Frequentist evaluation of small DSGE models

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Abstract

This paper proposes a new evaluation approach of the class of small-scale ‘hybrid’ New Keynesian Dynamic Stochastic General Equilibrium (NK-DSGE) models typically used in monetary policy and business cycle analysis. The novelty of our method is that the empirical assessment of the NK-DSGE model is based on a conditional sequence of likelihood-based tests conducted in a Vector Autoregressive (VAR) system in which both the low and high frequency implications of the model are addressed in a coherent framework. The idea is that if the low frequency behaviour of the original time series of the model can be approximated by unit roots, stationarity must be imposed by removing the stochastic trends. This means that with respect to the original variables, the solution of the NK-DSGE model is a VAR that embodies a set of recoverable unit roots/cointegration restrictions, in addition to the cross-equation restrictions implied by the rational expectations hypothesis. The procedure is based on the sequence ‘LR1 → LR2 → LR3’, where LR1 is the cointegration rank test, LR2 the cointegration matrix test and LR3 the cross-equation restrictions test: LR2 is computed conditional on LR1 and LR3 is computed conditional on LR2. The type-I errors of the three tests are set consistently with a pre-fixed overall nominal significance level and the NK-DSGE model is not rejected if no rejection occurs. We investigate the empirical size properties of the proposed testing strategy by a Monte Carlo experiment and illustrate the usefulness of our approach by estimating a monetary business cycle NK-DSGE model using U.S. quarterly data.

Keywords: DSGE models, LR test, Maximum Likelihood, New-Keynesian model, VAR J.E.L. C5, E4, E5

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1 Introduction

Dynamic stochastic general equilibrium (DSGE) models, in the particular the approach dubbed the New Keynesian (NK) models, are presently dominant both in policy and academic environments. It is therefore important to ascertain the validity of these models. Henceforth we denote this class of models with the acronym ‘NK-DSGE’.

There are several methods that can be used to evaluate the empirical performance of NK-DSGE models, including economic reliability, statistical fit and forecasting accuracy, see e.g. Schorfheide (2000), An and Schorfheide (2007) and Schorfheide (2011). It is often claimed that Bayesian techniques are preferable to standard likelihood-based methods because NK-DSGE models typically represent a false description of the Data Generating Process (DGP) and misspecification can be important in estimation, see e.g. Canova and Ferroni (2012). Schorfheide (2000) suggests using a loss function to assess the discrepancy between DSGE model predictions and overall posterior distribution of population characteristics that the researcher is trying to match. Del Negro et al. (2007) develop a set of tools within the Bayesian approach that can be used for assessing the time series fit of a DSGE model based on a systematic relaxation of the set of cross-equation restrictions (CER) that the structural model implies on the Vector Autoregressive (VAR) representation of the data.

In this paper we argue that the scientific validity of a model should not be exclusively based on its logical coherence or its intellectual appeal, but also on its capability of making empirical predictions that are not rejected by the data, see e.g. De Grauwe (2010) and Pesaran and Smith (2011). While misspecification in NK-DSGE models is a clear possibility, we do not think it represents a strong argument against the use of frequentist (classical) likelihood-based techniques. A model is purporting by definition to replicate some main properties of its subject, whatever the use or preferences made for its design, and a macroeconometric model should be able to generate the main properties of the actual macro economy.

The purpose of the analysis is therefore to see to what extent it is possible to test the empirical reliability of NK-DSGE models by classical methods. We not only want to use the CER as a ‘metric’, in line with the spirit of the early literature on the econometrics of rational expectations models, see Hansen and Sargent (1980), Wallis (1980) and Hansen and Sargent (1981), but we also want to test other implied restrictions, usually neglected in the literature, in a coherent and comprehensive framework. Schorfheide (2011) observes that one of the major challenges of current dynamic macro modelling is to recognize that many time series exhibit low frequency behavior that it is difficult to reconcile with the models being estimated. Gorodnichenko and Ng (2010) report in their Table 1 a non-exhaustive listing of how the high persistence of the variables has been addressed in the literature on DSGE models and propose robust estimators
that do not require researchers to take a stand on whether shocks have permanent or transitory
effects. We instead account for the low/high frequency behavior of the data by assuming that
the variables of interest are driven by unit roots and that the underlying common stochastic
trends cancel through steady-state relationships. In this respect, we do not need to take any a
priori stand about how to filter the model and the data—because ‘filtering’ is implicitly obtained
by a proper transformation of the model through the cointegration restrictions implied by the
theory under investigation.

We use classical frequentist statistical tests, in particular likelihood ratio (LR) tests, with
the idea of maximizing the role attached to the data as much as possible. Moreover, we analyze
long and short-run restrictions jointly.

We focus on a particular family of small-scale NK-DSGE models typically used in monetary
policy and business cycle analysis, see among many others Ireland (2004), Dave and DeJong
(2007), Carlstrom et al. (2009), Benati and Surico (2009) and Fanelli (2012) and references
therein. We test the NK-DSGE model by a sequential procedure computed in three steps. We
start from a finite order VAR involving the (observable) variables of the system. We first test
whether the cointegration rank is consistent with the predictions of NK-DSGE model. Next,
we test the implied overidentifying cointegrating restrictions, conditional on the chosen rank.
Finally, we test the implied overidentifying CER, conditional on the cointegrating restrictions
(steady state). Overall, the suggested method involves computing a sequence of three LR tests,
hereafter denoted LR1 (LR cointegration rank test), LR2 (LR cointegration matrix test) and
LR3 (LR test for CER), leading to a multiple hypothesis testing strategy, whose overall size
can be controlled for. For ease of exposition we denote our testing strategy with the symbol
‘LR1→LR2→LR3’.

The novelty of the ‘LR1→LR2→LR3’ approach is that the empirical evaluation of the NK-
DSGE model is based on the joint assessment of the low and high frequency implications of the
model: LR2 is run conditional upon that LR1 does not reject the cointegration rank and LR3
is run if LR2 does not reject the overidentification cointegrating restrictions.\(^1\) Since we have a
precise prediction from the theoretical model about the number of common stochastic trends
which should drive the NK-DSGE model, the chosen LR1 test used in the sequence is the ‘one

\(^1\)To our knowledge, King et al. (1991) and Vredin and Söderlind (1996) are early examples of the use of LR1
in related contexts, Juselius (2011) is a recent example of the use of LR2 in the context of NK-DSGE models,
while Guerron-Quintana et al. (2013) propose the inversion of a test like LR3 to build confidence sets for the
structural parameters of DSGE models robust to identification failure. Fanelli (2008) applies a testing strategy
similar to the one suggested in this paper in a single-equation framework. Fanelli (2012) and Castelnuovo and
Fanelli (2011) have recently proposed the use of LR3 (which in the former is actually a Lagrange multiplier test)
in the context of NK-DSGE models to test determinacy/indeterminacy.
shot’ version of Johansen’s LR Trace test, see Johansen (1996).

This paper has several connections with the existing literature. The work closer to ours in spirit is Canova et al. (1994), who propose a method to evaluate real business cycle models by eliciting the (highly) restricted VAR representation underlying them and comparing it with an unrestricted VAR for the data. Canova et al. (1994) recognize that the driving forces in these models may be integrated and hence account for the implied set of cointegration restrictions and also consider what they call ‘non-cointegrating restrictions’. Our approach is different from Canova et al. (1994) not only because we focus on a class of monetary policy business cycle models, but mainly because our ‘LR1→LR2 →LR3’ procedure accounts for long-run and short-run restrictions jointly in a comprehensive framework, allowing us to keep the overall size or the procedure under control. Similarly, Fukač and Pagan (2010) propose an evaluation approach to NK-DSGE models in which both the long and short-run behavior of the data are taken into account by modelling the common stochastic trends in an equilibrium-correction framework. However, while Fukač and Pagan (2010) put forth a ‘limited information’ approach, our analysis is developed in a ‘full information’ framework. Juselius (2011) also applies a ‘full information’ maximum likelihood (ML) approach but he limits attention to the steady-state implications of the NK-DSGE model, leaving the CER untested. Compared to Del Negro et al. (2007), who use a (cointegrated) VAR in error correction form as an approximating model for the DSGE model in their Bayesian evaluation method, we test, other than impose, the cointegration restrictions because testing these restriction is one of the crucial steps of the proposed model evaluation approach. Moreover, Del Negro et al. (2007) consider a model which is a combination of an unrestricted VAR for the data and the VAR subject to the CER implied by the DSGE model: the combination is indexed by a scalar parameter whose level, determined by the data, indicates whether the empirical evidence favours the unrestricted or constrained VAR representation. Instead, the third step of our procedure is explicitly designed to test the CER in the spirit of Hansen and Sargent (1980) and Hansen and Sargent (1981). Compared to Gorodnichenko and Ng (2010), who apply robust filters to both the model and the data, our approach is explicitly designed to testing both the long-run and short-run restrictions and, if the NK-DSGE model is not rejected by the data, delivers ML estimates of the structural parameters. Compared to the likelihood-based estimation and testing approach proposed by Johansen and Swensen (1999) for ‘exact’ linear rational expectation models (Hansen and Sargent, 1991), the ‘LR1→LR2 →LR3’ procedure is explicitly focused on the class of monetary policy NK-DSGE models which are prominent examples of ‘inexact’ linear rational expectations models. ‘Inexact’ models involve a tighter set of non-linear restrictions compared to their ‘exact’ counterparts, and this fact complicates the issue of maximizing the constrained likelihood function in just
one step. Moreover, in our set-up the knowledge of the ‘right’ number of common stochastic
trends and the cointegration rank is not taken for granted, but is tested explicitly and is part
of the overall testing strategy. In this respect, our approach can also be related to the method
put forward by Campbell and Shiller (1987) for estimating and testing present value models
through VAR systems. As in Campbell and Shiller (1987), we find the overall set of restrictions
that small NK-DSGE models impose on the VAR solution, but differently from Campbell and
Shiller (1987) we test all restrictions jointly. Finally, our procedure is very much in the spirit of
Hendry and Mizon (1993) who also consider testing of rank, cointegration and overidentifying
restrictions in a VAR mapped from non-stationary to stationary representations.

Under the conditions discussed in the paper, the tests LR1, LR2 and LR3, individually
considered, are correctly sized in the sense that their asymptotic size is equal to the pre-fixed
nominal type I error. Accordingly, using simple Bonferroni arguments, we can easily prove that
the overall asymptotic size of the testing strategy does not exceed the sum of the type I errors
pre-fixed for each test. Thus, if a practitioner wishes to test the NK-DSGE model at, say, the
5% nominal level of significance, the critical values of the tests LR1, LR2 and LR3 can be chosen
such that the sum of the individual type I errors is 5%. The ‘LR1→LR2→LR3’ test is consistent
against all main hypotheses with respect to which its three individual tests are consistent, i.e. (i)
DGPs in which the number of common stochastic trends is not consistent with what is implied
by the NK-DSGE model; (ii) DGPs in which the number of common stochastic trends is the one
predicted by the NK-DSGE model, but the identification structure of the cointegration matrix
is at odds with the requirements of the theoretical model; (iii) DGPs in which the CER do not
hold, respectively. Undoubtedly, one advantage of the ‘LR1→LR2→LR3’ testing strategy is
that one can monitor the data adequacy of the NK-DSGE model at the low and high frequency
and control at which stage the model is rejected when rejection occurs. The ‘LR1→LR2→LR3’
procedure can therefore be regarded as a diagnostic test for the NK-DSGE model by which the
researcher can control at which stage the model is rejected and the cause of rejection. Notably,
the procedure also delivers, if the NK-DSGE model is not rejected, the ML estimates of the
structural parameters.

We discuss the empirical performance of the ‘LR1→LR2→LR3’ testing strategy by a small
Monte Carlo experiment in which the data generating process is assumed to belong to a de-
terminate solution of the structural model of Benati and Surico (2009), which represents the
benchmark NK-DSGE specification of our paper. A remarkable by-product of this experiment
is the possibility to investigate the identifiability of some of the structural parameters of the
NK-DSGE model, in particular those associated with the policy rule, for which an important
recent contribution by Cochrane (2011) suggests the impossibility of making reliable inference.
We further show the empirical usefulness of our approach by evaluating the data adequacy of Benati and Surico’s (2009) model using U.S. quarterly data. Finally, we report some considerations which might be useful for practitioners.

