

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. There are theoretical reasons for making the lag length of the *VAR* proportional to $\lfloor \ln(T)^2 \rfloor$. Results are also derived for the orthogonalized estimated *IRs* which are generally more practically relevant. Simulation evidence strongly indicates the desirability for applying the Kilian small sample bias correction, which is found to improve both the estimated orthogonalized and the non-orthogonalized *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, essentially 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, or long memory processes. One of the great attractions of the methodology is that it is relatively simple to apply and also avoids the specification and estimation issues that can make multivariate time series modeling difficult to apply in practice. Hence, for the purpose of purely 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 $E(\boldsymbol{\epsilon}_t) = \mathbf{0}$, $E(\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t') = \boldsymbol{\Omega}$ 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 Ψ_j is a sequence of $m \times m$ matrices of constants. On defining $\Psi(\mathbf{L}) = \sum_{j=0}^{\infty} \Psi_j L^j$ then the spectral density matrix at frequency ω is $\mathbf{f}_y(\omega) = \frac{1}{2\pi} \Psi(e^{i\omega}) \boldsymbol{\Omega} \Psi(e^{-i\omega})$. It is also assumed that a square summability condition

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

is also 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 $E(\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t' | \boldsymbol{\epsilon}_{t-1}, \boldsymbol{\epsilon}_{t-2}, \dots) = \boldsymbol{\Omega}$ 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 $|z| \leq 1$.

Hence, the 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

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

where $\tilde{\boldsymbol{\Psi}}(\mathbf{L}) = \mathbf{\Pi}(\mathbf{L})^{-1}\boldsymbol{\Theta}(L)$, $\mathbf{\Pi}(L) = \sum_{j=0}^p \mathbf{\Pi}_j L^j$, $\boldsymbol{\Theta}(L) = \sum_{j=0}^q \boldsymbol{\Theta}_j L^j$ 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 $\boldsymbol{\Psi}_j = O(\mathbf{C}^j)$ 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 $\|\boldsymbol{\Psi}_j\| = O(j^{d-1})$ for $0 \leq d < 0.5$ as in Chung (2002). This implies that $\left\| \sum_{j=0}^{\infty} \boldsymbol{\Psi}_j \boldsymbol{\Psi}_j' \right\| < \infty$.

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 $\boldsymbol{\Omega}$. Hence an investigator may wish to provide estimates of $\{\boldsymbol{\Psi}_j \boldsymbol{\Omega}^{1/2}\}_{j=1}^h$ rather than $\{\boldsymbol{\Psi}_j\}_{j=1}^h$. Since $\boldsymbol{\Omega}^{1/2}$ is not unique, then for a given $\boldsymbol{\Omega}$, it is necessary to provide further identifying assumptions; for example see Bernanke, Boivin and Elias (2005) 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 Distributions of Estimated IRF

One standard parametric approach has been to specify a stationary and invertible *MVARFIMA* model such that $\mathbf{\Pi}(\mathbf{L})$ and $\boldsymbol{\Theta}(L)$, and therefore, $\boldsymbol{\Psi}(\mathbf{L})$ are parameterized so that they are functions of a vector of parameters given by $\boldsymbol{\theta}$, where $\boldsymbol{\theta}$ contains d_i , $i = 1, 2, \dots, m$, and to estimate $\boldsymbol{\theta}$ by either approximate or full *MLE* so that

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

Note that $\boldsymbol{\theta}_0$ denotes the true value of $\boldsymbol{\theta}$, and the symbol \xrightarrow{L} denotes convergence in distribution. The theory for full and approximate *MLE* of multivariate *ARFIMA* models is described by Sowell (1986, 1992) and Chung (2002)¹. Some applications of the methodology are given in Diebold, Husted and Rush (1991) for the univariate case and see Sowell (1992b), Baillie and Chung (2002) and Jensen (2009) for the multivariate case. In order to obtain confidence intervals

¹These 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.

for the estimated vectorized IR matrix at lag j , i.e. $vec(\Psi_{j,\hat{\theta}})$, where the subscript $\hat{\theta}$ denotes dependence of Ψ_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 ϵ_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 $j = 1, \dots, h$

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

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.

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 univariate processes, such as long memory processes and also near unit root processes; see Wright (2000), Kilian (1998, 1999) and Pesavento and Rossi (2007).

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

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

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 $\hat{\Phi}_j^{(p_T)}$. The estimated IRs are then obtained by inverting the truncated VAR . It follows from a straightforward extension of Theorem 5 of Poskitt (2007) that

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

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 $\alpha > 1$; $\lfloor \cdot \rfloor$ 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 ,² 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 (see, e.g., Kilian (1998)) and as analysed in the univariate long memory case by Baillie and Kapetanios (2013), can be implemented. For ease of reference, we give the relevant algorithm below:

1. Estimate a $VAR(p_T)$ model on y_t and obtain the estimated coefficients, $\widehat{\Phi}_j^{(p_T)}$, $j = 1, \dots, p_T$ and the residuals, $\hat{\epsilon}_t = y_t - \sum_{j=1}^{\min(p_T, t-1)} \widehat{\Phi}_j^{(p_T)} y_{t-j}$.
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 $\widehat{\Omega} = \frac{1}{T} \sum_t \hat{\epsilon}_t \hat{\epsilon}_t'$, and $\widehat{\Omega}^{1/2}$ denotes some suitably defined square root of $\widehat{\Omega}$.
3. Re-center $(\hat{\epsilon}_1, \dots, \hat{\epsilon}_T)'$.
4. Re-sample with replacement from this vector to obtain the bootstrap sample of error terms given by $(\epsilon_1^*, \dots, \epsilon_T^*)'$.
5. Use the above error terms together with $\widehat{\Phi}_j^{(p_T)}$, $j = 1, \dots, p_T$, to generate the bootstrap sample $(y_1^*, \dots, y_T^*)'$.
6. Estimate a $VAR(p_T)$ for $(y_1^*, \dots, y_T^*)'$ 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 $\widehat{\Psi}_j^{*(p_T)}$, $j = 1, \dots, h$.
8. Repeat the above algorithm B times and then use the resulting estimates of the IR to construct an empirical distribution of the IR .

²The use of an 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 $p_{\max, T} = T^\alpha$ $\alpha < 1/2$. Of course $p_{\min, T} < p_{\max, T}$. For the long memory case a different upper bound is needed. One possible form is given by $p_{\max, T} = \lfloor \ln(T)^\alpha \rfloor$, where $a > 0$. More details may be found in Poskitt (2007).

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,*

$$\sum_{j=1}^{p_T} \left\| \widehat{\Phi}_j^{(p_T)} - \Phi_j \right\|^2 = o_p(1). \quad (3)$$

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

$$d(P_{\widehat{\Phi}_j^{(p_T)}}, P_{\widehat{\Phi}_j^{*(p_T)}}) = o_p(1) \quad (4)$$

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,

$$d(P_{\widehat{\Omega}^*}, P_{\widehat{\Omega}}) = o_p(1). \quad (5)$$

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 $\mathbf{D}(\mathbf{L}) = (\mathbf{1} - \mathbf{L})^d \mathbf{I}_m$, 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 β determines the degree of short memory persistence, since the eigenvalues of Φ are 0.5

and β , where $\beta \in \{0.5, 0.9\}$. In all the experiments d was chosen as 0.4^3 . 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 "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*, which represents the case where the sieve *VAR*(p_T) bootstrap has been applied; $p_T = \lfloor c \ln(T)^2 \rfloor$, and the constant c is 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.

(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 portrayed in Figures 1 through 5 report results for the design with the less persistent short memory case of $\beta = 0.5$, for the sample size of $T = 250$. Each figure is divided into four parts. 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 Ω 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, we choose not to report these after the first two figures for each *DGP*. This aids 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.

³Simulation 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.

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 Ψ_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 $c = 0.75$ and $c = 1.00$ in Figures 3 and 4 respectively. Figure 5, 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.

Figures 6 through 10 present corresponding information to Figures 1 through 5, only for the larger sample size of $T = 500$. Figures 13 through 24 are analogous to the Figures 11 through 20 and differ only in terms of the short memory persistence parameter β being set at the higher level of persistence implied by $\beta = 0.9$. The conclusions are generally the same as for the initial tables 1 through 10.

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 exact numerical 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 21 and 22 for the sample size of 250. Figure 21 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 22 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 a feasible ways of conducting *IR* analysis and achieve good results.

(d) The persistence of the short memory process, as defined by β , 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 log 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 $p_T = \lfloor 1.00 \ln(T)^2 \rfloor$. Since inflation can be regarded as being causally prior to nominal interest rates, the ordering of variables and the Cholesky decomposition is clear. 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 23 to 30 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 (3) 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

$$\max_{0 \leq \tau \leq p_T} \|C_T(\tau) - \mathbf{\Gamma}(\tau)\| = O\left(\left(\frac{\log T}{T}\right)^{1/2-d}\right) \quad (6)$$

where $\mathbf{\Gamma}(\tau) = E(\mathbf{y}_t \mathbf{y}'_{t+\tau})$ and $C_T(\tau) = \frac{1}{T} \sum_{t=1}^T \mathbf{y}_t \mathbf{y}'_{t+\tau}$. 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 $E(\|C_T(\tau) - \mathbf{\Gamma}(\tau)\|^2) = O(T^{-2(1-2d)})$. It is necessary to prove this result, which for the univariate case is provided by Theorem 3 or 4 of Hosking (1996). The multivariate version of this result is provided by Corollary 1 of Chung (2002). It is further required to show that

$$\sum_{j=1}^{p_T} \left\| \mathbf{\Phi}_j^{(p_T)} - \mathbf{\Phi}_j \right\| = o(1) \quad (7)$$

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 essentially proves Equation (3).

Next, for Equation (4) we need to extend Theorem 6 of Baillie and Kapetanios (2013) to multivariate processes. But this extension is immediate once Theorem 1 of Poskitt (2007) is extended to autocovariances of multivariate processes which was shown above.

Finally, for Equation (5), it is sufficient to show the results of Theorem 1 of Inoue and Kilian (2002a) (Inoue and Kilian (2002a)) for Ω . First, it is necessary to show that the second block of (A.4) in Inoue and Kilian (2002a) converges to the normal distribution, which is sufficient for proving the above result. This 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). We need to prove

$$\|C_T(\tau) - \mathbf{\Gamma}(\tau)\| = o_p(1) \tag{8}$$

$$\left\| \widehat{\Phi}_j^{(p_T)} - \Phi_j \right\| = o_p(1) \tag{9}$$

$$\left\| \widehat{\Psi}_j^{(p_T)} - \Psi_j \right\| = o_p(1) \tag{10}$$

$$\|\Gamma^*(\tau) - \Gamma(\tau)\| = o_p(1) \tag{11}$$

$$\|\Gamma^{*-1}(\tau) - \Gamma^{-1}(\tau)\| = o_p(1) \tag{12}$$

where $\Gamma^*(\tau)$ is the bootstrap analog of $\Gamma(\tau)$. Equations (8) and (9) have been shown above; while Equation (9) together with Theorem 2.2 of Paparoditis (1996) gives Equation (10). Similarly, Theorem 2.5 of Paparoditis (1996) and Equations (8) through (10) can be used to prove Equations (11) and (12). On using Equations (8) through (12) 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) uses Theorem 24.3 of Davidson (1994) to prove that

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

where Ω^* and $\widehat{\Omega}^*$ are the bootstrap analogs of Ω and $\widehat{\Omega}$ and V is a positive definite covariance matrix. 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 (9). Only the rate in Theorem 2.3 of Paparoditis (1996) changes but this is inconsequential as only convergence in probability is used in the relevant steps of the proof of Theorem 1 of Inoue and Kilian (2002a) and not any rates (see 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: $\beta = 0.5$, $T = 250$, orthogonalized impulse responses. Effective coverage rates of selected 90% intervals with respect to different VAR orders.

\hat{p}	$\hat{\Psi}_{11}$							$\hat{\Psi}_{12}$						
	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
	SB							SB						
2	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
4	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
8	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
12	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
16	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
	KB							KB						
2	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
4	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
8	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
12	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
16	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}	$\hat{\Psi}_{21}$							$\hat{\Psi}_{22}$						
	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
	SB							SB						
2	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
4	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
8	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
12	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
16	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
	KB							KB						
2	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
4	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
8	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
12	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
16	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

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.

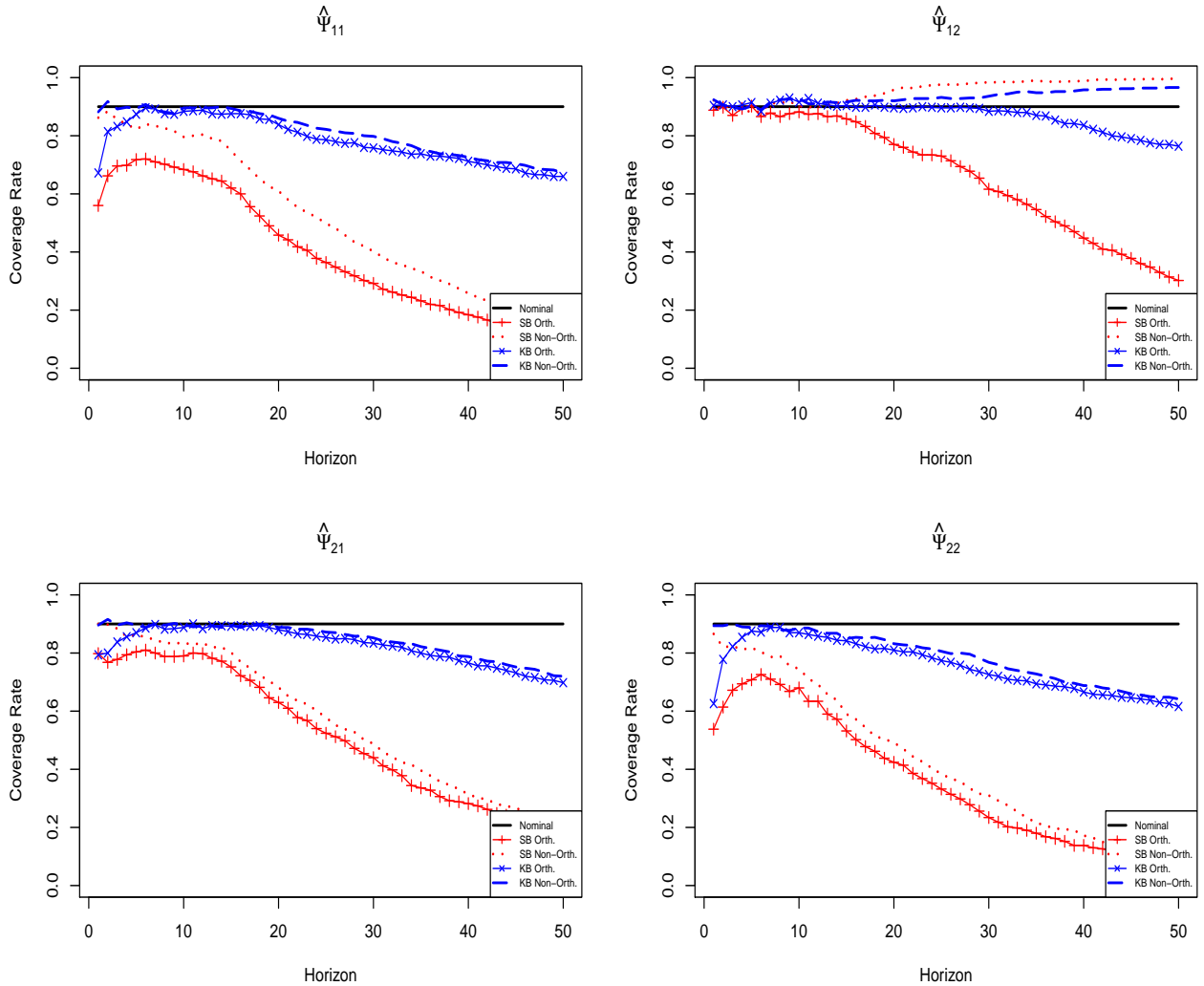
Table 2: $\beta = 0.5$, $T = 250$, Non-orthogonalized impulse responses. Effective coverage rates of selected 90% intervals with respect to different VAR orders.

