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Spillovers beyond the variance: Exploring the higher order risk linkages between commodity markets and global financial markets☆

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ABSTRACT

We explore the higher order linkages between commodity markets and global financial markets. We focus on spillovers of realized good and bad volatilities, realized sign jump variation, realized skewness, and realized kurtosis. Our results show that the measurement of risk spillovers is sensitive to the definition of risk used in their construction. Asymmetries between good and bad volatility transmission matter, and results when jumps and higher order risk measures are considered are substantially different from those obtained when traditional volatility measures are used. We provide empirical support for theoretical asset pricing models that conduct the optimization required for portfolio balancing in the mean-variance-skewness space by showing that risk diversification opportunities vary greatly when one considers variance or skewness as the fundamental proxy for risk.

1. Introduction

Commodities are known to be one of the most volatile asset classes. The reasons for this include liquidity issues, a greater exposure to natural disasters and geopolitical shocks, and the fact that in the short term both supply and demand of commodities are relatively price inelastic. Recent studies on volatility spillovers have shown that they change over time, being higher in periods of financial turmoil and when commodity extraction is more costly (see Gomez-Gonzalez et al., 2020). In fact, during the pandemic, the price of many commodities like aluminum, iron ore, copper, natural gas, and lumber has been extremely volatile. Economists are currently debating whether these are the first signs of structural shifts in supply chains related to the world energy transition, or just temporary deviations from structural conditions which will return to normal in the following years.

The increasing trade volume in stock and future commodity markets over the last decade has called for the attention of investors and policymakers to understand cross-market linkages between commodity and traditional financial markets. From an investor's

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Table 1
Univariate summary statistics.

	USA	CAN	GER	UK	CHI	FRA	ITA	JAP	GI1	WTI	NG
Panel A: Realized Volatility											
00-08*	30.84	42.17	48.16	35.72	72.31	43.73	40.18	39.94	43.61	112.32	247.04
09-21**	18.20	22.63	30.50	23.67	27.00	31.71	46.09	22.37	25.61	92.85	144.44
Total	23.96	31.54	38.55	29.16	47.66	37.19	43.40	30.38	33.82	101.73	191.22
Panel B: Realized Bad Volatility											
00-08*	14.62	21.28	24.00	17.19	37.90	20.96	18.64	21.34	21.70	55.10	103.94
09-21**	10.78	14.54	18.09	14.47	15.87	18.09	27.22	12.29	15.64	35.70	72.10
Total	12.35	17.31	20.51	15.59	24.90	19.27	23.70	16.00	18.12	43.65	85.15
Panel C: Realized Good Volatility											
00-08*	14.23	16.94	21.34	16.23	34.82	20.45	16.75	17.77	19.18	49.62	128.70
09-21**	9.78	12.35	15.74	11.73	14.37	16.17	21.74	12.02	13.28	46.80	90.35
Total	11.61	14.23	18.03	13.58	22.76	17.93	19.70	14.38	15.70	47.96	106.07
Panel D: Realized Singed Jump Variation											
00-08*	−0.39	−4.34	−2.66	−0.96	−3.08	−0.51	−1.88	−3.57	−2.53	−5.48	24.76
09-21**	−1.00	−2.19	−2.36	−2.74	−1.50	−1.92	−5.48	−0.27	−2.36	−2.41	18.25
Total	−0.75	−3.07	−2.48	−2.01	−2.15	−1.34	−4.01	−1.62	−2.43	−3.67	20.92
Panel E: Realized Skewness (std)											
00-08*	−0.13	0.58	2.48	0.32	1.96	2.09	0.03	−3.61	0.33	−0.33	4.30
09-21**	2.95	−1.41	0.58	−1.71	1.24	0.93	−2.88	1.68	−0.90	1.42	4.20
Total	1.69	−0.59	1.36	−0.88	1.53	1.41	−1.69	−0.49	−0.40	0.70	4.24
Panel F: Realized Kurtosis (std)											
00-08*	17.6	17.2	16.6	17.0	18.9	16.4	17.2	17.2	17.0	18.0	19.8
09-21**	19.34	18.57	19.90	19.07	17.62	19.99	19.91	18.64	19.41	18.32	18.53
Total	18.6	18.0	18.5	18.2	18.1	18.5	18.8	18.1	18.4	18.2	19.1

Note: The table shows the average of the statistics for the periods January 2000–December 2008, January 2009–October 2021 and for the total sample. Realized skewness and kurtosis were standardized and multiplied by 100.

viewpoint, higher volatility implies higher investment risk but also better opportunities for making larger returns. Indeed, the high volatility of commodities makes them particularly popular within speculative traders. Investors are interested in knowing the sources of risk shocks that affect their portfolios holdings, whether they come from traditional markets or from other commodity markets. Moreover, they are interested in the diversification opportunities offered by commodity assets, especially during periods of market distress.