The paper is organized as follows. We introduce the baseline NK-DSGE model and its assumptions in Section 2 and discuss a set of testable restrictions which are usually ignored in the literature on DSGE models in Section 3. We present our testing strategy in Section 4 and investigate its empirical size performance by a simulation experiment in Section 5. We present an empirical illustration in which our reference NK-DSGE model is taken to U.S. quarterly data and evaluated empirically in Section 6. A few of suggestions for practitioners are noted in Section 7 that concludes the paper. Two technical appendices summarize some aspects related to the asymptotic properties of the proposed test and the time series representation of the reference NK-DSGE model.

2 Model and assumptions

Our starting point is the structural representation of a typical NK-DSGE model, i.e. the system of equations resulting from the log-linearization around steady-state values of the equations that describe the behavior of economic agents.

Let \( W_t \) be the \( p \)-dimensional vector collecting all the variables of the model of interest. A typical structural NK-DSGE model which aims at capturing the stylized features of the business cycle takes the form of a linearized rational expectations model:

\[
B_0 W_t = B_f E_t W_{t+1} + B_b W_{t-1} + \eta_t^W, \tag{1}
\]

where \( B_0, B_f \) and \( B_b \) are \( p \times p \) matrices whose elements depend on the structural parameters collected in the vector \( \theta \), and \( \eta_t^W \) is a mean zero vector of disturbances. The term \( E_t W_{t+1} = E(W_t | \mathcal{F}_t) \) denotes conditional expectations, where \( \mathcal{F}_t \) is the available stochastic information set at time \( t \) and is such that \( \sigma(W_t, W_{t-1}, ..., W_1) \subseteq \mathcal{F}_t \), and \( \sigma(W_t, W_{t-1}, ..., W_1) \) is the sigma field generated by the variables.

As is standard in the literature, we posit that \( \eta_t^W \) obeys a vector autoregressive processes of order one, i.e.

\[
\eta_t^W = R_W \eta_{t-1}^W + u_t^W, \quad u_t^W \sim \text{WN}(0_{p \times 1}, \Sigma_{W,u}) \tag{2}
\]

where \( R_W \) is a stable matrix (i.e. with eigenvalues lying inside the unit disk) and \( u_t^W \) is a White Noise disturbance with covariance matrix \( \Sigma_{W,u} \). Hereafter \( u_t^W \) will be the vector of structural or ‘fundamental’ disturbances and it will be assumed that \( \dim(u_t^W) = \dim(W_t) = 6 \).
p, preventing the occurrence of the ‘stochastic singularity’ issue.\footnote{One feature of the class of NK-DSGE models considered in this paper is that the number of fundamental shocks is not lower than the number of endogenous variables. In other words, in this setup we do not consider the ‘stochastic singularity’ issue, see e.g. Ireland (2004) and Dave and DeJong (2007).} Theory does not generally provide indications about the correlation of the structural disturbances across equations; if cross-equation correlations are assumed for the structural disturbances, these can be captured either by specifying a non-diagonal $R_W$ matrix or a non-diagonal $\Sigma_{W,u}$ covariance matrix, or both non-diagonal. We follow the convention of taking $R_W$ to be diagonal, while we allow the possibility of non-diagonal $\Sigma_{W,u}$. The non-zero elements of $R_W$ and of $vech(\Sigma_{W,u})$ enter the vector of structural parameters $\theta$. All meaningful values of $\theta$ belong to the ‘theoretically admissible’ (compact) parameter space, denoted $\mathcal{P}$.

A solution of the model (1)-(2) is any stochastic process \(\{W_t^*\}_{t=0}^\infty\), \(W_t^* = W_t^*(\theta)\), such that for \(\theta \in \mathcal{P}\), \(E_t W_{t+1}^* = E(W_{t+1}^* | \mathcal{F}_t)\) exists, and for fixed initial conditions, if \(W_t^*\) is substituted for \(W_t\) into the structural equations, the model is verified for each $t$. A reduced form solution is a member of the solution set whose time series representation is such that $W_t$ depends on $u_t^W$, lags of $W_t$ and $u_t^W$ (and, possibly, other arbitrary martingale difference sequences (MDS) with respect to $\mathcal{F}_t$ independent of $u_t^W$, called ‘sunspot shocks’).

We confine the class of reduced-form solutions associated with the NK-DSGE model to a known family of linear models by the assumption that follows.

**Assumption 1** [Determinacy] The ‘true’ value $\theta_0$ of $\theta$ is an interior point of $\mathcal{P}^*$, where $\mathcal{P}^* \subset \mathcal{P}$ is such that for each $\theta \in \mathcal{P}^*$, the NK-DSGE model (1)-(2) has a determinate reduced-form solution, i.e. unique and asymptotically stationary (stable).

Assumption 1 is crucial to rule out the occurrence of arbitrary parameters unrelated to $\theta$ and sunspot shocks unrelated to $u_t^W$ from the time series representation of the system (other than non-stationary explosive processes), see Fanelli (2012). This assumption is standard in the literature on NK-DSGE models and hinges on the idea that the time series upon which model (1) is built and estimated are typically constructed as (or are thought of as being) stationary deviations from steady-state values. In the case of variables such as output, these are mostly log deviations from a steady-state path while, for variables such as interest rates and inflation, they are level deviations from a constant steady-state rate. However, it is well known that removing constants does not ensure stationarity if the persistence of the time series is governed by unit root processes, see Cogley (2001), Juselius and Franchi (2007), Dees et al. (2009), Gorodnichenko and Ng (2010) and Fukać and Pagan (2010). Moreover, treating non-stationary processes mistakenly as stationary may flaw standard inferential procedures, see Johansen (2006), Li (2007) and Fanelli (2008). Thus, for the purpose of testing the model, we will take the implications of
Assumption 1 seriously, in the sense that, given the gap between the time series properties observed in the data and Assumption 1, we pursue routes similar to the strategies A and B in Fukač and Pagan (2010), looking for explicit mappings to stationary variables which do not imply loss of information on the low and high frequency behavior of the variables.

We consider a ‘fully hybrid’ specification of the NK-DSGE system (1)-(2), meaning that in our set-up all diagonal elements of $B_b$ are different from zero. This assumption implies that each Euler equation of the system features at least one lag of the dependent variable.\footnote{When $B_b:=0_{p \times p}$ and $R_W:=0_{p \times p}$, system (1)-(2) collapses to a ‘purely forward-looking’ model. ‘Purely forward-looking’ models are highly discussed in the monetary policy literature but exhibit problems in the identifiability of some components of $\theta$, see e.g. Lubik and Schorfheide (2003) and Lubik and Schorfheide (2004).}

Under Assumption 1, the unique stable solution of the model (1)-(2) can be represented as the asymptotically stationary VAR system

$$W_t = \tilde{F}_1 W_{t-1} + \tilde{F}_2 W_{t-2} + \varepsilon^W_t, \quad \varepsilon^W_t = \tilde{Q} u^W_t$$

where $\tilde{F}_1 = F_1(\theta)$, $\tilde{F}_2 = F_2(\theta)$ and $\tilde{Q} = Q(\theta)$ are $p \times p$ matrices that depend non-linearly on $\theta$. The dependence is through the implicit set of non-linear CER:

$$(B^R_0 - B_f \tilde{F}_1)\tilde{F}_1 - \tilde{F}_2 B_b = 0_{p \times p}$$

$$(B^R_0 - B_f \tilde{F}_1)\tilde{F}_2 - B_b = 0_{p \times p}$$

$$\tilde{\Sigma}_{W, e} = \tilde{Q} \Sigma_{W, u} \tilde{Q}$$

where $B^R_0 = (B_0 + R_W B_f)$, $B_{b,1} = (B_b + R_W B_0)$, $B_{b,2} = -R_W B_b$, $\tilde{Q} = Q(\theta) = \left( B_0 - B_f \tilde{F}_1 \right)^{-1}$, and $\tilde{\Sigma}_{W, e}$ is the constrained covariance matrix of $\varepsilon^W_t$, see Binder and Pesaran (1995), Uhlig (1999) and Fanelli (2012). We discuss in Appendix B the so-called ‘A, B, C’s (and D’s)’ representation associated with determinate reduced form solution in Eq. (3), see e.g. Fernandez-Villaverde et al. (2007) and Ravenna (2007).

The identifiability of the NK-DSGE system depends on whether $\theta$ can be uniquely recovered from the mapping in Eq.s (4)-(6), that we compact for ease of exposition in the expression $\phi = g(\theta)$, where $\phi = (vec(F_1)’, vec(F_2)’, vech(\Sigma_{W, e})’)’$ is the vector of VAR coefficients and $g(\cdot)$ is a non-linear differentiable function, see Iskrev (2008), Iskrev (2010), and Fanelli (2011). Albeit the function $g(\cdot)$ is not generally available analytically, the Jacobian matrix $\frac{\partial g(\theta)}{\partial \theta}$ can be evaluated analytically by exploiting the implicit mapping in (4)-(6) and the implicit function theorem, see Iskrev (2008) and Fanelli (2011). If the system information matrix evaluated at $\theta_0$ is non-singular, the ML estimation of $\theta$ can be obtained by maximizing the (assumed Gaussian) likelihood of the VAR system (3) subject to numerical approximations of the non-linear constraints in (4)-(6), see among many others, Ruge-Murcia (2007), Dave and DeJong (2007).
There are cases in which all components in $W_t$ are observed or can be approximated, so the system can be taken directly to the data, see Section 6. In general, however, the NK-DSGE model in Eqs. (1)-(2) is ‘incomplete’ as it does not specify how any unobservable components of $W_t$, denoted $\tilde{W}_t$, are generated. Let $W_t^o$ be the sub-vector of $W_t$ that contains the observable variables. Given the $n$-dimensional ‘complete’ vector $Z_t = (W_t^o, \tilde{W}_t')'$ that collects the observable (first) and unobservable variables (last), $n \geq p$, one can interpret the vector $W_t$ in systems (1) and (3) as obtained from the linear combination

$$W_t = \zeta'Z_t$$  \hspace{1cm} (7)

where $\zeta$ is a known $n \times p$ matrix of full row-rank $p$ that combines the observed and unobserved variables and/or selects the stationary elements of $Z_t$ that enter the structural model. We thus complete the NK-DSGE model by Assumption 2.

Assumption 2 [Unobserved processes are integrated of order one] The vector $\tilde{W}_t$ is such that $\Delta \tilde{W}_t$ is covariance stationary.

Assumption 2 states that $\tilde{W}_t$ is integrated of order one ($\tilde{W}_t \sim I(1)$) and can be further specialized as shown in the next sub-section. Given the scope of the present paper, the idea of approximating the unobservable components with $I(1)$ processes meets two requirements. First, in the class of small-scale NK-DSGE models used in monetary policy and business cycle analysis, typical unobservable components are potential output and/or the inflation target (or trend inflation), for which the $I(1)$ hypothesis may represent a reasonable and interpretable choice, as suggested by Bekaert et al. (2010), Fukač and Pagan (2010) and Section 2.1 below. Second, Assumption 2 captures the idea that the persistence observed in many observed time series can be approximated by unit roots processes.

Under Assumptions 1-2, the ‘complete’ NK-DSGE model is given by

$$A_0Z_t = A_fE_tZ_{t+1} + A_bZ_{t-1} + \eta_t^Z$$  \hspace{1cm} (8)

$$\eta_t^Z = RZ\eta_{t-1}^Z + u_t^Z , \hspace{0.5cm} u_t^Z \sim WN(0_{n \times 1}, \Sigma_{u,Z}),$$  \hspace{1cm} (9)

where the matrices $A_0$, $A_f$, $A_b$ and $\Sigma_{u,Z}$ now depend on $\theta$ and on $\text{diag}(\Sigma_{\tilde{W}})$. The ‘extended’ vector of structural parameters is $\theta^e = (\theta', \theta^\alpha)'$, where $\theta^\alpha = \text{diag}(\Sigma_{\tilde{W}})'$ is the ‘additional’ $(n - p)$-dimensional vector containing the diagonal elements of $\Sigma_{\tilde{W}}$. It is worth emphasizing that the system (8)-(9) also incorporates the model postulated for the unobservable variables, hence it embodies the unit root hypothesis implied by Assumption 2.

