

Local linear impulse responses for a small open economy*

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Abstract

Traditional vector autoregressions derive impulse responses using iterative techniques that may compound specification errors. Local projection techniques are robust to this problem, and Monte Carlo evidence suggests they provide reliable estimates of the true impulse responses. We use local linear projections to investigate the dynamic properties of a model for a small open economy, New Zealand. We compare impulse responses from local projections to those from standard techniques, and consider the implications for monetary policy. We pay careful attention to the dimensionality of the model, and focus on effects of policy on GDP, interest rates, prices and exchange rates.

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1. Introduction

Impulse response functions are widely used in macroeconomics in order to assess the persistence and relative effects of various macroeconomic shocks. These empirical observations are also used in the development of theoretical models. To characterize the effects of macroeconomic shocks, the standard approach is to estimate a vector autoregressive (VAR) model.¹ In order to derive the impulse responses from such a VAR, it is transformed into a moving average representation by appealing to Wold's decomposition theorem.

In this paper we take an alternative approach, following Jordà (2005). We apply local linear projections to obtain the impulse responses, as an alternative to the moving average transformation. An impulse response can be regarded as a revision in the forecast of a variable at a future horizon $t + s$ to a one-time experimental shock at time t , assuming that no other shocks hit the system. Based on this definition, Jordà proposes using multi-step direct forecasts, which he refers to as local projections, to calculate impulse responses. Jordà proves that impulse responses derived from such direct forecasts are consistent and asymptotically normal.

Standard impulse responses based on the moving average (MA) representation face several potentially serious problems. First, the lag length required for estimating a VAR in order to produce reliable impulse responses may be very large.² Second, the vector-MA representation of a VAR may not be unique and different invertibility assumptions can produce very different impulses.³ Third, the presence of unit roots and cointegration in the VAR leads to inconsistent impulses at longer horizons.⁴

Local projections are robust to misspecification. If the model is correctly specified and a quadratic loss function (such as the mean-squared forecast error) is used to evaluate forecasts then estimation efficiency generally assures forecast efficiency. In this case, standard iterative forecasting procedures are efficient. However, Ing (2003) proves that in misspecified univariate autoregressive processes multi-step direct forecasting dominates usual one-step ahead iterative forecasting in terms of the

¹To identify structural shocks from the estimated reduced form shocks, either a recursive causal ordering or structural relations are imposed on contemporaneous shocks, and/or some long run effects of shocks are restricted.

²See Kapetanios, Pagan, and Scott (2007) for an extreme scenario.

³See Lippi and Reichlin (1993).

⁴See Phillips (1998) and Pesavento and Rossi (2006).

mean squared error. Furthermore, Lin and Tsay (1996) demonstrate in a Monte Carlo study that direct forecasting performs better in the presence of unknown unit roots and cointegration than forecasting with vector error-correction models (VECM), even though unit roots and cointegration are ignored in direct forecasting. The problem is that cointegration tests often indicate too few, or occasionally too many, unit roots in the VECM and therefore lead to misspecification.⁵ In addition, Marcellino, Stock, and Watson (2006) describe empirical situations, like low-order autoregressions, where direct forecasting is useful.

The potential for a misspecified VAR is manifold, from variable selection to lag length specification. Estimation procedures that are robust to misspecification are therefore highly desirable. Jordà's Monte Carlo evidence shows that impulse responses can be estimated more accurately by using local linear projections than by vector moving average (VMA) methods. Typical estimates of VARs are global approximations to the data generating process, and these approximations are optimally designed for one-period ahead forecasting. However, given the ubiquity of model misspecification, local approximations may be preferable to global approximations at longer horizons. Jordà's Monte Carlo results illustrate that the loss of efficiency from using local projection impulse responses (instead of a correctly specified VAR) is very small, and that local projection impulses are much more accurate at medium to longer horizons than VMA based methods when the model is misspecified.

Our paper contributes to the existing literature in several ways. Jordà provides an empirical example for his local projection-based impulses, using a recursive causal ordering to identify structural shocks for a large-economy model. In our paper we extend his method to a non-recursive identification scheme and apply the model to a small open economy instead. We explicitly account for the features of the New Zealand economy. Our model is related to that of Cushman and Zha (1997) for Canada, though, our set of variables is tailored to New Zealand and we use local projections instead of traditional VMA based methods. We compare impulse response

⁵Having too few unit roots in the VECM means that there are too many cointegrating vectors, and vice versa. On the other hand, a VAR specified in first differences assumes that variables are not cointegrated because no error-correction terms are included. If there is cointegration, then such a model is misspecified. Further, Hendry (2006) points out that structural breaks in the cointegrating relationship lead to systematic forecast failure for VECMs. Chevillon and Hendry (2005) demonstrate the usefulness of direct forecasting in small samples in the presence of breaks and unit roots.

functions based on local projections to those from VMAs. The dynamic responses to monetary policy shocks that we derive with Jordà’s method are consistent with standard macroeconomic theories, whereas traditional structural impulse responses reveal several idiosyncracies or “puzzles”.

The rest of the paper is organized as follows. Section 2 outlines the method used to calculate impulse response functions. Section 3 discusses the specification of the models and the criteria used to derive the specifications. Results are presented in section 4 and conclusions are drawn in section 5.

2. Impulse responses from local projections

We discussed in the introduction several studies that have pointed towards the benefits of using direct forecasting when a researcher is concerned about misspecification. We also identified three major problems with standard impulse response functions. We discuss these in more detail before outlining the procedure for calculating impulses from local projections based on direct forecasting.

It is a matter of controversy whether a VAR can adequately capture the dynamic process that drives the data in order to produce reliable standard impulse responses. In principal, MA components in a data generating process can be approximated by an autoregression. In practice, however, typical sample sizes may be too small to accommodate a sufficiently long lag structure. For example, Cooley and Dwyer (1998) argue that basic real business cycle models follow VARMA processes and that the VAR-approach fails to uncover the true impulse responses.⁶ Similarly, Kapetanios, Pagan, and Scott (2007) find that an “extremely high order” VAR is needed to extract standard impulses, much larger than is feasible in typical empirical studies.

Lippi and Reichlin (1993) draw attention to an additional problem with standard impulse response calculations. They see as arbitrary the invertibility assumption implicitly imposed on the MA process when the Wold decomposition is applied. A problem arises because the MA representation of an estimated VAR is not unique in terms of the covariance structure – so-called non-fundamental representations ex-

⁶Chari, Kehoe, and McGrattan (2005) provide further arguments along these lines, whereas Christiano, Eichenbaum, and Vigfusson (2006) disagree.

ist, as emphasized by Hansen and Sargent (1980). Lippi and Reichlin demonstrate for a specific VAR how different assumptions about the invertibility of the VMA representation lead to very different impulse responses.⁷

Most VARs for impulse response analysis are specified with variables in levels, and possible unit roots and cointegration are ignored. Consistent parameter estimates can be obtained by applying least squares to levels VARs, even when unit roots and cointegration are ignored (Sims, Stock, and Watson 1990). However, impulse responses are highly non-linear functions of the VAR parameters and the consistency results do not carry over to the impulse response functions. Phillips (1998) proves that impulses derived from a levels VAR are inconsistent at long horizons in the presence of unit roots, or near unit roots, and cointegration. Pesavento and Rossi (2006) provide Monte Carlo evidence on the relevance of Phillips' results in typical empirical applications.

