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# Error-Correction Factor Models for High-dimensional Cointegrated Time Series

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## Abstract

Cointegration inference is often built on the correct specification for the short-run dynamic vector autoregression. However, this specification is unknown a priori. A too small lag length leads to erroneous inference due to misspecification, while using too many lags leads to dramatic increase in the number of parameters, especially when the dimension of time series is high. In this paper, we develop a new methodology which adds an error correction term for long-run equilibrium to a latent factor model for modeling short-run dynamic relationship. Two eigenanalysis based methods for estimating, respectively, cointegration and latent factor process consist of the cornerstones of the inference. The proposed error correction factor model does not require to specify the short-run dynamics explicitly, and is particularly effective for high-dimensional cases when the standard error-correction suffers from overparametrization. It also increases the predictability over a pure factor model. Asymptotic properties of the proposed methods are established when the dimension of the time series is either fixed or diverging slowly as the length of time series goes to infinity. Illustration with both simulated and real data sets is also reported.

**KEYWORDS:** Cointegration; Eigenanalysis; Factor Models; Nonstationary processes; Vector time series

# 1 Introduction

Cointegration refers to the phenomenon that there exists a long-run equilibrium among several distinct nonstationary series, as illustrated in, for example, Box and Tiao (1977). Since the seminal work of Granger (1981), Granger and Weiss (1983) and Engle and Granger (1987), it has attracted increasing attention in econometrics and statistics. An excellent survey on the early developments of cointegration can be found in Johansen (1995).

Up to present, considerable effort has been devoted to the inference on the long-run trend (cointegration) restrictions in vector autoregression (VAR); see, among others, Engle and Granger (1987), Johansen (1991), Phillips (1991) for estimation and testing, and Engle and Yoo (1987), Lin and Tsay (1996) for forecasting. As shown in Engle and Granger (1987), VAR with cointegration restrictions can be represented as a vector error correction model (VECM) which reflects the correction on the long-run relationship by short-run dynamics. One of the remarkable features of VECM is that it identifies clearly the gain in prediction from using the cointegrated variables over the standard ARIMA approach, as noted by Engle and Yoo (1987), Lin and Tsay (1996) and Peña and Poncela (2004). However, it is a prerequisite to specify a finite autoregressive order for the short-run dynamic before the inference can be carried out on the cointegration part of the model. In many applications, using different orders for the VAR results in different conclusions on the cointegration. Especially when the VAR order is under-specified or the process lies outside the VAR class, the optimal inference on the unknown cointegration will lose validity (Hualde and Robinson, 2010). To overcome this shortcoming, information criteria such as AIC, BIC and HQIC have been applied to determine both the autoregressive order and the cointegration rank. See, for example, Chao and Phillips (1999) and Athansopoulos, et al. (2011). While appealing for practitioners, all these methods are nevertheless subject to pre-test biases and post model selection inferential errors (Liao and Phillips, 2015). Furthermore VECM is ineffective when the dimension of time series is high, not least due to the overparametrization of a VAR specification.

Relative to considerable effort on long-run restriction, one may argue that the importance of short-run restrictions has not received due attention in cointegrated literature. On the other hand, common cyclical movements exist extensively in macroeconomics. For example, Engle and Kozicki (1993) found common international cycles in GNP data for OECD countries. Issler and Vahid (2001) reported the common cycles for macroeconomic aggregates and sectoral and regional

outputs in US. It has been shown that using (short-run) rank restrictions in stationary VAR can improve short-term forecasting ability, as documented by Ahn and Reinsel (1988), Vahid and Isser (2002) and Athanasopoulos and Vahid (2008), Athanasopoulos et al. (2011). Hence it is reasonable to expect that imposing appropriate short-run structures will improve the model performance in cointegrated systems. Note that Athanasopoulos et al. (2011) recognized the factor structure in the short-run dynamics, but did not utilize it in their subsequent inference procedure. Issler and Vahid (2001) used a similar argument to the cointegration for the short-run effect. Based on VECM, they proposed to model the common cycles based on sample squared canonical correlations and Johansen's likelihood method is used to identify the cointegration relationship.

When the dimension of time series is high, VAR models suffer from having too many parameters even with some imposed rank restrictions. Furthermore most the classical inference methods for cointegration, including Johansen's likelihood method, will not work or not work effectively. See the numerical studies reported in Gonzalo and Pitarakis (1995) and Ho and Sørensen (1996). Although high-dimensional problems exist extensively in macroeconomic and financial data, the development in both theory and methodology in the context of cointegration is still in its infancy.

We propose in this paper an error correction factor model which is designed for catching the linear dynamical structures, in a parsimonious and robust fashion, for high-dimensional cointegrated series. More specifically the long-run equilibrium relationship among all nonstationary components is represented by a cointegration vector, i.e. the correction term to equilibrium. This term is then utilized to improve a factor representation for the short run dynamics for the differenced processes. Comparing to the classical VECM, our setting does not require to specify the short run dynamics explicitly, avoiding the erroneous inference on cointegration due to, for example, a misspecification of the autoregressive order.

Factor models have been popular for modeling high-dimensional time series to achieve dimension reduction. See, for example, Bai (2004), Bai and Ng (2004), Banerjee, Marcellino and Masten (2014a, b) and Barigozzi, Lippi and Luciani (2016a, b). In this paper, we adopt a latent and low-dimensional factor process to represent the high-dimensional short run dynamics. Comparing to a pure factor model, the cointegration term improves the modelling and the prediction for short run dynamics. In terms of inference, we first adopt the eigenanalysis based method of

Zhang, Robinson and Yao (2015) (ZRY, hereafter) to identify both the cointegration rank and cointegration space; no prespecification on the short run dynamics is required. We then calculate the regression estimation for the error correction term, and recover the latent factor process from the resulting residuals using the eigenanalysis based method of Lam and Yao (2012). Once the latent factor process has been recovered, we can model separately its linear dynamics using whatever an appropriate time series model. Due to the errors accumulated in estimation, fitting a dynamic model for the factor process turns out to be an error-in-observation problem in autoregression. This problem has not been thoroughly investigated in the literature, for which we propose a version of corrected Yule-Walker method. See Section 2.2.3 below.

The proposed methodology is further supported by the newly established asymptotic theory and numerical evidences. Especially our numerical results corroborate the findings from the asymptotic theory. In particular, Monte Carlo simulation reveals that the cointegration rank, the cointegration space, the number of factors and the factor co-feature space can all be estimated reasonably well with typical sizes of observed samples. Our empirical example on forecasting the twelve U.S. industrial production indices shows that the proposed error correction factor model outperforms both VECM and univariate AR models for each component in post-sample forecasting, for most forecast horizons considered.

The rest of the paper is organized as follows. We spell out the proposed error correction model and the associated estimation methods in Section 2. In Section 3 the asymptotic properties for the estimation methods are established with the dimension of time series both fixed or diverging slowly, when the length of time series goes to infinity. The proposed methodology is further illustrated numerically in Section 4 with both simulated and real data sets. Furthermore we compare the forecasting performance of the proposed error correction factor model to those of the reduced rank VECM, and the univariate AR models in each component. The forecasting performances for real data were evaluated for different forecast horizons based on the criterion of Clements and Hendry (1993). Section 5 concludes with remarks on future research. Technical lemmas and all proofs are in the online supplementary materials.

## 2 Methodology

### 2.1 Error Correction Factor Models

We call a vector process  $\mathbf{u}_t$  weakly stationary if (i)  $E\mathbf{u}_t$  is a constant vector independent of  $t$ , and (ii)  $E\|\mathbf{u}_t\|^2 < \infty$ , and  $\text{Cov}(\mathbf{u}_t, \mathbf{u}_{t+s})$  depends on  $s$  only for any integers  $t, s$ , where  $\|\cdot\|$  denotes the Euclidean norm. Denoted by  $\nabla$  the difference operator, i.e.  $\nabla\mathbf{u}_t = \mathbf{u}_t - \mathbf{u}_{t-1}$ . We use the convention  $\nabla^0\mathbf{u}_t = \mathbf{u}_t$ . A process  $\mathbf{u}_t$  is said to be weakly integrated process with order 1, abbreviated as weak  $I(1)$ , if  $\nabla\mathbf{u}_t$  is weakly stationary with spectral density finite and positive definite at frequency 0 but  $\mathbf{u}_t$  itself is not. Since we only deal with weak  $I(1)$  processes in this paper, we simply call them weakly integrated processes.

