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# Inference for Impulse Response Coefficients From Multivariate Fractionally Integrated Processes

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## Abstract

This paper considers a multivariate system of fractionally integrated time series and investigates the most appropriate way for estimating Impulse Response (*IR*) coefficients and their associated confidence intervals. The paper extends the univariate analysis recently provided by Baillie and Kapetanios (2013), and uses a semi parametric, time domain estimator, based on a vector autoregression (*VAR*) approximation. Results are also derived for the orthogonalized estimated *IRs* which are generally more practically relevant. Simulation evidence strongly indicates the desirability of applying the Kilian small sample bias correction, which is found to improve the coverage accuracy of confidence intervals for *IRs*. The most appropriate order of the *VAR* turns out to be relevant for the lag length of the *IR* being estimated.

## 1 Introduction

The analysis of individual Impulse Responses (*IRs*), and the complete Impulse Response Function (*IRF*), have long been recognized as an important device for interpreting a time series model, or dynamic econometric model. Sims (1980) wrote a seminal article on the practical importance and interpretation of these methods in a Vector Autoregression (*VAR*) context. However, the variability and derivation of confidence intervals for this approach was first derived for weakly stationary, or stable processes by Schmidt (1973, 1977). In particular, Schmidt developed techniques for matrix differentiation that allowed the derivation of the asymptotic distribution of estimated *IRs* from a covariance stationary dynamic simultaneous equation model.

This work led to the derivation of asymptotic distributions of estimated  $IRs$  from covariance stationary Vector Autoregressive ( $VAR$ ) models in articles by Baillie (1987) and Lütkepohl (1988, 1989). While these theoretical results are quite elegant, they essentially rely on a linearized Taylor series expansion of the estimated  $IRs$  around the true parameter values. These articles and indeed the current study, deal with pointwise inference on  $IR$  coefficients, as opposed to the analysis of a vector of  $IRs$ , or the  $IRF$  function. Some analysis of the latter problem for covariance stationary  $VARs$  is to be found in Inoue and Kilian (2013).

This paper focuses on the problem of inference for estimating  $IRs$  and their confidence intervals for a multivariate fractionally integrated process. These models have been used in several areas of financial economics and empirical macroeconomics; see for example, Sowell (1992) and Jensen (2009). Some of the necessary technical machinery builds on the methodology for the univariate case developed by Baillie and Kapetanios (2013), which uses a semi parametric, time domain estimator, based on an autoregressive ( $AR$ ) approximation and finds that it has good theoretical and small sample properties for the estimation of the  $IRs$ . Baillie and Kapetanios (2013) also recommend using a generic semi parametric sieve bootstrap, based on an autoregressive approximation for the construction of confidence intervals for the estimated  $IRs$ . In this context, is important to note the preceding work of Inoue and Kilian (2002a), Inoue and Kilian (2002b) and Goncalves and Kilian (2007) who focus on impulse response analysis for short memory processes.

This paper develops the methodology for the multivariate situation and shows that a valid method for conducting inference on  $IRs$  for fractionally integrated processes can be based on estimating an approximating  $VAR$ . As a result, it is important to note that our work allows for data generating processes that have not been covered previously in the literature. The validity of this approach is proven under quite mild assumptions. The findings in this paper also indicate that a good strategy for analyzing  $IRs$  is to estimate a semi parametric  $VAR$ , and to then use a sieve bootstrap for estimating confidence intervals. Simulation evidence indicates this approach appears to be a very good strategy for both short and long memory processes. For the purpose of estimating  $IRs$  and their associated confidence intervals, the various difficulties related with the identification and specification of multivariate  $ARMA$  models alluded to by Tsay (1989), Kapetanios, Pagan and Scott (2007) and Poskitt (2011), do not arise. It should also be noted that some forms of nonlinearity can be mistaken for long memory, or very persistent processes. The sieve  $VAR$  approach advocated in this paper could be used in such a situation and has the advantage of not relying on the parametric specification of a complicated “structural” nonlinear model.

One of the major findings of this paper is that the semi parametric sieve bootstrap, based on a  $VAR$  approximation, appears to have a remarkably good coverage rate for the construction of confidence intervals of estimated  $IRs$  for a wide range of data generating processes, including both weakly stationary and fractionally integrated processes.

The plan of the rest of this paper is as follows; Section 2 reviews some basic theory and

assumptions, while Section 3 discusses the standard approach of deriving the asymptotic distribution for the estimated  $IRs$  and the problems with the theory in the presence of fractionally integrated processes. Section 4 then derives the basic ideas behind the Sieve  $VAR$  Bootstrap and the theory behind its validity. Section 5 describes some detailed simulation evidence on the performance of the  $VAR$  for estimation of  $IRs$  and the Sieve  $VAR$  for the derivation of confidence intervals of the estimated  $IRs$ . Section 6 provides an empirical application of our new methodology to the long run Fisher effect; and Section 7 provides some conclusions.

## 2 Basic Theory

This paper considers the vector time series process where  $\mathbf{y}_t$  is defined as an  $m$  dimensional multivariate stochastic process of the form

$$\mathbf{y}_t = \sum_{j=0}^{\infty} \Psi_j \boldsymbol{\epsilon}_{t-j},$$

where  $\boldsymbol{\epsilon}_t$  is an unobserved, vector white noise process, such that  $E(\boldsymbol{\epsilon}_t) = \mathbf{0}$ ,  $E(\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t') = \Omega$  which is an  $m$  dimensional, positive semi definite, covariance matrix and  $E(\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_s') = \mathbf{0}$  for  $t \neq s$ . The sequence of  $IRs$  or Wold Decomposition matrices are defined such that  $\Psi_0 = \mathbf{I}$ , and  $\Psi_j$  is a sequence of  $m \times m$  matrices of constants. On defining  $\Psi(\mathbf{L}) = \sum_{j=0}^{\infty} \Psi_j L^j$ , the square summability condition

$$\sum_{j=0}^{\infty} \Psi_j \Omega \Psi_j' < \infty$$

is assumed to be satisfied. For subsequent analysis, the following assumptions are invoked:

**Assumption 1**  $\boldsymbol{\epsilon}_t$  is an  $m$  dimensional ergodic martingale difference sequence, so that  $E(\boldsymbol{\epsilon}_t | \boldsymbol{\epsilon}_{t-1}, \boldsymbol{\epsilon}_{t-2}, \dots) = \mathbf{0}$ , and  $E(\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t' | \boldsymbol{\epsilon}_{t-1}, \boldsymbol{\epsilon}_{t-2}, \dots) = \Omega$  and its third and fourth moments matrices are finite constants.

**Assumption 2**  $\Psi(L) = \mathbf{D}(L)^{-1} \tilde{\Psi}(L)$ , where  $\mathbf{D}(L)$  is a diagonal matrix with typical diagonal element given by  $(1 - L)^{d_i}$  and  $d_i$  is the long memory parameter for the  $i$ -th equation and  $-0.5 < d_i < 0.5$  for  $i = 1, 2, \dots, m$ . Also,  $\tilde{\Psi}(\mathbf{L}) = \sum_{j=0}^{\infty} \tilde{\Psi}_j L^j$  and  $\sum_{j=0}^{\infty} j^{1/2} \|\tilde{\Psi}_j\| < \infty$ , where  $\|\cdot\|$  denotes the Euclidean matrix norm. Furthermore,  $\Phi(z) \equiv \Psi(L)^{-1} = \sum_{j=0}^{\infty} \Phi_j z^j$  exists for all  $|z| \leq 1$ .

For subsequent use of the bootstrap, Assumption 1 has to be replaced by the condition that  $\boldsymbol{\epsilon}_t$  is i.i.d. The above framework is essentially restricted to one of linearity with corresponding constraints on the error process. The above class of processes is quite wide and includes many processes considered in the literature. Clearly, the leading univariate case is the basic  $ARFIMA$  model of Granger (1980), Granger and Joyeux (1980) and Hosking (1981). The multivariate version of this model is the  $MVARFIMA(p, d, q)$  which is given by

$$\Pi(\mathbf{L})\mathbf{D}(\mathbf{L})(\mathbf{y}_t - \boldsymbol{\mu}) = \Theta(L)\boldsymbol{\epsilon}_t$$

where  $\tilde{\Psi}(\mathbf{L}) = \mathbf{\Pi}(\mathbf{L})^{-1}\Theta(L)$ ,  $\mathbf{\Pi}(L) = \sum_{j=0}^p \mathbf{\Pi}_j L^j$ ,  $\Theta(L) = \sum_{j=0}^q \Theta_j L^j$  and  $\boldsymbol{\mu}$  is a vector of constants. Details of the population aspects of this multivariate model are to be found in Sowell (1986, 1992) and Chung (2002). Note that the standard assumption, in empirical work, is that the process is weakly stationary with exponentially decaying *IRs* with  $\Psi_j = O(\mathbf{C}^j)$  where  $\mathbf{C}$  is a matrix of constants with eigenvalues that are bounded from above by one in absolute value. Rather than invoking this standard assumption, this paper considers the case where there is strong persistence due to fractional integration in the *IRs*, so that the  $\|\Psi_j\| = O(j^{d-1})$  for  $0 \leq d < 0.5$  as in Chung (2002). This implies that  $\left\| \sum_{j=0}^{\infty} \Psi_j \Psi_j' \right\| < \infty$ .

In many practical applications of *VARs* and of *IR* analysis, there can be an issue of identification and the desire to obtain the orthogonalized *IRs*, which are standardized in the sense that the covariance matrix of the innovations are equal to the identity matrix rather than  $\Omega$ . Hence an investigator may wish to provide estimates of  $\{\Psi_j \Omega^{-1/2}\}_{j=1}^h$  rather than  $\{\Psi_j\}_{j=1}^h$ . Since  $\Omega^{1/2}$  is not unique, then for a given  $\Omega$ , it is necessary to provide further identifying assumptions; for example see Inoue and Kilian (2013) and chapter 4 of Canova (2007) for a discussion. Details of inference from orthogonalized *IRs* are provided in Sections 4 and 5 of this paper.

### 3 Asymptotic Distribution of Estimated IRs

One standard parametric approach has been to specify a stationary and invertible *MVARFIMA* model such that  $\mathbf{\Pi}(\mathbf{L})$  and  $\Theta(L)$ , and therefore,  $\Psi(\mathbf{L})$  are parameterized so that they are functions of a vector of parameters given by  $\boldsymbol{\theta}$ . In particular, for the *MVARFIMA* model with  $\mathbf{D}(\mathbf{L})\mathbf{y}_t = \mathbf{u}_t$  and

$$\mathbf{\Pi}(\mathbf{L})\mathbf{u}_t = \Theta(L)\epsilon_{t-j}$$

the system can be expressed as the Markovian, or companion form representation of  $\mathbf{U}_t = \mathbf{C}\mathbf{U}_{t-1} + \mathbf{v}_t$  where  $\mathbf{U}_t' = [\mathbf{y}_t, \mathbf{y}_{t-1}, \dots, \mathbf{y}_{t-r+1}, \epsilon_t, \epsilon_{t-1}, \dots, \epsilon_{t-r+1}]$ . The lag order  $r = \max(p, q)$ , while  $\mathbf{v}_t' = [\epsilon_t, \mathbf{0}, \epsilon_t, \mathbf{0}]$ , and with null matrices of the appropriate dimension. Then,

$$\mathbf{C} = \begin{bmatrix} \mathbf{\Pi}_1 \mathbf{\Pi}_2 \dots \mathbf{\Pi}_{r-1} & \mathbf{\Pi}_r & \Theta_1 \Theta_2 \dots \Theta_{r-1} & \Theta_r \\ \mathbf{I} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{I} & \mathbf{0} \end{bmatrix}$$

Then  $\boldsymbol{\theta}' = [d_1, \dots, d_m, \text{vec}(\mathbf{N}'\mathbf{C}), \text{vech}(\Omega)]$  and  $\mathbf{N}' = [\mathbf{I}, \mathbf{0}]$ , which is of dimension  $m$  by  $2mr$ . Then on estimation of the structural parameters  $\boldsymbol{\theta}$  by either approximate or full *MLE*,

$$\sqrt{T} \left( \hat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0 \right) \xrightarrow{L} N(\mathbf{0}, \mathbf{V}). \quad (1)$$

Note that  $\boldsymbol{\theta}_0$  denotes the true value of  $\boldsymbol{\theta}$ , and the symbol  $\xrightarrow{L}$  denotes convergence in distribution<sup>1</sup>. The theory for full and approximate *MLE* of multivariate *ARFIMA* models is described by

<sup>1</sup>For ease of exposition,  $\boldsymbol{\mu}$  is assumed to either be the null vector, or known; so that the *MVARFIMA* model is expressed in deviation form. The *MLE* of  $\boldsymbol{\mu}$  converges at a slower rate than  $T^{1/2}$  and hence the full *MLE* of the system requires different normalizations for the estimated  $\boldsymbol{\mu}$  parameters. The properties of the other parameter estimates remain unchanged.

Sowell (1986, 1992) and Chung (2002)<sup>2</sup>. Some applications of the methodology are given in Diebold, Husted and Rush (1991) for the univariate case, while articles by Sowell (1992), Baillie and Chung (2002) and Jensen (2009) describe applications in the multivariate case.

