly state space form of GMR.

B Monthly economic indicators

In Table 3 we list four different samples of economic indicators that have been selected using proposed variable selection methodology and then used for the purposes of this paper. Table 5 below provides a complete list of monthly economic indicators that are considered for being bridged with the monthly model. These are variables that are often found to be relevant for predicting GDP. Column one represents the vintage, column 2 indicates a country to which the variable corresponds to, column 3 provides a short description of variable and finally column 4 indicates the number of days after the end of month when new observation is published. Table 6 lists the abbreviations of auxiliary variables used throughout the paper.

'DSGE-Exp'	**'DSGE-Fw17'**	**'DSGE-fr7'**	**'DSGE-Efr21'**
IFOERW	BAEINKAUFMAN	BAEINKAUFMAN	BAEINKAUFMAN
ECOSEN	EUR/YEN	EUR/YEN	EUR/YEN
BAEINKAUFMAN	EXPG	EMPL	EMPL
PMI	EMPL	DOWJONESIND 3	DOWJONESIND 3
VACANCIES	DOWJONESIND 3	VACANCIES 3	IFOKL 2
CARREG	US10YEARSYIELD 1	EMPL 3	IFOKL
LOANS EA	IFOKL 2	M2	INDPRODNEXTM
	IFOKL		M1
	INDPRODNEXTM		NASDAQ 3
	CARSALES		NASDAQ 2
	M1		M1 2
	NASDAQ 3		OIL1MFWRD 3
	NASDAQ 2		INDPRODNEXTM 3
	M1 2		
	EXPG 1		
	OIL1MFWRD 3		
	INDPRODNEXTM 3		
	INDPROD 1		
	M2 2		
	IMPG 3		

Table 3: Samples of Auxiliary Variables

	Timing	Variables	Publication lag
1	last day of the last month of the previous quarter	IFO, ISE, PMI -at	m
2	1st business day of the 1st month of the quarter	PMI - usa, IR, RR, Oil/Stock prices	m-1
3	5th business day of the 1st month of the quarter	Employment, Vacancies	m-1
4	1st week of the 1st month of the quarter	Trade, Loans	m-3
5	10th day of the 1st month of the quarter	-	-
6	10th business day of the 1st month of the quarter	Wage Index, Inflation	m-1
7	3rd week of the st month of the quarter	New Cars	m-1
8	Last week of the 1st month of the quarter	IP expectations, IP	m-1, m-3
9	last day of the 1st month of the quarter	M1, M2, Unemployment	m-1
10	last day of the 1st month of the quarter	IFO, ISE, PMI -at	m
11	1st business day of the 2nd month of the quarter	PMI - usa, IR, RR, Oil/Stock prices	m-1
12	5th business day of the 2nd month of the quarter	Employment, Vacancies	m-1
13	1st week of the 2nd month of the quarter	Trade, Loans	m-3
14	10th day of the 2nd month of the quarter	-	-
15	10th business day of the 2nd month of the quarter	Wage Index, Inflation	m-1
16	3rd week of the 2nd month of the quarter	New Cars	m-1
17	Last week of the 2nd month of the quarter	IP expectations, IP	m-1, m-3
18	last day of the 2nd month of the quarter	M1, M2, Unemployment, C	m-1, C q-1
19	last day of the 2nd month of the quarter	IFO, ISE, PMI -at	m-1
20	1st business day of the 1st month of the quarter	PMI - usa, IR, RR, Oil/Stock prices	m
21	5th business day of the 3rd month of the quarter	Employment, Vacancies	m-1
22	1st week of the 3rd month of the quarter	Trade, Loans	m-3
23	10th day of the 3rd month of the quarter	GDP, World Demand	q-1
24	10th business day of the 3rd month of the quarter	Wage Index, Inflation	m-1
25	3rd week of the 3rd month of the quarter	New Cars	m-1
26	Last week of the 3rd month of the quarter	IP expectations, IP	m-1, m-3
27	last day of the 3rd month of the quarter	M1, M2, Unemployment	m-1

Table 4: Data releases, both auxiliary and model observable variables

	Variable	Time lag
1	IFO business climate index for Germany	at the latest the last day of the month
2	IFO business situation in Germany	at the latest the last day of the month
3	IFO business expectations for Germany	at the latest the last day of the month
4	Economic Sentiment Indicator	at the latest the last day of the month
5	Economic Sentiment Indicator - Industry	at the latest the last day of the month
6	Economic Sentiment Indicator - Construction	at the latest the last day of the month
7	Economic Sentiment Indicator - Retail	at the latest the last day of the month
8	Economic Sentiment Indicator - Industry, EZ	at the latest the last day of the month
9	Economic Sentiment Indicator - Consumer sentiment	at the latest the last day of the month
10	Bank Austria Purchasing Managers' Index	at the latest the last day of the month
11	PMI Purchasing Managers' Index - USA	first working day of following month
12	Interest Rate, 3-month Euribor	first working day of following month
13	ECB Reference Rates EUR/GBP	first working day of following month
14	ECB Reference Rates EUR/USD	first working day of following month
15	ECB Reference Rates EUR/JPY	first working day of following month
16	Crude Oil Price, USD per Barrel	first working day of following month
17	Oil Price, Brent Crude, 1 Month in Advance, USD/Barr	first working day of following month
18	Stock Exchange Prices, Dow Jones Euro Stoxx	first working day of following month
19	Stock Exchange Prices, Nasdaq	first working day of following month
20	Stock Exchange Prices, Austrian Traded Index	first working day of following month
21	Stock Exchange Prices, Dow Jones Industrial	first working day of following month
22	Stock Exchange Prices, DAX	first working day of following month
23	Yield, US Treasury Notes and Bonds, 10 Years - USA	5th business day of the following month
24	Employees, dependent employment	5th business day of the following month
25	Employees, dependent employment, SA	5th business day of the following month
26	Vacancies	5th business day of the following month
27	Open training positions	5th business day of the following month
28	Wholesale Price Index	5th business day of the following month
29	Retail trade, excl.cars - USA	10th business day of the following month
30	Wage Index	10th business day of the following month
31	Wage Index, Employees	10th business day of the following month
32	Consumer Prices Index	2 weeks after the end of the month
33	Capacity utilization, manufacturing - USA	2 weeks after the end of the month
34	New cars registration, pieces	2 weeks after the end of the month
35	Industry production expectations over next months	Last week of the following month
36	M1	at the latest the last day of the next month
37	M2	at the latest the last day of the next month
38	Unemployment rate, national definition	Last day of the following month
39	Unemployment rate, national definition , SA	Last day of the following month
40	Exports	1st week 3rd month
41	Imports	1st week 3rd month
42	Trade, wholesale trade (without Cars), Nominal Index	1st week 3rd month
43	Trade, wholesale trade (without Cars), Real Index	1st week 3rd month
44	Retail (without cars and gas stations), Real Index	1st week 3rd month
45	Loans - Households + Enterprises	1st week 3rd month
46	Loans - Households	1st week 3rd month
47	Loans - Enterprises	1st week 3rd month
48	Industrial production, w/o Construction and Energy	t+85

Table 5: Monthly economic indicators

	Abbreviation	Variable Name
1	IFOKL	IFO business climate index for Germany
2	IFOGL	IFO business situation in Germany
3	IFOERW	IFO business expectations for Germany
4	ECOSEN	Economic Sentiment Indicator
5	INDSEN	Economic Sentiment Indicator - Industry
6	EBAUSE	Economic Sentiment Indicator - Construction
7	EHANSE	Economic Sentiment Indicator - Retail
8	EINDSE ER1	Economic Sentiment Indicator - Industry, EUROZONE
9	EKONSE	Economic Sentiment Indicator - Consumer sentiment
10	BAEINKAUFMAN	Bank Austria Purchasing Managers' Index
11	PMI	PMI Purchasing Managers' Index - USA
12	HEEAXM32	Interest Rate, 3-month Euribor
13	EUR GBP	ECB Reference Rates EUR/GBP
14	EUR USD	ECB Reference Rates EUR/USD
15	EUR YEN	ECB Reference Rates EUR/JPY
16	OIL	Crude Oil Price, USD per Barrel
17	OIL1MFWRD	Oil Price, Brent Crude, 1 Month in Advance, USD per Barrel
18	DOWJONES	Stock Exchange Prices, Dow Jones Euro Stoxx
19	NASDAQ	Stock Exchange Prices, Nasdaq
20	ATX	Stock Exchange Prices, Austrian Traded Index
21	DOWJONESIND	Stock Exchange Prices, Dow Jones Industrial
22	DAX	Stock Exchange Prices, DAX
23	US10YEARSYIELD	Yield, US Treasury Notes, Bonds, 10 Years - USA
24	STANDR	Employees, dependent employment
25	EMPL	Employees, dependent employment, SA
26	VACANCIES	Vacancies
27	OFLEHRSTG	Open training positions
28	GHPIG	Wholesale Price Index
29	USRETAILTR	Retail trade, excl.cars - USA
30	TLIG86	Wage Index
31	TLIANG86	Wage Index, Employees
32	VPIG86	Consumer Prices Index
33	USCAPUTILMAN	Capacity utilization, manufacturing - USA
34	CARREG	New cars registration, pieces
35	INDPRODNEXTM	Industry production expectations over next months
36	M1	M1
37	M2	M2
38	URXNSA	Unemployment rate, national definition
39	URXSA	Unemployment rate, national definition , SA
40	EXPG	Exports
41	IMPG	Imports
42	WHOLESALE	Trade, wholesale trade (without Cars), Nominal Index
43	CARSALES	Trade, wholesale trade (without Cars), Real Index
44	RETAIL	Retail (without cars and gas stations), Real Index
45	LOANS EA	Loans - Households + Enterprises
46	LOANS EA HH	Loans - Households
47	LOANS EA FIRM	Loans - Enterprises
48	INDPROD	Industrial production, without Construction and Energy