From the perspective of a commodity-dependent economy, a better understanding of commodities' price instability is useful for designing effective strategies for mitigating risk exposure to price changes in such markets, and also to safeguard international reserves and governments' revenue from resources exploitation, which are generally linked to commodity prices for this set of economies. Thus, understanding the way in which spillovers propagate across commodity, stock and FX global markets, allows a better financial risk management from a macroeconomic perspective for both, import and export countries of commodity goods. The role of commodity markets for financial stability in our globalized economy remains largely underexplored by the literature, except perhaps for oil markets.

This study contributes to our understanding of cross-spillovers in global commodity markets, which is relevant for both investors and policymakers. We study risk spillovers within commodity markets, and between commodity markets and traditional asset classes, including stocks and foreign exchange (FX) markets. Our approach and main conclusions enhance the previous literature not only because we use a larger and more diversified set of commodity prices (a global commodity index, oil, natural gas, soybean, wheat, corn, coffee, sugar, cotton, aluminum, silver, copper, and gold) alongside the main world stock and FX market indexes, to estimate our models, but also, because we analyze market risk spillovers using a more general definition of risk than that found in the current literature on market connectedness. We estimate spillovers statistics between different (realized) moments of market returns, including measures of sign jump variation, skewness, and kurtosis, on top of volatility and semi-volatility indicators. Each statistic reflects a different dimension of risk. For instance, skewness is related to the probability of market crashes (e.g. Daniel and Moskowitz, 2016), while kurtosis reflects the probability of extreme market realizations. Jumps and co-jumps are importantly related to price discontinuities and price discovery of market information (e.g. Lahaye et al., 2011). We also use commodity futures in addition to spot prices, which provides additional information on the functioning of commodity markets through their effects on storage, risk-sharing and information discovery (Cheng and Xiong, 2014; Daskalaki et al., 2014, 2017; Daskalaki and Skiadopoulos, 2016).

We follow the econometric approach developed by Demirer et al. (2018), which combines a traditional vector autoregression setup with selection and shrinkage of the parameter space by the LASSO (Least Absolute Shrinkage and Selection Operator). In this way, we construct dynamic spillover statistics that would be unfeasible in a traditional regression framework due to the curse of dimensionality.

ZS	W	C	KC	SB	CT	AL	SI	COOP	GOLD	EUR	JPY	GBP	CAD	CNY
Panel A: Realized Volatility														
43.67	60.61	48.68	76.52	67.48	51.72	30.29	64.19	58.39	22.67	7.07	7.33	5.96	6.03	0.09
26.44	51.38	42.34	62.73	56.20	36.82	22.58	60.16	31.01	16.71	4.54	4.88	5.22	4.00	0.58
34.30	55.59	45.23	69.02	61.34	43.61	26.09	62.00	43.49	19.42	5.69	6.00	5.55	4.93	0.36
Panel B: Realized Bad Volatility														
21.37	28.21	22.47	41.39	34.07	26.12	14.07	35.26	26.80	10.81	3.26	3.61	2.66	2.60	0.08
14.26	26.72	22.65	30.82	28.05	19.73	12.77	35.63	17.78	9.58	2.57	2.57	3.19	2.25	0.26
17.18	27.33	22.58	35.15	30.52	22.35	13.30	35.48	21.48	10.08	2.85	3.00	2.97	2.39	0.19
Panel C: Realized Good Volatility														
20.19	30.05	22.31	38.39	32.71	24.45	13.05	26.18	26.21	11.16	3.50	3.42	2.48	2.55	0.02
14.98	27.01	22.89	30.72	29.52	19.05	12.61	26.76	19.11	8.07	2.38	2.71	2.65	2.53	0.28
17.12	28.26	22.65	33.86	30.83	21.27	12.79	26.52	22.02	9.34	2.84	3.00	2.58	2.53	0.17
Panel D: Realized Singed Jump Variation														
−1.18	1.84	−0.16	−3.01	−1.36	−1.67	−1.02	−9.08	−0.59	0.35	0.24	−0.19	−0.18	−0.05	−0.06
0.72	0.29	0.24	−0.10	1.47	−0.67	−0.15	−8.87	1.33	−1.51	−0.19	0.14	−0.54	0.28	0.02
−0.06	0.93	0.08	−1.29	0.31	−1.08	−0.51	−8.96	0.54	−0.74	−0.02	0.00	−0.39	0.14	−0.01
Panel E: Realized Skewness (std)														
0.16	0.30	−0.92	−5.41	2.73	−1.81	0.02	−3.81	3.20	0.86	3.02	0.14	2.06	−3.48	−5.24
1.80	−0.79	−0.47	−3.82	2.88	0.02	−0.56	−4.75	2.01	−1.02	−1.77	1.49	1.78	3.71	−4.37
1.13	−0.34	−0.65	−4.47	2.82	−0.73	−0.32	−4.36	2.50	−0.25	0.20	0.94	1.89	0.76	−4.73
Panel F: Realized Kurtosis (std)														
17.9	17.7	18.6	21.8	19.5	18.6	17.5	20.3	19.6	19.7	17.1	19.3	17.3	17.1	19.6
20.37	18.62	20.49	18.45	18.59	19.51	17.34	23.43	19.56	23.28	18.19	21.00	18.65	17.88	22.85
19.4	18.2	19.7	19.8	19.0	19.1	17.4	22.2	19.6	21.8	17.7	20.3	18.1	17.5	21.5

