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Abstract

Based on a General Dynamic Factor Model with infinite-dimensional factor space, we develop a new estimation and forecasting procedures for conditional covariance matrices in high-dimensional time series. The performance of our approach is evaluated via Monte Carlo experiments, outperforming many alternative methods. The new procedure is used to construct minimum variance portfolios for a high-dimensional panel of assets. The results are shown to achieve better out-of-sample portfolio performance than alternative existing procedures.

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1 Introduction

Volatility forecasting plays an essential role in a variety of economic and financial applications, such as portfolio allocation, risk management, option pricing, hedging strategies, etc.: see Engle (2009), Hlouskova et al. (2009), Aramonte et al. (2013), Becker et al. (2015), Trucíos et al. (2018) and Engle et al. (2019), to quote only a few.

Several multivariate models have been proposed to model and forecast the conditional covariance matrix of a collection of assets; see Bauwens et al. (2006) or de Almeida et al. (2018) for some reviews. Unfortunately, most of multivariate GARCH (MGARCH) type models badly suffer from the so-called "curse of dimensionality" as the number of assets grows, and cannot be implemented in a high-dimensional context. Therefore, alternative procedures have been proposed, such as Fan et al. (2008), Alessi et al. (2009), Matteson and Tsay (2011), Engle and Kelly (2012), Hu and Tsay (2014), Santos and Moura (2014), Li et al. (2016), Pakel et al. (2017), Chang et al. (2018) and Engle et al. (2019), among others.

Dynamic factor models with high-dimensional asymptotics offer a promising alternative in that context; see the surveys by Barhoumi et al. (2014) and Bai and Wang (2016) for details. Factor models are based on the assumption that prices and volatilities of different assets are driven by a small number of latent factors, which account for their co-movements. They have been used by several authors to model and forecast conditional covariance matrices: see Diebold and Nerlove (1989), Harvey et al. (1992), Aguilar and West (2000), Vrontos et al. (2003), Han (2005), Sentana et al. (2008), Aguilar (2009), Alessi et al. (2009), García-Ferrer et al. (2012), Aramonte et al. (2013) and Dovonon (2013), among others. All these contributions are based on a *static* factor-loading scheme[1] (Bai and Ng, 2002; Stock and Watson,

[1] The latent factors are loaded contemporaneously via some loading matrix, so that the dimension of the factor space reduces to the (finite) number of linearly independent factors.

2002a,b)[2] leading to finite-dimensional factor spaces whose main advantage is to allow for estimation methods based on traditional principal components, which are easy to implement and widely used in practice.

However, as pointed out in Forni and Lippi (2011) and Section 1.1 of Forni et al. (2015), the assumption of a static factor-loading scheme considered in that literature is quite restrictive and rules out some very simple and plausible cross-correlation patterns, leading to infinite-dimensional factor spaces. To overcome this issue, Forni et al. (2000) introduced the so-called *generalized* or *general dynamic factor model* (GDFM), in which factors (equivalently, common shocks) are loaded through filters rather than matrices. As shown in Hallin and Lippi (2013), the GDFM actually follows from a representation result which holds, essentially, without placing any restrictions—beyond second-order stationarity and the existence of a spectrum—on the data-generating process.

The role of traditional principal components in the GDFM is taken over by Brillinger's *dynamic principal components*[3] (Brillinger, 1981), and the estimation method proposed by Forni et al. (2000) naturally relies on this concept. Dynamic principal components, however, involve two-sided filters, producing estimators that are inadequate in forecasting problems. Forni and Lippi (2011) and Forni et al. (2015, 2017)[4] therefore developed an alternative estimation method involving only one-sided filters. Moreover, Monte Carlo simulations indicate that, for estimating impulse-response functions and predicting returns, this one-sided approach outperforms the *static* method of Stock and Watson (2002a,b) and Bai and Ng (2002) even when the actual loading scheme is of the static type (see Section 4 in Forni et al. (2017)).

The Forni et al. (2015, 2017) procedure has been successfully used to forecast inflation and financial returns; see Della Marra (2017), Forni et al. (2018) and Gio-

[2]Similar ideas have been developed also in a non-econometric context, see, e.g., Peña and Box (1987), Stoffer (1999), or Pan and Yao (2008).

[3]Hallin et al. (2018) show that those dynamic principal components, based on the factorization of spectral density matrices, inherit, in a time-series context, the optimality properties that make traditional principal components a successful dimension-reduction device in i.i.d. samples.

[4]The assumptions in those three references yield slight variations; in this paper, unless otherwise stated, we refer to the assumptions in Barigozzi and Hallin (2018).

vannelli et al. (2018). It has also been used in the prediction of conditional variances by (Barigozzi and Hallin, 2016, 2017, 2018), but never, as far as we know, in the prediction of conditional covariance matrices and portfolio optimization.[5] This point constitutes the main goal of this paper.

The rest of the paper is organised as follows. Section 2 briefly describes the GDFM and Section 3 introduces our forecasting procedure. Section 4.1 reports a Monte Carlo study of the finite-sample properties of the proposed procedure. In Section 5, we apply the new procedure in the problem of constructing minimum variance portfolios from a large collection of assets. In Sections 4.1 and 5 we also compare the proposed procedure with other methods. Finally, Section 6 presents the main conclusions and discusses some directions for future research.

2 The general dynamic factor model

In this section, we briefly describe the GDFM to be considered throughout, which basically contains as particular cases all other factor models proposed in the econometric and time series literature, along with the regularity assumptions we need for consistency, which are borrowed, essentially, from Barigozzi and Hallin (2018).

Let $\{\mathbf{X}_t := (X_{1t}\ X_{2t} \dots)',\ t \in \mathbb{Z}\}$, be a double-indexed zero-mean second-order stationary stochastic process, where the first index is cross-sectional and typically refers to assets, while t, as usual, stands for time. The GDFM is based on the decomposition

$$X_{it} = \chi_{it} + \xi_{it}, \qquad i \in \mathbb{N}_0, \quad t \in \mathbb{Z} \tag{1}$$

with

$$\chi_{it} = \sum_{j=1}^{q} \sum_{k=0}^{\infty} b_{ijk} u_{jt-k} = \mathbf{b}_i'(L)\mathbf{u}_t \ \text{ and } \ \xi_{it} = \sum_{k=0}^{\infty} d_{ik} v_{it-k} = d_i(L) v_{it}, \tag{2}$$

where the *common components* χ_{it}, the *idiosyncratic components* ξ_{it}, the *common shocks* or *factors* $\mathbf{u}_t := (u_{1t}\ u_{2t}\ \dots\ u_{qt})'$ driving the common components, and the *idiosyncratic shocks* v_{it} driving the idiosyncratic components all are non-observable.

[5]See, however, Alessi et al. (2009) who assume a factor model decomposition with finite-dimensional factor space on te model of Forni et al. (2005 and 2009).

Letting $\mathbf{X}_n := \{X_{it}|i = 1, ..., n, t \in \mathbb{Z}\}$, $\boldsymbol{\chi}_n := \{\chi_{it} \mid i = 1, ..., n,\ t \in \mathbb{Z}\}$, and $\boldsymbol{\xi}_n := \{\xi_{it}|i = 1, ..., n, t \in \mathbb{Z}\}$, equation (2) in vector notation takes the form

$$\mathbf{X}_{nt} = \boldsymbol{\chi}_{nt} + \boldsymbol{\xi}_{nt} = \mathbf{B}_n(L)\mathbf{u}_t, + \mathbf{D}_n(L)\mathbf{v}_{nt}, \quad n \in \mathbb{N}_0, \quad t \in \mathbb{Z} \tag{3}$$

with $\mathbf{B}_n(L) := (\mathbf{b}_1(L)...\mathbf{b}_n(L))'$, $\mathbf{D}_n(L) := (d_1(L)...d_n(L))'$, and $\mathbf{v}_{nt} := (v_{1t} \dots v_{nt})'$.

On the decomposition (1), we assume the following:

(i) the vector process $\mathbf{u}_t$ is a zero-mean q-dimensional second-order white noise process, with full-rank covariance $\boldsymbol{\Gamma}^{\mathbf{u}}$;

(ii) writing $\mathbf{b}_{ik} := (b_{i1k}...b_{iqk})'$ for the $q \times 1$ coefficient of L^k in $\mathbf{b}_i(L)$, there exists a constant $M_1 > 0$ such that $\sum_{k=0}^{\infty} ||\mathbf{b}_{ik}||k^{1/2} \leq M_1$ for all $i \in \mathbb{N}$;

(iii) $\mathbf{v}_{nt}$ is a zero-mean second-order stationary process with positive definite covariance $\boldsymbol{\Gamma}_n^v$; moreover, $\mathrm{E}[v_{it}|v_{is}] = 0$ for all $i \in \mathbb{N}$ and $t > s \in \mathbb{Z}$;

(iv) there exists a constant $C_v > 0$ such that $||\boldsymbol{\Gamma}_n^v||_1 \leq C_v$ for all $n \in \mathbb{N}$, and a constant $M_2 > 0$ such that $\sum_{k=0}^{\infty} |d_{ik}|k^{1/2} \leq M_2$ for all $i \in \mathbb{N}$;

(v) $\mathrm{Cov}(u_{jt}, v_{is}) = 0$ for all $i \in \mathbb{N}$, $j = 1, ..., q$, and t, $s \in \mathbb{Z}$;[6]

(vi) there exists a constant $M_3 > 0$ such that, for all j_1, j_2, j_3, j_4,

$$\sum_{k_1,k_2,k_3 \in \mathbb{Z}} |\mathrm{E}(u_{j_1 t} u_{j_2,t-k_1} u_{j_3,t-k_2} u_{j_4,t-k_3})| \leq M_3,$$

and a constant $M_4 > 0$ such that, for all i_1, i_2, i_3, i_4,

$$\sum_{k_1,k_2,k_3 \in \mathbb{Z}} |\mathrm{E}(v_{i_1 t} v_{i_2,t-k_1} v_{i_3,t-k_2} v_{i_4,t-k_3})| \leq M_4;$$

(vii) for all $i \in \mathbb{N}$, $j = 1, \dots, q$ and $z \in \mathbb{C}$, $b_{ij}(z) = \sum_{k=0}^{\infty} b_{ijk} z^k$ has square-summable coefficients, and is the ratio of two finite-order polynomials in z, $b_{ij}(z) = \gamma_{ij}(z)/\delta_{ij}(z)$, where $\gamma_{ij}(z) = \sum_{k=0}^{S_\gamma} \gamma_{ijk} z^k$ and $\delta_{ij}(z) = \sum_{k=0}^{S_\delta} \delta_{ijk} z^k$, with $\delta_{ij}(0) = 1$, have roots outside the closed unit disk only and no common roots, and the orders S_γ and S_δ are independent of i.[7]

Assumption (iii) is the typical assumption of martingale difference innovations used in the GARCH literature. Assumption (vii) entails the existence of a VAR filtering

[6] This implies that the common and idiosyncratic processes are mutually uncorrelated at all leads and lags.