Table 6: Monthly economic indicators - abbreviations

C The DSGE model in detail

C.1 Endogenous variables

$\widehat{c}$	Consumption
$\widehat{h}$	Hours worked
$\widehat{i}$	Investment
$\widehat{k}$	Capital stock
$\widehat{\lambda}$	Marginal value of consumption
$\widehat{m}$	Import
$\widehat{nfa}$	Net foreign assets
$\widehat{\pi}$	Inflation of final good
$\widehat{\pi}_d$	Inflation of domestically produced goods
$\widehat{p}_d$	Relative price of domestically produced goods
$\widehat{q}$	Value of one unit of capital today
$\widehat{r}_k$	Return on capital
$\widehat{w}$	Real wage
$\widehat{y}$	Output
$\widehat{z}$	Capacity utilization

Observable shock processes

$\widehat{G}$	Government spending
$\widehat{\pi}_f$	Foreign inflation
$\widehat{R}_f$	World interest rate
$\widehat{x}$	Exports

Unobservable shock processes

$\widehat{e}^a$	Technology
$\widehat{e}^m$	Import adjustment costs
$\widehat{e}^b$	Preference
$\widehat{e}_i$	Investment
$\widehat{e}^L$	Labor supply
$\widehat{e}^\lambda$	Price markup domestic
$\widehat{e}^{RP}$	Risk premium
$\widehat{e}^{pio}$	Relative prices
$\widehat{e}^{nfa}$	Net foreign assets

C.2 Exogenous variables

$\hat{\epsilon}^a$	Technology
$\hat{\epsilon}^m$	Import adjustment costs
$\hat{\epsilon}^b$	Preference
$\hat{\epsilon}^G$	Government spending
$\hat{\epsilon}^i$	Investment
$\hat{\epsilon}^L$	Labour supply
$\hat{\epsilon}^\lambda$	Price markup domestic
$\hat{\epsilon}^R$	Foreign interest rate
$\hat{\epsilon}^{yf}$	Export demand
$\hat{\epsilon}^{RP}$	Risk premium
$\hat{\epsilon}^{nfa}$	Net foreign assets
$\hat{\epsilon}^{pio}$	Relative prices
$\hat{\epsilon}^{\pi f}$	World inflation

C.3 Parameters

Fixed parameters	
α	Technology
β	Discount factor
σ_c	Coefficient of relative risk aversion of households
τ	Depreciation rate of capital
Estimated parameters	
χ	Inverse of second derivative of investment adjustment cost function
chi_m	Import adjustment costs
γ_p	Degree of indexation for goods prices
κ	Degree of habit formation
$\bar{\phi}$	Share of fixed cost in production
ψ	Parameter of capital utilisation function
$\tilde{\phi}_a$	Risk premium on foreign bond holdings
σ^L	Inverse intertemporal elasticity of labour supply
ξ_p	Calvo parameter (share of non-adjusters) for prices
σ_m	Price elasticity of imports
Autoregressive parameters	
ρ_a	Persistence stationary technology shock
ρ_b	Persistence preference shock
ρ_g	Persistence government spending shock
ρ_i	Persistence investment shock
ρ_l	Persistence labour supply shock
ρ_λ	Persistence markup shock
ρ_μ	Persistence import preference shock
ρ_{nfa}	Persistence net foreign assets shock
ρ_{π_f}	Persistence foreign inflation shock
ρ_{π_o}	Persistence relative price shock
ρ_r	Persistence interest rate shock
ρ_{rp}	Persistence risk premium shock
ρ_{yf}	Persistence world demand shock
Steady state values	
$\bar{c}_y$	Steady state consumption
$\bar{g}_y$	Steady state government consumption
$\bar{k}_y$	Steady state capital stock
$\bar{i}_y$	Steady state investment
$\bar{r}_k$	Steady state return on capital
$\bar{x}_y$	Steady state exports

C.4 Composite parameters

Steady state return on capital

$$\bar{r}_k = 1/\beta - 1 + \tau$$

Capital to GDP ratio

$$\bar{k}_y = \bar{i}_y/\tau$$

C.5 The log-linearized model

Phillips curve for domestically produced goods

$$\begin{aligned}\widehat{\pi}_{d,t} &= (\beta/(1+\beta\gamma_p))\widehat{\pi}_{d,t+1} + (\gamma_p/(1+\beta\gamma_p))\widehat{\pi}_{d,t-1} \\ &+(1-\beta\xi_p)(1-\xi_p)/((1+\beta\gamma_p)\xi_p)(\alpha/\psi\widehat{z}_t + (1-\alpha)\widehat{w}_t - \widehat{e}^a_t - \widehat{p}_{d,t}) + \widehat{e}^\lambda_t \end{aligned} \tag{47}$$

Evolution of relative prices

$$\widehat{p}_{d,t} = \widehat{p}_{d,t-1} + \widehat{\pi}_{d,t} - \widehat{\pi}_t - \widehat{e}^{pio}_t \tag{48}$$

Evolution of domestic inflation

$$\widehat{\pi}_t = 1/(1+\bar{x}_y)\widehat{\pi}_{d,t} + \bar{x}_y/(1+\bar{x}_y)\widehat{\pi}_{f,t} \tag{49}$$

Capital accumulation

$$\widehat{k}_t = (1-\tau)\widehat{k}_{t-1} + \tau\widehat{i}_t \tag{50}$$

Marginal utility of consumption

$$\widehat{\lambda}_t = 1/(1-\rho_b)\widehat{e}^b_t - \sigma_c/(1-\kappa)(\widehat{c}_t - \kappa\widehat{c}_{t-1}) \tag{51}$$

Euler equation

$$\widehat{\lambda}_t - \widehat{\lambda}_{t+1} = \widehat{R}_{f,t} - \widehat{\pi}_{t+1} - \tilde{\phi}_a(\widehat{nfa}_t - \widehat{e}^{RP}_t) \tag{52}$$

Investment

$$\widehat{i}_t = 1/(1+\beta)\widehat{i}_{t-1} + \beta/(1+\beta)\widehat{i}_{t+1} + \chi/(1+\beta)\widehat{q}_t + \widehat{e}_{i,t} \tag{53}$$

Tobin's q equation

$$\widehat{q}_t = \widehat{\lambda}_{t+1} - \widehat{\lambda}_t + (1-\tau)\beta\widehat{q}_{t+1} + \bar{r}_k\beta\widehat{r}_{k,t+1} \tag{54}$$

Capital utilization rate

$$\widehat{z}_t = \psi\widehat{r}_{k,t} \tag{55}$$

Labour demand

$$\widehat{w}_t + \widehat{h}_t = \widehat{r}_{k,t} + \widehat{z}_t + \widehat{k}_{t-1} \tag{56}$$

Optimal working hours

$$\widehat{w}_t = \widehat{e}_t^L + \sigma^L \widehat{h}_t + \sigma_c/(1-\kappa)(\widehat{c}_t - \kappa \widehat{c}_{t-1}) \tag{57}$$

Production function for domestically produced goods

$$\widehat{y}_t = (1+\bar{\phi})(\widehat{e}_t^a + (1-\alpha)\widehat{h}_t + \alpha(\widehat{z}_t + \widehat{k}_{t-1})) \tag{58}$$

Market clearing for final goods

$$\widehat{y}_t = \bar{c}_y \widehat{c}_t + \bar{i}_y \widehat{i}_t + \bar{g}_y \widehat{G}_t + \bar{x}_y(\widehat{x}_t - \widehat{m}_t) \tag{59}$$

Relative import demand with adjustment costs

$$\begin{aligned}(1+1/\bar{x}_y)\widehat{p}_{d,t} &= (1+\sigma_m)/\sigma_m(-\widehat{y}_t + \widehat{m}_t) \\ &\quad -2\bar{x}_y chi_m(\widehat{y}_t - \widehat{m}_t - \widehat{y}_{t-1} + \widehat{m}_{t-1} + \widehat{e}_t^m) \\ &\quad -2chi_m(\widehat{y}_t - \widehat{m}_t - \widehat{y}_{t-1} + \widehat{m}_{t-1} + \widehat{e}_t^m)\end{aligned} \tag{60}$$