In general lines, our main result is that we demonstrate that the market origins and destines of cross-spillovers change depending on the definition of risk that we use to estimate such spillovers. From the perspective of a policymaker, with financial stability considerations in mind, this is relevant because we identify commodity markets that generate shocks to the system, especially during distress episodes (like natural gas), which are better captured by skewness and sign jump variations spillovers, and which are not evident when looking exclusively at volatility spillovers. From the perspective of investors, we show that diversification opportunities of some commodities are considerably reduced when we analyze skewness spillovers (remarkably the case of coffee, but also cotton and soybean), compared to traditional volatility spillovers. This latter point motivates a portfolio construction that considers skewness (or other indicators of asymmetry in the distribution of market returns) in the optimization process. As shown by Harvey et al. (2010) considering higher order moments (such as skeweness, coskewness and kurtosis) in the optimization of portfolio shares, allows utility gains with respect to the Markowitz framework, whenever return distributions are not normal, or when there is uncertainty on the parameters of the relevant probability distribution required to conduct the optimization process, which in Harvey's et al. (2010) framework is the posterior predictive distribution.

For both policymakers and investors, a simultaneous close monitoring of all the risk dimensions that we propose here is fundamental. There is not and overall "best measure of risk" because different measures are useful for different ends. Second moment shocks are related to risk in regular market periods, skewness and sign jumps, in turn, relate with market crashes and asymmetries in market dynamics, and kurtosis with the occurrence of extreme events both positive and negative. Even if we conduct our optimization in the mean-variance space, it would be useful to keep and eye on the diversification benefits that can be lost during market distress episodes, which are better understood looking at the spillovers of asymmetric higher order moments.

In short, we show that the information flows are very different depending on the definition of risk that we use to estimate the market cross-spillovers and therefore an effective monitoring tool should track not only traditional spillovers of the second moment shocks of commodity market returns, but also higher order moments. Interestingly, spillovers are different and generally more significant for commodity markets in skewness than in volatility, but the same does not hold for the kurtosis. Kurtosis spillovers are considerable smaller, kurtosis' networks are not very dense and dynamic kurtosis spillovers do not change in time as much as skewness spillovers or traditional volatility spillovers. This means that while monitoring skewness spillovers is fundamental, the information that kurtosis spillovers provide is not equally relevant.

Our results also contribute with new evidence regarding the financialization of commodity markets. We show that cross-spillovers have increased during the last years in our sample, especially between stocks and commodity markets, while some level of decoupling has been observed between FX and commodity markets. The global financial risk profile is remarkably dissimilar depending on the period of the series under analysis. Realized volatility spillovers (both total and semi-volatilities) increased, as expected, during the

Table 2
Variance decomposition of the total, good and bad realized volatilities.