Let  $\mathbf{y}_t$  be observable  $p \times 1$  weakly  $I(1)$  process with the initial values  $\mathbf{y}_t = 0$  for  $t \leq 0$ . Suppose that cointegration exists, i.e., there are  $r$  ( $\geq 1$ ) stationary linear combinations of  $\mathbf{y}_t$ , where  $r$  is called the cointegration rank and is often unknown. The error correction factor model is defined as

$$\nabla\mathbf{y}_t = \mathbf{C}\mathbf{y}_{t-1} + \mathbf{B}\mathbf{f}_t + \boldsymbol{\varepsilon}_t, \quad (2.1)$$

where  $\mathbf{C}$  is a  $p \times p$  matrix with rank  $r$  and  $\mathbf{C}\mathbf{y}_t$  is weakly stationary,  $\mathbf{f}_t$  is an  $m \times 1$  weakly stationary process and  $\mathbf{B}$  is a  $p \times m$  matrix,  $\boldsymbol{\varepsilon}_t$  is a  $p \times 1$  white noise with mean zero and covariance matrix  $\Sigma_\varepsilon$ , and uncorrelated with  $\mathbf{y}_{t-1}$  and  $\{\mathbf{f}_t\}$ . Comparing with VECM, (2.1) represents the short-run dynamics by the latent process  $\mathbf{f}_t$ . Its linear dynamic structure is completely unspecified. Note that  $\mathbf{f}_t$  does not enter the inference for the error correction term  $\mathbf{C}\mathbf{y}_{t-1}$ . Model (2.1) is particularly useful when  $p$  is large and  $m$  is small, which is often the case with many real data sets, as it leads to an effective dimension-reduction in modelling high-dimensional time series.

Without loss of generality, we assume in (2.1)  $\mathbf{B}$  to be an orthogonal matrix, i.e.,  $\mathbf{B}'\mathbf{B} = \mathbf{I}_m$ , where  $\mathbf{I}_m$  denotes the  $m \times m$  identity matrix. This is due to the fact that any non-orthogonal  $\mathbf{B}$  admits the decomposition  $\mathbf{B} = \mathbf{Q}\mathbf{U}$ , where  $\mathbf{Q}$  is an orthogonal matrix and  $\mathbf{U}$  is an upper-triangular matrix, and we may then replace  $(\mathbf{B}, \mathbf{f}_t)$  in (2.1) by  $(\mathbf{Q}, \mathbf{U}\mathbf{f}_t)$ .

## 2.2 Estimation

In model (2.1),  $\mathbf{C}$  is a  $p \times p$  matrix with the reduced rank  $r (< p)$ . Hence it can be expressed as  $\mathbf{C} = \mathbf{D}\mathbf{A}'_2$ , where  $\mathbf{D}$ ,  $\mathbf{A}_2$  are two  $p \times r$  matrices. Furthermore, columns of  $\mathbf{A}_2$  are the cointegration vectors,  $r$  is the cointegration rank. Although  $\mathbf{A}_2$  is not unique, the coefficient matrix  $\mathbf{C}$  is uniquely determined by (2.1). Once we specify an  $\mathbf{A}_2$  such that  $\mathbf{A}'_2\mathbf{y}_{t-1}$  is weakly stationary, consequently  $\mathbf{D}$  can be uniquely determined. Thus, to fit model (2.1), the key is to estimate  $r$ ,  $\mathbf{A}_2$ , the factor dimension  $m$  and the factor loading matrix  $\mathbf{B}$ . Then the coefficient matrix  $\mathbf{D}$  can be estimated by a multiple regression, the latent factors  $\mathbf{f}_t$  can be recovered easily, and the forecasting can be based on a fitted time series model for  $\mathbf{f}_t$ .

To simplify the inference, in the sequel we always assume that  $\mathbf{C}\mathbf{y}_{t-1}$  and  $\mathbf{f}_t$  are uncorrelated. This avoids the identification issues due to possible endogeneity. Note that this condition is always fulfilled if we replace  $(\mathbf{C}, \mathbf{f}_t)$  in (2.1) by  $(\mathbf{C}^*, \mathbf{f}_t^*)$ , where

$$\begin{aligned}\mathbf{C}^* &= \{\mathbf{D} + \mathbf{B}\mathbf{E}[\mathbf{f}_t(\mathbf{A}'_2\mathbf{y}_{t-1})']][\mathbf{E}((\mathbf{A}'_2\mathbf{y}_{t-1})(\mathbf{A}'_2\mathbf{y}_{t-1})')]^{-1}\}\mathbf{A}'_2, \\ \mathbf{f}_t^* &= \mathbf{f}_t - \mathbf{E}(\mathbf{f}_t(\mathbf{A}'_2\mathbf{y}_{t-1})')[\mathbf{E}((\mathbf{A}'_2\mathbf{y}_{t-1})(\mathbf{A}'_2\mathbf{y}_{t-1})')]^{-1}(\mathbf{A}'_2\mathbf{y}_{t-1}).\end{aligned}$$

### 2.2.1 Estimation for cointegration

While the representation of the cointegration vector  $\mathbf{A}'_2\mathbf{y}_t$  is not unique, the cointegration space  $\mathbf{M}(\mathbf{A}_2)$ , i.e. the linear space spanned by the columns of  $\mathbf{A}_2$ , is uniquely determined by the process  $\mathbf{y}_t$ ; see ZRY. In fact we can always assume that  $\mathbf{A}_2$  is a half-orthogonal matrix in the sense that  $\mathbf{A}'_2\mathbf{A}_2 = \mathbf{I}_r$ . Let  $\mathbf{A}_1$  be a  $p \times (p - r)$  half orthogonal matrix such that  $\mathbf{A} = (\mathbf{A}_1, \mathbf{A}_2)$  be a  $p \times p$  orthogonal matrix. Let  $\mathbf{x}_{t,i} = \mathbf{A}'_i\mathbf{y}_t$  for  $i = 1, 2$ . Then  $\mathbf{x}_{t,2}$  is a weakly stationary process, and all the components of  $\mathbf{x}_{t,1}$  are weak  $I(1)$ .

We adopt the eigenanalysis based method proposed by ZRY to estimate  $r$  as well as  $\mathbf{A}_2$ . To this end, let

$$\widehat{\mathbf{W}} = \sum_{j=0}^{j_0} \widehat{\mathbf{\Sigma}}_j \widehat{\mathbf{\Sigma}}_j',$$

where  $j_0 \geq 1$  is a prescribed and fixed integer, and

$$\widehat{\mathbf{\Sigma}}_j = \frac{1}{n} \sum_{t=1}^{n-j} (\mathbf{y}_{t+j} - \bar{\mathbf{y}})(\mathbf{y}_t - \bar{\mathbf{y}})', \quad \bar{\mathbf{y}} = \frac{1}{n} \sum_{t=1}^n \mathbf{y}_t.$$

We use the product  $\widehat{\Sigma}_j \widehat{\Sigma}'_j$  instead of  $\widehat{\Sigma}_j$  to make sure that each term in the sum is non-negative definite, and that there is no information cancellation over different lags. Let  $\tilde{\lambda}_1 \geq \dots \geq \tilde{\lambda}_p$  be the eigenvalues of  $\widehat{\mathbf{W}}$ , and  $\tilde{\gamma}_1, \dots, \tilde{\gamma}_p$  be the corresponding eigenvectors. Then  $\mathbf{A}_2$  is estimated by  $\widehat{\mathbf{A}}_2 = (\tilde{\gamma}_{p-r+1}, \dots, \tilde{\gamma}_p)$ , and the cointegration rank is estimated by

$$\hat{r} = \arg \min_{1 \leq l \leq p} IC(l), \quad (2.2)$$

where  $IC(l) = \sum_{j=1}^l \tilde{\lambda}_{p+1-j} + (p-l)\omega_n$ , and  $\omega_n \rightarrow \infty$  and  $\omega_n/n^2 \rightarrow 0$  in probability (as we allow  $\omega_n$  to be data-dependent). ZRY has shown that both  $\mathcal{M}(\widehat{\mathbf{A}}_2)$  and  $\hat{r}$  are consistent estimators for, respectively,  $\mathcal{M}(\mathbf{A}_2)$  and  $r$ .

