South African Reserve Bank
Working Paper Series
WP/16/08

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Shakill Hassan and Leonardo Morales-Arias

Authorised for distribution by Chris Loewald

June 2016

South African Reserve Bank

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Enquiries

Head: Research Department
South African Reserve Bank
P O Box 427
Pretoria 0001

Tel. no.: +27 12 313-3911
0861 12 SARB (0861 12 7272)

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Shakill Hassan* and Leonardo Morales-Arias†

April 27, 2016

Abstract

In this article we propose a dynamic factor framework for modeling and forecasting financial and commodity term structures in a unified global setting. The novelty of our approach is that it exploits a large set of information (i.e. data properties, time and forward dimensions, and cross-country, market, sector and weather dimensions) summarized in a set of heteroskedastic components that have a clear time series interpretation and that can be modeled dynamically to generate forecasts in real-time. The approach is motivated by evidence of rising financial integration, and interdependence between commodity and asset markets. We employ a battery of in-sample and out-of-sample techniques to evaluate our framework and concentrate on relevant statistical and economic performance measures. To preview our results with practical implications, we find that our framework provides significant in-sample information in terms of product specific factors and commonalities driving commodity and financial markets. Moreover, the specification proposed for modeling the dynamics of financial and commodity term structures generates accurate out-of-sample interval and point forecasts and leads to variance reduction when hedging a portfolio made up of spot and futures contracts.

JEL Classification: C58, F7, G15

Keywords: Term structure forecasting, Fractional CVAR, Orthogonal GARCH, Regime-Switching, Dynamic Hedging.

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*South African Reserve Bank and University of Cape Town. Email: shakill.hassan@resbank.co.za

†Corresponding author. University of Kiel and South African Reserve Bank. Email: moralesl78@hotmail.com.
We would like to thank participants at the staff meetings of the South African Reserve Bank, Guilherme Moura, Thomas Lux for valuable comments and suggestions. Very special thanks to Elmarie Nel and Luchelle Soobyah whose excellent research assistance made this article possible. This research was conducted while the second author was a visiting fellow at the South African Reserve Bank whose excellent hospitality is also hereby acknowledged. The usual disclaimer applies.

1 Introduction

Modeling and forecasting term structures in financial and commodity markets is very important for industry practitioners and policy makers. Appropriate methods that approximate term structures -and thus the expected future path of financial and commodity prices- allow practitioners to take better decisions, for instance, with respect to optimal portfolio holdings and dynamic hedging strategies. Monetary authorities also benefit from information embedded in financial and commodities term structures: forecasts of the future evolution of exchange rates, asset prices, and commodity prices, are important inputs used by central banks when setting policy interest rates (Rigobon and Sack, 2002; Bernanke, 2008).

In this article we propose a dynamic factor framework for modeling and forecasting financial and commodity variables in a unified global setting. The novelty of our approach is that it exploits a large set of information at the daily frequency (i.e. data properties, time and forward dimensions as well as cross-country, market, sector and weather dimensions) summarized in a set of heteroskedastic components that have a time series interpretation and that can be modeled dynamically to generate forecasts on real time. We employ a battery of in-sample and out-of-sample techniques to evaluate our framework and we concentrate on statistical and economic performance measures relevant for decision makers (e.g. porfolio managers, central bankers).

Our study is motivated by the fact that, to the best of our knowledge, no research has been done so far that brings together a unified framework for modeling and forecasting financial and commodity futures at the international level. Such a unified approach may be increasingly important due to the degree of financial spillovers and interdependence, across borders, and between asset classes (e.g., IMF (2016)). Commodity prices affect the demand for currencies and equities of commodity exporters (e.g., Australia, Canada, Chile, Norway, South Africa); and commodity currencies have been shown to help forecast commodity prices (Chen et al., 2010). Rising commodity prices also raise the terms-of-trade and growth rates of commodity-rich economies; the associated increase in aggregate demand induces monetary policy tightening under inflation-targeting regimes, raising bond market yields. Moreover, international financial integration has contributed to an erosion of monetary policy independence, and strengthened the responsiveness of bond yields (particularly along the long end of the yield curve, in advanced and emerging economies) to the global financial cycle, which is largely driven by monetary conditions in the US (Rey, 2014; Obstfeld, 2015). Last but not least, growth spillovers (e.g., from China) cause a degree of international co-movement in rates of output growth, and short-term interest rates.

One of the most popular term structure modeling benchmarks (albeit in the interest rate literature) is the Nelson and Siegel (1987) model which decomposes the term structure of interest rates into three factors, namely, the level, slope and curvature of the yield curve. Diebold et al. (2008) and Diebold and Li (2006) have extended the NS approach to incorporate other global factors and time-series structures and have demonstrated its good forecasting capabilities and its applicability for macroeconomic analysis (Diebold et al., 2006). Recent work has also highlighted the good fit of the NS structure for commodity markets (Karstanje et al., 2015) vis-a-vis other important benchmarks in the commodities pricing literature such as the seminal work by Schwartz (1997) and Schwartz and Smith (2000).

In general, factor models have shown to be a promising avenue for modeling futures and/or yield curves and to explain the variation of the macroeconomy (Ang and Piazessi, 2003; Cochrane and Piazessi, 2005, 2008). This is not surprising as term structures contain important information along the time and forward dimensions which are difficult to account for with large scale macro models. Nevertheless, research on term structures is still in its infancy, in particular studies that account for both financial and commodity markets in a unified approach.

A handful of studies have recently put forward models for commodity products at the daily frequency with 'real world' applications such as hedging and portfolio allocation (Boswijk et al., 2015; Cavalier et al., 2015; Dolatabadi and Nielsen, 2015; Dolatabadi et al., 2015). What seems to be a common finding is that accounting for fractional cointegration, fits well the data in-sample and out-of-sample. Previous studies have also found evidence of fractional cointegration in daily equity and exchange rate dynamics which imply a dissipation of shocks to equilibrium relations only at long horizons; thus hinting at the promising applicability of fractional cointegrated models for forecasting with data at higher frequencies (de Truchis, 2013; Baillie and Bollerslev, 1994). Moreover, as shown both empirically and theoretically in the behavioral finance literature, regime-switching mechanisms can help explain the stylized features found in financial data as well as adapt to structural breaks (Grauwe and Grimaldi, 2006; Huisman, 2009). However, to what extend the commonalities of financial and commodity markets can be modeled via fractional cointegration dynamics as well as heteroskedasticity and regime-switching features and their contribution to in-sample and out-of-sample information is, to the best of our knowledge, not known. In this study we contribute to the rising literature on term structure modeling by bridging commodities and financial markets in a unified framework that accounts for important commonalities between these markets with realistic time-series mechanisms.

The specific contributions of our study are threefold. First, we extend the NS-type structure to account for stochastic seasonalities which are important determinants of some commodity markets (e.g., gas, gasoline, livestock, grains, etc). Moreover, we adapt the model to incorporate global, market, sector and idiosyncratic components by introducing commonalities that account for the effects of different countries, financial and commodity markets, alternative sectors (i.e. oil and gas, metals, foreign exchange, equity, bonds) and idiosyncratic (i.e. product) specific shocks. Bond market yields have a strong 'global' commonality; and commodities, exchange rates, and equities are driven by demand and supply conditions which have a strong global spectrum. Thus the importance of modeling all the markets and sectors considered here in a unified setting.

Second, we propose a Regime-Switching Fractional Cointegrated VAR with Orthogonal GARCH-in-mean errors (RSFCVAR-OGARCH-M) to model the dynamics of the global, market, sector and seasonalities at the daily frequency. The latter specification accounts for many 'stylized facts' of financial and commodity markets data at the daily frequency, namely, jumps, leptokurtosis, (conditional) heteroskedasticity, fractional integration, amongst others (Lux, 2009; Huisman, 2009). This is important as market practitioners deal daily with hedging decisions of financial and commodity products and policy authorities study the daily effects of monetary policy on term structures (e.g. yield curves) so that an appropriate framework should account for characteristics in data dynamics as close as possible.

Third, we adopt a battery of in-sample and out-of-sample analyses that should allow practitioners not only to extract useful and relevant information in real-time (e.g., variance term structures, variance decompositions, macroeconomic mapping) but also to generate and evaluate point and density forecasts of crucial financial and commodity variables.

The article is organized as follows. The next section describes the model. Section 3 discusses the data and estimation approach and Section 4 the forecasting methodology. Section 5 and Section 6 are devoted to discussing the results and our final remarks, respectively.

2 The model

The model is based on previous work by Nelson and Siegel (1987), Diebold et al. (2008), Diebold and Li (2006), Karstanje et al. (2015) and Boswijk et al. (2015). We consider the NS structure which is extended to incorporate seasonality components found in commodity markets such as natural gas, gasoline, some grains and livestock, amongst others:

$$z_{it}(\tau) = l_{it} + \Lambda_s(\lambda_{it}, \tau)s_{it} + \Lambda_c(\lambda_{it}, \tau)c_{it} + \Lambda_f(\kappa_{it}, \cos(\tau, \eta), \sin(\tau, \eta))f_{it} + \varepsilon_{it}(\tau). \qquad (1)$$

In the above expression $z_{it}(\tau) = \ln Z_{it}(\tau)$ is used to denote the natural logarithm of the futures price of product $i = 1, ..., N$ at day $t = 1, ..., T$ and forward month $\tau = 1, ..., \mathcal{T}$, l_{it} is the so-called level factor, s_{it} is the slope factor, c_{it} is the curvature factor, f_{it} is the seasonality factor introduced for our framework and $\varepsilon_{it}(\tau)$ is a 'measurement error'.

The base loadings $\Lambda_s(\bullet), \Lambda_c(\bullet), \Lambda_f(\bullet)$ quantify the loads of the slope, curvature and seasonality along the forward dimension. In principle, the latter loadings can take alternative analytical forms, for instance, cublic spline loadings (Wold, 1974; Suits et al., 1977). In our context, the base loadings are given by:

$$\Lambda_s(\lambda_{it}, \tau) = \frac{1 - e^{-\lambda_{it}\tau}}{\lambda_{it}\tau}, \qquad (2)$$

$$\Lambda_c(\lambda_{it}, \tau) = \frac{1 - e^{-\lambda_{it}\tau}}{\lambda_{it}\tau} - e^{-\lambda_{it}\tau}, \qquad (3)$$

$$\Lambda_f(\kappa_{it}, \cos(\tau, \eta), \sin(\tau, \eta)) = \frac{\kappa_{it}\left[1 - \cos(\eta\tau) + \sin(\eta\tau)\right]}{2\eta\tau}, \qquad (4)$$

where λ_{it} is the so-called maturity parameter which quantifies the steepness and the shape of the term structure. More precisely, the latter parameter can be interpreted as the 'mean reversion' rate of the slope and curvature factors. Moreover, we introduce the trigonometric funtions $\cos(\cdot)$ and $\sin(\cdot)$ which allow us to incorporate a cyclical effect along the forward dimension of the term structure with time-varying amplitude given by κ_{it} and constant number of cycles with respect to the forward month τ given by $\eta = 2\pi 3^{-1}$.[1] To illustrate the latter functions, Figure 1 displays the behavior of the above base loadings for fixed (estimated) parameter values of λ_i and κ_i for the products considered.

The commonalities of the level, slope, curvature and seasonality factors are modeled by means of the following factor decomposition for each product i at day t:

$$
\begin{aligned}
l_{it} &= \bar{l}_i + \gamma^g_{l,i} L_{g,t} + \gamma^m_{l,i} L_{m,t} + \gamma^n_{l,i} L_{n,t} + \epsilon_{l,it}, &(5)\\
s_{it} &= \bar{s}_i + \gamma^g_{s,i} S_{g,t} + \gamma^m_{s,i} S_{m,t} + \gamma^n_{s,i} S_{n,t} + \epsilon_{s,it}, &(6)\\
c_{it} &= \bar{c}_i + \gamma^g_{c,i} C_{g,t} + \gamma^m_{c,i} C_{m,t} + \gamma^n_{c,i} C_{n,t} + \epsilon_{c,it}, &(7)\\
f_{it} &= \bar{f}_i + \gamma^u_{f,i} F_{u,t} + \gamma^v_{f,i} F_{v,t} + \gamma^w_{f,i} F_{w,t} + \epsilon_{f,it}, &(8)
\end{aligned}
$$

where $L_{g,t}$, $S_{g,t}$, $C_{g,t}$ denote the global components $g = \{\text{global}\} = \{\text{glb}\}$, the variables $L_{m,t}, S_{m,t}, C_{m,t}$ denote the market components $m = \{\text{commodities, financial}\} = \{\text{com, fin}\}$ and $L_{n,t}, S_{n,t}, C_{n,t}$ denote the sector components $n = \{\text{energy, metals, softs, grains, livestock, foreign exchange, bonds, equity}\} = \{\text{ene, met, sof, gra, liv, forex, bon, eqt}\}$ of the level, slope and curvature factors, respectively.[2] Moreover, $F_{u,t}, F_{v,t}, F_{w,t}$ denote the components driving the stochastic behavior of the seasonality factors (e.g. weather). Finally, the components $\epsilon_{\bullet,it}$ for $\bullet = l, s, c, f$ are the idiosyncratic shocks of the level, slope, curvature and seasonality factors. In the above decomposition, we assume that the components per factor (global, market, sector and idiosyncratic) are uncorrelated.

The dynamics of $L_{j,t}$, $S_{j,t}$, $C_{j,t}$ for $j = g, m, n$ and $F_{j,t}$ for $j = u, v, w$ are modeled by

[1] We derive the seasonality specification in (4) by integrating the function $f(\tau, \kappa_i) = \kappa_{1,i}\sin(\eta\tau) + \kappa_{2,i}\cos(\eta\tau)$ forward over $[0, \tau]$ and dividing the result by τ to remain along the lines of the original NS derivation. To reduce on the number of parameters to be estimated we assume $\kappa_{1,i} = w_1\kappa_i$, $\kappa_{2,i} = w_2\kappa_i$ with $w_1 = w_2 = 1/2$ a weighting factor and κ_i the amplitude parameter.

[2] 'Global' component is taken here as a common component amongst all products and country specific markets.

means of the following Regime-Switching Fractionally-Cointegrated VAR process with Orthogonal GARCH-in-mean (FCVAR-OGARCH-M) innovations:

$$
\begin{aligned}
\Delta^{d_{j,r_t}} X_{j,t} &= \alpha_{j,r_t}\beta'_{j,r_t}\Delta^{d_{j,r_t}-b_{j,r_t}}\Upsilon_{j,b_{j,r_t}}X_{j,t} + \sum_{p=1}^{P}\Gamma^{p}_{j,r_t}\Delta^{d_{j,r_t}}\Upsilon^{p}_{j,b_{j,r_t}}X_{j,t} \\
&+ \zeta_j \odot \mathrm{diag}(H_{j,t}) + \xi_{j,t}, \qquad (9)\\
\xi_{j,t} &\sim N(0, H_{j,t}), \qquad (10)\\
H_{j,t} &= B_j E_t\left[u_{j,t}u'_{j,t}|\mathcal{I}_{t-1}\right] B'_j = B_j\Omega_{j,t}B'_j, \qquad (11)\\
\Omega_{j,t} &= (I_3 - \mathrm{diag}(\theta_j) - \mathrm{diag}(\delta_j)) + \mathrm{diag}(\theta_j)\odot\Omega_{j,t-1} + \mathrm{diag}(\delta_j)\odot u_{j,t-1}u'_{j,t-1}, \qquad (12)
\end{aligned}
$$

where the vector $X_{j,t}$ is given by $X_{j,t} = [L_{j,t}, S_{j,t}, C_{j,t}]'$ for $j = g, m, n$ or $X_{j,t} = [F_{u,t}, F_{v,t}, F_{w,t}]'$ for $j = f$. In (9), Δ^d is the fractional difference operator (ignoring regime-switching) and $\Upsilon_{j,b} = 1 - \Delta^b$ is the fractional lag operator. Following Johansen and Nielsen (2012) a time series is said to be fractional of order d, denoted $X_t \in I(d)$, if $\Delta^d X_t$ is fractional of order zero, that is if $\Delta^d X_t \in I(d)$. A k-dimensional time series $X_t \in I(d)$ is said to be fractionally cointegrated when one or more linear combinations are fractional of a lower order, that is, when a $k \times r$ matrix β exists such that $\beta' X_t \in I(d-b)$ with $b > 0$. In addition, the matrices α and Γ are the loadings of equilibrium adjustment and of short-run dynamics, respectively. The reason for employing a FCVAR structure here is that at higher frequency of the data, equilibrium relations may exhibit long-memory and accounting for this feature can have important practical implications for, e.g. hedging, as found in various studies (Brunetti and Gilbert, 2000; Dark, 2007; Coakley et al., 2008). Although findings on fractional cointegration with daily data have not been categorized as 'stylized facts' per se, they seem to be the rule rather than the exception when cointegration is in fact present.

By introducing two regimes $r_t = 1, 2$, we assume that the FCVAR definitions apply but at different degrees over time. We opt for a specification with regime-switching for three main reasons. First, regime-switching mechanisms can account for structural and/or random breaks in the data due to, for instance, changes in investor preferences, which can affect the (parameter) stability of a particular model. Second, given that the proposed unified framework accounts for different common components (global, market, sector and weather), we can expect a certain degree of heterogeneity amongst the commonalities, so that a model with regime-switching can potentially 'absorb' such heterogeneity. Third, regime switching features can approximate jumps which are usually found in data of commodity and financial markets (see e.g., Lux (2009); Huisman (2009)).

In the above specification, the covariance of the error process $\xi_{j,t}$ is given by $H_{j,t}$ for $j = g, m, n, f$ and is conditional on the information set $\mathcal{I}_{t-1}$. We assume that the conditional covariances $H_{j,t}$ follow Orthogonal GARCH (OGARCH) processes. We also allow for the variances in $H_{j,t}$ to have an effect on the conditional mean of $X_{j,t}$ so that the coefficients in the 3×1 vector ζ_j can be interpreted as the 'price' of common components risk with $\odot$ the element-by-element (Hadamard) multiplication operator. In addition, considering volatility-in-mean is advantageous as it may price uncertainty and risk in the common components as well as approximate arbitrage-free models with volatility-in-mean applicable to derivative pricing (Duan, 1995; Ludvigson and Ng, 2007; Bollerslev et al., 2008).

Last but not least, another advantage of (10) is that it is general enough to account for other popular specifications. For instance, with $d_{r_t} = b_{r_t} = 1$ and $\alpha_{r_t} = 0$, the model is a VAR in first differences, with $d_{r_t} = b_{r_t} = 1$ and $\alpha_{r_t} = \alpha < 0$ the model is a Cointegrated VAR (CVAR) and with $d_{r_t} = d$, $b_{r_t} = b$ and $\alpha_{r_t} = \alpha < 0$ the model becomes a Fractional Cointegrated VAR (FCVAR). By considering a general model with various embedded specifications, we can vary the structure on the set of components at hand (e.g. financial vs. commodities, vs. weather, etc).

For the idiosyncratic components $\epsilon_{\bullet,it}$, $\bullet = l, s, c, f$, we assume simple heteroskedastic autoregressive models of order one, i.e.

$$\epsilon_{\bullet,it} = \phi_{\bullet,i}\epsilon_{\bullet,it-1} + a_{\bullet,it},\ a_{\bullet,it} \sim N(0, \omega_{\bullet,it}), \tag{13}$$

where $\omega_{\bullet,it}$ follow GARCH(1,1) processes. Similarly, the measurement errors follow heteroskedastic autoregressive processes of order one:

$$\varepsilon_{it}(\tau) \quad = \quad \varphi_i(\tau)\varepsilon_{it-1}(\tau) + \varrho_{it}(\tau),\ \varrho_{it}(\tau) \sim N(0, \upsilon_{it}(\tau)), \tag{14}$$

$\upsilon_{it}(\tau)$ follow simple GARCH(1,1) processes. Moreover, we assume that the shocks $a_{\bullet,it}$ and $\varrho_{it}(\tau)$ are uncorrelated across i's, i.e. we assume a diagonal (co)variance structure for these quantities are given by $D_t = \text{diag}([\omega_{l,1t}, \omega_{s,1t}, ..., \omega_{c,Nt}, \omega_{f,Nt}])$ and $V_t = \text{diag}([\upsilon_{1t}(1), \upsilon_{1t}(2), ..., \upsilon_{Nt}(\mathcal{T}-1), \upsilon_{Nt}(\mathcal{T})])$, respectively.[3] The full model can be represented compactly in state-space form, i.e.

$$\mathcal{Z}_t = \mathcal{K} + \Pi\mathcal{X}_t + \mathcal{E}_t, \tag{15}$$

$$\mathcal{X}_t|\mathcal{I}_{t-1} \sim N(0, Q_t), \tag{16}$$

$$\mathcal{E}_t|\mathcal{I}_{t-1} \sim N(0, V_t), \tag{17}$$

where $\mathcal{Z}_t = [z_{1t}(1), ..., z_{1t}(\mathcal{T}), z_{2t}(1), ..., z_{2t}(\mathcal{T}), ..., z_{Nt}(1), ..., z_{Nt}(\mathcal{T})]'$, $\mathcal{X}_t = [L_{glb,t}, S_{glb,t}, C_{glb,t}, ..., L_{fin,t}, S_{fin,t}, C_{fin,t}, ..., L_{met,t}, S_{met,t}, C_{met,t}, ..., F_{u,t}, F_{v,t}, F_{w,t}, ..., \epsilon_{l,Nt}, \epsilon_{s,Nt}, \epsilon_{c,Nt}, \epsilon_{f,Nt}]'$ and $\mathcal{E}_t = [\varepsilon_{1t}(1), ..., \varepsilon_{1t}(\mathcal{T}), \varepsilon_{2t}(1), ..., \varepsilon_{2t}(\mathcal{T}), ..., \varepsilon_{Nt}(1), ..., \varepsilon_{Nt}(\mathcal{T})]'$. Moreover, $\mathcal{K}$ is a $N \cdot \mathcal{T}$ vector of constants, Π is a $N \cdot \mathcal{T} \times 204$ matrix of coefficients with Q_t and V_t the conditional covariances of $\mathcal{X}_t$ and $\mathcal{E}_t$, respectively. More details about the functional form of the above state-space representation can be found in the Appendix.

3 Data and estimation

3.1 Data description

Term structure data is obtained mainly from Bloomberg and in some particular cases from Datastream. Table 1 summarizes the data collected and the specific sources. We employ monthly rollover futures series for 36 months at the daily frequency starting from 2010-10-01 and ending on 2015-09-30.[4] The sample period chosen was based on data availability and covering up to eight (8) 'seasonality years'.[5] As it is usually the case, some products had the full

[3]While one could argue that the product and seasonality specific shocks or measurement errors might exhibit more complex dynamic structures, previous studies have used similar specifications (albeit for monthly data) and have demonstrated that such simple structures work well in-sample and out-of-sample (Diebold and Li, 2006). In our context, given our large scale model we opt for simple specifications for the idiosyncratic shocks to keep our estimations tractable.

[4]Note that 3 years $\times$ 12 months = 36 months $\div$ 6 months = 6 cylces/seasons for the seasonality along the forward dimension τ

[5]A seasonal year is defined here as one that starts on October 1st and ends in September 30th, commonly known in the gas and power industry as a 'gas year'.

