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

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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 in its infancy. Besides theory-based restrictions, the timeliness of data is an important issue. Since DSGE models are based on quarterly data, they suffer from the publication lag of quarterly national accounts. In this paper we present a framework for the short-term forecasting of GDP based on a medium-scale DSGE model for a small open economy within a currency area. We utilize the information available in monthly indicators based on the approach proposed by Giannone et al. (2009). Using Austrian data, we find that the forecasting performance of the DSGE model can be improved considerably by incorporating monthly indicators, while still maintaining the story-telling capability of the model.

1. Introduction

In recent years, DSGE models have become a common tool for the provision of macroeconomic policy advice. Almost all central banks have devoted considerable resources to the building of DSGE models in order to analyze relevant policy issues.[1] These efforts have been motivated mainly by the fact that DSGE models have much sounder theoretical foundations than traditional macroeconometric models. Furthermore, since the work of Smets and Wouters (2003), it is well known that the forecasting performances of DSGE models are comparable to those of unconstrained Bayesian VAR models. Nevertheless, most central banks still rely on traditional macroeconometric models for producing their regular forecasts. Within the Euro area, the only national central bank that uses DSGE models for forecasting is the Bank of Finland. Beside the various 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 investments in the old forecasting infrastructure and a general skepticism about new technologies are factors that impede their wide-spread use in regular forecasting.

One area in which DSGE models have not previously been applied is short-term forecasting. The reasons for this are obvious and straightforward. Whilst DSGE models allow for a coherent representation of an economy, they are based on quarterly data, which 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 therefore unable to exploit the information contained in monthly indicators such as e.g. consumer and business surveys. Instead,

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[1] 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).

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a short-term forecast (usually up to two quarters) is typically produced using a statistical framework. This forecast 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 adjustment (in traditional macroeconometric models) or by manipulating structural shocks (in DSGE models).

The Oesterreichische Nationalbank (OeNB) publishes a regular short-term forecast of the 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, Schneider, & Spitzer, 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 modelling resources towards the development of a quarterly DSGE model of the Austrian economy (Fenz, Reiss, & Schneider, 2012). Thus, it seems rather natural to employ this model for the short-term forecasting as well. However, the crucial question is how to integrate monthly conjunctural indicators into 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.[2]

Recently, Giannone, Monti, and Reichlin (2009) (GMR) proposed a methodology that suits our needs and meets the above-mentioned criteria. The approach is based on a statistical framework developed by Giannone, Reichlin, and Small (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 ragged edge problem, and thus makes it possible to update the forecasts from the DSGE model continuously, every time new information becomes available. By exploiting additional relevant information, the approach is expected to improve on the forecasting performance of the DSGE model. Since the forecasts are now also based on the information contained in monthly indicators, the choice of those indicators is of crucial importance for the forecasting performance.

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 how to select the subset of monthly indicators that perform best for predicting GDP. Third, we demonstrate the ability of the approach to produce regular short-term forecasts with a meaningful structural interpretation.

The paper is organized as follows. Section 2 describes the DSGE model. 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 our 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.

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 be mindful of the 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 the quarterly to monthly frequency requires that the size of the model be not too large.[3] In addition, the state estimates of the quarterly and transformed monthly forms are identical only when the quarterly states do not exhibit signs of non-stationarity.[4] Note that the model is a simplified version of the model of Fenz et al. (2012). 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 modelled by three exogenous processes for demand for Austrian exports, foreign inflation and the foreign interest rate. The model consists of 15 endogenous variables plus 13 shock processes, and is estimated using ten time series.[5]

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

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

[2] See Foroni and Marcellino (in press) for an exhaustive survey of the literature on forecasting with mixed-frequency data.

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

[4] In order to achieve the latter requirement, we have added two shocks that do not have meaningful economic interpretations, but are included in order to ensure the stationarity of the corresponding states. For further details, see Section 2.5.

[5] Compared to the model of Fenz et al. (2012), 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 modelled by three exogenous processes instead of a three-equation system.

where $C_{h,t}$ is the consumption of household h, $H_{h,t}$ are working hours supplied by household 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

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

where I_t is investment, T_t is a lump-sum tax, $B^f_{h,t}$ are foreign bonds held in period t,[6] P_t is the price level, R^f_t is the (gross) foreign interest rate paid on bonds, $\tilde{\phi}\left(nfa_t, e^{rp}_t\right)$ denotes a risk premium on foreign bond holdings,[7] R^k_t is the rate of returns on physical capital, $W_{h,t}$ is the real wage rate, Z_t is capital utilization, $\Psi(Z_t)$ is the cost of capital utilization ($\Psi(1) = 0$ 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 levels of consumption, bond holdings and investment, and the capital utilization rate, subject to Eqs. (1) and (2). In addition, they optimize wages after receiving a signal indicating that they are allowed to do so (more on that later in this section). $D_{h,t}$ and $\Gamma_{h,t}$ are taken as given. Thus, the complete household problem has the following form:

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

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:

$$\frac{\partial \Omega_{h,t}}{\partial B^f_{h,t}} \to E_t\left[\beta \frac{\Lambda_{t+1}}{\Lambda_t} \frac{R^f_t \tilde{\phi}\left(nfa_t, e^{rp}_t\right) P_t}{P_{t+1}}\right] = 1 \tag{3}$$

$$\frac{\partial \Omega_{h,t}}{\partial C_{h,t}} \to \Lambda_t = e^b_t (C_{h,t} - \kappa C_{t-1})^{-1} \tag{4}$$

$$\begin{aligned} \frac{\partial \Omega_{h,t}}{\partial K_{h,t}} \to Q_t = E_t \beta \frac{\Lambda_{t+1}}{\Lambda_t} \big[& Q_{t+1}(1-\tau) \\ & + Z_{h,t+1}R^k_{t+1} - \Psi(Z_{h,t+1})\big] \end{aligned} \tag{5}$$

$$\begin{aligned} \frac{\partial \Omega_{h,t}}{\partial I_{h,t}} \to\ & 1 + Q_t \left(S'\left(e^i_t \frac{I_{h,t}}{\mu^a I_{h,t-1}}\right) e^i_t \frac{I_{h,t}}{\mu^a I_{h,t-1}} \right. \\ & \left. - 1 + S\left(e^i_t \frac{I_{h,t}}{\mu^a I_{h,t-1}}\right)\right) \\ = \ & \beta E_t Q_{t+1} \frac{\Lambda_{t+1}}{\Lambda_t} S'\left(e^i_{t+1} \frac{I_{t+1}}{\mu^a I_{h,t}}\right) e^i_{t+1} \frac{I^2_{h,t+1}}{\mu^a I^2_{h,t}} \end{aligned} \tag{6}$$

$$\frac{\partial \Omega_{h,t}}{\partial Z_{h,t}} \to R^k_t = \Psi'(Z_{h,t}). \tag{7}$$

Eq. (3) gives us the consumption Euler equation. The marginal utility of consumption (Λ_t) is defined in Eq. (4), where we use the fact that all agents consume the same amount of the final good (due to the contingent securities). The law of motion for the real value of capital Q_t is given in Eq. (5). The investment equation is given by Eq. (6). The first order condition for the capital utilization rate is given by Eq. (7).

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 goods assembling firm buys these differentiated intermediate goods and transforms them into a homogeneous domestic good. The final goods firm combines the domestic and imported goods into final goods using a CES technology. For the sake of simplicity, we assume that there is only one type of 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

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

[7] For the definition of net foreign assets, see Section 2.4.

goods from a continuum of domestic intermediate goods producers and transforms them into a homogeneous domestic good.

