VAR meets DSGE:
Uncovering the Monetary Transmission Mechanism
in Low-Income Countries

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Abstract: VAR methods suggest that the monetary transmission mechanism is weak and unreliable in low-income countries. But are structural VARs identified via short-run restrictions capable of detecting a transmission mechanism when one exists, under research conditions typical of these countries? Using small DSGEs as data-generating processes, we assess the impact on VAR-based inference of short data samples, macroeconomic volatility, high-frequency supply shocks, and other features of the LIC environment. Many of these features undermine the precision of estimated impulse responses to monetary policy shocks, but their impact on finite-sample bias appears to be relatively modest when identification is valid.

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1. Introduction

Mishra, Montiel and Spilimbergo (2010) and Mishra and Montiel (2012) survey a vast empirical literature and conclude that the monetary transmission mechanism or ‘MTM’ – meaning the impact of monetary policy on output and inflation – is weak and unreliable in low-income countries, both in absolute terms and by comparison with countries at higher levels of development. By weak they mean that monetary policy instruments have small effects on aggregate demand. By unreliable they mean that the impacts on aggregate demand are not precisely estimated, leaving a lot of statistical uncertainty about what the true mechanism is.

Mishra et al. (2010, 2013) suggest two broad explanations for what we will call the missing MTM:

- “Facts on the ground”: Financial markets are small and poorly arbitraged in low-income countries (LICs), so the link between the short-term interest rates that central banks can control and the variables that matter for aggregate demand (e.g., longer-term interest rates, the exchange rate) are weak or absent. Even the bank lending channel may be weak in a situation of imperfect competition and excess reserves in the banking system and limited financial participation by households.

- “Limitations of the method”: The monetary transmission mechanism (MTM) is not in fact weak, but standard empirical approaches based on structural VARs identified through short-run restrictions are not capable of uncovering it under conditions characteristic of LICs. It is the VAR evidence in LICs that is weak and unreliable, not the MTM itself.

The stakes here seem high. If the ‘facts on the ground’ explanation is correct, the missing MTM suggests that there is little scope for successful monetary stabilization policy in LICs. Given low and uncertain instrument multipliers, policymakers are relegated to choosing between aggressive and risky interventions and more gradualist ones with limited and unclear effects. Along first-generation monetarist lines, the LIC environment would appear to favor a monetary policy that is not only rules-based but also non-activist. On the other hand, if the missing MTM mainly reflects methodological limitations, then the results of the VAR-based literature should be discounted by policymakers; and in building the empirical basis for stabilization policies, researchers should adopt empirical approaches that are robust to the peculiar weaknesses of these methods in LIC-like environments.
These divergent interpretations – both of which may hold some truth – suggest at least three broad research strategies. One is to pursue complementary empirical approaches to uncovering the facts on the ground. These include the narrative approach (e.g., Berg et al. 2013) and the use of bank-level or even loan-level data to investigate the lending channel (e.g., Mbowe 2012). The findings from complementary approaches can inform policy directly, and may also suggest ways in which VAR specifications – through the choice of variables and identifying restrictions – should be differentiated across levels of development. A second strategy is to impose enough theoretically-motivated identifying restrictions to overcome the paucity or poor quality of the data. This includes methods that combine prior information with theoretically-motivated cross-equation restrictions, as in the Bayesian DSGE literature (e.g., Peiris and Saxegaard 2007). A final strategy, which we pursue in this paper, is to ask whether the characteristics of the LIC research environment are particularly hostile to VAR-based approaches. Under LIC-like data conditions, if a strong MTM is present, can standard VAR methods uncover it?

We address this question by applying VAR-based methods to a world in which a strong MTM exists but the research environment has some of the features that are characteristic of LICs. These include volatility and measurement error in the data, short samples due to nonexistent data or structural changes (including major policy reforms), and large temporary supply shocks. Our metric for ‘uncovering the MTM’ is two-fold: we look for estimated impulse response functions that are reasonably close to the true, model-based impulse responses on average; and, since the latter are nonzero by construction, we look for significance tests that allow the researcher to reject a null hypothesis of zero at conventional (for VARs) levels of significance.³

Failures of the methodology, in our context, can be driven either by inadequate identification of the structural shocks to monetary policy or by econometric limitations in the presence of valid identification. While the former have been the central preoccupation of the VAR literature, issues of identification do not usually cut sharply between high- and low-income applications. Since the missing MTM depends by definition on features that are disproportionately prevalent in LICs, we steer clear of identification issues for most of the paper. Our evidence therefore applies mainly to the empirical performance of validly identified VARs. Later in the paper we develop a single example to underscore

³ Given the high standard errors associated with VAR-based impulse responses, researchers often apply less stringent significance levels in assessing IR evidence than in standard hypothesis testing. These hurdles are routinely surpassed in emerging-market and high-income applications, where inflation and output responses are typically characterized as having an economically and statistically significant ‘hump’ shape.
the important point that in terms of small-sample bias, problems of identification will easily swamp other features of the research environment.

To implement our simulation-based approach, we need to be specific enough about the underlying structural shocks to generate Monte Carlo evidence on the sampling properties of VAR estimators, and specific enough about propagation mechanisms to fully control the nature of the ‘true’ MTM. In both respects, small dynamic and stochastic general-equilibrium models (DSGEs) provide an ideal platform for our analysis. We therefore flip the familiar dialogue between VAR evidence and DSGEs on its head. Instead of assessing the properties of DSGEs against the VAR evidence, as in Christiano, Eichenbaum and Evans (2005), Sims and Zha (2005), and many others, we assess VAR methodologies against a DSGE-based data-generating process. We develop a simple DSGE that embodies an MTM with well-defined interest-rate and exchange-rate channels, use the solution to this DSGE to generate multiple independent runs of data, and then within each of these runs, mimic the process of an empirical researcher using VAR-based methods to infer the nature of the MTM.

Section 2 of the paper introduces a stripped-down and linearized stationary DSGE in four macroeconomic variables: the GDP gap, the inflation rate, the real exchange rate, and the nominal interest rate. In section 3 we discuss the relationship between DSGE models and structural VARs that can be identified using restrictions on the contemporaneous interactions between the variables. Drawing on Christiano, Eichenbaum and Evans (1999), we motivate the imposition of restrictions that retain a high degree of simultaneity while allowing the successful identification of shocks to monetary policy. Section 4 presents a baseline experiment that successfully uncovers the MTM in the presence of adequate data and a valid identification scheme. The remainder of the paper then develops Monte Carlo evidence on the performance of VAR estimates under research conditions that are characteristic of LICs. We address in turn the implications of short data samples (Section 5), volatility and measurement error (section 6), and high-frequency supply shocks (Section 7), assuming valid identification of the monetary policy shocks in each case.

Two central features of the DSGE platform are its explicit treatments of the information environment and the conduct of monetary policy. We stress the first of these themes throughout the paper, starting in section 2 where information assumptions play a role in shaping a data-generating process that can be identified via short-run restrictions. Section 8 returns briefly to this theme by using alternative information structures to illustrate the impact of poor identification on empirical performance. In Section 9 we examine a ‘facts on the ground’ explanation by contrasting two potential sources of low ‘true’ impulse responses, one associated with limited interest-rate smoothing among LICs
and the other with low elasticities of transmission in the IS and Phillips curves. In Section 10, we examine the robustness of the preceding findings to an alteration of the information assumptions.

