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A DSGE Model of China

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Abstract

We use available methods for testing macro models to evaluate a model of China over the period from Deng Xiaoping's reforms up until the crisis period. Bayesian ranking methods are heavily influenced by controversial priors on the degree of price/wage rigidity. When the overall models are tested by Likelihood or Indirect Inference methods, the New Keynesian model is rejected in favour of one with a fair-sized competitive product market sector. This model behaves quite a lot more 'flexibly' than the New Keynesian.

JEL categories: C11, C15, C18, E27

Key Words: China, DSGE, Bayesian Inference, Indirect Inference

There is much work on how China has developed and achieved rapid growth in the past three decades. There is also much commentary on the day-to-day behaviour of the Chinese economy, and some efforts to model this behaviour. There is also a body of work modelling the Chinese economy's business cycle behaviour as a Dynamic Stochastic General Equilibrium (DSGE) model, in the manner applied to major developed economies. Le et al (2014) review these developments in the context of a model of China spanning the financial crisis. Even though China is at an earlier stage of development than these, a DSGE model does not appear to make assumptions that restrict its application to countries at earlier stages, provided these economies have normal market structures. Since such market structures have evolved rapidly since the end of the 1970s (Coase and Wang, 2012), there seems to be every reason to expect that a DSGE model could explain the business cycle behaviour of China in the past three decades.

In this paper we examine whether China can be explained by a model that has been successfully applied to the US (Le et al, 2012; Smets and Wouters,

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2007). The model, that of Smets and Wouters following Christiano et al (2005), is only suitable for a large continental economy since it assumes a closed economy. It might be thought that since China has a large export and import sector, it cannot be modelled as a closed economy. However, China's export and import sector has developed rapidly as a result of decisions to invest in new infrastructure in cities and transportation; once these decisions were taken, the resulting output of goods was sold on world markets at the prices needed to absorb it. This suggests that neither world demand nor the exchange rate would have much effect as prices would be adjusted to ensure available goods were sold. Because the industrial structure is largely dominated by multi-national companies, imports too are closely related to export volumes. Thus we would argue that net imports can reasonably be modelled as exogenous processes in China, with little connection to domestic business cycle fluctuations; this is how they enter in the Smets-Wouters model, as an exogenous error process in the goods market-clearing equation whereby output equals demand for goods. In their recent work Le et al (2014) find that a model of this type, if augmented by a banking sector, can successfully capture the key features of Chinese macro behaviour over the past two and a half decades including the financial crisis period.

Our purpose in this paper is complementary to this work on understanding China's recent behaviour and is twofold: methodological and empirical. We apply a powerful testing procedure to the Smets-Wouters theoretical set-up, and check whether China's business cycle behaviour since the late 1970s up to 2007, just before the recent crisis, can be regarded as explained by this theory; we use an unpublished data set obtained from official sources for this large sample period since the reforms of Deng Xiaoping. In this procedure we combine previously used methods in a novel, comprehensive way- a new methodology. We begin in a now-standard way with Bayesian estimation, on the basis of a set of New Keynesian priors used by Smets and Wouters for the US. We then consider how an alternative set of priors that allow for part of the economy to be competitive (a 'Hybrid' set-up that Le et al, 2011, found to be extremely helpful in accounting for US macro behaviour) affects our Bayesian estimates and the ranking of New Keynesian versus Hybrid models of China. We then go on to test how well each of these models, as estimated by Bayesian ML, fit the dynamics and volatility behaviour of the data- an indirect inference test; we know from Monte Carlo experiments carried out by Le et al (2011, 2012) that this method of indirect inference has considerable power in testing model specification- it seems because it is checking whether the model can generate the reduced form VAR found in the data and a model can only do this if its coefficients are compatible with those in the reduced form. This is a different and more powerful criterion than the model's likelihood which we also compute and which checks whether the model can closely forecast the data- apparently mis-specified models can also forecast data well by respecifying error processes. Having carried out these tests we find a set of parameters that are best able to satisfy the test criterion ('indirect estimation'); we regard this set as providing us with a 'credible' model- unfortunately available macro theory and evidence is not able on its own yet to provide strongly based priors, as might be the case in some natural sciences. We then compare the test results and estimates under these different approaches. We contend that by combining these evaluative methods we can reach a rounded view of different models' ability to explain Chinese data.

Our empirical results for China are similar to those of Le et al (2014) but less successful than they are with their more limited data period and published data. The work here originated with Dai (2012) whose data from internal Chinese sources we use. We find that the model can explain the behaviour of the main macroeconomic variables, GDP, inflation and interest rates. Like the same model for the US, it is less able to explain the finer detail of economic behaviour, including consumption and investment. However, this is a less vital task for a macro model than the primary one of explaining broad macro behaviour. Our final assessment is that China is best explained by the hybrid model.

In the rest of this paper, we begin by setting out the model in its New Keynesian form and explain the Hybrid generalisation. In the second section, we explain our methods. In the third section, we set out the empirical results for the models. In the fourth we review the preferred Hybrid model's properties and how they differ from the New Keynesian. Our final section concludes.

1 The Model

There is a continuum of firms producing intermediate goods, households, and a monetary as well as fiscal authority. The final good Y_t is a composite made up of a continuum of intermediate goods $Y_t(i)$; these intermediate producers operate in imperfectly competitive markets and set their prices with a mark-up over costs reflecting this; however they are not free to reset prices every period but face an exogenous probability (as in Calvo, 1983) that they can reset them in any given period. Final goods producers buy the intermediate goods on the market and package for Y_t resale to consumers, investors and the government in a perfectly competitive market. Households buy these goods for consumption subject to external habit persistence; and they supply labour via unions at a wage that reflects the union's imperfectly competitive monopoly power, again with a Calvo probability of being able to reset the wage in any given period. Households also invest in capital goods, subject to adjustment costs, as investors on behalf of the intermediate goods firms that they own. The firms hire labour and use capital to maximise profits on behalf of their owners. The model set-up follows that of Smets and Wouters (2007) and we do not repeat it here.

The model is used in practice in a form log-linearised around its steady state growth trend with the resulting equations set out in what follows.

The log-linearised aggregate resource constraint is:

$$y_t = (1 - G_Y - I_Y) \times c_t + I_Y \times i_t + R_*^k K_Y \times z_t + \varepsilon_t^g$$

where G_Y, I_Y, K_Y and R_*^k are steady state ratios, while ε_t^g is the exogenous spending shock, including government expenditure and export fluctuations.

The consumption Euler equation is given by:

$$
\begin{aligned}
c_t \quad = \quad & \frac{h/\gamma}{1+h/\gamma} \times c_{t-1} + \left(1 - \frac{h/\gamma}{1+h/\gamma}\right) \times E_t c_{t+1} \\
& + \frac{(\sigma_c - 1)\left(W_*^h L_*/C_*\right)}{\sigma_c\,(1+h/\gamma)} \times (l_t - E_t l_{t+1}) \\
& - \frac{1-h/\gamma}{\sigma_c\,(1+h/\gamma)} \times \left(r_t - E_t \pi_{t+1} + \varepsilon_t^b\right)
\end{aligned}
$$

The investment Euler equation is given by:

$$
\begin{aligned}
i_t \quad = \quad & \frac{1}{1+\beta\gamma^{1-\sigma_c}} \times i_{t-1} + \frac{\beta\gamma^{1-\sigma_c}}{1+\beta\gamma^{1-\sigma_c}} \times E_t i_{t+1} \\
& + \frac{1}{\left(1+\beta\gamma^{1-\sigma_c}\right)\gamma^2\varphi} \times q_t + \varepsilon_t^i
\end{aligned}
$$

The corresponding arbitrage equation for the shadow value of capital is:

$$
\begin{aligned}
q_t \quad = \quad & \beta\gamma^{-\sigma_c}(1-\delta) \times E_t q_{t+1} + \left(1 - \beta\gamma^{-\sigma_c}(1-\delta)\right) \times E_t r_{t+1}^k \\
& - r_t + E_t \pi_{t+1} - \varepsilon_t^b
\end{aligned}
$$

On the supply side of the final goods market, the aggregate production function is:

$$
y_t = \phi_p\left(\alpha \times k_t + (1-\alpha) \times l_t + \varepsilon_t^a\right)
$$

where the current capital stock used in production (k_t) is a function of capital installed in the previous period and the degree of capital utilisation (z_t):

$$
k_t = k_{t-1} + z_t
$$

Furthermore, the optimisation behaviour of households implies that:

$$
z_t = \frac{1-\psi}{\psi} \times r_t^k
$$

and the law of motion for installed capital is:

$$
\begin{aligned}
k_t \quad = \quad & \frac{1-\delta}{\gamma} \times k_{t-1} + \left(1 - \frac{1-\delta}{\gamma}\right) \times i_t \\
& + \left(1 - \frac{1-\delta}{\gamma}\right)\left(1+\beta\gamma^{1-\sigma_c}\right)\gamma^2\varphi \times \varepsilon_t^i
\end{aligned}
$$

In the intermediate goods market, the price mark-up (μ_t^p) is the difference between the marginal product of labour and the real wage (w_t):

$$\mu_t^p = mpl_t - w_t = \alpha\left(k_t - l_t\right) + \varepsilon_t^a - w_t$$

The New Keynesian Phillips curve with Indexed Calvo is:

$$\begin{aligned}
\pi_t &= \frac{\iota_p}{1+\beta\gamma^{1-\sigma_c}\iota_p} \times \pi_{t-1} + \frac{\beta\gamma^{1-\sigma_c}}{1+\beta\gamma^{1-\sigma_c}\iota_p} \times E_t\pi_{t+1} \\
&\quad - \frac{1}{1+\beta\gamma^{1-\sigma_c}\iota_p} \frac{\left(1-\beta\gamma^{1-\sigma_c}\xi_p\right)\left(1-\xi_p\right)}{\xi_p\left(1+\left(\Phi-1\right)\varepsilon_p\right)} \times \mu_t^p + \varepsilon_t^p
\end{aligned}$$