The next sub-section provides a detailed example about the relationship between the representation in Eqs. (1)-(2) and (8)-(9) of the NK-DSGE model.
2.1 An example

To focus the discussion, we will throughout use an example based on Benati and Surico (2009). Let \( W_t = (\tilde{y}_t, \pi_t, i_t)' \) be the \( p \)-dimensional vector (\( p = 3 \)), while the vector of structural shocks is \( \eta^W_t = (\eta_{\tilde{y},t}, \eta_{\pi,t}, \eta_{i,t})' \) and the vector of fundamental shocks is \( u^W_t = (u_{\tilde{y},t}, u_{\pi,t}, u_{i,t})' \). The model is then made up of the following equations:

\[
\begin{align*}
\tilde{y}_t &= \gamma E_t \tilde{y}_{t+1} + (1 - \gamma) \tilde{y}_{t-1} - \delta (i_t - E_t \pi_{t+1}) + \eta_{\tilde{y},t} \\
\pi_t &= \omega_f E_t \pi_{t+1} + \omega_b \pi_{t-1} + \kappa \tilde{y}_t + \eta_{\pi,t} \\
i_t &= \rho_i t_{t-1} + (1 - \rho) (\varphi_\pi \pi_t + \varphi_y \tilde{y}_t) + \eta_{i,t} \\
\eta_{a,t} &= \rho_a \eta_{a,t-1} + u_{a,t}, \quad u_{a,t} \sim WN \left( 0, \sigma^2_a \right), \quad a = \tilde{y}, \pi, i
\end{align*}
\]

In this model, \( \tilde{y}_t = (y_t - y^p_t) \) is the output gap, where \( y_t \) is the log of output and \( y^p_t \) potential output; \( \pi_t \) is the inflation rate and \( i_t \) is the nominal interest rate; \( \eta_{\tilde{y},t}, \eta_{\pi,t} \) and \( \eta_{i,t} \) are stochastic disturbances autocorrelated of order one and \( u_{\tilde{y},t}, u_{\pi,t} \) and \( u_{i,t} \) can be interpreted as demand, supply and monetary shocks, respectively. Benati and Surico (2009) restricts the parameters \( \omega_f \) and \( \omega_b \) of the New Keynesian Phillips Curve (NKPC) in (11) such that

\[
\omega_f = \varphi/(1 + \varphi \varphi) \quad \text{and} \quad \omega_b = \varphi/(1 + \varphi \varphi),
\]

where \( \varphi \) is the firms’ discount factor and \( \varphi \) captures the extent of firms’ indexation to past prices. This parameterization implies the restriction \( \omega_f + \omega_b < 1 \). Under these assumptions, the vector of structural parameters is given by \( \theta = (\gamma, \delta, \varphi, \rho, \varphi_\pi, \varphi_y, \rho_\pi, \rho_i, \sigma^2_y, \sigma^2_\pi, \sigma^2_\pi, \sigma^2_i)' \).

The model (1)-(2) is ‘incomplete’ as it does not specify how the unobservable component \( \tilde{W}_t = y^p_t \) is generated. We complete the model by specializing our Assumption 2 as follows.

**Assumption 2’ [Potential output is a Random Walk]**

\[
y^p_t = y^p_{t-1} + \eta_{y^p,t}
\]

where \( \eta_{y^p,t} \) is a white noise term with variance \( \sigma^2_{y^p} \).

In addition to the \( I(1) \) hypothesis, Assumption 2’ captures the need of modelling the unobservable components by simple models whose estimation does not involve many ‘extra’ parameters to those in \( \theta \); in this case, only the variance of potential output \( \sigma^2_{y^p} \) is added. The usual interpretation of Assumption 2’ is that the flexible price level of output \( y^p_t \) is driven by a combination of a stationary demand shock and a non-stationary technology shock, as in Ireland (2004). Moreover, \( \theta^a = \text{diag}(\Sigma^W) = \sigma^2_{y^p} \).  

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Under Assumption 2', the vector $W_t = (\tilde{y}_t, \pi_t, i_t)'$ featured by the model (10)-(12) can be thought of as being obtained through the linear combination in Eq. (7) which we report here for convenience

$$W_t = \begin{pmatrix} 1 & 0 & 0 & -1 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} y_t \\ \pi_t \\ i_t \\ \tilde{y}_t' \end{pmatrix},$$

where $y_t$ is output and $Z_t = (W_o', \tilde{W}_t')' = Z_t^o$ and unobserved $\tilde{W}_t = y_t^p$ variables. Given the specification of $Z_t$ in Eq. (16), the three equations (10)-(12) jointly with (15) imply the following configuration of the matrices $A_0$, $A_f$ and $A_b$ of the general model (8)-(9) for the example model

$$A_0 = \begin{pmatrix} 1 & 0 & \delta & -1 \\ -\kappa & 1 & 0 & \kappa \\ - (1 - \rho) \varphi_y & - (1 - \rho) \varphi_\pi & 1 & (1 - \rho) \varphi_y \\ 0 & 0 & 0 & 1 \end{pmatrix},$$

$$A_f = \begin{pmatrix} \gamma & \delta & 0 & -\gamma \\ 0 & \omega_f & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix},$$

$$A_b = \begin{pmatrix} (1 - \gamma) & 0 & 0 & -(1 - \gamma) \\ 0 & \omega_b & 0 & 0 \\ 0 & 0 & \rho & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}. $$

The ‘extended’ vector of parameters is defined as $\theta^e = (\theta', \theta^a)'$, where $\theta^a = \sigma_{y^p}^2$.

### 3 Testable restrictions

Consider the representation in Eq.s (8)-(9) of the NK-DSGE model. Under Assumptions 1 and 2, $Z_t \sim I(1)$. Because of the non-stationarity of $Z_t$, we need to transform this system such that only stationary variables are involved before its unique stable (determinate) solution can be derived and tested.

To achieve this aim, one possibility is to consider the $n$-dimensional vector of transformed variables

$$Y_t = \begin{pmatrix} \beta_0' \\ \tau' (1 - L) \end{pmatrix} Z_t = G(\beta_0, \tau, 1 - L) Z_t, \quad \text{det}(\tau' \beta_{0\perp}) \neq 0, \quad (17)$$

where $\beta_0$ is the $n \times r$ identified cointegration matrix, and $\tau$ is a $(n - r) \times r$ selection matrix which is restricted to be not orthogonal to $\beta_{0\perp}$. The role of $\tau$ is to pick out a proper set of variables in
first differences from the vector \((1 - L) Z_t = \Delta Z_t\), where \(L\) is the lag operator \((L^j Z_t = Z_{t-j})\). The choice of \(\tau\) in Eq. (17) is not necessarily unique, however. The case discussed below show that despite there are many possible choices of \(\tau\), one is consistent with the theoretical features of the NK-DSGE model. In principle, \(\beta_0\) may temporarily depend on some ‘additional’ parameters that we collect in the vector \(\nu\), and which are not necessarily related to \(\theta\). We write \(\beta_0 = \beta_0(\nu)\) to make clear such a dependence. Under the null hypothesis that the NK-DSGE model is valid, and with all constraints implied by the NK-DSGE model imposed on the system for \(Z_t\), the joint restriction

\[ r = p, \quad \beta_0 = \beta_0^b = \zeta \]  

must hold, where the symbol \(\beta_0^b\) denotes the counterpart of the identified cointegration matrix \(\beta_0\) that leads to what we call a ‘balanced’ representation of the NK-DSGE model. The condition (18) maintains that under the null hypothesis that the NK-DSGE model is ‘true’, the identified cointegration matrix \(\beta_0\) must be equal to the selection matrix \(\zeta\) introduced in Section 2 and, accordingly, must not depend on any parameter. Hence, the dependence of \(\beta_0\) on \(\nu\) is suppressed in Eq. (18). We observe that under the restrictions in Eq. (18) and for a proper choice of the selections matrix \(\tau\), the vector \(Y_t\) defined in Eq. (17) represents a transformation of the original variables in \(Z_t\) which mimics the transformations used by Campbell and Shiller (1987) to address the analysis for present value models.

Under the restriction (18), we can recover \(W_t\) from \(Y_t\) as follows:

\[
Y_t = \left( \begin{array}{c} \beta_0^b \\ \tau' (1 - L) \end{array} \right) Z_t = G(\beta_0^b, \tau, 1 - L) Z_t
\]

\[
= \left( \begin{array}{c} \zeta \\ \tau' \Delta Z_t \end{array} \right) Z_t = \left( \begin{array}{c} \zeta Z_t \\ \tau' \Delta Z_t \end{array} \right) = \left( \begin{array}{c} W_t \\ \tau' \Delta Z_t \end{array} \right).
\]

Hence the vector \(W_t\) becomes part of the transformed system for \(Y_t\). Since the \(G(\beta_0, \tau, 1 - L)\) (or \(G(\beta_0^b, \tau, 1 - L)\)) matrix in (17) is non-singular by construction, the representation (17) can be used in the model (8) to obtain

\[
A_0 G(\beta_0, \tau, 1 - L)^{-1} Y_t = A_f G(\beta_0, \tau, 1 - L)^{-1} E_t Y_{t+1} + A_0 G(\beta_0, \tau, 1 - L)^{-1} Y_{t-1} + \eta_t Z_t. \tag{19}
\]

The appealing feature of the representation in Eq. (19) is that, other than involving stationary variables (i.e. those in \(Y_t\)), the (inverse of the) difference operator \((1 - L)\) cancels out from the equations if one restricts \(\beta_0\) as in Eq. (18) and imposes a proper set of restrictions on \(\theta\) such that the transformed model is ‘balanced’. With the term ‘balanced’ we mean that all left-hand and right-hand side variables appearing in system (18) variables are stationary once \(G(\beta_0, \tau, 1 - L)^{-1}\) is replaced with \(G(\beta_0^b, \tau, 1 - L)^{-1}\) and some restrictions are placed on the elements of \(\theta\). The nature of these restrictions will be demonstrated in the two example cases that follow.
Hereafter we use the representation

\[ A^Y_0 Y_t = A^Y_f Y_{t+1} + A^Y_b Y_{t-1} + \eta^Y_t \]

\[ \eta^Y_t = R^Y Y_{t-1} + u^Y_t \]

(20)  

(21)

to denote the ‘balanced’ counterpart of system (19). The system (20)-(21) can be regarded as an equilibrium-correction representation of the NK-DSGE model and is consistent with the specification strategies A and B in Fukač and Pagan (2010, section 4).

The structural parameters in the matrices \( A^Y_0, A^Y_f, A^Y_b, R^Y \) and \( \Sigma^Y = E(u^Y_t u^Y_t') \) are collected in the vector \( \theta^Y \), where \( \theta^Y \) is obtained from \( \theta^e \) by imposing the restrictions that map system (19) into the transformed representation in (20)-(21). In general, \( \dim(\theta^Y) = \dim(\theta^e) - c \), where \( c \) is the total number of restrictions on \( \theta^e \) necessary for balancing.

We now discuss a specific example which helps to clarify the essence of the transformations in Eqs. (17)-(20) and the resulting set of testable restrictions.

Suppose that \( r = p = 3 \) and that \( \beta_0 = \beta_0^b = \zeta \) is specified such that

\[ \beta_0^{b'} Z_t = \begin{pmatrix} 1 & 0 & 0 & -1 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} y_t \\ \pi_t \\ i_t \\ y_t^p \end{pmatrix} = W_t. \]

(22)

In this case, the output gap, inflation and the short term interest rate are jointly stationary, as typically assumed in small NK-DSGE models. The vector \( Y_t \) in Eq. (17) is given by

\[ Y_t = G(\beta_0^{b'}, \tau, 1 - L) Z_t = \begin{pmatrix} \beta_0^{b'} \\ (1 - L) 0 0 0 \end{pmatrix} \begin{pmatrix} y_t \\ \pi_t \\ i_t \\ y_t^p \end{pmatrix} = (W_t', \Delta y_t)', \]

(23)

where it can be noticed that \( \tau = (1, 0, 0, 0)', \beta_{0\perp} = (1, 0, 0, 1)' \), and hence \( \det(\tau' \beta_{0\perp}) = \det(1) \neq 0 \). Correspondingly, the inverse of the transformation matrix \( G(\beta_0^{b'}, \tau, 1 - L) \) in Eq. (19) is

\[
G(\beta_0^{b'}, \tau, 1 - L)^{-1} = \begin{pmatrix} 0 & 0 & 0 & \frac{1}{1-L} \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ -1 & 0 & 0 & \frac{1}{1-L} \end{pmatrix}.
\]
In particular, the four equations of system (19) are given as

\[
\begin{align*}
\tilde{y}_t &= \gamma E_t \tilde{y}_{t+1} - \delta (i_t - E_t \pi_{t+1}) + (1 - \gamma) \tilde{y}_{t-1} + \eta_{i,t} \\
\pi_t &= \omega_f E_t \pi_{t+1} + \omega_b \pi_{t-1} + \kappa \tilde{y}_t + \eta_{\pi,t} \\
i_t &= \rho i_{t-1} + (1 - \rho)(\varphi \pi_t + \varphi \tilde{y}_t) + \eta_{i,t} \\
- \tilde{y}_t + (1 - L)^{-1} (1 - L) y_t &= - \tilde{y}_{t-1} + (1 - L)^{-1} (1 - L) y_{t-1} + \eta^p_{i,t},
\end{align*}
\]

where we have left the operator \((1 - L)^{-1}\) in the final equation to highlight the point about balancing. To see that \((1 - L)^{-1}\) cancels out from this equation, it is sufficient to rewrite it in the form (using Assumption 2)

\[
\tilde{y}_t = \tilde{y}_{t-1} + \Delta y_t + \eta^p_{i,t}^*
\]

where \(\eta^p_{i,t}^* = - \eta^p_{i,t}\). In this case, \(\theta^Y = \theta^e\) and the matrices \(A^Y_0\), \(A^Y_f\) and \(A^Y_b\), as well as the vector \(\eta^Y_t\) in the representation in Eq. (20) can easily be derived and are equal to

\[
A^Y_0 = \begin{pmatrix}
1 & 0 & \delta & 0 \\
-\kappa & 1 & 0 & 0 \\
-(1 - \rho) \varphi_y & -(1 - \rho) \varphi_\pi & 1 & 0 \\
1 & 0 & 0 & -1
\end{pmatrix},
\]