Section 11 concludes the paper with a summary of findings and a discussion of extensions.

2. DSGEs as a data-generating process

The MTM is about the ability of monetary policy to exert a temporary effect on aggregate demand. To focus on these effects we begin by ignoring stochastic trends in the data, implicitly assuming that these can be estimated with reasonable statistical confidence so that the stationary part of the data is cleanly isolated. Our DSGE models will therefore generate a stationary vector \( x_t = [\tilde{y}_t, \pi_t, \tilde{e}_t, i_t] \) of quarterly values for the GDP gap (\( \tilde{y}_t \), defined as the gap between actual GDP and unobservable potential GDP), the inflation rate (\( \pi_t \)), the real exchange rate (\( \tilde{e}_t \), with an increase being a real appreciation), and the annualized nominal interest rate (\( i_t \)). We introduce an underlying trend in section 7, where we argue that LIC applications confront particular difficulties in inferring the GDP gap from observed measures of output. But for the bulk of the paper we treat the model-generated GDP gap as observable.

The four endogenous variables in the model will in turn be functions of a vector \( \varepsilon_t = [\varepsilon^Y_t, \varepsilon^\pi_t, \varepsilon^e_t, \varepsilon^i_t] \) of structural shocks that are not directly observable by the researcher. The objects of interest to the researcher are the responses of \( x_{t+j} \) to a one-time shock to monetary policy (\( \Delta \varepsilon^i_t = 1 \)). To estimate these, the researcher starts by estimating a reduced-form VAR of the form

\[
 x_t = A(L)x_{t-1} + u_t, \tag{1}
\]

where \( A(L) \) contains enough lags to render the reduced-form innovations \( u_t \) approximately white noise. In the absence of measurement error or inappropriate truncation, this produces consistent estimates of the lag parameters in \( A(L) \) and the covariance matrix \( \Omega \) of the reduced-form innovations. The researcher then imposes enough restrictions on the reduced form to identify the structural shocks to monetary policy and their covariances with other structural shocks. In our case, these take the form of zero restrictions on elements of the square and invertible matrix \( B \) in

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4 The Mishra et al. (2010, 2012) evidence on weak transmission is perfectly consistent with money or the exchange rate being an effective long-run anchor for inflation.

5 The VAR representation of the DSGE solution may be infinite-order; see below.

6 In practice, we estimate the elements of \( A(L) \) and \( B \) simultaneously using Bayesian methods. In the just-identified case the results are extremely close to what we obtain by estimating \( A(L) \) by OLS in (1) and then solving for \( B \) using \( \hat{\Omega} = B(B^{-1})' \), where \( \hat{\Omega} \) is the estimated covariance matrix of the OLS residuals. Note that identification can
\[ u_t = B \varepsilon_t. \] (2)

The impulse responses can then be calculated as nonlinear functions of the estimated lag parameters and shock covariances. The researcher computes these estimated IRs and, in a final step, bootstraps their standard errors and calculates t ratios for each impulse-response step. When a ‘true’ MTM is present in the data-generating process, the researcher should see impulse responses that are appropriately signed and shaped, of roughly correct magnitude, and of reasonable statistical significance. We loop over multiple simulated datasets in order to study the population distribution of estimated impulse responses and associated t ratios in a wide variety of specific environments.

The model we employ for our experiments is a canonical New Keynesian open-economy model that combines an IS curve, a New Keynesian Phillips curve, an interest-parity condition, and a Taylor Rule for monetary policy (e.g., Berg, Karam and Laxton 2006). There is no empirical consensus on the appropriate parameterization of such a model for LICs, but in choosing parameters we can draw on recent research that develops partly-calibrated and partly-estimated DSGEs for low-income countries in Africa. We rely particularly on Berg, Portillo and Unsal (2010), who develop DSGEs with similar 4-equation structure for Kenya, Tanzania and Uganda, and Andrle et al. (2013) who estimate a somewhat more disaggregated DSGE for Kenya. Where the relevant parameters differ sharply across these two sources, we choose midpoint or close-to-midpoint values. Our basic model, complete with parameters, is:

**IS equation:**
\[ \tilde{\gamma}_t = 0.5 \cdot E_t[\bar{\gamma}_{t+1}] + 0.5 \cdot \tilde{\gamma}_{t-1} - 0.4 \cdot [0.5 \cdot (i_t - E_t[\pi_{t+1}] - \bar{r}) + 0.5 \cdot \tilde{\epsilon}_t] + \varepsilon_t^Y, \] (3.1)

**New Keynesian Phillips curve:**
\[ \pi_t = 0.5 \cdot E_t[\pi_{t+1}] + 0.5 \cdot \pi_{t-1} + 0.25 \cdot \tilde{\gamma}_t - 0.15 \cdot \tilde{\epsilon}_t + \varepsilon_t^\pi, \] (3.2)

**Uncovered interest parity equation:**
\[ \tilde{\epsilon}_t = 0.5 \cdot E_t[\epsilon_{t+1}] + 0.5 \cdot \tilde{\epsilon}_{t-1} + (1/4) \cdot [i_t - E_t[\pi_{t+1}] - \bar{r}^*] + \varepsilon_t^\epsilon, \] (3.3)

**Taylor-type rule for monetary policy:**
\[ i_t = 0.5 \cdot (\bar{r} + 1.4 \cdot E_t[\pi_{t+1}] + 0.5 \cdot E_t[\tilde{\gamma}_{t+1}]) + 0.5 \cdot i_{t-1} + \varepsilon_t^i, \] (3.4)

also take the form of zero restrictions on \( B_0 \) in \( B_0 u_t = \varepsilon_t \). When \( B \) is an invertible block-triangular matrix, the two approaches are equivalent.
Structural shocks:

$$\varepsilon_t \sim i.i.d \ N(0, I_k)$$  \hspace{1cm} (3.5)

Here $E_t$ denotes an expectation conditional on information available at time $t$. As explained below, we allow information sets to vary across equations, reflecting differences in the timing of economic decisions and the information available to agents. Note also that equation (3.5) departs from with the bulk of the DSGE literature by assuming $i.i.d.$ shocks, in preference to the standard AR(1) structure: our version allows for similar distributed lag responses, but these are governed completely by the lags within the behavioral equations. By eliminating purely exogenous dynamics, we substantially simplify the task of solving the DSGE and representing its solution as a structural VAR.

The model we are employing was of course not developed for LICs, and in characterizing the MTM it makes no effort to capture the financial architecture or other ‘facts on the ground’ that may differentiate LICs from the advanced countries for which these models were developed. Monetary policy follows a Taylor-style rule, for example, even though many LICs use the monetary base rather than a policy interest rate as the main operational target and may deploy additional instruments not represented here.\footnote{For example, changes in reserve requirements and foreign exchange intervention.} We omit a banking sector from the model, even though the nature of the credit channel may differ in LICs as compared to more advanced countries. Finally, we simplify by assuming that the structural shocks are mutually uncorrelated. This is standard when building a DSGE up from microfoundations, but cross-correlations can emerge when the behavioral relationships are ‘solved down’ to the four we feature here, and we have omitted these. These simplifications reflect our focus on aspects of the research environment that are largely model-independent. Our Monte Carlo approach can of course be applied to any structural model, a topic to which we return in the concluding section. Moreover, as we will see, the present model can accommodate widely divergent transmission patterns through variations in key parameters.