\hat{p}	$\hat{\Psi}_{11}$							$\hat{\Psi}_{12}$						
	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
	SB							SB						
2	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
4	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
8	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
12	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
16	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
	KB							KB						
2	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
4	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
8	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
12	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
16	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}	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$	$h = 1$	$h = 2$	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
	SB							SB						
2	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
4	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
8	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
12	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
16	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
	KB							KB						
2	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
4	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
8	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
12	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
16	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

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.

Simulation Results: Figures

Figure 1: $\beta = 0.5$, $T = 250$, $p_T = [0.25 \ln(T)^2] = 8$. Effective coverage rates of selected 90% intervals.



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: $\beta = 0.5$, $T = 250$, $p_T = \lfloor 0.50 \ln(T)^2 \rfloor = 15$. Effective coverage rates of selected 90% intervals.

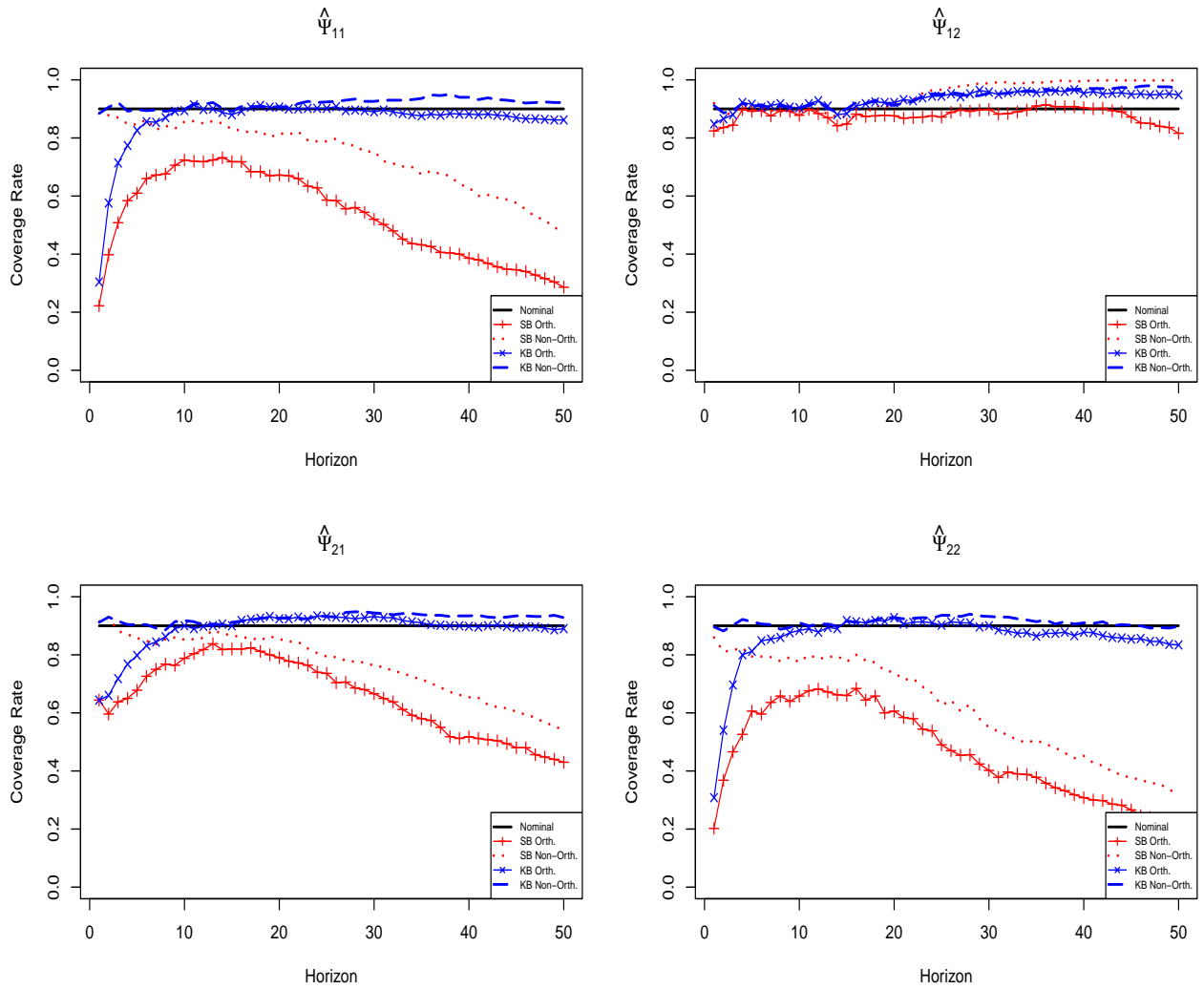


Figure 3: $\beta = 0.5$, $T = 250$, $p_T = \lfloor 0.75 \ln(T)^2 \rfloor = 23$. Effective coverage rates of selected 90% intervals.

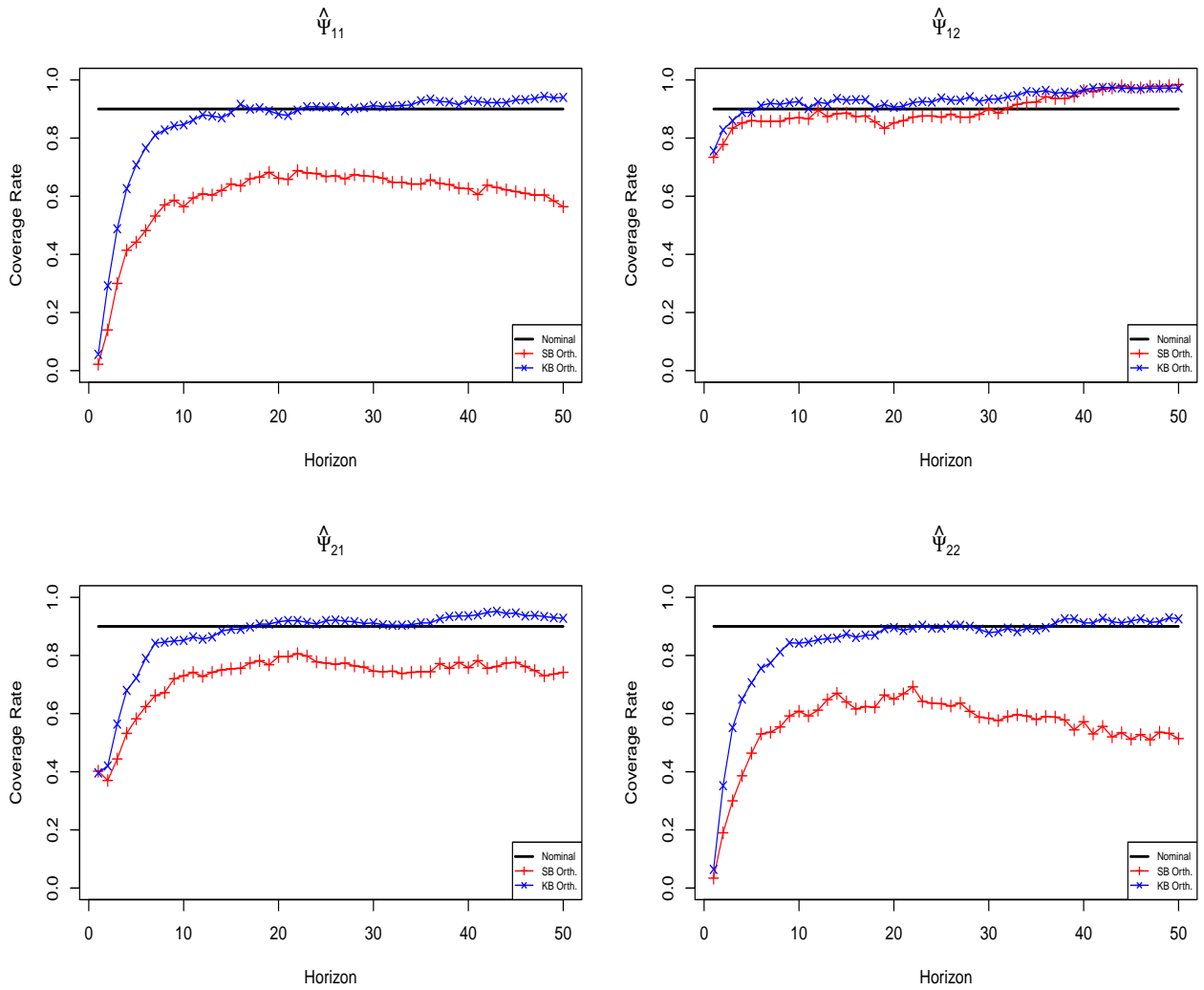


Figure 4: $\beta = 0.5$, $T = 250$, $p_T = \lfloor 1.00 \ln(T)^2 \rfloor = 30$. Effective coverage rates of selected 90% intervals.

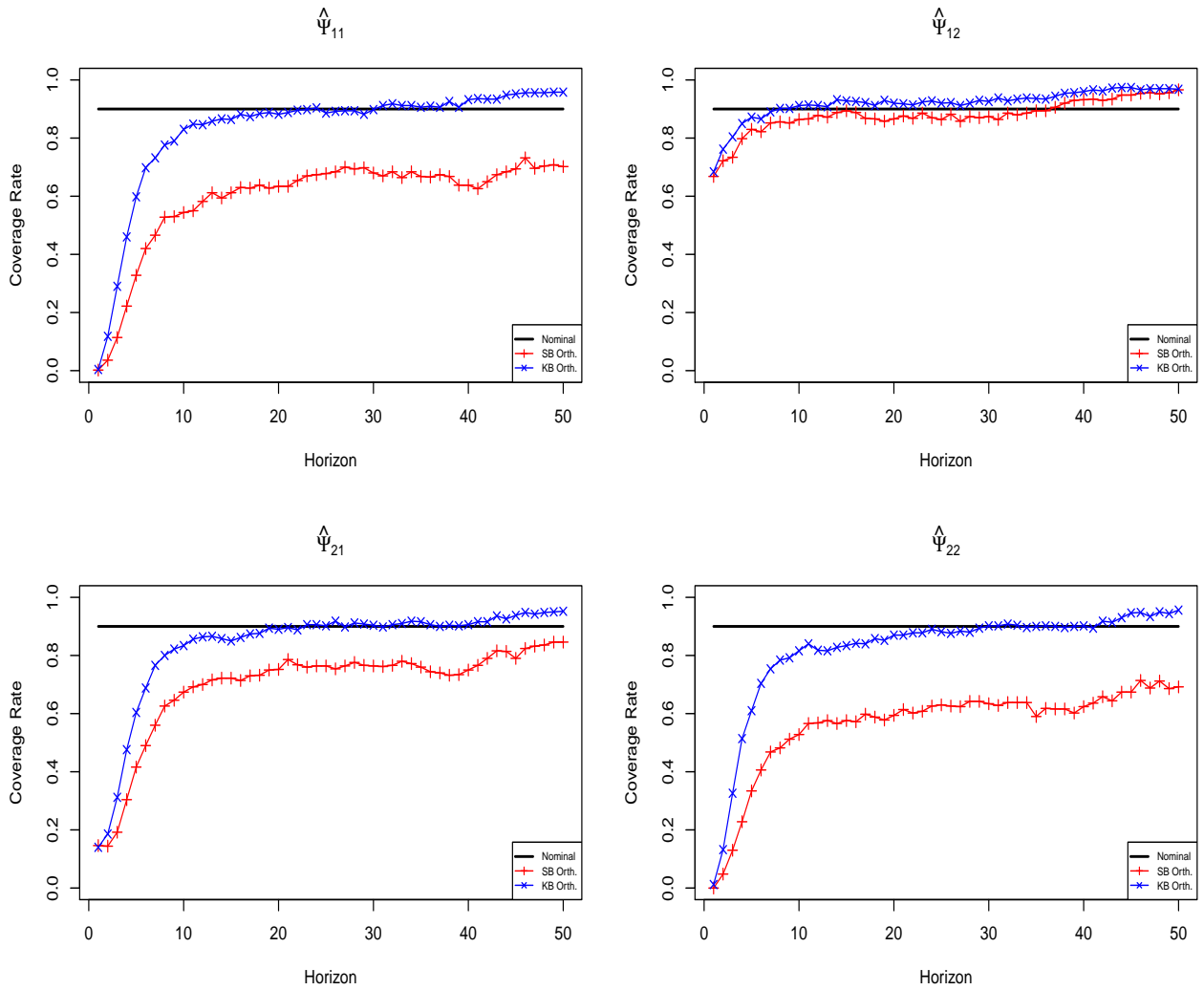


Figure 5: $\beta = 0.5$, $T = 250$, $p_T = AIC$. Effective coverage rates of selected 90% intervals.

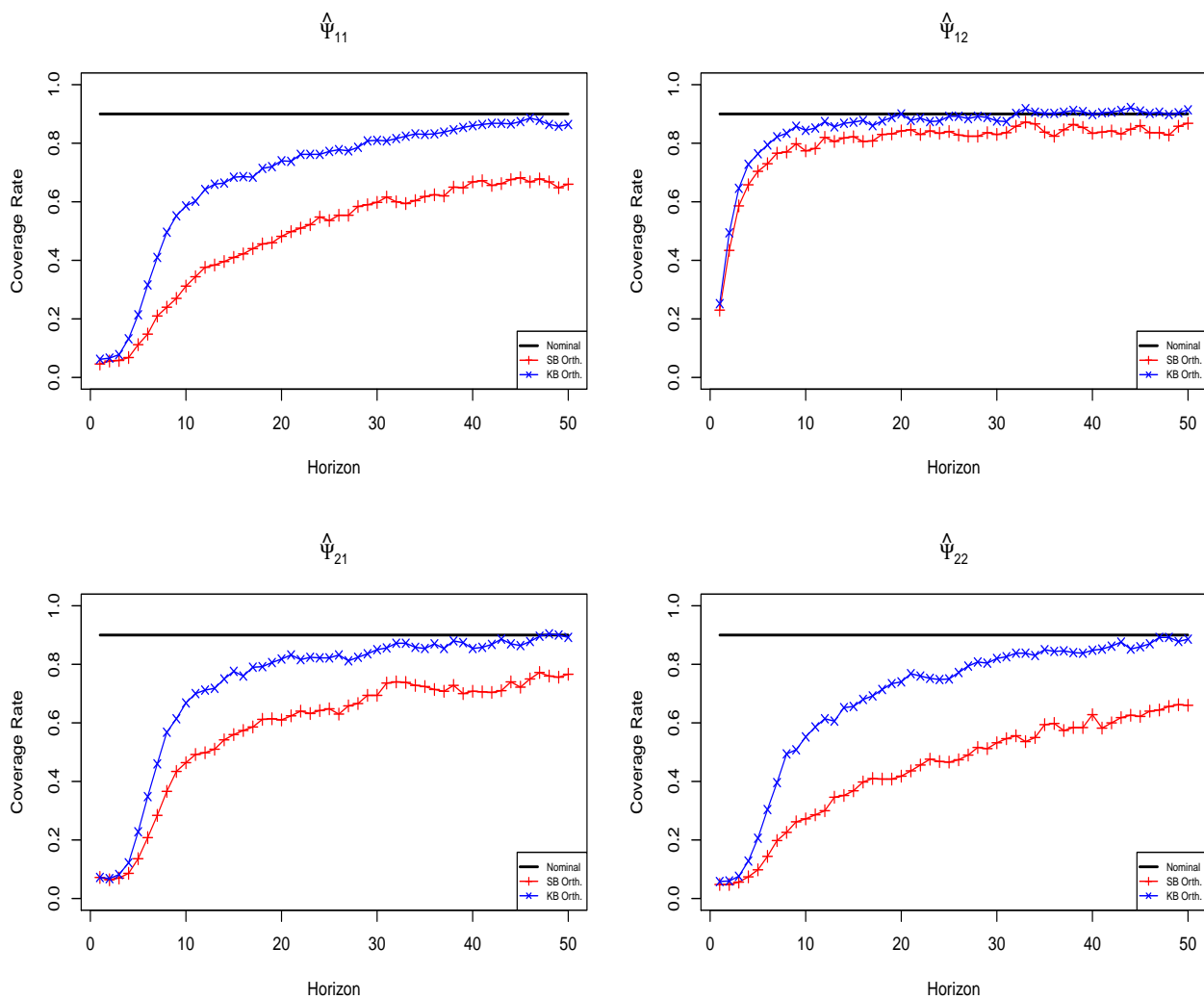


Figure 6: $\beta = 0.5$, $T = 500$, $p_T = \lfloor 0.25 \ln(T)^2 \rfloor = 10$. Effective coverage rates of selected 90% intervals.