(24)

\[
A^Y_f = \begin{pmatrix}
\gamma & -\delta & 0 & 0 \\
0 & \omega_f & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0
\end{pmatrix},
\]

\[
A^Y_b = \begin{pmatrix}
1 - \gamma & 0 & 0 & 0 \\
0 & \omega_b & 0 & 0 \\
0 & 0 & \rho & 0 \\
1 & 0 & 0 & 0
\end{pmatrix},
\]

(25)

and \(\eta^Y_t = (\eta_{i,t}, \eta_{\pi,t}, \eta_{i,t}, \eta^p_{i,t})'\). The testable cointegration restrictions relative to the strictly observable time series in \(Z_t\), \(Z^o_t = (y_t, \pi_t, i_t)' = W^o_t\), are

\[
Z_t^o = (y_t, \pi_t, i_t)' \sim I(1) \quad \text{and} \quad \left(\begin{array}{cc}
0 & 1 \\
0 & 0
\end{array}\right) Z_t^o \sim I(0)
\]

or, equivalently, \((\Delta y_t, \pi_t, i_t)' \sim I(0)\).

### 4 The test sequence

The example discussed in the previous section show one way to obtain the mapping from the complete non-stationary state vector \(Z_t\) and the stationary system for \(Y_t\), given the NK-DSGE model and different assumptions about the common stochastic trends driving the variables. It demonstrates that despite the presence of unobservable components, some of the restrictions
underlying the mapping from $I(1)$ to $I(0)$ are testable by cointegration analysis, see also Fanelli (2008) and Juselius (2011).

We now turn to our procedure to show how to evaluate the cointegration implications of the NK-DSGE along with other testable implications. Under Assumptions 1-2 (and the other minor assumptions in Section 2), the unique stable solution of the NK-DSGE model (20)-(21) can be represented in the form

$$ Y_t = \tilde{P}_1 Y_{t-1} + \tilde{P}_2 Y_{t-2} + \varepsilon_t^Y, \quad \varepsilon_t^Y = \tilde{S} u_t^Y \quad (27) $$

where $\tilde{P}_1 = P_1(\theta^V)$, $\tilde{P}_2 = P_2(\theta^V)$ and $\tilde{S} = S(\theta^V) = (A_0^{Y,R} - A_0^{Y,R} \tilde{P}_1)^{-1}$ are $n \times n$ matrices that depend non-linearly on $\theta^V$ through the set of non-linear CER:

$$ \begin{align*}
(A_0^{Y,R} - A_0^{Y,R} \tilde{P}_1) \tilde{P}_1 - A_0^{Y,R} \tilde{P}_2 - A_{b,1}^{Y,R} &= 0_{n \times n} \\
(\tilde{A}_0^{Y,R} - \tilde{A}_0^{Y,R} \tilde{P}_1) \tilde{P}_2 - A_{b,2}^{Y,R} &= 0_{n \times n} \\
\tilde{\Sigma}_{Y, \varepsilon} &= \tilde{S} \Sigma_{Y,u} \tilde{S}' 
\end{align*} \quad (28)-(30) $$

where $A_0^{Y,R} = (A_0^Y + R_Y A_0^Y)$, $A_{b,1}^{Y,R} = (A_0^Y + R_Y A_0^Y)$, $A_{b,2}^{Y,R} = -R_Y A_0^Y$, and $\tilde{\Sigma}_{Y, \varepsilon}$ is the covariance matrix of the reduced form disturbances $\varepsilon_t^Y$ subject to the constraints, see Section 2. The constraints in (28)-(30) mimic those derived in Eqs (4)-(6) for the ‘original’ specification of the NK-DSGE model, but refer here to a more general specification in which the role of unobservable components is accounted for by Assumption 2.

Our approach is based on the idea of testing the CER in Eqs (28)-(30) without disregarding the mapping which transforms $Z_t$ into $Y_t$. As argued in Section 3, the restrictions that lead from $Z_t$ to $Y_t$ are testable by cointegration techniques. This consideration motivates our overall testing strategy.

The null hypothesis is

$$ H_0: \text{the DGP belongs to the VAR solution (27)-(30) of the NK-DSGE model} \quad (31) $$

while the alternative hypothesis is

$$ H_1: \text{the DGP is not consistent with the VAR solution (27)-(30).} \quad (32) $$

To simplify our exposition without altering the logic of our method, we assume temporarily that all variables in $Z_t$ and $Y_t$ are observable. We turn to the role of unobservables later. Our procedure is based on the following testing steps:

**LR1 [Cointegration rank test]** We specify a VAR model for $Z_t$ and test for the cointegration rank $r = p$ (corresponding to $n - r$ common stochastic trends driving the system) against
\( r = n \) (corresponding to a stationary system), using the ‘one shot’ version of the LR Trace test (Johansen (1996)). This requires selecting the VAR deterministic components in accordance with the time series features observed in the variables in \( Z_t \). If \( r = p \) is rejected, we reject \( H_0 \) in Eq. (31) in favour of \( H_1 \) in Eq. (32). If instead the selected cointegration rank is found to be equal to the hypothesized rank \( r = p \), we consider the next step.

**LR2 [Overidentification cointegration restrictions test]** Given \( r = p \), we fix the (identified) cointegration matrix \( \beta_0 \) at the structure implied by the theoretical model, i.e. \( \beta_0 = \beta^\epsilon_0 = \zeta \), see Eq. (18). Then we compute a LR test for the implied set of over-identifying restrictions, see Johansen (1996). If the LR test rejects the over-identifying restrictions, we reject \( H_0 \) in Eq. (31) in favour of \( H_1 \) in Eq. (32), otherwise we build the transformed \( Y_t \) vector in Eq. (17) by keeping \( \beta_0 = \beta^\epsilon_0 = \zeta \) fixed at the non-rejected structure and consider the next step.

**LR3 [Test for CER]** We estimate the VAR representation associated with the NK-DSGE model in Eq. (27) by ML both unrestricted (i.e. by leaving \( P_1, P_2, \) and \( \Sigma_{Y,\epsilon} \) unrestricted) and subject to the CER in Eqs (28)-(30). Then we compute a LR test for the CER. If the CER are rejected, we reject \( H_0 \) in Eq. (31). If the CER are not rejected, \( H_0 \) is accepted and \( \hat{\theta}^Y \) is the ML estimator of the structural parameters of the NK-DSGE model.

Albeit to some extent cointegrated VAR models have been already used to evaluate DSGE models through ‘frequentist’ approaches, see e.g. Canova et al. (1994), the ‘LR1→LR2→LR3’ sequence is a novel approach in the literature. The null hypothesis \( H_0 \) in Eq. (31) can be rejected either because the model predicted cointegration rank is rejected (LR1), or because the predicted model structure of cointegration relationships is rejected (LR2) given that the cointegration rank implied by the model is accepted, or because the CER are rejected (LR3) given that the predicted model structure of cointegration relationships is not rejected. The null hypothesis is not rejected if all three tests pass.

\[ ^4 \text{Rational expectation models are often given an 'exact' representation, i.e. such that the structural disturbances } \eta^W_t \text{ in (1) are absent, see Hansen and Sargent (1991). Johansen and Swensen (1999) have shown how 'exact' linear rational expectations models, which feature non-stationary observable variables, can be nested within the cointegrated VAR model and tested by likelihood-based methods in just one solution. Given the 'exact' nature of the model they consider, in their approach the CER on the short run dynamics of the system do not have the highly non-linear nature featured by NK-DSGE models which are prominent examples of 'inexact' rational expectation systems. Our approach extends the original idea of Johansen and Swensen (1999) to 'inexact' models and, as we show at the end of this section, to the case in which the linear rational expectations model features unobserved (latent) components.} \]
The method discussed so far is based on the maintained assumption that the econometrician observes all components of \( Z_t \) and \( Y_t \). We now turn to the role of unobservable components. An obvious way to face this issue and apply the ‘LR1 → LR2 → LR3’ testing strategy is to appeal to ‘additional’ structural information related to the unobserved components in \( Y_t \). For instance, Bekaert et al. (2010) show how the information provided by the term structure of interest rates can be constructively incorporated and used to transform a standard NK-DSGE model featuring unobservable potential output and inflation target into a tractable linear system that can be estimated by ‘standard’ methods. Galí et al. (2001) follow a similar approach by assuming that under certain restrictions on technology and labour market structure, real marginal costs are proportionately related to the output gap within a local neighborhood of the steady state. We use a similar route in the empirical illustration of Section 6, where we approximate the output gap with the official measure provided by the Congressional Budget Office (CBO).

When proxies for the unobservables are not directly available and Assumption 2 is taken into explicit account, the ‘LR1 → LR2 → LR3’ testing strategy can be adapted. As is known, and as the previous example show, while cointegration is invariant to extensions of the information set, it is not invariant to its reductions. This means that one can recover part of the cointegration implications of the model from observing \( Z^o_t \) (\( Y^o_t \)), as shown in the previous sub-sections. Yet, some of the long-run implications of the NK-DSGE model are still testable (see also Juselius, 2011).

In this case, the procedure is based on the following testing steps:

**LR1 [Cointegration rank test: the case of unobservables]** We specify a VAR model (with possibly with many lags) for the vector \( Z^o_t = W^o_t \) (see Section 3) and test for the cointegration rank using the ‘one shot’ version of the LR Trace test. If the cointegration rank implied by the NK-DSGE model—see Eq. (26) for the example—is rejected, we reject \( H_0 \) in Eq. (31) in favour of \( H_1 \) in Eq. (32). If instead the selected cointegration rank is model consistent we consider the next step.

**LR2 [Overidentification cointegration restrictions test: the case of unobservables]** We

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5 We refer to Fukač and Pagan (2010) for a discussion of the impact of off-model filtering upon the estimation of DSGE models.

6 Our point is that the finite order VAR for \( Z^o_t \) with many lags should provide a reasonable approximation of the actual time series representation of \( Z^o_t \), which is of VARMA-type under the null of valid NK-DSGE model, see Appendix B. Admittedly, a reasonable concern here is whether the cointegration rank test performed on the finite order VAR for of \( Z^o_t \) retains its usual properties. In principle, under certain conditions and with qualifications, the cointegration properties of the data should be invariant to the specification of the transient dynamics. Moreover, it is possible to apply a number of alternative cointegration rank tests, reviewed in e.g. Lütkepohl and Claessen (1997), which do not require estimating a fully identified VARMA-type model, see also Stock and Watson (1988).
compute the LR2 test by considering the cointegration implications of the NK-DSGE model subsumed in the vector $Z_t^o = W_t^o$. If the LR test rejects the over-identifying restrictions, we reject $H_0$ in Eq. (31) in favour of $H_1$ in Eq. (32), otherwise we consider the next step.

**LR3 [Test for CER: the case of unobservables]** We compute the LR3 test by evaluating the constrained likelihood of the transformed VAR model for $Y_t$ by using a Kalman filter approach, see e.g. Ruge-Murcia (2007), Dave and DeJong (2007) and Fukač and Pagan (2010). If the CER are not rejected, $H_0$ is accepted and $\hat{\theta}^Y$ is the ML estimator of the structural parameters of the NK-DSGE model. In alternative to the LR3 test one can use, borrowing from the indirect inference literature, the cointegrated VAR for $Z_t^o = W_t^o$ not rejected in the previous two steps as the auxiliary model associated with the NK-DSGE system; this amounts to establishing a mapping from the NK-DSGE model parameters to the VAR parameters and then testing the data adequacy of the implied ‘binding function’ using the methods discussed in e.g. Smith (1993), Gourieroux et al. (1993) and Ruge-Murcia (2007).