Cost minimisation implies the negative relationship between marginal costs of capital and labour:

$$r_t^k = -\left(k_t - l_t\right) + w_t$$

Similarly, in the monopolistic labour market, the real wage mark-up (μ_t^w) is:

$$\mu_t^w = w_t - mrs_t = w_t - \left(\sigma_l l_t + \frac{1}{1-h/\gamma}\left(c_t - \frac{h}{\gamma}c_{t-1}\right)\right)$$

The real wage setting equation also follows Calvo with partial indexation:

$$\begin{aligned}
w_t &= \frac{1}{1+\beta\gamma^{1-\sigma_c}} \times w_{t-1} + \frac{\beta\gamma^{1-\sigma_c}}{1+\beta\gamma^{1-\sigma_c}} \times \left(E_t w_{t+1} + E_t\pi_{t+1}\right) \\
&\quad - \frac{1+\beta\gamma^{1-\sigma_c}\iota_w}{1+\beta\gamma^{1-\sigma_c}} \times \pi_t + \frac{\iota_w}{1+\beta\gamma^{1-\sigma_c}} \times \pi_{t-1} \\
&\quad - \frac{1}{1+\beta\gamma^{1-\sigma_c}} \frac{\left(1-\beta\gamma^{1-\sigma_c}\xi_w\right)\left(1-\xi_w\right)}{\xi_w\left(1+\left(\lambda_w-1\right)\varepsilon_w\right)} \times \mu_t^w + \varepsilon_t^w
\end{aligned}$$

Finally, monetary policy is modelled by an empirical reaction function, or Taylor rule:

$$r_t = \rho r_{t-1} + \left(1-\rho\right)\left(r_\pi \pi_t + r_y y_t\right) + r_{\Delta y}\left(y_t - y_{t-1}\right) + \varepsilon_t^r$$

In our procedures here which employ HP-detrended data y_t is the deviation of output from the HP trend.

As we will show below the New Keynesian version of the Smets and Wouters model cannot match the Chinese macro data. The reason essentially is that the model generates too little nominal variation. Other work too has found that the single sector Calvo price- and wage-setting behaviour captures the data poorly- Le et al (2011). An alternative is to model a large number of sectors with different behaviour, on a spectrum between highly competitive and highly rigid, as proposed by Dixon and Kara (2012). We propose here, following Le et al (2011) for the US, a two-sector ('hybrid') set-up, with one sector competitive and the other sector Calvo. We assume that the wage and price setters supply labour and intermediate goods partly in a competitive market in which prices and wages are flexible and partly in a market with imperfect competition. We also assume that the size of each sector is determined by the facts of competition and will not be changed in our sample. However, the degree of imperfect competition is allowed to differ between labour and product markets. The general idea behind these assumptions is that there are some product sectors of economies where rigidity prevails and also other sectors in which prices are flexible; essentially this reflects the degree of competition in these sectors. Similarly, we can apply these assumptions to labour markets to make some markets much more competitive than others. An economy could contain more or less flexibility in prices and wages due to the level of competition within the economy. Thus we can think of the economy as a weighted average of New Keynesian and New Classical behaviour. A final assumption is that a Taylor Rule that reflects the properties of the hybrid model must be pursued by the monetary authority.

Formally, to model the price and wage setting for the hybrid model we assume that firms that produce intermediate goods have a production function that combines a fixed proportion of labour in imperfect competition with labour from competitive markets, so the labour used by intermediate producers is:

$$l_t = l_{1t} + l_{2t} = \left\{ \left[\int_0^1 (l_{1it})^{\frac{1}{1+\lambda_{w,t}}} di \right]^{1+\lambda_{w,t}} + \left[\int_0^1 l_{2it} di \right] \right\}$$

where l_{1it} is the imperfect competitive labour and l_{2it} is the competitive labour provided by the ith household at time t. To make things more clear, we can imagine that l_t represents the activities of an intermediary "labour bundler".

Note that $l_{1t} = \omega_w l_t$, where ω_w is the share of total labour that is in the imperfectly competitive market, so

$$l_{2t} = (1 - \omega_w)\, l_t$$

and then

$$W_t = \omega_w W_{1t} + (1 - \omega_w)\, W_{2t}$$

Every household utility contains the two sorts of labour in the same way, that is:

$$U_{it} = ... - \frac{l_{1it}^{1+\sigma_n} \varepsilon_{1nt}}{1+\sigma_n} - \frac{l_{2it}^{1+\sigma_n} \varepsilon_{2nt}}{1+\sigma_n} ...$$

Now W_{1t} is set according to the Calvo wage-setting equation and W_{2t} is set equal to the current expected marginal disutility of work. In the latter case, there is a one quarter information lag for current inflation, but this is ignored as usual for convenience as it is unimportant in the Calvo setting over the whole future horizon. The labour bundler has these wages in hand and offers a labour unit as above this weighted average wage, and then firms buy these labour units for use in production.

By the same logic, retail output is made up of a fixed proportion of intermediate goods in an imperfectly competitive market and intermediate goods bought from an imperfectly competitive market. The retail output is:

$$y_t = y_{1t} + y_{2t} = \left\{ \left[\int_0^1 (y_{j1t})^{\frac{1}{1+\lambda_{p,t}}} dj \right]^{1+\lambda_{p,t}} + \left[\int_0^1 y_{j2t} dj \right] \right\}$$

The intermediate producers set the prices for y_{1t} according to the Calvo mark-up equation on marginal costs and set the prices for y_{2t} at marginal costs. Note that $y_{1t} = \omega_p y_t$, in which ω_p is the share of the imperfectly competitive goods market; so

$$y_{2t} = (1 - \omega_p)\, y_t$$

and

$$P_t = \omega_p P_{1t} + (1 - \omega_p)\, P_{2t}$$

The retailers in the economy then combine these goods as above in a bundle that they sell at this weighted average price.

Apart from these equations mentioned above the first order conditions of households and firms will not be changed no matter what markets they operate in.

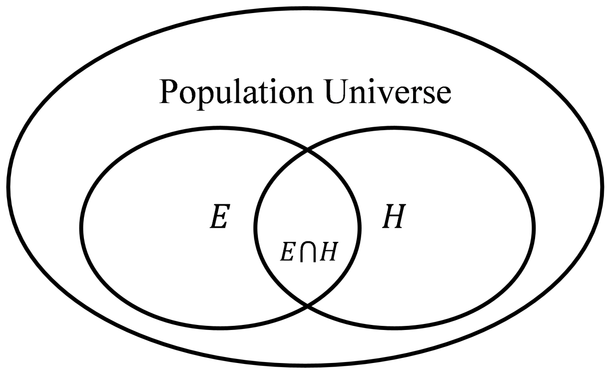
The initial sector weights used in estimation of the Hybrid model are $\omega_w = 0.5$ (the New Keynesian share for wages) and $\omega_p = 0.5$ (the New Keynesian share for prices). That is, 50% of the labour market and 50% of product market are imperfectly competitive. The hybrid model however still requires a large amount of nominal rigidity to match the data, especially in the labour market. This reflects the reality in China in which even after the economic reforms of 1978 there are still large parts of the product and labour markets with imperfect competition.

2 Estimation and Testing

2.1 The Bayesian Approach

We begin by discussing the Bayesian approach with which we begin our estimation processes. The approach estimates a model by Bayesian Maximum Likelihood where log total Likelihood = Sum (log data Likelihood as in FIML) + (log Likelihood of the estimated parameters according to their prior distribution). The latter likelihood falls as the distance of the estimates from the priors increases. The approach then ranks models by their relative likelihood. If a flat ('uninformative', uniformly distributed) prior is used, then the approach simply becomes FIML; note that when users iterate on their priors, continuously using the latest posterior as the prior for the next estimation iteration, this will also converge on FIML.

The process is illustrated in the Figure 1 below. There is a universe of all possible samples, the population Universe. Within this the Hypothesis H has a probability of generating data as shown; this is the prior probability of H, known from other previous work. We also observe data for this sample E. Finally there is a joint occurrence of E and H, i.e. the extent to which H is consistent with E ('could be generating E') in this sample.



E: Data for episode ("Evidence")

H: Hypothesis generating data (for this and other episodes)

$E \cap H$: Evidence accounted for by H

Figure 1: Illustration of Bayesian Inference

Bayes' Theorem uses the equation $\frac{E \cap H}{POP} = \frac{E \cap H}{E} \times \frac{E}{POP} = \frac{E \cap H}{H} \times \frac{H}{POP}$; or equivalently $P(H|E)P(E) = P(E|H)P(H)$ and recasts it to find the posterior probability of H given the evidence in this sample: $P(H|E) = \frac{P(E|H)P(H)}{P(E)}$. This 'posterior' probability of H (i.e. conditional on the Evidence) is equal to the chances of observing the evidence if H is true times ('prior') chances of H as a share of the total chances of observing the evidence.

The idea here is that the prior on H comes from previous well-founded knowledge on general chances of observing H. We then distinguish this general chance of observing H (in all episodes) from the chances of H being observed in this particular episode (posterior). These probabilities of H are both true; a genuine prior based on wide previous knowledge is never 'superseded'. Indeed it is obvious from the Bayesian estimate that the posterior relies on the continued validity of the prior. One may think of the police inspector figuring out the probability that Jack the Ripper is responsible for a newly found murder victim; there is a general (prior) probability that Jack the Ripper is the murderer, and then the evidence in this particular murder is used to assess the (posterior) probability that he is the murderer of this victim.