In order to obtain confidence intervals for the estimated vectorized  $IR$  matrix at lag  $j$ , i.e.  $vec(\Psi_{j,\hat{\theta}})$ , where the subscript  $\hat{\theta}$  denotes dependence of  $\Psi_j$  on  $\hat{\theta}$ , a traditional method has been to use the delta method, which is based on a linearized Taylor Series expansion around the true vectorized  $IRs$  at lag  $j$ ,  $vec(\Psi_{j,\theta_0})$ . On further assuming that  $\epsilon_t$  is an i.i.d. sequence, that  $\sum_{j=1}^{\infty} \sup_{\theta} |\Psi_{j,\theta}| < \infty$  and that  $\mathbf{V}$  defined above is nonsingular, then for all  $j = 1, \dots, h$

$$\sqrt{T} \left( vec(\Psi_{j,\hat{\theta}}) - vec(\Psi_{j,\theta_0}) \right) \xrightarrow{L} N(0, \mathbf{D}'_j \mathbf{V} \mathbf{D}_j) \quad (2)$$

where  $\mathbf{D}_j = \left. \frac{\partial vec(\Psi_{j,\theta})}{\partial \theta} \right|_{\theta=\theta_0}$ . For stationary and invertible  $VARMA$  models, there are parametric expressions available for the matrix  $\mathbf{D}_j$ ; see Baillie (1987). However, no corresponding results are yet available for the  $MVARFIMA$  model.

Analogous analysis can be conducted for orthogonalized  $IRs$  which are based on the quantities  $\widehat{\Psi}_j \widehat{\Omega}^{-1/2}$ , where  $\widehat{\Omega} = T^{-1} \sum_t \hat{\epsilon}_t \hat{\epsilon}'_t$ , and  $\widehat{\Omega}^{1/2}$  denotes some suitably defined square root of  $\widehat{\Omega}$ . Then,

$$\sqrt{T} \left( vec(\Psi_{j,\hat{\theta}} \widehat{\Omega}^{-1/2}) - vec(\Psi_{j,\theta_0} \Omega^{-1/2}) \right) \xrightarrow{L} N(0, \mathbf{G}'_j \mathbf{V} \mathbf{G}_j) \quad (3)$$

where  $\mathbf{G}_j = \left. \frac{\partial vec(\Psi_{j,\theta} \Omega^{-1/2})}{\partial \theta} \right|_{\theta=\theta_0}$ . It is important to note that high persistence can be a problem with the above traditional methodology, or "delta method". In particular, issues arise in the presence of very persistent processes, such as long memory processes and also near unit root processes; see Wright (2000), Kilian (1998, 1999) and Pesavento and Rossi (2007). This motivates the need for investigation of alternative approaches, as in Baillie and Kapetanios (2013) for univariate fractionally integrated processes.

## 4 Sieve VAR Bootstrap

Given the results in Baillie and Kapetanios (2013) for the univariate fractionally integrated process, the estimation and inference approach taken in this paper is to extend the sieve  $AR$  approximations with bootstrapped confidence intervals in the univariate case to a multivariate setting. Hence, this paper considers approximating a multivariate fractionally integrated process with a  $VAR(\infty)$  representation which exists under Assumption 2 by means of a  $VAR(p_T)$  model where the lag order,  $p_T$ , is allowed to tend to infinity with the sample size. In particular

$$\mathbf{y}_t = \sum_{j=1}^{p_T} \Phi_j^{(p_T)} \mathbf{y}_{t-j} + \mathbf{v}_t$$

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<sup>2</sup>These results have been explored in more detail for the univariate case by Baillie and Kapetanios (2013), who use results of Hosoya (1997) which do not necessarily require the innovations to be i.i.d.. The extension to vector long memory processes has not been attempted.

where  $\sum_{j=1}^{p_T} \Phi_j^{(p_T)} \mathbf{y}_{t-j}$  is the linear projection of  $\mathbf{y}_t$  on  $\mathbf{y}_{t-1}, \dots, \mathbf{y}_{t-p_T}$ . The *OLS* estimates of  $\Phi_j^{(p_T)}$  are obtained by fitting a *VAR*( $p_T$ ) model to the data and are denoted by  $\widehat{\Phi}_j^{(p_T)}$ . The estimated *IRs* are then obtained by inverting the truncated *VAR*. It follows from a straightforward extension of Theorem 5 of Poskitt (2007) that

$$\sum_{j=1}^{p_T} \left\| \widehat{\Phi}_j^{(p_T)} - \Phi_j^{(p_T)} \right\|^2 = o_p(1)$$

for all sequences  $\{p_T\}$  such that  $p_T \rightarrow \infty$  and  $p_T = o(T^\alpha)$  for all  $\alpha > 0$ . An acceptable sequence for  $p_T$  is  $p_T = \lfloor \ln(T)^\alpha \rfloor$  where  $\alpha > 1$  and  $\lfloor \cdot \rfloor$  denotes the integer part. Also, from an extension of Baxter's inequality proven by Inoue and Kasahara (2006),

$$\sum_{j=1}^{p_T} \left\| \Phi_j^{(p_T)} - \Phi_j \right\| = o(1)$$

as long as  $p_T \rightarrow \infty$ . The selection of  $p_T$  can be through a data dependent method such as an information criterion like the *AIC*,<sup>3</sup> or by some deterministic rule such as  $p_T = \lfloor \ln(T)^\alpha \rfloor$ , where  $a > 0$ . Then, the *IR* analysis proceeds by inverting the autoregressive polynomial with coefficient matrices  $\widehat{\Phi}_j^{(p_T)}$ ,  $j = 1, \dots, p_T$  to give estimated *IRs* of the form  $\widehat{\Psi}_j^{(p_T)}$ . Inference on  $\widehat{\Psi}_j^{(p_T)}$  can be carried out by means of the bootstrap. The sieve bootstrap, as usually applied in the literature; e.g. Inoue and Kilian (2002b), and as analyzed in the univariate long memory case by Baillie and Kapetanios (2013), can also be implemented in this study. For ease of reference, the relevant algorithm is given below:

1. Estimate a *VAR*( $p_T$ ) model on  $\mathbf{y}_t$  and obtain the estimated coefficients,  $\widehat{\Phi}_j^{(p_T)}$ ,  $j = 1, \dots, p_T$  and the residuals,  $\widehat{\boldsymbol{\epsilon}}_t = \mathbf{y}_t - \sum_{j=1}^{\min(p_T, t-1)} \widehat{\Phi}_j^{(p_T)} \mathbf{y}_{t-j}$ .
2. Invert the autoregressive polynomial with coefficient matrices  $\widehat{\Phi}_j^{(p_T)}$ ,  $j = 1, \dots, p_T$  to obtain the  $\widehat{\Psi}_j^{(p_T)}$ , for  $j = 1, \dots, h$ . In some applications it is desirable to orthogonalize the *IRs*, which are defined as  $\widehat{\Psi}_j^{(p_T)} \widehat{\Omega}^{-1/2}$ , where  $\widehat{\Omega} = \frac{1}{T} \sum_t \widehat{\boldsymbol{\epsilon}}_t \widehat{\boldsymbol{\epsilon}}_t'$ , and  $\widehat{\Omega}^{1/2}$  denotes some suitably defined square root of  $\widehat{\Omega}$ .
3. Re-center  $(\widehat{\boldsymbol{\epsilon}}_1, \dots, \widehat{\boldsymbol{\epsilon}}_T)'$ .
4. Re-sample with replacement from this vector to obtain the bootstrap sample of error terms given by  $(\boldsymbol{\epsilon}_1^*, \dots, \boldsymbol{\epsilon}_T^*)'$ .

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<sup>3</sup>The use of information criterion necessitates the specification of lower and upper bounds for the possible value of  $p_T$ . Usually for the short memory case the lower bound  $p_{\min} = p_{\min, T}$  is specified to diverge with  $T$  while the upper bound is of the form  $p_{\max, T} = T^\alpha$  and  $\alpha < 1/2$ . Of course  $p_{\min, T} < p_{\max, T}$ . For the long memory case a different upper bound is needed. This is because consistency of the parameter estimates cannot be obtained for all  $d < 1/2$  when  $p_{\max, T} = T^\alpha$  for any  $\alpha > 0$ , and a lower rate is needed. Therefore, it is usually assumed that  $p_{\max, T} = \lfloor \ln(T)^\alpha \rfloor$ , where  $\alpha > 0$ . More details may be found in Poskitt (2007).

5. Use the above error terms together with  $\widehat{\Phi}_j^{(p_T)}$ ,  $j = 1, \dots, p_T$ , to generate the bootstrap sample  $(\mathbf{y}_1^*, \dots, \mathbf{y}_T^*)'$  with initial values set to zeros.
6. Estimate a  $VAR(p_T)$  for  $(\mathbf{y}_1^*, \dots, \mathbf{y}_T^*)'$  to obtain the bootstrap estimated autoregressive coefficients given  $\widehat{\Phi}_j^{(p_T)}$  for  $j = 1, \dots, p_T$ .
7. Invert  $\widehat{\Phi}^{*(p_T)}(z) = \sum_{j=1}^{p_T} \widehat{\Phi}_j^{*(p_T)} z^j$  to obtain bootstrap estimates of the impulse responses given by  $\widehat{\Psi}_j^{*(p_T)}$ ,  $j = 1, \dots, h$ . Similarly, bootstrap estimates of orthogonalized impulse responses are derived from  $\widehat{\Psi}_j^{*(p_T)} \widehat{\Omega}^{-1/2}$ .
8. Repeat the above algorithm  $B$  times and then use the resulting estimates of the  $IR$  to construct an empirical distribution of the  $IR$ .

The properties of the sieve estimator discussed in this section, as well as those of the sieve bootstrap, are summarized in the following Theorem, which together with corollary 1 of Inoue and Kilian (2002a) imply the validity of the sieve bootstrap for  $IR$  analysis. The proof of the Theorem is in the appendix.

**Theorem 1** *Let Assumptions 1 and 2 hold and set  $p_T = o((\ln T)^a)$  for some  $a > 0$ . Then,*

$$\sum_{j=1}^{p_T} \left\| \widehat{\Phi}_j^{(p_T)} - \Phi_j \right\|^2 = o_p(1). \quad (4)$$

Further, for all  $j = 1, \dots$ ,

$$d(P_{\widehat{\Psi}_j^{(p_T)}}, P_{\widehat{\Psi}_j^{*(p_T)}}) = o_p(1) \quad (5)$$

where  $P_{\mathbf{Y}}$  denotes the probability law of a random matrix  $\mathbf{Y}$ , and  $d(P_{\mathbf{Y}_1}, P_{\mathbf{Y}_2})$  is the Mallows metric between  $P_{\mathbf{Y}_1}$  and  $P_{\mathbf{Y}_2}$ . Then,

$$d(P_{\widehat{\Omega}^*}, P_{\widehat{\Omega}}) = o_p(1). \quad (6)$$

## 5 Simulations

This section investigates the properties of the sieve  $VAR$  bootstrap procedure compared with various other schemes. In order to have a meaningful comparison, the data generating process is a  $MVARFIMA(1, d, 0)$  which can have substantial persistence given the choice of the long memory parameter,  $d$  and with  $m = 2$  dimensions. The data generating process is given by

$$\mathbf{D}(\mathbf{L})\mathbf{y}_t = \mathbf{u}_t$$

$$\mathbf{u}_t = \Phi \mathbf{u}_{t-1} + \varepsilon_t,$$

$$(\mathbf{I} - \Phi \mathbf{L}) = \begin{pmatrix} 1 - \beta L & 0 \\ -0.5L & -0.5L \end{pmatrix}$$



and

$$\varepsilon_t \stackrel{iid}{\sim} N \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0.3 \\ 0.3 & 1 \end{pmatrix} \right),$$

where  $\mathbf{D}(\mathbf{L})$  is an  $m$  dimensional square diagonal matrix and is constrained for convenience in the simulation study to have the same long memory parameter across equations so that  $\mathbf{D}(\mathbf{L}) = (\mathbf{I} - \mathbf{L})^d \mathbf{I}_m$ , where  $\mathbf{I}_m$  is an  $m$  dimensional identity matrix. A critical feature of the different simulation designs concerns the persistence of the short memory  $VAR(1)$  components. This paper adopts the same design as used by Kilian (1998), where  $(\mathbf{I} - \Phi\mathbf{L})$  is constructed so that  $\beta$  determines the degree of short memory persistence, since the eigenvalues of  $\Phi$  are 0.5 and  $\beta$ , where  $\beta \in \{0.5, 0.9\}$ . In all the experiments  $d$  was chosen as 0.4<sup>4</sup>. The sample size is  $T \in \{250, 500\}$  and the number of Monte Carlo replications is 500. For each realization, 1,000 bootstrap simulations to obtain the first order mean bias "Kilian corrected, ("bootstrap-after-bootstrap") version of the parameter estimates are used, as in Kilian (1998); and 2,000 bootstrap simulations are used for investigating the properties of the estimated  $IRs$ . Note that the Kilian bias correction is obtained using a double bootstrap as discussed on page 220 of Kilian (1998). Finally, and as previously noted, it can be desirable to use either orthogonalized or non orthogonalized  $IRs$ . The orthogonalized  $IRs$  are derived from imposing a recursive causal structure, from the first to the last variable, and is consistent with the standard Cholesky decomposition method.