Under Assumptions 1-2 and the null of correct specification $H_0$ in Eq. (31), the asymptotic properties of each of the three tests comprising the ‘LR1$\rightarrow$LR2$\rightarrow$LR3’ testing strategy are known. The asymptotic properties of LR1 and LR2 may be found in Johansen (1996), while the asymptotic properties of LR3 are standard. Since under $H_0$ the three tests are correctly sized (and in particular their asymptotic size is equal to the nominal type-I error pre-fixed by the researcher), a simple Bonferroni argument suggests that the asymptotic size of the overall procedure does not exceed the sum of the type I error pre-fixed for the individual tests. This means that if the test for $H_0$ in Eq. (31) against $H_1$ in Eq. (32) is conducted by fixing the overall significance level at e.g. the 5% level, the critical values of the tests LR1, LR2 and LR3 must be chosen accordingly. Thus, if the practitioner wishes to test the null $H_0$ in Eq. (31) against the alternative $H_1$ in Eq. (32) at the 5% overall nominal level of significance, a reasonable choice is to fix the nominal significance level of the test LR1 at the 1% level, and the type-I error of the tests LR2 and LR3 at the 2% level.

We have postponed to Appendix A a more detailed derivation based on a refinement of the Bonferroni argument of the asymptotic size properties of the ‘LR1$\rightarrow$LR2$\rightarrow$LR3’ testing strategy. The procedure will be consistent against all hypotheses with respect to which the individual tests LR1, LR2 and LR3 are consistent, including (i) DGPs in which the actual number of common stochastic trends is not the one implied by the NK-DSGE model, (ii) DGPs in which the number of common stochastic trends is the one predicted by the NK-DSGE model but the identification structure of the cointegration matrix is at odds with the requirements of the theoretical model, and (iii) DGPs in which the CER do not hold.
5 Simulation experiment

To evaluate the finite sample performance of the test sequence ‘LR1→LR2→LR3’ under the null \( H_0 \) in Eq. (31), we conduct a small Monte Carlo experiment.

The set-up of the experiments is as follows. We assume that the DGP belongs to the family of determinate solutions associated with the NK-DSGE model for \( Z_t = (y_t, \pi_t, i_t, y_{t}^p) \) discussed in the example of Section 3, reproduced here for completeness:

\[
(y_t - y_{t}^p) = \gamma E (y_{t+1} - y_{t+1}^p) - \delta (i_t - E_t \pi_{t+1}) + (1 - \gamma) (y_{t-1} - y_{t-1}^p) + \eta_{y, t}
\]

\[
\pi_t = \omega_f E_t \pi_{t+1} + \omega_b \pi_{t-1} + \kappa (y_t - y_{t}^p) + \eta_{\pi, t}
\]

\[
i_t = \rho i_{t-1} + (1 - \rho) [\varphi_\pi \pi_t + \varphi_y (y_t - y_{t}^p)] + \eta_i, t
\]

\[
y_{t}^p = y_{t-1} + \eta_{y^p, t}
\]

\[
\begin{pmatrix}
\eta_{y, t} \\
\eta_{\pi, t} \\
\eta_i, t \\
\eta_{y^p, t}
\end{pmatrix} =
\begin{pmatrix}
\rho \gamma & 0 & 0 & 0 \\
0 & \rho_\pi & 0 & 0 \\
0 & 0 & \rho_i & 0 \\
0 & 0 & 0 & R_z
\end{pmatrix}
\begin{pmatrix}
\eta_{y, t-1} \\
\eta_{\pi, t-1} \\
\eta_i, t-1 \\
\eta_{y^p, t-1}
\end{pmatrix} +
\begin{pmatrix}
\eta_{y, t-1} \\
\eta_{\pi, t-1} \\
\eta_i, t-1 \\
\eta_{y^p, t-1}
\end{pmatrix}
\]

\[
u_{t}^z \sim WNN (0_{4 \times 1}, \Sigma_{Z, u}) , \quad \Sigma_{Z, u} =
\begin{pmatrix}
\sigma^2_y & 0 & 0 & 0 \\
0 & \sigma^2_\pi & 0 & 0 \\
0 & 0 & \sigma^2_i & 0 \\
0 & 0 & 0 & \sigma^2_{y^p}
\end{pmatrix}
\]

The parameters \( \omega_f \) and \( \omega_b \) in the NKPC in Eq. (34) are restricted such that \( \omega_f = \varrho/(1 + \varrho \varpi) \), \( \omega_b = \varpi/(1 + \varrho \varpi) \), where \( \varrho \) is the firms’ discount factor which is kept fixed at the known value \( \varrho = 0.99 \), and \( \varpi \) captures the extent of firms’ indexation to past prices, see Sub-section 2.1. The ‘free’ structural parameters are \( \theta = (\gamma, \delta, \varpi, \rho, \varphi_\pi, \varphi_y, \rho_\pi, \rho_i, \sigma^2_y, \sigma^2_\pi, \sigma^2_i) \) and \( \theta^* = (\theta', \theta') \), where \( \theta^* = \text{Var}(u_{y^p, t}) = \sigma^2_{y^p} \). The vector of fundamental shocks \( u_{t}^z \) is assumed White Noise Gaussian with covariance matrix \( \Sigma_{Z, u} \) above. The parameter vector \( \theta \) is calibrated to the empirical estimates of Benati and Surico (2009), see in particular the last column of their Table 1 (‘After the Volcker stabilization’), while the variance of potential output \( \sigma^2_{y^p} \) is fixed at a value considered reasonable. The complete vector \( \theta^* (\theta^Y) \) chosen for this Monte Carlo experiment is reported in the left-most column of Panel 2 of our Table 1.

As shown in Section 4, the system (33)-(38) involves \( I(1) \) variables and can be mapped into the representation in Eqs. (20)-(21) which is based on the stationary variables in \( Y_t \). Thus, for a given \( \theta^* (\theta^Y) \) i.e. for given \( A_Y^Y, A_Y^Y, A_b^Y \) and \( \Sigma_{Y, u} \) and fixed the initial conditions \( Y_0 \) and \( Y_{-1} \), we generate the sequence \( Y_1, ..., Y_T \) from the VAR system (27)-(30). We next use the
restriction $\beta_0 = \beta_0^b = \zeta'$ from Eq. (18) and the mapping $Z_t = G(\beta_0^b, \tau, 1-L)^{-1} Y_t$ to obtain the observations $Z_1, ..., Z_T$. We then have all the ingredients to replicate $M$ times the ‘$LR1 \rightarrow LR2 \rightarrow LR3$’ procedure and evaluate the empirical sizes of the tests $LR1$, $LR2$ and $LR3$ individually and the overall empirical size, along with and the empirical performance of the ML estimator of $\theta^e$.

[Table 1 about here.]

We generate time series of size $T = 100, 200$ and $500$ from the NK-DSGE model $M = 10000$ times, and then compute the test sequence ‘$LR1 \rightarrow LR2 \rightarrow LR3$’. For each replication, a sample of $T+200$ observations of $Y_t$ (and then $Z_t$) is generated, and the first 200 observations are then discarded. To investigate the performance of our procedure, we use the overall nominal significance level of 5% ($\psi = 0.05$), and consistent with this choice, we fix the nominal type-I errors of three tests of the procedure as follows: 1% for the LR1 test ($\psi_1 = 0.01$), 2% for the test LR2 ($\psi_2 = 0.02$) and 2% for the test LR3 ($\psi_3 = 0.02$). The corresponding critical values are chosen accordingly. The 1% critical values of the ‘one-shot’ cointegration rank test LR1 are the asymptotic ones derived by Doornik (1998), see also Juselius (2006, p. 419).

The likelihood maximization of the VAR system (27) under the constraints in Eq.s (28)-(30) is carried out using a numerical approximation of the non-linear CER. To simplify the computation burden, the likelihood maximization is carried out by treating $\omega_f$ as ‘free’ parameter, hence we replace $\omega$ with $\omega_f$ in the vector $\theta$. Given the ML estimate of $\hat{\omega}_f$, we use the relationship $\omega_f = 0.99/(1+0.99\omega)$ to derive the indirect ML estimator of $\omega$, $\hat{\omega} = (1/\hat{\omega}_f - 1/0.99)$, and the restriction $\omega_b = (1/0.99)(1-\omega_f/0.99)$ to impose the condition $\omega_f + \omega_b < 1$.

The results of this Monte Carlo experiment are summarized in Table 1. The empirical sizes of the individual tests and of the overall testing procedure are reported in Panel 1, while the Monte Carlo means and standard errors of the ML estimates of $\theta^e$ are reported in Panel 2. The rejection frequencies of the test statistics in Panel 1 are computed conditional on the non-rejection of the NK-DSGE model by the tests which come earlier in the sequence ‘$LR1 \rightarrow LR2 \rightarrow LR3$’. These conditional rejection frequencies sum up to the overall empirical size of the ‘$LR1 \rightarrow LR2 \rightarrow LR3$’ procedure.

Before discussing the empirical size of the overall testing strategy, we discuss the empirical size of its components. The test LR1 is the ‘one-shot’ version of Johansen’s LR trace test for cointegration rank and is conducted with $H_c$: $r = 3$ (one common stochastic trend), as predicted by the NK-DSGE model, against the alternative $H_A$: $r = n = 4$ (stationary system),

---

7 All computations in this Monte Carlo experiment and in Section 6 where the NK-DSGE model is estimated using U.S. data have been computed in Ox.
using the 1% asymptotic critical value. The empirical size of the test is reported in the row labeled ‘LR1 ($\psi_1 = 0.01$): test of rank’ in Panel 1. The empirical size of the LR1 test is not much affected by the number of observations in the sample and is between 0.6% and 1.1% for all sample sizes. A closer look at Table 1 reveals that LR1 test is under-sized for small samples with $T = 100$. This result is unexpected, as one would typically expect a much higher empirical size in samples of length $T = 100$ compared to the case $T = 500$, since many simulation studies have shown that the asymptotic critical values might be of little use in small samples. However, it is well known that the finite sample performance of the LR cointegration rank test may well depend on the structure of the short-run dynamics of the system which, in our set-up, is ‘special’, in the sense of being highly restricted by the CER.\(^8\)

As concerns the test LR2, we recall that this is Johansen’s 1991 likelihood ratio test of over-identified cointegrating vectors for a given rank. In our experiment, the identified cointegration matrix $\beta_0$ is fixed at the structure of the theoretical model in Eq. (22), $\beta_0 = \beta_0^b = \zeta$. The test is asymptotically distributed as chi-square with 3 degrees of freedom under the null. If the LR2 test rejects the over-identifying restrictions, the NK-DSGE model is rejected for the realizations of the DGP in the relevant replication. The empirical size of the LR2 test is reported in the second row of Panel 1 in Table 1, labeled ‘LR2 ($\psi_2 = 0.02$): test of beta’. As recognized in Johansen (2000, 2002) the limit distribution of the test is often a poor approximation to the finite sample distribution, and earlier simulation studies have shown that the empirical sizes tend to be much higher than nominal sizes, see *inter alia* Bewley et al. (1994), Fachin (2000), Gonzalo (1994), Li and Maddala (1997), Omtzigt and Fachin (2006). Our results add to this evidence, but the size distortions are not as bad as might be expected. For a sample length of $T = 100$, the empirical size is 6.7% as opposed to the 2% nominal size. However, the empirical size tends to be uniformly diminishing towards the nominal size of 2% as the sample size increases. For a sample size of $T = 500$, the rejection frequency of the LR2 test is 2.8%.

Finally, the test LR3 for the CER is reported in the third row of Panel 1 in Table 1, labeled ‘LR3 ($\psi_3 = 0.02$): test of CER’. The test is conducted conditional on the non-rejection of the beta matrix by LR2. The test statistic is compared with the critical value taken from the chi-square distribution with 28 degrees of freedom, the difference between the number of unrestricted parameters in the VAR (32+10) and the structural parameters (dim ($\theta^e$) = 14). The empirical size is very good for samples of $T = 200$ and higher.

