

Regime Switching for Dynamic EquiCorrelation

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March 8, 2024

Abstract

We add a regime switching dynamic, in the spirit of [Pelletier \(2006\)](#) markov switching conditional correlation model, to [Engle and Kelly \(2012\)](#) Dynamic Equicorrelation model. The DECO model decomposes the correlation matrix into blocks for which conditional correlations are equal. Correlations between blocks can be common or block-specific. Our Regime Switching Dynamic EquiCorrelation (hence RSDECO) model is therefore adequate for fitting large conditional correlations in presence of level shifts. Extensive simulations show that the RSDECO is able to reproduce the true level of correlations for a large number of variables. The estimation of daily correlations between commodity, stock and bond returns from 01/04/2000 to 12/29/2022 show significant changes in the pattern of correlations over time. The first major and significant regime change occurs around September 15, 2008. The dynamics of the correlations between the three asset classes will have become unstable after the year 2020.

JEL classification: C22, G01, G10, G12, Q4

Keywords: Dynamic Correlations; Large cross-sections; Regime Switching.

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1 Introduction

Institutional investors routinely monitor hundreds or even thousands of assets and need an estimation of their return's volatilities and correlations for their investment decision. These correlations are a crucial ingredient in portfolio management, asset pricing, and risk management. Engle (2002) Dynamic Conditional Correlation (hence DCC) model is one of the most popular multivariate GARCH models. This model suffers from *curse of dimensionality* as the number of parameters increases much faster than the number of returns.¹ Estimation is possible for a limited number of returns, even if constraints are imposed on the parameters of the model.

Alessi et al. (2009), De Nard et al. (2021), and more recently Trucíos et al. (2023) rely on factor models to estimate high-dimensional covariance matrix. However, one issue with this approach is to identify factors. Engle et al. (2019) robustified DCC mixes the initial DCC model with shrinkage methods to obtain large covariance matrices less sensitive to estimation error. In some cases, such as portfolio selection, it's easier to directly estimate the inverse of the correlation matrix (precision matrix). Lee et al. (2021) model is a combination of the Fan and Lv (2016) estimation methods for precision matrix and Engle (2002) DCC.

More related to this paper, another strand of research relies on breaking down a complex numerical problem into a list of sub-problems easy to solve (Palandri (2009) and Engle (2009a,b)). The Dynamic Equicorrelation (DECO) model developed by Engle and Kelly (2012) has provided an interesting approach to addressing the high-dimension problem. This model assumes that correlations all are equal to a common value, named equicorrelation, which varies over time. The DECO can be extended to a B -Blocks DECO model, with block-specific equicorrelations, and the specific inter-block equicorrelations for each pair of blocks. Bauwens and Xu (2023) recently extended the DCC and the DECO models by introducing measures of realized variances and correlations estimated from intraday data.

¹See for instance Bauwens et al. (2006) and De Almeida et al. (2018) for a literature review

Several papers proposed multivariate GARCH with regime switching based on observable variables (Tse and Tsui (2002), Audrino and Trojani (2011), and Silvennoinen and Teräsvirta (2009)). As in practice the threshold variable is unknown, the question of how to determine it remains a major challenge. Pelletier (2006) proposes to use a Markov-switching model for the correlation. The value of the current correlation depends on the underlying regime, and the conditional covariance varies according to changes in conditional variances and correlation.

The innovation of this paper lies in adding a regime-switching dynamic to the DECO model in the spirit of Pelletier (2006). In our model, called Regime Switching Dynamic Equicorrelation (RSDECO), equicorrelations are constant within each regime but vary between regimes through a *first-order* Markov process. Our model introduces discrete breaks into the modelling of conditional correlation, meant to capture a finite number of switching regimes.

A set of Monte-Carlo simulations emphasizes the performance of our approach. The RSDECO model performs seemingly well reproducing the true correlation and also dealing with the high dimension problem.

As an empirical application, using a sample of 24 daily commodity returns and 4 US equity returns from January 4th, 2000 to December 29th, 2022, we estimate the conditional correlations. First, we detect two dynamic correlation regimes with a significant regime shift on September 15, 2008, coinciding exactly with the Lehman bankruptcy date. The second regime is associated with a dramatic correlation increase across the seemingly unrelated commodities.

The simple RSDECO version, however, detects a regime shift at the end of 2005, well before the financial crisis, which is associated with the commodity financialization process. Second, our results show that correlations reverted to their pre-crisis level by the end of 2013, indicating the temporary nature of the effect of the financial crisis on the commodity correlation trend. Finally, a more detailed commodity group correlation analysis from Block-RSDECO brings to light a heterogeneity between commodity group co-movements.

The paper is organized as follows. In section 2 we develop the RSDECO model and the estimation method. Section 3 contains the results of the simulation study. Section 4 represents our empirical application and section 5 concludes.

2 The model

2.1 The regime switching DECO

We consider the vector of $r_t = (r_{1t}, \dots, r_{kt})'$, of size $k \times 1$ assets returns such as $r_t | I_{t-1} \sim NID(\mu_t, H_t)$ where $I_t = \{r_s, s \leq t\}$ is the information set at time t . The conditional covariance matrix H_t is decomposed as:

$$H_t = D_t R_t D_t$$

where D_t is a $k \times k$ diagonal matrix containing the conditional standard deviations. In (Engle, 2002) classical DCC(1,1) model, the dynamics of R_t is modelled as:

$$\begin{aligned} R_t &= Q_t^{*-1/2} Q_t Q_t^{*-1/2} \\ Q_t &= C + A' \epsilon_{t-1} \epsilon_{t-1}' A + B' Q_{t-1} B \end{aligned}$$

where $\epsilon_t = D_t^{-1}(r_t - \mu)$ is the vector of standardized residuals, Q_t the quasi correlation matrix, and Q_t^* a diagonal matrix with the main diagonal of Q_t

The Dynamic EquiCorrelation Model (DECO) of Engle and Kelly (2012) is based on the assumption that all correlations are equal to the equicorrelation which varies over time. The conditional correlation matrix is therefore written as:

$$R_t = (1 - \rho_t) I_k + \rho_t J_k \tag{1}$$

where ρ_t refers to the equicorrelation, I_k is a k - dimensional identity matrix and J_k is a $k \times k$ matrix of ones. The estimation of the equicorrelation ρ_t is model-free. In the DECO

model, ρ_t is estimated as the average of the conditional correlations from a DCC model:

$$\rho_t = \frac{1}{k(k-1)} (\iota' R_t^{DCC} \iota - k) \quad (2)$$

where ι is a $k \times 1$ vector of ones. In this case, we face the same dimensionality issue when k increases.

In the spirit of [Pelletier \(2006\)](#), we adopt a regime-switching structure for the correlation process in the DECO model (RSDECO) and assume that the dynamic of the equicorrelation is characterized by N regimes. The transition between regimes is modelled by a first-order Markov chain. The equicorrelation at date t follows:

$$\rho_t = \sum_{n=1}^N \mathbb{1}_{\{s_t=n\}} \rho^n, s_t \in \{1, \dots, N\} \quad (3)$$

where $\{s_t\}_{t \in \mathbb{N}}$ is a sequence following a first-order Markov chain with N states. ρ^n is a conditional equicorrelation corresponding to regime n . The unobservable realisation of the regime $\{s_t\}_{t \in \mathbb{N}}$ is determined by the transition probability matrix P whose elements are $p_{ij} = P(s_t = j | s_{t-1} = i), i, j \in 1, \dots, N$. The resulting state-dependent correlation matrix at date t is therefore:

$$R_t = \begin{bmatrix} 1 & & & & \\ & \ddots & & & \\ & & 1 & & \\ & \rho_t & & \ddots & \\ & & & & 1 \end{bmatrix} \quad (4)$$

Following [Pelletier \(2006\)](#), we include the identification constraint: $\rho^1 > \rho^2 > \dots > \rho^N$ to deal with the relabelling switching problem. [Engle and Kelly \(2012\)](#) points out that the equicorrelation must verify the condition $\rho^n \in]\frac{-1}{k-1}, 1[$ to ensure that R_t is positive definite².

²It is noteworthy that as the number of variables k becomes more significant, the lower bound, $\frac{-1}{k-1}$, decreases and approaches zero. This would prevent the detection of negative correlations when we include a significant number of series in the analysis.

2.2 Block RSDECO

Just like for DECO, we decompose the correlation matrix R_t into blocks of equicorrelations to obtain a more flexible and realistic model for conditional correlation. One block, characterized by a single equicorrelation, can be associated with a specific asset class, while the correlation between blocks estimates the correlation between different asset classes. We make the simplifying assumption that inner-block correlation as well as inter-blocks correlation follows the same first-order Markov chain.

This decomposition by blocks appears to greatly improve both estimation and the explanatory power of our model. Given both economic assumptions and practical considerations, we present two ways to introduce block structure.

2.2.1 Reduced-Block RSDECO

As a first step, we assume that, for each state $s_t = 1, \dots, N$, each block has its equicorrelation, while the equicorrelation is the same between all blocks. This formulation is called *Reduced Block-RSDECO* (hereafter *RB-RSDECO*). Let B be the number of blocks, in this configuration the total number of correlations to be estimated is $(B + 1)N$. The conditional correlation matrix R_t is written as:

$$R_t = \sum_{n=1}^N \mathbb{1}_{\{s_t=i\}} R_n, \quad s_t = 1, \dots, n \quad (5)$$

Each state $n = 1, \dots, N$ is characterized by its conditional correlation matrix R_n :

$$R_n = \begin{bmatrix} \boxed{\begin{matrix} 1 & & \rho_1^n \\ & \ddots & \\ \rho_1^n & & 1 \end{matrix}} & & & \rho_{inter}^n \\ & \boxed{\begin{matrix} 1 & & \rho_2^n \\ & \ddots & \\ \rho_2^n & & 1 \end{matrix}} & & & \\ & & \dots & & & \\ & & & \boxed{\begin{matrix} 1 & & \rho_B^n \\ & \ddots & \\ \rho_B^n & & 1 \end{matrix}} & & \\ \rho_{inter}^n & & & & & \end{bmatrix} \quad (6)$$

$\rho_i^n, i = 1, \dots, B$ is equicorrelation for block i in state n while ρ_{inter}^n is the correlation between blocks supposed to be the same between all blocks. The correlation matrices are such as $R_n \neq R_{n'}$ for $n \neq n'$. The distribution of the process defined by $\{s_t\}_{t \in \mathbb{N}}$ is determined by a transition matrix P as previously.

At each date t , the conditional correlation matrix R_t is therefore equal to:

$$R_t = \begin{bmatrix} \boxed{\begin{matrix} 1 & & \rho_{1,t} \\ & \ddots & \\ \rho_{1,t} & & 1 \end{matrix}} & & & \rho_{inter,t} \\ & \boxed{\begin{matrix} 1 & & \rho_{2,t} \\ & \ddots & \\ \rho_{2,t} & & 1 \end{matrix}} & & & \\ & & \dots & & & \\ & & & \boxed{\begin{matrix} 1 & & \rho_{B,t} \\ & \ddots & \\ \rho_{B,t} & & 1 \end{matrix}} & & \\ \rho_{inter,t} & & & & & \end{bmatrix} \quad (7)$$

where $\rho_{i,t} = \sum_{n=1}^N \mathbb{1}_{\{s_t=n\}} \rho_i^n$ and $\rho_{inter,t} = \sum_{n=1}^N \mathbb{1}_{\{s_t=n\}} \rho_{inter}^n$ are respectively equicorrelation for block $i \in 1, \dots, B$ and the equicorrelation between blocks at date t .