[7] As a consequence, the common components have rational spectral densities; see Assumption (L2) in Barigozzi and Hallin (2018) for more details.

of $\mathbf{X}_n$ satisfying the assumptions of the static factor model where the common shocks $\mathbf{u}_t$ are loaded contemporaneously (see (4) below).

These assumptions also guarantee the existence of the spectral densities $\mathbf{\Sigma}_n^{\chi}(\theta)$, $\mathbf{\Sigma}_n^{\xi}(\theta)$, and $\mathbf{\Sigma}_n^{X}(\theta) = \mathbf{\Sigma}_n^{\chi}(\theta) + \mathbf{\Sigma}_n^{\xi}(\theta)$, $\theta \in [-\pi, \pi]$, of $\boldsymbol{\chi}_n$, $\boldsymbol{\xi}_n$ and $\mathbf{X}_n$, respectively. Then, let $\lambda_{nj}^{\chi}(\theta)$, $\lambda_{nj}^{\xi}(\theta)$ and $\lambda_{nj}^{X}(\theta)$ be the jth eigenvalues (in decreasing order of magnitude) of $\mathbf{\Sigma}_n^{\chi}(\theta)$, $\mathbf{\Sigma}_n^{\xi}(\theta)$ and $\mathbf{\Sigma}_n^{X}(\theta)$, respectively, satisfying the following assumption.

(viii) there exist a positive integer $\bar{n}$ and continuous functions α_j and β_{j-1} from $[-\pi, \pi]$ to $\mathbb{R}$, $j = 1, \ldots, q$, independent of n, and such that, for all $j = 1, \ldots, q$, and all $n > \bar{n}$, $0 < \beta_{j-1}(\theta) < \alpha_j(\theta) \le \lambda_{nj}^{\chi}(\theta)/n \le \beta_j(\theta) < \infty$, θ-a.e. in $[-\pi, \pi]$, while $\lambda_{n,q+1}^{\chi}(\theta)$ and $\lambda_{n1}^{\xi}(\theta)$ are bounded, uniformly in $\theta \in [-\pi, \pi]$, as $n \to \infty$.

Hence, as $n \to \infty$, the q idiosyncratic dynamic eigenvalues are exploding linearly (the assumption of factor pervasiveness), while all idiosyncratic eigenvalues are bounded (this is the definition of idiosyncrasy).

The main theoretical result behind the one-sided approach of Forni et al. (2015) is the existence of a block-diagonal VAR filtering of the observations turning the GDFM representation (1) into a static one. More precisely, Forni and Lippi (2011) and Forni et al. (2015) show that, for generic values of the coefficients γ_{ijk} and δ_{ijk} (i.e., except for a subset with Lebesgue measure zero in the $(q + 1)(S_\gamma + S_\delta)$-dimensional space of the relevant γ_{ijk} and δ_{ijk} coefficients), any $(q+1)$-dimensional vector $\boldsymbol{\chi}_t^{i_1 \ldots i_{q+1}} := (\chi_{i_1 t}, \ldots, \chi_{i_{q+1} t})'$ with $i_1 < \ldots < i_{q+1}$ admits a VAR representation of the form $\boldsymbol{A}(L)^{i_1 \ldots i_{q+1}} \boldsymbol{\chi}_t^{i_1 \ldots i_{q+1}} = \mathbf{R}^{i_1 \ldots i_{q+1}} \mathbf{u}_t$,[8] where $\boldsymbol{A}(L)^{i_1 \ldots i_{q+1}}$ has degree $S \le q S_\gamma + q^2 S_\delta$ and the $(q+1) \times q$ matrix $\mathbf{R}^{i_1 \ldots i_{q+1}}$ is of rank q. It follows that *generically*, for any $n = m(q + 1)$, partitioning $\boldsymbol{\chi}_{nt} = (\chi_{1t}, \ldots, \chi_{nt})'$ into m subvectors of dimension $(q + 1)$, $\boldsymbol{\chi}_{nt}$ admits a block-VAR representation of the form

$$\mathbf{A}_n(L)\boldsymbol{\chi}_{nt} = \begin{bmatrix} \mathbf{A}^1(L) & 0 & \ldots & 0 \\ 0 & \mathbf{A}^2(L) & \ldots & 0 \\ \vdots & \vdots & \ddots & \\ 0 & 0 & \ldots & \mathbf{A}^m(L) \end{bmatrix} \boldsymbol{\chi}_{nt} = \begin{bmatrix} \mathbf{R}^1 \\ \mathbf{R}^2 \\ \vdots \\ \mathbf{R}^m \end{bmatrix} \mathbf{u}_t, \quad t \in \mathbb{Z}. \tag{4}$$

[8]See Assumption (L4) in Barigozzi and Hallin (2018) for more details about this VAR representation.

Hence, for $\mathbf{X}_{nt} = (X_{1t}, \ldots, X_{nt})'$, we have

$$\mathbf{A}_n(L)\mathbf{X}_{nt} = \mathbf{A}_n(L)\boldsymbol{\chi}_{nt} + \mathbf{A}_n(L)\boldsymbol{\xi}_{nt} = \mathbf{R}_n\mathbf{u}_t + \boldsymbol{\epsilon}_{nt}, \quad t \in \mathbb{Z} \tag{5}$$

with $\mathbf{R}_n = \left[\mathbf{R}^{1\prime}\,\mathbf{R}^{2\prime}\,\ldots\,\mathbf{R}^{m\prime}\right]'$ and $\boldsymbol{\epsilon}_{nt} = \mathbf{A}_n(L)\boldsymbol{\xi}_{nt}$, where it can be shown that the process $\boldsymbol{\epsilon}_t := \{(\epsilon_{1t}\ \epsilon_{2t}\ldots)',\ t \in \mathbb{Z}\}$ is still idiosyncratic. In other words, using obvious notation

$$\mathbf{A}(L) := \begin{bmatrix} \mathbf{A}^1(L) & 0 & \ldots & 0 & \ldots \\ 0 & \mathbf{A}^2(L) & \ldots & 0 & \ldots \\ \vdots & \vdots & \ddots & & \vdots \\ 0 & 0 & \ldots & \mathbf{A}^m(L) & \ldots \\ \vdots & \vdots & \ldots & \ldots & \ddots \end{bmatrix} \quad \text{and} \quad \mathbf{R} := \begin{bmatrix} \mathbf{R}^1 \\ \mathbf{R}^2 \\ \vdots \\ \mathbf{R}^m \\ \vdots \end{bmatrix}, \tag{6}$$

the filtered process $\mathbf{Y}_t := \mathbf{A}(L)\mathbf{X}_t$ admits a *static* factor model representation

$$\mathbf{Y}_t = \mathbf{R}\mathbf{u}_t + \boldsymbol{\epsilon}_t, \quad t \in \mathbb{Z} \tag{7}$$

with q-dimensional factor space spanned by $\mathbf{u}_t$. While $\mathbf{R}$ and $\mathbf{u}_t$ are not individually identified, the product $\mathbf{R}\mathbf{u}_t$ is.

The static representation (7), under assumptions *(i)-(ix)*, holds *generically.* Assuming that it holds for the panel under study thus is not a strong requirement; we nevertheless need to make it an assumption:

(ix) For all $n^* \geq q+1$, letting $n = \lfloor n^*/(q+1)\rfloor(q+1)$, there exist block-diagonal filters $\mathbf{A}_n(L)$ and $n \times q$ matrices $\mathbf{R}_n$ such that (5) holds, irrespective of the cross-sectional ordering.

Assumptions *(i)-(ix)* are the main assumptions in Barigozzi and Hallin (2018); on top of these, they also require two less important and more technical ones (Assumptions (L4) and (L5), respectively), which we do not reproduce here. Under those assumptions, Barigozzi and Hallin (2018) show that a consistent reconstruction, based on $\mathbf{X}_t$, $\mathbf{X}_{t-1}$, ..., of the unobserved $\boldsymbol{\chi}_t$ and $\boldsymbol{\xi}_t$ is possible. It follows that $\boldsymbol{\chi}_t$ and $\boldsymbol{\xi}_t$ are $\mathcal{F}_t$-measurable, where $\mathcal{F}_t$ denotes the σ-field generated by $\mathbf{X}_t, \mathbf{X}_{t-1}, \ldots$ It is worth noting that, reinforcing the same assumptions (e.g., assuming that $\mathbf{u}_t$ and $\mathbf{v}_{nt}$ are jointly i.i.d., which rules out GARCH-type behaviors), Forni et al. (2017) derive estimators for (1)-(2) and provide a complete asymptotic analysis for

the same. On the other hand, Barigozzi and Hallin (2018) do not require i.i.d.ness and, under assumptions that include *(i)-(ix)*, provide consistency and consistency rates for the Forni et al. (2017) estimators. Finally, we assume the following.

(x) The common shocks $\mathbf{u}_t$ and the idiosyncratic shocks v_{it} are stable by aggregation MGARCH and univariate GARCH processes, respectively, and satisfy the conditions for consistent QMLE estimation.

The assumption that the MGARCH driving the common shocks is stable by aggregation is motivated by the fact that $\mathbf{u}_t$ is not fully identifiable (see the remark after (7)): under Assumption *(x)*, any linear transform $\mathbf{R}\mathbf{u}_t$ is driven by a MGARCH model of the same type as $\mathbf{u}_t$ itself. Examples of stable by aggregation MGARCH models are the full VECH (Bollerslev et al., 1988) and full BEKK (Engle and Kroner, 1995) models, which moreover can be consistently estimated via QMLE methods: see Theorems 11.2 and 11.4 in Francq and Zakoian (2010).

3 Predicting the conditional covariance matrix

We present a procedure to predict one-step ahead conditional covariance matrices,[9] i.e, to estimate the conditional covariance matrix $\mathrm{V}(\mathbf{X}_t|\mathcal{F}_{t-1})$ of the observable process $\mathbf{X}_t$. Section 3.1 provides a theoretical expression for that conditional covariance, and Section 3.2 introduces the estimation procedure.

3.1 The conditional covariance matrix

We start with a theoretical expression for the conditional covariance matrix of $\mathbf{X}_t$ in terms of the static representation (7).