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

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

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

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

$$P_t^d = \left[\int_0^1 (P_{j,t}^d)^{\frac{-1}{\lambda_{p,t}}} dj\right]^{-\lambda_{p,t}}. \tag{8}$$

2.2.2. Domestic intermediate goods producers

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

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

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

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

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

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

The intermediate goods producers solve two optimization problems. On the input side, they minimize their production costs. On the output side, they maximize the 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.[8] The cost-minimizing condition on the input side is given by

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

[8] See Fenz et al. (2012) and Smets and Wouters (2003) for a more detailed elaboration.

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

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

Using Eq. (8), we can obtain the price of the domestic good P_t^d as a CES aggregate over the prices of adjusters and non-adjusters

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

2.2.3. Final goods assembling firms

For the sake of simplicity, we assume that there is only one type of 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 goods assembling firms, which work under perfect competition and use both 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 goods assembling firm i

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

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. The 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 $t-1$.

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

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 modelled in a parsimonious way by assuming three shock processes for export demand, foreign prices and the foreign interest rate. We assume that domestic exports evolve according to the export demand, and that price competitiveness does not play a role. This helps to simplify the model.

Exports

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

Foreign inflation

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

Foreign interest rate

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

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

$$(C_t + I_t + X_t + G_t)\,P_t = P_t^d Y_t + P_t^M M_t,$$

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

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

The second market clearing condition equals the domestic production to demand

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

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 $B_{i,t}^f$, similarly to Adolfson, Lasen, Linde, and Villani (2007), which is a function of net foreign assets (nfa). $\tilde{\phi}$ has the following functional form:

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

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 the 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

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

2.5. The log-linear model

The log-linearized version of the model can be found in the working paper version of this article (Cervená & Schneider, 2010). For details on the log-linearization, see Fenz et al. (2012). A few issues are worth mentioning. As was stated in the beginning of this section, we had to introduce two shocks in order 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 the quarterly to monthly frequencies assumes stationary states. Hence, the quarterly and monthly state space forms exhibit different dynamics. 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

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

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 monthly models.

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

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

2.6. Estimation

As is common in the literature, we calibrate a subset of parameters. The bulk of the calibrated parameters refer 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 also 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 cannot 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 1987Q1–2009Q2 using Bayesian techniques. 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 used inverse gamma distributions for the shock variances (which have to be greater than zero), beta distributions for the shock autocorrelations (which are between zero and one) and normal distributions for the remaining parameters. We took 250,000 draws of the Metropolis–Hasting algorithm. Some of the parameters cannot be identified properly, since the posterior distributions equal the prior distributions. This is the case for σ_{RP}, ρ_{π_f}, ρ_{RP} and γ_p. Most of the remaining estimation parameter 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. A variance decomposition shows that GDP is driven to a large extent by foreign demand, proxied by exports. Exports explain more than half of the variation in the GDP. Furthermore, the most 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 gains some importance, but demand shocks remain the main driving force of GDP. The inflation of final goods (π) is driven mostly by export demand and imported inflation. Foreign inflation and the shock to import inflation explain about 1/3 of the variance of inflation. These results are more or less in line with those of Breuss and Fornero (2009) and Breuss and Rabitsch (2009), who also find both foreign and domestic demand shocks to play an important role for Austria. This is a key feature which distinguishes our model from similar models for the Euro area (e.g., Christoffel, Coenen, & Warne, 2008), where the GDP is driven to a larger extent by other types of shocks (especially interest rate and risk premium).

Figs. 1–4 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 for up to 100 quarters. A positive *technology shock* increases the productivity of the inputs into the production process. This gives firms an incentive to increase their investment. Since both consumption and investment adjust sluggishly, both labor demand and capacity utilization decrease initially. Accordingly, real wages fall. Domestic demand reaches its maximum after a year and a half, leading to small increases in hours worked and the capacity utilization. The fall in the domestic price level increases the price competitiveness of domestic production relative to imports, causing imports to fall. In addition, it causes the (nominal) net foreign asset position to deteriorate, resulting in an increase in 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 in hours worked has to be compensated by an increase in the capacity utilization. The increase in consumption is offset to a large extent by a fall in investment. Consequently, GDP rises only marginally on impact and then declines, 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, the labor supply decreases. The fall in 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 and the return to capital to increase. As a consequence, firms increase their investment and households work more. In addition, capacity utilization goes up. Investment reaches its peak after three and a half years, then returns to the steady state. Consumption shows a much weaker and smoother reaction. GDP reaches its maximum on impact and then declines. Compared to the model of Smets and 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 the statistical framework of Giannone et al. (2008), Giannone et al. (2009) proposed a methodology for incorporating 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. This is done 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 with 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[9] and is capable of handling unbalanced ("ragged-edge") 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

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

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 determined uniquely by the vector of model parameters θ. Furthermore, the model and the parameter vector are considered to be given.

First, the model is transformed from a quarterly into a monthly representation. This transformation enables us to use monthly observables when available (e.g., inflation and interest rates), and later to introduce a bridge equation linking the original system to a set of monthly indicators. We define the vector of monthly states as S_{t_m}, and the vector of monthly observables as Y_{t_m}.[10] Assuming that some of the observable variables used for the estimation or forecasting are available on a monthly basis, and others on a quarterly basis, Giannone et al. (2009) derive the corresponding monthly representation of the solution as

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

where

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

9 Variables available at a quarterly frequency are latent in the first two months of the quarter.

10 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 a quarterly frequency. This can be achieved by computing three-month moving averages of the data series. For further details, see for example Angelini, Camba-Mendez, Giannone, Reichlin, and Rünstler (2008) or Giannone et al. (2009).

