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Research Article

Do commodity prices matter for global systemic risk? Evidence from ML variable selection

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A B S T R A C T

We identify robust predictors of global systemic risk proxied by conditional capital shortfall (SRISK) among a comprehensive set of commodity prices for the period between January 2004 and December 2021. The search is based on a battery of ML variable selection algorithms which apply both to price levels and price shocks in the presence of control variables, including the first lag of SRISK, world industrial production, global economic policy uncertainty, geopolitical risk as well as the global stance of monetary and macroprudential policies. We find that these controls outweigh commodity prices as the predictors of global systemic risk. Of the commodities themselves, the prices for agricultural commodities, including food, e.g. chicken, bananas, beef, tea, cocoa, are more important predictors of global systemic risk than the prices for energy commodities, e.g. natural gas and oil prices. The financialization of agricultural commodities, bio-energy expansion as well as commodity-specific dependence of the major economies contributing to global systemic risk, e.g. China, account for our main finding. We also document the positive linkage between commodity prices and systemic risk for the majority of commodities. Thus, monitoring commodity prices to avoid their unbalanced growth is of vast importance to curb global systemic financial risk.

1. Introduction

The build-up of systemic risk is recognized as a precursor of financial crises (Freixas et al., 2015). Hence, identifying the drivers of systemic risk is crucial to safeguard financial stability. The majority of studies seek to pinpoint these drivers among the indicators capturing size, leverage, solvency and other firm-level characteristics of financial institutions (Laeven et al., 2016). A number of innovative researches zoom in on the institutional and cultural factors of systemic risk, e.g. Apergis et al. (2021), Andries and Balutel (2022).

Despite the ongoing search for the robust drivers of systemic financial risk, some variables, albeit perfectly tractable, remain largely overlooked. In particular, there is a scarce literature studying the impact of commodity prices on systemic risk. It comes as a surprise since the existing studies document non-negligible effects of commodity prices on the financial sector, for example, via the share of non-performing loans, bank costs and profits (Kinda et al., 2018). Moreover, negative commodity price shocks are found conducive to banking and currency crises (Eberhardt and Presbitero, 2021; Bodart and Carpantier, 2023). Importantly, recent studies document that the adverse impact of commodity price shocks on the financial sector is not only confined to resource-dependent emerging market economies (EMEs), but also affects high income countries, including G7, e.g. Tiwari et al. (2021). Overall, these effects of commodity

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prices largely stemming from the financialization of commodity markets have implications both for real and financial conditions worldwide (Reinhart et al., 2016; Fernández et al., 2020; Maghyereh and Ziadat, 2023). Thus, fluctuations in commodity prices may now matter for global financial stability. Against this backdrop, it is worth investigating how commodity prices affect worldwide systemic risk, a proxy of global financial (in-)stability.

In this study, we seek to tackle this research gap by identifying the commodities whose prices drive conditional capital shortfall, SRISK, a widely used systemic risk measure introduced by Brownlees and Engle (2017). The analysis spans the period between January 2004 and December 2021, building on a battery of machine learning (ML) variable selection algorithms: adaptive least absolute shrinkage and selection operator (LASSO), second generation p-values (SGPV), one-covariate-at-a-time multiple testing (OCMT), spike-and-slab regression and Bayesian structural time series (BSTS). These techniques are best suited for the time series setting, enabling to dissect statistically significant predictors out of 55 commodity price series retrieved from the World Bank commodity price database ("Pink Sheet") with up to 3 lags. Besides the comprehensive coverage of commodities, the ML variable selection is performed, conditional on a number of controls: a lagged value of SRISK to account for autocorrelation, world industrial production index (Baumeister and Hamilton, 2019), economic policy uncertainty index (Baker et al., 2016), global geopolitical risk (Caldara and Iacoviello, 2022), global macroprudential policy index based on Alam et al. (2019) and global monetary policy tracker maintained by the US Council on Foreign Relations. In addition to the levels of commodity prices, we conduct the variable selection with respect to the price shocks derived from the raw series using two approaches adopted in the literature. According to the first of them, price shocks are merely associated with logarithmic changes in price (Arezki and Brückner, 2012). Based on the second approach, price shocks emerge as the estimated residuals of the logarithm of commodity price regressed on the time trend (if any) and the lagged values of the price (Kinda et al., 2018). Besides, we extend the set of price shock series obtained via both methods by adding structural oil demand and structural oil supply shocks by Baumeister and Hamilton (2019). We determine the relevance of commodity prices as predictors of global systemic risk by aggregating the results of the ML variable selection for price levels and the two types of price shocks.

Our analysis reveals that in comparison with the controls, i.e. economic policy uncertainty, global geopolitical risk, world industrial production as well as the indices accounting for the worldwide intensity of macroprudential and monetary policy measures, commodity prices are less significant drivers of global systemic risk. Zooming in on the effect of commodity prices, we find that the role of agricultural commodities and fertilizers tends to outperform that of energy commodities. Namely, by aggregating the significant predictors across all the three lags, we document that the prices for chicken, beef, cocoa, tea and bananas matter for the dynamics of global systemic risk more than the prices for natural gas and crude oil. Alongside the agricultural commodities, the price for phosphate rock, a fertilizer, appears quite important. Conversely, oil prices and/or oil price shocks are not on the forefront: although the first lags of crude oil prices, WTI and Brent, belong in the top-20 predictors, the salience of oil prices considerably shrinks with the second and, especially, with the third lag. In contrast, the more distant lags of the key agricultural commodities and fertilizers are more successful in surviving this variable selection exercise. Similar to oil prices, the relevance of metals is limited, dramatically fading away with more distant lags. Based on the first lag, gold appears among the top-10 predictors of global systemic risk, whereas in the aggregate ranking accounting for all the lags, this precious metal hardly penetrates the top-30 list. Thus, we come up with a somewhat unexpected ranking of commodities in terms of their impact on global systemic risk, with energy commodities and metals lagging behind. Nonetheless, this finding remains robust when we further carry out such ML variable selection for the countries mostly contributing to global systemic risk, i.e. China, the USA, Japan, the UK and France.

As for the direction of impact exerted by most commodity prices on systemic risk, it appears mostly positive. Thus, increasing commodity prices tend to exacerbate systemic financial risk. At the same time, there are still commodities whose increasing prices tend to indicate a forthcoming decline in global systemic risk, e.g. gold, silver, zinc, lead, iron ore, thereby offering hedging opportunities for investors in terms of financial instability.

Regarding the controls, in line with intuition, surges in economic policy uncertainty and global geopolitical risk aggravate worldwide systemic risk. In fact, so do the increasing world industrial production and the indices of macroprudential and monetary policy, which appears a counter-intuitive result. However, the latter can merely capture the procyclical changes in systemic risk with respect to the mentioned variables, since in this study we are able to consider only up to three lags, while the dampening effect of rising real economic activity, tighter macroprudential and monetary policies on global systemic risk can be shaped by more distant lags.

Overall, the contribution of our study is three-fold. First, it extends the literature on the predictors of systemic risk by focusing on the global scale. Second, our research sheds light on the role of commodity prices/price shocks as relatively overlooked predictors of systemic risk. Moreover, our paper is distinctive, as it builds on a comprehensive set of commodities rather than focusing on oil and gold which are commonly studied in the context of global financial (in-)stability. Finally, we make an important methodological innovation by testing for the predictive potential of commodity prices in a very rich dataset and by means of a battery of ML variable selection techniques. Our findings are relevant for policy makers in international financial organizations as well as national regulators seeking to identify the factors impacting global financial (in-)stability. They can also be of interest from the perspective of investigating risk spillovers from commodity markets to financial institutions and markets.

The remainder of the paper is as follows. Section 2 presents a brief review of the literature on the relationships between commodity prices and systemic risk. Section 3 describes the data, Section 4 introduces the methodology. Section 5 discusses the results, while Section 6 concludes.

2. Commodity prices and systemic risk: a brief literature review

There are several strands of literature linking commodity prices and systemic risk.

The first of them has much in common with the conventional estimation of systemic risk contribution at the firm level, though instead of banks and insurance companies it is measured for major companies from the resource sector. Caporin et al. (2023) examine the contribution of US oil and gas companies to systemic financial risk during the period 2000–2020 and find that it has notably increased since the year 2010. Chuliá et al. (2023) identify the originators and transmitters of systemic risk among energy firms from emerging market economies (EMEs). Building on a vast sample of renewable and non-renewable resource companies from advanced economies and EMEs during 1981–2017, Irawan and Okimoto (2022) argue that their systemic risk based on the conditional capital shortfall/surplus appears significantly lower in the post-2000 period due to the boom of commodity sector stocks and improved capital structure management of such companies.

The second strand of scholarly works assesses systemic risk for standalone commodity markets as well as its cross-market spillovers. For example, Yang and Hamori (2021) study the systemic risk of the crude oil market and find that it is fueled by global economic policy uncertainty. Anwer et al. (2022) and Ouyang et al. (2022a) concur in that energy commodities tend to exhibit higher systemic importance compared to non-energy commodities. Morelli (2023) confirms the paramount role of energy commodities, in particular, crude oil, but also highlights the systemic importance of some metals, e.g. nickel and zinc. Zhang et al. (2022) construct a network of commodity markets accounting for systemic risk spillovers and find that oil is a central node under both bearish and bullish price regimes, while some agricultural commodities, e.g. sugar and soybean, are also notable transmitters of risk.

The third strand of literature is closer to our research, encompassing the studies which examine the impact of commodity prices on systemic risk in the financial sector. Most of such research focuses on oil prices. For instance, Yin et al. (2021) document that oil prices matter for conditional value-at-risk (CoVaR) of major stock markets. They conclude that this systemic risk measure is driven by oil prices in case of the G7 stock markets. In a similar vein, Tiwari et al. (2021) find that oil prices spill over to the systemic risk of G7 stock markets proxied by CoVaR and marginal expected shortfall (MES) measures. The spillover effects are particularly strong for Canada. Maghyereh and Abdoh (2021) find that the CoVaR and MES measures of banks in the oil-rich economies are driven by oil supply shocks. This effect appears especially pronounced during the Global Financial Crisis and the COVID-19 pandemic. Maghyereh et al. (2022) confirm that oil supply shocks remain significant drivers of bank systemic risk in the oil-rich economies if bank business models, size, leverage, income diversification and profitability are taken into account. Ouyang et al. (2022b) find that the effect of oil shocks is asymmetric, i.e. the impact of negative price shocks is greater than that of positive shocks. Moreover, the significance of oil supply and oil demand shocks is conditional on systemic risk conditions, i.e. oil supply shocks prevail when systemic risk is medium or low, whereas under high risk conditions only oil demand shocks appear significant. Apart from oil prices, Chiu and Ratner (2014) examine the relationship between gold prices and bank systemic risk in 21 countries, concluding that gold possesses certain safe haven characteristics in terms of financial instability.

Nonetheless, as far as we know, there are no studies that would involve a more comprehensive set of commodity prices and examine their effects on the worldwide systemic risk, which constitutes a major research gap.

3. Data

In contrast to most studies surveyed in Section 2 and building on the CoVaR and MES measures of systemic risk, we opt for conditional capital shortfall, SRISK, proposed by Brownlees and Engle (2017). This measure accounts for a financial entity's size, leverage and expected equity loss arising from a severe stock market decline. SRISK can be represented as follows:

$$SRISK_{it} = kD_{it} - (1-k)W_{it}(1 - LRMES_{it}) \tag{1}$$

where W_{it} is the market value of equity, D_{it} - the book value of debt, k - the prudential capital adequacy ratio. $LRMES_{it}$, long-run marginal expected shortfall, measures the sensitivity of the financial institution's equity value to the severe market decline.[1] Positive SRISK values can be aggregated across financial institutions into a nationwide measure. The SRISK data come from the New York Stern University Volatility Lab (https://vlab.stern.nyu.edu). Unlike the CoVaR and MES measures which build only on market data, SRISK synthesizes market and balance sheet data. Besides, as empirical horse races reveal, SRISK fares quite well against competing measures (Brownlees et al., 2020; Dissem and Lobez, 2020; Banulescu-Radu et al., 2021). The SRISK series is for the period between January 2004 and December 2021.

Commodity prices are retrieved from the World Bank commodity price database (“Pink Sheet”). After removing the series with missing data and those with indices rather than with raw prices, we come up with 55 variables. They cover prices for all commodity categories: energy, agriculture, fertilizers, metals and minerals, precious metals. To overcome the endogeneity issue, we consider the lagged values of commodity prices. Since we assume that information transmission from commodity to financial markets can occur fast enough, the maximum leg length is set to three months in our estimations.

Besides the commodity prices in levels, we also consider price shocks derived in two ways. In line with Kinda et al. (2018), the first approach assumes that a price shock is merely a logarithmic price change from month to month, while, according to the second approach, price shocks are obtained as the residuals of the logarithm of commodity price regressed on the time trend (if any) and the lagged values of this price (up to three lags). In addition to the computed price shocks, our dataset includes structural oil demand and oil supply shocks denoted as OIL DEMAND and OIL SUPPLY, provided by Baumeister and Hamilton (2019) since the origin of oil shocks may matter.

Alongside the commodity prices and their shocks, we include a number of control variables which can influence systemic risk. Global real economic activity is proxied by world industrial production index, WIP (Baumeister and Hamilton, 2019). We exploit global

[1] In line with Brownlees and Engle (2017), k is set to 8%, while the severe market decline implies a 40-percent semiannual shrinkage in global stock market indices, e.g. the MSCI world index.

geopolitical risk, GPR (Caldara and Iacoviello, 2022), and economic policy uncertainty index, GEPU (Baker et al., 2016), to gauge an adverse economic agents' sentiment. The effects of macroprudential and monetary policies are captured by global macroprudential policy index, IMAPP, based on Alam et al. (2019) and global monetary policy tracker, MP_TRACKER, maintained by the US Council on Foreign Relations. Also, based on the autocorrelation function, we include the first lag of SRISK into the set of control variables.

The variable definition and their descriptive statistics are provided in Tables A1 and A2 of the Appendix.

4. Methodology

Our dataset consists of a large number of independent variables. Thus, conventional approaches to variable selection, e.g. stepwise inclusion or deletion of regressors are not computationally efficient, resulting in uncertainty about the best model. To mitigate the problem, we employ state-of-the-art algorithms from machine learning (ML): adaptive least absolute shrinkage and selection operator (LASSO), second generation p-values (SGPV), one-covariate-at-a-time multiple testing (OCMT), spike-and-slab regression and Bayesian structural time series (BSTS).These techniques are well-suited for variable selection in a data-rich time series setting like ours. Below we briefly review the essence and some technicalities related to these algorithms.