Proposition 1. *Let Assumptions (i)-(ix) of Section 2 hold—ensuring the existence of the static representation* (7). *Assume moreover that $\boldsymbol{u}_t$ and $\boldsymbol{\xi}_t$, conditional on $\mathcal{F}_{t-1}$, are uncorrelated at all leads and lags. Then, the covariance matrix of $\boldsymbol{X}_t$*

[9] The terminology (conditional) covariance *matrix* is used here with a slight abuse: by $\mathrm{V}(\mathbf{X}_t|\mathcal{F}_{t-1})$ we mean the infinite array with (i,j)-element the (conditional) covariance of X_{it} and X_{jt}, $(i,j) \in \mathbb{N}^2$. The same notation $\mathrm{V}(\,.\,|\mathcal{F}_{t-1})$, and the notation $\mathrm{Cov}(\,.,\,.\,|\mathcal{F}_{t-1})$ are used in an obvious fashion for other processes.

conditional on $\mathcal{F}_{t-1}$ *is*

$$\mathrm{V}(\mathbf{X}_t|\mathcal{F}_{t-1}) = \mathbf{R}\mathrm{V}(\mathbf{u}_t|\mathcal{F}_{t-1})\mathbf{R}' + \mathrm{V}(\boldsymbol{\xi}_t|\mathcal{F}_{t-1}). \tag{8}$$

Proof. From (7), we have that

$$\begin{aligned}
\mathrm{V}(\mathbf{Y}_t|\mathcal{F}_{t-1}) &= \mathrm{V}(\mathbf{R}\mathbf{u}_t + \boldsymbol{\epsilon}_t|\mathcal{F}_{t-1}) \\
&= \mathbf{R}\mathrm{V}(\mathbf{u}_t|\mathcal{F}_{t-1})\mathbf{R}' + \mathrm{V}(\boldsymbol{\epsilon}_t|\mathcal{F}_{t-1}) + \mathrm{Cov}(\mathbf{R}\mathbf{u}_\mathrm{t}, \boldsymbol{\epsilon}_\mathrm{t}|\mathcal{F}_{\mathrm{t}-1}) \\
&\qquad + \mathrm{Cov}(\boldsymbol{\epsilon}_\mathrm{t}, \mathbf{R}\mathbf{u}_\mathrm{t}|\mathcal{F}_{\mathrm{t}-1}), \quad \mathrm{t} \in \mathbb{Z}.
\end{aligned} \tag{9}$$

Without loss of generality we can assume that all VAR filters $\mathbf{A}^k(L)$ in (5) are of the form $\mathbf{A}^k(L) = \mathbf{I}_{q+1} - \boldsymbol{\phi}_1^k L - \cdots - \boldsymbol{\phi}_S^k L^S$ (with $\boldsymbol{\phi}_S^k \neq \mathbf{0}$ for at least one k). Consequently, $\mathbf{A}(L)$ can be written as $\mathbf{A}(L) = \mathbf{I} - \mathbf{\Phi}_1 L - \cdots - \mathbf{\Phi}_S L^S$. Then, it is easy to check that

$$\begin{aligned}
\mathrm{V}(\boldsymbol{\epsilon}_t|\mathcal{F}_{t-1}) &= \mathrm{V}(\mathbf{A}(L)\boldsymbol{\xi}_t|\mathcal{F}_{t-1}) = \mathrm{V}\left(\left[\mathbf{I} - \mathbf{\Phi}_1 L - \cdots - \mathbf{\Phi}_S L^S\right]\boldsymbol{\xi}_t|\mathcal{F}_{t-1}\right) \\
&= \mathrm{V}(\boldsymbol{\xi}_t|\mathcal{F}_{t-1}),
\end{aligned} \tag{10}$$

since $\boldsymbol{\xi}_{t-k}$ is $\mathcal{F}_{t-1}$-measurable for $k \geq 1$.

Similarly, we have

$$\mathrm{V}(\mathbf{Y}_t|\mathcal{F}_{t-1}) = \mathrm{V}(\mathbf{A}(L)\mathbf{X}_t|\mathcal{F}_{t-1}) = \mathrm{V}(\mathbf{X}_t|\mathcal{F}_{t-1}). \tag{11}$$

Moreover, since $\mathbf{u}_t$ and $\boldsymbol{\xi}_t$ are conditionally uncorrelated, both $\mathrm{Cov}(\mathbf{R}\mathbf{u}_\mathrm{t}, \boldsymbol{\epsilon}_\mathrm{t}|\mathcal{F}_{\mathrm{t}-1})$ and $\mathrm{Cov}(\boldsymbol{\epsilon}_\mathrm{t}, \mathbf{R}\mathbf{u}_\mathrm{t}|\mathcal{F}_{\mathrm{t}-1})$ in (9) equal zero. Whence,

$$\mathrm{Cov}(\mathbf{R}\mathbf{u}_\mathrm{t}, \boldsymbol{\epsilon}_\mathrm{t}|\mathcal{F}_{\mathrm{t}-1}) = \mathrm{Cov}(\mathbf{R}\mathbf{u}_\mathrm{t}, \mathbf{A}(\mathrm{L})\boldsymbol{\xi}_\mathrm{t}|\mathcal{F}_{\mathrm{t}-1}) = \mathbf{R}\mathrm{Cov}(\mathbf{u}_\mathrm{t}, \mathbf{A}(\mathrm{L})\boldsymbol{\xi}_\mathrm{t}|\mathcal{F}_{\mathrm{t}-1}).$$

Now,

$$\begin{aligned}
&\mathrm{Cov}(\mathbf{u}_\mathrm{t}, \mathbf{A}(\mathrm{L})\boldsymbol{\xi}_\mathrm{t}|\mathcal{F}_{\mathrm{t}-1}) = \mathrm{Cov}(\mathbf{u}_\mathrm{t}, \left[\mathrm{I} - \Phi_1\mathrm{L} - ... - \Phi_\mathrm{S}\mathrm{L}^\mathrm{S}\right]\boldsymbol{\xi}_\mathrm{t}|\mathcal{F}_{\mathrm{t}-1}) \\
&\quad = \mathrm{E}(\mathbf{u}_t\left[\boldsymbol{\xi}_t - \mathbf{\Phi}_1\boldsymbol{\xi}_{t-1} - ... - \mathbf{\Phi}_S\boldsymbol{\xi}_{t-S}\right]'|\mathcal{F}_{t-1}) \\
&\qquad - \mathrm{E}(\mathbf{u}_t|\mathcal{F}_{t-1})\mathrm{E}(\left[\boldsymbol{\xi}_t - \mathbf{\Phi}_1\boldsymbol{\xi}_{t-1} - ... - \mathbf{\Phi}_S\boldsymbol{\xi}_{t-S}\right]'|\mathcal{F}_{t-1}) \\
&\quad = \mathrm{E}(\mathbf{u}_t\boldsymbol{\xi}_t'|\mathcal{F}_{t-1}) \\
&\qquad - \mathrm{E}(\mathbf{u}_t|\mathcal{F}_{t-1})\mathrm{E}(\boldsymbol{\xi}_t'|\mathcal{F}_{t-1}) - \underbrace{\left[\mathrm{E}(\mathbf{u}_t\boldsymbol{\xi}_{t-1}'\mathbf{\Phi}_1'|\mathcal{F}_{t-1}) - \mathrm{E}(\mathbf{u}_t|\mathcal{F}_{t-1})\mathrm{E}(\boldsymbol{\xi}_{t-1}'\mathbf{\Phi}_1'|\mathcal{F}_{t-1})\right]}_{\mathbf{0}} \\
&\qquad\qquad - \ldots - \underbrace{\left[\mathrm{E}(\mathbf{u}_t\boldsymbol{\xi}_{t-S}'\mathbf{\Phi}_S'|\mathcal{F}_{t-1}) - \mathrm{E}(\mathbf{u}_t|\mathcal{F}_{t-1})\mathrm{E}(\boldsymbol{\xi}_{t-S}'\mathbf{\Phi}_S'|\mathcal{F}_{t-1})\right]}_{\mathbf{0}} \\
&\quad = \mathrm{E}(\mathbf{u}_t\boldsymbol{\xi}_t'|\mathcal{F}_{t-1}) - \mathrm{E}(\mathbf{u}_t|\mathcal{F}_{t-1})\mathrm{E}(\boldsymbol{\xi}_t'|\mathcal{F}_{t-1}) = \mathrm{Cov}(\mathbf{u}_t\boldsymbol{\xi}_t'|\mathcal{F}_{t-1}) = \mathbf{0}
\end{aligned}$$

since $\text{Cov}(\mathbf{u}_t \boldsymbol{\xi}'_{t+k} | \mathcal{F}_{t-1}) = \mathbf{0}$ for any k. It then follows from (8)-(11), along with the fact that $\text{Cov}(\boldsymbol{\epsilon}_\text{t}, \mathbf{R}\mathbf{u}_\text{t} | \mathcal{F}_{\text{t}-1}) = 0$, that

$$\text{V}(\mathbf{X}_t | \mathcal{F}_{t-1}) = \text{V}(\mathbf{Y}_t | \mathcal{F}_{t-1}) = \mathbf{R}\text{V}(\mathbf{u}_t | \mathcal{F}_{t-1})\mathbf{R}' + \text{V}(\boldsymbol{\xi}_t | \mathcal{F}_{t-1}),$$

as was to be proved. □

3.2 Estimation

It follows from Proposition 1 that, if $\text{V}(\mathbf{X}_t | \mathcal{F}_{t-1})$ is to be estimated at time $(t-1)$, assumptions have to be made on the dynamics of $\text{V}(\mathbf{u}_t | \mathcal{F}_{t-1})$ and $\text{V}(\boldsymbol{\xi}_t | \mathcal{F}_{t-1})$.

As in Alessi et al. (2009) and Aramonte et al. (2013), we therefore assume that the conditional covariance matrices of the common shocks can be modelled as some q-dimensional MGARCH process. Since q is typically small, this approach escapes the curse of dimensionality. As for the idiosyncratic conditional covariance matrix $\text{V}(\boldsymbol{\xi}_t | \mathcal{F}_{t-1})$, since idiosyncratic cross-correlations are small, it can be approximated by a diagonal matrix where each diagonal element (each marginal conditional variance) is modelled by a univariate GARCH-type model—in the sequel, we use GARCH(1,1) models. In both cases, the MGARCH and the n GARCH(1,1) models are estimated by Gaussian quasi-maximum likelihood (QMLE) (we refer to Francq and Zakoian (2010) for sufficient consistency conditions).

In practice, the actual number of observed series is large, but finite: denote it by N. The estimation of $\text{V}(\mathbf{X}_t | \mathcal{F}_{t-1})$ proceeds as follows.

- **Step 1.** Determine the number q of common shocks, for instance via the Hallin and Liška (2007) criterion.
- **Step 2.** Randomly reorder the N observed series.
- **Step 3.** Compute a consistent[10] estimator

$$\widehat{\boldsymbol{\Sigma}}^X_{NT}(\theta) = \frac{1}{2\pi} \sum_{k=-M_T}^{M_T} e^{-ik\theta} K\left(\frac{k}{B_T}\right) \widehat{\boldsymbol{\Gamma}}^X_k$$

[10]Consistency requires conditions on K, M_T and B_T, for which again we refer to Barigozzi and Hallin (2018).

of the $N \times N$ spectral density matrix of the $\mathbf{X}_t$'s, where $K(\cdot)$ is a kernel function, M_T a truncation parameter, B_T the bandwidth, and $\widehat{\mathbf{\Gamma}}_k^X$ the sample lag-k cross-covariance matrix computed from the observed $N \times T$ panel of $\mathbf{X}_t$ values.