	Stocks								Commodities													Foreign Exchange						
	USA	CAN	GER	UK	CHI	FRA	ITA	JAP	GI1	WTI	NG	ZS	W	C	KC	SB	CT	AL	SI	COOP	GOLD	EUR	JPY	GBP	CAD	CNY	FROM	NET
Panel A: Realized Volatility																												
USA	11.8	10.0	7.8	9.7	3.3	8.4	7.5	5.2	6.0	4.0	0.0	0.5	0.6	0.5	0.1	0.3	0.9	0.2	2.4	2.4	3.0	2.5	5.1	2.8	4.2	0.6	88.2	35.8
CAN	9.4	10.9	7.0	8.1	4.0	7.8	7.1	4.7	6.4	4.1	0.0	0.7	0.6	0.8	0.2	0.4	1.2	0.5	3.0	3.0	3.2	2.6	5.3	3.1	5.1	0.6	89.1	41.6
GER	7.9	7.5	11.5	9.0	4.3	10.8	9.0	5.0	4.3	1.7	0.0	0.6	0.9	0.9	0.2	0.5	1.5	0.5	2.5	3.2	2.6	3.1	4.4	2.9	5.0	0.3	88.5	31.8
UK	8.7	7.7	8.0	10.6	4.4	9.0	8.2	6.1	4.5	1.7	0.0	0.8	1.0	1.0	0.0	0.4	1.4	0.5	2.1	3.7	2.2	2.5	5.5	4.5	5.4	0.3	89.4	52.0
CHI	4.9	5.5	5.8	7.0	16.0	6.4	4.9	9.4	3.6	0.4	0.0	2.2	1.5	1.6	0.1	0.6	2.1	1.4	2.3	6.3	2.4	2.4	6.0	1.4	5.8	0.0	84.0	4.1
FRA	7.8	7.5	9.8	9.1	4.3	10.7	9.2	5.0	4.3	1.7	0.0	0.6	0.9	1.0	0.1	0.5	1.4	0.6	2.6	3.4	2.7	3.1	4.8	3.4	5.3	0.2	89.3	45.2
ITA	7.4	7.4	8.8	8.9	3.3	9.9	11.5	4.4	4.6	2.3	0.0	0.4	0.8	0.9	0.0	0.4	1.1	0.5	2.5	3.0	2.6	3.7	5.2	4.8	4.9	0.4	88.5	34.9
JAP	6.5	6.0	6.2	8.5	8.5	6.7	5.6	14.6	3.6	0.7	0.0	1.6	1.4	1.5	0.0	0.6	2.1	0.9	1.3	5.4	1.4	1.9	7.1	2.1	5.7	0.0	85.4	13.6
GI1	8.2	8.6	5.7	7.0	3.3	6.2	6.1	4.0	12.2	7.1	0.4	1.0	1.1	1.0	0.1	0.5	1.4	0.6	3.4	2.5	4.6	3.1	5.1	2.5	3.8	0.5	87.8	17.8
WTI	10.6	10.3	5.6	6.7	1.3	6.0	6.4	2.7	10.9	15.3	0.1	0.2	0.2	0.3	0.3	0.2	0.4	0.1	2.8	0.9	4.4	3.0	4.1	3.3	2.1	1.7	84.7	−36.3
NG	0.2	0.1	0.2	0.1	0.0	0.0	0.0	0.0	3.6	0.4	93.9	0.4	0.1	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.3	6.1	−4.7
ZS	1.8	2.0	1.9	3.1	4.8	2.2	1.5	4.2	2.6	0.1	0.2	35.7	7.0	11.5	0.0	0.7	4.0	0.9	2.1	3.4	1.3	1.2	4.3	0.7	2.5	0.2	64.3	−24.0
W	1.9	1.7	2.7	3.6	3.0	2.9	2.4	3.6	3.0	0.1	0.0	5.6	37.0	8.5	0.0	1.6	5.6	1.0	2.4	3.3	1.4	1.4	3.1	0.6	3.6	0.0	63.0	−16.6
C	1.8	2.4	2.6	3.6	3.2	3.2	2.6	3.7	2.5	0.2	0.0	8.9	8.9	30.7	0.4	1.3	3.9	1.1	2.3	3.5	2.2	2.2	3.1	1.8	3.5	0.2	69.3	−18.6
KC	0.7	1.6	1.4	0.3	0.3	0.8	0.4	0.2	1.1	1.4	0.1	0.1	0.0	0.6	89.9	0.1	0.2	0.2	0.0	0.2	0.0	0.1	0.1	0.1	0.1	0.0	10.1	−8.0
SB	1.5	2.3	2.7	2.3	2.4	3.1	2.2	2.6	2.4	0.4	0.0	1.3	3.4	2.2	0.1	52.9	5.7	2.7	1.9	1.5	0.6	1.8	1.8	0.6	1.7	0.0	47.1	−30.2
CT	2.7	3.3	4.0	4.5	4.3	4.2	3.3	4.8	3.4	0.2	0.0	4.8	5.4	4.4	0.1	2.4	27.4	1.3	2.2	3.7	0.9	2.7	4.0	1.0	4.8	0.1	72.6	−26.6
AL	1.8	2.7	2.7	3.0	4.2	3.4	2.8	3.2	2.9	0.3	0.0	1.4	1.9	1.9	0.2	2.4	2.2	34.6	5.3	10.7	3.1	1.0	2.7	0.8	5.0	0.0	65.4	−41.9
SI	4.9	5.6	4.4	4.6	2.5	5.0	4.8	1.8	5.2	2.7	0.0	1.2	1.9	1.4	0.0	0.7	1.5	2.0	22.6	4.2	12.3	2.3	3.6	1.3	3.4	0.2	77.4	−8.4
COOP	4.0	4.8	4.7	6.2	6.4	5.6	4.7	6.1	3.3	0.6	0.0	1.5	1.7	1.9	0.0	0.4	1.9	4.3	4.6	16.2	3.9	2.0	4.9	1.9	8.2	0.1	83.8	−0.7
GOLD	5.9	5.5	4.2	4.7	2.2	4.8	4.6	1.9	6.7	4.6	0.0	0.8	1.4	1.3	0.0	0.3	0.6	1.1	12.3	2.6	22.4	2.9	4.9	1.9	2.3	0.1	77.6	−9.4