Given the various theoretical methods and issues discussed earlier, three different  $VAR$  estimation approaches were implemented in the simulations. The application of the  $VARs$  essentially vary in the way the maximum lag length is selected. The methods are:

(i)  $VAR$  represents the case where the sieve  $VAR(p_T)$  bootstrap has been applied with  $p_T = \lfloor c \ln(T)^2 \rfloor$ , and with the constant  $c$  allowed to take the values 0.25, 0.50, 0.75 and 1.00. For example, for the sample sizes of  $T = 250$  and 500 and for  $c = 1$ , the lag length,  $p_T$  is 30 and 39 respectively. However, the results for the  $c = 0.75$  case are suppressed from this version of the paper since they turned out to be extremely similar to those for  $c = 1$ ; but are available from the authors on request. Similarly, the results for  $c = 0.5$  are only presented for one design.

(ii)  $VAR - K$  denotes the sieve  $VAR(p_T)$  bootstrap,  $p_T = \lfloor c \ln(T)^2 \rfloor$ , using the Kilian (1998) correction for bias. The same values for  $c$  are used.

(iii)  $AIC - K$  involves the sieve  $VAR$  bootstrap, where  $p$  is chosen by the  $AIC$ , and also the bias correction method of Kilian (1998) is implemented. The maximum order for the  $AIC$  is set as  $p_T = \lfloor \ln(T)^2 + 20 \rfloor$ .

All the results for the coverage rates are calculated at the 90% level. The first set of results presented in Figures 1 through 4 report results for the design with the less persistent short

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<sup>4</sup>Simulation work was also completed for the case of  $d = 0.2$ , but the results do not add significant extra information and are not reported for reasons of conserving space. These results are available from the authors on request.

memory case of  $\beta = 0.5$ , for the sample size of  $T = 250$ . Each figure is divided into four panels. Starting with the top left corner and continuing in a clockwise direction, the first panel depicts the coverage rates for the *IRs* of  $y_1$  to  $y_1$ , then  $y_1$  to  $y_2$ , then  $y_2$  to  $y_2$  and finally  $y_2$  to  $y_1$ . The first two figures present both orthogonalized and non-orthogonalized *IRs*. As expected, the latter perform better since they do not require estimates of the  $\Omega$  matrix. This pattern is consistent for all other cases considered in the simulation experiment. Since non-orthogonalized *IRs* are far less relevant for applied work, it was decided not to report these results after the first two figures for each *DGP*. This increases the clarity of the graphical exposition in the remaining figures.

Tables 1 and 2 report the coverage rates when estimating *IRs* at lags  $h = 2, 4, 8, 12$  and  $h = 16$ . One of the most interesting aspects of these tables is the substantial increase in coverage provided from using the Kilian bias correction method compared to the regular sieve bootstrap *VAR*. The two tables also indicate the extra degree of difficulty introduced by estimating the orthogonalized, rather than non orthogonalized *IRs* and the relative importance of the Kilian bias correction in both cases.

It can generally be seen that the use of  $p_T = \lfloor c \ln(T)^2 \rfloor$ , is extremely sensitive to the choice of  $c$ . In Figure 1 with  $c = 0.25$ , the coverage is quite good for low order lags  $\Psi_h$  for  $h < 10$ , but very poor for higher order lags of the *IRs* for  $h \geq 10$ . For higher values of  $c$ , beginning with  $c = 0.50$  in Figure 2, the performance is seen to be radically improved for the higher order lags beyond  $h > 10$ , but conversely very poor for the low order lags of  $h < 10$ . This pattern is almost identical to the case where  $c = 1.00$  in Figure 3. As previously mentioned the situation for  $c = 0.75$  is extremely similar to the  $c = 1.00$  case and is therefore not reported. Figure 4, summarizes results for the same design, only with the lag length determined by the *AIC*. These coverage rates are extremely poor and appear to be due to excessively high lag values for the *VAR* being chosen by the *AIC* method. The general poor performance of the *AIC* turned out to be typical for all the designs being considered and hence are not reported in the remaining figures in order to conserve space.

Figures 5 and 6 present corresponding information to Figures 1 through 4, only for the larger sample size of  $T = 500$  and with  $c = 0.25$  and  $c = 1.00$  respectively. Figures 7 through 8 are analogous to the Figures 5 through 6 and differ only in terms of the short memory parameter  $\beta$  being fixed at the higher level of persistence of  $\beta = 0.9$  and with a sample size of  $T = 250$ . Finally, Figures 9 and 10 are for the cases of higher level of short memory persistence with  $\beta = 0.9$  and with the higher sample size of  $T = 500$  and for  $c = 0.25$  and  $c = 1.00$  respectively. The conclusions are generally the same as for the initial tables 1 through 4.

The following broad conclusions can be reached on the basis of the simulation results:

(a) The orthogonalized estimated *IRs* perform considerably worse than the corresponding non-orthogonalized *IRs*. The intuition behind this is quite clear since the latter also use the estimate of the covariance matrix of the error term. This is a very important conclusion, since it demonstrates that the extension from univariate to multivariate *IRs* is not a trivial one

in practice and hence many of the results obtained by Baillie and Kapetanios (2013) for the univariate case need to be re-examined for the multivariate case.

(b) The bias correction method is extremely useful and very substantially improves the performance of both the estimated orthogonalized and the non-orthogonalized *IRs* estimators. As previously noted, tables 1 and 2 present the coverage rates at lags 1, 2, 4, 8, 12, 16 and 20, for the sample sizes of 250 and 500 respectively.

(c) Superior estimates of the *IRs* at short horizons can be obtained from using *VARs* with fewer lags. Whereas the opposite seems to be the case for long horizons of the *IRs* being better estimated with high order *VARs*. The corollary is that a sensible approach is to make the lag order of the *VAR* depend on the horizon of the *IRs* one desires to estimate. A reasonable horizon cut-off point appears to be around 10 periods ahead. Given these results, such a mixed *VAR* approach was used for the *IR* analysis and the results are given in Figures 11 and 12 for the sample size of 250. Figure 11 reports results for using two different order *VARs*; with the lag order chosen on the basis for  $c = 0.25$  when estimating *IRs* up to lag 10 and then from using a *VAR* with lags chosen on the basis of  $c = 0.5$  for estimating *IRs* for lags 11 through 25. Figure 12 presents results for when the *VAR* has a lag order equal  $h + 1$  for estimating *IRs* up to lag  $h = 1, \dots, 10$ ; and on the basis of  $c = 0.5$  is chosen for longer horizons. These both choices appear to be feasible ways of conducting *IR* analysis and achieve good results.

(d) The persistence of the short memory process, as defined by  $\beta$ , does not seem to affect the performance of any of the methods, or any of the above three conclusions.

(e) As expected, the performance of all the methods improves with increasing sample size.

(f) *AIC* seems to choose too high a value for  $p$ , the lag length of the *VAR*, for small sample size; and too low a value of  $p$  for larger sample sizes. Consequently it does well at long horizons in smaller samples and vice versa for longer samples. An interesting feature of *AIC* is that it performs much better on the non-orthogonalized *IRs*, which are of rather less economic interest than the orthogonalized version. In general it does not appear to be a very good method to use in this context.

## 6 Application to Long Run Fisher equation

An interesting application of the above methodology concerns the relationship between inflation and nominal interest rates and the long run Fisher equation. In a recent article, Jensen (2009), has considered the reasons that previous literature has failed to find support for the long run Fisher effect; and attributes that to the inappropriate assumption that inflation may be a unit root process. Jensen assumes that both inflation and nominal interest rates are described by a fractionally integrated, mean reverting, bivariate *MVARFIMA* model. Jensen (2009) argues that since there is no evidence that inflation is a unit root process and since permanent changes to inflation do not occur, then the issue on whether permanent changes to inflation affect the long run nominal interest rate will be uninformative, as to the truth or otherwise of the long

run Fisher hypothesis.

The following analysis uses the same data set as Jensen (2009) with the *US* and *UK* variables being analysed using quarterly series published in the International Financial Series database. The inflation rate is the usual definition of the differenced logarithm of each country’s consumer price index; and the nominal interest rate is the annualized rate of return of the relevant Treasury bill. The data is from 1957–Q1 through 2004–Q4 for the *US* and 1957–Q1 through 2004–Q3 for the *UK*. The *VAR* maximum lag length for the *AIC* was set as  $p_T = \lfloor 1.00 \ln(T)^2 \rfloor$ . On adopting the standard monetary policy rule assumption that inflation is causally prior to nominal interest rates, the ordering of variables and the Cholesky decomposition is clear. For example see Bernanke et al (2005) for discussion of this modeling approach. Following the conclusions of the above simulation study, the lag length of the *VAR* was chosen on the basis of a lag order equal  $h + 1$  for estimating *IRs* up to lag  $h = 1, \dots, 10$ ; and subsequently on the basis of  $c = 0.5$  for longer horizons. As expected the *IRs* for own shocks; i.e. the effect of inflationary shocks on current levels of inflation, and the analogous effect of interest rate shocks on current interest rates, are both positive and significant. Figures 13 and 14 indicate that interestingly, the *UK* has a larger *IR* at short horizons for a *CPI* shock compared with an interest rate shock. Also, past *CPI* innovations have a positive effect on interest rates. However, this effect is relatively small, which possibly indicates that before the Volcker regime authorities did not really try seriously to combat inflation.

Furthermore, past interest rate shocks appear to positively effect inflation. This is a common finding in the literature and has been termed as the ‘price puzzle’. According to Castelnuovo and Surico (2010), during periods of passive monetary policy, such as prior to the Volcker regime, a price puzzle in the *US* is to be expected. More specifically, these authors find that a positive response of prices to a monetary policy shock is historically limited to the sub-samples that are typically associated with a weak interest rate response to inflation.

## 7 Conclusion

This paper considers a fractionally integrated system and investigates the most appropriate method for estimating Impulse Responses and their associated confidence intervals. The paper has extended the univariate analysis recently provided by Baillie and Kapetanios (2013), and has used a semi parametric, time domain estimator, based on a vector autoregressive (*VAR*) approximation. We find that a deterministic rule of choice of the *VAR* lag length based on  $c \ln(T)^2$  seems to perform reasonably well. Simulation evidence strongly indicates the desirability for applying the Kilian (1998) small sample bias correction method, which improves both the estimated orthogonalized and non-orthogonalized *IRs*.

One interesting finding is that superior estimates of the *IRs* for short horizons can be obtained from using *VARs* with fewer lags, while *IRs* at long horizons are better estimated with high order *VARs*. This method appears quite attractive and is used in an empirical example of the

inflation and interest rate relationship.

One of the major findings of this paper is that the semi parametric sieve bootstrap, based on a *VAR* approximation, appears to have a remarkably good coverage rate for the construction of confidence intervals of estimated *IRs* for a wide range of data generating processes, including both weakly stationary and fractionally integrated processes.

## 8 Appendix

This Appendix provides a proof of Theorem 1 in this paper. For the validity of Equation (4) in our Theorem 1, it is necessary to show that Theorem 1 of Poskitt (2007) extends to the autocovariances of multivariate fractionally integrated processes. In particular it is required to prove that

$$\max_{0 \leq \tau \leq p_T} \|\mathbf{C}_T(\tau) - \mathbf{\Gamma}(\tau)\| = O\left(\left(\frac{\log T}{T}\right)^{1/2-d}\right) \quad (7)$$

where  $\mathbf{\Gamma}(\tau) = E(\mathbf{y}_t \mathbf{y}'_{t+\tau})$  and  $\mathbf{C}_T(\tau) = \frac{1}{T} \sum_{t=1}^T \mathbf{y}_t \mathbf{y}'_{t+\tau}$ . However, the proof of Theorem 1 of Poskitt (2007) proceeds in the multivariate case exactly as in the univariate case once it is established that

$$E(\|\mathbf{C}_T(\tau) - \mathbf{\Gamma}(\tau)\|^2) = O(T^{2d-1}). \quad (8)$$

Hence it is necessary to prove the above result, which for the univariate case is provided by Theorem 3 of Hosking (1996). The multivariate version of this result can be obtained by considering Corollary 1 of Chung (2002). That corollary proves the convergence in distribution of  $T^{1/2-d} \text{vec}(\mathbf{C}_T(\tau) - \mathbf{\Gamma}(\tau))$  to a random variable with finite variance. This immediately implies (8). On using similar arguments to those in the proof of Theorems 4 and 5 of Poskitt (2007), (8), implies the following

$$\sum_{j=1}^{p_T} \left\| \hat{\mathbf{\Phi}}_j^{(p_T)} - \mathbf{\Phi}_j^{(p_T)} \right\| = o(1) \quad (9)$$

It is further required to show that

$$\sum_{j=1}^{p_T} \left\| \mathbf{\Phi}_j^{(p_T)} - \mathbf{\Phi}_j \right\| = o(1) \quad (10)$$

as long as  $p_T \rightarrow \infty$ . However, Theorem 4.1 of Inoue and Kasahara (2006) can be extended to this case, with some tedious but relatively straightforward algebra. This then proves equation (4).

