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Comparing Models of Macroeconomic Fluctuations: How Big Are the Differences?*

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Abstract

I generate priors for a VAR from four competing models of economic fluctuations: a standard RBC model, Fisher's (2002) investment-specific technology shocks model, an RBC model with capital adjustment costs and habit formation, and a sticky price model with an unaccommodating monetary authority. I compare the accuracy of the forecasts made with each of the resulting VARs. The economic models generate similar forecast errors to one another. However, at horizons of one to two years and greater, the models generally yield superior forecasts to those made using both an unrestricted VAR and a VAR that uses shrinkage from a Minnesota prior.

Key Words: Model Evaluation. Priors from DSGE Models. Economic Fluctuations. Hours Debate. Business Cycles.

JEL: C11, C52, E32.

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1. Introduction

The analysis of economic fluctuations, or business cycles, using dynamic stochastic general equilibrium (DSGE) models is one of the most active areas of macroeconomic research. However, there remains no agreement about how to test models of economic fluctuations. The common way of evaluating DSGE models by comparing the simulated moments with those of the data lacks precision and makes it difficult to evaluate the success of competing models: within such a framework, there is no criterion to compare models when one matches some moments well and another performs better at explaining others. Further, the mapping between replicating moments and explaining economic fluctuations is at best rough. This has led many researchers to use long-run restrictions in VARs to test whether the data supports the approximate predictions of these models. While SVAR analysis is surely a useful check on DSGE models, the impulse response functions (IRFs) from such models are often imprecisely estimated (Erceg, Guerrieri, and Gust, 2006; Chari, Kehoe, and McGrattan, 2005). Further, the relationship between a fluctuation in a DSGE model and in an SVAR is unclear and in some cases the IRF from an SVAR does not correspond with that from the economic model (Fernandez-Villaverde, Rubio-Ramirez, and Sargent, 2005). A final problem with relying exclusively on SVARs to test theories is that many structural models are consistent with the finding that, for instance, a technology shock raises or lowers hours worked. Improving our understanding of economic fluctuations will eventually require the ability to more finely discriminate between models.

A recent and active debate regarding the plausibility of the technology-driven RBC model highlights the difficulties in relying on SVAR analysis. This debate has come to be known as the “hours debate” since it centers on whether hours worked rise or fall following a positive technology shock. Gali (1999) sparked this discourse when he found that for the majority of the G7 countries, hours worked fall following a technology shock. He estimated a VAR of the first differences of hours and labour productivity and then restricted one of the shocks to have no effect on the long-run level of labour productivity identifying the other shock as the technology shock. However, Christiano, Eichenbaum, and Vigfusson (CEV) (2003) and Altig, Christiano, Eichenbaum, and Linde (ACEL) (2004) estimate similar empirical models but use hours in levels in their VAR. Despite the failure of ADF tests to reject the null of a unit root in hours per capita, they discuss several sensible reasons for this specification. Using this specification,

both CEV and ACEL find that hours rise following a technology shock. Francis and Ramey (2005a) perform a series of robustness checks on the results in Gali (1999), including adding control variables and verifying that the technology shock identified is exogenous rather than capturing monetary shocks, oil shocks, or war dates. Consistent with the results above, they find that changing only how hours enter into the VAR changes the sign of the effect of technology shocks on hours. However, they find that the technology shock identified using the hours-in-differences specification is exogenous while the technology shock found using the hours-in-levels specification is Granger-caused by all three alternative shocks and thus conclude that their results corroborate Gali's.²

Given the problems with SVAR analysis discussed above, and the importance of resolving this debate for our understanding of fluctuations, it is useful to consider an alternative way of approaching the question. To this end, I use recently developed Bayesian econometric techniques to compare the performance of four contrasting models of economic fluctuations, two of which predict that hours decline following a technology shock and three that generate an increase in hours. Specifically, I evaluate a standard RBC model with indivisible labour and Fisher's (2006) investment-specific technology shocks model, both of which generate an increase in hours following a technology shock. For the models predicting a decline in hours following a technology shock, I use an RBC model augmented with capital adjustment costs and habit formation and a sticky price model with an unaccommodating monetary authority.

I follow Ingram and Whiteman (1994) and Del Negro and Schorfheide (2004) in using these models to shrink the parameter space of an unrestricted VAR towards that of the restricted VAR implied by the economic model. A tightness parameter, λ , controls the weight placed on the model versus the unrestricted VAR. The VAR(λ , i), where i indexes the economic model, is then used to forecast output, investment, hours, and consumption. This is analogous to using λT artificial observations and T actual observations to estimate the parameters of the VAR. I also compare the forecasting performance of the VAR(λ , i) with a VAR that uses shrinkage from the uninformative Minnesota prior introduced by Doan, Litterman, and Sims (1984) and Litterman (1986). Since it is well-known that the OLS estimator, i.e., the

² Recent contributions to this debate also include Fernald (2004), Pesavento and Rossi (2005), Francis and Ramey (2005b), and Basu, Fernald, and Kimball (2006).

unrestricted VAR, is inadmissible when the loss function is mean squared forecast error (MSFE), and that many shrinkage estimators dominate OLS for this loss function (see, for example, Judge et al., 1985), it is a victory for the model only if the VAR(λ , i) outperforms the VAR with shrinkage using the Minnesota prior.

I find little difference in forecast accuracy across models even at horizons where the models have sharply different implications for the effects of technology. While the investment specific technology shocks model gives slightly better forecasts for investment and hours, the improvement is slight. The sticky price model with a high degree of price rigidity (corresponding to price contracts lasting five quarters) fares worse than the other three models in general but, again, the differences are very modest and its performance improves when the price inertia is lowered to imply contracts lasting only two quarters. However, all of the models considered usually outperform the Minnesota prior and unrestricted VARs at horizons of 8-20 quarters when an estimation window of 160 quarters is used; the economic models generally do better than the atheoretical models at horizons of 4-20 quarters for estimation windows of alternative lengths. The similarity in performance across models suggests that there may be some factor all of the models incorporate that helps predict real variables at the two to five year horizon but casts doubt on technology as the dominant factor in economic fluctuations.

To my knowledge, this is the first paper to use a Bayesian approach to try to distinguish between the basic RBC model with that of seemingly distant competitors in forecasting real variables. Other work has used Bayesian techniques to compare alternative sticky price models: Korenok and Swanson (2005) compare the forecasting performance of a variety of sticky price models in predicting the output gap and inflation while Rabanal and Rubio-Ramirez (2005) compare the ability of several sticky price models to reproduce the observed persistence in inflation, output, and wages by computing posterior odds ratios. I also build on the literature contrasting the forecasting ability of priors from DSGE models with the Minnesota prior.

The remainder of the paper is organized as follows: Section 2 briefly describes the models under consideration. Section 3 describes how to generate priors for the VAR parameters from the models as well as the specification of the Minnesota prior. Section 4 contains the results and robustness exercises. Section 5 offers a brief discussion of the results while section 6 concludes.

2. The Models

I consider four models: 1) Hansen's (1985) RBC model with indivisible labour, 2) a formulation of 1) augmented by habit formation and capital adjustment costs the exact specification of which follows Beaudry and Guay (1996), 3) Fisher's (2006) RBC model with investment-specific technology shocks, and 4) a sticky price model with a fixed money supply. As discussed in Francis and Ramey (2005a), models 2) and 4) generate a decline in hours worked in the short run contrary to the prediction of models 1) and 3).³ Figures 1-4 present the theoretical impulse response functions for these models which confirm the posited effects on hours in each of the models.

2.1 A Standard RBC Model with Indivisible Labour

Now a canonical specification of the RBC model, Hansen's (1985) model postulates that the social planner's problem is

$$\begin{aligned} & \text{Max}_{\{C_t, H_t\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t U(C_t, H_t) = \\ & \text{Max}_{\{C_t, H_t\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t [\ln C_t - \gamma H_t], \quad \beta \in (0,1), \gamma > 0 \end{aligned} \quad (2.1)$$

subject to

$$Y_t = A_t K_t^\theta (\eta^t H_t)^{1-\theta}, \quad \theta \in (0,1) \quad (2.2)$$

$$K_{t+1} = (1 - \delta)K_t + I_t, \quad \delta \in (0,1) \quad (2.3)$$

$$Y_t = C_t + I_t \quad (2.4)$$

$$\ln A_t = (1 - \rho_A) \ln A + \rho_A \ln A_{t-1} + \varepsilon_t^A, \quad \rho_A \in (-1,1), A > 0, \varepsilon_t^A \sim (0, \sigma_A^2) \quad (2.5)$$

where C_t , H_t , Y_t , A_t , K_t , and I_t are consumption, hours worked, output, the level of technology, capital, and investment.

Ireland (2003) derives the state-space representation for this model using a first-order accurate log-linearization and Blanchard and Kahn's (1980) methodology. Table 1 summarizes the calibration for the four models. I set $A=1$, $\theta = 0.36$, $\delta = 0.021$, $\beta = 0.99$ following Francis and Ramey (2005). η is set at

³ As noted by Manuelli (2003), Rotemberg (2003), and Linde (2005), however, the rise in hours in models 1) and 3) depends crucially on the immediate diffusion of the technology shock; slow diffusion of the technology shock will instead generate a decline in hours.

1.0059 to be consistent with the average growth rate of per capita output in the data. ρ_A is set at 0.95 and σ_A is calibrated to 0.0066.

2.2 An RBC Model with Habit Formation and Capital Adjustment Costs

The second model is identical to that of 2.1 except for the addition of habit formation and capital adjustment costs. The literature considers several particular functional forms for the habit formation and capital adjustment costs; the treatment here follows Beaudry and Guay (1996) with the functional form of the utility function that of section 2.1 and with a deterministic trend in the growth component of technology rather than the stochastic trend of Beaudry and Guay. The social planner's problem is thus identical to that of 2.1 with equations (2.1) and (2.4) replaced by

$$\text{Max}_{\{C_t, H_t\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t [\ln(C_t - \nu C_{t-1}) - \gamma H_t], \quad \beta \in (0,1), \gamma > 0 \quad (2.1)'$$

$$Y_t = C_t + I_t + \frac{q(K_{t+1} - \eta K_t)^2}{2K_t} \quad (2.4)'$$

The intuition behind the decline in hours following a technology shock in this model is as follows: with habit formation, individuals prefer a smoother consumption path than in the standard model and so increase consumption only gradually in response to an increase in expected income. In the absence of capital adjustment costs, individuals spend the increase in expected income on investment to take advantage of the temporarily higher productivity shock. However, with capital adjustment costs, this aperture is substantially less valuable and instead individuals spend the windfall on leisure.

The appendix of Beaudry and Guay provides the first order conditions, first-order accurate log-linearization, and solution method for this model which follows Blanchard-Kahn (1980). The calibration of ν and q reflects a compromise between the GMM estimates in Beaudry and Guay and the higher values for habit persistence and implied capital adjustment costs in Jermann (1998), Boldrin, Christiano, and Fisher (2001), and Francis and Ramey (2005a). While the midpoints of Beaudry and Guay's estimates of $\nu=0.4$ and $q=11$ generate a decline in hours, the decline is modest and lasts only four quarters. Conversely, Boldrin, Christiano, and Fisher estimate $\nu=0.9$ conditional on their chosen parameter value for their capital adjustment costs; Jermann (1998) finds that $\nu=0.82$ maximizes the model's ability to match selected

moments in the data. I compromise and set $v=0.7$ and $q=25$ in the benchmark model. This generates a 13 quarter decline in hours.

2.3 Investment Specific Technology Shocks

Fisher (2006) studies the possibility that investment-specific technological change, first studied to explain long-run growth by, among others, Greenwood, Hercowitz, and Krusell (1997) and Hulten (1992), can drive business cycles. He finds that when investment-specific shocks are added to the model, neutral technology shocks account for little of the variation in hours worked over the business cycle. However, investment-specific technology shocks generate a significant rise in hours worked, consistent with traditional RBC models, and thus suggest that the technology-driven theory of the business cycle is alive and well.