EUR	5.1	5.3	5.9	5.8	4.7	6.6	6.7	4.1	5.0	2.3	0.0	1.2	1.5	1.9	0.0	1.2	1.9	0.6	2.8	3.1	3.5	16.0	6.2	3.1	5.0	0.4	84.0	−26.1
JPY	6.2	6.5	5.1	7.4	5.1	6.1	6.4	6.8	4.9	1.8	0.0	1.7	1.3	1.3	0.0	0.4	1.6	0.7	2.5	3.9	3.6	3.7	13.7	3.8	5.2	0.4	86.3	18.8
GBP	5.5	6.3	5.5	9.1	2.3	6.9	8.9	3.5	4.0	2.8	0.0	0.5	0.6	1.3	0.0	0.3	0.8	0.4	1.7	2.7	2.4	3.7	6.3	19.4	4.6	0.9	80.6	−26.7
CAD	5.5	6.6	5.9	7.2	5.7	6.9	6.0	5.6	4.5	0.9	0.0	1.4	1.9	2.2	0.0	0.5	2.1	1.4	3.2	6.4	3.2	3.1	5.7	2.6	11.3	0.2	88.7	9.6
CNY	3.1	3.7	1.5	1.9	0.3	1.5	2.3	0.4	2.3	5.8	0.4	0.9	0.3	0.7	0.0	0.2	0.2	0.1	0.7	0.3	0.3	2.0	1.9	2.8	1.2	65.4	34.6	−26.9
TO	124.0	130.7	120.3	141.4	88.1	134.6	123.4	99.0	105.6	48.3	1.4	40.3	46.4	50.7	2.1	16.9	45.9	23.6	69.0	83.1	68.2	57.9	105.1	53.9	98.3	7.7	TOTAL	72.5
Panel B: Realized Good Volatility																												
USA	13.1	11.9	7.9	9.5	4.9	8.3	6.7	5.6	3.0	3.5	0.0	0.5	0.7	0.2	0.2	0.1	0.1	0.0	2.8	1.3	3.5	1.1	6.2	3.8	3.9	1.3	86.9	50.2
CAN	11.8	13.0	6.6	8.6	5.1	7.2	6.2	5.6	4.0	4.4	0.0	0.5	0.7	0.2	0.3	0.1	0.0	0.1	3.4	1.6	4.1	1.2	6.1	4.4	3.5	1.3	87.0	54.3
GER	9.3	8.1	14.2	9.5	5.6	12.9	10.1	5.2	2.1	1.2	0.0	0.4	1.1	0.3	0.4	0.2	0.1	0.2	2.6	2.2	2.7	1.3	4.2	2.1	3.6	0.3	85.8	20.8
UK	9.6	8.6	8.4	13.7	6.6	9.5	8.4	8.1	2.0	1.1	0.0	0.6	0.8	0.2	0.0	0.2	0.1	0.1	2.1	2.0	2.0	0.7	6.1	3.4	5.2	0.3	86.3	50.9
CHI	6.8	6.9	6.4	9.3	18.3	7.4	7.0	8.7	2.1	0.8	0.0	1.2	1.0	0.4	0.1	0.3	0.1	0.5	3.0	3.2	3.5	1.4	5.4	2.3	3.9	0.1	81.7	13.0
FRA	8.9	7.9	11.5	9.8	5.9	13.3	10.9	5.1	2.2	1.4	0.0	0.4	0.8	0.3	0.2	0.3	0.1	0.3	3.0	2.2	3.1	1.3	4.5	2.3	3.9	0.3	86.7	35.7
ITA	7.8	7.3	10.0	9.5	5.6	12.0	14.9	5.3	2.1	1.0	0.0	0.5	0.8	0.4	0.1	0.4	0.1	0.5	3.2	2.6	3.0	1.9	4.4	2.6	3.8	0.3	85.1	28.1
JAP	7.8	7.9	6.4	11.2	8.9	6.7	6.6	18.7	3.0	0.8	0.0	1.2	0.9	0.4	0.0	0.5	0.2	0.3	1.1	2.6	1.0	0.4	7.6	2.4	4.0	0.2	82.3	11.2
GI1	6.6	8.2	3.5	5.2	3.3	4.2	3.8	3.6	19.8	10.9	1.2	1.0	1.0	0.9	0.1	0.3	0.4	0.9	4.1	2.1	5.7	1.6	4.0	2.7	2.8	2.0	80.2	1.9
WTI	8.6	10.0	3.2	5.2	2.6	3.9	3.0	3.7	11.2	19.1	0.0	0.3	0.3	0.2	0.2	0.1	0.0	0.1	3.9	0.6	7.8	1.2	4.9	3.7	2.7	4.3	81.9	−20.0
NG	0.0	0.1	0.2	0.0	0.1	0.0	0.0	0.0	6.2	0.2	89.3	0.0	0.1	1.2	0.0	0.5	0.0	0.7	0.0	0.0	0.1	0.1	0.5	0.0	0.3	0.3	10.7	−7.3
ZS	1.8	2.0	1.3	2.4	3.1	1.5	1.8	3.2	1.5	0.1	0.0	44.8	7.3	17.1	0.0	0.1	4.7	0.3	0.9	1.5	0.7	0.2	2.5	0.5	0.7	0.1	55.2	−12.4
W	2.3	2.4	3.4	2.7	2.4	2.7	2.3	2.2	1.5	0.0	0.1	7.2	44.4	13.9	0.2	0.8	2.7	0.9	1.5	2.4	0.5	0.7	0.8	0.6	1.2	0.2	55.6	−12.2
C	0.9	1.1	1.1	1.6	2.0	1.5	1.8	2.6	1.6	0.2	0.6	17.1	14.3	43.4	0.3	1.3	2.7	0.6	1.2	1.2	0.9	0.2	0.7	0.3	0.8	0.1	56.6	−13.7
KC	1.5	1.9	2.8	0.2	0.3	1.4	0.3	0.1	0.3	0.4	0.0	0.0	0.3	0.0	88.1	0.7	1.0	0.0	0.1	0.1	0.1	0.0	0.0	0.2	0.1	0.0	11.9	−8.0
SB	0.6	0.9	1.1	1.6	1.5	2.2	2.6	2.3	2.1	0.2	0.4	0.1	1.1	0.4	0.6	78.7	0.6	1.2	0.5	0.5	0.4	0.1	0.1	0.1	0.8	0.4	22.3	−10.3