Next, for Equation (5) it is necessary to extend Theorem 6 of Baillie and Kapetanios (2013) to multivariate processes. However, this extension is immediate once Theorem 1 of Poskitt (2007) is extended to autocovariances of multivariate processes, which was shown above.

Finally, to prove equation (6), it is sufficient to show the results of Theorem 1 of Inoue and Kilian (2002a) are valid for  $\Omega$ . First, it is necessary to show that the second block of equation (A.4) in Inoue and Kilian (2002a) converges to the normal distribution, which is sufficient for proving the above result. This proof is facilitated by obtaining versions of (A.1) through (A.3) in Inoue and Kilian (2002a). It is important to note that deriving (A.4) requires only that (A.1) through (A.3) hold with the right hand side being replaced by  $o_p(1)$ . This is first done by reviewing the results of Paparoditis (1996). To achieve this it is necessary to prove

$$\|C_T(\tau) - \mathbf{\Gamma}(\tau)\| = o_p(1) \quad (11)$$

$$\sum_{j=1}^{p_T} \left\| \widehat{\Phi}_j^{(p_T)} - \Phi_j \right\| = o_p(1) \quad (12)$$

$$\sum_{j=1}^{p_T} \left\| \widehat{\Psi}_j^{(p_T)} - \Psi_j \right\| = o_p(1) \quad (13)$$

$$\|\Gamma^*(\tau) - \Gamma(\tau)\| = o_p(1) \quad (14)$$

$$\|\Gamma^{*-1}(\tau) - \Gamma^{-1}(\tau)\| = o_p(1) \quad (15)$$

where  $\Gamma^*(\tau)$  is the bootstrap analog of  $\Gamma(\tau)$ . Equations (11) and (12) have been shown above; while Equation (12) together with Theorem 2.2 of Paparoditis (1996) gives Equation (13). Similarly, Theorem 2.5 of Paparoditis (1996) and Equations (11) through (13) can be used to prove Equations (14) and (15). On using Equations (11) through (15) gives (A.4) of Inoue and Kilian (2002a). The rest of the steps of the proof of Theorem 1 of Inoue and Kilian (2002a) follow straightforwardly. In particular, Inoue and Kilian (2002a) use Theorem 24.3 of Davidson (1994) to prove that

$$(T - k)^{1/2} \text{vech} \left( \widehat{\Omega}^* - \Omega^* \right) \xrightarrow{d} N(0, V)$$

where  $\Omega^*$  and  $\widehat{\Omega}^*$  are the bootstrap analogs of  $\Omega$  and  $\widehat{\Omega}$ , while  $V$  is a positive definite covariance matrix, and  $\xrightarrow{d}$  denotes convergence in distribution. Then Equation (A.6) of Inoue and Kilian (2002a) which shows that  $\widehat{\Omega}^* - \Omega^*$  is made up of terms that follow a martingale difference, is self contained and does not change between the short and long memory cases. The rest of the steps using Theorems 2.3 and 2.4 of Paparoditis (1996) again follow from Equation (12). Only the rate of convergence in Theorem 2.3 of Paparoditis (1996) changes. However, this is inconsequential since only convergence in probability is used in the relevant steps of the proof of Theorem 1 of Inoue and Kilian (2002a), and not any of the rates of convergence in the second half of page 325, and first half of page 326 of Inoue and Kilian (2002a).

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# Simulation Results: Tables

Table 1: Orthogonalized Estimated Impulse Responses from Design with  $\beta = 0.5$  and  $T = 250$ . Effective coverage rates for 90% confidence intervals derived from different order VARs.

$\hat{p}$	$\hat{\Psi}_{11}$							$\hat{\Psi}_{12}$						
	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
	<b>SB</b>							<b>SB</b>						
<b>2</b>	0.86	0.78	0.70	0.62	0.48	0.35	0.23	0.85	0.85	0.85	0.83	0.75	0.66	0.55
<b>4</b>	0.72	0.76	0.77	0.73	0.59	0.47	0.38	0.86	0.86	0.85	0.85	0.82	0.77	0.66
<b>8</b>	0.54	0.63	0.71	0.68	0.69	0.59	0.49	0.84	0.85	0.86	0.84	0.87	0.86	0.76
<b>12</b>	0.36	0.52	0.63	0.67	0.70	0.68	0.61	0.83	0.84	0.86	0.86	0.84	0.87	0.87
<b>16</b>	0.17	0.39	0.56	0.67	0.71	0.70	0.69	0.82	0.84	0.85	0.85	0.87	0.88	0.88
	<b>KB</b>							<b>KB</b>						
<b>2</b>	0.88	0.86	0.83	0.82	0.73	0.66	0.56	0.87	0.87	0.86	0.87	0.85	0.82	0.76
<b>4</b>	0.80	0.85	0.88	0.83	0.83	0.78	0.72	0.89	0.87	0.87	0.84	0.85	0.85	0.84
<b>8</b>	0.64	0.74	0.85	0.85	0.86	0.84	0.82	0.85	0.88	0.87	0.89	0.90	0.90	0.88
<b>12</b>	0.46	0.69	0.80	0.87	0.87	0.88	0.88	0.84	0.86	0.89	0.91	0.89	0.93	0.92
<b>16</b>	0.27	0.56	0.76	0.87	0.91	0.91	0.90	0.85	0.88	0.88	0.90	0.92	0.92	0.91
$\hat{p}$	$\hat{\Psi}_{21}$							$\hat{\Psi}_{22}$						
	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
	<b>SB</b>							<b>SB</b>						
<b>2</b>	0.88	0.74	0.83	0.86	0.80	0.63	0.48	0.79	0.81	0.80	0.62	0.44	0.27	0.16
<b>4</b>	0.87	0.87	0.80	0.84	0.77	0.62	0.50	0.73	0.78	0.75	0.66	0.49	0.34	0.25
<b>8</b>	0.83	0.79	0.79	0.77	0.76	0.68	0.60	0.54	0.63	0.68	0.68	0.65	0.50	0.40
<b>12</b>	0.71	0.69	0.74	0.78	0.79	0.76	0.68	0.36	0.52	0.60	0.66	0.65	0.61	0.51
<b>16</b>	0.61	0.61	0.66	0.71	0.75	0.78	0.79	0.19	0.36	0.54	0.61	0.66	0.64	0.63
	<b>KB</b>							<b>KB</b>						
<b>2</b>	0.88	0.76	0.87	0.85	0.87	0.84	0.77	0.85	0.87	0.86	0.80	0.71	0.63	0.50
<b>4</b>	0.87	0.89	0.87	0.91	0.89	0.86	0.82	0.84	0.87	0.88	0.85	0.79	0.74	0.64
<b>8</b>	0.82	0.83	0.86	0.88	0.89	0.89	0.85	0.69	0.79	0.86	0.89	0.87	0.83	0.80
<b>12</b>	0.70	0.72	0.82	0.89	0.89	0.89	0.90	0.48	0.72	0.83	0.88	0.87	0.86	0.86
<b>16</b>	0.62	0.66	0.77	0.84	0.87	0.90	0.92	0.29	0.58	0.78	0.86	0.89	0.91	0.91

Key: **SB** denotes the coverage rates obtained from a standard Sieve VAR bootstrap. **KB** denotes the coverage rates obtained from a Sieve VAR bootstrap using Kilian (1998) bias correction.  $\hat{\Psi}_{11}$  stands for the response of variable 1 to a shock in variable 1.  $\hat{\Psi}_{12}$  stands for the response of variable 1 to a shock in variable 2.  $\hat{\Psi}_{21}$  stands for the response of variable 2 to a shock in variable 1.  $\hat{\Psi}_{22}$  stands for the response of variable 2 to a shock in variable 2. Results from 500 Monte Carlo replications. Kilian (1998) corrected parameter estimates are obtained using 1,000 bootstrap resamples. The *IRs* are obtained using 2,000 bootstrap resamples.

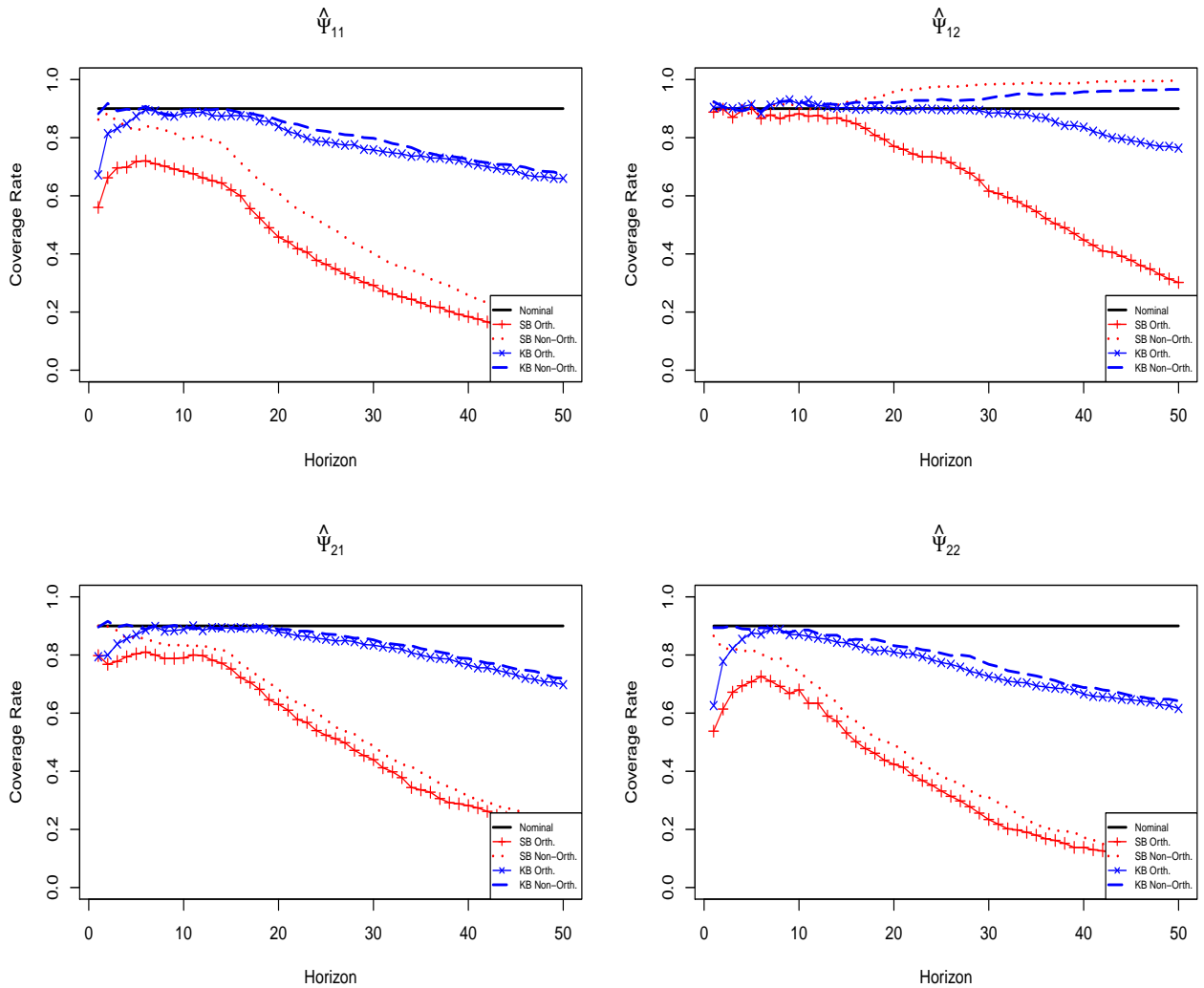
Table 2: Non - Orthogonalized Estimated Impulse Responses from Design with  $\beta = 0.5$  and  $T = 250$ . Effective coverage rates for 90% confidence intervals derived from different order VARs.