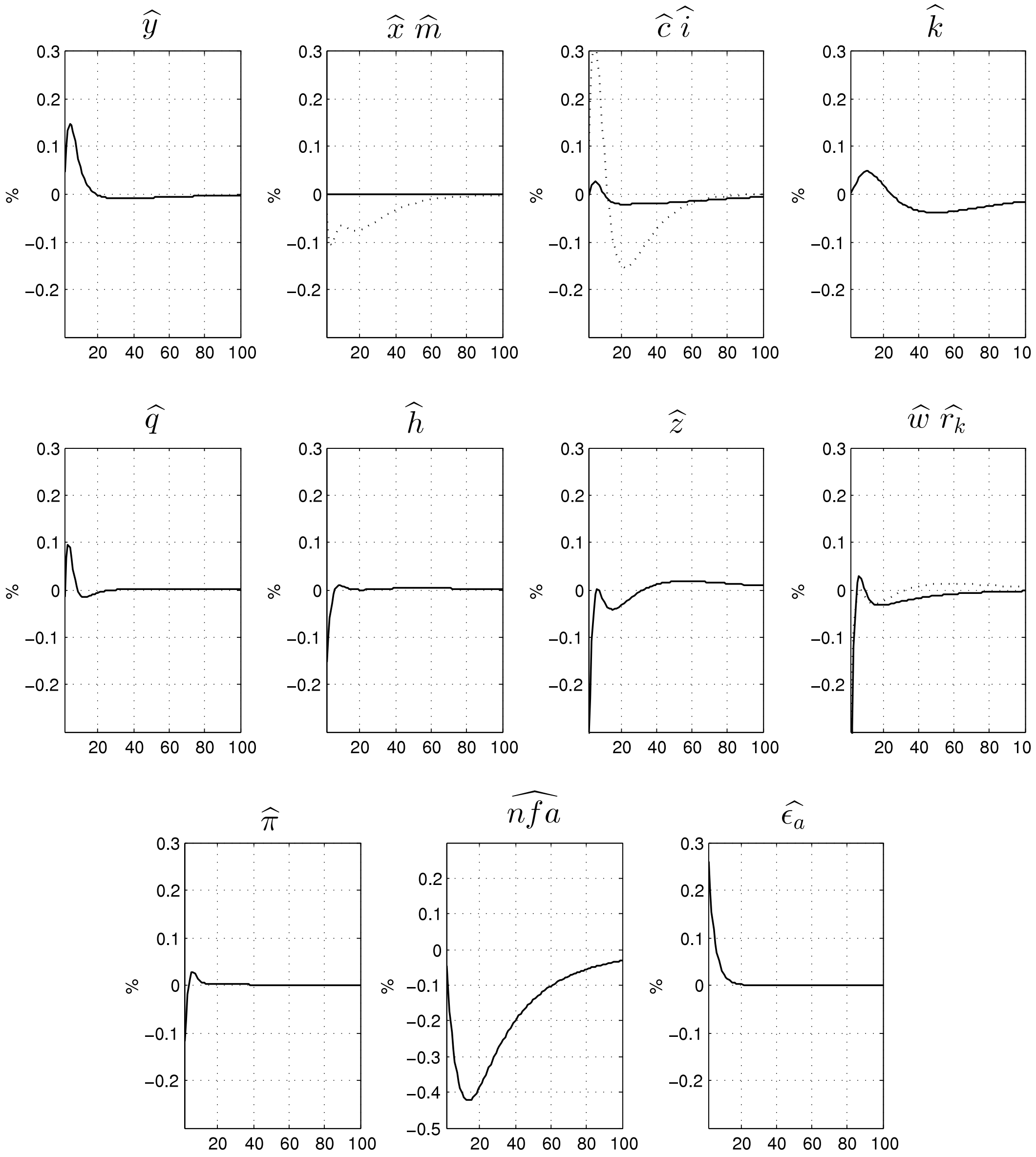

Fig. 1. Impulse responses for the technology shock (ϵ_a).

Second, a mechanism for incorporating auxiliary variables into the monthly model is introduced. We denote the auxiliary variables as X, where X_{t_q} is a $k \times 1$ vector, and use the quarterly observations of 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[11]

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

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

$$X_{t_m} = \mu + \Lambda Y_{t_m} + e_{t_m}, \tag{9}$$

where e_{t_m} is such that $var(e_{i,t_m}) = 0$ if X_{i,t_m} is available and infinity otherwise.

Finally, Eq. (9) is used to augment the monthly system. Eq. (10) 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 indicators

$$\begin{aligned} S_{t_m} &= \mathcal{T}_m S_{t_{m-1}} + \mathcal{B}_m \epsilon_{m,t_m} \\ Y_{t_m} &= \mathcal{M}_m(L) S_{t_m} + V_{t_m} \\ X_{t_m} - \mu &= \Lambda \mathcal{M}_m(L) S_{t_m} + e_{t_m}. \end{aligned} \tag{10}$$

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

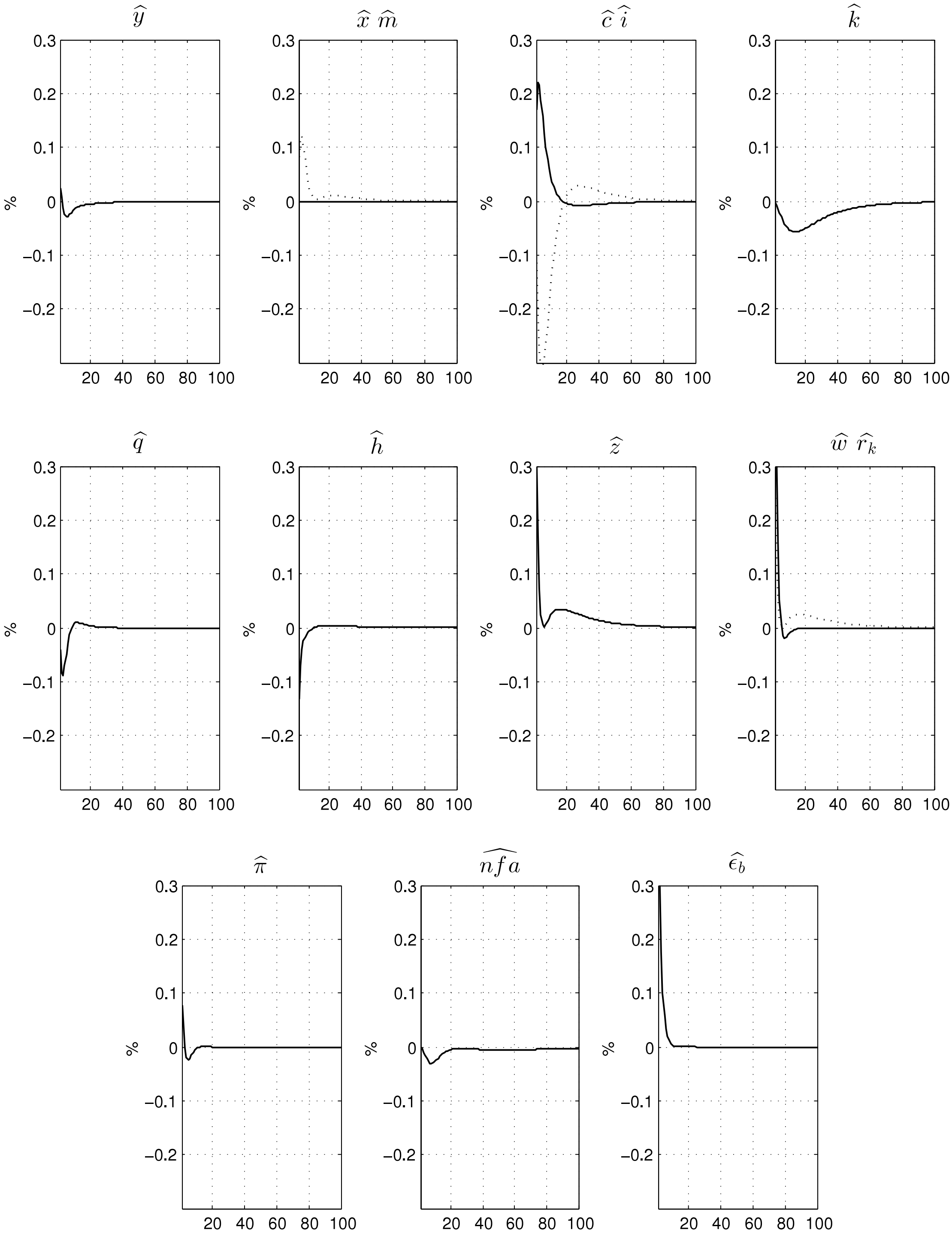

Fig. 2. Impulse responses for the consumption preference shock (ϵ_b).

4. Forecasting performance

In this section, we analyse the forecasting performances of the DSGE model with and without monthly indicators. To do this, we design a pseudo real-time forecasting exercise, in which we simulate the data flow of the monthly indicators within the quarter for a given subset of the indicators (Section 4.1). In Section 4.2, we present the data. The issue of variable selection is discussed in Section 4.3. The results are presented in Section 4.4.