The third model I consider follows Fisher's closely with a few exceptions. First, to be consistent with the models of 2.1 and 2.2, the utility function is logarithmic in consumption and embodies indivisible labour. Second, since the interest here is not the long-run, I relegate the growth component of both technologies to a secular trend in labour-augmenting technology shock. This is without loss of generality since, with a constant returns to scale production function, the growth component in technological change must be expressible as Harrod-neutral progress (King, Plosser, and Rebelo, 1988). Finally the analysis here does not require the ability to empirically distinguish between investment-specific and neutral shocks as Fisher's empirical work does; I therefore do not impose a unit root in either technology process. The model is thus that of section 2.1 with (2.3) replaced by

$$K_{t+1} = (1 - \delta)K_t + V_t I_t \quad \delta \in (0,1) \quad (2.3)'$$

where

$$\ln V_t = (1 - \rho_V) \ln V + \rho_V \ln V_{t-1} + \varepsilon_t^V, \quad \rho_V \in (-1,1), V > 0, \quad \varepsilon_t^V \sim (0, \sigma_V^2) \quad (2.6)$$

I derive the state-space representation of the model using a first-order accurate log-linearization and the method of Blanchard-Kahn (1980). The calibration of the model has $\rho_A = \rho_V = 0.95$ and $\sigma_A = \sigma_V = 0.0066$.

2.4 A Sticky Price Model with an Unaccommodating Monetary Authority

The sticky price model is relatively standard in the literature and is similar to the models of Yun (1996) and Chari, Kehoe, and McGrattan (2000); Walsh (2003) and Woodford (2003) offer textbook treatments of the sticky price model. To be consistent with the models in 2.1-2.3, I add a trend in the labour-augmenting technology of intermediate goods firms as in Yun (1996). The demand for real balances arises through inserting money into the utility function, monopolistically competitive intermediate goods firms set their prices in Calvo (1983) -style staggering, and final goods firms behave perfectly competitively.

Specifically, there is a continuum of intermediate goods firms on the interval $[0, 1]$, indexed by j , each of which produces $Y_{j,t}$. Perfectly competitive final goods producers produce the composite commodity consumed by households using

$$Y_t = \left[\int_0^1 (Y_{j,t})^{\frac{\xi-1}{\xi}} dj \right]^{\frac{\xi}{\xi-1}} \quad (2.8)$$

where ξ is the elasticity of substitution between goods. Profit maximization yields the demands for the intermediate goods

$$Y_{j,t}^d = \left(\frac{P_t}{P_{j,t}} \right)^{\xi} Y_t \quad (2.9)$$

and the zero profit condition implies that the price of the composite good is

$$P_t = \left[\int_0^1 (P_{j,t})^{1-\xi} dj \right]^{\frac{1}{1-\xi}} \quad (2.10)$$

where $P_{j,t}$ is the price of firm j 's good.

The capital and consumption goods are exchangeable at a one-to-one rate. The household's problem is thus

$$\text{Max}_{\{C_t, H_t, M_t^D\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t [\ln C_t + \omega \ln(\frac{M_t^D}{P_t}) - \gamma H_t], \quad \beta \in (0,1), \gamma > 0 \quad (2.11)$$

subject to

$$P_t K_t + M_t^D = (1 - \delta + r_t) P_t K_{t-1} + P_t W_t H_t + M_{t-1}^D + T_t + PR_t - P_t C_t \quad (2.12)$$

where M_t^D is the household's date t nominal balances, C_t is units of consumption of the composite good, W_t and r_t are the real wage and rental rates, T_t is transfers from the monetary authority, and PR_t are the profits from household's ownership of firms.

Intermediate goods firms produce goods using

$$Y_{j,t} = A_t K_{j,t}^\theta (\eta^t H_{j,t})^{1-\theta}$$

where A_t follows the process given in (2.5). The price stickiness is modeled as simple Calvo price staggering following the finding of Korenok and Swanson (2005) that price indexation does not improve the performance of the sticky price model for real variables.⁴ That is, each period a firm faces the probability $1-\alpha$ of being able to change its nominal price. This leads to the maximization problem

$$\underset{P_{j,t}}{\text{Max}} E_t \sum_{k=0}^{\infty} (\alpha\beta)^k m_{t+k} (P_{j,t} - mc_{t+k} P_{t+k}) Y_{j,t+k}^d \quad (2.13)$$

where mc_{t+k} , marginal cost, is given by

$$mc_t = \min_{K_{j,t}, H_{j,t}} r_t K_{j,t} + W_t H_{j,t} \quad \text{subject to} \quad Y_{j,t} = A_t K_{j,t}^\theta (\eta^t H_{j,t})^{1-\theta} = 1$$

and m_{t+k} is the current value of a dollar received by the household in period $t+k$ which the firm treats as exogenous.

Finally, the monetary authority follows a $k\%$ rule,

$$M_{t+1}^S = \mu M_t^S \quad (2.14)$$

and remits all seignorage revenue to the household:

$$T_t = (\mu - 1) M_{t-1}^S.$$

Since the value of μ does not affect the model's dynamics, μ is set at 1 for simplicity.

In this model, the proximate effect of a technology shock is to lower the intermediate good firm's marginal costs. With sticky prices, this drives a wedge between the real wage and its marginal revenue product. Since households expect the wedge to decrease over time as prices adjust, they increase their consumption of leisure now. With a Cobb-Douglas production function, labour and capital are

⁴ Note, however, that both Korenok and Swanson (2005) and Rabanal and Rubio-Ramirez (2005) find that price indexation improves the performance of the sticky price model for inflation.

complements such that the firm decreases its demand for capital and, in response to this decline in the return to capital, the household disinvests to satisfy its intertemporal Euler equation until prices adjust.

Figure 4 illustrates these dynamics.

In the interests of space, I omit the first order conditions, first-order accurate log-linearization, and solution of this model. The solution uses the Blanchard-Kahn (1980) method. There is disagreement in the literature regarding the value of the elasticity of substitution between goods, ξ , which must be consistent with a steady-state markup of price over marginal cost equal to $\frac{\xi}{\xi-1}$: Korenok and Swanson (2005) set it at

11, Chari, Kehoe, and McGrattan (2000) set it at 10, Yun (1996), Ireland (2001), and Rabanal and Rubio-Ramirez (2005) set it at 6, while Christiano, Eichenbaum, and Evans (2005) and Eichenbaum and Fisher (2004) estimate to be around 3. In the benchmark specification I set it equal to 6. There is similarly some controversy regarding the value of $1-\alpha$, the probability a firm can adjust its price: Bils and Klenow (2004), Eichenbaum and Fisher (2004), and Christiano, Eichenbaum, and Evans (2005) both suggest that firms reoptimize prices on average once every two quarters implying $\alpha=0.5$ while Rabanal and Rubio-Ramirez (2005) and other earlier work cited by Bils and Klenow (2004) find that firms reoptimize only every four to seven quarters. In the benchmark model, I parameterize the model with $\alpha=0.8$, implying that firms readjust prices every five quarters – the lower value of 0.5 did not yield a decline in hours following a technology shock that is of interest in this paper.

3. Incorporating Prior Information

3.1 Prior Information from DSGE Models

Let y_t , i_t , h_t , and c_t denote data on output, investment, hours worked, and consumption. We are interested in using the models above to generate forecasts from the model

$$x_t = \sum_{i=1}^p x_{t-i} \phi_i + z_t \phi_0 + u_t \quad \text{where } x_t = [y_t, i_t, h_t, c_t] \text{ and } z_t = 1.$$

This system can be written in matrix form as

$$Y = X\Phi + u, \text{ where } X=[z, x_{-1}, x_{-2}, \dots, x_{-p}], \Phi = [\phi_0', \phi_1', \dots, \phi_p']' \quad (3.1)$$

Now assume that

$$u \sim N(0, \Sigma_u).$$

Ingram and Whiteman (1994) originated the idea of using prior information from a DSGE model to induce shrinkage. However, I use the shrinkage estimators for Φ proposed by Del Negro and Schorfheide (2004) which take the form

$$\tilde{\Phi}_i = (\lambda T \Gamma_{XX}^*(i) + X'X)^{-1} (\lambda T \Gamma_{X'Y}^*(i) + X'Y)$$

$$\Gamma_{XX}^*(i) = E(X_i^* X_i^*)$$

$$\Gamma_{XY}^*(i) = E(X_i^* Y_i^*)$$

where * denotes that the data is simulated from model i , $i=1,2,3,4$ with i corresponding to the model

discussed in section 2.1. $\Gamma_{XX}^*(i), \Gamma_{XY}^*(i), \Gamma_{YY}^*(i)$ are generated from the state-space representation of the DSGE models as described in appendix A.2 of Del Negro and Schorfheide. The resulting empirical VAR(λ, i) models are denoted RBC, HABIT, ISHOCK, and STICKY.

Because the number of shocks in the models is less than the number of variables, the DSGE models all contain a stochastic singularity such that the VAR(λ, i) models are degenerate as $\lambda \rightarrow \infty$. The VAR(λ, i) models therefore explicitly rule out the possibility that the true DGP is the DSGE model. Instead, the incorporation of real data alongside the ‘dummy observations’ generated by the DSGE models can be seen as a way of capturing all the dynamics of the economy not captured by the DSGE model.⁵

It remains to choose a procedure for selecting λ for the models, the parameter that controls how much weight is put on the models relative to the data. Del Negro and Schorfheide propose choosing this parameter to maximize the log likelihood of the data over some grid, $\Lambda = \{\lambda_1, \lambda_2, \dots, \lambda_l\}$. However, this procedure requires that the models have as many shocks as there are variables in the VAR such that the models are not stochastically singular. Again, none of the models have enough structural shocks to satisfy this constraint; I instead simply compare the forecasting performance for a range of values of λ .

3.2 The Minnesota Prior

⁵ Del Negro and Schorfheide and Ireland (2004) propose adding errors to the equations to create a well-defined likelihood function; however, this would require specification of the variances for these errors. It is unclear how including more shocks or the choice of variance would alter the effect of technology shocks.

Since the OLS estimator is inadmissible for the loss function considered here (see, e.g., Elliott and Timmerman, 2003), I compare the forecasting performance of a shrinkage estimator using the Minnesota prior. Todd (1984) provides an excellent intuitive explanation why this estimator often outperforms an unrestricted and many kinds of structural VARs. Essentially, an unrestricted VAR puts equal likelihood on all values of the VAR parameters and so does not reflect even the most naive forecaster's true beliefs about the values of the parameters. Since the OLS parameter estimates are identical to the maximum likelihood estimates for the coefficients of an unrestricted VAR, the OLS procedure is identical to having a diffuse prior over the coefficients. To see this, let w , $p(\Phi)$, $p(\Phi|w)$, and $l(w|\Phi)$ denote a vector of data, the prior, the posterior, and the likelihood function. Then if the econometrician has a diffuse prior over Φ , i.e., $p(\Phi) \propto 1$, then

$$p(\Phi | w) \propto p(\Phi)l(w | \Phi) = l(w | \Phi) .$$

Structural VARs similarly impose dogmatic priors on some parameters in their use of zero restrictions while again placing equal weight on all possible values for the remaining parameters of the model. Both of these procedures are at odds with common sense and so it is not surprising that professional forecasters using some judgment rather than formal econometric models were generally able to outperform econometric models until the advent of Bayesian VARs (Litterman, 1986).

While many priors not derived from economic theory perform well relative to unrestricted VARs⁶, the Minnesota prior of Doan, Litterman, and Sims (1984) and Litterman (1986) has proven difficult to consistently outperform and remains the benchmark for many analyses (see, for example, Ingram and Whiteman, 1994, Kadiyala and Karlsson, 1997, Sims and Zha, 1998, and Del Negro and Schorfheide, 2004). This prior posits that a good first approximation of the data is that each series follows a univariate random walk. In particular, the coefficients are normally distributed with a variance that decreases with the order of the lag and a smaller variance for cross lags than for own lags. The idea behind this specification of the variance structure is that the variance should be higher for parameters that are likely to be more important in estimating the VAR so that an overly tight prior does not seriously bias the results. My implementation of this prior follows Litterman (1986) with the tightness parameters, θ and λ , set at 0.2 and

⁶ See Kadiyala and Karlsson (1997) for a review of some of these priors.