$\hat{p}$	$\hat{\Psi}_{11}$							$\hat{\Psi}_{12}$						
	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
	<b>SB</b>							<b>SB</b>						
<b>2</b>	0.88	0.83	0.78	0.62	0.47	0.33	0.23	0.86	0.88	0.91	0.91	0.92	0.94	0.96
<b>4</b>	0.86	0.85	0.85	0.80	0.69	0.57	0.43	0.90	0.86	0.87	0.85	0.88	0.90	0.92
<b>8</b>	0.84	0.84	0.86	0.82	0.80	0.73	0.61	0.92	0.90	0.88	0.88	0.89	0.92	0.95
<b>12</b>	0.85	0.84	0.83	0.83	0.82	0.80	0.77	0.89	0.89	0.91	0.91	0.89	0.89	0.95
<b>16</b>	0.87	0.85	0.85	0.84	0.86	0.85	0.83	0.91	0.87	0.90	0.90	0.90	0.91	0.91
	<b>KB</b>							<b>KB</b>						
<b>2</b>	0.86	0.86	0.83	0.82	0.72	0.60	0.52	0.85	0.88	0.90	0.90	0.91	0.91	0.92
<b>4</b>	0.88	0.91	0.88	0.87	0.84	0.79	0.74	0.89	0.87	0.88	0.85	0.86	0.87	0.88
<b>8</b>	0.87	0.89	0.89	0.89	0.89	0.88	0.85	0.92	0.90	0.89	0.88	0.91	0.91	0.92
<b>12</b>	0.88	0.87	0.90	0.90	0.89	0.89	0.91	0.88	0.89	0.91	0.91	0.90	0.91	0.92
<b>16</b>	0.90	0.89	0.89	0.92	0.92	0.94	0.93	0.92	0.89	0.91	0.92	0.92	0.93	0.93
	$\hat{\Psi}_{21}$							$\hat{\Psi}_{22}$						
$\hat{p}$	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
	<b>SB</b>							<b>SB</b>						
<b>2</b>	0.90	0.80	0.84	0.88	0.82	0.64	0.50	0.89	0.88	0.83	0.65	0.45	0.28	0.18
<b>4</b>	0.90	0.89	0.85	0.87	0.81	0.67	0.53	0.90	0.87	0.81	0.72	0.54	0.39	0.28
<b>8</b>	0.90	0.91	0.89	0.83	0.80	0.72	0.64	0.89	0.84	0.81	0.77	0.71	0.58	0.46
<b>12</b>	0.90	0.89	0.86	0.84	0.83	0.79	0.74	0.85	0.85	0.83	0.77	0.74	0.68	0.62
<b>16</b>	0.86	0.88	0.88	0.82	0.82	0.84	0.83	0.86	0.83	0.81	0.76	0.77	0.77	0.75
	<b>KB</b>							<b>KB</b>						
<b>2</b>	0.91	0.80	0.87	0.83	0.86	0.85	0.78	0.88	0.88	0.85	0.81	0.73	0.64	0.52
<b>4</b>	0.90	0.89	0.90	0.91	0.89	0.87	0.84	0.92	0.90	0.90	0.86	0.79	0.75	0.67
<b>8</b>	0.90	0.92	0.91	0.90	0.89	0.90	0.87	0.91	0.91	0.92	0.90	0.89	0.86	0.82
<b>12</b>	0.90	0.89	0.89	0.91	0.91	0.89	0.90	0.88	0.90	0.92	0.91	0.88	0.86	0.89
<b>16</b>	0.87	0.88	0.91	0.89	0.90	0.91	0.92	0.89	0.87	0.90	0.89	0.91	0.91	0.92

Key: as for table 1.

# Simulation Results: Figures

Figure 1: Effective Coverage Rates from Design with  $\beta = 0.5$ ,  $T = 250$  and  $p_T = \lfloor 0.25 \ln(T)^2 \rfloor = 8$ .



**Key to all Simulations Figures:** The solid line represents the nominal coverage rate at the 90 % level in all cases. The line denoted by "+" represents the coverage rate of the orthogonalized *IRs* from a standard Sieve *VAR* bootstrap (*SB Orth.*). The line denoted by "x" represents the coverage rate of the orthogonalized *IRs* from a Sieve *VAR* bootstrap using the Kilian (1998) bias correction (*KB Orth.*). For Figures 1 and 2, the dotted line represents the coverage rate of the non-orthogonalized *IRs* from a standard Sieve *VAR* bootstrap (*SB Non-Orth.*). The dashed line represents the coverage rate of the non-orthogonalized *IRs* from a Sieve *VAR* bootstrap using the Kilian (1998) bias correction (*KB Non-Orth.*). The variable  $\hat{\Psi}_{ij}$  denotes the response of variable *i* to a shock in variable *j*; for  $i, j = 1, 2$ . The results are from 500 Monte Carlo replications; while the Kilian (1998) bias corrected parameter estimates are obtained from using 1,000 bootstrap resamples. The *IRs* are obtained from using 2,000 bootstrap resamples.

Figure 2: Effective Coverage Rates from Design with  $\beta = 0.5$ ,  $T = 250$  and  $p_T = \lfloor 0.50 \ln(T)^2 \rfloor = 15$ .

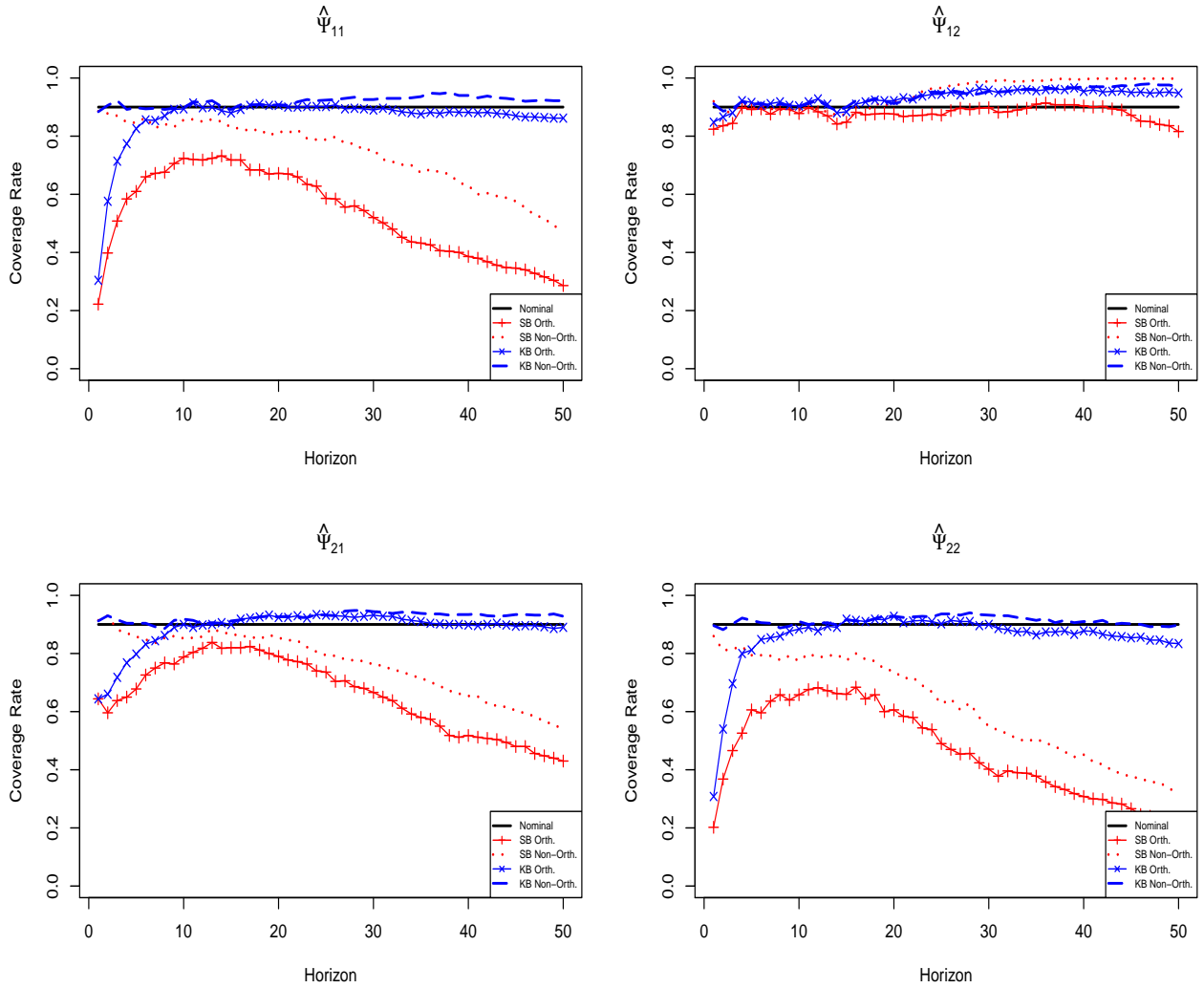


Figure 3: Effective Coverage Rates from Design with  $\beta = 0.5$ ,  $T = 250$  and  $p_T = \lfloor 1.00 \ln(T)^2 \rfloor = 30$ .

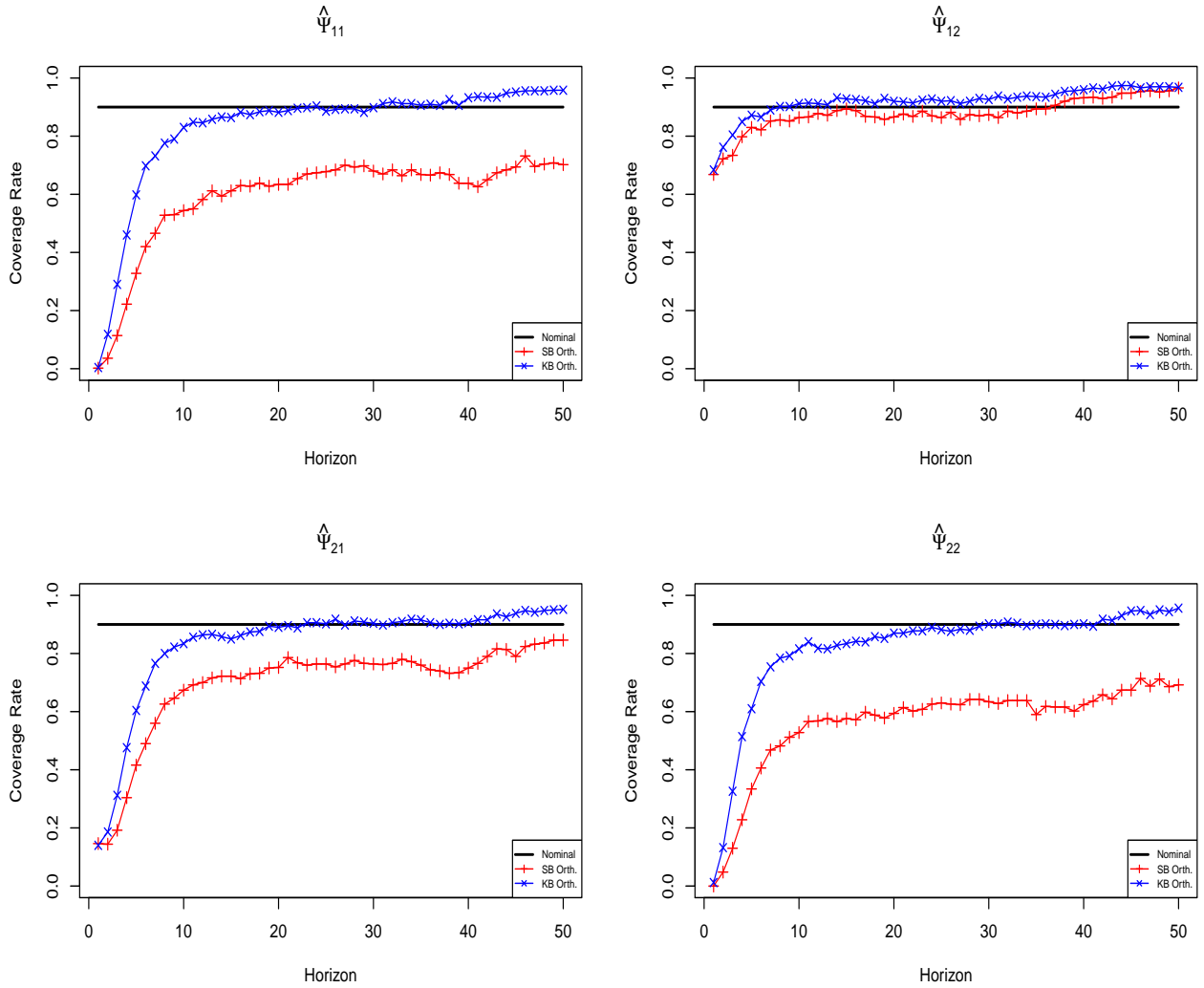


Figure 4: Effective Coverage Rates from Design with  $\beta = 0.5$ ,  $T = 250$  and  $p_T = AIC$ .