As for the simple RSDECO, identification constraints are required. For a block B of size n_B , the equicorrelation parameters $\rho_B^n, n = 1, \dots, N$, must satisfy the identification constraint $\rho_B^1 > \rho_B^2 > \dots > \rho_B^N$ for $n = 1, \dots, N$. R_t matrix is a positive definite if and only

if $\rho_B^n \in]\frac{-1}{k_B-1}, 1[$.

The constraints on the inter-block equicorrelation are slightly different due to the estimation procedure. As shown in the Estimation subsection, a B -block RSDECO is estimated by maximizing the sum of the likelihoods of all possible pairs of B -blocks that are estimated from the two-block RSDECO likelihood. As in [Engle and Kelly \(2012\)](#), the equicorrelation in regime n between two blocks i and j of size k_i and k_j respectively, denoted by ρ_{ij}^n , must be checked:

$$\rho_{ij}^n \in (-l_{ij}^n, l_{ij}^n) \quad (8)$$

with

$$l_{ij}^n = \sqrt{\frac{(\rho_i^n(k_i - 1) + 1)(\rho_j^n(k_j - 1) + 1)}{k_i k_j}} \quad (9)$$

for $n = 1, \dots, N$. To respect the positive definite constraint, the inter-block equicorrelation $\rho_{inter,t}^n$ in regime n must satisfy the relation (9) for every pair, which is equivalent to having:

$$l_{inter}^n = \min(l_{ij}^n) \quad (10)$$

for $i, j = 1, \dots, B$ and $i \neq j$. This constraint may seem strong, but it keeps the model parsimonious as the number of groups increases.

2.2.2 Full-block RSDECO

A more complete way to express Block-RSDECO is to relax the assumption of a common inter-block equicorrelation ρ_t^{inter} . We assume specific equicorrelation for each pair of blocks. Within this formulation, called *Full Block*-RSDECO (hereafter *FB*-RSDECO), the

conditional correlation matrices for each state $n = 1, \dots, N$ has the following specification:

$$R^n = \begin{array}{|c|c|c|c|} \hline 1 & \rho_1^n & & \\ & \ddots & & \\ \rho_1^n & 1 & \rho_{12}^n & \cdots & \rho_{1B}^n \\ \hline & & 1 & \rho_2^n & \cdots & \rho_{2B}^n \\ & \rho_{21}^n & & \ddots & & \\ & & \rho_2^n & 1 & & \\ \hline & \vdots & \vdots & \ddots & \vdots & \\ \hline & & & & 1 & \rho_B^n \\ \rho_{B1}^n & & \rho_{B2}^n & \cdots & & \ddots \\ & & & & \rho_B^n & 1 \\ \hline \end{array} \quad n = 1, \dots, N$$

The Correlation matrix R_t is now equal to:

$$R_t = \begin{array}{|c|c|c|c|} \hline 1 & \rho_{1,t} & & \\ & \ddots & & \\ \rho_{1,t} & 1 & \rho_{12,t} & \cdots & \rho_{1B,t} \\ \hline & & 1 & \rho_{2,t} & \cdots & \rho_{2B,t} \\ & \rho_{21,t} & & \ddots & & \\ & & \rho_{2,t} & 1 & & \\ \hline & \vdots & \vdots & \ddots & \vdots & \\ \hline & & & & 1 & \rho_{B,t} \\ \rho_{B1,t} & & \rho_{B2,t} & \cdots & & \ddots \\ & & & & \rho_{B,t} & 1 \\ \hline \end{array}$$

where $\rho_{i,t} = \sum_{n=1}^N \mathbb{1}_{\{s_t=n\}} \rho_i^n$ and $\rho_{ij,t} = \sum_{n=1}^N \mathbb{1}_{\{s_t=n\}} \rho_{ij}^n$ are respectively equicorrelation for block $i \in 1, \dots, B$ and the equicorrelation between blocks i and j at date t .

As shown in Table 1, because the *FB*-RSDECO structure is more complete and accurate than the *RB*-RSDECO structure, it requires more equicorrelations to be estimated.

Block equicorrelations are bounded as shown in equation (8), while inter-block equicorrelations are bounded as shown in equation (9).

Table 1: Number of estimated correlations.

Model	Number of correlations	Bounds
RSDECO	N	$\left(\frac{-1}{k-1}, 1\right)$
<i>RB</i> -RSDECO	$B(N + 1)$	$\left(\frac{-1}{k_i-1}, 1\right)$ (Block i) $\min(l_{ij}^n)$ (inter-Block)
<i>FB</i> -RSDECO	$\left(B + \frac{B(B-1)}{2}\right)N$	$\left(\frac{-1}{k_i-1}, 1\right)$ (Block i) (l_{ij}^n) (inter-Block)

2.3 Estimation

Our model can be estimated using the two-step procedure of [Engle and Sheppard \(2001\)](#). $\Theta = (\varphi, \theta)$ is the parameter space of the RSDECO, where φ are the parameters of the univariate volatility model and θ are the parameters of the correlation model. Assuming Gaussian innovations, the first step involves estimating the k univariate GARCH and corresponds to the volatility component of the log-likelihood:

$$\ell_v(\varphi|\mathbf{r}_t) = -\frac{1}{2} \sum_{t=1}^T (k \log(2\pi) + 2 \log(|D_t|) + \mathbf{r}_t' D_t^{-2} \mathbf{r}_t) \quad (11)$$

These variance estimates of r_t are used to construct the matrix D_t :

$$D_t = \text{diag}\{h_{i,t}^{1/2}\} \quad (12)$$

Then the standardized residuals are given by:

$$\epsilon_t = D_t^{-1} \mathbf{r}_t \quad (13)$$

In the second step, the correlation component is estimated by maximising the likelihood conditional on the volatility parameters estimated in the first step:

$$\ell_c(\theta|\mathbf{r}_t, \varphi) = -\frac{1}{2} \sum_{t=1}^T (\log(|R_t|) + \epsilon'_t R_t^{-1} \epsilon_t) \quad (14)$$

The *reduced* and *full* block RSDECO are estimated using the same strategy as for Engle and Kelly (2012). A simple way to estimate the B block likelihood is to sum the estimated $B(B-1)/2$ two-block likelihoods.

$$\ell_c(\theta|\mathbf{r}_t, \varphi) = \sum_{i=1}^B \sum_{j=i+1}^B \ell_{ij,c}(\theta|\mathbf{r}_t, \varphi) \quad (15)$$

where $\ell_{ij,c}$ is the two-block likelihood of the submodel consisting of blocks i and j .

As explained above, the transition from one regime to another is done using the *first-order* Markov chain. Since the Markov chain s_t is an unobservable regime variable, we will need to infer the state of these Markov chains through a filtration step (see Hamilton (1989, 1990, 1994)). Let ξ_{jt} be the probability of being in regime j . The inference about the state of the Markov chain is then defined by

$$\hat{\xi}_{t|t} = \frac{(\hat{\xi}_{t|t-1} \odot \eta_t)}{\mathbf{1}'(\hat{\xi}_{t|t-1} \odot \eta_t)} \quad (16)$$

where \odot denotes element-by-element multiplication. $\hat{\xi}_{t|t}$ contains the probability to be in each regime at time t given the observations set up to t . Assuming a *first-order* Markov process, the probability at time $t+1$ is conditional only on information included in $\hat{\xi}_{t|t}$:

$$\hat{\xi}_{t+1|t} = P \times \hat{\xi}_{t|t} \quad (17)$$

Smoothed probabilities can be computed from the regular Markov-Switching representation. These filtered probabilities refer to inferences on the state conditional on all the information set of the sample. Computation is done using the filter of Kim (1994)

given by:

$$\hat{\xi}_{t|T} = \hat{\xi}_{t|t} \odot \{P'[\hat{\xi}_{t+1|T} \oslash \hat{\xi}_{t+1|t}]\} \quad (18)$$

where \oslash denotes element-by-element division.

The conditional correlation matrix is:

$$\hat{R}_{t|T} = \sum_{n=1}^N \hat{R}_{s_t=n} \hat{\xi}_{s_t=n,t|T}$$

Determining the number of identifiable regimes required for the Markov process to characterise the observed process is a particular problem for our RSDECO model, as it is for the RSDC model of [Pelletier \(2006\)](#). As explained in [Krolzig \(1997\)](#), testing procedures suffer from non-standard asymptotic distributions of the likelihood ratio test statistic due to the presence of nuisance parameters under the null hypothesis. Alternatively, and following [Pelletier \(2006\)](#), the number of regimes is determined in an ad hoc manner. In other words, we have to estimate models by incrementally increasing the number of regimes and then selecting the appropriate number of regimes using the resulting quality for the additional regime as a criterion. If, during the additional regime, the smoothed probabilities and correlations are represented only by a few blips that cannot be explained by an event study, they look more like outliers than effective regimes. This may be an indication of the appropriate number of regimes.

3 Simulation study

In this section, we perform a simulation exercise to demonstrate the performance of our model. The results of our RSDECO model are then compared with those of DECO using simulated correlation data. The simulations are carried out in an environment where the true correlations are known. The data generated then correspond to the standardised residuals after the de-garching step. The idea is to avoid the search step, which is useless for our experiments. Under this assumption, for each simulated standardised residual we generate data as follows:

$$\varepsilon_t = \eta_t R_t^{0.5} \quad (19)$$

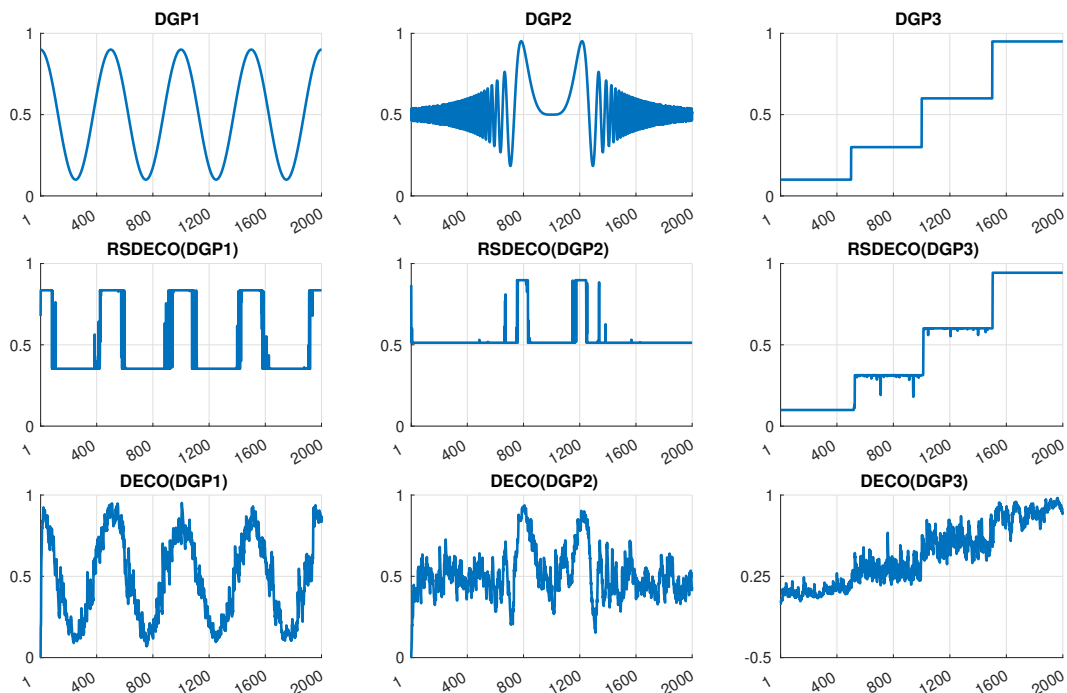
where η_t are normally distributed random numbers. We generate five artificial equicorrelation data sets using a variety of models:

- DGP 1: $R_t^{sim} = 0.5 + 0.4 \cos(2\pi t/500)$.
- DGP 2: $R_t^{sim} = 0.5 + \sin(s^4)/(1 + \sqrt{|s^4|})$, with $s = 5 - t/200$.
- DGP 3: $R_t^{sim} = \begin{cases} 0.1 & \text{if } t \in [1; 500] \\ 0.3 & \text{if } t \in [501; 1000] \\ 0.6 & \text{if } t \in [1001; 1500] \\ 0.95 & \text{if } t \in [1501; 2000] \end{cases}$
- DGP 4: a 2-Block DECO with DCC dynamics with two regimes.
 $R_t^{sim} = \begin{cases} \rho_{1,1,t} = -0.1, \rho_{2,2,t} = 0.3, \rho_{1,2,t} = -0.1 & \text{if } t \in [750, 1250] \\ \rho_{1,1,t} = 0.8, \rho_{2,2,t} = 0.4, \rho_{1,2,t} = -0.3 & \text{otherwise} \end{cases}$
- DGP 5: a 3-Block DECO with DCC dynamics with two regimes.
 $R_t^{sim} = \begin{cases} \left. \begin{array}{l} \rho_{1,1,t} = 0.9, \rho_{2,2,t} = 0.7, \rho_{3,3,t} = 0.5 \\ \rho_{1,2,t} = 0.3, \rho_{1,3,t} = 0.1, \rho_{2,3,t} = 0.3 \end{array} \right\} & \text{if } t \in [750, 1250] \\ \left. \begin{array}{l} \rho_{1,1,t} = 0.2, \rho_{2,2,t} = 0.2, \rho_{3,3,t} = 0.2 \\ \rho_{1,2,t} = 0.15, \rho_{1,3,t} = 0.1, \rho_{2,3,t} = 0.1 \end{array} \right\} & \text{otherwise} \end{cases}$

Each simulation contains $T = 2000$ observations. However, the number of series K increases from $K = 50$ to $K = 400$. Using sufficiently large samples allows us to test whether our model does not suffer from the high dimensional problem. While DGP 1 and 2 are based on trigonometric functions and were chosen to reproduce smooth regime changes, DGP 3 is based on an RSDECO dynamic with four regimes. We then introduce blocks when generating DGP 4 and 5, which are respectively a 2-block DECO with DCC dynamics with two regimes and a 3-block DECO with DCC dynamics with two regimes. The correlation value for each of the DGPs 4 and 5 is chosen so that the condition in Equation (8) is satisfied, which guarantees that R_t is positive definite. DGP 5 is used to compare the B-block RSDECO and the B-block DECO in their *full* and *reduced* forms.

Our RSDECO model is compared with the DECO model proposed by [Engle and Kelly \(2012\)](#). Two different error measures are used for this purpose, namely the Mean Squared Error (MSE) and the Mean Absolute Deviation (MAD).³ Figure 1 illustrates simulated and estimated correlations using the DECO and RSDECO models. Comparing the two model estimates suggests that both models appear to perform well in reproducing the true correlation, with a natural relative advantage for the RSDECO model in capturing regime switching. The overall result of the error measure is satisfactory. As shown in Table 2, both MAE and MAD are quite weak, indicating that the estimated correlations from either RSDECO or DECO are very close to the true values. The MAD statistic tends to favour RSDECO when the DPG is either DGP 2 or DGP 3, regardless of the number of series. However, the results for the MAE are mixed. In conclusion, the error measure statistics do not provide conclusive evidence in favour of one model over the other but show that the RSDECO model tends to perform better when the data-generating process is subject to structural breaks as well as switching regimes. It is worth noting that the same qualitative result is obtained for a different number of series, suggesting that both RSDECO and DECO deal well with the high dimensional problem.

Figure 1: Simulated results for DGP 1-DGP 3



³ $MAE = \frac{1}{T} \sum_{t=1}^T (\hat{R}_t - R_t)^2$ and $MAD = \frac{1}{T} \sum_{t=1}^T |\hat{R}_t - R_t|$.

Figure 2: Simulated results for DGP 4

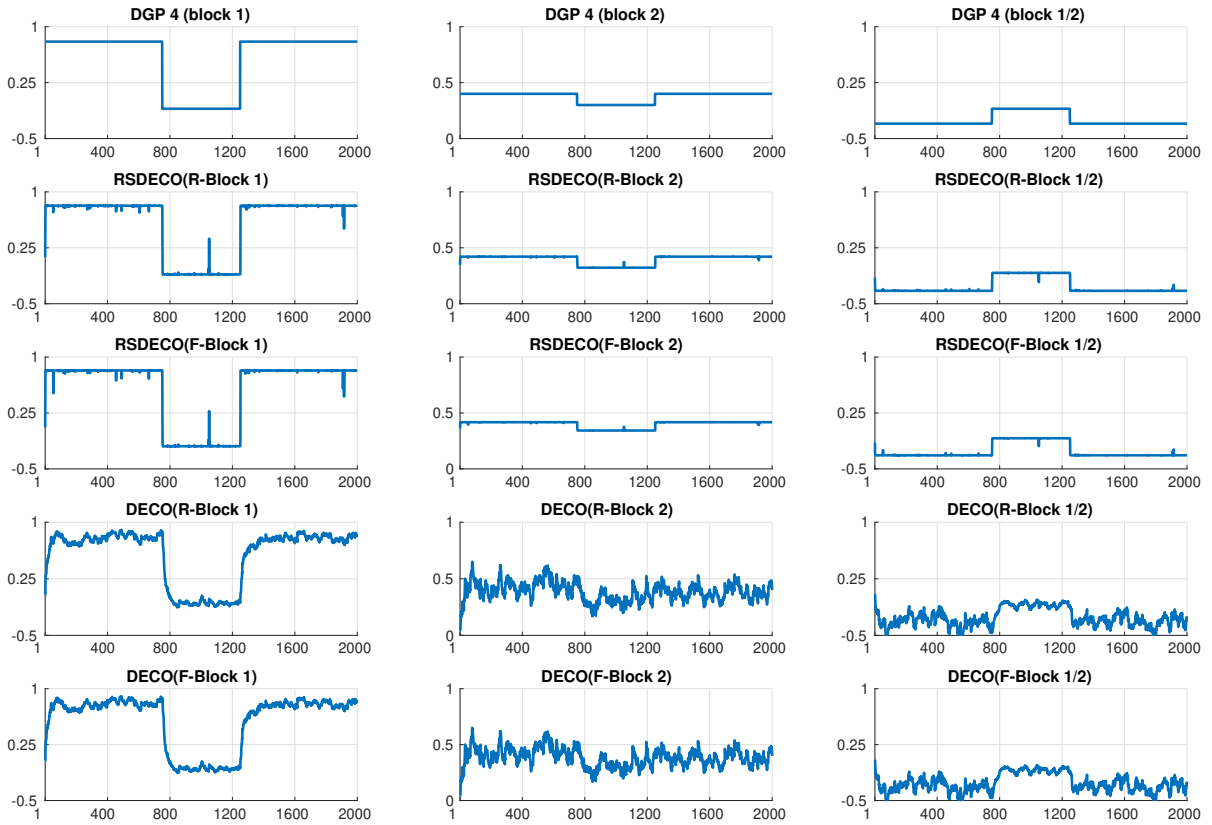
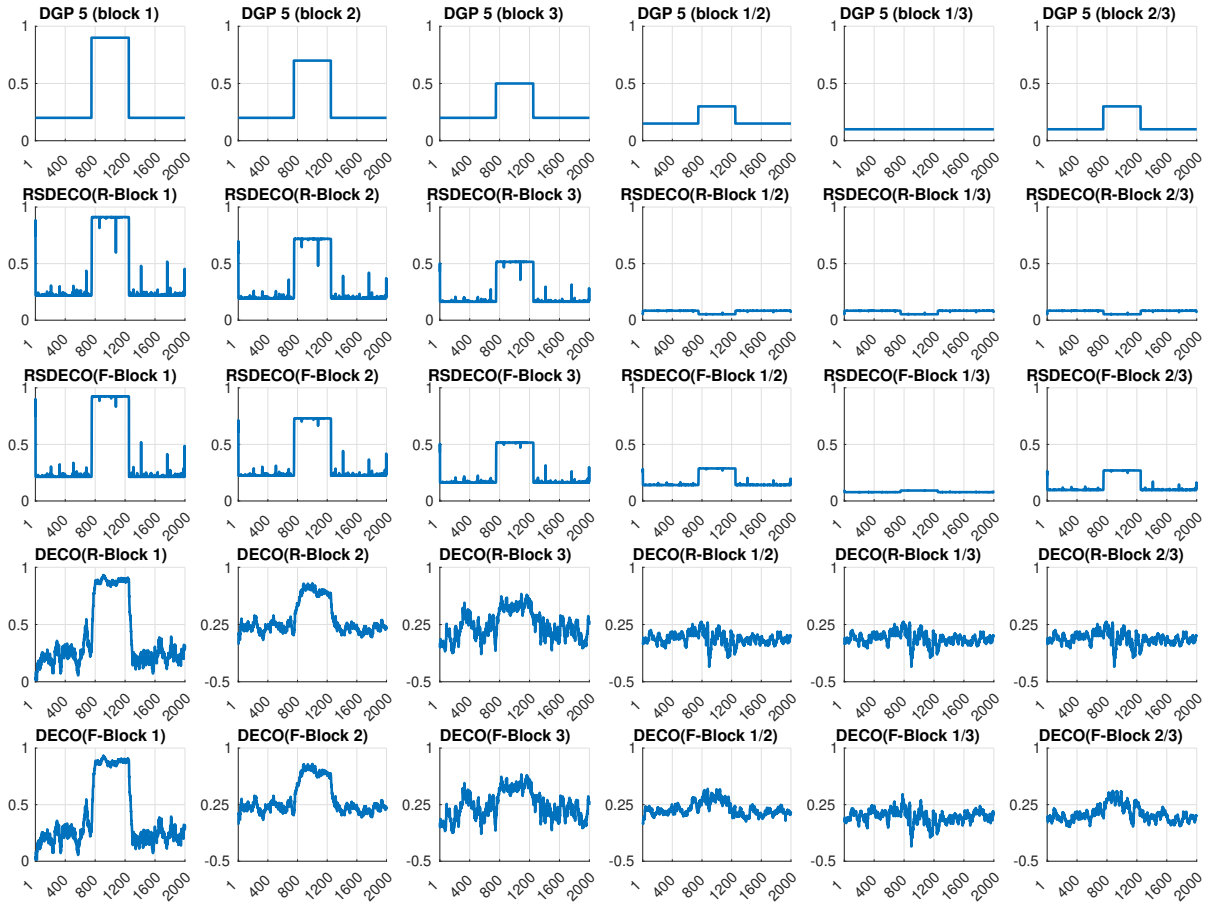