36 forward months available (e.g. gas and oil, softs and grains) while others had intermittent data over the 36 forward months (e.g. exchange rates, bonds and some metals). We have interpolated weekends and holidays for simplicity as weekend data were not available for many of the products under consideration.[6]

The data employed for the analyses at the monthly frequency, i.e. the data used for the mapping of the extracted components to macroeconomic factors (as will be explained below), are mainly obtained from DATASTREAM and the World Bank Database with some exceptions which were obtained from the HAVER. We collected macroeconomic data at the country level for a balanced panel of 19 countries for the same period as for the futures data, i.e. 2010-10 and ending on 2015-09. All groups of macro data contain the main industrialized economies (G7) and the main emerging markets (BRICS) amongst others. Detailed information about the data is provided in Table 1.

3.2 Model estimation

The model described in the preceding section considers time, cross-section and forward dimensions along with a heteroskedastic and regime-switching dynamic specification of the common components. While the model (or a restricted version of it) could in principle be estimated by means of the so-called 'first generation' dynamic factor approaches (e.g., Kalman-Nelson-Kim filter given its linear-Gaussian state-space representation) or Bayesian techniques, a large parameter space renders such estimation approaches computationally cumbersome in particular when forecasting exercises are at hand. Given that we are dealing with quite a large-scale model, we opt for the 'third generation' approach as detailed in Stock and Watson (2011) whereby parameters and factors/components of the model are estimated in various steps, and the state-space representation is subsequently employed for in-sample and out-of-sample analyses. This approach reduces computational time for forecasting and allows for more general dynamic specifications as opposed to (say) simpler autoregressive models as is the case in other applications.[7]

[6] We have also employed business days as opposed to interpolated weekend data and the results do not differ qualitatively. We decided for interpolation in order to smooth out any weekend effects out of the analysis.

[7] In fact, Diebold and Li (2006) show that k-step estimation approaches within the NS framework that are relatively easy to implement have the advantage that they can be succesfully applied for forecasting without much

In what follows we describe the main steps of the base estimation approach considered here. Additional details can be found in the Appendix of this article.

1. The first step consists of estimating a product's level, slope, curvature and seasonality factors $l_{it}, s_{it}, c_{it}, f_{it}$ as well as the maturity and amplitude parameters λ_{it} and κ_{it} in equation (1) by means Bayesian Averaging (BAV) based on various procedures which are summarized in Table 2 along with their advantages and disadvantages. Note that by employing BAV based on different estimation approaches (Non-linear Least Squares, Ordinary Least Squares, Generalized Least Squares) and alternative specifications of the maturity and amplitude parameters (e.g., time-varying product vs. constant product vs. time-varying sector vs. constant sector) we should reduce uncertainty in the factor estimates (Hoeting et al., 1999).

2. The second step consists of estimating the factor decomposition in (5)-(8). We start by standardizing the BAV estimates of the level, slope, curvature and seasonality factors denoted $\hat{l}_{it}^{BAV}$, $\hat{s}_{it}^{BAV}$, $\hat{c}_{it}^{BAV}$ and we employ principal component analysis (PCA) to identify the common components by sequentially (i) extracting the estimated global components $\hat{L}_{g,t}$, $\hat{S}_{g,t}$, $\hat{C}_{g,t}$ from the factors along time and cross-section dimensions, (ii) regrouping the residuals into financial and commodity markets and extracting the corresponding financial and commodity estimated components $\hat{L}_{m,t}$, $\hat{S}_{m,t}$, $\hat{C}_{m,t}$ from each market, (iii) regrouping the residuals into sectors (energy, metals, etc) and extracting the estimated sector components $\hat{L}_{n,t}$, $\hat{S}_{n,t}$, $\hat{C}_{n,t}$ from each sector. The seasonality components $\hat{F}_{ut}$, $\hat{F}_{vt}$, $\hat{F}_{wt}$ are the three first principal components of the seasonality factors $\hat{f}_{it}^{BAV}$ obtained along both time and cross-section dimensions. Given the estimated common components $\hat{L}_{j,t}$, $\hat{S}_{j,t}$, $\hat{C}_{j,t}$ for $j = g, m, n$ and $\hat{F}_{u,t}$, $\hat{F}_{v,t}$, $\hat{F}_{w,t}$ we employ system Generalized Method of Moments (GMM) to (re)estimate the parameters in (5)-(8) for all $i = 1, ..., N$. We employ one lag of the component estimates as instruments and a Newey-West HAC covariance as weighting matrix. The idiosyncratic component estimates $\hat{\epsilon}_{\bullet,it}$ for $\bullet = l, s, c, f$ are the

computational burden. Similar findings on the out-of-sample applicability of multi-step estimation are provided by Caldeira et al. (2015, 2016). For a deeper discussion on the advantages and disadvantages of alternative dynamic factor modeling approaches, we refer the reader to Stock and Watson (2011) and leave the comparison between alternative estimation methods for future research.

residuals resulting from the GMM system regression.

3. The third step consists of estimating the RSFCVAR-OGARCH-M model in (10)-(12) (or restricted versions) for the global, market, sector and seasonality common components by means of (concentrated) Maximum Likelihood (ML). The likelihood function for $j = g, m, n, f$ is given by

$$\mathcal{L}_j = \sum_{t \in T} \log \left[\pi_{j,t}^{(1)} \cdot \mathcal{N}\left(Y_{j,t} | r_t = 1\right) + (1 - \pi_{j,t}^{(1)}) \cdot \mathcal{N}\left(Y_{j,t} | r_t = 2\right) \right], \tag{18}$$

where $\pi_{j,t}^{(1)} = \mathcal{P}(r_t = 1 | \mathcal{I}_{t-1})$ is the probability of regime 1 conditional on the information set $\mathcal{I}$ at period $t-1$, $\mathcal{N}(\cdot | r_t = r)$ is the conditional Normal distribution given that regime $r = 1, 2$ occurs at time t for $Y_{j,t} = X_{j,t} | \mathcal{I}_{t-1}$. We employ the Hamilton Filter (HF) in order to approximate the conditional probabilities $\pi_{j,t}^{(1)}$ and the contribution of $\mathcal{N}(\cdot | r_t = r)$ to the likelihood for each regime $r = 1, 2$. Note that we account for different versions of (9), whose restrictions are found in Table 3 and for which the HF is not needed.

4. The fourth and last step consists of estimating (13) and (14) by employing the idiosyncratic component estimates $\hat{\epsilon}_{\bullet,it}$ obtained from the GMM residuals in step two and the measurement error estimates $\hat{\varepsilon}_{it}(\tau)$ obtained from $\hat{\mathcal{E}}_t = \mathcal{Z}_t - \hat{\Pi}\hat{\mathcal{X}}_t$ in (15) and employing ML to estimate the autoregressive and GARCH(1,1) parameters for each i and τ. In this case, the likelihoods reduce to $\mathcal{L}_i = \sum_{t \in T} \log \left[\mathcal{N}\left(\hat{\epsilon}_{\bullet,it} | \mathcal{I}_{t-1}\right)\right]$ and $\mathcal{L}_i(\tau) = \sum_{t \in T} \log \left[\mathcal{N}\left(\hat{\varepsilon}_{it}(\tau) | \mathcal{I}_{t-1}\right)\right]$, respectively.

Once the parameters of the model have been estimated, we employ the state-space representation in (15)-(17) to conduct various in-sample and out-of-sample analyses which are described in the following sections.

4 In-sample analysis

4.1 Variance decompositions

The factor decomposition of our model presented in Section 2.1 provides an excellent platform for analyzing the contribution of each of the common components to explaining the percentage variation in the variance of the level, slope, curvature and seasonality factors of the term structures considered. Since our model accounts for conditional variances, we can decompose the variance contributions of the components at every point in time. For the purpose of this study we consider the following factor decompositions in percentage terms:

$$\begin{aligned} 1 &= \widehat{\mathrm{Var}}_{\%,i\mu}\left[L_{g,\mu}\right] + \widehat{\mathrm{Var}}_{\%,i\mu}\left[L_{m,\mu}\right] + \widehat{\mathrm{Var}}_{\%,i\mu}\left[L_{n,\mu}\right] + \widehat{\mathrm{Var}}_{\%,i\mu}\left[\epsilon_{l,i\mu}\right], \\ &+ \widehat{\mathrm{Var}}_{\%,i\mu}\left[S_{g,\mu}\right] + \widehat{\mathrm{Var}}_{\%,\mu}\left[S_{m,\mu}\right] + \widehat{\mathrm{Var}}_{\%,i\mu}\left[S_{n,\mu}\right] + \widehat{\mathrm{Var}}_{\%,i\mu}\left[\epsilon_{s,i\mu}\right], \\ &+ \widehat{\mathrm{Var}}_{\%,i\mu}\left[C_{g,\mu}\right] + \widehat{\mathrm{Var}}_{\%,i\mu}\left[C_{m,\mu}\right] + \widehat{\mathrm{Var}}_{\%,i\mu}\left[C_{n,\mu}\right] + \widehat{\mathrm{Var}}_{\%,i\mu}\left[\epsilon_{c,i\mu}\right], \\ &+ \widehat{\mathrm{Var}}_{\%,i\mu}\left[F_{k,\mu}\right] + \widehat{\mathrm{Var}}_{\%,i\mu}\left[F_{v,\mu}\right] + \widehat{\mathrm{Var}}_{\%,i\mu}\left[F_{w,\mu}\right] + \widehat{\mathrm{Var}}_{\%,i\mu}\left[\epsilon_{f,i\mu}\right], \end{aligned} \tag{19}$$

where $\mu = 1, ..., T_\mu$ is used to denote a particular month whereby $t \in \mu$ and $\widehat{\mathrm{Var}}_{\%,\mu}[\bullet]$ is the average percentage variance contribution of component $\bullet = L_{g,\mu}, L_{m,\mu}, ...$ over month μ. We aggregate the daily decompositions at the monthly level for two main reasons. First, in practice most macroeconomic analyses are performed at the monthly, quarterly or yearly frequencies. Second, by aggregating at the monthly level we can reduce 'noise' that may occur at the daily level due to volatility 'jumps' while conserving the overall trends in the percentage variance contributions.

4.2 Macroeconomic mapping

As mentioned previously, several studies have documented the strong explanatory power of term structure factors vis-a-vis the macroeconomy (Ang and Piazessi, 2003; Diebold et al., 2006; Cochrane and Piazessi, 2008). Our study takes this type of analyses forward by mapping the estimated global, market and sector components of the level, slope and curvature factors obtained from commodities and financial term structures to the macroeconomy. Note, however, that in the case of a macroeconomic analysis at the monthly level, the large dataset considered here and relatively few data points at the monthly frequency (60) makes it impossible to use all country specific data in single regression models. Thus, we aggregated all country information in a set of common factors obtained from each of the categories of macroeconomic data (consumption, consumer prices, industrial production, etc) as detailed in Table 1. The factors are computed by means of PCA, and we chose the number of principal components based on the percentage variance explained which we truncated to 95%.[8] Specifically we consider the following model:

$$\Delta^{12}\mathbf{X}_{j,\mu} \;=\; \Phi_j \Delta^{12}\mathbf{M}_\mu + \mathbf{E}_{j,\mu}, \tag{20}$$

where Δ^{12} denotes the year-on-year (yoy) difference operator $\mathbf{X}_{j\mu} = \left[\hat{L}_{j\mu}, \hat{S}_{j\mu}, \hat{C}_{j\mu}\right]'$ is the vector of yoy changes of the estimated level, slope and curvature components for $j = g, m, n$ at month μ, $\mathbf{M}_\mu = \left[\widehat{CPI}_{1\mu}, \widehat{CPI}_{2\mu}, ..., \widehat{EMP}_{1\mu}, \widehat{EMP}_{2\mu}\right]'$ is the vector of yoy changes of the estimated macroeconomic components, Φ_j is a matrix of macroeconomic loadings and $\mathbf{E}_{j,\mu}$ is a vector of measurement errors.[9] To correct for possible endogeneity in the regressors, as well as heteroskedasticity and autocorrelation in the measurement errors we employed system GMM estimation with one lag of the factors as instruments and an estimate of the inverse of the Newey-West HAC covariance as weighting matrix.

5 Forecasting Methodology

In the following subsections, we describe the forecasting strategy designed for this study. In order to save on space, we concentrate on the most relevant issues. Specific details that are not described here or in the Appendix to this article can be provided upon request.

5.1 Forecasting design

We employ a forecasting scheme whereby we estimate all parameters needed to 'calibrate' the state-space representation in (15)-(17) with in-sample data up to time $t = 1, ..., \tilde{T}$ and obtain multi-step ahead forecasts $\tilde{T} + h, \tilde{T} + h + 1, ...$ for horizons $h = 1, 7, 30$, i.e. daily, weekly and monthly (the most frequently used horizons in practice). The chosen set of out-of-sample dates

[8] Nevertheless, in some cases the later procedure resulted in too many factors relative to the data points available. Thus, we truncated the number of factors to two (2) when more than two factors were needed to reach the 95% cumulative variance threshold.

[9] The variables in $\mathbf{M}_\mu$ are all in logs except for interest rate data and inventory changes.

run from 10/2014 to 09/2015. Formally, forecasts are computed as

$$\hat{\mathcal{Z}}_{t+h|t} = \hat{\mathcal{K}} + \hat{\Pi}\hat{\mathcal{X}}_{t+h|t} + \hat{\mathcal{E}}_{t+h|t}, \tag{21}$$

$$\hat{\Sigma}_{t+h|t} = \hat{\Pi}\hat{Q}_{t+h|t}\hat{\Pi}' + \hat{V}_{t+h|t}. \tag{22}$$

In order to illustrate the forecasting procedure in the following discussion, we concentrate on general concepts and refer the reader to the Appendix for other details. In our context, we have two regimes $r_t = 1, 2$ embedded in the full dynamic specification in (9). That is, forecasts generated from (9) apply for each of the regimes with corresponding parameters $d_r, b_r, \beta_r, \alpha_r, \Gamma_r^p$ for $r = 1, 2$. More precisely, forecasts $\hat{X}_{j,t+h|t} = \left[\hat{L}_{j,t+h|t}, \hat{S}_{j,t+h|t}, \hat{C}_{j,t+h|t}\right]'$ for $j = g, m, n$ or $\hat{X}_{j,t+h|t} = \left[\hat{F}_{u,t+h|t}, \hat{F}_{v,t+h|t}, \hat{F}_{w,t+h|t}\right]'$ for $j = f$ are computed as

$$\hat{X}_{j,t+h|t} = \hat{\pi}^{(1)}_{j,t+h|t} \cdot \hat{X}^{(1)}_{j,t+h|t} + (1 - \hat{\pi}^{(1)}_{j,t+h|t}) \cdot \hat{X}^{(2)}_{j,t+h|t}, \tag{23}$$

where $\hat{X}^{(r)}_{j,t+h|t}$ for $r = 1, 2$ are the forecasts corresponding to each regime and $\hat{\pi}^{(r)}_{j,t+h|t}$ is an estimate of the conditional regime-switching probabilities at horizon h. Note also that multi-step ahead forecasts $\hat{H}_{j,t+h|t}$ can be obtained recursively so that they can be applied for the GARCH-in-mean estimates or as input for the conditional covariance matrix $\hat{Q}_{t+h|t}$ in (22).

In the case of the measurement errors in (14) and idiosyncratic components in (13) it is relatively straightforward to obtain multi-step ahead forecasts $\hat{\epsilon}_{\bullet,it+h|t}$ and $\hat{\varepsilon}_{it+h|t}(\tau)$ as these quantities follow simple autoregressive processes. The same applies for the conditional variance forecasts $\hat{\omega}_{it+h|t}$ and $\hat{\upsilon}_{it+h|t}(\tau)$ which assume GARCH(1,1) processes and whose multi-step ahead specifications are well-known (Tsay, 2010). The term structure forecasts that result from (21) conditioned upon $\hat{\mathcal{X}}_{t+h|t}$ and $\hat{\mathcal{E}}_{t+h|t}$ are given by:

$$\begin{aligned} \hat{z}_{it+h|t}(\tau) &= \hat{l}_{it+h|t} + \Lambda_s(\hat{\lambda}_i, \tau)\hat{s}_{it+h|t} + \Lambda_c(\hat{\lambda}_i, \tau)\hat{c}_{it+h|t} \\ &+ \Lambda_f(\hat{\kappa}_i, \cos(\tau, \eta), \sin(\tau, \eta))\hat{f}_{it+h|t} + \hat{\varepsilon}_{it+h|t}(\tau). \end{aligned} \tag{24}$$

Analogously, the volatility term structures that result from (22) conditioned upon $\hat{Q}_{t+h|t}$ and

$\hat{V}_{t+h|t}$ are given by

$$
\begin{aligned}
\widehat{\mathrm{Var}}_t\left[z_{it+h}(\tau)\right] &= \widehat{\mathrm{Var}}_t\left[l_{it+h}\right] + \Lambda_s(\hat{\lambda}_i,\tau)^2 \cdot \widehat{\mathrm{Var}}_t\left[s_{it+h}\right] + \Lambda_c(\hat{\lambda}_i,\tau)^2 \cdot \widehat{\mathrm{Var}}_t\left[c_{it+h}\right], \\
&+ \Lambda_f(\hat{\kappa}_i,\cos(\tau,\eta),\sin(\tau,\eta))^2 \cdot \widehat{\mathrm{Var}}_t\left[f_{it+h}\right] \\
&+ 2\Lambda_s(\hat{\lambda}_i,\tau)\widehat{\mathrm{Cov}}_t\left[l_{it+h},s_{it+h}\right] + 2\Lambda_c(\hat{\lambda}_i,\tau)\widehat{\mathrm{Cov}}_t\left[l_{it+h},c_{it+h}\right] \\
&+ 2\Lambda_f(\hat{\kappa}_i,\cos(\tau,\eta),\sin(\tau,\eta))\widehat{\mathrm{Cov}}_t\left[l_{it+h},f_{it+h}\right] \\
&+ 2\Lambda_s(\hat{\lambda}_i,\tau)\Lambda_c(\hat{\lambda}_i,\tau)\widehat{\mathrm{Cov}}_t\left[s_{it+h},c_{it+h}\right] \\
&+ 2\Lambda_s(\hat{\lambda}_i,\tau)\Lambda_f(\hat{\kappa}_i,\cos(\tau,\eta),\sin(\tau,\eta))\widehat{\mathrm{Cov}}_t\left[s_{it+h},f_{it+h}\right] \\
&+ 2\Lambda_c(\hat{\lambda}_i,\tau)\Lambda_f(\hat{\kappa}_i,\cos(\tau,\eta),\sin(\tau,\eta))\widehat{\mathrm{Cov}}_t\left[c_{it+h},f_{it+h}\right] + \widehat{\mathrm{Var}}_t\left[\varepsilon_{it+h}(\tau)\right], \quad (25)
\end{aligned}
$$

where $\widehat{\mathrm{Var}}_t\left[\bullet\right]$ and $\widehat{\mathrm{Cov}}_t\left[\bullet\right]$ are estimated (co)variances conditional on information available up to period t.[10]

Ideally, we could estimate the model up to its forecasting origin and roll the estimation to the next forecasting origin and so on, i.e., we could employ a rolling window (or recursive) scheme for the estimation of parameters and subsequent forecasting. However, in our context, rolling (or recursive) estimation is cumbersome due to the large scale model under consideration. Instead, we have broken down the analysis into three sample periods for estimation (10/2010-09/2012, 10/2012-09/2013, 10/2010-09/2014) and used a Jacknifing procedure first introduced by Quenouille (1956) and employed empirically and in Monte Carlo simulation settings more recently by other studies (Chiquoine and Hjalmarsson, 2009). The Jacknife estimator of our model(s) is given by

$$\hat{\Psi}_{r_t,Jack} = \frac{\mathcal{S}}{\mathcal{S}-1} \cdot \hat{\Psi}_{r_t,\tilde{T}} - \frac{\sum_{l=1}^{S} \hat{\Psi}_{r_t,l}}{\mathcal{S}^2 - \mathcal{S}}. \quad (26)$$

where, $\mathcal{S}$ is the number of consecutive subsamples and $\hat{\Psi}_{r_t,\tilde{T}}$, $\hat{\Psi}_{r_t,l}$ are the vectors of estimated parameters for the full sample $\tilde{T}$ and the l-th subsample. The above estimator has been shown to reduce the bias induced by estimating parameters when using a limited number of calibration

[10]Note that in the expressions in (24) and (25) we assume constant estimates $\hat{\lambda}_i$ and $\hat{\kappa}_i$ as opposed to their time-varying versions. This is done because the time-varying case would imply assuming and estimating a dynamic specification for $\hat{\lambda}_{it}$ and $\hat{\kappa}_{it}$ which is out of the scope of this paper. Thus, for the purpose of this study we use the mean of the BAV estimates $\hat{\lambda}_{it}^{BAV}$ and $\hat{\kappa}_{it}^{BAV}$ up to the forecasting origin for subsequent forecasting.

windows instead of, e.g., rolling (or recursive) estimation schemes.[11] Moreover, in our context we are assuming time variability (i.e. regime-switching) in some parameters of the model so that, together with the Jacknifing approach, should help us circumvent the drawbacks of not employing a rolling (or recursive) estimation scheme.

As mentioned previously, some restricted versions of (9) might fit some components better than others, i.e. there could be a certain degree of heterogeneity with respect to global, market or sector specific data dynamics. In order to reduce model uncertainty we employ Bayesian averaging of the parameters obtained from the restricted versions considered of the dynamic specification in (9).[12]

5.2 Forecast evaluation

We employ a battery of tools to evaluate the out-of-sample performance of the proposed framework. We focus on statistical and economic performance measures that aim to uncover the accuracy of point and interval forecasts of the dynamic specifications as well as the hedging performance within a portfolio of spot and futures contracts.