4.1. Adaptive LASSO

The conventional LASSO regression (Zou, 2006) uses the modified OLS loss function by adding a penalty term, which contains absolute values of the coefficients multiplied by a constant. Thus, when minimizing the loss function, LASSO penalizes the coefficients, which have large positive or negative values. Such large numbers of parameters are considered by the model as improbable and are shrunk to zero. Adaptive LASSO extends the conventional approach by applying adaptive weights, which are used instead of a constant in the penalty term:

$$\widehat{\theta}_{alasso}(\lambda) = \arg\min\left\{ -\mathrm{L}(\theta) + \lambda\sum_{d=1}^{p+q}\tau_d\left|\theta_d\right| \right. \tag{2}$$

where $\tau = (\tau_1, \tau_2, \ldots, \tau_{p+q})$ are adaptive weights, which can be set to $1/|\widehat{\theta}|$, where $\widehat{\theta}$ are consistent estimators to θ, e.g. OLS-estimators $\widehat{\theta}_{OLS}$ or maximum likelihood estimators $\widehat{\theta}_{MLS}$. When $\tau_i = 1$ for every i, this transforms adaptive LASSO penalty into a conventional LASSO term. λ represents a tuning parameter for the penalty term and is chosen by minimizing BIC criterion.

In our particular case, the model to which we apply the OCMT and adaptive LASSO algorithms is specified as follows:

$$y_{it} = \alpha + \sum_{p=1}^{3}\beta_i y_{i,t-p} + \sum_{i=1}^{k}\gamma x_{i,t-1} + \varepsilon_{i,t} \tag{3}$$

where y_t stands for the SRISK index, y_{t-1} – lagged values of commodities' prices and control variables; ε_t is an error term.

4.2. Second generation p-values

Penalized regression with second generation p-values (ProSGPV) is a novel variable selection approach which possesses good predictive properties and performs well even in case of strong collinearity among features (Zuo et al., 2021). The idea of the method is to determine variable importance based on the magnitude of their effect on the dependent variable: regressors with small effects are ruled out, while the variables with effects exceeding a certain threshold, namely δ, remain in the equation for further testing.

Let θ be the parameter of interest and let $I = (\theta_l, \theta_u)$ be an interval estimate of θ, whose length is equal to $|I| = \theta_u - \theta_l$.Let us define $H_0 = (-\delta, \delta)$ as a pre-specified interval null, which would serve a buffer region between "null" and "non-null" effects.

If we denote the length of the interval null by $|H_0|$, then the SGPV p_δ is calculated in a following way:

$$p_\delta = \frac{|I \cap H_0|}{|I|} \times \max\left\{\frac{|I|}{2|H_0|}, 1\right\} \tag{4}$$

where $I \cap H_0$ is the intersection of two intervals. When the interval estimate is very wide, i.e., when $|I| > 2|H_0|$, the correction term, equal to $\max\left\{\frac{|I|}{2|H_0|}, 1\right\}$, applies. In case $p_\delta = 1$, the data is compatible with null hypothesis, while when $p_\delta = 0$ - the data is compatible with the alternative hypothesis. When $0 < p_\delta < 1$, the data is inconclusive.

ProSGPV is a two-stage selection algorithm. In the first stage, it standardizes the input variables, fits a LASSO regression and then, additionally, fits an OLS model on the set of variables, selected by LASSO. In the second stage, ProSGPV extracts confidence intervals for the variables included in the OLS model, calculates the mean coefficient standard error and keeps only the variables with the effects larger than a certain threshold. That is, coefficients are estimated in the following way:

$$\widehat{\beta}_{\mathrm{pro}} = \beta^{\mathrm{OLS}}_{|S} \in R^p, \text{ where}$$

$$S = \left\{k \in C : |\widehat{\beta}_k^{\text{OLS}} > \lambda_k\right\}, C = \left\{j \in \{1, 2, \ldots, p\} : |\widehat{\beta}_j^{\text{lasso}} > 0\right\} \tag{5}$$

where $\beta_{|S}^{\text{OLS}}$ is a vector of length ρ with non-zero elements being the OLS coefficient estimates for the variables in the final selection set S. C is the candidate set from the first-stage screening. $\widehat{\beta}_j^{\text{lasso}}$ is the jth LASSO solution evaluated at λ_{gic} identified with the use of the general information criterion. In the second stage, SGPV for each variable k is calculated as $I_k = \widehat{\beta}_k \pm 1{,}96\text{SE}_k$, while the interval null is defined as $H_0 = -\text{SE}_k, \text{SE}_k$. ProSGPV finally keeps only the variables with SGPV, equal to zero.[2]

4.3. One-covariate-at-a-time multiple testing

The OCMT represents a multi-step process of variable selection. It is often regarded as an alternative to penalized regression, outperforming the latter in computational speed, ease of interpretation, and yielding better results for smaller samples.

Suppose there is a target variable y_t and a subset of possible predictors $S_{nt} = \{x_{i,t}, i = 1, 2, \ldots, n)$. In the OCMT, a data generating process can be represented in the following form:

$$y_t = a' z_t + \sum_{i=1}^{k} \beta_i x_{i,t} + u_t \tag{6}$$

where y_t is a target variable, z_t – the vector of pre-selected variables, which can be deterministic variables (constants, trends and indicator variables), stochastic variables (lags of y_t and common factors) or some variables whose relevance is supported by theoretical assumptions; $x_{i,t}$ – the set of k unknown signal variables, $i = 1, 2, \ldots, k$; u_t is an error term, $t = 1, 2, \ldots, T$ – the number of observations.

The algorithm performs as follows. First, it estimates statistical significance of each independent variable through an OLS regression of y_t on a full set of predictors $\{x_{i,t}, i = 1, 2, \ldots, n)$ and selects those whose t-statistics exceed the threshold:

$$c_p(n, \delta^*) = \Phi^{-1}\left(1 - \frac{p}{2f(n, \delta^*)}\right) \tag{7}$$

where $\Phi(\cdot)$ - is a standard normal distribution function, $f(n, \delta) = cn^{\delta}$ for c and δ being some positive constants, and δ is called a critical value exponent. The variables selected in the first step are included in the model as k true signals.

In the second step, the OCMT uses specification identified on the previous step and tests statistical significance of other variables which have not been selected before. The algorithm continues until no variable from the set is found statistically significant. Thus, the algorithm relates all the variables to one of three categories: k signals, which collectively generate y_t; k^* pseudo-signals which are correlated with signal variables but are not included in the data generating model; $(n - k - k^*)$ noise variables which are not correlated with signals.

4.4. Spike-and-slab regression

This is a Bayesian variable selection technique, involving Markov chain Monte Carlo (MCMC) algorithm for regression models with a specific prior which places some amount of posterior probability at zero for a subset of the regression coefficients. In this study, we apply a spike-and-slab regression to dissect the commodity prices driving global systemic risk both in the linear and non-linear settings.[3] The nonlinear setting involves smoothing a non-linear component, using cubic B-splines. Overall, the method selects variables which have the odds of inclusion into the best model over 25%.

4.5. Bayesian structural time series

Bayesian structural time series (BSTS) is a tool for decomposing, forecasting and variable selection for time series. The method represents a mix of a structural time series model capturing a trend or seasonal components of the target time series, and a regression model.

The structural time series model is formally described by two equations: observation equation and transition equation. Adding some regression components to this framework makes the model useful for simultaneously analyzing seasonality and trend as well as getting the estimates of the regression coefficients.

The general specification of the model is represented as follows:

$$y_t = \mu_t + \tau_t + \beta^T x_t + \epsilon_t$$

[2] To implement the described method, we use the following R package ***ProSGPV*** – for penalized regression with second-generation p-values (https://cran.r-project.org/web/packages/ProSGPV/index.html).

[3] Spike-and-slab regression is performed, using an R code *spikeSlabGAM*. See https://cran.r-project.org/web/packages/spikeSlabGAM/index.html.

$$\mu_t = \mu_{t-1} + \delta_{t-1} + u_t$$

$$\delta_t = \delta_{t-1} + v_t$$

$$\tau_t = -\sum_{s=1}^{S-1} \tau_{t-s} + w_t \tag{8}$$

where $\eta_t = (u_t, v_t, w_t)$ contains individual components of Gaussian random noise. The current level of the trend is represented by μ_t, and δ_t stands for the slope of the trend. τ_t is a seasonal component, which can be thought as a number of S dummy variables, constrained to have zero expectation over a full cycle of S seasons. β^T represents the vector of regression coefficients.

As the model may theoretically contain a large number of regression predictors, a spike-and-slab prior is applied. It induces sparcity and allows for substantial reduction in the size of the regression problem (Scott and Varian, 2014).

The main output of the analysis is the report with marginal posterior inclusion probabilities for each predictor, mean and standard deviation of the corresponding coefficients.

5. Results and discussion

We evaluate the salience of commodity prices as predictors of global systemic risk by aggregating the results of the ML variable selection for price levels and the two types of price shocks described in Section 3.

Table 1 reports the importance of predictors accounting for all the three lags considered, while Table 2 provides a more granular assessment by ranking the predictors with different lags, thereby enabling to track the variable importance of a specific predictor

Table 1
Aggregate importance ranking of predictors of global systemic risk.

VARIABLE	RANK
GEPU	23
GPR	20
WIP	17
CHICKEN	16
IMAPP	16
MP_TRACKER	15
BEEF	14
COCOA	14
LIQUEFIED NATURAL gas, JAPAN	14
NATURAL gas, EUROPE	14
PHOSPHATE ROCK	14
Tea, KOLKATA	14
Banana, EUROPE	13
Banana, US	13
FISH MEAL	13
MAIZE	13
NATURAL gas, US	13
ORANGE	13
Wheat, US HRW	13
CRUDE OIL, WTI	12
Rice, THAI A.1	12
SOYBEAN MEAL	12
SOYBEANS	12
Tea, COLOMBO	12
Coal, AUSTRALIAN	11
COCONUT OIL	11
Coffee, ARABICA	11
GOLD	**11**
GROUNDNUTS	11
PALM KERNEL OIL	11
Sugar, EU	11
Sugar, WORLD	11
SUNFLOWER OIL	11
Coal, SOUTH AFRICAN	10
Cotton, a INDEX	10
DAP	10
IRON ore, CFR SPOT	**10**
LEAD	**10**
Logs, MALAYSIAN	10
NICKEL	10

(*continued on next page*)

Table 1 (*continued*)

VARIABLE	RANK
OIL SUPPLY	**10**
RAPESEED OIL	10
Rice, THAI 5%	10
Rubber, RSS3	10
Sawnwood, CAMEROON	10
Sawnwood, MALAYSIAN	10
Sugar, US	10
Tobacco, US IMPORT U.V.	10
UREA	**10**
Coffee, ROBUSTA	9
CRUDE OIL, BRENT	9
Logs, CAMEROON	9
PALM OIL	9
POTASSIUM CHLORIDE	9
SILVER	**9**
SOYBEAN OIL	9
SRISK	9
TEA, MOMBASA	9
TSP	9
ALUMINUM	8
CRUDE OIL, DUBAI	8
GROUNDNUT OIL	8
PLYWOOD	8
TEA, AVG 3 AUCTIONS	8
TIN	8
PLATINUM	7
Rubber, TSR20	7
ZINC	**7**
CRUDE OIL, AVERAGE	6
COPPER	5
OIL DEMAND	**3**

Note: the variables leading to a decrease in global systemic risk are in bold.

ranging from the first to the third lag. The importance rank in Table 1 is a number of ML variable selection exercises which select this or that commodity price/price shock accounting for all its lags. In case of Table 2, this metric is obtained with respect to each lag.

Both tables indicate that commodity prices and/or price shocks are not as important as the controls capturing economic policy uncertainty, geopolitical risk, real economic activity as well as the intensity of macroprudential and monetary policies worldwide. Based on Table 1, from 33 to 51% of our variable selection exercises corroborate the significance of these control variables. This finding is consistent with the literature examining the interdependence across different asset classes and macroeconomic fundamentals, which reveals a moderate role of commodities, e.g. Diebold and Yilmaz (2012).

Of the commodities, agricultural products, including food, and fertilizers appear the key drivers of global systemic risk. For instance, the significance of lagged prices for chicken, beef, tea and cocoa is confirmed in more than 30% of our variable selection exercises. They are closely followed by bananas and phosphate rock, a fertilizer.

Against this backdrop, the predictive potential of energy commodities appears modest. In the aggregate ranking encompassing all the three lags, natural gas in the European market as well as liquefied natural gas in Japan belong in the top-10 of predictors, while crude oil WTI occupies the 20th position. Such moderate performance is due to a highly asymmetric impact of the lagged prices for these commodities on global systemic risk. While the first and second lags of natural gas and crude oil are found significant in a notable number of variable selection exercises, the relevance of the third lag dramatically diminishes. For example, based on Table 2, the third lag of crude oil WTI appears significant just in a single variable selection exercise. Meanwhile, the importance of the prices for agricultural commodities, including food, decays in a less dramatic way. This is especially true for beef, cocoa, tea and bananas. Although we do not measure the magnitude of the effect produced by different lags of the predictors on global systemic risk, the results in Tables 1 and 2 indicate that this effect turns out more persistent in case of the prices for agricultural rather than for energy commodities. Thus, we provide the empirical evidence questioning the dominant impact of oil prices/price shocks on systemic financial risk compared to other commodity prices, in particular, as regards the prices for agricultural products. This finding contrasts with the prevailing literature which promotes the pivotal role of energy commodities for financial (in-) stability, as discussed in Section 2. At the same time, it is consistent with the recent studies documenting causal linkages running from agricultural and food prices to energy ones, e.g. Kirikkaleli and Güngör (2021), Tiwari et al. (2022).[4]

[4] The causality running from agricultural and food prices to energy ones is far from being the prevailing result in the literature. Nonetheless, in the recent years, the salience of agricultural and food commodities as well as their decoupling from the dynamics of energy prices have consolidated, driven by financialization of these commodities and an increasing demand for biofuel. This trend has become more pronounced in the post 2010 period. See, for example, Sun et al. (2021).

Table 2
Granular importance ranking of predictors of global systemic risk.