Table 2: Error measures of correlation estimates MSE
(MAD)

	DGP 1	DGP 2	DGP 3	DGP 4	DGP 5
<u>50 series:</u>					
RSDECO	0.023 (0.124)	0.033 (0.073)	0.034 (0.009)	0.045 (0.055)	0.045 (0.055)
DECO	0.006 (0.060)	0.018 (0.087)	0.023 (0.054)	0.028 (0.044)	0.028 (0.044)
<u>100 series:</u>					
RSDECO	0.021 (0.119)	0.032 (0.076)	0.032 (0.005)	0.042 (0.051)	0.042 (0.051)
DECO	0.006 (0.061)	0.017 (0.087)	0.022 (0.050)	0.028 (0.045)	0.028 (0.045)
<u>200 series:</u>					
RSDECO	0.024 (0.125)	0.034 (0.075)	0.034 (0.003)	0.046 (0.056)	0.046 (0.056)
DECO	0.005 (0.057)	0.015 (0.078)	0.020 (0.052)	0.025 (0.043)	0.025 (0.043)
<u>400 series:</u>					
RSDECO	0.023 (0.124)	0.032 (0.071)	0.033 (0.002)	0.044 (0.051)	0.044 (0.051)
DECO	0.018 (0.117)	0.028 (0.080)	0.036 (0.080)	0.042 (0.044)	0.042 (0.044)

MAE: Mean Absolute Error. In brackets, MAD: Mean Absolute Deviation

Figure 3: Simulated results for DGP 5



4 Empirical application

We use the three specifications of the RSDECO model to estimate conditional correlations between commodity futures, stock indices and bonds. The advantage of using the RSDECO, and especially its Block versions, to deal with this issue is not only to detect structural changes in correlation dynamics but also to be able to provide an accurate measure of both intra and inter-commodity, stock and bond-group correlations. The common strategy in previous papers in measuring intra and inter-commodity group correlations is respectively to either calculate the average of all pairwise correlations or to use indices. In the case of the RSDECO, inter and intra-commodity group correlations are estimated measures.

4.1 Data

The data set is made up of 24 US daily commodity futures, 4 US equity indices (The MSCI, the Standard & Poors 500, the NASDAQ and the RUSSELL 200), and the one-year, five-year and ten-year US holding bond returns⁴ covering the period from January 4th, 2000 to December 29th, 2022. The commodity futures contracts belong mainly to the Goldman Sachs Commodity Index (GSCI), which is the most popular commodity index. Our data originated from Bloomberg which constructs and provides continuous price series from futures data. Commodities can be classified into 5 groups, namely Energy, Industrial Metals, Precious Metals, Agriculture and Livestock. The full list of commodity futures series with the group classification can be found in Appendix A. It updates the appendix in Charlot et al. (2016), who studied 32 commodity futures between 2000 and 2015. All series are then transformed into first logarithmic differences.

Tables 4, 5 and 6 report summary statistics respectively for the commodity futures returns, the equity index returns and the bond returns. We take futures returns (changes in log prices multiplied by 100) and collateralize them with the daily 3-month US Treasury Bill (T-bill) secondary market rate. Figure 14 in Appendix A shows all data series returns used for this exercise.

4.2 Empirical Results

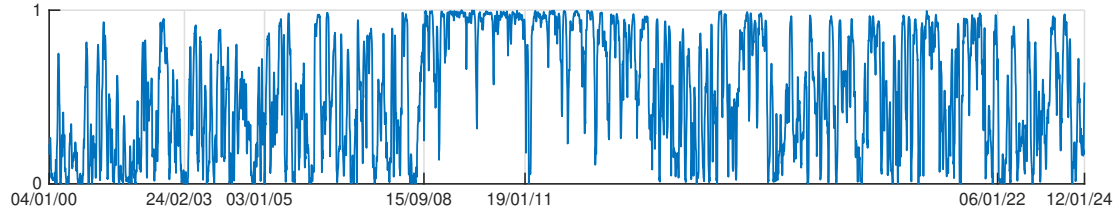
We separate our data into three blocks corresponding to commodities, stocks and bonds and estimate Markov-switching models with two regimes. Figure 4 displays the smoothed probabilities for the simple RSDECO (sub-figure 4a), the Reduced Block RSDECO (sub-figure 4b) and the Full Block RSDECO (sub-figure 4c). All of these figures show the same changes in regimes. The first major change happens towards September 15, 2008 when we can observe a swift range in regime. It is noteworthy that, before the financial crisis regime, smoothed probabilities show a slight increase, confirming the view that commodity financialisation began impacting the correlation between commodity and financial assets

⁴See in appendix C for the computation of these returns.

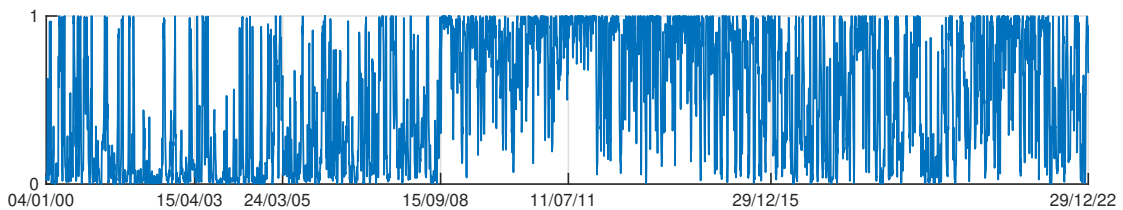
starting from 2004 (Tang and Xiong, 2012; Charlot et al., 2016, among others).⁵ Finally, at the end of the sample, we observe the beginning of a return to the first regime.

Figure 4: Smoothed Probabilities.

(a) RSDECO



(b) 3-Blocks Reduced Form RSDECO



(c) 3-Blocks Full Block RSDECO

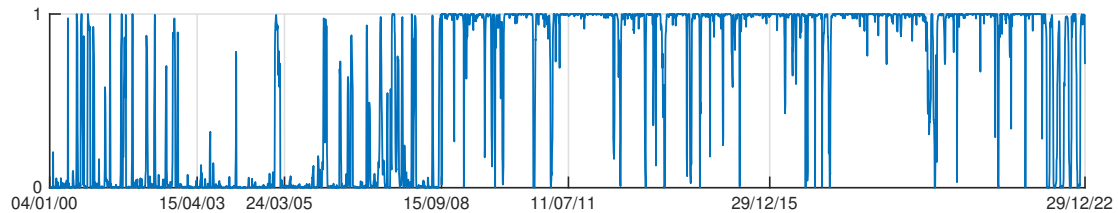
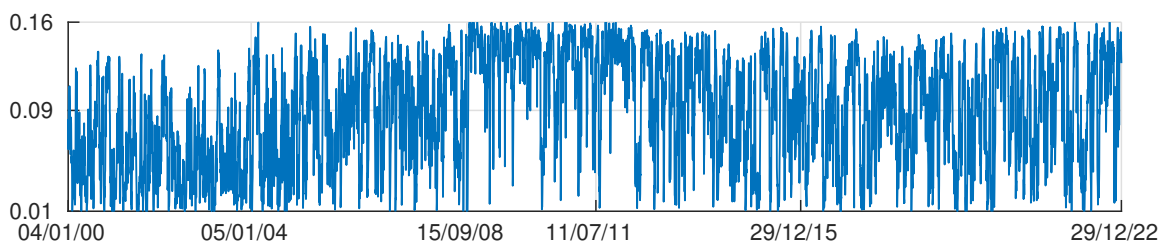


Figure 5: Correlations for simple RSDECO.



Figures 5, 6 and 13 display corresponding estimated equicorrelations for the simple RSDECO, the Reduced Block RSDECO and the Full Block RSDECO models, respectively.

We focus on equicorrelations given by the Full Block RSDECO. Interblock equicorrelations between the three asset classes changed sign after the financial crisis in 2008.

⁵This is also in line with theoretical findings of Basak and Pavlova (2016) that all commodity and commodity-equity correlations rise with financialization.

The equity-bond and the commodity-bond correlations which were negligible before 2008 become negative after this date. We observe the opposite pattern for the commodity-equity correlation which becomes more positive after 2008. It is worth noting that all intra-correlations increase after 2008 but with varying magnitudes reflecting heterogeneity across blocks. During the low correlation regime, intra-correlations for different blocks range on average between 5% and 20%. During the financial crisis regime, while commodity intra-correlation rises to only about 15%, equity and bond intra-correlations reach about 70% and 40%, respectively. Both intra and commodity-equity estimated correlations are consistent with the "loss spiral" view ([Brunnermeier and Pedersen \(2009\)](#); [Kyle and Xiong \(2001\)](#)) that when the market collapses, investors, especially if they are leveraged, sell assets to raise liquidity, causing unrelated asset returns to fall, increasing correlation between them.

As for commodity and equity-bond inter-correlations, results reflect the "flight to quality" phenomena. [Vayanos \(2004\)](#) has shown that when risk-averse investors experience a negative wealth effect in times of financial crisis, it reduces their risk-bearing capacity and leads them to sell risky assets to buy risk-free assets such as government bonds. During the financial crisis regime correlations between commodity and bond returns dropped from about 0% to about -30%, and that between equity and bond returns from 0% to about -40%.

The literature on the relationship between oil prices and stock prices can also help to understand the variations in the sign of the equity-commodity correlation. [Killian and Park. \(2009\)](#) shows that the impact of an oil price shock on stock prices depends on the origin of this shock. Before 2008, an increase in commodity prices could be perceived as an increase in expected inflation. [Alquist et al. \(2020\)](#) explain the positive equity-commodity correlation after 2008 by a reduction in the inflation premium. In a deflationary context, an increase in commodity prices is less prone to raise inflation expectations. We can observe that regime changes become more frequent after 2020. This could be related to rising uncertainty in the financial market in the context of higher inflation and geopolitical uncertainty.

Figure 6: Correlations: 3-Block-RSDECO (Reduced Form).