Evolution of net foreign assets

$$\beta \widehat{nfa}_t = \widehat{nfa}_{t-1} + \bar{x}_y(\widehat{x}_t - \widehat{m}_t) + \widehat{p}_{d,t} + \widehat{e}_t^{nfa} \tag{61}$$

Technology shock

$$\widehat{e}_t^a = \rho_a \widehat{e}_{t-1}^a + \hat{\epsilon}_t^a \tag{62}$$

Preference shock

$$\widehat{e}_t^b = \rho_b \widehat{e}_{t-1}^b + \hat{\epsilon}_t^b \tag{63}$$

Labour supply shock

$$\widehat{e}_t^L = \rho_l \widehat{e}_{t-1}^L + \hat{\epsilon}_t^L \tag{64}$$

Price markup shock

$$\widehat{e}_t^\lambda = \rho_\lambda \widehat{e}_{t-1}^\lambda + \hat{\epsilon}_t^\lambda \tag{65}$$

Home bias shock

$$\widehat{e}_t^m = \rho_\mu \widehat{e}_{t-1}^m + \hat{\epsilon}_t^m \tag{66}$$

Risk premium shock

$$\widehat{e}_t^{RP} = \rho_{rp}\widehat{e}_{t-1}^{RP} + \hat{\epsilon}_t^{RP} \tag{67}$$

Government spending shock

$$\widehat{G}_t = \rho_g \widehat{G}_{t-1} + \hat{\epsilon}_t^{G} \tag{68}$$

Investment shock

$$\widehat{e}_{i,t} = \rho_i \widehat{e}_{i,t-1} + \hat{\epsilon}_t^{i} \tag{69}$$

World price shock

$$\widehat{\pi}_{f,t} = \rho_{\pi_f} \widehat{\pi}_{f,t-1} + \hat{\epsilon}^{\pi_{f,t}} \tag{70}$$

World interest rate

$$\widehat{R}_{f,t} = \rho_r \widehat{R}_{f,t-1} + \hat{\epsilon}_t^{R} \tag{71}$$

World demand (export) shock

$$\widehat{x}_t = \rho_{yf} \widehat{x}_{t-1} + \hat{\epsilon}_t^{yf} \tag{72}$$

Net foreign assets shock

$$\widehat{e}_t^{nfa} = \rho_{nfa}\widehat{e}_{t-1}^{nfa} + \hat{\epsilon}_t^{nfa} \tag{73}$$

Relative prices shock

$$\widehat{e}_t^{pio} = \rho_{\pi_o}\widehat{e}_{t-1}^{pio} + \hat{\epsilon}_t^{pio} \tag{74}$$

D Tables

	Prior mean	Posterior mean	Confidence	intervall	Prior type	Prior Stddev
ρ_a	0.75	0.7603	0.6997	0.8221	beta	0.05
ρ_b	0.7	0.5662	0.4805	0.6479	beta	0.1
ρ_G	0.6	0.7168	0.6599	0.7693	beta	0.05
ρ_i	0.5	0.4530	0.3748	0.5255	beta	0.05
ρ_L	0.5	0.6367	0.5779	0.7004	beta	0.05
ρ_{mu}	0.5	0.7162	0.6545	0.781	beta	0.1
ρ_{pif}	0.2	0.2029	0.1294	0.2739	beta	0.05
ρ_R	0.5	0.7668	0.708	0.8278	beta	0.1
ρ_{RP}	0.5	0.5022	0.3214	0.6794	beta	0.1
ρ_{yf}	0.93	0.8663	0.8402	0.8924	beta	0.05
ρ_{pio}	0.75	0.6009	0.5247	0.6746	beta	0.05
κ	0.8	0.7823	0.7671	0.797	norm	0.01
γ_p	0.3	0.3002	0.2836	0.3175	norm	0.01
ϕ	0.55	0.6769	0.6007	0.7577	norm	0.05
ψ	1.3	1.4202	1.2582	1.5751	norm	0.1
σ_L	3	3.4989	2.8241	4.1907	norm	0.5

Table 7: Estimation results for structural parameters

	Prior mean	Posterior mean	Confidence	intervall	Prior type	Prior Stddev
ϵ_a	0.3	0.2663	0.2312	0.3020	invg	Inf
ϵ_b	2.0	0.5499	0.4179	0.6674	invg	Inf
ϵ_G	3.0	2.272	1.9819	2.5356	invg	Inf
ϵ_i	1.5	0.2263	0.1893	0.2644	invg	Inf
ϵ_L	1.5	1.7166	1.4540	1.9635	invg	Inf
ϵ_λ	1	0.2299	0.1855	0.2697	invg	Inf
ϵ_μ	0.2	1.8614	1.6139	2.1285	invg	Inf
$\epsilon_{\pi f}$	1.0	0.322	0.2796	0.3611	invg	Inf
ϵ_R	0.35	0.1154	0.101	0.1310	invg	Inf
ϵ_{RP}	20	13.8619	4.7574 2	3.1389	invg	Inf
ϵ_{yf}	3.0	1.6412	1.4260	1.8439	invg	Inf
ϵ_{nfa}	1.0	2.5714	1.6520	3.5829	invg	Inf
ϵ_{π_o}	1.0	0.1771	0.1433	0.212	invg	Inf

Table 8: Estimation results for shock variances

Forecasting horizon: 1 quarter

	y	**c**	**i**	**m**	**h**	**w**	**pi**	**pi**$_d$
ϵ_a	0.004	0.000	0.011	0.002	0.179	0.068	0.069	0.082
ϵ_m	0.161	0.050	0.036	0.174	0.043	0.094	0.083	0.098
ϵ_b	0.001	0.462	0.015	0.007	0.131	0.114	0.029	0.035
ϵ_G	0.108	0.005	0.014	0.079	0.098	0.018	0.004	0.005
ϵ_i	0.008	0.002	0.330	0.006	0.011	0.001	0.000	0.000
ϵ_L	0.003	0.000	0.009	0.001	0.354	0.184	0.049	0.058
ϵ_λ	0.004	0.002	0.005	0.002	0.000	0.003	0.064	0.076
ϵ_R	0.004	0.044	0.084	0.006	0.005	0.017	0.008	0.010
ϵ_{yf}	0.678	0.247	0.215	0.707	0.163	0.421	0.323	0.381
ϵ_{RP}	0.000	0.004	0.003	0.000	0.001	0.001	0.000	0.000
ϵ_{nfa}	0.005	0.102	0.145	0.015	0.015	0.035	0.036	0.043
ϵ_{pio}	0.018	0.071	0.122	0.000	0.002	0.038	0.153	0.181
ϵ_{pif}	0.006	0.010	0.011	0.001	0.000	0.007	0.180	0.032
Sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Forecasting horizon: 4 quarters

	y	**c**	**i**	**m**	**h**	**w**	**pi**	**pi**$_d$
ϵ_a	0.033	0.002	0.030	0.006	0.142	0.045	0.053	0.058
ϵ_m	0.199	0.059	0.040	0.081	0.093	0.132	0.089	0.098
ϵ_b	0.001	0.329	0.031	0.010	0.091	0.075	0.020	0.022
ϵ_G	0.059	0.011	0.027	0.027	0.080	0.011	0.003	0.004
ϵ_i	0.013	0.006	0.181	0.006	0.020	0.001	0.000	0.000
ϵ_L	0.019	0.003	0.017	0.003	0.340	0.124	0.034	0.037
ϵ_λ	0.007	0.003	0.004	0.001	0.003	0.005	0.040	0.044
ϵ_R	0.007	0.038	0.077	0.013	0.003	0.017	0.007	0.008
ϵ_{yf}	0.597	0.325	0.268	0.792	0.197	0.482	0.339	0.373
ϵ_{RP}	0.000	0.002	0.001	0.000	0.000	0.001	0.000	0.000
ϵ_{nga}	0.013	0.158	0.223	0.060	0.012	0.054	0.045	0.050
ϵ_{pio}	0.044	0.058	0.094	0.000	0.015	0.047	0.242	0.266
ϵ_{pif}	0.009	0.006	0.006	0.001	0.004	0.007	0.128	0.039
Sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Forecasting horizon: 12 quarters