5.2.1 Statistical performance measures

Let $\mathcal{M}$ and $\mathcal{M}_b$ indicate a particular competing model and the benchmark, respectively. Our benchmark model is the random walk model for the factors. We chose this specific benchmark since the random walk model is the most widely used benchmark in practice to forecast the evolution of financial prices an other assets (Grauwe and Grimaldi, 2006). The average performance $\mathcal{M}_c$ relative to $\mathcal{M}_b$ for each product i is computed as

$$dr_i(\mathcal{M}) = \frac{\bar{d}_i(\mathcal{M}_c)}{\bar{d}_i(\mathcal{M}_b)}, \tag{27}$$

[11] We have also experimented with rolling-window and recursive schemes for estimation of parameters and subsequent forecasting with a smaller version of the model. However, rolling estimations of some of the specifications estimated with the Hamilton filter were very time consuming and the results were qualitatively not better than with a few sample windows and the Jacknifing procedure. Indeed, the latter corroborates findings by Chiquoine and Hjalmarsson (2009)

[12] We experimented with combining forecasts directly with different forecast combination routines but the results turned out to be qualitatively similar to Bayesian averaging of the parameters in some cases and not better statistically in other cases.

where $\bar{d}_i(\mathcal{M}_b)$ and $\bar{d}_i(\mathcal{M}_c)$ are defined as the average MSE of the benchmark and of the competing model, respectively. There are several tests available to analyze, whether a particular benchmark model $\mathcal{M}_b$ has the same predictive ability as a competing model $\mathcal{M}_c$, against the alternative that model $\mathcal{M}_b$ has a better predictive ability based on Mean Squared Errors (MSE) (Diebold and Mariano, 1995; Harvey et al., 1997; Clark and West, 2007; McCracken, 2007). In this study we employ the test proposed by Clark and West (2007), which corrects the non-standard limiting distribution under the null of equal forecasting accuracy to a nested model. Moreover, we test interval forecasts generated from the model by means of the three-step procedure proposed by Christoffersen (1998) which evaluates whether interval forecasts satisfy the so-called (i) unconditional, (ii) conditional and (iii) independence hypothesis.[13]

5.2.2 Economic performance measures

We test the economic significance of the futures forecasts by 'simulating' a dynamic hedging strategy whereby an agent enters into a spot position and into a futures contract position with the aim to reduce the variability of his/her portfolio's value. That is, the agent seeks to minimize the variance of his/her portfolio by chosing an optimal amount of futures position per unit of spot position. The set up is very similar to the one found in previous studies where conditional as opposed to unconditional moments are treated (Kroner and Sultan, 1993; Brunetti and Gilbert, 2000; Moschini and Myers, 2003). In our context, the minimization problem reduces to the following hedge ratio:

$$\mathcal{HR}_{it,h} = \frac{\text{Cov}_t\left[\mathbf{r}_{it+h}(1), \mathbf{r}_{it+h}(\tau)\right]}{\text{Var}_t\left[\mathbf{r}_{it+h}(\tau)\right]}, \tag{28}$$

where $\mathbf{r}_{it}(1) = z_{it}(1) - z_{it-1}(1)$ is the (log) return of the spot (month-ahead) product, $\mathbf{r}_{it}(\tau) = z_{it}(\tau) - z_{it-1}(\tau)$ is the (log) return of the futures price at forward month τ for product i, and $\text{Cov}_t[\cdot]$ and $\text{Var}_t[\cdot]$ are the time-dependent (co)variances of $\mathbf{r}_{it}(1)$ and $\mathbf{r}_{it}(\tau)$ conditional on information available up to time t. Our benchmark model is a constant hedge ratio denoted $\mathcal{HR}_{b,h}$ obtained by replacing (28) with unconditional moments estimated up to the forecasting

[13]To save on space, we refer the interested reader to the Clark and West (2007) and Christoffersen (1998) articles for details about the respective tests.

origin.[14] We evaluate the performance of the dynamic hedging strategy by means of the so-called variance reduction measure:

$$\mathcal{VN}_{i,h} = \sqrt{\frac{\mathrm{Var}[\mathbf{r}_{h,p}]}{\mathrm{Var}[\mathbf{r}^b_{h,p}]}} - 1, \tag{29}$$

where $\mathrm{Var}[\mathbf{r}_{h,p}]$ is the variance of the portfolio resulting from hedging with conditional moments fitted from our model and $\mathrm{Var}[\mathbf{r}^b_{h,p}]$ is the variance of the portfolio resulting from hedging with the benchmark. Following Lee (2009a,b), in order to test the statistical significance of variance reduction we use a test of predictive accuracy such as the Clark and West (2007) test.

6 Results

In what follows we discuss the in-sample results of our analysis and subsequently the out-of-sample results. We opted to display our subsequent results in relevant figures that highlight the main features of our modelling framework as far as possible as opposed to large tables for space considerations. Detailed results not displayed here can be provided upon request.

6.1 In-sample results

Figures 5 and 6 display the results of the in-sample estimation for the parameters λ_{it} and κ_{it} by means of BAV. The figures display the degree of heterogeneity for the maturity parameters amongst the different products under inspection and this finding holds not only for commodity markets but also for financial markets. This result indicates that when fitting such a NS-type model with alternative markets, sectors and global data, it is advisable to estimate the maturity parameter as opposed to 'calibrate' it as it is done in previous studies (Diebold and Li, 2006). The latter result also confirms recent findings by Karstanje et al. (2015) who put forward a non-trivial degree of heterogeneity in the maturity parameters of their commodities model. The figures show not only that the maturity differs across products but that it varies with time in

[14] Note that we assume a 'pair' strategy for simplicity, i.e. we assume that the hedging is done with respect to one of the futures contract with forward dimension τ and do not consider cross-commodity hedges. This is indeed very interesting for practitioners but is out of the scope of this article.

most cases as proposed by Koopman et al. (2010). Since the λ_{it}'s can be interpreted as the mean-reversion rate of the slope and curvatures of the term structures, the heterogeneity and time-variability of this parameter suggests that the 'velocity' and shape of adjustment into, say, contango or backwardation of terms structures differs amongst products and over time. The amplitude parameters also seems to be time dependent but the level of heterogeneity is not as strong.

Figure 7 displays selected examples of the estimated level l_{it}, slope s_{it}, curvature c_{it} and seasonality f_{it} factors of the products considered with four of the different estimation approaches employed (OLSPRD, GLSPTV, OLSSEC, BAV). As can be noted from the figures, the approaches differ quantitatively (as expected) in some time periods but overall they exhibit similar path profiles. In terms of the Bayesian weights computed, however, it appears as if the OLSPTV and GLSPTV approaches provide more useful information in terms of Bayesian Information Criteria (see Table 2 for further details). Figure 2 displays the fitted smoothed futures prices over the time dimension for all the products considered. Moreover, Figures 3 and 4 show futures price and volatility term structures over time and forward dimensions for selected examples of the products considered. The latter figures show an interesting implementation of the model as the model-based term structure data over several forward months can be employed for approximating expectations of future price and volatility paths of the products considered every day and for every forward month wished. This application is important for practitioners as for some products only intermittent data is readily available at the daily and forward dimensions (e.g. foreign exchange, equity futures, aluminium, etc) and practitioners use these data as inputs for taking decisions (i.e. option pricing, hedging, etc).

Tables 4 to 8 show the in-sample estimation results of the component loadings, the long-run and short-run parameter estimates of the RSFCVAR-OGARCH-M and some diagnostics of the alternative dynamic specifications considered, respectively.[15] The results of a likelihood ratio test favors the heteroskedastic specification (FCVAR-OGARCH) vis-a-vis the homoskedastic specifications (VAR, CVAR, FCVAR) for most of the component estimates. Similarly, we find that the likelihood ratio test favors the heteroskedastic and regime-switching specifica-

[15] We only present the results of the full specification RSFCVAR-OGARCH-M to save on space. Detailed estimation results for the restricted versions can be provided upon request.

tions (RSFCVAR-OGARCH, RSFCVAR-OGARCH-M) over the heteroskedastic but non-regime switching counterpart (FCVAR-OGARCH) for most component estimates. Parameters of the RSFCVAR-OGARCH-M model are statistically significant for the most part except for some cases, for instance, the volatility-in-mean parameters of some of the components (Table 7). The latter result suggests that risk is not significantly 'priced' in the conditional mean (in a statistical sense) in most components.[16] In fact, previous studies that analyze the risk-return relationship have found mixed results with respect to direction or statistical significance of the effect of risk variables in the (conditional) mean of asset pricing models (Campbell and Hentschel, 1992; Ludvigson and Ng, 2007; Bollerslev et al., 2008). Overall, we find that the dynamic specifications that account for fractional cointegration, regime switching and heteroskedasticity fit well the data in-sample and are statistically better than their restricted and 'simpler' counterparts (VAR, CVAR, FCVAR) for most components according to the in-sample diagnostics considered ($\mathcal{LR}$, BIC).

Figure 9 displays the variance decomposition of the factors for each product at each point in time aggregated at the monthly frequency while Table 11 presents results aggregated over the full sample and over sectors. We find that the global components can explain on average about 20% of the variance of the factors across all products considered while the market, sector and idiosyncratic factors can explain up to 20%, 20% and 30% respectively. With respect to the seasonality components, we find that these variables can explain up to 5% of the variance of the term structures while the seasonality idiosyncratic component explains up to 5%. While it is not possible here to compare these results to previous studies directly as there are, to the best of our knowledge, no one-to-one comparable models, we find that other studies have found similar results on the contributions of global, sector specific and idiosyncratic components to total variation in term structures (Diebold et al., 2008; Diebold and Li, 2006; Karstanje et al., 2015). Moreover, it is worth noting that the results on previous studies hold 'on average' while we show that the variance decompositions appear to be strongly time dependent as depicted in Figure 9.

[16] An earlier (experimental) version of our model accounted for regime changes in the GARCH-in-mean parameters. However, the large parameter space made it very cumbersome computationally without some evident forecasting gains. Thus, we decided for the simpler specification treated here.

Table 9 and 10 show the mapping of the extracted components to macroeconomic factors as introduced in Section 3. We find that the global components are related to variables such as exchange rates, wages, price-earnings ratios, leading economic indicators, employment and house prices. In turn, the market component of commodity products is related to variables such as output growth, exchange rates, volatility of exchange rates, business confidence, amongst others while the market component of financial products is explained by inflation, dividend yields, wages and terms of trade. The bond component is related to variable such as term spreads, wages, employment and house prices amongst others. The foreign exchange component is related to exchange rates, business confidence, leading economic indicator, term spreads, amongst others. The equity component is related to leading economic indicators, PE ratios and wages, amongst others.

The energy component is related to business confidence, exchange rates, volatility, house prices, amongst others. The metals component is related to output growth, exchange rates, leading economic indicators, consumption, amongst others. Other commodity sector components (grains, livestock and softs) are related to macroeconomic factors of the energy sector in general. Our results follow the same line of previous studies where unobservable components in financial and commodity prices can be successfully mapped to the U.S. macroeconomy (Fama and French, 1987, 1988; Ang and Piazessi, 2003; Diebold et al., 2006). Our study takes the mapping one step forward as we show that the world, market and sector commonalities of financial and commodity term structures have information that can 'replicate' movements in the macroeconomy in an international context.

Overall, we find that the dynamic specifications proposed for the components fit the data well in-sample. We also find some degree of heterogeneity amongst model specifications within alternative components which hints at the possibility that 'hybrid' specifications obtained trough combined models (e.g. through Bayesian averaging) might reduce forecasting uncertainty. Moreover, we uncover an economic and statistical significant relationship of the unobservable components to the macroeconomy which suggests that these variables might serve as complement or alternative to macroeconomic data at lower (e.g. monthly) or higher (e.g. daily) frequencies. What degree of predictability power these components have at the daily frequency will be uncovered in the next section.

6.2 Out-of-sample results

In this section we discuss the out-of-sample results. We start by discussing the results of the statistical performance measures and subsequently the economic performance measures.

As discussed in Section 4.1, we perform evaluations with alternative tests that aim to analyze different features of the out-of-sample forecasts generated by our model. Given the large set of forecasts generated by our model (cross-section, time and forward dimension) we have summarized the results of our various tests in boxplots which are displayed in figures 9 and 10. The boxplots show the tests aggregated over the cross-section dimension for multi-step ahead horizons $h = 1, 7, 30$ (daily, weekly, monthly) and for the forward dimensions $\tau = 1, 3, 6$ (month-ahead, quarter-ahead and semester-ahead).

In terms of forecasting accuracy by means of the Clark and West test, we find that many products generate forecasts that are statistically better than those of a random walk type model. However, we find that at the aggregate level the forecasting accuracy of the model is only slightly better than the random walk specification when observing the median of the distribution of test statistics. The latter result is in line with the relative MSE results which show that the model generates more accurate forecasts than a random walk benchmark for various products but at the aggregate level, relative MSE are only slightly better at higher horizons as shown by the median of the distribution.

Interestingly, however, we find that the interval forecasts generated comply with the unconditional, conditional and independence hypothesis at alternative forecasting horizons and forward dimensions. The latter result holds at the aggregate level as well as at the product specific level. While the accuracy of point forecasts vis-a-vis a naive benchmark appears to be product specific, interval (i.e. density) forecasts generated from the model provide accurate information with respect to the out-of-sample distribution of term structures.

As introduced in Section 4.3, we also test the economic significance of the forecasts of our proposed model by testing the performance of a hedging strategy resulting from the variance minimization problem of a portfolio constructed of a spot and a futures position. Results over all 42 products are displayed in Figure 10. The results indicate that the model generates on average a reduction of about 20% in portfolio variance in relation to a naive strategy. Results on the statistical significance of the variance reduction by means of the Clark and West test show that, as in the case of point forecasts, the reduction in variance significantly improves upon a naive strategy at the product specific level but is only slightly better than a naive strategy at the aggregate level.

Our results confirm findings in the rising literature on hedging in commodity markets which show that fractional cointegrated and regime switching models have good forecasting capabilities vis-a-vis naive benchmarks from both a statistical an economic perspective. However the results depend many times on the product, horizon and forward dimension analyzed (Boswijk et al., 2015; Cavalier et al., 2015; Dolatabadi and Nielsen, 2015; Dolatabadi et al., 2015).

7 Conclusion

The present article proposed a framework for modeling and forecasting financial and commodity term structures in a unified global setting. Our framework not only allows analysts to extract interesting and useful information in-sample such as time-varying variance decompositions, dynamic correlations, mapping to the macroeconomy, but also provides a value added for forecasting both in terms of statistical and economic performance measures. The main results of our study show that the extracted components can account for an important amount of the total variation in the data. The mapping to the macroeconomic fundamentals show that there is, as expected, a statistically significant relationship of the extracted components to macroeconomic variables.

As for the out-of-sample evaluation we find that the proposed model can generate forecasts that outperform a naive benchmark (random walk) at the product level in terms of point-forecast accuracy and variance reductions resulting from an artificial hedging strategy. At the product and aggregate level we find that the proposed model generates accurate interval (i.e. density) forecasts according to the unconditional, conditional and independence hypothesis tests.

The results of this study are not only useful for academics extending versions of the NS model but also for practioners who use term structures to take decisions with respect to hedging, portfolio optimization or financial and monetary policies. An interesting extension to the present analysis would be whether other volatility structures (e.g. stochastic volatility or dynamic conditional correlations) can improve upon the current results in terms of statistical and economic performance. We leave these issues to future research.

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A State-space representation

The state-space representation of our model is given by:

$$
\begin{aligned}
\begin{bmatrix} z_{1t}(1) \\ z_{1t}(2) \\ \vdots \\ z_{1t}(\mathcal{T}) \\ \vdots \\ z_{Nt}(1) \\ \vdots \\ z_{Nt}(\mathcal{T}) \end{bmatrix}
&= A \begin{bmatrix} \bar{l}_1 \\ \bar{s}_1 \\ \bar{c}_1 \\ \bar{f}_1 \\ \vdots \\ \bar{l}_N \\ \bar{s}_N \\ \bar{c}_N \\ \bar{f}_N \end{bmatrix}
+ B \begin{bmatrix} L_{glb,t} \\ S_{glb,t} \\ C_{glb,t} \end{bmatrix}
+ C \begin{bmatrix} L_{com,t} \\ S_{com,t} \\ C_{com,t} \\ L_{fin,t} \\ S_{fin,t} \\ C_{fin,t} \end{bmatrix}
+ D \begin{bmatrix} L_{ene,t} \\ S_{ene,t} \\ C_{ene,t} \\ L_{met,t} \\ S_{met,t} \\ C_{met,t} \\ \vdots \\ L_{eqt,t} \\ S_{eqt,t} \\ C_{eqt,t} \end{bmatrix} \\
&+ E \begin{bmatrix} F_{u,t} \\ F_{v,t} \\ F_{w,t} \end{bmatrix}
+ A \begin{bmatrix} \epsilon_{l,1t} \\ \epsilon_{s,1t} \\ \epsilon_{c,1t} \\ \epsilon_{f,1t} \\ \vdots \\ \epsilon_{l,Nt} \\ \epsilon_{s,Nt} \\ \epsilon_{c,Nt} \\ \epsilon_{f,Nt} \end{bmatrix}
+ \begin{bmatrix} \varepsilon_{1t}(1) \\ \vdots \\ \varepsilon_{1t}(\mathcal{T}) \\ \vdots \\ \varepsilon_{Nt}(1) \\ \vdots \\ \varepsilon_{Nt}(\mathcal{T}) \end{bmatrix} \\
&= A \cdot \mathcal{J} + B \cdot \mathcal{X}_{g,t} + C \cdot \mathcal{X}_{m,t} + D \cdot \mathcal{X}_{n,t} + E \cdot \mathcal{F}_t + A \cdot \mathcal{U}_t + \mathcal{E}_t \\
&= \mathcal{K} + [B,\, C,\, D,\, E,\, A][\mathcal{X}_{g,t};\, \mathcal{X}_{m,t};\, \mathcal{X}_{n,t};\, \mathcal{F}_t;\, \mathcal{U}_t] + \mathcal{E}_t, \qquad (30) \\
&= \mathcal{K} + \Pi \mathcal{X}_t + \mathcal{E}_t. \qquad (31)
\end{aligned}
$$

where we use semi-colon (;) to denote *vertical* concatenation. The matrices of coefficients are given by:

$$
A = \begin{bmatrix}
1 & \Lambda_s(\lambda_1,1) & \Lambda_c(\lambda_1,1) & \Lambda_f(\kappa_1,\cos(1,\eta),\sin(1,\eta)) & 0 & \cdots & \cdots & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
1 & \Lambda_s(\lambda_1,\mathcal{T}) & \Lambda_c(\lambda_1,\mathcal{T}) & \Lambda_f(\kappa_1,\cos(\mathcal{T},\eta),\sin(\mathcal{T},\eta)) & 0 & \cdots & \cdots & 0 \\
\ddots & \ddots & \ddots & \ddots & \ddots & & \ddots & \ddots \\
0 & \cdots & \cdots & 0 & 1 & \Lambda_s(\lambda_N,1) & \Lambda_c(\lambda_N,1) & \Lambda_f(\kappa_N,\cos(1,\eta),\sin(1,\eta)) \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
0 & \cdots & \cdots & 0 & 1 & \Lambda_s(\lambda_N,\mathcal{T}) & \Lambda_c(\lambda_N,\mathcal{T}) & \Lambda_f(\kappa_N,\cos(\mathcal{T},\eta),\sin(\mathcal{T},\eta))
\end{bmatrix}, \tag{32}
$$

$$
B = \begin{bmatrix}
\gamma^{glb}_{l,1} & \Lambda_s(\lambda_1,1)\gamma^{glb}_{s,1} & \Lambda_c(\lambda_1,1)\gamma^{glb}_{c,1} \\
\vdots & \vdots & \vdots \\
\gamma^{glb}_{l,1} & \Lambda_s(\lambda_1,\mathcal{T})\gamma^{glb}_{s,1} & \Lambda_c(\lambda_1,,\mathcal{T})\gamma^{glb}_{c,1} \\
\vdots & \vdots & \vdots \\
\gamma^{glb}_{l,N} & \Lambda_s(\lambda_N,1)\gamma^{glb}_{s,N} & \Lambda_c(\lambda_N,1)\gamma^{glb}_{c,N} \\
\vdots & \vdots & \vdots \\
\gamma^{glb}_{l,N} & \Lambda_s(\lambda_N,\mathcal{T})\gamma^{glb}_{s,N} & \Lambda_c(\lambda_N,\mathcal{T})\gamma^{glb}_{c,N}
\end{bmatrix}, \tag{33}
$$

$$
C = \begin{bmatrix}
\gamma^{com}_{l,1} & \Lambda_s(\lambda_1,1)\gamma^{com}_{s,1} & \Lambda_c(\lambda_1,1)\gamma^{com}_{s,1} & 0 & \cdots & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & 0 \\
\gamma^{com}_{l,1} & \Lambda_s(\lambda_1,\mathcal{T})\gamma^{com}_{s,1} & \Lambda_c(\lambda_1,\mathcal{T})\gamma^{com}_{s,1} & 0 & \cdots & 0 \\
\ddots & \ddots & \ddots & \ddots & \ddots & \ddots \\
0 & \cdots & 0 & \gamma^{fin}_{l,N} & \Lambda_s(\lambda_1,1)\gamma^{fin}_{s,N} & \Lambda_c(\lambda_N,1)\gamma^{fin}_{s,N} \\
\vdots & \vdots & \vdots & \vdots & \vdots & 0 \\
0 & \cdots & 0 & \gamma^{fin}_{l,N} & \Lambda_s(\lambda_N,\mathcal{T})\gamma^{fin}_{s,N} & \Lambda_c(\lambda_N,\mathcal{T})\gamma^{fin}_{s,N}
\end{bmatrix} \tag{34}
$$

$$D = \begin{bmatrix} \gamma_{l,1}^{ene} & \Lambda_s(\lambda_1,1)\gamma_{s,1}^{ene} & \Lambda_c(\lambda_1,1)\gamma_{s,1}^{ene} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & 0 \\ \gamma_{l,1}^{ene} & \Lambda_s(\lambda_1,\mathcal{T})\gamma_{s,1}^{ene} & \Lambda_c(\lambda_1,\mathcal{T})\gamma_{s,1}^{ene} & 0 & \cdots & 0 \\ \ddots & \ddots & \ddots & \ddots & \ddots & \ddots \\ 0 & \cdots & 0 & \gamma_{l,N}^{eqt} & \Lambda_s(\lambda_1,1)\gamma_{s,N}^{eqt} & \Lambda_c(\lambda_N,1)\gamma_{s,N}^{eqt} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & \gamma_{l,N}^{eqt} & \Lambda_s(\lambda_N,\mathcal{T})\gamma_{s,N}^{eqt} & \Lambda_c(\lambda_N,\mathcal{T})\gamma_{s,N}^{eqt} \end{bmatrix}, \tag{35}$$

$$E = \begin{bmatrix} \Lambda_f(\kappa_1,\cos(1,\eta),\sin(1,\eta))\gamma_{f,1}^{u} & \Lambda_f(\kappa_1,\cos(1,\eta),\sin(1,\eta))\gamma_{f,1}^{v} & \Lambda_f(\kappa_1,\cos(1,\eta),\sin(1,\eta))\gamma_{f,1}^{w} \\ \vdots & \vdots & \vdots \\ \Lambda_f(\kappa_1,\cos(\mathcal{T},\eta),\sin(\mathcal{T},\eta))\gamma_{f,1}^{u} & \Lambda_f(\kappa_1,\cos(\mathcal{T},\eta),\sin(\mathcal{T},\eta))\gamma_{f,1}^{v} & \Lambda_f(\kappa_1,\cos(\mathcal{T},\eta),\sin(\mathcal{T},\eta))\gamma_{f,1}^{w} \\ \vdots & \vdots & \vdots \\ \Lambda_f(\kappa_N,\cos(1,\eta),\sin(1,\eta))\gamma_{f,N}^{u} & \Lambda_f(\kappa_N,\cos(1,\eta),\sin(1,\eta))\gamma_{f,N}^{v} & \Lambda_f(\kappa_N,\cos(1,\eta),\sin(1,\eta))\gamma_{f,N}^{w} \\ \vdots & \vdots & \vdots \\ \Lambda_f(\kappa_N,\cos(\mathcal{T},\eta),\sin(\mathcal{T},\eta))\gamma_{f,N}^{u} & \Lambda_f(\kappa_N,\cos(\mathcal{T},\eta),\sin(\mathcal{T},\eta))\gamma_{f,N}^{v} & \Lambda_f(\kappa_N,\cos(\mathcal{T},\eta),\sin(\mathcal{T},\eta))\gamma_{f,N}^{w} \end{bmatrix}. \tag{36}$$

Term structure conditional (co)variances and correlations are given by:

$$\Sigma_t = \Pi Q_t \Pi' + V_t, \tag{37}$$

$$\rho_t = \operatorname{diag}(\Sigma_t)^{-1} \Sigma_t \operatorname{diag}(\Sigma_t)^{-1}. \tag{38}$$

with

$$Q_t = \begin{bmatrix} H_{glb,t} & 0_3 & \cdots & \cdots & \cdots & 0_3 & \cdots & \cdots & \cdots & 0_3 \\ 0_3 & H_{com,t} & 0_3 & \cdots & \cdots & \vdots & \ddots & & & \vdots \\ \vdots & 0_3 & H_{fin,t} & 0_3 & \cdots & \vdots & & \ddots & & \vdots \\ \vdots & \vdots & \vdots & \ddots & \ddots & \vdots & & & \ddots & \vdots \\ 0_3 & \cdots & \cdots & 0_3 & H_{f,t} & 0_3 & \cdots & \cdots & \cdots & 0_3 \\ 0 & \cdots & \cdots & \cdots & 0 & \omega_{l,1t} & 0 & \cdots & \cdots & 0 \\ \vdots & \ddots & & & \vdots & 0 & \omega_{s,1t} & 0 & \cdots & 0 \\ \vdots & & \ddots & & \vdots & \vdots & \ddots & \ddots & \ddots & 0 \\ \vdots & & & \ddots & \vdots & \vdots & \ddots & 0 & \omega_{c,Nt} & 0 \\ 0 & \cdots & \cdots & \cdots & 0 & 0 & \cdots & \cdots & 0 & \omega_{f,Nt} \end{bmatrix},$$

$$= \begin{bmatrix} \iota_{glb} \otimes H_{glb,t} & 0_3 & \cdots & 0_3 \\ \iota_{com} \otimes H_{com,t} & 0_3 & \cdots & 0_3 \\ \vdots & \vdots & \ddots & \vdots \\ \iota_w \otimes H_{f,t} & 0_3 & \cdots & 0_3 \\ 0_{1\times 36} & \omega_{l,1t} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0_{1\times 36} & 0 & \cdots & \omega_{f,Nt} \end{bmatrix} = \begin{bmatrix} H_t & 0_{36\times N} \\ 0_{N\times 36} & D_t \end{bmatrix}, \tag{39}$$

$$V_t = \begin{bmatrix} \upsilon_{1t}(1) & 0 & \cdots & \cdots & \cdots & 0 \\ 0 & \upsilon_{1t}(2) & 0 & \cdots & & 0 \\ 0 & 0 & \upsilon_{1t}(3) & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & \cdots & & \upsilon_{Nt}(\mathcal{T}-2) & 0 & 0 \\ 0 & \cdots & \cdots & 0 & \upsilon_{Nt}(\mathcal{T}-1) & 0 \\ 0 & \cdots & \cdots & & 0 & \upsilon_{Nt}(\mathcal{T}) \end{bmatrix}$$

$$= \operatorname{diag}([\upsilon_{1t}(1), \upsilon_{1t}(2), ..., \upsilon_{Nt}(\mathcal{T}-1), \upsilon_{Nt}(\mathcal{T})]), \tag{40}$$

where 0_3 is a 3×3 matrix of zeros, $H_t = [\iota_{glb} \otimes H_{glb,t}; \iota_{com} \otimes H_{com,t}; ...; \iota_f \otimes H_{f,t}]$, with $\iota_{glb} = (1, 0, ..., 0)'$, $\iota_{com} = (0, 1, ..., 0)'$,..., $\iota_f = (0, 0, ..., 1)'$, $\otimes$ is the Kronecker product and $D_t = \operatorname{diag}([\omega_{l,1t}, \omega_{s,1t}, ..., \omega_{c,Nt}, \omega_{f,Nt}])$.