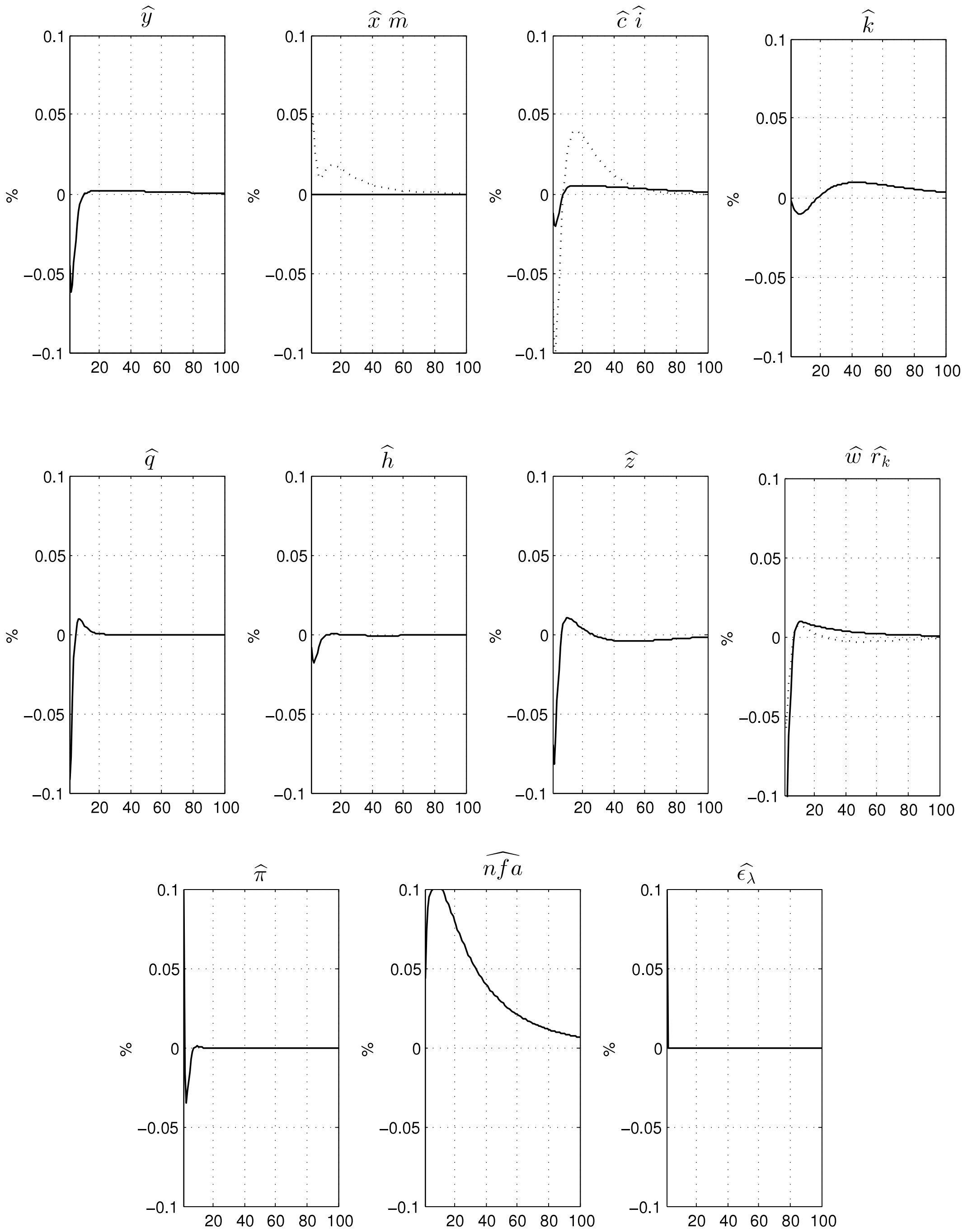

Fig. 3. Impulse responses for the price markup shock (ϵ_λ).

4.1. 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 the monthly indicators within the quarter. For each of the last $T = 20$ quarters (i.e., 2004Q3–2009Q2), and each of the $R = 27$ release dates within a quarter, we construct the data set that was available at that point in time. We re-estimate all economic relationships (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. For assessing the forecasting performances of a given set of monthly indicators, we compute the root mean squared

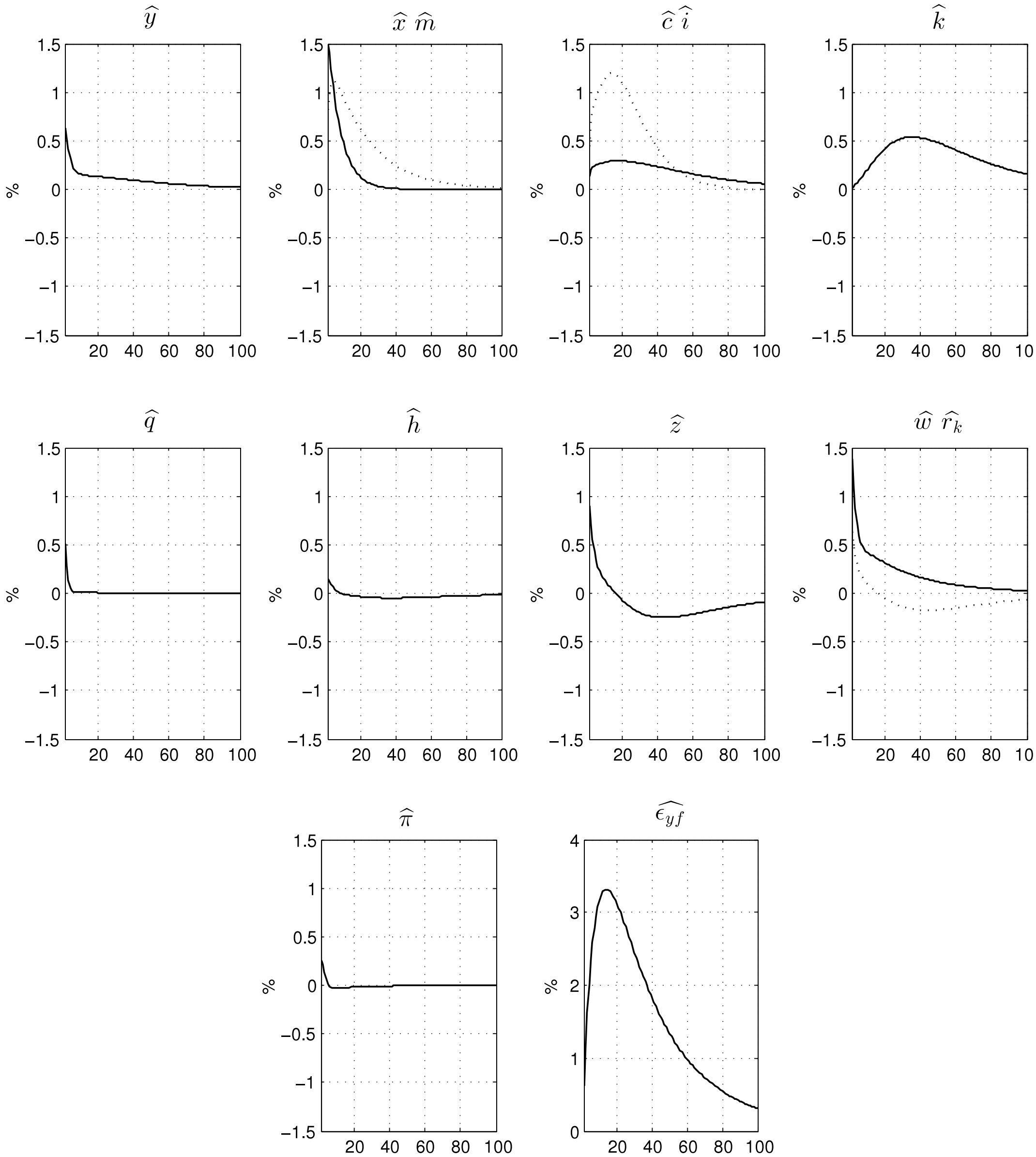

Fig. 4. Impulse responses for the export shock (ϵ_{yf}).

errors (RMSE) of real GDP growth for $h = 0, \ldots, 4$ quarters ahead for all $r = 1, \ldots, 27$ data vintages within a quarter.

4.2. Data

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,[12] we have constructed a candidate set of 48 variables that we deemed to be the most relevant. The data set contains variables such as indicators of economic sentiment, purchasing manager's indices, ECB reference rates, stock market price indices, money supply, car registrations, vacancies, unemployment rates, industrial production, commodity prices, unemployment and trade. Besides Austrian series, variables for Germany, the euro area and the US are included. The pre-selected data set has been augmented by introducing leads of up to 3 months ahead for each of the variables, leading to a candidate set of 192 series.