	y	**c**	**i**	**m**	**h**	**w**	**pi**	**pi**$_d$
ϵ_a	0.060	0.002	0.020	0.005	0.133	0.036	0.057	0.062
ϵ_m	0.174	0.091	0.083	0.053	0.092	0.130	0.090	0.099
ϵ_b	0.002	0.149	0.024	0.004	0.085	0.060	0.023	0.025
ϵ_G	0.046	0.013	0.026	0.010	0.075	0.010	0.004	0.005
ϵ_i	0.012	0.007	0.062	0.003	0.021	0.001	0.001	0.001
ϵ_L	0.025	0.002	0.009	0.002	0.347	0.098	0.037	0.040
ϵ_λ	0.006	0.001	0.001	0.001	0.004	0.004	0.039	0.042
ϵ_R	0.008	0.017	0.034	0.007	0.004	0.014	0.010	0.011
ϵ_{yf}	0.588	0.476	0.416	0.806	0.194	0.527	0.332	0.364
ϵ_{RP}	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000
ϵ_{nga}	0.028	0.216	0.287	0.108	0.017	0.074	0.045	0.049
ϵ_{pio}	0.043	0.023	0.034	0.001	0.024	0.039	0.241	0.264
ϵ_{pif}	0.007	0.002	0.002	0.000	0.004	0.006	0.122	0.037
Sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Forecasting horizon: 20 quarters

	y	**c**	**i**	**m**	**h**	**w**	**pi**	**pi**$_d$
ϵ_a	0.055	0.002	0.015	0.006	0.127	0.033	0.056	0.061
ϵ_m	0.168	0.108	0.109	0.066	0.095	0.129	0.090	0.099
ϵ_b	0.002	0.089	0.015	0.003	0.082	0.053	0.023	0.025
ϵ_G	0.043	0.011	0.018	0.008	0.073	0.009	0.004	0.005
ϵ_i	0.011	0.005	0.040	0.003	0.020	0.001	0.001	0.001
ϵ_L	0.023	0.002	0.007	0.002	0.333	0.088	0.036	0.040
ϵ_λ	0.006	0.001	0.001	0.001	0.004	0.004	0.038	0.042
ϵ_R	0.007	0.011	0.023	0.006	0.004	0.013	0.010	0.011
ϵ_{yf}	0.598	0.544	0.493	0.786	0.206	0.546	0.336	0.368
ϵ_{RP}	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000
ϵ_{nga}	0.042	0.212	0.253	0.115	0.029	0.082	0.046	0.051
ϵ_{pio}	0.039	0.015	0.025	0.003	0.023	0.035	0.238	0.260
ϵ_{pif}	0.007	0.001	0.002	0.000	0.004	0.005	0.120	0.037
Sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 9: Forecast error variance decomposition