0.1 where the θ is that in the Litterman paper and not to be confused with the capital share parameter of section 2. The value of θ is set as in Litterman (1986) while $\lambda=0.1$ was the value yielding the best forecasts for output. Henceforth I refer to this model as VAR-MINN.

4. Results

4.1 Data

The data set is seasonally adjusted and covers 1947:1-2005:3. Consumption and investment, c_t and i_t , are NIPA series in chained 2000 dollars for personal consumption expenditures and gross private fixed investment retrieved from the Bureau of Economic Analysis website. Since none of the models considered here include government or export sectors, output, y_t , is defined as the sum of real consumption and investment where these series are put in real terms by deflating the nominal series by their GDP deflators. I do not define output as the sum of the chain weighted NIPA consumption and investment series since, as Whelan (2000) and Jones (2002) discuss, the chain-weighted series suffer from a lack of additivity. The hours series, h_t , is an index (1992=100) for non-farm business employment which we take from the Bureau of Labor Statistics. The series ID is PRS85006033. All variables are used in natural logs and put on per capita terms by dividing by the US population, data which comes from the US Bureau of the Census. Population data is only available on an annual basis so quarterly values are obtained by linear interpolation.

Since all the models have steady states and are solved in terms of detrended variables, output, consumption, and investment are linearly detrended. I do not detrend the data using an HP or a Baxter-King (1999) bandpass (6, 32) filter for several reasons: first, none of the models stipulate which frequencies are affected by the driving process. Accordingly, each of the models should be treated as able to explain economic fluctuations in general rather than those only at frequencies corresponding to approximately 6-32 quarters. Second, as discussed by Comin and Gertler (2006), there are substantial and economically significant movements in output at what they term medium-term frequencies, i.e., those corresponding to cycles of 32-200 quarters. Moreover, as Perron and Wada (2005) emphasize, trend-cycle decompositions based on the Hodrick-Prescott filter bear little resemblance to NBER chronology. Finally, linear detrending makes it straightforward for a real-time forecaster to use the results to forecast output by simply reinserting the growth component.

4.2 Results for the Benchmark Model

Kim and Nelson (1999) and McConnell and Perez-Quiros (2000) document the structural instability in the real side of the US macroeconomy over the course of the dataset. It is beyond the scope of this paper to explicitly model such instability; instead I follow the recommendations of Giacomini and White (2005) and West (2005) and use a rolling window forecasting scheme to minimize the effect of this instability. The benchmark model uses four lags of output, investment, hours, and consumption, a common lag length for VAR analysis in macroeconomics, and a 160 quarter estimation window.

Tables 2-5 report the results for several values of the tightness parameter. The most striking result is how similar the MSFEs are across the different models. While ISHOCK gives slightly better forecasts for investment and hours, the improvement is slight. STICKY fares worse than the other three economic models in general but, except at the shortest horizons, the differences are very modest.⁷ The second thing to remark from tables 2-5 is that all of the economic models substantially outperform the VAR-MINN and unrestricted VAR at horizons of greater than 8 quarters.

4.3 Sensitivity Analysis

The sticky price model considered has an unaccommodating monetary authority, such that the model generates a decline in hours following a technology shock. However, King and Wolman (1996) document that the dynamics in sticky price models are highly sensitive to the specification of the monetary rule as monetary economists would expect. Further, Clarida, Gali, and Gertler (1999) and Gali, Lopez-Salido, and Valles (2003) present evidence that the Federal Reserve Board optimally responded to technology shocks during the Volcker-Greenspan era but followed a constant money growth rule in the pre Volcker era, suggesting that the model of section 2.4 may be the right model to consider for many of the estimation periods but a poor approximation for the forecasting periods, all of which are in the Volcker-Greenspan era.

⁷ As discussed in Giacomini and White (2005), the commonly used Diebold and Mariano (1995) tests for differences in MSFEs are inappropriate for Bayesian estimation schemes because asymptotic irrelevance does not apply. While the tests proposed by Giacomini and White (2005) are easy to implement for testing differences in one-step ahead forecasting ability, the interesting results here are at longer horizons where practical implementation of the Giacomini and White tests has no precedent in the literature and no computationally convenient algorithm exists at this time. I am thus unable to test whether these small differences are statistically significant.

I therefore consider a specification of the sticky price model that allows the central bank to respond to technology shocks. This model is the same as that in 2.4 but with (2.14) replaced by

$$\ln M_{t+1}^S = \rho_M \ln M_t^S + (1 - \rho_M) \ln M + E_t \ln A_{t+1} \quad (2.14)'$$

That is, the monetary authority matches any increase in the expected level of technology with an immediate increase in the money supply in the period following the shock. The money supply then follows a continuous hump-shaped pattern analogous to that of the real variables until the shock dies out and the money supply returns to its steady state level. ρ_M is calibrated to 0.5. Table 6 reports the results for this specification of STICKY. The similarity of the forecasting accuracy across models remains the most noticeable result.

Some might be concerned that the results presented here are in fact comparisons of particular calibrations rather than the overall models being considered. This concern could be addressed by introducing priors over the theoretical parameters as in Del Negro and Schorfheide (2004), Fernandez-Villaverde and Rubio-Ramirez (2004), Rabanal and Rubio-Ramirez (2005), and Del Negro, Schorfheide, Smets, and Wouters (2005), among others. However this substantially increases the computational cost of the exercise and, unlike most of the literature using this approach, this paper is not interested in estimating structural parameters. Instead, I examine the robustness of the results to a number of different theoretical parameterizations in the range considered in the literature; the results above hold for all plausible calibrations.

Tables 7-9 present the results for an alternative calibration of each model that is a major departure from the benchmark model but still plausible. In the interest of space, the tables include only the results for the intermediate value of the tightness parameter, i.e., $\lambda=1$. Table 7 presents the results for when the habit persistence parameter, v , and the investment adjustment cost parameter, q , in HABIT are set at 0.4 and 11 to match the estimates in Beaudry and Guay (1996) rather than 0.7 and 25 as in the benchmark model. The basic findings are unaltered by this change. In the benchmark ISHOCK model, the volatility of the investment-specific shock is set equal to that of the neutral shock. This choice is somewhat arbitrary owing to the lack of literature on this parameter; table 8 presents the results when σ_v is doubled to 0.0132, twice the volatility of the neutral shock. The results are not substantially different from those in the benchmark model. Finally, in table 9 I set α , which governs the degree of price stickiness STICKY to 0.5 to match the

findings of Bilts and Klenow (2004), Eichenbaum and Evans (2004), and Christiano, Eichenbaum, and Evans (2005) that price contracts last an average of 2 quarters rather than the 5 quarters used to calibrate the benchmark model. I also lower ξ , the elasticity of substitution between goods, from 6 to 3 as found by Christiano, Eichenbaum, and Evans (2005). The results for STICKY improve with this calibration suggesting some evidence against a high degree of nominal rigidity.

The choice of 160 quarters as the length of the estimation window is somewhat arbitrary. I also considered windows of 120, 140, and 180 quarters. Tables 10-12 report the results for the three alternative estimation window lengths. All three of the alternative windows gave results more favourable for the economic models than the atheoretical models: for the other three windows, the models generally outperformed the VAR-MINN and unrestricted VAR at horizons of two quarters and greater. However, the forecasting accuracy across models remains similar. The relative improvement of the economic models when 180 quarters are used owes to a worsening in the performance of VAR-MINN.

Finally, there may be concern that the success of the models relative to VAR-MINN owes to a poor specification of the Minnesota prior: there are many ways of specifying the Minnesota prior and the performance is often sensitive to the choice of the tightness parameter (Ni and Shu, 2003). I therefore also consider the specification in Kadiyala and Karlsson (1997), where the variances of the coefficients decrease with lag length at a slower rate than in Litterman, and two looser Litterman priors ($\lambda=0.3$ and $\lambda=0.5$). The results favour the benchmark specification of the Minnesota prior but are not reported in the interest of space.

4.4 Similar Forecasts or Similar Forecast Errors?

That the mean of the forecast errors is similar does not necessarily indicate that the models all yield similar results; it may be the case that the models make mistakes in the opposite directions of one another, with one model over-predicting a variable and another under-predicting, and yet the average forecast error is the same. This section demonstrates that the models yield similar forecasts to one another, not simply similar forecast errors.

As evidence of the similarity in forecasts across models, figures five through eight plot the two quarter ahead dynamic forecast for each of the DSGE models and the Minnesota prior for the four variables. The forecasts are made using $\lambda = 1$ and the 120 quarter estimation window. The models rarely

generate forecast errors that are opposite in sign to one another and they are often almost on top of one another. Perhaps more importantly, none of the DSGE models capture turning points in the data. That is, the dynamic component of the models fails quite badly with the models consistently generating forecasts that lag the cycle. The results for the four quarter horizon were similarly dismal.

4.5 DSGE Models vs. Cointegrating Prior

All of the DSGE models have the same steady state, and thus similar implications for the long run, and it may be the case that the medium-run success of the models comes merely from their imposition of long run equilibrium relationships between the variables. Indeed, King, Plosser, Stock, and Watson (1991) find that over half of all movements in postwar U.S. GNP come from shocks to the long run component when only real variables are included in the VAR, as is the case here. This suggests that perhaps the only part of the economy that the DSGE models are capturing is these long run components. While the DSGE models as specified do not contain unit roots, and thus are not exactly cointegrated, one way of capturing these long run equilibrium relationships is by imposing cointegrating relationships. Comparing the DSGE models to a forecasting model that only imposes cointegration may shed some light on the common element these models that provides decent forecasts at horizons greater than one year.

To this end, table 13 compares the benchmark RBC model with a VAR that uses cointegration as the prior (VAR-COINT). The VAR-COINT estimation is implemented by using a dummy observation; Robertson and Tallman (1999) provide an excellent overview of the mechanics for this procedure. Following Robertson and Tallman (1999) and the literature cited there, I use $\mu_6=5$ for the hyperparameter that controls how much weight to attach to the cointegrating ‘dummy’ observation. The results suggest that the success of the DSGE models is not exclusively due to their imposition of long-run equilibrium relationships; the DSGE models outperform the cointegration prior for all series except hours at the

5. Discussion

The main finding of the paper that all of the models generate similar results, despite the different effects of neutral technology shocks in them. The exception is that the benchmark specification of STICKY performs particularly poorly at short horizons. This finding suggests that neutral technology is not the driving force

behind economic fluctuations. Even for the hours series, where at short horizons the impulse response functions from the different models move in opposite directions, it is the similarity of the MSFEs that stands out. The results instead indicate that all four models contain some element that outperforms the random walk in the medium term but it seems unlikely that the factor at work is technology shocks.

The results perhaps both vindicate and indict the DSGE approach to modeling economic fluctuations. In one sense, the poor performance of the more sophisticated models relative to the basic RBC model implies that many model refinements are not improving our ability to understand the source of fluctuations. Furthermore, none of the DSGE models are able to predict turning points in the data, suggesting that technology shocks are not what drive the economy from expansion to recession states. That is, the dynamic aspect of the models simply does not capture the important dynamic features in the data.

The poor performance of STICKY at short-horizons is especially disappointing. It is important to note that it is the only model with *any* implications for prices and inflation; the comparison using only real variables is thus not entirely fair to STICKY. Robustness exercises also showed that a lower degree of price stickiness and using an accommodating monetary authority improve the performance of STICKY at short horizons, although these changes do not alter STICKY's ranking. Finally, the comparison exercise here is silent on the sticky wage model of Erceg, Henderson, and Levin (2000), a nominal rigidity that recent work by Malley, Muscatelli, and Woitek (2005) and Christiano, Eichenbaum, and Evans (2005) suggests is substantially more plausible than sticky prices.

On the other hand, all of the economic models substantially outperform the atheoretical models at horizons of one to two years and greater. This is a more favorable result for the RBC model than Ingram and Whiteman (1994) who find that the RBC model performs only comparably, rather than better, than the Minnesota prior. However, Ingram and Whiteman only examine horizons of up to four quarters where I find similar results; it is only at longer horizons that the RBC's performance exceeds that of the Minnesota prior. These results also accord with those of Del Negro and Schorfheide (2004) and Korenok and Swanson (2005) who find that sticky price models outperform the Minnesota prior in forecasting, respectively, output growth and the output gap at similar horizons. Furthermore, the favourable results for ISHOCK provide support for the idea that investment-specific technology shocks are a promising new direction for business cycle research.