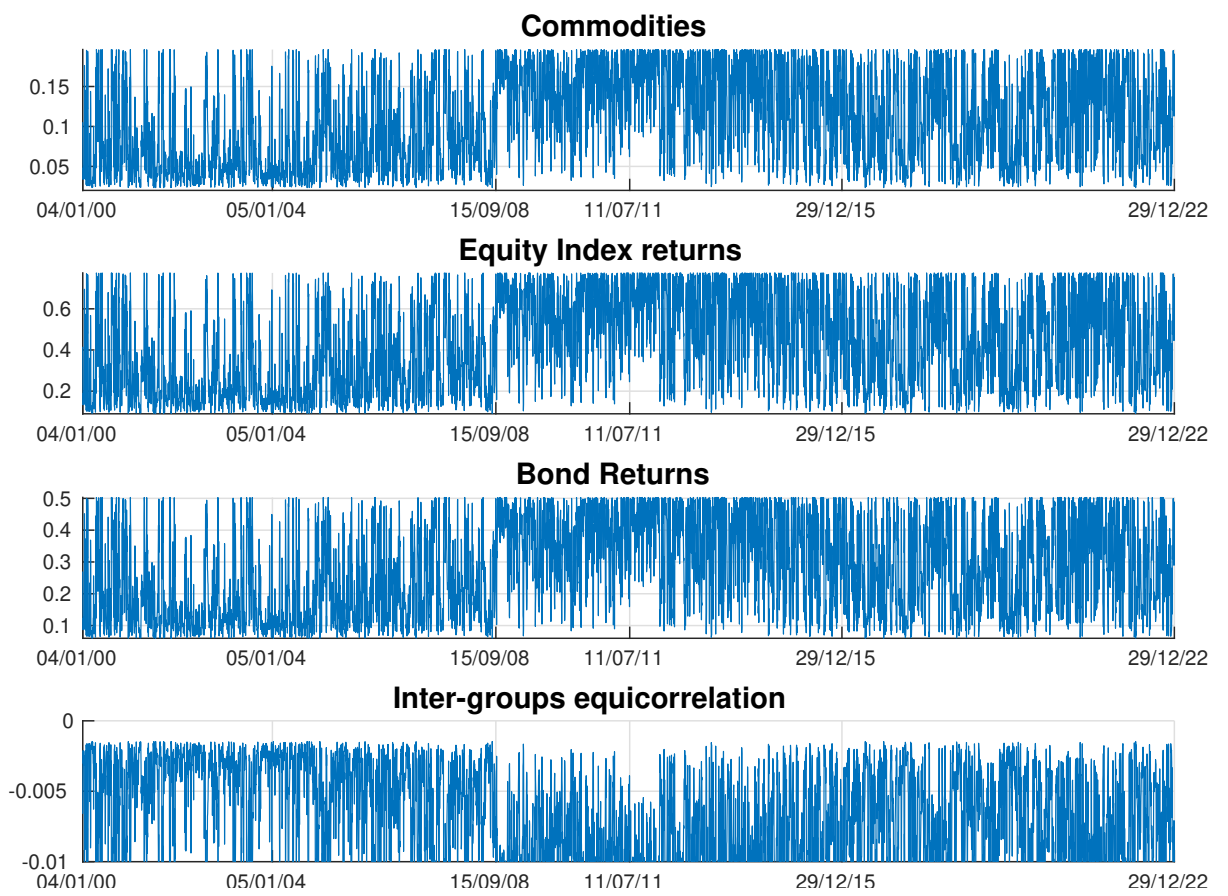


Figure 7: Correlations: 3-Block-RSDECO (Full Block).

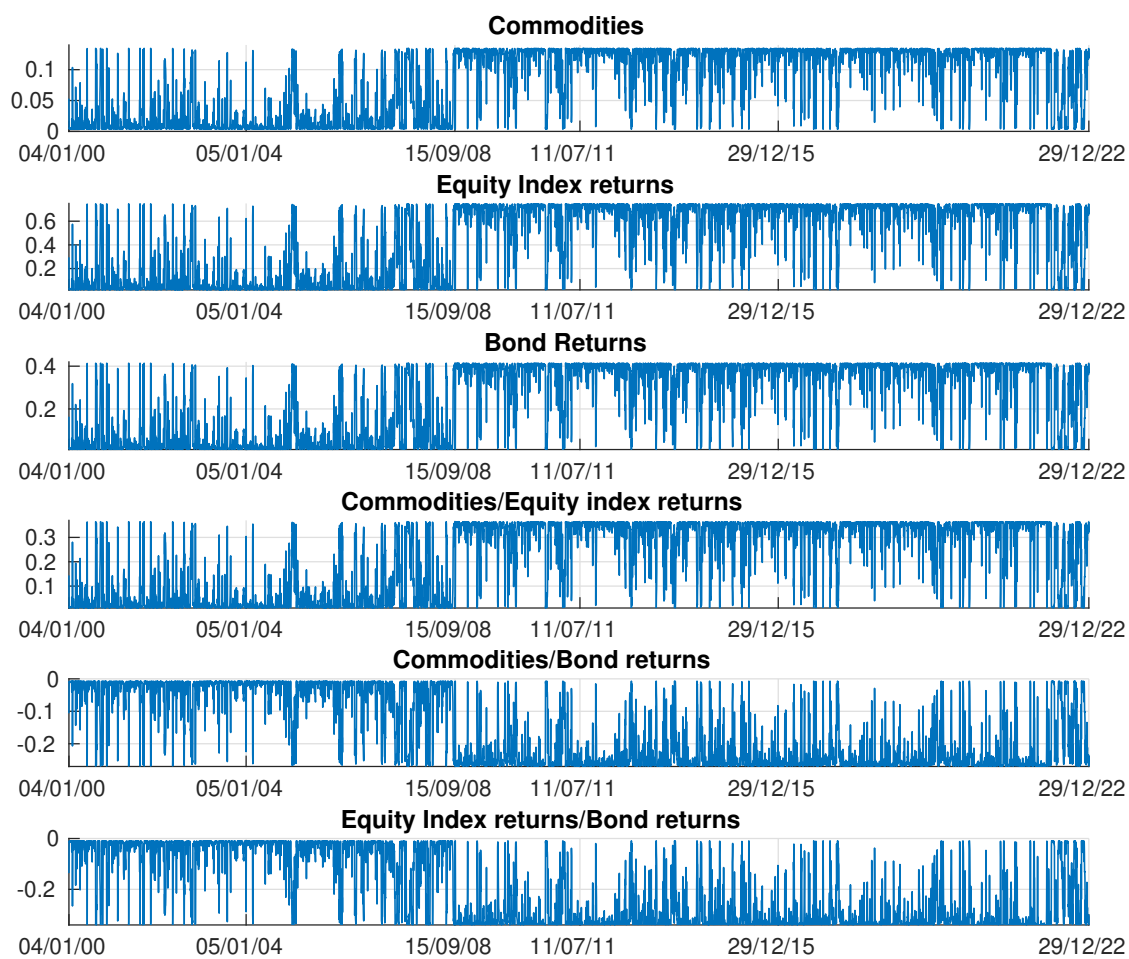


Figure 8: Correlations: 7-Block-RSDECO (Full Block).

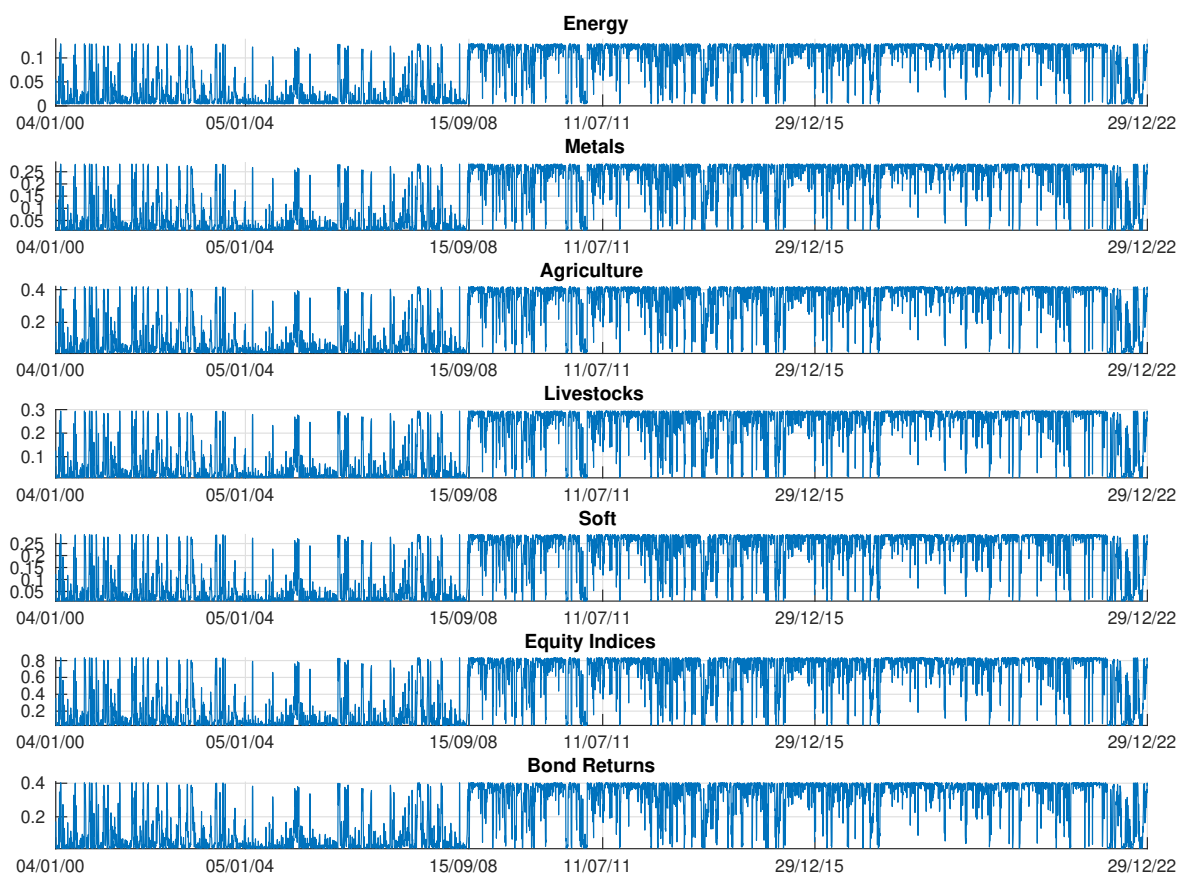


Figure 9: Correlations: 7-Block-RSDECO (Full Block).