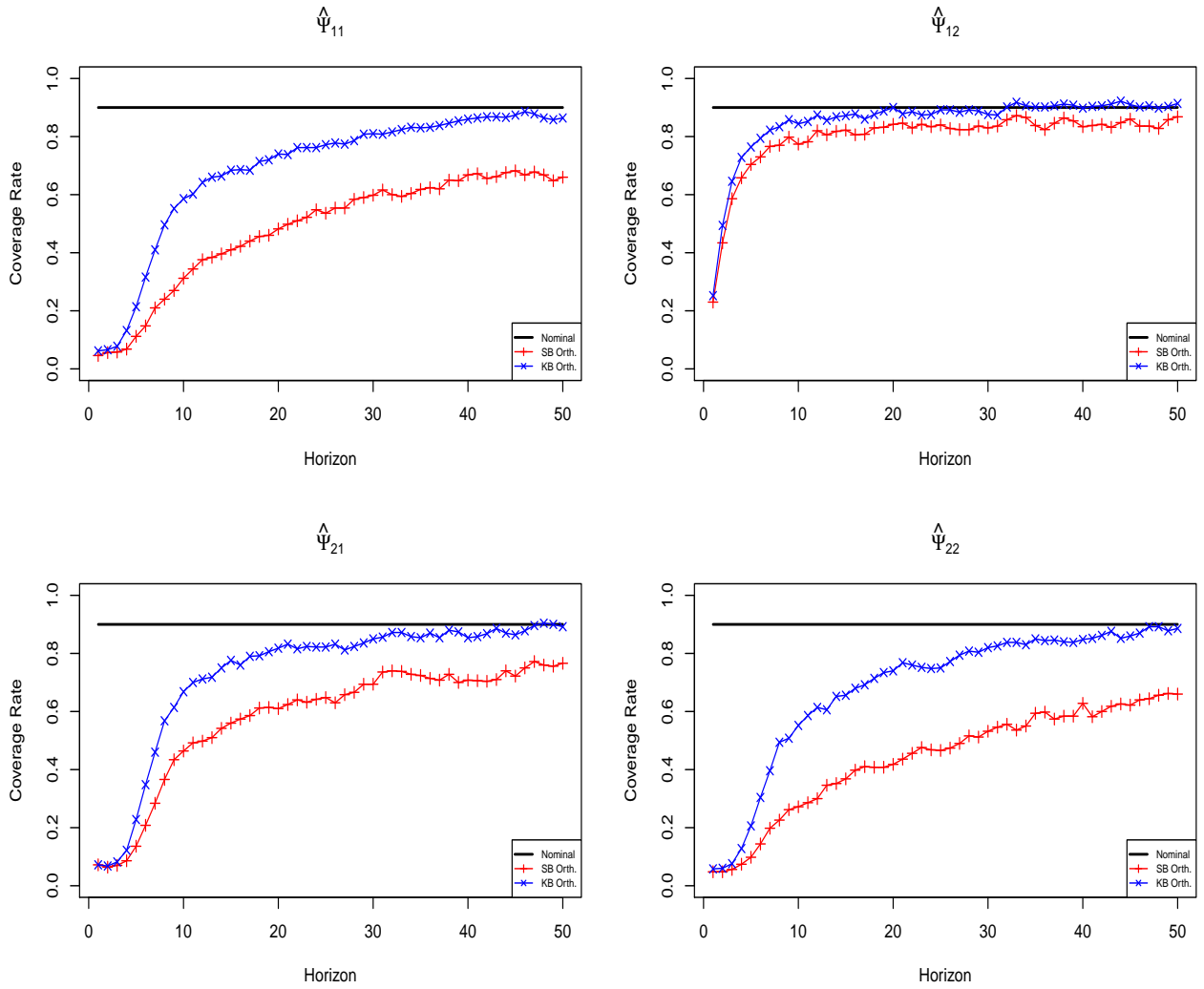


Figure 5: Effective Coverage Rates from Design with  $\beta = 0.5$ ,  $T = 500$  and  $p_T = \lfloor 0.25 \ln(T)^2 \rfloor = 10$ .

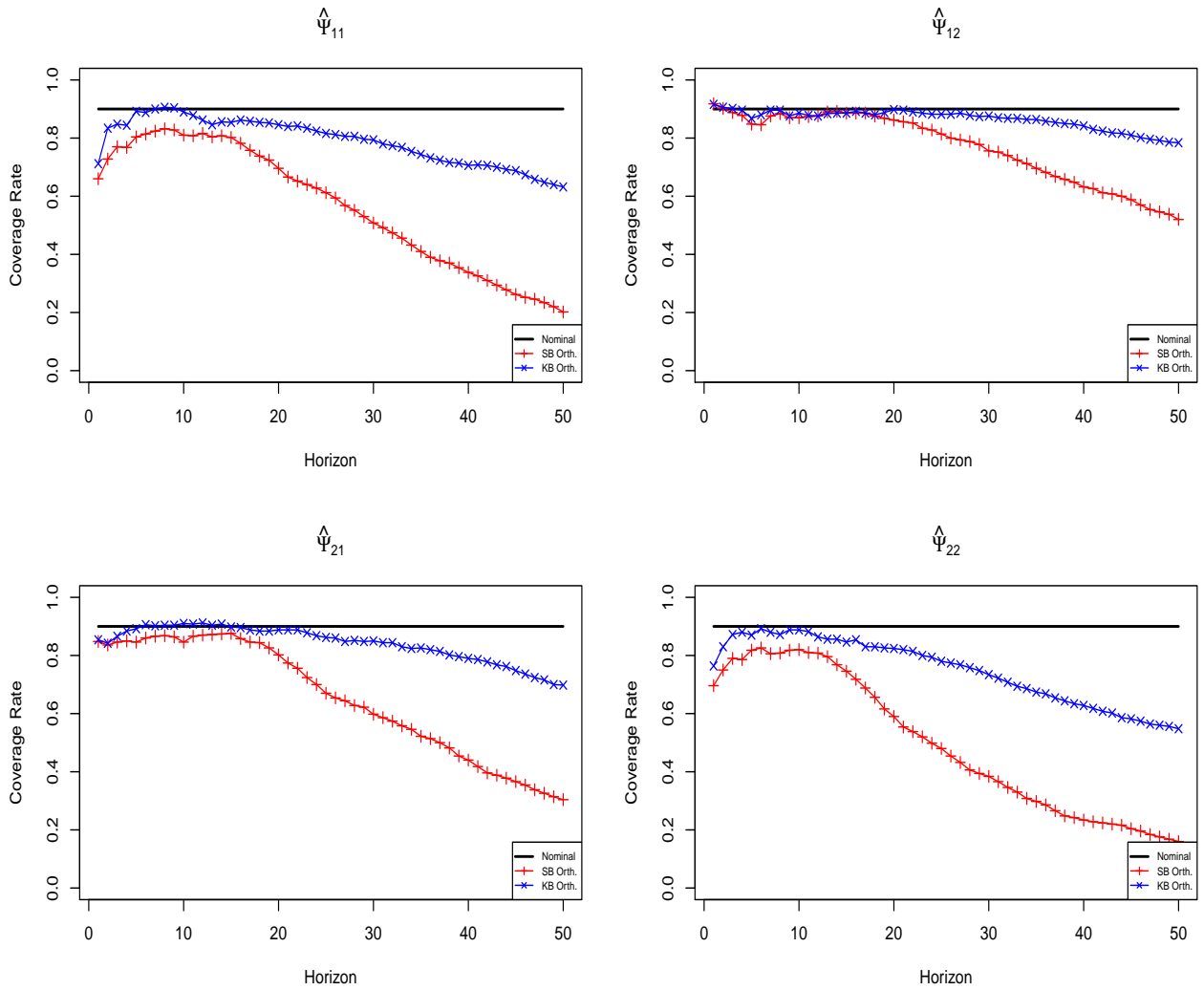




Figure 6: Effective Coverage Rates from Design with  $\beta = 0.5$ ,  $T = 500$  and  $p_T = \lfloor 1.00 \ln(T)^2 \rfloor = 39$ .

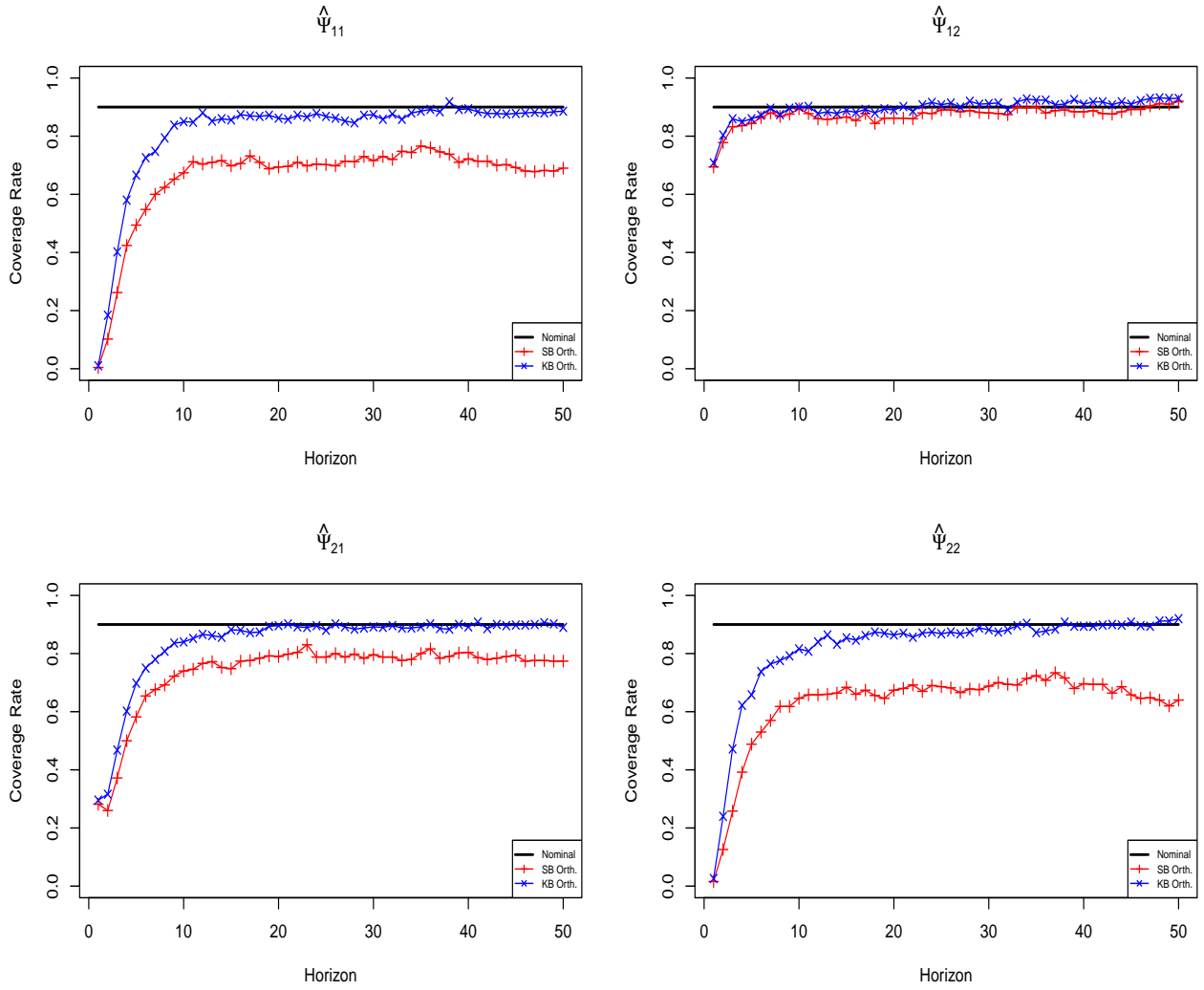


Figure 7: Effective Coverage Rates from Design with  $\beta = 0.9$ ,  $T = 250$  and  $p_T = \lfloor 0.25 \ln(T)^2 \rfloor = 8$ .

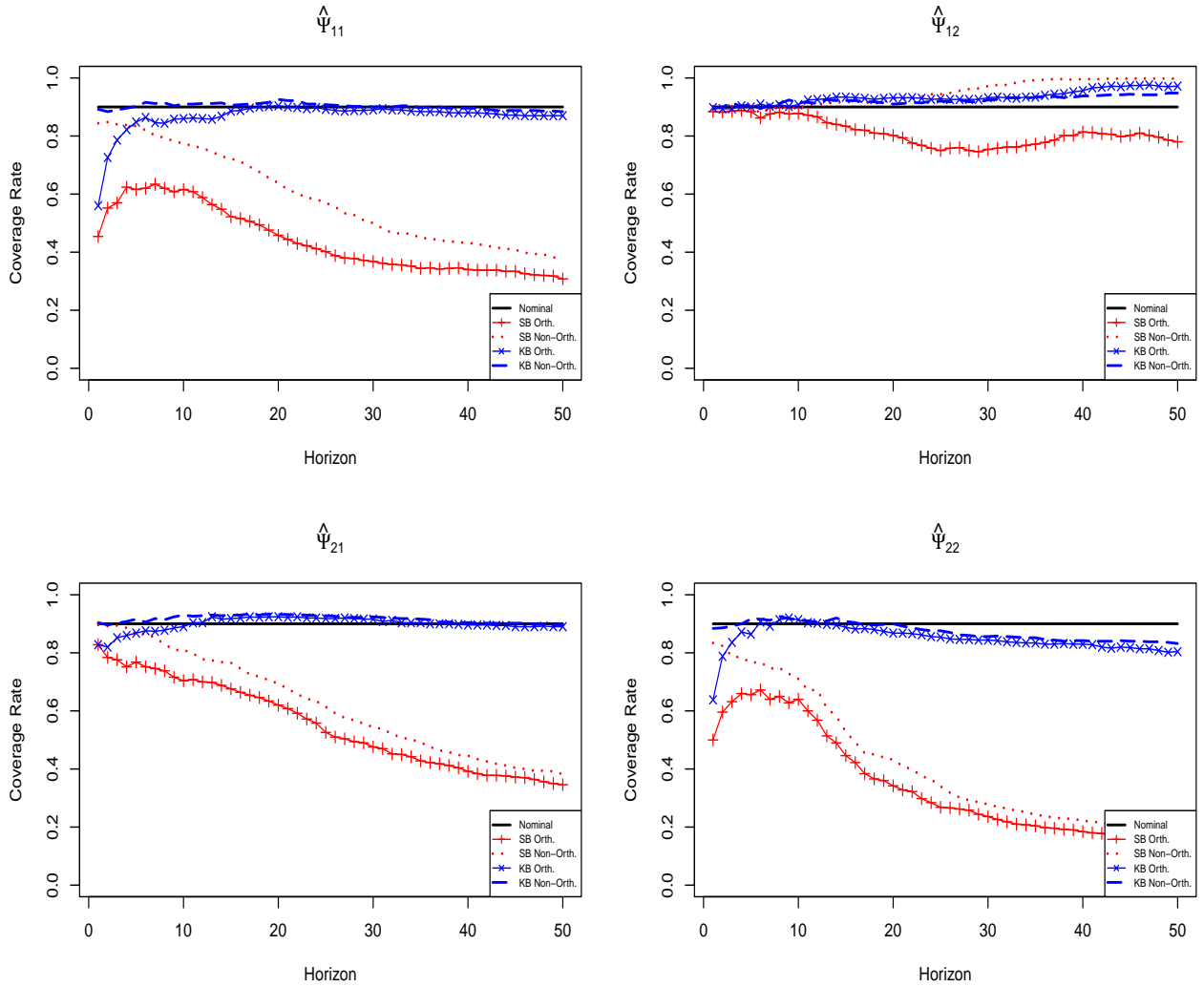


Figure 8: Effective Coverage Rates from Design with  $\beta = 0.9$ ,  $T = 250$  and  $p_T = \lfloor 1.00 \ln(T)^2 \rfloor = 30$ .