As noted above, when a prior is merely an initial iteration but not based on any previous knowledge, and is being treated as 'flat' or 'uninformative', only in this case will the posterior be unaffected by it and will simply be the FIML estimate; here an equivalent way of thinking about the process is as continuously updating the prior by the posterior and thus converging on FIML.

To assess $P(H|E)$, the procedure begins with $P(E|H)$: a modern Bayesian estimation programme such as Dynare simulates H many times to see how often you get E. To obtain $P(E) = P(E|H_1)P(H_1) + P(E|H_2)P(H_2) + ...$ one may simulate all possible hypotheses that could be generating E: so $P(E)$ is a probability-weighted average of all the ways E could be generated. This step can be bypassed if one is only interested in a relative probability of two or more models. Modern computers can do these huge simulation jobs extremely quickly, which accounts for the practical emergence of Bayesian methods in applied work.

However to establish $P(H|E)$ there is still the key missing element $P(H)$ which must be supplied by prior knowledge. Without it the Bayesian approach can get no further than standard FIML and estimate/maximise $P(E|H)$.

The priors are thus assumed to reflect knowledge in the scientific community. Researchers adopt this communal knowledge, use it to assess this new episode; and thus build up this knowledge for future research.

Yet, embarrassingly, we must be honest and admit that applied macroeconomics does not really have any such knowledge. This is evidenced by the numerous reversals of accepted macro understanding that have occurred during modern history including: the Great Depression, the Great Inflation, the Great Moderation, and latterly the Great Recession. Each time known models have been found wanting by a series of 'revolutionaries' such Keynes and Friedman. $P(H)$ in effect has constantly been questioned and has been and still is the object of serious scientific controversy. This status of controversy attaching to proposed priors in macroeconomics should therefore put us on our guard when such priors are used to evaluate the relative probability of two hypotheses which may themselves be suggested by different priors. For example, New Keynesians will no doubt propose New Keynesian priors while those who argue that nominal rigidity is not particularly important will tend to propose Hybrid priors.

In the Bayesian approach rival hypotheses are ranked by their relative posterior probability: $\frac{P(H_1|E)}{P(H_2|E)} = \frac{P(E|H_1)P(H_1)}{P(E|H_2)P(H_2)}$. As is plain the priors are important in this ranking since the relative prior probability of the two Hypotheses under comparison, H_1 and H_2, is a component of the ratio. Thus the log relative posterior probability = (log of likelihood of data under H_1 minus that under H_2) + log of Prior likelihood of H_1 minus that of H_2. The possible situation is illustrated in the Figure 2 that follows.

In this illustration we see that there are two rival priors θ^0_{NK} and θ^0_{HY}, respectively New Keynesian and Hybrid priors. The model parameters under examination are ranged along a spectrum of distance between these two extreme views (measuring this distance could be done in terms of the Wald statistic implied by a model with parameters calibrated either with NK or HY priors). The red curve shows how the data likelihood varies along this spectrum, reaching its maximum at $\widehat{\theta}^{ML}$. The prior likelihood of the parameters when θ^0_{NK} is the prior is shown by the thick black curve, while that when θ^0_{HY} is the prior is shown by the dotted black curve. The Bayesian ML estimate in each case is shown respectively as $\widehat{\theta}^B_{NK}$ and $\widehat{\theta}^B_{HY}$. We may note two things about this illustration: the Bayesian estimates are biased strongly towards the priors and the posterior

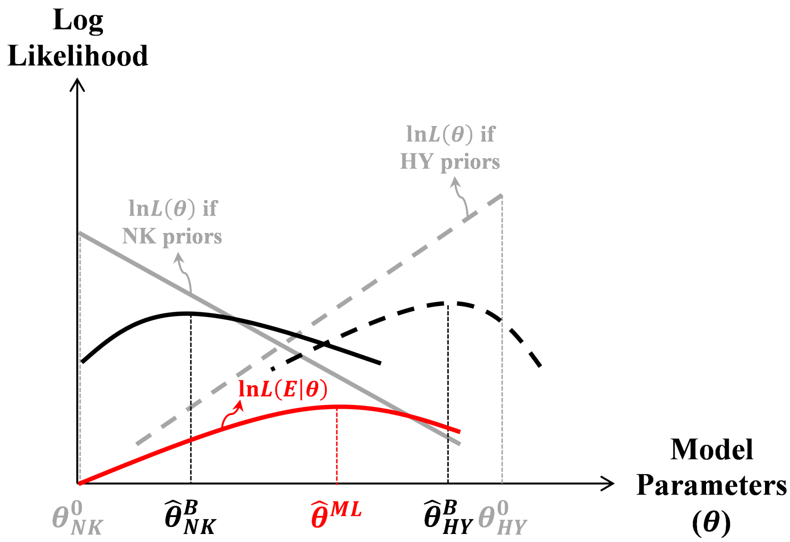


Figure 2: Illustration of Influences of Different Priors

likelihood ranking is dominated by the priors. Thus with NK priors the NK model is ranked ahead, while with HY priors the HY model is ranked ahead.

This comes about in our illustration because the competing priors are strong and far apart while the likelihood function of the data is rather flat. This situation is, we suggest, fairly common in applied macroeconomics; Canova and Sala (2009) suggested that data likelihood functions of macro model parameters were fairly flat, while priors strongly held by different parts of the macro profession clearly differ substantially. We will see below that this situation applies in our case of China since the 1970s. Meanwhile we consider methods by which we could test such rival models (including the original priors) objectively, i.e. when prior information cannot be considered to be objectively known as is assumed in the Bayesian approach. The full Bayesian approach, assisted by such prior knowledge, may have to be deferred until a body of objective knowledge, based on the rejection of poor models, can be built up. We now turn to methods for achieving testing and rejection and through it knowledge-building.

2.2 Methods for Testing Model Structures

A key test of a model is whether it is consistent with the dynamics and volatility found in the data and it is this testing approach that we pursue with respect to the models here. There is a large literature in macroeconomics that compares model simulations with 'stylised facts'. We preserve the spirit of that literature here but we implement it using a test that is statistically based on indirect inference- Le et al (2010) review this transition. To summarise the stylised facts we estimate a VAR on the data and retrieve its coefficients and the data variances; the stylised facts (including the impulse response functions) often used are derived from such a VAR and these variances. Our Wald test statistic is based on the joint distribution of these elements. The model is initially adapted from the Smets and Wouters model, and is then respecified and reestimated through indirect inference in a manner set out later.

The estimation of a macroeconomic model by indirect inference involves several steps (Smith, 1993, Gregory and Smith, 1991, 1993, Gourieroux et al., 1993, Gourieroux and Monfort, 1995 and Canova, 2005).

First, suppose that y_t is an $m \times 1$ vector of actual observed data and $x_t(\theta)$ is an $m \times 1$ vector of simulated time series generated from the structural macroeconomic model and that θ is a $k \times 1$ vector of the parameters of the macroeconomic model and both the actual and simulated data are assumed to be stationary and ergodic. The auxiliary model is $f(y_t, \alpha)$, where α is a vector of parameters of the auxiliary model. The estimation of indirect inference is that a particular value of θ exists given by θ_0 such that

$$f\left(x_t\left(\theta_0\right), \alpha\right) = f\left(y_t, \alpha\right)$$

The maximum likelihood estimators of the parameters of the model based on actual and simulated data are

$$f\left(x_t\left(\theta_0\right), \alpha\right) = f\left(y_t, \alpha\right)$$

and

$$\alpha_S = \arg\max \zeta_S\left(y_t, \alpha\right)$$

Then, the simulated quasi-maximum likelihood estimator of θ is

$$\theta_{T,S} = \arg\max \zeta_T\left(y_t, \alpha_S\left(\theta\right)\right)$$

This is the value of θ that produces parameter values of the auxiliary model that maximise the likelihood function using the actual data. We can use the extended method of simulated moments estimator (EMSME) as an alternative to the simulated quasi-maximum likelihood estimator; this can be obtained as follows. Consider the continuous $p \times 1$ vector of functions $g(\alpha_T)$ and $g(\alpha_S(\theta))$ which could be moments or scores, for examples $g(\cdot)$ could be impulse response functions, then let $G_T(\alpha_T) = \frac{1}{T}\sum_{t=1}^{T} g(\alpha_T)$ and $G_S(\alpha_S(\theta)) = \frac{1}{S}\sum_{s=1}^{S} g(\alpha_S(\theta))$. And there is a requirement that $\alpha_T \to \alpha_S$ in probability and that $G_T(\alpha_T) \to G_S(\alpha_S(\theta))$ in probability for each θ. Then the EMSME is:

$$\theta_{T,S} = \arg\min[G_T(\alpha_T) - G_S(\alpha_S(\theta))]'W(\theta)[G(\alpha_T) - G_S(\alpha_S(\theta))]$$

θ is thus being chosen to minimise $[G_T(\alpha_T) - G_S(\alpha_S(\theta))]'W(\theta)[G(\alpha_T) - G_S(\alpha_S(\theta))]$ which is the Wald test statistic for the chosen descriptors $g(\cdot)$ for any given θ.The resulting estimator of θ is consistent and asymptotically normal.