Having obtained the estimated cointegration vector  $\widehat{\mathbf{A}}'_2 \mathbf{y}_{t-1}$ , the coefficient matrix  $\mathbf{D}$  can be estimated using the standard least squares estimation. Let  $\mathbf{d}_i$ ,  $i = 1, 2, \dots, p$  be the row vectors of  $\mathbf{D}$  and  $\nabla \mathbf{y}_t = (\nabla y_t^1, \dots, \nabla y_t^p)'$ . The least square estimator for  $\mathbf{d}_i$  is defined as

$$\widehat{\mathbf{d}}_i = \arg \min_{\mathbf{d}_i} \sum_{t=1}^n (\nabla y_t^i - \mathbf{d}_i \widehat{\mathbf{A}}'_2 \mathbf{y}_{t-1})^2, \quad (2.3)$$

which leads to  $\widehat{\mathbf{d}}_i = \sum_{t=1}^n \nabla y_{ti} (\widehat{\mathbf{A}}'_2 \mathbf{y}_{t-1})' \left( \sum_{i=1}^n (\widehat{\mathbf{A}}'_2 \mathbf{y}_{t-1}) (\widehat{\mathbf{A}}'_2 \mathbf{y}_{t-1})' \right)^{-1}$ . Consequently, the estimator for the coefficient matrix  $\mathbf{D}$  can be written as

$$\widehat{\mathbf{D}} = \sum_{t=1}^n \nabla \mathbf{y}_t (\widehat{\mathbf{A}}'_2 \mathbf{y}_{t-1})' \left( \sum_{i=1}^n (\widehat{\mathbf{A}}'_2 \mathbf{y}_{t-1}) (\widehat{\mathbf{A}}'_2 \mathbf{y}_{t-1})' \right)^{-1}.$$

### 2.2.2 Estimation for latent factors

We adopt the eigenanalysis based method of Lam and Yao (2012) to estimate the factor loading space  $\mathcal{M}(\mathbf{B})$  and the latent factor process  $\mathbf{f}_t$  based on the residuals  $\widehat{\mathbf{v}}_t \equiv \nabla \mathbf{y}_t - \widehat{\mathbf{D}} \widehat{\mathbf{A}}'_2 \mathbf{y}_{t-1}$ ,  $t = 1, \dots, n$ . To this end, let

$$\widehat{\mathbf{W}}_v = \sum_{j=1}^{j_0} \widehat{\Sigma}_v(j) \widehat{\Sigma}'_v(j), \quad (2.4)$$

where  $j_0 \geq 1$  is a prespecified and fixed integer, and

$$\widehat{\Sigma}_v(j) = \frac{1}{n} \sum_{t=1}^{n-j} (\widehat{\mathbf{v}}_{t+j} - \bar{\mathbf{v}})(\widehat{\mathbf{v}}_t - \bar{\mathbf{v}})', \quad \bar{\mathbf{v}} = \frac{1}{n} \sum_{t=1}^n \widehat{\mathbf{v}}_t.$$

where  $j_0 \geq 1$  is a prespecified and fixed integer. One distinctive advantage of using the quadratic form  $\widehat{\Sigma}_v(j)\widehat{\Sigma}_v(j)'$  instead of  $\widehat{\Sigma}_v(j)$  in (2.4) is that there is no information cancellation over different lags. Therefore this approach is insensitive to the choice of  $j_0$  in (2.4). Often small values such as  $j_0 = 5$  are sufficient to catch the relevant characteristics, as serial dependence is usually most predominant at small lags. See Lam and Yao (2012) and Chang et al. (2015). Let  $(\widehat{\gamma}_1, \dots, \widehat{\gamma}_m)$  be the orthonormal eigenvectors of  $\widehat{\mathbf{W}}_v$  corresponding to the  $m$  largest eigenvalues. Consequently, we estimate  $\mathbf{B}$  and  $\mathbf{f}_t$  by

$$\widehat{\mathbf{B}} = (\widehat{\gamma}_1, \dots, \widehat{\gamma}_m), \quad \text{and} \quad \widehat{\mathbf{f}}_t = \widehat{\mathbf{B}}'\widehat{\mathbf{v}}_t. \quad (2.5)$$

Since  $m$  is usually unknown and the last  $p - m$  eigenvalues of  $\widehat{\mathbf{W}}_v$  may not be exactly 0 due to the random fluctuation, the determination of  $m$  is required. We propose to select  $m$  by using the ratio-based method of Lam and Yao (2012). In particular, let  $\widehat{\lambda}_1 \geq \widehat{\lambda}_2 \geq \dots \geq \widehat{\lambda}_p$  be the eigenvalues of  $\widehat{\mathbf{W}}_v$ . We define an estimator for the number of factors  $m$  as follows:

$$\widetilde{m} = \arg \min_{1 \leq i \leq R} \widehat{\lambda}_{i+1}/\widehat{\lambda}_i, \quad (2.6)$$

with  $m < R < p$ . In practice we may pick, for example,  $R = p/2$ , following the recommendation of Lam and Yao (2012).

**Remark 1.** *The above ratio estimator of  $m$  is not necessarily consistent, though it works fine in practice. See Lam and Yao (2012), and also Tables 1, 2 and 3 in Section 4.1 below. To establish the consistency, one can estimate  $m$  using the information criterion defined as*

$$\widehat{m} = \arg \min_{1 \leq l \leq p} IC(l),$$

where  $IC(l) = \sum_{j=l+1}^p \widehat{\lambda}_j + l\omega_n$ , is the information criterion and  $\omega_n$  is the turning parameter. It can be shown as  $\omega_n \rightarrow 0$  and  $\omega_n n^{1/2}/p \rightarrow \infty$ ,  $\widehat{m}$  is consistent for  $m$ .

### 2.2.3 Fitting linear dynamics for factors

Once we have recovered the factor process  $\widehat{\mathbf{f}}_t$ , we can fit an appropriate model to represent its linear dynamic structure. As an illustration, below we fit  $\mathbf{f}_t$  with a VAR model.

Let

$$\mathbf{f}_t = \sum_{i=1}^s \mathbf{E}_i \mathbf{f}_{t-i} + \mathbf{e}_t, \quad (2.7)$$

where  $\mathbf{E}_i$ ,  $1 \leq i \leq s$  are  $m \times m$  matrices and  $\{\mathbf{e}_t\}$  is a sequence of independent vectors with mean zero and independent of  $\{\mathbf{x}'_{t2}, \mathbf{f}'_t, \boldsymbol{\varepsilon}'_t\}$ . In our setting,  $\mathbf{f}_t$  are unobservable latent factors and estimated by  $\widehat{\mathbf{f}}_t = \widehat{\mathbf{B}}' \widehat{\mathbf{v}}_t$  is given in (2.5). It can be shown that

$$\widehat{\mathbf{f}}_t = \mathbf{f}_t + \mathbf{B}' \boldsymbol{\varepsilon}_t + \sum_{i=2}^4 \boldsymbol{\zeta}_{t,i}.$$

If we ignore the term  $\sum_{i=2}^4 \boldsymbol{\zeta}_{t,i}$ ,  $\widehat{\mathbf{f}}_t$  can be viewed as the observation of  $\mathbf{f}_t$  with measurement error. Thus,  $\mathbf{E}_i$  can be estimated through a VAR model with observations in errors. This is an interesting and important topic and has been actively pursued in various contexts, see for example, Carroll, Ruppert and Stefanski (1995). However, time series models with measurement errors have not received enough attention. Note that when  $\widehat{\mathbf{f}}_t = \mathbf{f}_t + \mathbf{B}' \boldsymbol{\varepsilon}_t$ , then (2.7) can be written as a vector ARMA model (VARMA) with same order of AR and MA parts. One can estimate  $\mathbf{E}_i$  based on VARMA models. An alternative method is to use the classic least squares procedure, which estimates  $\mathbf{E}_i$  based on  $\{\widehat{\mathbf{f}}\}$ , i.e.,

$$(\widetilde{\mathbf{E}}_1, \dots, \widetilde{\mathbf{E}}_s) = \operatorname{argmin}_{\mathbf{E}_1, \dots, \mathbf{E}_s} \sum_{t=s+1}^n \|\widehat{\mathbf{f}}_t - \sum_{i=1}^s \mathbf{E}_i \widehat{\mathbf{f}}_{t-i}\|^2. \quad (2.8)$$

However, just as in simple linear regression for independent data,  $\widetilde{\mathbf{E}}_i$  can not estimate  $\mathbf{E}_i$  consistently when the spectral norm of the covariance of  $\mathbf{B}' \boldsymbol{\varepsilon}_t + \sum_{i=2}^4 \boldsymbol{\zeta}_{t,i}$  has the same order as that of  $\widehat{\mathbf{f}}_t$  and a correcting factor is required. To see this, we simply assume  $\widehat{\mathbf{f}}_t = \mathbf{f}_t + \mathbf{B}' \boldsymbol{\varepsilon}_t$  and  $s = 1$ , then

$$\begin{aligned} \widetilde{\mathbf{E}}'_1 - \mathbf{E}'_1 &= \left( \sum_{t=2}^n \widehat{\mathbf{f}}_{t-1} \widehat{\mathbf{f}}'_{t-1} \right)^{-1} \sum_{t=1}^n (\mathbf{f}_{t-1} + \mathbf{B}' \boldsymbol{\varepsilon}_{t-1}) (\mathbf{e}_t + \mathbf{B}' \boldsymbol{\varepsilon}_t - \mathbf{E}_1 \mathbf{B}' \boldsymbol{\varepsilon}_{t-1})' \\ &= \left( \sum_{t=2}^n \widehat{\mathbf{f}}_{t-1} \widehat{\mathbf{f}}'_{t-1} \right)^{-1} \sum_{t=1}^n [(\mathbf{f}_{t-1} + \mathbf{B}' \boldsymbol{\varepsilon}_{t-1}) \mathbf{e}'_t + \mathbf{f}_{t-1} (\boldsymbol{\varepsilon}'_t \mathbf{B} - \boldsymbol{\varepsilon}'_{t-1} \mathbf{B} \mathbf{E}'_1)] \\ &\quad - \left( \sum_{t=2}^n \widehat{\mathbf{f}}_{t-1} \widehat{\mathbf{f}}'_{t-1} \right)^{-1} \sum_{t=1}^n \mathbf{B}' \boldsymbol{\varepsilon}_{t-1} \boldsymbol{\varepsilon}'_{t-1} \mathbf{B} \mathbf{E}'_1. \end{aligned}$$

