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Abstract

We introduce the new F-Riesz distribution to model tail-heterogeneity in fat-tailed covariance matrix observations. In contrast to the typical matrix-valued distributions from the econometric literature, the F-Riesz distribution allows for different tail behavior across all variables in the system. We study the consistency properties of the maximum likelihood estimator in both static and dynamic models with F-Riesz innovations using both one-step and two-step (targeting) estimation techniques. Allowing for tail-heterogeneity when modeling covariance matrices appears empirically highly relevant. When applying the new distribution to realized covariance matrices of 30 U.S. stocks over a 14 year period, we find huge likelihood increases both in-sample and out-of-sample compared to all competing distributions, including the Wishart, inverse Wishart, Riesz, inverse Riesz, and matrix-F distribution.

Key words: Matrix Distributions, Tail Heterogeneity, (inverse) Riesz Distribution, Fat-Tails, Realized Covariance Matrices.

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1 Introduction

An important challenge in contemporary time series econometrics is designing parsimonious yet flexible models for high dimensional, fat-tailed covariance-matrix-valued time series. Such data is ever more abundant in today's data rich environment, particularly in financial markets. For recent examples, see for instance Andersen et al. (2003); Barndorff-Nielsen and Shephard (2004); Chiriac and Voev (2011); Lunde et al. (2016); Callot et al. (2017); Bollerslev et al. (2018, 2020) and the references cited therein. Most of the models currently available for these data are highly restrictive. For instance, the often used Wishart or inverse Wishart distribution for matrix-valued time series only features a mean and a single degrees of freedom parameter (Golosnoy et al., 2012; Jin and Maheu, 2013, 2016), while the matrix-F distribution only features two tail parameters (Konno, 1991; Opschoor et al., 2018). While such distributions might be suitable for low-dimensional matrices, in moderate to high dimensions the implied constraints on tail behavior are typically too restrictive empirically. For instance, a Wishart distribution restricts all diagonal elements of a random covariance matrix to have exactly the same distributional shape.

One solution opted for in the literature is the use of copulas and conditional copulas (Patton, 2009; Oh and Patton, 2017, 2018; Opschoor et al., 2020). Copulas allow one to split the marginal modeling stage from the modeling of the dependence structure. As such, the tail behavior between different marginals can be arbitrarily different. Though convenient in many settings, the copula approach also has several drawbacks. First, by splitting the marginal models from the copula, key characteristics of the joint distribution may no longer be available in closed form. This may result in substantial simulation effort to obtain simple distributional characteristics like the mean and covariance matrix of the joint distribution based on the copula model and the underlying marginals. Second, though the different marginals may allow for flexibility in tail behavior, the typical copulas used in the literature like the Gaussian, (skewed) Student's t, and Archimedean copulas are still tightly parameterized, with very little heterogeneity in the tail-dependence structure. Third, there are substantial limitations to applying the copula methodology for more complex data structures beyond the vector case. For instance, if we observe positive-definite matrix-valued random variables, like in the context of realized covariance matrix modeling, defining the

probability space for each of the marginal elements of the matrix random variables is highly complex and largely impractical. In such cases, modeling the multivariate structure directly by specifying a tractable yet flexible multivariate distribution on the space of positive definite matrices may be a better way forward. Unfortunately, as mentioned before, current alternatives like the Wishart, inverse Wishart, and matrix-F distribution appear too tightly parameterized to be useful empirically for high dimensional data.

This paper aims to provide a substantial step forward by introducing the F-Riesz distribution, deriving the consistency properties of the maximum likelihood estimator for the parameters of static and dynamic versions of it, and showing the empirical relevance of the new distribution. The F-Riesz distribution allows for different tail-heterogeneity in each of its coordinates. The increases in in-sample and out-of-sample likelihood are strikingly high for this new distribution, illustrating we are dealing with an empirically relevant and sizeable phenomenon. We obtain the F-Riesz distribution by mixing a Riesz distribution (Hassairi and Lajmi, 2001; Díaz-García, 2013) and Inverse Riesz distribution (Tounsi and Zine, 2012; Louati and Masmoudi, 2015), which are generalizations of the Wishart and Inverse Wishart distributions. Their domain is the space of positive (semi)-definite matrices. The Riesz distribution has been used in the physics literature (Andersson and Klein, 2010). In econometrics, we could only trace the concurrent and independent recent paper by (Gribisch and Hartkopf, 2020), who apply the Riesz distribution to financial data. The main difference between the Riesz and the Wishart distribution is that the Riesz distribution is characterized by as many degrees of freedom as the dimension of the data, whereas the Wishart only has one single degrees of freedom parameter. This allows for much more heterogeneity in tail behavior. The Riesz distribution, however, still has thin-tailed behavior for its coordinates. This is at odds with many empirical data sets in finance and economics, which typically exhibit fat-tailed behavior. Be mixing a Riesz and inverse Riesz distribution, the F-Riesz distribution as constructed in this paper allows for heterogeneous fat-tailed behavior in all directions. The F-Riesz distribution is characterized by a matrix-valued mean, and two *vectors* of degrees of freedom parameters, thus allowing for considerable extra flexibility in tail behavior. If each of these vectors is scalar (i.e., has the same elements), then the F-Riesz reduced to the matrix-F distribution (see Konno, 1991; Opschoor et al., 2018).

We apply the F-Riesz distribution to a sample of daily realized covariance matrices of dimension up to 30 using U.S. stock data over 2001–2014. The full-sample results indicate that tail heterogeneity is an important feature of the data: we find huge log-likelihood increases when assuming a conditional F-Riesz distribution is used instead of a matrix-F or (inverse) Riesz or (inverse) Wishart distribution. We strongly reject the matrix-F distribution as an adequate model for the realized covariance matrix data, despite it being already substantially better (by a wide margin) than the Wishart and inverse Wishart distribution, both with and without allowing for a time-varying mean of the realized covariance matrices. This strong result is confirmed in an out-of-sample analysis, where we forecast the density of the realized covariance matrix one-step ahead. Using the log-score to discriminate among our different distributions, we again find that the F-Riesz distribution is superior against the competitors by a wide margin. Given the ease of estimation, the F-Riesz distribution might therefore be a highly relevant tool for econometric modeling, both in a classical and a Bayesian framework.

The rest of this paper is set-up as follows. In Section 2 we briefly introduce the Riesz distribution and its main properties. In Section 3, we derive the F-Riesz distribution and its dynamic extension. Section 4 considers consistency properties of the maximum likelihood estimator using a one-step or a two-step targeting approach. Section 5 presents the new model's performance using simulated data. Section 6 presents the empirical results, in particular the major increases in likelihood possible with the additional flexibility of the F-Riesz. Section 7 concludes. An appendix gathers all the technical results. As a general notation guide, scalars have normal type face, vectors are bolded, and matrices are bolded and capitalized. We number theorems, propositions, definitions and assumptions consecutively.

2 The Riesz distribution

This section starts with a brief introduction of the Riesz distribution as an extension of the Wishart distribution that allows for more tail heterogeneity. We discuss the Riesz distribution's most important properties and review some key notation that is also required for the definition of the F-Riesz distribution in the next section.

The Riesz distribution (Hassairi and Lajmi, 2001) is defined over the space of positive definite matrices. It generalizes the well-known Wishart distribution, which has probability density function (pdf)

$$p_{\mathcal{W}}(\boldsymbol{Y};\boldsymbol{\Sigma},\nu) = \frac{|\boldsymbol{Y}|^{0.5(\nu-k-1)} \cdot \operatorname{etr}\left(-\frac{1}{2}\boldsymbol{\Sigma}^{-1}\boldsymbol{Y}\right)}{|\boldsymbol{\Sigma}|^{0.5\nu} \cdot \Gamma_k\left(\nu/2\right) \cdot 2^{k\cdot\nu/2}}, \tag{1}$$

for a positive definite matrix random variable $\boldsymbol{Y} \in \mathbb{R}^{k\times k}$, a positive definite scaling matrix $\boldsymbol{\Sigma} \in \mathbb{R}^{k\times k}$, and a positive scalar degrees of freedom parameter ν, where $\operatorname{etr}(\cdot) = \exp(\operatorname{trace}(\cdot))$ denotes the exponential trace operator, and $\Gamma_k(\cdot)$ is the multivariate gamma function,

$$\Gamma_k\left(\nu\right) = \pi^{k(k-1)/4} \prod_{i=1}^{k} \Gamma\left(\nu + \tfrac{1-i}{2}\right). \tag{2}$$

A Wishart distributed random variable, denoted as $\mathcal{W}(\boldsymbol{\Sigma},\nu)$, thus has two key parameters: one matrix-valued, and one scalar. Interestingly, the Wishart distribution can be constructed using the so-called Bartlett decomposition; see Anderson (1962). Define the lower triangular matrix $\boldsymbol{G} \in \mathbb{R}^{k\times k}$ with all its elements independent random variables with $\boldsymbol{G}_{ii}^2 \sim \chi^2_{\nu-i+1}$ and $\boldsymbol{G}_{ij} \sim \mathcal{N}(0,1)$ for $i > j$, i.e.,

$$\boldsymbol{G} = \begin{pmatrix} \sqrt{\chi^2_\nu} & 0 & \cdots & 0 \\ \mathcal{N}(0,1) & \ddots & 0 & \vdots \\ \vdots & \mathcal{N}(0,1) & \ddots & 0 \\ \mathcal{N}(0,1) & \cdots & \mathcal{N}(0,1) & \sqrt{\chi^2_{\nu-k+1}} \end{pmatrix}. \tag{3}$$

Then $\boldsymbol{Y} = \boldsymbol{G}\boldsymbol{G}^\top \sim \mathcal{W}(\mathbf{I}_k,\nu)$, and $\boldsymbol{Y} = \boldsymbol{L}\boldsymbol{G}\boldsymbol{G}^\top\boldsymbol{L}^\top \sim \mathcal{W}(\boldsymbol{\Sigma},\nu)$ for a matrix $\boldsymbol{L}$ such that $\boldsymbol{\Sigma} = \boldsymbol{L}\boldsymbol{L}^\top$. A key property of the Bartlett decomposition is that the same degrees of freedom parameter ν plays a role in all the diagonal elements of $\boldsymbol{G}$ in (3). The Riesz distribution generalizes the Wishart by instead introducing a vector $\boldsymbol{\nu} = (\nu_1,\ldots,\nu_k)^\top$ of degrees of freedom parameters, and inserting it into (3). This is done in Definition 4 below. A Riesz distribution $\mathcal{R}(\boldsymbol{\Sigma},\boldsymbol{\nu})$ is thus characterized by a scaling matrix $\boldsymbol{\Sigma}$ and a vector $\boldsymbol{\nu}$.

To write the appropriate pdf of a $\mathcal{R}(\boldsymbol{\Sigma},\boldsymbol{\nu})$ random variable (and of a F-Riesz random variable later), we introduce the concepts of the generalized multivariate gamma function

and the power weighted determinant.

Definition 1 (**generalized multivariate gamma functions**)**.** The *lower* generalized multivariate gamma function for a vector-valued argument $\boldsymbol{\nu} = (\nu_1, \ldots, \nu_k)^\top \in \mathbb{R}^{k\times 1}$ is defined as

$$\overline{\Gamma}(\boldsymbol{\nu}) = \pi^{k(k-1)/4} \prod_{i=1}^{k} \Gamma\left(\nu_i + \frac{1-i}{2}\right), \tag{4}$$

with $2\nu_i > i-1$ for $i = 1, \ldots, k$.

The *upper* generalized multivariate gamma function is defined similarly as

$$\overline{\Gamma}_U(\boldsymbol{\nu}) = \pi^{k(k-1)/4} \prod_{i=1}^{k} \Gamma\left(\nu_i + \frac{i-k}{2}\right) = \overline{\Gamma}(\boldsymbol{\nu} + \tilde{\boldsymbol{\gamma}}), \tag{5}$$

for $2\nu_i > k-i$ for $i = 1, \ldots, k$, and

$$\tilde{\boldsymbol{\gamma}} = \tfrac{1}{2}(k+1) - \Big(k, k-1, \ldots, 1\Big)^\top = \Big(-\tfrac{1}{2}(k-1), \ldots, \tfrac{1}{2}(k-1)\Big)^\top. \tag{6}$$

The upper and lower generalized multivariate gamma functions enter the integrating constant of the Riesz distribution. Note that if $\boldsymbol{\nu} = (\nu, \ldots, \nu)^\top$ in (4) such that all its elements are the same, then $\overline{\Gamma}(\boldsymbol{\nu}) = \Gamma_k(\nu)$, with $\Gamma_k(\nu)$ the standard multivariate gamma function from (2).

Next, we introduce the concept of Lower Power Weighted Determinants (LPWD) and Upper Power Weighted Determinants (UPWD). The power weighted determinants for the Riesz density take a similar role as the standard determinants in expression (1) for the Wishart density.