The complete list of indicators together with their release dates can be found in Appendix B in Table 5. Note that there are 27 different release dates spread throughout the quarter; i.e., depending on the set of indicators

[12] To name only a few, references include Barhoumi et al. (2008), Boivin and Giannoni (2006), Giannone et al. (2008), Golinelli and Parigi (2007), Ruenstler and Sedillot (2003), Schneider and Spitzer (2004) and Schumacher and Breitung (2008).

selected, 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 the national accounts variables are published only at the quarterly frequency and with significant time lags. 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 (though a number of series have a shorter availability). Furthermore, we have stationarized and standardized all auxiliary variables.[13]

4.3. Variable selection

After constructing our candidate data set of monthly indicators, we then have to deal with the problem of how to utilize these indicators optimally for forecasting GDP. The literature suggests a variety of strategies for coping with the resulting curse-of-dimensionality problem that arises when the size of the cross-section n is large relative to the time dimension T. One popular strategy is the use of *dimension-reducing methods* such as factor models, where the information included in the data set is condensed in a small number of factors. One open question is whether a factor model should utilize the full data set for forecasting, or only a subset of it. Many researchers have found that for data sets which are used in practice, the forecasting performances of factor models deteriorate when more data are included beyond a certain threshold (Boivin & Ng, 2006; Caggiano, Kapetanios, & Labhard, 2009; Schneider & Spitzer, 2004). On the other hand, Banbura, Giannone, and Reichlin (2011) analysed the inclusion of disaggregated data in dynamic factor models, and found that including more variables does not improve the forecasting accuracy, but does not affect the stability negatively. Using a factor model to reduce the dimensionality of the monthly data set would add additional complexity to our framework, since it would require the adoption of a factor model approach that allows us to deal with unbalanced panels (Banbura, Giannone, Modugno, & Reichlin, 2012; Liebermann, 2012). Recently, Banbura, Giannone, and Reichlin (2010) have established large Bayesian VARs as an alternative to dynamic factor models for forecasting. *Shrinkage strategies* (such as ridge regression, see Hoerl & Kennard, 1970, or the Lasso, see Tibshirani, 1996) aim to shrink the estimated parameters of the regression model in order to overcome the instability of the estimated parameters in large models. Shrinkage strategies are suitable for situations where most predictors have a non-zero effect on the regression function, while dimension-reducing methods are appropriate for the case of high multicollinearity of the data set (Ng, 2012).

The most widely used strategy (and the one that we will employ here) is *subset selection*. The main problem in selecting an optimal subset is the high dimensionality of the data set. Evaluating all possible subsets would require $2^N - 1$ steps, which is clearly not feasible in our case ($N = 192$). Miller (2002) surveys a variety of algorithms for searching the variable space in an efficient manner (forward selection, backward selection, Efroymson's algorithm, branch-and-bound techniques, grouping variables, etc.). One important caveat of the variable selection approach is its potential instability over time (Stock & Watson, 2012). However, De Mol, Giannone, and Reichlin (2008) have shown that small models with accurately selected variables exhibit forecasting performances comparable to those of methods that use large data sets.

In our paper, we focus on three algorithms, namely *random selection, forward stepwise selection* and *forward stepwise selection with deletion (Efroymson-type algorithm)*, which we apply to the whole candidate data set. The first algorithm is *random selection*. We evaluate 20,000 subsets. For each of the subsets, we determine first the size and then the composition of the subset, where we assume uniform distributions. 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 risk 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 (see below).

The second algorithm 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 select a second variable from the remaining candidates. We proceed until the forecasting performance deteriorates. This method has the advantage that it permits the variable space to be searched without prohibitive computing costs. On the other hand, there is no guarantee that the subset of p variables that exhibits the best forecasting performance will 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 fail to find the best subset.

Third, we use *forward selection with deletion* (*Efroymson 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 causing the forecasting performance of the model to deteriorate. The algorithm stops if no variable can be included or deleted without worsening the results. This method works very well when combined 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.

[13] 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 of the monthly and quarterly versions of the model. This in turn would lead to distorted GDP forecasts.

Table 1
RMSEs for GDP growth for the GMR toy model and for the DSGE model without auxiliary variables (Q0–Q4 denote the forecasting horizon in quarters).

	'DSGE-Toy-Q'	'DSGE-Toy-M'	'DSGE-Q'	'DSGE-M'
Q0	0.889	0.891	0.780**	0.790**
Q1	0.951	0.967	0.884**	0.885**
Q2	0.974	0.989	0.917**	0.918**
Q3	0.996	1.004	0.928*	0.920*
Q4	0.975	0.973	0.877*	0.877*

Table 2
RMSEs for GDP growth using the DSGE model with different sets of auxiliary variables.

	'DSGE-Q'	'DSGE-ExpSurv7'	'DSGE-ExpM10'	'DSGE-Fw17'	'DSGE-Efr7'	'DSGE-Efr21'
Q0	0.780	0.682**	0.631**	0.489**	0.392***	0.362***
Q1	0.884	0.838	0.822*	0.842	0.811*	0.854
Q2	0.917	0.863	0.875	0.855	0.813*	0.864
Q3	0.928	0.881	0.872	0.828	0.888	0.873
Q4	0.877	0.879	0.881	0.873	0.903	0.879

4.4. Results

We start by presenting the results of our forecasting exercise by looking at the performance of our medium-scale DSGE model relative to that of the toy model of GMR (both without auxiliary monthly indicators). In Table 1, we report the average RMSE of the GDP growth rate forecasts for all models for different horizons. The RMSE is reported for the nowcast of the current quarter (Q0) and for forecasts of up to four periods ahead (Q1–Q4).[14] The comparison of our rich DSGE model ('DSGE-Q', 'DSGE-M') with the toy model ('DSGE-Toy-Q', 'DSGE-Toy-M') shows that our model clearly outperforms the toy model. The results of a Diebold–Mariano test show that the gain in forecasting performance is significant.[15]

4.5. Forecasting performances of the models with monthly indicators

As a next step, we analyse the results of the pseudo-forecasting exercise for a number of subsets of auxiliary monthly indicators. First, we introduce two 'expert-guess' subsets. The first subset ('DSGE-ExpSurv7') was selected according to the experience of the authors with short-term forecasting, and consists of seven (survey) indicators. The second subset ('DSGE-ExpMM10') was also constructed as an expert guess, and consists of 10 (mainly financial) variables that are known to be monitored closely by financial markets (so-called "market-movers"). The third subset, consisting of 17 indicators, was determined by pure forward selection ('DSGE-Fw17'). We find that the forecasting performance deteriorates rather quickly for samples with 18 variables and more. The fourth subset was determined by the Efroymson algorithm, with an initial subset constructed by random selection ('DSGE-Efr7'). For the fifth subset, the Efroymson algorithm was utilized in combination with forward selection ('DSGE-Efr21'). Table 4 in Appendix B lists the composition of the subsets.[16]

Adding auxiliary variables to the monthly DSGE model clearly improves the forecasting performance for the current quarter (Q0). The percentage gain in RMSE ranges from 13% ('DSGE-ExpSurv7') to 54% ('DSGE-Efr21') compared to the quarterly model without additional variables ('DSGE-Q'), and is significant at the 5% (**) and the 1% (***) level, respectively. For longer forecasting horizons, there is (almost) no gain from adding monthly indicators to the DSGE model. This is not surprising, since the indicators are available only contemporaneously (see Table 2).

The next step is to look at the forecasting performances for the different release dates of auxiliary indicators within a quarter (Fig. 5). Dates M1-1, M1-2,…, M3-9 refer to the 27 release dates of the three months of a quarter. At date M1-1 at the beginning of the first month of the quarter, national accounts data for the previous quarter are not available. Hence, we have to forecast two quarters (the previous and the current quarter). When new data are published, the forecasting performance usually improves (although there are some exceptions). The largest improvement is reported when national accounts data for the previous quarter are published at date M3-5. Interestingly, this improvement is negligible for the best performing data sets ('DSGE-Fw17' and 'DSGE-Efr21'), indicating that the included auxiliary

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 ('DSGE-Q'). The monthly model without auxiliary variables ('DSGE-M') is the quarterly model transformed according to GMR without bridging the system with the 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 in the information contained in these two variables. All other model variables are latent during the first two months of each quarter, and have to be estimated by the Kalman filter.