6. Conclusions

This paper evaluated the forecasting performance of VARs with priors derived from four competing models of economic fluctuations: a standard RBC model, Fisher's (2002) investment-specific technology shocks model, an RBC model augmented with capital adjustment costs and habit formation, and a sticky price models with an unaccommodating monetary authority. The models generate similarly accurate forecasts for output, investment, hours, and consumption. The investment specific technology shocks model gives slightly better forecasts for investment and hours while the sticky price model with a high degree of price rigidity (corresponding to price contracts lasting five quarters) fares somewhat worse than the other three models in general and did especially poorly at short horizons. With this last exception, the inter-DSGE model differences are quite modest. All of the models substantially outperform VAR forecasts made using the atheoretical random walk prior and those from an unrestricted VAR at horizons of two or more years when a 160 quarter estimation window is used and at horizons of a year and more when 120, 140, and 180 quarter estimation windows are used. These results are robust to alternative calibrations, a range of choices for the tightness parameter governing the weight accorded to the model, alternative specifications of the Minnesota prior.

The similarity of forecast accuracy across models contrasts with the starkly different predictions of these models for the labour market following a technology shock. However, the DSGE models fail to detect business cycle turning points suggesting further evidence against neutral technology shocks as a driving force behind the cycle. Given its simplicity, it is surprising that the basic RBC model performs so well; the more sophisticated models do not yield better forecasts in general. The results endorse the DSGE approach to modeling macroeconomic fluctuations in their ability to generate superior forecasts at the one year and greater horizons.

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Figure 1: Responses to a Positive Technology Shock in the Basic RBC Model

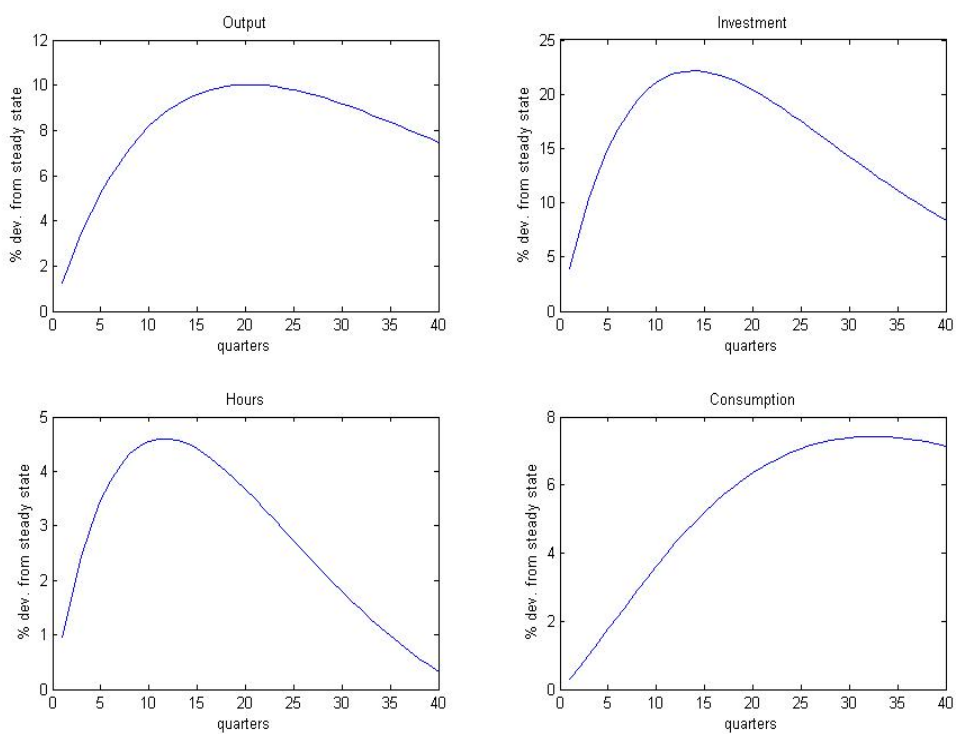


Figure 2: Responses to a Positive Technology Shock with Habit Formation and Capital Adjustment Costs

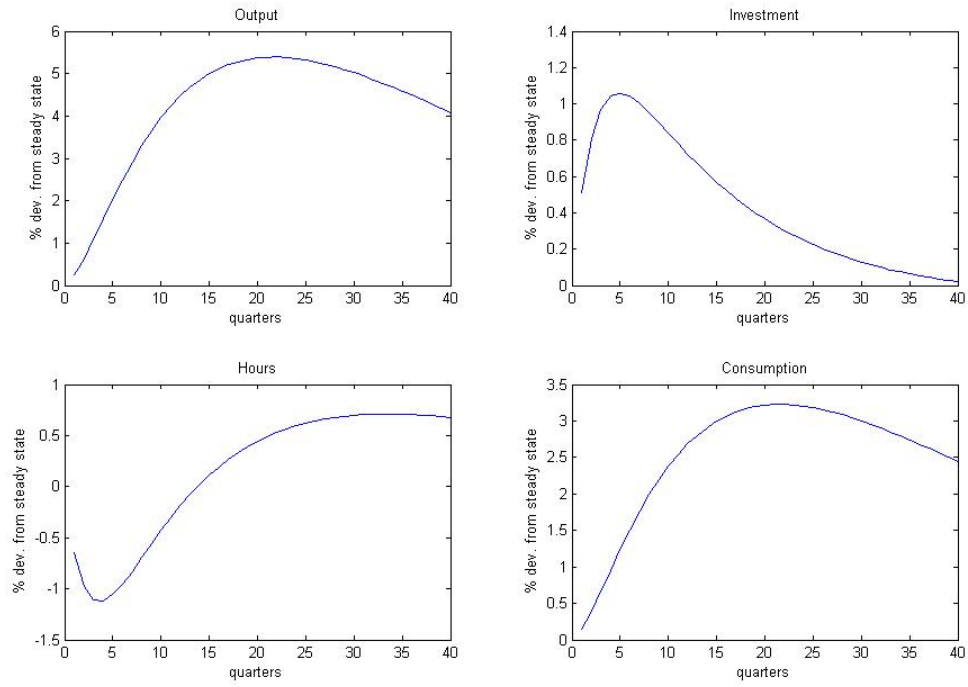


Figure 3: Responses to a Positive Technology Shock with Investment Specific Technology

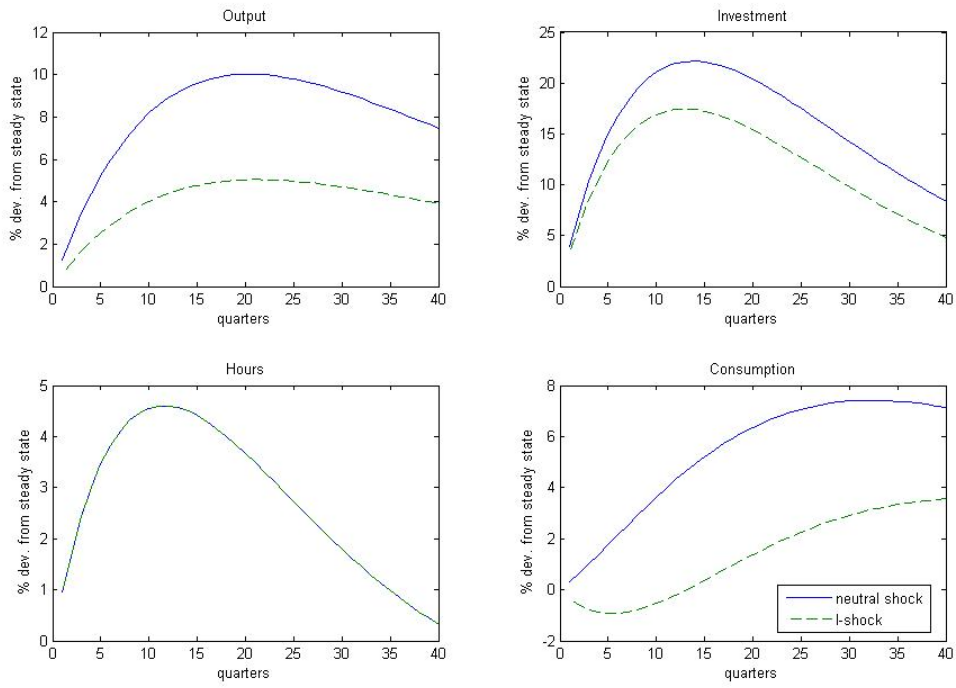


Figure 4: Responses to a Positive Technology Shock with Sticky Prices and an Unaccommodating Monetary Authority