B Estimation

In what follows we describe in more detail the estimation approach.

1. We first estimate the product's level, slope, curvature and seasonality factors $l_{it}, s_{it}, c_{it}, f_{it}$ as well as the maturity and amplitude parameters λ_{it} and κ_{it} in equation (1) by means of Nonlinear Least Squares (NLS) at each point in time. In addition, we obtain Least Squares and Generalized Least Squares estimates of the factors l_{it}, s_{it}, c_{it} and f_{it} at each point in time by (i) using the NLS time-varying estimates $\hat{\lambda}_{it}$ and $\hat{\kappa}_{it}$ (OLSPTV/GLSPTV), (ii) using the mean NLS estimates per product $\bar{\lambda}_i$ and $\bar{\kappa}_i$ (OLSPRD/GLSPRD), (iii) using 'Mean Group' NLS time-varying estimates averaged over sectors $\hat{\lambda}_{nt}$ and $\hat{\kappa}_{nt}$ (OLSSTV/GLSSTV), (iv) using 'Mean Group' NLS mean estimates averaged over sectors $\bar{\lambda}_n$ and $\bar{\kappa}_n$ (OLSSEC/GLSSEC).[17] Given the candidate estimates of the factors obtained via NLS, OLSPTV, GLSPTV, OLSPRD, GLSPRD, OLSSTV, GLSSTV, OLSSEC, GLSSEC we compute Bayesian average (BAV) estimates of the factors l_{it}, s_{it}, c_{it} and f_{it} as well as maturity λ_{it} and amplitude κ_{it} as:

$$\hat{l}_{it}^{BAV} = \tilde{\mathbf{w}}_{it}' \hat{\mathbf{l}}_{it}, \tag{41}$$
$$\hat{s}_{it}^{BAV} = \tilde{\mathbf{w}}_{it}' \hat{\mathbf{s}}_{it}, \tag{42}$$
$$\hat{c}_{it}^{BAV} = \tilde{\mathbf{w}}_{it}' \hat{\mathbf{c}}_{it}, \tag{43}$$
$$\hat{f}_{it}^{BAV} = \tilde{\mathbf{w}}_{it}' \hat{\mathbf{f}}_{it}, \tag{44}$$
$$\hat{\lambda}_{it}^{BAV} = \tilde{\mathbf{w}}_{it}' \hat{\mathbf{m}}_{it}, \tag{45}$$

where $\tilde{\mathbf{w}}_{it} = \frac{\exp(-0.5\text{BIC}_{j,it})}{\sum_{j=1}^{J}\exp(-0.5\text{BIC}_{j,it})}$ with BIC_{jt} the Bayesian information criterion of (1) obtained from estimation type j at time t for each i. Moreover, $\hat{\mathbf{l}}_{it}, \hat{\mathbf{s}}_{it}, \hat{\mathbf{c}}_{it}, \hat{\mathbf{f}}_{it}$ are vectors containing the factor estimates and $\hat{\mathbf{m}}_{it}, \hat{\mathbf{a}}_{it}$ are vectors containing the estimated maturity and amplitude parameters obtained with the candidate estimation procedures. The weights hold given diffuse priors and equal model prior probabilities which is assumed here for simplicity (Hoeting et al., 1999).

2. Given the BAV estimates for the level, slope, curvature and seasonality parameters, we demean and standardize the BAV factor estimates denoted $\tilde{\hat{l}}_{it}^{BAV}$, $\tilde{\hat{s}}_{it}^{BAV}$, $\tilde{\hat{c}}_{it}^{BAV}$ for $i = 1, ..., N$. We extract the first principal component from each of the BAV factor estimates denoted $\hat{L}_{g,t}$, $\hat{S}_{g,t}$, $\hat{C}_{g,t}$, with corresponding factor loading estimates $\hat{\gamma}_{j,i}^{g}$ for $j = l, s, c$, $g = \{\text{global}\}$ and $i = 1, ..., N$ by means of Principal Component Analysis (PCA). Let $\hat{a}_{l,it}^{g} = \tilde{\hat{l}}_{it}^{BAV} - \hat{\gamma}_{l,i}^{g}\hat{L}_{g,t}$, $\hat{a}_{s,it}^{g} = \tilde{\hat{s}}_{it}^{BAV} - \hat{\gamma}_{s,i}^{g}\hat{S}_{g,t}$, $\hat{a}_{c,it}^{g} = \tilde{\hat{c}}_{it}^{BAV} - \hat{\gamma}_{c,i}^{g}\hat{C}_{g,t}$, for $i = 1, ..., N$ be the resulting residuals. We break $\hat{a}_{j,it}^{g}$ for $j = l, s, c$ and $i = 1, ..., N$ into two market groups, i.e., commodity markets (energy, metals, softs, grains, livestock)

[17]We experimented with median as opposed to mean estimates of the NLS $\hat{\lambda}_{it}$ and $\hat{\kappa}_{it}$ but results turn out to be very similar.

and financial markets (forex, bonds, equity) and extract the first principal components from each group denoted $\hat{L}_{m,t}$, $\hat{S}_{m,t}$, $\hat{C}_{m,t}$ with corresponding factor loading estimates $\hat{\gamma}^{m}_{j,i}$ for $j = g, s, c$, $m = \{\text{commodities}, \text{financials}\}$ and $i = 1, ..., N$ by means of PCA. Let $\hat{a}^{m}_{l,it} = \hat{a}^{g}_{l,it} - \hat{\gamma}^{m}_{l,i}\hat{L}_{m,t}$, $\hat{a}^{m}_{s,it} = \hat{a}^{g}_{s,it} - \hat{\gamma}^{m}_{s,i}\hat{S}_{m,t}$, $\hat{a}^{m}_{c,it} = \hat{a}^{g}_{c,it} - \hat{\gamma}^{m}_{c,i}\hat{C}_{g,t}$ for $i = 1, ..., N$. We break $a^{m}_{j,it}$ for $j = l, s, c$ and $i = 1, ..., N$ into eight sector groups, i.e., energy, metals, softs, grains, livestock, forex, bonds, equity and extract the first principal components from each group denoted $\hat{L}_{n,t}$, $\hat{S}_{n,t}$, $\hat{C}_{n,t}$ with corresponding factor loading estimates $\hat{\gamma}^{n}_{j,i}$ for $j = g, s, c$, $n = \{\text{energy}, \text{metals}, \text{softs}, \text{grains}, \text{livestock}, \text{forex}, \text{bonds}, \text{equity}\}$ and $i = 1, ..., N$ by means of PCA. In the case of the stochastic seasonality factors f_{it}, we demean and standardize the BAV estimates denoted $\tilde{\hat{f}}^{BAV}_{it}$ for $i = 1, ..., N$ and obtain the first three principal components of the data denoted $\hat{F}_{u,t}$, $\hat{F}_{v,t}$, $\hat{F}_{w,t}$, with corresponding factor loading estimates $\hat{\gamma}^{\bullet}_{f,i}$ for $\bullet = u, v, w$. Given the candidate component estimates $\hat{L}_{g,t}$, $\hat{S}_{g,t}$, $\hat{C}_{g,t}$, $\hat{L}_{m,t}$, $\hat{S}_{m,t}$, $\hat{C}_{m,t}$, $\hat{L}_{n,t}$, $\hat{S}_{n,t}$, $\hat{C}_{n,t}$, $\hat{F}_{u,t}$, $\hat{F}_{v,t}$, $\hat{F}_{w,t}$ and the BAV factor estimates obtained in the previous step, we (re)estimate the parameters of the system specification (5)-(8) for all $i = 1, ..., N$ by means of system GMM. We employ one lag of the components as instruments and the inverse of a Newey-West HAC covariance (obtained from the OLS residuals in a first step) as weighting matrix. The idiosyncratic components $\hat{\epsilon}_{\bullet,it}$ for $\bullet = l, s, c, f$ are the residuals of the system GMM regressions for all i.

3. Let $X_{j,it} = [\hat{L}_{j,t},\ \hat{S}_{j,t},\ \hat{C}_{j,t}]'$, for $j = g, m, n$ or $X_{j,t} = [\hat{F}_{u,t},\ \hat{F}_{v,t},\ \hat{F}_{w,t}]'$ for $j = f$. The state variable r_t in the conditional mean of (9) which drives the time-variability of the parameters d, α, β, Γ is assumed to evolve with respect to a first-order Markov chain, with transition probability given by:

$$\mathcal{P}(r_t = y | r_t = x) \quad = \quad \pi_{xy}. \tag{46}$$

The expression above describes the probability of switching from regime x at time $t-1$ to regime y at time t. In this article we consider two regimes, that is $r_t = 1, 2$, so that the uncoditional (ergodic) probabilities of being in state $r_t = 1$ or state $r_t = 2$ are given by $\bar{\pi}_1 = (1 - \pi_{xx})/(2 - \pi_{xx} - \pi_{yy})$. In what follows let $\mathcal{I}_t$ denote the information set available to the econometrician at time t. To save on notation, we write (9) compactly as,

$$Y_{j,t} = X^{(r)}_{j,t} = V^{(r)}_{j,t} + \xi_{j,t}, \tag{47}$$

where $V^{(r)}_{j,t} = Y_{j,t} - \xi_{j,t} = E\left[Y_{j,t}|\mathcal{I}_{t-1}\right] = \Upsilon_{j,d_{j,r}} X^{(r)}_{j,t} + \alpha_{j,r}\beta'_{j,r}\Delta^{d_{j,r}-b_{j,r}}\Upsilon_{j,b_{j,r}} X^{(r)}_{j,t} + \sum_{p=1}^{P}\Gamma^{p}_{j,r}\Delta^{d_{j,r}}\Upsilon^{p}_{j,b_{j,r}} X^{(r)}_{j,t}$ for every $j = g, m, n, f$. We write:

$$Y_{j,t}|\mathcal{I}_{t-1} \sim \begin{cases} \mathcal{N}\left(\Xi^{(1)}_t\right) & for \quad \pi^{(1)}_{jt} \\ \mathcal{N}\left(\Xi^{(2)}_t\right) & for \quad 1 - \pi^{(1)}_{jt} \end{cases}, \Xi^{(r)}_t = (d_r, b_r, \beta'_r, \alpha'_r, \text{vec}(\Gamma_r)', \text{diag}(\theta)', \text{diag}(\delta)', \zeta')', \tag{48}$$

where $\mathcal{N}(\bullet)$ denotes the conditional normal distribution, $\Xi_t^{(r)}$ is the vector of parameters for the r-th regime and $\pi_{jt}^{(1)} = \mathcal{P}(r_t = 1|\mathcal{I}_{t-1})$ is the probability of regime 1 conditional on the information set at period $t-1$. The parameters $\beta_r', \alpha_r', \mathrm{vec}(\Gamma_r)'$ are concentrated out of the Likelihood estimation and estimated via canonical correlation analysis and OLS (Johansen and Nielsen, 2012). The conditional probability $\pi_{j.t}^{(1)}$ is given by:

$$\begin{aligned}\pi_{j,t}^{(1)} = \mathcal{P}(r_t = 1|\mathcal{I}_{t-1}) &= (1-\pi_{22})\left[\frac{\mathcal{N}(Y_{j,t-1}|r_{t-1}=2)(1-\pi_{jt-1}^{(1)})}{\mathcal{N}(Y_{j,t-1}|r_{t-1}=1)\pi_{j,t-1}^{(1)} + \mathcal{N}(Y_{j,t-1}|r_{t-1}=2)(1-\pi_{j,t-1}^{(1)})}\right] \\ &+ \pi_{11}\left[\frac{\mathcal{N}(Y_{j,t-1}|r_{t-1}=1)\pi_{j,t-1}^{(1)}}{\mathcal{N}(Y_{j,t-1}|r_{t-1}=1)\pi_{j,t-1}^{(1)} + \mathcal{N}(Y_{j,t-1}|r_{t-1}=2)(1-\pi_{j,t-1}^{(1)})}\right]. \quad (49)\end{aligned}$$

The likelihood function is then given by (18) and the conditional Normal distribution given that regime r occurs at time t is given by

$$\mathcal{N}\left(Y_{j,t}|r_t = r\right) = \frac{1}{2}\left|H_{j,t}\right|^{-1/2}\exp\left\{-\frac{1}{2}\left(Y_{j,t} - \mathcal{V}_{j,t}^{(r)}\right)H_{j,t}^{-1}\left(Y_{j,t} - \mathcal{V}_{j,t}^{(r)}\right)\right\}. \quad (50)$$

4. Given the estimated idiosyncratic components $\hat{\epsilon}_{\bullet,it}$ obtained from the system GMM regression in step two and the measurement errors $\hat{\varepsilon}_{it}(\tau)$ obtained from $\hat{\mathcal{E}}_t = \mathcal{Z}_t - \hat{\Pi}\hat{\mathcal{X}}_t$ using the estimated matrix of parameters $\hat{\Pi}$ in (32)-(36), we employ ML to estimate the autoregressive and GARCH(1,1) parameters in (13) and (14) for each i and τ.

C Forecasting

Following Dolatabadi et al. (2015), the multi-step ahead forecasts of the FCVAR for each $j = l, s, c, f$ can be obtained in the case of no regime-switching and no volatility-in-mean as

$$\hat{X}_{j,t+h|t} = \Upsilon_{j,\hat{d}}\hat{X}_{j,t+h|t} + \hat{\alpha}_j\hat{\beta}_j'\Delta^{\hat{d}-\hat{b}}\Upsilon_{j,\hat{b}}\hat{X}_{j,t+h|t} + \sum_{p=1}^{k}\hat{\Gamma}_{j,p}\Delta^{\hat{d}}\Upsilon_{j,\hat{b}}^{p}\hat{X}_{j,t+h|t} \quad (51)$$

Note that since $\Upsilon_{j,\bullet}$ is a lag operator, the right hand side of (53) is conditional on past information. In the case of regime switching parameters and volatility-in-mean we have

$$\begin{aligned}\hat{X}_{j,t+h|t}^{(r)} &= \Upsilon_{j,\hat{d}_r}\hat{X}_{j,t+h|t}^{(r)} + \hat{\alpha}_{j,r}\hat{\beta}_{j,r}'\Delta^{\hat{d}_r-\hat{b}_r}\Upsilon_{j,\hat{b}_r}\hat{X}_{j,t+h|t}^{(r)} + \sum_{p=1}^{k}\hat{\Gamma}_{j,r}^{p}\Delta^{\hat{d}_r}\Upsilon_{j,\hat{b}_r}^{p}\hat{X}_{j,t+h|t}^{(r)} \quad (52)\\ &+ \hat{\zeta}_j \odot \mathrm{diag}\left(\hat{H}_{j,t+h|t}\right).\end{aligned}$$

with $r = 1, 2$ and the weigthed forecasts are then given by (23). Moreover, in order to compute forecasts of the conditional (co)variances of the term structures we start by noting that the

OGARCH volatilities for each $j = g, m, n, f$ can be computed from (12) recursively as:

$$\hat{\Omega}_{jt+h|t} = I_K + \mathrm{diag}(\hat{\theta}_j + \hat{\delta}_j)^{h-1} \odot \left(\hat{\Omega}_{jt+1|t} - I_K\right), \quad (53)$$

$$\hat{H}_{jt+h|t} = \hat{B}_j \hat{\Omega}_{jt+h|t} \hat{B}_j', \quad (54)$$

where I_K is an identity matrix of order $K = 3$. Given $\hat{H}_{jt+h|t}$ for $j = glb, fin, com, ...$ in (54) and estimates for the GARCH(1,1) volatilities of the idiosyncratic components $\hat{\omega}_{\bullet,it+h|t}$ and of the measurement errors $\hat{\upsilon}_{it+h|t}(\tau)$ we can compute $\hat{D}_{t+h|t}$ and $\hat{V}_{t+h|t}$ and subsequently (39), (40) and (22) with the estimated $\hat{\Pi}$.

Term Structures							
Commodities					Financials		
Energy	Metals	Grains	Softs	Livestock	Forex	Bonds	Equity
BRENT (B)	Gold (B)	Cocoa (B)	Cotton (B)	Live cattle (B)	USD/EUR (B)	US Rates (D)	SP500 (B)
WTI (B)	Silver (B)	Coffee (B)	Wheat (B)	Lean hogs (B)	USD/ZAR (B)	EU Rates (E)	FTSE 100 (B)
Gasoline (B)	Copper (B)	Sugar (B)	Soybeans (B)	Feeder cattle (B)	GBP/EUR (B)	UK Rates (D)	
Heating Oil (B)	Aluminium (B)	Orange	Soybean oil (B)		USD/RMB (B)	JP Rates (D)	
Natural Gas (B)	Lead (B)	Lumber (B)	Rough rice (B)		YEN/USD (B)	SA Rates (D)	
Gasoil (B)	Nickel (B)	Rubber (B)	Canola (B)				
Coal (B)	Zinc (B)	Ethanol (B)	Corn (B)				
CO2 (B)	Steel (B)						

Macroeconomy		
Real Economy	Financial and Housing Markets	Confidence Indicators
CPI: Consumer Prices (W)	XRS: Exchange Rates (D)	LEI: Leading Economic (D)
INP: Ind Production (W)	TST: Term Spreads (D)	BCI: Business Confidence (D)
MSP: Money Supply (W)	SVO: Stock Market Vola(D)	
TOT: Terms of Trade (W)	HPR: House Prices (H)	
WAG: Wages (HAR)	XVO: FX Volatility (D)	
CON: Consumption (D)	PER: PE Ratios (D)	
INV: Investment (H)	DYD: Dividend Yields (D)	
INT: Inventories (D)		
UNE: Unemployment (W)		
EMP: Employment (D)		

Table 1: Data description for term structures and macroeconomic variables considered. Data are obtained from Bloomberg (B), Datastream (D), Haver (H), European Central Bank (E), World Bank Database (W). Term structure data are rolling monthly futures contracts at the daily frequency from the period 01-01-2010 to 10-01-2015. Macroeconomic data are at the monthly frequency and for the same time period 01-2010 to 09-2015. Countries considered for the macroeconomic data are: Australia, Brazil, Canada, China, EU, France, Germany , India, Italy, Japan, Korea, Malaysia, Russia, South Africa, Sweden, Switzerland, Thailand, UK and US.