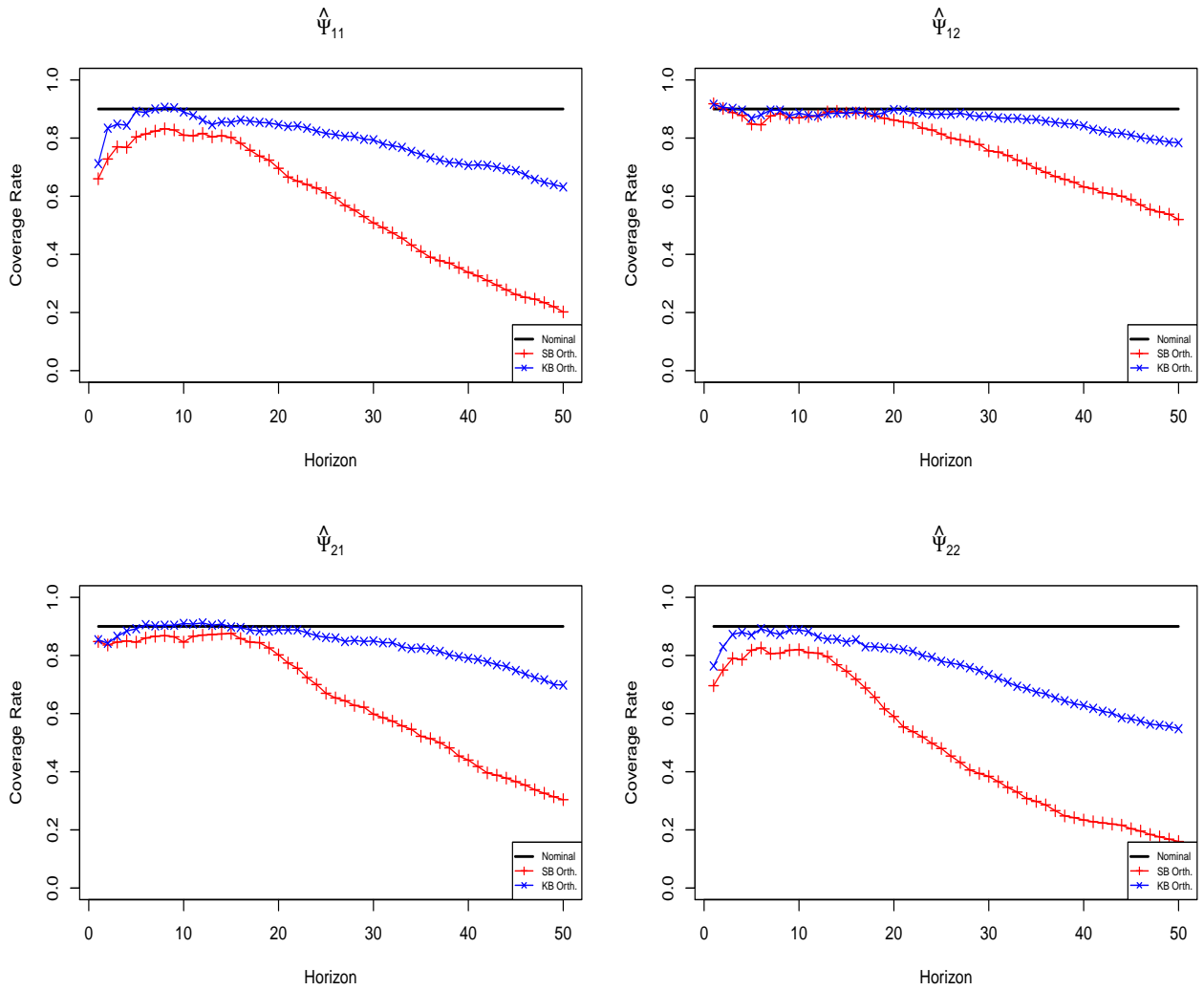


Figure 7: $\beta = 0.5$, $T = 500$, $p_T = \lfloor 0.50 \ln(T)^2 \rfloor = 19$. Effective coverage rates of selected 90% intervals.

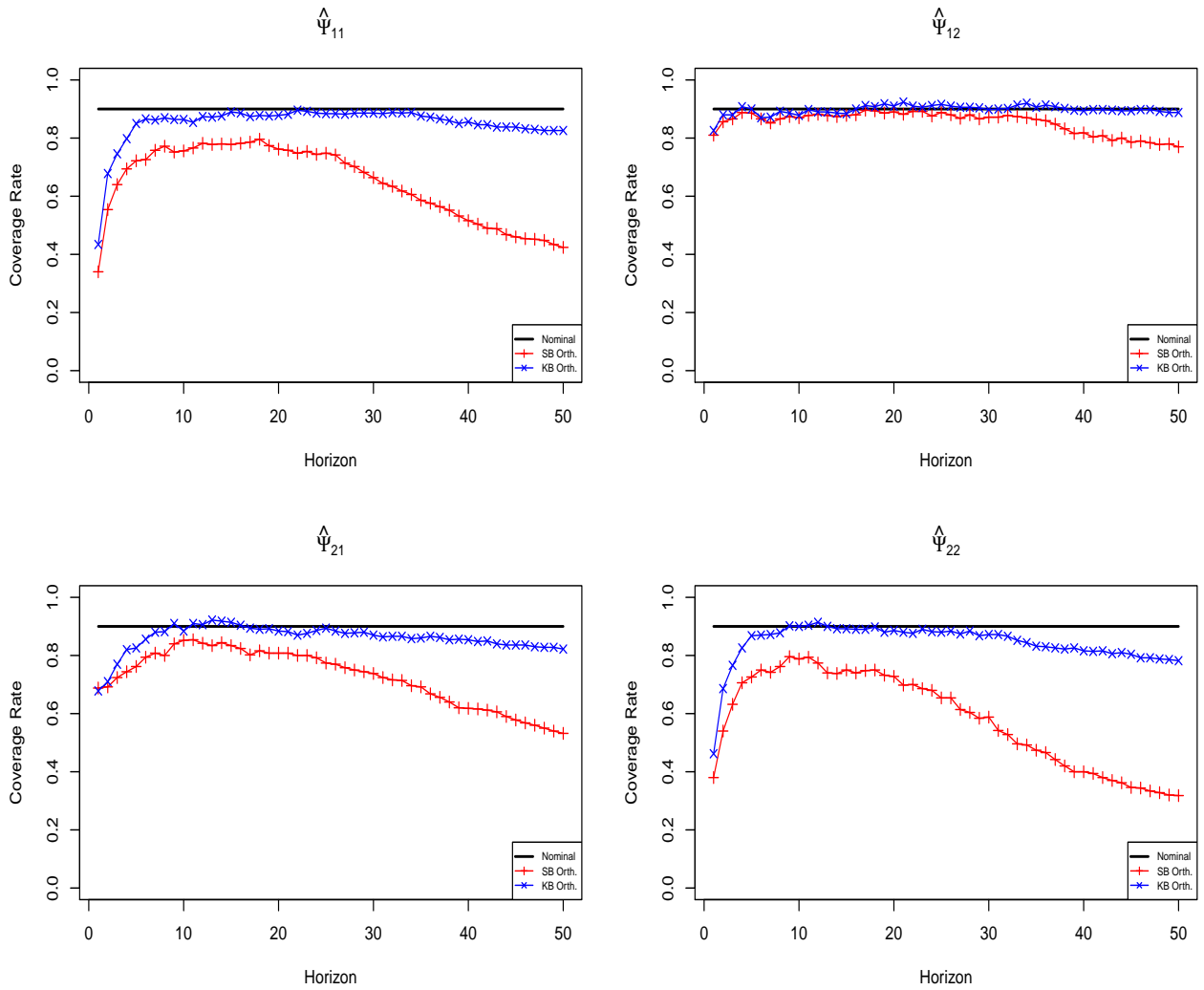


Figure 8: $\beta = 0.5$, $T = 500$, $p_T = \lfloor 0.75 \ln(T)^2 \rfloor = 29$. Effective coverage rates of selected 90% intervals.

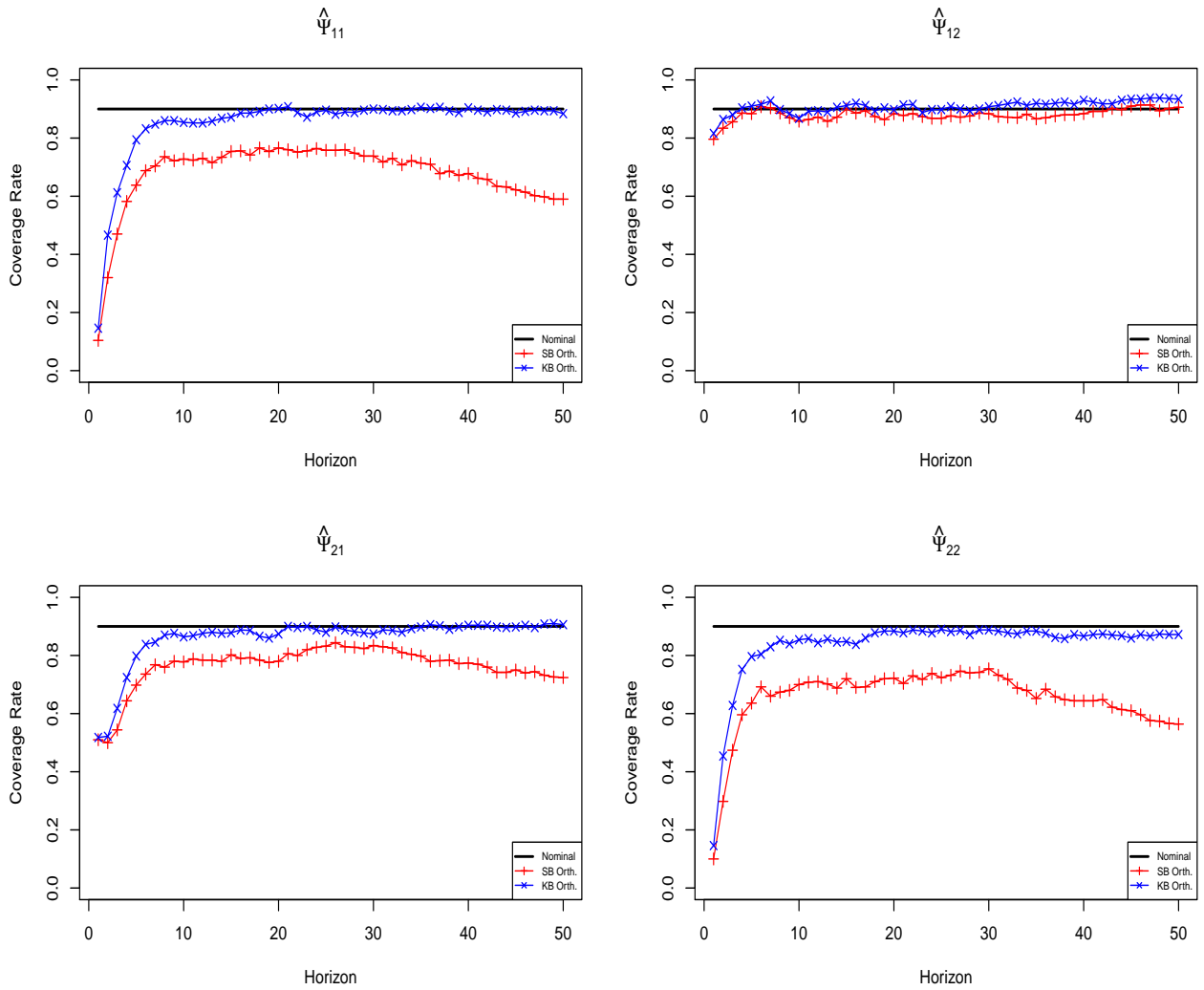


Figure 9: $\beta = 0.5$, $T = 500$, $p_T = \lfloor 1.00 \ln(T)^2 \rfloor = 39$. Effective coverage rates of selected 90% intervals.

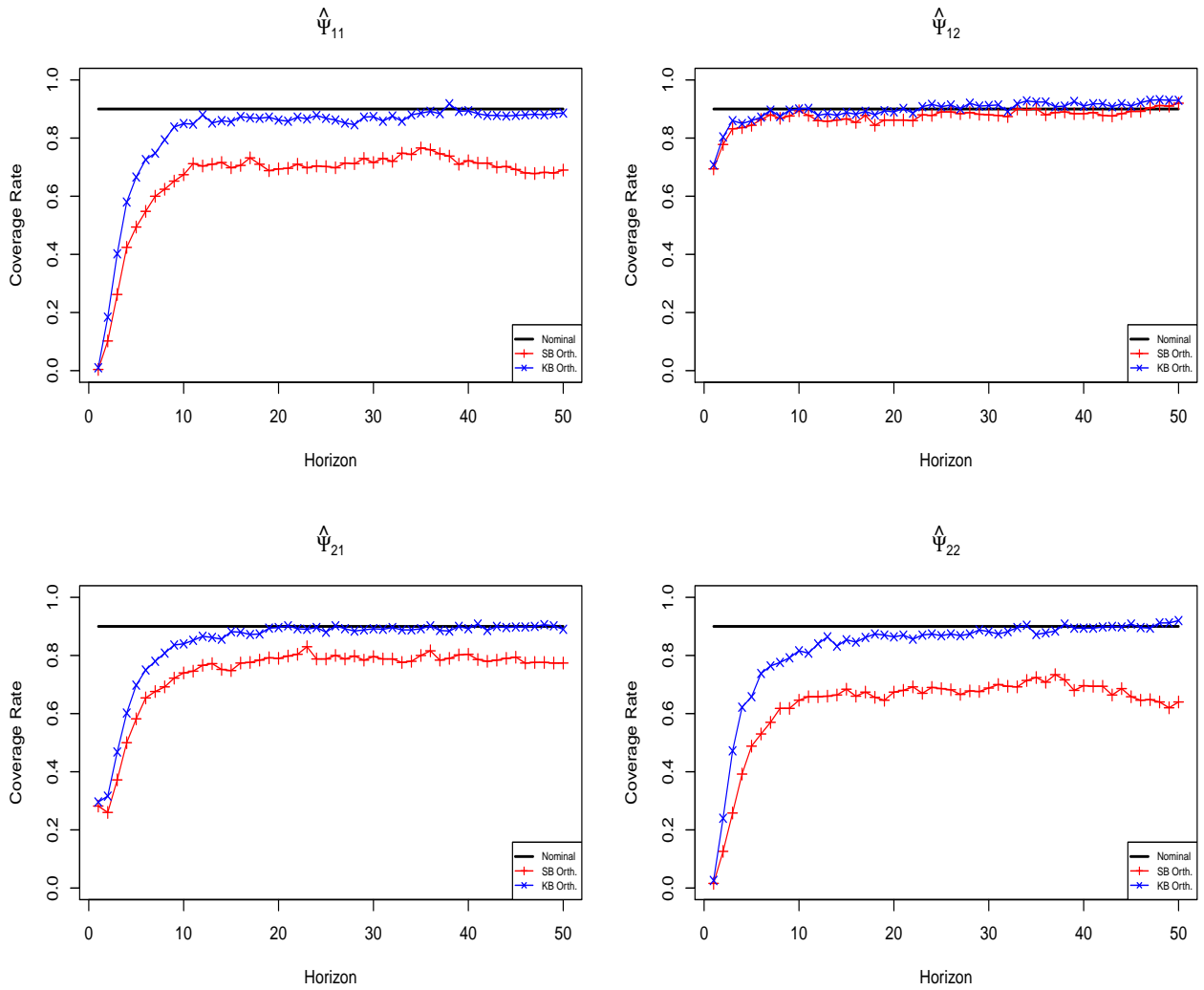


Figure 10: $\beta = 0.5$, $T = 500$, $p_T = AIC$. Effective coverage rates of selected 90% intervals.