Schwert (1987) has shown in a very influential paper that many macroeconomic time series are well characterized by unit root processes with large negative MA components. Furthermore, Zellner and Palm (1974) and Wallis (1977) show that omitting from a VAR a variable that is part of the true data generating process leads the included subset of variables to follow a VARMA process instead of a VAR.⁸ Clements and Hendry (1996) find in a Monte Carlo study that direct forecasts can outperform iterated forecasts in such cases when the negative MA component is large.⁹ Chevillon and Hendry (2005) extend the study of Clements and Hendry to unit root processes with deterministic terms and structural breaks. Chevillon and Hendry (p. 217) recommend direct forecasting when the data “exhibit either stochastic or deterministic non-stationarity (unit root and breaks) and the available sample is too small for reliable inference.” Furthermore, Ing (2003) and Marcellino, Stock and Watson (2005) have carried out extensive empirical comparisons of the forecast performance of direct versus iterative methods for variables specified in stationary form. Marcellino et al. find that iterated forecasts generally outperform direct forecasts if

⁷See also Blanchard and Quah (1993) for a critical response, and Sims and Zha (2006, footnote 16, p. 269) for a possible solution that was explored further by Giannone and Reichlin (2006).

⁸Of course, the true data generating process is unknown and any VAR or VARMA is an approximation to the unknown statistical model. Tsay (1993, p. 140) goes as far as to postulate that “all statistical models are wrong” and “local approximations are more relevant than global ones in forecasts.”

⁹Bhansali (2002) provides a survey on direct forecasting.

it is feasible to select long-lag specifications. However, in low-order autoregressions and at short horizons, direct forecasts are preferable for several series.¹⁰ In the rest of this section we briefly discuss the direct forecasts that form the basis of Jordà's (2005) local projection-based impulse response functions (IRFs).

Standard forecasting several periods ahead is based on estimating model parameters for a given sample period and then using this set of parameters for forecasting iteratively one step ahead at a time. In contrast, direct forecasting estimates a new optimal set of parameters for each forecasting horizon, minimizing a quadratic loss function for the forecast errors at each horizon.

Consider an n -dimensional vector \mathbf{y}_t of random variables. Impulse responses can be defined as the revision to the best mean-squared-error predictor when a shock hits, without reference to the unknown data generating process and even if the Wold decomposition does not exist.¹¹ Following Jordà (2005), we define the impulse response at time $t + s$ arising from the experimental shocks in \mathbf{d}_i at time t as:

$$IR(t, s, \mathbf{d}_i) = \frac{\partial \mathbf{y}_{t+s}}{\partial \delta_t} = E(\mathbf{y}_{t+s} | \delta_t = \mathbf{d}_i; \mathbf{X}_t) - E(\mathbf{y}_{t+s} | \delta_t = \mathbf{0}; \mathbf{X}_t), \quad (1)$$

where $i = 0, 1, 2, \dots, n$; $s = 0, 1, 2, \dots$; $\mathbf{X}_t \equiv (\mathbf{y}_{t-1}, \mathbf{y}_{t-2}, \dots)'$; \mathbf{d}_i is a vector additively conformable to \mathbf{y}_t ; and $\mathbf{0}$ is a vector of zeroes. The expectations are formed by projecting \mathbf{y}_{t+s} on to the linear space of \mathbf{X}_t (i.e., from local linear projections):

$$\mathbf{y}_{t+s} = \alpha^s + \mathbf{B}_1^{s+1} \mathbf{y}_{t-1} + \mathbf{B}_2^{s+1} \mathbf{y}_{t-2} + \dots + \mathbf{B}_p^{s+1} \mathbf{y}_{t-p} + \mathbf{e}_{t+s}^s, \quad (2)$$

where α^s is a vector of constants and the \mathbf{B}_j^{s+1} are coefficient matrices at lag j and horizon $s + 1$. For every $s = 0, 1, 2, \dots, h$ a projection is carried out. The estimated IRF is then given by

$$\widehat{IR}(t, s, \mathbf{d}_i) = \widehat{\mathbf{B}}_1^s \mathbf{d}_i \quad (3)$$

with the normalization $\mathbf{B}_1^0 = \mathbf{I}$ (where \mathbf{I} is an identity matrix of an appropriate dimension). For example, \mathbf{d}_i can be thought of as an innovation to the vector \mathbf{y}_t , yielding an impulse response of $\widehat{\mathbf{B}}_1^s$.¹² The horizon of the forecast is thus s , indicating how $E(\mathbf{y}_{t+s} | \delta_t; \mathbf{X}_t)$ changes in response to a shock at time t .

¹⁰Schorfheide (2005) has recently suggested a new final prediction-error criterion to choose between the two forecasting methods in stationary VARs. In addition, he confirms that direct forecasting performs better than iterated forecasting when misspecification is "large."

¹¹See Koop, Pesaran, and Potter (1996) and Potter (2000).

¹²See Jordà for details on the timing of the \mathbf{B}_j^{s+1} .

The impulse responses from local approximations are conceptually simple and are easy to implement since one can conduct univariate least squares regressions for each variable at every horizon. Weiss (1991) establishes consistency and asymptotic normality of direct forecasts in general.¹³ Jordà demonstrates that impulse response estimates from local projections are consistent and that inference can be performed using standard heteroscedastic and autocorrelation (HAC) robust standard errors, such as Newey-West standard errors. These HAC standard errors correct for the moving average terms that exist in forecast errors.

We apply the local projections to levels data. We are prepared to admit – though not impose – the possibility of unit roots and cointegration for the macroeconomic variables in our data set. We justify the specification of \mathbf{y}_t in levels based on the Monte Carlo results of Lin and Tsay (1996), among others.¹⁴ Furthermore, to ensure the robustness of our results, we investigate whether our results are sensitive to the inclusion of additional regressors.

3. Model specification

3.1 Choice of variables

The Reserve Bank of New Zealand Act of 1989, together with the Policy Targets Agreement (PTA) signed by the Governor of the Reserve Bank of New Zealand and the Minister of Finance, determines the objectives of the Reserve Bank. The Reserve Bank Act identifies price stability as the pre-eminent goal of the Reserve Bank, while clause 4b of the 2002 version of the PTA requires the Reserve Bank “to seek to avoid unnecessary instability in output, interest rates, and the exchange rate”. Consequently, prices, output, interest rates and the exchange rate provide a minimal domain whose behaviour needs to be modelled for New Zealand monetary policy purposes. We thus include in our model: real gross domestic product (GDP); the consumers price index (CPI) excluding goods and services tax effects and interest charges; the 90 day bank bill rate; and the real exchange rate.¹⁵ Our quarterly data

¹³Local linear projections are part of the class of direct forecasts. Some authors refer to direct forecasting as dynamic estimation, adaptive forecasting or multi-step forecasting.

¹⁴For empirical evidence with New Zealand data, showing that VECM-based IRFs are very sensitive to model specification, see Haug, Karagedikli, and Ranchhod (2005).