ESTIMATION APPROACHES		
Type	**Advantages**	**Disadvantages**
NLS	Relatively simple Product specific time-varying parameters Flexible for dynamic specification	Numerical optimization for factors estimation Static factor estimation No factor uncertainty correction
OLSPRD	Very simple No numerical optimization for factor estimation Flexible for dynamic specification	Constant parameters Static factor estimation No factor uncertainty correction Product specific constant maturity and amplitude Not robust under heteroskedasticity
GLSPRD	Very simple No numerical optimization for factor estimation Flexible for dynamic specification Robust under heteroskedasticity	Constant parameters Static factor estimation No factor uncertainty correction Product specific constant maturity and amplitude
OLSSEC	Very simple No numerical optimization for factor estimation Flexible for dynamic specification	Constant parameters Static factor estimation No factor uncertainty correction Sector specific constant maturity and amplitude Not robust under heteroskedasticity
GLSSEC	Very simple No numerical optimization for factor estimation Flexible for dynamic specification Robust under heteroskedasticity	Constant parameters Static factor estimation No factor uncertainty correction Sector specific constant maturity and amplitude
OLSPTV	Very simple No numerical optimization for factor estimation Flexible for dynamic specification Product specific time maturity and amplitude	Static factor estimation No factor uncertainty correction Not robust under heteroskedasticity
GLSPTV	Very simple No numerical optimization for factor estimation Flexible for dynamic specification Product specific time-varying maturity and amplitude Robust under heteroskedasticity	Static factor estimation No factor uncertainty correction
OLSSTV	Very simple No numerical optimization for factor estimation Flexible for dynamic specification Sector specific time maturity and amplitude	Static factor estimation No factor uncertainty correction Not robust under heteroskedasticity
GLSSTV	Very simple No numerical optimization for factor estimation Flexible for dynamic specification Sector specific time maturity and amplitude	Static factor estimation No factor uncertainty correction Robust under heteroskedasticity
BAV	Weighted estimation Weighted factor uncertainty correction Flexible for dynamic specification 'Hybrid' dynamic specification Weighted time-varying/constant maturity and amplitude Weighted OLS, GLS, NLS	'Hybrid' estimation Factor uncertainty reduced

Table 2: Description of factor estimation approaches considered

Alternative Dynamic Specifications of Common Components		
Model	**Parameter Space Ξ_{j,r_t}**	**Estimation**
RW	$d_{j,r_t} = b_{j,r_t} = 1$, $\alpha'_{j,r_t} = \mathbf{0}$,$\beta'_{j,r_t} = \mathbf{0}$, $\varsigma'_j = \mathbf{0}$, $\mathrm{diag}(\delta_j)' = \mathbf{0}$, $\mathrm{diag}(\Theta_j)' = \mathbf{0}'$, $\Gamma_j = 0$	—
VAR	$d_{j,r_t} = b_{j,r_t} = 1$, $\alpha'_{j,r_t} = \mathbf{0}$,$\beta'_{j,r_t} = \mathbf{0}$, $\varsigma'_j = \mathbf{0}$, $\mathrm{diag}(\delta_j)' = \mathbf{0}$, $\mathrm{diag}(\Theta_j)' = \mathbf{0}'$	OLS
CVAR	$d_{j,r_t} = b_{j,r_t} = 1$, $\alpha'_{j,r_t} \neq \mathbf{0}$, $\beta'_{j,r_t} \neq \mathbf{0}$, $\varsigma'_j = \mathbf{0}$, $\mathrm{diag}(\delta_j)' = \mathbf{0}$, $\mathrm{diag}(\Theta_j)' = \mathbf{0}'$	Concentrated ML
FCVAR	$d_{j,r_t} = b_{j,r_t} = d_j = b_j \neq 0$, $\alpha'_{j,r_t} \neq \mathbf{0}$, $\beta'_{j,r_t} \neq \mathbf{0}$, $\varsigma'_j = \mathbf{0}$, $\mathrm{diag}(\delta_j)' = \mathbf{0}$, $\mathrm{diag}(\Theta_j)' = \mathbf{0}'$	Concentrated ML
FCVAR-OGARCH	$d_{j,r_t} = b_{j,r_t} = d_j = b_j \neq 0$, $\alpha'_{j,r_t} = \alpha'_j \neq \mathbf{0}$, $\beta'_{j,r_t} = \beta'_j \neq \mathbf{0}$, $\varsigma'_j = \mathbf{0}$, $\mathrm{diag}(\delta_j)' > \mathbf{0}$, $\mathrm{diag}(\Theta_j)' > \mathbf{0}'$	Concentrated ML
RSFCVAR-OGARCH	$d_{j,r_t} = b_{j,r_t} \neq 0$, $\alpha'_{j,r_t} \neq \mathbf{0}$, $\beta'_{j,r_t} \neq \mathbf{0}$, $\varsigma'_j = \mathbf{0}$, $\mathrm{diag}(\delta_j)' > \mathbf{0}$, $\mathrm{diag}(\Theta_j)' > \mathbf{0}'$	Concentrated ML and HF
RSFCVAR-OGARCH-M	$d_{j,r_t} = b_{j,r_t} \neq 0$, $\alpha'_{j,r_t} \neq \mathbf{0}$, $\beta'_{j,r_t} \neq \mathbf{0}$, $\varsigma'_j \neq \mathbf{0}$, $\mathrm{diag}(\delta_j)' > \mathbf{0}$, $\mathrm{diag}(\Theta_j)' > \mathbf{0}'$	Concentrated ML and HF

Table 3: Parameter restrictions for nested versions of the dynamic component specification.

	Level			Slope			Curvature			Seasonality		
Product	GLO	MAR	SEC	GLO	MAR	SEC	GLO	MAR	SEC	SF1	SF2	SF3
BRENT	0.01 (0.00)	-0.04 (0.01)	0.00 (0.03)	-0.09 (0.01)	0.01 (0.01)	-0.04 (0.03)	0.02 (0.01)	-0.03 (0.01)	0.02 (0.02)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
WTI	0.02 (0.00)	-0.01 (0.01)	0.00 (0.01)	-0.05 (0.01)	0.01 (0.02)	-0.04 (0.03)	0.03 (0.01)	-0.04 (0.01)	0.05 (0.02)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
GASOLINE	0.03 (0.00)	-0.00 (0.01)	-0.02 (0.03)	0.03 (0.05)	0.02 (0.04)	-0.11 (0.08)	0.09 (0.06)	-0.13 (0.09)	-0.21 (0.13)	-0.55 (0.41)	0.57 (0.53)	0.11 (0.35)
HEATINGOIL	0.03 (0.02)	-0.04 (0.05)	-0.11 (0.14)	-0.03 (0.04)	0.06 (0.08)	-0.10 (0.16)	0.02 (0.04)	-0.09 (0.09)	-0.04 (0.12)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
GASOIL	0.03 (0.00)	0.00 (0.02)	-0.02 (0.06)	-0.03 (0.00)	0.01 (0.01)	-0.02 (0.02)	0.03 (0.01)	-0.03 (0.01)	-0.01 (0.02)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
NATURALGAS	0.03 (0.00)	-0.02 (0.01)	0.04 (0.03)	0.02 (0.02)	0.02 (0.03)	0.05 (0.06)	0.03 (0.04)	0.01 (0.05)	0.21 (0.13)	0.45 (0.38)	-0.07 (0.51)	-0.04 (0.60)
COAL	0.06 (0.00)	0.01 (0.01)	-0.01 (0.02)	0.03 (0.01)	-0.02 (0.01)	-0.03 (0.02)	-0.00 (0.01)	0.00 (0.02)	-0.02 (0.02)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
CO2	0.06 (0.04)	-0.08 (0.10)	0.23 (0.34)	0.03 (0.04)	-0.02 (0.10)	0.13 (0.13)	-0.01 (0.08)	0.10 (0.17)	0.04 (0.23)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
GOLD	0.03 (0.01)	0.02 (0.02)	0.03 (0.02)	-0.00 (0.01)	0.00 (0.01)	-0.00 (0.01)	0.00 (0.01)	-0.00 (0.02)	-0.01 (0.03)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
SILVER	0.05 (0.02)	0.05 (0.16)	0.12 (0.24)	-0.01 (0.03)	-0.06 (0.12)	-0.16 (0.32)	0.04 (0.06)	0.06 (0.18)	-0.20 (0.41)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
COPPER	0.06 (0.02)	0.00 (0.02)	-0.04 (0.04)	0.05 (0.02)	0.01 (0.03)	0.04 (0.07)	-0.04 (0.03)	0.03 (0.03)	-0.02 (0.08)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
ALUMINUM	0.03 (0.00)	-0.00 (0.01)	0.02 (0.01)	0.02 (0.00)	-0.02 (0.01)	0.01 (0.01)	0.00 (0.01)	0.01 (0.01)	0.02 (0.02)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
LEAD	0.02 (0.00)	-0.01 (0.01)	0.01 (0.01)	0.00 (0.00)	-0.02 (0.01)	0.02 (0.01)	0.01 (0.00)	0.01 (0.01)	0.01 (0.01)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
NICKEL	0.03 (0.00)	-0.02 (0.01)	0.03 (0.01)	0.01 (0.00)	-0.04 (0.01)	0.02 (0.01)	0.02 (0.00)	0.03 (0.01)	0.03 (0.01)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
ZINC	0.01 (0.00)	-0.01 (0.01)	0.03 (0.01)	0.01 (0.00)	-0.01 (0.01)	0.01 (0.01)	0.00 (0.01)	0.02 (0.01)	0.02 (0.01)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
COTTON	0.02 (0.00)	0.02 (0.02)	0.07 (0.05)	0.01 (0.02)	-0.04 (0.10)	0.04 (0.16)	0.12 (0.10)	0.10 (0.14)	0.34 (0.19)	0.35 (0.44)	0.27 (0.35)	1.35 (0.96)
WHEAT	0.02 (0.00)	0.00 (0.01)	-0.01 (0.02)	-0.01 (0.01)	0.01 (0.01)	0.07 (0.03)	0.07 (0.03)	0.03 (0.04)	-0.16 (0.07)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
CORN	0.01 (0.01)	0.02 (0.01)	0.02 (0.02)	-0.01 (0.02)	-0.04 (0.04)	0.17 (0.08)	0.11 (0.06)	0.03 (0.06)	-0.37 (0.16)	-0.04 (0.43)	0.58 (0.62)	-0.58 (0.57)
SOYBEAN	0.02 (0.00)	0.04 (0.02)	0.09 (0.06)	-0.01 (0.02)	-0.02 (0.05)	0.09 (0.05)	0.08 (0.03)	0.06 (0.05)	0.12 (0.10)	0.21 (0.25)	0.09 (0.21)	-0.12 (0.31)
SUGAR	0.02 (0.02)	0.04 (0.03)	0.07 (0.20)	-0.00 (0.03)	-0.12 (0.05)	0.13 (0.13)	0.06 (0.04)	0.05 (0.06)	-0.34 (0.43)	-0.17 (0.51)	0.48 (1.09)	-0.08 (0.53)
ORANJE	0.02 (0.02)	-0.09 (0.17)	-0.16 (0.54)	-0.02 (0.03)	0.06 (0.16)	0.20 (0.53)	-0.04 (0.08)	-0.07 (0.24)	-0.04 (0.27)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
COCOA	-0.01 (0.00)	-0.05 (0.01)	0.05 (0.03)	0.00 (0.01)	0.00 (0.01)	-0.01 (0.03)	-0.01 (0.02)	-0.00 (0.02)	-0.03 (0.04)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
COFFEE	0.02 (0.01)	0.01 (0.02)	0.05 (0.05)	0.01 (0.01)	-0.08 (0.01)	0.04 (0.02)	0.05 (0.02)	0.08 (0.03)	-0.09 (0.06)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
ETHANOL	0.03 (0.00)	0.01 (0.01)	-0.00 (0.02)	-0.03 (0.02)	-0.01 (0.03)	0.07 (0.10)	0.01 (0.03)	0.04 (0.04)	-0.13 (0.14)	-0.10 (0.21)	-0.35 (0.21)	-0.23 (0.39)
LUMBER	-0.01 (0.02)	0.01 (0.03)	0.05 (0.08)	-0.00 (0.02)	0.02 (0.05)	0.08 (0.13)	0.09 (0.04)	0.04 (0.08)	0.17 (0.21)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
LIVECATTLE	-0.00 (0.02)	0.00 (0.04)	0.01 (0.07)	0.05 (0.06)	0.03 (0.05)	0.52 (0.16)	-0.04 (0.17)	-0.01 (0.14)	0.67 (0.54)	0.56 (2.41)	0.81 (1.71)	-0.43 (1.83)
LEANHOGS	0.01 (0.03)	0.09 (0.04)	0.31 (0.10)	0.00 (0.12)	-0.04 (0.14)	0.21 (0.19)	0.22 (0.26)	0.31 (0.20)	1.43 (0.55)	2.99 (1.80)	-0.04 (2.22)	-0.90 (3.44)
FEEDERCATTLE	-0.03 (0.01)	0.02 (0.01)	0.08 (0.02)	0.05 (0.02)	0.01 (0.02)	0.17 (0.05)	0.03 (0.05)	0.02 (0.03)	0.26 (0.11)	0.34 (0.43)	0.24 (0.40)	0.01 (0.44)
USDEUR	-0.00 (0.00)	0.01 (0.01)	0.01 (0.01)	-0.02 (0.00)	-0.02 (0.00)	0.00 (0.01)	0.03 (0.00)	-0.01 (0.00)	-0.01 (0.01)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
ZARGBP	-0.05 (0.01)	0.04 (0.03)	0.08 (0.03)	-0.01 (0.02)	-0.00 (0.02)	0.02 (0.05)	0.01 (0.04)	-0.03 (0.07)	0.03 (0.20)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
GBPEUR	0.01 (0.00)	0.01 (0.00)	-0.00 (0.01)	-0.00 (0.00)	-0.01 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.01 (0.01)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
ZARUSD	-0.05 (0.01)	0.04 (0.01)	0.04 (0.01)	-0.02 (0.00)	0.01 (0.01)	0.03 (0.01)	0.01 (0.01)	-0.06 (0.02)	0.03 (0.04)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
JPYUSD	-0.03 (0.00)	0.02 (0.01)	-0.01 (0.01)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
RENUSD	-0.01 (0.00)	-0.01 (0.00)	0.01 (0.01)	-0.01 (0.00)	-0.02 (0.00)	0.02 (0.00)	0.01 (0.00)	0.01 (0.01)	0.01 (0.01)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
USINTR	0.01 (0.02)	-0.03 (0.04)	0.08 (0.06)	0.02 (0.03)	-0.01 (0.05)	0.01 (0.06)	-0.02 (0.03)	0.11 (0.07)	0.00 (0.06)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)

EUINTR	-0.48 (0.06)	-0.19 (0.12)	0.58 (0.14)	-0.68 (0.05)	-0.54 (0.07)	0.39 (0.10)	0.83 (0.06)	-0.34 (0.15)	0.41 (0.16)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
SAINTR	-0.20 (0.04)	-0.09 (0.09)	0.40 (0.12)	-0.31 (0.04)	-0.23 (0.07)	0.35 (0.09)	0.27 (0.05)	-0.05 (0.09)	0.41 (0.10)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
UKINTR	-0.01 (0.00)	-0.04 (0.01)	0.03 (0.01)	0.11 (0.09)	-0.25 (0.10)	-0.39 (0.13)	0.07 (0.09)	-0.53 (0.21)	0.40 (0.17)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
JPINTR	0.00 (0.00)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.00 (0.00)	0.02 (0.01)	-0.01 (0.01)	0.01 (0.01)	0.03 (0.01)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
CHINTR	-0.06 (0.02)	-0.02 (0.04)	0.05 (0.06)	-0.04 (0.02)	-0.11 (0.04)	0.02 (0.05)	0.09 (0.02)	0.10 (0.04)	0.03 (0.04)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
SP500TSX60	-0.01 (0.00)	0.02 (0.01)	0.04 (0.02)	-0.00 (0.00)	0.00 (0.00)	-0.00 (0.01)	-0.00 (0.00)	-0.00 (0.00)	-0.01 (0.02)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
FTSE100	-0.02 (0.00)	0.03 (0.01)	0.05 (0.03)	-0.01 (0.01)	0.00 (0.01)	0.04 (0.05)	0.01 (0.02)	-0.01 (0.02)	0.11 (0.21)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)

Table 4: Component loadings for level, slope, curvature and seasonality factors

	Global	Market		Sector								Seasonality
Ξ	GLO	COM	FIN	OAG	MET	GRA	SOF	LIV	FEX	BON	EQT	SEA
$\hat{\beta}_{1,1}$	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	(NaN)	(NaN)	(NaN)	(NaN)	(NaN)	(NaN)	(NaN)	(NaN)	(NaN)	(NaN)	(NaN)	(NaN)
$\hat{\beta}_{2,1}$	-0.212	-0.371	-4.770	-0.294	-3.705	1.661	2.283	-4.580	-2.400	-0.522	3.630	0.190
	(0.129)	(0.150)	(0.319)	(0.125)	(0.174)	(0.149)	(0.101)	(0.765)	(1.584)	(0.144)	(3.204)	(0.102)
$\hat{\beta}_{3,1}$	-2.308	0.444	-9.474	-0.087	-4.389	1.537	-0.830	-5.832	4.414	1.222	-12.668	-1.124
	(0.220)	(0.160)	(0.440)	(0.107)	(0.155)	(0.137)	(0.081)	(0.879)	(2.417)	(0.180)	(3.635)	(0.167)
$\hat{\beta}_{1,2}$	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	(NaN)	(NaN)	(NaN)	(NaN)	(NaN)	(NaN)	(NaN)	(NaN)	(NaN)	(NaN)	(NaN)	(NaN)
$\hat{\beta}_{2,2}$	-0.125	-0.464	0.515	-0.287	-2.866	1.224	2.210	-1.420	-5.265	-3.599	-5.112	-0.014
	(0.120)	(0.134)	(0.124)	(0.128)	(0.125)	(0.101)	(0.102)	(0.535)	(0.755)	(0.469)	(3.721)	(0.071)
$\hat{\beta}_{3,2}$	-2.138	0.226	0.568	-0.085	-0.922	0.704	-0.750	-4.043	9.021	5.412	6.897	-0.558
	(0.203)	(0.152)	(0.159)	(0.110)	(0.119)	(0.082)	(0.082)	(0.533)	(1.290)	(0.569)	(4.210)	(0.107)
$\hat{d}_1$	0.962	0.759	0.836	0.978	0.988	0.876	0.919	0.901	0.852	0.551	0.335	0.843
	(0.451)	(0.137)	(0.280)	(0.697)	(0.455)	(0.398)	(0.100)	(0.300)	(0.649)	(0.098)	(0.012)	0.215
$\hat{d}_2$	0.996	0.629	0.543	0.989	0.849	0.647	0.965	0.525	0.985	0.990	1.000	0.587
	(0.472)	(0.240)	(0.149)	(2.676)	(0.378)	(0.047)	(0.300)	(0.080)	(0.830)	(3.733)	(1.434)	(0.541)
$\hat{p}_{11}$	0.915	0.725	0.773	0.568	0.960	0.899	0.989	0.801	0.177	0.034	0.511	0.990
	(0.505)	(0.359)	(0.358)	(0.579)	(0.447)	(0.184)	(0.490)	(0.390)	(0.990)	(0.990)	(0.209)	(0.990)
$\hat{p}_{22}$	0.933	0.618	0.233	0.988	0.983	0.890	0.856	0.966	1.000	0.980	0.548	0.501
	(0.520)	(0.304)	(0.990)	(0.327)	(0.490)	(0.316)	(0.990)	(0.990)	(0.990)	(0.990)	(0.199)	(0.190)

Table 5: Estimation results of long-run, fractional coefficients and transition probabilities for the full RSFCVAR-OGARCH-M specification.

		Non-Regime Switching				Regime Switching	
Component	Diag	VAR	CVAR	FCVAR	FCVAR-OG	RSFCVAR-OG	RSFCVAR-OGM
	$\mathcal{L}$	4018.638	4010.820	4012.203	4274.291	4314.816	4431.828
GLO	LR_p	0.000	1.000	0.096	0.000	0.000	0.000
	$\mathcal{L}$	3057.168	3068.470	3040.458	3285.717	3282.048	3216.401
COM	LR_p	0.000	0.000	1.000	0.000	1.000	1.000
	$\mathcal{L}$	2167.301	2171.892	2190.021	2725.699	2866.797	2693.152
FIN	LR_p	0.000	0.002	0.000	0.000	0.000	1.000
	$\mathcal{L}$	3076.458	3082.519	3085.464	2848.062	2543.828	2879.110
ENE	LR_p	0.000	0.000	0.015	1.000	1.000	0.000
	$\mathcal{L}$	2225.004	2213.219	2228.412	1994.807	2095.854	2198.392
MET	LR_p	0.000	1.000	0.000	1.000	0.000	0.000
	$\mathcal{L}$	2160.538	2143.805	2145.606	3513.031	3673.814	3602.652
GRA	LR_p	0.000	1.000	0.058	0.000	0.000	1.000
	$\mathcal{L}$	2655.370	2675.327	2679.610	2717.519	2932.087	2938.100
SOF	LR_p	0.000	0.000	0.003	0.000	0.000	1.000
	$\mathcal{L}$	3029.695	3024.042	3031.817	3666.757	3748.355	3694.890
LIV	LR_p	0.000	1.000	0.000	0.000	0.000	1.000
	$\mathcal{L}$	2757.695	2755.534	2767.369	3163.390	2424.060	2830.182
FEX	LR_p	0.000	1.000	0.000	0.000	1.000	0.000
	$\mathcal{L}$	3517.987	3521.230	3536.950	3937.453	3996.207	3944.632
BON	LR_p	0.000	0.011	0.000	0.000	0.000	1.000
	$\mathcal{L}$	1089.600	1064.085	1036.178	1143.612	1144.499	1160.232
EQT	LR_p	0.000	0.000	0.000	0.000	1.000	1.000
	$\mathcal{L}$	1574.418	1584.657	1590.112	2183.107	2252.260	2354.177
SEA	LR_p	0.000	0.000	0.001	0.000	0.000	0.000

Table 6: Diagnostics for alternative dynamic component specifications

	Global			Commodities			Financials			Energy			Metals			Grains		
Ξ	LEV	SLO	CUR	LEV	SLO	CUR	LEV	SLO	CUR	LEV	SLO	CUR	LEV	SLO	CUR	LEV	SLO	CUR
$\hat{\alpha}_{j,1}$	-0.003 (0.001)	-0.002 (0.001)	0.003 (0.002)	0.004 (0.002)	-0.005 (0.002)	0.009 (0.002)	-0.002 (0.001)	0.001 (0.001)	-0.004 (0.002)	-0.257 (0.019)	-0.001 (0.002)	0.013 (0.002)	-0.001 (0.002)	0.002 (0.002)	-0.006 (0.003)	0.001 (0.003)	0.002 (0.003)	-0.002 (0.003)
$\hat{\alpha}_{j,2}$	0.015 (0.003)	0.008 (0.001)	-0.008 (0.002)	0.001 (0.003)	0.004 (0.002)	-0.010 (0.003)	0.017 (0.002)	-0.013 (0.002)	0.035 (0.006)	0.001 (0.002)	0.008 (0.002)	-0.004 (0.002)	-0.006 (0.003)	-0.002 (0.002)	-0.001 (0.003)	-0.078 (0.010)	-0.162 (0.023)	-0.029 (0.005)
$\hat{\Gamma}_{j1,1}$	0.191 (0.037)	-0.212 (0.048)	-0.188 (0.031)	0.639 (0.030)	-0.136 (0.097)	0.062 (0.075)	0.572 (0.038)	-0.052 (0.048)	-0.111 (0.029)	-0.077 (0.120)	-0.164 (0.069)	-0.141 (0.088)	0.224 (0.033)	-0.085 (0.047)	-0.076 (0.033)	0.462 (0.071)	0.023 (0.028)	-0.025 (0.037)
$\hat{\Gamma}_{j1,2}$	-0.021 (0.028)	0.386 (0.033)	-0.004 (0.025)	-0.013 (0.031)	0.485 (0.041)	0.134 (0.037)	-0.040 (0.044)	0.373 (0.079)	0.068 (0.038)	0.117 (0.068)	0.300 (0.076)	-0.043 (0.042)	-0.082 (0.025)	0.325 (0.034)	-0.044 (0.024)	0.049 (0.043)	0.480 (0.035)	0.018 (0.037)
$\hat{\Gamma}_{j2,1}$	-0.098 (0.047)	-0.189 (0.054)	0.277 (0.034)	-0.022 (0.029)	0.245 (0.082)	0.533 (0.063)	0.025 (0.055)	-0.004 (0.047)	0.275 (0.040)	0.090 (0.041)	-0.039 (0.037)	0.315 (0.030)	-0.073 (0.036)	-0.069 (0.048)	0.222 (0.035)	-0.007 (0.031)	-0.055 (0.027)	0.510 (0.045)
$\hat{\Gamma}_{j2,2}$	0.164 (0.035)	-0.210 (0.041)	-0.161 (0.027)	0.859 (0.029)	-0.101 (0.056)	0.042 (0.048)	0.959 (0.044)	-0.044 (0.047)	-0.116 (0.045)	-0.059 (0.094)	0.199 (0.031)	0.017 (0.039)	0.415 (0.035)	-0.081 (0.049)	-0.095 (0.036)	1.027 (0.095)	0.251 (0.083)	-0.007 (0.059)
$\hat{\Gamma}_{j3,1}$	-0.015 (0.030)	0.348 (0.038)	0.011 (0.028)	-0.017 (0.024)	0.755 (0.027)	0.105 (0.024)	0.027 (0.037)	0.948 (0.054)	0.075 (0.044)	0.115 (0.063)	0.299 (0.072)	-0.038 (0.041)	-0.074 (0.026)	0.513 (0.034)	-0.055 (0.027)	0.473 (0.134)	1.316 (0.084)	0.015 (0.080)
$\hat{\Gamma}_{j3,2}$	-0.102 (0.050)	-0.189 (0.063)	0.222 (0.039)	0.020 (0.026)	0.158 (0.054)	0.770 (0.045)	-0.097 (0.098)	-0.074 (0.101)	0.709 (0.056)	0.087 (0.030)	-0.061 (0.032)	0.292 (0.029)	-0.074 (0.035)	-0.007 (0.048)	0.378 (0.039)	0.091 (0.039)	0.020 (0.031)	0.848 (0.035)
$\hat{\zeta}_j$	0.018 (0.007)	-0.015 (0.253)	-0.008 (0.172)	0.020 (0.023)	0.017 (0.174)	0.001 (0.151)	0.008 (0.004)	0.051 (0.153)	0.017 (0.095)	-0.040 (0.112)	0.070 (0.186)	0.004 (0.191)	0.005 (0.160)	-0.003 (0.205)	0.020 (0.146)	0.050 (0.088)	0.011 (0.129)	-0.001 (0.127)
$\hat{\Theta}_j$	0.890 (0.207)	0.718 (0.226)	0.739 (0.132)	0.357 (0.070)	0.311 (0.064)	0.342 (0.082)	0.459 (0.174)	0.570 (0.037)	0.422 (0.120)	0.265 (0.157)	0.510 (0.103)	0.483 (0.820)	0.550 (0.239)	0.942 (0.141)	0.867 (0.121)	0.364 (0.058)	0.429 (0.085)	0.365 (0.047)
$\hat{\delta}_j$	0.040 (0.004)	0.074 (0.031)	0.096 (0.009)	0.340 (0.108)	0.412 (0.146)	0.385 (0.051)	0.103 (0.059)	0.157 (0.260)	0.170 (0.064)	0.717 (0.286)	0.131 (0.020)	0.017 (0.900)	0.056 (0.033)	0.039 (0.187)	0.084 (0.167)	0.478 (0.117)	0.262 (0.139)	0.260 (0.136)

Table 7: Results of short-run, GARCH and volatility in-mean coefficients for the full RSFCVAR-OGARCH-M specification (Part I).

