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Abstract

We consider estimation of the cointegrating relation in the stationary fractional cointegration model which has found important application recently, especially in financial economics. Previous research on this model has considered a semiparametric narrow-band least squares (NBLS) estimator in the frequency domain, often under a condition of non-coherence between regressors and errors at the zero frequency. We show that in the absence of this condition, the NBLS estimator is asymptotically biased, and also that the bias can be consistently estimated. Consequently, we introduce a fully modified NBLS estimator which eliminates the bias, and indeed enjoys a faster rate of convergence than NBLS in general. We also show that local Whittle estimation of the integration order of the errors can be conducted consistently on the residuals from NBLS regression, whereas the estimator has the same asymptotic distribution as if the errors were observed only under the condition of non-coherence. Furthermore, compared to much previous research, the development of the asymptotic distribution theory is based on a different spectral density representation, which is relevant for multivariate fractionally integrated processes, and the use of this representation is shown to result in lower asymptotic bias and variance of the narrow-band estimators. We also present simulation evidence and a series of empirical illustrations to demonstrate the feasibility and empirical relevance of our methodology.

Keywords: Fractional cointegration, frequency domain, fully modified estimation, long memory, semiparametric.

JEL Classifications: C22.

1 Introduction

Recently, the concept of fractional cointegration has attracted increasing attention from both theoretical and empirical researchers in economics and finance. In this theory, a p-vector time series

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z_t is said to be cointegrated if each element of z_t is integrated of order d, denoted $I(d)$, but there exists a linear combination that is $I(d-b)$ with $b>0$. Originally, the concept of cointegration does not restrict d and b to be integers, e.g. Granger (1981), but estimation methods have been developed mostly for the so-called $I(1)-I(0)$ cointegration, where it is assumed that $d=b=1$.

For a precise statement, a covariance stationary time series $x_t \in I(d)$, $d<1/2$, if

$$(1-L)^d x_t = v_t, \tag{1}$$

where $v_t \in I(0)$, i.e. has continuous spectral density that is bounded and bounded away from zero at all frequencies, and $(1-L)^d$ is defined by its binomial expansion in the lag operator L ($Lx_t = x_{t-1}$). The time series $\{x_t\}$ generated by (1) has spectral density

$$f(\lambda) \sim g\lambda^{-2d} \text{ as } \lambda \to 0^+, \tag{2}$$

where $g \in (0,\infty)$ is a constant and the symbol "$\sim$" means that the ratio of the left- and right-hand sides tends to one in the limit. The parameter d determines the memory of the process: if $d \in (0,1/2)$ the process is covariance stationary with long memory and if $d=0$ the spectral density is bounded at the origin and the process has only weak dependence. A well-known model satisfying (2) is the fractional ARIMA model. For surveys see, e.g., Baillie (1996) and Robinson (2003).

We consider estimation of the single-equation cointegrating regression

$$y_t = \alpha + \beta' x_t + u_t, \quad t=1,...,T, \tag{3}$$

where both the regressors and the errors have long memory but the errors have less memory than the regressors, i.e. where $x_t \in I(d_x)$ and $u_t \in I(d_u)$ with $d_x > d_u \geq 0$. This is the single-equation fractional cointegration setup. In particular, we consider semiparametric analysis of model (3) with stationary regressors, $d_x < 1/2$, termed *stationary fractional cointegration* by Robinson (1994) and Robinson & Marinucci (2003) and subsequently considered by many authors. For example, Marinucci (2000), Robinson & Yajima (2002), Chen & Hurvich (2003*a*, 2003*b*), Christensen & Nielsen (2006), Hualde & Robinson (2006), and Robinson (2008) consider theoretical issues, whereas Lobato & Velasco (2000) and Fleming & Kirby (2006) apply the model to stock market trading volume, Bandi & Perron (2006) and Christensen & Nielsen (2006) to stock return volatility, and Robinson & Yajima (2002) to spot prices for crude oil. Hence, this model has become an important tool for the analysis of long-run relations, especially in financial economics.[1] Henry & Zaffaroni (2003) survey empirical applications of fractional integration and long memory in macroeconomics and financial economics.

Since our model is stationary, a comparison with the standard time series regression model with weakly dependent regressors is natural. It is well known that, in the standard case, under a wide variety of regularity conditions, the ordinary least squares (OLS) estimator of β in (3) is asymptotically normal, see e.g. Hannan (1979). The new complication is that, as pointed out by Robinson (1994) and Robinson & Hidalgo (1997), when the regressors and the errors both have long memory and are possibly non-orthogonal, the OLS estimator is in general no longer consistent. To deal with this issue, Robinson (1994) proposed a semiparametric narrow-band least squares (NBLS) estimator in the frequency domain (as opposed to a fixed band estimator as considered by

[1] For additional empirical examples, see the references in section 5 below.

e.g. Phillips (1991) in a cointegration context) that assumes only a multivariate version of (2), see (4) and (6) below, and essentially performs OLS on a degenerating band of frequencies around the origin. The consistency of the estimator in the stationary case was proved by Robinson (1994), and Christensen & Nielsen (2006) showed that its asymptotic distribution is normal when the collective memory of the regressors and the error term is less than 1/2, i.e. when $d_x + d_u < 1/2$, and under the condition that the regressors and the errors have zero coherence at the origin. In contrast, Robinson & Marinucci (2001, 2003) consider several cases where the regressors are nonstationary fractionally integrated and the limiting distributions for the NBLS estimator involve fractional Brownian motion, and Chen & Hurvich (2003*a*) add deterministic polynomial trends.

The semiparametric approach followed here is characterized by assuming only a local model such as (2) for the spectral density, and using a degenerating part of the periodogram around the origin to estimate the model. This approach has the advantage of being invariant to any short-term dynamics (as well as mean terms since the zero frequency is usually left out). Specifically, a local Whittle estimator of the memory parameter d based on the maximization of a local Whittle approximation to the likelihood based on (2), has been developed by Künsch (1987) and Robinson (1995*a*). Of course, a fully parametric estimator would be more efficient, but is inconsistent if the parametric model is misspecified.

The methods described above are combined by Marinucci & Robinson (2001*b*) and Christensen & Nielsen (2006), who suggest conducting a (stationary) fractional cointegration analysis in several steps. First, the integration orders of the observed data are estimated by the local Whittle estimator. Secondly, the NBLS estimator of the cointegrating vector is calculated, and finally the integration order of the residuals is estimated assuming that the local Whittle approach is equally valid for residuals. Hypothesis testing is then conducted on d_u as if u_t were observed, and on β as if d_u (which enters in the limiting distribution of the NBLS estimator) were known. Moreover, the distribution theory for the NBLS estimator developed by Christensen & Nielsen (2006) assumes that the long-run (zero frequency) coherence between the regressors and the errors is zero.

In this paper, we show that in the non-zero coherence case a bias term appears in the mean of the asymptotic normal distribution of the NBLS estimator. The bias term is proportional to the square-root of the bandwidth, with factor of proportionality depending on the integration orders and the coherence at frequency zero. However, we show that the bias can be estimated and hence removed by a fully modified type procedure in the spirit of Phillips & Hansen (1990). The result is a fully modified NBLS (FMNBLS) estimator, which has no asymptotic bias and the same asymptotic variance as the NBLS estimator. As a side remark, our first result regarding the asymptotic distribution of the NBLS estimator in the general case actually shows that the rate result proven by Robinson & Marinucci (2003) is sharp, as conjectured in their paper. However, the FMNBLS estimator will have a better rate of convergence in general, i.e. the same rate as the NBLS estimator under non-coherence as in Christensen & Nielsen (2006).

We also consider inference on the integration order of the error term in the stationary cointegrating relation, and show that it can be consistently estimated by the local Whittle estimator based on the residuals from a NBLS regression. However, the local Whittle estimator converges at a slower rate than if the errors were observed, except if there is no long-run coherence between regressors and errors in which case the asymptotic distribution theory for the local Whittle estimator is unaffected by the fact that the estimator is based on residuals.

Extensions of the well known fully modified least squares procedure of Phillips & Hansen (1990) to the case of nonstationary fractional cointegration have been examined by Dolado & Marmol (1996), Kim & Phillips (2001), and Davidson (2004) in parametric frameworks. An alternative fully modified procedure for the standard $I(1)-I(0)$ model was suggested in a NBLS framework by Marinucci & Robinson (2001a), who considered the estimator of Phillips & Hansen (1990) based on NBLS residuals rather than OLS residuals. It was shown that because the NBLS estimator has a smaller second-order asymptotic bias than OLS this yields improved inference in the $I(1)-I(0)$ model. The same approach was implemented by Robinson & Marinucci (2003) in simulations.

However, the approach taken in the present paper is more direct. We derive an expression for the asymptotic bias term, which depends on the integration orders of the regressors and the errors and also on the coherence matrix at the zero frequency. We show that under appropriate conditions on the bandwidth parameters the bias term can be estimated consistently, e.g., by running an auxiliary NBLS regression, and this can be used to modify the initial NBLS estimate to eliminate the bias.

Furthermore, we derive the relevant distribution theory for the NBLS and FMNBLS estimators based on the spectral representation of multivariate fractionally integrated models (see (4) and (5) below) rather than a simplified version (see (6) below) applied in previous work on stationary fractional cointegration including Robinson & Marinucci (2003) and Christensen & Nielsen (2006). The resulting normal distribution in the stationary case is shown to have both smaller asymptotic bias and variance than that derived by Christensen & Nielsen (2006) for the model based on (6).

In a simulation study we document the finite sample feasibility of the proposed FMNBLS estimator. The simulations demonstrate the superiority in terms of bias of FMNBLS relative to NBLS in the presence of non-zero long-run coherence between the regressor and the error, which comes at the cost of an increased finite sample variance. In terms of RMSE, FMNBLS also clearly outperforms NBLS in most cases with long-run coherence.

To demonstrate the empirical relevance of our proposed methodology, we include several brief empirical illustrations. We first revisit the implied-realized volatility relation analyzed by, e.g., Bandi & Perron (2006) and Christensen & Nielsen (2006). We then show that there is a stationary fractional cointegrating relation between the inflation rates of European Union countries, exemplified through the harmonized consumer price indices of France and Spain. Lastly, we investigate the relationship between the volatilities of the General Electric stock and two stock indices.

The remainder of the paper is laid out as follows. Next, we describe NBLS estimation of (3) and derive the relevant asymptotic distribution theory. We also discuss inference with the local Whittle estimator of the integration order of the errors when the errors are not observed and residuals are used instead. In section 3 we consider the FMNBLS modification to the NBLS estimator. Sections 4 and 5 present simulation evidence and empirical illustrations, respectively, and section 6 offers some concluding remarks. All proofs are gathered in the appendices.

2 Narrow-Band Least Squares Estimation

We begin with some remarks about the spectral representation of multivariate long memory models. Suppose the spectral density of $w_t = (x_t', u_t)'$ is

$$f(\lambda) \sim \Lambda(\lambda)^{-1} G \bar{\Lambda}(\lambda)^{-1} \text{ as } \lambda \to 0^+, \tag{4}$$

where the bar denotes complex conjugation, $\Lambda(\lambda) = \text{diag}(e^{-i\pi d_1/2}\lambda^{d_1}, ..., e^{-i\pi d_p/2}\lambda^{d_p})$, and G is a real, symmetric, positive definite matrix. The spectral density representation (4) is motivated by the multivariate stationary long memory model with $d_a \in (-1/2, 1/2), a = 1, ..., p$:

$$\begin{bmatrix} (1-L)^{d_1} & & 0 \\ & \ddots & \\ 0 & & (1-L)^{d_p} \end{bmatrix} \begin{bmatrix} w_{1t} - Ew_{1t} \\ \vdots \\ w_{pt} - Ew_{pt} \end{bmatrix} = \begin{bmatrix} v_{1t} \\ \vdots \\ v_{pt} \end{bmatrix}, \quad t = 1, ..., T, \tag{5}$$

where $v_t = (v_{1t}, ..., v_{pt})'$ is a covariance stationary process with spectral density matrix that is finite and bounded away from zero (in the sense of positive definite matrices) at all frequencies, i.e. v_t is $I(0)$. When v_t is an ARMA model, w_t is a multivariate fractional ARIMA model. This class of models is very popular in both theoretical and applied time series analysis. Since $(1 - e^{i\lambda})^d = \lambda^d e^{-i\pi d/2}(1 + O(\lambda))$ as $\lambda \to 0$ the representation (4) follows by defining $G = \lim_{\lambda \to 0} f_v(\lambda)$.

Note that the spectral representation (4) differs from the simpler representation

$$h_{ab}(\lambda) \sim G_{ab}\lambda^{-d_a - d_b} \text{ as } \lambda \to 0^+, \quad a, b = 1, ..., p, \tag{6}$$

applied by, e.g., Robinson (1995*b*) and Lobato & Robinson (1998) for inference on the integration orders and by Robinson & Marinucci (2003) and Christensen & Nielsen (2006) in the context of stationary fractional cointegration. The most important difference is that $f(\lambda)$ has non-zero complex part even at the origin unless $d_a = d$ for all $a = 1, ..., p$. In particular, d_a and d_b appear in

$$f_{ab}(\lambda) \sim G_{ab}\lambda^{-d_a - d_b} e^{i\pi(d_a - d_b)/2} \text{ as } \lambda \to 0^+, \quad a, b = 1, ..., p,$$

both in the power decay and in the phase shift. Neglecting the latter is a source of misspecification and may lead to erroneous inferences. For a detailed comparison of $f(\lambda)$ and $h(\lambda)$, see Shimotsu (2007) and Robinson (2008) who derive multivariate local Whittle estimators based on (4).

We remark here that the assumptions of Christensen & Nielsen (2006) (and hence also those of, e.g., Lobato & Robinson (1998) and Lobato (1999)) and much subsequent research are, unfortunately, incompatible. The reason is that the real-valued cross-spectral density (6) imposed in their Assumption A implies that the cross-autocorrelations are symmetric with respect to time, which implies a two-sided moving average with equal lead and lag weights and not a one-sided moving average as imposed in their Assumption B. The assumptions of Christensen & Nielsen (2006) (and subsequent research on narrow-band estimation of stationary fractional cointegration) are easily fixed, however, in light of their condition that $G_{ap} = G_{pa} = 0$, by assuming that the integration orders of the regressors are all equal, i.e. that $d_a = d_x$ for $a = 1, \ldots, p-1$ and $d_x > d_p$. In that case, their assumptions are compatible (and the representations (4) and (6) are equivalent) and their results correct.

To consider frequency domain least squares inference on β in the cointegrating relation (3) we define the discrete Fourier transform (DFT) of an observed vector $\{a_t, \ t = 1, \ldots, T\}$,

$$w_a(\lambda) = \frac{1}{\sqrt{2\pi T}} \sum_{t=1}^{T} a_t e^{-it\lambda}. \tag{7}$$

If $\{b_t, \ t = 1, \ldots, T\}$ is another observed vector, the cross-periodogram matrix between a_t and b_t is $I_{ab}(\lambda) = w_a(\lambda) w_b^*(\lambda)$, where the asterisk denotes transposed complex conjugation. We then form the discretely averaged co-periodogram

$$\hat{F}_{ab}(k,l) = \frac{2\pi}{T}\sum_{j=k}^{l} \mathrm{Re}\left(I_{ab}(\lambda_j)\right), \quad 0 \le k \le l \le T-1, \tag{8}$$

for $\lambda_j = 2\pi j/T$. By setting $k \ge 1$ and thus excluding the zero frequency, the estimator becomes invariant to non-zero means, i.e. invariant to α in (3). We could also have considered a continuously averaged version of (8) as in Marinucci (2000), but it would not be invariant to mean terms.

With $\hat{F}$ defined in (8) we consider the frequency domain least squares estimator

$$\hat{\beta}_m = \hat{F}_{xx}^{-1}(1,m)\,\hat{F}_{xy}(1,m) \tag{9}$$

of β in the regression (3). Notice that, by this definition, $\hat{\beta}_{T-1}$ is algebraically identical to the usual OLS estimator of β with allowance for a non-zero mean. On the other hand, if

$$\frac{1}{m} + \frac{m}{T} \to 0 \text{ as } T \to \infty, \tag{10}$$

then $\hat{\beta}_m$ is the NBLS estimator using only a degenerating band of frequencies near the origin. We need m to tend to infinity to gather information, but we also need to remain in a neighborhood of zero where we have assumed knowledge about the spectral density, so m/T must tend to zero.

To prove our main results we assume, with obvious implications for y_t, the following conditions on $w_t = (x_t', u_t)'$ and the bandwidth parameter.

Assumption 1 *The spectral density matrix of w_t given in (4) with typical element $f_{ab}(\lambda)$, the cross-spectral density between w_{at} and w_{bt}, satisfies*

$$|f_{ab}(\lambda) - G_{ab}\lambda^{-d_a-d_b}e^{i(\pi-\lambda)(d_a-d_b)/2}| = O(\lambda^{\alpha-d_a-d_b}) \text{ as } \lambda \to 0^+, \ a,b = 1,...,p, \tag{11}$$

for some $\alpha \in (0,2]$. The matrix G is positive definite and the memory parameters satisfy $0 \le d_a < 1/2$ for $a = 1,...,p$, $d_a + d_p < 1/2$ for $a = 1,...,p-1$, and $\min_{1\le a\le p-1} d_a - d_p = \delta_{\min} > 0$.