Under some regular condition,  $(\sum_{t=1}^{n-1} \widehat{\mathbf{f}}_t \widehat{\mathbf{f}}_t')^{-1} \sum_{t=1}^{n-1} \mathbf{B}' \boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t' \mathbf{B} \xrightarrow{p} [\text{Var}(\mathbf{f}_1 + \mathbf{B}' \boldsymbol{\varepsilon}_1)]^{-1} \text{Var}(\mathbf{B}' \boldsymbol{\varepsilon}_1)$ . Thus, a corrected factor is required and one may use the modified LSE:  $\widehat{\mathbf{E}}_1' = [\text{Var}(\mathbf{f}_1)]^{-1} [\text{Var}(\mathbf{f}_1 + \mathbf{B}' \boldsymbol{\varepsilon}_1)] \widetilde{\mathbf{E}}_1'$  to estimate  $\mathbf{E}_1'$ . One simple method is to correct the LSE given in (2.8) by

$$(\widehat{\mathbf{E}}_1, \dots, \widehat{\mathbf{E}}_s)' = \left[ \sum_{t=s+1}^n (\widehat{\mathbf{f}}'_{t-1}, \dots, \widehat{\mathbf{f}}'_{t-s})' (\widehat{\mathbf{f}}'_{t-1}, \dots, \widehat{\mathbf{f}}'_{t-s}) - M \right]^{-1} \left[ \sum_{t=s+1}^n \widehat{\mathbf{f}}_t (\widehat{\mathbf{f}}'_{t-1}, \dots, \widehat{\mathbf{f}}'_{t-s}) \right]', \quad (2.9)$$

where  $M = \text{diag}(\widehat{\Sigma}_{\mathbf{B}\boldsymbol{\varepsilon}}(1), \dots, \widehat{\Sigma}_{\mathbf{B}\boldsymbol{\varepsilon}}(s))$  and  $\widehat{\Sigma}_{\mathbf{B}\boldsymbol{\varepsilon}}(i) = \sum_{t=s+1}^n \mathbf{B}' \boldsymbol{\varepsilon}_{t-i} \boldsymbol{\varepsilon}_{t-i}' \mathbf{B}$ . This is in the same spirit as the corrected Yule-Walker estimator proposed by Staudenmayer and Buonaccorsi (2005) for AR model with measurement error. The autoregressive order  $s$  may be determined by, for example, the standard criteria such as AIC or BIC. See, for example, Section 4.2.3 of Fan and Yao (2015).

Combining (2.1), (2.7) and (2.9), we have  $h$ -step ahead forecast, for  $h = 1, 2$ , as:

$$\begin{aligned} \mathbf{y}_{t+1|t} &= (\mathbf{I} + \widehat{\mathbf{C}}) \mathbf{y}_t + \widehat{\mathbf{B}} \widehat{\mathbf{f}}_{t+1} = (\mathbf{I} + \widehat{\mathbf{C}}) \mathbf{y}_t + \widehat{\mathbf{B}} \left( \sum_{i=1}^s \widehat{\mathbf{E}}_i \widehat{\mathbf{f}}_{t+1-i} \right), \\ \mathbf{y}_{t+2|t} &= (\mathbf{I} + \widehat{\mathbf{C}}) \mathbf{y}_{t+1|t} + \widehat{\mathbf{B}} \widehat{\mathbf{f}}_{t+2|t} \\ &= (\mathbf{I} + \widehat{\mathbf{C}})^2 \mathbf{y}_t + (\mathbf{I} + \widehat{\mathbf{C}}) \widehat{\mathbf{B}} \left( \sum_{i=1}^s \widehat{\mathbf{E}}_i \widehat{\mathbf{f}}_{t+1-i} \right) + \widehat{\mathbf{B}} \left[ \sum_{i=1}^{s-1} \widehat{\mathbf{E}}_i \widehat{\mathbf{f}}_{t+1-i} + \widehat{\mathbf{E}}_1 \left( \sum_{i=1}^s \widehat{\mathbf{E}}_i \widehat{\mathbf{f}}_{t+1-i} \right) \right]. \end{aligned}$$

We can similarly deduce any  $h$ -step ahead forecast  $\mathbf{y}_{t+h|t}$ , for  $h \geq 3$ , by recursive iteration.

### 3 Asymptotic Theory

In this section, we investigate the asymptotic properties of the proposed estimators. For given  $m$ , we measure the distance between the cofeature space  $\mathcal{M}(\mathbf{B})$  and its estimate by

$$D(\mathcal{M}(\widehat{\mathbf{B}}), \mathcal{M}(\mathbf{B})) = \sqrt{1 - \frac{1}{m} \text{tr}(\widehat{\mathbf{B}} \widehat{\mathbf{B}}' \mathbf{B} \mathbf{B}')}. \quad (3.1)$$

Then  $D(\mathcal{M}(\widehat{\mathbf{B}}), \mathcal{M}(\mathbf{B})) \in [0, 1]$ , being 0 if and only if  $\mathcal{M}(\widehat{\mathbf{B}}) = \mathcal{M}(\mathbf{B})$ , and 1 if and only if  $\mathcal{M}(\widehat{\mathbf{B}})$  and  $\mathcal{M}(\mathbf{B})$  are orthogonal. We consider two asymptotic modes: (i)  $p$  is fixed while  $n \rightarrow \infty$ , and (ii) both  $p$  and  $n$  diverge, but  $r$  is fixed.

### 3.1 When $n \rightarrow \infty$ and $p$ is fixed

We introduce the regularity conditions first.

**Condition 1.** The process  $\{\mathbf{x}'_{t2}, \nabla \mathbf{y}'_t, \boldsymbol{\varepsilon}'_t\}$  is a stationary  $\alpha$ -mixing process with mean zero,  $E\|(\mathbf{x}'_{t2}, \nabla \mathbf{y}'_t, \boldsymbol{\varepsilon}'_t)\|_\infty^{4\gamma} < \infty$  for some constant  $\gamma > 1$  and the mixing coefficients  $\alpha_t$  satisfying the condition  $\sum_{t=1}^\infty \alpha_t^{1-1/\gamma} < \infty$ , where  $\|\mathbf{x}\|_\infty$  denote the maximum norm of a vector  $\mathbf{x} = (x_1, \dots, x_n)$ , i.e.,  $\|\mathbf{x}\|_\infty = \max(|x_1|, \dots, |x_n|)$ .

**Condition 2.** The characteristic polynomial of VAR model (2.7) has no roots on or outside of the unit circle so that it is a causal VAR model.

**Theorem 1.** *Let Condition 1 hold.*

(a) *Let  $\text{vech}(\mathbf{D}) = (\mathbf{d}_1, \dots, \mathbf{d}_p)'$ . As  $n \rightarrow \infty$  and  $p$  fixed, it holds that*

$$\sqrt{n}(\text{vech}(\hat{\mathbf{D}}) - \text{vech}(\mathbf{D})) \xrightarrow{d} N(0, \boldsymbol{\Omega}_1),$$

where  $\boldsymbol{\Omega}_1$  is an  $rp \times rp$  positive definite matrix and  $\|\hat{\mathbf{C}} - \mathbf{C}\|_2 = O_p(n^{-1/2})$ , and  $\|\cdot\|_2$  denotes the spectral norm of a matrix.

(b) *Let  $m$  be known, then  $D(\mathcal{M}(\hat{\mathbf{B}}), \mathcal{M}(\mathbf{B})) = O_p(n^{-1/2})$ .*

(c) *If Condition 2 and  $E\|\mathbf{e}_t\|^{2\gamma} < \infty$  hold in addition, then*

$$\|(\hat{\mathbf{E}}_1 - \mathbf{E}_1, \dots, \hat{\mathbf{E}}_s - \mathbf{E}_s)\|_2 = O_p(n^{-1/2}).$$

**Theorem 2.** *Let  $1 \leq m < p$  and Condition 1 hold. For  $\tilde{m}$  defined in (2.6),*

$$\lim_{n \rightarrow \infty} P(\tilde{m} \geq m) = 1.$$

### 3.2 When $n \rightarrow \infty$ and $p = o(n^c)$

Let  $z_t^j \equiv \nabla x_t^j$ ,  $j = 1, \dots, p - r$ ,  $\mathbf{z}_t = (z_t^1, \dots, z_t^{p-r})'$  and  $\boldsymbol{\nu}_t = (\mathbf{z}'_t, \mathbf{x}'_{t2})'$ . In this subsection, we extend the asymptotic results in the previous section to the cases when  $p \rightarrow \infty$  and  $p = o(n^c)$  for some  $c \in (0, 1/2)$ . Technically we employ a normal approximation method to establish the results.