15 Asterisks in the table denote significance of the Diebold–Mariano test: * 10%, ** 5%, *** 1%. In Table 1, the null hypothesis is that the DSGE-model ('DSGE-Q', 'DSGE-M') does not outperform the toy model at the same frequency ('DSGE-Toy-Q', 'DSGE-Toy-M'). In Table 2, the null hypothesis is that the augmented model ('DSGE-ExpSurv7', 'DSGE-ExpSurvM10', 'DSGE-Fw17', 'DSGE-Efr7', 'DSGE-Efr21') does not outperform the quarterly DSGE model ('DSGE-Q').

16 The variables are also described in the same appendix. The number specified after the name of the variable stands for the lead in months.

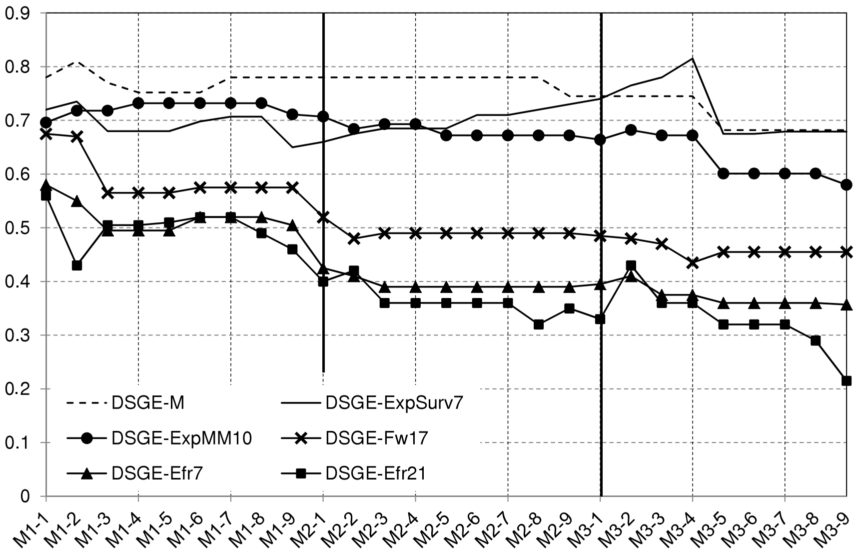

Fig. 5. RMSE of GDP growth per release date for different subsets.

Table 3
RMSEs for GDP growth for different models.

	'DSGE-Efr 21'	'Naïve'	'Time series'	'Dynamic factor model'
Q0	0.362	0.831	0.841	0.649
Q1	0.854	0.799	0.802	0.732
Q2	0.864	0.791	0.785	0.774
Q3	0.873	0.784	0.773	0.780
Q4	0.879	0.789	0.743	0.789

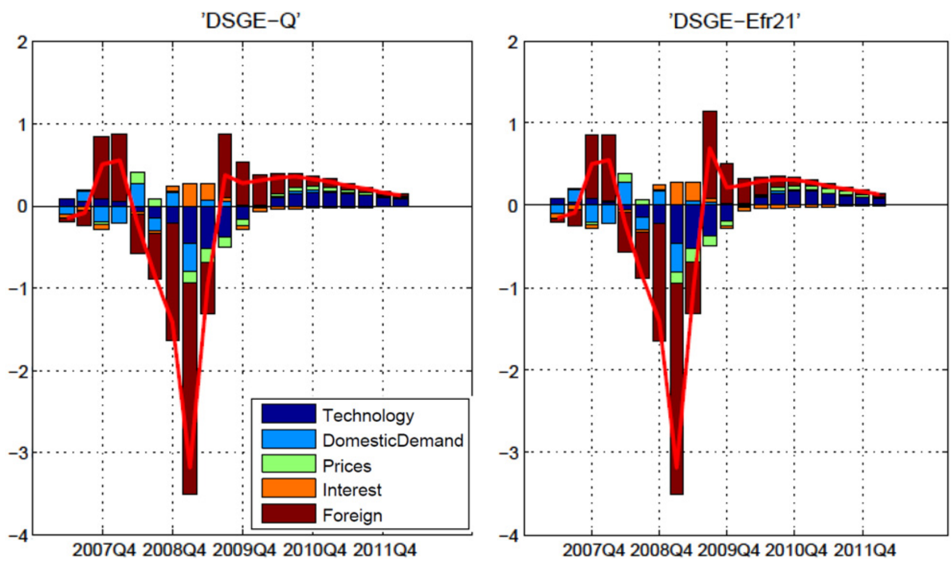

Fig. 6. Historical forecast error variance decomposition for GDP.

variables have already helped to improve the forecasting performance for GDP. For the majority of our models, considerable improvements are also seen for release dates M1-9 and M2-1, when business surveys and financial variables are released. We compare the best performing model ('DSGE-Efr21') with three benchmark time series models: a naïve forecast, a time series forecast, and a dynamic factor model. For the naïve forecast, we take the

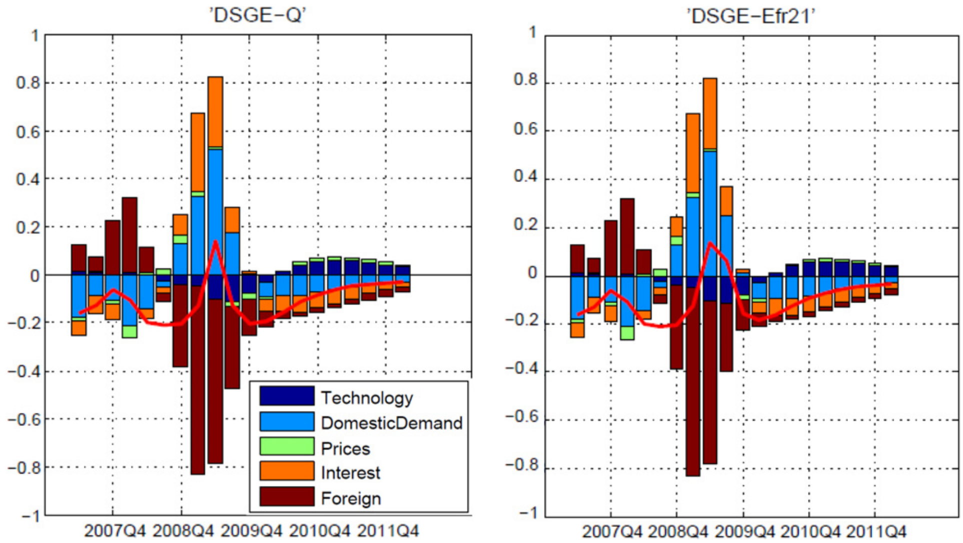

Fig. 7. Historical forecast error variance decomposition for consumption.