Definition 2 (**power weighted determinants**)**.** Consider the vector $\boldsymbol{\nu} \in \mathbb{R}^{k\times 1}$ and a positive definite matrix $\boldsymbol{Y}$. Let $\boldsymbol{L}$ and $\boldsymbol{U}$ be the (unique) *lower* and *upper* triangular Cholesky decompositions of $\boldsymbol{Y}$, i.e., $\boldsymbol{Y} = \boldsymbol{L}\boldsymbol{L}^\top = \boldsymbol{U}\boldsymbol{U}^\top$, with $\boldsymbol{L}$ and $\boldsymbol{U}$ a lower and upper triangular matrix, respectively, each with positive diagonal elements. Then the Lower Power Weighted Determinant (LPWD) and Upper Power Weighted Determinant (UPWD) of $\boldsymbol{Y}$,

denoted as $|\boldsymbol{Y}|_{\boldsymbol{\nu}}$ and ${}_U|\boldsymbol{Y}|_{\boldsymbol{\nu}}$, respectively, are given by

$$|\boldsymbol{Y}|_{\boldsymbol{\nu}} = \prod_{i=1}^{k} \boldsymbol{L}_{i,i}^{2\nu_i}, \qquad {}_U|\boldsymbol{Y}|_{\boldsymbol{\nu}} = \prod_{i=1}^{k} \boldsymbol{U}_{i,i}^{2\nu_i}. \tag{7}$$

In the physics literature, the power weighted determinants are commonly introduced via so-called weight functions; see for instance Gross and Richards (1987). In this paper, we instead use the notation of power weighted determinants as it is closer to the econometric literature and stresses the analogy between the Wishart and Riesz density expressions. It also allows us to easily see that the Wishart is a special case of the Riesz. To facilitate the latter, we provide some manipulation rules for power weighted determinants that will prove convenient. In particular, we note that the power weighted determinant is *not* a regular determinant. Simple properties like $|\boldsymbol{A} \cdot \boldsymbol{B}| = |\boldsymbol{A}| \cdot |\boldsymbol{B}|$ for matrices $\boldsymbol{A}, \boldsymbol{B} \in \mathbb{R}^{k \times k}$ need (and in general will) no longer hold for power weighted determinants. The following lemma is proved in the online appendix and lists a number of useful properties. For instance, while properties (i)–(iii) and (v) are intuitive, property (iv) is an important difference with the standard determinant. In particular, $|\boldsymbol{Y}|_{\boldsymbol{\nu}} \neq |\boldsymbol{Y}^{-1}|_{-\boldsymbol{\nu}}$ in general, whereas for a positive definite $\boldsymbol{Y}$, non-zero ν, and a regular determinant we have $|\boldsymbol{Y}|^{\nu} = |\boldsymbol{Y}^{-1}|^{-\nu}$.

Lemma 3. *Given a scalar ν, a vector $\boldsymbol{\nu} = (\nu_1, \ldots, \nu_k)^\top \in \mathbb{R}^{k \times 1}$, a vector of ones $\boldsymbol{\iota}_k \in \mathbb{R}^{k \times 1}$, and $\boldsymbol{Y} \in \mathbb{R}^{k \times k}$ a positive definite matrix, then we have the following identities.*

(i) If $\boldsymbol{\nu} = \nu \cdot \boldsymbol{\iota}_k$, then $|\boldsymbol{Y}|_{\nu \cdot \boldsymbol{\iota}_k} = {}_U|\boldsymbol{Y}|_{\nu \cdot \boldsymbol{\iota}_k} = |\boldsymbol{Y}|^{\nu}$. As special case, when $\nu = 1$, we have $|\boldsymbol{Y}|_{\boldsymbol{\iota}_k} = {}_U|\boldsymbol{Y}|_{\boldsymbol{\iota}_k} = |\boldsymbol{Y}|$.

(ii) Let $\boldsymbol{\nu}_1, \boldsymbol{\nu}_2 \in \mathbb{R}^{k \times 1}$ be two vectors of constants, then we have $|\boldsymbol{Y}|_{\boldsymbol{\nu}_1} \cdot |\boldsymbol{Y}|_{\boldsymbol{\nu}_2} = |\boldsymbol{Y}|_{\boldsymbol{\nu}_1 + \boldsymbol{\nu}_2}$, and ${}_U|\boldsymbol{Y}|_{\boldsymbol{\nu}_1} \cdot {}_U|\boldsymbol{Y}|_{\boldsymbol{\nu}_2} = {}_U|\boldsymbol{Y}|_{\boldsymbol{\nu}_1 + \boldsymbol{\nu}_2}$.

(iii) $(|\boldsymbol{Y}|_{\boldsymbol{\nu}})^{-1} = |\boldsymbol{Y}|_{-\boldsymbol{\nu}}$, and $({}_U|\boldsymbol{Y}|_{\boldsymbol{\nu}})^{-1} = {}_U|\boldsymbol{Y}|_{-\boldsymbol{\nu}}$.

(iv) $|\boldsymbol{Y}|_{\boldsymbol{\nu}} = {}_U|\boldsymbol{Y}^{-1}|_{-\boldsymbol{\nu}}$.

(v) If $\boldsymbol{L}, \boldsymbol{\Sigma} \in \mathbb{R}^{k \times k}$, where $\boldsymbol{\Sigma}$ is positive definite with lower triangular Cholesky decomposition $\boldsymbol{L}$ such that $\boldsymbol{\Sigma} = \boldsymbol{L}\boldsymbol{L}^\top$, then $|\boldsymbol{L}^{-1}\boldsymbol{Y}(\boldsymbol{L}^{-1})^\top|_{\boldsymbol{\nu}} = |\boldsymbol{Y}|_{\boldsymbol{\nu}} \cdot |\boldsymbol{\Sigma}|_{-\boldsymbol{\nu}}$. Similarly, if $\boldsymbol{U}$ is the upper triangular Cholesky decomposition of $\boldsymbol{\Sigma}$ with $\boldsymbol{\Sigma} = \boldsymbol{U}\boldsymbol{U}^\top$, then ${}_U|\boldsymbol{U}^{-1}\boldsymbol{Y}(\boldsymbol{U}^{-1})^\top|_{\boldsymbol{\nu}} = {}_U|\boldsymbol{Y}|_{\boldsymbol{\nu}} \cdot {}_U|\boldsymbol{\Sigma}|_{-\boldsymbol{\nu}}$.

We can now introduce the lower triangular (type-I) and upper triangular (type-II) version of the Riesz distribution; see also for instance Díaz-García (2013) and Louati and Masmoudi (2015).

Theorem 4 (Riesz distribution type I and II).

(i) Consider the Bartlett decomposition $\boldsymbol{G} \in \mathbb{R}^{k\times k}$*, defined as*

$$\boldsymbol{G} = \begin{pmatrix} \sqrt{\chi^2_{\nu_1}} & 0 & \cdots & 0 \\ \mathcal{N}(0,1) & \ddots & 0 & \vdots \\ \vdots & \mathcal{N}(0,1) & \ddots & 0 \\ \mathcal{N}(0,1) & \cdots & \mathcal{N}(0,1) & \sqrt{\chi^2_{\nu_k-k+1}} \end{pmatrix}, \tag{8}$$

for $\nu_i > i-1$ *for* $i = 1,\ldots,k$*, and let* $\boldsymbol{Y} = \boldsymbol{L}\boldsymbol{G}\boldsymbol{G}^\top\boldsymbol{L}^\top$*, where* $\boldsymbol{L}$ *is the lower triangular Cholesky decomposition of* $\boldsymbol{\Sigma}$*, such that* $\boldsymbol{\Sigma} = \boldsymbol{L}\boldsymbol{L}^\top$*. Then* $\boldsymbol{Y}$ *has density function*

$$p_{\mathcal{R}^I}(\boldsymbol{Y};\boldsymbol{\Sigma},\boldsymbol{\nu}) = \frac{|\boldsymbol{Y}|_{0.5(\boldsymbol{\nu}-k-1)} \cdot \operatorname{etr}\left(-\frac{1}{2}\boldsymbol{\Sigma}^{-1}\boldsymbol{Y}\right)}{|\boldsymbol{\Sigma}|_{0.5\boldsymbol{\nu}} \cdot \overline{\Gamma}\left(\boldsymbol{\nu}/2\right) \cdot 2^{\boldsymbol{\nu}^\top\boldsymbol{\iota}_k/2}}, \tag{9}$$

also known as a Riesz type-I density, $\mathcal{R}^I(\boldsymbol{\Sigma},\boldsymbol{\nu})$*, where the generalized multivariate Gamma function* $\overline{\Gamma}(\cdot)$ *and the Lower Power Weighted Determinant* $|\cdot|_{\boldsymbol{\nu}}$ *were defined in Definitions 1 and 2, respectively.*

(ii) Let the Bartlett decomposition $\boldsymbol{H} \in \mathbb{R}^{k\times k}$ *be defined as*

$$\boldsymbol{H} = \begin{pmatrix} \sqrt{\chi^2_{\nu_1-k+1}} & \mathcal{N}(0,1) & \cdots & \mathcal{N}(0,1) \\ 0 & \ddots & \mathcal{N}(0,1) & \vdots \\ \vdots & 0 & \ddots & \mathcal{N}(0,1) \\ 0 & \cdots & 0 & \sqrt{\chi^2_{\nu_k}} \end{pmatrix}, \tag{10}$$

for $\nu_i > k-i$ *for* $i = 1,\ldots,k$*, and let* $\boldsymbol{X} = \boldsymbol{U}\boldsymbol{H}\boldsymbol{H}^\top\boldsymbol{U}^\top$*, where* $\boldsymbol{U}$ *is the upper triangular Cholesky decomposition of* $\boldsymbol{\Sigma}$*, such that* $\boldsymbol{\Sigma} = \boldsymbol{U}\boldsymbol{U}^\top$*. Then* $\boldsymbol{X}$ *has density function*

$$p_{\mathcal{R}^{II}}(\boldsymbol{X};\boldsymbol{\Sigma},\boldsymbol{\nu}) = \frac{{}_U|\boldsymbol{X}|_{0.5(\boldsymbol{\nu}-k-1)} \cdot \operatorname{etr}\left(-\frac{1}{2}\boldsymbol{\Sigma}^{-1}\boldsymbol{X}\right)}{{}_U|\boldsymbol{\Sigma}|_{0.5\boldsymbol{\nu}} \cdot \overline{\Gamma}_U\left(\boldsymbol{\nu}/2\right) \cdot 2^{\boldsymbol{\nu}^\top\boldsymbol{\iota}_k/2}}, \tag{11}$$

also known as a Riesz type-II density, $\mathcal{R}^{II}(\boldsymbol{\Sigma}, \boldsymbol{\nu})$*, with* $\overline{\Gamma}_U(\cdot)$ *and* ${}_U|\cdot|_{\boldsymbol{\nu}}$ *as defined in Definitions 1 and 2.*

The Riesz distributions of type I and II bear a close resemblance to the Wishart distribution. Using manipulation rule (i) from Lemma 3, we directly establish the following corollary.

Corollary 5. *If* $\boldsymbol{\nu} = (\nu, \ldots, \nu)^\top$ *for some positive scalar* $\nu > k - 1$*, then the Wishart, Riesz-I, and Riesz-II densities from* (1)*,* (9)*, and* (11)*, respectively, all coincide.*

The Wishart distribution is thus a special case of the Riesz. The Bartlett decompositions in (8) and (10), moreover, provide a direct way to simulate from the Riesz-I and Riesz-II distribution. Also note that the density expressions in Theorem 4 are easy to implement for numerical maximization of a likelihood function to estimate $\boldsymbol{\Sigma}$ and $\boldsymbol{\nu}$. They only require determinants and Cholesky decompositions.

Given the use of the Cholesky decomposition, it is clear that the ordering of the variables matters. This is well-known and accepted in the Riesz literature. For instance for $k = 2$ and $\boldsymbol{\Sigma} = \mathbf{I}_2$, switching both rows and columns of $\boldsymbol{Y} \sim \mathcal{R}^I(\mathbf{I}_2, \boldsymbol{\nu})$ for $\boldsymbol{\nu} = (\nu_1, \nu_2)^\top$ does not yield a Riesz distribution with $(\nu_2, \nu_1)^\top$ degrees of freedom. The order of the variables can be recovered from the data under the assumption of correct specification by maximizing the likelihood also over the order of the variables in the system, rather than over $\boldsymbol{\Sigma}$ and $\boldsymbol{\nu}$ only. In high dimensional systems, this additional optimization is of combinatorial complexity. Empirically, we found that changes in the orders of the variables in the system typically result only in second order improvements of the likelihood function. The dominant increase in the likelihood is obtained by generalizing the Wishart into a Riesz, or the matrix-F into an F-Riesz. Nevertheless, we also propose a heuristic approach later in the paper to optimize efficiently over the ordering of the variables in order to maximize the likelihood.