Our data-generating process will not be the DSGE model itself, but rather its solution in terms of the endogenous state variables and the shock vector $\varepsilon_t$. This introduces a set of technical issues that are well understood in the DSGE and VAR literatures but that appear here in combination. First, for VAR-based methods to have a chance of uncovering the features of the MTM, the solution to the DSGE must be representable at least approximately as a finite-order VAR in observable variables. The relevant conditions are developed in Fernandez-Villaneuva \textit{et al.} (2005). As we show below, our model solutions have exact representations as finite-order VARs (a side effect of which is to eliminate truncation bias.
from our results). Second, the monetary policy shocks must be identifiable through the imposition of conventional structural-VAR restrictions on this representation. We focus on short-run restrictions, because these remain the dominant approach to identification in the applied literature reviewed by Mishra et al. (2012, 2013). As discussed below, such restrictions work by limiting the contemporaneous interactions between the variables in the VAR. A glance at equations (3.1) – (3.4), however, confirms that the solution to a DSGE will tend to be highly simultaneous. This is in part because endogenous variables appear directly in more than one equation, but it also reflects the important role of expectational variables in the DSGE. Any variable that is in the information set of agents may end up in the VAR representation of the solution indirectly, via forecasts or ‘now-casts’ that condition on available information. We will therefore have to impose information restrictions on the DSGE in order to get a data-generating process that is identifiable via short-run restrictions and therefore capable of reproducing the success of this standard structural-VAR identification in advanced-country settings.

3. Motivating CEE-recursive structure

The restrictions we impose at the estimation stage are typically motivated in the structural VAR literature by appealing to a structural simultaneous equations model of the form

\[ B_0 x_t = B(L)x_{t-1} + \epsilon_t. \]  

(4)

The shocks \( \epsilon_t \) are i.i.d. and mutually uncorrelated variables that can be normalized without loss of generality to have unit variances (\( E[\epsilon_t \epsilon'_t] = I \)).\(^8^\) As long as \( B_0 \) is invertible, equation (4) implies the reduced-form VAR representation in equation (1), with \( A(L) = B_0^{-1}B(L) \). The relationship between the structural and reduced-form innovations is then given by equation (2), with \( B = B_0^{-1} \). When we refer to ‘short-run restrictions’ in a structural VAR context, we mean restrictions on the elements of \( B_0 \) or its inverse.

Within the class of short-run restrictions, the most common are those that impose a recursive structure on \( B_0 \). Cholesky decompositions assume that the model is fully recursive, so that \( B_0 \) is lower triangular. As Christiano, Eichenbaum and Evans (1999) have shown, however, the impulse responses to monetary-policy shocks can be recovered from the reduced form VAR under the considerably weaker

\(^8^\) If the structural shocks have covariance matrix \( \Lambda \), then the model can be written \( \Lambda^{-1/2} C x_t = \Lambda^{-1/2} D(L)x_{t-1} + \epsilon_t \), where \( E[\epsilon_t \epsilon'_t] = I \), and \( B = C^{-1} \Lambda^{1/2} \). A one-unit shock to \( \epsilon'_t \) is then equivalent to one standard deviation of the structural shock to monetary policy.
condition that the system be \textit{contemporaneously block-lower-triangular, with the interest rate occupying its own diagonal block}. We will refer to any system with this property as ‘CEE-recursive’. Note that in this case it is immaterial whether the zero restrictions are motivated with reference to $B_0$ or $B$, because matrix inversion preserves block-triangular structure.

Equation (5) illustrates the concept of CEE recursiveness in a seven-variable case, using ‘$X$’ as a placeholder for any element of $B_0$ that is not restricted to be zero.

\[
B_0x_t = \begin{bmatrix}
X & X & X & 0 & 0 & 0 & 1 \\
X & X & X & 0 & 0 & 0 & 0 \\
X & X & X & 0 & 0 & 0 & 0 \\
X & X & X & X & X & X & X \\
X & X & X & X & X & X & X \\
X & X & X & X & X & X & X \\
\end{bmatrix}
\begin{bmatrix}
x_{1t} \\
x_{2t} \\
x_{3t} \\
i_t \\
x_{5t} \\
x_{6t} \\
x_{7t} \\
\end{bmatrix}. \tag{5}
\]

A CEE-recursive model can be ordered into two or more block-recursive segments. The upper block in (5) is occupied by a three-variable system that is recursively prior to the interest rate and also to the three-variable system in the third block. The monetary authority responds contemporaneously to these variables, but they respond to the interest rate and the remaining variables in the model only with a lag. The third block in (5), in contrast, is occupied by variables that are recursively posterior to the interest rate and its determinants. Monetary policy affects these variables immediately, but they do not respond to the interest rate and its contemporaneous determinants except with a lag.\footnote{The example in (5) happens to be symmetric in the sense that the upper and lower blocks are of identical size and configuration. This is useful for expositional purposes below, but the only conditions that matter are that the interest rate occupy its own diagonal block and that the overall structure be block recursive.}

When a structural VAR model is CEE-recursive, the impulse responses to monetary policy shocks can be recovered from the reduced-form VAR even if the remaining impulse responses cannot.\footnote{Note that the $B_0$ matrix in (5) is six restrictions short of being lower triangular. The impulse responses to the monetary policy shock can nonetheless be recovered through any Cholesky decomposition that places the interest rate in its proper position in the ordering.} For the same reason, the ordering of variables within each of the recursively prior and posterior blocks is irrelevant to obtaining the responses to interest-rate shocks (Christiano, Eichenbaum and Evans 1999).

We investigate two CEE-recursive structures in what follows: one in which the interest rate is last in the ordering, so that our four-variable system corresponds to the sub-system defined by $[x_{1t}, x_{2t}, x_{3t}, i_t]$ in equation (5), and one in which it is first, so that our model corresponds to the sub-system defined by $[i_t, x_{5t}, x_{6t}, x_{7t}]$. 

\[9\]

\[10\]
Information assumptions play an important role in our analysis. In the presence of full information, a CEE-recursive solution will not emerge from a forward-looking DSGE model unless we impose a highly contrived set of behavioral lags in order to prevent expectations formed at time $t$ from affecting current economic decisions. We avoid this route by relying on informational asymmetries that have played a key role in the applied VAR literature. For most of the paper, we focus on a model in which the central bank has full information, while the private sector does not observe the contemporaneous shock to monetary policy. This structure follows Christiano, Eichenbaum and Evans (2005), and reflects the common practice in the VAR literature of attributing an information advantage to the central bank, and therefore placing the interest rate late in the recursive ordering. As a robustness check, we also examine a structure which the private sector has an information advantage – an assumption that may have greater plausibility in a LIC context than in higher-income countries. In the latter model, the central bank observes all variables except the interest rate with a lag, while the private sector has full information.

Partial information, and particularly mixed information, where different agents have different information sets, complicates the solution of DSGE models. As explained in the Appendix, we define our information sets over shocks rather than variables, and solve these models using a version of the undetermined coefficients approach developed by Christiano (2002). The solutions have VAR(1) representations with CEE-recursive $B$ matrices. We refer to the models used below as ‘CEE-CB’ when the central bank has the advantage and CEE-PS when the private sector has the advantage.