Assumption 2 *w_t is a linear process, $w_t = \mu + \sum_{j=0}^{\infty} A_j\varepsilon_{t-j}$, with square summable coefficient matrices, $\sum_{j=0}^{\infty}\|A_j\|^2 < \infty$. The innovations satisfy, almost surely, $E(\varepsilon_t|\mathcal{F}_{t-1}) = 0$, $E(\varepsilon_t\varepsilon_t'|\mathcal{F}_{t-1}) = I_p$, $E(\varepsilon_t \otimes \varepsilon_t\varepsilon_t'|\mathcal{F}_{t-1}) = \mu_3$, and $E(\varepsilon_t\varepsilon_t' \otimes \varepsilon_t\varepsilon_t'|\mathcal{F}_{t-1}) = \mu_4$, where μ_3 and μ_4 are nonstochastic, finite, and do not depend on t, and $\mathcal{F}_t = \sigma(\{\varepsilon_s, s \le t\})$.*

Assumption 3 *Let $A_a(\lambda)$ denote the a'th row of $A(\lambda) = \sum_{j=0}^{\infty} A_j e^{ij\lambda}$. Then, as $\lambda \to 0^+$,*

$$\frac{\partial A_a(\lambda)}{\partial\lambda} = O(\lambda^{-1}||A_a(\lambda)||), \ a = 1,...,p.$$

Assumption 4 *The bandwidth parameter $m_0 = m_0(T)$ satisfies*

$$\frac{1}{m_0} + \frac{m_0^{1+2\min(1,\alpha)}}{T^{2\min(1,\alpha)}} \to 0 \text{ as } T \to \infty.$$

Our assumptions are a multivariate generalization of those in Robinson (1994, 1995*a*), see also Lobato (1999) and Christensen & Nielsen (2006). Since our assumptions are semiparametric in nature they naturally differ from those employed by e.g. Robinson & Hidalgo (1997) in their parametric setup, and are at least in some respects weaker than standard parametric assumptions. In particular, we avoid standard assumptions (from stationary time series regressions) of independence or uncorrelatedness between x_t and u_t as well as complete and correct specification of $f(\lambda)$.

The first part of Assumption 1 specializes (4) by imposing smoothness conditions on the spectral density matrix of w_t commonly employed in the literature. They are satisfied with $\alpha = 2$ if, for instance, w_t is a vector fractional ARIMA process. The more precise approximation offered by Assumption 1 relative to (4) reflects the approximation $(1 - e^{i\lambda})^d = |2\sin(\lambda/2)|^d e^{-i(\pi-\lambda)d/2} = \lambda^d e^{-i(\pi-\lambda)d/2}(1 + O(\lambda^2))$ as $\lambda \to 0$, see Shimotsu (2007). The positive definiteness condition on G is a no multicollinearity or no cointegration condition within the components of x_t, which is typical in single-equation cointegration models and in regression models. In view of the results from, e.g., Fox & Taqqu (1986, Prop. 1), showing that quadratic forms of long memory processes with square-summable autocovariances ($2d < 1/2$) are asymptotically Gaussian, we work with a quadratic form with $d_a + d_p < 1/2$, see also Lobato & Robinson (1996). The last condition of Assumption 1 is the essential assumption of cointegration, with $\delta_{\min}$ denoting the strength of the cointegrating relation.

The single-equation cointegrating regression model (3) is similar to the usual cointegrating regression model in the $I(1) - I(0)$ case, and the nature of the regression setup is subject to the same advantages and disadvantages. An important issue, given a set of more than two variables, is to justify the single-equation regression. That is, since cointegration among the regressors is ruled out by Assumption 1 (as is standard in cointegrating regression models), in practice one would have to establish that only one cointegrating relationship exists among the given set of variables. This could be done, e.g., by the approach of Robinson & Yajima (2002) as in the empirical application in section 5.3 below.

Much of the previous literature on semiparametric frequency domain inference in the stationary fractional cointegration model distinguish (either explicitly or implicitly) between cases of coherence and non-coherence between the regressors and the error process at the zero frequency, e.g. Robinson & Marinucci (2001, 2003), Christensen & Nielsen (2006), and Robinson (2008). In the present notation this condition is $G_{ap} = G_{pa} = 0$, for $a = 1, ..., p-1$. Indeed, in the stationary case, asymptotic distribution theory for the NBLS estimator is only available in the case with non-coherence at the zero frequency, Christensen & Nielsen (2006). Our assumptions avoid the non-coherence condition and thus allow correlation between the errors and regressors at any frequency.

Assumptions 2 and 3 follow Robinson (1995*a*) and Lobato (1999) in imposing a linear structure on w_t with square summable coefficients and martingale difference innovations with finite fourth moments. The assumption of constant conditional variance for the innovations could presumably be relaxed by assuming boundedness of higher moments as in Robinson & Henry (1999). Under Assumption 2 we can write the spectral density matrix of w_t as

$$f(\lambda) = \frac{1}{2\pi} A(\lambda) A^*(\lambda). \tag{12}$$

Assumption 3 is a smoothness condition imposing differentiability of the spectral density near the origin, analogous to those imposed on the spectral density at any frequency in parametric frameworks, see for example Fox & Taqqu (1986). The condition is satisfied, e.g., by fractional ARIMA models.

The statement of Assumptions 1 and 3 is made in the frequency domain whereas the statement of Assumption 2 is in the time domain, which follows the tradition in the literature on semiparametric estimation in long memory models. Clearly, the assumptions are closely related, and in particular the matrix G in Assumption 1 is a function of the lag weights $\{A_j, j \geq 0\}$ from Assumption 2. The connection between the representations (4) (or Assumption 1) and (6) and the lag weights in the linear process (Assumption 2) is explored in Theorems 1 and 2 of Robinson (2008). In particular, it is shown there that our Assumptions 1 and 2 are compatible.[2]

Finally, Assumption 4 restricts the expansion rate of the bandwidth parameter $m_0 = m_0(T)$. The bandwidth is required to tend to infinity for consistency, but at a slower rate than T to remain in a neighborhood of the origin, where we have assumed some knowledge of the form of the spectral density. When α is high, (11) is a better approximation to (12) as $\lambda \to 0^+$, and hence (by the second term of Assumption 4) a higher expansion rate of the bandwidth can be chosen. The weakest constraint is implied by $\alpha \geq 1$, in which case the condition is $m_0 = o(T^{2/3})$. A slightly weaker bandwidth condition was employed by Christensen & Nielsen (2006) due to their assumption of real-valued spectral density at the origin.

We next derive the distribution of the NBLS estimator of the stationary fractional cointegration relation (3). This generalizes the consistency (with rates) result of Robinson & Marinucci (2003) and the asymptotic normality result of Christensen & Nielsen (2006) (who assumed non-coherence at the origin and a different spectral density model).

Theorem 1 *Let Assumptions 1-4 be satisfied. Then the NBLS estimator $\hat{\beta}_{m_0}$ in (9) satisfies*

$$\sqrt{m_0}\left(\lambda_{m_0}^{d_p}\Lambda_{m_0}^{-1}(\hat{\beta}_{m_0} - \beta) - K^{-1}H\right) \xrightarrow{d} N\left(0, K^{-1}JK^{-1}\right) \text{ as } T \to \infty, \tag{13}$$

where $\Lambda_m = \operatorname{diag}(\lambda_m^{d_1}, ..., \lambda_m^{d_{p-1}})$ and, for $a, b = 1, ..., p-1$, $K = (K_{ab})$, $H = (H_a)$, and $J = (J_{ab})$ are given by

$$\begin{aligned} K_{ab} &= \tfrac{G_{ab}}{1-d_a-d_b}\cos\left(\tfrac{\pi}{2}(d_a - d_b)\right), \\ H_a &= \tfrac{G_{ap}}{1-d_a-d_p}\cos\left(\tfrac{\pi}{2}(d_a - d_p)\right), \\ J_{ab} &= \tfrac{G_{ap}G_{bp}}{2(1-d_a-d_b-2d_p)}\cos\left(\tfrac{\pi}{2}(d_a + d_b - 2d_p)\right) + \tfrac{G_{ab}G_{pp}}{2(1-d_a-d_b-2d_p)}\cos\left(\tfrac{\pi}{2}(d_a - d_b)\right). \end{aligned}$$

Proof. See appendix A. ■

Theorem 1 refines the result of Christensen & Nielsen (2006) in two ways: first, our result uses the representation (4) of the multivariate spectral density, and secondly we allow for non-zero coherence at the origin. The cosine terms in the asymptotic distribution are a result of using the representation (4) rather than the simpler (6), in which case these terms would not be present. In the absence of any coherence between the regressors and the errors at the origin, the distribution theory follows from the above results by setting $G_{ap} = G_{pa} = 0$ for $a = 1, ..., p-1$. Also note that the theorem presents a simple and closed form expression for the asymptotic bias term $K^{-1}H$.

[2]Note that we could alternatively write our Assumptions 1-3 in terms of the model (5) and the errors v_t, as in e.g. Shimotsu & Phillips (2005).

Thus, if $K^{-1}H$ can be estimated consistently with a sufficient rate, the bias could be removed and a centered distribution can be obtained. This is the idea behind the following developments.

To illustrate the distribution theory and the developments leading to the below FMNBLS estimator, we consider briefly an illustrative example. Consider the two-variable case, i.e. the regression (3) with only one regressor. Denote the integration orders d_x and d_u and the spectral density matrix at the origin $G = (G_{ab})$ with $a, b = x, u$. In this case the result (13) reduces to

$$\sqrt{m_0}(\lambda_{m_0}^{d_u - d_x}(\hat{\beta}_{m_0} - \beta) - \eta) \xrightarrow{d} N(0, \omega),$$

where the asymptotic bias and variance terms are given by

$$\begin{aligned} \eta &= \frac{G_{xu}}{G_{xx}} \frac{(1 - 2d_x)}{(1 - d_x - d_u)} \cos\left(\frac{\pi}{2}(d_x - d_u)\right), \\ \omega &= \frac{(1 - 2d_x)^2}{2(1 - 2d_x - 2d_u)} \left(\frac{G_{uu}}{G_{xx}} + \frac{G_{ux}^2}{G_{xx}^2} \cos(\pi(d_x - d_u))\right). \end{aligned}$$

Note that, if the spectral representation (6) were used instead of (4), the cosine terms in both η and ω would be replaced by unity, their upper bound. Hence, the simpler representation (6) results in a distribution theory that is less precise, both in terms of bias and variance, than the distribution presented in Theorem 1. The increased variance obtained using (6) when the true model is (4) is a consequence of the misspecification of the spectral density at the origin since the non-zero complex part in (4) is ignored in (6). In addition to the bias, the absence of the zero coherence condition results in an additive variance inflation of

$$\frac{(1 - 2d_x)^2}{2(1 - 2d_x - 2d_u)} \frac{G_{ux}^2}{G_{xx}^2} \cos(\pi(d_x - d_u)) \geq 0.$$

Note that consistency of the estimator is not affected by the presence of non-zero coherence between the regressors and the errors at the zero frequency, and that the rate result established by Robinson (1994) and Robinson & Marinucci (2003) is, in fact, sharp in this case as conjectured by Robinson & Marinucci (2003). This is easily seen from Theorem 1, where

$$\hat{\beta}_{m_0} - \beta = \frac{\lambda_{m_0}^{d_x - d_u}}{\sqrt{m_0}} \sqrt{\omega} Z + \lambda_{m_0}^{d_x - d_u} \eta + o_P(m_0^{-1/2} \lambda_{m_0}^{d_x - d_u}),$$

for $Z \sim N(0, 1)$. The consistency and rate of $\hat{\beta}_{m_0}$ follows immediately, and in particular, $\lambda_{m_0}^{d_u - d_x}(\hat{\beta}_{m_0} - \beta) \xrightarrow{d} \eta$. That is, when normalized as in Robinson (1994) and Robinson & Marinucci (2003), the NBLS estimator converges to a degenerate distribution (a constant) in the case of non-zero coherence between the regressors and the errors at the origin. However, in the absence of coherence between the regressors and the errors at the origin and normalized by an additional $\sqrt{m_0}$, the NBLS estimator has an asymptotic normal distribution.

Given an estimate $\hat{\eta}$ of η, we can consider the FMNBLS estimator,

$$\tilde{\beta}_{m_0} = \hat{\beta}_{m_0} - \lambda_{m_0}^{d_x - d_u} \hat{\eta},$$

which should be asymptotically unbiased (i.e. mean zero in the asymptotic normal distribution) if $\hat{\eta} \xrightarrow{P} \eta$ at an appropriate rate. The correction is asymptotically negligible in the sense that

$\lambda_{m_0}^{d_x-d_u}\hat{\eta} \xrightarrow{P} 0$. However, conditions are obviously needed to ensure consistency of $\hat{\eta}$ and we need to be careful in the choice of bandwidth parameter used to estimate η. In section 3 below we discuss these issues and show how η can be estimated, e.g., by a simple auxiliary NBLS regression.

Using a completely different approach, Robinson (2008) has developed joint multiple local Whittle (MLW) estimation of the memory parameters, the cointegration coefficient, and a phase parameter in a two-dimensional stationary fractionally cointegrated system. The MLW estimator also has a centered asymptotic distribution and the estimator of β converges at the same rate as our FMNBLS estimator. The multivariate method clearly enjoys the advantages of a systems approach such as possible efficiency gains. However, it is based on numerical optimization of a multiparameter objective function and is therefore computationally more demanding than our regression approach. Moreover, the MLW objective function may have multiple local optima. Finite sample performance of the MLW estimator of β and our FMNBLS estimator is compared in simulations in section 4.

We next show that, under the assumptions above and assuming that β has been estimated by NBLS, the local Whittle estimator of d_p, the memory of the error term, remains, at least to some extent, valid in our stationary model even when based on NBLS residuals. A similar result has been derived by Velasco (2003) for nonstationary fractional cointegration. Thus, suppose d_p is estimated by

$$\hat{d}_p = \arg\min_{d\in\Delta} \hat{R}(d), \tag{14}$$

$$\hat{R}(d) = \log \hat{G}(d) - \frac{2d}{m_1}\sum_{j=1}^{m_1}\log\lambda_j, \quad \hat{G}(d) = \frac{1}{m_1}\sum_{j=1}^{m_1}\lambda_j^{2d}\hat{I}_{pp}(\lambda_j),$$

where $\Delta = [0, \Delta_2], 0 < \Delta_2 < 1/2$, is the parameter space and

$$\hat{I}_{pp}(\lambda_j) = I_{pp}(\lambda_j) + (\beta - \hat{\beta}_m)' \operatorname{Re}(I_{xx}(\lambda_j))(\beta - \hat{\beta}_m) + 2(\beta - \hat{\beta}_m)' \operatorname{Re}(I_{xp}(\lambda_j)) \tag{15}$$

is the periodogram of the residual series $\hat{u}_t = y_t - \hat{\beta}_m' x_t = u_t + (\beta - \hat{\beta}_m)' x_t$. The subscript xp in (15) denotes the cross-periodogram between x_t and u_t (or equivalently, between x_t and w_{pt}). The lower bound of the parameter space reflects prior information that $d_p \geq 0$, which seems reasonable from a practical/empirical point of view. This condition could be relaxed at the cost of a longer proof of the following theorem.

We introduce the following condition on the expansion rate of the bandwidth parameter used for the local Whittle estimator of d_p.

Assumption 5 *The bandwidth parameter $m_1 = m_1(T)$ satisfies*

$$(\log T)^2 (\log m_1)\left(\frac{m_0}{m_1}\right)^{\delta_{\min}} + \frac{m_1^{1+2\alpha}(\log m_1)^2}{T^{2\alpha}} \to 0 \text{ as } T \to \infty,$$

where m_0 is the bandwidth parameter from Assumption 4.

The first part of Assumption 5 is essentially satisfied if m_1 diverges to infinity at a faster rate than m_0. The second part is the standard assumption on the bandwidth parameter for local Whittle estimation, e.g. Robinson (1995*a*).

Theorem 2 *Let Assumptions 1-5 be satisfied and suppose* $\hat{d}_p$ *is given by (14) based on residuals* $\hat{u}_t = y_t - \hat{\beta}'_{m_0} x_t$*, where* $\hat{\beta}_{m_0}$ *is the NBLS estimator (9). Suppose* d_p *belongs to the interior of* Δ*. Then, as* $T \to \infty$*,*

$$\hat{d}_p - d_p = O_P\left((\log m_1) (m_0/m_1)^{\delta_{\min}} \right) \xrightarrow{P} 0.$$

If, in addition, $G_{ap} = G_{pa} = 0$ *for* $a = 1, \ldots, p-1$ *and* $(m_0/m_1)^{2\delta_{\min}} \sqrt{m_1}/m_0 \to 0$*, then*

$$\sqrt{m_1}(\hat{d}_p - d_p) \xrightarrow{d} N(0, 1/4) \text{ as } T \to \infty.$$

Proof. See appendix B. ■

The second part of Theorem 2 shows that, under an additional (weak) restriction on the bandwidth, the local Whittle estimator of the integration order of the errors is unaffected by the fact that it is based on NBLS residuals only in the absence of long-run coherence between regressors and errors. In the general case the local Whittle estimator remains consistent, although it converges at a slower rate. Moreover, this result shows that in fact the three step procedure employed by Marinucci & Robinson (2001*b*) and Christensen & Nielsen (2006) is only valid when there is no long-run coherence, as in Christensen & Nielsen (2006). That is, inference on d_p may, in the setup of Christensen & Nielsen (2006), be conducted based on our distributional result in Theorem 2 and is equivalent to disregarding the fact that the estimator is based on residuals, as long as the bandwidth parameter is chosen according to our assumptions.

3 Fully Modified NBLS Estimation

We next consider estimation of the bias in NBLS from Theorem 1, i.e. estimation of $K^{-1}H$. Note that, from the definitions of K and H in Theorem 1 and its proof, we can equivalently write

$$K = \lambda_m^{-1} \Lambda_m F_{xx}(\lambda_m) \Lambda_m, \quad H = \lambda_m^{d_p - 1} \Lambda_m F_{xp}(\lambda_m), \tag{16}$$

where $F_{ab}(\lambda) = \int_0^\lambda \mathrm{Re}(f_{ab}(\theta))\, d\theta$ is the integrated co-spectrum between w_{at} and w_{bt}. Thus, K is the (scaled) integrated co-spectrum of x_t and H is the (scaled) integrated co-spectrum between x_t and u_t. By rewriting K and H in this way, the bias term $K^{-1}H$ is recognized to be the (scaled) population equivalent to the coefficient estimate in a regression of the errors from (3) on the regressors. This mimics the corresponding well-known result from ordinary least squares when the errors and regressors are correlated. However, in our stationary fractional cointegration setup the bias term can be estimated and hence eliminated.