(*continued on next page*)

Table 2 (*continued*)

	Stocks								Commodities													Foreign Exchange						
	USA	CAN	GER	UK	CHI	FRA	ITA	JAP	GI1	WTI	NG	ZS	W	C	KC	SB	CT	AL	SI	COOP	GOLD	EUR	JPY	GBP	CAD	CNY	FROM	NET
CT	1.9	1.7	1.7	2.5	2.6	2.0	1.9	2.3	1.9	0.4	0.0	6.1	4.0	3.5	1.0	3.0	54.8	0.2	1.6	1.1	1.8	1.2	1.3	0.7	0.8	0.0	45.2	−31.3
AL	0.4	0.7	1.1	1.0	1.9	1.4	2.4	1.4	3.2	0.2	0.5	0.5	1.4	0.3	0.0	0.9	0.1	63.4	2.9	14.7	0.5	0.2	0.3	0.2	0.3	0.0	36.6	−22.9
SI	5.2	6.0	3.0	4.8	3.0	4.4	4.8	1.7	4.7	3.9	0.0	0.6	1.3	0.6	0.0	0.3	0.2	1.1	27.4	2.4	14.9	2.6	2.4	3.1	1.4	0.3	72.6	0.6
COOP	4.0	4.8	4.5	5.2	5.4	5.1	5.4	4.1	4.6	1.7	0.0	1.1	1.6	0.5	0.0	0.2	0.2	5.1	7.1	23.2	5.9	1.5	3.5	2.3	3.8	0.2	77.8	−24.0
GOLD	5.7	6.3	2.3	4.8	2.6	3.4	3.4	1.7	6.0	7.8	0.0	0.7	0.9	0.5	0.0	0.1	0.1	0.2	14.2	1.1	27.2	2.7	2.8	3.5	1.4	0.5	72.8	7.6
EUR	5.6	5.5	4.7	5.9	5.7	5.6	6.1	3.6	3.0	2.2	0.1	0.5	1.0	0.5	0.1	1.0	0.3	0.3	4.9	1.6	6.9	21.7	4.4	4.5	4.2	0.3	78.3	−50.4
JPY	8.9	8.9	5.0	8.7	5.4	6.1	5.4	7.8	3.3	2.6	0.1	1.0	0.4	0.1	0.0	0.0	0.0	0.0	1.8	2.0	2.2	1.3	19.0	4.3	6.0	0.6	82.0	5.5
GBP	7.9	9.2	3.6	7.1	3.6	4.6	4.7	3.8	3.1	3.7	0.0	0.4	0.6	0.2	0.0	0.1	0.1	0.1	3.8	1.6	4.8	3.5	6.1	23.2	3.3	1.0	76.8	−21.4
CAD	7.6	7.2	5.8	9.4	6.5	7.0	6.4	5.5	2.1	1.5	0.1	0.7	1.0	0.6	0.0	0.2	0.0	0.1	2.9	3.1	3.5	0.8	6.9	3.1	17.6	0.6	82.4	−18.5
CNY	5.7	5.8	1.1	1.4	0.1	1.2	1.1	0.5	5.0	11.5	0.2	0.1	0.3	0.0	0.0	0.3	0.0	0.0	0.6	0.2	0.9	0.7	1.7	2.2	1.7	57.6	42.4	−27.5
	137.1	141.3	106.6	137.3	94.6	122.3	113.3	93.5	82.1	61.9	3.4	42.8	43.4	42.9	3.9	12.0	13.9	13.7	73.2	53.9	80.4	27.9	87.5	55.4	64.0	15.0	TOTAL	66.1
Panel C: Realized Bad Volatility																												
USA	14.7	12.6	9.6	10.1	2.7	10.4	9.3	3.0	6.0	1.4	0.0	0.4	0.2	1.0	0.1	0.2	1.4	0.5	2.4	3.3	2.2	3.0	1.8	2.5	1.2	0.0	85.3	16.4
CAN	11.9	13.9	8.4	9.7	3.5	9.7	8.4	3.3	4.8	0.9	0.0	0.5	0.4	1.2	0.2	0.3	1.9	1.1	2.8	5.4	2.6	3.2	1.7	2.7	1.7	0.0	86.1	27.1
GER	8.9	8.2	13.5	10.6	3.3	12.5	10.0	4.0	4.1	1.1	0.0	0.5	0.5	1.4	0.2	0.5	1.8	0.8	2.3	3.3	2.1	4.4	1.7	3.1	1.2	0.0	86.5	28.7
UK	8.1	8.2	9.2	11.8	3.4	10.5	9.2	4.6	3.9	1.0	0.0	0.7	0.7	2.0	0.1	0.4	2.0	1.0	2.3	4.2	2.1	4.0	3.0	5.3	2.2	0.0	88.2	55.4
CHI	3.9	5.4	5.2	6.1	21.3	5.8	3.5	10.6	2.0	1.8	0.0	2.3	1.2	1.9	0.0	0.3	3.9	2.2	2.5	7.8	2.6	2.2	3.0	1.1	3.2	0.0	78.7	0.1
FRA	8.5	8.3	11.1	10.7	3.2	12.0	10.1	3.9	4.1	0.9	0.0	0.5	0.6	1.6	0.1	0.6	1.8	1.1	2.5	3.9	2.3	4.5	2.0	3.9	1.7	0.0	88.0	49.4
ITA	8.6	8.2	10.0	10.6	2.3	11.5	13.6	3.0	4.8	1.1	0.0	0.3	0.4	1.4	0.1	0.4	1.6	0.7	2.3	2.9	1.8	4.5	2.5	6.0	1.3	0.0	86.4	30.2