Finally, like the Wishart, the Riesz distribution also allows for an inverse version, called the inverse Riesz type-I $i\mathcal{R}^I(\boldsymbol{\Sigma}, \boldsymbol{\nu})$ and type II $i\mathcal{R}^{II}(\boldsymbol{\Sigma}, \boldsymbol{\nu})$. This will be important for constructing F-Riesz distributions in the next section. The definition of the type I and II inverse Riesz distributions is given in the following definition and theorem.

Definition 6.

(i) Let $\boldsymbol{Y}$ be a Riesz distribution of type I, $\mathcal{R}^I(\boldsymbol{\Sigma}^{-1}, \boldsymbol{\nu})$, and let $\boldsymbol{X} = \boldsymbol{Y}^{-1}$, then $\boldsymbol{X}$ is inverse Riesz distributed of type I, $i\mathcal{R}^I(\boldsymbol{\Sigma}, \boldsymbol{\nu})$.

(ii) Similarly, if $\boldsymbol{Y} \sim \mathcal{R}^{II}(\boldsymbol{\Sigma}^{-1}, \boldsymbol{\nu})$, then $\boldsymbol{X} = \boldsymbol{Y}^{-1}$ is inverse Riesz type II, $i\mathcal{R}^{II}(\boldsymbol{\Sigma}, \boldsymbol{\nu})$.

Theorem 7. *The pdf of an $i\mathcal{R}^I(\boldsymbol{\Sigma}, \boldsymbol{\nu})$ distributed random variable $\boldsymbol{X}$ is given by*

$$p_{i\mathcal{R}^I}(\boldsymbol{X}; \boldsymbol{\Sigma}, \boldsymbol{\nu}) = \frac{|\boldsymbol{X}^{-1}|_{0.5(\boldsymbol{\nu}+k+1)} \cdot \operatorname{etr}\left(-\frac{1}{2}\boldsymbol{\Sigma}\boldsymbol{X}^{-1}\right)}{|\boldsymbol{\Sigma}^{-1}|_{0.5\boldsymbol{\nu}} \cdot \overline{\Gamma}\left(\boldsymbol{\nu}/2\right) \cdot 2^{\boldsymbol{\nu}^\top \boldsymbol{\iota}_k/2}}. \tag{12}$$

The pdf of an $i\mathcal{R}^{II}(\boldsymbol{\Sigma}, \boldsymbol{\nu})$ distributed random variable $\boldsymbol{X}$ is given by

$$p_{i\mathcal{R}^{II}}(\boldsymbol{X}; \boldsymbol{\Sigma}, \boldsymbol{\nu}) = \frac{{}_U|\boldsymbol{X}^{-1}|_{0.5(\boldsymbol{\nu}+k+1)} \cdot \operatorname{etr}\left(-\frac{1}{2}\boldsymbol{\Sigma}\boldsymbol{X}^{-1}\right)}{{}_U|\boldsymbol{\Sigma}^{-1}|_{0.5\boldsymbol{\nu}} \cdot \overline{\Gamma}_U\left(\boldsymbol{\nu}/2\right) \cdot 2^{\boldsymbol{\nu}^\top \boldsymbol{\iota}_k/2}}. \tag{13}$$

The first moments of the Riesz and inverse Riesz distributions have been derived by Díaz-García (2013) and Louati and Masmoudi (2015).

3 The F-Riesz distribution

3.1 The static F-Riesz model

Given the Riesz and inverse Riesz distributions, we can now introduce the F-Riesz distributions. A family tree of the different distributions considered in this paper is provided in Figure 1. Starting from a Wishart distribution, the matrix-F distribution of Olkin et al. (1964); Konno (1991) can be obtained by mixing a Wishart and an inverse-Wishart, i.e., considering a random variable $\boldsymbol{X}$ such that $(\boldsymbol{X} \mid \boldsymbol{Y}) \sim \mathcal{W}(\boldsymbol{Y}, \mu)$, where $\boldsymbol{Y} \sim i\mathcal{W}(\boldsymbol{\Sigma}, \nu)$. The random variable $\boldsymbol{X}$ then has a matrix-F distribution. Analogously, the F-Riesz type I distribution can be constructed by mixing a Riesz and inverse-Riesz distribution, i.e., $(\boldsymbol{X} \mid \boldsymbol{Y}) \sim \mathcal{R}^I(\boldsymbol{Y}, \boldsymbol{\mu})$ with $\boldsymbol{Y} \sim i\mathcal{R}^{II}(\boldsymbol{\Sigma}, \boldsymbol{\nu})$. In that case, $\boldsymbol{X}$ had a F-Riesz type I distribution. A similar construction holds for the F-Riesz type II.[1] Theorem 8 presents the pdf of the F-Riesz distribution.

[1] F-Riesz distributions can be constructed in different ways. An earlier attempt for a beta type II Riesz distribution, similar to our F-Riesz, was given by Díaz-García (2016). The density expression in that paper contains a subtle error that it does not affect the estimation of the $\boldsymbol{\mu}$ and $\boldsymbol{\nu}$ parameters for the standard version of the distribution, i.e., for $\boldsymbol{\Sigma} = \mathbf{I}_k$. However, if $\boldsymbol{\Sigma}$ needs to be estimated the expression results in severe biases in the parameter estimates. Theorem 25 following the proof of Theorem 8 in the online appendix provides the appropriate correction.

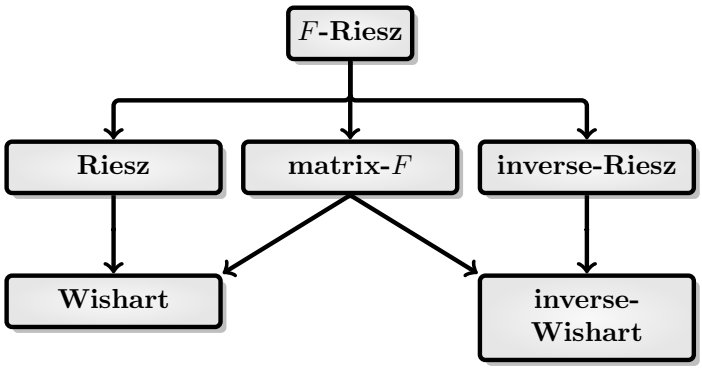

Figure 1: Family of matrix distributions
This figure shows a family tree of the F-Riesz distributions. Connected lines means that distributions are related by generalization.

Theorem 8 (**F-Riesz distribution**). *(i) Assume* $\boldsymbol{X}|\boldsymbol{Y} \sim \mathcal{R}^{I}(\boldsymbol{Y}, \boldsymbol{\mu})$ *and* $\boldsymbol{Y} \sim i\mathcal{R}^{II}(\boldsymbol{\Sigma}, \boldsymbol{\nu})$, *then* $\boldsymbol{X}$ *is* $\mathcal{FR}^{I}$ *distributed with density function*

$$p_{\mathcal{FR}^{I}}(\boldsymbol{X}; \boldsymbol{\Sigma}, \boldsymbol{\mu}, \boldsymbol{\nu}) = \frac{\overline{\Gamma}_U\left(\frac{\boldsymbol{\mu}+\boldsymbol{\nu}}{2}\right) \cdot |\boldsymbol{\Sigma}|_{0.5\boldsymbol{\nu}}}{\overline{\Gamma}_U\left(\frac{\boldsymbol{\nu}}{2}\right)\overline{\Gamma}\left(\frac{\boldsymbol{\mu}}{2}\right)} |\boldsymbol{X}|_{0.5(\boldsymbol{\mu}-k-1)} |\boldsymbol{\Sigma}+\boldsymbol{X}|_{-0.5(\boldsymbol{\mu}+\boldsymbol{\nu})}.$$

(ii) Assume $\boldsymbol{X}|\boldsymbol{Y} \sim \mathcal{R}^{II}(\boldsymbol{Y}, \boldsymbol{\mu})$ *and* $\boldsymbol{Y} \sim i\mathcal{R}^{I}(\boldsymbol{\Sigma}, \boldsymbol{\nu})$, *then* $\boldsymbol{X}$ *is* $\mathcal{FR}^{II}$ *distributed with density function*

$$p_{\mathcal{FR}^{II}}(\boldsymbol{X}; \boldsymbol{\Sigma}, \boldsymbol{\mu}, \boldsymbol{\nu}) = \frac{\overline{\Gamma}\left(\frac{\boldsymbol{\mu}+\boldsymbol{\nu}}{2}\right) \cdot {}_U|\boldsymbol{\Sigma}|_{0.5\boldsymbol{\nu}}}{\overline{\Gamma}\left(\frac{\boldsymbol{\nu}}{2}\right)\overline{\Gamma}_U\left(\frac{\boldsymbol{\mu}}{2}\right)} {}_U|\boldsymbol{X}|_{0.5(\boldsymbol{\mu}-k-1)} {}_U|\boldsymbol{\Sigma}+\boldsymbol{X}|_{-0.5(\boldsymbol{\mu}+\boldsymbol{\nu})}.$$

(iii) Let $\boldsymbol{\Sigma} = \boldsymbol{L}\boldsymbol{L}^\top = \boldsymbol{U}\boldsymbol{U}^\top$ *for lower and upper triangular matrix* $\boldsymbol{L}$ *and* $\boldsymbol{U}$, *respectively. If* $\boldsymbol{X} \sim \mathcal{FR}^{I}(\boldsymbol{\Sigma}, \boldsymbol{\mu}, \boldsymbol{\nu})$ *then* $\boldsymbol{L}^{-1}\boldsymbol{X}(\boldsymbol{L}^\top)^{-1} \sim \mathcal{FR}^{I}(\mathbf{I}_k, \boldsymbol{\mu}, \boldsymbol{\nu})$. *Similarly, if* $\boldsymbol{X} \sim \mathcal{FR}^{II}(\boldsymbol{\Sigma}, \boldsymbol{\mu}, \boldsymbol{\nu})$ *then* $\boldsymbol{U}^{-1}\boldsymbol{X}(\boldsymbol{U}^\top)^{-1} \sim \mathcal{FR}^{II}(\mathbf{I}_k, \boldsymbol{\mu}, \boldsymbol{\nu})$.

The following corollary establishes that the matrix-F distribution of Konno (1991) as used by Opschoor et al. (2018) is a special case of the F-Riesz distribution.

Corollary 9. *From Theorem 8.(i), if we assume* $\boldsymbol{\mu} = \mu \cdot \boldsymbol{\iota}_k$ *and* $\boldsymbol{\nu} = \nu \cdot \boldsymbol{\iota}_k$, *then* $\boldsymbol{X}$ *has a matrix-F distribution* $\mathcal{F}(\mu, \nu)$, *and*

$$p_{\mathcal{FR}^{I}}(\boldsymbol{X}; \boldsymbol{\Sigma}, \mu \cdot \boldsymbol{\iota}_k, \nu \cdot \boldsymbol{\iota}_k) = p_{\mathcal{F}}(\boldsymbol{X}; \boldsymbol{\Sigma}, \mu, \nu). \tag{14}$$

The corollary makes clear that it is possible to test whether the F-Riesz collapses to the matrix-F distribution by testing whether all elements in $\boldsymbol{\mu}$ are the same, as well as all elements in $\boldsymbol{\nu}$. This is a simple likelihood ratio test, and we revisit this in the simulation section later on.

We close this section by formulating the moments of the F-Riesz type I and II distributions. These moments turn out to be useful for re-parameterizing the model and for designing a two-step targeting approach to estimation. More details on this targeting approach are provided in Section 3.2.

Theorem 10 (**Expectation of the F-Riesz distribution**).

(i) Let $\boldsymbol{Y} \sim \mathcal{FR}^{I}(\mathbf{I}, \boldsymbol{\mu}, \boldsymbol{\nu})$, *then* $\mathbb{E}[\boldsymbol{Y}] = \boldsymbol{A}_k$, *where* $\boldsymbol{A}_k$ *is a diagonal matrix with ith diagonal element* a_i *equal to*

$$a_i = \begin{cases} \frac{\mu_1}{\nu_1 - k - 1}, & \text{for } i = 1, \\ \frac{1}{\nu_i - k + i - 2} \left(\mu_i + \sum_{i=1}^{i-1} a_i \right), & \text{for } i = 2, \ldots, k. \end{cases}$$

(ii) Let $\boldsymbol{Y} \sim \mathcal{FR}^{II}(\mathbf{I}, \boldsymbol{\mu}, \boldsymbol{\nu})$, *then* $\mathbb{E}[\boldsymbol{Y}] = \boldsymbol{A}_k$, *where* $\boldsymbol{A}_k$ *is a diagonal matrix with ith diagonal element* a_i *equal to*

$$a_i = \begin{cases} \frac{1}{\nu_i - i - 1} \left(\mu_i + \sum_{i=i+1}^{k} a_i \right), & \text{for } i = 1, \ldots, k-1, \\ \frac{\mu_k}{\nu_k - k - 1}, & \text{for } i = k. \end{cases}$$

From Theorem 8.(iii), the expectation of a general $\mathcal{FR}^{I}(\boldsymbol{\Sigma}, \boldsymbol{\mu}, \boldsymbol{\nu})$ random variable equals $\boldsymbol{L}\boldsymbol{A}_k\boldsymbol{L}^\top$ for $\boldsymbol{\Sigma} = \boldsymbol{L}\boldsymbol{L}^\top$, with $\boldsymbol{L}$ lower triangular. Similarly, the expectation of a $\mathcal{FR}^{II}(\boldsymbol{\Sigma}, \boldsymbol{\mu}, \boldsymbol{\nu})$ random variable equals $\boldsymbol{U}\boldsymbol{A}_k\boldsymbol{U}^\top$ for $\boldsymbol{\Sigma} = \boldsymbol{U}\boldsymbol{U}^\top$, with $\boldsymbol{U}$ upper triangular.