- **Step 4.** Collecting the q normalized column eigenvectors associated with $\widehat{\mathbf{\Sigma}}_{NT}^X(\theta)$'s q largest eigenvalues into the $N \times q$ matrix $\widehat{P}_{NT}^X(\theta)$ (with complex conjugate $\widehat{P}_{NT}^{X*}$) and the corresponding eigenvalues into the $q \times q$ diagonal matrix $\widehat{\mathbf{\Lambda}}_{NT}^X(\theta_h)$, compute
$$\widehat{\mathbf{\Sigma}}_{NT}^{\chi}(\theta) := \widehat{P}_{NT}^X(\theta)\widehat{\mathbf{\Lambda}}_{NT}^X(\theta)\widehat{P}_{NT}^{X*}(\theta)$$
as an estimator of the spectral density matrix of the $\boldsymbol{\chi}_t$'s.

- **Step 5.** Let $N_* := m(q+1)$ with $m := \left\lceil \frac{N}{q+1} \right\rceil$. Dropping the last $N - m(q+1)$ series, denote by $\widehat{\mathbf{\Sigma}}_{N_*T}^{\chi}(\theta)$ the $N_* \times N_*$ spectral density matrix corresponding to the remaining N_* series[11].

- **Step 6.** By inverse Fourier transform of $\widehat{\mathbf{\Sigma}}_{N_*T}^{\chi}(\theta)$, compute the estimated autocovariance matrices $\widehat{\mathbf{\Gamma}}_k^{\chi}$ of the m $(q+1)$-dimensional sub-vectors $\boldsymbol{\chi}_t^k = (\chi_{(k-1)(q+1)+1,t} \cdots \chi_{k(q+1),t})'$, $k = 1, ..., m$. Then, from the latter, obtain, via Akaike order identification and Yule-Walker equations, estimators $\hat{\mathbf{A}}^k(L)$ of the m VAR filters $\mathbf{A}^k(L)$; stacking them into a block-diagonal matrix $\hat{\mathbf{A}}(L)$, compute the estimates $\widehat{\mathbf{Y}}_t := \hat{\mathbf{A}}(L)\mathbf{X}_t$.

- **Step 7.** Obtain the estimates $\widehat{\mathbf{Ru}}_t$ of $\mathbf{Ru}_t$ by computing the first q standard principal components of $\widehat{\mathbf{Y}}_t$; inverting[12] the block-diagonal filters $\hat{\mathbf{A}}(L)$ then using appropriate identification constraints, we obtain the identified quantities $\widehat{\mathbf{R}}$ and $\widehat{\mathbf{u}}_t$, and the corresponding estimates of the impulse-response function $\widehat{\mathbf{B}}_n = [\hat{\mathbf{A}}(L)]^{-1}\widehat{\mathbf{R}}$.

Following Forni et al. (2017) we chose a Cholesky identification scheme to obtain the identification of $\widehat{\mathbf{R}}$ and $\widehat{\mathbf{u}}_t$ (see Section 4.1 of Forni et al. (2017) for more details)—other choices are possible, though.

[11] For the sake of simplicity we keep the same notation for the N_* reordered observed series.

[12] The inverse of $\hat{\mathbf{A}}(L)$ being the block-diagonal filter with $(q+1)\times(q+1)$ diagonal blocks $[\hat{\mathbf{A}}^k(L)]^{-1}$ where q is small; this inversion thus is easily performed.

Steps 1-7 are those described in Forni et al. (2015, 2017) and Barigozzi and Hallin (2018), where we refer to for details. The resulting estimator $\widehat{\boldsymbol{\chi}}_t$, however, depends on the ordering of the panel obtained at Step 2: that ordering indeed determines which elements of $\widehat{\boldsymbol{\Sigma}}^{\chi}_{NT}(\theta)$ are kept in $\widehat{\boldsymbol{\Sigma}}^{\chi}_{N_*T}(\theta)$ and belong to the diagonal blocks of $\widehat{\boldsymbol{\Sigma}}^{\chi}_{N_*T}(\theta)$. Forni et al. (2017) and Barigozzi and Hallin (2018) explain how to deal with this by iterating Steps 2-7 (going back to Step 2, choosing a new random permutation, hence a new N_*-dimensional subpanel, etc.) until numerical stabilization of the averaged (over the permutations) $\widehat{\boldsymbol{\chi}}_t$ values; this typically takes place after few iterations[13].

- **Step 8.** Iterate Steps 2 through 7; average (after obvious reordering of the cross-section) the resulting estimates $\widehat{\mathbf{R}}$, $\widehat{\mathbf{u}}_t$ and $\widehat{\mathbf{B}}_n$. Denote, for the sake of simplicity, the final estimates also by $\widehat{\mathbf{R}}$, $\widehat{\mathbf{u}}_t$ and $\widehat{\mathbf{B}}_n$. Let $\widehat{\boldsymbol{\chi}}_t := \widehat{\mathbf{B}}_n\widehat{\mathbf{u}}_t$ and $\widehat{\boldsymbol{\xi}}_t := \mathbf{X}_t - \widehat{\boldsymbol{\chi}}_t$.

The procedure described so far is the one that has been used in Della Marra (2017), Forni et al. (2018), and Giovannelli et al. (2018) in their forecasting of inflation and financial returns. In order to estimate conditional covariance matrices, we will now exploit the MGARCH and GARCH features of Assumption *(x)*. Thanks to the assumption of stability under aggregation, the choice of identification constraints has no impact, and VECH or BEKK QMLEs can be computed from the $\widehat{\mathbf{u}}_t$'s obtained in Step 8. We then proceed with the following final steps.

- **Step 9a.** Run, over the q-dimensional T-tuple $\widehat{\mathbf{u}}_1, \ldots, \widehat{\mathbf{u}}_T$, a QML estimation procedure for the parameters of the MGARCH model of Assumption *(x)*; this yields an estimator $\widehat{\mathrm{V}}(\mathbf{u}_t|\mathcal{F}_{t-1})$ of $\mathrm{V}(\mathbf{u}_t|\mathcal{F}_{t-1})$.

- **Step 9b.** Similarly run, over each of the N univariate T-tuples $\widehat{\boldsymbol{\xi}}_1, \ldots, \widehat{\boldsymbol{\xi}}_T$, a GARCH QML estimation procedure. This yields N estimators $\widehat{\mathrm{v}}(\xi_{it}|\mathcal{F}^{\xi_i}_{t-1})$ of the variances $\mathrm{v}(\xi_{it}|\mathcal{F}^{\xi_i}_{t-1})$ of the ξ_{it}'s conditional on their past values; the $N \times N$ diagonal matrix $\widehat{\mathrm{V}}(\boldsymbol{\xi}_t|\mathcal{F}_{t-1})$ with diagonal entries $\widehat{\mathrm{v}}(\xi_{it}|\mathcal{F}^{\xi_i}_{t-1})$ is our estimator of $\mathrm{V}(\boldsymbol{\xi}_t|\mathcal{F}_{t-1})$.

[13] Averaging, of course, is performed after rearrangement of the cross-sectional items in the original ordering.

Our estimator $\widehat{\mathrm{V}}(\mathbf{X}_t|\mathcal{F}_{t-1})$ finally is defined as

$$\widehat{\mathrm{V}}(\mathbf{X}_t|\mathcal{F}_{t-1}) := \widehat{\mathbf{R}}\widehat{\mathrm{V}}(\mathbf{u}_t|\mathcal{F}_{t-1})\widehat{\mathbf{R}}' + \widehat{\mathrm{V}}(\boldsymbol{\xi}_t|\mathcal{F}_{t-1}). \tag{12}$$

The following proposition establishes its consistency properties.

Proposition 2. *Assume that $B_T = o(\sqrt{T})$ and $M_T = o(\sqrt{T})$. Under Assumptions (i)-(x) and Assumptions (L4) and (L5) in Barigozzi and Hallin (2018), we have*

$$\widehat{\mathrm{V}}(\mathbf{X}_t|\mathcal{F}_{t-1}) - \mathrm{V}(\mathbf{X}_t|\mathcal{F}_{t-1}) = o_{\mathrm{P}}(1) \tag{13}$$

for any $t \in \mathbb{Z}$ as $n, T \to \infty$ with $n = O(T^c)$ for some finite $c > 0$.

Proof. It follows from Proposition 1 in Barigozzi and Hallin (2018) that, under the assumptions made, letting $\rho_{nT} := \max\left(B_T/\sqrt{T}, 1/B_T, 1/\sqrt{n}\right)$,

$$\frac{1}{\sqrt{n}}\|\widehat{\mathbf{R}} - \mathbf{RJ}\| = \mathrm{O_P}(\rho_{\mathrm{nT}}), \quad \text{and} \quad \max_{\mathrm{t}=1,\ldots,\mathrm{T}} \|\hat{\mathbf{u}}_{\mathrm{t}} - \mathbf{J}\mathbf{u}_{\mathrm{t}}\| = \mathrm{O_P}(\rho_{\mathrm{nT}} \log \mathrm{T}),$$

for some $q \times q$ diagonal matrix $\mathbf{J}$ with entries ± 1, and

$$\max_{1\leq i\leq n} \max_{1\leq t\leq T} |\widehat{\xi}_{it} - \xi_{it}| = O_{\mathrm{P}}(\rho_{nT} \log \mathrm{T}).$$