JAP	4.1	4.8	5.9	7.7	9.9	6.5	4.5	19.9	2.5	1.6	0.0	2.0	1.1	2.4	0.1	0.5	3.1	1.8	1.2	5.0	1.7	2.8	4.7	1.8	4.5	0.0	80.1	5.5
GI1	8.0	6.8	5.9	6.5	1.9	6.6	6.9	2.5	19.5	7.1	0.7	0.9	1.3	1.6	0.4	1.1	2.0	1.5	3.2	1.7	2.3	4.6	2.8	1.9	1.8	0.5	80.5	9.9
WTI	3.8	2.5	3.3	3.5	3.4	3.2	3.2	3.1	14.5	39.8	1.3	0.4	0.5	0.7	0.7	0.3	1.2	0.6	1.0	2.2	0.8	4.4	3.6	1.6	0.5	0.0	60.2	−27.1
NG	0.1	0.0	0.1	0.1	0.1	0.1	0.1	0.1	3.3	2.9	91.4	0.0	0.1	0.2	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.0	1.0	0.0	0.0	0.2	8.6	−5.8
ZS	1.0	1.5	1.3	2.3	4.4	1.7	0.9	4.0	1.7	0.4	0.0	39.4	7.9	11.1	0.0	1.6	5.7	3.3	2.2	3.4	1.5	2.3	1.8	0.5	0.2	0.1	60.6	−19.8
W	0.7	1.0	1.5	2.4	2.4	1.9	1.3	2.2	2.7	0.5	0.0	8.0	40.0	9.7	0.0	2.2	6.3	1.9	3.7	2.6	2.5	3.1	1.7	0.5	1.3	0.0	60.0	−19.7
C	1.9	2.4	2.9	5.0	2.6	4.0	3.0	3.5	2.3	0.5	0.0	8.2	7.1	29.1	0.1	1.4	4.9	3.0	2.3	3.9	1.7	3.9	2.6	2.6	1.1	0.1	70.9	−9.1
KC	0.6	1.0	1.2	0.9	0.2	1.0	0.8	0.5	1.9	1.5	0.0	0.0	0.1	0.2	81.3	0.1	0.1	0.2	1.1	0.1	0.3	2.2	0.1	0.3	0.3	4.2	18.7	−15.7
SB	0.8	1.0	1.8	1.6	0.8	2.5	1.7	1.2	2.9	0.4	0.0	2.1	2.8	2.5	0.0	51.9	7.8	5.4	2.1	0.8	0.9	4.2	0.3	0.4	0.4	3.7	48.1	−26.6
CT	2.6	3.7	3.6	4.5	5.0	4.2	3.2	4.3	2.8	0.8	0.0	3.9	4.3	4.6	0.0	4.1	27.3	3.0	2.6	5.2	1.4	4.5	1.6	1.2	1.4	0.0	72.7	−7.9
AL	1.1	2.6	2.1	2.9	3.6	3.1	1.9	3.2	2.7	0.5	0.0	2.8	1.6	3.5	0.0	3.5	3.7	34.3	5.9	9.0	4.9	3.3	1.2	0.7	1.8	0.2	65.7	−19.2
SI	4.1	5.0	4.2	4.8	2.9	5.3	4.2	1.5	4.1	0.6	0.0	1.4	2.3	2.0	0.3	1.0	2.4	4.2	24.8	6.7	13.3	2.7	0.9	0.8	0.7	0.0	75.2	−8.4
COOP	4.2	7.4	4.6	6.6	6.9	6.1	4.1	4.7	1.6	1.0	0.0	1.6	1.2	2.5	0.0	0.3	3.6	4.9	5.1	18.8	5.4	2.5	1.8	1.7	3.3	0.0	81.2	11.8
GOLD	3.9	5.0	4.2	4.8	3.2	5.2	3.6	2.2	3.1	0.6	0.0	1.0	1.6	1.6	0.1	0.4	1.4	3.8	14.2	7.7	26.6	2.4	1.7	0.8	0.8	0.1	73.4	−14.8
EUR	4.3	4.9	6.8	7.1	2.2	8.0	7.1	3.0	5.0	2.3	0.0	1.2	1.7	2.8	0.4	1.7	3.5	2.0	2.3	2.9	1.9	21.1	1.7	4.3	1.7	0.1	78.9	0.3
JPY	3.6	3.5	3.5	7.2	4.1	4.8	5.3	6.8	4.1	2.6	0.3	1.3	1.2	2.5	0.0	0.2	1.7	1.0	1.0	2.8	1.9	2.3	28.9	5.3	4.1	0.1	71.1	−18.1
GBP	4.3	4.8	5.6	11.2	1.3	8.0	10.9	2.3	2.4	1.0	0.0	0.3	0.3	2.2	0.1	0.2	1.1	0.5	0.8	2.2	0.8	5.0	4.7	24.6	1.1	4.5	75.4	−25.2
CAD	2.9	4.3	3.2	6.5	5.2	4.9	3.5	7.9	3.1	0.4	0.0	0.2	1.1	1.3	0.0	0.3	1.8	1.6	1.0	6.1	1.1	2.7	5.0	1.3	34.6	0.1	65.4	−27.8
CNY	0.1	0.1	0.0	0.1	0.3	0.0	0.1	0.2	0.0	0.1	0.2	0.1	0.0	0.1	0.0	0.0	0.1	0.6	0.0	0.0	0.3	0.6	0.4	0.1	0.1	96.4	3.6	10.2
	101.7	113.3	115.2	143.7	78.8	137.4	116.7	85.6	90.4	33.1	2.8	40.8	40.3	61.8	3.0	21.5	64.7	46.5	66.8	93.0	58.6	79.2	53.1	50.2	37.6	13.8	TOTAL	67.3