3.2 Conditional Autoregressive F-Riesz models

We apply the F-Riesz distribution later in this paper to observations $\boldsymbol{X}_t$ of realized covariance matrices. Of course, one can assume that these are i.i.d. observations from the F-Riesz or related distributions. This, however, is empirically implausible for realized covariance matrices, which typically exhibit quite some persistence over time. To illustrate the usefulness of the new distributions, we therefore consider a model specification that

allows for more persistence in $\boldsymbol{X}_t$. As an example, we consider the F-Riesz type I distribution. A similar set-up can be made for the other distributions discussed in this paper. Let $\boldsymbol{\Sigma}_t = \boldsymbol{L}_t \boldsymbol{L}_t^\top$ for a lower triangular matrix, then we consider the model

$$\boldsymbol{X}_t \mid \mathcal{F}_{t-1} \sim \mathcal{FR}^I(\boldsymbol{\Sigma}_t, \boldsymbol{\mu}, \boldsymbol{\nu}), \tag{15}$$

$$\boldsymbol{V}_t = \mathbb{E}[\boldsymbol{X}_t \mid \mathcal{F}_{t-1}] = \boldsymbol{L}_t \boldsymbol{M}(\boldsymbol{\mu}, \boldsymbol{\nu}) \boldsymbol{L}_t^\top, \tag{16}$$

$$\boldsymbol{V}_{t+1} = (1 - A - B)\boldsymbol{\Omega} + A \boldsymbol{X}_t + B \boldsymbol{V}_t, \tag{17}$$

where $\mathcal{F}_{t-1} = \{\boldsymbol{X}_1, \ldots, \boldsymbol{X}_{t-1}\}$ contains the lagged observations, and $\boldsymbol{M}(\boldsymbol{\mu}, \boldsymbol{\nu})$ is a diagonal matrix-valued function containing the expectation of the standard ($\boldsymbol{\Sigma}_t = \mathbf{I}_k$) F-Riesz type I distribution. We take $\boldsymbol{\Omega}$ as a symmetric positive definite parameter matrix, and A and B as scalar parameters. The model will be labeled as the Conditional Autoregressive F-Riesz model (CAFr). If we consider the Wishart rather than the F-Riesz distribution, the model resembles the Conditional Autoregressive Wishart (CAW) model of Golosnoy et al. (2012) In that case, the model is also one of the core equations of the Multivariate HEAVY model of Noureldin et al. (2012). Of course, the model can easily be extended to have non-scalar A and B, more lags of $\boldsymbol{V}_t$ and/or $\boldsymbol{X}_t$, and other dynamics including long-memory or HAR type dynamics (Corsi, 2009). For the sake of this paper, the current specification suffices and already shows that we obtain large increases in likelihood by allowing for tail-heterogeneity using the F-Riesz distribution. The size of additional gains obtained by changing to more persistent dynamics can be found in for instance Corsi (2009) and is not the core of our contribution in this paper.

Model (15)–(17) is observation driven and thus allows for easy parameter estimation via maximum likelihood using a standard prediction error decomposition. Standard errors are obtained using the standard sandwich covariance matrix estimator.

To reduce the dimensionality of the optimization, we use a targeting approach to estimate the matrix $\boldsymbol{\Omega}$. First note that there is a simple mapping between $\boldsymbol{\Sigma}_t$ and $\boldsymbol{V}_t$ for given $\boldsymbol{\mu}$ and $\boldsymbol{\nu}$. In particular for the F-Riesz type I distribution, $\boldsymbol{L}_t = \boldsymbol{L}_{\boldsymbol{V}_t} \boldsymbol{M}(\boldsymbol{\mu}, \boldsymbol{\nu})^{-1/2}$, where $\boldsymbol{L}_{\boldsymbol{V}_t}$ is a lower triangular matrix such that $\boldsymbol{V}_t = \boldsymbol{L}_{\boldsymbol{V}_t} \boldsymbol{L}_{\boldsymbol{V}_t}^\top$. Similar expressions hold for the other distributions. The targeting approach works as follows. Assuming stationarity and the existence of unconditional first moments, we can take unconditional expectations of the

left and right-hand sides of (17) to obtain $\overline{\boldsymbol{V}} = \mathbb{E}[\boldsymbol{V}_t] = \boldsymbol{\Omega}$. We use this to estimate $\boldsymbol{\Omega}$ by the sample average, $\hat{\boldsymbol{\Omega}} = n^{-1} \sum_{t=1}^{n} \boldsymbol{X}_t$. The likelihood then holds only in the remaining parameters A, B, $\boldsymbol{\mu}$, and $\boldsymbol{\nu}$.

3.3 Ordering of variables

A final issue for likelihood maximization is determining the order of the variables in the system. As mentioned earlier, the order of the variable matters for the specification of the Riesz type distributions. Enumeration of all possible orders and picking the highest likelihood value is typically unfeasible in high dimensions. To approximate the optimal order, we propose a heuristic approach, the core of which is described in the following algorithm.

Algorithm 11 (**Approximating the optimal ordering of variables in the system**). *Let $o = (o_1, \ldots, o_k)$ be a permutation of the first k integers, indicating the order of the variables in the system that make up the covariance matrix observations $\boldsymbol{X}_t$. Also, let $\boldsymbol{\theta}$ denote the static parameters that characterize the model and that need to be estimated by maximum likelihood.*

Step 0 *Set $j = 0$.*

Step 1 *Select a random order $o^{(j)} = (o_1^{(j)}, \ldots, o_k^{(j)})$.*

Step 2 *Given the ordering $o^{(j)}$, estimate $\boldsymbol{\theta}$ by maximum likelihood (possibly combined with a targeting approach) to obtain $\hat{\boldsymbol{\theta}}^{(j)}$.*

Step 3 *Loop over asset i, $i = 1, \ldots, k$:*

- *Step 3a* *Find $i^\star$ such that $i = o_{i^\star}^{(j)}$, i.e., find the position of asset i in the current ordering $o^{(j)}$.*
- *Step 3b* *Put asset i in each of the possible positions $1, \ldots, k$, while keeping the order of the other variables as in $o^{(j)}$, i.e., consider the permutations $(o_{i^\star}^{(j)}, o_1^{(j)}, \ldots, o_{i^\star-1}^{(j)}, o_{i^\star+1}^{(j)}, \ldots, o_k^{(j)})$, $(o_1^{(j)}, o_{i^\star}^{(j)}, o_2^{(j)}, \ldots, o_{i^\star-1}^{(j)}, o_{i^\star+1}^{(j)}, \ldots, o_k^{(j)})$, up to $(o_1^{(j)}, \ldots, o_{i^\star-1}^{(j)}, o_{i^\star+1}^{(j)}, \ldots, o_k^{(j)}, o_{i^\star}^{(j)})$. Retain the ordering that yields the highest log-likelihood value for* given $\hat{\boldsymbol{\theta}}^{(j)}$ *and store it as $o^{(j+1)}$.*

Step 3c *Increase j to $j+1$ and re-estimate $\hat{\boldsymbol{\theta}}^{(j)}$.*

Step 3d *Continue the loop by proceeding to the next asset $i+1$.*

Step 4 *Repeat steps 1–3 for p different random initial orderings, retaining the final order that yields the highest log-likelihood. Call this final order $o^{(opt)}$ with corresponding parameter estimate $\hat{\boldsymbol{\theta}}^{(opt)}$.*

Some more details and possible variations on this heuristic algorithm are provided in the online appendix. The algorithm ensures that the maximized likelihood never decreases for the different orderings of the variables in the system considered during the search. Moreover, the algorithm is efficient in that it limits the number of times we re-estimate the parameter $\boldsymbol{\theta}$. The latter is costly due to the (possibly high-dimensional) non-linear optimization problem. In particular, we only re-estimate $\boldsymbol{\theta}$ $p(k+1)$ times. This is substantially smaller for large k than the full $k!$ enumerated possible orderings and therefore provides an enormous computational gain. Though no guarantee is given that we arrive at the true optimum using this algorithm, the simulation evidence in the next section shows that it results in some considerable likelihood increases and typically gets close to the correct order of the variables measured in terms of rank correlations.

4 Consistency results

In this section, we establish the consistency of several estimators for the parameters of the F-Riesz distribution. For the case of a sample $\{\boldsymbol{X}_t\}_{t=1,\dots,T}$ composed of random i.i.d. draws from a F-Riesz distribution, we study the consistency of the estimator $\hat{\boldsymbol{V}}_T$ of the matrix $\boldsymbol{V} = \mathbb{E}[\boldsymbol{X}_t]$, the estimator $\hat{\boldsymbol{\Sigma}}_T$ of the scale matrix $\boldsymbol{\Sigma}$, and the estimator $(\hat{\boldsymbol{\mu}}_T, \hat{\boldsymbol{\nu}}_T)$ of the vector $(\boldsymbol{\mu}, \boldsymbol{\nu})$, as a two-step maximum likelihood estimator relying on a plug-in formulation of the log likelihood function. Additionally, for the case of a sample $\{\boldsymbol{X}_t\}_{t=1,\dots,T}$ generated by the conditional autoregressive F-Riesz model in (15)-(17), we obtain the consistency of the MLE for all the static parameters.

4.1 Consistency results for an i.i.d. sample

We first consider the consistent estimation of the unknown parameters of interest for an i.i.d. random sample from a F-Riesz distribution using the maximum likelihood estimator (MLE). Assumption 12 below states the distributional nature of the data generating process. Assumption 13 imposes the finiteness of the true $\boldsymbol{\Sigma}_0$ as well as restrictions on the parameter space for the vector $(\boldsymbol{\mu}, \boldsymbol{\nu})$.

Assumption 12. *The sequence* $\{\boldsymbol{X}_t\}_{t=1,...,T}$ *is i.i.d. with* $X_t \sim \mathcal{FR}^I(\boldsymbol{\Sigma}_0, \boldsymbol{\mu}_0, \boldsymbol{\nu}_0)$ *for every* $t = 1, ..., T$.

Assumption 13. *The positive definite matrix* $\boldsymbol{\Sigma}_0$ *satisfies* $\|\boldsymbol{\Sigma}_0\| < \infty$ *and* $(\boldsymbol{\mu}, \boldsymbol{\nu})$ *lie on a compact set satisfying* $\boldsymbol{\nu}_i > i + 1 \ \forall \ i$, *and* $\boldsymbol{\mu}_j > K + 1 \ \forall \ j$ *and containing* $(\boldsymbol{\mu}_0, \boldsymbol{\nu}_0)$.

Proposition 14 now establishes the strong consistency of the sample average as an estimator of $\boldsymbol{V}_0 = \mathbb{E}[\boldsymbol{X}_t]$.

Proposition 14. *Let assumptions 12 and 13 hold. Then* $\hat{\boldsymbol{V}}_T = \frac{1}{T}\sum_{t=1}^{T} \boldsymbol{X}_t \overset{a.s.}{\to} \boldsymbol{V}_0 = \mathbb{E}[\boldsymbol{X}_t]$ *as the sample diverges,* $T \to \infty$.

To prove the consistency of the two-step estimation procedure, we reparameterize the model using the fact that $\boldsymbol{\Sigma} = \boldsymbol{L}_{\boldsymbol{V}} \boldsymbol{A}_k^{-1} \boldsymbol{L}_{\boldsymbol{V}}^\top$, where $\boldsymbol{L}_{\boldsymbol{V}}$ is the (unique) Cholesky decomposition of $\boldsymbol{V}$. We define $\tilde{p}_{\mathcal{FR}^I}$ as the reparameterized density function which takes $\boldsymbol{V}$ rather than $\boldsymbol{\Sigma}$ as an argument, i.e., $\tilde{p}_{\mathcal{FR}^I}(\,\cdot\,; \boldsymbol{V}, \boldsymbol{\mu}, \boldsymbol{\nu}) \equiv p_{\mathcal{FR}^I}(\,\cdot\,; \boldsymbol{L}_{\boldsymbol{V}} \boldsymbol{A}_k^{-1} \boldsymbol{L}_{\boldsymbol{V}}^\top, \boldsymbol{\mu}, \boldsymbol{\nu})$.