Consequently, $\widehat{\mathbf{R}} - \mathbf{RJ}$, $\hat{\mathbf{u}}_t - \mathbf{J}\mathbf{u}_t$ and $\widehat{\boldsymbol{\xi}}_t - \boldsymbol{\xi}_t$ all are $o_{\mathrm{P}}(1)$. The same "two-step estimator" arguments as in Proposition 4 of Alessi et al. (2009) thus apply: since $\hat{\mathbf{u}}_t$ and $\widehat{\xi}_{it}$ consistently estimate $\mathbf{u}_t$ and ξ_{it} in "the first step", computing in "the second step" a maximum likelihood estimator from $\hat{\mathbf{u}}_t$ and $\widehat{\xi}_{it}$ is asymptotically equivalent to computing it from the actual values $\mathbf{u}_t$ and $\boldsymbol{\xi}_t$, and thus leads to consistent estimates of $\mathrm{V}(\mathbf{J}\mathbf{u}_t|\mathcal{F}_{t-1})$ and $\mathrm{V}(\boldsymbol{\xi}_t|\mathcal{F}_{t-1})$, respectively. Now,

$$\mathbf{RJ}\mathrm{V}(\mathbf{J}\mathbf{u}_t|\mathcal{F}_{t-1})\mathbf{J}'\mathbf{R}' = \mathbf{RJJ}\mathrm{V}(\mathbf{u}_t|\mathcal{F}_{t-1})\mathbf{JJR}' = \mathbf{R}\mathrm{V}(\mathbf{u}_t|\mathcal{F}_{t-1})\mathbf{R}',$$

so that

$$\widehat{\mathbf{R}}\widehat{\mathrm{V}}(\mathbf{u}_t|\mathcal{F}_{t-1})\widehat{\mathbf{R}}' + \widehat{\mathrm{V}}(\boldsymbol{\xi}_t|\mathcal{F}_{t-1}) - \mathbf{RJ}\mathrm{V}(\mathbf{J}\mathbf{u}_t|\mathcal{F}_{t-1})\mathbf{J}'\mathbf{R}' - \mathrm{V}(\boldsymbol{\xi}_t|\mathcal{F}_{t-1}) = o_{\mathrm{P}}(1)$$

implies

$$\widehat{\mathbf{R}}\widehat{\mathrm{V}}(\mathbf{u}_t|\mathcal{F}_{t-1})\widehat{\mathbf{R}}' + \widehat{\mathrm{V}}(\boldsymbol{\xi}_t|\mathcal{F}_{t-1}) - \mathrm{V}(\mathbf{X}_t|\mathcal{F}_{t-1}) = o_{\mathrm{P}}(1),$$

as was to be proved. $\square$

In practice, VECH and BEKK QMLEs, however, are numerically quite unstable, and typically strongly depend on the initial values considered in the numerical solution of the likelihood equations. This is a well-documented fact; see, for instance, Lien et al. (2002) and Asai (2015). Rather than VECH or BEKK, we therefore compute DCC QMLEs which are known to be quite robust to missespecification; see Chang et al. (2011), Chevallier (2012), Laurent et al. (2012), Amendola and Candila (2017), or de Almeida et al. (2018). Our Monte Carlo experiments (see Section 4) confirm that, even though the actual data-generating process is BEKK, misspecified DCC QMLEs outperform the correctly specified full BEKK ones.

4 Finite-sample performances

4.1 Monte Carlo experiments

In this section, we investigate the finite-sample performance of the proposed procedure through Monte Carlo simulations.

Simulations were performed from four data generating processes (DGPs). The first two DGPs are static factor models with one and two common factors, respectively; the third and fourth DGPs are dynamic factor models with finite and infinite-dimensional factor spaces, respectively. The common shocks and the idiosyncratic components in all four cases are conditionally heteroscedastic. The first three DGPs are particular cases of the GDFM with static representation and can be consistently estimated by the procedure of Alessi et al. (2009) which, however, cannot consistently estimate the fourth DGP, where the assumption of a finite-dimensional factor space does not hold.

In all DGPs, the idiosyncratic components satisfy $\boldsymbol{\xi}_t|\mathcal{F}_{t-1} \sim N(\mathbf{0}, \mathbf{P}_t)$, where $\mathbf{P}_t$ is an $N \times N$ diagonal matrix containing the conditional variances P_{it} of GARCH(1,1) processes of the form

$$P_{it} = \omega_i + \alpha_i \xi_{it}^2 + \beta_i P_{i,t-1}, \quad i = 1, ..., N,$$

where $\omega_i > 0$, $\alpha_i, \beta_i \geq 0$ and $\alpha_i + \beta_i < 1$; the parameters values α_i and β_i are generated independently from uniform distributions over [0.01, 0.045] and [0.85, 0.95], respectively, and $\omega_i := 1 - \alpha_i - \beta_i$, so that the unconditional variance of ξ_{it}

is $\mathrm{V}(\xi_{it}) = 1$. As for the factors $\mathbf{u}_t$ driving the common components $\boldsymbol{\chi}_t$, they were generated from the following four DGPs.

DGP1. (one common shock; static loadings) One common shock u_t is generated from a univariate GARCH(1,1) model

$$u_t|\mathcal{F}_{t-1} \sim N(0, \sigma_t^2) \quad \text{with } \sigma_t^2 = 1 + 0.07u_{t-1}^2 + 0.83\sigma_{t-1}^2;$$

here $\boldsymbol{\chi}_t = \mathbf{R}u_t$, where $\mathbf{R}$ is an $N \times 1$ matrix with modulus one randomly generated via the *RandOrthMat* Matlab function.

DGP2. (two common shocks; static loadings) Two common shocks $\mathbf{u}_t = (u_{1t}, u_{2t})'$, generated from a BEKK(1,1,1) model

$$\mathbf{u}_t|\mathcal{F}_{t-1} \sim N(\mathbf{0}, \mathbf{Q}_t) \;\; \text{with } \mathbf{Q}_t = \mathbf{C}_0'\mathbf{C}_0 + \mathbf{C}_1'\mathbf{u}_{t-1}\mathbf{u}_{t-1}'\mathbf{C}_1 + \mathbf{C}_2'\mathbf{Q}_{t-1}\mathbf{C}_2. \tag{14}$$

In order to guarantee $\mathrm{E}(\mathbf{Q}_t) = \mathrm{E}(\mathbf{u}_{t-1}\mathbf{u}_{t-1}') = \mathbf{I}_q$, we set $\mathbf{C}_0'\mathbf{C}_0 = \mathbf{I}_q - \mathbf{C}_1'\mathbf{C}_1 - \mathbf{C}_2'\mathbf{C}_2$. Parameters of the BEKK are extracted from uniform distributions with ranges as in Alessi et al. (2009): $\mathbf{C}_1$ has diagonal in [0.1,0.5] and off-diagonal elements in [-0.2,0.2], while $\mathbf{C}_2$ has diagonal in [0.8,0.95] and off-diagonal elements in [-0.15,0.15]. At each extraction of the parameters, covariance stationary of the BEKK model has been checked before proceeding. Here, $\boldsymbol{\chi}_t = \mathbf{R}\mathbf{u}_t$ where $\mathbf{R}$ is an $N \times 2$ matrix with orthonormal columns randomly generated via the *RandOrthMat* Matlab function.

DGP3. (four factors driven by $q = 2$ common shocks; static loadings) Four factors $\mathbf{F}_t = (F_{1t}, \ldots, F_{4t})'$ driven by $q = 2$ common shocks $\mathbf{u}_t$, yielding a GDFM with finite-dimensional factor space. The shocks are generated from the same BEKK model as in DGP2, the factors are a VAR(4) driven by $\mathbf{u}_t$:

$$\mathbf{F}_t = \boldsymbol{\Phi}\mathbf{F}_{t-1} + \mathbf{K}\mathbf{u}_t \quad \text{and} \quad \mathbf{u}_t|\mathcal{F}_{t-1} \sim N(\mathbf{0}, \mathbf{Q}_t),$$

with $\mathbf{Q}_t$ as in (14), $\boldsymbol{\Lambda}$ is $n \times 4$, $\boldsymbol{\Phi}$ is 4×4 and $\mathbf{K}$ is 4×2. The entries of $\boldsymbol{\Lambda}$ and $\mathbf{K}$ are independently uniformly distributed over $[-1, 1]$. The entries of $\boldsymbol{\Phi}$ are generated as follows: first we generate entries independently uniformly distributed on the interval[-1,1]; second, we divide the resulting matrix by its spectral norm; third, we multiply the resulting matrix by a random variable uniformly distributed

on the interval [0.4,0.9] to ensure stationarity while preserving sizeable dynamic responses[14].

DGP4. (two common shocks; dynamic loadings) The two common shocks $\mathbf{u}_t = (u_{1t}, u_{2t})'$ are generated from the same bivariate BEKK model as in (14); the model is a GDFM with infinite-dimensional factor space. Here,

$$\boldsymbol{\chi}_{it} = \begin{pmatrix} a_{i1}(1-\alpha_{i1})^{-1} \\ a_{i2}(1-\alpha_{i2})^{-1} \end{pmatrix} \mathbf{u}_t,$$

where a_{ij} and α_{ij}, $i = 1, ..., n$, $j = 1, 2$ are independent and uniformly distributed over the intervals [-1,1] and [-0.8,0.8], respectively.

For each DGP, we simulated 500 replications of a panel of dimensions N=60 and T=1000. From each replication, the conditional covariance matrix $\boldsymbol{\Sigma}_{T+1|T}$ was estimated using

(a) classical PCA[15] combined with (M)GARCH modelling,
(b) the DCC model with composite likelihood, as described in Pakel et al. (2017),
(c) the procedure of Alessi et al. (2009), and
(d) our method,[16]

denoted as PCA-(M)GARCH, DCC, ABC, and GDFM-CHF, respectively[17]. For simplicity, the correct numbers of factors (for DGP3) and common shocks (for DGPs 1-4) are assumed to be known, since this does not play a role in the comparative performances of procedures (a)-(d). For DGP4, since there are not static factors in its representation, the identification procedure by Bai and Ng (2002) was used in each simulated panel to compute the number of static factors for the estimation of the PCA-(M)GARCH and ABC procedures.[18]

[14]This DGP is similar to the one considered by Alessi et al. (2009).

[15]In the spirit of Diebold and Nerlove (1989) and Van der Weide (2002), static factors are extracted via principal component analysis; an (M)GARCH model then is fitted to the extracted factors. Idiosyncratic components are modelled as independent univariate GARCH processes.

[16]Throughout, we considered 30 cross-sectional permutations and set the order S of the VAR block-diagonal models to one.

[17]GDFM-CHF: General Dynamic Factor Model with Conditionally Heteroscedastic Factors.

[18]In practice, the identification procedures by Bai and Ng (2002) or Alessi et al. (2010) in the static case, by Hallin and Liška (2007) in the GDFM case, should be used prior to the estimation procedure in each replication.