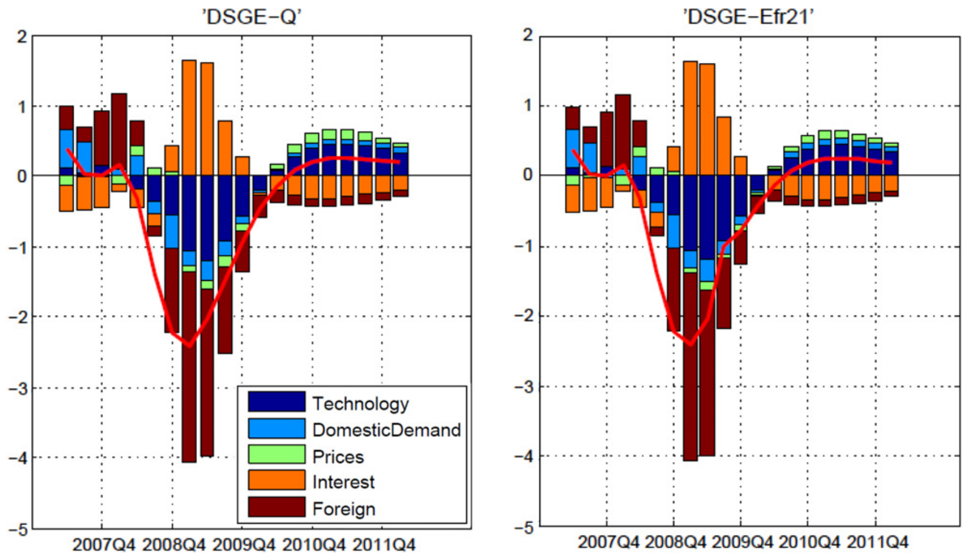

Fig. 8. Historical forecast error variance decomposition for investment.

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. Our third benchmark model is the dynamic factor model that is used by the OeNB for short-term forecasting on a regular basis (Schneider & Spitzer, 2004). It consists of 143 variables covering national accounts, industrial production, surveys, prices, foreign trade, the labour market and financial data.

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. This is not surprising, since we have not made any effort to forecast the auxiliary variables. 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 (Q0). We can reject this hypothesis at the 1% level for all benchmark models, indicating that the improvement in forecast accuracy for the current quarter is significant (see Table 3).

5. A structural interpretation of the forecast

In this section we demonstrate the ability 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

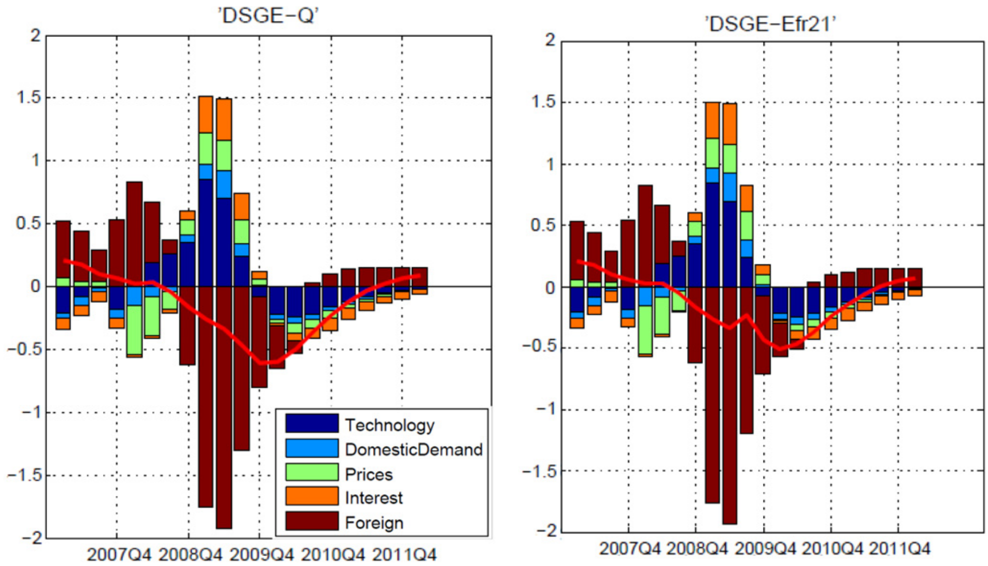

Fig. 9. Historical forecast error variance decomposition for inflation.

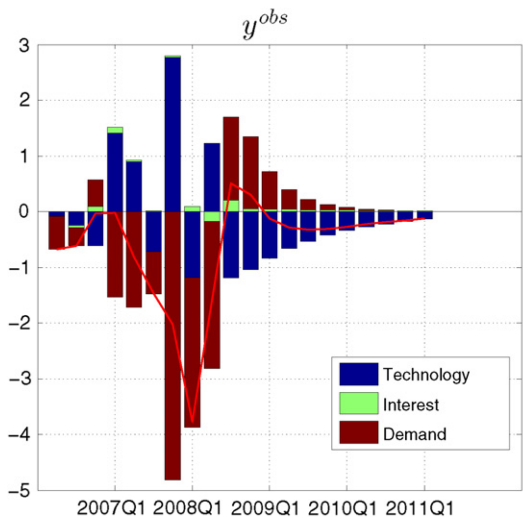

Fig. 10. Historical forecast error variance decomposition for the quarterly toy model without indicators ('DSGE-Toy').

variance decomposition of the main model variables for the last historical quarters and for the projection horizon. We do this exercise both for our medium-scale DSGE model and for the toy model of GMR.

5.1. Medium-scale DSGE model

Our medium-scale DSGE model includes twelve structural shocks. For the sake of clarity, we have aggregated them into four groups. While we have only one technology shock, there are three domestic demand shocks (consumption preference, government spending and investment), four price shocks (price markup, labor supply, foreign inflation, shock to relative prices), two interest rate shocks (foreign interest rate, risk premium) and two foreign shocks (export demand and import adjustment costs). Figs. 6–9 show the historical forecast error variance decomposition for the model without and with monthly indicators for the period 2007Q1–2012Q1 for GDP, consumption, investment and inflation. The downturn in GDP in the first quarter of 2009 was driven mainly by 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 co-movement of GDP and real wages. Due to strong increases in agreed wages, real wages rose strongly in the course of 2008. Further negative contributions came from price shocks (i.e., price markup shock and labor supply shock). Similarly to the technology shock, price shocks are identified by a negative co-movement 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 in the opposite direction. Due to the introduction of short-term employment schemes, hours worked fell less than output. Private consumption was surprisingly strong in the second quarter of 2009, driven mainly by policy measures such as the car scrapping scheme, and 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 declined, driven mainly 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. Investment activity has been declining since the second quarter of 2008, driven by the negative contributions of foreign and technology shocks. It is projected to decline further until the second quarter of 2010, since the positive impact of the interest rate decreases fades out. The steep decline in 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 faded out, inflation then continued to fall, before picking up again in the

Table 4
Subsets of auxiliary monthly indicators.

'ExpSurv7'	'ExpMM10'	'Efr7'	'Fw17'	'Efr21'
CARREG(m)	DAX(m)	DOWJONES($m-3$)	CARSALES(m)	CARREG(m)
ECOSEN(m)	DOWJONES(m)	EMPL(m)	DOWJONES($m-3$)	ECOSEN(m)
IFOBEXP(m)	EURIBOR(m)	EMPL($m-3$)	EMPL(m)	EURUSD($m-1$)
LOANS(m)	EURUSD(m)	EURYEN(m)	EURYEN(m)	EXPC(m)
PMIAT(m)	IFOBC(m)	M2(m)	EXPC(m)	EXPC($m-3$)
PMIUS(m)	INDSEN(m)	PMIAT(m)	EXPC($m-1$)	IFOBEXP(m)
VACANCIES(m)	OIL(m)	VACANCIES($m-3$)	IFOBC($m-2$)	IMPC($m-3$)
	IP(m)		IFOBC(m)	IP($m-1$)
	YIELDUS(m)		IPNEXTM(m)	IP($m-2$)
	YIELDSPR(m)		IPNEXTM($m-3$)	IP($m-3$)
			M1(m)	IPNEXTM($m-3$)
			M1($m-2$)	INDSEN($m-3$)
			NASDAQ($m-3$)	LOANSH($m-3$)
			NASDAQ($m-2$)	M1(m)
			OIL1MFWRD($m-3$)	M1($m-3$)
			PMIAT(m)	M2(m)
			YIELDUS($m-1$)	PMIAT($m-1$)
				URXNSA(m)
				URXNSA($m-3$)
				URXSA($m-2$)
				WSPI($m-1$)

course of 2010. 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 mainly changes the picture in the first quarter of the projection horizon (2009Q3). The majority of the selected monthly indicators point upwards, and hence, the augmented model suggests a stronger recovery in the third quarter of 2009. The variance decomposition shows that this is due mainly to a stronger recovery of exports than is implied by the dynamics of the DSGE model only. For the following quarters, there is almost no difference in the growth forecast.