Theorem 15 below establishes the strong set-consistency of the two-step MLE as $T \to \infty$. Note that in this two-step estimator $(\hat{\boldsymbol{\mu}}_T, \hat{\boldsymbol{\nu}}_T)$ depends on the first-step estimator for $\boldsymbol{V}_0$. Specifically, we define the MLE $(\hat{\boldsymbol{\mu}}_T, \hat{\boldsymbol{\nu}}_T)$ as the maximizer of the plug-in estimates $\log \tilde{p}_{\mathcal{FR}^I}(\boldsymbol{X}_t; \hat{\boldsymbol{V}}_T, \boldsymbol{\mu}, \boldsymbol{\nu})$,

$$(\hat{\boldsymbol{\mu}}_T, \hat{\boldsymbol{\nu}}_T) = \arg \max_{(\boldsymbol{\mu}, \boldsymbol{\nu}) \in \mathcal{U} \times \mathcal{V}} \frac{1}{T} \sum_{t=1}^{T} \log \tilde{p}_{\mathcal{FR}^I}(\boldsymbol{X}_t; \hat{\boldsymbol{V}}_T, \boldsymbol{\mu}, \boldsymbol{\nu}), \tag{18}$$

rather than of the true log-likelihood contributions $\log \tilde{p}_{\mathcal{FR}^I}(\boldsymbol{X}_t; \boldsymbol{V}_0, \boldsymbol{\mu}, \boldsymbol{\nu})$. We build on Wald's consistency and follow Theorem 5.14 in van der Vaart (2000) to obtain the consistency of our MLE to the set of parameters $\mathcal{U}_0 \times \mathcal{V}_0 \subseteq \mathbb{R}^{2k}$ that maximize the limit log

likelihood. In the case this set collapses to a singleton, we obtain the standard consistency result to the (pseudo) true parameter value. The theorem is as follows.

Theorem 15. *Let assumptions 12 and 13 hold. Then the MLE* $(\hat{\boldsymbol{\mu}}_T, \hat{\boldsymbol{\nu}}_T)$ *defined in (18) satisfies*

$$\lim_{T\to\infty} P_0\big(\ d_T \geq \varepsilon \ \wedge\ (\boldsymbol{\mu}_0, \boldsymbol{\nu}_0) \in \mathcal{U} \times \mathcal{V}\ \big) \ = \ 0,$$

for every $\varepsilon > 0$ *and every compact subset* $\tilde{\mathcal{U}} \times \tilde{\mathcal{V}} \subseteq \mathcal{U} \times \mathcal{V}$*, where* d_T *denotes the standard set distance between the vector* $(\boldsymbol{\mu}_0, \boldsymbol{\nu}_0)$ *and* $\mathcal{U}_0 \times \mathcal{V}_0$*,*

$$d_T := \inf\Big\{\ d\big(\ (\hat{\boldsymbol{\mu}}_T, \hat{\boldsymbol{\nu}}_T)\ , (\boldsymbol{\mu}, \boldsymbol{\nu})\ \big)\ :\ (\boldsymbol{\mu}, \boldsymbol{\nu}) \in \mathcal{U}_0 \times \mathcal{V}_0\Big\}.$$

Let $(\mathcal{U}_0, \mathcal{V}_0) = (\boldsymbol{\mu}_0, \boldsymbol{\nu}_0) \in \mathbb{R}^{2k}$ *be a singleton. Then the MLE* $(\hat{\boldsymbol{\mu}}_T, \hat{\boldsymbol{\nu}}_T)$ *satisfies* $(\hat{\boldsymbol{\mu}}_T, \hat{\boldsymbol{\nu}}_T) \xrightarrow{p} (\boldsymbol{\mu}_0, \boldsymbol{\nu}_0)$ *as* $T \to \infty$*.*

Corollary 16 builds on the strong consistency of $\hat{\boldsymbol{V}}_T$ from Proposition 14 and the weak consistency of $(\hat{\boldsymbol{\mu}}_T, \hat{\boldsymbol{\nu}}_T)$ from Theorem 15 to obtain the consistency of the estimator $\hat{\boldsymbol{\Sigma}}_T$ towards Σ_0.

Corollary 16. *Let assumptions 12 and 13 hold. Then* $\hat{\boldsymbol{\Sigma}}_T \xrightarrow{p} \Sigma_0$ *as* $T \to \infty$*.*

4.2 Consistency results for the conditional autoregressive F-Riesz model

We now turn to the consistency of the MLE for the unknown static parameter of the conditional autoregressive F-Riesz model. Assumption 17 below defines the conditional autoregressive F-Riesz model in (15)-(17) as the data generating process. Assumption 18 imposes the finiteness of the true intercept parameter $\boldsymbol{\Omega}_0 = \mathbb{E}[\boldsymbol{V}_t]$ and the compactness of the parameter space of the remaining parameters. Additionally, Assumption 19 imposes conditions on the parameters A_0 and B_0 which ensure positivity and contracting or stable stochastic behavior for the data generated by our dynamic model in (15)–(17).

Assumption 17. *The sequence* $\{\boldsymbol{X}_t\}_{t=1,\dots,T}$ *is generated by (15)-(17) under some* $(\boldsymbol{\Omega}_0, A_0, B_0, \boldsymbol{\mu}_0, \boldsymbol{\nu}_0)$ *for every* $t = 1, ..., T$*.*

Assumption 18. *$\boldsymbol{\Omega}_0$ is positive definite and $(A_0, B_0, \boldsymbol{\mu}_0, \boldsymbol{\nu}_0)$ lies in a compact parameter space Θ ensuring that $\hat{\boldsymbol{\Sigma}}_t$ is positive definite almost surely, uniformly over Θ, where $\boldsymbol{\nu}_i > i + 1 \; \forall \; i$, and $\boldsymbol{\mu}_j > K + 1 \; \forall \; j$.*

Assumption 19. *$A_0 \geq 0$, $B_0 \geq 0$ and $|A_0 + B_0| < 1$.*

Under the conditions laid down in assumptions 17-19, we can obtain the strong consistency of the sample average $\hat{\boldsymbol{\Omega}} = n^{-1} \sum_{t=1}^{n} \boldsymbol{X}_t$ with respect to $\boldsymbol{\Omega}_0$ by application of the ergodic theorem.

Proposition 20. *Let assumptions 17-19 hold. Then $\hat{\boldsymbol{\Omega}} = n^{-1} \sum_{t=1}^{n} \boldsymbol{X}_t \overset{a.s.}{\to} \boldsymbol{\Omega}_0$ as $T \to \infty$.*

We now turn to the invertibility of the filtering equation (17). Following the literature (e.g. Straumann and Mikosch (2006) and Wintenberger (2013)), invertibility ensures that the filter 'forgets' the incorrect initialization; i.e. the filtered sequence $\{\hat{\boldsymbol{V}}_t\}_{t \in \mathbb{N}}$ initialized at some point $\hat{\boldsymbol{V}}_1$ converges pathwise and exponentially fast to a unique stationary and ergodic limit sequence $\{\boldsymbol{V}_t\}_{t \in \mathbb{N}}$. This means that $c^t \|\hat{\boldsymbol{V}}_t - \boldsymbol{V}_t\| \overset{a.s.}{\to} 0$ as $t \to \infty$ for some $c > 1$, regardless of the fact that the initialization $\hat{\boldsymbol{V}}_1$ is almost surely incorrect (as the true $\boldsymbol{V}_1$ is an unobserved continuous random variable).

In the current setting, filter invertibility can be obtained by ensuring that the following conditions hold:

(i) stationarity of the data $\{\boldsymbol{X}_t\}_{t \in \mathbb{Z}}$;

(ii) a *logarithmic bounded moment* for $\boldsymbol{X}_t \; \forall \; t$;

(iii) a *contraction condition* for the filtering equation.

The stationarity of the data in (i), and the logarithmic moment in (ii), follow from assumptions 17-19. The contraction condition for the filtering equation, however, requires additional restrictions on the parameter space. Assumption 21 ensures that the filtered $\hat{\boldsymbol{V}}_t$ is positive definite and the contracting behavior of the stochastic sequence $\{\hat{\boldsymbol{V}}_t\}_{t \in \mathbb{N}}$.

Assumption 21. *The parameter space $\mathcal{A} \times \mathcal{B}$ is such that $A \geq 0$, $B \geq 0$ and $\sup_{B \in \mathcal{B}} |B| < 1$.*

Proposition 22 now establishes the invertibility of the filter $\hat{\boldsymbol{V}}_t$ for $\boldsymbol{V}_t$, and opens the door to the consistency of the MLE.

Proposition 22. *Let assumptions 17-21 hold. Then the filter* $\{\hat{\boldsymbol{V}}_t\}_{t\in\mathbb{N}}$ *is invertible.*

We are now ready to formulate our consistency result of the MLE $(\hat{A}_T, \hat{B}_T, \hat{\boldsymbol{\mu}}_T, \hat{\boldsymbol{\nu}}_T)$ for the vector $(A_0, B_0, \boldsymbol{\mu}_0, \boldsymbol{\nu}_0)$. Again, this MLE takes the form of a targeted two-step estimator as it depends on the first-step estimator for $\boldsymbol{\Omega}_0$. Additionally, as is common for filtering models, the log-likelihood depends directly on the properties of the filter $\hat{\boldsymbol{V}}_t$, which is itself a function of the estimated $\hat{\boldsymbol{\Omega}}_T$, the parameters A and B, and the initialization $\hat{V}_1$ as noted above. Specifically, we define the MLE as the maximizer of the plug-in loglikelihood $\log \tilde{p}_{\mathcal{FR}^I}(\boldsymbol{X}_t; \hat{\boldsymbol{V}}_t(\hat{\boldsymbol{\Omega}}_T, A, B), \boldsymbol{\mu}, \boldsymbol{\nu})$,

$$(\hat{A}_T, \hat{B}_T, \hat{\boldsymbol{\mu}}_T, \hat{\boldsymbol{\nu}}_T) = \arg\max_{(A,B,\boldsymbol{\mu},\boldsymbol{\nu})} \sum_{t=1}^{T} \log \tilde{p}_{\mathcal{FR}^I}(\boldsymbol{X}_t; \hat{\boldsymbol{V}}_t(\hat{\boldsymbol{\Omega}}_T, A, B), \boldsymbol{\mu}, \boldsymbol{\nu}). \tag{19}$$

Just as for the i.i.d. case, we build on Wald's consistency proof and follow Theorem 5.14 in van der Vaart (2000) to establish the set-consistency of the MLE towards the set $\mathcal{A}_0 \times \mathcal{B}_0 \times \mathcal{U}_0 \times \mathcal{V}_0$ of optimizers of the limit log-likelihood function.

Theorem 23. *Let assumptions 17-21 hold. Then the targeted MLE* $(\hat{A}_T, \hat{B}_T, \hat{\boldsymbol{\mu}}_T, \hat{\boldsymbol{\nu}}_T)$ *defined in (19) satisfies*

$$\lim_{T\to\infty} P_0\Big(\; d_T \geq \varepsilon \;\wedge\; (A_0, B_0, \boldsymbol{\mu}_0, \boldsymbol{\nu}_0) \in \tilde{\mathcal{A}} \times \tilde{\mathcal{B}} \times \tilde{\mathcal{U}} \times \tilde{\mathcal{V}} \; \Big) \;=\; 0,$$

for every $\varepsilon > 0$ *and every compact subset* $\tilde{\mathcal{A}} \times \tilde{\mathcal{B}} \times \tilde{\mathcal{U}} \times \tilde{\mathcal{V}} \subseteq \mathcal{A} \times \mathcal{B} \times \mathcal{U} \times \mathcal{V}$*, where* d_T *denotes the standard set distance between the vector* $(A_0, B_0, \boldsymbol{\mu}_0, \boldsymbol{\nu}_0)$ *and* $\mathcal{A}_0 \times \mathcal{B}_0 \times \mathcal{U}_0 \times \mathcal{V}_0$*,*

$$d_T := \inf\Big\{ \; \big\|(\hat{A}_T, \hat{B}_T, \hat{\boldsymbol{\mu}}_T, \hat{\boldsymbol{\nu}}_T) - (A, B, \boldsymbol{\mu}, \boldsymbol{\nu})\big\| \;:\; (A, B, \boldsymbol{\mu}, \boldsymbol{\nu}) \in \mathcal{A}_0 \times \mathcal{B}_0 \times \mathcal{U}_0 \times \mathcal{V}_0 \Big\}.$$

As in the i.i.d. case, if $(A_0, B_0, \boldsymbol{\mu}_0, \boldsymbol{\nu}_0)$ is identified so that it uniquely maximizes the limit criterion $\mathbb{E}[\log \tilde{p}_{\mathcal{FR}^I}(\boldsymbol{X}_t; \boldsymbol{V}_t(\boldsymbol{\Omega}_0, A, B), \boldsymbol{\mu}, \boldsymbol{\nu})]$, the set $\mathcal{A}_0 \times \mathcal{B}_0 \times \mathcal{U}_0 \times \mathcal{V}_0$ collapses to a singleton and we recover the standard consistency result to the unique true parameters.

5 Simulation experiment

This section shows results of a Monte Carlo study which investigates the statistical properties of the maximum likelihood estimator of the parameters corresponding with the newly developed distributions. We perform five simulation experiments.