The Wald test statistic for a particular $\hat{\theta}$ is based on the distribution of $G_T(\alpha_T) - G_S(\alpha_S(\hat{\theta}))$ and can be written as

$$[G_T(\alpha_T) - G_S(\alpha_S(\hat{\theta}))]'W[G_T(\alpha_T) - G_S(\alpha_S(\hat{\theta}))]$$

where the estimate of the optimal weighting matrix is the inverse of the variance-covariance matrix of the descriptors as simulated by the model:

$$W(\hat{\theta}) = \left\{ [\frac{\partial G(\alpha(\hat{\theta}))}{\partial \alpha}](\hat{\theta})[\frac{\partial G(\alpha(\hat{\theta}))}{\partial \alpha}]' \right\}^{-1}$$

We obtain the distribution of $G_T(\alpha_T) - G_S(\alpha_S(\hat{\theta}))$ and the Wald statistic through bootstrapping the implied model errors (these can be extracted by the LIML methods proposed by McCallum, 1976, and Wickens, 1982; and also by full information methods using the expectations generated by the model). The optimal values of $\hat{\theta}$ can in practice most easily be obtained by using a global optimization algorithm such as Simulated Annealing (e.g. Ingber, 1996) and Direct Search (also called pattern search, e.g. Kolda et al, 2006).

The procedure of performing the Wald test by bootstrapping can be summarised as follows. First, estimate the errors of the economic model conditional on the observed data and $\hat{\theta}$. Then estimate the empirical distribution of the structural errors. The structural errors give the empirical distribution of the $\{\varepsilon_t\}_{t=1}^{T}$ errors that are omitted in the null hypothesis. The simulated disturbances are drawn from these structural errors. We draw these disturbances from a time vector to preserve the simultaneity between them. Finally, we compute the Wald statistic.

In addition to the basic Wald statistic, a number of related Wald statistics are considered. We refer to the Wald test based on the full joint distribution of the VAR coefficients as implied by their full covariance matrix as the full Wald test. This Wald test checks whether the coefficients based on the VAR data lie within the DSGE model's implied joint distribution and is a test of the DSGE model's specification. The Mahalanobis distance based on the same joint distribution is used to measure the overall closeness between the model and the data and is normalised as a t-statistic.

We also want to check on the specific features of the macroeconomic model, for example, how well the model can reproduce the behaviour of Chinese GDP and inflation. This can be done using a Wald statistic based on the VAR equation for these two variables alone. This type of Wald test is referred to as a Directed Wald statistic that can be used to evaluate how well a particular variable or limited set of variables is modelled. The Directed Wald test can also be used to determine how well the structural model captures the effects of a particular set of shocks. This requires creating a joint distribution of the impulse response functions for the particular set of shocks and calculating a Wald statistic for this distribution. Even if a macroeconomic model is rejected by the indirect inference test, the Directed Wald test can still evaluate whether the model is well-specified enough to deal with specific aspects of economic behaviour.

Traditional statistics are also useful in this test, such as the ability to match data variances, cross-correlations, and VAR-based Impulse Response Functions. The cross-correlations and the Impulse Response Functions are all derived from the VAR coefficients, so we focus on these coefficients alone, while the data variances are included among the elements included in the Wald statistic.

3 Estimating and Testing the DSGE Model of China

3.1 The Data

We apply our procedures for the period after the Economic reform of China in 1978, up to 2007. In this paper we decided not to use the raw, nonstationary data but rather to apply the widely-used Hodrick-Prescott filter to make it stationary. More recently Meenagh et al (2012) have developed methods to carry out Indirect Inference on non-stationary data; and the Bayesian approach can also be applied to such data. Le et al (2014) used Indirect Inference on the raw data from the early 1990s and this proved helpful in analysing the recent crisis. However, it seems that those results are not at variance with the ones here in a general way. So the use of HP detrending does not seem to have distorted our results here.

To achieve stationarity it was necessary to filter the data by more than simple linear detrending, the least intrusive method. The unit root tests revealed substantial evidence of trend non-stationarity. After HP filtering, though not before, tests of stationarity were satisfied as shown by the ADF tests on the seven observable series in Table 1.

	Before HP-Filter		**After HP-Filter**	
Variable	Statistic	P-Value	Statistic	P-Value
Real Wage	1.934	0.987	-3.835	0.0010
Interest Rate	-0.657	0.409	-4.666	0.0010
Employment	2.821	0.999	-3.676	0.0010
Investment	2.783	0.998	-3.321	0.0012
Consumption	2.567	0.997	-3.256	0.0017
Inflation	-1.403	0.149	-3.907	0.0010
Output	4.433	0.999	-3.419	0.0010

Table 1: ADF Tests for the Pre- and Post- HP Filter

The stationarised series are graphed in Figure 3 and Figure 4.

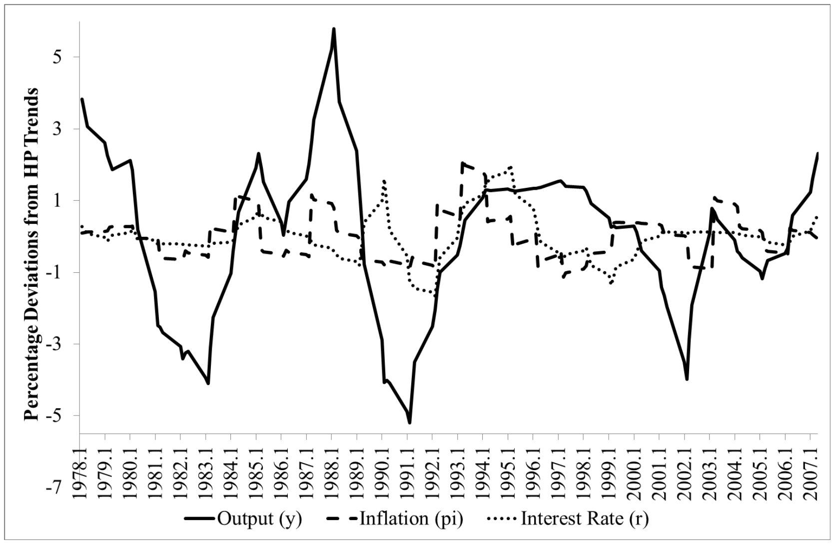


Figure 3: HP-filtered Output, Inflation and Interest Rate

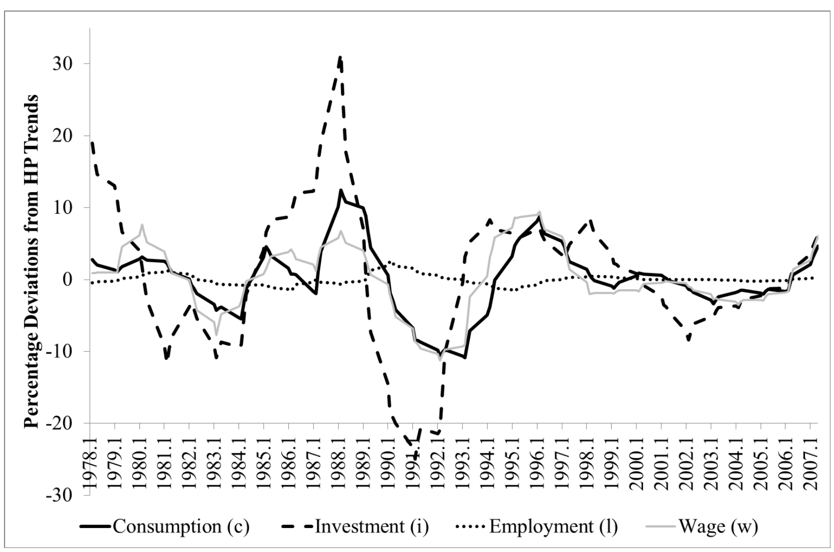


Figure 4: HP-filtered Consumption, Investment, Employment and Wage

3.2 Indirect Inference–Tests and Reestimation

We now proceeded to test the model using this data. The descriptors we chose for the Wald statistic were the coefficients of a VAR(1) on the three key macro variables, output, inflation and interest rates, with in addition the variances of each of these, giving a vector of 12 descriptors in all. If we include the coefficients of a higher order VAR or of a VAR with more variables, such as consumption and investment, we find that for China, as for the US, the model is rejected for reasons identified by Le et al (2011), namely that the description of the data is a much finer one. Essentially, provided we try to match a description of the data that is broad-grained and confined to key variables only, the model can match the data but not if this fineness of the match is raised.

Method	Measure	NK	HY	Dominant
Bayesian (prior = NK)	Log Posterior	-1141.1	-1448.9	NK
Bayesian (prior = HY)	Log Posterior	-917.2	-897.7	HY
ML (prior = flat)	Log Likelihood	744.035	752.438	HY
II estimated models	Wald (P-Value)	19.61 (7%)	13.85 (31%)	HY

Table 2: Test Results of the Two Models

In Table 2, we compare the three available tests of DSGE models–Bayesian, Indirect Inference and Maximum Likelihood. Starting with the Bayesian method, we consider two priors, NK and HY, both of them listed in Table 2; the NK prior is taken from the Smets-Wouters US estimates and the HY prior from some early II estimates for China together with the assumption that half the economy is competitive. The Log Posterior of NK outperforms that of HY, if we use the NK prior. If on the other hand we use the HY prior, the ranking is reversed. It follows that the Bayesian ranking is crucially dependent on the priors chosen, in the manner illustrated in Figure 2 above.

If we turn to the other tests in which priors have no influence (thus in terms of our earlier discussion they assess $P(E|H)$, or p-values of the models), we find that the HY dominates in all cases. Under the II test (once the models are reestimated by II), HY has a significantly higher p-value (0.31) compared with NK, which is marginally accepted with a p-value of 0.07. The Likelihood ratio test after FIML estimation also suggests that the unrestricted HY model is preferred to the restricted NK model. The LR statistic (χ^2 distribution) can be calculated as 16.8 and the p-value of accepting the NK model is 0.0002.

What in short we see from these tests is that only if one has a strong NK prior does one favour the NK model, with its assumption that there are no competitive sectors in either the product or labour markets. The Chinese evidence alone supports a model in which there is a substantial competitive sector in the product market and only a small one in the labour market. The estimates from the two models are set out in Tables 3 and 5, as well as the simulated values they produce for our data features- Table 4. We also show below the shocks and innovations from the two models in chart form- Figures 5 and 6.