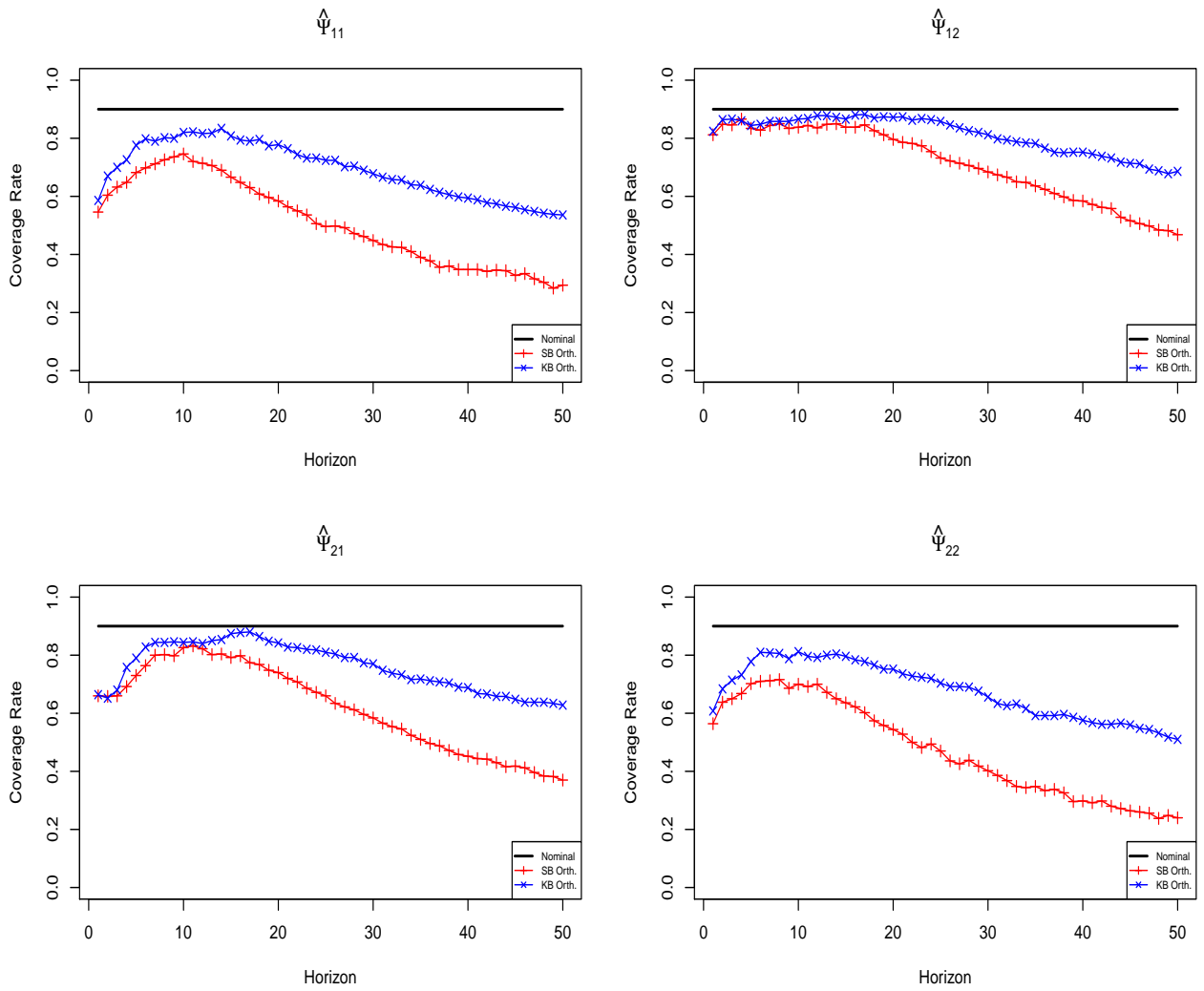


Figure 11: $\beta = 0.9$, $T = 250$, $p_T = \lfloor 0.25 \ln(T)^2 \rfloor = 8$. Effective coverage rates of selected 90% intervals.

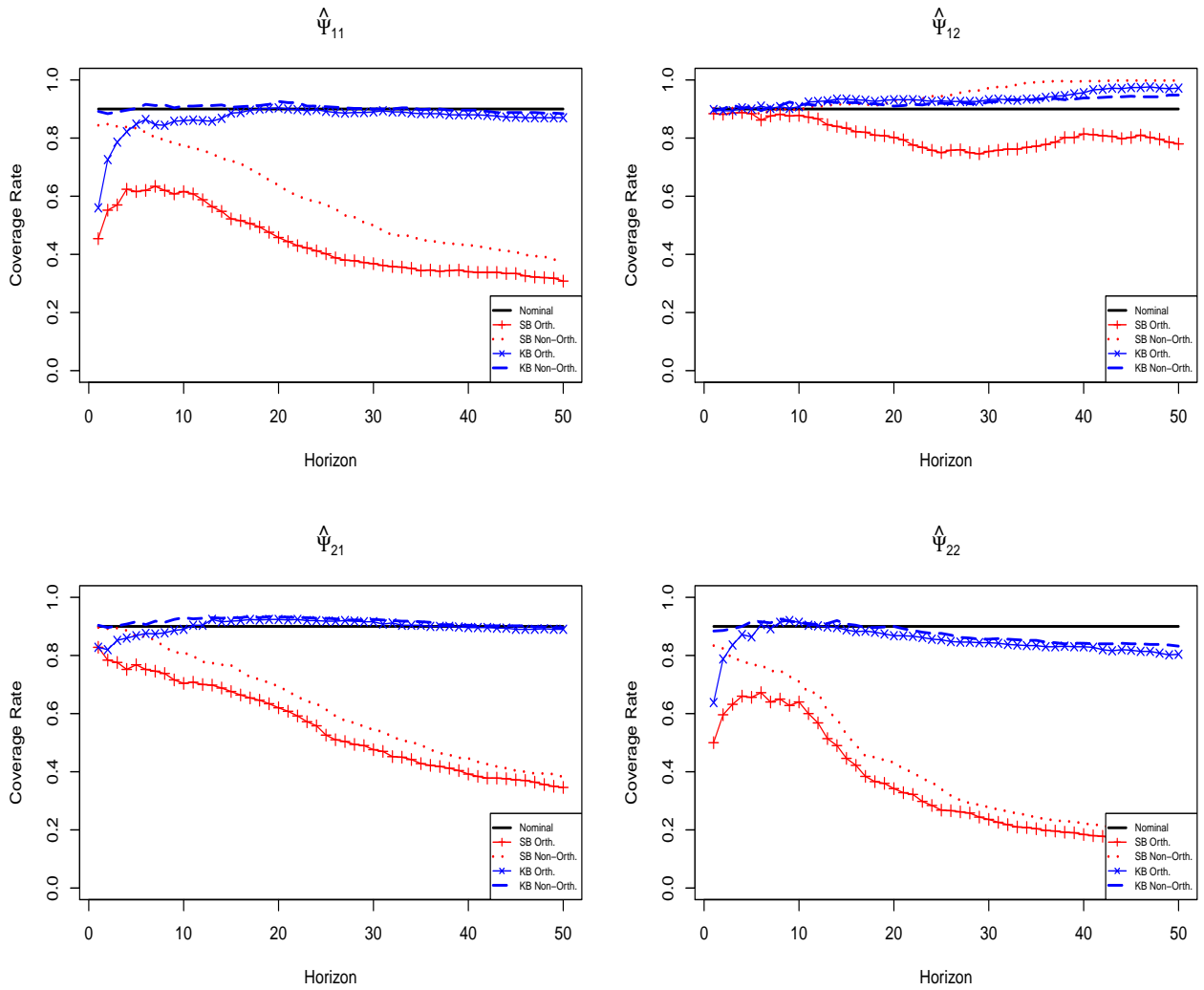


Figure 12: $\beta = 0.9$, $T = 250$, $p_T = \lfloor 0.50 \ln(T)^2 \rfloor = 15$. Effective coverage rates of selected 90% intervals.

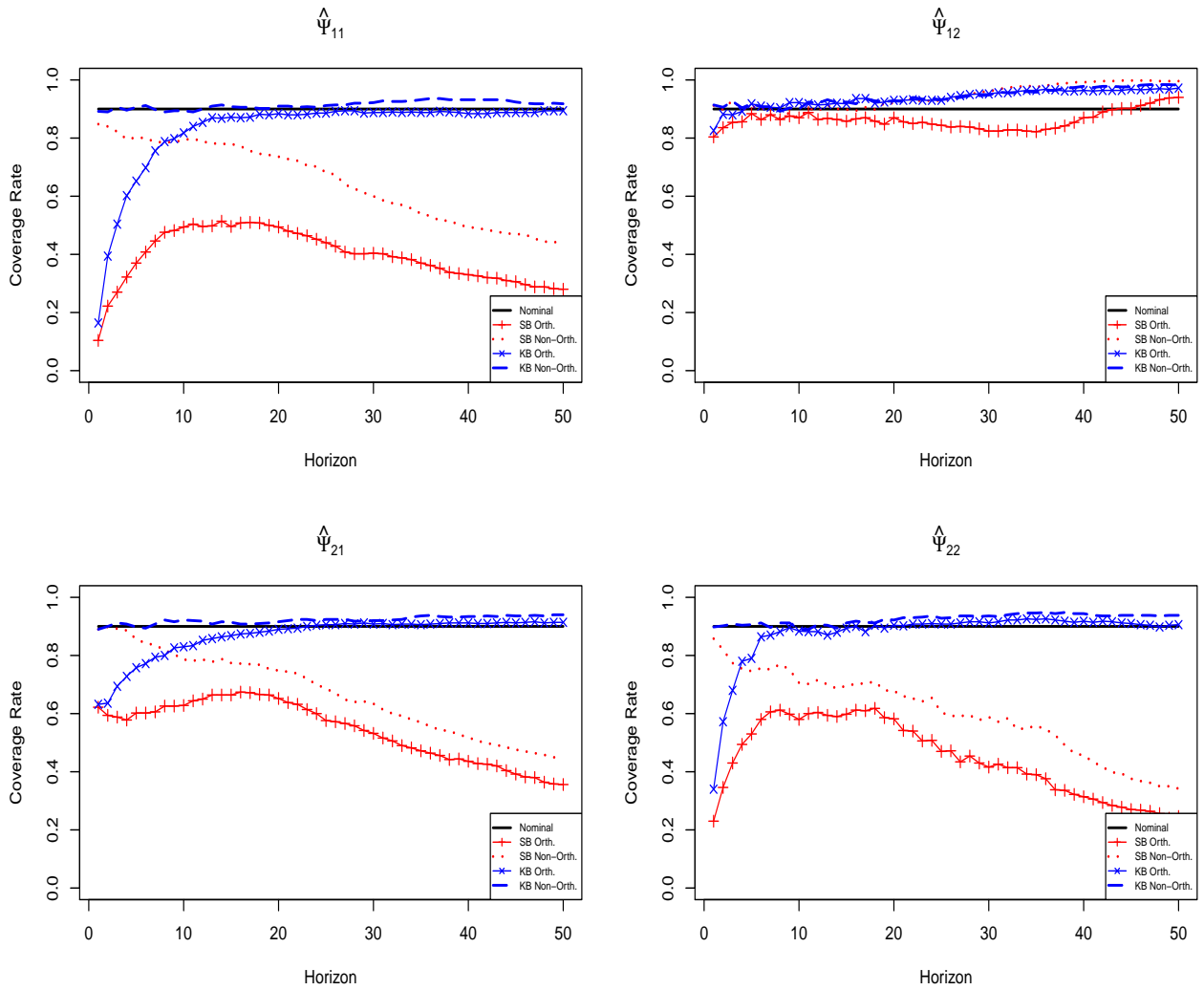


Figure 13: $\beta = 0.9$, $T = 250$, $p_T = \lfloor 0.75 \ln(T)^2 \rfloor = 23$. Effective coverage rates of selected 90% intervals.

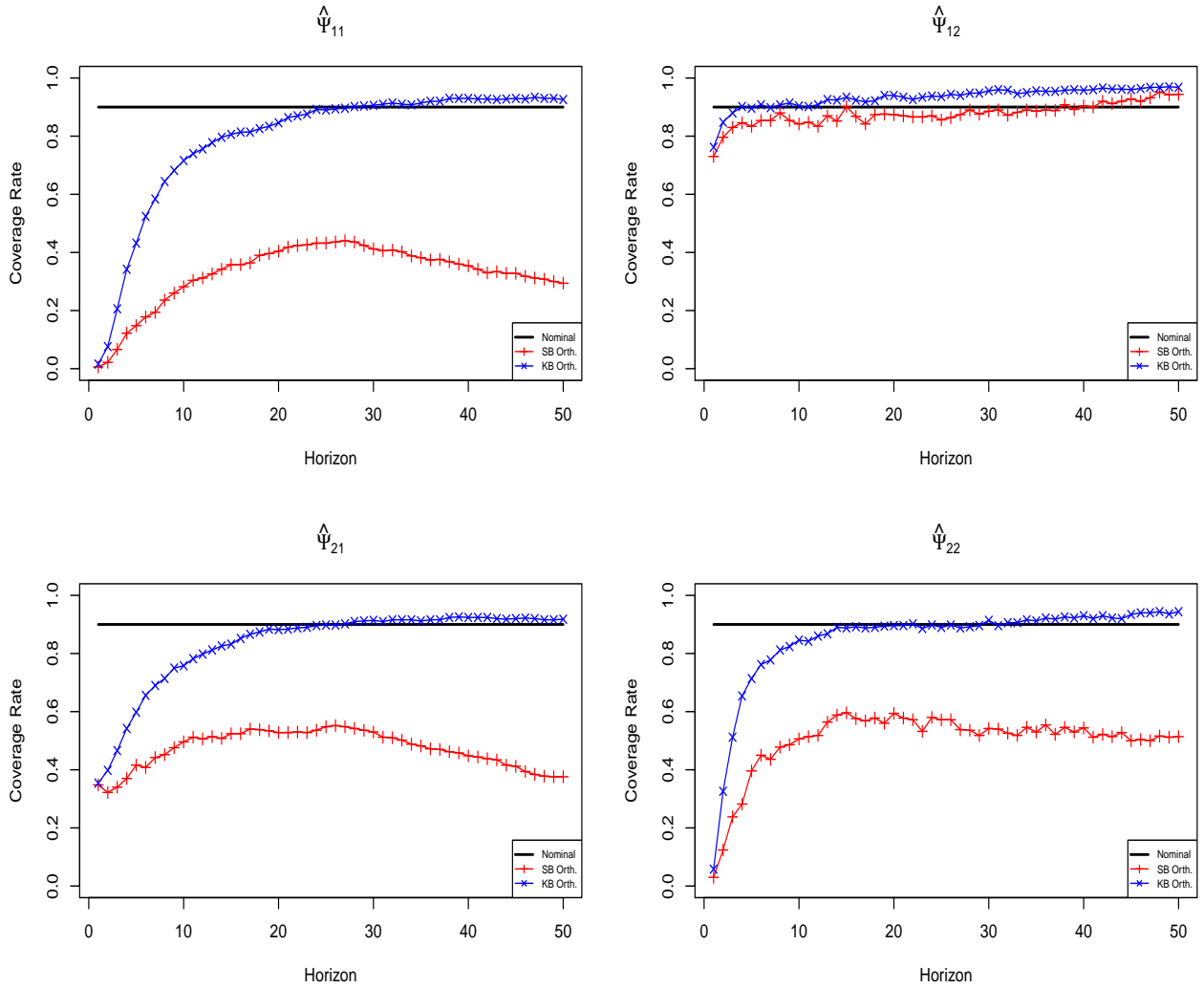


Figure 14: $\beta = 0.9$, $T = 250$, $p_T = \lfloor 1.00 \ln(T)^2 \rfloor = 30$. Effective coverage rates of selected 90% intervals.