¹⁵A more complete description of the data is provided in table 1.

cover the sample period from 1987Q3 through to 2006Q1. Economic reforms in New Zealand during the 1980s have influenced our choice of the starting date for the sample. We tried to avoid the periods of major structural changes. The endpoint was chosen based on the availability of data at the time when we took up this research.

We regard the 90 day bank bill rate as a good proxy for the policy stance of the Reserve Bank for the following reasons. Since March 1999 the Reserve Bank's official policy interest rate has been the official cash rate (OCR). The Reserve Bank remunerates commercial bank deposits held overnight at the Reserve Bank at the OCR less 25 basis points, and is prepared to lend to commercial banks overnight at the OCR plus 25 basis points, via repurchase agreements. Although the 90 day bank bill rate is not directly determined by monetary policy, it is clear from the data that the bulk of the variation in the 90 day rate is determined by the current official cash rate and expectations of future official cash rates.

Since New Zealand is a small open economy, we incorporate a world sector that includes 'world' GDP, 'world' prices, and a short-term 'world' interest rate.¹⁶ These world variables, constructed by the Reserve Bank of New Zealand, enter the Reserve Bank's main macroeconomic model as exogenous inputs. Given that New Zealand is a small economy, and following Buckle et al. (2002), we assume that there is limited informational content from New Zealand's lagged behaviour to contemporary foreign variables, and therefore assume that the world variables only respond to their own lags. Our model thus takes the following form, with the lag length $p = 1$ and ignoring constant terms:

$$\begin{bmatrix} \mathbf{y}_t^{NZ} \\ \mathbf{y}_t^W \end{bmatrix} = \begin{bmatrix} \mathbf{B}_{1,11}^1 & \mathbf{B}_{1,12}^1 \\ \mathbf{0} & \mathbf{B}_{1,22}^1 \end{bmatrix} \begin{bmatrix} \mathbf{y}_{t-1}^{NZ} \\ \mathbf{y}_{t-1}^W \end{bmatrix} + \begin{bmatrix} \mathbf{e}_t^{0,NZ} \\ \mathbf{e}_t^{0,W} \end{bmatrix}$$

The vector \mathbf{y}_t^{NZ} contains the 4 domestic variables: GDP, CPI, interest rate (R90D), and the real exchange rate denoted RER. The rest of the world is represented by \mathbf{y}_t^W , which contains wGDP, wCPI, and the world interest rate denoted wR90D. All variables are in natural logarithms, except for the domestic and world interest rate. The $\mathbf{B}_{1,ij}^1$ are sub-matrices of \mathbf{B}_1^1 , and $\mathbf{e}_t^{0,NZ}$ and $\mathbf{e}_t^{0,W}$ are the reduced-form shock vectors that form \mathbf{e}_t^0 in equation (2) when $s = 0$.

¹⁶See Smith (2004) on the construction of 'world' GDP for New Zealand from the GDP of 12 major trading partners. 'World' prices are constructed in a similar fashion from the CPIs of 5 countries. The 'world' interest rate is an 80/20 average of US and Australian 90-day interest rates.

Standard impulse response functions have been calculated for small open economies by various authors. The domestic variables included in our model differ from Cushman and Zha's (1997) set for Canada in that we use the real exchange rate instead of the nominal exchange rate, and we do not include the value of total exports or imports. Furthermore, we do not find a useful role for a measure of money (M0 in our case). In our model we regard the real exchange rate as a summary measure of changes in the international trade sector, and changes in trade flows are captured in real GDP, since it includes exports and imports. Several studies of European monetary transmission mechanisms have employed the same basic set of variables that we use in our study.¹⁷ For example, Mojon and Peersman (2003) use these variables for individual country vector autoregressions, and Peersman and Smets (2003) use the equivalent synthetic data to model the euro-area as a whole. Their domestic variables are real GDP, the CPI, a short-term interest rate and a real exchange rate. Their world-block variables are world commodity prices, US real GDP, the US CPI and a US short-term interest rate. Cushman and Zha used the same world-block variables. We differ in omitting world commodity prices, in our basic model version, which others have found necessary to include in order to deal with the so-called price-puzzle.¹⁸

We explore the sensitivity of the IRFs from the 7-variable model to the inclusion of additional variables used in the literature: the price of oil, the terms of trade and commodity prices. We add one variable at a time so that our model does not exceed eight variables in total. Our aim is parsimony.

In our first model variant we add the world oil price to the baseline model, as a fourth world-sector variable expressed in US dollars. In this respect, we follow Kim and Roubini (2000) who found a crucial role for oil prices in non-US G7-countries. Since oil is ubiquitous in production processes and consumption bundles, it is not surprising that the impact of oil price shocks has received considerable attention over the decades. This interest has also been prompted by the substantial shocks that have affected the price of oil. For example, the nominal price of crude oil (in US dollars) trebled between 2002 and 2006.

In our second model variant we add the terms-of-trade to the domestic block

¹⁷See the studies in Angeloni, Kashyap, and Mojon (2003).

¹⁸See for example Sims (1992). Kim and Roubini (2000) discuss various other empirical anomalies that plague the IRF literature.

of our baseline model. Recent New Keynesian dynamic stochastic general equilibrium (DSGE) models for small open economies attribute an important role to the terms of trade, which prompts us to include it in our analysis.^{19,20}

The third model variant incorporates commodity prices. Sims (1992) suggested including commodity prices in order to eliminate or lessen the price-puzzle. This puzzle refers to IRFs that show an increase in prices following a monetary policy tightening via interest rate increases. The commodity price may contain information that a central bank uses but that is not otherwise captured in a VAR. We include the world commodity price in our model as a fourth world-sector variable.

Our sample period is relatively short, so we opt for a parsimonious model in order to preserve degrees of freedom and to avoid problems with over-parameterization. Extending the sample period to earlier dates is problematic because of the structural changes in the New Zealand economy in the 1980s. For the same reason, we estimate a smaller New Zealand model than Buckle et al. (2002) and Buckle, Kim, and McLellan (2003). For example, we exclude the soil moisture deficit as a regressor. Although it is widely believed that a substantial drought contributed to the recession that was experienced in 1997/98 (in tandem with the flow-on effects of the Asian financial crisis), the seasonally adjusted soil moisture deficit does not Granger-cause the other variables in our model. There is also no statistical evidence of a contemporaneous relationship between the soil moisture deficit and the other variables in the model.²¹

Our model abstracts from a number of other macroeconomic factors. In contrast to Buckle et al. (2002) for New Zealand, and Dungey and Pagan (2000) for Australia, we exclude equity prices and do not model ‘domestic demand’. Nor do we separately account for the run up in international commodity prices in the 1990s and the concomitant boom in house prices. Whether omitting these additional factors is material or not cannot be readily determined. What is clear is that data limitations severely circumscribe the number of relationships that can be estimated. As mentioned above, any misspecification of the vector of endogenous variables induces a

¹⁹See Carlstrom and Fuerst (2006) for additional empirical evidence on the role of oil prices in US monetary policy and Galí and Monacelli (2005) for a (Calvo-type) sticky-price DSGE model with a role for the terms of trade.