E Figures

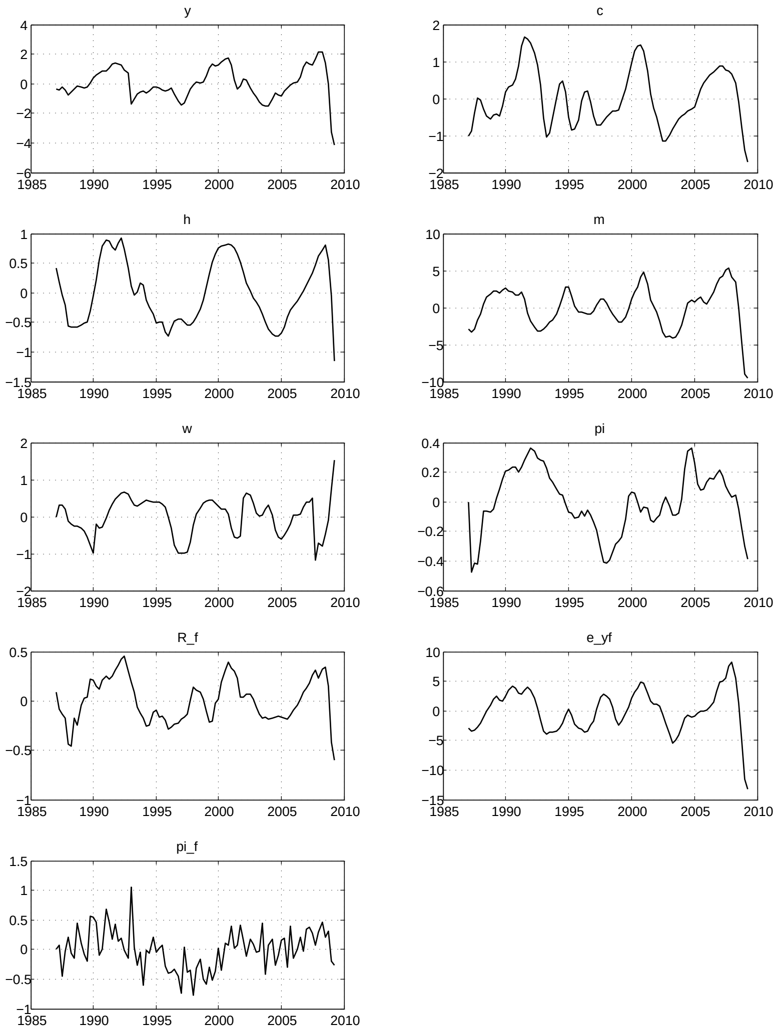


Figure 1: Historical data series

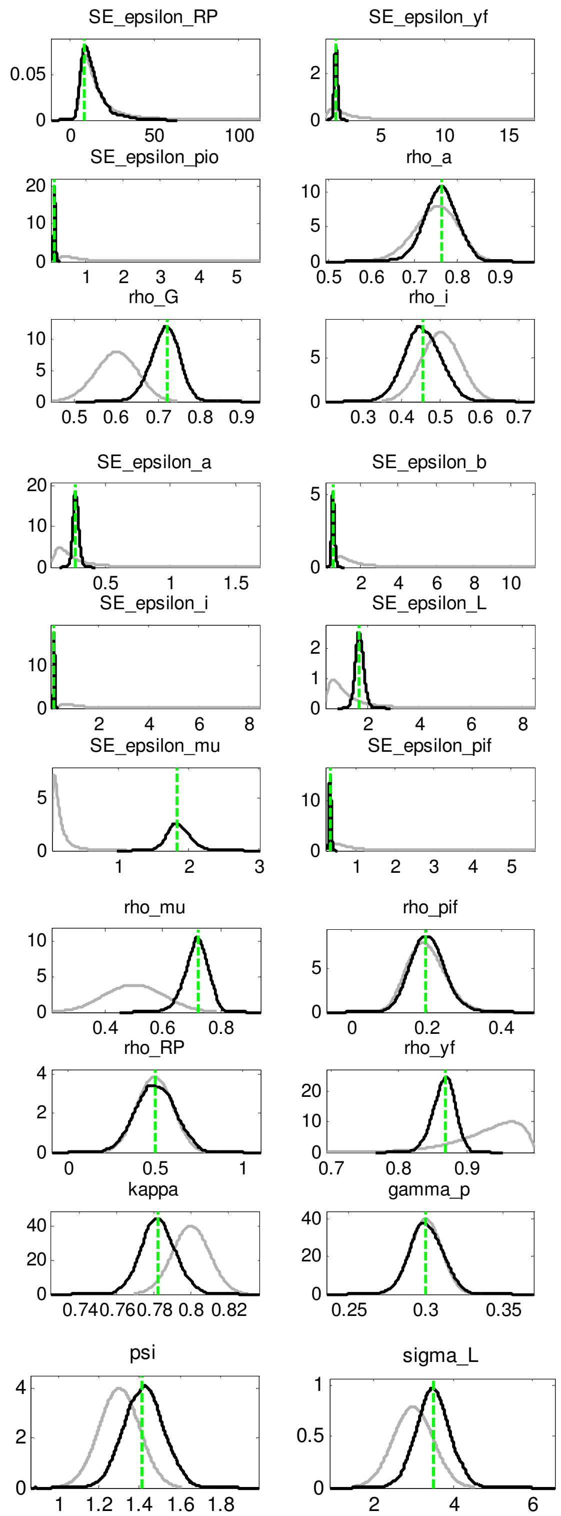


Figure 2: Priors and posteriors

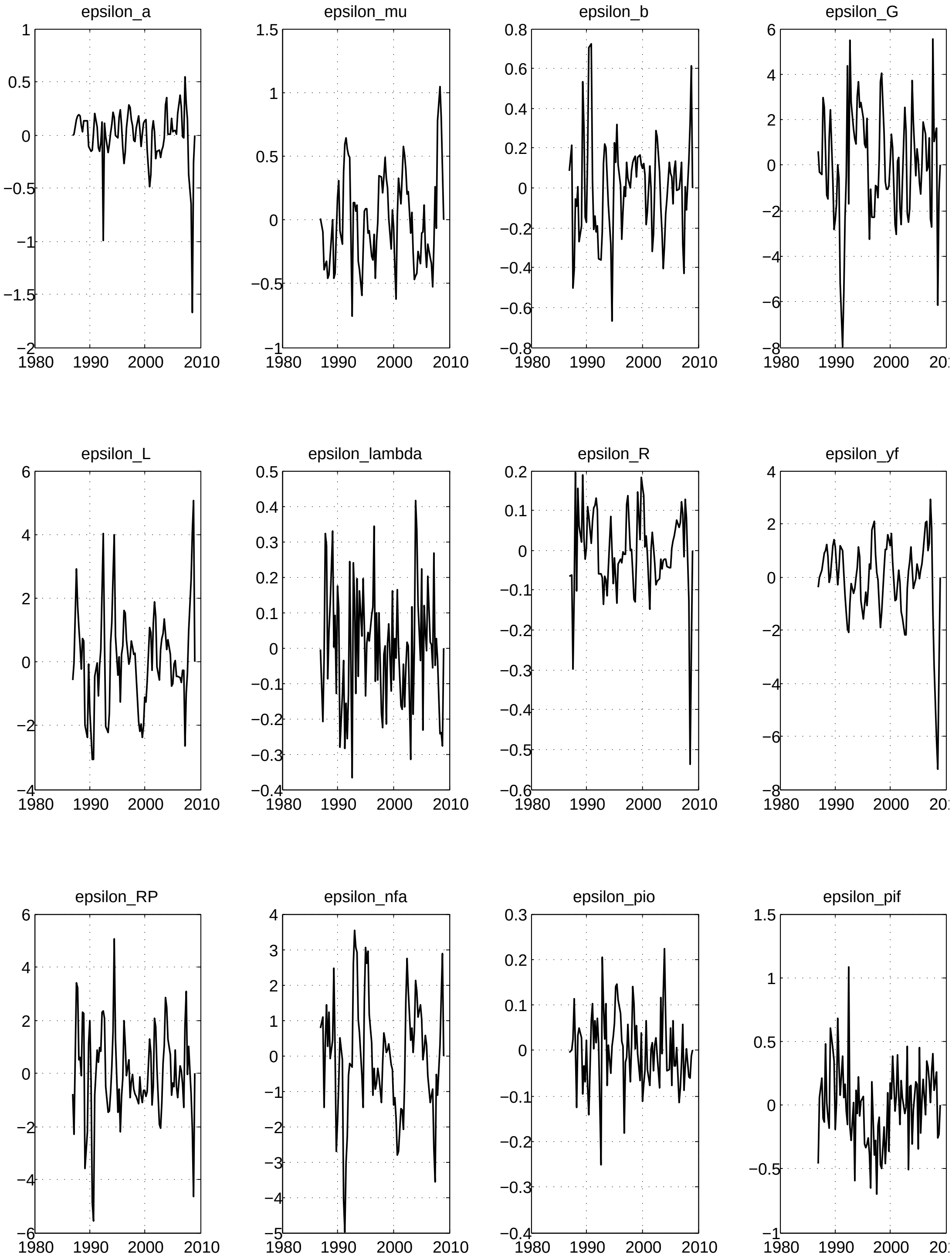


Figure 3: Smoothed Shocks

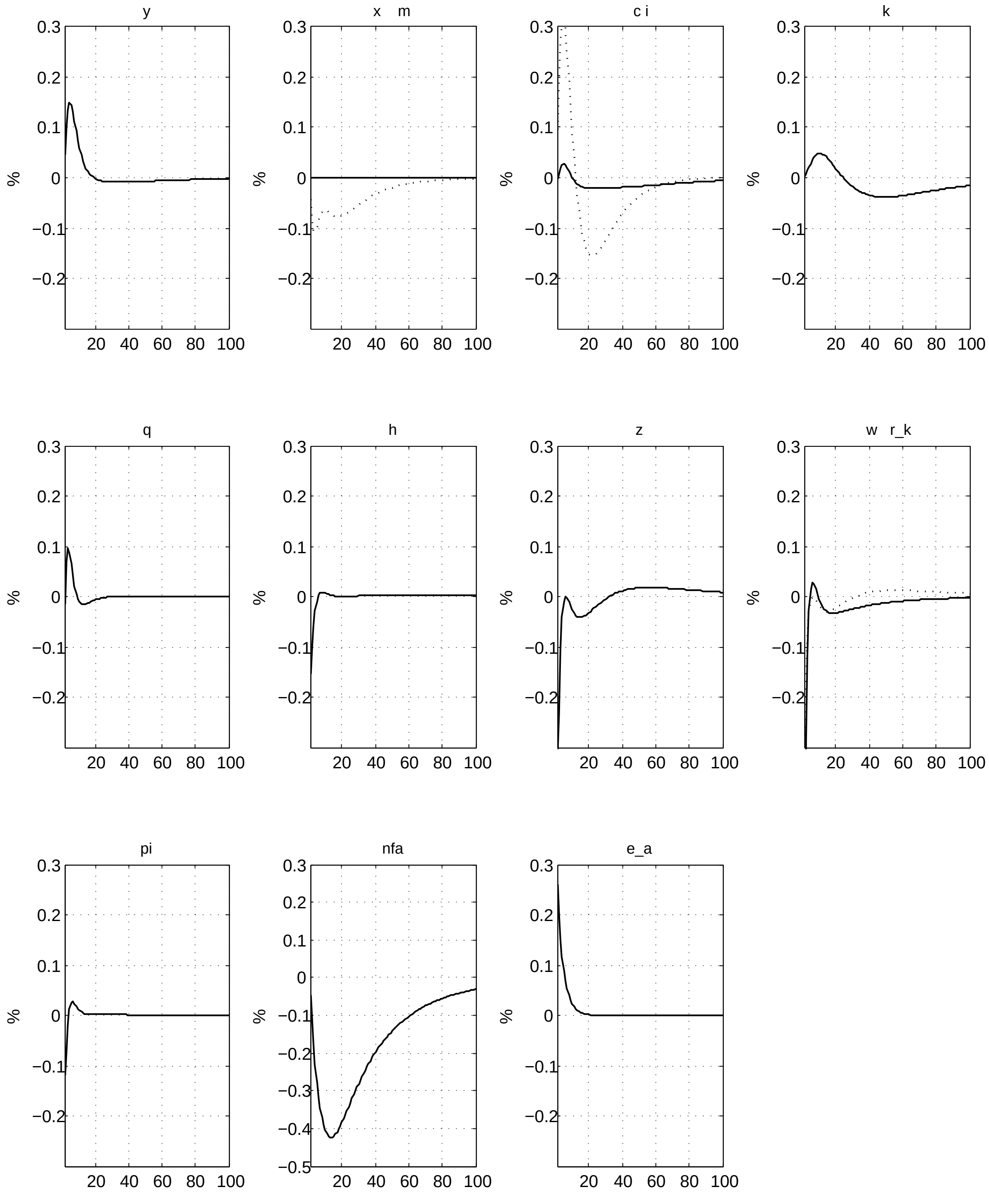


Figure 4: Impulse responses for a technology shock (ϵ_a)