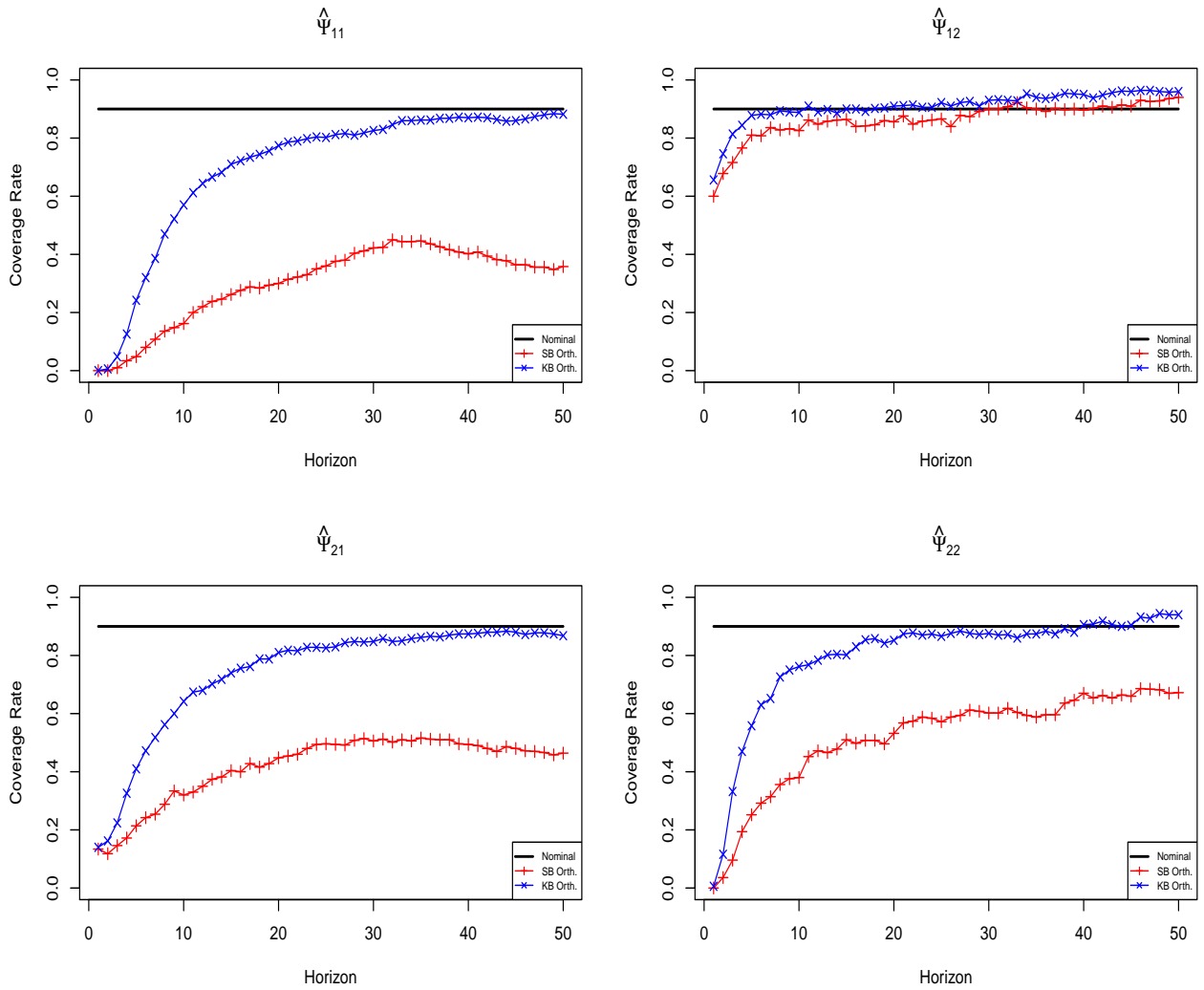


Figure 15: $\beta = 0.9$, $T = 250$, $p_T = AIC$. Effective coverage rates of selected 90% intervals.

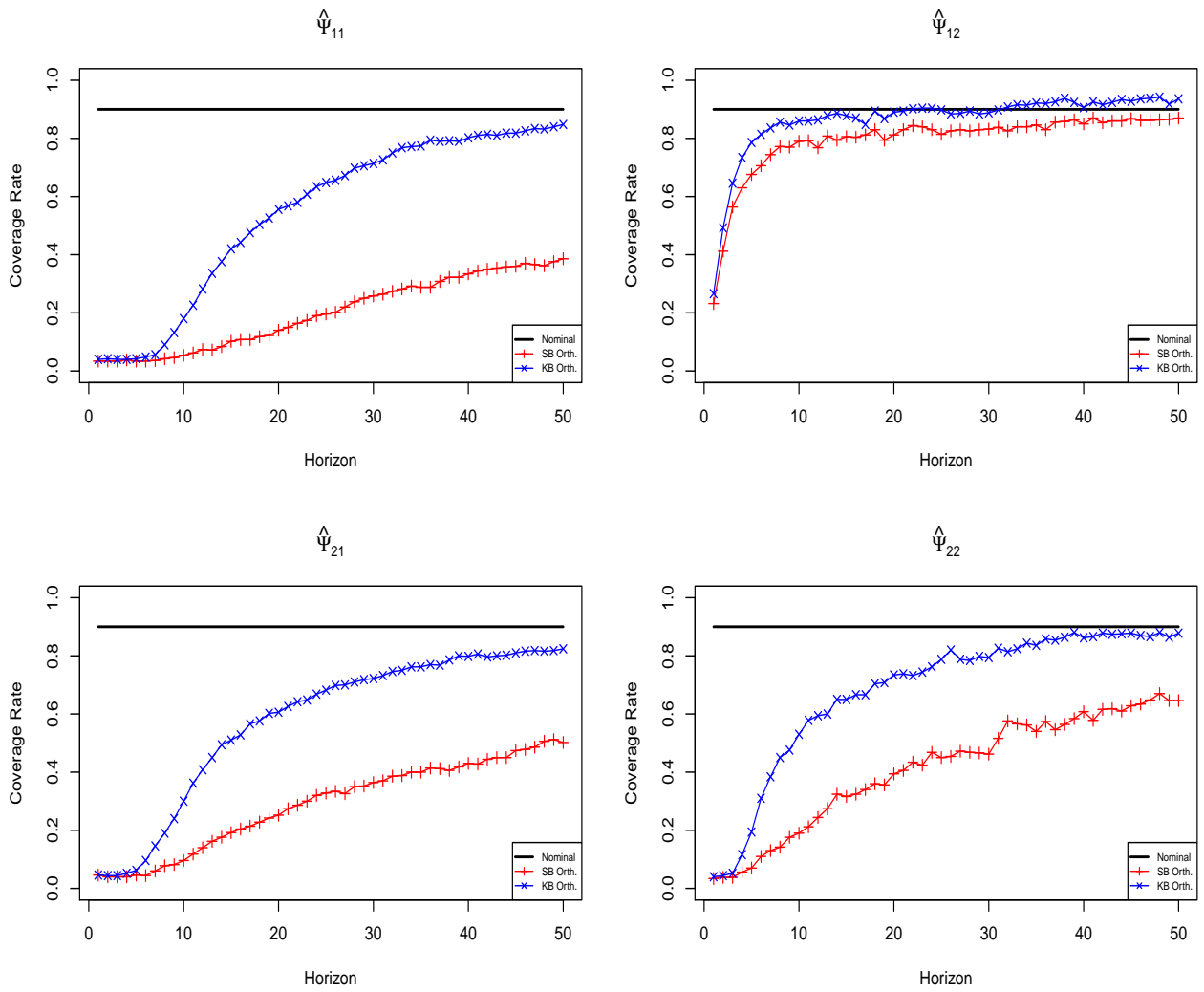


Figure 16: $\beta = 0.9$, $T = 500$, $p_T = \lfloor 0.25 \ln(T)^2 \rfloor = 10$. Effective coverage rates of selected 90% intervals.

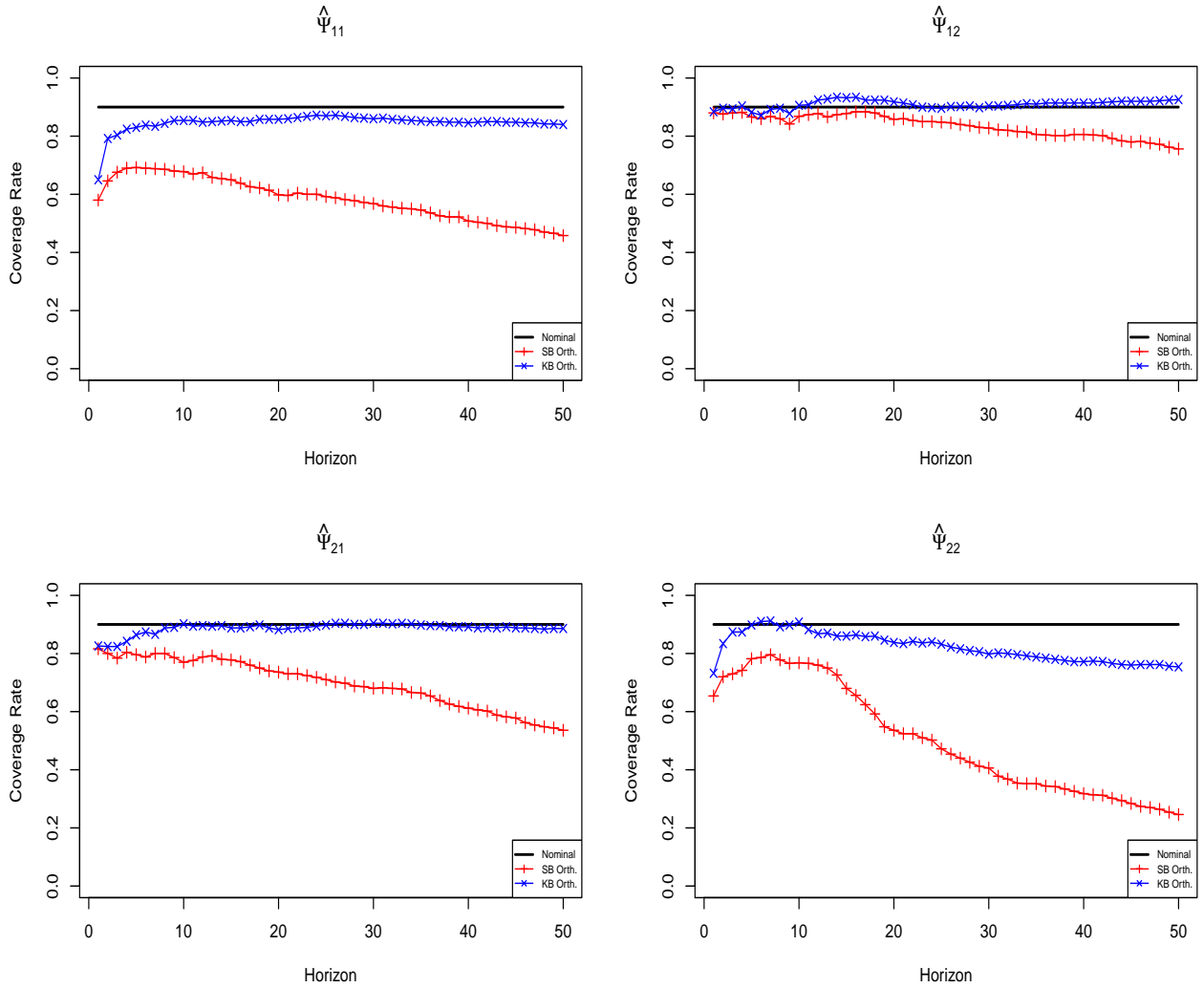


Figure 17: $\beta = 0.9$, $T = 500$, $p_T = \lfloor 0.50 \ln(T)^2 \rfloor = 19$. Effective coverage rates of selected 90% intervals.

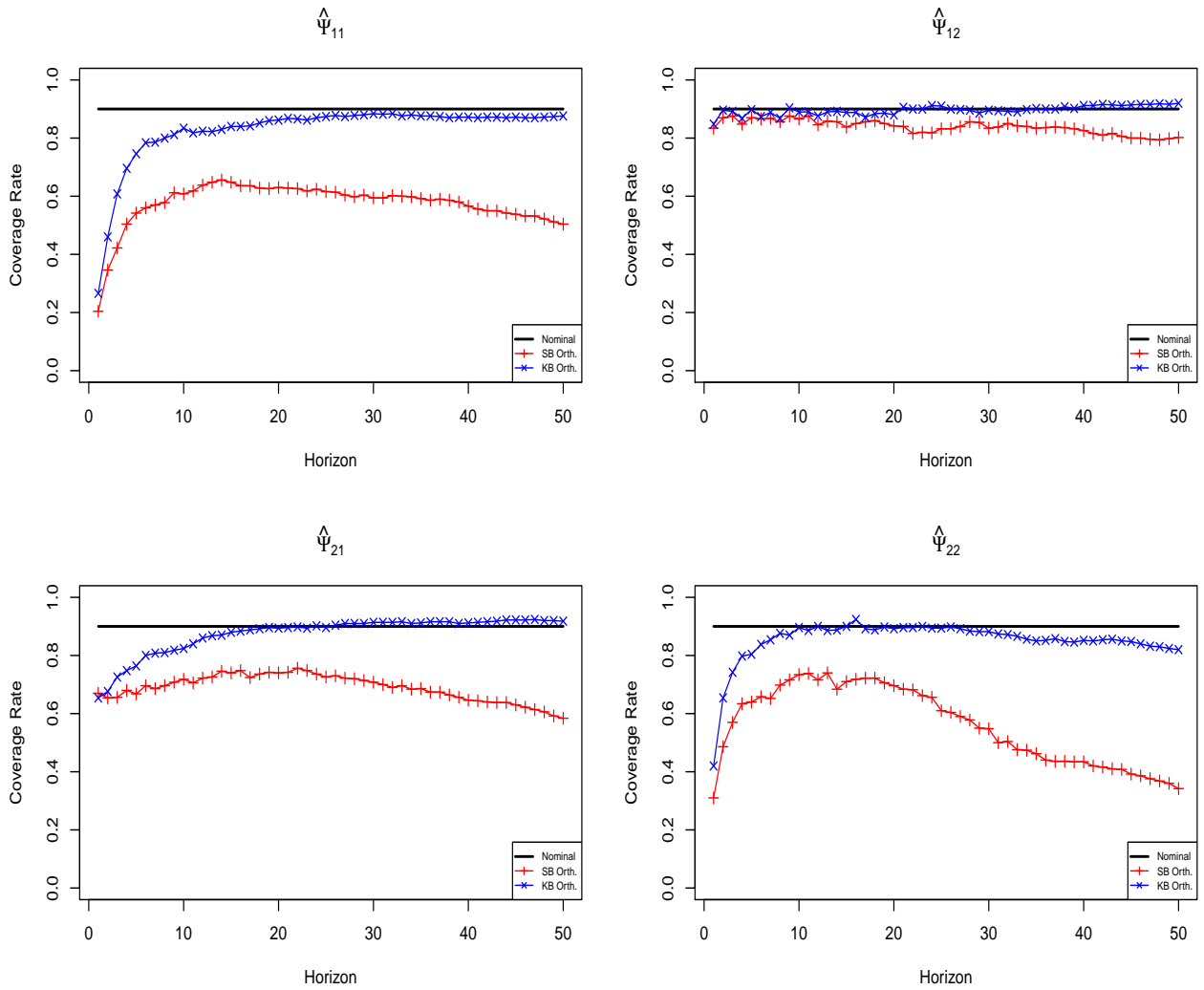


Figure 18: $\beta = 0.9$, $T = 500$, $p_T = \lfloor 0.75 \ln(T)^2 \rfloor = 29$. Effective coverage rates of selected 90% intervals.