Kim and Roubini (2000) pose a serious challenge to recursively-identified VARs in an open-economy context. As they point out, the interest rate cannot occupy its own diagonal block unless either the central bank or the private sector does not respond to the current exchange rate either directly or indirectly. Neither condition is appealing, but when both are dropped the interest rate and exchange rate are simultaneously determined regardless of the recursive structure of the remainder of the model. This is handled within the structural VAR literature by appealing to non-recursive short-run restrictions, sometimes in combination with theoretically motivated long-run restrictions (e.g., that monetary policy has no long-run impact on real variables). Non-recursive identification is a promising area for extensions of our analysis, and we return to it in the concluding section.

4. Strong VAR performance under baseline conditions

Figure 1a and 1b report the performance of a validly identified CEE-recursive VAR using 40 years of quarterly data. The experiment assumes equal variances for the four structural shocks, and the
information structure is CEE-CB, implying that the private sector does not observe the monetary policy shock. The researcher estimates the VAR with four lags.\textsupert{11} Since Figures like 1a and 1b will appear throughout the paper, we begin by describing their content.

The researcher is trying to uncover the true, model-based impulse responses, which appear as a bold line identified by dots in Figure 1a. In the CEE-CB case, these IRs display the conventional hump-shaped responses of inflation and output to a monetary contraction. The empirical performance of the VARs is summarized by the three lighter lines in Figure 1a. These lines show the 5th, 50th, and 95th percentiles of the population distribution of simulated point estimates for the impulse responses (with percentiles computed separately for each impulse-response step). The population distribution is based on 200 simulations of the DSGE solution, each independently generated by 40 quarters of independent draws on the shock vector $\epsilon_t$.\textsupert{12}

Figure 1b describes the VAR researcher’s inference environment. For each of the 200 simulations, the researcher generates bootstrapped standard errors for the impulse-response coefficients using 200 independent draws from the empirical distribution of the VAR residuals. The Figure shows the probability of rejecting the null hypothesis of a zero impulse-response coefficient at each step. We assume that the researcher treats the $t$ ratios as asymptotically normal and applies the relatively undemanding hurdle of 10 percent significance.

Figures 1a and 1b establish that in the presence of ample and high-quality data, an appropriately-ordered structural VAR does very well. The estimated impulse responses show only a trivial degree of small-sample attenuation at the median,\textsupert{13} and for the first few quarters fully 90 percent or more of the point estimates lie on the correct side of zero. The researcher’s own inference will of course frequently be less confident than suggested by Figure 1b, because the researcher has only one data sample. Figure 1c shows the full distribution of $t$ ratios across the 200 runs. The structure of the exercise suggests that the width of bootstrapped confidence intervals for the IR coefficients will not be far from that implied by the population distribution of impulse responses, and Figures 1a and 1c bear this out. When one end of the population distribution of IRs is close to zero in Figure 1a, roughly half of the $t$ statistics reported in Figure 1c (corresponding loosely to the point estimates that lie closer to zero

\textsupert{11} It would be straightforward to embed a data-driven choice of lag length, but we leave this for future work.
\textsupert{12} We find that the population distributions settle down relatively rapidly. The results for 1000 draws are very similar to those for 200 draws.
\textsupert{13} The VAR residuals $B \epsilon_t$ are correlated with later-dated values of $x_{t+j}$, violating the assumption required for unbiasedness of OLS. In simple autoregressive models, this produces attenuation of OLS lag coefficients towards zero, to a greater degree the more persistent the dynamics. See Favero (2001).
than the median) fail to reject the null.\textsuperscript{14} The power of the t-ratio test is therefore relatively modest (Figure 1b), although there is no evidence here of a missing MTM.

Figures 2a and 2b show the baseline CEE-PS experiment, where the private sector has the information advantage and the model solution places the interest rate first. The VAR results are even stronger. The improvement over Figures 1a and 2a reflects the favorable effect on inference of larger true effect sizes. The model parameters are identical in the two cases, so the order-of-magnitude difference in the true impulse responses (comparing Figures 2a with Figure 1a) is driven by the effect of lags in diluting the impact of a monetary policy change in the CEE-CB case.

The overall impression from Figures 1a/2a and 2a/2b is that given 40 years of data, a valid block-recursive identification scheme, and a strong MTM, structural VARs identified through short-run restrictions will do very well at uncovering the true MTM.

5. Small sample sizes generate attenuation and low precision

The following sections assess the impact on VAR performance of a set of LIC-specific features, beginning here with short data samples, which are surely among the most daunting constraints in the LIC research environment. We focus on the CEE-CB experiments, leaving a discussion of robustness to section 9.

Structural economic reforms (e.g., financial liberalization) and changes in the monetary policy regime (e.g., a move to a flexible exchange rate) are often of sufficiently recent vintage that the researcher cannot expect that the current data-generating process has been in place for very long. Data-collection limitations also undermine the availability of long data samples in LICs; quarterly data on the real economy, for example, may be unavailable well through the 1990s or even more recently.

Figures 3a/3b and 4a/4b show an experiment that is identical to the CEE-CB baseline, with the exception that the researcher has 10 years rather than 40 years of quarterly data. Figures 3 and 4 are based on the same underlying data; the difference between the two is that Figures 3a/3b refer to one-unit impulses while Figures 4a/4b take the more conventional approach of scaling impulses by the estimated standard deviation of the interest rate shock. While the basic shape of the impulse responses is very strongly reproduced in both cases, Figure 4a shows extremely sharp attenuation of the early impulse responses, which are pushed towards zero by roughly 50 percent. Much of this, however, is associated with attenuation of the estimated shock variance of the interest-rate shock: the responses to a 1-unit impulse show much less attenuation (Figure 3a). The differences with by comparison with

\textsuperscript{14} The inference plots are very consistent with this effect. This suggests that the bootstrapped standard errors calculated by the researcher on each run of data tend to closely approximate the spread of the population distribution.
Figures 1a/1b are striking. In both cases, the reduction in sample size produces a substantial widening in the population distribution of point estimates and, consistent with this, a very sharp deterioration in the scope for confident inference about the MTM (Figures 3b and 4b).

6. Volatility does not undermine VAR-based inference, but measurement error does

Macroeconomic variables display greater volatility at business-cycle frequencies in LICs than in higher-income countries. One dimension of variability is of course crucial to uncovering the MTM in a VAR context: even a perfectly-specified VAR will fail if the variance of monetary policy shocks is small enough relative to that of other shocks. In this section we abstract from differences in the relative variability of interest rates, a topic we will return to in section 8 below. Here we focus on two drivers of data variability that clearly differ systematically across income level. We show that true economic volatility and measurement error have sharply different impacts on VAR-based inference about the MTM. To a first approximation, economic volatility leaves VAR-based inference unchanged, while measurement error rapidly undermines it.