**Condition 3.**

- (i) Let  $\mathbf{M}$  be a  $p \times k$  constant matrix with  $k \geq p$  and  $c_1 \leq \lambda_{\min}(\mathbf{M}) \leq \lambda_{\max}(\mathbf{M}) \leq c_2$ , where  $c_1, c_2$  are two positive constants. Suppose that  $\boldsymbol{\nu}_t = \mathbf{M}\mathbf{v}_t$ , all the components of  $\mathbf{v}_t = (v_t^1, \dots, v_t^k)'$  are independent and with mean zero.
- (ii) The process  $\{\mathbf{v}'_t, \nabla \mathbf{y}'_t, \boldsymbol{\varepsilon}'_t\}$  is a stationary  $\alpha$ -mixing process with  $E\|(\mathbf{v}'_t, \nabla \mathbf{y}'_t, \boldsymbol{\varepsilon}'_t)\|_\infty^{2\theta} < \infty$  for some  $\theta > \eta \in (2, 4]$  and the mixing coefficients  $\alpha_m$  satisfying

$$\sum_{m=1}^{\infty} \alpha_m^{(\theta-\eta)/(\theta\eta)} < \infty. \quad (3.2)$$

- (iii)  $c_3 \leq \lambda_{\min}(\mathbf{D}) \leq \lambda_{\max}(\mathbf{D}) \leq c_4$  for some positive constants  $c_3, c_4$ .

**Theorem 3.** *Let  $m$  be known. Suppose Condition 3 holds with  $k = o(n^{1/2-1/\eta})$  and  $p = O(n^{1/2-1/\eta}/(\log n)^2)$ , then the following assertions hold.*

- (a)  $\max\{\|\widehat{\mathbf{D}} - \mathbf{D}\|_2, \|\widehat{\mathbf{C}} - \mathbf{C}\|_2\} = O_p((pr)^{1/2}n^{-1/2} + p^{1/2}k^2n^{-1})$ .
- (b)  $D(\mathcal{M}(\widehat{\mathbf{B}}), \mathcal{M}(\mathbf{B})) = O_p(pn^{-1/2})$ .
- (c)  $\|(\widehat{\mathbf{E}}_1 - \mathbf{E}_1, \dots, \widehat{\mathbf{E}}_s - \mathbf{E}_s)\|_2 = O_p((pm)^{1/2}n^{-1/2} + p^{1/2}k^2n^{-1})$ , provided that Condition 2 and  $E\|\mathbf{e}_t\|^\theta < \infty$  hold in addition.

**Theorem 4.** *Let  $1 \leq m < p$ , Condition 3 holds with  $k = o(n^{1/2-1/\eta})$  and  $p = O(n^{1/2-1/\eta}/(\log n)^2)$ . For  $\tilde{m}$  defined in (2.6),*

$$\lim_{n \rightarrow \infty} P(\tilde{m} \geq m) = 1.$$

**Remark 2.** *All the above asymptotic theorems can be generalized to other stationary noise  $\boldsymbol{\nu}_t$  considered by ZRY.*

## 4 Numerical Studies

In this section, we first evaluate the finite sample performance of our proposed inference procedure via Monte Carlo simulation. We then illustrate the advantage in forecasting of the proposed error correction factor model via a real data example.

## 4.1 Monte Carlo Simulations

In our simulation, we let  $\mathbf{y}_t = \mathbf{A}\mathbf{x}_t$ , where  $\mathbf{A} = (\mathbf{A}_1, \mathbf{A}_2)$  is an orthogonal matrix which was drawn elementwisely from  $U[0, 1]$  independently first and was then orthogonalized, and  $\mathbf{x}_t = (\mathbf{x}'_{t1}, \mathbf{x}'_{t2})'$  in which the  $r$  components of  $\mathbf{x}_{t2}$  are independent Gaussian AR(1) processes with identical autoregressive coefficient 0.5, and the  $(p - r)$  vector  $\mathbf{x}_{t1}$  is  $I(1)$  according to a factor augmented AR(1) defined as

$$\mathbf{x}_{t1} = \mathbf{x}_{t-1,1} + \mathbf{\Upsilon}\mathbf{f}_t + \mathbf{e}_t. \quad (4.3)$$

In the above expression,  $\mathbf{\Upsilon}$  is a  $(p - r) \times m$  half orthogonal matrix (i.e.  $\mathbf{\Upsilon}'\mathbf{\Upsilon} = \mathbf{I}_m$ ) generated in the same manner as  $\mathbf{A}$ , the components of factor  $\mathbf{f}_t$  are independent stationary Gaussian AR(1) with identical autoregressive coefficient 0.5, and  $\mathbf{e}_t$  are independent and  $N(0, \mathbf{I}_{p-r})$ . Then it is easy to see that  $\mathbf{y}_t$  satisfies equation (2.1) with  $\mathbf{C} = 0.5\mathbf{A}_2\mathbf{A}'_2$  and  $\mathbf{B} = \mathbf{A}_1\mathbf{\Upsilon}$ .

With  $p = 5, 10, 20, 40, 60$ ,  $r = 1, 2, 4, 6, 8, 10$ , and  $m = 1, 2, 4, 6, 8, 10$  ( $m \leq p - r$ ), we generate a time series  $\mathbf{y}_t$  with length  $n = 100, 200, 400, 800, 1200, 1600, 2000, 2400$  and estimate  $r$ ,  $\mathbf{C}$ ,  $m$  and  $\mathbf{B}$ . For estimating  $r$ , we use the IC criterion (2.2) with the penalty  $w_n = \log n\tilde{\lambda}_p$ . The number of factor  $m$  is estimated using the ratio method (2.6), with  $j_0 = 5$ . For each setting we replicated the experiment 1000 times.

Tables 1-3 list the relative frequencies of the occurrence of the events ( $\hat{r} = r$ ) and ( $\tilde{m} = m$ ) in simulation with 1000 replications. We make the following observations from Table 1 which contains the results with  $p = 5, 10$  and 20. First, with  $p = 5$  or 10, the relative frequencies for the correct specification for the cointegration rank  $r$  and the number of factors  $m$  are as high as 85% even for the sample size  $n$  as small as 200. When  $n$  increases to 400, those relative frequencies increase to 100%. Secondly, with fixed  $n$  and  $r$  the correct estimation rates for  $m$  increases when dimension  $p$  increases, a phenomenon coined as the ‘‘blessing-of-dimensionality’’. This is consistent with the findings in Lam and Yao (2012) which only dealt with purely stationary processes. Thirdly, the inference on  $r$  tends to be more challenging when  $p$  increases. For example, the relative frequency for correct estimation of  $r(= 2)$ , when  $m = 1$  and  $n = 200$ , decreases from 68.5% to 65.4% with  $p$  increasing from 5 to 10. This is in line with the findings in ZRY. Lastly, we note that the increase in  $p$ ,  $r$  and  $m$  would generally demand a larger  $n$  to maintain the same level of estimation accuracy. This is consistent with our theory that requires  $p = o(n^c)$  for  $c \in (0, 1/2)$ .

Some similar conclusions can be drawn from results reported in Table 2-3. In particular, the

inference on the number of factor (when  $m$  is relatively small compared to  $p$ ) is relatively easy when  $p = 40$  and  $60$ , with a sample size equal to  $800$ . Unreported results for  $n = 200, 400$  also corroborate this conclusion. However, the inference on the cointegration rank is more difficult when  $n$  is small or/and  $r$  is large.

To evaluate the performance of the estimation for both cointegration space and factor cofeature space, we present the boxplots of  $D(\mathcal{M}(\hat{\mathbf{A}}_2), \mathcal{M}(\mathbf{A}_2))$  and that of  $D(\mathcal{M}(\hat{\mathbf{B}}), \mathcal{M}(\mathbf{B}))$  in Figure 1, for a few (selected) combinations of  $p, r$  and  $m$ , with  $n = 400, 800, 1600, 3200$ . The overall profile of the estimation accuracy is similar to those in Tables 1-3. For example, when  $p$  increase, the estimation accuracy of cointegration space becomes worse, while that of factor cofeature space tends to improve. That is, the “curse-of-dimensionality” in inferring cointegration space is coupled with the “blessing-of-dimensionality” in estimating the factor cofeature space. It is further observed that the estimation in general improves as  $n$  increases, which confirms our consistency theory.

Next, we investigate how would the autoregressive coefficient for the process of  $x_{t,2}$ , denoted by  $\rho$  and the error variance of this autoregressive process, denoted by  $\sigma^2$ , affect the performance of the proposed method. To save space, we only report the results for the case with  $p = 60$ ,  $m = 2, 4, 6$ ,  $r = 2, 4$ ,  $\rho = 0.8, 0.93$  and  $\sigma^2 = 4, 8$  in Table 4. It is first observed that as the error variance  $\sigma^2$  increases, the selection for the factor seems to deteriorate. It is also noted that as  $\rho$  increases, the performance of the cointegration rank selection procedure deteriorates, especially when  $\rho$  reaches  $0.93$ . This is the nature of the problem, from which most methods would suffer as noted by a referee. Nevertheless, we observe that the performance of our procedure generally improves as sample size increases.