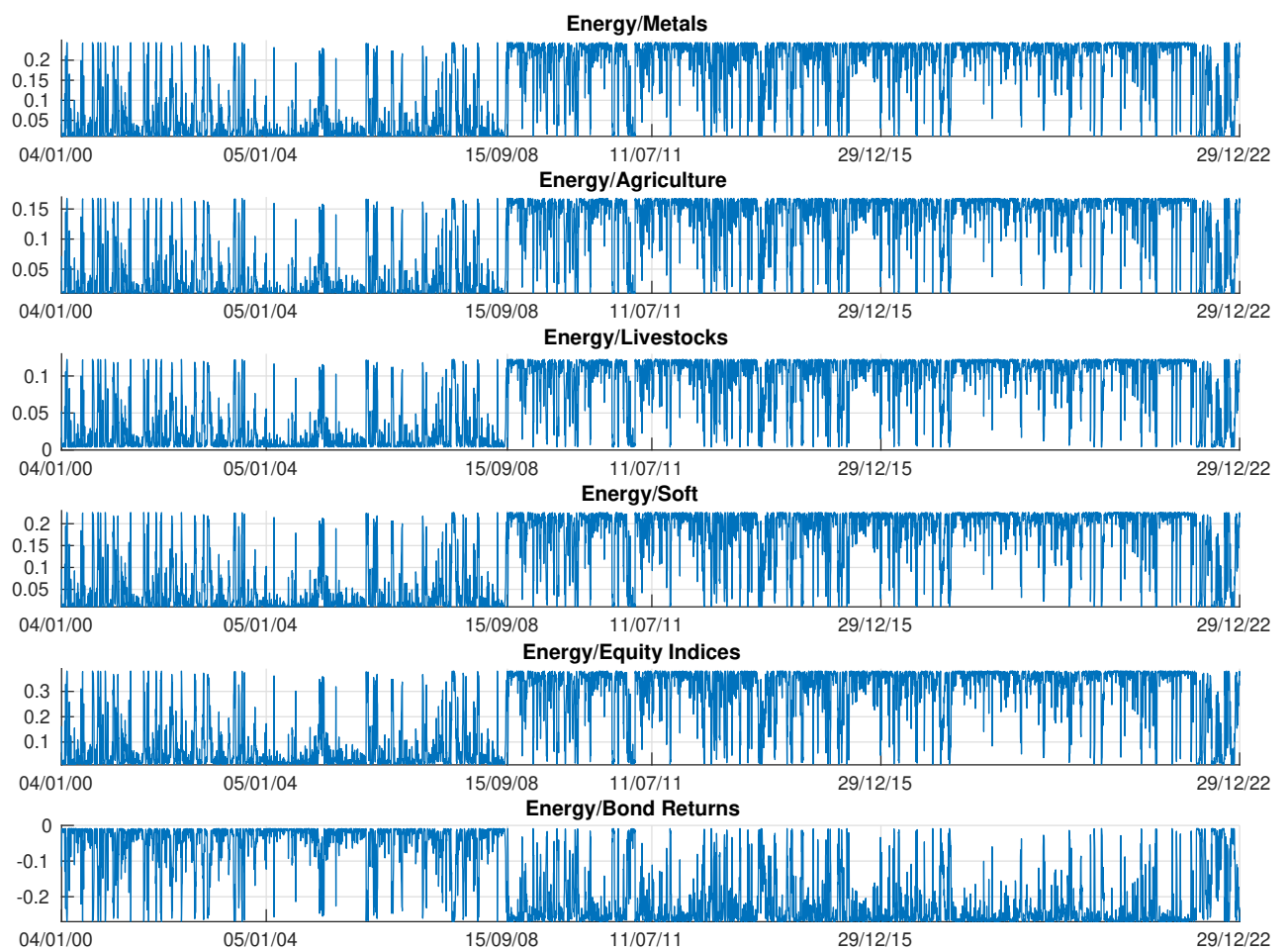


Figure 10: Correlations: 7-Block-RSDECO (Full Block).

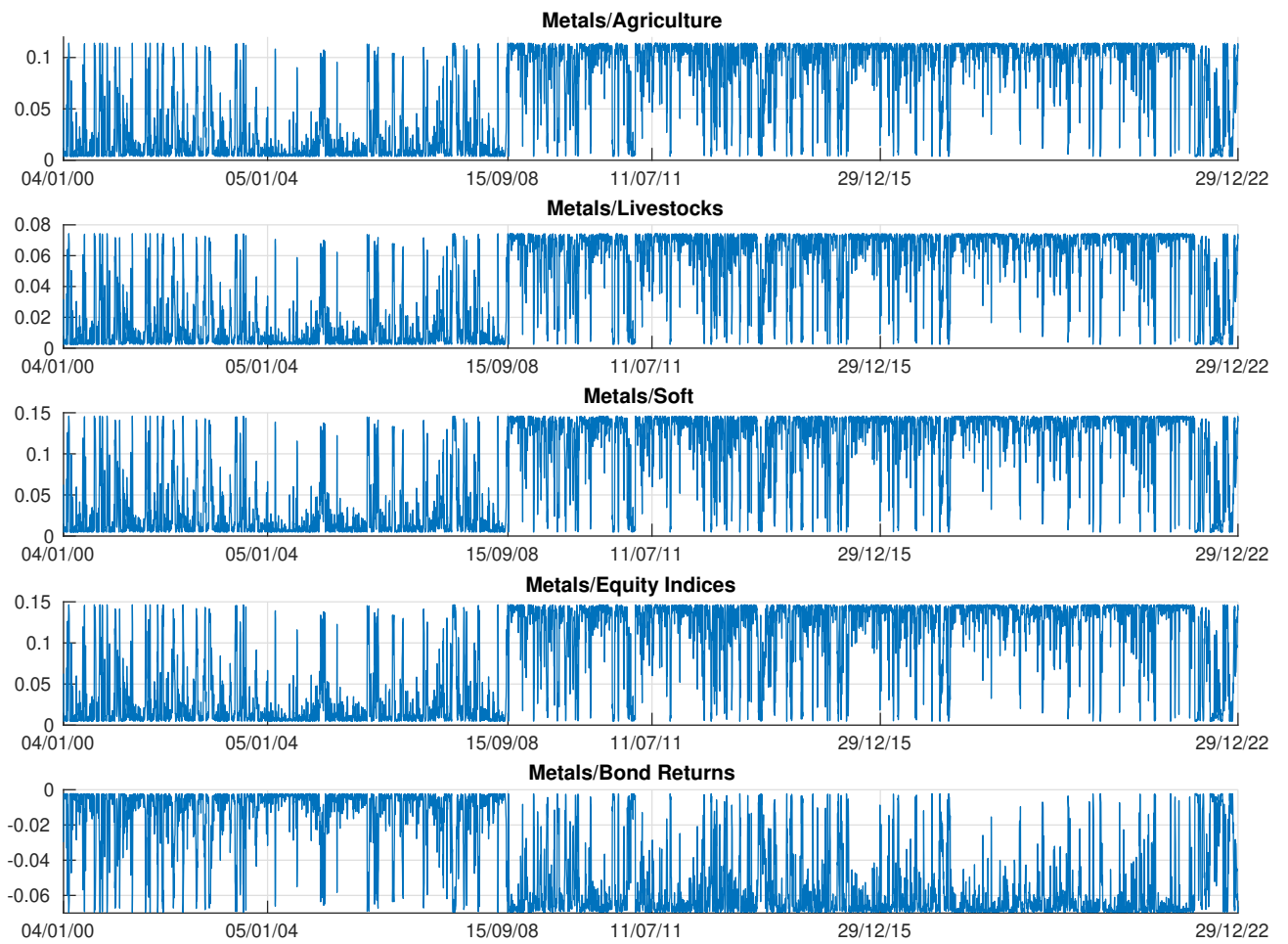


Figure 11: Correlations: 7-Block-RSDECO (Full Block).

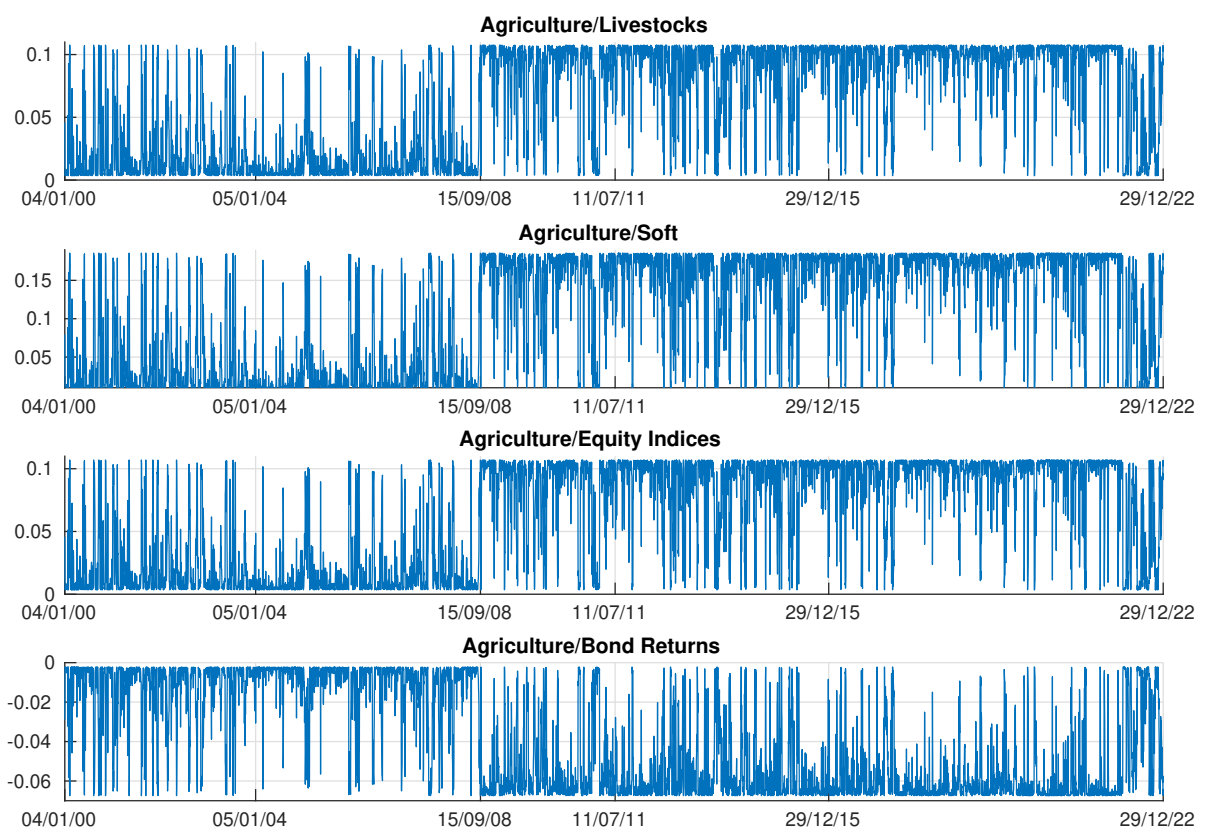


Figure 12: Correlations: 7-Block-RSDECO (Full Block).