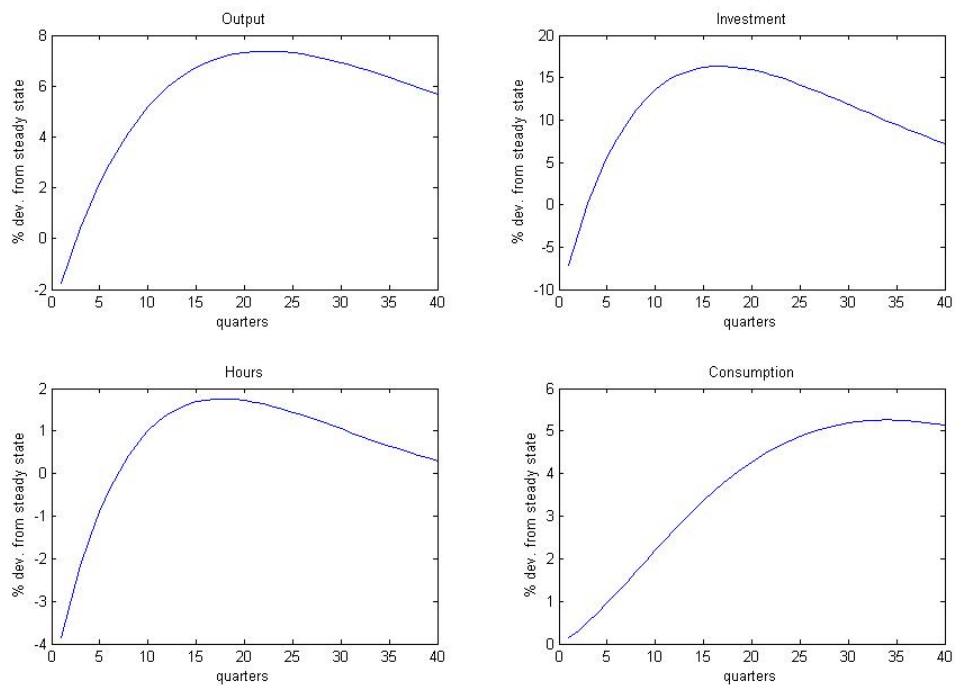


Figure 5: Two Quarter Ahead Forecast Comparison for Output

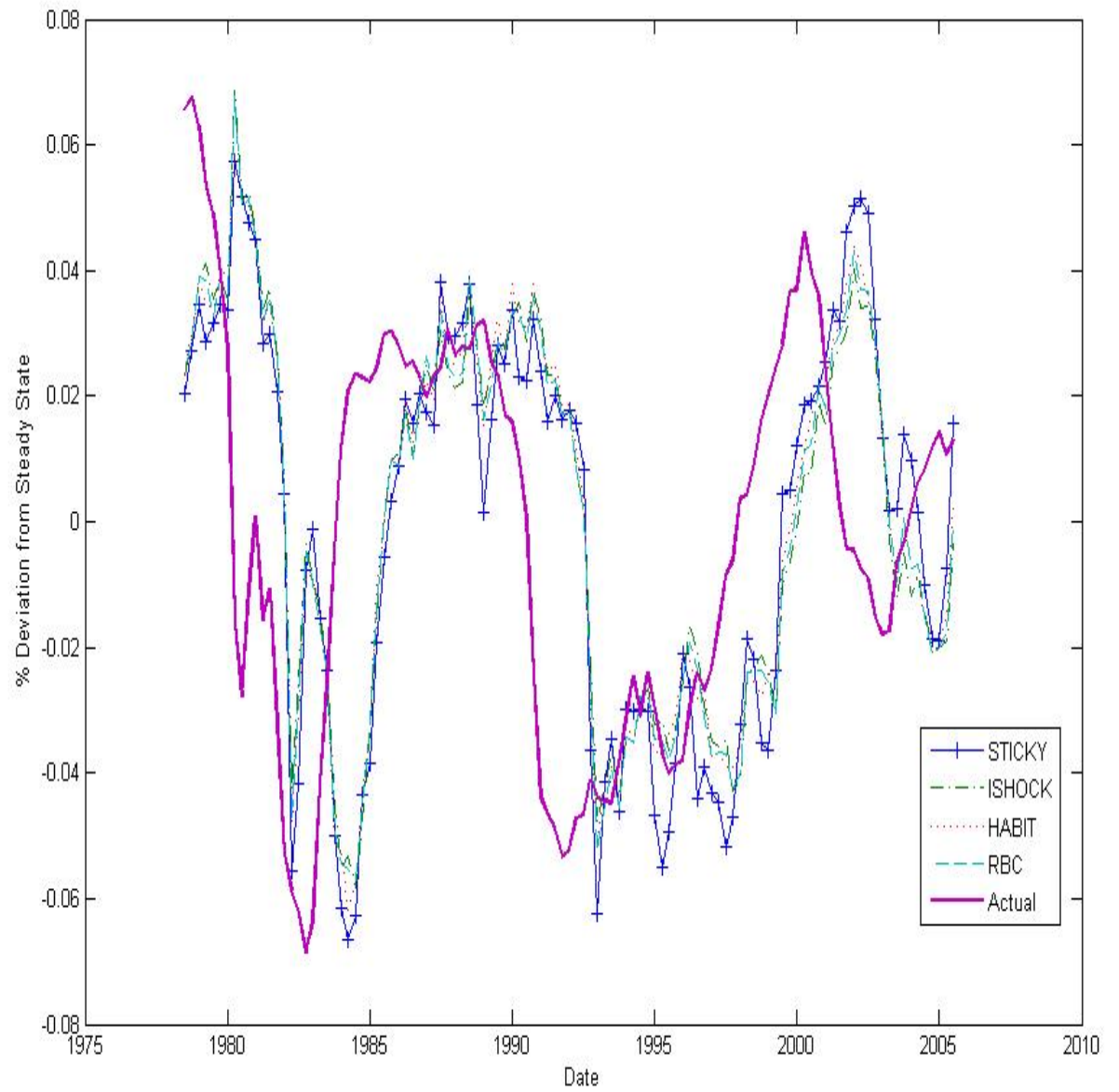


Figure 6: Two Quarter Ahead Forecast Comparison for Investment

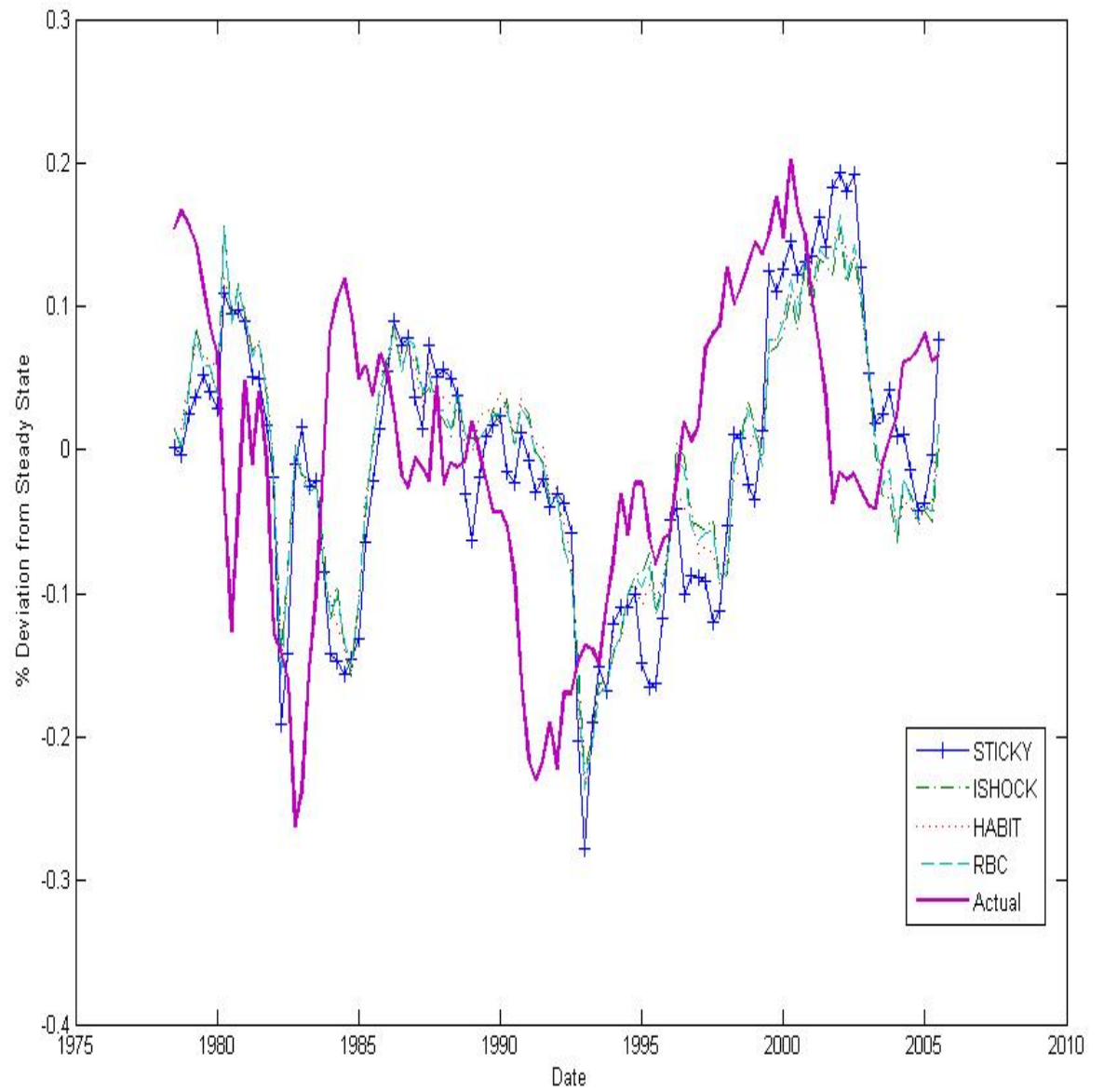


Figure 7: Two Quarter Ahead Forecast Comparison for Hours

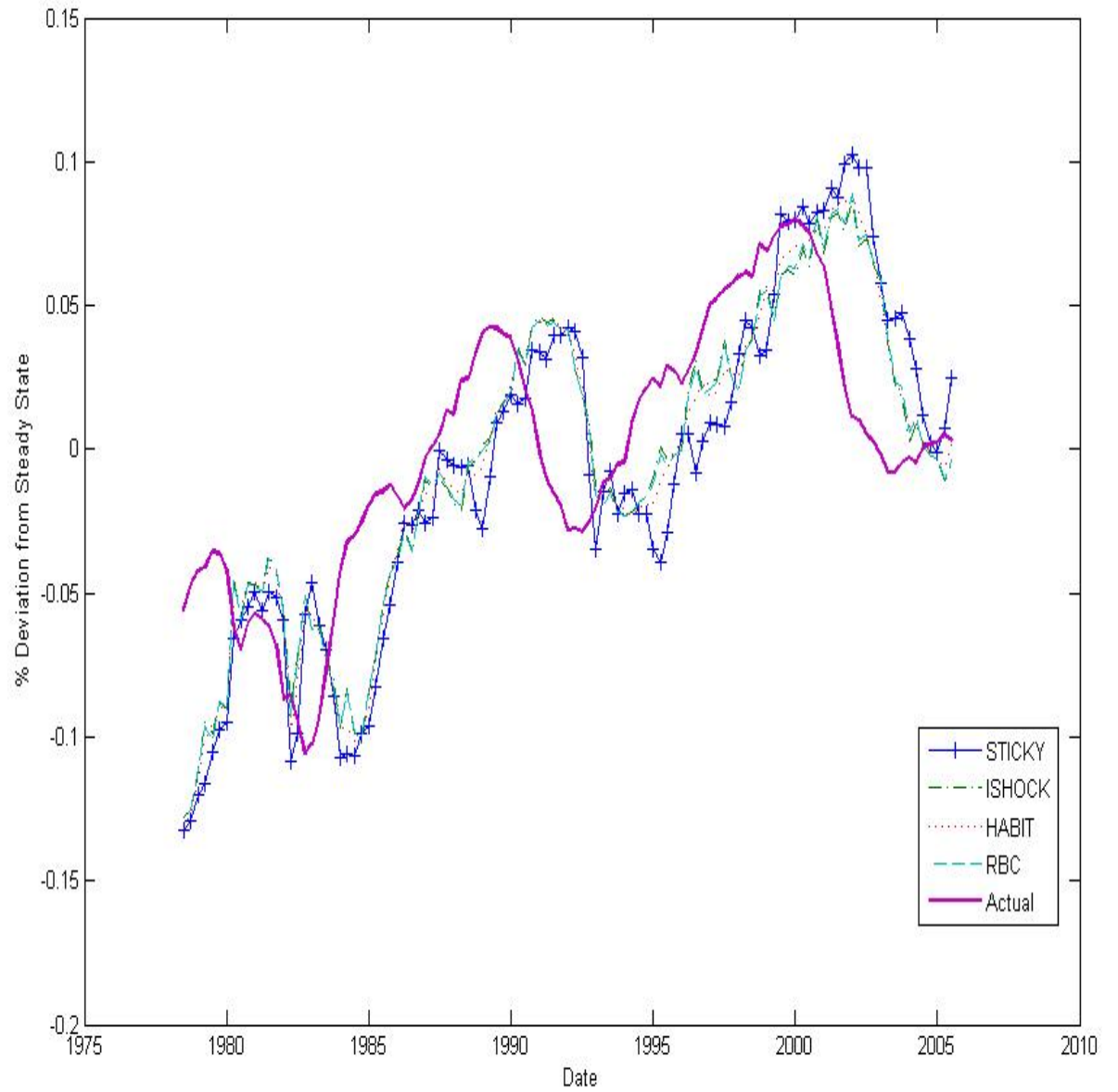


Figure 8: Two Quarter Ahead Forecast Comparison for Consumption

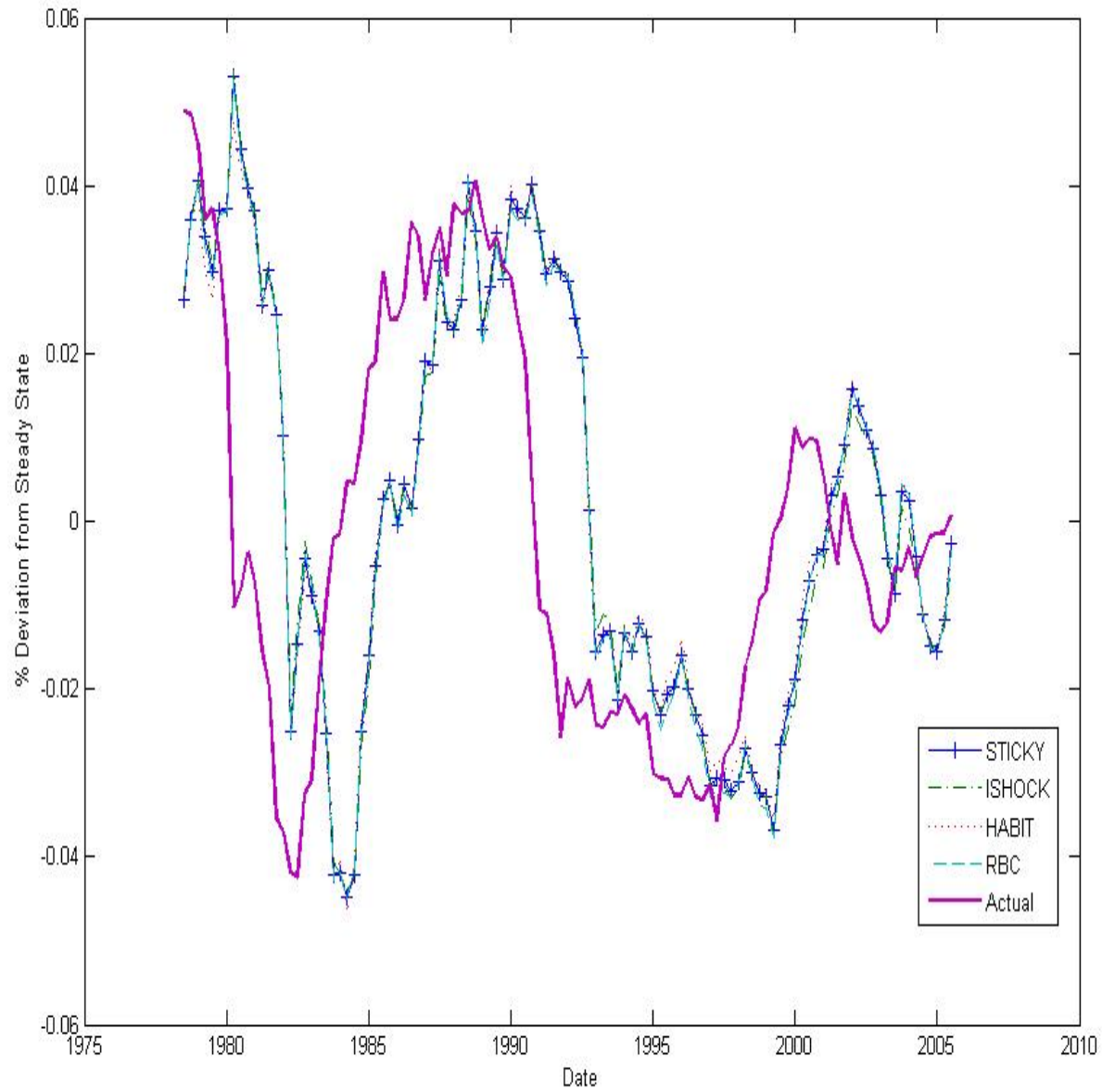


Table 1: Benchmark Calibration

Parameter	Description	Model(s)	Benchmark Calibration
β	Discount Factor	All	0.99
γ	Disutility from Labour	All	Does not appear in solution
θ	Capital Share	All	0.36
η	Growth of Labour-Augmenting Technology	All	1.0059
δ	Depreciation Rate	All	0.025
ρ_A	Persistence of Neutral Shocks	All	0.95
ρ_V	Persistence of Investment Specific Shocks	ISHOCK	0.95
σ_A	Std. Dev. of Neutral Shocks	All	0.0066
σ_V	Std. Dev. of Investment Specific Shocks	ISHOCK	0.0066
ν	Degree of Habit Formation	HABIT	0.7
q	Size of Capital Adjustment Costs	HABIT	25
ω	Utility from Real Balances	STICKY	Does not appear in solution
ξ	Elasticity of Substitution between Goods	STICKY	6
μ	Growth of Money Supply	STICKY	1
α	Fraction of Firms not Adjusting Prices	STICKY	0.8

Table 2: MSFEs for Output

λ	Horizon	Unrestricted RMSFE	VAR- MINN	RBC	HABIT	ISHOCK	STICKY
0.25	1	<i>0.011</i>	1.01	1.11	1.11	1.10	1.30
	2	0.016	<i>0.99</i>	1.13	1.16	1.11	1.23
	4	0.028	<i>0.82</i>	0.95	1.00	0.93	0.97
	6	0.042	<i>0.68</i>	0.73	0.79	0.72	0.73
	8	0.052	0.61	0.60	0.66	0.60	0.61
	12	0.065	0.59	0.52	0.55	0.51	0.53
	16	0.070	0.62	0.51	0.52	0.51	0.53
	20	0.072	0.70	0.48	0.48	0.47	0.48
0.5	1	<i>0.011</i>	1.01	1.11	1.11	1.10	1.43
	2	0.016	<i>0.99</i>	1.13	1.17	1.12	1.27
	4	0.028	<i>0.82</i>	0.95	1.01	0.94	0.97
	6	0.042	<i>0.68</i>	0.73	0.79	0.73	0.73
	8	0.052	0.61	0.60	0.66	0.61	0.61
	12	0.065	0.59	0.52	0.54	0.52	0.54
	16	0.070	0.62	0.51	0.52	0.51	0.53
	20	0.072	0.70	0.48	0.47	0.47	0.49
1	1	<i>0.011</i>	1.01	1.10	1.11	1.11	1.70
	2	0.016	<i>0.99</i>	1.12	1.17	1.13	1.35
	4	0.028	<i>0.82</i>	0.94	1.02	0.96	0.96
	6	0.042	<i>0.68</i>	0.73	0.80	0.75	0.72
	8	0.052	0.61	0.61	0.66	0.63	0.60
	12	0.065	0.59	0.52	0.54	0.52	0.54
	16	0.070	0.62	0.52	0.52	0.52	0.54
	20	0.072	0.70	0.48	0.47	0.48	0.51
5	1	<i>0.011</i>	1.01	1.08	1.11	1.16	2.55
	2	0.016	<i>0.99</i>	1.10	1.18	1.21	1.65
	4	0.028	<i>0.82</i>	0.93	1.02	1.04	0.97
	6	0.042	<i>0.68</i>	0.74	0.80	0.81	0.71
	8	0.052	0.61	0.62	0.66	0.66	0.58
	12	0.065	0.59	0.53	0.53	0.54	0.52
	16	0.070	0.62	0.52	0.51	0.53	0.53
	20	0.072	0.70	0.49	0.47	0.49	0.51
10	1	<i>0.011</i>	1.01	1.08	1.11	1.18	2.80
	2	0.016	<i>0.99</i>	1.09	1.18	1.25	1.74
	4	0.028	<i>0.82</i>	0.93	1.02	1.07	0.98
	6	0.042	<i>0.68</i>	0.74	0.80	0.83	0.70
	8	0.052	0.61	0.62	0.66	0.67	0.58
	12	0.065	0.59	0.53	0.53	0.54	0.51
	16	0.070	0.62	0.53	0.51	0.53	0.52
	20	0.072	0.70	0.49	0.47	0.49	0.50

The entries in the column "Unrestricted" are Root MSFEs. The entries in the five other columns are MSFEs relative to "Unrestricted". Notes: 1) *Italicized* entries denote the smallest MSFE. 2) **Bold** entries are those for which a model VAR outperforms both the unrestricted VAR and the VAR-MINN. 3) Results are for a rolling forecasting scheme with a window of 160 quarters starting in 1947:1. 4) Results are shown for VARs with four lags.