It follows that a natural estimator of the bias can be based on

$$\Gamma_{m_2} = \hat{F}_{xx}^{-1}(1, m_2)\, \hat{F}_{xp}(1, m_2),$$

using bandwidth parameter $m_2 = m_2(T)$. However, the estimator Γ_{m_2} is infeasible since the errors u_t are unobserved. Instead, the residuals from an initial NBLS regression, $\hat{u}_t$, may be used. Defining $\tilde{F}_{xp}(l, m) = \frac{2\pi}{T} \sum_{j=l}^{m} \mathrm{Re}(\hat{I}_{xp}(\lambda_j))$ and noting that $\tilde{F}_{xp}(1, m_0) = 0$ from the first order condition for $\hat{\beta}_{m_0}$, yields the feasible estimator

$$\hat{\Gamma}_{m_2} = \hat{F}_{xx}^{-1}(m_0 + 1, m_2)\, \tilde{F}_{xp}(m_0 + 1, m_2). \tag{17}$$

Thus, estimation of $K^{-1}H$ can be based on simply calculating the coefficient estimate in an auxiliary NBLS regression of the residuals from the initial NBLS regression on the same set of regressors, x_t, i.e. on NBLS estimation of the auxillary regression

$$\hat{u}_t = \gamma + \Gamma' x_t + v_t, \quad t = 1, ..., T. \tag{18}$$

Based on the discussion of the representations (4), (6), and (11), we also consider the estimator

$$\check{\Gamma}_{m_2} = \check{F}_{xx}^{-1}(m_0+1, m_2)\, \check{F}_{xp}(m_0+1, m_2), \tag{19}$$

where $\check{F}_{xx}$ and $\check{F}_{xp}$ are based on

$$\check{F}_{ab}(k,l) = \frac{2\pi}{T}\sum_{j=k}^{l} \mathrm{Re}(e^{i\lambda_j(d_a-d_b)/2} I_{ab}(\lambda_j)), \quad 0 \le k \le l \le T-1,$$

which should more precisely approximate the integrated co-spectrum $F_{ab}(\lambda)$, c.f. Assumption 1.

For the estimation of the bias term we need the following condition on the bandwidth m_2.

Assumption 6 *The bandwidth parameter $m_2 = m_2(T)$ satisfies*

$$\frac{m_0}{m_2} + \frac{m_2}{T} \to 0 \textit{ as } T \to \infty,$$

where m_0 is the bandwidth from Assumption 4.

The first term in Assumption 6 ensures that (17) is based on an increasing number of periodogram ordinates, $m_2 - m_0$. The second term ensures that estimation is conducted in a neighborhood of the origin, which is sufficient for consistent NBLS estimation. We can now state the following result regarding the estimation of the NBLS bias term.

Theorem 3 *Let Assumptions 1-4 and 6 be satisfied and assume that $\hat{\Gamma}_{m_2}$ in (17) and $\check{\Gamma}_{m_2}$ in (19) are based on residuals $\hat{u}_t = y_t - \hat{\beta}_{m_0}' x_t$, where $\hat{\beta}_{m_0}$ is the NBLS estimator (9). Then, as $T \to \infty$,*

$$\lambda_{m_2}^{d_p}\Lambda_{m_2}^{-1}\hat{\Gamma}_{m_2} - K^{-1}H = O_P\left(n + \left(\frac{m_2}{T}\right)^{\min(1,\alpha)} + \left(\frac{m_0}{T}\right)^{\min(1,\alpha)}\right) \xrightarrow{P} 0,$$

$$\lambda_{m_2}^{d_p}\Lambda_{m_2}^{-1}\check{\Gamma}_{m_2} - K^{-1}H = O_P\left(n + \left(\frac{m_2}{T}\right)^{\alpha} + \left(\frac{m_0}{T}\right)^{\alpha}\right) \xrightarrow{P} 0,$$

where

$$n = n(T) = \left(\frac{m_0}{m_2}\right)^{\delta_{\min}} + m_2^{-1/2}(\log m_2). \tag{20}$$

Proof. See appendix C. ■

This result implies that $\lambda_{m_2}^{d_p}\Lambda_{m_2}^{-1}\hat{\Gamma}_{m_2}$ or $\lambda_{m_2}^{d_p}\Lambda_{m_2}^{-1}\check{\Gamma}_{m_2}$ based on residuals are consistent estimates of $K^{-1}H$. The theorem also implies, in conjunction with Theorem 2, that the bias $\lambda_{m_0}^{-d_p}\Lambda_{m_0}K^{-1}H$ of the NBLS estimate in Theorem 1 can be consistently estimated. It is even possible, based on Theorems 2 and 3, to obtain a rate result for the bias, which we shall apply in the derivation of the fully modified estimator.

The FMNBLS estimator is based on a new bandwidth parameter $m_3 = m_3(T)$. In particular,

$$\tilde{\beta}_{m_3} = \hat{\beta}_{m_3} - \lambda_{m_3}^{-\hat{d}_p} \hat{\Lambda}_{m_3} \lambda_{m_2}^{\hat{d}_p} \hat{\Lambda}_{m_2}^{-1} \check{\Gamma}_{m_2}, \tag{21}$$

where $\hat{\Lambda}_m = \operatorname{diag}(\lambda_m^{\hat{d}_1}, \ldots, \lambda_m^{\hat{d}_{p-1}})$. I.e., the fully modified estimator $\tilde{\beta}_{m_3}$ is simply the NBLS estimator corrected for the asymptotic bias. All the estimates of the integration orders are based on the bandwidth m_1. The bias correction term $\check{\Gamma}_{m_2}$ is estimated using bandwidth m_2 for (19) and bandwidth m_0 for the $\hat{\beta}$ needed to obtain the residuals upon which both (19) and $\hat{d}_p$ are based. We could have equivalently considered $\hat{\Gamma}_{m_2}$, but Theorem 3 shows that $\check{\Gamma}_{m_2}$ converges at a faster rate than $\hat{\Gamma}_{m_2}$. Note that in Theorem 3 the estimator of $K^{-1}H$ is based on the periodograms integrated over $\lambda_{m_0+1}, \ldots, \lambda_{m_2}$ and therefore truncates the first m_0 Fourier frequencies, which may introduce variance inflation in finite samples. For example, Hurvich, Deo & Brodsky (1998) report Monte Carlo variance inflation from trimming the lowest frequencies in the log-periodogram regression, even though theoretically trimming the lowest frequencies has no detrimental effect. However, as noted above, we cannot use the lowest m_0 frequencies due to the first order condition for the initial NBLS estimator. This differs from the fully modified estimator in Phillips & Hansen (1990), which uses the frequencies closest to the origin to estimate the bias term.

For the bandwidth $m_3 = m_3(T)$ of the FMNBLS estimator, we need the following condition.

Assumption 7 *The bandwidth parameter $m_3 = m_3(T)$ satisfies*

$$\frac{1}{m_3} + \frac{m_3^{1+2\min(1,\alpha)}}{T^{2\min(1,\alpha)}} + m_3\left(\frac{m_0}{m_2}\right)^{2\delta_{\min}} + m_3\left(\frac{m_2}{T}\right)^{2\alpha} + \frac{(\log m_2)^2 m_3}{m_2} + (\log T)^2 (\log m_1)^2 m_3 \left(\frac{m_0}{m_1}\right)^{2\delta_{\min}} \to 0$$

as $T \to \infty$, where m_0, m_1, and m_2 are the bandwidth parameters from Assumptions 4-6, and α is the smoothness parameter from Assumption 1.

The condition on m_3 is in some ways complicated and in others quite mild and simple. The first two terms state that m_3 has to satisfy the NBLS assumption for the bandwidth, c.f. Assumption 4. At the same time, m_3 must diverge to infinity at a slower rate than m_2 (third through fifth terms on the left-hand side) and a slower rate than m_1 (sixth term on the left-hand side). Note that if m_1 and m_2 diverge to infinity at much faster rates than m_0 and the cointegrating strength, $\delta_{\min}$, is large, Assumption 7 is less restrictive. Furthermore, Assumption 7 is simple and easily satisfied because it is always feasible to choose $m_3 = m_0$, in which case there is no need to obtain a new NBLS estimate upon which to base the FMNBLS estimate (21). In that case the condition simplifies significantly, and in particular the relevant assumption then becomes

$$\frac{m_0^{1+2\delta_{\min}}}{m_2^{2\delta_{\min}}} + m_0\left(\frac{m_2}{T}\right)^{2\alpha} + \frac{(\log m_2)^2 m_0}{m_2} + (\log T)^2 (\log m_1)^2 \frac{m_0^{1+2\delta_{\min}}}{m_1^{2\delta_{\min}}} \to 0 \text{ as } T \to \infty, \tag{22}$$

in addition to Assumptions 4-6 already placed on m_0, m_1, and m_2. Note that the third term only adds a logarithmic factor relative to Assumption 6. To illustrate the restriction placed on the bandwidths by the first and last terms of (22), suppose we are in the empirically relevant (see section 5 below) situation $\delta_{\min} = 0.4$. Then choosing $m_0 = m_3 = T^{0.3}$ is feasible if at the same time $m_1 = T^{0.675+\psi_1}$ and $m_2 = T^{0.675+\psi_2}$ for any $\psi_1, \psi_2 > 0$. On the other hand, if $m_1 = m_2 = T^{0.8}$ then choosing $m_0 = m_3 = T^{32/90-\psi_0}$ for any $\psi_0 > 0$ is feasible which is only slightly restrictive in light of Assumption 4 on m_0. Also note that it is in fact feasible in some cases to choose m_2 to diverge faster than $T^{0.8}$, which is even faster than the rate allowed in NBLS estimation, c.f. Assumption 4.

In any case, the rate of convergence of $\tilde{\beta}_{m_3}$ in the following theorem is mostly affected by the distance $\delta_{\min}$ and not so much by the choice of $m_0 = m_3$. For example, if $\delta_{\min} = 0.4$ and $m_0 = m_3 = T^{0.3}$, the rate of convergence of $\tilde{\beta}_{m_3}$ in (23) is $T^{0.43}$ which is close to the usual $\sqrt{T}$-convergence in spite of the low bandwidth rate for m_3. In general, when $m_0 = m_3 = T^{\zeta}$ and $\delta_{\min} = \xi$, the rate of convergence of $\tilde{\beta}_{m_3}$ is $T^{\zeta(0.5-\xi)+\xi}$. Therefore, for any ζ, when $\xi \to 1/2$ the rate of convergence of $\tilde{\beta}_{m_3}$ approaches $\sqrt{T}$, which is the best rate attainable for fully parametric estimators based on complete and correct specification of the spectral density at all frequencies.

Theorem 4 *Let Assumptions 1-7 or Assumptions 1-6 and (22) be satisfied and let $\tilde{\beta}_{m_3}$ be the FMNBLS estimator (21). Then*

$$\sqrt{m_3}\lambda_{m_3}^{d_p}\Lambda_{m_3}^{-1}(\tilde{\beta}_{m_3} - \beta) \xrightarrow{d} N\left(0, K^{-1}JK^{-1}\right) \text{ as } T \to \infty, \tag{23}$$

where K and J are defined in Theorem 1.

Proof. See appendix D. ■

The result in Theorem 4 demonstrates that it is possible to obtain an asymptotically unbiased estimate of the cointegration vector in the stationary fractional cointegration model (3) even in the presence of long-run coherence. More generally, it proves that it is possible to consistently estimate (with a mean zero asymptotic distribution) the relation between stationary time series even when the regressors and the errors are correlated at any frequency. A necessary condition is that the time series in question are stationary fractionally cointegrated. A similar result to Theorem 4 is obtained by Hualde & Robinson (2006) who derive the asymptotic distribution theory for a related inverse spectral density weighted estimator, see also Nielsen (2005), which is shown to be asymptotically normal in the stationary case.

Compared to the NBLS estimator of Theorem 1, the fully modified estimator incurs no asymptotic variance inflation, only bias correction. Indeed, the FMNBLS estimator enjoys a faster rate of convergence than the NBLS estimator in the general case with non-zero coherence between the regressors and the errors at the origin. In particular, in the notation of the example following Theorem 1, the asymptotic mean squared error of the two estimators are related as

$$AMSE(\hat{\beta}_{m_3}) = m_3\lambda_{m_3}^{2d_u-2d_x}E(\hat{\beta}_{m_3} - \beta)^2 = \omega + m_3\eta^2 = AMSE(\tilde{\beta}_{m_3}) + m_3\eta^2.$$

Thus, FMNBLS with the asymptotic distribution theory of Theorem 4 constitutes a much more useful inferential tool for the stationary fractional cointegration model than the NBLS estimator, which is commonly used in previous work in this area and applied especially in financial economics.

Consistent estimation of the parameters appearing in the variance of the limiting distribution in (23) can be based on Theorem 2 in conjunction with the estimator

$$\hat{G}_{ab}(\beta, d) = \frac{1}{m_2}\sum_{j=1}^{m_2} \mathrm{Re}\left(\lambda_j^{d_a+d_b} e^{i(\lambda_j-\pi)(d_a-d_b)/2} I_{ab}(\lambda_j)\right),$$

where $d = (d_1, ..., d_p)$. Note that β enters in $I_{ab}(\lambda_j)$ if $a = p$ and/or $b = p$. In particular, if $\tilde{I}(\lambda_j)$ is based on the fully modified residuals $\tilde{u}_t = y_t - \tilde{\beta}'_{m_3} x_t$, we have

$$\hat{G}(\tilde{\beta}_{m_3}, \hat{d}) = \frac{1}{m_2} \sum_{j=1}^{m_2} \mathrm{Re}\left(\lambda_j^{\hat{d}_a + \hat{d}_b} e^{i(\lambda_j - \pi)(\hat{d}_a - \hat{d}_b)/2} \tilde{I}_{ab}(\lambda_j)\right) \xrightarrow{P} G$$

as $T \to \infty$. The proof of this statement follows as in Propositions 2 and 3 of Robinson & Yajima (2002) by noting that $\tilde{\beta}_{a,m_3} - \beta_a = O_P(m_3^{-1/2} \lambda_{m_3}^{d_a - d_p})$, and is therefore omitted.[3]

4 Simulation Evidence

In this section we investigate the finite sample behavior of the FMNBLS estimator introduced above and compare with the performance of the NBLS estimator and the MLW estimator[4] of Robinson (2008). We consider the following three two-dimensional generating mechanisms for x_t and u_t in the cointegrating relation (3),

$$\begin{aligned}
&\text{Model A} : \quad x_t = (1-L)^{-d_x} \varepsilon_{1t}, \quad u_t = (1-L)^{-d_u} \varepsilon_{2t}, \\
&\text{Model B} : \quad x_t = (1-L)^{-d_x} v_{1t}, \quad u_t = (1-L)^{-d_u} \varepsilon_{2t}, \quad v_{1t} = a_1 v_{1,t-1} + \varepsilon_{1t}, \\
&\text{Model C} : \quad x_t = (1-L)^{-d_x} \varepsilon_{1t}, \quad u_t = (1-L)^{-d_u} v_{2t}, \quad v_{2t} = a_2 v_{2,t-1} + \varepsilon_{2t},
\end{aligned}$$

where $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ is independently and identically $N(0, \Omega)$ distributed with

$$\Omega = \begin{bmatrix} \xi & \rho\xi^{1/2} \\ \rho\xi^{1/2} & 1 \end{bmatrix}.$$

Thus, $\xi = var(\varepsilon_{1t})/var(\varepsilon_{2t})$ is the signal-to-noise ratio and $\rho = corr(\varepsilon_{1t}, \varepsilon_{2t})$ is the contemporaneous correlation between the innovations ε_{1t} and ε_{2t}.

Based on the pair (x_t, u_t) we generate y_t from (3) with $\beta = 1$. For all the simulations we generate the data with $(d_x, d_u) = (0.4, 0)$ which is close to what is expected in many practical situations concerning e.g. financial volatility series. This choice is also supported by the empirical applications below where we find estimates very close to these values in almost all cases. Unreported simulations reveal that the bias in NBLS is more severe when the integration orders are closer, e.g. $(d_x, d_u) = (0.3, 0.1)$, which also reduces the effectiveness of the bias correction procedure.[5] However, the bias reduction in FMNBLS relative to NBLS remains noteworthy in that case, and for larger sample sizes the bias reduction works as well as with $(d_x, d_u) = (0.4, 0)$.

Models A, B, and C satisfy all the assumptions of the model, and are increasing in complexity with Model A having no short-run dynamics whereas Models B and C include short-run dynamics. Model B adds short-run dynamics to the regressor and thus disturbs the signal due to the contamination of the low frequencies of x_t from the higher frequencies which are dominated by the short-run dynamics. In Model C short-run dynamics is present in u_t instead of x_t. Note that

$$G = \begin{bmatrix} \xi(1-a_1)^{-2} & \rho\xi^{1/2}(1-a_1)^{-1}(1-a_2)^{-1} \\ \rho\xi^{1/2}(1-a_1)^{-1}(1-a_2)^{-1} & (1-a_2)^{-2} \end{bmatrix} \tag{24}$$

[3] Also note that, as in Theorem 2, local Whittle estimation of the integration order of the errors based on FMNBLS residuals is consistent and, if $m_0 = m_3$, then $\tilde{d}_p - d_p = O_P(m_0^{-1/2} (\log m_1) (m_0/m_1)^{\delta_{\min}})$, which converges faster than when based on NBLS residuals.

[4] I thank the editor and an anonymous referee for suggesting this comparison.

[5] The results for $(d_x, d_u) = (0.3, 0.1)$ are available from the authors upon request.

such that when $\rho \neq 0$ the G matrix is not diagonal and the distribution theory for NBLS from Christensen & Nielsen (2006) no longer applies, see Theorem 1. However, the NBLS estimator is still consistent when $\rho \neq 0$. On the other hand, FMNBLS should be able to handle the presence of the long-run endogeneity that is due to $\rho \neq 0$, as shown in Theorem 4 above.