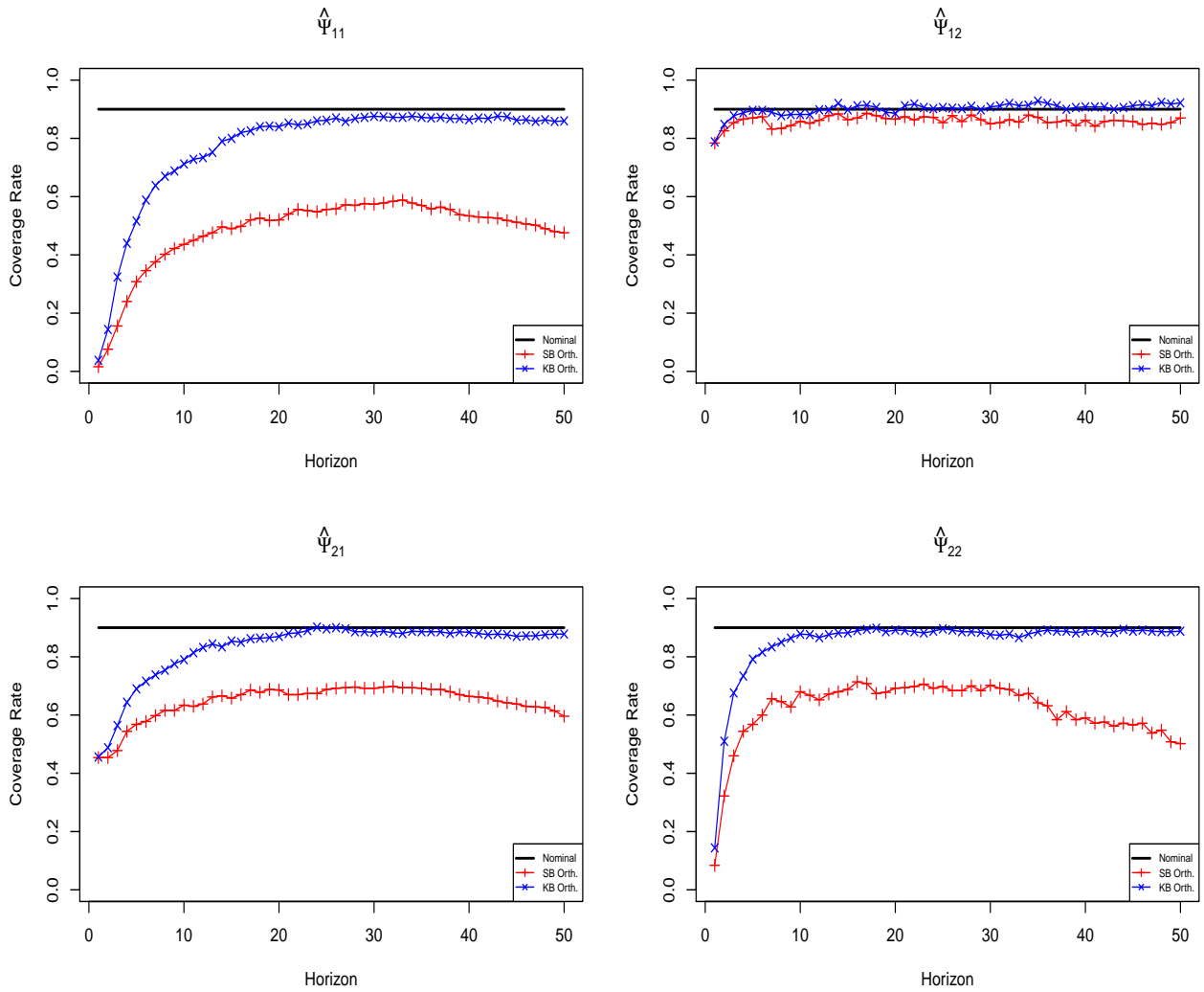


Figure 19: $\beta = 0.9$, $T = 500$, $p_T = \lfloor 1.00 \ln(T)^2 \rfloor = 39$. Effective coverage rates of selected 90% intervals.

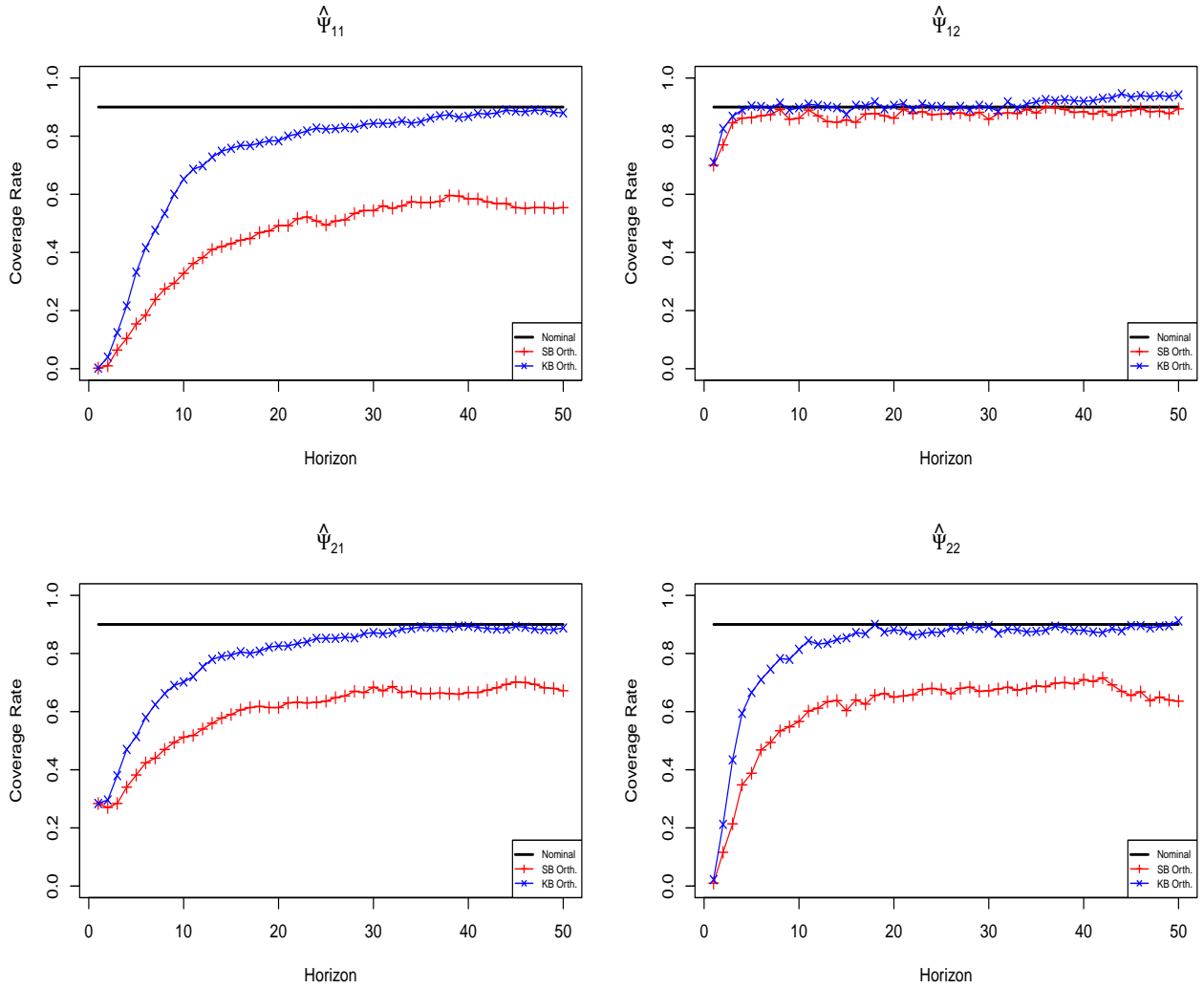


Figure 20: $\beta = 0.9$, $T = 500$, $p_T = AIC$. Effective coverage rates of selected 90% intervals.

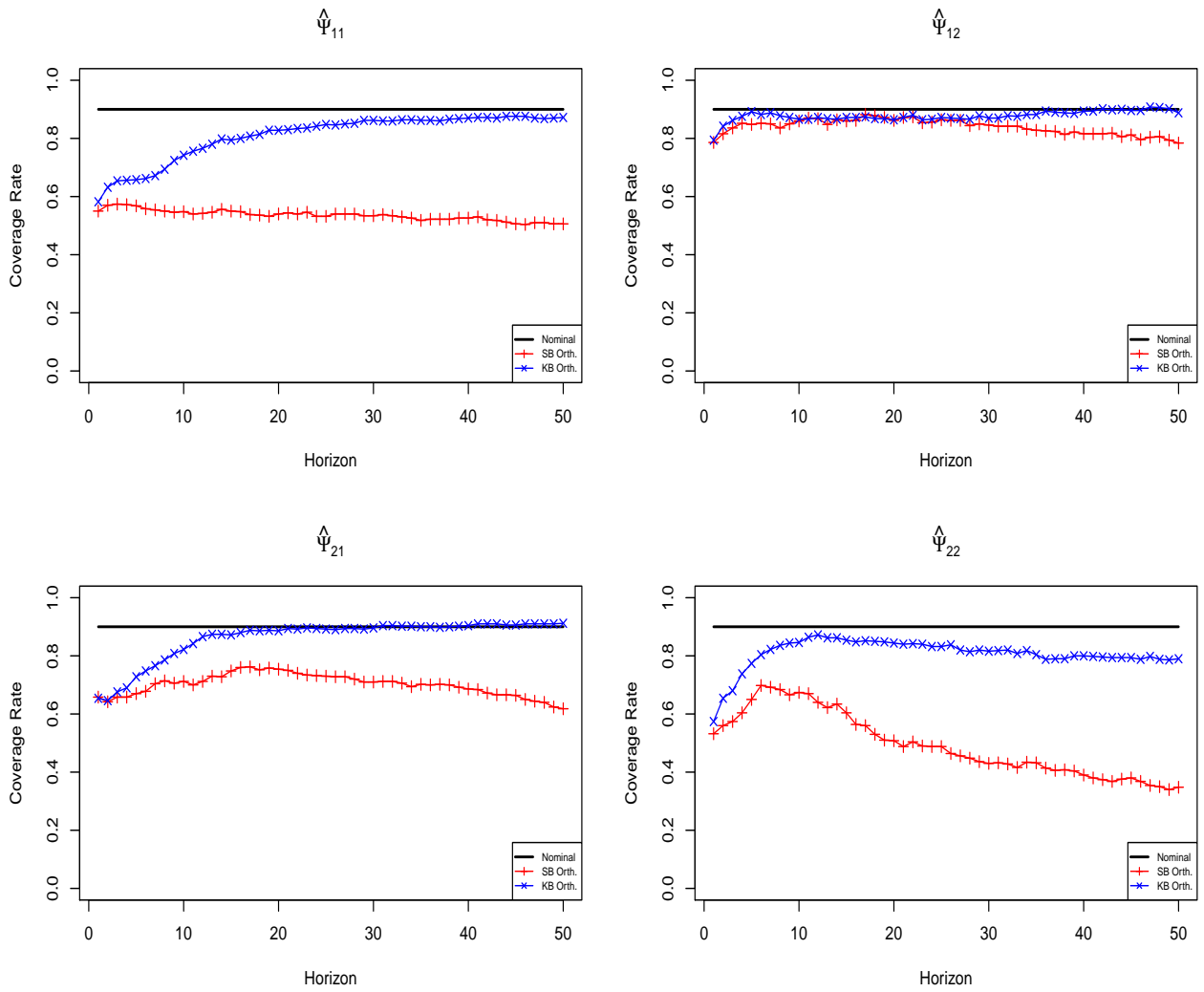


Figure 21: $\beta = 0.5$, $T = 250$. Effective coverage rates of selected 90% intervals. Lag order selected in short horizons (1-10): $\hat{p}_{h=\{1,\dots,10\}} = \lfloor 0.25 \ln(T)^2 \rfloor = 8$, Lag order selected in long horizons (11-25): $\hat{p}_{h=\{11,\dots,25\}} = \lfloor 0.50 \ln(T)^2 \rfloor = 15$