As mentioned in the previous section, estimation of BEKK models is numerically quite unstable and strongly depends on the choice of initial values. For the sake of comparison, for DGPs 2-4 we considered both a DCC(1,1) and a BEKK(1,1,1) estimate of the conditional covariance matrix of the common shocks in the PCA-(M)GARCH, ABC and GDFM-CHF procedures: the DCC-based procedures are denoted as PCA-(M)GARCH-DCC and ABC-DCC and GDFM-CHF-DCC, the BEKK-based ones as PCA-(M)GARCH-BEKK, ABC-BEKK and GDFM-CHF-BEKK, respectively.[19]

In order to compare the performances of those four procedures, we compute, for each simulated panel and each method, a distance between the estimated one-step-ahead conditional covariance matrix $\widehat{\mathbf{\Sigma}}_{T+1|T}$ and the theoretical one $\mathbf{\Sigma}_{T+1|T}$. Let

$$\mathbf{H}_{T+1|T} := \mathbf{R}\,\mathrm{V}(\mathbf{u}_{\mathrm{T}+1}|\mathcal{F}_{\mathrm{T}})\mathbf{R}' + \mathrm{V}(\boldsymbol{\xi}_{\mathrm{T}+1}|\mathcal{F}_{\mathrm{T}}) \quad \text{for DGP1 and DGP2,}$$

$$\mathbf{H}_{T+1|T} := \mathbf{\Lambda}\mathbf{K}\mathrm{V}(\mathbf{u}_{T+1}|\mathcal{F}_{T})\mathbf{K}'\mathbf{\Lambda}' + \mathrm{V}(\boldsymbol{\xi}_{T+1}|\mathcal{F}_{T}) \quad \text{for DGP3,}$$

and

$$\mathbf{H}_{T+1|T} = \mathbf{A}\,\mathrm{V}(\mathbf{u}_{T+1}|\mathcal{F}_{T})\mathbf{A}' + \mathrm{V}(\boldsymbol{\xi}_{T+1}|\mathcal{F}_{T}) \quad \text{for DGP4,}$$

where $\mathbf{A}$ is the matrix with elements $a_{i,j}$, $i = 1, ..., N$, $j = 1, 2$. Following Amendola and Candila (2017), we consider four distances, $\mathrm{D}_1, \ldots, \mathrm{D}_4$, of the form

$$\mathrm{D}(\mathbf{H}_{T+1|T}, \widehat{\mathbf{\Sigma}}_{T+1|T}) = \sum_{i=1}^{N}\sum_{j=i}^{N} \omega(i,j)(h_{i,j} - \widehat{\sigma}_{i,j})^2, \tag{15}$$

where $h_{i,j}$ and $\widehat{\sigma}_{i,j}$ are the (i, j) entries of $H_{T+1|T}$ and $\widehat{\mathbf{\Sigma}}_{T+1|T}$, respectively, and the weights $\omega(i, j)$ are provided in Table 1.

Distance D_1, which gives equal weights for the variance and covariances, yields a "total" unweighted squared Euclidean distance between $\mathrm{Vech}(\widehat{\mathbf{\Sigma}}_{T+1|T})$ and $\mathrm{Vech}(\mathbf{H}_{T+1|T})$; distance D_2 is an unweighted squared Euclidean distance between $\mathrm{Diag}(\widehat{\mathbf{\Sigma}}_{T+1|T})$ and $\mathrm{Diag}(\mathbf{H}_{T+1|T})$ (hence disregards the covariances);[20] distance D_3 penalizes negative errors, while D_4 penalizes the positive ones. It is important to note that, in D_3

[19]DCC and BEKK estimations were performed by using the MFE toolbox of Kevin K. Sheppard, freely available at http://www.kevinsheppard.com/MFE_Toolbox.

[20]The classical notation $\mathrm{Vech}(\mathbf{M})$ stands for the vector stacking the upper diagonal entries of a square matrix $\mathbf{M}$, and $\mathrm{Diag}(\mathbf{M})$ for the vector of its diagonal elements.

Table 1: Weights $\omega(i, j)$, $i = 1, \ldots, N$, $j = i, \ldots, N$ in the distances D_1-D_4 in (15).

D_1	$w(i,j) = 1$	for all i and j
D_2	$w(i,j) = 1$	when $i = j$; 0 otherwise
D_3	$w(i,j) = 2$	when $\widehat{\sigma}_{i,j} > h_{i,j}$; 1 otherwise
D_4	$w(i,j) = 2$	when $\widehat{\sigma}_{i,j} < h_{i,j}$; 1 otherwise

and D_4, the weights themselves are data-driven, so that, for a given replication, different methods lead to different weights.

4.2 Simulation results

The results of the Monte Carlo experiments are summarized in Figures 1-4 and Table 2. Figures 1-4 present boxplots of the distances defined in (15), in logarithmic scale and for DGP1, DGP2, DGP3, and DGP4, respectively. Table 2 reports the number of times each estimation procedure achieves the smallest values of the distances for each DGP.

FIGURES 1-4 and TABLE 2 AROUND HERE

Inspection of Figure 1 (DGP1) reveals that ABC and GDFM-CHF perform as well as the simpler PCA-(M)GARCH procedure (with higher variability for GDFM-CHF, though), while DCC is, by far, the worst. According to Figures 2-3, the BEKK-based procedures present much higher variability than the DCC-based ones due, probably, to the numerical instability of BEKK QMLEs. Even when misspecified, DCC-based methods thus are preferable. In Figures 3 (DGP3) and 4 (DGP4), we can observe the good performance of GDFM-CHF-DCC, while ABC-DCC for DGP4, as well as PCA-(M)GARCH-DCC and DCC for DGP3 and DGP4, perform quite poorly.

Due to the high instability of BEKK-based procedures, Table 2 only reports the DCC-based procedures. It appears clearly that, in agreement with the results in Figures 1-4, the DCC method performs worst, except for DGP2. For DGP1 and DGP2, the GDFM-CHF-DCC procedure overperforms PCA-(M)GARCH-DCC and ABC-DCC for all distances but D_2 (where only the conditional variances, not the

covariances, are taken into account). In the DGP3 case, the GDFM-CHF-DCC procedure is best for all distances, closely followed by ABC. Finally, for DGP4, the GDFM-CHF-DCC procedure is by far the best for all distances while ABC-DCC performs poorly and PCA-(M)GARCH-DCC even worse. When both conditional variances and covariances are considered (distances D1, D3, and D4), the GDFM-CHF-DCC procedure, irrespective of the DGP, is uniformly best.

Table 2: For each choice of a DGP (DGP1-DGP4) and a distance (D_1-D_4), this table provides the number of times each of the four estimation procedures (PCA-(M)GARCH, DCC, ABC and GDFM-CHF) is the winner across 500 Monte Carlo replications. For DGPs 2-4 we use the DCC-based versions of the PCA-(M)GARCH, ABC, and GDFM-CHF procedures. Highest values are in bold.

	DGP1				DGP2			
Procedure	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4
PCA-(M)GARCH	103	155	114	88	35	75	39	34
DCC	13	38	13	12	45	**214**	45	43
ABC	92	**164**	82	109	59	87	53	62
GDFM-CHF	**292**	143	**291**	**291**	**361**	124	**363**	**361**
	DGP3				DGP4			
Procedure	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4
PCA-(M)GARCH	42	67	41	40	9	1	11	7
DCC	19	7	20	20	3	1	4	3
ABC	211	208	207	219	92	80	91	91
GDFM-CHF	**228**	**218**	**232**	**221**	**396**	**418**	**394**	**399**

5 An application to dynamic portfolio optimization

In this section, we assess our proposal (GDFM-CHF-DCC) in the problem of dynamic portfolio optimisation. The dataset we are considering consists in returns X_{it} from stocks entering the composition of the S&P 500 index, the National Association of Securities Dealers Automated Quotations (NASDAQ-100) and the NYSE

Amex Composite Index (AMEX), on July 27, 2018 and traded from January 2, 2011 through June 29, 2018 (T=1884). It was obtained from *Yahoo Finance* using the R package *quantmod* by Ryan and Ulrich (2017). Because we only considered stocks traded through the whole period, we ended up with $N = 656$ assets.

A window size of 750 days is used for estimation, which represents a concentration ratio of $656/750 = 0.875$; the out-of-sample period was set to 1134 days. An estimator $\widehat{\mathbf{\Sigma}}_{t+1|t}$ of $\mathrm{V}(\boldsymbol{X}_{t+1}|\mathcal{F}_t)$ is computed from the 656×750 subpanel $\{X_{is}|1 \leq i \leq 656,\, t-749 \leq s \leq t\}$ for $t = 750, \dots, T-1 = 1883$. That estimator is used in the construction, at times $t = 750, \dots, 1883$ (1134 time points), of a one-step ahead minimal variance portfolio (optimality at time $t+1$)—viz., a vector of weights

$$\widehat{\boldsymbol{\omega}}_{t+1|t} = (\widehat{\omega}_{1;t+1|t}, \dots, \widehat{\omega}_{656;t+1|t})' = \operatorname*{argmin}_{\boldsymbol{\omega}} \boldsymbol{\omega}' \widehat{\mathbf{\Sigma}}_{t+1|t} \boldsymbol{\omega}$$

where minimisation is with respect to all $\boldsymbol{\omega} = (\omega_1, \dots, \omega_{656})'$ such that $\omega_i \geq 0$ and $\sum_{i=1}^{656} \omega_i = 1$. The resulting (out-of-sample) portfolio return

$$r_{p,t+1} := \sum_{i=1}^{656} \widehat{\omega}_{i;t+1|t} X_{i,t+1}$$

at time $t+1$ then is computed from the observation at time $t+1$.

The minimum-variance portfolio we are proposing is the one based on $\widehat{\mathbf{\Sigma}}_{t+1|t} = \widehat{\mathrm{V}}(\mathbf{X}_{t+1}|\mathcal{F}_t)$, as described in Section 3.2 (but computed from the adequate subpanels), denoted as GDFM-CHF-DCC. For the sake of comparison, we also include the results of the GDFM-CHF-BEKK procedure. We compare its performance with those of (a) the naive equal-weighted portfolio strategy, denoted here by 1/N, (b) the RiskMetrics 2006 methodology (Zumbach, 2007), (c) the OGARCH approach of Alexander and Chibumba (1996), (d) the ABC method of Alessi et al. (2009), (e) the generalized principal volatility components (GPVC)[21] of Li et al. (2016), and (f) the procedure called PCA4TS proposed by Chang et al. (2018), which ex-

[21] A robust version of the GPVC procedure, denoted by RPVC, was proposed by Trucíos et al. (2019). That procedure is based on a robust estimator of the unconditional covariance matrix which can be applied only when the concentration ratio N/T is lower than 0.5. For this reason we did not implement it here. Of course, an adequate robust estimator in an high-dimensional context would be welcome. However, the performance of the RPVC in a $N/T > 0.5$ context has not been analyzed yet.

tends the principal component analysis to second-order stationary vector time series. Those procedures were selected for their feasibility in high-dimensional data.

The GDFM-CHF with DCC or BEKK was implemented with 30 cross-sectional permutations; the order of the VAR block-diagonal models was set to $S = 1$. In practice (when one portfolio is to be estimated at a time), information criteria can be used to determine the order of those VARs. Likewise, following Alessi et al. (2009), the number of static factors, common shocks, volatility components (Li et al., 2016) and groups (Chang et al., 2018) were determined once for all.

The ABC-DCC procedure (Alessi et al., 2009) was implemented with eight static factors and three common shocks determined by the criteria of Bai and Ng (2002) and Hallin and Liška (2007), respectively. The same number of common shocks was used in the GDFM-CHF approach. The GPVC procedure was applied with eight volatility components determined by the criterion of Bai and Ng (2002), the PCA4TS one with 654 groups (two of them with two assets and the remaining ones with only one asset; the groups were obtained following Chang et al. (2018)). The OGARCH procedure was applied as in Becker et al. (2015), that is, with the number of components equal to the number of series.