²⁰Many recent DSGE studies employ Bayesian methods, including Smets and Wouters (2003) and Lubik and Schorfheide (2005). Sims (2003) is very critical of the Bayesian approach in the context of DSGE models because results turn out to be very sensitive to minor changes in model specification and assumptions about prior distributions, even for “uninformative” priors.

²¹Results are available on request.

moving average process, which suggests that local linear impulse responses may provide a more accurate characterization of the dynamics induced by structural shocks than the iterative methods that are usually used.²²

3.2 Identification

Jordà does not explore non-recursive identification schemes for structural shocks. Jordà’s method to derive IRFs describes the consequences of a reduced form shock to a particular data series. However, reduced form shocks reflect a variety of underlying ‘structural’ innovations. In his empirical example, Jordà applies a standard Choleski decomposition that imposes a recursive ordering for the contemporaneous effects of shocks. The impulse responses crucially depend on the ordering of the variables in the VAR.²³ Cushman and Zha (1997), among many others, have criticized this approach. They suggest structural identification schemes should be used, where the imposed structure is based on economic theory.

We fit a VAR to the data in order to estimate the one-step ahead shocks. At the one-step horizon vector autoregressions and local linear projections coincide exactly. A VAR produces reliable one-period ahead forecasts even when the model is misspecified,²⁴ and VAR-based forecasts are optimal for one-period ahead forecasting. We (over-)identify our structural shocks using assumptions about contemporaneous relationships, rather than relying on the strict temporal ordering implied by a Choleski decomposition. Our identification scheme, like that of others, indicates how our ‘structural’ shocks are translated into the reduced form (contemporaneous) shocks.

Consider a structural vector autoregression of the following form:

$$\mathbf{B}_0 \mathbf{y}_t = \alpha + \mathbf{B}_1 \mathbf{y}_{t-1} + \dots + \mathbf{B}_p \mathbf{y}_{t-p} + \mathbf{u}_t \quad (4)$$

where \mathbf{y}_t is an $n \times 1$ vector of macroeconomic variables at time t , α is an $n \times 1$ vector of constants; \mathbf{B}_j is an $n \times n$ matrix of parameters for $j = 0, 1, \dots, p$, and \mathbf{u}_t is an $n \times 1$ vector of structural shocks with, as usual in the literature, a diagonal

²²Also, every additional variable added to the model introduces a further structural shock. In the standard identification schemes used in the literature, structural shocks are assumed to be mutually uncorrelated. One would like to keep empirical models in line with theoretical ones. However, standard theoretical macroeconomic models, like real business cycle models for example, are usually driven by only a very few shocks.

²³Pesaran and Shin (1998) suggest an alternative method that does not depend on the ordering.

²⁴See Stock and Watson (1999).

variance-covariance matrix \mathbf{D} and $\mathbf{u}_t \sim N(0, \mathbf{D})$. The reduced form equation, which is equation (2) for $s = 0$, is given by:

$$\mathbf{y}_t = \alpha^0 + \mathbf{B}_1^1 \mathbf{y}_{t-1} + \mathbf{B}_2^1 \mathbf{y}_{t-2} + \cdots + \mathbf{B}_p^1 \mathbf{y}_{t-p} + \mathbf{e}_t^0,$$

Comparing the structural and reduced form equations implies $\alpha = \mathbf{B}_0 \alpha^0$; $\mathbf{B}_j = \mathbf{B}_0 \mathbf{B}_j^1$; and $\mathbf{u}_t = \mathbf{B}_0 \mathbf{e}_t^0$.

Our identification scheme depends on restrictions on the contemporaneous matrix:

$$\mathbf{e}_t^0 = \mathbf{B}_0^{-1} \mathbf{u}_t \tag{5}$$

where \mathbf{u}_t is the vector of *interpretable* structural shocks, \mathbf{e}_t^0 is the vector of reduced form shocks, and \mathbf{B}_0 is the impact matrix that has sufficient restrictions imposed upon it to identify the structural shocks from the variance-covariance matrix of reduced-form errors.²⁵ Thus, we use an estimate of the variance-covariance matrix $\text{Var}(\mathbf{e}_t^0) \equiv \mathbf{\Omega}$ from one-period ahead forecasts in order to identify the impact of structural shocks. $\mathbf{\Omega}$ relates to the variance-covariance matrix \mathbf{D} of the structural shocks as follows:

$$\mathbf{\Omega} = \mathbf{B}_0^{-1} \mathbf{D} \mathbf{B}_0^{-1'}$$

Using an estimate of \mathbf{B}_0^{-1} and a structural shock $\mathbf{u}_i = [0 \dots 0 \ \sigma_i \ 0 \dots 0]'$, one can derive a reduced-form innovation $\mathbf{B}_0^{-1} \mathbf{u}_i = \mathbf{d}_i$ as needed for the above local projections. The expected effect can then be traced out for all of the variables in \mathbf{X}_{t+s} , using local projections at every horizon. Conventionally, σ_i would be the estimated standard deviation of the i^{th} structural shock or perhaps unity. We employ only short-run (or, equivalently, contemporaneous) restrictions on contemporaneous relations and no long-run restrictions. Christiano, Eichenbaum, and Vigfusson (2006, p. 3) argue that structural VARs based on short-run restrictions perform “reasonably well”.

3.3 Non-recursive identification

Table 2 illustrates our baseline identification scheme. We broadly assume a near-recursive structure in the impact matrix, but with the following exceptions:

- foreign interest rates are allowed to affect domestic interest rates, but not vice-versa;

²⁵See for example chapter 11 of Hamilton (1994).

- every variable can affect the real exchange rate contemporaneously (consistent with its role as an asset price);
- we impose block exogenous restrictions on the world variables.

We have thus assumed that (domestic and world) interest rate shocks do not have an instantaneous effect on output or prices. We also assume that output shocks have a contemporaneous effect on prices, on interest rates, and on the exchange rate, but not vice-versa. For convenience, we choose an identity matrix for the diagonal variance-covariance matrix \mathbf{D} , but conversely allow the diagonal elements of \mathbf{B}_0 to assume any non-zero values. We identify each structural shock with a particular equation and variable.

The regressors differ across individual equations in our reduced form model and we allow for interactions of the error terms across equations. For this reason, we apply seemingly unrelated regressions for the estimation of the reduced form residuals.

We impose our identification scheme by first estimating the variance-covariance matrix of the reduced-form errors for a VAR(1). The lag length of the reduced form VAR is determined using Schwarz's Bayesian information criterion (BIC), with a constant effective sample size for the comparisons against models with up to four lags.²⁶

Following Hamilton (1994), we maximize the concentrated log-likelihood to obtain estimates of \mathbf{B}_0 :

$$\max_{\mathbf{B}_0} -\frac{Tn}{2} \ln(2\pi) + \frac{T}{2} \ln |\mathbf{B}_0|^2 - \frac{T}{2} \ln |\mathbf{D}| - \frac{T}{2} \text{Trace} [\mathbf{B}'_0 \mathbf{D}^{-1} \mathbf{B}_0 \hat{\mathbf{\Omega}}] \quad (6)$$

where \mathbf{D} is restricted to be an identity matrix, and $\hat{\mathbf{\Omega}}$ is the estimate of the variance-covariance matrix of the reduced form residuals. This method provides consistent parameter estimates, but because of the block exogenous lag restrictions the parameter estimates are not fully efficient. Diaz, Machado, and Pinheiro (1996) suggest a recursive method that partitions the parameter space to obtain full-information maximum likelihood parameter estimates. Employing this method for our baseline model and identification scheme results in trivial changes to our parameter estimates, and so for convenience we continue with the method described above.