We also consider the three-dimensional generating mechanism

$$\text{Model D:} \quad x_{1t} = (1-L)^{-d_1} \varepsilon_{1t}, \quad x_{2t} = (1-L)^{-d_2} \varepsilon_{2t}, \quad y_t = x_{1t} + x_{2t} + (1-L)^{-d_3} \varepsilon_{3t},$$

where $d_1 \geq d_2 > d_3$ and $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t})'$ is independently and identically $N(0, \Omega)$ distributed with

$$\Omega = \begin{bmatrix} 1 & 0.5 & -0.75 \\ 0.5 & 1 & -0.75 \\ -0.75 & -0.75 & 1 \end{bmatrix}.$$

Note that in Model D the cointegrating regression (3) is $y_t = x_{1t} + x_{2t} + u_t$, i.e., $\beta = (1,1)', x_{1t} \in I(d_1), x_{2t} \in I(d_2), u_t \in I(d_3)$, and $y_t \in I(d_1)$. Hence, this illustrates a three-dimensional model where the integration orders of the regressors are not necessarily the same, while at the same time all assumptions are satisfied; in particular there is no cointegration among the regressors. When $d_1 > d_2$ there is also cointegration between y_t and x_{1t} since $y_t - x_{1t} = x_{2t} + u_t \in I(d_2)$, although this is dominated in the three-dimensional system by the cointegrating relation $y_t - x_{1t} - x_{2t} = u_t \in I(d_3)$.

For each model we use $10,000$ replications for sample sizes $T = 128$ and $T = 512$, which are close to what is found in practical applications, see also the following section, although many applications in finance will have much larger sample sizes. The bandwidth parameters chosen for the simulation study are $m_i = \lfloor T^{\psi_i} \rfloor, i = 0,1,2,3$, where $\psi_0 = 0.3, 0.5$, $\psi_1 = 0.6, 0.8$, $\psi_2 = 0.8$, $\psi_3 = \psi_0$, and $\lfloor x \rfloor$ denotes the largest integer less than or equal to x.

Tables 1-3 present the Monte Carlo bias and root mean squared error (RMSE) results for Models A-C. As expected from (13), we find that changing the sign of the contemporaneous correlation ρ only causes the bias to change sign but not size, so we only report results for $\rho \leq 0$. For comparison, we also report the corresponding results for the MLW estimator of Robinson (2008) with bandwidth m_1 and using the NBLS, d_x, and d_u estimates also applied in FMNBLS as starting values, see Robinson (2008, Remark 3). The MLW objective function is optimized by the BFGS algorithm and terminated when the convergence criterion $\epsilon = 10^{-6}$ is satisfied or after 100 iterations[6].

Table 1 presents the results for Model A. A general finding is that increasing the signal-to-noise ratio ξ from 1/2 to 2, halves the bias of NBLS and thus also improves the bias-reducing ability of the FMNBLS procedure. This is due to the fact that the contemporaneous covariance between ε_{1t} and ε_{2t} is halved when ξ increases from 1/2 to 2. Furthermore, estimating $K^{-1}H$ in (13) when it in fact is zero because $\rho = 0$ inflates the variance (and hence the RMSE) of FMNBLS relative to that of NBLS, but the fully modified procedure still yields unbiased estimates of β. For $\rho = -0.75$ (and $\rho = 0.75$), the FMNBLS procedure bias-corrects NBLS although this comes at the expense of an increase in the finite sample standard error of up to 50%. However, the RMSE of FMNBLS in that case is (much) lower than that of NBLS. For the larger sample size, $T = 512$, FMNBLS yields almost unbiased estimates for all bandwidths with RMSEs much smaller than those of NBLS,

[6]In the case of non-convergence after 100 iterations the replication in question was dropped from the experiment. Increasing the number of iterations required before termination of the numerical optimization significantly worsens the results for the MLW estimator.

Table 1: Simulation Results for Model A

ξ	m_0	m_1	$\rho=-0.75$ NBLS Bias	RMSE	FMNBLS Bias	RMSE	MLW Bias	RMSE	$\rho=0$ NBLS Bias	RMSE	FMNBLS Bias	RMSE	MLW Bias	RMSE
Panel A: $T=128$														
1	$\lfloor T^{0.3}\rfloor$	$\lfloor T^{0.6}\rfloor$	-0.221	0.249	-0.067	0.178	0.218	0.987	0.001	0.158	0.002	0.238	0.004	0.935
		$\lfloor T^{0.8}\rfloor$			-0.060	0.170	0.279	0.612			0.003	0.232	-0.004	0.534
	$\lfloor T^{0.5}\rfloor$	$\lfloor T^{0.6}\rfloor$	-0.296	0.309	-0.028	0.145	0.165	0.905	0.001	0.114	0.002	0.195	0.008	1.025
		$\lfloor T^{0.8}\rfloor$			-0.028	0.141	0.279	0.612			0.002	0.194	0.001	0.364
2	$\lfloor T^{0.3}\rfloor$	$\lfloor T^{0.6}\rfloor$	-0.156	0.175	-0.046	0.125	0.163	0.725	0.001	0.112	0.001	0.166	0.006	0.810
		$\lfloor T^{0.8}\rfloor$			-0.041	0.119	0.195	0.458			0.001	0.163	-0.000	0.320
	$\lfloor T^{0.5}\rfloor$	$\lfloor T^{0.6}\rfloor$	-0.209	0.218	-0.020	0.102	0.128	0.703	0.001	0.081	0.000	0.137	-0.001	0.751
		$\lfloor T^{0.8}\rfloor$			-0.020	0.099	0.200	0.512			0.000	0.136	0.001	0.299
Panel B: $T=512$														
1	$\lfloor T^{0.3}\rfloor$	$\lfloor T^{0.6}\rfloor$	-0.139	0.150	-0.039	0.085	0.068	0.252	0.000	0.080	0.001	0.107	-0.005	0.385
		$\lfloor T^{0.8}\rfloor$			-0.035	0.082	0.102	0.146			0.001	0.105	0.001	0.093
	$\lfloor T^{0.5}\rfloor$	$\lfloor T^{0.6}\rfloor$	-0.203	0.208	0.005	0.068	0.066	0.227	0.000	0.057	0.001	0.089	0.002	0.330
		$\lfloor T^{0.8}\rfloor$			0.000	0.067	0.102	0.146			0.001	0.089	0.001	0.093
2	$\lfloor T^{0.3}\rfloor$	$\lfloor T^{0.6}\rfloor$	-0.099	0.106	-0.029	0.060	0.043	0.149	-0.000	0.056	-0.001	0.075	0.000	0.150
		$\lfloor T^{0.8}\rfloor$			-0.025	0.058	0.071	0.102			-0.000	0.075	-0.001	0.067
	$\lfloor T^{0.5}\rfloor$	$\lfloor T^{0.6}\rfloor$	-0.144	0.147	0.003	0.048	0.043	0.158	-0.000	0.040	-0.001	0.063	-0.000	0.151
		$\lfloor T^{0.8}\rfloor$			0.000	0.047	0.071	0.102			-0.001	0.063	-0.001	0.067

Note: The simulations are based on 10,000 replications under the empirically relevant scenario $(d_x, d_u) = (0.4, 0)$, with bandwidths $m_2 = \lfloor T^{0.8}\rfloor$ and $m_3 = m_0$.

except when $\rho = 0$. Even though the bias of NBLS increases (and becomes fairly large) for larger m_0, the fully modified procedure is still able to correct this, and indeed the bias of FMNBLS is smaller when m_0 $(= m_3)$ is larger. Since there is no short-run dynamics, the choice of m_1 appears less important. The MLW estimator performs quite poorly compared to both NBLS and FMNBLS, especially for $T = 128$. Interestingly, the sign of the bias of MLW is opposite that of NBLS.

Table 2 presents the simulation results for Model B with autoregressive coefficients $a_1 = -1/2$ or $a_1 = 1/2$.[7] Now, (4) is a worse approximation to (12) when moving only a short distance away from the origin, due to the contamination from higher frequencies (short-run dynamics), and we therefore expect the bias of NBLS (and possibly also of FMNBLS) to be larger than for the case of no short-run dynamics. Interestingly, for Model B it appears that the biases and RMSEs of NBLS and FMNBLS are lower than for Model A when $a_1 = 1/2$ and higher than for Model A when $a_1 = -1/2$. In Model B the MLW estimator is sometimes equal to or better than FMNBLS in terms of RMSE, but this is only when $a_1 = 1/2$ and $m_1 = \lfloor T^{0.8}\rfloor$ and $T = 512$. In all other cases it does not perform as well as FMNBLS, and it even has some convergence problems in some cases which are marked by asterisks in the table.

Next, we turn to Model C, and Table 3 presents the simulation results, which are quite different for $a_2 = -1/2$ and $a_2 = 1/2$. Compared to the results of Model A, the NBLS estimator is actually less biased in this setup when $a_2 = -1/2$. This suggests that the negative autocorrelation in u_t offsets some of the bias in the NBLS estimate introduced by the contemporaneous covariance

[7] For Models B and C we report the simulation results for $\xi = 2$ only. The results for $\xi = 1/2$ are qualitatively similar, see also Table 1.

Table 2: Simulation Results for Model B

	Bandwidths		$\rho=-0.75$						$\rho=0$					
			NBLS		FMNBLS		MLW		NBLS		FMNBLS		MLW	
a_1	m_0	m_1	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE
Panel A: $T=128$														
$-1/2$	$\lfloor T^{0.3}\rfloor$	$\lfloor T^{0.6}\rfloor$	-0.241	0.269	-0.121	0.213	0.370	1.357	0.002	0.167	0.003	0.255	0.011	1.360
		$\lfloor T^{0.8}\rfloor$			-0.044	0.201	0.612	2.019*			0.004	0.287	0.012	1.314
	$\lfloor T^{0.5}\rfloor$	$\lfloor T^{0.6}\rfloor$	-0.328	0.342	-0.176	0.232	0.248	1.323	0.001	0.120	0.002	0.202	0.002	1.182
		$\lfloor T^{0.8}\rfloor$			-0.125	0.206	0.441	2.176*			0.002	0.224	0.010	1.419
$1/2$	$\lfloor T^{0.3}\rfloor$	$\lfloor T^{0.6}\rfloor$	-0.072	0.082	-0.031	0.061	-0.017	0.105	0.000	0.056	0.000	0.076	0.003	0.226
		$\lfloor T^{0.8}\rfloor$			-0.043	0.064	0.003	0.051			0.000	0.067	0.000	0.061
	$\lfloor T^{0.5}\rfloor$	$\lfloor T^{0.6}\rfloor$	-0.089	0.095	0.038	0.065	-0.018	0.109	0.000	0.043	0.000	0.071	0.002	0.229
		$\lfloor T^{0.8}\rfloor$			0.015	0.048	0.003	0.051			0.000	0.062	0.000	0.061
Panel B: $T=512$														
$-1/2$	$\lfloor T^{0.3}\rfloor$	$\lfloor T^{0.6}\rfloor$	-0.149	0.161	-0.048	0.093	0.122	0.339	0.000	0.084	0.001	0.114	-0.000	0.265
		$\lfloor T^{0.8}\rfloor$			-0.008	0.085	0.249	0.345			0.001	0.121	0.000	0.121
	$\lfloor T^{0.5}\rfloor$	$\lfloor T^{0.6}\rfloor$	-0.221	0.227	-0.030	0.078	0.118	0.327	0.000	0.060	0.001	0.093	0.001	0.224
		$\lfloor T^{0.8}\rfloor$			0.001	0.074	0.247	0.332			0.001	0.100	0.000	0.121
$1/2$	$\lfloor T^{0.3}\rfloor$	$\lfloor T^{0.6}\rfloor$	-0.048	0.052	-0.024	0.034	-0.014	0.036	-0.000	0.028	-0.000	0.036	0.000	0.053
		$\lfloor T^{0.8}\rfloor$			-0.034	0.041	-0.019	0.026			-0.000	0.032	-0.000	0.026
	$\lfloor T^{0.5}\rfloor$	$\lfloor T^{0.6}\rfloor$	-0.066	0.068	0.002	0.023	-0.014	0.036	-0.000	0.020	-0.000	0.032	0.001	0.097
		$\lfloor T^{0.8}\rfloor$			-0.017	0.027	-0.019	0.026			-0.000	0.027	-0.000	0.026

Note: The simulations are based on 10,000 replications under the empirically relevant scenario $(d_x, d_u) = (0.4, 0)$, with bandwidths $m_2 = \lfloor T^{0.8}\rfloor$ and $m_3 = m_0$. An asterisk indicates that MLW did not converge for 5-10% of the replications.

between x_t and u_t, see (24). Consequently, the FMNBLS procedure works very well and generally yields large reductions in bias and also smaller RMSEs when $a_2 = -1/2$. When $a_2 = 1/2$, Model C renders extremely high biases (in absolute value) for NBLS. For the small sample size the NBLS biases (when $\rho \neq 0$) range from 0.33 to 0.43 in absolute value, and for the large sample size the biases are still about two-thirds of the bias for the smaller sample size. For the small sample size, this yields an imprecise estimate of $K^{-1}H$ in (13), and as a result FMNBLS is still biased, although the fully modified procedure generally still manages to reduce the bias quite considerably while having a smaller RMSE than NBLS. For $T = 512$ FMNBLS has low bias and the RMSE is again (much) smaller than that of NBLS. The performance of MLW is similar to that in Table 2 with convergence problems when $a_2 = 1/2$, even for the large sample size, and performance equal to or better than that of FMNBLS only when $a_2 = -1/2$ and $m_1 = \lfloor T^{0.8}\rfloor$.

Finally, we turn to Model D with two regressors with memory parameters (d_1, d_2). In this case, as in Model A, the bandwidth m_1 has no significant effect since there is no short-run dynamics. The bandwidth m_0 appears to also be of no real importance for RMSE comparisons. However, it is important for the bias of NBLS, which increases with m_0, but not for the bias of FMNBLS. The most interesting aspect of Model D is the comparison across different values of (d_1, d_2). In this respect we find that for NBLS and especially FMNBLS the RMSE appears to be higher for the coefficient on the variable with the lowest memory parameter. This finding is in line with unreported simulations of Models A-C with $(d_x, d_u) = (0.3, 0.1)$.

Table 3: Simulation Results for Model C

			$\rho = -0.75$						$\rho = 0$					
	Bandwidths		NBLS		FMNBLS		MLW		NBLS		FMNBLS		MLW	
a_2	m_0	m_1	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE
Panel A: $T = 128$														
$-1/2$	$\lfloor T^{0.3} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.102	0.115	-0.018	0.080	0.035	0.326	0.000	0.075	0.001	0.112	0.003	0.456
		$\lfloor T^{0.8} \rfloor$			-0.040	0.078	-0.014	0.075			0.001	0.096	0.001	0.100
	$\lfloor T^{0.5} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.133	0.139	0.033	0.077	0.026	0.311	0.000	0.055	0.001	0.096	0.003	0.400
		$\lfloor T^{0.8} \rfloor$			0.010	0.062	-0.014	0.075			0.001	0.085	0.001	0.100
$1/2$	$\lfloor T^{0.3} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.329	0.364	-0.195	0.326	0.279	2.024*	0.002	0.219	0.002	0.372	0.020	2.046
		$\lfloor T^{0.8} \rfloor$			-0.067	0.342	-0.420	2.040**			0.002	0.456	0.001	2.516*
	$\lfloor T^{0.5} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.430	0.446	-0.331	0.392	-0.085	1.898**	0.001	0.152	0.002	0.273	0.008	1.849
		$\lfloor T^{0.8} \rfloor$			-0.282	0.374	-0.573	1.941*			0.001	0.316	-0.009	2.368*
Panel B: $T = 512$														
$-1/2$	$\lfloor T^{0.3} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.065	0.070	-0.018	0.040	0.010	0.073	0.000	0.038	0.000	0.050	-0.001	0.117
		$\lfloor T^{0.8} \rfloor$			-0.028	0.043	-0.014	0.033			0.000	0.046	0.000	0.040
	$\lfloor T^{0.5} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.093	0.096	0.007	0.032	0.010	0.075	0.000	0.027	0.000	0.042	-0.001	0.107
		$\lfloor T^{0.8} \rfloor$			-0.006	0.031	-0.014	0.033			0.000	0.040	0.000	0.040
$1/2$	$\lfloor T^{0.3} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.202	0.218	-0.092	0.141	0.327	0.762	-0.001	0.113	-0.001	0.158	-0.008	0.493
		$\lfloor T^{0.8} \rfloor$			0.058	0.158	0.385	2.770**			-0.001	0.206	-0.006	1.415
	$\lfloor T^{0.5} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.301	0.308	-0.137	0.168	0.301	0.708	-0.001	0.080	-0.001	0.126	-0.013	0.675
		$\lfloor T^{0.8} \rfloor$			-0.042	0.127	-0.217	2.693**			-0.002	0.154	-0.003	1.248

Note: The simulations are based on 10,000 replications under the empirically relevant scenario $(d_x, d_u) = (0.4, 0)$, with bandwidths $m_2 = \lfloor T^{0.8} \rfloor$ and $m_3 = m_0$. One and two asterisks indicate that MLW did not converge for 5-10% of the replications and 10-25% of the replications, respectively.

Overall, the simulations clearly demonstrate the superiority (especially in terms of bias) of the fully modified estimator relative to NBLS in the presence of non-zero long-run coherence between the regressor and the error. In all models, the bias-reduction of FMNBLS relative to NBLS is considerable, and for the larger sample size the bias practically disappears. The cost of this bias correction is an increase in the finite sample standard deviation of approximately 30-50% for the models considered here, although the results indicate that this is more than off-set by the large bias reduction when $\rho \neq 0$ to yield reductions in the RMSE.

5 Empirical Illustrations

We apply NBLS and FMNBLS to three different empirically relevant examples.