The first experiment aims to assess the small sample properties of the MLE for all degrees-of-freedom (DoF) parameters plus the parameters from the covariance matrix in a static model setting ($A = B = 0$). We simulate covariance matrices $\boldsymbol{X}_t$ of dimension 2 from the Riesz, inverse Riesz and F-Riesz distributions respectively. We set $\boldsymbol{V} = \boldsymbol{L}\boldsymbol{L}^\top = \boldsymbol{U}\boldsymbol{U}^\top$ with $\boldsymbol{L}$ ($\boldsymbol{U}$) the lower (upper) Cholesky matrix with elements $\boldsymbol{L}_{11} = 2.752$, $\boldsymbol{L}_{21} = 2.125$, $\boldsymbol{L}_{22} = 3.006$ and $\boldsymbol{U}_{11} = 2.247$, $\boldsymbol{U}_{21} = 1.588$, $\boldsymbol{U}_{22} = 3.682$. We set $\boldsymbol{\nu} = (10, 20)$ for the Riesz, as well as for the inverse Riesz distribution. For the F-Riesz distribution, we set $\boldsymbol{\mu} = (10, 15)$ and $\boldsymbol{\nu} = (15, 10)$.

The second experiment focuses on the estimation of the DoF parameters in a 5-variate case, where now the elements of $\boldsymbol{V}$ are estimated using a targeting approach as explained in Section 3.2. We set $\boldsymbol{\nu} = (10, 15, 20, 14, 12)$ for the (inverse) Riesz distribution, while $\boldsymbol{\mu} = (10, 15, 20, 14, 12)$ and $\boldsymbol{\nu} = (10, 15, 20, 12, 14)$ for the F-Riesz distribution.

Both simulation experiments are based on samples of 1000 observations from the three distributions. We then use Maximum Likelihood to estimate the parameters of interest. In addition, we estimate their standard errors by computing the inverse of the (negative) Hessian at the optimum. We replicate each experiment 1000 times.

Table 1 presents the results of the first two simulation experiments. Panels A and B correspond to the type I distributions, while Panels C and D show results for the type II distributions. In all panels, we find that all parameters are estimated near their true values. Comparing the Monte-Carlo standard error of the estimates (std column in Table 1) with the mean of the estimated standard error over all replications (mean(s.e.) column), we find that our computed standard errors fairly reflect estimation uncertainty. Only the true variability of the $\boldsymbol{\nu}$ parameters for the inverse Riesz and F-Riesz appears slightly higher than estimated by the usual standard errors, but the difference is minor.

The third and fourth simulation experiments are designed to address the different possible orderings of the variables in the system that make up the covariance matrix $\boldsymbol{X}_t$.

Table 1: Parameter estimations of (inverse) Riesz and the F-Riesz distributions

This table shows Monte Carlo averages and standard deviations (in parentheses) of parameter estimates of simulated covariance matrices from the Riesz, inverse Riesz and F-Riesz distributions of dimension two and five. Panel A and B show results of the type I distributions, while panels C and D list results of the type II distributions. Panels A and C correspond to the bivariate case, where both the (Cholesky elements $\boldsymbol{L}_{11}$ ($\boldsymbol{U}_{11}$), $\boldsymbol{L}_{21}$ ($\boldsymbol{U}_{21}$) and $\boldsymbol{L}_{22}$ ($\boldsymbol{U}_{22}$) of) $\boldsymbol{V}_t$ as well as the degrees of freedom (DoF) parameters $\boldsymbol{\nu}$ and $\boldsymbol{\mu}$ are estimated. Panels B and D shows results of the five-variate case, where the elements of $\boldsymbol{V}$ are estimated by targeting in a first step, and the DoF parameters are estimated in a second step by maximum likelihood. The table reports the true values, the mean and standard deviation of the estimated coefficients, as well as the mean of the computed standard error. Results are based on 1000 Monte Carlo replications.

	Panel A: dimension 2					Panel B: dimension 5 (targeting)				
Distribution	Coef.	True	mean	std	mean(s.e.)	Coef.	True	mean	std	mean(s.e.)
Riesz I	L_{11}	2.752	2.752	0.019	0.019	ν_1	10	10.02	0.43	0.43
	L_{21}	2.125	2.126	0.025	0.026	ν_2	20	20.03	0.61	0.60
	L_{22}	3.006	3.006	0.015	0.015	ν_3	15	15.02	0.35	0.35
						ν_4	18	18.01	0.37	0.36
	ν_1	10	10.03	0.43	0.43	ν_5	12	12.01	0.18	0.19
	ν_2	20	20.01	0.60	0.60					
Inv Riesz I	L_{11}	2.752	2.752	0.019	0.020	ν_1	10	10.05	0.42	0.35
	L_{21}	2.125	2.126	0.027	0.027	ν_2	20	20.01	0.61	0.54
	L_{22}	3.006	3.006	0.018	0.018	ν_3	15	15.03	0.33	0.28
						ν_4	18	18.02	0.33	0.29
	ν_1	10	10.03	0.41	0.44	ν_5	12	12.00	0.18	0.11
	ν_2	20	20.04	0.61	0.61					
F-Riesz I	L_{11}	2.752	2.752	0.028	0.028	μ_1	10	10.02	0.57	0.55
	L_{21}	2.125	2.126	0.038	0.037	μ_2	15	15.03	0.64	0.62
	L_{22}	3.006	3.006	0.036	0.036	μ_3	20	20.05	0.73	0.72
						μ_4	14	14.01	0.40	0.40
	μ_1	10	10.08	0.87	0.86	μ_5	12	12.00	0.28	0.27
	μ_2	15	15.16	1.17	1.12					
	ν_1	15	15.23	1.85	1.87	ν_1	10	10.06	0.54	0.47
	ν_2	10	10.06	0.72	0.69	ν_2	15	15.06	0.73	0.66
						ν_3	20	20.10	0.96	0.93
						ν_4	12	12.05	0.43	0.39
						ν_5	14	14.12	0.75	0.69

To investigate this sensitivity in experiment three, we study the full enumeration approach for all available orderings in a low-dimensional setting. We simulate 1000 matrices $\boldsymbol{X}_t$ from a 5-variate $\mathcal{R}^I(\boldsymbol{\Sigma}, \boldsymbol{\nu})$ distribution with $\boldsymbol{\nu} = (10, 20, 15, 18, 12)^\top$ and an arbitrarily chosen matrix $\boldsymbol{\Sigma}$. In each simulation run, we consider all 120 possible orderings of the variables in the system and estimate $\boldsymbol{\Sigma}$ and $\boldsymbol{\nu}$ using the targeting approach. We retain the ordering that has the highest maximized log-likelihood. We obtain such a final, optimal ordering $o^{(opt)}$ for each simulation run. To check whether the optimally estimated order coincides

(continued from previous page)

	Panel C: dimension 2					Panel D: dimension 5 (targeting)				
Distribution	Coef.	True	mean	std	mean(s.e.)	Coef.	True	mean	std	mean(s.e.)
Riesz II	U_{11}	2.247	2.248	0.016	0.016	ν_1	10	10.01	0.15	0.14
	U_{21}	1.588	1.589	0.023	0.024	ν_2	20	20.01	0.39	0.40
	U_{22}	3.682	3.681	0.019	0.018	ν_3	15	15.02	0.36	0.35
						ν_4	18	18.03	0.53	0.54
	ν_1	10	10.02	0.28	0.29	ν_5	12	12.02	0.53	0.52
	ν_2	20	20.07	0.87	0.88					
Inv Riesz II	U_{11}	2.247	2.247	0.020	0.020	ν_1	10	10.01	0.15	0.07
	U_{21}	1.588	1.589	0.028	0.029	ν_2	20	20.00	0.42	0.34
	U_{22}	3.682	3.682	0.027	0.028	ν_3	15	15.02	0.35	0.28
						ν_4	18	17.98	0.58	0.47
	ν_1	10	10.02	0.29	0.29	ν_5	12	12.03	0.53	0.44
	ν_2	20	20.05	0.89	0.89					
F-Riesz II	U_{11}	2.247	2.247	0.025	0.025	μ_1	10	9.99	0.21	0.20
	U_{21}	1.588	1.588	0.039	0.039	μ_2	15	14.97	0.44	0.44
	U_{22}	3.682	3.682	0.043	0.041	μ_3	20	20.00	0.74	0.72
						μ_4	14	13.98	0.61	0.57
	μ_1	10	10.06	0.71	0.69	μ_5	12	12.00	0.67	0.67
	μ_2	15	15.14	1.39	1.40					
	ν_1	15	15.29	1.87	1.82	ν_1	10	10.06	0.43	0.29
	ν_2	10	10.08	0.70	0.69	ν_2	15	15.11	0.70	0.63
						ν_3	20	20.17	1.04	0.94
						ν_4	12	12.05	0.53	0.46
						ν_5	14	14.14	0.89	0.78

with the true DGP ordering, we compute the rank correlation between $o^{(opt)}$ and $o^{(dgp)}$ in each simulation run, and average across simulation runs. We also compute the difference between the maximum value of the optimized log-likelihood and the log-likelihood of the DGP for each simulation run. Finally, we apply Algorithm 11 on 20 randomly chosen orders o^j and report the final order o^{opt} with the associated maximized log-likelihood.

Results of the third experiment are shown in Panel A of Table 2. The average rank correlation between the ordering with the highest log-likelihood and the true ordering is almost 1. Moreover, in more than 99% of the cases we are able to find the true ordering using the full set of 120 enumerated different orderings. Interestingly, applying the Heuristic gives exactly the same results, indicating that it works well in this simulation exercise. Panel A.2 shows that the average difference in log-likelihood between the highest and the DGP log-likelihood equals 2.6 points on average across all simulations, which is very low.

In the fourth experiment, we test the performance of Algorithm 11 in improving the

Table 2: Simulation results on the ordering of variables

This table shows Monte Carlo results of two simulation experiments. Panels A.1 and A.2 present results for estimating parameters of a 5-dimensional $\mathcal{R}^I(\boldsymbol{\Sigma}, \boldsymbol{\nu})$ distribution across 120 possible orderings of $\boldsymbol{X}$. In addition, it lists results of applying Heuristic I with 20 randomly chosen orders o^j. Panel A.1 shows the average rank correlation between the true ordering and 1) the ordering with the highest maximized log-likelihood, or 2) the final order o^{opt} in case of the Heuristic. Also the percentage of cases that this ordering matches the ordering of the DGP exactly is shown. Panel A.2 shows summary statistics of the range of the highest minus the log-likelihood of the DGP across all 120 possible orderings, summarized over simulation replications. Moreover, we also report the difference between the associated maximized log-likelihood of the final order of the Heuristic and the DGP. Panel B lists results of applying the Heuristic to a 15-variate $\mathcal{R}^I$ distribution with ordering $1, \ldots, 15$, using $p = 50$ randomly chosen initial orderings, labeled as Heu(1). Having obtained the final order and associated maximized log-likelihood, we repeat the Heuristic with the final order as the starting order. We label this as Heu(2). Panel B.1 shows the average rank correlation between the true ordering and the optimal ordering estimated using our algorithm once and twice. In addition, it presents the rank correlation between $o^{(opt)}$ for a pair of two random initial orderings, averaged across all pairs, and across all simulations. Finally, it lists the percentage of cases that part of the optimal ordering (1-5), (1-10) and the full ordering (1-15) matches exactly (part of the) ordering of the DGP. Panel B.2 reports summary statistics of the difference between the optimized log likelihood after applying Algorithm 11 and the log likelihood from the correct DGP. We run 1000 Monte Carlo replications for Panel A, while 500 Monte Carlo replications are used for panel B.

Panel A.1: Rank correlations

	FE	Heu
average rank corr $(o^{(opt)}, o^{(dgp)})$	0.999	0.999
perc correct rank $(o^{(opt)} = o^{(dgp)})$	0.994	0.994

Panel A.2: Summary statistics on $\log \mathcal{L}_{max} - \log \mathcal{L}_{DGP}$

	mean	sd	min	max
Full Enumeration	2.6	1.6	0.1	10.7
Heuristic	2.6	1.6	0.1	10.7

Panel B.1: Testing Heuristic I on $k = 15$: rank correlations

	Heu(1)	Heu(2)
average rank corr $(o^{(opt)}, o^{(dgp)})$	0.982	0.989
average rank corr of $o^{(opt)}$ across simulation pairs	0.807	0.951
perc correct rank $(o^{(opt)} = o^{(dgp)})$(1-5)	0.944	0.966
perc correct rank $(o^{(opt)} = o^{(dgp)})$(1-10)	0.676	0.784
perc correct rank $(o^{(opt)} = o^{(dgp)})$(1-15)	0.348	0.510

Panel B.2: Summary statistics on $\log \mathcal{L}_{opt} - \log \mathcal{L}_{DGP}$

	mean	sd	min	max
Heuristic(1)	7.10	3.85	-9.53	15.63
Heuristic(2)	8.37	3.05	1.05	16.38

likelihood and in finding the true variable ordering. In each replication in this experiment, we simulate 1000 matrices $\boldsymbol{X}_t$ from a 15-variate $\mathcal{R}^I(\boldsymbol{\Sigma}, \boldsymbol{\nu})$ distribution with ordering $o_{DGP} = (1, \ldots, 15)$ for a given $\boldsymbol{\Sigma}$ and $\boldsymbol{\nu}$. Note that for 15 variables there are more than 1.3 trilion possible orderings, such that trying all of them becomes impractical to impossible. We apply our algorithm for $p = 50$ different randomly chosen initial orderings. After obtaining

the optimal order $o^{(opt)}$ from the Heuristic, we apply the Heuristic again using this order as the starting ordering. The final outcome is labeled as Heuristic(2). We report the average (across replications) of the rank correlation between $o^{(opt)}$ and $o^{(dgp)}$. In addition, we list the percentage of cases where (part of) the optimal ordering exactly matches (part of) the ordering of the DGP. Moreover, to check the sensitivity of the algorithm to the p random initial orderings, we also compute the rank correlation of $o^{(opt)}$ for all pairs of two simulation replications, and then average over all pairs. The closer this number is to one, the smaller is the dependence on the precise initial random orderings. Also this fourth experiment is replicated 1000 times.