²⁶ Schwarz's BIC chooses the lag length consistently. Ivanov and Kilian (2005) found that the BIC produces the most accurate VMA-based IRFs in terms of relative mean-squared errors in a Monte Carlo comparison of six alternative information criteria. This result holds for quarterly samples with less than 120 observations. In larger samples, the Hannan-Quinn criterion dominates.

Clements and Hendry (1996) find that direct forecasts are most appropriate when the data are integrated and the errors of the misspecified model exhibit large negative MA components; ignoring such MA terms increases the downward bias in least squares estimates of integrated processes. We inspected the sample autocorrelation and partial autocorrelation functions for the reduced form residuals. Given that these residuals are for a VAR(1), there is some indication that the equations for the domestic and world 90-day rates, and the equation for the real exchange rate, are overly parsimonious, with significant autocorrelations at some longer lags. Whether these autocorrelations reflect omitted moving average terms or simply omitted lags in the regressions is difficult to determine. However, they do provide good reasons for applying direct forecasts.

4. Empirical results

4.1 Local projection impulses from a world-augmented model

Figures 1 and 2 display the local projection-based impulse response functions for the basic identification scheme in table 2. This 7-variable model includes the four domestic variables together with the three world variables: GDP, CPI, R90D, RER, wGDP, wCPI, and wR90D. For the purposes of comparison, we depict the local projection IRFs alongside the VMA-based IRFs from a VAR(1). We discuss results for standard IRFs in section 4.4 and concentrate before then on projection-based IRFs instead. The confidence intervals, derived from the local projections, treat the identification scheme as known. Given that the parameters of the impact matrix \mathbf{B}_0 are imprecisely estimated, the confidence intervals, delimited by the short-dashed lines, understate the imprecision in the IRF estimates.

The impulse responses support a fairly conventional view of many macroeconomic dynamics. In figure 1, a domestic GDP shock shows a significantly positive and persistent effect on GDP over time. Positive domestic GDP shocks also have a significant and positive impact on prices with a lag of about 4 quarters and a duration of some 4 quarters for the significant range. This price effect is consistent with a short-run Phillips-curve trade-off.

Interest rates and the exchange rate are significantly positively related to GDP

shocks, though interest rates react with a delay of around 3 quarters. The local linear projections imply that the peak interest rate response to a GDP shock comes about 6 quarters after the shock. Positive shocks to GDP increase the real exchange rate for about $3\frac{1}{2}$ years. Thereafter, these effects are reversed. A similar significant reversal happens after 3-4 years for GDP and the CPI in response to the GDP shock.

A price shock persists and is significant for about 7 quarters. Interestingly, in the context of New Zealand's policy of inflation targeting, interest rates do not respond strongly to positive CPI shocks; there are periods of slight increases in interest rates but they are not statistically significant. CPI shocks do not appear to have a statistically significant effect on GDP and a limited significant effect on real exchange rates 1014 quarters after the impact.

Positive interest rate shocks cause interest rates to increase on impact, but then these effects are unwound from the 3rd to 6th quarter after the impact. An increase in domestic interest rates does not result in a significant increase in prices – there is no price puzzle. There is instead a very significant drop in prices after a delay of 2 quarters. Domestic interest rate shocks have mostly a negligible, statistically insignificant, impact on GDP. Interest rate shocks have a significant (but fairly trivial) near-term effect on the real exchange rate, but after the first quarter the effects are no longer statistically or economically significant.

In the context of this 7-variable VAR, positive exchange rate shocks (and the attendant interest rate response) serve to place significant downward pressure on both GDP and the CPI. The impact on gross domestic product is reasonably pronounced and prolonged, and occurs after a short delay. In this context the behaviour of interest rates in response to exchange rate shocks is rather unusual. In contrast to results from DSGE models (e.g., Lubik and Schorfheide 2006 and Lubik 2007), there is some indication that, after a slight delay, interest rates respond positively and significantly to exchange rate shocks for 2 quarters, despite the ongoing weakness in output. At short to medium horizons real exchange rate shocks persist, however the effects are only significant for the first 4 quarters and eventually are reversed after about 10 quarters.

The responses of domestic variables to world shocks in figure 2 are quite pronounced. The domestic price level is strongly positively related to a world GDP

shock; a positive world GDP shock also lowers the real exchange rate significantly for a substantial period of time. In addition, a world GDP shock significantly decreases domestic interest rates after about a year and leads to a significant increase in domestic GDP after a long (3 year) delay.

World price shocks appear to have no lasting significant effects on the domestic CPI, judging by the confidence band. The same is true for the effects on domestic interest rates. The effects of world price shocks on domestic GDP and the RER are also basically insignificant.

Foreign interest rate shocks appear to depress domestic output very significantly for a long period of time. It takes almost 4 years for New Zealand GDP to recover from a world interest rate shock. Notwithstanding the domestic output effects, there is some indication that domestic interest rates initially increase in response to a foreign interest rate shock before they start to fall, though this initial effect is barely significant, based on the confidence band. The effect of world interest rate shocks on the real exchange rate is statistically insignificant, except for the 10th to 15th quarter after the impact, although the confidence band is rather wide, indicating that the effects are very imprecisely estimated. However, despite this mostly negligible effect on the real exchange rate, a positive shock to the world interest rate does significantly increase the domestic price level for a few quarters, though the effect is not very large.

4.2 Sensitivity to the identification assumptions

The baseline identification restrictions reflect fairly common views as to the propagation mechanism, with output shocks preceding price movements and policy having a delayed effect on the economy. However, table 3 reveals that this model does not allow for some of the contemporaneous correlations that are evident in the data. In particular, the baseline identification scheme does not replicate the contemporaneous correlations that exist between domestic variables and world GDP and the world CPI.

In this section we explore what happens to the impulse responses when we allow domestic GDP to be contemporaneously related to world GDP and the world CPI, and simultaneously allow the domestic CPI to be correlated to the world CPI. This alternative identification scheme for our 7-variable model is therefore the same as the scheme in table 2, except that b_{15} , b_{16} and b_{26} are not set equal to zero but are

instead left unrestricted.

Overall, altering the identification scheme has virtually no impact on the impulse responses from domestic GDP shocks and domestic interest shocks, and the impulse responses from shocks to the world variables. In both scale and shape, these impulse response functions change very little overall.²⁷

The same cannot be said of the impulse responses associated with the CPI and the impulses associated with the real exchange rate. With the alternative identification scheme GDP responds significantly negatively to CPI shocks at medium horizons. The CPI response to an initially positive price shock is largely negative. Under the alternative identification scheme the impulse to interest rates from positive CPI shocks is now significantly positive on impact, and becomes insignificantly different from zero afterwards. The real exchange rate response to CPI shocks changes dramatically: CPI shocks now have a significant and positive impact on the exchange rate for the first 3 quarters and eventually a negative significant effect after about 2 $\frac{1}{2}$ years.