5.1 The Implied-Realized Volatility Relation

Recent contributions by, e.g., Comte & Renault (1998), Bandi & Perron (2006), and Christensen & Nielsen (2006), including empirical evidence, have pointed towards viewing the predictive regression between implied volatility (IV) and realized volatility (RV) as one of stationary fractional cointegration. However, the possible existence of a volatility risk premium that is correlated with IV can bias the NBLS estimate from a regression of RV on IV, which ultimately can lead to a wrongful rejection of the long-run unbiasedness hypothesis, see Bandi & Perron (2006). Furthermore, the existence of an unobserved risk premium can also imply a negative intercept in the regression, and

Table 4: Simulation Results for Model D

	Bandwidths		NBLS				FMNBLS			
(d_1, d_2)	m_0	m_1	Bias_1	Bias_2	RMSE_1	RMSE_2	Bias_1	Bias_2	RMSE_1	RMSE_2
Panel A: $T = 128$										
$(0.25, 0.25)$	$\lfloor T^{0.3} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.247	-0.209	0.262	0.250	-0.175	-0.128	0.220	0.250
		$\lfloor T^{0.8} \rfloor$					-0.169	-0.120	0.216	0.233
	$\lfloor T^{0.5} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.290	-0.259	0.295	0.271	-0.198	-0.159	0.219	0.214
		$\lfloor T^{0.8} \rfloor$					-0.200	-0.160	0.218	0.211
$(0.40, 0.25)$	$\lfloor T^{0.3} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.159	-0.143	0.176	0.207	-0.073	-0.027	0.132	0.244
		$\lfloor T^{0.8} \rfloor$					-0.063	-0.016	0.126	0.242
	$\lfloor T^{0.5} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.210	-0.204	0.216	0.223	-0.073	-0.050	0.114	0.174
		$\lfloor T^{0.8} \rfloor$					-0.075	-0.054	0.112	0.167
$(0.40, 0.40)$	$\lfloor T^{0.3} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.161	-0.141	0.178	0.186	-0.086	-0.058	0.134	0.182
		$\lfloor T^{0.8} \rfloor$					-0.079	-0.048	0.129	0.179
	$\lfloor T^{0.5} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.212	-0.201	0.218	0.216	-0.088	-0.074	0.121	0.153
		$\lfloor T^{0.8} \rfloor$					-0.090	-0.074	0.120	0.147
Panel B: $T = 512$										
$(0.25, 0.25)$	$\lfloor T^{0.3} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.190	-0.150	0.198	0.173	-0.117	-0.067	0.140	0.142
		$\lfloor T^{0.8} \rfloor$					-0.114	-0.060	0.137	0.139
	$\lfloor T^{0.5} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.241	-0.205	0.243	0.211	-0.142	-0.095	0.152	0.127
		$\lfloor T^{0.8} \rfloor$					-0.146	-0.097	0.155	0.126
$(0.40, 0.25)$	$\lfloor T^{0.3} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.099	-0.069	0.107	0.115	-0.031	0.040	0.062	0.142
		$\lfloor T^{0.8} \rfloor$					-0.024	0.050	0.059	0.143
	$\lfloor T^{0.5} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.147	-0.128	0.150	0.140	-0.021	0.033	0.050	0.105
		$\lfloor T^{0.8} \rfloor$					-0.025	0.027	0.051	0.096
$(0.40, 0.40)$	$\lfloor T^{0.3} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.098	-0.076	0.106	0.099	-0.040	-0.013	0.065	0.083
		$\lfloor T^{0.8} \rfloor$					-0.036	-0.003	0.062	0.083
	$\lfloor T^{0.5} \rfloor$	$\lfloor T^{0.6} \rfloor$	-0.147	-0.127	0.150	0.135	-0.033	-0.008	0.056	0.072
		$\lfloor T^{0.8} \rfloor$					-0.038	-0.009	0.057	0.068

Note: The simulations are based on 10,000 replications with $d_3 = 0$ and bandwidths $m_2 = \lfloor T^{0.8} \rfloor$ and $m_3 = m_0$.

thus long-run unbiasedness is typically upheld if the cointegrating coefficient is $\beta = 1$ regardless of the presence of the intercept.

We sample S&P500 index options (SPX) data from the Berkeley options data base covering the period January 1988 through December 1995 and calculate $T = 412$ weekly Black-Scholes implied volatilities and the corresponding S&P500 realized volatilities, see Christensen & Nielsen (2006) for details. In particular, Christensen & Nielsen (2006) find that the log-volatilities are stationary, with insignificantly different long memory estimates, and that NBLS regression yields a cointegrating coefficient β ranging from 0.84 to 0.89 for different bandwidth choices.

Panel A of Table 5 shows the memory estimates for the two log-volatility series. As found by Christensen & Nielsen (2006), the series are stationary ($d < 1/2$) and exhibit long memory with fairly stable estimates across bandwidths. Since the memory estimates are approximately equal, we next turn to the long-run relation estimates.

In Panel B of the table we show estimates (with asymptotic standard errors in parentheses) of the stationary fractional cointegration relation between the two log-volatility series, IV and RV.

Table 5: Implied-Realized Volatility Application

Panel A: Long Memory Estimates, $\hat{d}$		
	Realized volatility	Implied volatility
Bandwidth	$y_t = \ln \sigma_{RV,t}$	$x_t = \ln \sigma_{IV,t}$
$m_1 = \lfloor T^{0.6} \rfloor$	0.4476 (0.0822)	0.4527 (0.0822)
$m_1 = \lfloor T^{0.7} \rfloor$	0.4162 (0.0606)	0.3503 (0.0606)
$m_1 = \lfloor T^{0.8} \rfloor$	0.4180 (0.0449)	0.2801 (0.0449)

Panel B: Cointegration Analysis						
	NBLS			FMNBLS		
Bandwidths	$\hat{\alpha}_{m_3}$	$\hat{\beta}_{m_3}$	$\hat{d}_{\hat{u}}$	$\tilde{\alpha}_{m_3}$	$\tilde{\beta}_{m_3}$	$\hat{d}_{\tilde{u}}$
$m_0 = \lfloor T^{0.3} \rfloor, m_1 = \lfloor T^{0.7} \rfloor$	−0.9305	0.8412 (0.1521)	0.0974 (0.0606)	−0.4789	1.0631 (0.1660)	0.0873 (0.0606)
$m_0 = \lfloor T^{0.3} \rfloor, m_1 = \lfloor T^{0.8} \rfloor$	−0.9305	0.8412 (0.1459)	0.0704 (0.0449)	−0.4088	1.0975 (0.1703)	0.0550 (0.0449)
$m_0 = \lfloor T^{0.4} \rfloor, m_1 = \lfloor T^{0.7} \rfloor$	−0.9403	0.8364 (0.1325)	0.0987 (0.0606)	−0.3846	1.1094 (0.1616)	0.0945 (0.0606)
$m_0 = \lfloor T^{0.4} \rfloor, m_1 = \lfloor T^{0.8} \rfloor$	−0.9403	0.8364 (0.1227)	0.0718 (0.0449)	−0.3149	1.1436 (0.1540)	0.0600 (0.0449)

Panel A reports local Whittle estimates of the fractional integration orders as described in Robinson (1995a). Numbers in parentheses are asymptotic standard errors using $\sqrt{m_1}(\hat{d} - d) \xrightarrow{d} N(0, 1/4)$. Panel B reports NBLS and FMNBLS estimates with $m_2 = \lfloor T^{0.8} \rfloor$ and $m_3 = m_0$. The asymptotic standard errors for the NBLS and FMNBLS estimates are based on (13) and (23), respectively. Standard errors for $\hat{d}_{\hat{u}}$ and $\hat{d}_{\tilde{u}}$ are based on the same asymptotic distribution as $\hat{d}$, and should be used with caution, see Theorem 2.

We follow Marinucci & Robinson (2001b) and Christensen & Nielsen (2006) and choose rather narrow bandwidths for the NBLS and FMNBLS estimates, in this case $m_0 = m_3 = \lfloor T^{0.3} \rfloor$ and $m_0 = m_3 = \lfloor T^{0.4} \rfloor$, see also Assumption 7 and the discussion thereafter. The NBLS estimates are of course in line with the results of Christensen & Nielsen (2006), with the parameter of interest, β, estimated to be 0.84 which is not significantly different from unity when applying the asymptotic distribution theory in Theorem 1. The FMNBLS procedure corrects for the possible correlation between the regressor and the error term; those estimates are displayed in the final columns. With our choice of $m_2 = \lfloor T^{0.8} \rfloor$ and $m_1 = \lfloor T^{0.7} \rfloor$ or $m_1 = \lfloor T^{0.8} \rfloor$ we obtain point estimates of β that are now slightly above unity, but clearly still insignificantly different from unity. Thus, all our estimates support the long-run unbiasedness hypothesis, $\beta = 1$. Notice that both the NBLS and FMNBLS estimates support an $I(d) - I(0)$ relation with d around $0.35 - 0.4$, although the usual asymptotic distribution may not apply for $\hat{d}_{\hat{u}}$ and $\hat{d}_{\tilde{u}}$, see Theorem 2.

5.2 Inflation Rate Harmonization in the European Union

We also examine consumer price indices of France and Spain. Methods for calculating the consumer price index vary across different countries, which makes international comparison more difficult, and because of this we use the harmonized index for consumer prices (HICP) developed within the European Union based on a coordinated methodology.

Since the differentials between the inflation rates of individual member countries of the European Union are constrained, we expect that there exists a stable relationship between the inflation rates. Furthermore, based on evidence of long memory in inflation rates in Doornik & Ooms (2004) we

Table 6: Inflation Rate Harmonization Application

Panel A: Long Memory Estimates, $\hat{d}$		
	Spain	France
Bandwidth	$y_t = \pi_{S,t}$	$x_t = \pi_{F,t}$
$m_1 = \lfloor T^{0.5} \rfloor$	0.4007 (0.1443)	0.3048 (0.1443)
$m_1 = \lfloor T^{0.6} \rfloor$	0.0990 (0.1118)	−0.0690 (0.1118)
$m_1 = \lfloor T^{0.7} \rfloor$	−0.1847 (0.0857)	−0.1377 (0.0857)

Panel B: Cointegration Analysis						
	NBLS			FMNBLS		
Bandwidths	$\hat{\alpha}_{m_3}$	$\hat{\beta}_{m_3}$	$\hat{d}_{\hat{u}}$	$\tilde{\alpha}_{m_3}$	$\tilde{\beta}_{m_3}$	$\hat{d}_{\tilde{u}}$
$m_0 = \lfloor T^{0.3} \rfloor, m_1 = \lfloor T^{0.5} \rfloor$	0.0011	1.1395 (0.3139)	0.0852 (0.1443)	0.0006	1.4789 (0.2561)	0.0276 (0.1443)
$m_0 = \lfloor T^{0.4} \rfloor, m_1 = \lfloor T^{0.5} \rfloor$	0.0012	1.0577 (0.2965)	0.1063 (0.1443)	0.0007	1.4037 (0.2290)	0.0368 (0.1443)

Panel A reports local Whittle estimates of the fractional integration orders as described in Robinson (1995a). Numbers in parentheses are asymptotic standard errors using $\sqrt{m_1}(\hat{d} - d) \xrightarrow{d} N(0, 1/4)$. Panel B reports NBLS and FMNBLS estimates with $m_2 = \lfloor T^{0.8} \rfloor$ and $m_3 = m_0$. The asymptotic standard errors for the NBLS and FMNBLS estimates are based on (13) and (23), respectively. Standard errors for $\hat{d}_{\hat{u}}$ and $\hat{d}_{\tilde{u}}$ are based on the same asymptotic distribution as $\hat{d}$, and should be used with caution, see Theorem 2.

expect that relationship to be one of stationary fractional cointegration. We calculate $T = 159$ monthly inflation rates based on the HICP of France and Spain. This data was obtained from Eurostat and covers the period January 1992 through April 2005.

Panel A of Table 6 shows that the memory estimates decrease as the bandwidth increases. This may be due to an added noise perturbation or, more likely, due to the distinct seasonal patterns in inflation series; possibly reflecting seasonal long memory, see Doornik & Ooms (2004). Instead of filtering this out by ad hoc procedures, we focus on the results for the lowest bandwidth, $m_1 = \lfloor T^{0.5} \rfloor$, which should be less sensitive to contamination from higher (e.g. seasonal) frequencies. For this bandwidth, the memory estimates for both inflation rates imply that the series are stationary.

Panel B of Table 6 again supports the notion of $I(d) - I(0)$ cointegration with d around 0.35. Here, the FMNBLS estimates appear somewhat higher than the NBLS estimates. In particular, the FMNBLS estimates of the cointegration coefficient are significantly higher than unity at the 10% level in both cases, implying that the long-run rate of inflation in Spain is higher than that of France (by about 40% according to the point estimates). In addition, the estimates of d for the residuals are lower for FMNBLS than for NBLS although all appear insignificantly different from zero (again, the usual asymptotic distribution may not apply, see Theorem 2).

5.3 Realized Volatility Relations

Finally, we analyze the relation between the realized volatility of the General Electric (GE) stock and those of the Dow Jones Industrial Average and NASDAQ 100 indices. I.e., there are three variables in this application. The realized volatilites are monthly and are constructed based on daily returns calculated as the difference in log-close and log-open prices. The sample covers January 1990 to December 2008, i.e. $T = 228$.

Table 7: Realized Volatility Relations Application

Panel A: Long Memory Estimates, $\hat{d}$			
	GE	Dow Jones	NASDAQ
Bandwidth	$y_t = \sigma^2_{GE,t}$	$x_{1t} = \sigma^2_{DJ,t}$	$x_{2t} = \sigma^2_{ND,t}$
$m_1 = \lfloor T^{0.6} \rfloor$	0.4350 (0.1000)	0.3526 (0.1000)	0.4383 (0.1000)
$m_1 = \lfloor T^{0.7} \rfloor$	0.5114 (0.0754)	0.4192 (0.0754)	0.6119 (0.0754)
$m_1 = \lfloor T^{0.8} \rfloor$	0.4027 (0.0574)	0.4319 (0.0574)	0.3894 (0.0574)

Panel B: Cointegration Rank Analysis						
	Eigenvalues of P			$L(u)$		
Bandwidths	1	2	3	$u=0$	$u=1$	$u=2$
$m_0 = \lfloor T^{0.3} \rfloor, m_1 = \lfloor T^{0.6} \rfloor$	2.4673	0.5106	0.0221	−1.4241	−1.9273	−1.9420
$m_0 = \lfloor T^{0.3} \rfloor, m_1 = \lfloor T^{0.8} \rfloor$	2.4677	0.5102	0.0221	−1.4241	−1.9273	−1.9424
$m_0 = \lfloor T^{0.4} \rfloor, m_1 = \lfloor T^{0.6} \rfloor$	2.3523	0.5889	0.0588	−1.6942	−2.0706	−1.9170
$m_0 = \lfloor T^{0.4} \rfloor, m_1 = \lfloor T^{0.8} \rfloor$	2.3527	0.5885	0.0588	−1.6942	−2.0707	−1.9174

Panel C: Cointegration Regression Analysis								
	NBLS				FMNBLS			
Bandwidths	$\hat{\alpha}_{m_3}$	$\hat{\beta}_{m_3}$		$\hat{d}_{\hat{u}}$	$\tilde{\alpha}_{m_3}$	$\tilde{\beta}_{m_3}$		$\hat{d}_{\tilde{u}}$
$m_0 = \lfloor T^{0.3} \rfloor, m_1 = \lfloor T^{0.6} \rfloor$	−0.0000	1.6913 (0.1334)	0.1939 (0.0171)	−0.0048 (0.1000)	−0.0004	1.8408 (0.1570)	0.2103 (0.0220)	0.0137 (0.1000)
$m_0 = \lfloor T^{0.3} \rfloor, m_1 = \lfloor T^{0.8} \rfloor$	−0.0000	1.6913 (0.1120)	0.1939 (0.0328)	0.0268 (0.0574)	−0.0004	1.8187 (0.2664)	0.2158 (0.0407)	0.0588 (0.0574)
$m_0 = \lfloor T^{0.4} \rfloor, m_1 = \lfloor T^{0.6} \rfloor$	0.0001	1.6478 (0.1337)	0.1825 (0.0208)	0.0192 (0.1000)	−0.0003	1.8434 (0.1345)	0.1892 (0.0179)	−0.0010 (0.1000)
$m_0 = \lfloor T^{0.4} \rfloor, m_1 = \lfloor T^{0.8} \rfloor$	0.0001	1.6478 (0.1091)	0.1825 (0.0307)	0.0296 (0.0574)	−0.0003	1.8081 (0.1430)	0.1924 (0.0351)	0.0420 (0.0574)

Panel A reports local Whittle estimates of the fractional integration orders as described in Robinson (1995*a*). Numbers in parentheses are asymptotic standard errors using $\sqrt{m_1}(\hat{d} - d) \xrightarrow{d} N(0, 1/4)$. Panel B reports rank statistics from Robinson & Yajima (2002) and Panel C reports NBLS and FMNBLS estimates with $m_2 = \lfloor T^{0.8} \rfloor$ and $m_3 = m_0$. The asymptotic standard errors for the NBLS and FMNBLS estimates are based on (13) and (23), respectively. Standard errors for $\hat{d}_{\hat{u}}$ and $\hat{d}_{\tilde{u}}$ are based on the same asymptotic distribution as $\hat{d}$, and should be used with caution, see Theorem 2.

Panel A of Table 7 shows that the memory estimates of the three realized volatilities are very similar and stable across bandwidths with point estimates around 0.4, except for the middle bandwidth where point estimates are higher and suggest nonstationarity. Hence, we ignore bandwidth $m_1 = \lfloor T^{0.7} \rfloor$. A test of the hypothesis that all memory parameters are equal, see Robinson & Yajima (2002, section 3), is insignificant at conventional levels for all bandwidth choices in the table. In Panel B of Table 7 we present cointegration rank statistics from Robinson & Yajima (2002) using bandwidth m_0 for rank statistics and m_1 to estimate memory parameters. In particular, Panel B presents the eigenvalues of the correlation-type matrix P, and the value of the model determination function $L(u)$ (using $v(T) = m_0^{-0.4}$). The rank can be found as $\arg\min L(u)$, which clearly suggests that the rank is one when $m_0 = \lfloor T^{0.4} \rfloor$ and only narrowly indicates a rank of two when $m_0 = \lfloor T^{0.3} \rfloor$. Thus, we conclude that a regression approach is appropriate in this multivariate system.