The empirical rejection frequency associated with the ‘LR1 $\rightarrow$ LR2 $\rightarrow$ LR3’ testing strategy

\(^8\)We notice for completeness that if for $T = 100$ one uses the asymptotic critical values taken from Table 15.1 in Johansen (1996) for the LR1 cointegration rank test in place of the critical values from Doornik (1998), the empirical size of the LR1 test turns out to be 0.015 (1.5%). We do not find significant differences in the results in samples of length $T = 200$ and $T = 500$.\(^21\)
is summarized in the seventh row of Panel 1 in Table 1 and can be compared to the overall empirical rejection frequency of the DSGE model reported in the eighth row. The performance of the ‘LR1→LR2→LR3’ testing strategy obviously reflects the empirical size behavior already discussed of the three tests. It can be noticed that it ranges from 9.8% when \( T = 100 \) to 5.7% when \( T = 500 \), as opposed to a nominal type-I error of 5%. We deduce, therefore, that in samples of lengths typically available to practitioners, the use of small sample correction methods may improve the empirical performance of the testing strategy. For instance, albeit in this experiment the empirical performance of the cointegration rank test is satisfactory, in more general contexts it can be refined by using the methods recently proposed by Swensen (2006) and Cavaliere et al. (2012); similarly, the empirical performance of the LR2 test can be improved by using standard Bartlett corrections or bootstrap techniques, as advocated by Johansen (2000, 2002), Fachin (2000), Li and Maddala (1997), Omtzig and Fachin (2006). As regards the test LR3, Cho and Moreno (2006) and Fanelli and Palomba (2011) have shown that bootstrap methods deliver reasonable size coverage in the presence of the highly non-linear CER implied by the rational expectations hypothesis.\(^{9}\)

Panel 2 of Table 1 reports the Monte Carlo means of the structural parameters with the Monte Carlo standard errors in parentheses, i.e. the average of the \( i \)-th component of \( \hat{\theta}_e \), \( \hat{\theta}_f \), computed as \( \hat{E}_{MC} \left( \hat{\theta}_i \right) = \frac{1}{B} \sum_{j=1}^{B} \hat{\theta}_{ij} \), where \( \hat{\theta}_{ij} \) is ML estimate of \( \theta_i \) obtained in the \( j \)-th simulation and \( B < M \) is the number of DGPs for which the ‘LR1→LR2→LR3’ test does not reject the NK-DSGE model; the associated Monte Carlo standard errors are calculated accordingly.

The structural parameters are recovered with surprising precision. The only exceptions, in samples of length \( T = 100 \), are the parameters of the policy rule \( \varphi_y \) and \( \varphi_\pi \), although the estimation precision is increasing with the sample size. This lack of precision is a common finding and source of misunderstandings in the literature. In a recent influential paper, Cochrane (2011) has argued that the parameters of Taylor-type rules like that in Eq. (35) are not identifiable. Cochrane (2011), however, does not consider the ‘hybrid’ specification in Eqs (33)-(37) but a less dynamic formulation of the NK-DSGE model. As it is known, identification problems in a system of variables featuring highly non-linear restrictions may involve the rank condition of the information matrix, or the relationship between the structural parameters and the sample objective function (in our case the likelihood function) which may display ‘small’ curvature in certain regions of the parameter space. The former concept of identification is also referred to as ‘mathematical identification’ (Johansen, 2010, p. 262) or ‘population identification’ (Canova

\(^{9}\)We observe, however, that when the ML estimation is carried out through a grid search on all or part of the structural parameters (see Section 6), the implied computation burden may discourage the use of bootstrap techniques for the test LR3.
and Sala, 2009), as opposed to the latter, often termed ‘sample identification’, because it is specific to a particular data set and sample size. The results in Table 1 show that the chosen ‘hybrid’ NK-DSGE model is only moderately affected by ‘sample identification’ issues and this fact is confirmed by the empirical size of the LR3 test which for $T = 200$ is remarkably close to the 2% nominal level.

In our Monte-Carlo experiment, the policy inertia parameter $\rho$ is calibrated in the DGP to a relatively high value (0.834) and this fact might explain, in line with what argued by Mavroeidis (2010), why the coefficients $\varphi_y$ and $\varphi_\pi$ of the reaction function are less accurately estimated in small samples.

That the difficulty of identifying the policy parameters $\varphi_y$ and $\varphi_\pi$ reflects a small sample issue rather than a ‘population identification’ issue is further confirmed by the graphs we have reported in Figures 1 and 2. Here we have plotted the marginal empirical distributions of the ML estimators of some of the elements in the vector $\theta^e$ obtained from the Monte Carlo experiment, for the cases $T = 100$ and $T = 500$, respectively. We notice that the sample distributions of $\hat{\varphi}_y$ and $\hat{\varphi}_\pi$ tend to be more concentrated around their ‘true’ values as the sample size increases. Instead, we observe that the marginal sample distributions of the ML estimator of the forward-looking parameter of the NKPC, $\omega_f$, displays a substantial bimodality which does not disappear in samples of length $T = 500$ (recall that $\omega_f = 0.99/(1 + 0.99\kappa)$ and that in our Monte Carlo experiment we estimated $\omega_f$ freely and $\kappa$ indirectly). The graphs also confirm that difficulties that characterize the estimation of the slope parameter of the NKPC, $\kappa$, must be ascribed to small sample issues. We leave a detailed investigation of these interesting issues, which perhaps helps to explain some controversial results about the estimation of the NKPC in the literature, to future research.

For large samples, the test sequence ‘LR1 $\rightarrow$ LR2 $\rightarrow$ LR3’ seems to work well. For small samples, the overall size is somewhat distorted by the well-known small sample problems of the LR2 test.

Keeping these results in mind, we next turn to an empirical application of our test procedure.

6 An estimated NK-DSGE model of the U.S. economy

When all variables $W_t$ (not to be confounded with the case of $Z_t$) of our reference small NK-DSGE model are observed, the ‘LR1 $\rightarrow$ LR2 $\rightarrow$ LR3’ testing strategy discussed in this paper can be
properly adapted as illustrated in this section. We estimate the reference NK-DSGE monetary model summarized in Eq.s (1)-(2) using U.S. quarterly data, approximating potential output with the official measure provided by the Congressional Budget Office (CBO) estimation like, *inter alia*, Cho and Moreno (2006) and Castelnuovo and Fanelli (2011). This solution allows us not to consider Assumption 2 because we treat the output gap as an observed variable. Thus, we take system (1)-(2) directly to the data.

Contrary to what we have done in the Monte Carlo experiment, we treat the indexation parameter \( \varkappa \) of the NKPC as a ‘free’ parameters (for reasons that will be clear below) and estimate \( \omega_f \) and \( \omega_b \) accordingly. Moreover, differently from Benati and Surico (2009), we do not force the covariance matrix of structural disturbances, \( \Sigma_{W;u} \), to be diagonal, see e.g. Dufour et al. (2009) and Castelnuovo and Fanelli (2011) for similar choices. We split the vector \( \theta \) as \( \theta = (\theta_s', \theta_u')' \), where \( \theta_s = (\gamma, \delta, \varkappa, \varphi, \varphi_y, \rho_y, \rho_x, \rho_R)' \) and \( \theta_u = vech(\Sigma_{W;u}) \).

We employ quarterly data relative to the ‘Great Moderation’ sample 1985q1-2008q3. Four arguments motivate our choice: (i) the ‘credibility build-up’ undertaken by the Federal Reserve in the early 1980s, a period during which private agents gradually changed their view on the Fed’s ability to deliver low inflation (Goodfriend and King, 2005); (ii) the first years of Volcker’s tenure (until October 1982) were characterized by non-borrowed reserves targeting, hence one can hardly expect a good fit of conventional policy rules within this period, a fact that would carry consequences on the estimates of all parameters of the system, see Mavroeidis (2010) and references therein; (iii) the end of the sample 2008q3 is justified by our intention to avoid dealing with the ‘zero-lower bound’ phase began in December 2008, which triggered a series of non-standard policy moves by the Federal Reserve; (iv) formal testing analysis by Castelnuovo and Fanelli (2011) shows that the reference NK-DSGE model in Eq.s (10)-(13) has a unique stable solution over the 1985q1-2008q3 period, while the picture is more controversial if other sample periods are considered, and our approach requires the system to be in a determinate state.

The variables used in the empirical analysis are real GDP, \( GDP_t \); the CBO measure of potential output, \( GDP^p_t \); the inflation rate \( \pi_t \) which is the quarterly growth rate of the GDP deflator; the short-term nominal interest rate, \( i_t \), given by the effective Federal funds rate expressed in quarterly terms (averages of monthly values). The output gap \( \tilde{y}_t \) is computed as percent log-deviation of the real GDP with respect to the CBO potential output: \( \tilde{y}_t = y_t - y^p_t = \log(GDP_t) - \log(GDP^p_t) \approx \left( \frac{GDP_t}{GDP^p_t} - 1 \right) \). The source of the data is the Federal Reserve Bank of St. Louis’ web site.

The assumption that \( GDP^p_t \) is proxied with an observable time series allows us to treat the
vector $W_t = (\tilde{y}_t, \pi_t, i_t)' = W_t^\omega$ as observable.\textsuperscript{10} The unique asymptotically stable solution of the NK-DSGE model is given by the constrained VAR model in Eq. (3), where the reduced form coefficients $F_1 = F_1(\theta)$, $F_2 = F_2(\theta)$ and $Q = Q(\theta)$ depend non-linearly on the structural parameters $\theta$ through the CER in Eqs (4)-(6). The ML estimation of $\theta$ is obtained by taking system (3) directly to the data.

In this set-up, the null hypothesis under investigation is

$$H'_0: \text{the DGP belongs to the VAR solution in Eqs (3)-(6) of the NK-DSGE model}$$

and the alternative is

$$H'_1: \text{the DGP is not consistent with the VAR solution in Eqs (3)-(6)}.$$  

The ‘LR1$\rightarrow$LR2 $\rightarrow$LR3’ testing strategy collapses to the ‘LR1&2 $\rightarrow$LR3’ sequence, whose steps are described in the following.

**LR1&2 [stationary $W_t^\omega$ system]** Estimate the unrestricted counterpart of the VAR model for $W_t^\omega = (\tilde{y}_t, \pi_t, i_t)'$, see Eq. (3), and test for the stationarity of $W_t^\omega$. If stationarity is rejected, $H'_0$ is rejected, otherwise consider the next test.

**LR3 [Test for CER]** Estimate $\theta$ from the VAR representation in Eqs (3)-(6) by ML, obtaining $\hat{\theta} = (\hat{\theta}_s', \hat{\theta}_u')'$. Then compute a LR test for the CER: if the CER are rejected, $H'_0$ is rejected, otherwise the NK-DSGE model is supported by the data.

Thus, in this simplified set-up, we have simply ‘merged’ the tests LR1 and LR2 in a single LR test which assesses the stationarity of the VAR for $W_t^\omega$.

\[\text{[Table 2 about here.]}\]

Our empirical analysis starts with the estimation of an unrestricted VAR system for $W_t^\omega = (\tilde{y}_t, \pi_t, i_t)'$ with two lags (henceforth VAR(2)) on the 1985q1-2008q3 period. Estimation is performed by including a constant in the equations because the variables in $W_t^\omega$ were not demeaned prior to estimation. The upper panel of Table 2 reports the estimated unrestricted reduced form VAR coefficients, while the lower panel summarizes some diagnostic tests, including a test for the absence of autocorrelation in the disturbances, a test for the absence of ARCH-type

\[\text{[Table 2 about here.]}\]

\textsuperscript{10}Obviously, the econometric analysis could be also based on the system $Z_t = (y_t, \pi_t, i_t, GDP^p_t)'$, but the information set is less well suited to model potential output. Another alternative would be to treat potential output as exogenous and use the approach of Harbo et al. (1998). The results of these alternative approaches are available upon request.
components in the disturbances and a test for the hypothesis of Gaussian disturbances. Table 3 reports the eigenvalues of the companion matrix of the unrestrictedly estimated VAR(2) and the LR cointegration rank test for the hypothesis that there are two cointegrating relations in the system (i.e. one common stochastic trend) against the alternative of a stationary VAR. This LR test acts as the LR1&2 test described above.

[Table 3 about here.]

Overall, the results in Tables 2-3 suggest that a stationary VAR representation for the variables in $W_t = (\tilde{y}_t, \pi_t, i_t)'$ stands as a reasonably good approximation of U.S. quarterly data over the period 1985.q1-2008.q3. We will turn on the interpretation of the LR1&2 test reported in the bottom part of Table 3 at the end of this section.

We then proceed with the estimation of the structural parameters $\theta = (\theta'_s, \theta'_u)'$ by maximizing the log-likelihood of the VAR(2) under the CER in Eqs. (4)-(6). We use a grid search for the parameters $\delta, \varrho, \varsigma, \varphi_y$ and $\varphi_\pi$, which are notoriously difficult to estimate through non-Bayesian techniques. Estimation results are summarized in the upper panel of Table 4, while the test LR3 for the CER is reported in the lower panel.