Panel B of Table 2 shows the results. Again, we find a very high rank correlation of 0.982 between the true order of the variables and the optimal estimated order. This implies that the algorithm works adequately. Second, the average (across all pairs) rank correlation for any combination of $o^{(opt)}$ based on two different initial random orderings is 0.802. This is high, and indicates that there is limited dependence of the final optimal ordering $o^{(opt)}$ on the $p = 50$ random initial orderings. Applying the Heuristic again increases this number to 0.951, hence the influence of the random initial ordering becomes very small. Furthermore, panel B.1 also indicates that repeating the Heuristic considerably improves the optimal ordering in the middle and in the end of the DGP ordering vector, as the percentages of correct rank increases from 0.676 (0.348) to 0.784 (0.510) respectively. As long as p is not chosen too small, the algorithm typically produces substantial likelihood increases. This pattern is corroborated by the difference between the maximized likelihood for all 50 different initial orderings and the maximized likelihood based on the DGP ordering ($\log \mathcal{L}_{dgp}$. The range of likelihoods is only 25 points wide (differences ranging form -9.63 to 15.63), and decreases if we repeat the Heuristic.

This is also illustrated by Figure 2, which shows a histogram of log likelihoods of the $\mathcal{R}^I$ distribution. The blue bars show $\log \mathcal{L}$ of the Riesz distribution of 50 randomly chosen initial orderings. These exhibit substantial dispersion, and are clearly inferior to the maximized likelihood value for the DGP ordering (red bar). However, after applying Algorithm 11 to the 50 initial random orderings twice, we obtain twice 50 optimal orderings $o^{(opt)}$. The latter are plotted with the green and yellow bars and are clearly much more concentrated, and close to the maximized log-likelihood value corresponding to the DGP ordering. The algorithm

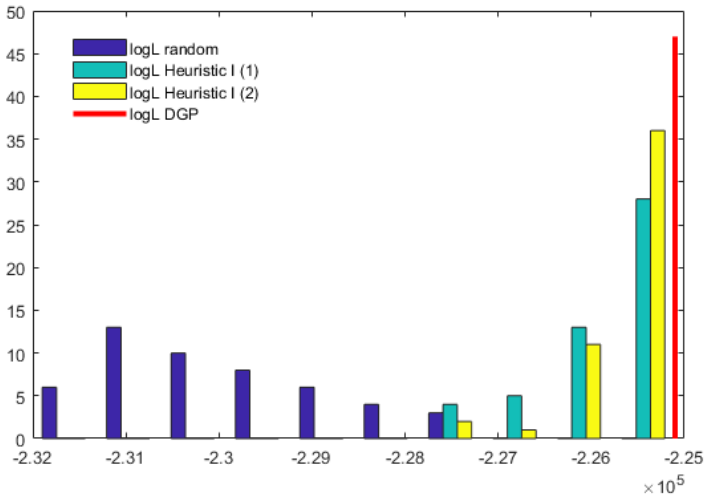

Figure 2: Heuristic I: log-likelihood values of the $\mathcal{R}^I$ distribution
This figure shows a histogram of $\log \mathcal{L}$ values of the 15-variate $\mathcal{R}^I$ distribution. The blue bars correspond to the likelihood values of 50 randomly chosen order *before* applying Heuristic I, while the green (yellow) bars show $\log \mathcal{L}$ values *after* applying the heuristic (twice). The red bar denotes the log-likelihood with the correct ordering from the DGP.

thus succeeds very well in eliminating much of the randomness of the initial orderings, and getting close to the optimal ordering.

The last simulation experiment investigates the statistical gain of the F-Riesz distribution over the matrix F distribution. Guided by the empirical application, we focus on a 5-variate F-Riesz I distribution with degrees of freedom vectors $\boldsymbol{\mu} = (18.7, 35.8, 58.2, 89.4, 143.9)^\top$ and $\boldsymbol{\nu} = (22.8, 24.3, 28.6, 22.3, 18.2)^\top$. We define $\bar{\mu} = 69.2$ and $\bar{\nu} = 23.3$ as the average values of the vectors $\boldsymbol{\mu}$ and $\boldsymbol{\nu}$ respectively and $\boldsymbol{\mu}_{range} = \boldsymbol{\mu} - \bar{\mu}\boldsymbol{\iota}_k$ and $\boldsymbol{\nu}_{range} = \boldsymbol{\nu} - \bar{\nu}\boldsymbol{\iota}_k$. The simulation experiment now consists of the following steps. First, we simulate 1000 matrices $\boldsymbol{X}_t$ from a $\mathcal{FR}^I(\boldsymbol{\Sigma}, \tilde{\boldsymbol{\mu}}, \tilde{\boldsymbol{\nu}})$ with $\tilde{\boldsymbol{\mu}} = \bar{\mu}\boldsymbol{\iota}_k + \lambda\boldsymbol{\mu}_{range}$ and $\tilde{\boldsymbol{\nu}} = \bar{\nu}\boldsymbol{\iota}_k + \lambda\boldsymbol{\nu}_{range}$ for $\lambda = (0, 0.02, \ldots, 0.08, 0.10)$. Note that if $\lambda = 0$, the $\mathcal{FR}^I$ distribution collapses to a matrix-F distribution with $\bar{\mu}$ and $\bar{\nu}$ degrees of freedom. Second, we estimate $\boldsymbol{\Sigma}$ (using the targeting approach) and the degrees of freedom parameters assuming a matrix F or $\mathcal{FR}^I$ distribution. For each λ we test the null-hypotheses $\boldsymbol{\mu} = \bar{\mu}\boldsymbol{\iota}_k$ and $\boldsymbol{\nu} = \bar{\nu}\boldsymbol{\iota}_k$. This boils down to Likelihood-Ratio test with $2*k-2$ degrees of freedom. We repeat this exercise 1000 times.

Table 3 shows the results. In Panel A, we see that if we simulate from a matrix-F distribution (i.e. $\lambda = 0$), the likelihood ratio test has been rejected in 8.4 % of all cases.

Table 3: The matrix F vs the F-Riesz distributions

This table shows Monte Carlo results on the difference between the F-Riesz and the matrix-F distribution. Panel A lists results on simulating 1000 matrices from a $\mathcal{FR}^I(\boldsymbol{\Sigma}, \tilde{\boldsymbol{\mu}}, \tilde{\boldsymbol{\nu}})$ distribution with $\tilde{\boldsymbol{\mu}} = \bar{\mu}\boldsymbol{\iota}_k + \lambda\boldsymbol{\mu}_{range}$ and $\tilde{\boldsymbol{\nu}} = \bar{\nu}\boldsymbol{\iota}_k + \lambda\boldsymbol{\nu}_{range}$ for $\lambda = (0, 0.02, \ldots, 0.08, 0.10)$ with $\bar{\mu} = 69.2$, $\bar{\nu} = 23.3$, $\boldsymbol{\mu}_{range} = \boldsymbol{\mu} - \bar{\mu}\boldsymbol{\iota}_k$ and $\boldsymbol{\nu}_{range} = \boldsymbol{\nu} - \bar{\nu}\boldsymbol{\iota}_k$ and $\boldsymbol{\mu} = (18.7, 35.8, 58.2, 89.4, 143.9)^\top$ and $\boldsymbol{\nu} = (22.8, 24.3, 28.6, 22.3, 18.2)^\top$. We estimate the parameters assuming a matrix-F or $\mathcal{FR}^I$ distribution. For each value of λ we perform a likelihood ratio test on the null-hypothesis $\boldsymbol{\mu} = \bar{\mu}\boldsymbol{\iota}_k$ and $\boldsymbol{\nu} = \bar{\nu}\boldsymbol{\iota}_k$. Panel A lists the percentage rejections of this hypothesis for different values of λ. Further, Panel B reports results on the estimated degrees-of-freedom parameters of the matrix- F and/or F-Riesz I distribution for the case $\lambda = 0$. The panel reports the true values, the mean and standard deviation of the estimated coefficients. All results are based on 1000 Monte Carlo replications.

Panel A: Matrix F vs F-Riesz I						
λ	0	0.02	0.04	0.06	0.08	0.10
rejection rate	0.084	0.126	0.311	0.594	0.839	0.980

Panel B: DoF parameters when $\lambda = 0$						
matrix-F		$\bar{\mu}$	$\bar{\nu}$			
	true	69.20	23.25			
	mean	69.25	23.33			
	sd	5.72	0.63			
F-Riesz I		$\boldsymbol{\mu}_1$	$\boldsymbol{\mu}_2$	$\boldsymbol{\mu}_3$	$\boldsymbol{\mu}_4$	$\boldsymbol{\mu}_5$
	true	69.20	69.20	69.20	69.20	69.20
	mean	69.60	69.47	69.54	69.44	69.42
	sd	7.26	6.52	6.29	6.05	5.83
		$\boldsymbol{\nu}_1$	$\boldsymbol{\nu}_2$	$\boldsymbol{\nu}_3$	$\boldsymbol{\nu}_4$	$\boldsymbol{\nu}_5$
	true	23.25	23.25	23.25	23.25	23.25
	mean	23.36	23.32	23.34	23.40	23.42
	sd	0.99	0.91	0.99	1.17	1.52

Further, when we deviate slightly from the matrix-F setting, we immediately reject the null-hypothesis of a scalar μ and ν in all cases. Panel B lists that the correct matrix-F parameters are indeed estimated back on average. Also the average parameter estimates of the F-Riesz I corresponds to the simulated values of 69.2 and 23.25.

6 Empirical application

In this section, we apply the F-Riesz distribution to an empirical data set of 30 U.S. equities from the S&P 500 index over the period January 2, 2001, until July 31, 2014, a total of 3415 trading days. We extract transaction prices from the Trade and Quote (TAQ) database and clean the high-frequency data in line with Brownlees and Gallo (2006) and Barndorff-Nielsen et al. (2009). After this cleaning procedure we construct realized covariance matrices $\boldsymbol{X}_t$ using 5 minute returns with subsampling.

We consider six different matrix distributions with a time-varying mean $\boldsymbol{V}_t$ for the realized covariance matrices: the Wishart, the Riesz, the inverse Wishart, the inverse Riesz, the Matrix-F, and the F-Riesz distribution. For the Riesz related distributions, we only consider the type I version. The type II versions of these distributions yield very similar results. The dynamic specification is as in (15)–(17), with only equation (15) modified for the distribution at hand. We use the two-step targeting approach from Section 3.2 to estimate $\boldsymbol{\Omega}$, and the algorithm from Section 3.3 with $p = 50$ on the CAFr model to determine the order of the different stocks in the system. In order to effectively compare the likelihoods, we use the same optimal order from this model to the conditional autoregressive Wishart (CAW) and inverse Wishart (CAiW) models. Table 4 reports the results for full-sample estimation.

The table shows three main results. First, the maximized log-likelihood shows that the model with the F-Riesz distribution is superior against the other specifications. The gain increases with the dimension of the system. For example the difference between the F-Riesz and the matrix-F distribution equals 5000, 30,000 and 90,000 for dimension 5, 15 and 30 respectively. This result is striking and suggests substantial heterogeneity in the tails. The AIC values further support the usefulness of the F-Riesz distribution: the large differences in likelihoods persist if we correct for the number of estimated parameters.

Second, tail heterogeneity plays an important role at all levels of the analysis. When relaxing the Wishart to the Riesz specification, the likelihood increases substantially for all dimensions considered. The same holds when relaxing the inverse Wishart to the inverse Riesz. Interestingly, it seems that both effects more than accumulate when generalizing the matrix-F to the F-Riesz distribution: the jump in likelihood from the matrix-F to the F-Riesz is in all cases more than the jump from the Wishart to the Riesz plus that of the inverse Wishart to the inverse Riesz. This is the more interesting result given that the matrix-F already heavily outperforms the Wishart, inverse Wishart, Riesz, and to a lesser extent also the inverse Riesz distributions. The F-Riesz distribution thus seems a major step forward in capturing the empirical features of realized covariance matrices.