Structural real exchange rate shocks do not lead to a significant response of GDP and the CPI, except for an initial decline of the CPI in the first quarter after the shock. The impact of real exchange rate shocks on interest rates is now contemporaneously negative – reducing interest rates by about 40 basis points – and mostly insignificant after the first quarter. Real exchange rate shocks now reveal less persistence with only limited longer run significant effects.

We have experimented with other variants of the basic identification scheme, guided by the empirical correlations in the data. However, the overall results were within the range of the results for the two identification schemes that we have discussed here.

4.3 Extensions of the 7-variable model

We explore the sensitivity of the IRFs from the baseline 7-variable model used so far to the inclusion of additional variables. We consider an 8-variable model that incorporates the price of oil, the terms of trade and commodity prices in turn. We

²⁷We do not provide the figures in the paper in order to conserve space. However, they are available from the authors on request.

add one variable at a time as described in section 3.1.²⁸

We first include oil prices into our baseline model as an additional world-sector variable. The identification scheme for the model is an extension of the basic scheme in table 2, with all additional b_{ij} unrestricted, except for b_{38} , b_{78} , b_{81} , b_{82} , b_{83} and b_{84} which are all set equal to zero. Introducing oil into the model essentially leaves the IRFs of the other seven shocks unchanged, with only minor effects on the timing of the peaks and the magnitudes. The oil shock itself has a positive effect on GDP on impact, but then contracts output for almost two years (not all of which is significant). Unsurprisingly, the initial CPI price effects of an oil shock are positive, but then after about two years prices decline, consistent with the depressing effect from lower output. The transmission from oil shocks to interest rates is largely insignificant, though qualitatively an increase in interest rates is later followed by a period when interest rates fall, relative to the initial baseline. The real exchange rate consequences of an oil price increase are insignificant, except for a limited increase in the medium term.

As mentioned earlier, minimalist New Keynesian DSGE models of small open economies include the terms of trade as an important model variable. In the 8-variable model that includes the terms of trade we obtain an empirical perspective on the impact of terms-of-trade shocks, and ascertain how the other IRFs change when the terms-of-trade variable is introduced. The residuals from the terms-of-trade equation exhibit fairly weak correlations with the residuals from the other equations. As in our baseline identification scheme, all variables (including the terms of trade) are allowed to affect the real exchange rate contemporaneously. The world variables are allowed to have a contemporaneous impact on the terms of trade, but not vice-versa. Although terms-of-trade shocks have no contemporaneous effect on domestic or world variables, they can theoretically have lagged effects on the domestic and world variables. However, we find that when we employ an identification scheme that is otherwise the same as the baseline one, the inclusion of the terms of trade has little impact on the other impulse responses. Thus, in this section it suffices to discuss only the impact of the terms-of-trade shock. The terms-of-trade shock appears to increase GDP for around 8 quarters (or is on the cusp of significance), but decreases output

²⁸Figures with the IRFs are available on request from the authors.

somewhat at longer horizons. The impact on consumer prices is fairly indeterminate, but the terms-of-trade shock has a positive and significant effect on the real exchange rate, for some 2 years, and on the interest rate over a medium term (2-8 quarter) horizon.

Last, we consider world commodity prices as an additional variable. In this model we allow world commodity price shocks to have a contemporaneous impact on domestic interest rates and on the exchange rate, but not on other domestic variables. In this 8-variable model, commodity prices are the last variable of the recursive structure within the world block. The IRF results are very similar to those in figures 1 and 2. A comparison shows that the responses of the domestic variables to domestic shocks are almost identical.

As far as the response of domestic variables to world shocks is concerned, a comparison of the results with figure 2 leads to the same conclusion. The responses of domestic variables to world GDP shocks, to world CPI shocks and to world interest rate shocks barely change once we add commodity prices.²⁹ On the other hand, a positive commodity price shock leads to a significant increase in the RER over a period of 12 quarters after the shock, followed by a decline into slightly negative territory. Domestic GDP eventually falls after an initial period of insignificant upward movements. The CPI follows a pattern similar to that of GDP. Interest rates respond significantly and positively to commodity price shocks, but only from the 2nd to the 5th quarter after the shock.

4.4 Comparison of projection-based IRFs to standard IRFs

All our figures depict the standard IRFs as a solid line alongside the projection-based IRFs. It is obvious that the standard IRFs are smoother than the projection-based ones. The empirical example reported by Jordà reveals the same features when one compares the standard IRFs to the projection-based IRFs. This is due to the way the VMA-based IRFs are constructed across horizons based on the same VAR coefficients, whereas the linear projections involve for each horizon a new estimate

²⁹It should be noted that the baseline model exhibits a ‘world price puzzle’ in that world interest rate shocks have a positive impact on the world price level initially before it declines. However, because the commodity series that we use is New Zealand-specific, we do not allow for it to affect world interest rates contemporaneously.

for the coefficients based on direct forecasting at that specific horizon. Increasing the lag order in the regressions does not alter the smoothness profile of the two types of IRFs much and it also leads in several cases to unstable VARs.³⁰

Figure 1 shows that standard impulse responses generally follow a pattern similar to that of projection-based IRFs, with some exceptions. CPI shocks, R90D shocks and RER shocks lead to quite different responses in some instances. In particular, a RER shock has almost no effect on output for VMA-based IRFs but a significantly negative effect for projection-based IRFs.

The local projection IRFs for the CPI are also quite different for CPI and R90D shocks. For VMA-based IRFs, a positive interest rate shock leads to a persistent increase in the CPI and therefore to a price puzzle. The VMA-based IRFs suggest that the price level exhibits long memory or a unit root, whereas the local projection IRFs do not. The local projection IRFs clearly illustrate that positive interest rate shocks depress the CPI over the medium term, an effect that is statistically significant. In other words, tighter monetary policy leads to a fall in prices, and there is no price puzzle in the domestic economy.

The IRF profile for R90D and RER in response to own shocks differs for projection-based IRFs and VMA-based IRFs. Local-projection IRFs for interest rate shocks are initially positive, but then become significantly negative. The VMA-based IRFs have the opposite sign from 2 quarters onwards. Likewise, the long horizon effects of RER shocks on the real exchange rate are statistically negative for projection-based IRFs and positive or zero for VMA-based IRFs.

Figure 2 depicts the standard IRFs for world shocks. The reaction of domestic variables to such shocks shows some sensitivity to the way the impulses are calculated. Standard IRFs differ from projection-based IRFs markedly for the effects of world GDP shocks on domestic GDP. The same is the case for the effects of shocks to the world CPI on the domestic CPI and the RER.

The alternative identification scheme applied has quite strong effects on the standard IRFs relative to the standard IRFs with the basic identification scheme used for figures 1 and 2. The exceptions are that the effects of GDP shocks and world

³⁰Following Jordà (2005), we keep the lag length fixed across horizons for the linear projections. We experimented with using the BIC to select the lag length of each direct forecast (for each variable at each horizon) and got qualitatively the same results, though the IRFs were slightly less smooth.

shocks on domestic variables are little changed under the new identification scheme.