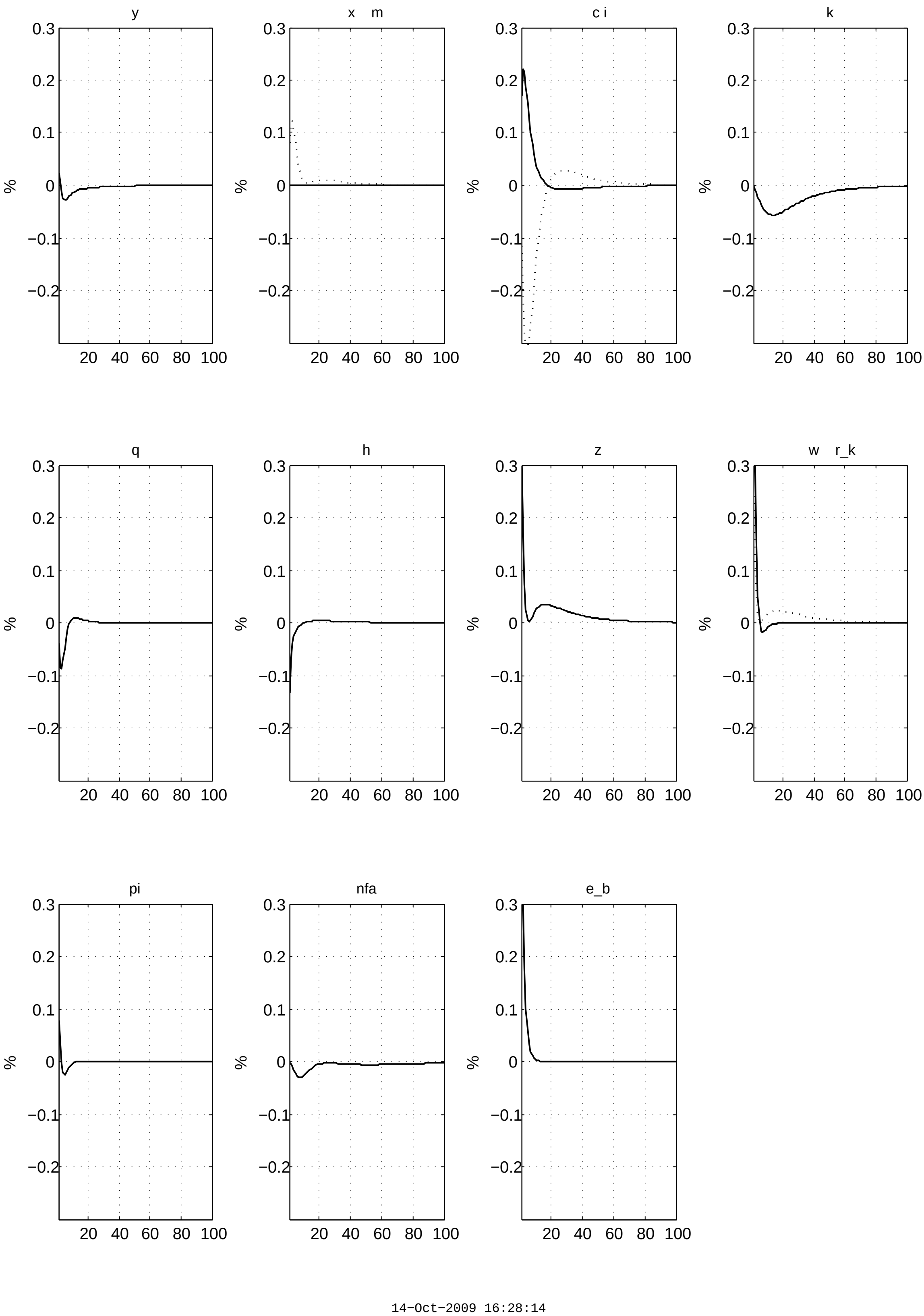


Figure 5: Impulse responses for a consumption preference shock(ϵ_b)

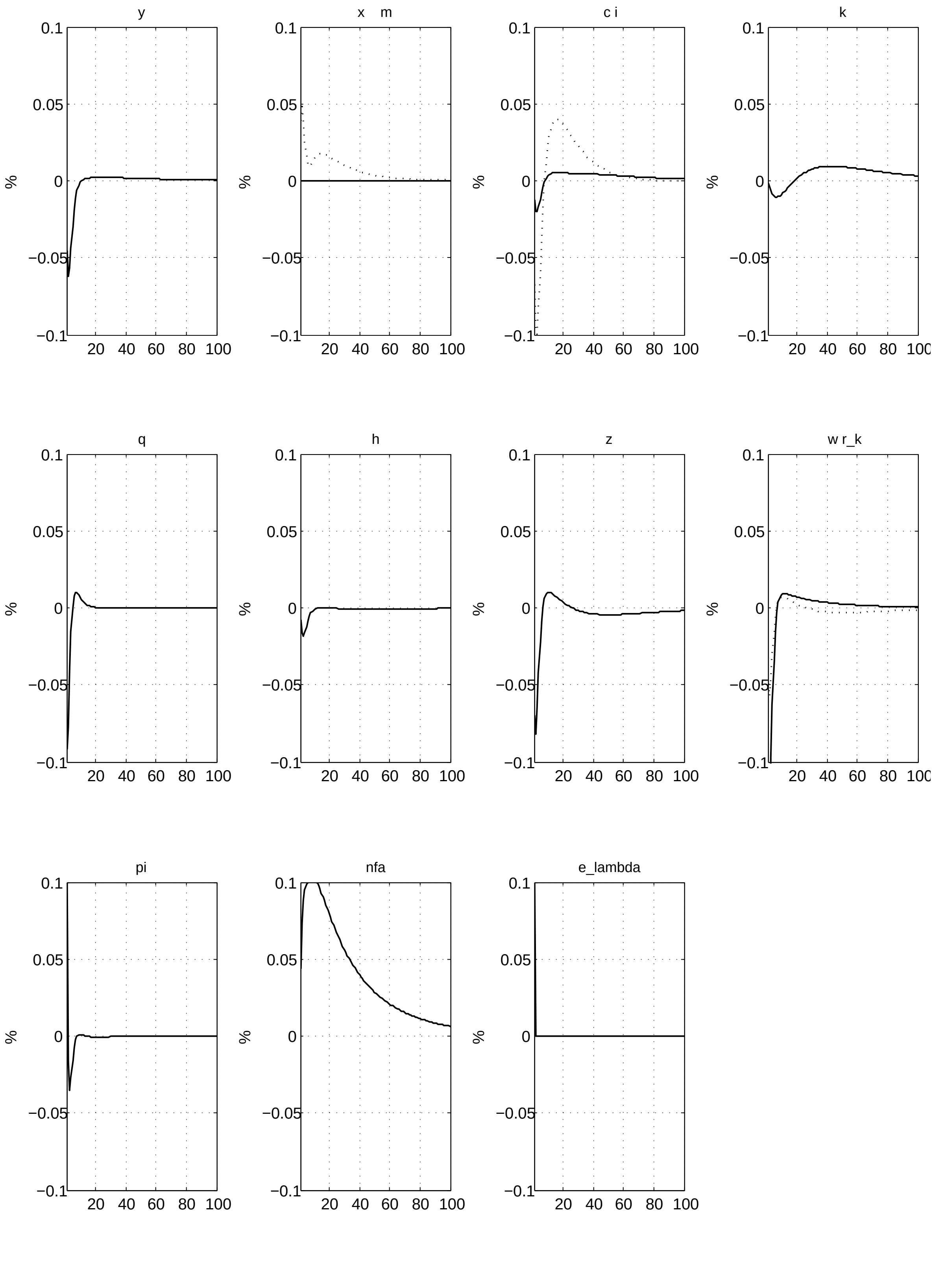


Figure 6: Impulse responses for a price markup shock(ϵ_λ)

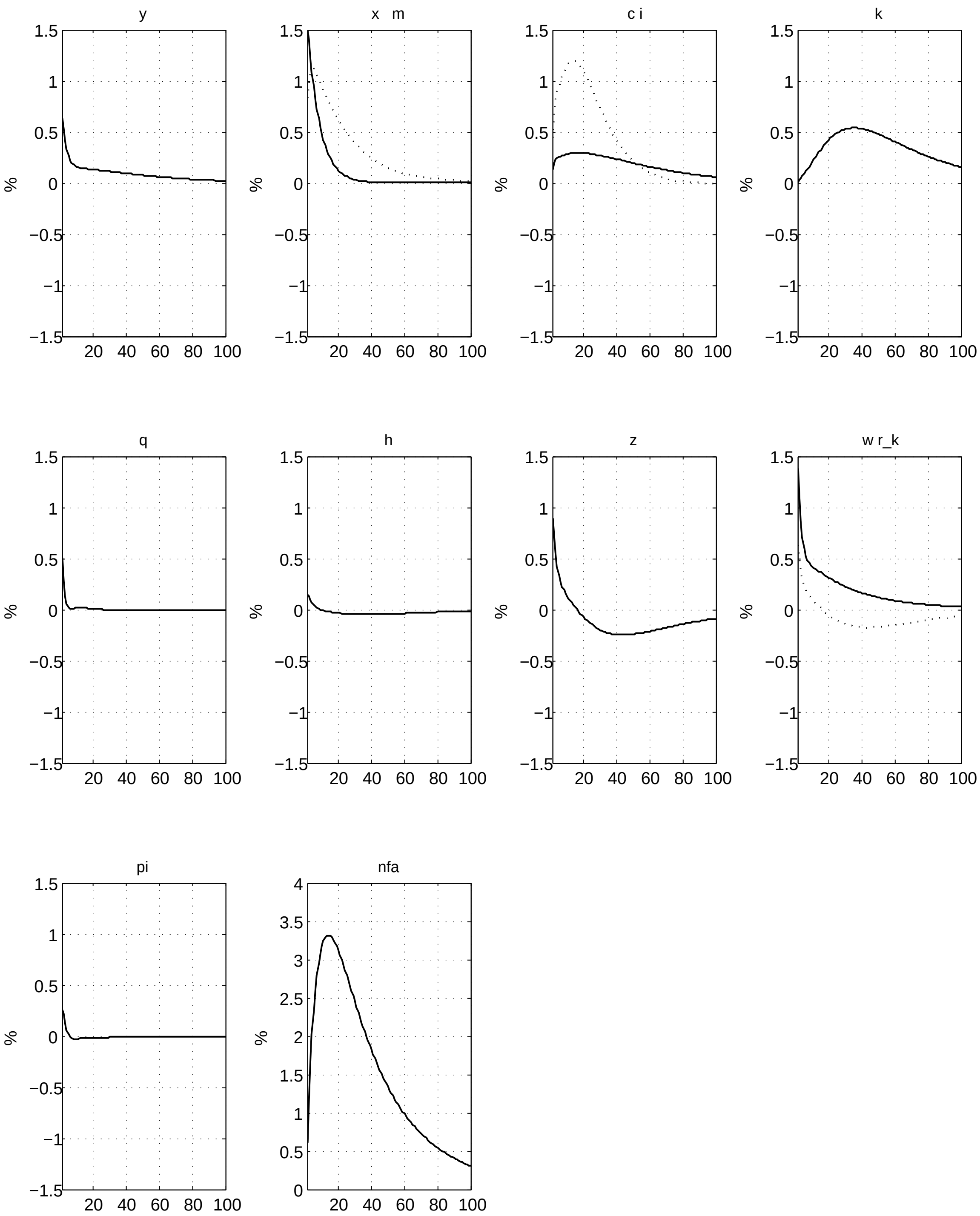
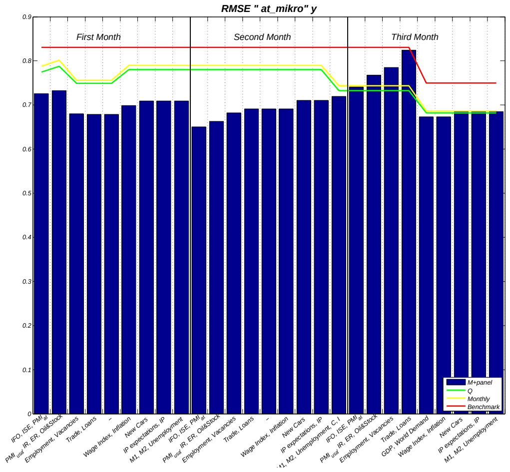
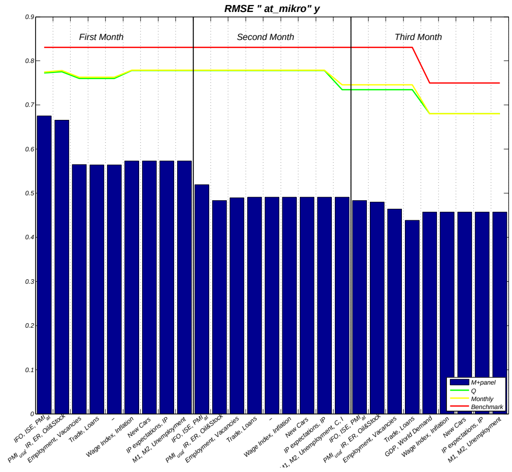