Following Gambacciani and Paolella (2017), Trucíos et al. (2018), or Engle et al. (2019), among many others, we use annualized performance measures to evaluate out-of-sample portfolio performances. These measures are defined as follows.

(i) Annualized average portfolio (AV):

$$\text{AV} := 252\bar{r}_p = 252 \left[\frac{1}{1134} \sum_{t=750}^{1883} r_{p,t+1} \right]$$

(average of the out-of-sample portfolio returns multiplied by 252);

(ii) Annualized standard deviation (SD):

$$\text{SD} = \sqrt{252} \left[\frac{1}{1134} \sum_{t=750}^{1883} (r_{p,t+1} - \bar{r}_p)^2 \right]^{1/2}$$

(standard deviation of the out-of-sample portfolio return multiplied by $\sqrt{252}$);

(iii) Annualized information ratio (AV): IR = AV/SD;

(iv) Annualized Sortino's ratio (SR): $\text{SR} = \text{AV}/\left(\text{S}\sqrt{252}\right)$, where

$$S = \left[\frac{1}{1134} \sum_{t=750}^{1883} \min\left(0, r_{p,t+1} - \mathrm{MAR}\right)^2 \right]^{1/2},$$

and the minimal accepted return (MAR) is set to zero.

Because our objective is the selection of a minimum variance portfolio, the most pertinent performance measure should be the SD criterion, as stressed out also by Ledoit and Wolf (2017) and Engle et al. (2019).

The results are reported in Table 3. They reveal that the best performance, for the SD, IR and SR criteria, is achieved by the GDFM-CHF-DCC. The OGARCH model has the second best performance, according to the SD criterion, followed by the ABC-DCC method. The GPVC and the OGARCH procedures exhibit the worst performance according to the AV criterion while ABC has the best performance according to the same criterion, followed by the GDFM-CHF-DCC proposal. The worst out-of-sample performance is obtained by the equal-weight portfolio strategy according to all criteria, but for the AV one. It is worth noting the relative good performance of RM2006, which outperforms GPVC and PCA4TS according to all criteria and loses for OGARCH only through the SD criterium. Finally, note that the results of GDFM-CHF-BEKK are worse than those of GDFM-CHF-DCC, mainly in terms of the SD criterion. This is not surprising since, as mentioned previously, the estimation of the Full BEKK model is hard, unstable and strongly dependent on the initial values, leading to a poor performance (Lien et al., 2002; Laurent et al., 2012; Asai, 2015; Amendola and Candila, 2017; de Almeida et al., 2018).

Taking into account all criteria, the GDFM-CHF-DCC proposal exhibits the best performance, followed by the ABC-DCC procedure.

Table 3: Annualized performance measures: AV, SD, IR and SR stand for the annualized average, standard deviation, information ratio and Sortino's ratio of the out-of-sample portfolio returns, respectively. The dataset is formed by 656 stocks used in the composition of the S&P500, NASDAQ-100 and AMEX indexes and the window size for estimation is equal to 750 days (concentration ratio N/T equal to 0.875). The out-of-sample period goes from January 2, 2014 to June 29, 2018. A ranking of the various methods is provided in parenthesis for each criterion.

	AV	SD	IR	SR
1/N	5.7708 (3)	11.5067 (8)	0.5015 (8)	0.6834 (8)
RM2006	5.5983 (4)	4.5447 (4)	1.2318 (3)	1.7229 (3)
OGARCH	4.9227 (7)	4.4551 (2)	1.1050 (6)	1.5614 (6)
ABC-DCC	6.5267 (1)	4.5313 (3)	1.4404 (2)	1.9677 (2)
GPVC	4.5989 (8)	4.5889 (5)	1.0022 (7)	1.4077 (7)
PCA4TS	5.3677 (6)	4.7255 (6)	1.1359 (5)	1.6024 (5)
GDFM-CHF-DCC	6.2369 (2)	4.0209 (1)	1.5511 (1)	2.2137 (1)
GDFM-CHF-BEKK	5.5834 (5)	4.8954 (7)	1.1405 (4)	1.6287 (4)

6 Conclusions

Based on the one-sided procedure of Forni et al. (2015, 2017) and Barigozzi and Hallin (2018), we propose a forecasting method for the conditional covariance matrix in high-dimensional time series, which we apply to dynamic portfolio optimization.

A Monte Carlo performance comparison of our method with alternative methods is conducted over four different DGPs, using the distance measures proposed in Amendola and Candila (2017). Overall, our method has an excellent performance, and outperforms all its competitors—except, under static factor model DGPs, for the distance D2 which disregards the covariances.

The superiority of our estimator is also empirically established in an application to dynamic portfolio optimisation based on a dataset of 656 assets. Our method achieves the best out-of-sample performance according to the (annualized) standard deviation SD (arguably, the most relevant criterion in the context), information ratio (IR) and Sortino's ratio (SR) criteria, and is second best (after Alessi et al. (2009))

with respect to the (annualized) average criterion.

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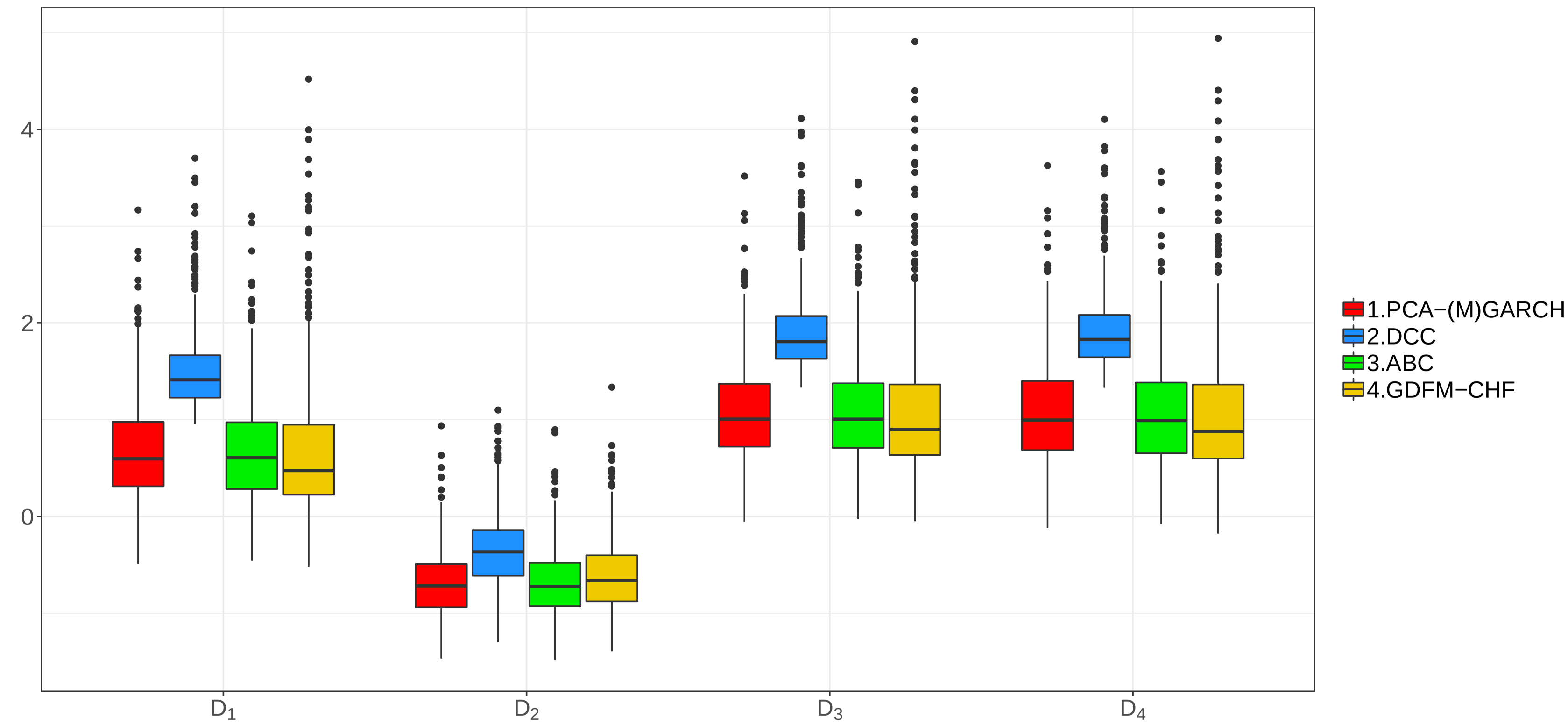

Figure 1: Boxplots of the logarithms of the distances D_1, D_2, D_3, and D_4 for DGP1 across 500 Monte Carlo replications. PCA-(M)GARCH (1), DCC (2), ABC (3) and GDFM-CHF (4) stand for a GARCH model on the common shock with univariate GARCH models on the idiosyncratic components, the DCC with composite likelihood (Pakel et al., 2017), the procedure of Alessi et al. (2009) and our proposal, respectively.