N OF VARIABLE	VARIABLE	RANK	N OF VARIABLE	VARIABLE	RANK
1	GEPU_L1	10	107	PALM KERNEL OIL_L1	4
2	SRISK_L1	9	108	PALM KERNEL OIL_L2	4
3	GPR_L3	8	109	Rubber, RSS3_L1	4
4	CHICKEN_L1	8	110	WIP_L2	4
5	PHOSPHATE ROCK_L1	8	111	PHOSPHATE ROCK_L3	4
6	GEPU_L2	7	112	SOYBEAN MEAL_L1	4
7	GOLD_L1	7	113	RAPESEED OIL_L2	4
8	TEA, Kolkata_L2	7	114	CRUDE OIL, AVERAGE_L1	3
9	FISH MEAL_L1	7	115	CRUDE OIL, AVERAGE_L2	3
10	WIP_L1	7	116	CRUDE OIL, BRENT_L2	3
11	POTASSIUM CHLORIDE_L1	6	117	CRUDE OIL, DUBAI_L2	3
12	CRUDE OIL, BRENT_L1	6	118	RICE, THAI 5% _L2	3
13	MAIZE_L1	6	119	IRON ore, CFR SPOT_L2	3
14	RICE, THAI 5% _L1	6	120	Wheat, US HRW_L3	3
15	IRON ore, CFR SPOT_L1	6	121	LEAD_L3	3
16	CRUDE OIL, WTI_L1	6	122	Banana, EUROPE_L3	3
17	Wheat, US HRW_L1	6	123	TIN_L3	3
18	LEAD_L1	6	124	Banana, US_L3	3
19	Banana, EUROPE_L1	6	125	NATURAL gas, EUROPE_L3	3
20	NATURAL gas, US_L1	6	126	BEEF_L3	3
21	GEPU_L3	6	127	GOLD_L3	3
22	NICKEL_L1	6	128	COCOA_L3	3
23	GPR_L1	6	129	SILVER_L3	3
24	GPR_L2	6	130	Coffee, ROBUSTA_L2	3
25	NATURAL gas, EUROPE_L1	6	131	Sugar, US_L1	3
26	ORANGE_L2	6	132	Sugar, US_L3	3
27	LIQUEFIED NATURAL gas, Japan_L1	6	133	TEA, AVG 3 AUCTIONS_L2	3
28	BEEF_L2	6	134	OIL SUPPLY_L2	3
29	IMAPP_L2	6	135	OIL SUPPLY_L3	3
30	COCOA_L2	6	136	LOGS, MALAYSIAN_L1	3
31	CHICKEN_L2	6	137	LOGS, MALAYSIAN_L3	3
32	MP_TRACKER_L2	6	138	PLYWOOD_L2	3
33	GROUNDNUTS_L2	6	139	GROUNDNUT OIL_L1	3
34	SOYBEANS_L2	6	140	Cotton, a INDEX_L2	3
35	WIP_L3	6	141	PALM OIL_L1	3
36	DAP_L1	6	142	PALM KERNEL OIL_L3	3
37	SUNFLOWER OIL_L1	5	143	Rubber, RSS3_L2	3
38	SUNFLOWER OIL_L2	5	144	Rubber, RSS3_L3	3
39	MAIZE_L2	5	145	SOYBEAN OIL_L1	3
40	ALUMINUM_L1	5	146	SOYBEAN OIL_L2	3
41	CRUDE OIL, WTI_L2	5	147	SOYBEAN OIL_L3	3
42	RICE, THAI A.1_L1	5	148	DAP_L3	3
43	RICE, THAI A.1_L2	5	149	SOYBEAN MEAL_L3	3
44	Coal, AUSTRALIAN_L2	5	150	UREA _L3	3
45	Coal, SOUTH AFRICAN_L2	5	151	POTASSIUM CHLORIDE_L3	2
46	NATURAL gas, US_L2	5	152	MAIZE_L3	2
47	Banana, US_L1	5	153	ALUMINUM_L2	2
48	Banana, US_L2	5	154	RICE, THAI A.1_L3	2
49	NATURAL gas, EUROPE_L2	5	155	Coal, AUSTRALIAN_L3	2
50	ORANGE_L1	5	156	NATURAL gas, US_L3	2
51	BEEF_L1	5	157	NICKEL_L2	2
52	IMAPP_L1	5	158	NICKEL_L3	2
53	IMAPP_L3	5	159	ORANGE_L3	2
54	COCOA_L1	5	160	ZINC_L3	2
55	PLATINUM_L1	5	161	CHICKEN_L3	2
56	Coffee, ARABICA_L2	5	162	PLATINUM_L3	2
57	Sugar, EU_L2	5	163	Coffee, ARABICA_L3	2
58	SILVER_L1	5	164	Sugar, EU_L3	2
59	Coffee, ROBUSTA_L1	5	165	Sugar, WORLD_L3	2
60	Sugar, WORLD_L1	5	166	Tea, COLOMBO_L3	2
61	MP_TRACKER_L1	5	167	Tobacco, US IMPORT U.V._L3	2
62	Tea, COLOMBO_L1	5	168	Tea, Kolkata_L3	2
63	Tea, COLOMBO_L2	5	169	OIL DEMAND_L2	2
64	Tea, Kolkata_L1	5	170	COCONUT OIL_L3	2
65	Tea, MOMBASA_L2	5	171	Sawnwood, Cameroon_L3	2
66	COCONUT OIL_L1	5	172	Sawnwood, MALAYSIAN_L3	2
67	GROUNDNUTS_L1	5	173	FISH MEAL_L3	2
68	Cotton, a INDEX_L1	5	174	Cotton, a INDEX_L3	2

(*continued on next page*)

Table 2 (*continued*)

N OF VARIABLE	VARIABLE	RANK	N OF VARIABLE	VARIABLE	RANK
69	Rubber, TSR20_L1	5	175	PALM OIL_L3	2
70	SOYBEANS_L1	5	176	Rubber, TSR20_L3	2
71	SOYBEAN MEAL_L2	5	177	PHOSPHATE ROCK_L2	2
72	TSP_L1	5	178	TSP_L2	2
73	RAPESEED OIL_L1	5	179	TSP_L3	2
74	UREA _L1	5	180	UREA _L2	2
75	CRUDE OIL, DUBAI_L1	4	181	SUNFLOWER OIL_L3	1
76	COPPER_L1	4	182	POTASSIUM CHLORIDE_L2	1
77	Coal, AUSTRALIAN_L1	4	183	ALUMINUM_L3	1
78	Wheat, US HRW_L2	4	184	CRUDE OIL, DUBAI_L3	1
79	Coal, SOUTH AFRICAN_L1	4	185	Rice, THAI 5% _L3	1
80	Banana, EUROPE_L2	4	186	IRON ore, CFR SPOT_L3	1
81	TIN_L1	4	187	CRUDE OIL, WTI_L3	1
82	ZINC_L1	4	188	COPPER_L3	1
83	LIQUEFIED NATURAL gas, Japan_L2	4	189	LEAD_L2	1
84	LIQUEFIED NATURAL gas, Japan_L3	4	190	Coal, SOUTH AFRICAN_L3	1
85	Coffee, ARABICA_L1	4	191	TIN_L2	1
86	Sugar, EU_L1	4	192	ZINC_L2	1
87	Sugar, US_L2	4	193	GOLD_L2	1
88	Tea, AVG 3 AUCTIONS_L1	4	194	SILVER_L2	1
89	Sugar, WORLD_L2	4	195	Coffee, ROBUSTA_L3	1
90	MP_TRACKER_L3	4	196	Tea, AVG 3 AUCTIONS_L3	1
91	Tobacco, US IMPORT U.V._L1	4	197	OIL DEMAND_L1	1
92	Tobacco, US IMPORT U.V._L2	4	198	Logs, Cameroon_L3	1
93	OIL SUPPLY_L1	4	199	PLYWOOD_L3	1
94	Logs, Cameroon_L1	4	200	GROUNDNUT OIL_L3	1
95	Logs, Cameroon_L2	4	201	SOYBEANS_L3	1
96	Tea, MOMBASA_L1	4	202	DAP_L2	1
97	Logs, MALAYSIAN_L2	4	203	RAPESEED OIL_L3	1
98	COCONUT OIL_L2	4	204	CRUDE OIL, AVERAGE_L3	0
99	Sawnwood, Cameroon_L1	4	205	CRUDE OIL, BRENT_L3	0
100	Sawnwood, Cameroon_L2	4	206	COPPER_L2	0
101	Sawnwood, MALAYSIAN_L1	4	207	PLATINUM_L2	0
102	Sawnwood, MALAYSIAN_L2	4	208	OIL DEMAND_L3	0
103	FISH MEAL_L2	4	209	Tea, MOMBASA_L3	0
104	PLYWOOD_L1	4	210	GROUNDNUTS_L3	0
105	GROUNDNUT OIL_L2	4	211	Rubber, TSR20_L2	0
106	PALM OIL_L2	4			

Note: L1 denotes the first lag of a variable, L2 - the second lag, L3 - the third lag.

The more pronounced significance of the prices for agricultural vs. energy commodities meshes well with the outcome of ML variable selection for the countries mostly contributing to global systemic risk, i.e. China, the USA, Japan, the UK and France. We have run additional estimations for these countries, adopting the same methodology as for global systemic risk. The results are summarized in Tables A3-A12 in the Appendix. They reveal that the predictive power of the prices for agricultural commodities, including food, for the country-level SRISK appears quite notable, especially in case of China which accounts for about 40% of global systemic risk. In particular, this country-level analysis validates the high positions of bananas, tea, beef, chicken and phosphate rock prices in the importance rankings, as they can matter a lot for the Chinese systemic risk. Thus, our results point to a transmission channel translating volatility from the agricultural commodity prices to the Chinese financial markets, which in their turn impact global systemic risk. The suggested channel links the literature on the integration between commodity and financial markets in China (Ouyang and Zhang, 2020) with that underscoring the role of Chinese financial markets for global financial (in-)stability (Lodge et al., 2023).

Furthermore, in Tables A13-A14 we report correlation coefficients between the global importance ranking of systemic risk drivers and the national ones, both aggregate and granular. It appears that the national importance rankings for China exhibit the highest statistically significant correlation ratios with the global ones. Thus, our country-level exercises reinforce the viewpoint that nowadays China plays a pivotal role in the overall performance of commodity markets, thereby driving so called commodity cycle, and shaping its interaction with the global financial cycle (Arnade et al., 2017; Miranda-Agrippino and Rey, 2022; Kabundi and Zahid, 2023).

Against this backdrop, energy commodity prices as the drivers of national systemic risk are of limited importance in case of all the top contributors to global systemic risk except Japan. For the latter, structural oil supply shocks as well as coal and natural gas prices play a significant role. As for other major contributors to global systemic risk, apart from the control variables, metals (zinc, gold) appear the key drivers of systemic risk for the USA, for the UK, the most salient predictors are tin, beef and potashium chloride, while in case of France they are sawnwood and potashium choloride. Of the energy indicators, only structural oil supply shocks matter to a certain extent for systemic risk in case of the USA and France.

Based on Table 1, the prices for about 88% of the commodities we consider are positively linked with SRISK, i.e. increasing commodity prices tend to fuel global systemic risk. This evidence comports with the studies reporting the adverse impact of rising commodity prices on financial stability in the key economies, first and foremost, the USA which largely determine global financial conditions, e.g. Shahbaz et al. (2019). Nonetheless, there are a few exceptions among the commodities considered whose increasing prices signal a forthcoming decline in global systemic risk, e.g. gold, silver, zinc, lead, iron ore. This finding complies with the studies arguing that metals possess the potential for hedging against financial instability, e.g. Chiu and Ratner (2014), Kyriazis et al. (2023). Our country-level estimations generally support this assertion, though most of the hedging potential is associated with lead, silver and iron ore, not with gold. Notably, increases in lead prices are associated with a subsequent decline in the national SRISK measures for China and the USA. This result comports with the studies arguing that prices for non-ferrous metals help predict the dynamics of financial markets and exhibit a strong hedging potential quite comparable with precious metals, e.g. Jacobsen et al. (2019).

As regards the control variables, higher levels of economic policy uncertainty and global geopolitical risk exacerbate worldwide systemic risk. This result comes as no surprise and is well-entrenched in the extant literature, e.g. Matousek et al. (2020), Phan et al. (2021), Trinh and Tran (2023). Also, global systemic risk is driven by the increasing world industrial production and the indices of macroprudential and monetary policy, which seems a counter-intuitive result. However, it can merely point to the procyclicality of systemic risk with respect to the mentioned variables, since in this study we manage to consider only up to three lags, while the dampening effect of rising real economic activity, tighter macroprudential and monetary policies on global systemic risk may be shaped by more distant lags.

Overall, our findings indicate that in order to predict the dynamics of global systemic risk, policymakers at the national level and in international financial institutions need to pay particular attention to the prices for agricultural commodities, including food, whereas the importance of the prices for energy commodities appears less pronounced. The policymakers should also factor in the dependence of the countries contributing most to global systemic risk on specific commodities, as such dependence is transmitted through the financial markets of such countries to the global scale. Besides, given the prevailing positive relationship between most of commodity prices and global systemic risk, constant monitoring and, when necessary, policy efforts are to be undertaken to circumvent various situations, e.g. shortages, supply disruptions, etc., potentially leading to price surges in the commodity markets which in turn can adversely affect financial sector.

6. Conclusion

The paper aims to dissect the robust predictors of global systemic risk proxied by conditional capital shortfall (SRISK) among a nearly complete universe of commodity prices retrieved from the World Bank database and in the presence of control variables. The analysis builds on a battery of ML variable selection techniques and covers the period between January 2004 and December 2021. It is worth noting that, in addition to price levels, our variable selection exercises also apply to commodity price shocks.

The control variables capturing global economic policy uncertainty, geopolitical risk as well as world industrial production and the intensity of macroprudential and monetary policies are found the most salient predictors of global systemic risk, outperforming the commodity prices.

In contrast to the extant literature, we find that the prices for agricultural commodities, including food, are more important predictors of global systemic risk than the prices for energy commodities. We offer two explanations for this result. First, it may stem from the changing relationship between agricultural and energy prices in the recent years. The degree of their co-movement has notably increased, and bidirectional causality or even the causal linkage running from agricultural prices to energy ones are nowadays reported more widely. This change is likely to be driven by the increasing financialization of agricultural commodities and bio-energy revolution. Second, the commodity prices which are crucial for predicting country-level systemic risk of the top contributors to global systemic risk naturally appear salient on the global scale. The high importance of bananas, tea, beef, chicken and phosphate rock, a fertilizer, exemplifies this finding in case of China which accounts for nearly 40% of global systemic risk.