The intuition for the neutral effect of volatility can be illustrated by considering the stochastic-regressor model $y_t = \beta x_t + \epsilon_t$, where $x_t$ and $\epsilon_t$ are mutually uncorrelated with mean zero. Let $b_T$ be the OLS estimator of $\beta$ in a sample of size $T$. This estimator is consistent, and converges in distribution to a normal random variable:

$$\sqrt{T}(b_T - \beta) \xrightarrow{L} N(0, \sigma^2 / \text{Var}[x_t]). \tag{6a}$$

The precision of the OLS estimator in any finite sample therefore depends approximately on the two variances on the right-hand side. These variances have the familiar effects: volatility in the disturbance term undermines inference about $\beta$, while volatility in the independent variable enhances inference.\footnote{These statements about inference can be re-cast more properly in terms of the power of $t$ ratios against the null hypothesis $\alpha = 0$. The relevant $t$ ratios take the form $t^D = a_T / \sqrt{\sigma^2 / \sum x_{t-1}^2}$, where $s_T$ is the OLS estimator of $\sigma^2$. The $t$ ratios are not asymptotically normal except under the null, but when the null is false the ratio of variances that appear on the right-hand side of (6a) or (6b) serve as a shift factor that reduces the power of the test for any finite $T$.}

A similar expression characterizes the OLS estimator in the AR(1) model $x_t = \alpha x_{t-1} + \epsilon_t$, viewed here as the simplest possible stationary VAR ($\epsilon_t$ is white noise with variance $\sigma^2$ and finite higher-order moments, and $|\alpha| < 1$):
\[
\sqrt{T}(a_T - \alpha) \xrightarrow{L} N(0, \sigma_x^2 / \text{Var}[x_{t-1}]) = N(0, 1 - a^2).
\] (6b)

But there is only one source of underlying volatility in a VAR model, which is the volatility of the shocks. In contrast to the conventional stochastic-regressor case, therefore, the variance of \(x_t\) in a VAR model is a function of the variance of the shocks. After solving for \(\text{Var}[x_{t-1}]\) from the moving average representation, the limiting distribution in (6) is completely independent of \(\sigma_x^2\) (Hamilton, 1994).

Any factor that uniformly scales up the variances of the shocks in a VAR therefore has little effect on inference about the VAR coefficients, because the sampling variances of the estimated coefficients are simultaneously pushed upwards by the variances of the shocks and downwards by the variances of the lagged variables in the VAR. These effects cancel, leaving the finite-sample variances of VAR coefficients approximately invariant to the variances of the structural shocks. This property carries over to the variances of the IR coefficients, because the latter are continuous (though nonlinear) functions of the VAR coefficients.\(^{16}\) A straightforward Monte Carlo experiment confirms this effect: doubling the variances of all four shocks in our DSGE model has no discernible effect on the population distributions of either the impulse responses or the \(t\) ratios (results not shown).

Measurement error, in contrast, unambiguously undermines the precision of VAR estimates. Figures 5a and 5b quantify this effect for the simple case of measurement error that affects the researcher but not the agents in the model.\(^{17}\) For this and subsequent experiments, we return to the full sample of 40 years of quarterly data. To induce classical measurement error in inflation and the GDP gap, we add white noise to the model-generated values of these variables, with a variance that is equal to 20 percent of the variance of the structural shocks. The point estimates show substantial attenuation towards zero in the first quarter for the GDP gap, but little impact in later quarters. The inflation impacts are larger and more persistent, with attenuation persisting through the first three quarters (Figure 5a). In both cases, the power of \(t\)-ratio tests deteriorates very badly (Figure 5b).

\(^{16}\) We have not reported an experiment in which we scaled up the standard deviations of all 4 shocks by a factor of 2.5. The population distributions of \(t\)-statistics were virtually unchanged by this sharp increase in volatility.

\(^{17}\) To assess the impact of measurement error more fully, a natural approach would be to confront the agents in the VAR with the same measurement error faced by the econometrician. This seems likely to reinforce the deterioration of VAR performance in at least two respects: first and more importantly, by weakening the true MTM; second, by inducing infinite lags in the DSGE solution and therefore exposing the VAR results to truncation bias.
7. High-frequency supply shocks obscure transmission to output

We have been assuming that the GDP gap is observable. In reality, the gap must be inferred – even when actual output is measured without error – by developing an empirical proxy for potential GDP. In this section we show that the high-frequency real-side shocks that are characteristic of LICs exacerbate measurement error in the GDP gap. When we use the usual two-sided filter to measure the gap, this effect substantially weakens inference about the real side of the monetary transmission mechanism. The transmission to inflation remains surprisingly robust, however, and we find that a one-sided filter does sharply better at uncovering the GDP gap responses than a two-sided filter, both in terms of bias and in terms of statistical power.

The GDP gap is typically measured in empirical applications by assuming that potential GDP follows a slow-moving trend. This trend is then either extracted from the actual series by differencing or filtering (leaving a stationary gap variable that can be used in the VAR) or controlled for within the VAR by expanding the set of variables to include slow-moving proxies for aggregate supply (e.g., a deterministic trend or the economy-wide capital stock and labor force). As emphasized in the literature on the New Keynesian Phillips curve, however, the concept of potential GDP that matters for inflation dynamics is the natural or ‘flex-price equilibrium’ level of GDP. Natural GDP is a function of slow-moving processes like factor accumulation and technological change, but it also depends on transitory real-side shocks that can affect output in the absence of sticky prices. Such shocks – droughts, for example – are likely to play a greater role in determining natural GDP in countries with larger agricultural sectors and less diversified non-agricultural sectors. If this is indeed the case, then the practice of proxying potential GDP with a slow-moving trend will induce more serious measurement errors in LICs than elsewhere.

To formalize this idea and assess its impact on VAR-based inference, we rely on the fact that the DSGE specifies the stationary interactions of macroeconomic variables once stochastic trends have been removed. This leaves us free to construct the path of actual output as the sum of our model-generated GDP gap (now denoted $\tilde{y}_t^N$) and a new, exogenous stochastic process for natural GDP, $y_t^N$:

$$y_t = y_t^N + \tilde{y}_t^M. \tag{7}$$

In each simulation run, therefore, we construct output from the two components on the right-hand side of (7). The researcher receives the vector $[\epsilon_t, \delta_t, y_t, \pi_t]$, which includes observable output $y_t$ rather than the unobservable gap $\tilde{y}_t^M$. The researcher approximates the gap by applying a Hodrick-Prescott (HP) filter to actual GDP, with the standard quarterly smoothing parameter of 1600. The VAR is then
estimated on $[\ell_t, \tilde{e}_t, \bar{y}_t, \pi_t]$, where the researcher’s GDP gap, $\bar{y}_t$, is the HP-cycle in actual GDP. Given the known drawbacks of two-sided filters in a VAR context, we run identical simulations for 2-sided and otherwise-equivalent 1-sided HP filters.