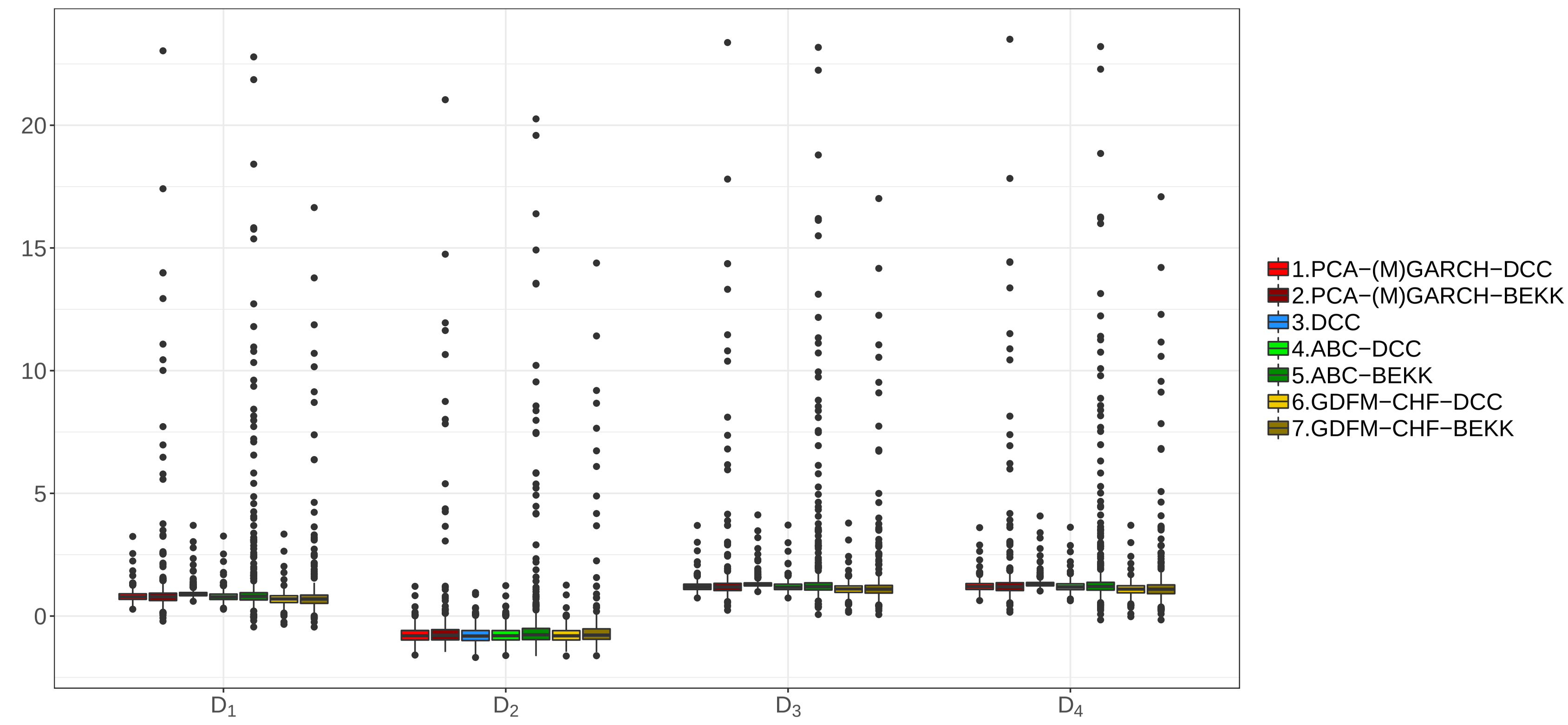

Figure 2: Boxplots of the logarithms of the distances D_1, D_2, D_3, and D_4 for DGP2 across 500 Monte Carlo replications. PCA-(M)GARCH-DCC (1), PCS-(M)GARCH-BEKK (2), DCC (3), ABC-DCC (4), ABC-BEKK (5), GDFM-CHF-DCC (6), GDFM-CHF-BEKK (7) stand for an MGARCH model on the shocks and univariate GARCH models on the idiosyncratic components, the DCC with composite likelihood (Pakel et al., 2017), the procedure of Alessi et al. (2009), and our proposal, respectively.

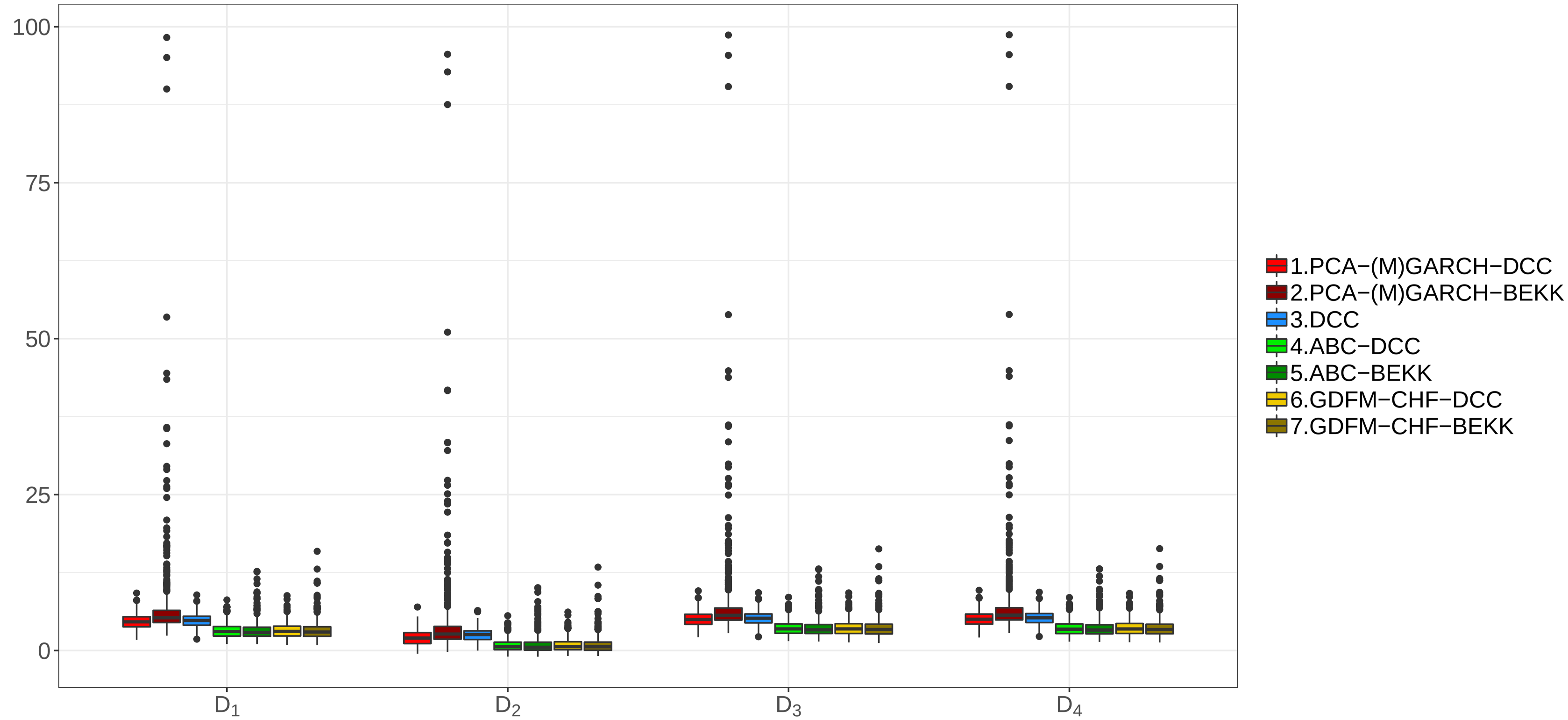

Figure 3: Boxplots of the logarithms of the distances D_1, D_2, D_3, and D_4 for DGP3 across 500 Monte Carlo replications. PCA-(M)GARCH-DCC (1), PCS-(M)GARCH-BEKK (2), DCC (3), ABC-DCC (4), ABC-BEKK (5), GDFM-CHF-DCC (6), GDFM-CHF-BEKK (7) stand for an MGARCH model on the shocks and univariate GARCH models on the idiosyncratic components, the DCC with composite likelihood (Pakel et al., 2017), the procedure of Alessi et al. (2009), and our proposal, respectively.

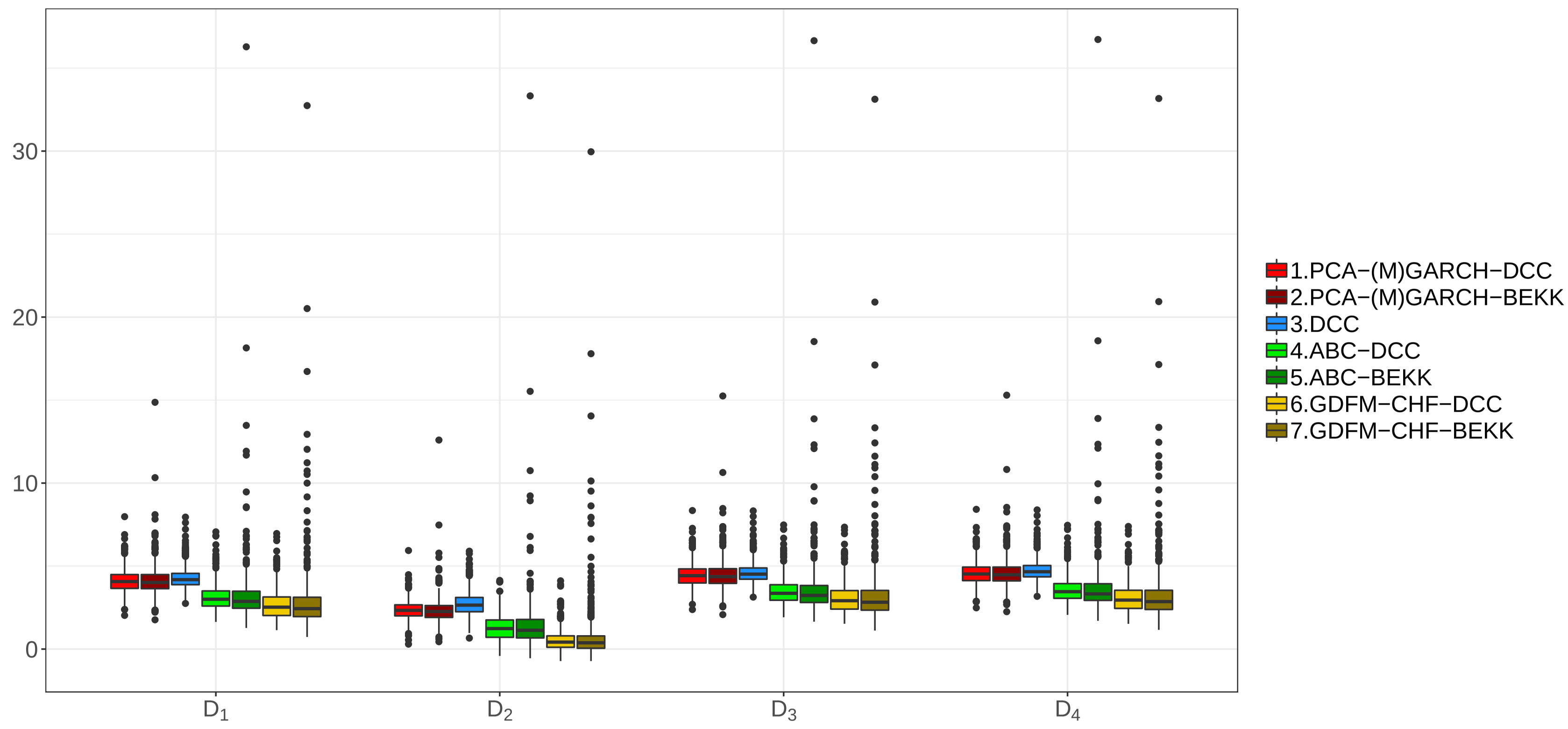

Figure 4: Boxplots of the logarithms of the distances D_1, D_2, D_3, and D_4 for DGP4 across 500 Monte Carlo replications. PCA-(M)GARCH-DCC (1), PCS-(M)GARCH-BEKK (2), DCC (3), ABC-DCC (4), ABC-BEKK (5), GDFM-CHF-DCC (6), GDFM-CHF-BEKK (7) stand for an MGARCH model on the shocks (number of shocks selected via the Bai and Ng (2002) criterion) and univariate GARCH models on the idiosyncratic components, the DCC with composite likelihood (Pakel et al., 2017), the procedure of Alessi et al. (2009), and our proposal, respectively.