In Panel C we report estimates of the stationary fractional cointegration relation between the realized volatilities of GE and the DJIA and NASDAQ indices. We are interested in analyzing how the volatility of GE depends on the volatilities of the two indices, so we choose y_t to be the realized volatility of GE. It appears that the NBLS estimator underestimates the slope coefficient on DJIA in the cointegrating relation, although not by much. Both the NBLS and the FMNBLS results indicate that the volatility of GE depends mostly on that of the DJIA.

6 Concluding Remarks

We have considered estimation of the cointegrating relation in the stationary fractional cointegration model. This model has found important application recently, especially in financial economics. Previous research has considered Robinson's (1994) semiparametric frequency domain narrow-band least squares (NBLS) estimator. For this estimator, a condition of non-coherence between regressors and errors at the zero frequency has sometimes been imposed, e.g. Christensen & Nielsen (2006). We have shown that in the absence of this condition, NBLS suffers from an asymptotic bias although it remains consistent as proven by Robinson (1994). We have also shown that the bias can be consistently estimated, and consequently we have introduced a fully modified NBLS (FMNBLS) estimator which eliminates the bias while still having the same asymptotic variance as the NBLS estimator. Indeed, FMNBLS enjoys a faster rate of convergence than NBLS in the general case with non-zero coherence between the regressors and the errors at the origin.

Furthermore, the development of the asymptotic distribution theory is based on a different spectral density representation compared to much previous research. This representation is relevant for multivariate fractionally integrated processes, e.g. fractionally integrated vector autoregressive moving average models. It is demonstrated that the use of this spectral representation results in lower asymptotic bias and variance of the narrow-band estimators.

In a simulation study we have documented the finite sample feasibility of the proposed FMNBLS estimator. The simulations clearly demonstrate the superiority with respect to bias of the fully modified estimator relative to NBLS in the presence of non-zero long-run coherence between the regressors and the errors. Although this comes at the cost of increased finite sample variance, FMNBLS is superior in terms of RMSE in simulations with long-run coherence between regressors and errors. The simulations also indicate that the bias correction method works well in the presence of short-run dynamics in regressors and errors. To demonstrate the empirical relevance of our proposed methodology we have considered a series of brief empirical illustrations, all of which support the notion of a stationary fractional cointegration relation.

Appendix A: Proof of Theorem 1

First write

$$\sqrt{m_0}\lambda_{m_0}^{d_p}\Lambda_{m_0}^{-1}(\hat{\beta}_{m_0}-\beta) = \left(\Lambda_{m_0}\lambda_{m_0}^{-1}\frac{2\pi}{T}\sum_{j=1}^{m_0}\mathrm{Re}\left(I_{xx}\left(\lambda_j\right)\right)\Lambda_{m_0}\right)^{-1}\Lambda_{m_0}\lambda_{m_0}^{d_p-1}\sqrt{m_0}\frac{2\pi}{T}\sum_{j=1}^{m_0}\mathrm{Re}\left(I_{xp}\left(\lambda_j\right)\right).$$

From Lemma 5(c) it follows that $\Lambda_{m_0}\lambda_{m_0}^{-1}\frac{2\pi}{T}\sum_{j=1}^{m_0}\mathrm{Re}\left(I_{xx}\left(\lambda_j\right)\right)\Lambda_{m_0}\xrightarrow{P}K$. Note that G, and thus the leading $(p-1)\times(p-1)$ submatrix of G and therefore K, is invertible by Assumption 1.

For the second term we show that

$$\sqrt{m_0}\left(\Lambda_{m_0}\lambda_{m_0}^{d_p-1}\frac{2\pi}{T}\sum_{j=1}^{m_0}\mathrm{Re}\left(I_{xp}\left(\lambda_j\right)\right)-H\right)\xrightarrow{d}N\left(0,J\right).$$

By the Cramer-Wold device, for any $(p-1)$-vector η, we need to examine

$$\begin{aligned}
& \eta' \sqrt{m_0} \left(\lambda_{m_0}^{d_p - 1} \Lambda_m \hat{F}_{xp}(1, m_0) - H \right) \\
= & \sum_{a=1}^{p-1} \eta_a \sqrt{m_0} \left(\lambda_{m_0}^{d_a + d_p - 1} \frac{2\pi}{T} \sum_{j=1}^{m_0} \mathrm{Re}\left(I_{ap}(\lambda_j) \right) - H_a \right) \\
= & \sum_{a=1}^{p-1} \eta_a \sqrt{m_0} \lambda_{m_0}^{d_a + d_p - 1} \frac{2\pi}{T} \sum_{j=1}^{m_0} \mathrm{Re}\left(I_{ap}(\lambda_j) - A_a(\lambda_j) J(\lambda_j) A_p^*(\lambda_j) \right) \qquad (25) \\
& + \sum_{a=1}^{p-1} \eta_a \sqrt{m_0} \lambda_{m_0}^{d_a + d_p - 1} \frac{2\pi}{T} \sum_{j=1}^{m_0} \mathrm{Re}\left(A_a(\lambda_j) J(\lambda_j) A_p^*(\lambda_j) - f_{ap}(\lambda_j) \right) \qquad (26) \\
& + \sum_{a=1}^{p-1} \eta_a \sqrt{m_0} \left(\lambda_{m_0}^{d_a + d_p - 1} \frac{2\pi}{T} \sum_{j=1}^{m_0} \mathrm{Re}\left(f_{ap}(\lambda_j) \right) - H_a \right), \qquad (27)
\end{aligned}$$

where $J(\lambda_j)$ is the periodogram of ε_t from Assumption 2.

By Lemma 5(a) it follows that (25) is $O_P(m_0^{-1/6} (\log m_0)^{2/3} + m_0^{-1/2} (\log m_0) + T^{-1/4})$, and by Lemma 5(b) that (27) is $O(m_0^{\min(1,\alpha)+1/2} T^{-\min(1,\alpha)})$. Thus, both terms are $o_P(1)$ by Assumption 4.

Eq. (26) is

$$\begin{aligned}
& \sum_{a=1}^{p-1} \eta_a \sqrt{m_0} \lambda_{m_0}^{d_a + d_p - 1} \frac{2\pi}{T} \sum_{j=1}^{m_0} \mathrm{Re}\left(A_a(\lambda_j) \frac{1}{2\pi} \left(T^{-1} \sum_{t=1}^{T} \varepsilon_t \varepsilon_t' - I_p \right) A_p^*(\lambda_j) \right) \qquad (28) \\
& + \sum_{a=1}^{p-1} \eta_a \sqrt{m_0} \lambda_{m_0}^{d_a + d_p - 1} \frac{2\pi}{T} \sum_{j=1}^{m_0} \mathrm{Re}\left(A_a(\lambda_j) \frac{1}{2\pi T} \sum_{t=1}^{T} \sum_{s \neq t} \varepsilon_t \varepsilon_s' e^{-i(t-s)\lambda_j} A_p^*(\lambda_j) \right). \qquad (29)
\end{aligned}$$

Note that $D = T^{-1} \sum_{t=1}^{T} \varepsilon_t \varepsilon_t' - I_p$ satisfies $||D|| = O_P(T^{-1/2})$ since $\varepsilon_t \varepsilon_t' - I_p$ is a martingale difference sequence with finite second moments. Then, by the Cauchy-Schwarz inequality and since $||A_a(\lambda)|| = O(\sqrt{f_{aa}(\lambda)})$,

$$\begin{aligned}
(28) &= O_P\left(\max_{1 \le a \le p-1} m_0^{-1/2} \|D\| \lambda_{m_0}^{d_a + d_p} \left(\sum_{j=1}^{m_0} \|A_a(\lambda_j)\|^2 \right)^{1/2} \left(\sum_{j=1}^{m_0} \|A_p(\lambda_j)\|^2 \right)^{1/2} \right) \\
&= O_P\left(\max_{1 \le a \le p-1} m_0^{-1/2} T^{-1/2} \lambda_{m_0}^{d_a + d_p} \left(\sum_{j=1}^{m_0} f_{aa}(\lambda_j) \right)^{1/2} \left(\sum_{j=1}^{m_0} f_{pp}(\lambda_j) \right)^{1/2} \right),
\end{aligned}$$

which is $O_P(\lambda_{m_0}^{1/2})$. The term inside the parenthesis in eq. (29) can be rewritten as

$$\begin{aligned}
& \frac{1}{2\pi T} A_a(\lambda_j) \left(\sum_{t=2}^{T} \sum_{s=1}^{t-1} \varepsilon_t \varepsilon_s' e^{-i(t-s)\lambda_j} + \sum_{t=1}^{T-1} \sum_{s=t+1}^{T} \varepsilon_t \varepsilon_s' e^{-i(t-s)\lambda_j} \right) A_p^*(\lambda_j) \\
= & \frac{1}{2\pi T} A_a(\lambda_j) \sum_{t=2}^{T} \sum_{s=1}^{t-1} \left(\varepsilon_t \varepsilon_s' e^{-i(t-s)\lambda_j} + \varepsilon_s \varepsilon_t' e^{i(t-s)\lambda_j} \right) A_p^*(\lambda_j),
\end{aligned}$$

so that

$$(29) \quad = \sum_{a=1}^{p-1} \eta_a \frac{\sqrt{m_0}}{T^2} \lambda_{m_0}^{d_a+d_p-1} \sum_{j=1}^{m_0} \sum_{t=2}^{T} \varepsilon_t' \sum_{s=1}^{t-1} \mathrm{Re}\left(A_a' (\lambda_j) \bar{A}_p (\lambda_j) e^{-i(t-s)\lambda_j} + A_p^* (\lambda_j) A_a (\lambda_j) e^{i(t-s)\lambda_j} \right) \varepsilon_s$$

$$= \sum_{t=2}^{T} \varepsilon_t' \sum_{s=1}^{t-1} c_{t-s} \varepsilon_s,$$

where

$$\begin{aligned} c_{t-s} &= \frac{1}{2\pi T \sqrt{m_0}} \sum_{j=1}^{m_0} \theta_j, \\ \theta_j &= \mathrm{Re}\left(\sum_{a=1}^{p-1} \eta_a \lambda_{m_0}^{d_a+d_p} A_a' (\lambda_j) \bar{A}_p (\lambda_j) e^{-i(t-s)\lambda_j} + \sum_{a=1}^{p-1} \eta_a \lambda_{m_0}^{d_a+d_p} A_p^* (\lambda_j) A_a (\lambda_j) e^{i(t-s)\lambda_j} \right) \\ &= \mathrm{Re}\left(\omega_j e^{-i(t-s)\lambda_j} + \omega_j' e^{i(t-s)\lambda_j} \right) \\ &= \left(\mathrm{Re}\, \omega_j + \mathrm{Re}\, \omega_j' \right) \cos\left((t-s) \lambda_j \right) + \left(\mathrm{Im}\, \omega_j - \mathrm{Im}\, \omega_j' \right) \sin\left((t-s) \lambda_j \right), \end{aligned}$$

and we have defined $\omega_j = \sum_{a=1}^{p-1} \eta_a \lambda_{m_0}^{d_a+d_p} A_a' (\lambda_j) \bar{A}_p (\lambda_j)$. By defining the triangular array (subscript T is omitted for brevity) $z_1 = 0$ and $z_t = \varepsilon_t' \sum_{s=1}^{t-1} c_{t-s} \varepsilon_s, t = 2, ..., T$, we can apply the martingale difference central limit theorem of Brown (1971) and Hall & Heyde (1980, chp. 3.2) if

$$\sum_{t=1}^{T} E\left(z_t^2 \middle| \mathcal{F}_{t-1} \right) - \sum_{a=1}^{p-1} \sum_{b=1}^{p-1} \eta_a \eta_b J_{ab} \xrightarrow{P} 0, \tag{30}$$

$$\sum_{t=1}^{T} E\left(z_t^4 \right) \to 0, \tag{31}$$

since z_t is a martingale difference array with respect to the filtration $(\mathcal{F}_t)_{t \in \mathbb{Z}}$, $\mathcal{F}_t = \sigma\left(\{ \varepsilon_s, s \leq t \} \right)$.

We first show (30). The first term on the left-hand side is

$$\sum_{t=2}^{T} E\left(\sum_{s=1}^{t-1} \sum_{r=1}^{t-1} \varepsilon_s' c_{t-s}' \varepsilon_t \varepsilon_t' c_{t-r} \varepsilon_r \middle| \mathcal{F}_{t-1} \right) = \sum_{t=2}^{T} \sum_{s=1}^{t-1} \varepsilon_s' c_{t-s}' c_{t-s} \varepsilon_s + \sum_{t=2}^{T} \sum_{s=1}^{t-1} \sum_{r \neq s} \varepsilon_s' c_{t-s}' c_{t-r} \varepsilon_r. \tag{32}$$

It follows by slight modification of Lemma 4 of Nielsen (2005) that the second term on the right-hand side is $o_P(1)$. We need to show that the mean of the first term on the right-hand side of (32) is asymptotically equal to $\sum_{a=1}^{p-1} \sum_{b=1}^{p-1} \eta_a \eta_b J_{ab}$. Thus,

$$\sum_{t=2}^{T} \sum_{s=1}^{t-1} E\, \mathrm{tr}\left(c_{t-s}' c_{t-s} \varepsilon_s \varepsilon_s' \right) = \sum_{t=2}^{T} \sum_{s=1}^{t-1} \mathrm{tr}\left(c_{t-s}' c_{t-s} \right)$$

$$= \sum_{t=2}^{T} \sum_{s=1}^{t-1} \sum_{j=1}^{m_0} \frac{1}{4\pi^2 T^2 m_0} \mathrm{tr}\left(\theta_j' \theta_j \right) \tag{33}$$

$$+ \sum_{t=2}^{T} \sum_{s=1}^{t-1} \sum_{j=1}^{m_0} \sum_{k \neq j} \frac{1}{4\pi^2 T^2 m_0} \mathrm{tr}\left(\theta_j' \theta_k \right). \tag{34}$$

Note that, from standard trigonometric identities, see also Lemma 3 of Shimotsu (2007),

$$\begin{array}{l}\sum_{t=1}^{T-1}\sum_{s=1}^{T-t}\cos\left(s\lambda_j\right)\cos\left(s\lambda_k\right)=O\left(T\right), \quad j\neq k,\\ \sum_{t=1}^{T-1}\sum_{s=1}^{T-t}\sin\left(s\lambda_j\right)\sin\left(s\lambda_k\right)=O\left(T\right), \quad j\neq k,\\ \sum_{t=1}^{T-1}\sum_{s=1}^{T-t}\cos\left(s\lambda_j\right)\sin\left(s\lambda_k\right)=O(T^2\left(j+k\right)^{-1}+T^2\left|j-k\right|^{-1}), \quad j\neq k,\\ \sum_{t=1}^{T-1}\sum_{s=1}^{T-t}\cos^2\left(s\lambda_j\right)=\frac{T^2}{4}+o\left(T^2\right), \quad j=1,...,m,\\ \sum_{t=1}^{T-1}\sum_{s=1}^{T-t}\sin^2\left(s\lambda_j\right)=\frac{T^2}{4}+o\left(T^2\right), \quad j=1,...,m.\end{array}$$

It is thus easily seen that (34) is of smaller order than (33), so we focus on (33),

$$\begin{aligned}\operatorname{tr}\left(\theta_j'\theta_j\right) &= \operatorname{tr}\left(\left(\operatorname{Re}\omega_j+\operatorname{Re}\omega_j'\right)\left(\operatorname{Re}\omega_j+\operatorname{Re}\omega_j'\right)\cos^2\left(\left(t-s\right)\lambda_j\right)\right)\\ &\quad +\operatorname{tr}\left(\left(\operatorname{Im}\omega_j-\operatorname{Im}\omega_j'\right)'\left(\operatorname{Im}\omega_j-\operatorname{Im}\omega_j'\right)\sin^2\left(\left(t-s\right)\lambda_j\right)\right)\\ &\quad +\operatorname{tr}\left(\left(\operatorname{Re}\omega_j+\operatorname{Re}\omega_j'\right)\left(\operatorname{Im}\omega_j-\operatorname{Im}\omega_j'\right)\cos\left(\left(t-s\right)\lambda_j\right)\sin\left(\left(t-s\right)\lambda_j\right)\right)\\ &\quad +\operatorname{tr}\left(\left(\operatorname{Im}\omega_j-\operatorname{Im}\omega_j'\right)'\left(\operatorname{Re}\omega_j+\operatorname{Re}\omega_j'\right)\cos\left(\left(t-s\right)\lambda_j\right)\sin\left(\left(t-s\right)\lambda_j\right)\right).\end{aligned}$$

The last two terms cancel and the sum of the first two terms can be written as

$$\begin{aligned}\operatorname{tr}\left(\theta_j'\theta_j\right) &= \operatorname{tr}\left(\left(\operatorname{Re}\omega_j+\operatorname{Re}\omega_j'\right)^2\cos^2\left(\left(t-s\right)\lambda_j\right)\right)-\operatorname{tr}\left(\left(\operatorname{Im}\omega_j-\operatorname{Im}\omega_j'\right)^2\sin^2\left(\left(t-s\right)\lambda_j\right)\right)\\ &= \operatorname{tr}\left(\left(\operatorname{Re}\omega_j+\operatorname{Re}\omega_j'\right)^2-\left(\operatorname{Im}\omega_j-\operatorname{Im}\omega_j'\right)^2\right)\cos^2\left(\left(t-s\right)\lambda_j\right)\\ &\quad -\operatorname{tr}\left(\left(\operatorname{Im}\omega_j-\operatorname{Im}\omega_j'\right)^2\right)\left(\sin^2\left(\left(t-s\right)\lambda_j\right)-\cos^2\left(\left(t-s\right)\lambda_j\right)\right),\end{aligned}$$

where the second of these terms is of smaller order by the trigonometric relations above. Using the fact that $2\operatorname{Re}(X)=X+\bar{X}$ and $2i\operatorname{Im}(X)=X-\bar{X}$ for any complex matrix X, the first term can be written as

$$\begin{aligned}&\operatorname{tr}\left(2^{-2}\left(\omega_j+\bar{\omega}_j+\omega_j'+\omega_j^*\right)^2-(2i)^{-2}\left(\omega_j-\bar{\omega}_j-\omega_j'+\omega_j^*\right)^2\right)\cos^2\left(\left(t-s\right)\lambda_j\right)\\ =\ &\frac{1}{2}\operatorname{tr}\left(\omega_j^2+\omega_j^{*2}+\omega_j\omega_j^*+\omega_j^*\omega_j+\bar{\omega}_j^2+\omega_j'^2+\bar{\omega}_j\omega_j'+\omega_j'\bar{\omega}_j\right)\cos^2\left(\left(t-s\right)\lambda_j\right)\\ =\ &\operatorname{tr}\left(\omega_j^2+\omega_j^{*2}+\omega_j\omega_j^*+\omega_j^*\omega_j\right)\cos^2\left(\left(t-s\right)\lambda_j\right).\end{aligned}$$