[Table 4 about here.]

Our point estimates turn out to be quite similar to those in a variety of contributions in the literature, hence we do not discuss these results in details. Nevertheless, a note of caution is needed for the policy parameters: as suggested by the Monte Carlo section, with about 100 observations it is extremely difficult to obtain precise estimates of the policy reaction function $\varphi_y$ and $\varphi_\pi$; the same is true for the slope of the NKPC $\kappa$ and the indexation parameter $\varsigma$. Our results confirm this evidence and the one recently reported in Mavroeidis (2010).

If the overall type-I error for the null hypothesis that the NK-DSGE model is valid (our $H'_0$) is pre-fixed at the 5% level, a reasonable choice for our sequential testing procedure is the 2.5% level for the test LR1&2 and the 2.5% level for the test LR3. The results in Table 4 show that, quite surprisingly, that LR1&2 accepts the stationarity of the system while LR3 rejects the CER, albeit only marginally. Unfortunately, we can not easily provide a bootstrap version of the test LR3 because the grid search procedure used to maximize the likelihood function is computationally intensive and the computation burden would be relevant. Nonetheless, the indication emerging from our analysis is that the overall set of restrictions implied by the NK-DSGE model is rejected only marginally, hence the model is not completely at odds with the data on the period 1985q1-2008q3.11

11Our testing result has been obtained by specifying the covariance matrix of fundamental disturbances, $\Sigma_{W,u}$. 26
7 Lessons for practitioners

In this paper we have proposed a new approach to evaluate the empirical reliability of the class of NK-DSGE models used in monetary policy analysis based on the idea of testing jointly all restrictions these models places on their unique stable solution under rational expectations. We adopt a likelihood-based perspective and consider the set of restrictions at low and high frequencies which the NK-DSGE model places on its reduced form VAR solution. The novelty of our evaluation method is that the empirical assessment of the NK-DSGE model is based on a conditional sequence of likelihood-ratio tests which assess the long-run and short-run features of the model jointly and through which we can control at which stage of the process the system is rejected by the data. Our approach is logically comparable, with many qualifications discussed throughout the paper, with the methodology originally proposed by Campbell and Shiller (1987) for estimating and testing present value models through VAR systems. Furthermore, it complements the evaluation approach suggested by Fukač and Pagan (2010) in a ‘limited-information’ framework and generalizes the seminal method advocated by Canova et al. (1994) to evaluate real business cycle models to a wider set-up.

Our analysis, based on a simulation experiment and the estimation of a monetary NK-DSGE model using U.S. data, reveals that some conclusions about the frequentist approach to the estimation of NK-DSGE models can be reached.

First, the empirical evaluation of a NK-DSGE model should be carried out by considering all long-run and short-run restrictions, not just a sub-set of them.

Second, even though our procedure consists of several tests, the size of the overall procedure is under control. The ‘LR1→LR2→LR3’ testing strategy has been explicitly designed to assess the empirical validity of the joint set of restrictions implied by the NK-DSGE model at a pre-fixed significance level. Our simulation experiment shows that despite the highly non-linear nature of the CER, the overall empirical size can be controlled.

Third, the size control of the proposed testing strategy can be improved by various methods. In particular, the test for steady-state restrictions, LR2, is probably best performed using a small sample adjustment, in the form of a Bartlett correction or a bootstrap procedure, see in particular the evidence presented in Omtzigt and Fachin (2006).

\[ \text{vec}(\Sigma_{W,u}) = [(I_p \otimes I_p) - (R_W \otimes R_W)] \text{vec}(\Sigma_{W,u}) \]

where \( \Sigma_{W,u} \) is the covariance matrix of the disturbances \( \eta_t^W \) of the NK-DSGE model: the significant cross-correlations found in \( \Sigma_{W,u} \) might simply reflect a non-diagonal structure of the \( R_W \) matrix in the DGP. Interestingly, with both \( R_W \) and \( \Sigma_{W,u} \) diagonal, we would have rejected the NK-DSGE model by the test LR3.
Fourth, ML estimation is involved for two reasons. On the one hand, it requires a numerical approximation of the non-linear CER; the structural parameters are subject to bound (other than sign) constraints whose omission gives rise to the so-called ‘absurd values’ phenomenon, on the other hand. These arguments, however, are not sufficient to discourage the use of ML estimation. The use of grid search for the parameters which are notoriously difficult to pick out from the data is a solution which, albeit the computational burden involving, guarantees that all restrictions are met, and allows one to retain, if certain conditions are met, some of the desirable properties of ML estimation.

Fifth, the claim that the parameters associated with the policy rule of a NK-DSGE model are unidentified (in the sense of not being associated with a singular information matrix) is false for ‘hybrid’ specifications. Obviously, in samples of lengths typically available to practitioners, weak identification (the difficulty of estimating these parameters precisely also under the null) is a concern that deserves attention; reliable inference in NK-DSGE models requires identification-robust methods as suggested by e.g. Guerron-Quintana et al. (2013), among many others.

Finally, our empirical application has shown that, despite the highly constrained nature of the model, a statistical evaluation of NK-DSGE models that account for the time series properties of the variables does not necessarily lead to rejection. The estimation conducted using U.S. quarterly data (and some simplifying hypotheses) shows that the rejection of the monetary policy NK-DSGE model used in the recent literature is only marginal. In light of the recent developments in business cycle dynamics and the conduct of monetary policy, it will be crucial to re-evaluate the model as soon as enough data become available, especially if a paradigm that incorporates ‘new’ ingredients within the baseline framework will emerge.

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Appendix A  Size properties of the testing strategy

To fully understand the mechanics of testing evaluation procedure of the NK-DSGE model, in this Appendix we derive the asymptotic size properties of the ‘LR1→LR2→LR3’ sequence.\(^{12}\)

Denote with \(LR_{i,T}, i = 1, 2, 3\), the three LR test statistics and let \(\psi_i\) be the nominal significance level (type-I error) pre-fixed for the \(i\)-th test; moreover, let \(\psi_{i,T} = P_{i,T}^{H_0}(LR_{i,T} \geq cr_{i,T}^{\psi_i})\) be the exact size of the \(i\)-th test based on a sample of length \(T\), where \(P_{i,T}^{H_0}(\cdot)\) is the probability measure associated with the null distribution of \(LR_{i,T}\) and \(cr_{i,T}^{\psi_i}\) is the corresponding critical value at nominal level \(\psi_i\). Under \(H_0\) the three tests, individually considered, are correctly sized and in particular such that

\[
\psi_{i,\infty} = \limsup_{T \to \infty} \psi_{i,T} = \psi_i, \quad i = 1, 2, 3 \tag{A39}
\]

where \(\psi_{i,\infty}\) is the asymptotic size of the \(i\)-th test. Let \(P_{1,2,T}^{H_0}(\cdot ; \cdot)\) and \(P_{2,3,T}^{H_0}(\cdot ; \cdot)\) be the probability measures associated with the joint null distributions of the test statistics \(LR_{1,T}\) and \(LR_{2,T}\) and the test statistics \(LR_{2,T}\) and \(LR_{3,T}\), respectively. It turns out that the overall asymptotic size of the test for \(H_0\) in Eq. (31) is given by

\[
\psi_{\infty} = \limsup_{T \to \infty} \psi_T \tag{A40}
\]

where

\[
\psi_T = P_{1,T}^{H_0}(LR_{1,T} \geq cr_{1,T}^{\psi_1}) + P_{1,2,T}^{H_0}(LR_{1,T} < cr_{1,T}^{\psi_1}; LR_{2,T} \geq cr_{2,T}^{\psi_2}) + P_{2,3,T}^{H_0}(LR_{2,T} < cr_{2,T}^{\psi_2}; LR_{3,T} \geq cr_{3,T}^{\psi_3}). \tag{A41}
\]

The first addend of Eq. (A41) captures the probability, on a sample of length \(T\), that the LR1 test incorrectly rejects the cointegration rank; the second addend captures the joint probability that the LR2 test incorrectly rejects the structure of the cointegration matrix and the LR1 test correctly selects the cointegration rank and, finally, the last addend captures the joint probability that the LR3 test incorrectly rejects the CER and the LR2 correctly rejects the structure of the cointegration matrix.

By using the inequalities

\[
P_{1,2,T}^{H_0}(LR_{1,T} < cr_{1,T}^{\psi_1}; LR_{2,T} \geq cr_{2,T}^{\psi_2}) \leq \psi_{2,T}
\]

\[
P_{1,2,3,T}^{H_0}(LR_{2,T} < cr_{2,T}^{\psi_2}; LR_{3,T} \geq cr_{3,T}^{\psi_3}) \leq \psi_{3,T},
\]

\(^{12}\)We refer to Spanos (2011) for a comprehensive treatment of size in general-to-specific sequential testing procedures.
the limit in Eq.s (A40)-(A41) is such that

\[ \psi_\infty \leq \psi_{1,\infty} + \psi_{2,\infty} + \psi_{3,\infty} = \psi_1 + \psi_2 + \psi_3 \]  

(A42)

hence the asymptotic size of the overall test sequence does not exceed the sum of the type I error pre-fixed for the individual tests. This result suggests that in empirical analyses it is convenient to fix the overall nominal significance level of the procedure at \( \psi = (\psi_1 + \psi_2 + \psi_3) \).
Appendix B A, B, C (and D’s) representation of the reference NK-DSGE model

Given the representation in Eq. (3) of our NK-DSGE model, we start from the state-space (companion) representation

\[
\begin{pmatrix}
W_t \\
W_{t-1} \\
x_t
\end{pmatrix}
= \begin{pmatrix}
\tilde{F}_1 & \tilde{F}_2 \\
I_n & 0_{n \times n}
\end{pmatrix}
\begin{pmatrix}
W_{t-1} \\
x_{t-1}
\end{pmatrix}
+ \begin{pmatrix}
\tilde{Q} \\
0_{n \times n}
\end{pmatrix}
\begin{pmatrix}
W_t \\
x_t
\end{pmatrix}
\]

(B43)

where the matrices \(\tilde{F}_1 = \tilde{F}_1(\theta), \tilde{F}_2 = \tilde{F}_2(\theta)\) and \(\tilde{Q} = \tilde{Q}(\theta)\) depend non-linearly on the structural parameters \(\theta\) through the CER in Eqs. (4)-(6). A convenient way to summarize system (B43) is

\[
x_t = \begin{pmatrix}
A \\
B
\end{pmatrix}
\begin{pmatrix}
x_{t-1} \\
\varepsilon_t
\end{pmatrix}
+ \begin{pmatrix}
u_t^W \end{pmatrix}
\]

(B44)

where the definition of the vectors \(x_t\) and \(\varepsilon_t = u_t^W\) and of the matrix \(A = A(\theta)\) is obvious. We notice that in this case the covariance matrix of the error term \(v_t = B\varepsilon_t\) is singular. Let \(y_t\) be the \(m \times 1\) vector that contains the endogenous observable variables; a natural choice for the measurement equation is given by

\[
y_t = \begin{pmatrix}
H \\
\end{pmatrix}
\begin{pmatrix}
x_t
\end{pmatrix}
\]

(B45)

where \(H\) is a (known) \(m \times 2p\) selection matrix that picks out the endogenous observable variables from \(x_t\), see e.g. Dave and DeJong (2007), Iskrev (2008) and Iskrev (2010).

The system given by Eq.s (B44)-(B45) represents a conventional state-space representation of the NK-DSGE model and under the assumption that \(\varepsilon_t = u_t^W\) is Gaussian, the Kalman filter can be used to build and evaluate the likelihood function, see, among many others, Ruge-Murcia (2007) and Dave and DeJong (2007). However, depending on the model at hand, solution method one uses to arrive from the structural equations to the representation in Eq. (B44), other choices for \(x_t\) and \(y_t\) are equally possible, see e.g. Uhlig (1999).