To implement this approach we assume that natural GDP is composed of two components: a stochastic trend $y_t^{nT}$ that follows an integrated random walk with deterministic drift, and a stationary component $y_t^{nS}$ that is present only in a LIC environment. Thus

$$y_t^n = y_t^{nT} + y_t^{nS}, \quad \Delta y_t^{nT} = \tilde{g} + \varepsilon_t^{nT}, \quad y_t^{nS} = \varepsilon_t^{nS},$$

where $\varepsilon_t^{nT}$ and $\varepsilon_t^{nS}$ are mutually uncorrelated white noise, and where the variance of $\varepsilon_t^{nS}$ is zero outside of a LIC environment. Hodrick and Prescott (1997) show that given this particular combination of trend and cycle, a two-sided HP filter applied to natural GDP provides an optimal (minimum MSE) estimate of the cyclical component $\varepsilon_t^{nS}$. To justify the use of the standard two-sided smoothing parameter of 1600, we calibrate the variance of $\varepsilon_t^{nT}$ in both cases to be $1/1600^{th}$ of that of the model-based gap.18

The researcher in these experiments estimates $\bar{y}_t^M$ as the HP cycle in actual GDP. This induces some degree of measurement error in the GDP gap even when there is no high-frequency component of natural GDP.19 To benchmark this ‘unavoidable’ deterioration, we first show results for the high-income-economy or ‘Canada’ case, where the GDP gap is unobservable but where we assume that the true variance of $\varepsilon_t^{nS}$ is zero. A comparison of Figures 6a/6b(Canada) and 7a/7b(Canada) with Figure 1a/1c reveals the impact on VAR-based inference of the need to pre-filter, under optimal conditions for the filter. The impacts on inference are confined to the GDP responses, where the two-sided results show modest attenuation towards zero while the one-sided results show estimated responses that are slightly larger than the true, model-based responses at the median. The t ratios are not very strongly affected, particularly in the one-sided case where power against the null hypothesis is actually stronger

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18 The optimal smoothing parameter for the HP filter in the case of an integrated stochastic trend and a white noise cycle is given by the ratio of the two variances. This property is of course not precisely relevant in either of our cases: in Figure 7a, the cyclical component of actual output is the model-based gap, which is not white noise, while in Figure 7b the additional source of variance in the cyclical component would justify a smoothing parameter of roughly twice 1600. The researcher, in our environments, is not aware of these details of the data-generating process.

19 The HP filter yields $y_t = y_t^{HPT} + \bar{y}_t^R$ where HPT denotes the Hodrick-Prescott trend. Combining this with the equation used to construct $y_t$, we can see that $\bar{y}_t^R = \bar{y}_t^H + [y_t - y_t^{HPT}]$. The measurement error in $\bar{y}_t^H$ is therefore the difference between two highly persistent series. Estimating the gap in this way tends to produce a measurement error that is persistent, even in the ‘best’ of circumstances, in which actual GDP is measured without error.
than in the baseline case. These results are consistent with Table 1, which shows the average across simulations of the correlation between the true, model-based GDP gap and the HP-filtered gap.

**Table 1** Correlations of model-based and filtered GDP gaps

<table>
<thead>
<tr>
<th></th>
<th>Canada</th>
<th>LIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Two-sided HP filter</td>
<td>0.96</td>
<td>0.67</td>
</tr>
<tr>
<td>One-sided HP filter</td>
<td>0.81</td>
<td>0.57</td>
</tr>
</tbody>
</table>

*Note:* Each cell shows the average correlation coefficient across 200 independent simulations.

The ‘Canada’ results suggest that despite unavoidable measurement error, considerable scope remains for confident and qualitatively accurate inference about the transmission of monetary policy to output, at least for the impact effect and the early steps of the process. Inference about inflation is even stronger. What we show in Figures 6a/6b(LIC) and 7a/7b(LIC), however, is that this conclusion depends strongly on the absence of transitory shocks to potential GDP. The LIC figures show the case in which natural GDP has a white noise component with a variance equal to that of the true model-based GDP gap. The researcher proceeds as before, but since natural GDP now includes a high-frequency component, the HP filter over-smooths the GDP series and thereby exacerbates the measurement error in the GDP gap. Correlations between the true and simulated GDP gaps fall substantially (Table 1). In the 2-sided case, the impulse responses are sharply attenuated towards zero on average, and their spread is much wider than in the absence of temporary shocks. Inference deteriorates correspondingly, so that with respect to the GDP gap, Figures 6a/6b(LIC) portray a transmission mechanism that is both weak and unreliable.

The VAR results are much stronger in the 1-sided case, however. There is unavoidable loss of power, particularly for the GDP responses, but the impulse responses show very limited bias at the median, except at the first step. Comparing 7a/7b(LIC) with 7a/7b(Canada), there is very little deterioration in inference regarding the transmission of monetary policy to inflation.

**8. Identification is (of course) crucial**

We have steered clear of identification issues, on the grounds that they do not usually cut very strongly between LIC applications and higher-income applications. We briefly depart from this strategy in Figures 7a and 7b, in order to show the impact of a relatively straightforward error in which the researcher places the interest rate too late in the recursive structure of the model. If our CEE-PS
ordering has any plausibility in low-income applications, this error might be a natural one for a researcher trained in the advanced-country literature. The researcher in Figures 8a/8b assumes a CEE-CB information structure when the true structure is in fact CEE-PS.

The result of this error is to produce impulse responses that are ‘weak and unreliable’ in the extreme: they are essentially zero, both economically and statistically. At the median, they reproduce the shapes of the true impulse responses; this is a feature we have observed in other experiments in which the identification is invalid but the researcher places the interest rate last in the ordering. The same result emerges, for example, in a full-information version of the model. There is no valid block-recursive ordering in this case, and an ordering that places the interest rate first then produces wildly implausible impulse responses at the median, by comparison with strongly muted but correctly-shaped responses when the interest rate is placed last. In the present case, of course, an enterprising researcher would presumably discard these muted results after trying alternative orderings and ‘discovering’ the correct one.

9. Small effect sizes mean weaker inference
In this section, we focus on the impact of small true effect sizes on VAR-based inference. Even within a tightly-parameterized DSGE, there are many parameters that may differ substantially between LIC and higher-income applications. The private-sector block incorporates both an interest-rate channel that operates through the IS curve and an exchange-rate channel that branches off from the interest parity condition to the IS and Phillips curves, while the monetary policy rule incorporates feedback from both inflation and the GDP gap along with a parameter that governs the degree of interest-rate smoothing. Based on Mishra et al. (2012, 2013), we focus here on two simple experiments. In Figures 9a and 9b, where we scale down the transmission elasticities in the IS and Phillips curves by a uniform 75 percent relative to the baseline model. In Figures 10a/10b we leave the transmission elasticities untouched and reduce the lag parameter in the monetary-policy rule by 75 percent.

Figures 9a/9b show the impact of uniformly low interest-rate and exchange-rate elasticities in the private-sector block. The true MTM is much weaker than in the baseline, particularly with respect to real activity. The estimated impulse responses continue to show very strong fidelity at the median, however, as expected in a situation of adequate data and strong identification. Comparing Figures 9a and 1a, there is also no discernible impact on the spread of estimated impulse responses. To a first approximation, therefore, the impact of weak transmission elasticities operates exclusively through the impact of small true effect sizes on the power of t-ratio tests against the null hypothesis. The impact is
substantial, however, with the scope for confident inference cut roughly in half (Figure 9b). For comparison purposes, Figure 9a also shows the true impulse responses when only the interest elasticity in the IS curve is reduced. The exchange-rate channel is quantitatively important in our model; if it is only the interest-rate elasticity that differs between LIC and non-LIC applications, the deterioration in the inference about the MTM (not shown) is mild.20

Figures 10a and 10b exploit the structure of the New Keynesian model to emphasize a transmission channel that may differ sharply between LICs and higher-income countries. Mishra and Montiel (2013) show that the pass-through of short-term interest rates to lending rates becomes progressively weaker at lower levels of development. While equations (3.1) – (3.4) do not directly incorporate a lending channel, the IS curve and interest-parity condition can be solved forward to express the levels of the current GDP gap and real exchange rate gap as functions of current and expected future short-term interest rates. As emphasized by Woodford (2001), monetary policy shocks affect the ‘tilt’ of the spending and real exchange rate gaps via the short-term interest rate, but they alter the equilibrium level of these variables only to the degree that they change an equally-weighted average of current and expected future short-term rates – or equivalently, applying an expectations theory of the terms structure, to the degree that they change current long-term rates. The pass-through of short rates to long rates is in turn governed both by the parameters of the private sector block and, very importantly, by the degree of interest-rate smoothing implemented by the central bank.21 In Figures 9a/9b, we leave the transmission elasticities unchanged and reduce the smoothing parameter in the monetary policy rule by 75 percent. Monetary policy shocks now pass through much more weakly into long rates and spending.