Hence, we have found that (33) is asymptotically negligibly different from

$$\begin{aligned}&\sum_{t=2}^{T}\sum_{s=1}^{t-1}\sum_{j=1}^{m_0}\frac{1}{4\pi^2T^2m_0}\operatorname{tr}\left(\omega_j^2+\omega_j^{*2}+\omega_j\omega_j^*+\omega_j^*\omega_j\right)\cos^2\left(\left(t-s\right)\lambda_j\right)\\ =\ &\sum_{t=2}^{T}\sum_{s=1}^{t-1}\frac{1}{4\pi^2T^2m_0}\sum_{a=1}^{p-1}\sum_{b=1}^{p-1}\eta_a\eta_b\lambda_{m_0}^{d_a+d_b+2d_p}\\ &\times\sum_{j=1}^{m_0}\left[4\pi^2\left(f_{pa}\left(\lambda_j\right)f_{pb}\left(\lambda_j\right)+f_{ap}\left(\lambda_j\right)f_{bp}\left(\lambda_j\right)+f_{pp}\left(\lambda_j\right)f_{ba}\left(\lambda_j\right)+f_{pp}\left(\lambda_j\right)f_{ab}\left(\lambda_j\right)\right)\cos^2\left(\left(t-s\right)\lambda_j\right)\right]\\ =\ &\frac{1}{4m_0}\sum_{a=1}^{p-1}\sum_{b=1}^{p-1}\eta_a\eta_b\lambda_{m_0}^{d_a+d_b+2d_p}\sum_{j=1}^{m_0}\left(f_{pa}\left(\lambda_j\right)f_{pb}\left(\lambda_j\right)+f_{ap}\left(\lambda_j\right)f_{bp}\left(\lambda_j\right)+f_{pp}\left(\lambda_j\right)f_{ba}\left(\lambda_j\right)+f_{pp}\left(\lambda_j\right)f_{ab}\left(\lambda_j\right)\right)\end{aligned}$$

where the first equality follows from (12) and the second from the trigonometric identities above. Applying (4) and that $\cos(x) = (e^{ix} + e^{-ix})/2$, this is equal to

$$
\begin{aligned}
& \frac{1}{4}\sum_{a=1}^{p-1}\sum_{b=1}^{p-1}\eta_a\eta_b\frac{1}{1-d_a-d_b-2d_p} \\
& \times\Big[G_{ap}G_{bp}(e^{i\pi(d_a+d_b-2d_p)/2}+e^{-i\pi(d_a+d_b-2d_p)/2})+G_{ab}G_{pp}(e^{i\pi(d_a-d_b)/2}+e^{-i\pi(d_a-d_b)/2})\Big]+o\left(1\right) \\
= \; & \frac{1}{2}\sum_{a=1}^{p-1}\sum_{b=1}^{p-1}\eta_a\eta_b\frac{1}{1-d_a-d_b-2d_p}\left[G_{ap}G_{bp}\cos\left(\pi\left(d_a+d_b-2d_p\right)/2\right)+G_{ab}G_{pp}\cos\left(\pi\left(d_a-d_b\right)/2\right)\right]+o\left(1\right) \\
= \; & \sum_{a=1}^{p-1}\sum_{b=1}^{p-1}\eta_a\eta_b J_{ab}+o\left(1\right).
\end{aligned}
$$

Finally, to show (31),

$$
\begin{aligned}
\sum_{t=1}^{T}E\left(z_t^4\right) &= \sum_{t=2}^{T}E\left(\sum_{s=1}^{t-1}\varepsilon_s' c_{t-s}\varepsilon_t\varepsilon_t'\sum_{r=1}^{t-1}c_{t-r}\varepsilon_r\sum_{p=1}^{t-1}\varepsilon_p' c_{t-p}\varepsilon_t\varepsilon_t'\sum_{q=1}^{t-1}c_{t-q}\varepsilon_q\right) \\
&\leq C\left(\sum_{t=2}^{T}\operatorname{tr}\left(\sum_{s=1}^{t-1}c_{t-s}'c_{t-s}c_{t-s}'c_{t-s}\right)+\sum_{t=2}^{T}\operatorname{tr}\left(\sum_{s=1}^{t-1}c_{t-s}'\sum_{r=1}^{t-1}c_{t-r}c_{t-r}'c_{t-s}\right)\right)
\end{aligned}
$$

for some constant $C > 0$ by Assumption 2. Using the arguments of Lemma 4 of Nielsen (2005), this expression can be bounded by $O(T(\sum_{t=1}^{T}||c_t^2||)^2) = O(T^{-1})$, which completes the proof.

Appendix B: Proof of Theorem 2

First we show that $(\log T)(\hat{d}_p - d_p) \xrightarrow{P} 0$. Rewriting equations (A.1)-(A.4), (A.24), (A.25), and (A.30) from the proof of Theorem 3 of Robinson (1997) it suffices to show that

$$m_1^{2(d_p-\Delta_1)-1}\sum_{j=1}^{m_1}j^{2(\Delta_1-d_p)}\left|h_j\right| \xrightarrow{P} 0 \quad \text{for } 0 \leq \Delta_1 < d_p, \tag{35}$$

$$\left(\log T\right)^2 m_1^{2\tau-1}\sum_{j=1}^{m_1}j^{-2\tau}\left|h_j\right| \xrightarrow{P} 0 \quad \text{for some } \tau > 0, \tag{36}$$

$$\frac{\left(\log T\right)^2}{m_1}\sum_{j=1}^{m_1}\left|h_j\right| \xrightarrow{P} 0, \tag{37}$$

$$\frac{1}{m_1}\sum_{j=1}^{m_1}\left(\left(j/q\right)^{2(\Delta_1-d_p)}-1\right)h_j \xrightarrow{P} 0, \tag{38}$$

where $q = \exp(m_1^{-1}\sum_{j=1}^{m_1}\log j)$ and

$$h_j = \frac{\hat{I}_{pp}\left(\lambda_j\right)-I_{pp}\left(\lambda_j\right)}{G_{pp}\lambda_j^{-2d_p}} \tag{39}$$

is a normalized measure of the impact of using the periodogram of residuals instead of the periodogram of observed data. Our assumption that $d_p \geq 0$ allows a simplification of the conditions

(35)-(38) compared to their counterparts in Robinson (1997) which shortens this proof somewhat. It could easily be relaxed at the expense of a longer proof.

Note that, by Assumption 1, Theorem 1 above, (15), and the proof of Theorem 2 of Robinson (1995*b*), the random variables h_j satisfy

$$|h_j| = O_P((j/m_0)^{-\delta_{\min}} + (j/m_0)^{-2\delta_{\min}}). \tag{40}$$

Using (40) and the fact that

$$\sup_{-1\leq\alpha\leq C}\left|m^{-\alpha-1}\left(\log m\right)^{-1}\sum_{j=1}^{m} j^{\alpha}\right| = O\left(1\right) \text{ for } C\in\left(1,\infty\right), \tag{41}$$

it is easy to show that (35) is

$$(35) = O_P\left(m_1^{2(d_p-\Delta_1)-1}\sum_{j=1}^{m_1} j^{2(\Delta_1-d_p)-\delta_{\min}} m_0^{\delta_{\min}}(1+j^{-\delta_{\min}}m_0^{\delta_{\min}})\right) = O_P\left(\left(\log m_1\right)\left(\frac{m_0}{m_1}\right)^{\delta_{\min}}\right),$$

and similarly (36) and (37) are both $O_P((\log T)^2(\log m_1)(m_0/m_1)^{\delta_{\min}})$. We will need (41) throughout, and we shall use it automatically and without special reference in what follows. Using the fact that $q \sim m_1/e$ ($e = 2.71...$) as $T \to \infty$, the left-hand side of (38) is bounded, for large T, by

$$\frac{1}{m_1}\sum_{j=1}^{m_1}\left(\frac{ej}{m_1}\right)^{2(\Delta_1-d_p)}|h_j| + \frac{1}{m_1}\sum_{j=1}^{m_1}|h_j|,$$

which is negligible by (35) and (37).

Thus, we have shown $(\log T)$-consistency of $\hat{d}_p$ and proceed to prove the rate and asymptotic distribution results. With probability approaching one as $T \to \infty$, $\hat{d}_p$ satisfies

$$0 = \frac{\partial \hat{R}(\hat{d}_p)}{\partial d} = \frac{\partial \hat{R}(d_p)}{\partial d} + \frac{\partial^2 \hat{R}(\bar{d}_p)}{\partial d^2}(\hat{d}_p - d_p),$$

where $|\bar{d}_p - d_p| \leq |\hat{d}_p - d_p|$. Following Robinson (1995*a*, pp. 1641-1644) we have that

$$\frac{\partial^2 \hat{R}(d)}{\partial d^2} = \frac{4(\tilde{G}_{0,\hat{u}}\left(d\right)\tilde{G}_{2,\hat{u}}\left(d\right) - \tilde{G}_{1,\hat{u}}\left(d\right)^2)}{\tilde{G}_{0,\hat{u}}\left(d\right)^2} = \frac{4(\tilde{F}_{0,\hat{u}}\left(d\right)\tilde{F}_{2,\hat{u}}\left(d\right) - \tilde{F}_{1,\hat{u}}\left(d\right)^2)}{\tilde{F}_{0,\hat{u}}\left(d\right)^2}.$$

If we show that

$$\sup_{d\in\Delta\cap N_\zeta}\left|\frac{\tilde{G}_{0,\hat{u}}\left(d\right) - \tilde{G}_{0,u}\left(d\right)}{\bar{G}\left(d\right)}\right| = o_P((\log m_1)^{-10}), \tag{42}$$

$$\left|\tilde{F}_{k,\hat{u}}\left(d_p\right) - \tilde{F}_{k,u}\left(d_p\right)\right| \xrightarrow{P} 0, \quad k = 0,1,2, \tag{43}$$

where

$$\tilde{G}_{k,a}\left(d\right) = \tfrac{1}{m_1}\textstyle\sum_{j=1}^{m_1}\left(\log\lambda_j\right)^k\lambda_j^{2d}I_{aa}\left(\lambda_j\right),$$
$$\bar{G}\left(d\right) = G_{pp}\tfrac{1}{m_1}\textstyle\sum_{j=1}^{m_1}\lambda_j^{2(d-d_p)},$$
$$\tilde{F}_{k,a}\left(d\right) = \tfrac{1}{m_1}\textstyle\sum_{j=1}^{m_1}\left(\log j\right)^k\lambda_j^{2d}I_{aa}\left(\lambda_j\right),$$

with $N_\zeta = \{d : |d_p - d| < \zeta\}$ for $0 < \zeta < 1/2$, then

$$\frac{\partial^2 \hat{R}(\bar{d}_p)}{\partial d^2} \xrightarrow{P} 4. \tag{44}$$

Note that, following Andrews & Sun (2004, p. 600), in our eq. (42) we use $(\log m_1)^{-10}$ rather than $(\log m_1)^{-6}$ as in Robinson's (1995*a*) eq. (4.6). By (4.7) in Robinson (1995*a*), (42) follows if

$$(\log m_1)^{10} \sum_{j=1}^{m_1} \left(\frac{j}{m_1}\right)^{1-2\tau} j^{-2} \left|\sum_{k=1}^{j} h_k\right| \xrightarrow{P} 0 \quad \text{for some } \tau > 0,$$

which holds by (36) and (37) above. The left-hand side of (43) is bounded by

$$\left|\frac{G_{pp}}{m_1} \sum_{j=1}^{m_1} (\log j)^k h_j\right| \leq \frac{G_{pp} (\log m_1)^k}{m_1} \sum_{j=1}^{m_1} |h_j| = O_P\left((\log m_1)^{k+1} \left(\frac{m_0}{m_1}\right)^{\delta_{\min}}\right)$$

by the same arguments as applied to (37) above. This proves (44).

Having established (44) it follows that

$$\sqrt{m_1}(\hat{d}_p - d_p) = (4 + o_P(1))^{-1} \sqrt{m_1} \frac{\partial \hat{R}(d_p)}{\partial d}, \tag{45}$$

and the first statement of the theorem will follow below by examining the right-hand side of (45). In order to prove the second statement of the theorem we have to show that

$$\sqrt{m_1} \left|\frac{\partial R_{\hat{u}}(d_p)}{\partial d} - \frac{\partial R_u(d_p)}{\partial d}\right| \xrightarrow{P} 0, \tag{46}$$

where

$$\begin{aligned} \frac{\partial R_a(d)}{\partial d} &= 2\frac{\tilde{G}_{1,a}(d)}{\tilde{G}_{0,a}(d)} - \frac{2}{m_1} \sum_{j=1}^{m_1} \log \lambda_j = 2\frac{\tilde{H}_a(d)}{\tilde{G}_{0,a}(d)}, \\ \tilde{H}_a(d) &= \frac{1}{m_1} \sum_{j=1}^{m_1} \nu_j \lambda_j^{2d} I_{aa}(\lambda_j), \end{aligned}$$

and $\nu_j = \log j - m_1^{-1} \sum_{j=1}^{m_1} \log j$. Now we write

$$\begin{aligned} (46) &= 2\sqrt{m_1} \left|\frac{\tilde{H}_{\hat{u}}(d_p) - \tilde{H}_u(d_p)}{\tilde{G}_{0,\hat{u}}(d_p)} - \frac{\tilde{H}_u(d_p)}{\tilde{G}_{0,u}(d_p)} \frac{(\tilde{G}_{0,\hat{u}}(d_p) - \tilde{G}_{0,u}(d_p))}{\tilde{G}_{0,\hat{u}}(d_p)}\right| \\ &\leq 2\sqrt{m_1} \left|\tilde{G}_{0,\hat{u}}(d_p)\right|^{-1} \left|\tilde{H}_{\hat{u}}(d_p) - \tilde{H}_u(d_p)\right| \qquad (47) \\ &\quad + 2\sqrt{m_1} \left|\tilde{G}_{0,\hat{u}}(d_p)\right|^{-1} \left|\tilde{G}_{0,\hat{u}}(d_p) - \tilde{G}_{0,u}(d_p)\right| \left|\frac{\tilde{H}_u(d_p)}{\tilde{G}_{0,u}(d_p)}\right|. \qquad (48) \end{aligned}$$

To show that (48) is $o_P(1)$ note that $\frac{\tilde{H}_u(d_p)}{\tilde{G}_{0,u}(d_p)} = \frac{1}{2} \frac{\partial R_u(d_p)}{\partial d}$, i.e. the score for the estimation problem with observed series, such that $\left|\frac{\tilde{H}_u(d_p)}{\tilde{G}_{0,u}(d_p)}\right| = O_P(m_1^{-1/2})$ as in Robinson (1995*a*, p. 1644). Thus, we need only to show that $|\tilde{G}_{0,\hat{u}}(d_p) - \tilde{G}_{0,u}(d_p)| \xrightarrow{P} 0$. Based on the previous results, we easily get

$$\left|\tilde{G}_{0,\hat{u}}(d_p) - \tilde{G}_{0,u}(d_p)\right| \leq \frac{1}{m_1} \sum_{j=1}^{m_1} \left|\lambda_j^{2d_p} \left(\hat{I}_{pp}(\lambda_j) - I_{pp}(\lambda_j)\right)\right| \leq \frac{|G_{pp}|}{m_1} \sum_{j=1}^{m_1} |h_j| = O_P\left((m_0/m_1)^{\delta_{\min}}\right),$$

which is $o_P(1)$ by Assumption 5. Since $\tilde{G}_{0,\hat{u}}(d_p) = G_{pp} + o_P(1)$ by (43) with $k = 0$ and Robinson (1995a), (47) is of the same order as $\sqrt{m_1}|\tilde{H}_{\hat{u}}(d_p) - \tilde{H}_u(d_p)|$ which is equal to

$$\frac{G_{pp}}{\sqrt{m_1}}\left|\sum_{j=1}^{m_1}\nu_j h_j\right| = O_P\left(\frac{(\log m_1)}{\sqrt{m_1}}\sum_{j=1}^{m_1}|h_j|\right) = O_P\left((\log m_1)\sqrt{m_1}\,(m_0/m_1)^{\delta_{\min}}\right).$$

Hence, (46) is, in general, $O_P((\log m_1)\sqrt{m_1}\,(m_0/m_1)^{\delta_{\min}})$. By (45) it follows that $\sqrt{m_1}(\hat{d}_p - d_p)$ has the same asymptotic order of magnitude which proves the first statement of the theorem.