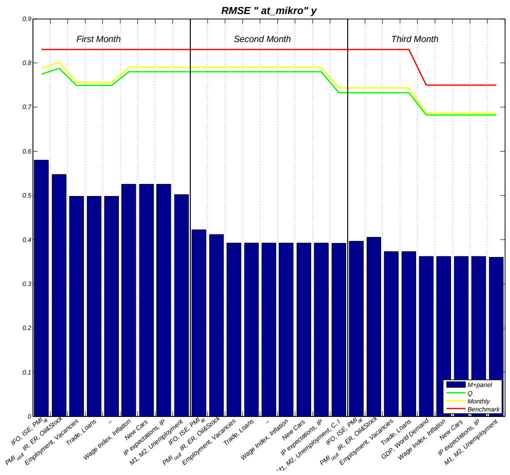
Figure 7: Impulse responses for an export shock(ϵ_{yf})



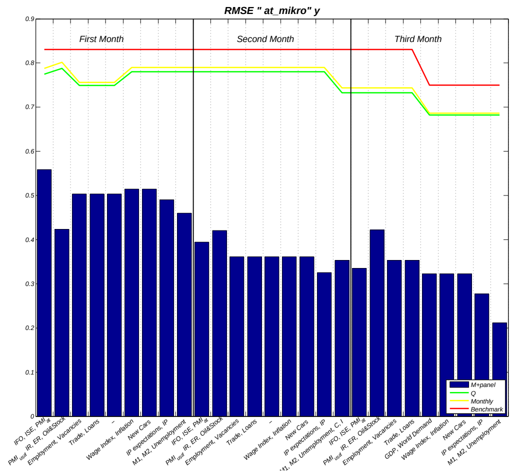
(a) DSGE-Exp



(b) DSGE-Fw17



(c) DSGE-Efr7



(d) DSGE-Efr21

Figure 8: RMSE of GDP growth per release date for different subsets

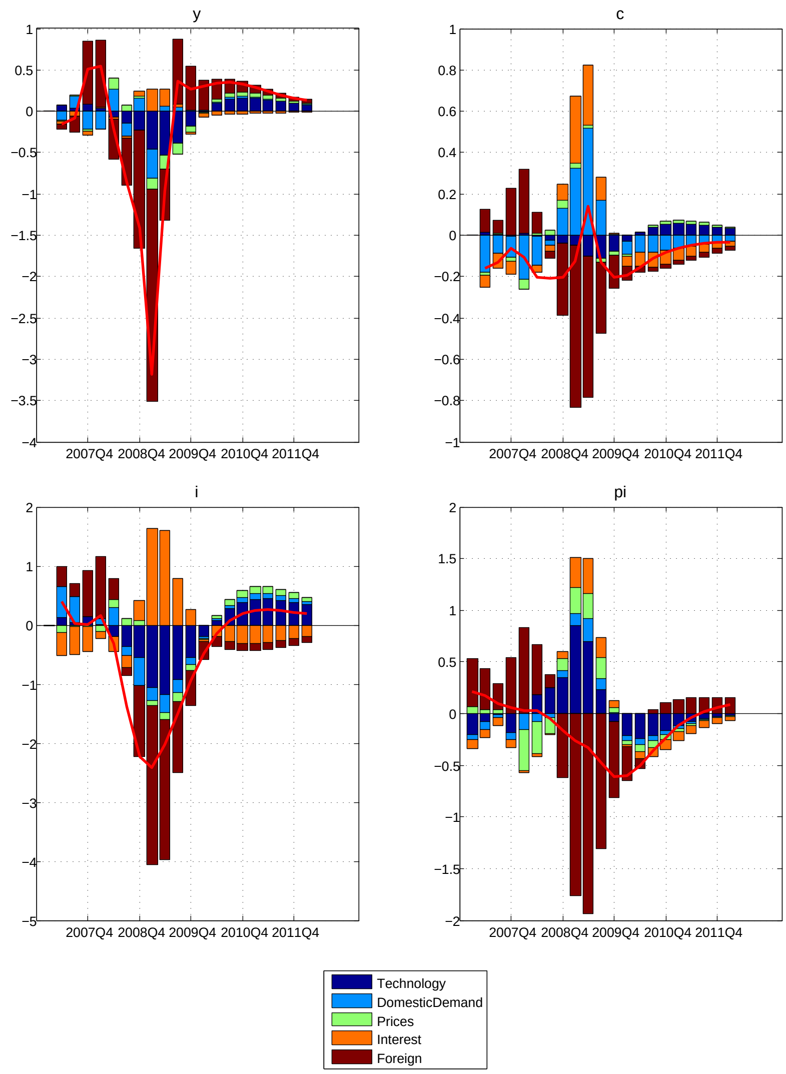


Figure 9: Historical forecast error variance decomposition for the quarterly model

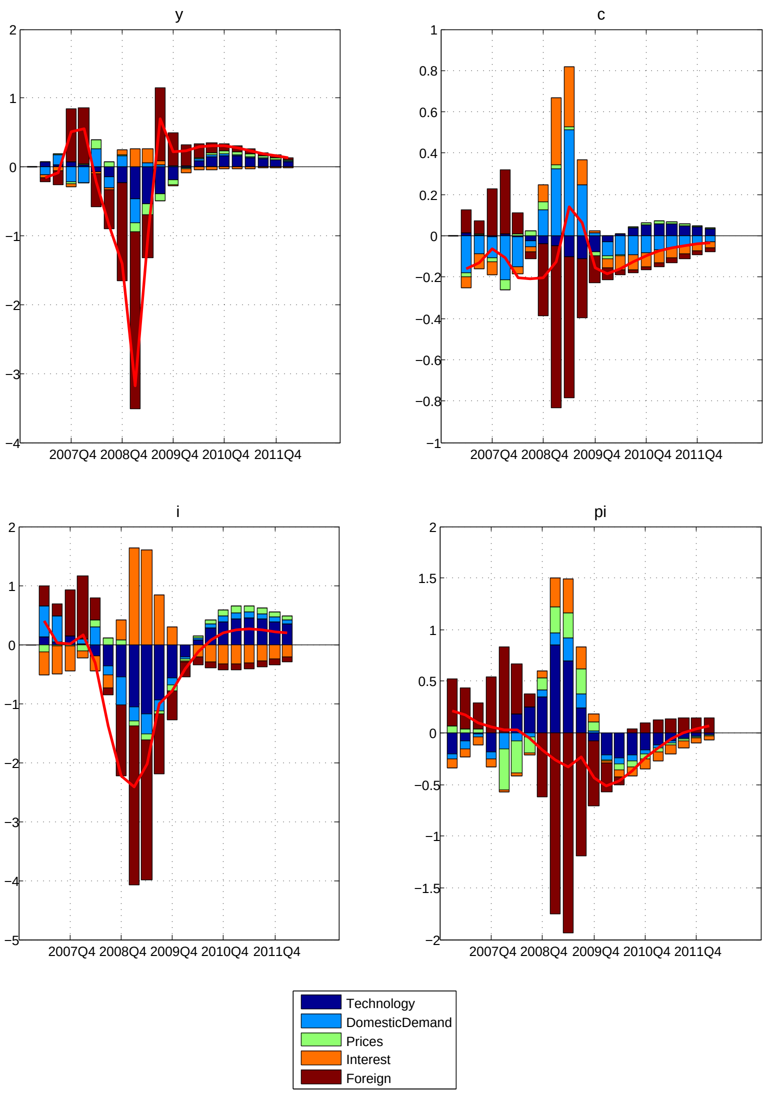


Figure 10: Historical forecast error variance decomposition for the monthly model with indicators ('DSGE-Efr21')