What we see in the estimated structural parameters is that HY differs from NK in three key ways:

1) prices are almost entirely competitive which implies they simply track current marginal costs instead of reflecting the whole future of marginal costs as in NK. The result is that inflation responds less to long-lasting shocks in marginal costs. We also find that this is associated with a lower variance of the prices shock; this in turn seems to be connected with the smaller variance of the consumption shock since expected future inflation(which affects consumption via the Euler equation) also is dampened.

2) the Taylor Rule responds to inflation with a coefficient only just above unity in HY, roughly half the NK response. This further reduces the economy's response to shocks via the inflation/monetary policy transmission mechanism.

3) the elasticity of capacity utilisation is again roughly halved in HY compared to NK. This implies that when the marginal product of capital (so profitability and Q) rises capacity is brought into action more cheaply under HY (and as Q falls it is mothballed more easily). Hence investment reacts less to Q. This can be thought of as a diminished 'accelerator' mechanism in the model.

When we turn to the effects of these differences on the simulated stylised facts or data features, we find that there is little difference in the means or bounds of either model except for the variances. Both models are in fact easily accepted on the dynamics alone (i.e. see the p-values on the VAR coefficients). Both are rejected on the variances alone (the worst is output) but HY gets much closer to these than NK, which is strongly rejected whereas NK is at least not rejected at 99% confidence. This better matching of variability by HY is connected to the smaller shocks and weaker transmission mechanisms in 1)-3).

	Innovations	**NK**	**HY**
η_a	productivity	0.658	0.622
η_b	consumption/preference	1.513	0.768
η_g	government expenditure	0.513	0.462
η_i	investment	0.223	0.218
η_r	monetary policy	0.093	0.091
η_p	price mark-up	0.346	0.079
η_w	wage mark-up	0.429	0.441

Table 3: II-Estimated Standard Deviations of Innovations

Equation	Regressor	Data	NK				HY			
			5%	Mean	95%		5%	Mean	95%	
y_t	y_{t-1}	0.933	0.885	0.957	1.006	IN	0.875	0.956	1.009	IN
	π_{t-1}	0.181	-0.442	-0.115	0.194	IN	-0.238	0.062	0.354	IN
	r_{t-1}	-0.091	-0.328	-0.056	0.189	IN	-0.422	-0.148	0.101	IN
π_t	y_{t-1}	0.012	-0.012	0.011	0.042	IN	-0.013	0.020	0.057	IN
	π_{t-1}	0.764	0.581	0.724	0.848	IN	0.561	0.726	0.869	IN
	r_{t-1}	-0.068	-0.133	-0.024	0.085	IN	-0.149	-0.034	0.078	IN
r_t	y_{t-1}	-0.003	-0.008	0.007	0.026	IN	-0.004	0.015	0.039	IN
	π_{t-1}	0.142	0.064	0.162	0.256	IN	0.027	0.109	0.195	IN
	r_{t-1}	0.893	0.812	0.877	0.938	IN	0.796	0.873	0.935	IN
S. D.	y_t	0.528	0.900	1.136	1.425	OUT	0.785	1.015	1.291	OUT
	π_t	0.187	0.153	0.210	0.268	IN	0.124	0.190	0.266	IN
	r_t	0.052	0.050	0.067	0.087	IN	0.044	0.059	0.074	IN
Dynamics		Wald(9)		5.158				3.996		
(coefficients)		P-Value		0.8203				0.9117		
Volatility		Wald(3)		15.220				10.046		
(standard deviations)		P-Value		0.0016				0.0182		
Total		Wald(12)		19.61				13.85		
(dynamics and volatility)		P-Value		0.0749				0.3105		

Table 4: Auxilliary VAR(1) Coefficients and Shock Standard Deviations

Parameter	**Meaning**	**NK Priors**	**HY Priors**	**NK II Estimates**	**HY II Estimates**
α	Share of capital in production	0.3	0.175	0.110	0.117
h	External habit formation	0.7	0.766	0.352	0.329
ι_p	Degree of price indexation	0.5	0.438	0.258	0.234
ι_w	Degree of wage indexation	0.5	0.694	0.769	0.340
ξ_p	Degree of price stickiness	0.5	0.575	0.585	0.679
ξ_w	Degree of wage stickiness	0.5	0.702	0.301	0.301
μ_p	Price mark-up MA coefficient	0.5	0.368	0.997	0.138
μ_w	Wage mark-up MA coefficient	0.5	0.999	0.093	0.056
φ	Elasticity of capital adj. cost	4	4.602	6.447	6.132
Φ	1+share of fixed cost	1.25	2.243	1.902	1.721
ψ	Elasticity of capital utilization	0.5	0.566	0.771	0.411
ρ	TR coeff. (r smoothing)	0.75	0.657	0.782	0.776
ρ_a	AR coeff.	0.5	0.760	0.847	0.840
ρ_b	AR coeff.	0.5	0.770	0.776	0.855
ρ_{ga}	MA coeff. of ε_t^g	0.5	0.944	0.999	0.998
ρ_g	AR coeff.	0.5	0.140	0.113	0.061
ρ_i	AR coeff.	0.5	0.805	0.941	0.998
ρ_p	AR coeff.	0.5	0.611	0.746	0.518
ρ_r	AR coeff.	0.5	0.762	0.638	0.364
ρ_w	AR coeff.	0.5	0.586	0.601	0.514
$r_{\Delta y}$	TR coeff.	0.12	0.586	0.201	0.209
r_π	TR coeff.	1.5	1.001	1.712	1.001
r_y	TR coeff.	0.12	0.165	0.320	0.340
σ_c	Elasticity of substitution C	1.5	2.121	2.236	2.163
σ_l	Elasticity of substitution L	2	2.618	3.999	4.000
ω_p	NK share in price setting	1	0.5	1	0.131
ω_w	NK share in wage setting	1	0.5	1	0.877