We also document that, for a vast majority of commodities, increasing prices are conducive to higher levels of global systemic risk. Hence, policymakers are to be vigilant on the commodity prices to forecast the dynamics of systemic risk. There are still several commodities, e.g. gold, silver, zinc, lead, iron ore whose prices are negatively linked with global systemic risk, thereby offering hedging opportunities against global financial instability.

Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A1
List of variables

Variable name	Variable Description	Source
SRISK	Predicted system capital shortfall	V-Lab: Systemic risk analysis summary (nyu.edu)
GEPU	Global economic policy uncertainty index	Economic policy uncertainty index
GPR	Geopolitical risk index	The index - geopolitical risk index (geopriskindex.com)
WIP	World industrial production index	Christiane Baumeister - datasets (google.com)
IMAPP	Integrated macroprudential policy index	IMF macroprudential database
MP_TRACKER	Global monetary policy tracker	Global monetary policy tracker | Council on Foreign relations (cfr.org)
OIL SUPPLY	Monthly structural oil supply shocks	Christiane Baumeister - datasets (google.com)
OIL DEMAND	Monthly structural oil demand shocks	Christiane Baumeister - datasets (google.com)
ALUMINUM	Aluminum price	Commodity markets (worldbank.org)
BANANA, EUROPE	Banana, Europe price	Commodity markets (worldbank.org)
BANANA, US	Banana, US price	Commodity markets (worldbank.org)
BEEF	Beef price	Commodity markets (worldbank.org)
CHICKEN	Chicken price	Commodity markets (worldbank.org)
COAL, AUSTRALIAN	Coal, Australian price	Commodity markets (worldbank.org)
COAL, SOUTH AFRICAN	Coal, South African price	Commodity markets (worldbank.org)
COCOA	Cocoa price	Commodity markets (worldbank.org)
COCONUT OIL	Coconut oil price	Commodity markets (worldbank.org)
COFFEE, ARABICA	Coffee, Arabica price	Commodity markets (worldbank.org)
COFFEE, ROBUSTA	Coffee, Robusta price	Commodity markets (worldbank.org)
COPPER	Copper price	Commodity markets (worldbank.org)
COTTON, A INDEX	Cotton, A index price	Commodity markets (worldbank.org)
CRUDE OIL, AVERAGE	Crude oil, average price	Commodity markets (worldbank.org)
CRUDE OIL, BRENT	Crude oil, Brent price	Commodity markets (worldbank.org)
CRUDE OIL, DUBAI	Crude oil, Dubai price	Commodity markets (worldbank.org)
CRUDE OIL, WTI	Crude oil, WTI price	Commodity markets (worldbank.org)
DAP	DAP price	Commodity markets (worldbank.org)
FISH MEAL	Fish meal price	Commodity markets (worldbank.org)
GOLD	Gold price	Commodity markets (worldbank.org)
GROUNDNUT OIL	Groundnut oil price	Commodity markets (worldbank.org)
GROUNDNUTS	Groundnuts price	Commodity markets (worldbank.org)
IRON ORE, CFR SPOT	Iron ore, cfr spot price	Commodity markets (worldbank.org)
LEAD	Lead price	Commodity markets (worldbank.org)
LIQUEFIED NATURAL GAS, JAPAN	Liquefied natural gas, Japan price	Commodity markets (worldbank.org)
LOGS, CAMEROON	Logs, Cameroon price	Commodity markets (worldbank.org)
LOGS, MALAYSIAN	Logs, Malaysian price	Commodity markets (worldbank.org)
MAIZE	Maize price	Commodity markets (worldbank.org)
NATURAL GAS, EUROPE	Natural gas, Europe price	Commodity markets (worldbank.org)
NATURAL GAS, US	Natural gas, US price	Commodity markets (worldbank.org)
NICKEL	Nickel price	Commodity markets (worldbank.org)
ORANGE	Orange price	Commodity markets (worldbank.org)
PALM KERNEL OIL	Palm kernel oil price	Commodity markets (worldbank.org)
PALM OIL	Palm oil price	Commodity markets (worldbank.org)
PHOSPHATE ROCK	Phosphate rock price	Commodity markets (worldbank.org)
PLATINUM	Platinum price	Commodity markets (worldbank.org)
PLYWOOD	Plywood price	Commodity markets (worldbank.org)
POTASSIUM CHLORIDE	Potassium chloride price	Commodity markets (worldbank.org)
RAPESEED OIL	Rapeseed oil price	Commodity markets (worldbank.org)
RICE, THAI 5%	Rice, Thai 5% price	Commodity markets (worldbank.org)
RICE, THAI A.1	Rice, Thai A.1 price	Commodity markets (worldbank.org)
RUBBER, RSS3	Rubber, RSS3 price	Commodity markets (worldbank.org)
RUBBER, TSR20	Rubber, TSR20 price	Commodity markets (worldbank.org)
SAWNWOOD, CAMEROON	Sawnwood, Cameroon price	Commodity markets (worldbank.org)
SAWNWOOD, MALAYSIAN	Sawnwood, Malaysian price	Commodity markets (worldbank.org)
SILVER	Silver price	Commodity markets (worldbank.org)
SOYBEAN MEAL	Soybean meal price	Commodity markets (worldbank.org)
SOYBEAN OIL	Soybean oil price	Commodity markets (worldbank.org)
SOYBEANS	Soybeans price	Commodity markets (worldbank.org)
SUGAR, EU	Sugar, EU price	Commodity markets (worldbank.org)
SUGAR, US	Sugar, US price	Commodity markets (worldbank.org)
SUGAR, WORLD	Sugar, world price	Commodity markets (worldbank.org)
SUNFLOWER OIL	Sunflower oil price	Commodity markets (worldbank.org)
TEA, AVG 3 AUCTIONS	Tea, avg 3 auctions price	Commodity markets (worldbank.org)
TEA, COLOMBO	Tea, Colombo price	Commodity markets (worldbank.org)
TEA, KOLKATA	Tea, Kolkata price	Commodity markets (worldbank.org)
TEA, MOMBASA	Tea, Mombasa price	Commodity markets (worldbank.org)

(*continued on next page*)

Table A1 (*continued*)

Variable name	Variable Description	Source
TIN	Tin price	Commodity markets (worldbank.org)
TOBACCO, US IMPORT U.V.	Tobacco, US import u.v. price	Commodity markets (worldbank.org)
TSP	TSP price	Commodity markets (worldbank.org)
UREA	Urea price	Commodity markets (worldbank.org)
WHEAT, US HRW	Wheat, US HRW price	Commodity markets (worldbank.org)
ZINC	Zinc price	Commodity markets (worldbank.org)

Table A2
Descriptive Statistics

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Observations
ALUMINUM	2043.68	1938.51	3071.24	1330.20	391.51	213
BANANA EUROPE	1.00	0.96	1.64	0.60	0.15	213
BANANA, US	0.93	0.94	1.30	0.40	0.20	213
BEEF	3.89	4.08	6.17	2.43	0.91	213
CHICKEN	1.92	1.91	2.72	1.27	0.26	213
COAL, AUSTRALIAN	82.95	78.65	224.51	38.06	30.49	213
COAL, SOUTH AFRICAN	79.06	76.03	199.65	38.08	25.97	213
COCOA	2.43	2.41	3.53	1.40	0.55	213
COCONUT OIL	1092.61	1031.00	2256.00	550.00	389.99	213
COFFEE ARABICA	3.46	3.27	6.62	1.62	0.99	213
COFFEE ROBUSTA	1.85	1.88	2.69	0.70	0.43	213
COPPER	6473.69	6675.60	10161.97	2686.71	1717.64	213
Cotton, A INDEX	1.79	1.71	5.06	1.07	0.58	213
CRUDE OIL, AVERAGE	70.54	65.06	132.83	21.04	24.01	213
CRUDE OIL, BRENT	72.75	67.40	133.87	23.34	25.39	213
CRUDE OIL, DUBAI	70.12	64.91	131.22	23.27	24.86	213
CRUDE OIL, WTI	68.74	63.94	133.93	16.52	22.28	213
DAP	400.78	387.00	1075.75	190.63	163.44	213
FISH MEAL	1313.31	1390.91	1926.47	624.00	324.31	213
GEPU	149.00	130.22	435.31	54.42	75.10	213
GOLD	1179.55	1242.26	1968.63	383.78	415.45	213
GPR	93.75	90.01	165.90	60.60	19.58	213
GROUNDNUT OIL	1560.01	1433.00	2502.25	936.96	376.89	213
GROUNDNUTS	1410.94	1335.87	2528.43	753.00	403.69	213
IMAPP	0.05	0.04	1.62	−1.04	0.19	213
IRON ore, CFR SPOT	102.33	88.99	214.43	37.90	44.34	213
LEAD	1938.70	2020.47	3719.72	753.68	518.77	213
LIQUEFIED NATURAL gas, JAPAN	10.56	10.04	18.11	4.91	3.58	213
LOGS, CAMEROON	412.28	408.07	562.84	306.51	55.02	213
LOGS, MALAYSIAN	277.94	272.90	453.63	188.43	46.76	213
MAIZE	187.34	166.96	333.05	93.75	60.29	213
MP_TRACKER	−1.85	−3.30	9.98	−10.00	5.92	213
NATURAL GAS, EUROPE	8.44	8.04	38.03	1.58	4.27	213
NATURAL GAS, US	4.44	3.80	13.52	1.61	2.31	213
NICKEL	17322.48	15672.95	52179.05	8298.50	7340.40	213
OIL_DEMAND	0.07	0.55	8.66	−20.69	4.06	213
OIL_SUPPLY	−0.14	−0.12	3.43	−10.66	1.30	213
ORANGE	0.84	0.81	1.43	0.51	0.18	213
PALM KERNEL OIL	1004.57	926.63	2307.63	514.50	361.66	213
PALM OIL	792.65	762.75	1377.22	418.86	236.03	213
PHOSPHATE ROCK	114.07	96.88	450.00	44.00	76.11	213
PLATINUM	1194.71	1121.65	2052.45	753.86	322.00	213
PLYWOOD	541.64	526.16	649.25	441.29	60.63	213
POTASSIUM CHLORIDE	312.79	279.50	807.50	112.50	144.19	213
RAPESEED OIL	976.44	890.21	1825.34	642.01	254.57	213
RICE, THAI 5%	439.63	425.00	907.00	229.00	112.66	213
RICE THAI, A.1	382.80	391.70	762.67	201.25	102.66	213
RUBBER RSS3	2.26	1.92	6.26	1.18	0.96	213
RUBBER TSR20	2.04	1.65	5.58	1.08	0.93	213
SAWNWOOD, CAMEROON	707.25	690.70	1087.54	524.42	108.48	213
SAWNWOOD, MALAYSIAN	784.03	785.62	973.60	552.45	92.87	213
SILVER	18.25	16.95	42.70	5.86	7.43	213
SOYBEAN MEAL	393.31	386.12	651.35	209.60	101.04	213
SOYBEAN OIL	917.03	858.18	1574.67	495.73	259.36	213
SOYBEANS	430.70	409.79	684.02	249.00	105.34	213
SRISK	2951.75	2979.94	5731.00	846.56	1238.04	213
SUGAR, EU	0.48	0.43	0.78	0.34	0.13	213
SUGAR_US	0.58	0.56	0.89	0.42	0.12	213

(continued on next page)

Table A2 (*continued*)

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Observations
SUGAR, WORLD	0.35	0.32	0.65	0.14	0.11	213
SUNFLOWER OIL	1001.58	877.14	2045.00	591.00	330.01	213
TEA, COLOMBO	3.03	3.12	4.27	1.53	0.64	213
TEA, AVG 3 AUCTIONS	2.57	2.70	3.29	1.59	0.46	213
TEA, KOLKATA	2.39	2.44	4.07	1.27	0.56	213
TEA, MOMBASA	2.30	2.30	3.39	1.39	0.49	213
TIN	18236.98	18683.50	39422.52	6160.00	6395.88	213
TOBACCO, US IMPORT U.V.	4163.79	4366.90	5117.56	2675.17	715.28	213
TSP	369.69	337.60	1131.50	177.50	173.70	213
UREA	297.44	262.50	900.50	128.38	120.99	213
WHEAT, US HRW	237.71	218.26	439.72	140.88	66.92	213
WIP	118.83	119.05	140.81	95.46	11.67	213
ZINC	2267.02	2200.17	4405.40	975.18	674.48	213

Table A3
Aggregate importance ranking of systemic risk predictors in China

VARIABLE	RANK
BANANA, US	**8**
GEPU	8
TEA, MOMBASA	**8**
GROUNDNUTS	7
NATURAL gas, EUROPE	7
SRISK	7
BEEF	6
CHICKEN	6
Coal, AUSTRALIAN	6
GOLD	6
LEAD	**6**
OIL SUPPLY	**6**
PLATINUM	**6**
RICE, THAI 5%	**6**
RUBBER, RSS3	6
TIN	6
WIP	6
COFFEE, ARABICA	**5**
COFFEE, ROBUSTA	5
CRUDE OIL, DUBAI	5
FISH MEAL	5
GPR	5
IRON ORE, CFR SPOT	5
LIQUEFIED NATURAL GAS, JAPAN	**5**
LOGS, CAMEROON	5
LOGS, MALAYSIAN	5
NATURAL gas, US	5
POTASSIUM CHLORIDE	5
SILVER	5
SOYBEANS	5
SUGAR, US	**5**
ZINC	5
ALUMINUM	4
BANANA, EUROPE	4
Coal, SOUTH AFRICAN	4
COCONUT OIL	4
GROUNDNUT OIL	4
NICKEL	4
RICE, THAI A.1	4
RUBBER, TSR20	**4**
SAWNWOOD, CAMEROON	**4**
SAWNWOOD, MALAYSIAN	4
SOYBEAN MEAL	4
SOYBEAN OIL	**4**
TEA, COLOMBO	4
UREA	4
COCOA	3
COPPER	3
COTTON, A INDEX	**3**
DAP	**3**

(*continued on next page*)

Table A3 (*continued*)

VARIABLE	RANK
MAIZE	**3**
MP_TRACKER	3
PALM KERNEL OIL	**3**
PALM OIL	3
PHOSPHATE ROCK	**3**
PLYWOOD	3
RAPESEED OIL	3
SUGAR, EU	**3**
SUGAR, WORLD	3
SUNFLOWER OIL	3
TEA, AVG 3 AUCTIONS	3
TOBACCO, US IMPORT U.V.	3
TSP	3
Wheat, US HRW	**3**
CRUDE OIL, WTI	2
IMAPP	**2**
ORANGE	2
TEA, KOLKATA	2
CRUDE OIL, AVERAGE	1
CRUDE OIL, BRENT	1
OIL DEMAND	1

Note: the variables leading to a decrease in global systemic risk are in bold.