The results in Figures 10a/10b underscore the leverage of interest-rate smoothing in the New Keynesian model. The true impulse responses decline much more sharply than when the transmission elasticities are reduced by the same proportion. There is minimal evidence of bias in the impulse responses, but virtually no scope for reject the null hypothesis that the MTM is missing.

20 Woodford (2001) develops a simple model of limited financial participation in which the interest rate elasticity in the IS curve latter is inversely related to the proportion of households with access to financial markets.

21 Our simple model does not incorporate a separate bank lending channel, which would introduce an additional potential source of weak transmission related to imperfect competition and/or high transaction costs in the banking sector of low-income economies (Mishra et al. 2010, 2013)
10. Robustness to an alternative information structure

As a check on robustness, we implemented each of the experiments reported in Sections 5-9 in the CEE-PS model. Recall from Section 4 that the true effect sizes are an order of magnitude higher in this model than in the CEE-CB case. We find that controlling for the much stronger baseline inference in the CEE-PS case, the qualitative effects of each dimension of the LIC environment are similar in the CEE-PS case to what we have already observed. By implication, of course, quantitatively stronger pathologies are required in the CEE-PS case to generate a missing MTM.

11. Conclusions and extensions

In an effort to come to grips with the “missing MTM” in the empirical literature on LICs, we have reversed the standard dialogue between DSGEs and VARs. In the standard dialogue, VAR-based impulse responses provide an empirical standard against which DSGEs or other theory-based models can be evaluated. We have instead used DSGEs as a data-generating process, in order to ask a question about the validity of VAR-based impulse responses. If an MTM is present in the data, can standard VAR methods uncover it?

No parametric method will do very well if it mis-specifies the data-generating process. This is the basis of Sims’s critique of structural econometric modeling, and as long as the data are generated by a stable but unknown data-generating process, this critique favors the use of as few structural restrictions as possible to identify the MTM. VARs identified via short-run restrictions are very widely used in the literature on LICs, and perhaps even more intensively there than elsewhere given the relative dearth of structural modeling in these countries. Within this class, we have focused on CEE-recursive VARs, which impose just enough recursive structure to identify the monetary policy impulse responses, while leaving the other responses potentially unidentified. An off-the-shelf DSGE will not generate a solution with this property, but we have demonstrated that an otherwise-canonical DSGE is capable of doing so under mixed-information assumptions of the type often seen in the structural VAR literature.

For most of the paper, we assume that the VAR researcher imposes a valid identification scheme. With ample and high-quality data, the virtues of the VAR approach come through strongly. The LIC environment nonetheless poses a set of well-defined challenges to a strategy that ‘lets the data speak’: we investigate short samples, volatile data, measurement error, and high-frequency shocks to natural GDP. Among these challenges, we find that only classical measurement error creates a
substantial attenuation problem in the estimated impulse responses of inflation and the GDP gap. Conventional pre-filtering practices (using a 2-sided HP filter) have a similar impact on the GDP gap side when there are unobserved temporary shocks to natural GDP, but we find that a 1-sided HP filter does much better in this situation, displaying only very mild bias at the median. With the exception of pure macroeconomic volatility, however, each of these data-related challenges sharply reduces the power of standard $t$-ratio tests against a null hypothesis of zero response. Considered in combination, they suggest that statistically significant impulse responses will be rare in a LIC environment, in the absence of large true effect sizes.

The situation is much more difficult when true effect sizes are small. Other things equal – i.e., for given variances of the structural shocks – small effect sizes are capable of delivering both sides of the missing MTM. The researcher systematically discovers a ‘weak’ MTM, because the point estimates show very small bias at the median; and the MTM is simultaneously ‘unreliable’ in the sense that the data cannot reject a null of zero response. Among the sources of weak transmission, we have emphasized a low degree of interest-rate smoothing as a channel that is consistent with the low observed pass-through of short-term to longer-term interest rates in LICs, and one that may operate alongside more conventional sources of low pass-through including transaction costs and imperfect competition in the banking sector.

On balance, the evidence presented here suggests that conditional on valid identification, a number of features of the LIC environment undermine inference; but also that with the exception of measurement error, they do so without dramatically exacerbating small-sample bias. These results suggest that VAR researchers face a double bind in LIC environments, where the features we have studied individually are likely to be present in combination. One, true effect sizes may well be small: our experiments suggest that attenuation effects are relatively modest when identification is sound. To this extent, our results lend credence to a ‘facts on the ground’ interpretation of the missing MTM. Two, however, our results suggest that the LIC research environment may often be one in which VAR-based approaches are incapable of distinguishing modest effect sizes from zero, even in the presence of valid identification.

We close by considering two potential extensions of our approach among many. The first would address one of the simplest questions posed by this analysis: why not use monthly data? There are two powerful reasons to do so in a LIC environment, and one potentially daunting constraint. The first reason for proceeding with monthly data is that ten years of monthly data yield 120 observations rather than 40. The sample information will of course increase much less than three-fold, because the data
cover the same time period and the monthly model will display greater short-run persistence. But other things equal, we would expect sharper inference from the increase in sample size. In a structural VAR context, however, the more important reason for going to monthly data is that contemporaneous timing restrictions become more plausible. CEE-recursiveness is the least demanding and therefore most \textit{a priori} plausible approach for a researcher seeking to identify the MTM via recursive structure, but it strains credulity when applied to quarterly data. By underscoring the leverage of valid identification, our results suggest that the gains in small-sample bias from better identification in monthly data may be very substantial. The constraint, of course, is that measurement error is likely to be greater in monthly data, especially for measures of real activity. Our Monte Carlo approach is well suited to running this horse race, as a natural extension of the current paper.