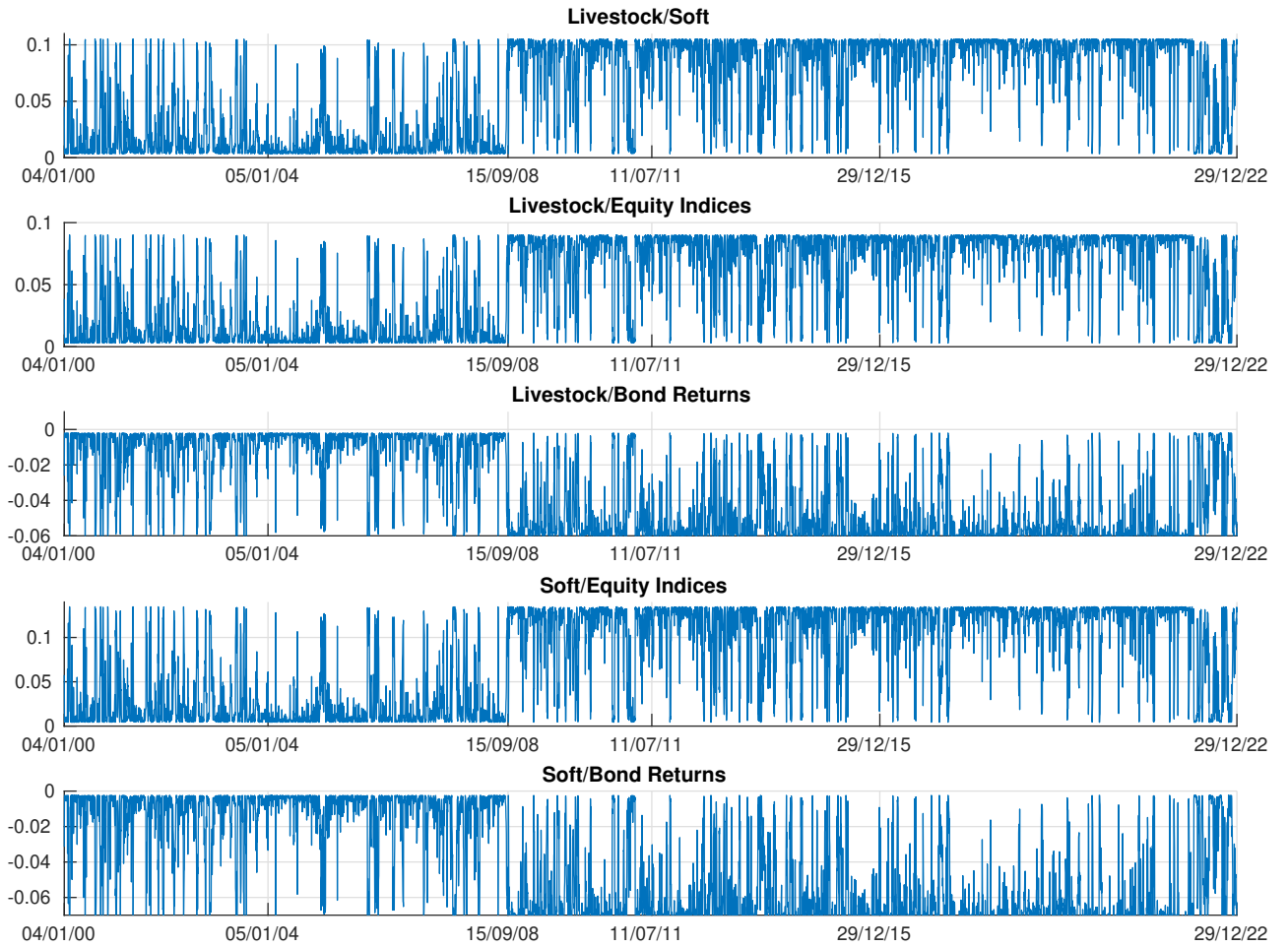
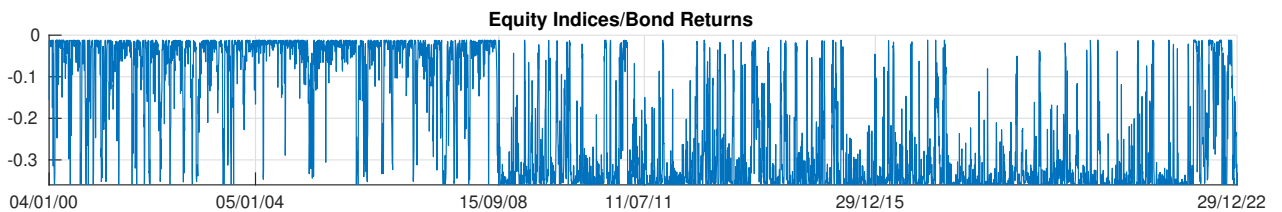


Figure 13: Correlations: 7-Block-RSDECO (Full Block).



5 Conclusion

In this paper, we have extended [Engle and Kelly \(2012\)](#) DECO model with a Markov-switching model. Our model is therefore able to estimate conditional correlations for a large number of assets while taking into account level shifts of these correlations. From an econometric point of view, our model could be extended in several directions. A first possible extension would be to consider independent regime-switching for each block. By doing so, we could uncover different degrees of persistence between regimes. Another possible extension would be to consider time-varying transition probabilities as [Diebold et al. \(1994\)](#) and [Filardo \(1994\)](#). The literature on stock-bond and stock-commodity correlations has shown the importance of macroeconomic or financial variables in shaping these correlations.

Considering the practical interest of our RS-DECO, it would be interesting to evaluate its performance in financial applications such as portfolio choice or risk management. Recently, [Moura and Ruiz \(2020\)](#) compared the performance of several DCC-type models and Stochastic volatility-type models to select mean-variance and minimum-variance portfolios with up to 1000 assets. The authors confirm previous results of [Engle et al. \(2019\)](#) and [De Nard et al. \(2021\)](#) who find DCC-type models give satisfying results if the objective is to select the minimum variance portfolio. It would be interesting to compare the performance of the RS-DECO to those obtained in these papers.

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Appendix

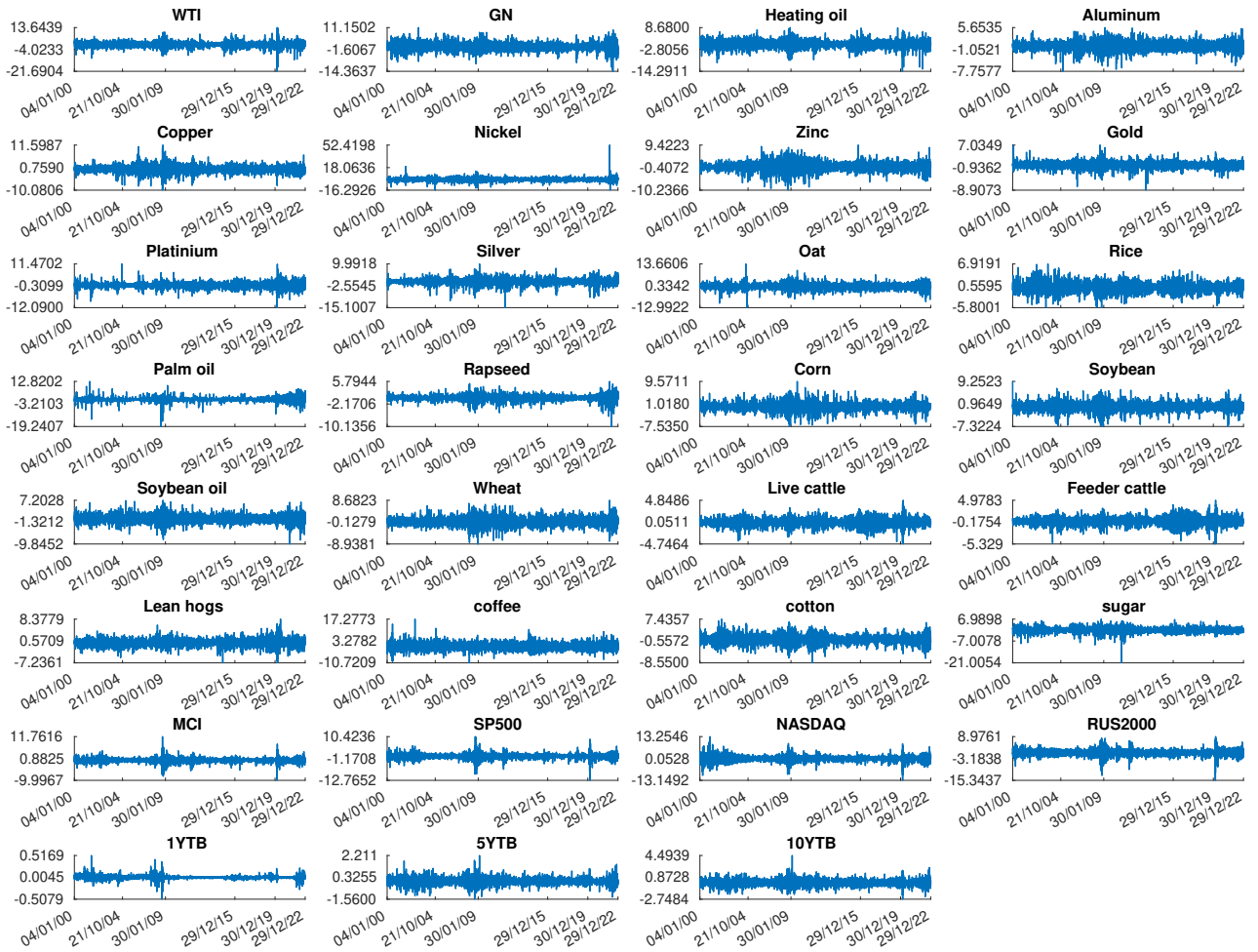
A Dataset

Table 3: Commodity futures data

Commodities	Exchange	Bloomberg Ticker	Contracts	GSCI (2023 RPDW)
Energy				61.46%
WTI crude oil	NYM	CL1-CL15	Every month	21.82%
Heating oil	NYM	HO1-HO15	Every month	4.62%
Natural gas	NYM	NG1-NG15	Every month	4.71%
Industrial Metals				10.57%
Aluminum	LME	LMAHDS (03 and 15)	Every month	3.8%
Copper	LME	LMCADS (03 and 15)	Every month	4.34%
Nickel	LME	LMNIDS (03 and 15)	Every month	0.98%
Zinc	LME	LMZSDS (03 and 15)	Every month	0.95%
Precious Metals				4.12%
Gold	CMX	GC1-GC12	Mar, May, Jul, Sep, Dec	3.73%
Silver	CMX	SI1-SI13	Mar, May, Jul, Sep, Dec	0.38%
Platinum	NYM	PL1-PL5	Jan, Apr, Jul, Oct	0
Agriculture				17.97%
1- Grain				14.08%
Corn	CBT	C1-C11	Jan, Mar, May, Jul, Aug, Nov	5.65%
Soybeans	CBT	S1-S7	Jan, Mar, May, Jul, Aug, Sep, Oct, Dec	3.60%
Rice	CBT	RR1-RR7	Mar, May, Jul, Sep, Nov, Jan	0
Oats	CME	O1-O5	Mar, May, Jul, Sep, Dec	0
Soybean oil	CBT	BO1-BO10	Jan, Mar, May, Jul, Aug, Sep, Oct, Dec	0
Palm oil	MDE	KO1-KO10	Jan, Mar, May, Jul, Aug, Sep, Nov	0
Rapeseed	MDE	IJ1-IJ7	Mar, May, Jul, Sep, Dec	0
Wheat	CBT	W 1-W 10	Mar, May, Jul, Sep, Dec	3.30%
2- Soft				3.89%
Sugar	ICE	SB1-SB8	Mar, May, Jul, Oct	1.45%
Coffee	ICE	KC1-KC8	Mar, May, Jul, Sep, Dec	0.93%
Cotton	ICE	CT1-CT10	Mar, May, Jul, Oct, Dec	1.26%
Livestock				5.85%
Feeder cattle	CME	FC1-FC8	Jan, Mar, Apr, May, Aug, Sep, Oct	1.04%
Live cattle	CME	LC1-LC7	Feb, Apr, Jun, Aug, Oct, Dec	2.98%
Lean hogs	CME	LH1-LH9	Feb, Apr, Jun, Aug, Oct, Dec	1.82%