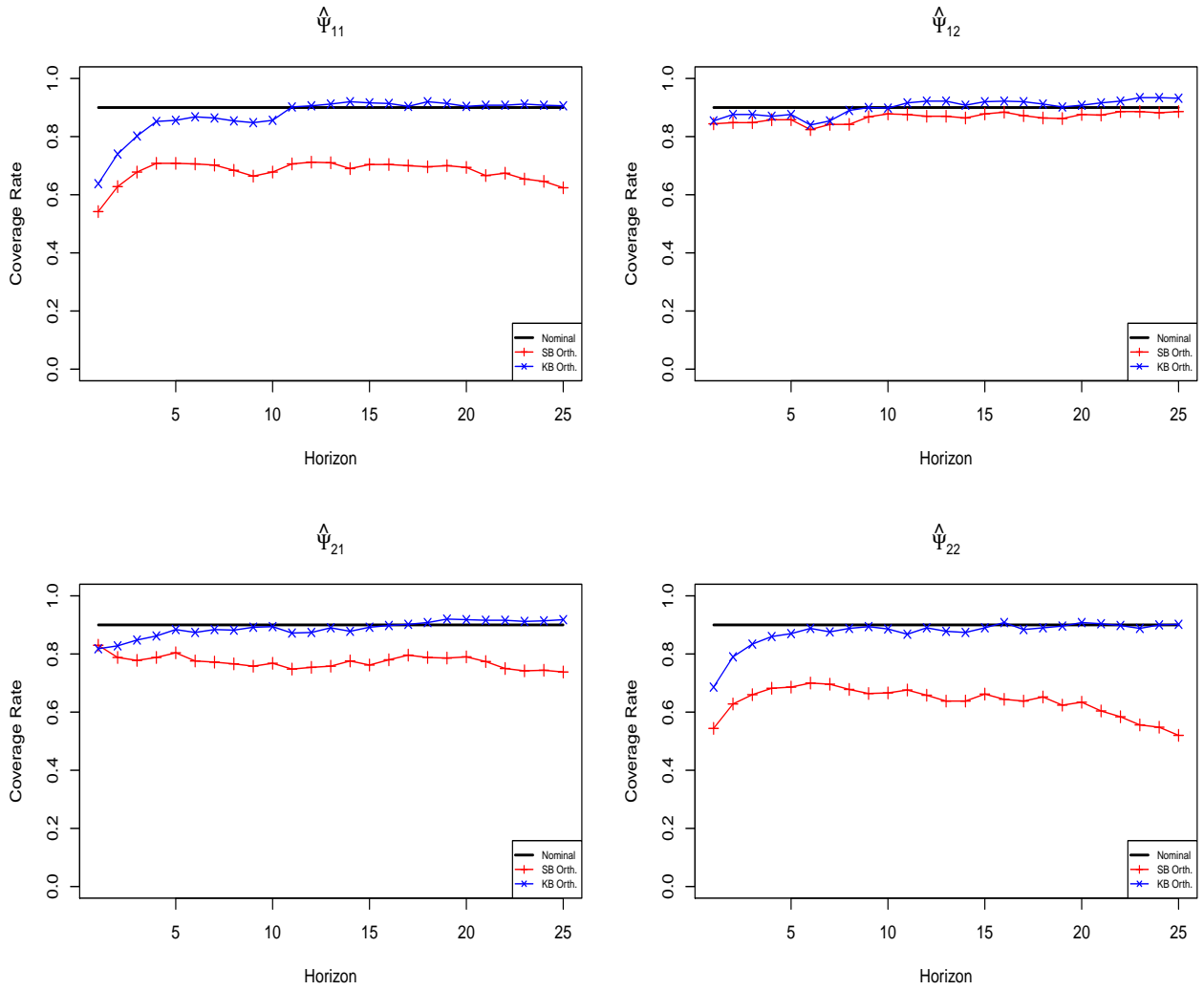
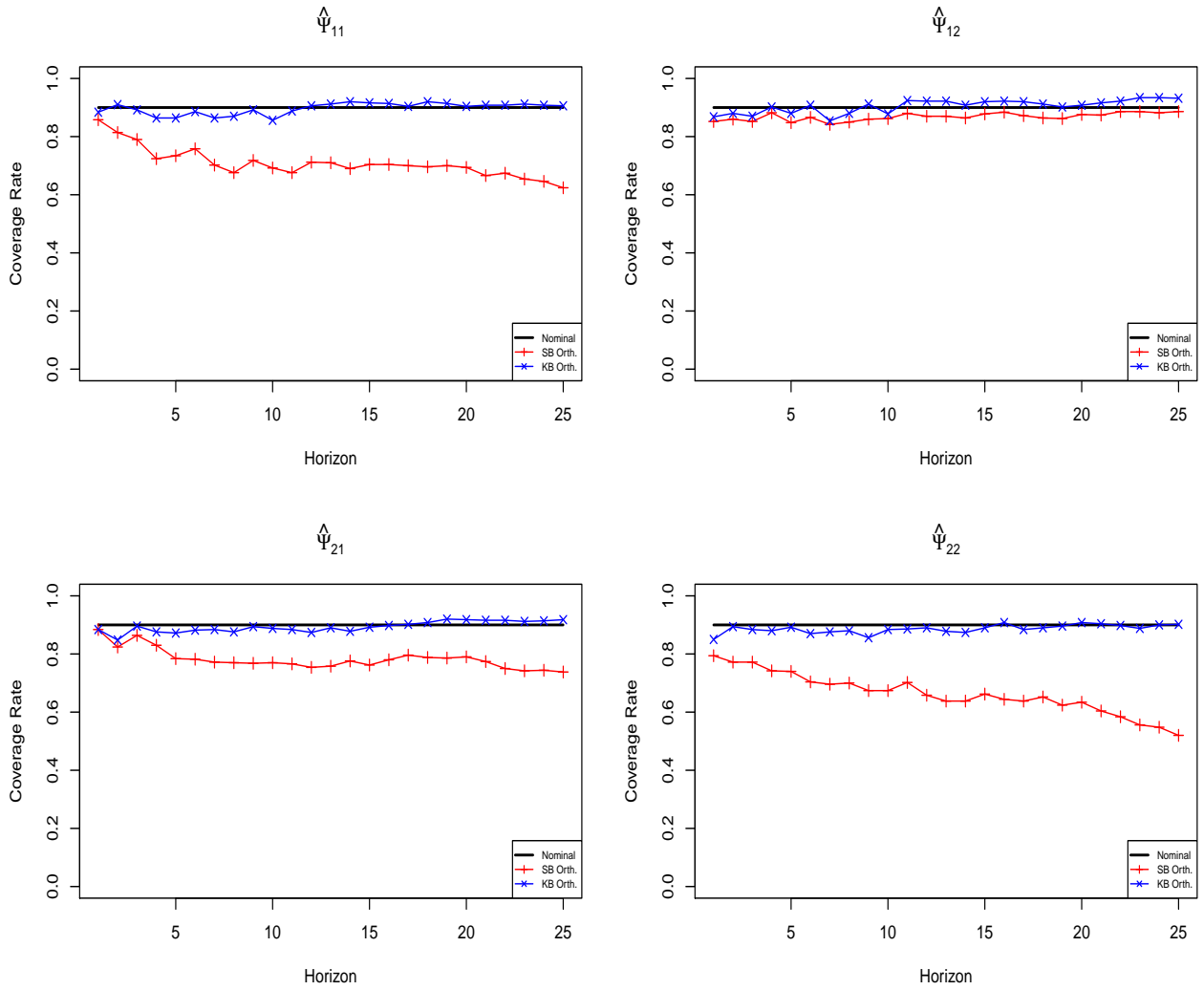
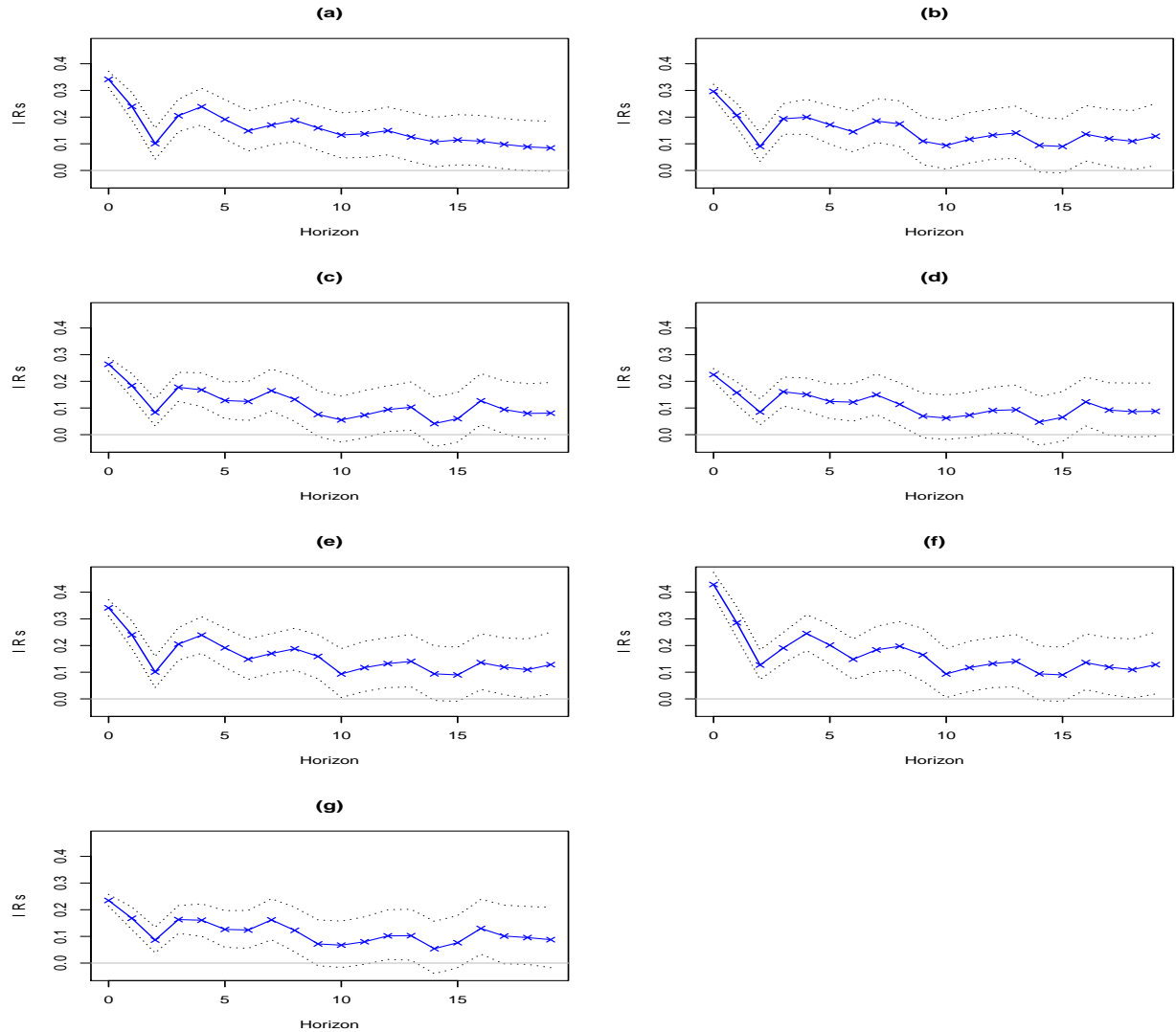


Figure 22: $\beta = 0.5$, $T = 250$. Effective coverage rates of selected 90% intervals. Lag order selected in short horizons (1-10): $\hat{p}_{h=\{1,\dots,10\}} = h + 1$, lag order selected in long horizons (11-25): $\hat{p}_{h=\{11,\dots,25\}} = \lfloor 0.50 \ln(T)^2 \rfloor = 15$.



Empirical Application: Figures

Figure 23: US: Response of CPI inflation to its own shock, $\hat{\Psi}_{11}$.



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). Panel (a) reports the results using $p_T = \lfloor 0.25 \ln(T)^2 \rfloor = 7$. Panel (b) reports the results using $p_T = \lfloor 0.50 \ln(T)^2 \rfloor = 14$. Panel (c) reports the results using $p_T = \lfloor 0.75 \ln(T)^2 \rfloor = 21$. Panel (d) reports the results using $p_T = \lfloor 1.00 \ln(T)^2 \rfloor = 28$. Panel (e) reports the results using different lag orders for short and long horizons: $p_{T,h=\{1,\dots,10\}} = \lfloor 0.25 \ln(T)^2 \rfloor = 7$, and $p_{T,h=\{11,\dots,20\}} = \lfloor 0.50 \ln(T)^2 \rfloor = 14$. Panel (f) reports the results using different lag orders for short and long horizons: $p_{T,h=\{1,\dots,10\}} = h + 1$, and $p_{T,h=\{11,\dots,20\}} = \lfloor 0.50 \ln(T)^2 \rfloor = 14$. Panel (g) reports the results from using the AIC for order selection, $p_T = 25$. Kilian (1998) corrected parameter estimates are obtained using 1,000 bootstrap resamples. The IRs are obtained using 2,000 bootstrap resamples.

Figure 24: US: Response of CPI inflation to a shock in the nominal interest rate, $\hat{\Psi}_{12}$.

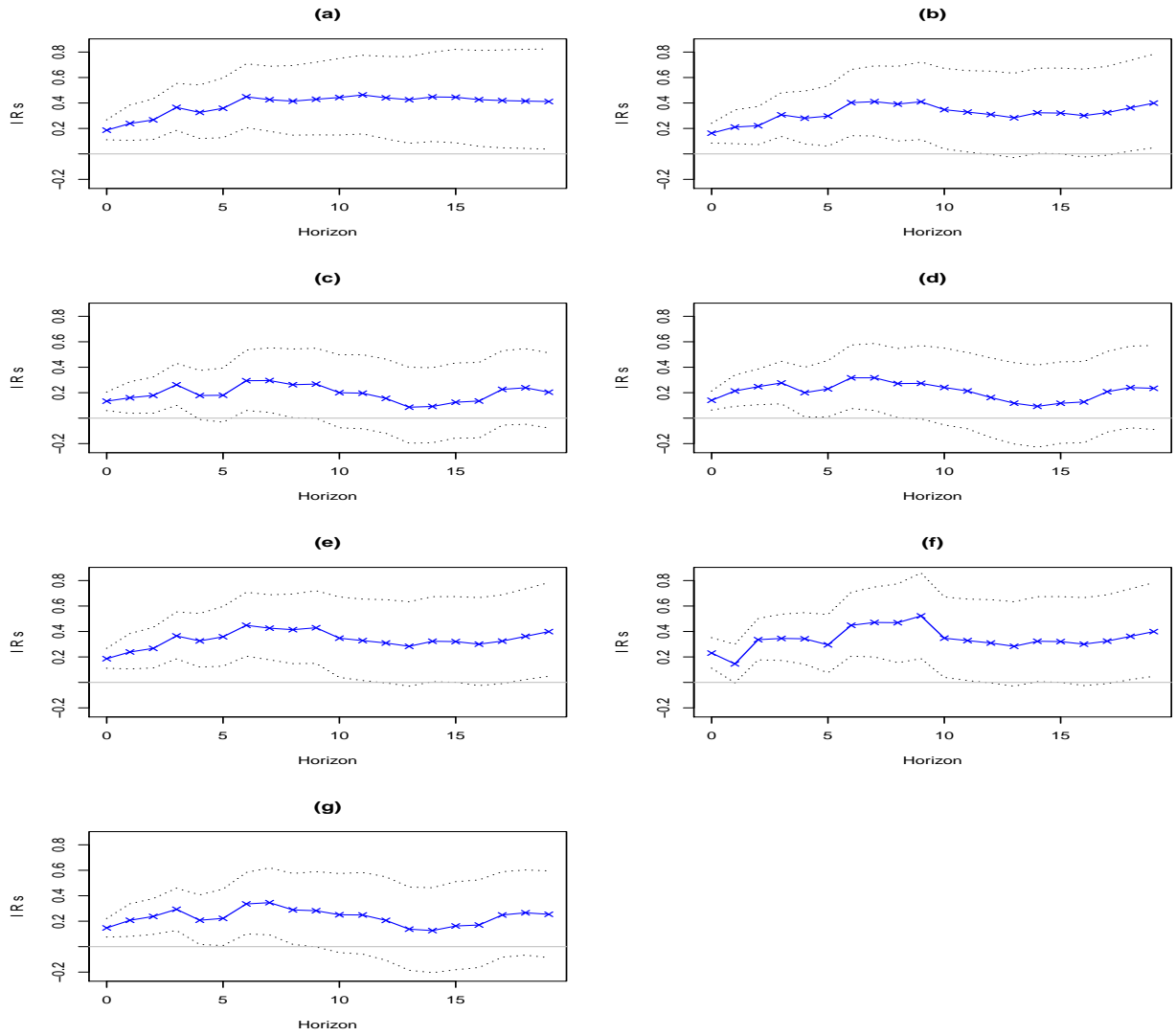


Figure 25: US: Response of the nominal interest rate to a shock in the CPI inflation, $\widehat{\Psi}_{21}$.

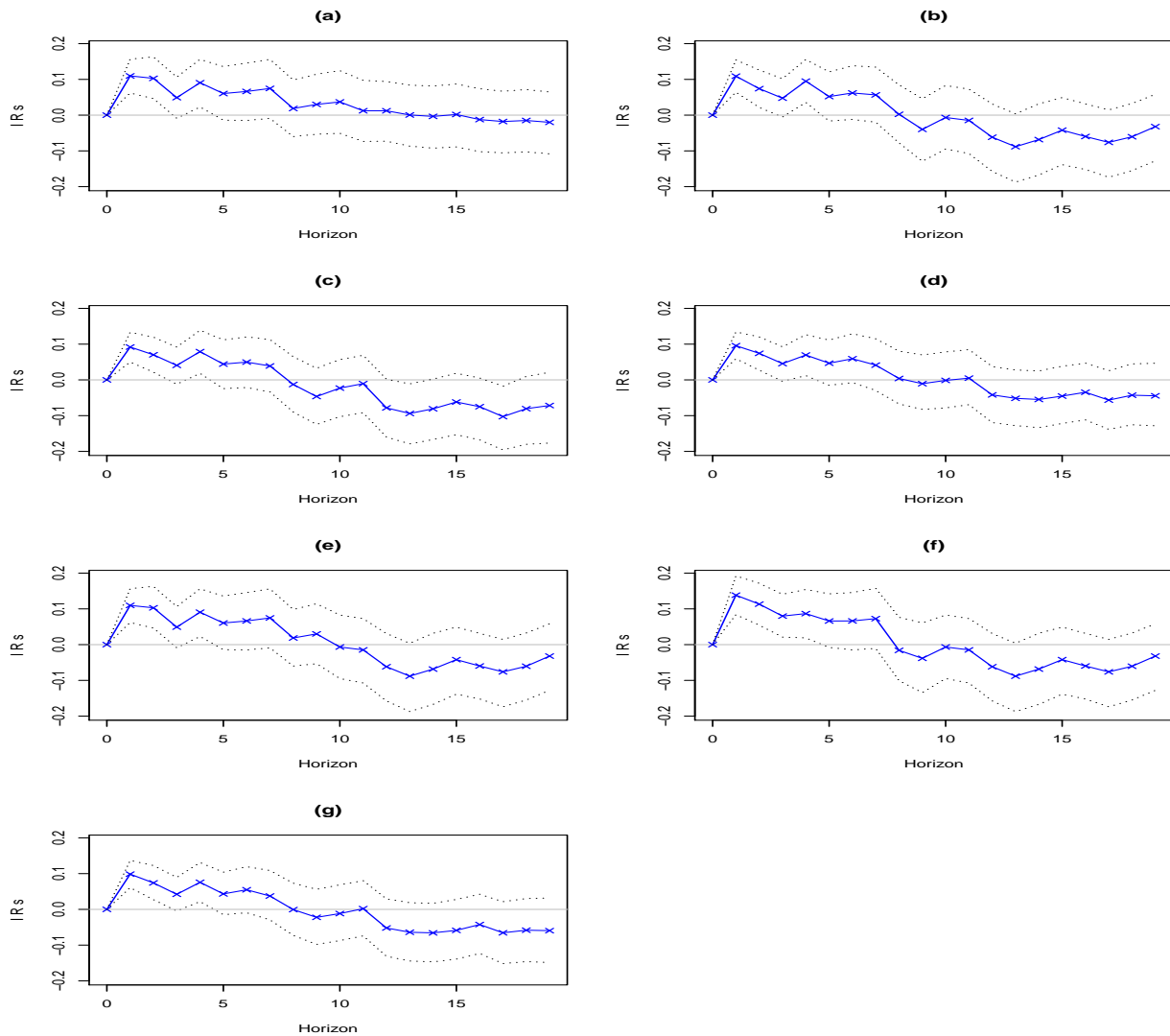


Figure 26: US: Response of the nominal interest rate to its own shock, $\hat{\Psi}_{22}$.