By using Eq. (B44) in Eq. (B45) yields

\[
y_t = HAx_{t-1} + HB\varepsilon_t
\]

which for \(C = HA\) and \(D = HB\) reads as

\[
y_t = Cx_{t-1} + D\varepsilon_t.
\]

(B46)

The system obtained by coupling Eq. (B44) and Eq. (B46), reported here for convenience

\[
x_t = Ax_{t-1} + B\varepsilon_t
\]
\[ y_t = Cx_{t-1} + D\varepsilon_t \]
captures the determinate equilibrium of the NK-DSGE model and defines the so-called ‘A, B, C (and D’s)’ representation, see Fernandez-Villaverde et al. (2007), Ravenna (2007) and Franchi and Paruolo (2012); see also Hannan and Deistler (1988). For the case \( m = p \) (\( D \) square) and \( D \) non-singular, Fernandez-Villaverde et al. (2007) and Ravenna (2007) discuss conditions under which \( y_t \) has a reduced form VAR (VAR(\( \infty \))) representation with \( \varepsilon_t \) as input variable; Franchi and Paruolo (2012) extend the analysis to the case of \( D \) non-square and possibly singular. Given our NK-DSGE model and the definition of \( y_t \) in Eq. (B46), we face the case \( m < p \), hence the results in Fernandez-Villaverde et al. (2007) and Ravenna (2007) can not be applied. A reasonable conjecture is that \( y_t \) has a finite order VARMA-type reduced form representation, as shown in e.g. Bekaert et al. (2010).
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4. ML estimates of the structural parameters $\theta$ of the NK-DSGE system (10)-(13) for for $W_t^0 := (\tilde{y}_t, \pi_t, i_t)'$; U.S. quarterly data 1985q1-2008q3, $T := 93$ (+2 initial lags). ................................. 45
Table 1: Monte Carlo results of \( M = 10000 \) replications of the size of tests of rank (LR1), long-run (LR2), and CER (LR3) of the NK-DSGE-model and averages across Monte Carlo simulations of the ML estimates of the structural parameters. Two lags are used in the VAR-representation.

<table>
<thead>
<tr>
<th>Tests</th>
<th>( T = 100 )</th>
<th>( T = 200 )</th>
<th>( T = 500 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( LR_1 (\psi_1 = 0.01) ): test of rank</td>
<td>0.006</td>
<td>0.009</td>
<td>0.011</td>
</tr>
<tr>
<td>( LR_2 (\psi_2 = 0.02) ): test of beta</td>
<td>0.067</td>
<td>0.040</td>
<td>0.028</td>
</tr>
<tr>
<td>( LR_3 (\psi_3 = 0.02) ): test of CER</td>
<td>0.027</td>
<td>0.020</td>
<td>0.018</td>
</tr>
<tr>
<td>( LR_1 (\hat{\psi}_1) \rightarrow LR_2 (\hat{\psi}_2) \rightarrow LR_3 (\hat{\psi}<em>3) ): ( \hat{\psi} = \sum</em>{i=1}^{3} \hat{\psi}_i )</td>
<td>0.100</td>
<td>0.069</td>
<td>0.057</td>
</tr>
<tr>
<td>Overall rejection frequency of DSGE model</td>
<td>0.098</td>
<td>0.067</td>
<td>0.056</td>
</tr>
</tbody>
</table>

Panel 1: Simulated empirical sizes \( \hat{\psi}_i \) of tests of NK-DSGE model

| Parameters | \( \phi_{MC} (\hat{\theta}_i) \) \( \phi_{MC} (\hat{\theta}_i) \) \( \phi_{MC} (\hat{\theta}_i) \) |
|------------|---------------|---------------|---------------|
| \( \kappa = 0.044 \) | 0.095 (0.111) | 0.067 (0.058) | 0.049 (0.029) |
| \( \delta = 0.12404 \) | 0.149 (0.082) | 0.136 (0.053) | 0.129 (0.032) |
| \( \gamma = 0.744 \) | 0.740 (0.079) | 0.745 (0.053) | 0.744 (0.033) |
| \( \omega_f = 0.93537 \) | 0.955 (0.180) | 0.932 (0.148) | 0.912 (0.122) |
| \( \rho = 0.834 \) | 0.826 (0.085) | 0.832 (0.060) | 0.832 (0.037) |
| \( \varphi_y = 1.146 \) | 1.440 (1.197) | 1.356 (0.841) | 1.207 (0.386) |
| \( \varphi_\pi = 1.749 \) | 2.436 (1.680) | 2.155 (1.206) | 1.859 (0.592) |
| \( \rho_y = 0.796 \) | 0.768 (0.141) | 0.784 (0.079) | 0.789 (0.043) |
| \( \rho_\pi = 0.418 \) | 0.404 (0.205) | 0.380 (0.079) | 0.362 (0.157) |
| \( \rho_i = 0.404 \) | 0.394 (0.135) | 0.402 (0.098) | 0.404 (0.062) |
| \( \sigma^2_\gamma = 0.055 \) | 0.072 (0.041) | 0.062 (0.024) | 0.058 (0.013) |
| \( \sigma^2_\pi = 0.391 \) | 0.450 (0.181) | 0.429 (0.108) | 0.421 (0.079) |
| \( \sigma^2_i = 0.492 \) | 0.515 (0.164) | 0.508 (0.106) | 0.496 (0.053) |
| \( \sigma^2_{yp} = 0.020 \) | 0.020 (0.003) | 0.020 (0.002) | 0.020 (0.001) |
Table 2: Unrestricted reduced form estimates of the VAR(2) for $W_t^0 := (\tilde{y}_t, \pi_t, i_t)^\prime$; U.S. quarterly data 1985q1-2008q3, $T := 93$ (+2 initial lags)

<table>
<thead>
<tr>
<th></th>
<th>$\hat{y}_t$</th>
<th>$\pi_t$</th>
<th>$i_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{y}_{t-1}$</td>
<td>1.041</td>
<td>0.045</td>
<td>0.075</td>
</tr>
<tr>
<td>$\pi_{t-1}$</td>
<td>-0.109</td>
<td>0.475</td>
<td>0.111</td>
</tr>
<tr>
<td>$i_{t-1}$</td>
<td>1.147</td>
<td>0.022</td>
<td>1.504</td>
</tr>
<tr>
<td>$\hat{y}_{t-2}$</td>
<td>-0.135</td>
<td>-0.041</td>
<td>-0.072</td>
</tr>
<tr>
<td>$\pi_{t-2}$</td>
<td>-0.424</td>
<td>0.215</td>
<td>-0.018</td>
</tr>
<tr>
<td>$i_{t-2}$</td>
<td>-1.08</td>
<td>-0.021</td>
<td>-0.552</td>
</tr>
<tr>
<td>$const$</td>
<td>0.239</td>
<td>0.193</td>
<td>-0.035</td>
</tr>
</tbody>
</table>

$\hat{\Sigma}_{W,e} = \begin{pmatrix}
0.500 & -0.256 & 0.292 \\
0.190 & 0.117 & 0.082
\end{pmatrix}$

Diagnostic tests

<table>
<thead>
<tr>
<th>Test</th>
<th>$LM_{AR}$</th>
<th>$LM_{ARCH}$</th>
<th>$LM_{Normality}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-5 test:</td>
<td>2.93</td>
<td>2.73</td>
<td>0.99</td>
</tr>
<tr>
<td>[0.02]</td>
<td>[0.025]</td>
<td>[0.43]</td>
<td></td>
</tr>
<tr>
<td>1-4 test:</td>
<td>0.20</td>
<td>0.87</td>
<td>0.77</td>
</tr>
<tr>
<td>[0.93]</td>
<td>[0.49]</td>
<td>[0.55]</td>
<td></td>
</tr>
<tr>
<td>Normality test:</td>
<td>0.27</td>
<td>7.08</td>
<td>2.93</td>
</tr>
<tr>
<td>[0.88]</td>
<td>[0.03]</td>
<td>[0.23]</td>
<td></td>
</tr>
</tbody>
</table>

LM AR 1-5 vector test: 1.67 [0.01]
LM vector Normality test: 10.07 [0.12]

NOTES: The estimated unrestricted VAR covariance matrix $\hat{\Sigma}_{W,e}$ is reported such that correlations appear in the o-diagonal terms. Asymptotic standard errors are reported in parentheses below estimates, P-values in brackets. ‘LM AR 1-5 test’ is the test for the absence of residuals autocorrelation against the alternative of correlation up to 5 lags; ‘LM ARCH 1-4’ test for the absence of ARCH components in the disturbances against the alternative of ARCH components up to lag order 4; ‘LM Normality test’ is the test for the null of Gaussian disturbances. Estimation is carried out by considering within-periods initial values.
Table 3: Estimated eigenvalues of the companion matrix associated with the unrestricted VAR(2) for for \( W_t' := (\tilde{y}_t, \pi_t, i_t)' \) and LR "one shot" Trace test for cointegration rank \( r := 2 \) (one unit root) vs \( r := 3 := p \) (stationary system); U.S. quarterly data 1985q1-2008q3, \( T := 93 \) (+2 initial lags).

<table>
<thead>
<tr>
<th>Estimated roots</th>
<th>real</th>
<th>imaginary</th>
<th>modulus</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9091</td>
<td>0</td>
<td></td>
<td>0.9091</td>
</tr>
<tr>
<td>0.8189</td>
<td>0.1257</td>
<td></td>
<td>0.8295</td>
</tr>
<tr>
<td>0.8189</td>
<td>-0.1257</td>
<td></td>
<td>0.8295</td>
</tr>
<tr>
<td>0.7420</td>
<td>0</td>
<td></td>
<td>0.7420</td>
</tr>
<tr>
<td>-0.3202</td>
<td>0</td>
<td></td>
<td>0.3202</td>
</tr>
<tr>
<td>0.0495</td>
<td>0</td>
<td></td>
<td>0.0495</td>
</tr>
</tbody>
</table>

| Test of rank    | \( LR \) for \( r = 2 \) vs \( r = 3 \) [LR1&2] 4.01 [0.045] |

NOTES: Estimation is carried out by considering within-periods initial values. P-values in brackets.
Table 4: ML estimates of the structural parameters $\theta$ of the NK-DSGE system (10)-(13) for for $W_0^r:=(\tilde{y}_t, \pi_t, i_t)'$; U.S. quarterly data 1985q1-2008q3, $T:=93$ (+2 initial lags).

<table>
<thead>
<tr>
<th>Parameters in $\theta_s$</th>
<th>Interpretation</th>
<th>ML$_{det}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma$</td>
<td>AD, forward look. term</td>
<td>0.735 (0.092)</td>
</tr>
<tr>
<td>$\delta$</td>
<td>AD, inverse elasticity of sub.</td>
<td>0.057 (0.013)</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>NKPC, indexation</td>
<td>0.021 (0.036)</td>
</tr>
<tr>
<td>implied value $\omega_f$</td>
<td>NKPC, forward-looking</td>
<td>0.969 (0.034)</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>NKPC, slope</td>
<td>0.058 (0.023)</td>
</tr>
<tr>
<td>$\rho$</td>
<td>Policy rule, smoothing term</td>
<td>0.623 (0.404)</td>
</tr>
<tr>
<td>$\varphi_y$</td>
<td>Policy rule, react. to out. gap</td>
<td>0.233 (0.680)</td>
</tr>
<tr>
<td>$\varphi_\pi$</td>
<td>Policy rule, react. to inflation</td>
<td>5.21 (3.18)</td>
</tr>
<tr>
<td>$\rho_y$</td>
<td>AD, disturbance persist.</td>
<td>0.889 (0.179)</td>
</tr>
<tr>
<td>$\rho_\pi$</td>
<td>NKPC, disturbance persist.</td>
<td>0.921 (0.347)</td>
</tr>
<tr>
<td>$\rho_R$</td>
<td>Policy rule, disturbance persist.</td>
<td>0.826 (0.515)</td>
</tr>
</tbody>
</table>

$$\Sigma_{W,u} = \begin{pmatrix} 0.0196 & -0.0018 & 0.0014 \\ -0.00029 & 0.00031 & 0.00014 \\ -0.0014 & 0.00031 & 0.00017 \end{pmatrix}$$

<table>
<thead>
<tr>
<th>LR test for CER ($LR_3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constrained log-likelihood =60.855</td>
</tr>
<tr>
<td>Unrestricted log-likelihood =69.69</td>
</tr>
<tr>
<td>$LR_3$=17.66</td>
</tr>
</tbody>
</table>

NOTES: ML estimates have been obtained from the determinate VAR(2) solution for $W_0^r:=(\tilde{y}_t, \pi_t, i_t)'$ in Eq. (3) by maximizing the Gaussian log-likelihood under the CER in Eq.s (4)-(6). The variables in $W_0^r$ have been preliminarily demeaned. The constrained VAR(2) log-likelihood function has been maximized by the BFGS method using a grid search for $\delta$ (range [0.05, 0.15]), $\varphi_y$ (range [0.03, 0.06]), $\varphi_\pi$ (range [0.02, 0.05]), $\varphi_R$ (range [0.10, 1.50]) and $\varphi_\pi$ (range [1, 5.5]), and estimating $\gamma$, $\rho$, $\rho_y$, $\rho_\pi$ and $\rho_R$ freely. Asymptotic standard errors are reported in parentheses below estimates. The LR test for the CER ($LR_3$) has 24-16=8 degree of freedom.