Ξ	Softs			Livestock			Foreign Exchange			Bonds			Equity			Seasonalities		
	LEV	SLO	CUR	LEV	SLO	CUR	LEV	SLO	CUR	LEV	SLO	CUR	LEV	SLO	CUR	SF1	SF2	SF3
$\hat{\alpha}_{j,1}$	0.005 (0.004)	-0.007 (0.004)	0.006 (0.004)	0.005 (0.001)	0.002 (0.001)	-0.006 (0.001)	-0.006 (0.001)	0.009 (0.001)	0.050 (0.001)	-0.008 (0.003)	0.002 (0.003)	0.012 (0.004)	0.021 (0.006)	0.019 (0.010)	-0.048 (0.008)	0.002 (0.003)	-0.006 (0.002)	0.004 (0.003)
$\hat{\alpha}_{j,2}$	-0.058 (0.014)	0.394 (0.079)	0.394 (0.077)	0.030 (0.005)	-0.008 (0.002)	-0.010 (0.004)	-0.002 (0.001)	0.002 (0.001)	0.004 (0.001)	0.001 (0.001)	-0.004 (0.001)	0.002 (0.001)	-0.039 (0.028)	-0.004 (0.014)	0.061 (0.059)	0.275 (0.038)	0.043 (0.007)	-0.873 (0.088)
$\hat{\Gamma}_{j1,1}$	0.343 (0.055)	-0.147 (0.028)	0.115 (0.023)	0.502 (0.091)	0.060 (0.052)	0.097 (0.079)	0.459 (0.051)	0.059 (0.069)	0.043 (0.054)	1.028 (0.046)	-0.079 (0.035)	0.056 (0.041)	1.216 (0.083)	-0.090 (0.122)	0.333 (0.126)	0.533 (0.027)	-0.073 (0.031)	-0.024 (0.027)
$\hat{\Gamma}_{j1,2}$	-0.133 (0.042)	0.272 (0.039)	0.013 (0.025)	-0.066 (0.044)	0.407 (0.043)	-0.041 (0.047)	0.143 (0.047)	0.522 (0.086)	-0.056 (0.049)	-0.015 (0.037)	0.895 (0.045)	0.104 (0.037)	-0.083 (0.141)	1.168 (0.188)	0.413 (0.291)	0.024 (0.030)	0.482 (0.034)	-0.068 (0.041)
$\hat{\Gamma}_{j2,1}$	0.074 (0.035)	0.010 (0.040)	0.425 (0.027)	-0.049 (0.037)	-0.038 (0.046)	0.339 (0.042)	0.125 (0.064)	0.218 (0.104)	0.156 (0.071)	-0.040 (0.047)	0.057 (0.039)	0.907 (0.034)	0.162 (0.097)	0.182 (0.195)	0.438 (0.267)	-0.022 (0.023)	0.026 (0.036)	0.516 (0.045)
$\hat{\Gamma}_{j2,2}$	0.289 (0.071)	-0.047 (0.085)	0.078 (0.084)	0.958 (0.061)	0.355 (0.094)	0.464 (0.087)	0.264 (0.051)	0.072 (0.061)	0.024 (0.048)	0.398 (0.065)	-0.055 (0.025)	0.040 (0.044)	0.247 (0.139)	-0.131 (0.102)	0.128 (0.108)	0.008 (0.264)	0.300 (0.239)	0.030 (0.493)
$\hat{\Gamma}_{j3,1}$	-0.251 (0.236)	-0.368 (0.162)	0.207 (0.146)	-0.010 (0.067)	0.948 (0.054)	-0.088 (0.070)	0.166 (0.041)	0.348 (0.071)	-0.028 (0.043)	0.033 (0.032)	0.238 (0.055)	0.113 (0.031)	-0.223 (0.212)	0.126 (0.182)	-0.024 (0.140)	-0.140 (0.048)	0.934 (0.044)	-0.052 (0.067)
$\hat{\Gamma}_{j3,2}$	-0.044 (0.260)	-0.544 (0.162)	0.551 (0.148)	0.003 (0.143)	-0.159 (0.088)	0.799 (0.124)	0.282 (0.045)	0.242 (0.074)	0.146 (0.047)	0.011 (0.030)	0.089 (0.027)	0.257 (0.023)	-0.053 (0.109)	0.096 (0.183)	0.072 (0.229)	2.960 (0.272)	-1.066 (0.390)	0.690 (0.442)
$\hat{\zeta}_j$	-0.000 (1.000)	-0.028 (1.000)	0.011 (1.000)	-0.005 (0.185)	-0.015 (0.130)	0.015 (0.113)	0.017 (0.126)	-0.009 (0.134)	-0.021 (0.125)	0.007 (0.211)	0.029 (0.216)	0.003 (0.201)	-0.008 (0.091)	-0.045 (0.027)	0.015 (0.014)	-0.031 (1.000)	-0.017 (1.000)	-0.019 (1.000)
$\hat{\Theta}_j$	0.969 (0.400)	0.907 (0.330)	0.947 (0.510)	0.148 (0.210)	0.888 (0.090)	0.360 (0.153)	0.971 (0.263)	0.715 (0.121)	0.914 (0.373)	0.514 (0.196)	0.499 (0.134)	0.503 (0.500)	0.472 (0.103)	0.688 (0.029)	0.001 (0.019)	0.498 (0.280)	0.415 (0.150)	0.918 (0.640)
$\hat{\delta}_j$	0.026 (0.004)	0.071 (0.001)	0.047 (0.010)	0.003 (0.210)	0.101 (0.041)	0.075 (0.072)	0.020 (0.001)	0.114 (0.020)	0.078 (0.038)	0.105 (0.034)	0.092 (0.094)	0.012 (0.009)	0.225 (0.106)	0.230 (0.090)	0.920 (0.500)	0.003 (0.050)	0.164 (0.900)	0.066 (0.001)

Table 8: Results of short-run, GARCH and volatility in-mean coefficients for the full RSFCVAR-OGARCH-M specification (Part II).

	Global			Commodities			Financials			Energy			Metals			Grains		
Macro Comp.	LEV	SLO	CUR	LEV	SLO	CUR	LEV	SLO	CUR	LEV	SLO	CUR	LEV	SLO	CUR	LEV	SLO	CUR
CONS	-12.01	2.57	-4.50	0.21	77.44	-2.21	-4.64	12.49	-4.20	-1.47	1.21	2.10	-1.59	-4.73	-3.61	-0.10	-0.34	0.46
XRS1	-1.30	0.71	-1.26	1.78	2.10	-1.18	-1.91	2.21	0.67	1.27	-1.67	-0.95	2.01	1.92	0.98	0.72	0.69	1.43
XRS2	0.67	-1.92	2.07	1.16	-6.35	-1.70	-0.62	-1.70	0.05	0.12	-5.00	1.52	-8.06	0.21	0.97	-1.30	8.19	-6.42
CPI1	1.44	-1.37	1.16	-1.23	0.11	0.51	1.89	-0.94	-1.59	-1.22	-1.29	1.10	1.03	-1.01	-1.34	-1.05	-1.06	-3.28
CPI2	1.13	-1.22	1.20	-1.17	-0.93	1.55	1.19	-1.16	-1.17	-1.24	-1.42	1.17	-0.30	-0.95	-1.48	-1.43	1.16	-0.94
INP1	-0.98	0.94	-1.24	1.36	3.24	-2.10	-1.28	1.29	0.56	1.18	1.26	-0.96	1.57	0.63	1.45	0.85	-2.38	0.58
INP2	-1.10	1.14	-1.35	1.31	-0.22	-1.20	-1.52	1.45	1.16	1.28	1.03	-1.51	3.73	0.83	1.37	1.75	-1.61	0.45
TST1	-1.29	1.60	-1.55	1.02	0.17	-0.33	-0.27	1.00	1.53	1.29	1.61	-1.65	3.87	1.25	0.68	1.47	-1.72	2.50
TST2	1.27	-1.24	1.46	-1.31	-3.40	1.20	0.99	-1.42	-1.10	-1.19	-0.38	1.09	-3.57	-1.25	-0.97	-0.59	0.87	-1.48
BCI1	-1.21	1.43	-1.47	1.18	1.77	-0.50	-0.81	0.96	1.39	1.30	1.66	-1.43	2.97	0.60	0.33	1.17	-1.13	1.42
BCI2	-1.20	1.19	-1.22	1.23	1.20	-1.47	-0.98	1.16	1.19	1.22	1.14	-1.13	0.64	1.00	1.32	0.99	-1.06	2.03
LEI1	1.19	-1.31	1.34	-1.21	-1.15	1.04	0.96	-1.05	-1.41	-1.27	-1.29	1.27	-1.45	-0.80	-1.02	-1.07	0.84	-1.72
LEI2	1.39	-1.95	2.01	-0.83	-0.73	-0.66	0.69	-1.02	-1.57	-1.29	-2.29	1.64	-6.90	-0.63	-0.25	-0.92	1.24	-4.10
XVO1	1.10	-1.18	1.39	-1.22	-1.36	1.85	0.33	-0.99	-1.07	-1.24	-1.49	1.17	0.37	-0.02	-2.04	-0.98	2.43	-3.95
XVO2	-1.20	1.25	-1.26	1.22	0.90	-1.33	-1.07	1.13	1.32	1.27	1.40	-1.21	0.57	0.97	1.54	1.14	-1.00	1.77
PER1	-1.25	1.37	-1.55	1.35	5.37	0.21	-0.92	1.01	1.48	1.30	0.14	-1.27	3.37	2.05	0.85	0.63	0.49	2.42
PER2	1.45	-1.61	1.78	-1.09	-1.28	-0.19	1.01	-1.19	-1.35	-1.27	-1.40	1.54	-3.63	-0.98	-0.21	-0.68	1.44	-3.27
DYD1	-1.13	1.00	-1.23	1.57	6.63	0.78	-2.38	0.92	1.04	1.15	-1.83	-0.84	2.32	3.35	1.11	0.41	2.97	2.26
DYD2	1.23	-1.13	1.31	-1.30	-0.40	0.93	1.70	-1.14	-1.11	-1.19	-0.97	1.00	0.94	-1.11	-2.03	-0.75	1.16	-3.23
MSP1	-1.34	1.41	-1.37	1.21	2.73	-0.82	-1.21	1.22	1.18	1.26	1.38	-1.25	1.24	1.09	0.88	1.11	-0.92	1.67
MSP2	1.15	-1.19	1.21	-1.18	-4.08	1.53	1.14	-1.12	-0.94	-1.16	-1.28	1.07	-0.89	-0.93	-1.38	-0.88	1.60	-1.03
SVO1	-1.08	0.46	-0.77	1.72	3.72	-1.54	-2.79	1.84	0.44	1.07	-2.53	-0.54	1.96	2.50	1.30	0.40	1.68	0.24
SVO2	1.15	-1.27	1.34	-1.21	1.29	0.82	1.01	-1.17	-1.36	-1.27	-1.28	1.46	-2.50	-0.81	-1.08	-1.21	1.12	-1.46
CON1	1.26	-1.10	0.92	-1.33	-0.29	1.87	1.38	-1.05	-1.22	-1.17	-0.66	1.01	1.20	-1.44	-1.49	-1.22	0.48	0.43
CON2	-1.16	1.22	-1.01	1.10	-0.44	-2.02	-0.86	0.75	1.57	1.19	1.07	-0.94	-2.53	1.08	2.18	1.38	-0.71	2.10
TOT1	-1.06	0.99	-1.58	1.36	5.02	-1.36	0.17	1.03	1.01	1.16	0.80	-0.97	5.75	-0.45	-0.35	-0.65	-3.18	2.23
TOT2	-0.08	1.50	-1.04	-0.20	-24.78	1.69	2.09	-2.13	3.46	1.09	-2.36	-0.34	-4.06	0.22	3.96	4.21	8.76	12.52
HPR1	1.15	-1.79	1.97	-0.94	4.17	-1.49	-1.18	-0.71	-2.57	-1.51	-3.41	2.29	-6.28	0.69	-0.89	-1.82	1.63	-5.14
HPR2	-2.12	1.20	-0.86	1.15	-4.17	7.85	-4.09	1.26	-0.23	0.94	-0.37	-2.63	7.75	6.35	-1.92	0.22	1.93	-8.81
WAG1	-1.33	3.38	-2.82	-0.26	-5.10	4.95	1.91	-0.19	2.97	1.34	5.16	-2.58	10.07	-0.09	-0.20	1.83	-0.95	6.62
WAG2	-1.27	1.98	-1.39	0.54	-6.73	-1.02	0.38	0.27	2.85	1.26	3.89	-1.03	-3.56	-0.40	3.53	1.83	0.07	5.96
INS1	1.10	-1.33	1.42	-1.15	-1.67	1.06	0.29	-0.91	-1.25	-1.27	-2.02	1.53	-3.41	-0.33	-0.92	-1.46	2.33	-1.14
INS2	1.11	-1.29	1.27	-1.16	-0.05	0.98	0.97	-0.98	-1.39	-1.29	-1.62	1.29	-1.33	-0.75	-1.20	-1.43	0.83	-1.29
INT1	-1.26	1.45	-1.50	1.12	-1.49	-0.08	-1.11	1.28	1.61	1.33	1.59	-1.53	2.39	0.99	1.07	1.29	-0.69	3.23
INT2	-1.10	1.12	-1.26	1.33	1.18	-0.62	-1.51	1.35	1.10	1.30	0.93	-1.21	1.86	1.12	0.86	1.11	-0.22	0.97
UNE1	-1.52	1.21	-1.00	1.37	2.15	-1.05	-2.95	1.38	0.89	1.10	-0.50	-0.96	1.27	2.88	0.49	1.17	0.64	1.78
UNE2	-1.15	1.12	-1.56	1.49	11.89	-1.37	-2.00	2.28	0.36	1.12	1.15	-0.84	3.53	1.40	0.51	0.35	-0.30	-2.19
EMP1	-1.26	1.84	-1.56	0.84	1.97	-0.76	0.10	0.45	1.26	1.30	2.88	-1.44	-0.19	0.86	3.24	1.24	-3.12	1.55
EMP2	1.15	-1.23	1.24	-1.18	0.47	1.37	0.49	-0.98	-1.46	-1.26	-1.64	1.30	-1.44	-0.51	-1.24	-1.34	0.99	-1.58

Table 9: Macroeconomic mapping results (Part I). Note: The table shows t-ratios robust under heteroskedsaticity and autocorrelation. Acronym descriptions can be found in Table 1. An index 1, 2 refers to the first and second principal component obtained from the 19 countries under consideration within a particular category (consumption, exchange rates, etc).

	Softs			Livestock			Foreign Exchange			Bonds			Equity		
Macro Comp.	LEV	SLO	CUR	LEV	SLO	CUR	LEV	SLO	CUR	LEV	SLO	CUR	LEV	SLO	CUR
CONS	-1.61	1.22	2.16	1.52	-1.37	-1.00	-1.44	-2.39	1.46	0.41	0.79	1.14	1.40	0.73	-1.59
XRS1	-0.04	-1.05	1.33	-1.41	-6.31	1.69	-1.51	0.35	-0.89	0.78	-1.42	-1.16	-1.04	-0.86	1.27
XRS2	-9.27	0.50	-3.68	-0.24	9.36	-0.83	0.57	-9.15	-1.52	-2.17	1.26	0.49	-0.28	0.92	0.58
CPI1	-0.18	1.23	0.51	1.23	-3.03	-0.93	-1.20	1.42	1.27	-1.34	1.34	1.31	1.18	1.03	-1.13
CPI2	-1.38	1.23	-1.27	1.21	0.43	-1.22	-1.06	0.87	1.17	-1.36	1.29	1.26	1.23	1.06	-1.26
INP1	0.08	-1.32	1.54	-1.35	-2.57	1.53	-0.24	-0.45	-1.28	1.42	-1.55	-1.28	-1.15	-1.07	1.16
INP2	-0.40	-1.12	-0.01	-1.43	-1.54	1.65	2.50	-2.62	-1.50	1.26	-1.43	-1.18	-1.37	-1.48	1.37
TST1	0.46	-1.27	1.02	-1.31	-0.83	1.41	2.31	-1.02	-1.28	1.26	-1.11	-1.17	-1.38	-1.23	1.33
TST2	-1.88	1.33	-1.75	1.33	2.74	-1.54	-0.59	0.12	1.14	-1.18	1.28	1.25	1.26	1.08	-1.29
BCI1	0.75	-1.31	1.63	-1.29	-1.94	1.42	2.34	-1.89	-1.29	1.32	-1.21	-1.19	-1.34	-0.74	1.42
BCI2	1.42	-1.27	1.06	-1.25	-0.89	1.31	0.76	-0.67	-1.14	1.29	-1.24	-1.22	-1.21	-1.11	1.22
LEI1	-0.75	1.28	-1.58	1.27	1.02	-1.34	-1.97	1.58	1.22	-1.31	1.19	1.17	1.30	0.88	-1.35
LEI2	-1.49	1.61	-2.24	1.35	1.63	-1.67	-4.22	1.33	1.16	-1.16	0.88	1.12	1.59	0.46	-1.70
XVO1	-0.48	1.32	-0.90	1.18	1.50	-1.31	0.10	-0.10	1.17	-1.58	1.61	1.27	1.23	0.80	-1.13
XVO2	0.97	-1.31	1.41	-1.28	-0.22	1.29	1.10	-0.89	-1.17	1.26	-1.30	-1.25	-1.24	-1.09	1.27
PER1	1.80	-1.22	2.69	-1.30	-0.41	1.32	2.02	-0.57	-0.99	0.95	-0.83	-0.94	-1.29	-0.50	1.42
PER2	-1.92	1.31	-2.04	1.33	-0.14	-1.47	-2.93	0.97	1.26	-1.25	1.24	1.21	1.40	0.94	-1.51
DYD1	1.78	-0.95	1.76	-1.20	1.68	0.93	0.70	0.11	-0.86	0.67	-0.46	-0.70	-1.11	-0.10	1.37
DYD2	-0.21	1.20	-1.47	1.35	-0.06	-1.37	-1.03	0.66	1.25	-1.44	1.55	1.27	1.22	0.89	-1.31
MSP1	1.83	-1.33	1.32	-1.26	-0.85	1.24	1.35	-0.43	-1.06	1.37	-1.20	-1.26	-1.24	-0.91	1.26
MSP2	-1.40	1.27	-1.60	1.20	1.68	-1.23	-0.35	0.44	1.17	-1.34	1.17	1.18	1.16	1.03	-1.14
SVO1	0.24	-0.94	-0.53	-1.27	-0.36	1.11	-1.30	-0.44	-1.07	0.59	-1.12	-1.15	-0.82	-0.67	1.29
SVO2	0.66	1.23	-0.86	1.33	0.70	-1.39	-1.56	1.80	1.43	-1.14	1.38	1.26	1.29	1.31	-1.34
CON1	-1.89	1.32	-0.59	1.23	0.93	-1.11	0.58	1.04	1.14	-1.22	1.42	1.39	1.16	1.53	-1.08
CON2	1.75	-1.34	1.04	-1.11	0.48	1.07	0.98	-1.27	-1.07	1.50	-1.34	-1.27	-1.16	-1.07	1.09
TOT1	0.50	-1.31	2.87	-1.43	-4.62	1.97	0.50	-0.54	-1.30	0.96	-1.26	-1.04	-1.11	-1.15	1.32
TOT2	2.40	-0.72	2.88	-0.01	-6.92	0.55	3.77	1.13	0.31	2.70	-1.89	-0.88	-0.51	2.69	1.45
HPR1	2.73	1.32	0.03	1.40	1.91	-1.81	-4.58	4.16	1.67	-1.26	1.77	1.22	1.45	1.20	-1.50
HPR2	-4.65	-0.34	-3.34	-1.36	6.26	0.00	-1.08	-6.04	-1.62	-0.23	-1.90	-1.59	-1.29	-1.87	1.53
WAG1	2.90	-1.87	3.58	-0.87	6.54	0.90	7.63	1.18	-0.52	1.24	-0.28	-0.80	-1.68	-0.56	1.54
WAG2	2.69	-1.83	2.38	-0.95	1.00	1.01	2.37	-0.30	-0.79	2.06	-1.98	-1.71	-1.37	-1.05	1.07
INS1	1.13	1.36	-0.20	1.35	0.78	-1.39	-1.18	2.25	1.53	-1.28	1.39	1.16	1.21	1.54	-1.15
INS2	-0.84	1.25	-1.42	1.23	1.37	-1.31	-1.71	1.64	1.26	-1.38	1.29	1.24	1.24	0.89	-1.33
INT1	0.72	-1.17	1.56	-1.31	-0.73	1.46	3.00	-1.34	-1.16	1.31	-1.26	-1.21	-1.39	-0.74	1.55
INT2	0.92	-1.09	1.61	-1.27	-1.91	1.35	1.11	-0.79	-1.16	1.28	-1.31	-1.25	-1.22	-0.66	1.43
UNE1	2.22	-1.19	-0.07	-1.24	1.82	0.93	0.71	-1.03	-1.16	1.17	-1.19	-1.38	-1.21	-0.99	1.35
UNE2	6.37	-1.27	2.86	-1.23	-3.18	1.44	0.40	3.87	-0.50	1.19	-0.97	-1.18	-1.14	-0.18	1.25
EMP1	0.50	-1.58	1.48	-1.08	2.89	0.84	1.81	0.67	-1.07	1.63	-1.09	-1.18	-1.25	-0.91	1.02
EMP2	-0.88	1.27	-1.37	1.29	2.77	-1.49	-1.48	2.13	1.32	-1.24	1.26	1.22	1.30	1.17	-1.32

Table 10: Macroeconomic mapping results (Part II). Note: The table shows t-ratios robust under heteroskedasticity and autocorrelation. Acronym descriptions can be found in Table 1. An index 1, 2 refers to the first and second principal components, respectively, obtained from the 19 countries under consideration within a particular category (consumption, exchange rates, etc).