Table 3: MSFEs for Investment

λ	Horizon	Unrestricted RMSFE	VAR- MINN	RBC	HABIT	ISHOCK	STICKY
0.25	1	<i>0.041</i>	1.27	1.18	1.16	1.18	1.35
	2	<i>0.056</i>	1.34	1.27	1.32	1.25	1.41
	4	<i>0.092</i>	1.21	1.14	1.22	1.12	1.18
	6	0.134	0.98	0.86	0.95	0.85	0.87
	8	0.166	0.87	0.69	0.77	0.68	0.70
	12	0.201	0.85	0.58	0.62	0.57	0.61
	16	0.215	0.90	0.58	0.60	0.57	0.60
	20	0.218	0.92	0.51	0.53	0.51	0.53
0.5	1	<i>0.041</i>	1.27	1.17	1.16	1.17	1.48
	2	<i>0.056</i>	1.34	1.25	1.35	1.24	1.44
	4	<i>0.092</i>	1.21	1.13	1.25	1.11	1.16
	6	0.134	0.98	0.85	0.97	0.84	0.86
	8	0.166	0.87	0.68	0.77	0.67	0.70
	12	0.201	0.85	0.57	0.62	0.56	0.61
	16	0.215	0.90	0.57	0.60	0.56	0.61
	20	0.218	0.92	0.50	0.53	0.50	0.53
1	1	<i>0.041</i>	1.27	1.15	1.15	1.18	1.78
	2	<i>0.056</i>	1.34	1.22	1.36	1.23	1.53
	4	<i>0.092</i>	1.21	1.10	1.27	1.10	1.14
	6	0.134	0.98	0.83	0.98	0.83	0.84
	8	0.166	0.87	0.67	0.78	0.67	0.68
	12	0.201	0.85	0.56	0.62	0.55	0.60
	16	0.215	0.90	0.56	0.60	0.55	0.61
	20	0.218	0.92	0.49	0.53	0.48	0.54
5	1	<i>0.041</i>	1.27	1.11	1.14	1.22	2.73
	2	<i>0.056</i>	1.34	1.16	1.36	1.25	1.88
	4	<i>0.092</i>	1.21	1.04	1.29	1.12	1.08
	6	0.134	0.98	0.79	1.00	0.84	0.77
	8	0.166	0.87	0.64	0.79	0.66	0.61
	12	0.201	0.85	0.53	0.62	0.52	0.55
	16	0.215	0.90	0.52	0.60	0.52	0.56
	20	0.218	0.92	0.46	0.53	0.46	0.51
10	1	<i>0.041</i>	1.27	1.10	1.14	1.24	3.01
	2	<i>0.056</i>	1.34	1.15	1.36	1.27	1.99
	4	<i>0.092</i>	1.21	1.02	1.29	1.14	1.07
	6	0.134	0.98	0.79	1.00	0.84	0.75
	8	0.166	0.87	0.63	0.79	0.66	0.59
	12	0.201	0.85	0.52	0.62	0.52	0.53
	16	0.215	0.90	0.51	0.60	0.51	0.54
	20	0.218	0.92	0.46	0.53	0.45	0.49

See notes to table 2.

Table 4: MSFEs for Hours

λ	Horizon	Unrestricted RMSFE	VAR- MINN	RBC	HABIT	ISHOCK	STICKY
0.25	1	0.009	1.27	1.06	1.05	1.05	1.76
	2	0.013	1.35	1.10	1.07	1.08	1.53
	4	0.022	1.36	1.07	1.05	1.04	1.26
	6	0.033	1.23	0.93	0.92	0.90	1.02
	8	0.042	1.19	0.83	0.84	0.81	0.89
	12	0.054	1.31	0.80	0.81	0.77	0.84
	16	0.061	1.50	0.87	0.90	0.84	0.91
	20	0.067	1.79	0.94	0.99	0.92	0.98
0.5	1	0.009	1.27	1.06	1.07	1.05	2.56
	2	0.013	1.35	1.09	1.10	1.07	1.89
	4	0.022	1.36	1.05	1.08	1.02	1.34
	6	0.033	1.23	0.91	0.94	0.88	1.05
	8	0.042	1.19	0.82	0.84	0.79	0.91
	12	0.054	1.31	0.79	0.82	0.76	0.87
	16	0.061	1.50	0.86	0.90	0.82	0.94
	20	0.067	1.79	0.94	0.99	0.90	1.00
1	1	0.009	1.27	1.05	1.09	1.05	4.04
	2	0.013	1.35	1.07	1.14	1.07	2.60
	4	0.022	1.36	1.03	1.11	1.00	1.49
	6	0.033	1.23	0.89	0.95	0.87	1.10
	8	0.042	1.19	0.80	0.85	0.77	0.94
	12	0.054	1.31	0.77	0.82	0.73	0.89
	16	0.061	1.50	0.84	0.91	0.80	0.98
	20	0.067	1.79	0.92	0.99	0.87	1.04
5	1	0.009	1.27	1.02	1.14	1.08	8.33
	2	0.013	1.35	1.03	1.19	1.11	4.80
	4	0.022	1.36	0.97	1.15	1.03	2.05
	6	0.033	1.23	0.85	0.97	0.87	1.30
	8	0.042	1.19	0.76	0.86	0.76	1.04
	12	0.054	1.31	0.72	0.82	0.69	0.94
	16	0.061	1.50	0.80	0.91	0.75	1.03
	20	0.067	1.79	0.88	0.99	0.83	1.10
10	1	0.009	1.270	1.017	1.151	1.089	9.522
	2	0.013	1.35	1.02	1.21	1.13	5.45
	4	0.022	1.36	0.96	1.15	1.05	2.25
	6	0.033	1.23	0.83	0.97	0.88	1.37
	8	0.042	1.19	0.75	0.86	0.76	1.07
	12	0.054	1.31	0.71	0.82	0.69	0.95
	16	0.061	1.50	0.78	0.91	0.74	1.04
	20	0.067	1.79	0.87	0.99	0.82	1.11

See notes to table 2.