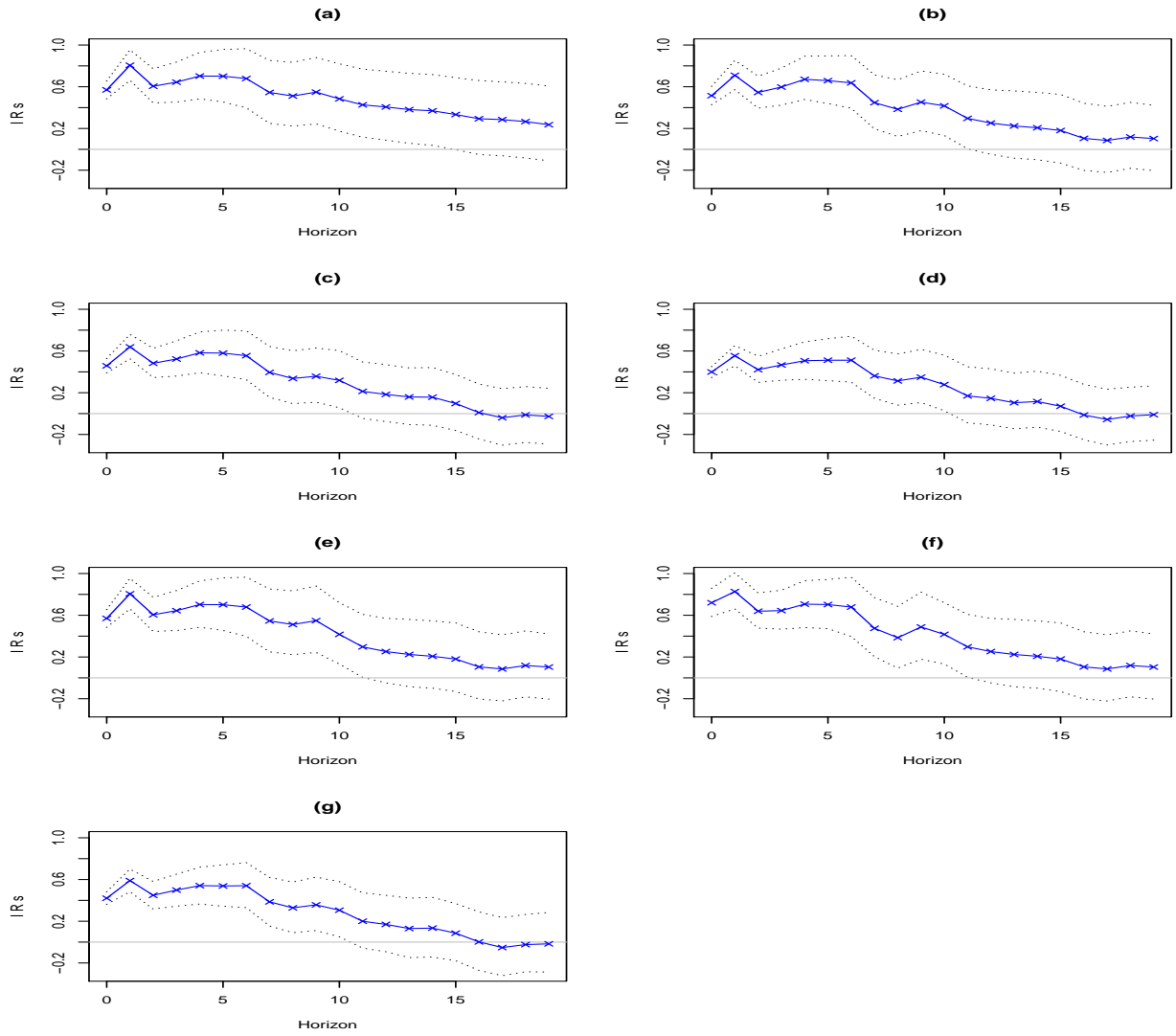


Figure 27: UK: Response of CPI inflation to its own shock, $\hat{\Psi}_{11}$.

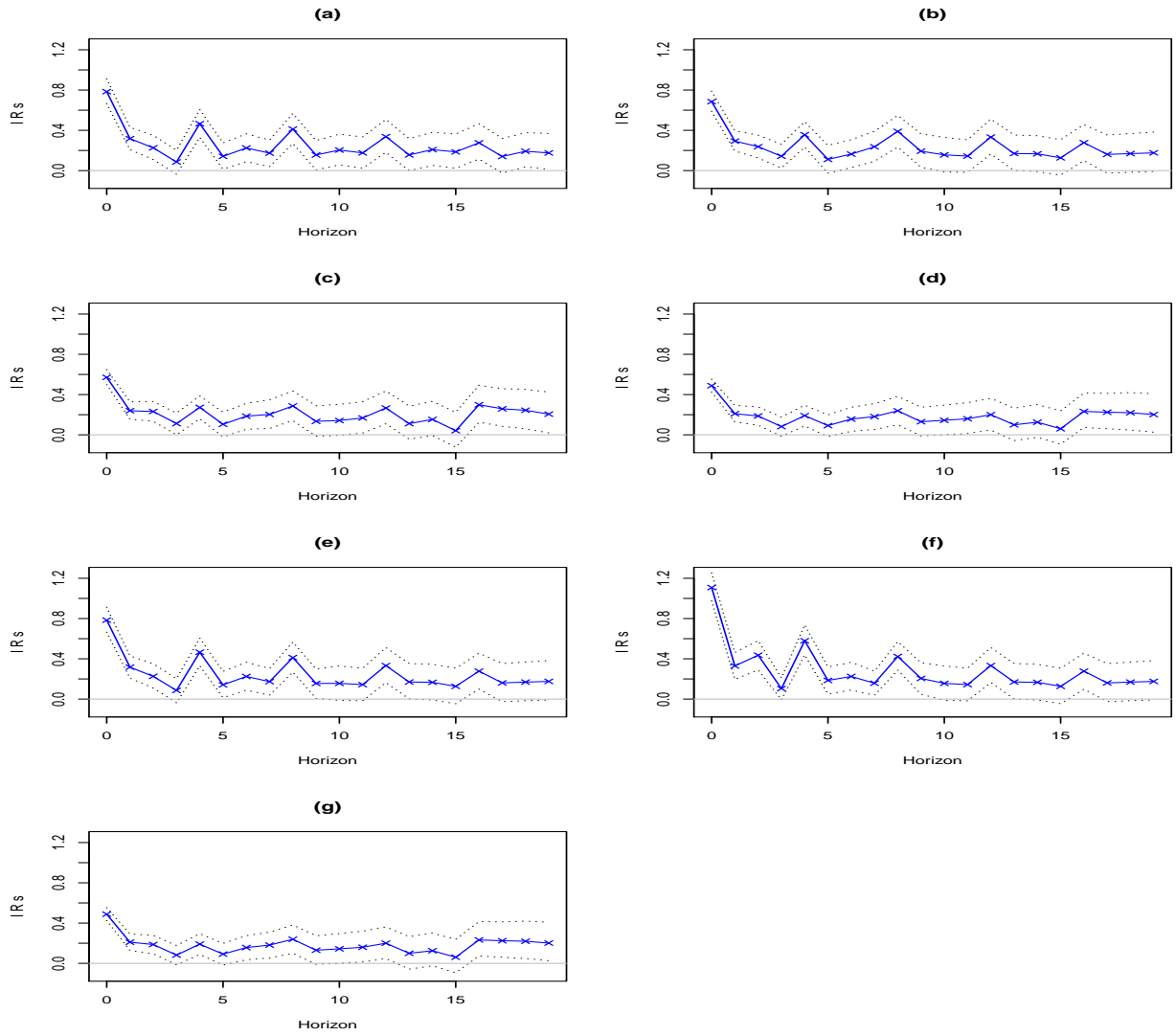


Figure 28: UK: Response of CPI inflation to a shock in the nominal interest rate, $\hat{\Psi}_{12}$.

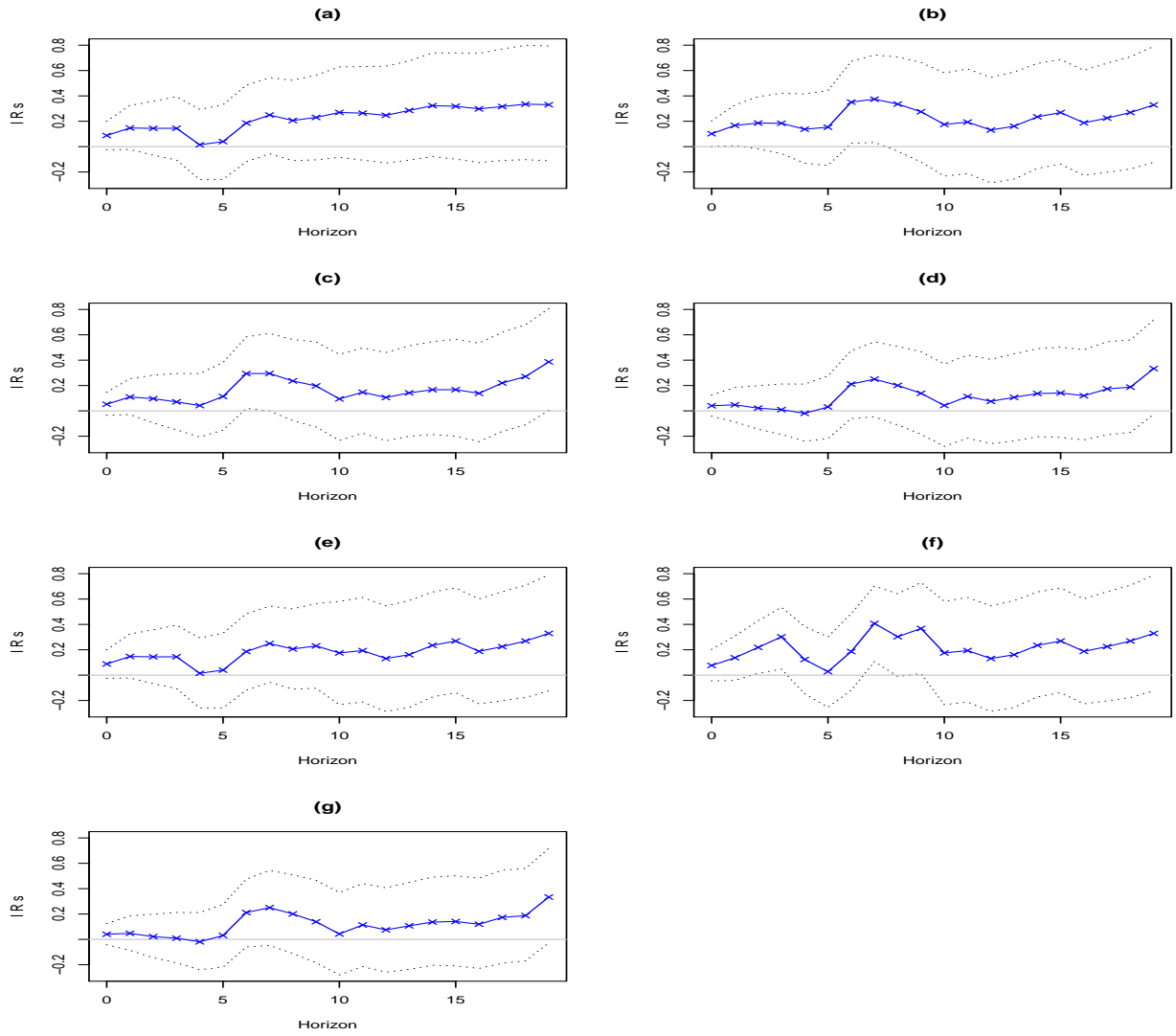


Figure 29: UK: Response of the nominal interest rate to a shock in the CPI inflation, $\hat{\Psi}_{21}$.

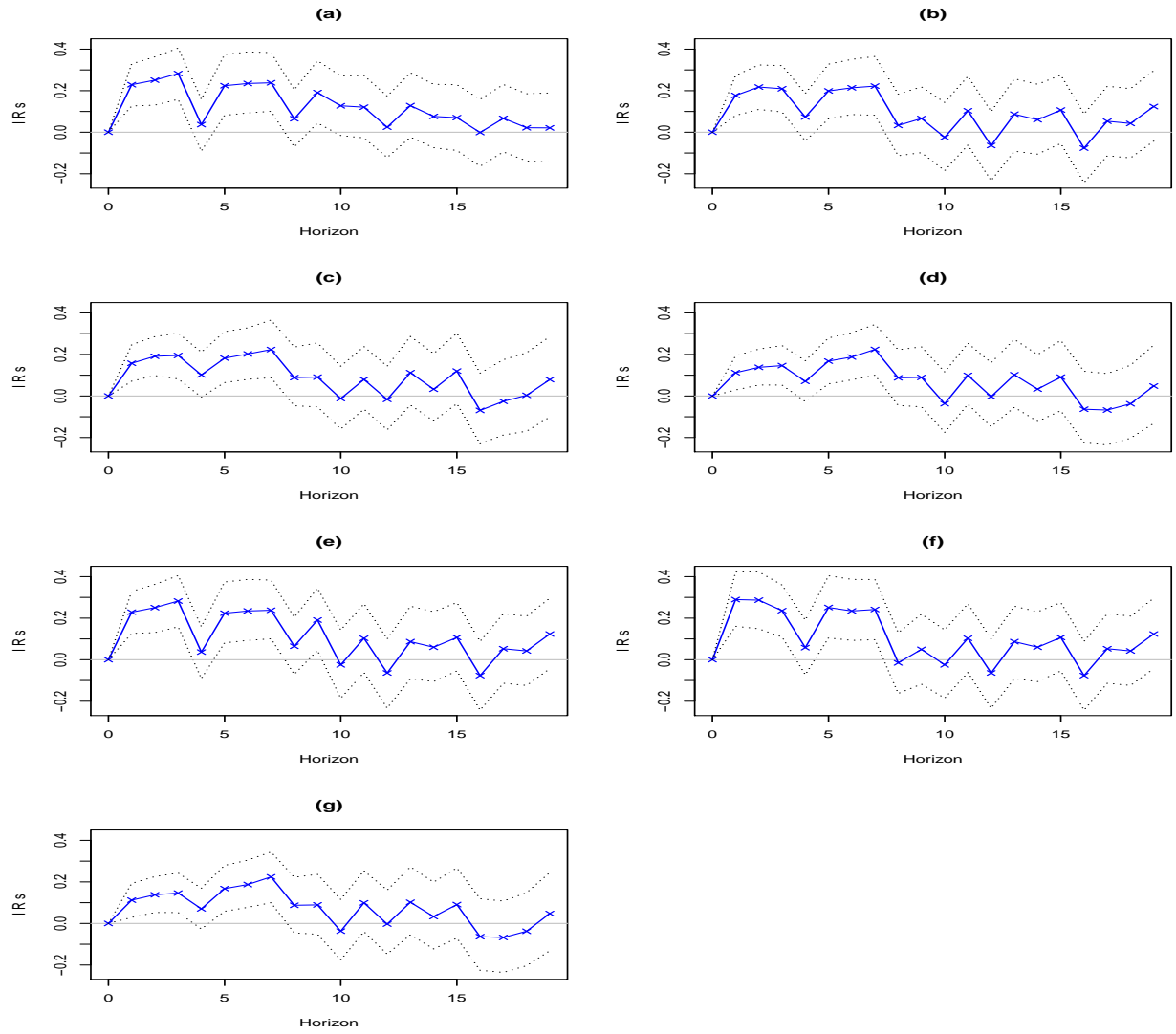


Figure 30: UK: Response of the nominal interest rate to its own shock, $\hat{\Psi}_{22}$.