## 4.2 A Real Data Example

To further illustrate the proposed approach, we apply the proposed error correction factor model (ECFM) to the twelve U.S. Industrial Production (manufacturing nondurable) monthly indices in January 1972 — August 2010, extracted from Stock and Watson (2014)\*, namely, Food, Beverage, Tobacco, Textile mills, Textile product mills, Apparel, Leather and allied product, Paper, Printing and related support activities, Petroleum and coal products, Chemical, Plastics and rubber products. The estimated cointegration rank is  $\hat{r} = 2$ , and the number of factor is  $\tilde{m} = 3$ .

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\*The data are available at <http://www.princeton.edu/~mwatson/>.

Table 1: Relative frequencies ( $\times 100$ ) of the occurrences of events  $\hat{r} = r$  (1st entries in parentheses) and  $\tilde{m} = m$  (2nd entries in parentheses).

	$p = 5$	$n = 100$	$n = 200$	$n = 400$	$n = 800$
$m = 1$	$r = 1$	(92.0, 93.5)	(100, 99.3)	(100, 99.9)	(100, 100)
	$r = 2$	(44.6, 89.3)	(68.5, 96.6)	(83.7, 99.8)	(98.6, 100)
	$p = 10$	$n = 200$	$n = 400$	$n = 800$	$n = 1200$
$m = 1$	$r = 1$	(85.3, 100)	(100, 100)	(100, 100)	(100, 100)
	$r = 2$	(65.4, 100)	(82.0, 100)	(95.4, 100)	(99.6, 100)
$m = 2$	$r = 1$	(86.5, 82.2)	(100, 97.7)	(100, 99.9)	(100, 100)
	$r = 2$	(62.4, 83.4)	(75.1, 97.8)	(94.3, 100)	(98.8, 100)
	$p = 20$	$n = 400$	$n = 800$	$n = 1200$	$n = 1600$
$m = 2$	$r = 2$	(85.5, 99.7)	(92.8, 100)	(96.7, 100)	(98.9, 100)
	$r = 4$	(20.5, 95.0)	(43.3, 99.8)	(68.8, 100)	(86.3, 100)
$m = 4$	$r = 2$	(82.0, 93.2)	(89.5, 99.9)	(93.8, 99.9)	(96.3, 100)

Table 2: Relative frequencies ( $\times 100$ ) of the occurrences of events  $\hat{r} = r$  (1st entries in parentheses) and  $\tilde{m} = m$  (2nd entries in parentheses).

	$p = 40$	$n = 800$	$n = 1200$	$n = 1600$	$n = 2000$
$m = 2$	$r = 2$	(72.8, 100)	(94.7, 100)	(100, 100)	(100, 100)
	$r = 4$	(64.0, 99.9)	(99.5, 100)	(99.3, 100)	(99.7, 100)
	$r = 6$	(86.4, 93.8)	(95.2, 98.9)	(96.2, 99.7)	(97.5, 100)
	$r = 8$	(53.8, 100)	(77.4, 100)	(82.2, 100)	(89.6, 100)
$m = 4$	$r = 2$	(73.3, 100)	(89.5, 100)	(99.9, 100)	(100, 100)
	$r = 4$	(66.8, 99.9)	(99.3, 100)	(99.5, 100)	(99.2, 100)
	$r = 6$	(75.1, 99.5)	(88.3, 100)	(89.5, 100)	(91.0, 100)
	$r = 8$	(27.1, 99.7)	(59.0, 100)	(64.4, 100)	(75.9, 100)
$m = 6$	$r = 2$	(72.7, 99.6)	(86.2, 100)	(99.6, 100)	(100, 100)
	$r = 4$	(69.2, 96.5)	(98.6, 99.4)	(98.3, 100)	(98.4, 100)
	$r = 6$	(65.6, 99.7)	(83.1, 100)	(86.1, 100)	(88.8, 100)
	$r = 8$	(16.9, 98.7)	(41.3, 100)	(50.8, 100)	(62.4, 100)
$m = 8$	$r = 2$	(73.7, 99.9)	(81.1, 100)	(99.8, 100)	(100, 100)
	$r = 4$	(71.0, 89.1)	(98.3, 99.2)	(98.2, 99.9)	(98.0, 100)
	$r = 6$	(60.8, 98.7)	(82.1, 99.9)	(82.1, 100)	(87.0, 100)
	$r = 8$	(12.7, 83.7)	(37.0, 96.5)	(45.3, 98.5)	(52.6, 99.6)

We also fit the data with a vector error correction model (VECM) using Johansen's trace test to determine the cointegration rank  $r$  for each given autoregressive order between 1 and 8, and then using the Akaike Information Criterion (AIC) to select the optimal autoregressive order. The corresponding estimated cointegration rank is also 2. Hence both the fitted models suggest the same cointegration rank 2, while VECM represents the short-run dynamics in terms of a twelve-dimensional vector AR(3) process (with reduced rank 2), and, in contrast, the newly proposed

Table 3: Relative frequencies ( $\times 100$ ) of the occurrences of events  $\hat{r} = r$  (1st entries in parentheses) and  $\tilde{m} = m$  (2nd entries in parentheses).

	$p = 60$	$n = 1200$	$n = 1600$	$n = 2000$	$n = 2400$
$m = 2$	$r = 2$	(20.8, 100)	(34.3, 100)	(97.3, 100)	(100, 100)
	$r = 4$	(16.2, 100)	(87.3, 100)	(100, 100)	(99.9, 100)
	$r = 6$	(63.4, 100)	(99.1, 100)	(99.5, 100)	(99.5, 100)
	$r = 8$	(88.4, 100)	(98.9, 100)	(97.5, 100)	(97.1, 100)
	$r = 10$	(72.0, 100)	(92.4, 100)	(89.7, 100)	(89.6, 100)
$m = 4$	$r = 2$	(19.8, 100)	(23.3, 100)	(94.3, 100)	(99.9, 100)
	$r = 4$	(16.7, 100)	(78.4, 100)	(100, 100)	(100, 100)
	$r = 6$	(59.3, 100)	(97.7, 100)	(99.1, 100)	(98.7, 100)
	$r = 8$	(80.1, 100)	(95.3, 100)	(92.7, 100)	(92.5, 100)
	$r = 10$	(51.0, 100)	(77.8, 100)	(73.4, 100)	(71.5, 100)
$m = 6$	$r = 2$	(20.4, 100)	(29.6, 100)	(86.6, 100)	(99.5, 100)
	$r = 4$	(13.4, 100)	(72.5, 100)	(99.8, 100)	(100, 100)
	$r = 6$	(58.9, 100)	(97.2, 100)	(98.6, 100)	(98.1, 100)
	$r = 8$	(73.3, 100)	(91.7, 100)	(87.0, 100)	(87.0, 100)
	$r = 10$	(29.9, 100)	(62.5, 100)	(59.2, 100)	(57.2, 100)
$m = 8$	$r = 2$	(20.7, 100)	(24.9, 100)	(79.3, 100)	(99.3, 100)
	$r = 4$	(33.2, 100)	(70.1, 100)	(99.5, 100)	(99.7, 100)
	$r = 6$	(59.3, 100)	(95.6, 100)	(98.8, 100)	(98.2, 100)
	$r = 8$	(67.9, 100)	(89.9, 100)	(84.3, 100)	(85.4, 100)
	$r = 10$	(23.7, 99.7)	(54.0, 100)	(50.9, 100)	(51.6, 100)
$m = 10$	$r = 2$	(20.3, 100)	(21.2, 100)	(76.6, 100)	(98.5, 100)
	$r = 4$	(33.8, 100)	(65.8, 100)	(99.4, 100)	(100, 100)
	$r = 6$	(60.0, 100)	(94.7, 100)	(98.7, 100)	(98.3, 100)
	$r = 8$	(61.6, 100)	(87.6, 100)	(84.7, 100)	(85.4, 100)
	$r = 10$	(18.6, 99.9)	(49.5, 100)	(48.0, 100)	(48.2, 100)

ECFM captures this dynamics in a three-dimensional latent factor process, achieving a massive reduction in the number of parameters required as can be seen from (2.1). The difference between the cointegration space estimated by our ECFM and that produced by Johansen's method is computed as

$$D(\mathcal{M}(\hat{\mathbf{A}}_2), \mathcal{M}(\tilde{\mathbf{A}}_2))^2 = 1 - \frac{1}{2} \text{tr}\{\hat{\mathbf{A}}_2 \hat{\mathbf{A}}_2' (\tilde{\mathbf{A}}_2 (\tilde{\mathbf{A}}_2' \tilde{\mathbf{A}}_2)^{-1} \tilde{\mathbf{A}}_2)'\} = 0.0009,$$

where columns of  $\hat{\mathbf{A}}_2$  denote the loadings of the five cointegrated variables identified by our method and those of  $\tilde{\mathbf{A}}_2$  by Johansen's. This suggests that the estimated cointegration spaces by both approaches be effectively equivalent.