Table 5: MSFEs for Consumption

λ	Horizon	Unrestricted RMSFE	VAR- MINN	RBC	HABIT	ISHOCK	STICKY
0.25	1	0.007	0.98	0.93	0.97	0.92	0.92
	2	0.010	0.93	0.94	0.98	0.92	0.90
	4	0.018	0.80	0.80	0.87	0.79	0.76
	6	0.025	0.71	0.67	0.74	0.67	0.63
	8	0.032	0.66	0.58	0.65	0.59	0.56
	12	0.041	0.63	0.51	0.55	0.51	0.51
	16	0.047	0.65	0.50	0.52	0.50	0.50
	20	0.051	0.72	0.48	0.49	0.48	0.48
0.5	1	0.007	0.98	0.93	0.98	0.93	0.93
	2	0.010	0.93	0.95	0.99	0.95	0.91
	4	0.018	0.80	0.82	0.88	0.82	0.77
	6	0.025	0.71	0.68	0.74	0.70	0.64
	8	0.032	0.66	0.59	0.65	0.61	0.57
	12	0.041	0.63	0.52	0.55	0.53	0.51
	16	0.047	0.65	0.51	0.51	0.52	0.50
	20	0.051	0.72	0.50	0.49	0.50	0.49
1	1	0.007	0.98	0.94	0.98	0.95	0.94
	2	0.010	0.93	0.96	1.00	0.98	0.93
	4	0.018	0.80	0.83	0.88	0.86	0.79
	6	0.025	0.71	0.70	0.74	0.74	0.66
	8	0.032	0.66	0.61	0.65	0.65	0.58
	12	0.041	0.63	0.54	0.55	0.56	0.52
	16	0.047	0.65	0.53	0.51	0.55	0.51
	20	0.051	0.72	0.52	0.48	0.53	0.50
5	1	0.007	0.98	0.96	0.99	1.02	0.97
	2	0.010	0.93	0.99	1.01	1.11	0.99
	4	0.018	0.80	0.87	0.89	0.98	0.86
	6	0.025	0.71	0.75	0.75	0.85	0.74
	8	0.032	0.66	0.67	0.65	0.74	0.64
	12	0.041	0.63	0.60	0.54	0.63	0.56
	16	0.047	0.65	0.60	0.51	0.63	0.55
	20	0.051	0.72	0.58	0.48	0.60	0.55
10	1	0.007	0.98	0.96	0.99	1.05	0.99
	2	0.010	0.93	0.99	1.02	1.15	1.02
	4	0.018	0.80	0.88	0.89	1.02	0.90
	6	0.025	0.71	0.76	0.75	0.88	0.77
	8	0.032	0.66	0.68	0.65	0.76	0.67
	12	0.041	0.63	0.62	0.54	0.65	0.59
	16	0.047	0.65	0.62	0.51	0.64	0.57
	20	0.051	0.72	0.60	0.48	0.61	0.57

See notes to table 2.

Table 6: Accommodating Monetary Authority in STICKY

Variable	Horizon	Unrestricted RMSFE	VAR- MINN	RBC	HABIT	ISHOCK	STICKY
Output	1	<i>0.011</i>	1.01	1.10	1.11	1.11	1.45
	2	0.016	<i>0.99</i>	1.12	1.17	1.13	1.53
	4	0.028	<i>0.82</i>	0.94	1.02	0.96	1.26
	6	0.042	<i>0.68</i>	0.73	0.80	0.75	0.96
	8	0.052	0.61	0.61	0.66	0.63	0.77
	12	0.065	0.59	0.52	0.54	0.52	0.62
	16	0.070	0.62	0.52	0.52	0.52	0.59
	20	0.072	0.70	0.48	0.47	0.48	0.55
Investment	1	<i>0.041</i>	1.27	1.15	1.15	1.18	1.52
	2	<i>0.056</i>	1.34	1.22	1.36	1.23	1.72
	4	<i>0.092</i>	1.21	1.10	1.27	1.10	1.52
	6	0.134	0.98	0.83	0.98	0.83	1.11
	8	0.166	0.87	0.67	0.78	0.67	0.86
	12	0.201	0.85	0.56	0.62	0.55	0.67
	16	0.215	0.90	0.56	0.60	0.55	0.64
	20	0.218	0.92	0.49	0.53	0.48	0.56
Hours	1	<i>0.009</i>	1.27	1.05	1.09	1.05	1.02
	2	<i>0.013</i>	1.35	1.07	1.14	1.07	1.02
	4	<i>0.022</i>	1.36	1.03	1.11	1.00	1.00
	6	0.033	1.23	0.89	0.95	0.87	0.88
	8	0.042	1.19	0.80	0.85	0.77	0.79
	12	0.054	1.31	0.77	0.82	0.73	0.78
	16	0.061	1.50	0.84	0.91	0.80	0.89
	20	0.067	1.79	0.92	0.99	0.87	1.01
Consumption	1	0.007	0.98	0.94	0.98	0.95	0.93
	2	0.010	<i>0.93</i>	0.96	1.00	0.98	0.96
	4	0.018	<i>0.80</i>	0.83	0.88	0.86	0.86
	6	0.025	0.71	0.70	0.74	0.74	0.74
	8	0.032	0.66	0.61	0.65	0.65	0.66
	12	0.041	0.63	0.54	0.55	0.56	0.57
	16	0.047	0.65	0.53	0.51	0.55	0.55
	20	0.051	0.72	0.52	0.48	0.53	0.54

Notes: 1) Results shown are for an accommodating monetary authority in STICKY. 2) Results are shown for $\lambda=1$. See also notes to table 2.

Table 7: Lower Habit Formation and Capital Adjustment Costs

Variable	Horizon	Unrestricted RMSFE	VAR- MINN	RBC	HABIT	ISHOCK	STICKY
Output	1	<i>0.011</i>	1.01	1.10	1.12	1.11	1.70
	2	0.016	<i>0.99</i>	1.12	1.21	1.13	1.35
	4	0.028	<i>0.82</i>	0.94	1.06	0.96	0.96
	6	0.042	<i>0.68</i>	0.73	0.83	0.75	0.72
	8	0.052	0.61	0.61	0.68	0.63	0.60
	12	0.065	0.59	0.52	0.55	0.52	0.54
	16	0.070	0.62	0.52	0.54	0.52	0.54
	20	0.072	0.70	0.48	0.49	0.48	0.51
Investment	1	<i>0.041</i>	1.27	1.15	1.21	1.18	1.78
	2	<i>0.056</i>	1.34	1.22	1.39	1.23	1.53
	4	<i>0.092</i>	1.21	1.10	1.29	1.10	1.14
	6	0.134	0.98	0.83	0.99	0.83	0.84
	8	0.166	0.87	0.67	0.79	0.67	0.68
	12	0.201	0.85	0.56	0.63	0.55	0.60
	16	0.215	0.90	0.56	0.61	0.55	0.61
	20	0.218	0.92	0.49	0.53	0.48	0.54
Hours	1	<i>0.009</i>	1.27	1.05	1.05	1.05	4.04
	2	<i>0.013</i>	1.35	1.07	1.11	1.07	2.60
	4	<i>0.022</i>	1.36	1.03	1.11	1.00	1.49
	6	0.033	1.23	0.89	0.97	0.87	1.10
	8	0.042	1.19	0.80	0.87	0.77	0.94
	12	0.054	1.31	0.77	0.83	0.73	0.89
	16	0.061	1.50	0.84	0.91	0.80	0.98
	20	0.067	1.79	0.92	0.99	0.87	1.04
Consumption	1	0.007	0.98	0.94	0.99	0.95	0.94
	2	0.010	0.93	0.96	1.03	0.98	0.93
	4	0.018	0.80	0.83	0.92	0.86	0.79
	6	0.025	0.71	0.70	0.77	0.74	0.66
	8	0.032	0.66	0.61	0.67	0.65	0.58
	12	0.041	0.63	0.54	0.56	0.56	0.52
	16	0.047	0.65	0.53	0.53	0.55	0.51
	20	0.051	0.72	0.52	0.51	0.53	0.50

Notes: 1) Results shown change v and q to 0.4 and 11 in HABIT. 2) Results are shown for $\lambda=1$. See also notes to table 2.

Table 8: Greater Volatility of Investment Specific Shocks

Variable	Horizon	Unrestricted RMSFE	VAR- MINN	RBC	HABIT	ISHOCK	STICKY
Output	1	<i>0.011</i>	1.01	1.10	1.11	1.11	1.70
	2	0.016	<i>0.99</i>	1.12	1.17	1.14	1.35
	4	0.028	<i>0.82</i>	0.94	1.02	0.97	0.96
	6	0.042	<i>0.68</i>	0.73	0.80	0.77	0.72
	8	0.052	0.61	0.61	0.66	0.64	0.60
	12	0.065	0.59	0.52	0.54	0.53	0.54
	16	0.070	0.62	0.52	0.52	0.52	0.54
	20	0.072	0.70	0.48	0.47	0.48	0.51
Investment	1	<i>0.041</i>	1.27	1.15	1.15	1.17	1.78
	2	<i>0.056</i>	1.34	1.22	1.36	1.19	1.53
	4	<i>0.092</i>	1.21	1.10	1.27	1.06	1.14
	6	0.134	0.98	0.83	0.98	0.81	0.84
	8	0.166	0.87	0.67	0.78	0.64	0.68
	12	0.201	0.85	0.56	0.62	0.52	0.60
	16	0.215	0.90	0.56	0.60	0.52	0.61
	20	0.218	0.92	0.49	0.53	0.46	0.54
Hours	1	<i>0.009</i>	1.27	1.05	1.09	1.04	4.04
	2	<i>0.013</i>	1.35	1.07	1.14	1.05	2.60
	4	0.022	1.36	1.03	1.11	0.97	1.49
	6	0.033	1.23	0.89	0.95	0.84	1.10
	8	0.042	1.19	0.80	0.85	0.74	0.94
	12	0.054	1.31	0.77	0.82	0.70	0.89
	16	0.061	1.50	0.84	0.91	0.76	0.98
	20	0.067	1.79	0.92	0.99	0.84	1.04
Consumption	1	0.007	0.977	0.941	0.983	0.979	0.937
	2	0.010	0.930	0.959	1.001	1.030	0.928
	4	0.018	0.798	0.832	0.884	0.910	0.786
	6	0.025	0.714	0.700	0.744	0.792	0.659
	8	0.032	0.661	0.612	0.650	0.699	0.579
	12	0.041	0.635	0.541	0.546	0.609	0.516
	16	0.047	0.652	0.532	0.512	0.601	0.510
	20	0.051	0.722	0.518	0.484	0.576	0.499

Notes: 1) Results shown change σ_v to 0.0132 in ISHOCK. 2) Results are shown for $\lambda=1$. See also notes to table 2.