To prove the second statement of the theorem, we need to show that in fact $\sqrt{m_1}|\tilde{H}_{\hat{u}}(d_p) - \tilde{H}_u(d_p)| \xrightarrow{P} 0$ if $G_{ap} = G_{pa} = 0$ for $a = 1, \ldots, p-1$. Thus, $\sqrt{m_1}|\tilde{H}_{\hat{u}}(d_p) - \tilde{H}_u(d_p)|$ is equal to

$$\begin{aligned}\frac{G_{pp}}{\sqrt{m_1}}\left|\sum_{j=1}^{m_1}\nu_j h_j\right| &\leq \frac{G_{pp}}{\sqrt{m_1}}\left|\sum_{j=1}^{m_1}\nu_j\lambda_j^{2d_p}\left[(\beta-\hat{\beta}_{m_0})'\operatorname{Re}(I_{xx}(\lambda_j))(\beta-\hat{\beta}_{m_0})/2 + (\beta-\hat{\beta}_{m_0})'\operatorname{Re}(I_{xp}(\lambda_j))\right]\right| \\ &\leq \frac{G_{pp}}{2\sqrt{m_1}}\left|\sum_{j=1}^{m_1}\nu_j\lambda_j^{2d_p}\sum_{a=1}^{p-1}\sum_{b=1}^{p-1}(\beta_a-\hat{\beta}_{a,m_0})(\beta_b-\hat{\beta}_{b,m_0})\operatorname{Re}(I_{ab}(\lambda_j))\right| \qquad (49)\\ &\quad+\frac{G_{pp}}{\sqrt{m_1}}\left|\sum_{j=1}^{m_1}\nu_j\lambda_j^{2d_p}\sum_{a=1}^{p-1}(\beta_a-\hat{\beta}_{a,m_0})\operatorname{Re}(I_{ap}(\lambda_j))\right|. \qquad (50)\end{aligned}$$

First, using summation by parts,

$$\sum_{j=1}^{m_1}\nu_j\lambda_j^{2d_p}\operatorname{Re}(I_{ap}(\lambda_j)) = \nu_{m_1}\sum_{j=1}^{m_1}\lambda_j^{2d_p}\operatorname{Re}(I_{ap}(\lambda_j)) - \sum_{j=1}^{m_1-1}(\nu_{j+1}-\nu_j)\sum_{k=1}^{j}\lambda_k^{2d_p}\operatorname{Re}(I_{ap}(\lambda_k)),$$

and for ν_j we know that $\nu_{m_1} = O(1)$ and $|\nu_{j+1} - \nu_j| = O(j^{-1})$ uniformly in j (by a mean value expansion). In the present case with $G_{ap} = G_{pa} = 0$ for $a = 1, \ldots, p-1$ we know from Theorem 1 that $\hat{\beta}_{a,m_0} - \beta_a = O_P(m_0^{-1/2}\lambda_{m_0}^{d_a-d_p})$. This implies, in conjunction with Lemma 5(c) with $G_{ap} = G_{pa} = 0$ for $a = 1, \ldots, p-1$, that (50) is

$$\begin{aligned}& O_P\left(\frac{1}{\sqrt{m_1}}\sum_{a=1}^{p-1}\frac{\lambda_{m_0}^{d_a-d_p}}{\sqrt{m_0}}\lambda_{m_1}^{d_p-d_a}\left(m_1^{1+\min(1,\alpha)}T^{-\min(1,\alpha)} + m_1^{1/2}(\log m_1)\right)\right) \\ & +O_P\left(\frac{1}{\sqrt{m_1}}\sum_{a=1}^{p-1}\frac{\lambda_{m_0}^{d_a-d_p}}{\sqrt{m_0}}\sum_{j=1}^{m_1-1}j^{-1}\lambda_j^{d_p-d_a}\left(j^{1+\min(1,\alpha)}T^{-\min(1,\alpha)} + j^{1/2}(\log j)\right)\right) \\ = \; & O_P\left(\frac{1}{\sqrt{m_0}}\left(\frac{m_0}{m_1}\right)^{\delta_{\min}}\left(m_1^{1/2+\min(1,\alpha)}T^{-\min(1,\alpha)} + (\log m_1)\right)\right),\end{aligned}$$

which is negligible by Assumption 5. Similarly, we get that (49) is also negligible since

$$O_P\left(\sqrt{m_1}\sum_{a=1}^{p-1}\sum_{b=1}^{p-1}\frac{\lambda_{m_0}^{d_a+d_b-2d_p}}{m_0}\lambda_{m_1}^{2d_p-d_a-d_b}\right) = O_P\left(\left(\frac{m_0}{m_1}\right)^{2\delta_{\min}}\frac{\sqrt{m_1}}{m_0}\right).$$

Appendix C: Proof of Theorem 3

To derive the asymptotic order of $\lambda_{m_2}^{d_p}\Lambda_{m_2}^{-1}\hat{\Gamma}_{m_2} - K^{-1}H$, first write

$$\lambda_{m_2}^{d_p}\Lambda_{m_2}^{-1}\hat{\Gamma}_{m_2} = \left(\Lambda_{m_2}\frac{1}{m_2-m_0}\sum_{j=m_0+1}^{m_2}\mathrm{Re}\left(I_{xx}\left(\lambda_j\right)\right)\Lambda_{m_2}\right)^{-1}\Lambda_{m_2}\lambda_{m_2}^{d_p}\frac{1}{m_2-m_0}\sum_{j=m_0+1}^{m_2}\mathrm{Re}(\hat{I}_{xp}\left(\lambda_j\right)).$$

We then show that

$$\Lambda_{m_2}\frac{1}{m_2-m_0}\sum_{j=m_0+1}^{m_2}\mathrm{Re}\left(I_{xx}\left(\lambda_j\right)\right)\Lambda_{m_2} - K = O_P\left(l(m_0,m_2)\right), \quad (51)$$

$$\Lambda_{m_2}\lambda_{m_2}^{d_p}\frac{1}{m_2-m_0}\sum_{j=m_0+1}^{m_2}\mathrm{Re}(\hat{I}_{xp}\left(\lambda_j\right)) - H = O_P(l(m_0,m_2)+(m_0/m_2)^{\delta_{\min}}), \quad (52)$$

where

$$l(m_0,m_2) = \left(\frac{m_2}{T}\right)^{\min(1,\alpha)} + m_2^{-1/2}(\log m_2) + \left(\frac{m_0}{T}\right)^{\min(1,\alpha)},$$

which is sufficient to prove the desired result since

$$\begin{aligned} & K^{-1}\left(1+O_P\left(l(m_0,m_2)\right)\right)^{-1}H(1+O_P(l(m_0,m_2)+(m_0/m_2)^{\delta_{\min}})) \\ = & K^{-1}H\left(1+O_P\left(l(m_0,m_2)\right)\right)(1+O_P(l(m_0,m_2)+(m_0/m_2)^{\delta_{\min}})) \\ = & K^{-1}H(1+O_P(l(m_0,m_2)+(m_0/m_2)^{\delta_{\min}})). \end{aligned}$$

The (a,b)'th element of the left-hand side of (51) is

$$\begin{aligned} & \frac{\lambda_{m_2}^{d_a+d_b}}{m_2-m_0}\sum_{j=m_0+1}^{m_2}\mathrm{Re}\left(I_{ab}\left(\lambda_j\right)\right) - K_{ab} \\ = & \frac{1}{m_2-m_0}\left(\lambda_{m_2}^{d_a+d_b}\sum_{j=1}^{m_2}\mathrm{Re}\left(I_{ab}\left(\lambda_j\right)\right) - K_{ab}\right) - \frac{1}{m_2-m_0}\left(\lambda_{m_2}^{d_a+d_b}\sum_{j=1}^{m_0}\mathrm{Re}\left(I_{ab}\left(\lambda_j\right)\right) - K_{ab}\right) \\ = & O_P\left((m_2/T)^{\min(1,\alpha)} + m_2^{-1/2}(\log m_2)\right) + O_P\left((m_0/m_2)^{1-d_a-d_b}(m_0/T)^{\min(1,\alpha)} + m_0^{1/2}m_2^{-1}(\log m_0)\right) \end{aligned}$$

by application of Lemma 5(c).

To prove (52) we write the a'th element of the left-hand side as

$$\begin{aligned} \frac{\lambda_{m_2}^{d_a+d_p}}{m_2-m_0}\sum_{j=m_0+1}^{m_2}\mathrm{Re}(\hat{I}_{ap}\left(\lambda_j\right)) - H_a = & \frac{\lambda_{m_2}^{d_a+d_p}}{m_2-m_0}\sum_{j=m_0+1}^{m_2}\mathrm{Re}(\hat{I}_{ap}\left(\lambda_j\right) - I_{ap}\left(\lambda_j\right)) \quad (53) \\ & +\frac{\lambda_{m_2}^{d_a+d_p}}{m_2-m_0}\sum_{j=m_0+1}^{m_2}\mathrm{Re}\left(I_{ap}\left(\lambda_j\right)\right) - H_a. \quad (54) \end{aligned}$$

Since $\hat{I}_{ap}\left(\lambda_j\right) = I_{ap}\left(\lambda_j\right) + I_{ax}\left(\lambda_j\right)(\beta - \hat{\beta}_{m_0}) = I_{ap}(\lambda_j) + \sum_{b=1}^{p-1} I_{ab}(\lambda_j)(\beta_b - \hat{\beta}_{b,m_0})$, eq. (53) depends on $\beta_a - \hat{\beta}_{a,m_0}$ which is $O_P(\lambda_{m_0}^{d_a-d_p})$ by Theorem 1. Thus,

$$\begin{aligned} (53) = & \sum_{b=1}^{p-1}(\beta_b - \hat{\beta}_{b,m_0})\frac{\lambda_{m_2}^{d_a+d_p}}{m_2-m_0}\sum_{j=m_0+1}^{m_2}\mathrm{Re}\left(I_{ab}\left(\lambda_j\right)\right) \\ = & O_P\left(\sum_{b=1}^{p-1}\lambda_{m_2}^{d_a+d_p}\lambda_{m_0}^{d_b-d_p}\lambda_{m_2}^{-d_a-d_b}\right) = O_P\left(\left(\frac{m_0}{m_2}\right)^{\delta_{\min}}\right). \end{aligned}$$

Lastly, the term (54) is $O_P((m_2/T)^{\min(1,\alpha)} + m_2^{-1/2}(\log m_2) + (m_0/T)^{\min(1,\alpha)} + m_0^{1/2}m_2^{-1}(\log m_0))$ by the same argument as for (51).

The same proof can be applied for $\check{\Gamma}_{m_2}$, although Lemma 5(c) must be modified as

$$\begin{aligned} & \lambda_r^{d_a+d_b-c-1}\int_0^{\lambda_r} \operatorname{Re}\left(e^{i\lambda(d_a-d_b)/2}\lambda^c f_{ab}\left(\lambda\right)\right) d\lambda \\ = \; & \lambda_r^{d_a+d_b-c-1}\int_0^{\lambda_r} G_{ab}\lambda^{c-d_a-d_b}\operatorname{Re}(e^{i\pi(d_a-d_b)/2})\left(1+O\left(\lambda^{\alpha}\right)\right) d\lambda \\ = \; & \lambda_r^{d_a+d_b-c-1}\int_0^{\lambda_r} G_{ab}\lambda^{c-d_a-d_b}\cos\left(\pi\left(d_a-d_b\right)/2\right)\left(1+O(\lambda^{\alpha})\right)d\lambda \\ = \; & \frac{(1-d_a-d_b)}{(1+c-d_a-d_b)}K_{ab}(1+O(\lambda_r^{\alpha})). \end{aligned}$$

Appendix D: Proof of Theorem 4

The result follows by application of the previous theorems. From (21) and (23),

$$\begin{aligned} \sqrt{m_3}\lambda_{m_3}^{d_p}\Lambda_{m_3}^{-1}(\tilde{\beta}_{m_3}-\beta) &= \sqrt{m_3}\lambda_{m_3}^{d_p}\Lambda_{m_3}^{-1}(\hat{\beta}_{m_3}-\lambda_{m_3}^{-\hat{d}_p}\hat{\Lambda}_{m_3}\lambda_{m_2}^{\hat{d}_p}\hat{\Lambda}_{m_2}^{-1}\check{\Gamma}_{m_2}-\beta) \\ &= \sqrt{m_3}\lambda_{m_3}^{d_p}\Lambda_{m_3}^{-1}(\hat{\beta}_{m_3}-\beta) \\ &\quad -\sqrt{m_3}\lambda_{m_2}^{d_p}\Lambda_{m_2}^{-1}\check{\Gamma}_{m_2}(1+O_P((\log T)\,(\log m_1)(m_0/m_1)^{\delta_{\min}})) \\ &= \sqrt{m_3}\lambda_{m_3}^{d_p}\Lambda_{m_3}^{-1}(\hat{\beta}_{m_3}-\beta)-\sqrt{m_3}\lambda_{m_2}^{d_p}\Lambda_{m_2}^{-1}\check{\Gamma}_{m_2}+o_P\left(1\right), \end{aligned}$$

where the second equality follows from $\lambda_{m_3}^{\hat{d}_a-d_a} = 1+O_P((\log T)\,(\log m_1)(m_0/m_1)^{\delta_{\min}})$ and $\lambda_{m_2}^{\hat{d}_p-\hat{d}_a} = \lambda_{m_2}^{d_p-d_a}(1+O_P((\log T)\,(\log m_1)(m_0/m_1)^{\delta_{\min}}))$ for $a=1,...,p$, which is a consequence of Theorem 2, and the third equality is by Assumption 7 (or (22) if $m_3=m_0$). From Theorem 3 it follows that

$$\begin{aligned} \sqrt{m_3}\lambda_{m_2}^{d_p}\Lambda_{m_2}^{-1}\check{\Gamma}_{m_2} &= \sqrt{m_3}K^{-1}H+\sqrt{m_3}O_P\left(\left(\frac{m_0}{m_2}\right)^{\delta_{\min}}+m_2^{-1/2}(\log m_2)+\left(\frac{m_2}{T}\right)^{\alpha}+\left(\frac{m_0}{T}\right)^{\alpha}\right) \\ &= \sqrt{m_3}K^{-1}H+o_P\left(1\right) \end{aligned}$$

by Assumption 7 (or (22) if $m_3=m_0$). The desired result now follows from Theorem 1.

Appendix E: Technical Lemma

Lemma 5 *Under Assumptions 1-3, as $T\to\infty$, for $1\le r\le m$ and $0\le c\le d_a+d_b$,*

$$(a)\quad \max_{a,b}\lambda_r^{d_a+d_b-c}\sum_{j=1}^{r}\operatorname{Re}\left(\lambda_j^c[I_{ab}\left(\lambda_j\right)-A_a\left(\lambda_j\right)J\left(\lambda_j\right)A_b^*\left(\lambda_j\right)]\right) = O_P(r^{1/3}(\log r)^{2/3}+(\log r)+r^{1/2}T^{-1/4}),$$

$$(b)\quad \max_{a,b}\lambda_r^{d_a+d_b-c}\sum_{j=1}^{r}\operatorname{Re}\left(\lambda_j^c f_{ab}\left(\lambda_j\right)-\lambda_r^{c-d_a-d_b}\frac{(1-d_a-d_b)}{(1+c-d_a-d_b)}K_{ab}\right) = O_P\left(r^{1+\min(1,\alpha)}T^{-\min(1,\alpha)}\right),$$

$$(c) \quad \max_{a,b} \lambda_r^{d_a+d_b-c} \sum_{j=1}^{r} \mathrm{Re}\left(\lambda_j^c I_{ab}(\lambda_j) - \lambda_r^{c-d_a-d_b} \frac{(1-d_a-d_b)}{(1+c-d_a-d_b)} K_{ab}\right) = O_P\left(r^{1+\min(1,\alpha)} T^{-\min(1,\alpha)} + r^{1/2}(\log r)\right),$$

where $J(\lambda_j)$ is the periodogram of ε_t from Assumption 2.

Proof. Decompose the terms inside the real operator as

$$\begin{aligned} H_{1j} &= \lambda_j^c[I_{ab}(\lambda_j) - A_a(\lambda_j) J(\lambda_j) A_b^*(\lambda_j)], \\ H_{2j} &= \lambda_j^c[A_a(\lambda_j) J(\lambda_j) A_b^*(\lambda_j) - f_{ab}(\lambda_j)], \\ H_{3j} &= \lambda_j^c f_{ab}(\lambda_j) - \lambda_r^{c-d_a-d_b} \frac{(1-d_a-d_b)}{(1+c-d_a-d_b)} K_{ab}. \end{aligned}$$

The proof of Lemma 1(b) in Shimotsu (2007) applies also to our terms H_{1j} and H_{2j} which shows that (a) holds and that $\max_{a,b} |\sum_{j=1}^r H_{2j}| = O_P(r^{1/2}(\log r))$. For H_{3j} we use Assumption 1 and $\mathrm{Re}(e^{i\lambda z}) = 1 + O(\lambda^2), \mathrm{Im}(e^{i\lambda z}) = O(\lambda)$ as $\lambda \to 0$ for any $z \in \mathbb{R}$, which imply

$$\begin{aligned} \mathrm{Re}(e^{i(\pi-\lambda)(d_a-d_b)/2}) &= \mathrm{Re}(e^{i\pi(d_a-d_b)/2}) \mathrm{Re}(e^{-i\lambda(d_a-d_b)/2}) - \mathrm{Im}(e^{i\pi(d_a-d_b)/2}) \mathrm{Im}(e^{-i\lambda(d_a-d_b)/2}) \\ &= \cos(\pi(d_a-d_b)/2)(1+O(\lambda^2)) - \sin(\pi(d_a-d_b)/2)O(\lambda) \end{aligned}$$

such that

$$\begin{aligned} \lambda_r^{d_a+d_b-c} r^{-1} \sum_{j=1}^{r} \mathrm{Re}\left(\lambda_j^c f_{ab}(\lambda_j)\right) &= \lambda_r^{d_a+d_b-c-1} \int_0^{\lambda_r} \mathrm{Re}\left(\lambda^c f_{ab}(\lambda)\right) d\lambda + R_T \\ = \ & \lambda_r^{d_a+d_b-c-1} \int_0^{\lambda_r} G_{ab} \lambda^{c-d_a-d_b} \mathrm{Re}(e^{i(\pi-\lambda)(d_a-d_b)/2}) (1 + O(\lambda^\alpha)) d\lambda + R_T \\ = \ & \lambda_r^{d_a+d_b-c-1} \int_0^{\lambda_r} G_{ab} \lambda^{c-d_a-d_b} \cos(\pi(d_a-d_b)/2) (1 + O(\lambda^{\min(1,\alpha)})) d\lambda + R_T \\ = \ & \frac{(1-d_a-d_b)}{(1+c-d_a-d_b)} K_{ab}(1 + O(\lambda_r^{\min(1,\alpha)})) + R_T. \end{aligned}$$

The approximation error R_T is $O(T^{c-d_a-d_b-1}(\log r))$ uniformly in r. ■

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