Table 5: Estimation Results of NK and Hybrid Models using II Approach

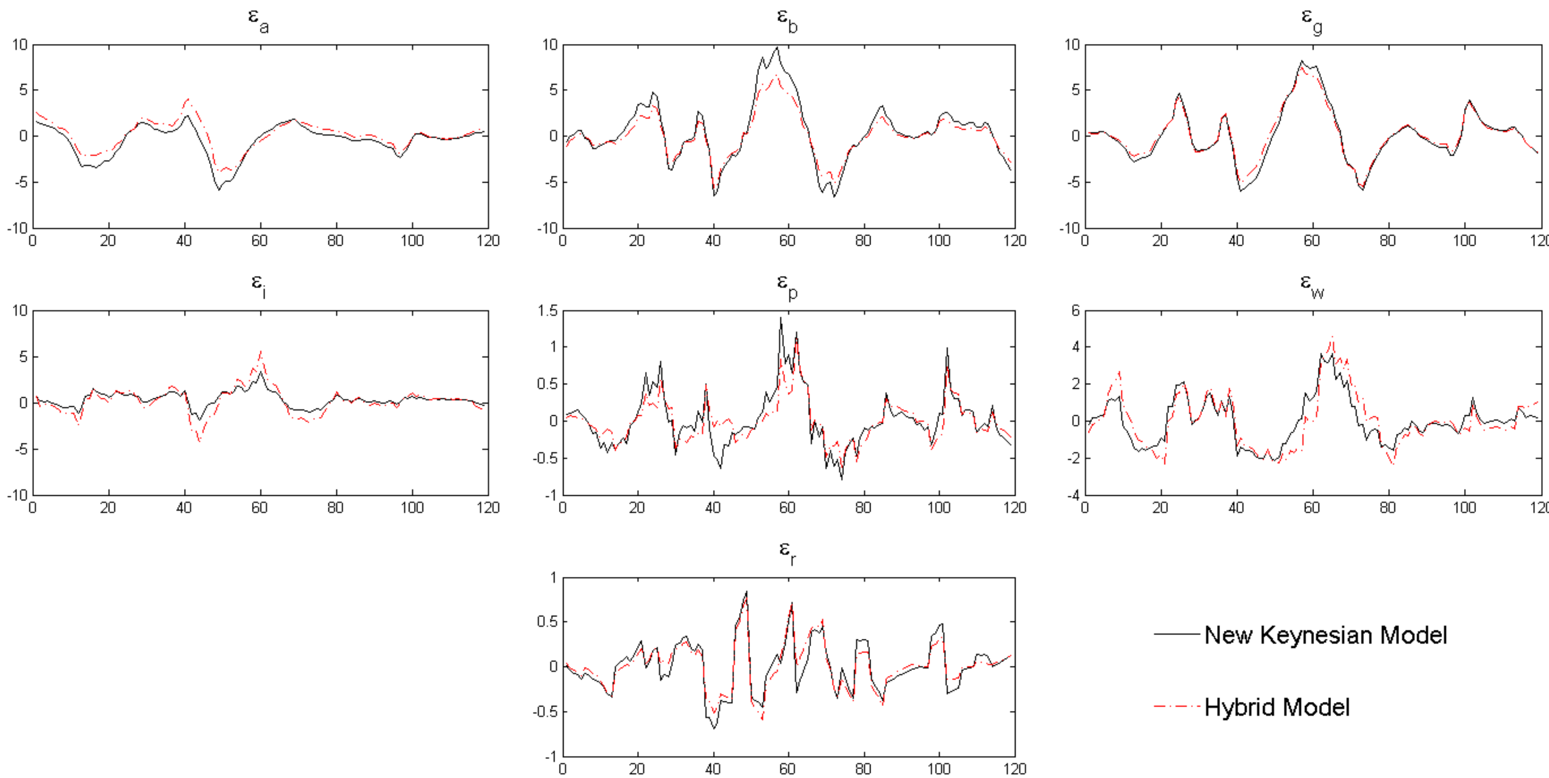


Figure 5: Structural Shocks of the Two Models

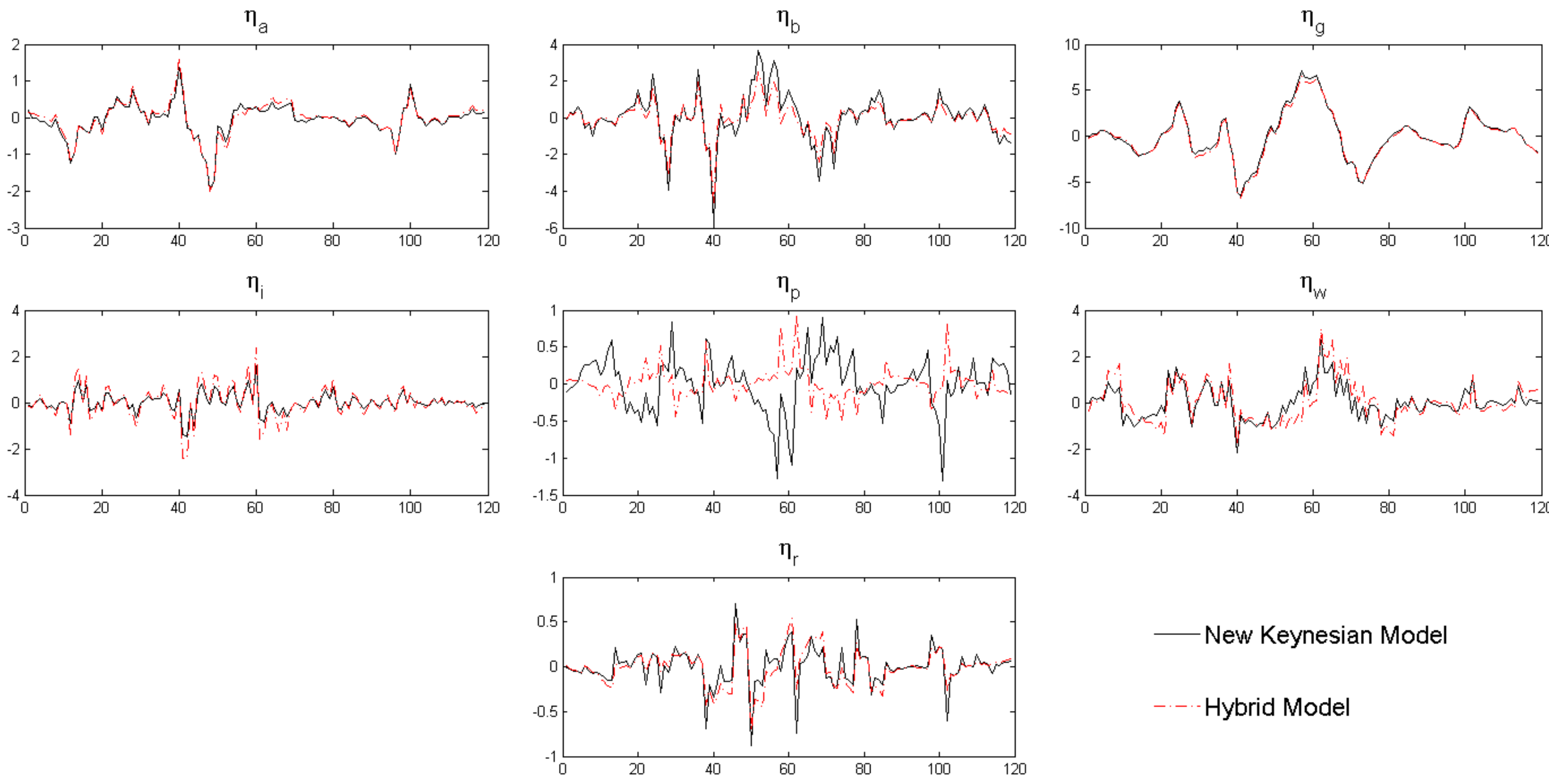


Figure 6: Innovations of the Two Models

3.3 Comparing Bayesian, ML and II Estimates of the Models

Table 6 comprehensively compares estimates of the two models by the variety of methods we are examining once we have abandoned the original priors, both sets of which we have seen are controversial and can prejudice our findings. In the two left hand columns we find the II estimates; in the next two we find the Bayesian estimates using these II estimates as priors. As we would expect these are hardly different from the II estimates that discipline the Bayesian process. However what may come as a surprise is the difference that is made by moving to FIML (Bayesian ML under flat priors) in columns 3 and 6 for NK and HY respectively (here we evaluate the likelihood on only the three key variables we used for II, so as to compare like with like); we know that FIML is asymptotically equivalent to II - both are consistent and asymptotically normal. In small samples however it makes a difference which estimator is used as they have different objective functions. Furthermore, if one uses the ML estimates and tests them by II, they are strongly rejected- see the Wald values at the bottom of the Table.

Le et al (2012) found that Likelihood and Wald distributions were not at all correlated for the same true model; and as we see here the ML and II estimates differ too. Researchers need to decide whether their interest in model performance lies in it forecasting the data well or matching the data features well. Viewed as tests of specification the Wald is far more powerful; here we take the view we want a model that is as well specified as possible for use in policy analysis and hence we adopt the II estimates. (Those wishing to use models for forecasting would no doubt take a different view.)

4 Using the Model to Understand the Workings of the Chinese Economy

In our examination of Chinese macro behaviour we use the II estimates as our preferred ones since we know that these are not rejected by our most powerful test, viz the II test; we also know that they fit the data behaviour which wish to match for any policy discussion that might be based on the model. If we turn to these estimates in Table 6, essentially the difference between the two models, as reviewed above, is that under HY there is less nominal price rigidity than in NK but roughly the same nominal wage rigidity. HY thus remains close to New Keynesian in the labour market- reflecting the high degree of organisation and control via company unions perhaps, of the wage-setting process. Nevertheless even here there is a non-negligible competitive share (of 12%) and also the degree of indexation in wage inflation is halved to a share of 0.34, implying that wages are less inherently persistent than assumed in the NK prior. In the product market HY implies a high degree of price competition (with a weight of around 87% on the competitive sector); this is consistent with the substantial

Model	NK	NK	NK	HY	HY	HY
Method	II	Bayes	ML	II	Bayes	ML
Prior	NA	II Est.	Flat	NA	II Est.	Flat
α	0.110	0.134	0.534	0.117	0.018	0.044
h	0.352	0.299	0.311	0.329	0.247	0.412
ι_p	0.258	0.268	0.519	0.234	0.172	0.593
ι_w	0.769	0.777	0.751	0.340	0.295	0.243
ξ_p	0.585	0.622	0.678	0.679	0.664	0.786
ξ_w	0.301	0.380	0.444	0.301	0.384	0.654
μ_p	0.997	0.999	0.300	0.138	0.082	0.513
μ_w	0.093	0.093	0.471	0.056	0.057	0.492
φ	6.447	6.577	6.183	6.132	5.816	7.454
Φ	1.902	2.271	1.329	1.721	2.101	2.512
ψ	0.771	0.758	0.638	0.411	0.429	0.533
ρ	0.782	0.803	0.411	0.776	0.788	0.064
ρ_a	0.847	0.966	0.815	0.840	0.974	0.849
ρ_b	0.776	0.799	0.571	0.855	0.824	0.437
ρ_{ga}	1.000	0.998	0.521	0.998	0.999	0.473
ρ_g	0.113	0.112	0.523	0.061	0.060	0.845
ρ_i	0.941	0.938	0.303	0.998	0.998	0.037
ρ_p	0.746	0.786	0.730	0.518	0.785	0.748
ρ_r	0.638	0.628	0.750	0.364	0.571	0.751
ρ_w	0.601	0.881	0.625	0.514	0.923	0.673
$r_{\Delta y}$	0.201	0.230	0.384	0.209	0.264	0.559
r_π	1.712	1.528	1.102	1.001	1.152	1.088
r_y	0.320	0.374	0.456	0.340	0.352	0.453
σ_c	2.236	2.266	1.016	2.163	2.225	1.795
σ_l	3.999	3.825	2.810	4.000	3.813	1.184
ω_p	1	1	1	0.131	0.131	0.195
ω_w	1	1	1	0.877	0.878	0.150
η_a	0.658	0.377	0.110	0.622	0.419	2.488
η_b	1.513	0.651	0.273	0.768	0.554	0.474
η_g	0.513	0.937	0.039	0.462	0.882	0.091
η_i	0.223	0.422	0.646	0.218	0.829	0.660
η_r	0.093	0.202	0.201	0.091	0.196	0.050
η_p	0.346	0.298	0.163	0.079	0.079	0.187
η_w	0.429	0.415	0.409	0.441	0.516	2.448
Wald (Total)	**19.61**	**39.01**	**78.96**	**13.85**	**47.93**	**75.79**
P-Value	**0.0749**	**0.0001**	**0.0000**	**0.3105**	**0.0000**	**0.0000**

Table 6: Estimation Results of NK and Hybrid Models

deregulation of product pricing and markets that has occurred since the 1978 reforms. HY otherwise differs from NK mainly because capacity utilisation responds strongly to the marginal user cost of capital (ψ is lower implying that existing capacity can be brought back into use cheaply so that the output supply curve is flatter); this in turn dampens the response of the user costs of capital to shocks to that investment responds less. In addition the Taylor Rule is much less responsive to inflation (the coefficient is only just above unity, the value assigned by the Taylor Principle). Thus overall HY embodies a more 'flexible' model than NK; output reacts quickly to shocks, dampening investment responses, and prices react little to shocks.