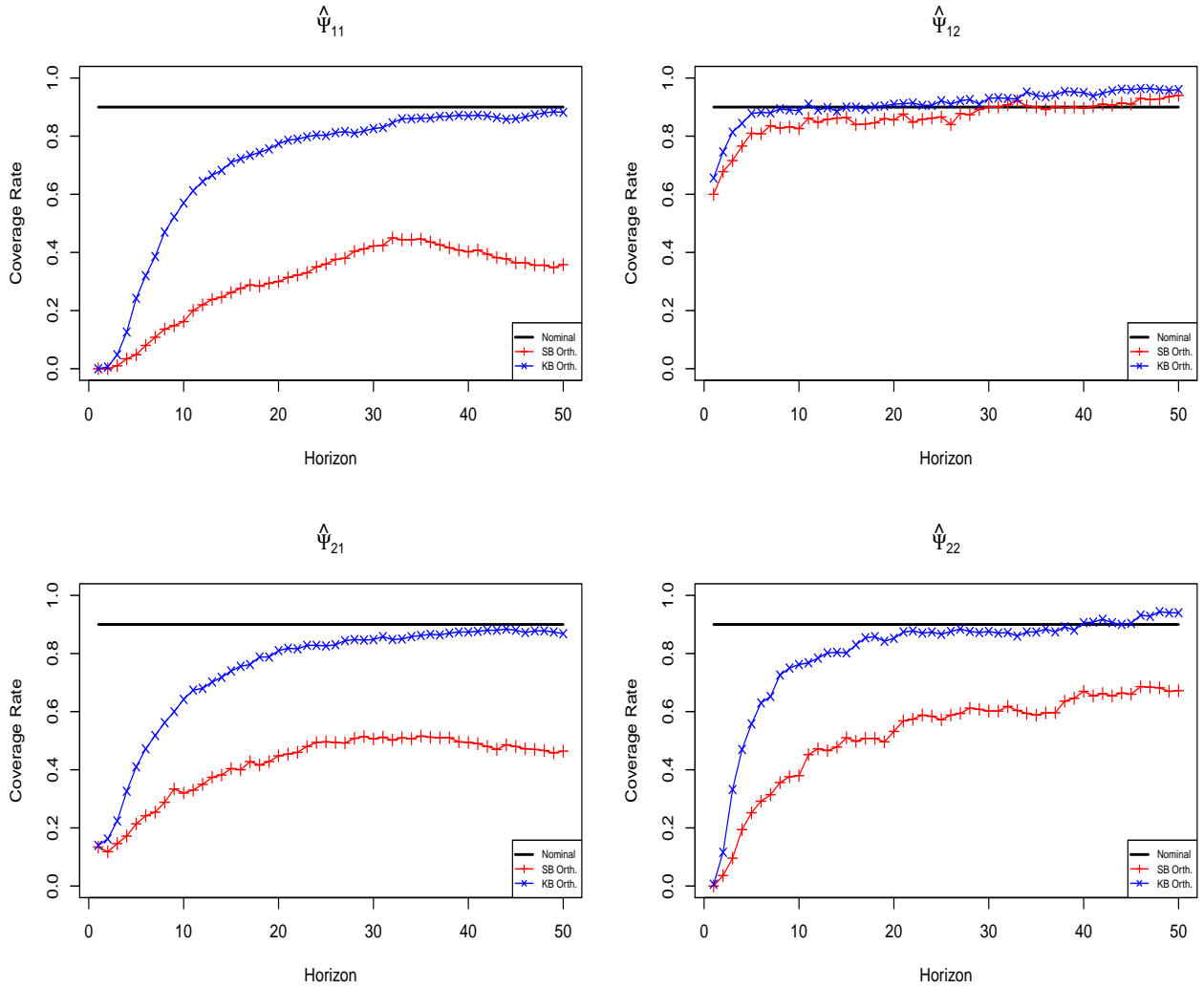


Figure 9: Effective Coverage Rates from Design with  $\beta = 0.9$ ,  $T = 500$  and  $p_T = \lfloor 0.25 \ln(T)^2 \rfloor = 10$ .

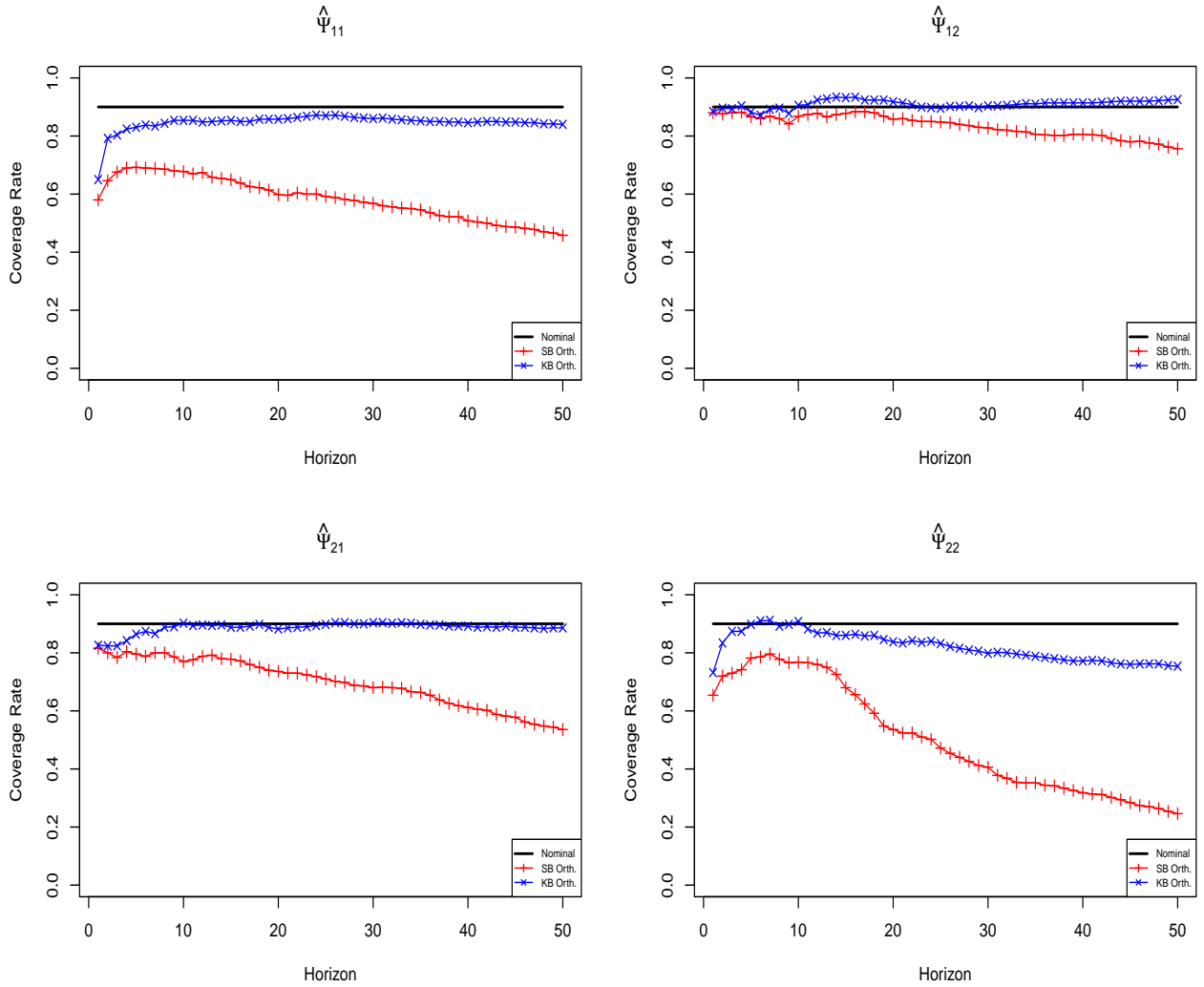


Figure 10: Effective Coverage Rates from Design with  $\beta = 0.9$ ,  $T = 500$  and  $p_T = \lfloor 1.00 \ln(T)^2 \rfloor = 39$ .

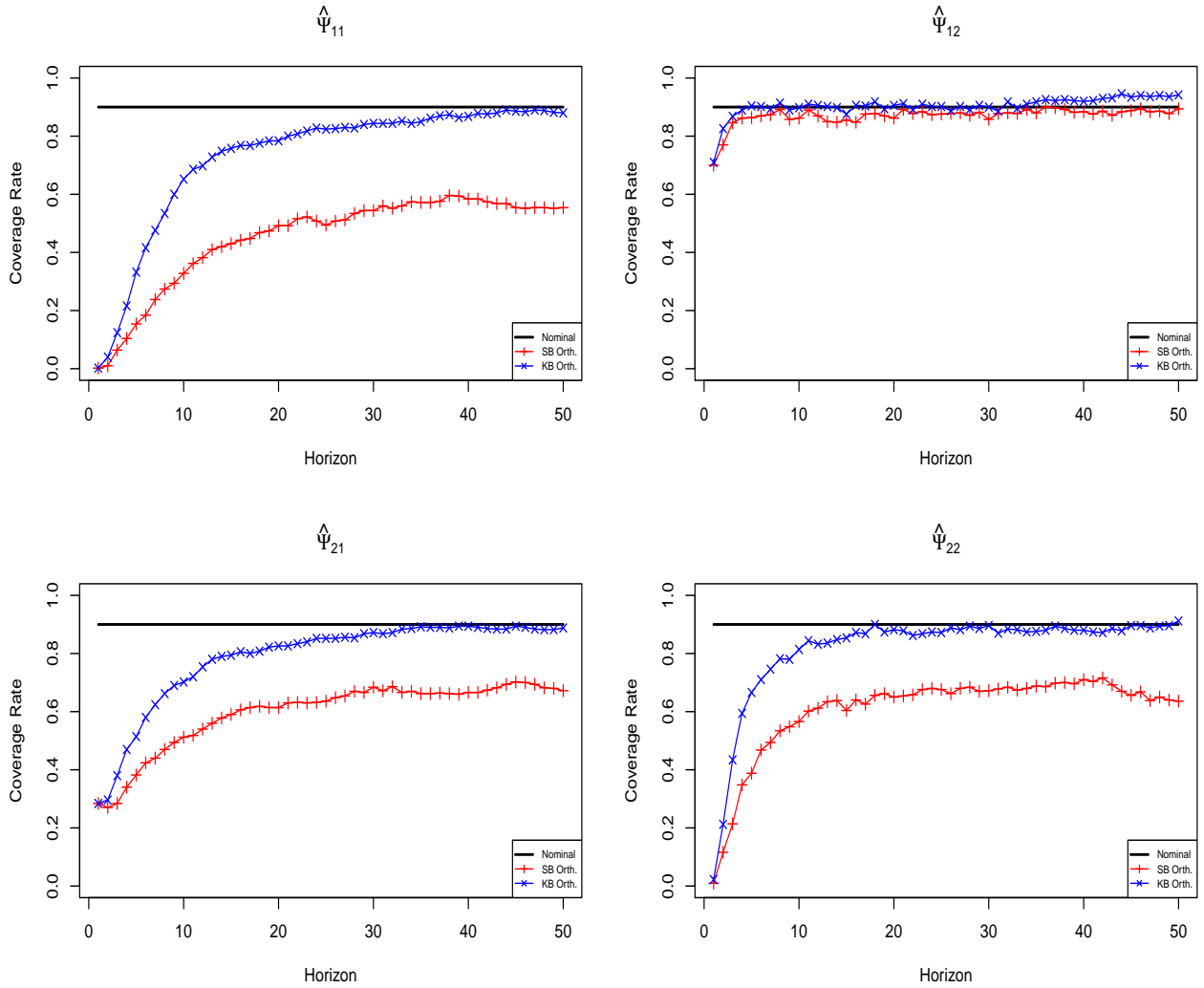


Figure 11: Effective Coverage Rates at 90% confidence intervals from Design with  $\beta = 0.5$ ,  $T = 250$ ; with the Impulse Responses estimated from Hybrid VARs. For lags  $h = 1, 2, \dots, 10$  use  $p_h = \lfloor 0.25 \ln(T)^2 \rfloor = 8$  and for lags  $h = 11, 12, \dots, 25$  use  $p_h = \lfloor 0.50 \ln(T)^2 \rfloor = 15$ .