Table A4
Granular importance ranking of systemic risk predictors in China

N OF VARIABLE	VARIABLE	RANK
1	SRISK_L1	7
2	BANANA, US_L1	6
3	GEPU_L1	4
4	WIP_L1	4
5	POTASSIUM CHLORIDE_L1	3
6	RICE, THAI 5% _L1	3
7	RICE, THAI A.1_L1	3
8	COAL, AUSTRALIAN_L2	3
9	LEAD_L3	3
10	BANANA, EUROPE_L1	3
11	NATURAL gas, EUROPE_L3	3
12	CHICKEN_L2	3
13	PLATINUM_L2	3
14	SUGAR, US_L3	3
15	TEA, MOMBASA_L1	3
16	TEA, MOMBASA_L3	3
17	GROUNDNUTS_L2	3
18	RUBBER, RSS3_L2	3
19	UREA _L3	3
20	SUNFLOWER OIL_L1	2
21	ALUMINUM_L2	2
22	CRUDE OIL, DUBAI_L2	2
23	CRUDE OIL, DUBAI_L3	2
24	RICE, THAI 5% _L2	2
25	IRON ORE, CFR SPOT_L1	2
26	IRON ORE, CFR SPOT_L3	2
27	COPPER_L3	2
28	Coal, AUSTRALIAN_L3	2
29	LEAD_L2	2
30	COAL, SOUTH AFRICAN_L2	2
31	COAL, SOUTH AFRICAN_L3	2
32	TIN_L1	2
33	TIN_L2	2
34	TIN_L3	2
35	NATURAL GAS, US_L2	2
36	NATURAL GAS, US_L3	2
37	GEPU_L2	2
38	GEPU_L3	2
39	NICKEL_L3	2
40	GPR_L1	2
41	GPR_L2	2

(*continued on next page*)

Table A4 (*continued*)

N OF VARIABLE	VARIABLE	RANK
42	NATURAL GAS, EUROPE_L1	2
43	NATURAL GAS, EUROPE_L2	2
44	ORANGE_L1	2
45	ZINC_L2	2
46	ZINC_L3	2
47	LIQUEFIED NATURAL GAS, JAPAN_L1	2
48	LIQUEFIED NATURAL GAS, JAPAN_L3	2
49	BEEF_L1	2
50	BEEF_L2	2
51	BEEF_L3	2
52	GOLD_L1	2
53	GOLD_L2	2
54	GOLD_L3	2
55	CHICKEN_L3	2
56	PLATINUM_L3	2
57	COFFEE, ARABICA_L1	2
58	COFFEE, ARABICA_L3	2
59	SILVER_L2	2
60	SILVER_L3	2
61	COFFEE, ROBUSTA_L1	2
62	COFFEE, ROBUSTA_L2	2
63	TEA, AVG 3 AUCTIONS_L2	2
64	TEA, COLOMBO_L2	2
65	OIL SUPPLY_L1	2
66	OIL SUPPLY_L2	2
67	OIL SUPPLY_L3	2
68	LOGS, CAMEROON_L1	2
69	LOGS, CAMEROON_L2	2
70	TEA, MOMBASA_L2	2
71	LOGS, MALAYSIAN_L2	2
72	LOGS, MALAYSIAN_L3	2
73	COCONUT OIL_L2	2
74	SAWNWOOD, CAMEROON_L2	2
75	GROUNDNUTS_L1	2
76	GROUNDNUTS_L3	2
77	SAWNWOOD, MALAYSIAN_L3	2
78	FISH MEAL_L1	2
79	FISH MEAL_L2	2
80	GROUNDNUT OIL_L2	2
81	PALM OIL_L2	2
82	RUBBER, TSR20_L1	2
83	RUBBER, RSS3_L3	2
84	SOYBEANS_L1	2
85	SOYBEANS_L2	2
86	PHOSPHATE ROCK_L1	2
87	SOYBEAN OIL_L1	2
88	SOYBEAN MEAL_L1	2
89	CRUDE OIL, AVERAGE_L3	1
90	SUNFLOWER OIL_L3	1
91	POTASSIUM CHLORIDE_L2	1
92	POTASSIUM CHLORIDE_L3	1
93	CRUDE OIL, BRENT_L3	1
94	MAIZE_L1	1
95	MAIZE_L2	1
96	MAIZE_L3	1
97	ALUMINUM_L1	1
98	ALUMINUM_L3	1
99	CRUDE OIL, DUBAI_L1	1
100	RICE, THAI 5% _L3	1
101	IRON ORE, CFR SPOT_L2	1
102	CRUDE OIL, WTI_L2	1
103	CRUDE OIL, WTI_L3	1
104	RICE, THAI A.1_L3	1
105	COPPER_L2	1
106	COAL, AUSTRALIAN_L1	1
107	WHEAT, US HRW_L1	1
108	WHEAT, US HRW_L2	1
109	WHEAT, US HRW_L3	1
110	LEAD_L1	1
111	BANANA, EUROPE_L3	1

(*continued on next page*)

Table A4 (*continued*)

N OF VARIABLE	VARIABLE	RANK
112	NATURAL GAS, US_L1	1
113	BANANA, US_L2	1
114	BANANA, US_L3	1
115	NICKEL_L1	1
116	NICKEL_L2	1
117	GPR_L3	1
118	ZINC_L1	1
119	LIQUEFIED NATURAL GAS, JAPAN_L2	1
120	IMAPP_L1	1
121	IMAPP_L2	1
122	COCOA_L1	1
123	COCOA_L2	1
124	COCOA_L3	1
125	CHICKEN_L1	1
126	PLATINUM_L1	1
127	COFFEE, ARABICA_L2	1
128	SUGAR, EU_L1	1
129	SUGAR, EU_L2	1
130	SUGAR, EU_L3	1
131	SILVER_L1	1
132	COFFEE, ROBUSTA_L3	1
133	SUGAR, US_L1	1
134	SUGAR, US_L2	1
135	TEA, AVG 3 AUCTIONS_L3	1
136	SUGAR, WORLD_L1	1
137	SUGAR, WORLD_L2	1
138	SUGAR, WORLD_L3	1
139	MP_TRACKER_L1	1
140	MP_TRACKER_L2	1
141	MP_TRACKER_L3	1
142	TEA, COLOMBO_L1	1
143	TEA, COLOMBO_L3	1
144	TOBACCO, US IMPORT U.V._L1	1
145	TOBACCO, US IMPORT U.V._L2	1
146	TOBACCO, US IMPORT U.V._L3	1
147	TEA, KOLKATA_L1	1
148	TEA, KOLKATA_L2	1
149	OIL DEMAND_L2	1
150	LOGS, CAMEROON_L3	1
151	LOGS, MALAYSIAN_L1	1
152	COCONUT OIL_L1	1
153	COCONUT OIL_L3	1
154	SAWNWOOD, CAMEROON_L1	1
155	SAWNWOOD, CAMEROON_L3	1
156	SAWNWOOD, MALAYSIAN_L1	1
157	SAWNWOOD, MALAYSIAN_L2	1
158	FISH MEAL_L3	1
159	PLYWOOD_L1	1
160	PLYWOOD_L2	1
161	PLYWOOD_L3	1
162	GROUNDNUT OIL_L1	1
163	GROUNDNUT OIL_L3	1
164	COTTON, A INDEX_L1	1
165	COTTON, A INDEX_L2	1
166	COTTON, A INDEX_L3	1
167	PALM OIL_L3	1
168	RUBBER, TSR20_L2	1
169	RUBBER, TSR20_L3	1
170	PALM KERNEL OIL_L1	1
171	PALM KERNEL OIL_L2	1
172	PALM KERNEL OIL_L3	1
173	RUBBER, RSS3_L1	1
174	SOYBEANS_L3	1
175	WIP_L2	1
176	WIP_L3	1
177	PHOSPHATE ROCK_L2	1
178	SOYBEAN OIL_L2	1
179	SOYBEAN OIL_L3	1
180	DAP_L1	1
181	DAP_L2	1

(*continued on next page*)

Table A4 (*continued*)

N OF VARIABLE	VARIABLE	RANK
182	DAP_L3	1
183	SOYBEAN MEAL_L2	1
184	SOYBEAN MEAL_L3	1
185	TSP_L1	1
186	TSP_L2	1
187	TSP_L3	1
188	RAPESEED OIL_L1	1
189	RAPESEED OIL_L2	1
190	RAPESEED OIL_L3	1
191	UREA _L1	1
192	CRUDE OIL, AVERAGE_L1	0
193	CRUDE OIL, AVERAGE_L2	0
194	SUNFLOWER OIL_L2	0
195	CRUDE OIL, BRENT_L1	0
196	CRUDE OIL, BRENT_L2	0
197	CRUDE OIL, WTI_L1	0
198	RICE, THAI A.1_L2	0
199	COPPER_L1	0
200	COAL, SOUTH AFRICAN_L1	0
201	BANANA, EUROPE_L2	0
202	ORANGE_L2	0
203	ORANGE_L3	0
204	IMAPP_L3	0
205	TEA, AVG 3 AUCTIONS_L1	0
206	TEA, KOLKATA_L3	0
207	OIL DEMAND_L1	0
208	OIL DEMAND_L3	0
209	PALM OIL_L1	0
210	PHOSPHATE ROCK_L3	0
211	UREA _L2	0
212		

Note: L1 denotes the first lag of a variable, L2 - the second lag, L3 - the third lag.

Table A5
Aggregate importance ranking of systemic risk predictors in France

VARIABLE	RANK
SAWNWOOD, MALAYSIAN	10
FISH MEAL	9
GPR	9
POTASSIUM CHLORIDE	9
OIL SUPPLY	8
RAPESEED OIL	8
RICE, THAI A.1	8
SOYBEANS	8
Wheat, US HRW	**8**
COAL, AUSTRALIAN	7
COCOA	7
COTTON, A INDEX	**7**
GOLD	7
GROUNDNUTS	7
LIQUEFIED NATURAL GAS, JAPAN	7
NATURAL GAS, EUROPE	7
PHOSPHATE ROCK	7
SOYBEAN OIL	7
SUNFLOWER OIL	7
TOBACCO, US IMPORT U.V.	7
BANANA, US	6
COAL, SOUTH AFRICAN	6
COCONUT OIL	**6**
COFFEE, ARABICA	6
CRUDE OIL, BRENT	6
GROUNDNUT OIL	6
IRON ORE, CFR SPOT	6
LEAD	6
LOGS, CAMEROON	6
LOGS, MALAYSIAN	6
NATURAL GAS, US	6

(*continued on next page*)

Table A5 (*continued*)

VARIABLE	RANK
PLYWOOD	6
RICE, THAI 5%	6
SAWNWOOD, CAMEROON	6
SILVER	6
SRISK	6
SUGAR, EU	6
SUGAR, WORLD	6
TEA, AVG 3 AUCTIONS	6
TEA, COLOMBO	6
TIN	6
BANANA, EUROPE	5
BEEF	5
CHICKEN	5
COFFEE, ROBUSTA	5
COPPER	5
DAP	5
MP_TRACKER	5
NICKEL	5
PALM KERNEL OIL	**5**
PALM OIL	5
PLATINUM	5
SOYBEAN MEAL	**5**
SUGAR, US	5
TEA, MOMBASA	5
TSP	5
WIP	**5**
ALUMINUM	4
CRUDE OIL, DUBAI	**4**
CRUDE OIL, WTI	4
GEPU	4
MAIZE	**4**
RUBBER, RSS3	4
TEA, KOLKATA	4
CRUDE OIL, AVERAGE	**3**
RUBBER, TSR20	**3**
UREA	3
IMAPP	2
ORANGE	2
ZINC	2
OIL DEMAND	0

Note: the variables leading to a decrease in global systemic risk are in bold.