5.2. A comparison with a toy model

A comparison of the results of our DSGE model with the simple three-equation model of Giannone et al. (2009) demonstrates the benefits for our purpose of using a rich structural model. We have estimated this model over the same time span as our model (1987Q1–2009Q2), and have produced a forecast for twelve quarters without monthly indicators (Fig. 10). With only three structural shocks, the simple model fails to provide a reasonable story of how the global financial crisis hit the Austrian economy. The downturn in 2008Q4 and 2009Q1 is attributed to large negative demand shocks. In 2009Q2, the impact of the negative demand shock on GDP is offset to a large extent by a positive technology shock. This shock is identified due to negative inflation, whereas the decline of GDP moderated. As the technology shock is much more persistent than the demand shock, its impact on GDP vanishes only gradually, whilst the impact of the demand shocks fades out rather quickly. Thus, the profile of the forecast is driven mainly by the difference in persistence between the two shocks.

6. Conclusion

In this paper we have utilized the methodological framework proposed by Giannone et al. (2009) for producing short-term forecasts for the Austrian economy. First, we have built and estimated a medium-scale DSGE model, which was then transformed to a monthly frequency and augmented by a set of monthly indicators. We have utilized various different methods for selecting subsets of the auxiliary monthly indicators. The results of a pseudo-forecasting exercise suggest that the best performance is obtained when an Efroymson-type algorithm is employed after a number of iterations of pure forward stepwise selection.

When 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 more than 50% lower than those of either the DSGE model without auxiliary variables or 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 for bridging 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 us to produce forecasts with a meaningful structural interpretation that can take advantage of the latest conjunctural information.

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Appendix A. The toy model

Giannone et al. (2009) have used a simple new-Keynesian model consisting of three equations to demonstrate their approach. We have estimated their model for Austria in order to provide a benchmark for the structural

Table 5
Monthly economic indicators for different release dates.

Code	Description	Publication lag
Last day of the last month		
EBAUSE	Construction confidence indicator	m
ECOSEN	Economic sentiment indicator	m
EHANSE	Retail trade sentiment indicator	m
EINDSE	Industrial confidence indicator	m
EKONSE	Consumer confidence indicator	m
IFOABS	Ifo assessment of business situation	m
IFOBC	Ifo business climate	m
IFOBEXP	Ifo business expectations	m
INDSEN	Industrial sentiment indicator	m
PMIAT	Purchasing manager index Austria	m
YIELDUS	Yield for 10-year government bonds, US	m
1st *business day of the month*		
ATX	Austrian stock price index	$m-1$
DAX	DAX stock price index	$m-1$
DOWJONES	Dow Jones index	$m-1$
EURGBP	Exchange rate Euro/ British Pound	$m-1$
EURIBOR	3-month money market rate (Euribor)	$m-1$
EURUSD	Exchange rate Euro/ US-Dollar	$m-1$
EURYEN	Exchange rate Euro/Yen	$m-1$
NASDAQ	NASDAQ stock price index	$m-1$
OIL	Oil price brent	$m-1$
OIL1MFWRD	Oil price 1-month forward	$m-1$
PMIUS	Purchasing manager index US	$m-1$
YIELDSPR	Yield spread (10y–3m)	$m-1$
5th *business day of the month*		
EMPL	Employment	$m-1$
VACANCIES	Vacancies	$m-1$
VACAPP	Vacancies for apprentices	$m-1$
1st *week of the month*		
EXPC	Exports of commodities	$m-3$
IMPC	Imports of commodities	$m-3$
LOANS	Loans to the private sector	$m-1$
LOANSF	Loans to firms	$m-1$
LOANSH	Loans to private households	$m-1$
10th *day of the month* (*for* 3rd *month of the quarter only*)		
	Quarterly national accounts data	$q-1$
10th *business day of the month*		
CPI	Consumer price index	$m-1$
NEGWG	Index of negotiated wages	$m-1$
NEGWGWC	Index of negotiated wages (white collar workers)	$m-1$
USCAPUTIL	Capacity utilization: US	$m-1$
USRETAILTR	Retail trade turnover: US	$m-1$
WSPI	Wholesale price index	$m-1$
3rd *week of the month*		
CARREG	Car registrations	$m-1$
CARSALES	Car sales	$m-1$
Last week of the month		
IP	Industrial production	$m-1$
IPNEXTM	Industrial production expected for next month	$m-1$

(*continued on next page*)

interpretation of the forecast. The log-linearized model consists of an IS equation, which describes the behaviour of the output gap, a Phillips equation and a Taylor rule.

$$\hat{y}_t - \hat{g}_t = E_t(\hat{y}_{t+1} - \hat{g}_{t+1}) - \frac{1}{\tau}(\hat{r}_t - E_t\hat{\pi}_{t+1} - \rho_z\hat{z}_t)$$
$$\hat{\pi}_t = \beta E_t\hat{\pi}_{t+1} + \kappa(\hat{y}_t - \hat{g}_t)$$
$$\hat{r}_t = \psi_1(1-\rho_r)\hat{\pi}_t + \psi_2(1-\rho_r)\hat{y}_t + \rho_r\hat{r}_{t-1} + \varepsilon_{r,t}.$$

The output gap excluding government spending ($\hat{y}_t - \hat{g}_t$) depends on the expected future output gap, the real interest rate, and the technology shock $\hat{z}_t$, which evolves according to the shock process $\hat{z}_t = \rho_z\hat{z}_{t-1} + \varepsilon^z_t$. Government spending is also modelled as a shock process $\hat{g}_{t+1} = \rho_g\hat{g}_t + \varepsilon^g_t$. The Phillips curve relates inflation ($\hat{\pi}_t$) to expected inflation and the output gap. The interest rate ($\hat{r}_t$) depends on the lagged interest rate, inflation, and the

Table 5 (*continued*)

Code	Description	Publication lag
Day before the last day of the month		
M1	Monetary aggregate M1	$m-1$
M2	Monetary aggregate M2	$m-1$
RETAIL	Retail trade turnover	$m-1$
JSPVAC	Job seekers per vacancy	$m-1$
URXNSA	Unemployment rate (NSA)	$m-1$
URXSA	Unemployment rate (SA)	$m-1$
WHOLESALE	Wholesale trade turnover	$m-1$

output gap. Finally, we have included three measurement equations that relate the model variables to the observables (y_t^{obs}, π_t^{obs} and r_t^{obs}, see Giannone et al., 2009). We have estimated the model over the same time horizon as our open-economy DSGE model (1987Q1–2009Q2).

Appendix B. Monthly economic indicators

In Table 4, we describe the five different subsets of monthly indicators that were proposed in Section 4.3. Furthermore, Table 5 summarizes the model observables together with the auxiliary variables according to their release dates.

Appendix C. Variables of the log-linearized model in Figs. 1–4

$\widehat{c}$	Consumption
$\widehat{h}$	Hours worked
$\widehat{i}$	Investment
$\widehat{k}$	Capital stock
$\widehat{m}$	Import
$\widehat{nfa}$	Net foreign assets
$\widehat{\pi}$	Inflation of final good
$\widehat{p}_d$	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
$\widehat{x}$	Exports
$\widehat{y}$	Output
$\widehat{z}$	Capacity utilization
$\hat{\epsilon}^a$	Technology shock
$\hat{\epsilon}^b$	Preference shock
$\hat{\epsilon}^\lambda$	Price markup domestic shock
$\hat{\epsilon}^{yf}$	Export demand shock

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