We further examine the forecasting performance of the proposed ECFM. To this end, we compare the out-of-sample forecasting performance of our ECFM with those of (i) univariate AR

Figure 1: Boxplot of  $D(\mathcal{M}(\hat{\mathbf{A}}_2), \mathcal{M}(\mathbf{A}_2))$  (left panel) and  $D(\mathcal{M}(\hat{\mathbf{B}}), \mathcal{M}(\mathbf{B}))$  (right panel),  $400 \leq n \leq 3200$

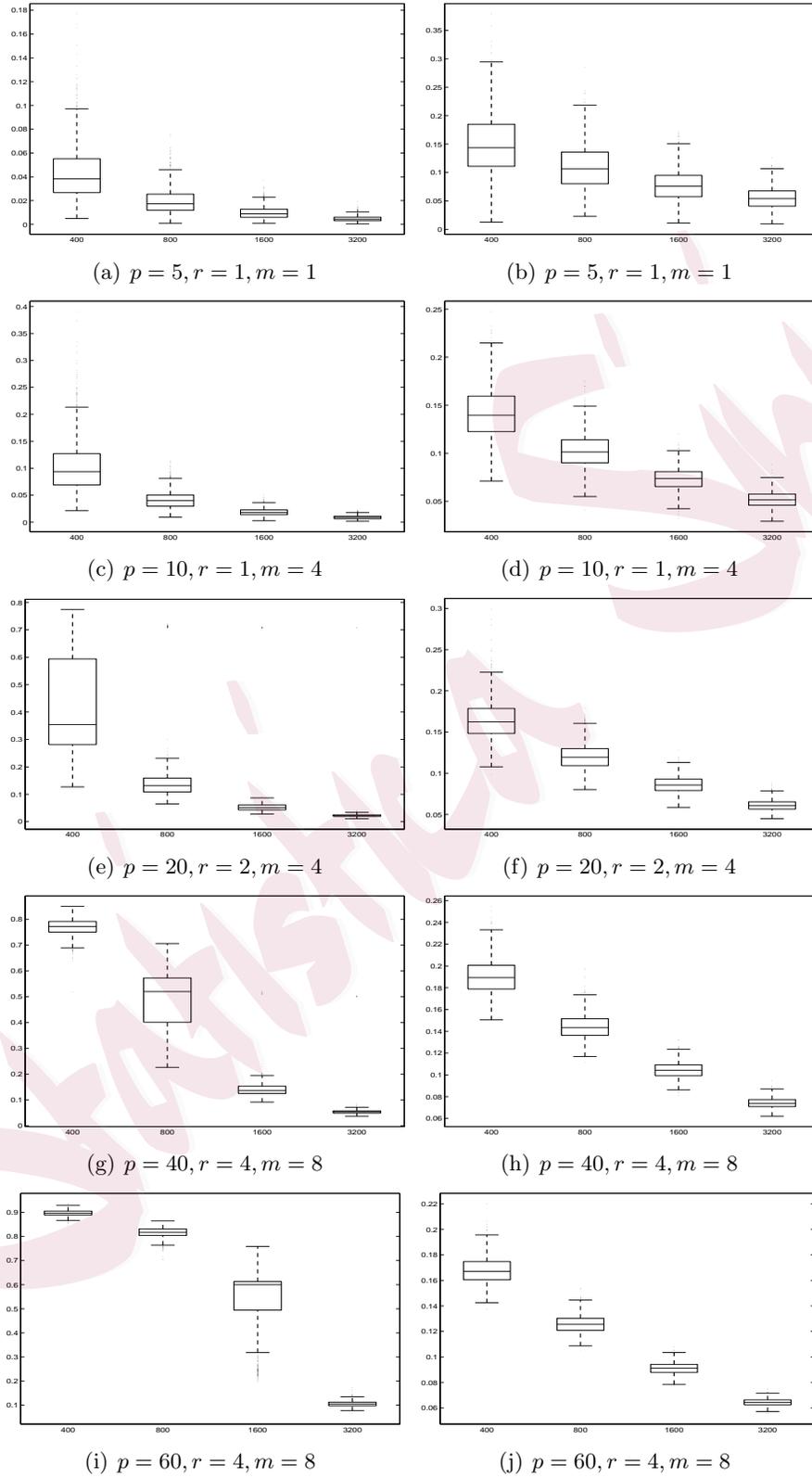


Table 4: Relative frequencies ( $\times 100$ ) of the occurrences of events  $\hat{r} = r$  (1st entries in parentheses) and  $\tilde{m} = m$  (2nd entries in parentheses).

$p = 60$		$n = 1200$		$n = 2400$	
		$\rho = 0.5, \sigma^2 = 4$		$\rho = 0.5, \sigma^2 = 8$	
$m = 2$	$r = 2$	(19.9,100)	(88.9,100)	(22.3,99.7)	(20.7,100)
	$r = 4$	(26.2,100)	(62.3,100)	(25.5,99.8)	(46.1,100)
$m = 4$	$r = 2$	(23.4,100)	(86.8,100)	(21.9,93.9)	(23.3,98.1)
	$r = 4$	(26.4,99.9)	(52.4,100)	(23.8,96.1)	(40.1,99.7)
$m = 6$	$r = 2$	(23.4,100)	(79.9,100)	(25.1,81.9)	(26.0,98.6)
	$r = 4$	(28.2,99.7)	(50.4,100)	(21.9,81.5)	(39.3,99.9)
		$\rho = 0.8, \sigma^2 = 1$		$\rho = 0.93, \sigma^2 = 1$	
$m = 2$	$r = 2$	(21.3,100)	(44.4,100)	(20.4,100)	(40.6,100)
	$r = 4$	(27.0,100)	(89.9,100)	(25.1,100)	(31.0,100)
$m = 4$	$r = 2$	(24.3,100)	(46.5,100)	(22.5,100)	(39.2,100)
	$r = 4$	(24.6,100)	(89.0,100)	(25.0,100)	(30.2,100)
$m = 6$	$r = 2$	(24.8,100)	(49.6,100)	(24.2,100)	(40.7,100)
	$r = 4$	(27.3,100)	(90.1,100)	(23.2,100)	(31.5,100)

(UAR) models with lag length for each component selected by the standard Schwarz criterion, and (ii) the reduced rank VECM with rank and lag length selected simultaneously using the Hannan-Quinn criterion and cointegration rank chosen by PIC (Athanasopoulos et al., 2011). For each of the last 10% of data points, we fit the models using the data upto its previous month and forecast the values using the three fitted models. Following Athanasopoulos et al. (2011), we measure the forecast accuracy using traditional trace of the mean-squared forecast error matrix (TMSFE) and the determinant of the mean-squared forecast error matrix  $|\text{MSFE}|$  at each forecast horizon  $h = 1, \dots, 16$ . We also calculate the generalized forecast error second moment (GFESM), i.e., the determinant of the expected value of the outer product of the vector of stacked forecast errors of all future times up to the horizon of interest, of Clements and Hendry (1993). GFESM is invariant to elementary operations that involve different variables, and also to elementary operations that involve the same variable at different horizons. The forecasting comparison results are presented in Table 5, with the maximum lag lengths for order selection set as 4. Results for maximum lag length set as 8 or 12 are very similar, and therefore are not presented for space consideration.

It is observed from Table 5 that ECFM provide more accurate forecasts than both the reduced rank VECM and the univariate AR models in most horizons. For example, for 12 month ahead forecast, ECFM achieves improvement in TMSFE,  $|\text{MSFE}|$  and GFESM by, respectively, 98.8%, 54.0%, 98.5%, compared to the univariate AR models. In addition, the improvement from

Table 5: Percentage improvement in forecast accuracy measures: US IP indices

Horizon ( $h$ )	ECFM versus VECM			ECFM versus UAR		
	MSFE	TMSFE	GFESM	MSFE	TMSFE	GFESM
1	-1.0	-1.9	-0.9	68.2	-3.5	68.2
4	61.2	2.5	12.4	94.8	32.6	90.8
8	40.6	-0.3	-2.1	97.2	47.5	97.1
12	83.5	2.6	55.4	98.8	54.0	98.5
16	93.9	9.0	83.3	99.1	56.7	99.3

using ECFM over univariate AR models tends to increase as the forecast horizon increases. The improvement from using ECFM over reduced rank VECM is obvious especially for long horizons, while it seems to be insignificant for short horizon predictions. These findings together illustrate the superiority of ECFM in forecasting.

## 5 Conclusions

Traditionally, cointegration inference is built on the correct specification for the short-run dynamic vector auto-regression. It is known that choosing too short a lag length will lead to size distortions, too many lags will leads to dramatic increase of the parameters, especially in high-dimensional systems. To avoid the misspecification and address the cofeature information on the short-run dynamic, in this paper we propose to model the dynamic relationship by dynamic factor model and estimate the vector error correction model (VECM) based on two-step eigenanalysis: the first step is to estimate the long-run coefficients based on the estimated cointegration space (Zhang, Robinson and Yao, 2015); the second step is to estimate the loading matrix and common factors for the short-run dynamic based on principle component analysis. It is shown from asymptotic theory and numerical studies that the proposed procedure perform well. We list below some open questions for future research.