Product	Level				Slope				Curvature				Seasonality			
	GLO	MAR	SEC	IDI	GLO	MAR	SEC	IDI	GLO	MAR	SEC	IDI	SF1	SF2	SF3	SID
BRENT	0.28	12.77	5.65	2.73	20.97	0.87	25.58	4.29	5.05	10.89	6.65	4.29	0.00	0.00	0.00	0.00
WTI	1.97	2.12	9.94	0.10	7.80	0.49	23.77	1.07	8.82	12.23	30.63	1.07	0.00	0.00	0.00	0.00
GASOLINE	0.02	0.00	2.90	0.00	0.02	0.02	1.47	1.98	0.58	1.56	2.68	1.98	57.72	27.53	1.53	0.00
HEATINGOIL	0.24	1.06	65.62	2.16	0.20	1.39	15.59	3.17	0.26	5.59	1.55	3.17	0.00	0.00	0.00	0.00
GASOIL	3.89	0.09	58.24	0.26	3.26	0.52	9.91	0.38	7.95	13.58	1.55	0.38	0.00	0.00	0.00	0.00
NATURALGAS	0.01	0.03	3.20	0.00	0.00	0.01	0.17	0.54	0.03	0.00	1.25	0.54	17.91	0.29	0.22	75.79
COAL	17.79	3.19	40.65	0.24	4.85	2.10	21.45	0.45	0.10	0.03	8.70	0.45	0.00	0.00	0.00	0.00
CO2	0.16	1.24	58.98	14.74	0.04	0.05	4.74	8.95	0.01	1.94	0.22	8.95	0.00	0.00	0.00	0.00
GOLD	5.25	9.18	43.84	6.31	0.02	0.16	0.50	8.92	0.02	0.21	16.67	8.92	0.00	0.00	0.00	0.00
SILVER	0.29	1.06	13.14	10.95	0.01	0.63	12.20	5.50	0.47	1.33	48.93	5.50	0.00	0.00	0.00	0.00
COPPER	7.87	0.22	31.57	5.08	4.53	0.55	17.01	1.92	12.79	7.19	9.35	1.92	0.00	0.00	0.00	0.00
ALUMINUM	6.90	0.08	24.51	1.08	2.46	4.96	8.19	0.93	0.09	1.42	48.45	0.93	0.00	0.00	0.00	0.00
LEAD	4.10	2.72	24.33	1.99	0.20	6.39	23.68	0.12	2.93	7.47	25.95	0.12	0.00	0.00	0.00	0.00
NICKEL	4.83	3.79	26.21	0.75	0.18	7.16	4.41	0.21	2.67	11.37	38.19	0.21	0.00	0.00	0.00	0.00
ZINC	0.31	4.87	36.86	0.35	1.09	1.63	6.07	0.17	0.13	9.31	39.05	0.17	0.00	0.00	0.00	0.00
COTTON	0.00	0.01	0.13	0.01	0.00	0.05	0.04	1.09	0.49	0.52	2.69	1.09	10.62	2.85	18.29	62.12
WHEAT	0.67	0.11	0.41	0.63	0.03	0.43	15.38	0.86	13.23	3.03	64.35	0.86	0.00	0.00	0.00	0.00
CORN	0.01	0.08	0.08	0.08	0.01	0.18	3.45	3.22	1.61	0.25	13.45	3.22	0.64	51.48	22.25	0.00
SOYBEAN	0.01	0.37	1.20	0.70	0.00	0.09	1.59	1.37	1.11	0.79	2.16	1.37	19.35	1.98	3.11	64.78
SUGAR	0.02	0.35	0.74	0.06	0.00	1.18	5.36	4.71	0.56	0.65	20.46	4.71	14.16	45.84	1.18	0.00
ORANJE	0.11	7.88	12.36	2.27	0.09	1.43	49.89	8.17	1.55	5.62	2.46	8.17	0.00	0.00	0.00	0.00
COCOA	0.40	36.13	24.26	0.91	0.00	0.13	2.54	4.10	0.85	0.07	26.49	4.10	0.00	0.00	0.00	0.00
COFFEE	0.42	1.08	6.98	1.36	0.13	8.95	11.82	2.87	7.57	22.70	33.25	2.87	0.00	0.00	0.00	0.00
ETHANOL	0.11	0.04	0.00	0.02	0.10	0.01	3.92	9.03	0.03	0.73	7.57	9.03	9.60	48.26	11.56	0.00
LUMBER	0.04	0.10	2.46	10.11	0.00	0.29	13.45	11.70	9.49	2.95	37.69	11.70	0.00	0.00	0.00	0.00
LIVECATTLE	0.00	0.00	0.00	0.00	0.00	0.00	0.68	0.27	0.00	0.00	2.80	0.27	1.17	1.12	0.48	93.21
LEANHOGS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.41	0.00	0.00	0.23	0.41	0.47	0.00	0.04	98.44
FEEDERCATTLE	0.01	0.01	0.11	0.00	0.02	0.01	0.75	0.19	0.03	0.04	5.10	0.19	5.24	1.36	0.00	86.96
USDEUR	0.10	1.65	3.52	0.08	4.32	10.52	0.98	0.14	17.81	7.73	53.04	0.14	0.00	0.00	0.00	0.00
ZARGBP	1.67	2.75	25.90	8.28	0.10	0.01	1.75	12.88	0.15	11.47	22.14	12.88	0.00	0.00	0.00	0.00
GBPEUR	3.70	8.02	3.09	0.07	0.31	7.08	2.15	0.02	2.18	4.46	68.90	0.02	0.00	0.00	0.00	0.00
ZARUSD	2.26	3.24	9.74	0.15	0.18	0.62	3.95	0.09	0.16	52.02	27.51	0.09	0.00	0.00	0.00	0.00
JPYUSD	33.15	48.27	6.12	0.57	0.01	0.02	0.94	0.00	0.01	0.04	10.86	0.00	0.00	0.00	0.00	0.00
RENUSD	0.76	4.08	6.89	0.49	0.48	14.28	16.89	0.31	4.73	23.83	26.96	0.31	0.00	0.00	0.00	0.00
USINTR	0.04	0.38	1.69	17.84	0.04	0.19	0.05	21.61	0.31	36.24	0.00	21.61	0.00	0.00	0.00	0.00
EUINTR	2.54	1.07	5.71	10.35	3.94	8.78	2.02	11.27	18.11	21.13	3.80	11.27	0.00	0.00	0.00	0.00
SAINTR	1.78	0.99	10.95	18.34	3.38	6.93	6.69	12.12	8.50	1.94	16.26	12.12	0.00	0.00	0.00	0.00
UKINTR	0.00	0.07	0.02	0.00	0.18	2.92	3.05	6.99	0.19	73.99	5.60	6.99	0.00	0.00	0.00	0.00
JPINTR	0.27	5.09	5.20	0.02	0.90	0.00	8.66	0.02	6.06	43.21	30.55	0.02	0.00	0.00	0.00	0.00
CHINTR	0.15	0.08	0.20	29.82	0.06	2.24	0.02	29.01	0.97	8.32	0.12	29.01	0.00	0.00	0.00	0.00
SP500TSX60	0.71	4.70	81.00	0.60	0.00	0.09	3.21	0.02	0.02	0.45	9.19	0.02	0.00	0.00	0.00	0.00
FTSE100	0.09	0.62	11.51	0.77	0.01	0.00	20.87	0.37	0.03	0.80	64.55	0.37	0.00	0.00	0.00	0.00

Table 11: Percentage variance explained by global, market, sector and idiosyncratic components.

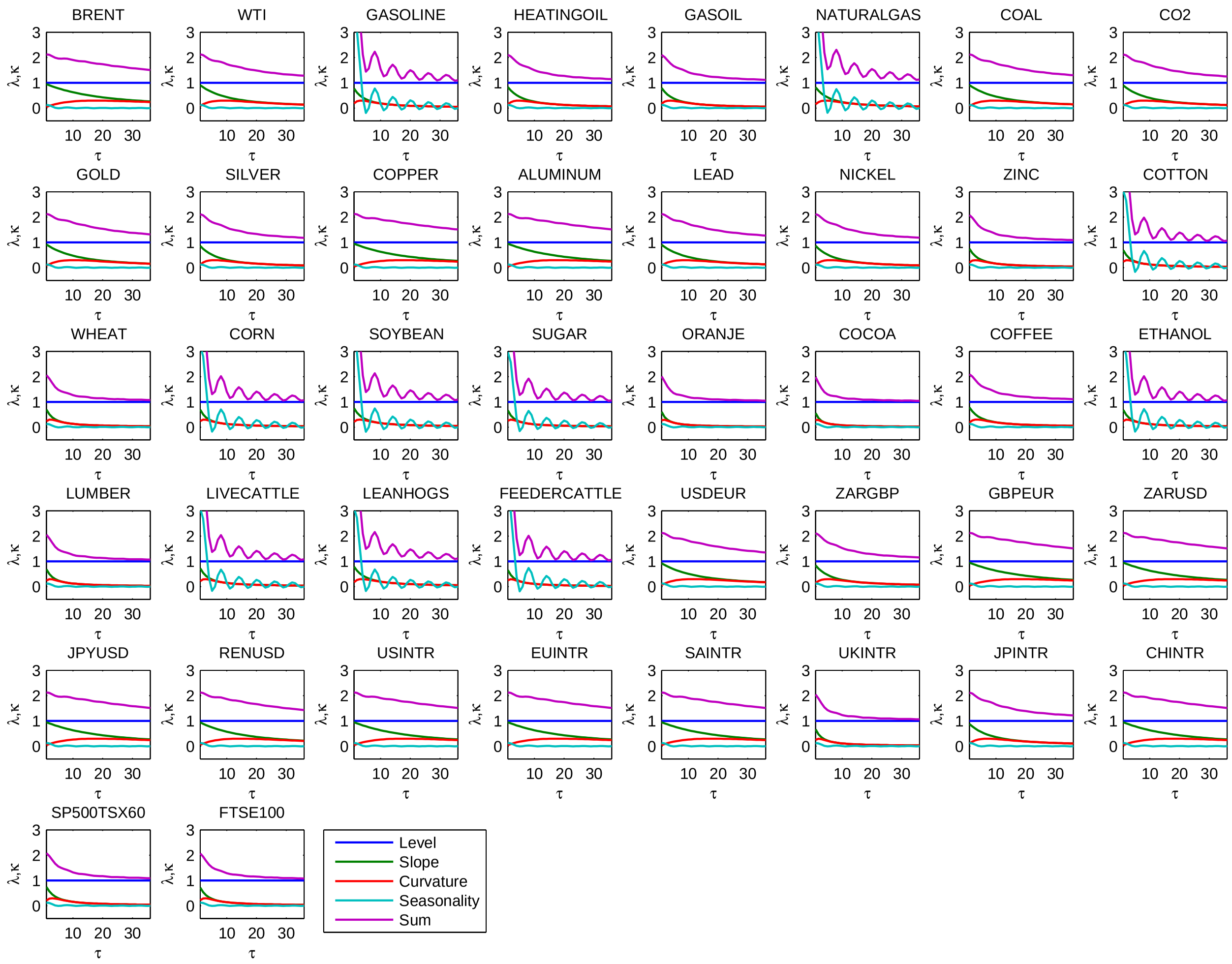

Figure 1: Estimated base load functions per product.

Figure 2: Model-based term structures over time.

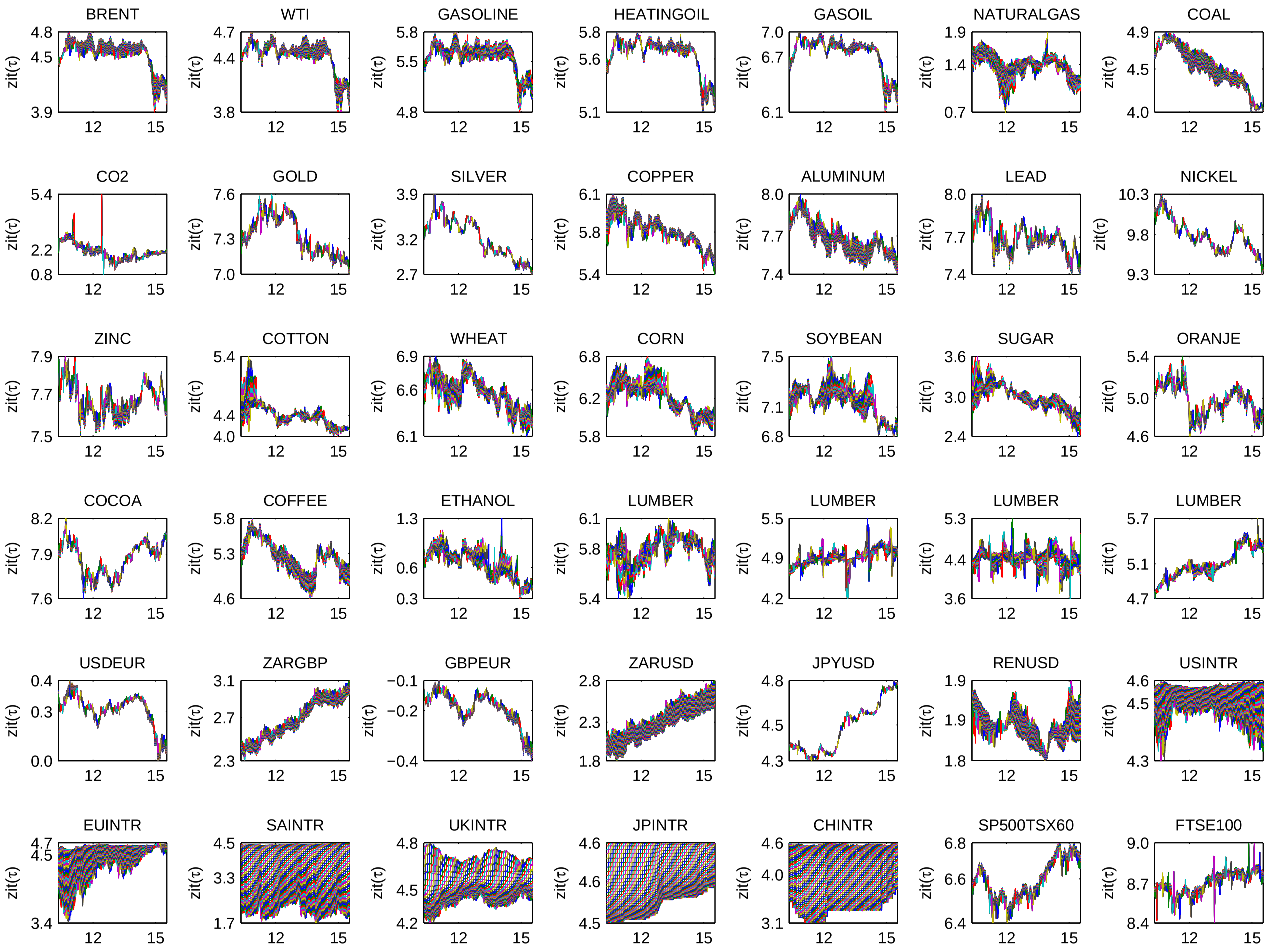

Figure 3: Selected model-based term structures over time and forward month.

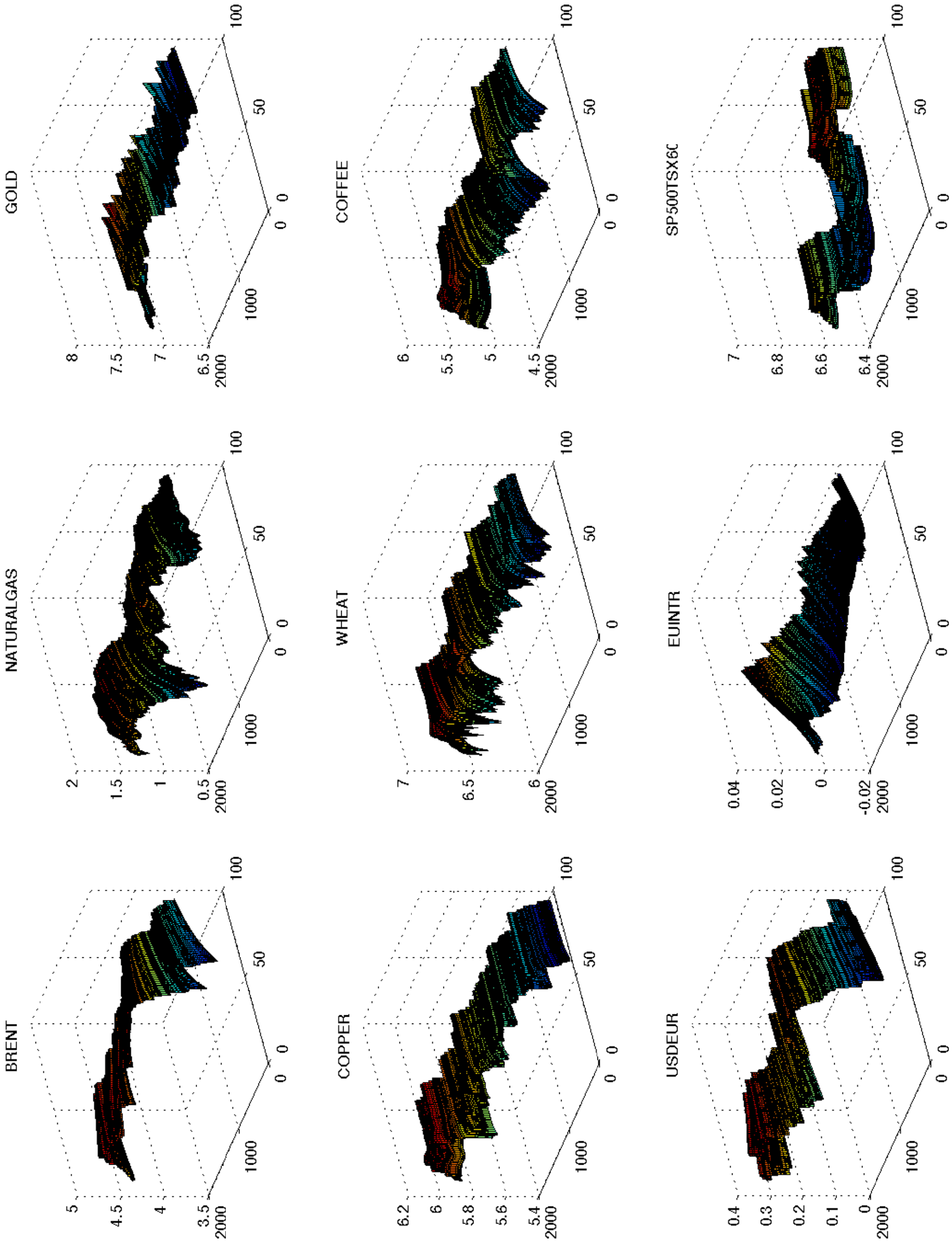

Figure 4: Selected model-based volatility term structures over time and forward month.

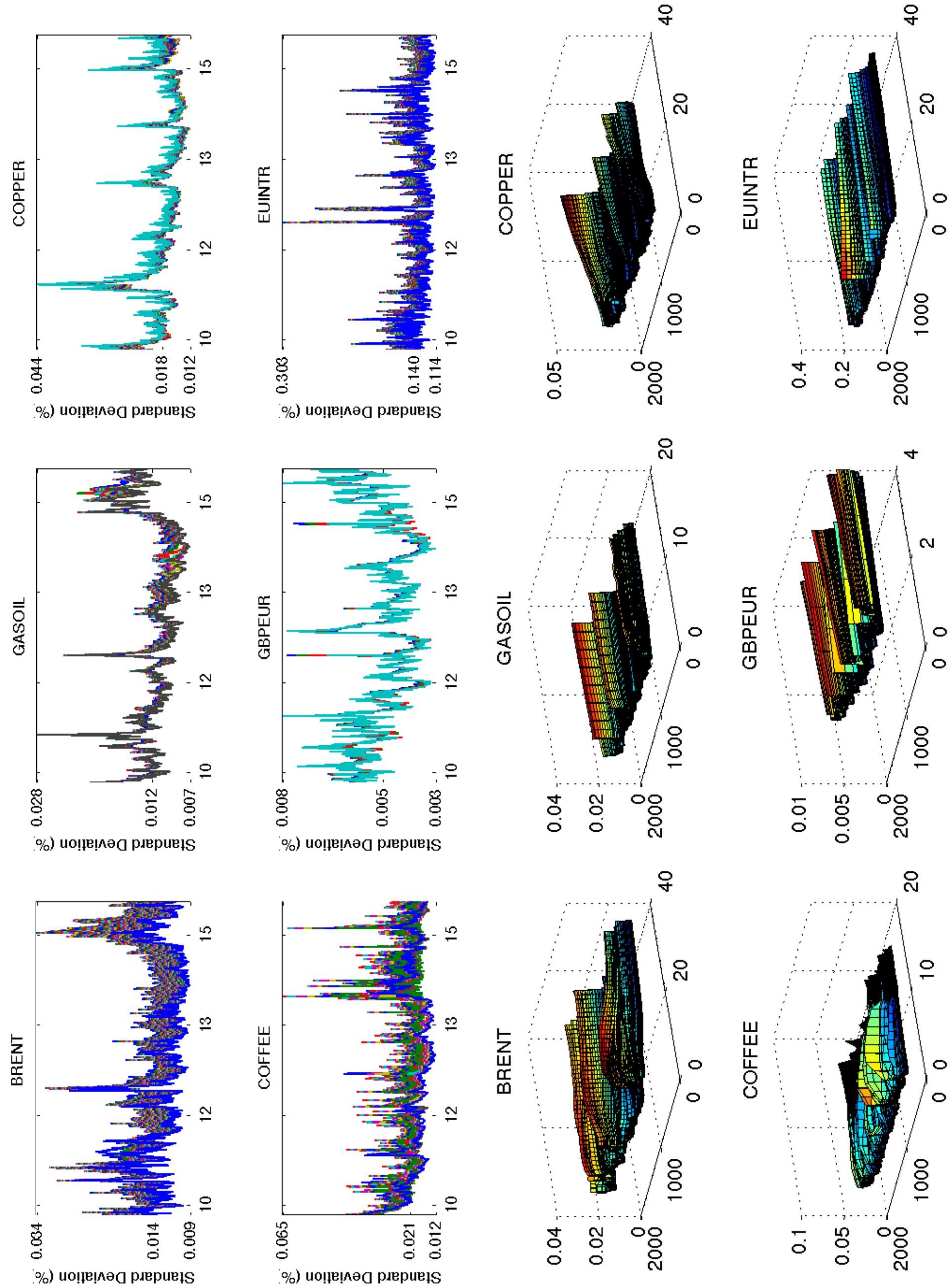

Figure 5: Estimated λ_{it}'s per product.