Table 9: Lower Price Rigidity and Elasticity of Substitution Between Goods

Variable	Horizon	Unrestricted RMSFE	VAR- MINN	RBC	HABIT	ISHOCK	STICKY
Output	1	<i>0.011</i>	1.01	1.10	1.11	1.11	1.06
	2	0.016	<i>0.99</i>	1.12	1.17	1.13	1.11
	4	0.028	<i>0.82</i>	0.94	1.02	0.96	0.94
	6	0.042	<i>0.68</i>	0.73	0.80	0.75	0.74
	8	0.052	0.61	0.61	0.66	0.63	0.61
	12	0.065	0.59	0.52	0.54	0.52	0.52
	16	0.070	0.62	0.52	0.52	0.52	0.51
	20	0.072	0.70	0.48	0.47	0.48	0.47
Investment	1	<i>0.041</i>	1.27	1.15	1.15	1.18	1.01
	2	<i>0.056</i>	1.34	1.22	1.36	1.23	1.19
	4	<i>0.092</i>	1.21	1.10	1.27	1.10	1.08
	6	0.134	0.98	0.83	0.98	0.83	0.83
	8	0.166	0.87	0.67	0.78	0.67	0.67
	12	0.201	0.85	0.56	0.62	0.55	0.56
	16	0.215	0.90	0.56	0.60	0.55	0.56
	20	0.218	0.92	0.49	0.53	0.48	0.49
Hours	1	<i>0.009</i>	1.27	1.05	1.09	1.05	1.28
	2	<i>0.013</i>	1.35	1.07	1.14	1.07	1.15
	4	<i>0.022</i>	1.36	1.03	1.11	1.00	1.10
	6	0.033	1.23	0.89	0.95	0.87	0.93
	8	0.042	1.19	0.80	0.85	0.77	0.82
	12	0.054	1.31	0.77	0.82	0.73	0.78
	16	0.061	1.50	0.84	0.91	0.80	0.84
	20	0.067	1.79	0.92	0.99	0.87	0.91
Consumption	1	0.007	0.977	0.941	0.983	0.951	0.964
	2	0.010	<i>0.930</i>	0.959	1.001	0.982	0.982
	4	0.018	<i>0.798</i>	0.832	0.884	0.857	0.849
	6	0.025	0.714	0.700	0.744	0.738	0.705
	8	0.032	0.661	0.612	0.650	0.649	0.612
	12	0.041	0.635	0.541	0.546	0.564	0.534
	16	0.047	0.652	0.532	0.512	0.554	0.521
	20	0.051	0.722	0.518	0.484	0.532	0.505

Notes: 1) Results shown lower α , the degree of price stickiness, to 0.5 and ξ , the elasticity of substitution between goods, to 3 in STICKY. 2) Results are shown for $\lambda=1$. See also notes to table 2.

Table 10: 120 Quarter Estimation Window

Variable	Horizon	Unrestricted RMSFE	VAR- MINN	RBC	HABIT	ISHOCK	STICKY
Output	1	<i>0.014</i>	1.30	1.08	1.08	1.11	1.53
	2	<i>0.019</i>	1.21	1.02	1.01	1.06	1.22
	4	0.030	1.05	0.90	0.88	0.94	0.95
	6	0.040	0.89	0.79	0.79	0.85	0.81
	8	0.049	0.79	0.73	0.73	0.77	0.73
	12	0.058	0.74	0.67	0.67	0.68	0.69
	16	0.063	0.70	0.61	0.60	0.61	0.64
	20	0.067	0.60	0.51	0.51	0.51	0.54
Investment	1	<i>0.054</i>	1.35	1.03	1.02	1.05	1.47
	2	0.071	1.18	0.96	0.97	0.97	1.20
	4	0.100	1.08	0.86	0.87	0.88	0.96
	6	0.124	0.96	0.80	0.82	0.83	0.86
	8	0.139	0.90	0.75	0.78	0.78	0.79
	12	0.152	0.90	0.69	0.73	0.68	0.75
	16	0.158	0.91	0.64	0.68	0.63	0.73
	20	0.167	0.83	0.56	0.61	0.56	0.63
Hours	1	<i>0.011</i>	1.33	1.03	1.10	1.04	3.02
	2	0.016	1.28	0.95	0.98	0.96	1.87
	4	0.028	1.14	0.76	0.80	0.77	1.07
	6	0.040	1.07	0.69	0.72	0.70	0.85
	8	0.049	1.08	0.66	0.70	0.66	0.76
	12	0.062	1.19	0.62	0.69	0.60	0.69
	16	0.074	1.23	0.56	0.69	0.54	0.64
	20	0.087	1.16	0.50	0.65	0.47	0.56
Consumption	1	<i>0.009</i>	1.05	1.04	1.04	1.08	1.03
	2	0.013	0.99	0.96	0.94	1.01	0.93
	4	0.021	0.88	0.84	0.85	0.88	0.81
	6	0.029	0.83	0.76	0.78	0.81	0.74
	8	0.036	0.79	0.71	0.74	0.75	0.69
	12	0.045	0.80	0.68	0.69	0.71	0.67
	16	0.052	0.76	0.61	0.60	0.63	0.60
	20	0.057	0.68	0.54	0.51	0.55	0.53

Notes: 1) Results shown here use a 120 quarter estimation window rather than the benchmark 160 quarters. 2) Results are shown for $\lambda=1$. See also notes to table 2.

Table 11: 140 Quarter Estimation Window

Variable	Horizon	Unrestricted RMSFE	VAR- MINN	RBC	HABIT	ISHOCK	STICKY
Output	1	<i>0.012</i>	1.31	1.01	1.07	1.03	1.69
	2	0.017	1.30	0.94	1.00	0.95	1.25
	4	0.029	1.05	0.73	0.76	0.74	0.80
	6	0.042	0.84	0.57	0.59	0.59	0.59
	8	0.051	0.76	0.51	0.53	0.53	0.53
	12	0.060	0.71	0.48	0.50	0.49	0.51
	16	0.064	0.66	0.47	0.49	0.47	0.50
	20	0.066	0.62	0.46	0.49	0.46	0.50
Investment	1	<i>0.050</i>	1.37	1.05	1.10	1.07	1.63
	2	<i>0.062</i>	1.42	1.05	1.16	1.06	1.41
	4	0.094	1.24	0.88	0.97	0.89	1.00
	6	0.126	0.91	0.63	0.70	0.63	0.68
	8	0.150	0.80	0.53	0.58	0.53	0.57
	12	0.166	0.83	0.50	0.54	0.49	0.55
	16	0.171	0.86	0.51	0.55	0.50	0.56
	20	0.178	0.86	0.51	0.55	0.50	0.56
Hours	1	<i>0.010</i>	1.46	1.04	1.12	1.04	3.53
	2	0.014	1.63	0.98	1.06	0.99	2.28
	4	0.025	1.48	0.76	0.83	0.76	1.14
	6	0.039	1.26	0.59	0.64	0.58	0.76
	8	0.051	1.18	0.52	0.57	0.51	0.63
	12	0.068	1.20	0.49	0.57	0.48	0.57
	16	0.080	1.24	0.51	0.62	0.49	0.59
	20	0.092	1.22	0.53	0.65	0.50	0.61
Consumption	1	0.008	1.10	0.91	0.95	0.93	0.89
	2	0.012	1.07	0.82	0.84	0.85	0.79
	4	0.020	0.90	0.67	0.69	0.69	0.64
	6	0.029	0.83	0.59	0.60	0.61	0.56
	8	0.035	0.80	0.55	0.57	0.58	0.54
	12	0.045	0.78	0.54	0.55	0.56	0.53
	16	0.050	0.72	0.53	0.54	0.54	0.52
	20	0.054	0.67	0.53	0.52	0.53	0.52

Notes: 1) Results shown here use a 140 quarter estimation window rather than the benchmark 160 quarters. 2) Results are shown for $\lambda=1$. See also notes to table 2.

Table 12: 180 Quarter Estimation Window

Variable	Horizon	Unrestricted RMSFE	VAR- MINN	RBC	HABIT	ISHOCK	STICKY
Output	1	<i>0.009</i>	1.02	1.08	0.98	1.10	1.91
	2	<i>0.014</i>	1.03	1.08	1.04	1.08	1.32
	4	0.027	0.94	0.82	0.83	0.83	0.82
	6	0.043	0.78	0.56	0.57	0.57	0.52
	8	0.056	0.72	0.41	0.41	0.42	0.39
	12	0.075	0.72	0.33	0.32	0.33	0.34
	16	0.087	0.79	0.30	0.28	0.30	0.32
	20	0.100	0.82	0.26	0.23	0.25	0.28
Investment	1	<i>0.041</i>	1.19	1.01	0.93	1.04	1.78
	2	<i>0.059</i>	1.26	1.02	1.06	1.02	1.32
	4	0.104	1.23	0.86	0.92	0.87	0.92
	6	0.153	1.04	0.62	0.67	0.63	0.62
	8	0.195	0.93	0.45	0.49	0.46	0.46
	12	0.250	0.88	0.37	0.38	0.36	0.41
	16	0.289	0.88	0.36	0.36	0.35	0.40
	20	0.337	0.85	0.34	0.34	0.34	0.39
Hours	1	<i>0.008</i>	1.19	1.06	1.04	1.03	4.67
	2	0.012	1.32	1.03	1.00	1.00	2.85
	4	0.019	1.63	0.88	1.00	0.80	1.74
	6	0.028	1.58	0.64	0.73	0.57	1.08
	8	0.038	1.59	0.52	0.58	0.45	0.83
	12	0.055	1.90	0.55	0.64	0.48	0.83
	16	0.071	2.23	0.70	0.84	0.63	0.97
	20	0.092	2.39	0.81	0.96	0.75	1.04
Consumption	1	0.005	1.08	0.92	0.90	0.95	0.93
	2	0.007	1.19	0.95	0.95	0.98	0.90
	4	0.014	1.06	0.67	0.72	0.70	0.59
	6	0.023	0.88	0.46	0.50	0.49	0.40
	8	0.031	0.82	0.36	0.39	0.38	0.31
	12	0.044	0.86	0.30	0.30	0.31	0.27
	16	0.053	0.97	0.26	0.25	0.27	0.25
	20	0.062	1.08	0.21	0.18	0.21	0.20

Notes: 1) Results shown here use a 180 quarter estimation window rather than the benchmark 160 quarters. 2) Results are shown for $\lambda=1$. See also notes to table 2.

Table 13: DSGE Models vs. Cointegration Prior

Variable	Horizon	Unrestricted RMSFE	VAR- COINT	RBC	HABIT	ISHOCK	STICKY
Output	1	0.011	<i>1.00</i>	1.10	1.11	1.11	1.70
	2	0.016	<i>0.99</i>	1.12	1.17	1.13	1.35
	4	0.028	0.96	0.94	1.02	0.96	0.96
	6	0.042	0.92	0.73	0.80	0.75	0.72
	8	0.052	0.86	0.61	0.66	0.63	0.60
	12	0.065	0.78	0.52	0.54	0.52	0.54
	16	0.070	0.74	0.52	0.52	0.52	0.54
Investment	20	0.072	0.66	0.48	0.47	0.48	0.51
	1	0.041	<i>0.97</i>	1.15	1.15	1.18	1.78
	2	0.056	<i>0.94</i>	1.22	1.36	1.23	1.53
	4	0.092	<i>0.90</i>	1.10	1.27	1.10	1.14
	6	0.134	0.84	0.83	0.98	0.83	0.84
	8	0.166	0.79	0.67	0.78	0.67	0.68
	12	0.201	0.73	0.56	0.62	0.55	0.60
Hours	16	0.215	0.72	0.56	0.60	0.55	0.61
	20	0.218	0.64	0.49	0.53	0.48	0.54
	1	<i>0.009</i>	1.06	1.05	1.09	1.05	4.04
	2	0.013	1.08	1.07	1.14	1.07	2.60
	4	0.022	1.09	1.03	1.11	1.00	1.49
	6	0.033	1.07	0.89	0.95	0.87	1.10
	8	0.042	1.02	0.80	0.85	0.77	0.94
Consumption	12	0.054	0.84	0.77	0.82	0.73	0.89
	16	0.061	0.63	0.84	0.91	<i>0.80</i>	0.98
	20	0.067	0.49	0.92	0.99	<i>0.87</i>	1.04
	1	0.007	1.05	0.94	0.98	0.95	0.94
	2	0.010	1.06	0.96	1.00	0.98	0.93
	4	0.018	1.05	0.83	0.88	0.86	0.79
	6	0.025	1.01	0.70	0.74	0.74	0.66
Consumption	8	0.032	0.96	0.61	0.65	0.65	0.58
	12	0.041	0.86	0.54	0.55	0.56	0.52
	16	0.047	0.77	0.53	0.51	0.55	0.51
	20	0.051	0.70	0.52	0.48	0.53	0.50

Note: Results shown here use a 160 quarter estimation window and $\lambda=1$. See also notes to table 2.