First, in order to apply the result of Zhang, Robinson and Yao (2015), the dimension  $p$  cannot be too large (i.e. not greater than  $O(n^{1/4})$ ). It would be interesting and more challenging to consider the cases with larger  $p$ . Note that the rank of the matrix  $\mathbf{C}$  is  $r$ . One possible solution is to replace the first step in the procedure via sparse shrinkage technique by solving the following

optimal problem:

$$\hat{\mathbf{C}} = \operatorname{argmin}_{\mathbf{C} \in \mathbb{R}^{p \times p}} \left\{ \sum_{t=1}^n \|\nabla \mathbf{y}_t - \mathbf{C} \mathbf{y}_{t-1}\|^2 + \lambda_n \|\mathbf{C}\|_{s_1} \right\}, \quad (5.4)$$

where  $\|\mathbf{C}\|_{s_1} = \sum_{j=1}^p \lambda_j(\mathbf{C})$ , and  $\lambda_1(\mathbf{C}), \lambda_2(\mathbf{C}), \dots, \lambda_p(\mathbf{C})$  denote the singular values of  $\mathbf{C}$ .

Secondly, since the focus of this paper is on prediction and inference for the cofeatures, we can impose the condition that  $\mathbf{C} \mathbf{y}_{t-1}$  and  $\mathbf{f}_t$  are uncorrelated; see the beginning of Section 2.2. However, for some applications the main concern may be on the original  $\mathbf{C}$  and  $\mathbf{f}_t$ . Since  $\mathbf{C} \mathbf{y}_{t-1}$  and  $\mathbf{f}_t$  may be correlated with each other, the inference method proposed in this paper will lead to inconsistent estimators. It would be interesting to consider the inference based on some iterative equations as in Bai (2009), i.e., estimate  $\{\mathbf{C}, \mathbf{F}, \mathbf{B}\}$  via the least squares loss defined as

$$\operatorname{SSR}(\mathbf{C}, \mathbf{F}, \mathbf{B}) = \sum_{t=1}^n (\nabla \mathbf{y}_t - \mathbf{C} \mathbf{y}_{t-1} - \mathbf{B} \mathbf{f}_t)' (\nabla \mathbf{y}_t - \mathbf{C} \mathbf{y}_{t-1} - \mathbf{B} \mathbf{f}_t) \quad (5.5)$$

subject to the constraint  $\mathbf{B}'\mathbf{B} = \mathbf{I}_m$ .

Finally, our approach is relevant only if there exists a low-dimensional factor structure. It is pertinent to develop appropriate tests for the existence of the low-dimensional structure.

## Supplementary Materials

The online supplementary materials contain some useful lemmas and the proofs of the main theorems.

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## References

- Ahn, S.K. and Reinsel, G.C. (1988). Nested Reduced-rank Autoregressive Models for Multiple Time Series. *Journal of the American Statistical Association*, **83**, 849–856.
- Athanasopoulos, G. and Vahid, F. (2008). VARMA versus VAR for macroeconomic forecasting. *Journal of Business & Economic Statistics*, **26**, 237–252.
- Athanasopoulos, G., Guillen, O. T. C., Issler, J. V. and Vahid, F. (2011). Model selection, estimation and forecasting in VAR models with short-run and long-run restrictions. *Journal of Econometrics*, **164**, 116–129.
- Bai, J. (2004). Estimating cross-section common stochastic trends in nonstationary panel data. *Journal of Econometrics*, **122**, 137–183.
- Bai, J. (2009). Panel data models with interactive fixed effects. *Econometrica*, **77**, 1229–1279.
- Bai, J. and Ng, S. (2004). A PANIC attack on unit roots and cointegration. *Econometrica*, **72**, 1127–1177.
- Banerjee, A., Marcellino, M. and Masten, I. (2014a). Forecasting with factor augmented error correction models. *International Journal of Forecasting*, **30**, 589–612.
- Banerjee, A., Marcellino, M. and Masten, I. (2014b). Structural FECM: Cointegration in large-scale structural FAVAR models. Working Paper 9858, CEPR.
- Barigozzi, M., Lippi, M. and Luciani, M. (2016). Dynamic factor models, cointegration, and error correction mechanisms. *FEDS*, 2016-018.
- Barigozzi, M., Lippi M. and Luciani, M. (2016). Non-Stationary Dynamic Factor Models for Large- Datasets. *FEDS*, 2016-024.
- Box, G. and Tiao, G. (1977). A canonical analysis of multiple time series. *Biometrika*, **64**, 355–365.
- Carroll, R., Ruppert, D. and Stefanski, L. (1995). *Measurement Error in Nonlinear Models*. Chapman & Hall, London.
- Chang, J. Y., Guo, B. and Yao, Q. (2015). Segmenting multiple time series by contemporaneous linear transformation. *A manuscript*.
- Chao, J. and Phillips, P. C. B. (1999). Model selection in partially nonstationary vector autoregressive processes with reduced rank structure. *Journal of Econometrics*, **91**, 227–271.
- Clements, M.P. and Hendry, D.F. (1993). On the limitations of comparing mean squared forecast errors (with discussion). *Journal of Forecasting*, **12**, 617–637.

- Engle, R. and Granger, C. W. J. (1987). Cointegration and error correction: representation, estimation and testing. *Econometrica*, **55**, 251–276.
- Engle, R. F., and Kozicki, S. (1993). Testing for Common Features (with comments). *Journal of Business & Economic Statistics*, **11**, 369–395.
- Engle, R. and Yoo, S. (1987). Forecasting and testing in cointegrated systems. *Journal of Econometrics*, **35**, 143–159.
- Fan, J. and Yao, Q. (2015). *The Elements of Financial Econometrics*. Science China Press, Beijing.
- Gonzalo, J. and Pitarakis, J. (1995). Comovements in Large Systems. Working Paper, Department of Economics, Boston University.
- Granger, C. W. J. (1981). Some properties of time series data and their use in econometric model specification. *Journal of Econometrics*, **16**, 121–130.
- Granger, C. W. J. and Weiss, A. A. (1983). Time series analysis of error-correcting models. In: S. Karlln et al. (eds.), *Studies in Econometrics, Time series and Multivariate Analysis*, Academic Press, New York, 255–278.
- Ho, M. S. and Sørensen, B. E. (1996). Finding Cointegration Rank in High Dimensional Systems Using the Johansen Test: An Illustration Using Data Based Monte Carlo Simulations. *Review of Economics and Statistics*, **78**, 726–732.
- Hualde, J. and Robinson, P. (2010). Semiparametric inference in multivariate fractionally cointegrated system. *Journal of Econometrics*, **157**, 492–511.
- Issler, J. V. and Vahid, F. (2001). Common cycles and the importance of transitory shocks to macroeconomic aggregates. *Journal of Monetary Economics*, **47**, 449–475.
- Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive model. *Econometrica*, **59**, 1551–1580.
- Johansen, S. (1995). *Likelihood-Based inference in Cointegrated Vector in Gaussian Vector Autoregressive Model*. Oxford University Press, Oxford.
- Lam, C. and Yao, Q. (2012). Factor modeling for high-dimensional time series: inference for the number of factors. *The Annals of Statistics*, **40**, 694–726.
- Liao, Z. and Phillips, P. C. B. (2015). Automated Estimation of Vector Error Correction Models, *Econometric Theory*, **31**, 581–646.
- Lin, Z. and Lu, C. (1997). *Limit Theory on Mixing Dependent Random Variables*. Kluwer Academic Publishers, New York.

- Lin, J. L. and Tsay, R. S. (1996). Cointegration constraints and forecasting: An empirical examination. *Journal of Applied Econometrics*, **11**, 519–538.
- Peña D. and Poncela P. (2004). Forecasting with nonstationary dynamic factor models. *Journal of Econometrics*, **119**, 291–321.
- Phillips, P. C. B. (1991). Optimal inference in cointegrated systems. *Econometrica*, **59**, 283–306.
- Staudenmayer, J. and Buonaccorsi, J. (2005). Measurement error in linear autoregressive models. *Journal of the American Statistical Association*, **100**, 841–852.
- Stock, J. H. and M. W. Watson (2008). Forecasting in Dynamic Factor Models Subject to Structural Instability, in *The Methodology and Practice of Econometrics, A Festschrift in Honour of Professor David F. Hendry*, Jennifer Castle and Neil Shephard (eds), Oxford: Oxford University Press.
- Vahid, F. and Issler, J. V. (2002). The importance of common cyclical features in VAR analysis: A Monte-Carlo study. *Journal of Econometrics*, **109**, 341–363.
- Zhang, R. M., Robinosn, P. and Yao, Q. (2015). Identifying Cointegration by Eigenanalysis. *A Manuscript*.