Our models here are ones in which money and banking is not included explicitly and hence it might be considered inadequate to analyse recent developments in China, since the financial crisis. However, in other recent work (Le et al, 2014) where monetary factors are included, it has been found that banking and monetary shocks were not big contributors to the crisis in China; in particular China has never suffered from the zero bound. Instead the main shocks came from external demand and internal policy responses, boosting government spending and (largely government-controlled) investment. While the investment response was mediated through bank lending, this was done under government direction through state-owned banks; hence it was in essence no different from government-mandated investment on public account. This will no doubt change as the current reform programme to liberalise the financial sector is rolled out; but this remains in the future.

In this section we discuss the two models' behaviour in the form of key impulse response functions: two in particular- for a productivity and for a monetary shock (all others can be found in the appendix).

When productivity rises, employment falls in both models because demand for labour is determined by output demand as well as real wages- which fall due to the Calvo forward-looking wage setting equation. Consumption and investment both rise. In the HY version they rise less first because investment responds less as explained above; secondly because inflation only falls a little, being largely determined in the competitive sector by current marginal costs- hence interest rates also fall by only a little, disturbing demand less.

When we turn to the monetary shock, driving up interest rates, the response of the HY model is qualitatively similar to NK but again smaller. Investment reacts less again. The shock has lower persistence in the HY model also.

In the appendix we show the other IRFs and we see throughout the way in which our three key mechanisms identified above dampen the HY responses compared with NK. Thus our careful estimation process has found that China's relative flexibility compared with the NK stereotype gives it a greater ability to absorb shocks.

Table 7 below shows the variance decomposition for all 7 variables. Both models are dominated by three shocks: productivity, consumption and investment. Productivity is the main supply shock but investment is another one: in this we see the Chinese planning process delivering infrastructure and industrial investment via both public borrowing and the state banking system. The con-

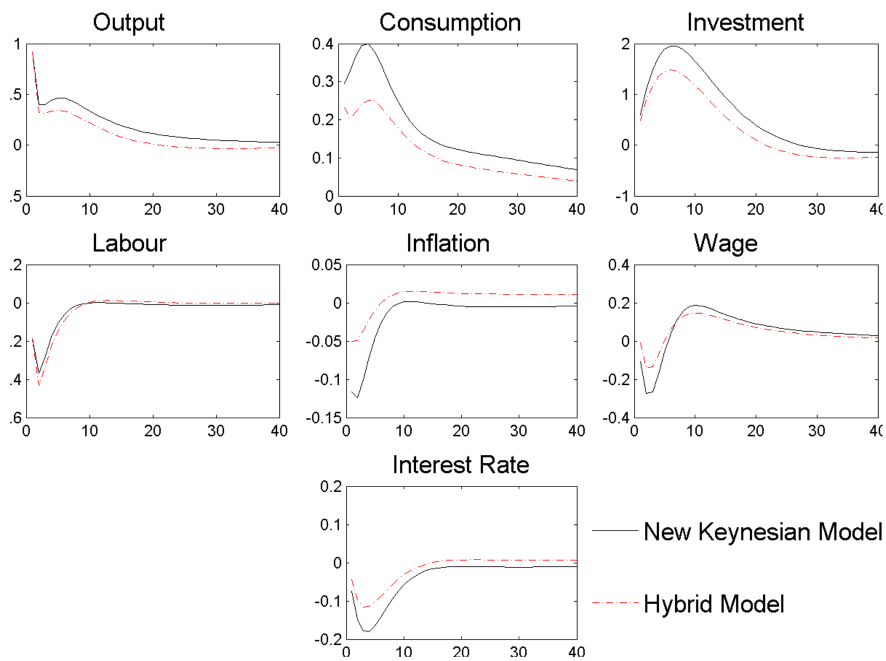


Figure 7: IRFs of Productivity Shock (η_a)

sumption shock can be seen as a 'consumer credit premium' effect coming via the rates charged to 'private' borrowers by Chinese state banks- in effect these loans are mediated through a 'shadow' banking system whereby wealth funds coordinated by high-wealth individuals borrow officially from state banks and lend the money on to private borrowers. The pattern across the two models is not hugely different. We can see that the Taylor Rule has a smaller effect on inflation in HY as we would expect both from its smaller inflation response and from the smaller response of inflation to shocks. Also price and wage shocks largely disappear from the HY model, even on wages and prices. The consumption/premium shock has generally smaller effects in HY which derives from its much smaller variance as explained earlier; it has a more dominating effect on inflation but this is relative to a lower inflation variance in the HY model.

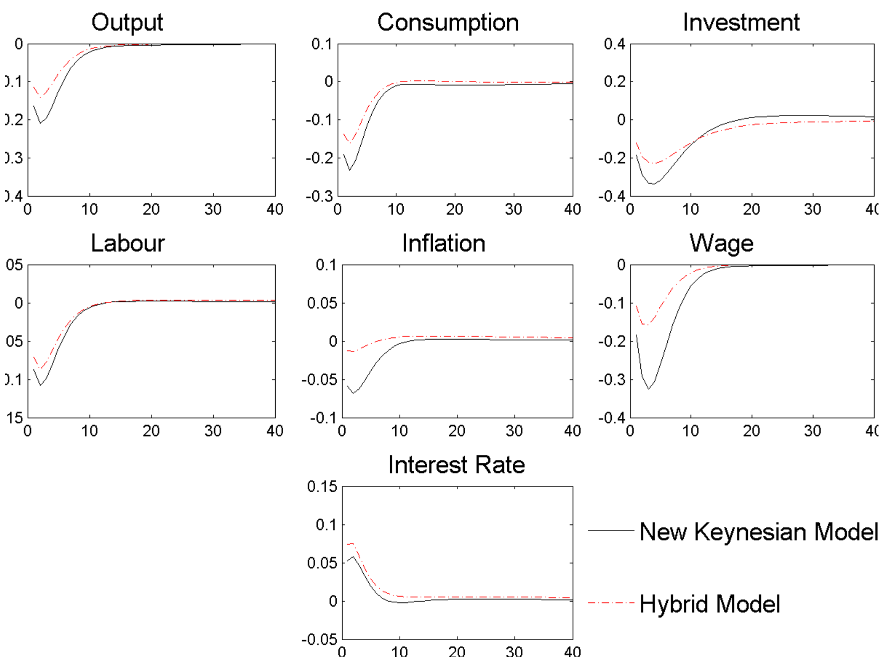


Figure 8: IRFs of Monetary Shock (η_r)

Model-Shock	Symbol	y	c	i	l	π	w	r
NK: Productivity	η_a	25.86	14.17	19.74	15.18	7.94	2.9	10.59
Consumption	η_b	45.13	54.11	6.63	67.07	49.04	64.68	75.52
Government	η_g	3.38	0.13	0.02	5.88	0.04	0.45	0.25
Investment	η_i	20.71	27.36	71.16	5.42	7.37	10.14	8.47
Taylor Rule	η_r	3.16	2.25	1.97	3.56	30.32	13.11	4.05
Prices	η_p	0.26	0.38	0.11	0.76	2.35	6.16	0.52
Wages	η_w	1.5	1.59	0.37	2.14	2.94	2.56	0.59
HY: Productivity	η_a	13.68	1.99	9.19	18.21	5.7	0.64	9.95
Consumption	η_b	33.46	12.67	15.32	68.89	66.57	15.51	78.63
Government	η_g	2.46	0.04	0.01	5.12	0.01	0.12	0.43
Investment	η_i	49.72	85.03	75.25	6.36	13.41	81.63	7.19
Taylor Rule	η_r	0.11	0.03	0.06	0.21	12.71	0.29	1.08
Prices	η_p	0.01	0	0.01	0.04	0.94	1.56	0.12
Wages	η_w	0.55	0.23	0.17	1.17	0.65	0.25	2.6

Table 7: Variance Decomposition of the Two Models under II

5 Conclusions

In this paper we have used the available toolkit for testing macro models to evaluate a model of China over the period from Deng Xiaoping's reforms up until the crisis period. The model, which is derived from the work of Christiano et al and Smets and Wouters, treats China as a closed economy, just as their original models treated the US. However, this has not appeared to be a problem since the model passes stringent tests of fit to the available stylised facts as summarised by a VAR. Bayesian ranking methods can be applied to China but rely on the availability of strong priors since the ranking is heavily influenced by these priors; yet there is controversy about them, particularly with regard to the degree of price/wage rigidity. When the models including their priors are tested by Likelihood or Indirect Inference methods, models that assume New Keynesian priors with universal imperfect competition and Calvo rigidity are rejected in favour of models with a fair-sized perfectly competitive sector, particularly in the product market. The model that fits best on both Likelihood and Indirect Inference criteria is one in which the product market in over 80% competitive but the labour market is over 80% imperfectly competitive and governed by Calvo contracts with a modest degree of indexation. This model behaves quite a lot more 'flexibly' than a New Keynesian, as witnessed by its smaller reactions to shocks.

At the same time as trying to discover the nature of the Chinese economy and specifically its degree of nominal rigidity, we have been concerned to illustrate the problems that can be encountered in evaluating macro models. We have shown that in estimating the model much hangs on the method used: the criteria used in ML and II differ and this matters in small samples. Strong priors can be used to force the two together; but the priors chosen for macro models may well be, as here, highly controversial. Bayesian estimation is therefore inappropriately biased by such priors. Researchers that wish to find a model capable of reliable use in policy evaluation should use II to estimate and test the model as this method generates the most powerful tests against mis-specification. Researchers wishing to find a model capable of forecasting accurately should use ML which effectively measures the forecasting accuracy of the model; nevertheless we found here that the ML-estimated models were rejected as mis-specified by the II test and so should not be used for policy evaluation.