For standard IRFs, adding oil prices to the model results in similar effects for GDP shocks as observed in the basic 7-variable model. However, the effects of CPI shocks, from VMA-based IRFs, are rather different once oil prices are included. The impact of interest rate shocks is not much changed, except that the price puzzle of VMA-based IRFs now disappears because prices do not react to interest rate shocks at all. The reaction of domestic GDP to RER shocks changed but the responses of other variables is largely unchanged relative to the baseline. World shocks have again similar effects on domestic variables as in the basic model.

Next, we add the terms-of-trade variable to the basic model instead of oil prices. This has a fairly minimal impact on the VMA-based IRFs of the domestic and world variables. The addition of commodity price to the basic 7-variable model on the other hand does not change standard impulses much either.

5. Conclusion

In this paper, using techniques developed by Jordà (2005), we have used local linear projections to examine macroeconomic dynamics for New Zealand, a small open economy. These techniques should be more robust than traditional iterative techniques to the misspecification errors that are endemic to macroeconomic models. Using non-recursive identification schemes, with block exogenous world variables, we have derived impulse responses for the New Zealand macro-economy.

We compared projection-based impulses to standard iterative impulse responses and found some important differences with our New Zealand data set. In particular the magnitude and volatility of the responses to shocks differs. The direction of the responses is opposite in some important cases, though it is similar for the majority of impulse response functions. Furthermore, standard impulse responses are perhaps more sensitive to changes in identification schemes and in model specification than projection-based impulses. This finding demonstrates the robustness of linear projection-based impulse response functions.

Our results consistently indicate that GDP shocks have a significant and persistent impact on output and the real exchange rate. Prices and interest rates also

increase in response to an output shock, but with a delay of around a year. Interest rate shocks have a negative impact on prices, at a medium horizon. Foreign interest rate shocks have a significantly negative effect on New Zealand's output. Domestic interest rates initially increase, but then decline after a couple of years in response to world interest rate increases.

By way of robustness checks, we considered an alternative identification scheme that relaxes some of the restrictions implicit in our baseline model. We also extended our model by including the world oil price, the terms of trade and world commodity prices, the latter two tailored to New Zealand.

Introducing the oil price, the terms of trade or commodity prices leaves the original impulse responses largely unchanged. However, relaxing the restrictions inherent in the identification scheme has a material impact on the structural impulses from CPI shocks and from real exchange rate shocks. The effects of CPI and real exchange rate shocks on output, and their effects on the level of the real exchange rate, depend critically on the identification scheme.

The oil price model indicates that an increase in the US dollar price of oil has a negative impact on New Zealand output over the medium term. The short horizon effect on prices is positive, but at a longer horizon an oil price increase significantly decreases the consumers price index.

The terms of trade and commodity prices exhibit similar dynamics. Most notably, there is a substantial positive correlation with the real exchange rate for a period of 3 years after the initial shock. The near-horizon output effects are positive, though not significantly so, but at horizons of 3 years or more positive commodity price or terms-of-trade shocks appear to depress output.

This analysis provides a useful lens in thinking about the dynamic relationships between the macroeconomic variables we have incorporated in our analysis. The perspective it provides may be useful in orienting more formal theoretical models, such as the dynamic stochastic general equilibrium models that are being developed for small open economies.

Table 1: Data description

Variable	Description	Code	Source
GDP	Log of real production GDP (seas. adj.)	NGDPP.Z.Q	Statistics NZ
CPI	Log of CPI (excl. interest charges and GST)	PCPIIG.Q	Statistics NZ
R90D	90 day bank bill interest rate	R90D.Q	RBNZ
RER	Log of real trade-weighted exchange rate	IRTWC.Q	RBNZ
wGDP	Log of 12-country trade-weighted average of real GDP	IWGDP.Z.Q	RBNZ
wCPI	Log of 5-country trade-weighted average of CPIs	IWCPI.Q	RBNZ
wR90D	80/20 average: US and Australian 90-day bank rates	IWSHORT.Q	RBNZ
wOilP	Log of Dubai oil price (in US\$)	IOIL.P.Q	Datastream
ToT	Log of terms-of-trade index	TTTOT.P.Q	Statistics NZ
CompP	Log of NZ-specific commodity price index in SDRs	IACOMWNSDR.Q	ANZ Bank
M0	Log of monetary base (seas.adj. by RBNZ)	MNCZQ	RBNZ

Note: “Code” refers to the Reserve Bank of New Zealand (RBNZ) data code. “Log” indicates that the variable is in natural logarithms and GST refers to the Goods and Services Tax. SDR refers to the IMF’s Special Drawing Rights units. Data are available from the authors on request.

Table 2: Basic identification scheme for contemporaneous relations: \mathbf{B}_0

Shock coefficient for reaction in period t:	Variable that is shocked in period t						
	GDP	CPI	R90D	RER	wGDP	wCPI	wR90D
GDP	b_{11}	0	0	0	0	0	0
CPI	b_{21}	b_{22}	0	0	0	0	0
R90D	b_{31}	b_{32}	b_{33}	0	0	0	b_{37}
RER	b_{41}	b_{42}	b_{43}	b_{44}	b_{45}	b_{46}	b_{47}
wGDP	0	0	0	0	b_{55}	0	0
wCPI	0	0	0	0	b_{65}	b_{66}	0
wR90D	0	0	0	0	b_{75}	b_{76}	b_{77}

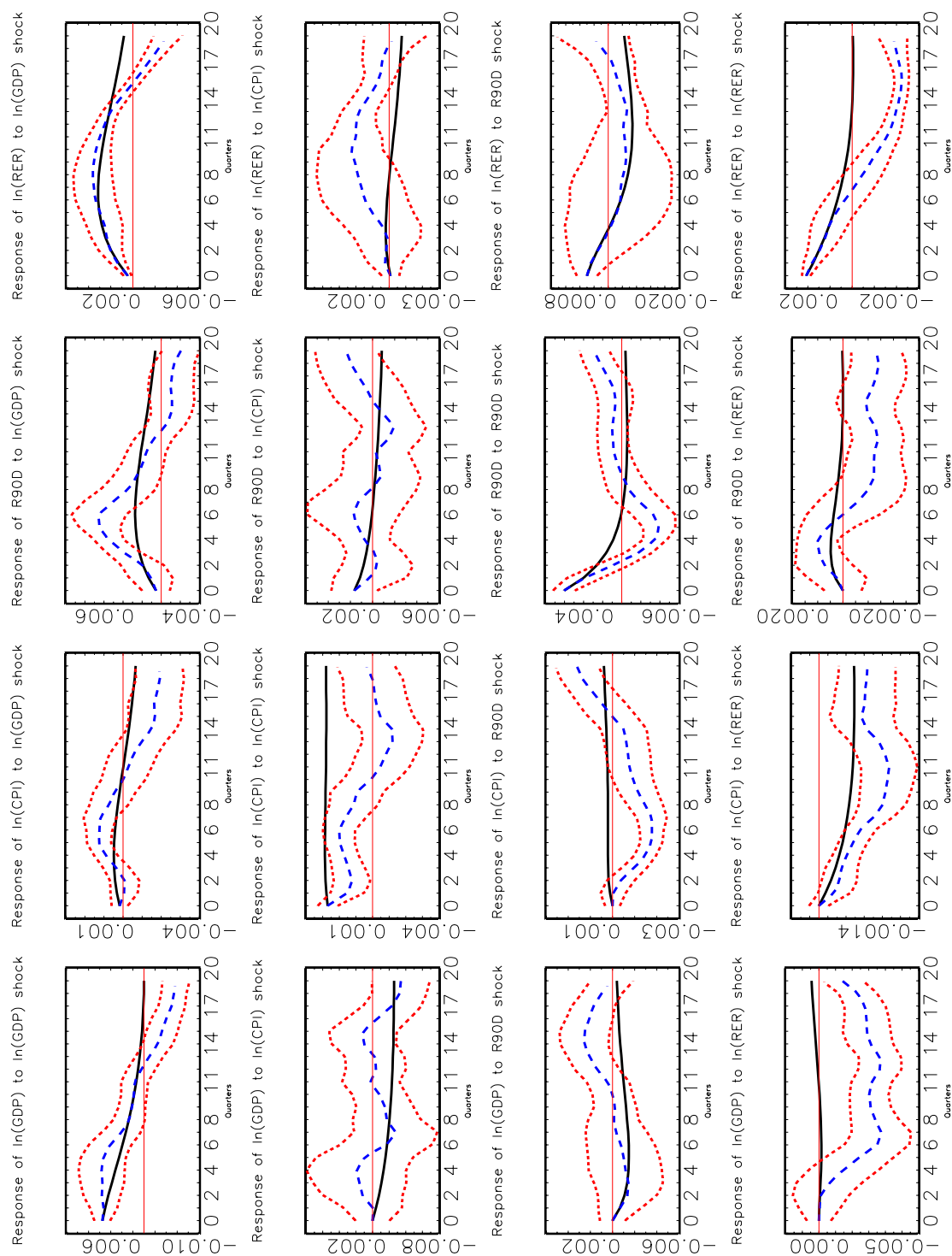
Note: The inner cells of the table form the matrix \mathbf{B}_0 with elements b_{ij} and $i, j = 1, \dots, 7$.