This table gives details of the 21 commodity futures contracts used in our study to calculate the daily log returns from January 04, 2000 to December 29, 2022. Commodity futures contracts are generic contracts which refer to as constructing continuous futures prices series from futures active contract data. For instance, CL1 is the WTI Generic 1st contract, based on a 1-month WTI contract. Exchange-traded commodity futures markets are given in the second column. The third and fourth column contain maturity months of futures contracts and their Bloomberg tickers and the last four columns report the market value weights of each individual commodity within the major commodity indices, principally Standard and Poor's Goldman Sachs Commodity Index (GSCI) and Dow Jones UBS Commodity Index (DJ-UBS) as well as Rogers International Commodity index (RICI) and Thomson Reuters/Jefferis CRB Index (CRB), as of 2023. As commodity futures expires every one to three months, indices need to specify a rolling rule to transfer weights of the futures from the expiring period's contract to the next available contract. The rollover schedules of the GSCI, DJ-UBS, RJ/CRB indices are business days 5-9, 6-10 and 1-4 respectively. For the RICI index, it runs from the day prior to the last RICI business day of the month to the first RICI business day of the following month (for more details see RICI handbook). Industrial metals are traded on LME and daily settlement prices are quoted for the futures contracts to a fixed maturity period of 3- and 15-months.

Figure 14: Commodity and financial data series returns



B Descriptive statistics

Table 4: Descriptive statistics: commodity futures returns.

	Min	Max	Mean	S. dev.	Med.	Kurtosis	Skewness	JB test *	ADF test**
WTI	-21.6904	13.6439	2.2219e-02	1.9904	0.1192	10.8189	-0.6670	15076.0992 (1.0000e-03)	1.0000 (1.0000e-03)
GN	-14.3637	11.1502	1.0279e-02	2.0672	0.0239	5.5543	-0.1375	1581.5100 (1.0000e-03)	1.0000 (1.0000e-03)
Heating oil	-14.2911	8.6800	2.8039e-02	1.8059	0.0762	6.4589	-0.3419	2978.9720 (1.0000e-03)	1.0000 (1.0000e-03)
Aluminum	-7.7577	5.6535	6.9598e-03	1.2440	0.0000	5.4992	-0.2089	1538.5355 (1.0000e-03)	1.0000 (1.0000e-03)
Copper	-10.0806	11.5987	2.5801e-02	1.5555	0.0000	7.7011	-0.0897	5303.5272 (1.0000e-03)	1.0000 (1.0000e-03)
Nickel	-16.2926	52.4198	2.3403e-02	2.3308	0.0000	51.1747	1.9009	559585.1770 (1.0000e-03)	1.0000 (1.0000e-03)
Zinc	-10.2366	9.4223	1.5618e-02	1.7123	0.0000	6.0051	-0.1494	2185.3337 (1.0000e-03)	1.0000 (1.0000e-03)
Gold	-8.9073	7.0349	3.2415e-02	1.0070	0.0348	8.4228	-0.3262	7148.6942 (1.0000e-03)	1.0000 (1.0000e-03)
Platinum	-12.0900	11.4702	1.6939e-02	1.3857	0.0701	9.2824	-0.2116	9500.6308 (1.0000e-03)	1.0000 (1.0000e-03)
Silver	-15.1007	9.9918	2.6521e-02	1.5414	0.0644	9.8036	-0.7569	11641.1972 (1.0000e-03)	1.0000 (1.0000e-03)
Oat	-12.9922	13.6605	1.9385e-02	1.5386	0.0228	8.1289	-0.1908	6338.3436 (1.0000e-03)	1.0000 (1.0000e-03)
Rice	-5.8001	6.9191	1.8876e-02	1.2003	0.0000	5.4020	0.1510	1404.3388 (1.0000e-03)	1.0000 (1.0000e-03)
Palm oil	-19.2407	12.8202	2.1976e-02	1.3035	0.0000	26.6896	-1.0372	135508.3855 (1.0000e-03)	1.0000 (1.0000e-03)
Rapeseed	-10.1356	5.7944	2.0671e-02	0.9123	0.0350	10.5672	-0.6777	14161.7165 (1.0000e-03)	1.0000 (1.0000e-03)
Corn	-7.5350	9.5711	1.7713e-02	1.3866	0.0000	6.2335	0.0052	2505.4609 (1.0000e-03)	1.0000 (1.0000e-03)
Soybean	-7.3224	9.2523	2.1165e-02	1.3675	0.0523	6.2740	-0.2372	2622.4492 (1.0000e-03)	1.0000 (1.0000e-03)
Soybean oil	-9.8452	7.2028	2.3065e-02	1.4068	-0.0083	5.7662	-0.0685	1838.0989 (1.0000e-03)	1.0000 (1.0000e-03)
Wheat	-8.9381	8.6823	1.8101e-02	1.5343	-0.0300	5.5158	0.0888	1524.2499 (1.0000e-03)	1.0000 (1.0000e-03)
Live cattle	-4.7464	4.8486	1.4073e-02	0.7768	0.0292	6.4936	-0.3403	3035.6416 (1.0000e-03)	1.0000 (1.0000e-03)
Feeder cattle	-5.3290	4.9783	1.4350e-02	0.8436	0.0267	6.2842	-0.2493	2644.2221 (1.0000e-03)	1.0000 (1.0000e-03)
Lean hogs	-7.2361	8.3779	8.9693e-03	1.1676	0.0555	6.4239	-0.1792	2839.9350 (1.0000e-03)	1.0000 (1.0000e-03)
coffee	-10.7209	17.2773	5.2532e-03	1.9275	0.0000	6.4981	0.3192	3029.9027 (1.0000e-03)	1.0000 (1.0000e-03)
cotton	-8.5500	7.4357	6.7928e-03	1.3701	0.0299	5.7047	-0.1237	1767.5880 (1.0000e-03)	1.0000 (1.0000e-03)
sugar	-21.0054	6.9898	1.8428e-02	1.4775	0.0000	12.6677	-0.7362	22915.8633 (1.0000e-03)	1.0000 (1.0000e-03)
Engle DCC test ^{**a}	(195.6000)								
	(0.0000e+00)								

* In brackets, critical values for the tests. ** Augmented Dickey-Fuller test.

^a In brackets, p-values for the tests. ** With 5 lags.

This table reports summary statistics for the 21 daily collateralized commodity futures returns from January 04, 2000 to January 15, 2024. We take futures returns (changes in log prices multiplied by 100) and collateralize them with the daily 3-month US Treasury Bill (T-bill) secondary market rate. Details about commodity futures contracts and sources are provided in Appendix A.

Table 5: Descriptive statistics: equity index returns.

	Min	Max	Mean	S. dev.	Med.	Kurtosis	Skewness	JB test *	ADF test**
MSCI	-9.9967	11.7616	1.0430e-02	1.0439	0.0595	14.8696	-0.4924	33992.3383 (1.0000e-03)	1.0000 (1.0000e-03)
SP500	-12.7652	10.4236	1.7550e-02	1.2558	0.0570	13.1231	-0.4093	24716.6558 (1.0000e-03)	1.0000 (1.0000e-03)
NASDAQ	-13.1492	13.2546	1.7158e-02	1.6036	0.0881	8.8796	-0.1725	8312.1643 (1.0000e-03)	1.0000 (1.0000e-03)
RUS2000	-15.3437	8.9761	2.2663e-02	1.5665	0.0820	9.6830	-0.5389	10980.4489 (1.0000e-03)	1.0000 (1.0000e-03)
Engle DCC test ^{***a}	(542.7586) (0.0000e+00)								

* In brackets, critical values for the tests. ** Augmented Dickey-Fuller test.

^a In brackets, p-values for the tests. ** With 5 lags.

This table reports summary statistics for four equity indices belonging the financial asset block. Details about equity indices and sources are provided in Appendix A.

Table 6: Descriptive statistics: bond returns.

	Min	Max	Mean	S. dev.	Med.	Kurtosis	Skewness	JB test *	ADF test**
1YTB	-0.5079	0.5169	7.3040e-03	0.0393	0.0030	24.9285	0.4585	115427.4471 (1.0000e-03)	1.0000 (1.0000e-03)
5YTB	-1.5600	2.2110	1.2477e-02	0.2770	0.0074	6.4973	0.0362	2932.1111 (1.0000e-03)	1.0000 (1.0000e-03)
10YTB	-2.7483	4.4939	1.7047e-02	0.4885	0.0133	5.9106	0.0435	2031.8698 (1.0000e-03)	1.0000 (1.0000e-03)

* In brackets, critical values for the tests. ** Augmented Dickey-Fuller test.

This table reports summary statistics for three bond returns belonging the financial asset block. Details about data and sources are provided in Appendix A.

C Computation of holding bond returns

We expose the method of [Jones et al. \(1998\)](#) to calculate the bond returns. We use the “daily constant maturity interest rate series” from the Federal Reserve Bank of St. Louis FRED economic data. The U.S. Treasury bonds have semiannual coupon payments and the coupon on the hypothetical bonds is half the stated coupon yield. Then the price of the bond at the beginning of the holding period is equal to its face value. We calculate an end-of-period price on this bond using the next day’s yield augmented with the accrued interest rate:

$$P_{n-\#hd,t+1} = \sum_{i=1}^{2n-1} \frac{\frac{1}{2}y_{nt}}{\left(1 + \frac{1}{2}y_{n,t+1}\right)^i} + \frac{1 + \frac{1}{2}y_{nt}}{\left(1 + \frac{1}{2}y_{n,t+1}\right)^{2n}} + \frac{\#holding\ days}{365}y_{nt}$$

where $P_{n-\#hd,t+1}$ is the end-of-period price of the bond, n is the number of years the bond is referring to, t is the time, and y_{nt} is the yield of an n -period bond at time t . The $\#hd$ -return is calculated as;

$$r_{t+1} = P_{n-\#hd,t+1} - 1$$

The excess returns are calculated using the three-month interest rate as the risk-free rate that accrues over the holding period, which varies between one and five days because of weekends and holidays:

$$r_{t+1}^e = r_{t+1} - \frac{\#holding\ days}{365}y_{3mo,t}$$

The stock and commodity indices are obtained from datastream. The returns on these indices are calculated as:

$$r_{index,t+1} = \frac{P_{index,t+1} - P_{index,t}}{P_{index,t}}$$

The risk-free rate that accrues over the holding period is subtracted to obtain the excess returns:

$$r_{index,t+1}^e = r_{index,t+1} - \frac{\#holding\ days}{365}y_{3mo,t}$$