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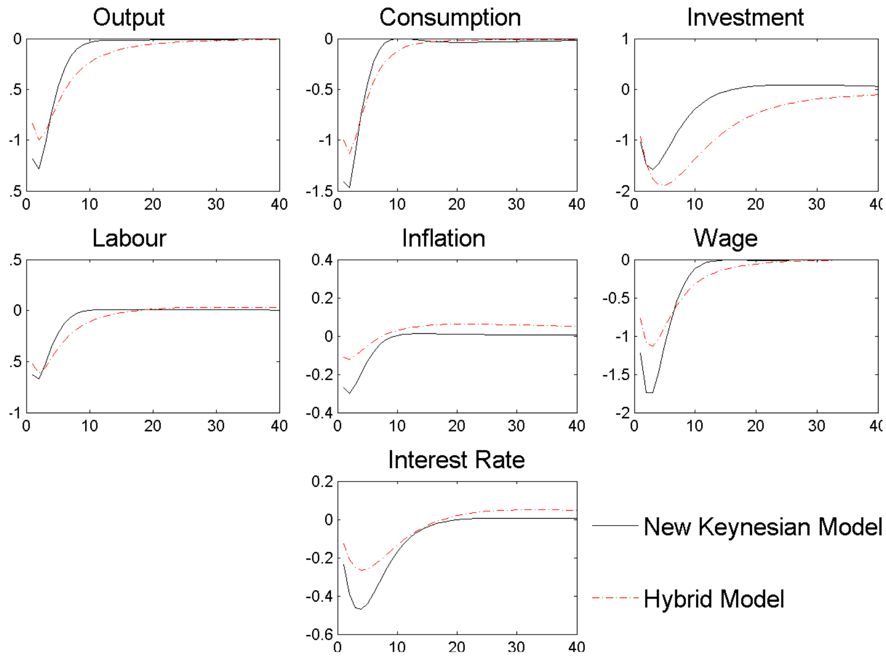
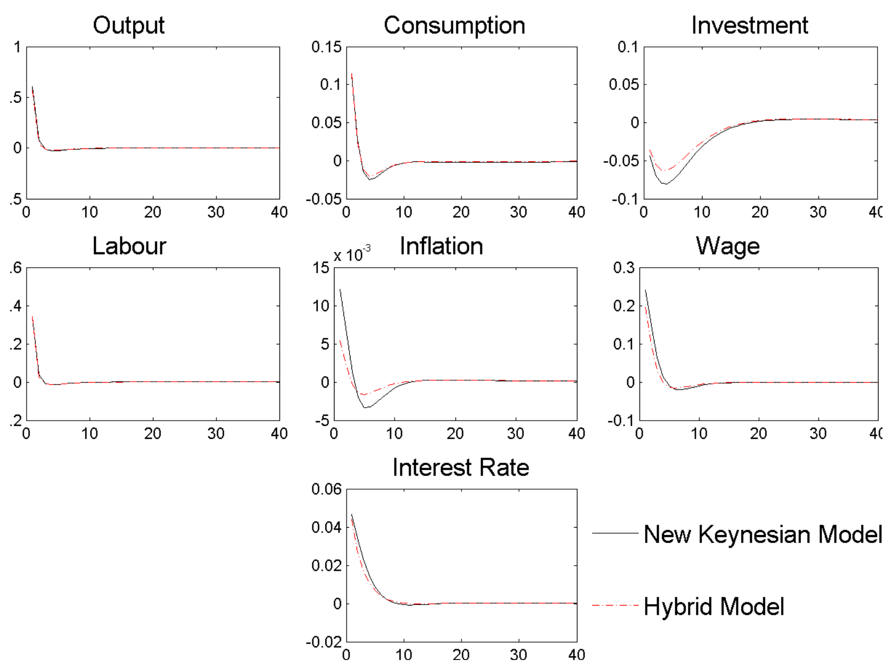
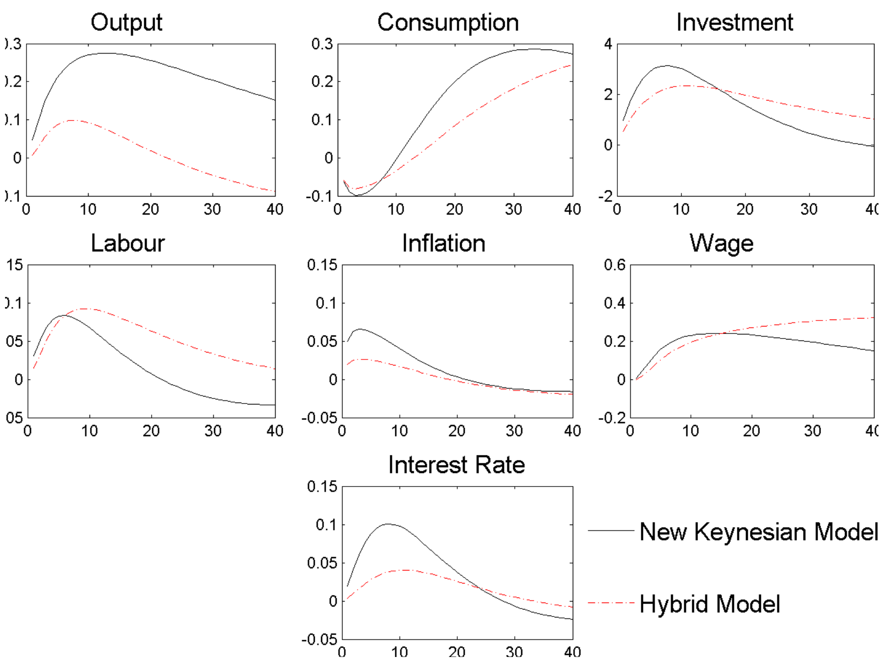
6 Appendix



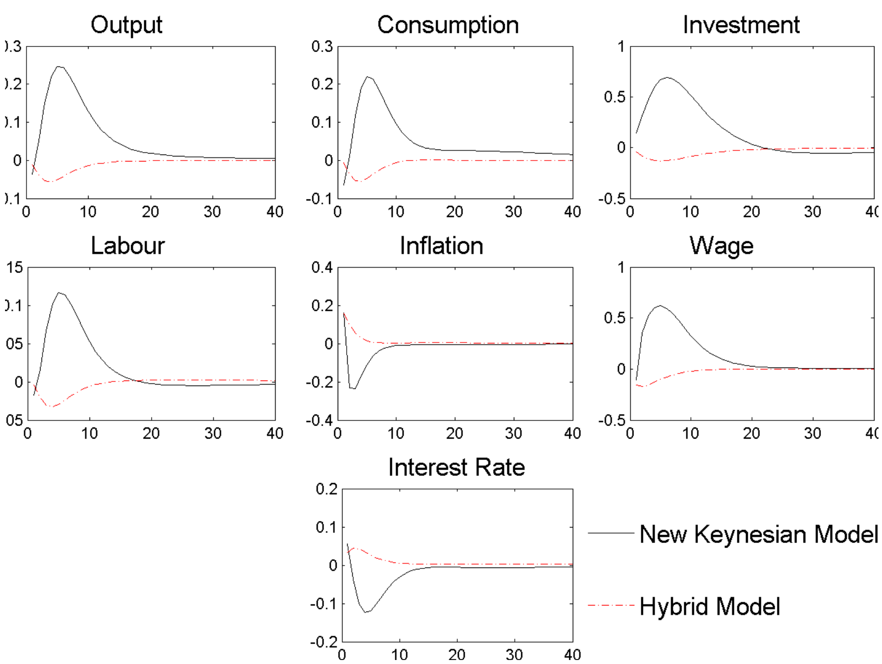
IRFs of Preference Shock (η_b)



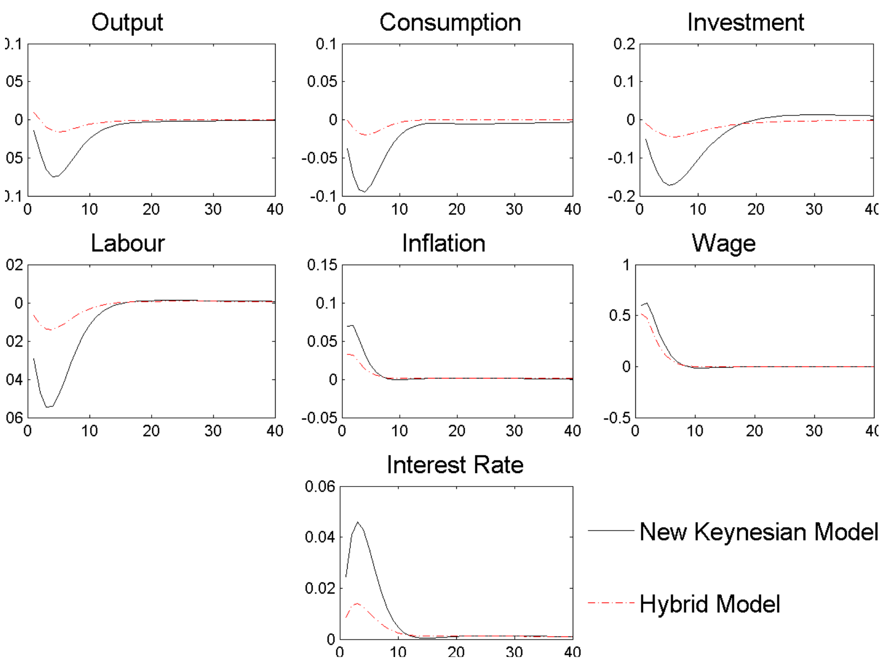
IRFs of Expenditure Shock (η_g)



IRFs of Investment Shock (η_i)



IRFs of Price Mark-Up Shock (η_p)



IRFs of Wage Mark-Up Shock (η_w)