The vector \mathbf{u}_t of structural shocks relates to the reduced form shocks \mathbf{e}_t^0 as follows: $\mathbf{u}_t = \mathbf{B}_0 \mathbf{e}_t^0$.

Table 3: Correlation matrix of reduced form residuals

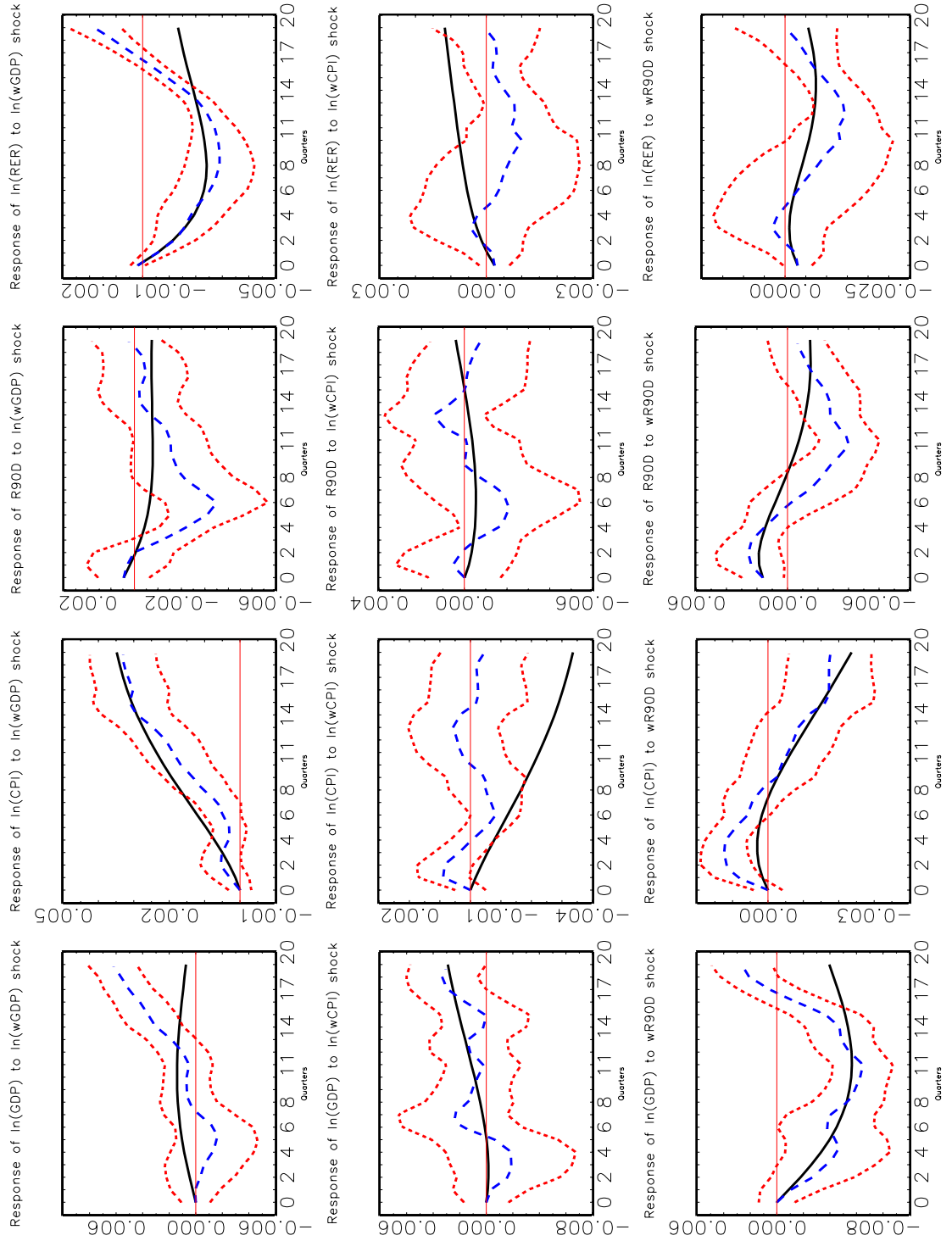
	GDP	CPI	R90D	RER	wGDP	wCPI	wR90D
GDP	1	0.065	0.122	0.206	0.259	0.159	0.151
CPI	0.065	1	0.292	-0.078	0.007	0.348	0.148
R90D	0.122	0.292	1	0.172	-0.144	0.317	0.302
RER	0.206	-0.078	0.172	1	0.072	-0.022	-0.078
wGDP	0.259	0.007	-0.144	0.072	1	-0.078	0.270
wCPI	0.159	0.348	0.317	-0.022	-0.078	1	-0.032
wR90D	0.151	0.148	0.302	-0.078	0.270	-0.032	1

Figure 1: Basic IRFs for domestic shocks: 7 variable model



Note: Local projection IRFs: (blue) dashed line with (red) dashed 95% confidence band. VAR(1) IRFs: (black) solid line. Note also that the interest rates have (for numerical reasons) been divided by 100, so that 0.01 corresponds to 1 percent; and the log of the real exchange rate has been divided by 10, so 0.001 corresponds to a 1 percent change in the real exchange rate.

Figure 2: Basic IRFs for world shocks: 7 variable model



Note: See Figure 1.

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