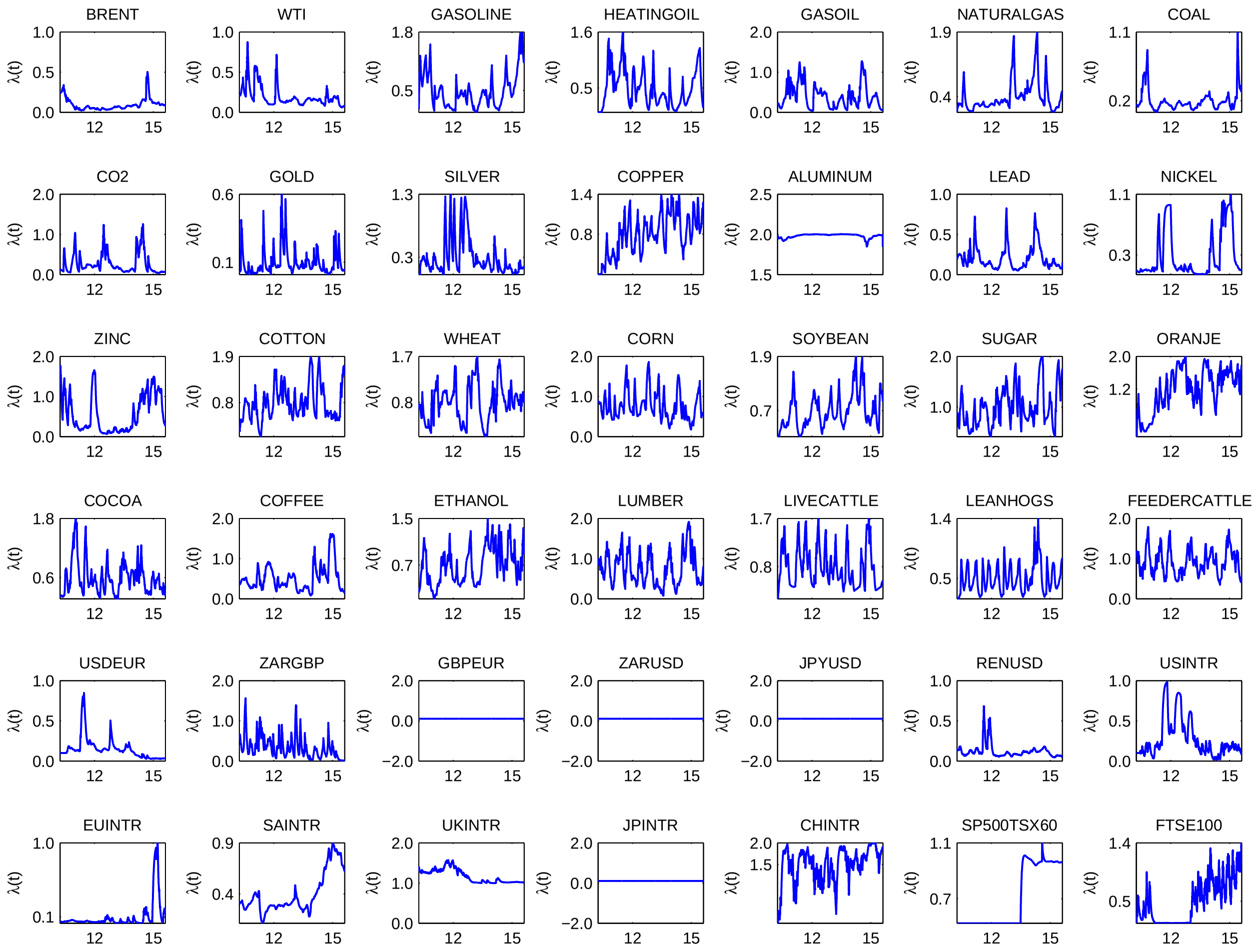

Figure 6: Selected estimated κ_{it}'s per product.

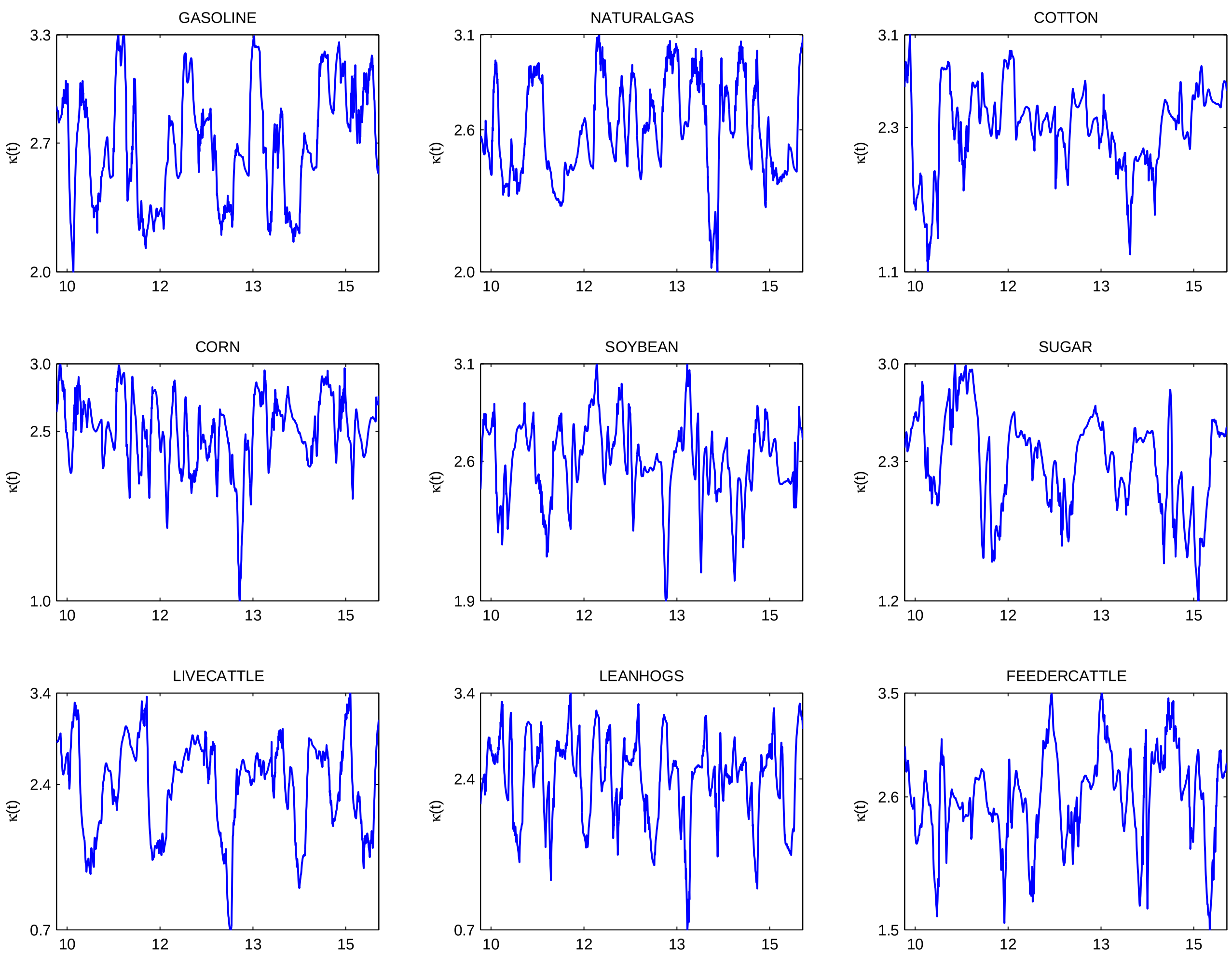

Figure 7: Selected examples of BAV factor estimates

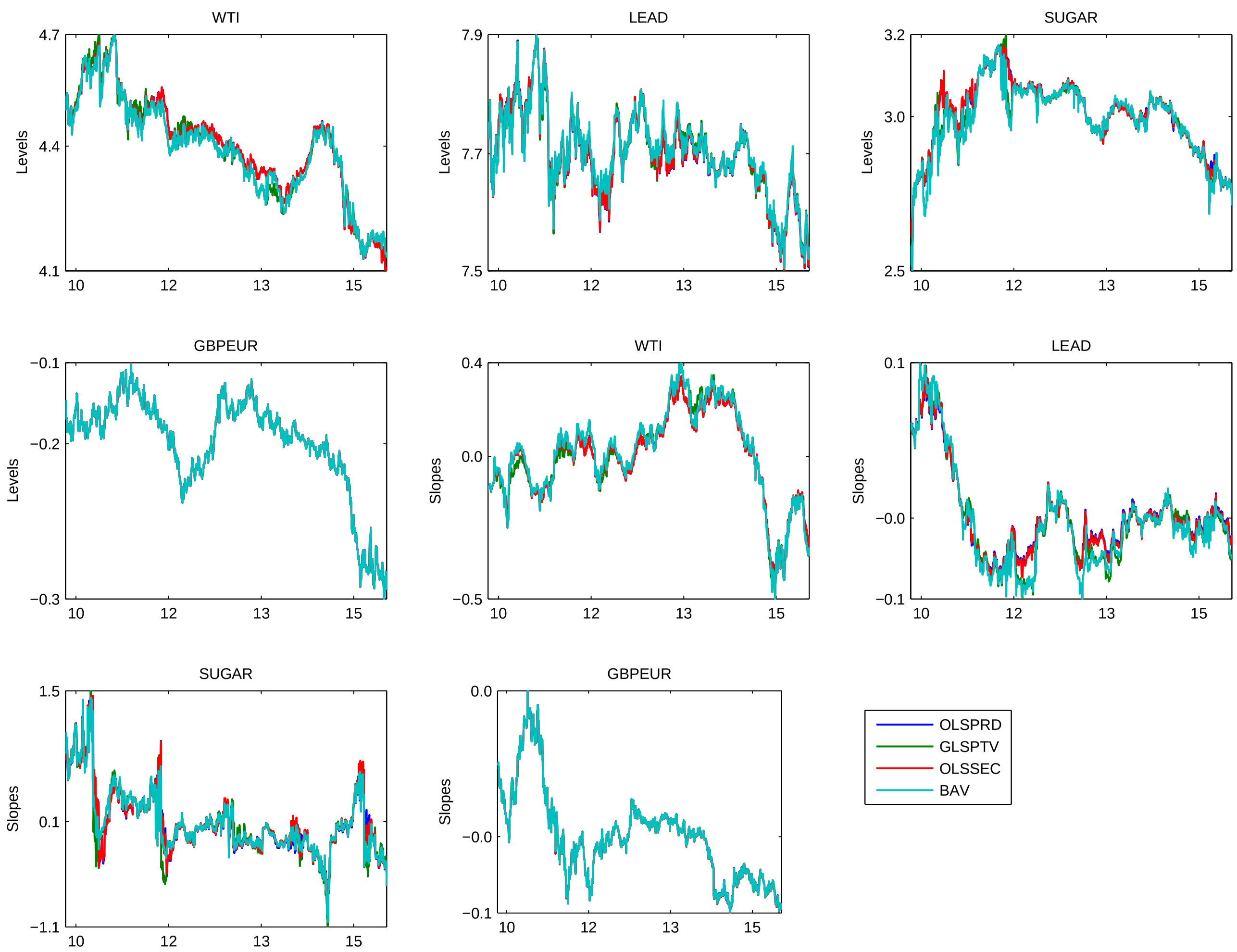

Figure 8: Estimated Global, Market and Sector components.

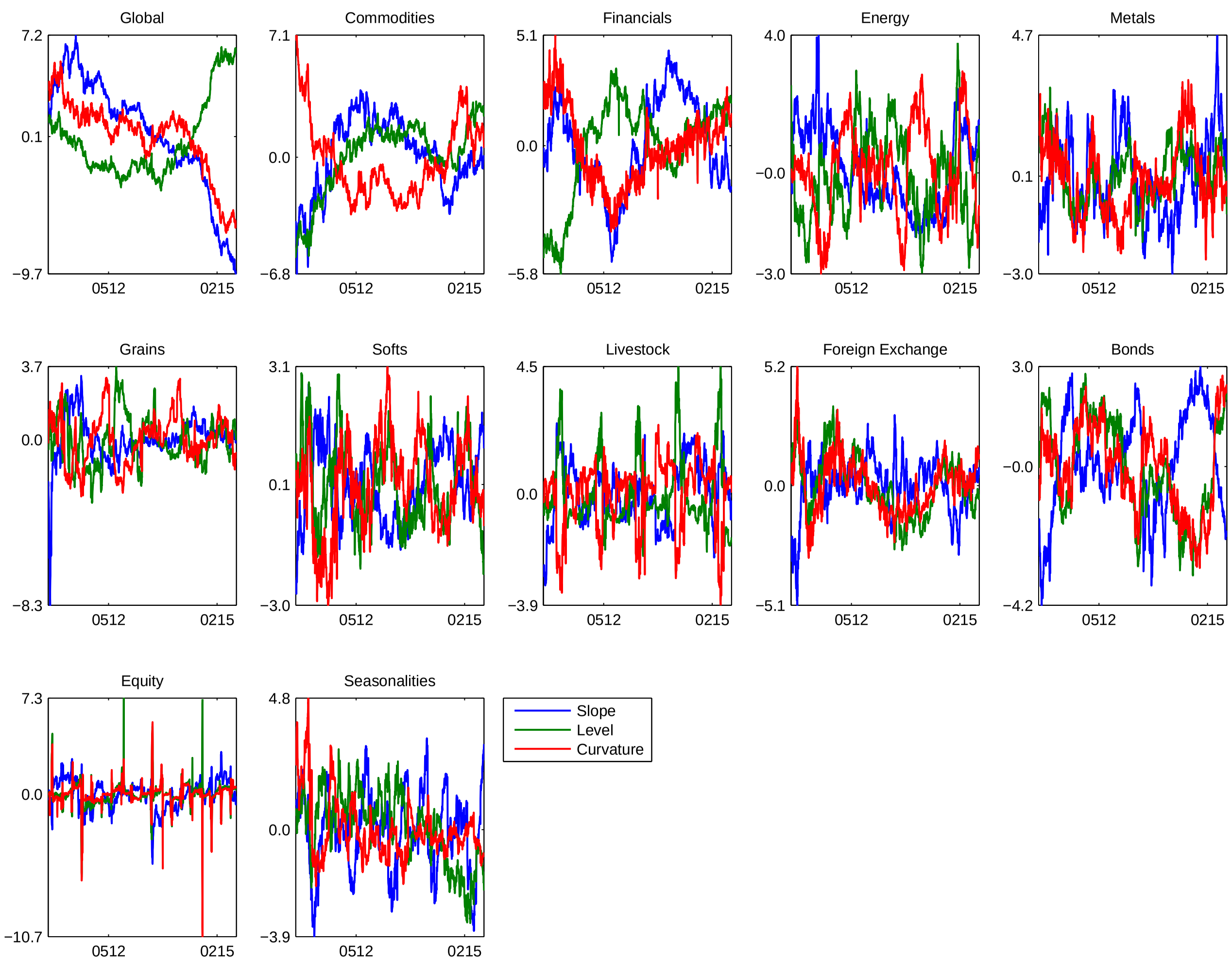

Figure 9: Variance decompositions per product over month.

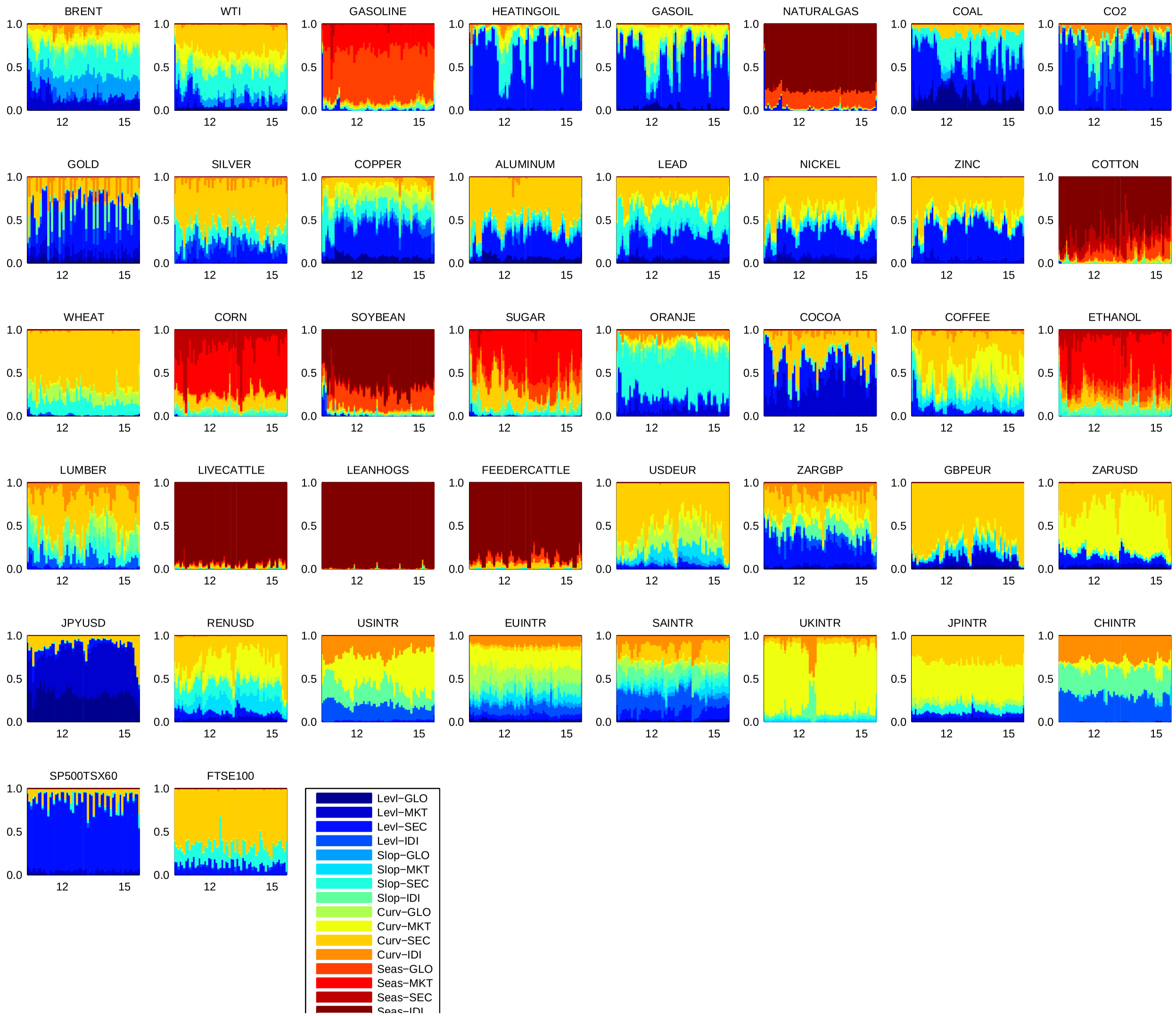

Figure 10: Out-of-sample forecasting results (statistical measures).

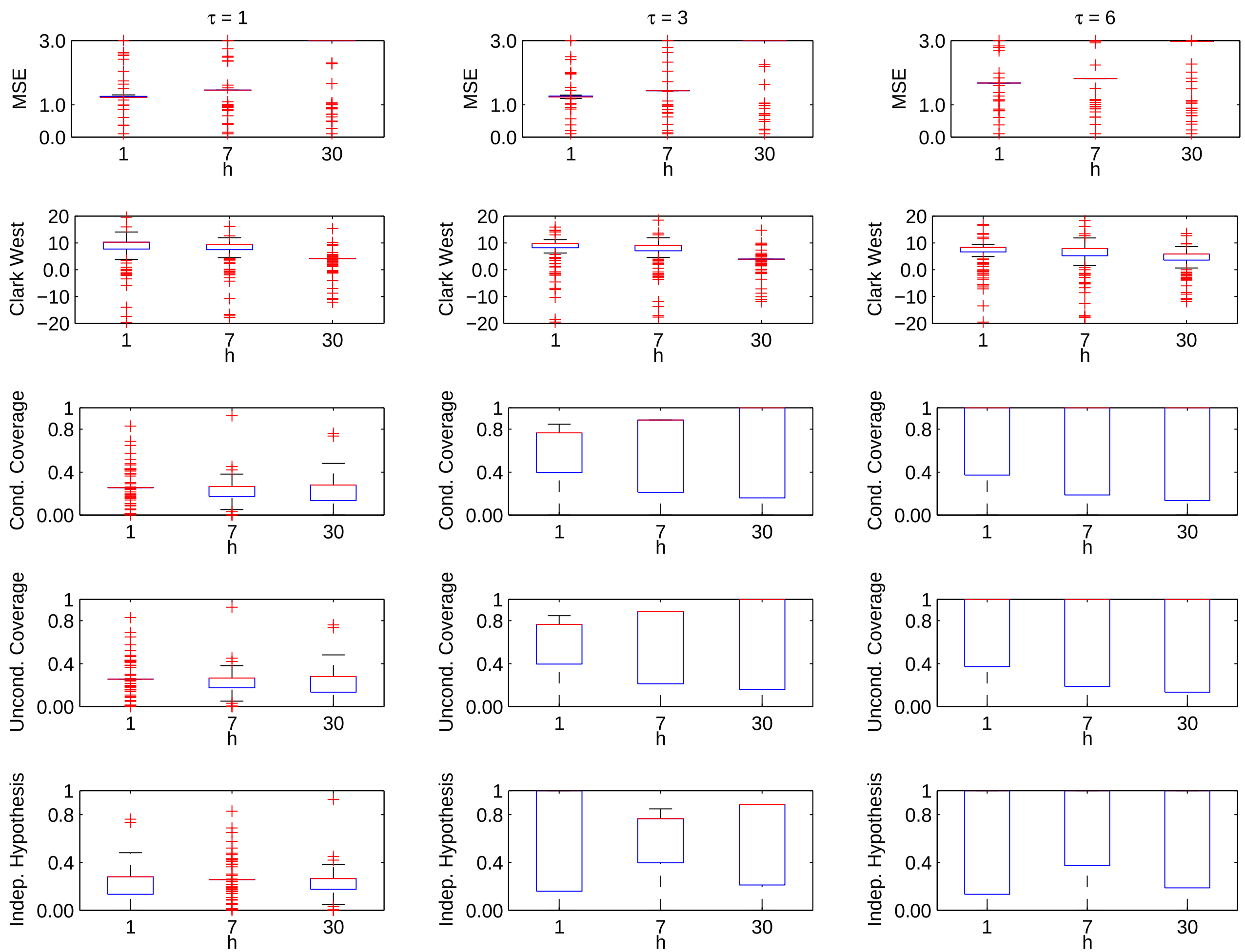

Figure 11: Out-of-sample forecasting results (economic measures).