A second extension would focus on the reality that agents in the economy (central bank and private sector alike) can observe both the exchange rate and the interest rate in real time. When these two variables form a simultaneous block, the monetary policy shock will not be identifiable by imposing a block-recursive structure. Kim and Roubini (2000) identify the monetary policy shock by imposing a non-recursive set of behavioral and information restrictions on the $B_0$ matrix; Sims and Zha (2007) motivate similar restrictions in a DSGE context. Putting these elements together would provide a useful robustness check on the results in this paper.
References


Figure 1(a): CEE-CB Baseline

Figure 1(b): CEE-CB Power (10% significance level)
Figure 1(c): CEE-CB T-stat
Figure 2(a): CEE-PS Baseline

Figure 2(b): CEE-PS Power (10% significance level)
Figure 3(a) and 3(b): to be added

Figure 4(a): CEE-CB Small Sample

Figure 4(b): CEE-CB Power (10% significance level)
Figure 5(a): CEE-CB Measurement Errors (y, πi)

Figure 5(b): CEE-CB Power (10% significance level)
Figure 6(a): CEE-CB Canada case - two-sided HP filter

Figure 6(b): CEE-CB Power (10% significance level)
Figure 6(a): CEE-CB LIC case - two-sided HP filter

Figure 6(b): CEE-CB Power (10% significance level)
Figure 7(a): CEE-CB Canada case - one-sided HP filter

Figure 7(b): CEE-CB Power (10% significance level)
Figure 7(a): CEE-CB LIC case - one-sided HP filter

Figure 7(b): CEE-CB Power (10% significance level)
Figure 8(a): CEE-CB Wrong Specification

Figure 8(b): CEE-CB Power (10% significance level)
Figure 9(a): CEE-CB Weak Transmission (elasticities scaled down by 75%)

Figure 9(b): CEE-CB Power (10% significance level)
Figure 10(a): CEE-CB Weak Transmission (i smoothing scaled down by 75%)

Figure 10(b): CEE-CB Power (10% significance level)
APPENDIX

The solution to a DSGE does not always imply reduced-form VAR representations for vectors of observable endogenous variables, and when such representations exist they may be infinite-order (Fernandez-Villanueva et al. 2005). When a VAR representation does exist, moreover, there is no guarantee that the structural shocks in the DSGE will be identifiable via short-run restrictions on the VAR. This appendix provides details on the DSGE models we use in the paper and the representation of their solutions as finite-order and CEE-recursive structural VARs.

Model Specification
As described in the text, our base model is New Keynesian open-economy model that combines an IS curve, a New Keynesian Phillips curve, an interest-parity condition, and a Taylor Rule for monetary policy (e.g., Berg, Karam and Laxton 2006). Using $\mathcal{I}_t$ and $\mathcal{I}_t^o$ to denote the information sets held by the central bank and the private sector at time $t$, the linearized and stationary form of this model can be written as

**IS equation:**

$$E[\bar{y}_t - a_1 \bar{y}_{t+1} - (1 - a_1)\bar{y}_{t-1} + a_2[a_3(i_t - \pi_{t+1} - \bar{r}) + a_4 \bar{e}_t] - e_t^y | \Omega_t^{PS}] = 0$$  \hspace{1cm} (A1)

**New Keynesian Phillips curve equation:**

$$E[\pi_t - b_1 \pi_{t+1} - (1 - b_1)\pi_{t-1} - b_2 \bar{y}_t + b_3 \bar{e}_t - e_t^\pi | \Omega_t^{PS}] = 0$$  \hspace{1cm} (A2)

**Uncovered interest parity equation:**

$$E[\bar{e}_t - c_1 \bar{e}_{t+1} - (1 - c_1)\bar{e}_{t-1} - (1/4) \cdot [i_t - \pi_{t+1} - \bar{r}] - e_t^e | \Omega_t^{PS}] = 0$$  \hspace{1cm} (A3)

**Monetary policy equation (Taylor rule):**

$$E[i_t - d_1(\bar{r} + d_2 \pi_{t+1} + d_3 \bar{y}_{t+1}) - (1 - d_1)i_{t-1} - e_t^i | \Omega_t^{CB}] = 0$$  \hspace{1cm} (A4)

**Structural shocks:**

$$\varepsilon_t \sim i. i. d \ N(0, \Sigma), \quad \Sigma \text{ is diagonal}$$  \hspace{1cm} (A5)

**Mixed information 1: CEE-CB**

Model solutions will depend sensitively on the assumed structure of information. We simplify very substantially in this paper by assuming that the contemporaneous component of agents' information sets are defined over shocks rather than over variables. Our first model follows Christiano, Eichenbaum and Evans (2005) in assuming that the central bank has full information while the private sector does not observe the contemporaneous shock to monetary policy. Thus $\Omega_t^{PS} = \{\Omega_{t-1}, \varepsilon_t^y, \varepsilon_t^\pi, e_t^e\}$ and $\Omega_t^{CB} = \{\Omega_t\} = \{\Omega_t^{PS}, \varepsilon_t^i\}$, where $\Omega_t$ (no superscript) denotes the full information set containing all shocks and variables up to and including period $t$.

Our solution procedure follows Christiano (2002), who adapts the undermined coefficients approach to a situation of mixed information. The general form of a solution should make all endogenous variables functions of the state variables of the model, including the exogenous shocks. In
our case, all four endogenous variables are state variables, given the structural lags in each equation. Our ‘guess’ solution for the model therefore takes the form

\[ x_t = Ax_{t-1} + B \epsilon_t, \]  

(A6)

for undetermined matrices \( A \) and \( B \), where \( x_t = [\bar{y}_t, \pi_t, \bar{e}_t, i_t] \). In contrast to Christiano (2002), lagged structural shocks do not enter (A6), because the shocks are \( i.i.d. \) in our case and are therefore not informative to agents, given the values of lagged variables. The solution proceeds by plugging (A6) into the structural equations (A1) – (A4) and solving out for \( x_t \), using the information assumptions to express expected values as the appropriate linear functions of past variables and current observed shocks. As described by Christiano (2002), \( A \) and \( B \) can then be solved sequentially, by equating coefficients between (A6) and the derived expression for \( x_t \).

Because the vector of interest to the VAR researcher is \( x_t \) itself, the structural VAR representation we are seeking is exactly the SVAR(1) in equation (A6). In our case, the VAR representation corresponds to the observable component of the state space representation of the solution to the DSGE.

The structure of \( B \) in the SVAR(1) representation of the solution will reflect our assumptions about observability of the contemporaneous shocks. In the CEE-CB case, our assumptions prevents the GDP gap, inflation rate, and real exchange rate gap from responding contemporaneously to the monetary policy shock, while the interest rate is capable of responding to all four structural shocks. Because the central bank responds to forecasts of inflation and the GDP gap, the structural shocks to the GDP gap, inflation and the real exchange rate gap enter the central bank’s reaction function because they are useful in predicting the future state of the economy.

For the parameterization reported in the text, the full model solution in the CEE-CB case is

\[
\begin{pmatrix}
\bar{y}_t \\
\pi_t \\
\bar{e}_t \\
i_t
\end{pmatrix} =
\begin{pmatrix}
0.63 & -0.01 & -0.30 & -0.30 \\
0.26 & 0.71 & -0.50 & -0.34 \\
0.08 & -0.02 & 0.74 & 0.23 \\
0.23 & 0.27 & -0.50 & 0.10
\end{pmatrix}
\begin{pmatrix}
\bar{y}_{t-1} \\
\pi_{t-1} \\
\bar{e}_{t-1} \\
i_{t-1}
\end{pmatrix} +
\begin{pmatrix}
1.27 & -0.02 & -0.60 & 0 \\
0.52 & 1.42 & -1.00 & 0 \\
0.17 & -0.05 & 1.48 & 0 \\
0.46 & 0.54 & -1.01 & 0.76
\end{pmatrix}
\begin{pmatrix}
\epsilon_y^t \\
\epsilon_i^t \\
\epsilon_e^t \\
\epsilon_t^i
\end{pmatrix}
\]

(A9)

Mixed information 2: CEE-PS

In the CEE-PS case, the private sector has full information while the central bank observes only the interest-rate shock. Proceeding as described above, the solution in this case is

\(<\text{to be added}>\)  

(A10)