Table A6
Granular importance ranking of systemic risk predictors in France

N OF VARIABLE	VARIABLE	RANK
1	SRISK_L1	6
2	GPR_L3	5
3	SAWNWOOD, MALAYSIAN_L1	5
4	POTASSIUM CHLORIDE_L3	4
5	RICE, THAI A.1_L1	4
6	COAL, AUSTRALIAN_L3	4
7	WHEAT, US HRW_L1	4
8	BANANA, US_L1	4
9	OIL SUPPLY_L3	4
10	FISH MEAL_L1	4
11	SOYBEANS_L3	4
12	RAPESEED OIL_L1	4
13	SUNFLOWER OIL_L1	3
14	POTASSIUM CHLORIDE_L1	3
15	ALUMINUM_L2	3
16	COAL, SOUTH AFRICAN_L3	3
17	BANANA, EUROPE_L1	3
18	NATURAL GAS, EUROPE_L3	3
19	LIQUEFIED NATURAL GAS, JAPAN_L1	3
20	GOLD_L1	3
21	COCOA_L3	3
22	SILVER_L3	3

(*continued on next page*)

Table A6 (*continued*)

N OF VARIABLE	VARIABLE	RANK
23	TOBACCO, US IMPORT U.V._L1	3
24	LOGS, MALAYSIAN_L1	3
25	COCONUT OIL_L3	3
26	GROUNDNUTS_L2	3
27	SAWNWOOD, MALAYSIAN_L3	3
28	FISH MEAL_L2	3
29	COTTON, A INDEX_L3	3
30	PALM OIL_L2	3
31	WIP_L1	3
32	PHOSPHATE ROCK_L1	3
33	SOYBEAN OIL_L1	3
34	SOYBEAN MEAL_L1	3
35	SUNFLOWER OIL_L2	2
36	SUNFLOWER OIL_L3	2
37	POTASSIUM CHLORIDE_L2	2
38	CRUDE OIL, BRENT_L1	2
39	CRUDE OIL, BRENT_L2	2
40	CRUDE OIL, BRENT_L3	2
41	MAIZE_L2	2
42	CRUDE OIL, DUBAI_L2	2
43	RICE, THAI 5% _L1	2
44	RICE, THAI 5% _L2	2
45	RICE, THAI 5% _L3	2
46	IRON ORE, CFR SPOT_L1	2
47	IRON ORE, CFR SPOT_L2	2
48	IRON ORE, CFR SPOT_L3	2
49	CRUDE OIL, WTI_L3	2
50	RICE, THAI A.1_L2	2
51	RICE, THAI A.1_L3	2
52	COPPER_L2	2
53	COPPER_L3	2
54	COAL, AUSTRALIAN_L2	2
55	WHEAT, US HRW_L2	2
56	WHEAT, US HRW_L3	2
57	LEAD_L1	2
58	LEAD_L2	2
59	LEAD_L3	2
60	COAL, SOUTH AFRICAN_L2	2
61	BANANA, EUROPE_L3	2
62	TIN_L1	2
63	TIN_L2	2
64	TIN_L3	2
65	NATURAL GAS, US_L1	2
66	NATURAL GAS, US_L2	2
67	NATURAL GAS, US_L3	2
68	GEPU_L2	2
69	NICKEL_L1	2
70	NICKEL_L2	2
71	GPR_L1	2
72	GPR_L2	2
73	NATURAL GAS, EUROPE_L1	2
74	NATURAL GAS, EUROPE_L2	2
75	LIQUEFIED NATURAL GAS, JAPAN_L2	2
76	LIQUEFIED NATURAL GAS, JAPAN_L3	2
77	BEEF_L1	2
78	BEEF_L3	2
79	GOLD_L2	2
80	GOLD_L3	2
81	COCOA_L1	2
82	COCOA_L2	2
83	CHICKEN_L1	2
84	CHICKEN_L2	2
85	PLATINUM_L2	2
86	PLATINUM_L3	2
87	COFFEE, ARABICA_L1	2
88	COFFEE, ARABICA_L2	2
89	COFFEE, ARABICA_L3	2
90	SUGAR, EU_L1	2
91	SUGAR, EU_L2	2
92	SUGAR, EU_L3	2

(*continued on next page*)

Table A6 (*continued*)

N OF VARIABLE	VARIABLE	RANK
93	SILVER_L1	2
94	COFFEE, ROBUSTA_L1	2
95	COFFEE, ROBUSTA_L3	2
96	SUGAR, US_L1	2
97	SUGAR, US_L2	2
98	TEA, AVG 3 AUCTIONS_L1	2
99	TEA, AVG 3 AUCTIONS_L2	2
100	TEA, AVG 3 AUCTIONS_L3	2
101	SUGAR, WORLD_L1	2
102	SUGAR, WORLD_L2	2
103	SUGAR, WORLD_L3	2
104	MP_TRACKER_L1	2
105	MP_TRACKER_L3	2
106	TEA, COLOMBO_L1	2
107	TEA, COLOMBO_L2	2
108	TEA, COLOMBO_L3	2
109	TOBACCO, US IMPORT U.V._L2	2
110	TOBACCO, US IMPORT U.V._L3	2
111	TEA, KOLKATA_L1	2
112	OIL SUPPLY_L1	2
113	OIL SUPPLY_L2	2
114	LOGS, CAMEROON_L1	2
115	LOGS, CAMEROON_L2	2
116	LOGS, CAMEROON_L3	2
117	TEA, MOMBASA_L1	2
118	TEA, MOMBASA_L2	2
119	LOGS, MALAYSIAN_L2	2
120	COCONUT OIL_L2	2
121	SAWNWOOD, CAMEROON_L1	2
122	SAWNWOOD, CAMEROON_L2	2
123	SAWNWOOD, CAMEROON_L3	2
124	GROUNDNUTS_L1	2
125	GROUNDNUTS_L3	2
126	SAWNWOOD, MALAYSIAN_L2	2
127	FISH MEAL_L3	2
128	PLYWOOD_L1	2
129	PLYWOOD_L2	2
130	PLYWOOD_L3	2
131	GROUNDNUT OIL_L1	2
132	GROUNDNUT OIL_L2	2
133	GROUNDNUT OIL_L3	2
134	COTTON, A INDEX_L1	2
135	COTTON, A INDEX_L2	2
136	PALM KERNEL OIL_L1	2
137	PALM KERNEL OIL_L3	2
138	RUBBER, RSS3_L1	2
139	SOYBEANS_L1	2
140	SOYBEANS_L2	2
141	PHOSPHATE ROCK_L2	2
142	PHOSPHATE ROCK_L3	2
143	SOYBEAN OIL_L2	2
144	SOYBEAN OIL_L3	2
145	DAP_L1	2
146	DAP_L3	2
147	TSP_L1	2
148	TSP_L2	2
149	RAPESEED OIL_L2	2
150	RAPESEED OIL_L3	2
151	CRUDE OIL, AVERAGE_L1	1
152	CRUDE OIL, AVERAGE_L2	1
153	CRUDE OIL, AVERAGE_L3	1
154	MAIZE_L1	1
155	MAIZE_L3	1
156	ALUMINUM_L1	1
157	CRUDE OIL, DUBAI_L1	1
158	CRUDE OIL, DUBAI_L3	1
159	CRUDE OIL, WTI_L1	1
160	CRUDE OIL, WTI_L2	1
161	COPPER_L1	1
162	COAL, AUSTRALIAN_L1	1

(*continued on next page*)

Table A6 (*continued*)

N OF VARIABLE	VARIABLE	RANK
163	COAL, SOUTH AFRICAN_L1	1
164	GEPU_L1	1
165	GEPU_L3	1
166	BANANA, US_L2	1
167	BANANA, US_L3	1
168	NICKEL_L3	1
169	ORANGE_L2	1
170	ORANGE_L3	1
171	ZINC_L2	1
172	ZINC_L3	1
173	BEEF_L2	1
174	IMAPP_L1	1
175	IMAPP_L2	1
176	CHICKEN_L3	1
177	PLATINUM_L1	1
178	SILVER_L2	1
179	COFFEE, ROBUSTA_L2	1
180	SUGAR, US_L3	1
181	MP_TRACKER_L2	1
182	TEA, KOLKATA_L2	1
183	TEA, KOLKATA_L3	1
184	TEA, MOMBASA_L3	1
185	LOGS, MALAYSIAN_L3	1
186	COCONUT OIL_L1	1
187	PALM OIL_L1	1
188	PALM OIL_L3	1
189	RUBBER, TSR20_L1	1
190	RUBBER, TSR20_L2	1
191	RUBBER, TSR20_L3	1
192	PALM KERNEL OIL_L2	1
193	RUBBER, RSS3_L2	1
194	RUBBER, RSS3_L3	1
195	WIP_L2	1
196	WIP_L3	1
197	DAP_L2	1
198	SOYBEAN MEAL_L2	1
199	SOYBEAN MEAL_L3	1
200	TSP_L3	1
201	UREA _L1	1
202	UREA _L2	1
203	UREA _L3	1
204	ALUMINUM_L3	0
205	BANANA, EUROPE_L2	0
206	ORANGE_L1	0
207	ZINC_L1	0
208	IMAPP_L3	0
209	OIL DEMAND_L1	0
210	OIL DEMAND_L2	0
211	OIL DEMAND_L3	0
212		

Note: L1 denotes the first lag of a variable, L2 - the second lag, L3 - the third lag.

Table A7
Aggregate importance ranking of systemic risk predictors in Japan

VARIABLE	RANK
OIL SUPPLY	**9**
BANANA, US	**6**
COAL, SOUTH AFRICAN	6
GEPU	6
LEAD	6
NATURAL GAS, EUROPE	**6**
POTASSIUM CHLORIDE	6
COAL, AUSTRALIAN	**5**
FISH MEAL	5
GROUNDNUT OIL	**5**
GROUNDNUTS	5
PALM KERNEL OIL	5

(*continued on next page*)

Table A7 (*continued*)

VARIABLE	RANK
PHOSPHATE ROCK	5
RICE, THAI A.1	5
SILVER	5
WHEAT, US HRW	**5**
BEEF	4
COTTON, A INDEX	4
GOLD	4
IRON ORE, CFR SPOT	4
LIQUEFIED NATURAL GAS, JAPAN	4
NICKEL	4
RAPESEED OIL	4
RICE, THAI 5%	**4**
SOYBEAN MEAL	4
SRISK	4
TEA, AVG 3 AUCTIONS	4
TEA, COLOMBO	4
TEA, MOMBASA	4
TIN	4
ALUMINUM	3
BANANA, EUROPE	3
CHICKEN	3
COCOA	3
COCONUT OIL	3
COFFEE, ARABICA	**3**
COFFEE, ROBUSTA	3
CRUDE OIL, BRENT	3
DAP	**3**
LOGS, CAMEROON	3
LOGS, MALAYSIAN	3
MAIZE	3
MP_TRACKER	**3**
ORANGE	3
PLATINUM	**3**
PLYWOOD	3
RUBBER, RSS3	3
RUBBER, TSR20	**3**
SAWNWOOD, CAMEROON	**3**
SAWNWOOD, MALAYSIAN	3
SOYBEAN OIL	**3**
SOYBEANS	**3**
SUGAR, EU	**3**
SUGAR, WORLD	3
SUNFLOWER OIL	3
TOBACCO, US IMPORT U.V.	3
TSP	3
UREA	3
WIP	3
COPPER	2
CRUDE OIL, AVERAGE	**2**
CRUDE OIL, WTI	**2**
GPR	**2**
SUGAR, US	2
ZINC	2
CRUDE OIL, DUBAI	1
NATURAL GAS, US	1
PALM OIL	1
TEA, KOLKATA	1
IMAPP	0
OIL DEMAND	0

Note: the variables leading to a decrease in global systemic risk are in bold.

Table A8
Granular importance ranking of systemic risk predictors in Japan

N OF VARIABLE	VARIABLE	RANK
1	BANANA, US_L1	4
2	SRISK_L1	4
3	RICE, THAI A.1_L1	3

(*continued on next page*)

Table A8 (*continued*)

N OF VARIABLE	VARIABLE	RANK
4	COAL, AUSTRALIAN_L3	3
5	WHEAT, US HRW_L1	3
6	LEAD_L3	3
7	COAL, SOUTH AFRICAN_L2	3
8	COAL, SOUTH AFRICAN_L3	3
9	NATURAL GAS, EUROPE_L3	3
10	OIL SUPPLY_L1	3
11	OIL SUPPLY_L2	3
12	OIL SUPPLY_L3	3
13	GROUNDNUTS_L2	3
14	FISH MEAL_L2	3
15	GROUNDNUT OIL_L2	3
16	WIP_L1	3
17	SOYBEAN MEAL_L1	3
18	POTASSIUM CHLORIDE_L1	2
19	POTASSIUM CHLORIDE_L2	2
20	POTASSIUM CHLORIDE_L3	2
21	MAIZE_L1	2
22	ALUMINUM_L2	2
23	RICE, THAI 5% _L1	2
24	IRON ORE, CFR SPOT_L3	2
25	LEAD_L2	2
26	TIN_L2	2
27	GEPU_L1	2
28	GEPU_L2	2
29	GEPU_L3	2
30	NICKEL_L3	2
31	NATURAL GAS, EUROPE_L1	2
32	LIQUEFIED NATURAL GAS, Japan_L1	2
33	BEEF_L2	2
34	GOLD_L1	2
35	CHICKEN_L2	2
36	SILVER_L2	2
37	SILVER_L3	2
38	TEA, AVG 3 AUCTIONS_L2	2
39	MP_TRACKER_L1	2
40	TEA, COLOMBO_L2	2
41	TEA, MOMBASA_L2	2
42	COCONUT OIL_L2	2
43	COTTON, A INDEX_L3	2
44	PALM KERNEL OIL_L1	2
45	PALM KERNEL OIL_L3	2
46	PHOSPHATE ROCK_L1	2
47	PHOSPHATE ROCK_L2	2
48	RAPESEED OIL_L1	2
49	UREA _L3	2
50	CRUDE OIL, AVERAGE_L1	1
51	CRUDE OIL, AVERAGE_L3	1
52	SUNFLOWER OIL_L1	1
53	SUNFLOWER OIL_L2	1
54	SUNFLOWER OIL_L3	1
55	CRUDE OIL, BRENT_L1	1
56	CRUDE OIL, BRENT_L2	1
57	CRUDE OIL, BRENT_L3	1
58	MAIZE_L2	1
59	ALUMINUM_L3	1
60	CRUDE OIL, DUBAI_L3	1
61	RICE, THAI 5% _L2	1
62	RICE, THAI 5% _L3	1
63	IRON ORE, CFR SPOT_L1	1
64	IRON ORE, CFR SPOT_L2	1
65	CRUDE OIL, WTI_L1	1
66	CRUDE OIL, WTI_L2	1
67	RICE, THAI A.1_L2	1
68	RICE, THAI A.1_L3	1
69	COPPER_L2	1
70	COPPER_L3	1
71	COAL, AUSTRALIAN_L1	1
72	COAL, AUSTRALIAN_L2	1
73	WHEAT, US HRW_L2	1

(*continued on next page*)

Table A8 (*continued*)