Third, the importance of allowing for tail heterogeneity is confirmed by looking at the estimates of the degrees of freedom parameters. For conciseness, the table only reports the minima and maxima of the elements of $\boldsymbol{\mu}$ and $\boldsymbol{\nu}$. Still, the picture is clear. For example,

Table 4: Parameter estimates, likelihoods and information criteria

This table reports maximum likelihood parameter estimates of the conditional autoregressive model (15)–(17), assuming a Wishart, Riesz I, Inverse Wishart, Inverse Riesz I, matrix-F, or F-Riesz I distribution in (15). Data consist of realized covariance matrices observed over the period January 2, 2001 until July 31, 2014 ($T = 3415$ trading days). Panels A and B list results for a randomly chosen subset of 5 and 15 different assets, respectively. Panel C shows the results for the full set of 30 assets. Standard errors are provided in parentheses. We report the likelihood $\mathcal{L}$, the AIC and the number of estimated parameters.

Distribution	A	B	$\mu_{\min}$	$\mu_{\max}$	$\nu_{\min}$	$\nu_{\max}$	$\mathcal{L}$	AIC	♯para
Panel A: AA/BA/CAT/GE/KO									
Wishart	0.313	0.669			21.17		-20,508	41,022	3
	(0.005)	(0.005)			(0.12)				
Riesz I	0.294	0.686			7.87	27.25	-18,727	37,468	7
	(0.005)	(0.005)			(0.18)	(0.31)			
iWishart	0.244	0.744			23.64		-17,164	34,335	3
	(0.004)	(0.004)			(0.11)				
iRiesz I	0.240	0.748			12.18	28.01	-16,320	32,654	7
	(0.004)	(0.004)			(0.24)	(0.28)			
F	0.259	0.729	74.51		33.72		-16,461	32,930	4
	(0.004)	(0.005)	(2.22)		(0.45)				
FRiesz I	0.205	0.783	16.94	143.23	15.26	32.61	-10,900	21,824	12
	(0.004)	(0.004)	(0.62)	(4.01)	(0.24)	(0.94)			
Panel B: AA/AXP/BA/CAT/GE/HD/HON/IBM/JPM/KO/MCD/PFE/PG/WMT/XOM									
Wishart	0.235	0.753			39.32		104,666	-209,327	3
	(0.001)	(0.001)			(0.07)				
Riesz I	0.209	0.777			7.46	53.60	122,079	-244,123	17
	(0.001)	(0.001)			(0.17)	(0.28)			
iWishart	0.167	0.826			44.52		135,490	-270,974	3
	(0.001)	(0.001)			(0.06)				
iRiesz I	0.158	0.834			11.23	51.04	144,673	-289,313	17
	(0.001)	(0.001)			(0.22)	(0.30)			
F	0.179	0.814	130.38		63.09		143,506	-287,004	4
	(0.001)	(0.001)	(1.19)		(0.26)				
FRiesz I	0.132	0.862	15.36	223.15	14.35	57.89	176,713	-353,361	32
	(0.001)	(0.001)	(0.39)	(2.28)	(0.32)	(0.71)			
Panel C: All equities ($k = 30$)									
Wishart	0.173	0.821			57.04		725,787	-1,451,568	3
	(0.001)	(0.001)			(0.05)				
Riesz I	0.157	0.835			4.48	78.74	792,880	-1,585,696	32
	(0.001)	(0.001)			(0.10)	(0.28)			
iWishart	0.117	0.880			66.35		871,345	-1,742,683	3
	(0.000)	(0.000)			(0.04)				
iRiesz I	0.107	0.888			7.35	76.06	912,590	-1,825,117	4
	(0.000)	(0.000)			(0.12)	(0.23)			
F	0.123	0.875	180.14		92.405		912,732	-1,825,400	32
	(0.000)	(0.000)	(0.72)		(0.17)				
FRiesz I	0.087	0.910	10.55	277.05	8.98	83.14	1,016,003	-2,031,882	62
	(0.000)	(0.000)	(0.27)	(1.41)	(0.18)	(0.67)			

the estimate of μ in Panel A for the matrix-F is around 75, while the elements of $\boldsymbol{\mu}$ of the F-Riesz distribution vary from around 17 to 144. The pattern persists for the other panels in the table, as well as for the $\boldsymbol{\nu}$ parameters. The Riesz and F-Riesz distributions also solve an empirical puzzle for the (inverse) Wishart and matrix-F distributions. As we can see in the table, increasing the dimension of the system from 5 to 15 to 30 augments the estimated degrees of freedom for the (inverse) Wishart and matrix-F. We can understand this by looking at the spreads of $\boldsymbol{\mu}$ and $\boldsymbol{\nu}$ for the F-Riesz distribution. These reveal that the tail fatness (low $\boldsymbol{\mu}$ and $\boldsymbol{\nu}$ values) persists across dimensions, as $\mu_{\min}$ and $\nu_{\min}$ remain relatively constant across panels A, B, and C. By contrast, $\mu_{\max}$ and $\nu_{\max}$ increase if we consider more stocks, indicating that some of the realized volatilities exhibit thinner tail behavior. As the (inverse) Wishart and matrix-F because of their one and two parameter set-up can only accommodate this by using some sort of average degrees of freedom value across assets, we see the empirical increase in the degrees of freedom for these distributions. By contrast, the F-Riesz (and also the (inverse) Riesz) distributions do not show this behavior.

Fourth, we see that the heterogeneity biases discussed in the previous point spill over into biases in the estimated persistence of $\boldsymbol{X}_t$. The B of the F-Riesz distribution is higher across all dimensions than that of the other models, while its A parameter is lower. This results in a much smoother pattern of $\boldsymbol{V}_t$ for the F-Riesz. Again, this is the accumulation of two effects: fat tails of $\boldsymbol{X}_t$, and tail heterogeneity. Fatter tails for $\boldsymbol{X}_t$ in the model imply the dynamics of $\boldsymbol{V}_t$ react less violently to incidental outliers in $\boldsymbol{X}_t$, similar to the effect of using a Student's t distribution in a GARCH model. This explains why the F-Riesz results in more persistence than the Riesz or inverted Riesz, for instance. The second effect is that of tail heterogeneity. Because the (inverse) Wishart and matrix-F only have one or two degrees of freedom parameters, they miss heavy-tailed behavior in part of the assets (see also the previous point). This missed out tail-fatness in some dimension makes the dynamics less persistent due to in increased sensitivity to outliers; compare for instance for the univariate volatility setting. This explains why the F-Riesz and Riesz have higher persistence compared to the matrix-F and Wishart, respectively.

Beyond a full-sample analysis, we also apply our newly developed distributions in an out-of-sample exercise, by performing 1-step ahead density forecasts, using again the model of (15). These density forecasts immediately depend on the 1-step ahead forecasts of $\boldsymbol{V}_t$.

We use a moving-window approach in the forecasting exercise with an in-sample period of 1,000 observations. This corresponds roughly to four calendar years. The out-of-sample period contains $P = 2415$ observations including the Great Financial Crisis, which therefore constitutes an important test for the robustness of the model. We re-estimate our model repeatedly after each 50 observations, which roughly corresponds to bi-monthly updating of the parameters. In case of the (i)Riesz and F-Riesz I distributions, we apply Heuristic I once on the first moving window to the CAFr model, and keep this ordering fixed throughout the whole exercise and for all different distributions.

We use the log scoring rule (see Mitchell and Hall, 2005; Amisano and Giacomini, 2007) to differentiate between the density forecasts of the models. Define the difference in log score between the two density forecasts M_1 and M_2 corresponding to the realized covariance matrix $\boldsymbol{X}_t$ as

$$d_{ls,t} = S_{ls,t}(\boldsymbol{X}_t, M_1) - S_{ls,t}(\boldsymbol{X}_t, M_2), \tag{20}$$

for $t = R, R+1, \ldots T-1$ with R the length of the estimation window and $S_{ls,t}(\boldsymbol{X}_t, M_j)$ $(j = 1, 2)$ the log score of the density forecast corresponding to model M_j at time t,

$$S_{ls,t}(\boldsymbol{X}_t, M_j) = \log p_t(\boldsymbol{X}_t | \boldsymbol{V}_t, \mathcal{F}_{t-1}, M_j), \tag{21}$$

where $p_t(\cdot)$ is the probability distribution function of our six considered distributions. The null hypothesis of equal predictive ability is given by $H_0 : \mathbb{E}[d_{ls}] = 0$ for all P out-of-sample forecasts. This null can be tested by means of a Diebold and Mariano (1995) (DM) statistic given by

$$DM_{ls} = \frac{\bar{d}}{\sqrt{\hat{\sigma}^2/N}}, \tag{22}$$

with $\bar{d}$ the out-of-sample average of the log score differences and $\hat{\sigma}^2$ a HAC-consistent variance estimator of the true variance σ^2 of $d_{ls,t}$. Under the assumptions of the framework of Giacomini and White (2006), DM_{ls} asymptotically follows a standard normal distribution. A significantly positive value means that model M_1 has a superior forecast performance over model M_2.

Table 5: Out-of-sample log-scores

This table shows the mean of log scores, defined in (21), based on 1-step ahead predictions of the covariance matrix, according to the Conditional Autoregressive model, assuming a Wishart, Riesz I, Inverse Wishart, Inverse Riesz I, matrix-F, or a F-Riesz I distribution. Panel A shows results of the model applied to five assets, Panel B and C show results corresponding to 15 and to all 30 equities. The highest value of the predictive log-score across the models are marked bold. In addition, we report HAC based test-statistics on the difference in predictive ability (DM_{DF}) between the CAFr model and the other considered models. Positive statistics indicate that the CAFr model has superior density forecasts. The out-of-sample period goes from January 2005 until July 2014 and contains 2514 observations.

	Wishart	Riesz I	iWishart	iRiesz I	matrix-F	Friesz I
Panel A: AA/BA/CAT/GE/KO						
$S^{ls}(\boldsymbol{X}_t)$	-4.324	-3.843	-3.083	-2.845	-2.921	**-1.363**
DM_{DF}	(13.22)	(11.36)	(23.36)	(21.18)	(25.44)	
Panel B: k = 15						
$S^{ls}(\boldsymbol{X}_t)$	49.38	54.33	59.75	62.28	61.42	**71.01**
DM_{DF}	(13.56)	(13.14)	(20.33)	(17.91)	(31.89)	
Panel C: All equities (k = 30)						
$S^{ls}(\boldsymbol{X}_t)$	277.4	297.1	325.6	337.8	334.8	**366.2**
DM_{DF}	(21.68)	(20.11)	(25.85)	(22.66)	(31.82)	

Table 5 shows the average values of the log score over the out-of-sample period for a set of five, 15, and the complete set of 30 assets. In addition, we provide corresponding t-statistics for the difference in the log predictive density scores of the realized covariance matrix between the CAFr model and competing models. Positive values means that the density forecasts of the former model is superior against its competitor. The results heavily reinforce our earlier full-sample analysis as the F-Riesz distribution again clearly outperform the other distributions, even at a 1% significance level. This result holds for all three considered dimensions. The differences in the mean log-score increases by dimension. In sum, the F-Riesz distribution outperforms both in-sample and out-of-sample the other competitors, indicating that it is able - in contrast to the (inverse) Riesz distributions - to capture the tail heterogeneity of realized covariance matrices.

7 Conclusions

We introduce the new F-Riesz distributions for econometric modeling of matrix valued random variables. The distribution is obtained by mixing the Riesz distribution (Hassairi

and Lajmi, 2001) with an inverse Riesz distribution (Tounsi and Zine, 2012) and allows for much more heterogeneity in tail behavior compared to well-known fat-tailed distributions like the Wishart, inverse Wishart, or the matrix-F distribution. While the latter distributions depend on one or two degrees-of-freedom parameters, our new distribution allows the degrees of freedom parameters to be vectors. These parameters can easily be estimated by a two-step targeted maximum likelihood approach, even in high dimensional settings.

An empirical application to realized covariance matrices of 30 U.S. stocks over 14 years shows a remarkably high increase of the likelihood of the developed F-Riesz distribution compared to the (inverse) Riesz distributions. The degrees of freedom parameters are significantly over the different coordinates. The new distribution even outperforms the fat-tailed matrix-F distribution, applied in financial econometrics by Opschoor et al. (2018). The margin of outperformance is as wide as that of switching from a Wishart to the matrix-F, and therefore empirically highly significant, essentially doubling the gain already obtained by using the fat-tailed matrix-F. Out-of-sample we confirm these results by means of one-step ahead density forecasts of the time-varying realized covariance matrix. Again the F-Riesz distribution is superior against the competitors by a very wide margin. Overall these results show that there is strong heterogeneity of tail behavior of realized covariance matrices, and that the F-Riesz distribution is a helpful vehicle to obtain better empirical models.

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