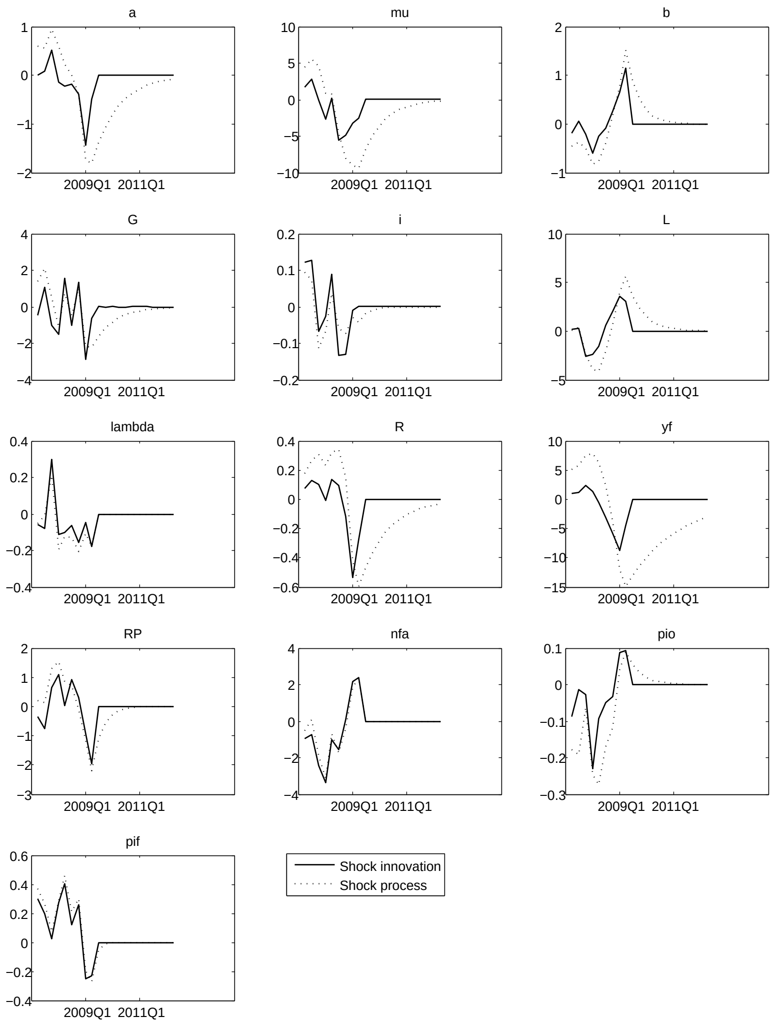


Figure 11: Shock innovations and shock processes for the quarterly model

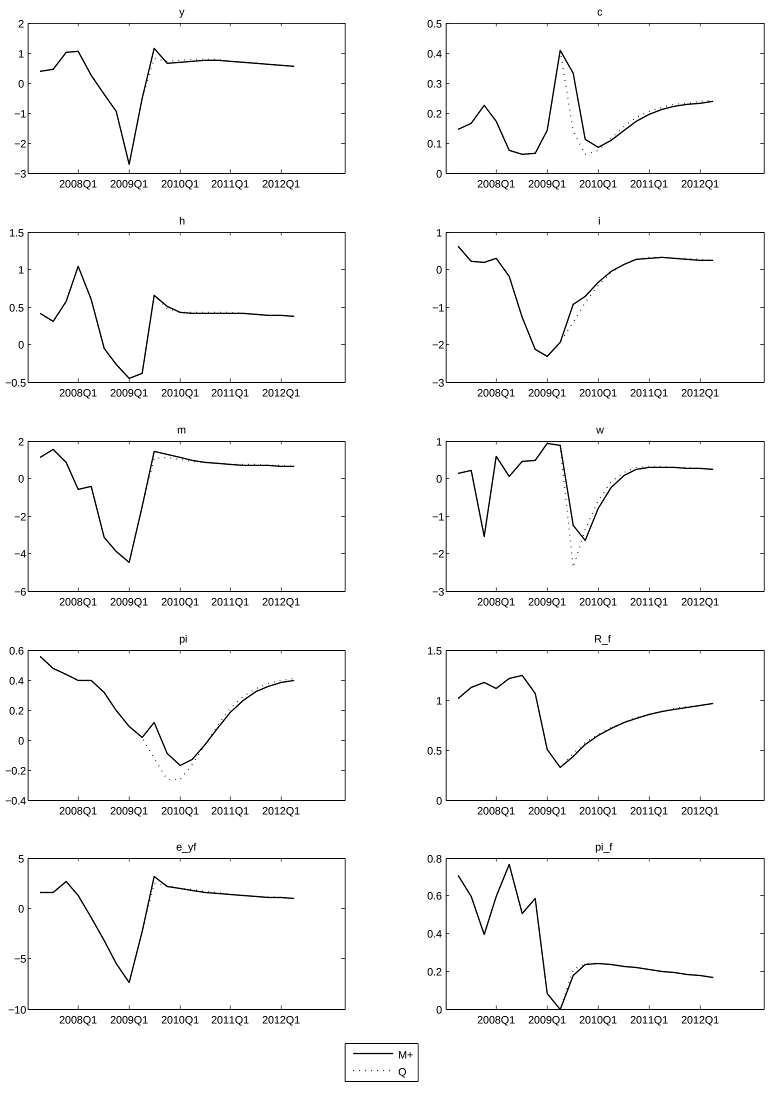


Figure 12: Forecasts for different models (in growth rates resp. levels for the interest rate)

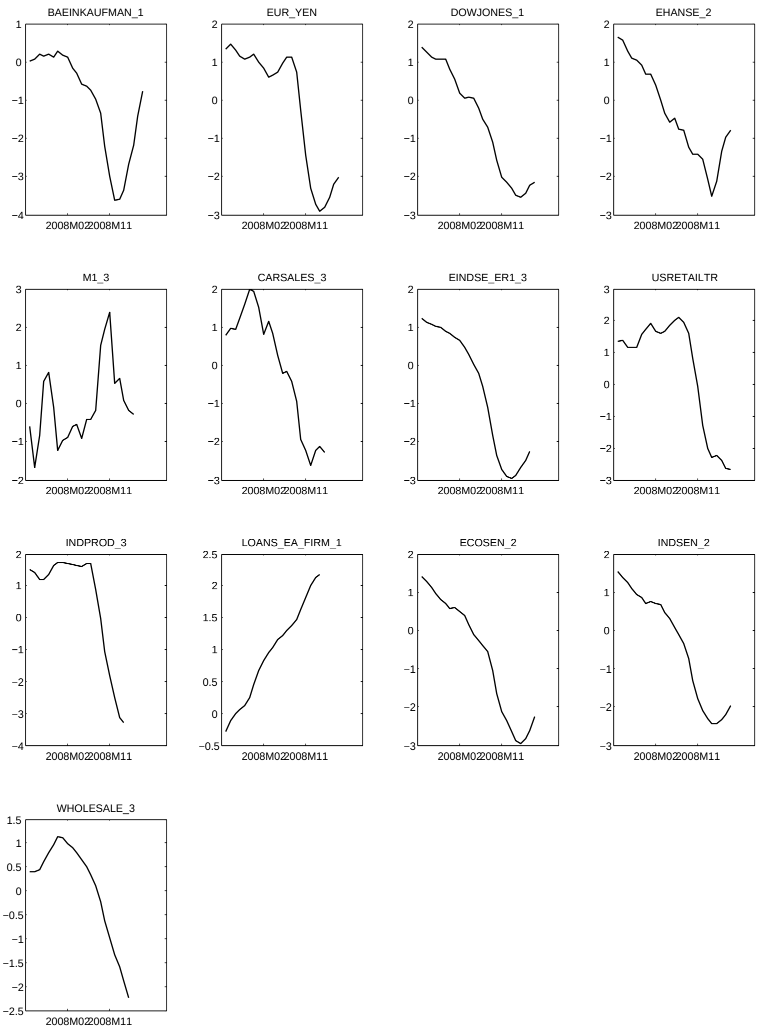


Figure 13: Auxiliary monthly indicators

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