N OF VARIABLE	VARIABLE	RANK
74	WHEAT, US HRW_L3	1
75	LEAD_L1	1
76	BANANA, EUROPE_L1	1
77	BANANA, EUROPE_L2	1
78	BANANA, EUROPE_L3	1
79	TIN_L1	1
80	TIN_L3	1
81	NATURAL GAS, US_L3	1
82	BANANA, US_L2	1
83	BANANA, US_L3	1
84	NICKEL_L1	1
85	NICKEL_L2	1
86	GPR_L1	1
87	GPR_L2	1
88	NATURAL GAS, EUROPE_L2	1
89	ORANGE_L1	1
90	ORANGE_L2	1
91	ORANGE_L3	1
92	ZINC_L1	1
93	ZINC_L2	1
94	LIQUEFIED NATURAL GAS, JAPAN_L2	1
95	LIQUEFIED NATURAL GAS, JAPAN_L3	1
96	BEEF_L1	1
97	BEEF_L3	1
98	GOLD_L2	1
99	GOLD_L3	1
100	COCOA_L1	1
101	COCOA_L2	1
102	COCOA_L3	1
103	CHICKEN_L3	1
104	PLATINUM_L1	1
105	PLATINUM_L2	1
106	PLATINUM_L3	1
107	COFFEE, ARABICA_L1	1
108	COFFEE, ARABICA_L2	1
109	COFFEE, ARABICA_L3	1
110	SUGAR, EU_L1	1
111	SUGAR, EU_L2	1
112	SUGAR, EU_L3	1
113	SILVER_L1	1
114	COFFEE, ROBUSTA_L1	1
115	COFFEE, ROBUSTA_L2	1
116	COFFEE, ROBUSTA_L3	1
117	SUGAR, US_L1	1
118	SUGAR, US_L3	1
119	TEA, AVG 3 AUCTIONS_L1	1
120	TEA, AVG 3 AUCTIONS_L3	1
121	SUGAR, WORLD_L1	1
122	SUGAR, WORLD_L2	1
123	SUGAR, WORLD_L3	1
124	MP_TRACKER_L3	1
125	TEA, COLOMBO_L1	1
126	TEA, COLOMBO_L3	1
127	TOBACCO, US IMPORT U.V._L1	1
128	TOBACCO, US IMPORT U.V._L2	1
129	TOBACCO, US IMPORT U.V._L3	1
130	TEA, KOLKATA_L2	1
131	LOGS, CAMEROON_L1	1
132	LOGS, CAMEROON_L2	1
133	LOGS, CAMEROON_L3	1
134	TEA, MOMBASA_L1	1
135	TEA, MOMBASA_L3	1
136	LOGS, MALAYSIAN_L1	1
137	LOGS, MALAYSIAN_L2	1
138	LOGS, MALAYSIAN_L3	1
139	COCONUT OIL_L3	1
140	SAWNWOOD, CAMEROON_L1	1
141	SAWNWOOD, CAMEROON_L2	1
142	SAWNWOOD, CAMEROON_L3	1
143	GROUNDNUTS_L1	1

(*continued on next page*)

Table A8 (*continued*)

N OF VARIABLE	VARIABLE	RANK
144	GROUNDNUTS_L3	1
145	SAWNWOOD, MALAYSIAN_L1	1
146	SAWNWOOD, MALAYSIAN_L2	1
147	SAWNWOOD, MALAYSIAN_L3	1
148	FISH MEAL_L1	1
149	FISH MEAL_L3	1
150	PLYWOOD_L1	1
151	PLYWOOD_L2	1
152	PLYWOOD_L3	1
153	GROUNDNUT OIL_L1	1
154	GROUNDNUT OIL_L3	1
155	COTTON, a INDEX_L1	1
156	COTTON, a INDEX_L2	1
157	PALM OIL_L2	1
158	RUBBER, TSR20_L1	1
159	RUBBER, TSR20_L2	1
160	RUBBER, TSR20_L3	1
161	PALM KERNEL OIL_L2	1
162	RUBBER, RSS3_L1	1
163	RUBBER, RSS3_L2	1
164	RUBBER, RSS3_L3	1
165	SOYBEANS_L1	1
166	SOYBEANS_L2	1
167	SOYBEANS_L3	1
168	PHOSPHATE ROCK_L3	1
169	SOYBEAN OIL_L1	1
170	SOYBEAN OIL_L2	1
171	SOYBEAN OIL_L3	1
172	DAP_L1	1
173	DAP_L2	1
174	DAP_L3	1
175	SOYBEAN MEAL_L3	1
176	TSP_L1	1
177	TSP_L2	1
178	TSP_L3	1
179	RAPESEED OIL_L2	1
180	RAPESEED OIL_L3	1
181	UREA _L2	1
182	CRUDE OIL, AVERAGE_L2	0
183	MAIZE_L3	0
184	ALUMINUM_L1	0
185	CRUDE OIL, DUBAI_L1	0
186	CRUDE OIL, DUBAI_L2	0
187	CRUDE OIL, WTI_L3	0
188	COPPER_L1	0
189	COAL, SOUTH AFRICAN_L1	0
190	NATURAL GAS, US_L1	0
191	NATURAL GAS, US_L2	0
192	GPR_L3	0
193	ZINC_L3	0
194	IMAPP_L1	0
195	IMAPP_L2	0
196	IMAPP_L3	0
197	CHICKEN_L1	0
198	SUGAR, US_L2	0
199	MP_TRACKER_L2	0
200	TEA, KOLKATA_L1	0
201	TEA, KOLKATA_L3	0
202	OIL DEMAND_L1	0
203	OIL DEMAND_L2	0
204	OIL DEMAND_L3	0
205	COCONUT OIL_L1	0
206	PALM OIL_L1	0
207	PALM OIL_L3	0
208	WIP_L2	0
209	WIP_L3	0
210	SOYBEAN MEAL_L2	0
211	UREA _L1	0
212		

Note: L1 denotes the first lag of a variable, L2 - the second lag, L3 - the third lag.

Table A9
Aggregate importance ranking of systemic risk predictors in the UK

VARIABLE	RANK
SRISK	10
PLYWOOD	6
SUGAR, EU	6
TIN	6
BEEF	5
DAP	5
PHOSPHATE ROCK	5
PLATINUM	5
POTASSIUM CHLORIDE	5
SAWNWOOD, CAMEROON	5
TOBACCO, US IMPORT U.V.	5
BANANA, EUROPE	4
COAL, AUSTRALIAN	4
COCONUT OIL	4
GOLD	4
GROUNDNUT OIL	4
LIQUEFIED NATURAL GAS, JAPAN	4
NATURAL GAS, US	4
RAPESEED OIL	4
SAWNWOOD, MALAYSIAN	4
TEA, AVG 3 AUCTIONS	4
ZINC	4
ALUMINUM	3
BANANA, US	3
COAL, SOUTH AFRICAN	3
COCOA	3
COPPER	3
CRUDE OIL, AVERAGE	3
CRUDE OIL, BRENT	3
FISH MEAL	3
GROUNDNUTS	3
LEAD	3
LOGS, CAMEROON	3
LOGS, MALAYSIAN	3
NATURAL GAS, EUROPE	3
OIL DEMAND	3
OIL SUPPLY	3
PALM OIL	3
RICE, THAI 5%	3
RUBBER, TSR20	3
SOYBEAN MEAL	3
SOYBEANS	3
SUGAR, US	3
SUNFLOWER OIL	3
COFFEE, ARABICA	2
COFFEE, ROBUSTA	2
COTTON, A INDEX	2
CRUDE OIL, WTI	2
GEPU	2
IRON ORE, CFR SPOT	**2**
NICKEL	2
ORANGE	2
PALM KERNEL OIL	2
SILVER	2
SOYBEAN OIL	2
SUGAR, WORLD	2
TEA, COLOMBO	2
TSP	2
CHICKEN	1
CRUDE OIL, DUBAI	1
MAIZE	1
RICE, THAI A.1	1
RUBBER, RSS3	1
TEA, KOLKATA	1
TEA, MOMBASA	1
UREA	1
WHEAT, US HRW	1

(*continued on next page*)

Table A9 (*continued*)

VARIABLE	RANK
WIP	1
GPR	0
IMAPP	0
MP_TRACKER	0

Note: the variables leading to a decrease in global systemic risk are in bold.

Table A10
Granular importance ranking of systemic risk predictors in the UK

N of variable	VARIABLE NAME	RANK
1	SRISK_L1	10
2	TIN_L3	3
3	SUNFLOWER OIL_L1	2
4	POTASSIUM CHLORIDE_L2	2
5	POTASSIUM CHLORIDE_L3	2
6	ALUMINUM_L1	2
7	COPPER_L1	2
8	COAL, AUSTRALIAN_L3	2
9	COAL, SOUTH AFRICAN_L3	2
10	BANANA, EUROPE_L1	2
11	TIN_L2	2
12	NATURAL GAS, US_L1	2
13	GEPU_L1	2
14	ZINC_L1	2
15	LIQUEFIED NATURAL GAS, JAPAN_L1	2
16	BEEF_L1	2
17	BEEF_L2	2
18	GOLD_L1	2
19	COCOA_L2	2
20	PLATINUM_L1	2
21	PLATINUM_L3	2
22	SUGAR, EU_L1	2
23	SUGAR, EU_L2	2
24	SUGAR, EU_L3	2
25	TEA, AVG 3 AUCTIONS_L3	2
26	TOBACCO, US IMPORT U.V._L1	2
27	TOBACCO, US IMPORT U.V._L2	2
28	LOGS, CAMEROON_L1	2
29	COCONUT OIL_L3	2
30	SAWNWOOD, CAMEROON_L1	2
31	SAWNWOOD, CAMEROON_L2	2
32	SAWNWOOD, MALAYSIAN_L1	2
33	SAWNWOOD, MALAYSIAN_L2	2
34	PLYWOOD_L1	2
35	PLYWOOD_L2	2
36	PLYWOOD_L3	2
37	GROUNDNUT OIL_L2	2
38	RUBBER, TSR20_L2	2
39	SOYBEANS_L2	2
40	PHOSPHATE ROCK_L2	2
41	PHOSPHATE ROCK_L3	2
42	DAP_L2	2
43	DAP_L3	2
44	SOYBEAN MEAL_L1	2
45	RAPESEED OIL_L1	2
46	CRUDE OIL, AVERAGE_L1	1
47	CRUDE OIL, AVERAGE_L2	1
48	CRUDE OIL, AVERAGE_L3	1
49	SUNFLOWER OIL_L2	1
50	POTASSIUM CHLORIDE_L1	1
51	CRUDE OIL, BRENT_L1	1
52	CRUDE OIL, BRENT_L2	1
53	CRUDE OIL, BRENT_L3	1
54	MAIZE_L1	1
55	ALUMINUM_L2	1
56	CRUDE OIL, DUBAI_L3	1
57	RICE, THAI 5% _L1	1
58	RICE, THAI 5% _L2	1

(*continued on next page*)

Table A10 (*continued*)

N of variable	VARIABLE NAME	RANK
59	RICE, THAI 5% _L3	1
60	IRON ORE, CFR SPOT_L2	1
61	IRON ORE, CFR SPOT_L3	1
62	CRUDE OIL, WTI_L2	1
63	CRUDE OIL, WTI_L3	1
64	RICE, THAI A.1_L1	1
65	COPPER_L3	1
66	COAL, AUSTRALIAN_L1	1
67	COAL, AUSTRALIAN_L2	1
68	WHEAT, US HRW_L1	1
69	LEAD_L1	1
70	LEAD_L2	1
71	LEAD_L3	1
72	COAL, SOUTH AFRICAN_L2	1
73	BANANA, EUROPE_L2	1
74	BANANA, EUROPE_L3	1
75	TIN_L1	1
76	NATURAL GAS, US_L2	1
77	NATURAL GAS, US_L3	1
78	BANANA, US_L1	1
79	BANANA, US_L2	1
80	BANANA, US_L3	1
81	NICKEL_L2	1
82	NICKEL_L3	1
83	NATURAL GAS, EUROPE_L1	1
84	NATURAL GAS, EUROPE_L2	1
85	NATURAL GAS, EUROPE_L3	1
86	ORANGE_L1	1
87	ORANGE_L2	1
88	ZINC_L2	1
89	ZINC_L3	1
90	LIQUEFIED NATURAL GAS, Japan_L2	1
91	LIQUEFIED NATURAL GAS, Japan_L3	1
92	BEEF_L3	1
93	GOLD_L2	1
94	GOLD_L3	1
95	COCOA_L3	1
96	CHICKEN_L1	1
97	PLATINUM_L2	1
98	COFFEE, ARABICA_L1	1
99	COFFEE, ARABICA_L3	1
100	SILVER_L2	1
101	SILVER_L3	1
102	COFFEE, ROBUSTA_L2	1
103	COFFEE, ROBUSTA_L3	1
104	SUGAR, US_L1	1
105	SUGAR, US_L2	1
106	SUGAR, US_L3	1
107	TEA, AVG 3 AUCTIONS_L1	1
108	TEA, AVG 3 AUCTIONS_L2	1
109	SUGAR, WORLD_L1	1
110	SUGAR, WORLD_L3	1
111	TEA, COLOMBO_L1	1
112	TEA, COLOMBO_L2	1
113	TOBACCO, US IMPORT U.V._L3	1
114	TEA, KOLKATA_L2	1
115	OIL DEMAND_L1	1
116	OIL DEMAND_L2	1
117	OIL DEMAND_L3	1
118	OIL SUPPLY_L1	1
119	OIL SUPPLY_L2	1
120	OIL SUPPLY_L3	1
121	LOGS, CAMEROON_L2	1
122	TEA, MOMBASA_L2	1
123	LOGS, MALAYSIAN_L1	1
124	LOGS, MALAYSIAN_L2	1
125	LOGS, MALAYSIAN_L3	1
126	COCONUT OIL_L1	1
127	COCONUT OIL_L2	1
128	SAWNWOOD, CAMEROON_L3	1

(*continued on next page*)

Table A10 (*continued*)

N of variable	VARIABLE NAME	RANK
129	GROUNDNUTS_L1	1
130	GROUNDNUTS_L2	1
131	GROUNDNUTS_L3	1
132	FISH MEAL_L1	1
133	FISH MEAL_L2	1
134	FISH MEAL_L3	1
135	GROUNDNUT OIL_L1	1
136	GROUNDNUT OIL_L3	1
137	COTTON, A INDEX_L1	1
138	COTTON, a INDEX_L3	1
139	PALM OIL_L1	1
140	PALM OIL_L2	1
141	PALM OIL_L3	1
142	RUBBER, TSR20_L3	1
143	PALM KERNEL OIL_L2	1
144	PALM KERNEL OIL_L3	1
145	RUBBER, RSS3_L3	1
146	SOYBEANS_L3	1
147	WIP_L1	1
148	PHOSPHATE ROCK_L1	1
149	SOYBEAN OIL_L1	1
150	SOYBEAN OIL_L2	1
151	DAP_L1	1
152	SOYBEAN MEAL_L2	1
153	TSP_L1	1
154	TSP_L3	1
155	RAPESEED OIL_L2	1
156	RAPESEED OIL_L3	1
157	UREA _L3	1
158	SUNFLOWER OIL_L3	0
159	MAIZE_L2	0
160	MAIZE_L3	0
161	ALUMINUM_L3	0
162	CRUDE OIL, DUBAI_L1	0
163	CRUDE OIL, DUBAI_L2	0
164	IRON ORE, CFR SPOT_L1	0
165	CRUDE OIL, WTI_L1	0
166	RICE, THAI A.1_L2	0
167	RICE, THAI A.1_L3	0
168	COPPER_L2	0
169	WHEAT, US HRW_L2	0
170	WHEAT, US HRW_L3	0
171	COAL, SOUTH AFRICAN_L1	0
172	GEPU_L2	0
173	GEPU_L3	0
174	NICKEL_L1	0
175	GPR_L1	0
176	GPR_L2	0
177	GPR_L3	0
178	ORANGE_L3	0
179	IMAPP_L1	0
180	IMAPP_L2	0
181	IMAPP_L3	0
182	COCOA_L1	0
183	CHICKEN_L2	0
184	CHICKEN_L3	0
185	COFFEE, ARABICA_L2	0
186	SILVER_L1	0
187	COFFEE, ROBUSTA_L1	0
188	SUGAR, WORLD_L2	0
189	MP_TRACKER_L1	0
190	MP_TRACKER_L2	0
191	MP_TRACKER_L3	0
192	TEA, COLOMBO_L3	0
193	TEA, KOLKATA_L1	0
194	TEA, KOLKATA_L3	0
195	LOGS, CAMEROON_L3	0
196	TEA, MOMBASA_L1	0
197	TEA, MOMBASA_L3	0
198	SAWNWOOD, MALAYSIAN_L3	0

(*continued on next page*)

Table A10 (*continued*)

N of variable	VARIABLE NAME	RANK
199	COTTON, a INDEX_L2	0
200	RUBBER, TSR20_L1	0
201	PALM KERNEL OIL_L1	0
202	RUBBER, RSS3_L1	0
203	RUBBER, RSS3_L2	0
204	SOYBEANS_L1	0
205	WIP_L2	0
206	WIP_L3	0
207	SOYBEAN OIL_L3	0
208	SOYBEAN MEAL_L3	0
209	TSP_L2	0
210	UREA _L1	0
211	UREA _L2	0

Note: L1 denotes the first lag of a variable, L2 - the second lag, L3 - the third lag.