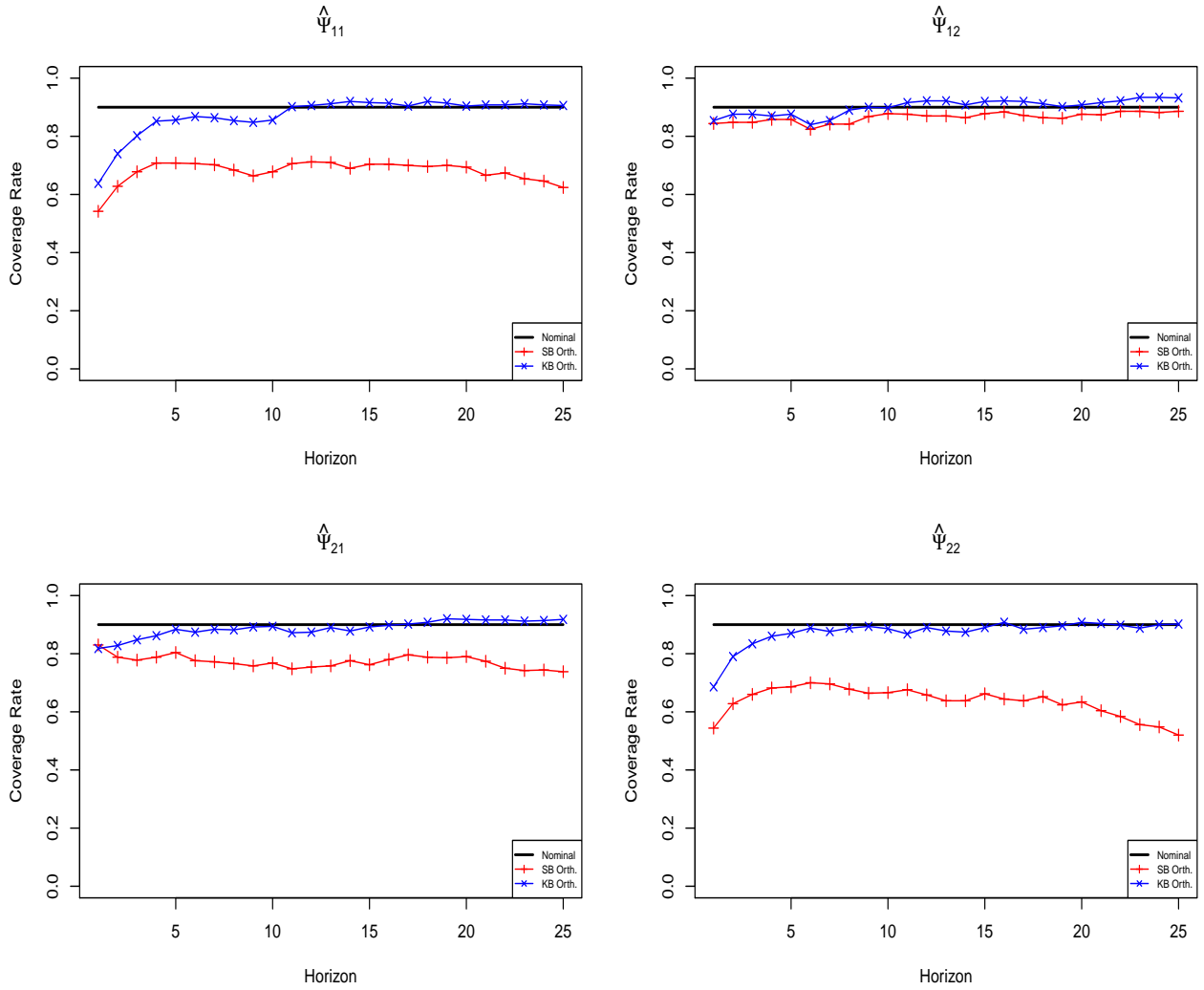
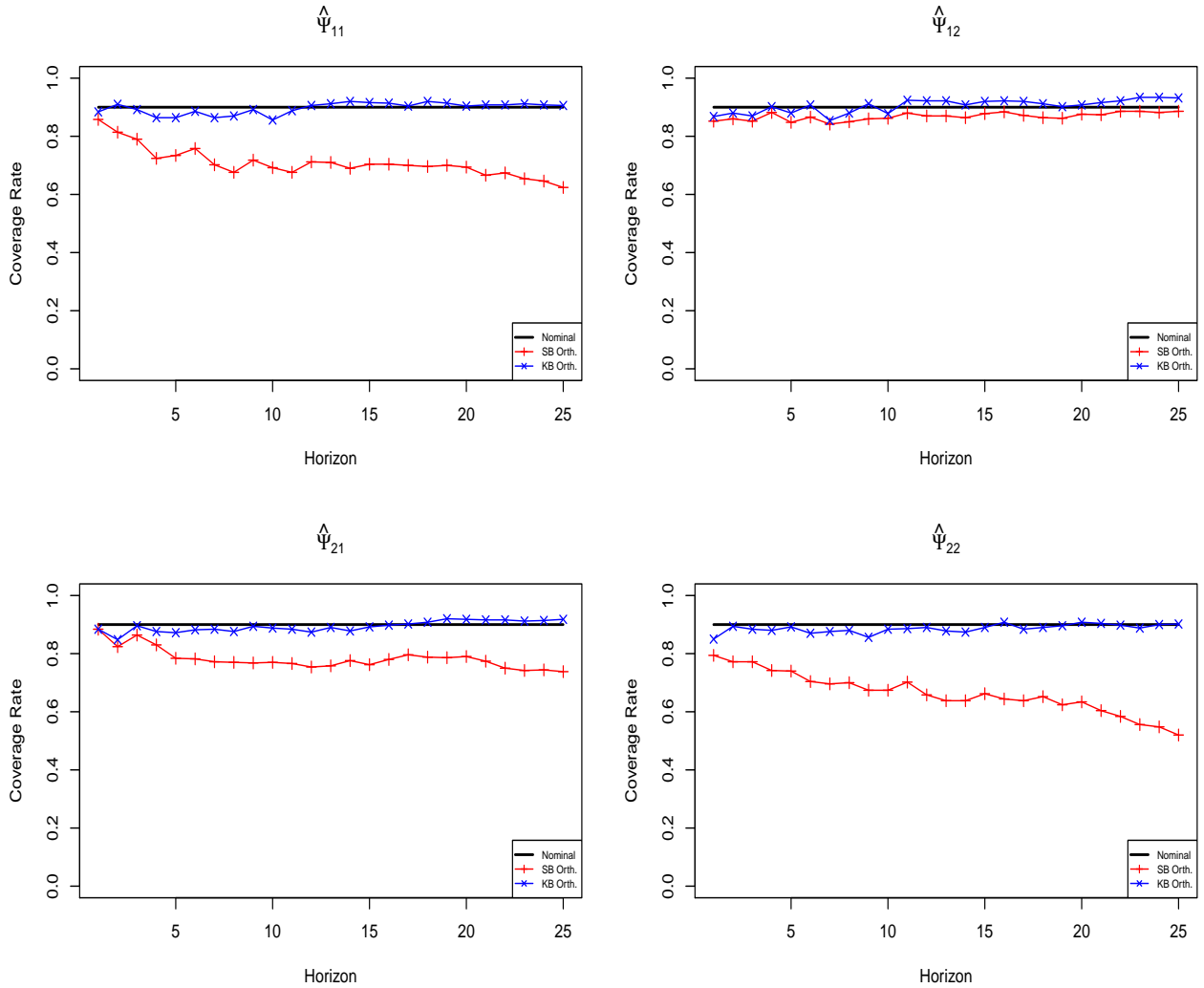
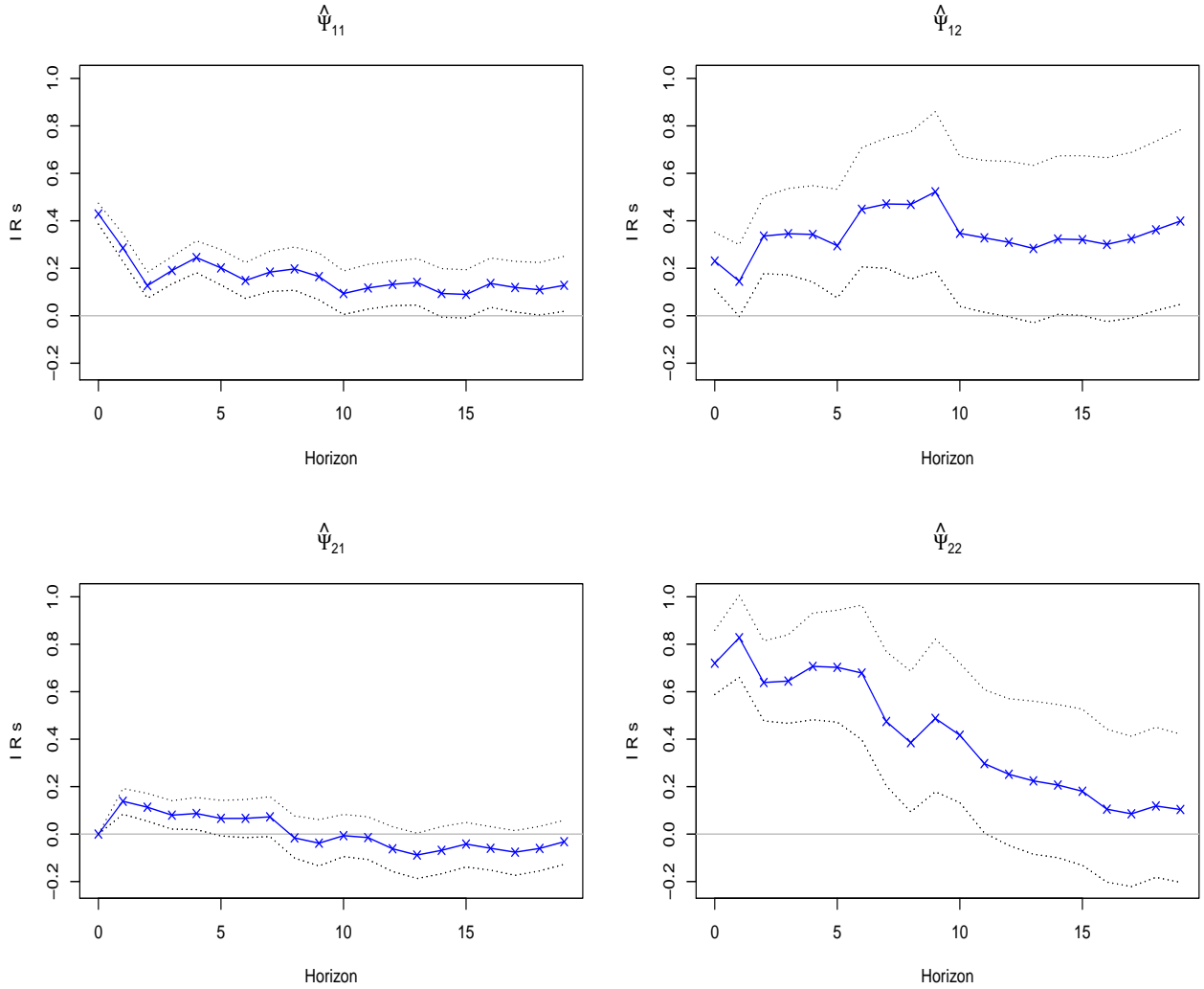


Figure 12: Effective Coverage Rates at 90% confidence intervals from Design with  $\beta = 0.5$ ,  $T = 500$ ; with the Impulse Responses estimated from Hybrid VARs. For lags  $h = 1, 2, \dots, 10$  use  $p_h = (h + 1)$  and for lags  $h = 11, 12, \dots, 25$  use  $p_h = \lfloor 0.50 \ln(T)^2 \rfloor = 15$ .



# Empirical Application: Figures

Figure 13: US



**Key to all Figures:** The line with "x" represents the orthogonalized *IRs* from a Sieve *VAR* bootstrap using Kilian (1998) bias correction (KB Orth.) along with the 90% confidence bounds (dotted lines). The reported results are produced using different lag orders for short and long horizons:  $p_{T,h=\{1,\dots,10\}} = h + 1$ , and  $p_{T,h=\{11,\dots,20\}} = \lfloor 0.50 \ln(T)^2 \rfloor = 14$ . Kilian (1998) corrected parameter estimates are obtained using 1,000 bootstrap resamples. The *IRs* are obtained using 2,000 bootstrap resamples.



Figure 14: UK