Table A11
Aggregate importance ranking of systemic risk predictors in the USA

VARIABLE	RANK
ZINC	10
GOLD	9
OIL SUPPLY	**8**
BANANA, US	7
COAL, SOUTH AFRICAN	7
PHOSPHATE ROCK	7
PLATINUM	7
RICE, THAI 5%	7
COAL, AUSTRALIAN	**6**
GPR	**6**
POTASSIUM CHLORIDE	6
SOYBEAN OIL	**6**
SRISK	6
SUNFLOWER OIL	6
TIN	6
TSP	6
CHICKEN	5
COCONUT OIL	5
COPPER	5
IRON ORE, CFR SPOT	5
LEAD	**5**
NATURAL GAS, EUROPE	5
PLYWOOD	5
RAPESEED OIL	5
SAWNWOOD, CAMEROON	5
SOYBEANS	5
TEA, COLOMBO	5
TEA, MOMBASA	5
WHEAT, US HRW	**5**
COFFEE, ROBUSTA	4
GROUNDNUT OIL	4
GROUNDNUTS	4
LIQUEFIED NATURAL GAS, JAPAN	4
LOGS, CAMEROON	4
NICKEL	4
RICE, THAI A.1	4
RUBBER, TSR20	**4**
SILVER	**4**
ALUMINUM	3
BANANA, EUROPE	3
BEEF	3
COCOA	3
COFFEE, ARABICA	**3**
COTTON, A INDEX	**3**
CRUDE OIL, BRENT	3
CRUDE OIL, DUBAI	3
FISH MEAL	3
GEPU	3
IMAPP	**3**

(*continued on next page*)

Table A11 (*continued*)

VARIABLE	RANK
MAIZE	**3**
MP_TRACKER	**3**
OIL DEMAND	3
ORANGE	**3**
PALM OIL	3
RUBBER, RSS3	3
SAWNWOOD, MALAYSIAN	3
SUGAR, EU	**3**
SUGAR, US	3
SUGAR, WORLD	3
TEA, AVG 3 AUCTIONS	**3**
TOBACCO, US IMPORT U.V.	3
UREA	3
DAP	**2**
LOGS, MALAYSIAN	2
SOYBEAN MEAL	2
TEA, KOLKATA	2
WIP	2
CRUDE OIL, AVERAGE	1
CRUDE OIL, WTI	1
NATURAL GAS, US	1
PALM KERNEL OIL	1

Note: the variables leading to a decrease in global systemic risk are in bold.

Table A12
Granular importance ranking of systemic risk predictors in the USA

N of variable	VARIABLE	RANK
1	SRISK_L1	6
2	BANANA, US_L1	4
3	ZINC_L3	4
4	OIL SUPPLY_L3	4
5	SUNFLOWER OIL_L1	3
6	POTASSIUM CHLORIDE_L1	3
7	RICE, THAI 5% _L1	3
8	COPPER_L3	3
9	COAL, AUSTRALIAN_L3	3
10	WHEAT, US HRW_L1	3
11	COAL, SOUTH AFRICAN_L3	3
12	TIN_L3	3
13	BANANA, US_L3	3
14	GPR_L3	3
15	ZINC_L1	3
16	ZINC_L2	3
17	GOLD_L1	3
18	GOLD_L2	3
19	GOLD_L3	3
20	CHICKEN_L1	3
21	PLATINUM_L1	3
22	PHOSPHATE ROCK_L1	3
23	SOYBEAN OIL_L3	3
24	TSP_L2	3
25	SUNFLOWER OIL_L3	2
26	POTASSIUM CHLORIDE_L2	2
27	ALUMINUM_L3	2
28	CRUDE OIL, DUBAI_L3	2
29	RICE, THAI 5% _L2	2
30	RICE, THAI 5% _L3	2
31	IRON ORE, CFR SPOT_L1	2
32	IRON ORE, CFR SPOT_L3	2
33	RICE, THAI A.1_L1	2
34	COPPER_L2	2
35	COAL, AUSTRALIAN_L2	2
36	LEAD_L1	2
37	LEAD_L3	2
38	COAL, SOUTH AFRICAN_L1	2
39	COAL, SOUTH AFRICAN_L2	2
40	BANANA, EUROPE_L1	2

(*continued on next page*)

Table A12 (*continued*)

N of variable	VARIABLE	RANK
41	TIN_L2	2
42	NICKEL_L3	2
43	GPR_L1	2
44	NATURAL GAS, EUROPE_L1	2
45	NATURAL GAS, EUROPE_L3	2
46	LIQUEFIED NATURAL GAS, JAPAN_L2	2
47	IMAPP_L1	2
48	PLATINUM_L2	2
49	PLATINUM_L3	2
50	SILVER_L3	2
51	COFFEE, ROBUSTA_L2	2
52	SUGAR, US_L3	2
53	TEA, COLOMBO_L1	2
54	TEA, COLOMBO_L2	2
55	OIL SUPPLY_L1	2
56	OIL SUPPLY_L2	2
57	LOGS, Cameroon_L3	2
58	TEA, MOMBASA_L2	2
59	TEA, MOMBASA_L3	2
60	COCONUT OIL_L2	2
61	COCONUT OIL_L3	2
62	SAWNWOOD, CAMEROON_L1	2
63	SAWNWOOD, CAMEROON_L3	2
64	GROUNDNUTS_L2	2
65	PLYWOOD_L1	2
66	PLYWOOD_L3	2
67	GROUNDNUT OIL_L2	2
68	PALM OIL_L2	2
69	RUBBER, TSR20_L3	2
70	SOYBEANS_L1	2
71	SOYBEANS_L3	2
72	PHOSPHATE ROCK_L2	2
73	PHOSPHATE ROCK_L3	2
74	SOYBEAN OIL_L1	2
75	SOYBEAN MEAL_L1	2
76	TSP_L3	2
77	RAPESEED OIL_L1	2
78	RAPESEED OIL_L3	2
79	CRUDE OIL, AVERAGE_L3	1
80	SUNFLOWER OIL_L2	1
81	POTASSIUM CHLORIDE_L3	1
82	CRUDE OIL, BRENT_L1	1
83	CRUDE OIL, BRENT_L2	1
84	CRUDE OIL, BRENT_L3	1
85	MAIZE_L1	1
86	MAIZE_L2	1
87	MAIZE_L3	1
88	ALUMINUM_L2	1
89	CRUDE OIL, DUBAI_L2	1
90	IRON ORE, CFR SPOT_L2	1
91	CRUDE OIL, WTI_L3	1
92	RICE, THAI A.1_L2	1
93	RICE, THAI A.1_L3	1
94	COAL, AUSTRALIAN_L1	1
95	WHEAT, US HRW_L2	1
96	WHEAT, US HRW_L3	1
97	LEAD_L2	1
98	BANANA, EUROPE_L2	1
99	TIN_L1	1
100	NATURAL GAS, US_L2	1
101	GEPU_L1	1
102	GEPU_L2	1
103	GEPU_L3	1
104	NICKEL_L1	1
105	NICKEL_L2	1
106	GPR_L2	1
107	NATURAL GAS, EUROPE_L2	1
108	ORANGE_L1	1
109	ORANGE_L2	1
110	ORANGE_L3	1

(*continued on next page*)

Table A12 (*continued*)

N of variable	VARIABLE	RANK
111	LIQUEFIED NATURAL GAS, JAPAN_L1	1
112	LIQUEFIED NATURAL GAS, JAPAN_L3	1
113	BEEF_L1	1
114	BEEF_L2	1
115	BEEF_L3	1
116	IMAPP_L2	1
117	COCOA_L1	1
118	COCOA_L2	1
119	COCOA_L3	1
120	CHICKEN_L2	1
121	CHICKEN_L3	1
122	COFFEE, ARABICA_L1	1
123	COFFEE, ARABICA_L2	1
124	COFFEE, ARABICA_L3	1
125	SUGAR, EU_L1	1
126	SUGAR, EU_L2	1
127	SUGAR, EU_L3	1
128	SILVER_L1	1
129	SILVER_L2	1
130	COFFEE, ROBUSTA_L1	1
131	COFFEE, ROBUSTA_L3	1
132	SUGAR, US_L1	1
133	TEA, AVG 3 AUCTIONS_L1	1
134	TEA, AVG 3 AUCTIONS_L2	1
135	TEA, AVG 3 AUCTIONS_L3	1
136	SUGAR, WORLD_L1	1
137	SUGAR, WORLD_L2	1
138	SUGAR, WORLD_L3	1
139	MP_TRACKER_L1	1
140	MP_TRACKER_L2	1
141	MP_TRACKER_L3	1
142	TEA, COLOMBO_L3	1
143	TOBACCO, US IMPORT U.V._L1	1
144	TOBACCO, US IMPORT U.V._L2	1
145	TOBACCO, US IMPORT U.V._L3	1
146	TEA, KOLKATA_L1	1
147	TEA, KOLKATA_L2	1
148	OIL DEMAND_L1	1
149	OIL DEMAND_L2	1
150	OIL DEMAND_L3	1
151	LOGS, CAMEROON_L1	1
152	LOGS, CAMEROON_L2	1
153	TEA, MOMBASA_L1	1
154	LOGS, MALAYSIAN_L2	1
155	LOGS, MALAYSIAN_L3	1
156	COCONUT OIL_L1	1
157	SAWNWOOD, CAMEROON_L2	1
158	GROUNDNUTS_L1	1
159	GROUNDNUTS_L3	1
160	SAWNWOOD, MALAYSIAN_L1	1
161	SAWNWOOD, MALAYSIAN_L2	1
162	SAWNWOOD, MALAYSIAN_L3	1
163	FISH MEAL_L1	1
164	FISH MEAL_L2	1
165	FISH MEAL_L3	1
166	PLYWOOD_L2	1
167	GROUNDNUT OIL_L1	1
168	GROUNDNUT OIL_L3	1
169	COTTON, A INDEX_L1	1
170	COTTON, A INDEX_L2	1
171	COTTON, A INDEX_L3	1
172	PALM OIL_L3	1
173	RUBBER, TSR20_L1	1
174	RUBBER, TSR20_L2	1
175	PALM KERNEL OIL_L3	1
176	RUBBER, RSS3_L1	1
177	RUBBER, RSS3_L2	1
178	RUBBER, RSS3_L3	1
179	SOYBEANS_L2	1
180	WIP_L1	1

(*continued on next page*)

Table A12 (*continued*)

N of variable	VARIABLE	RANK
181	WIP_L3	1
182	SOYBEAN OIL_L2	1
183	DAP_L2	1
184	DAP_L3	1
185	TSP_L1	1
186	RAPESEED OIL_L2	1
187	UREA _L1	1
188	UREA _L2	1
189	UREA _L3	1
190	CRUDE OIL, AVERAGE_L1	0
191	CRUDE OIL, AVERAGE_L2	0
192	ALUMINUM_L1	0
193	CRUDE OIL, DUBAI_L1	0
194	CRUDE OIL, WTI_L1	0
195	CRUDE OIL, WTI_L2	0
196	COPPER_L1	0
197	BANANA, EUROPE_L3	0
198	NATURAL GAS, US_L1	0
199	NATURAL GAS, US_L3	0
200	BANANA, US_L2	0
201	IMAPP_L3	0
202	SUGAR, US_L2	0
203	TEA, KOLKATA_L3	0
204	LOGS, MALAYSIAN_L1	0
205	PALM OIL_L1	0
206	PALM KERNEL OIL_L1	0
207	PALM KERNEL OIL_L2	0
208	WIP_L2	0
209	DAP_L1	0
210	SOYBEAN MEAL_L2	0
211	SOYBEAN MEAL_L3	0

Note: L1 denotes the first lag of a variable, L2 - the second lag, L3 - the third lag.

Table A13
Correlation between global and national aggregate importance rankings

	CHINA	FRANCE	JAPAN	GLOBAL	UK	USA
CHINA	1					
FRANCE	0.25**	1				
JAPAN	0.48***	0.51***	1			
GLOBAL	0.24**	0.20	0.15	1		
UK	0.12	0.21*	0.16	−0.34***	1	
USA	0.40***	0.27**	0.39***	−0.13	0.25*	1

Note: * - significant at 10%, ** - at 5%, *** - at 1%.

Table A14
Correlation between global and national granular importance rankings

	CHINA	FRANCE	JAPAN	GLOBAL	UK	USA
CHINA	1					
FRANCE	0.38***	1				
JAPAN	0.57***	0.50***	1			
GLOBAL	0.21***	0.19**	0.11*	1		
UK	0.33***	0.35***	0.32***	0.09	1	
USA	0.47***	0.39***	0.43***	0.02	0.35***	1

Note: * - significant at 10%, ** - at 5%, *** - at 1%.

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