We estimate forecast error variance decompositions for the system. Shadowed columns correspond to the commodity markets series.

Table 3
Variance decomposition of the realized jumps, skewness, and kurtosis.

	Stocks								Commodities													Foreign Exchange						
	USA	CAN	GER	UK	CHI	FRA	ITA	JAP	GI1	WTI	NG	ZS	W	C	KC	SB	CT	AL	SI	COOP	GOLD	EUR	JPY	GBP	CAD	CNY	FROM	NET
Panel D: Realized Singed Jump Variation																												
USA	29.7	7.4	12.0	11.3	3.2	10.7	11.2	3.4	0.4	0.7	0.0	0.6	0.3	0.9	0.1	0.2	0.3	0.7	0.1	0.0	2.4	0.9	0.0	0.6	2.3	0.7	70.3	−10.1
CAN	4.9	19.6	7.6	7.3	1.8	8.3	7.3	1.9	6.7	3.9	0.1	0.9	0.2	1.7	0.3	0.6	1.4	4.7	2.2	3.7	0.0	3.2	1.0	1.8	8.5	0.6	80.4	38.7
GER	7.7	7.4	19.2	12.0	2.4	15.8	12.5	2.4	2.2	1.8	0.0	0.4	0.4	1.0	0.4	0.3	0.6	1.8	0.8	0.8	0.0	2.5	0.2	3.0	3.7	0.6	80.8	28.2
UK	6.9	6.7	11.3	18.1	1.1	14.3	13.8	1.1	2.5	2.2	0.0	0.4	0.3	1.0	0.2	0.4	1.1	1.7	1.5	1.1	0.0	3.2	0.2	6.9	2.8	1.4	81.9	37.5
CHI	5.6	4.8	6.7	3.0	52.5	4.1	3.1	7.7	0.7	0.3	0.1	0.5	0.5	0.1	0.2	0.5	0.8	1.2	1.1	0.6	0.1	0.8	0.0	0.8	3.3	0.9	47.5	−19.5
FRA	6.2	7.3	14.2	13.6	1.3	17.2	14.1	1.3	2.6	2.6	0.0	0.4	0.2	1.2	0.2	0.7	0.8	1.8	1.4	1.0	0.0	3.3	0.2	3.9	3.5	0.8	82.8	41.8
ITA	7.0	6.9	12.1	14.1	1.1	15.2	18.5	1.1	3.1	3.6	0.0	0.2	0.1	1.1	0.1	0.6	0.5	1.0	0.9	0.5	0.1	2.7	0.1	6.0	2.6	0.8	81.5	30.4
JAP	5.6	4.8	6.0	3.0	7.2	3.8	2.8	49.0	1.9	0.3	0.3	2.7	0.2	0.5	0.6	0.2	0.1	2.9	0.1	0.3	1.5	0.6	0.0	1.3	3.9	0.4	51.0	−17.7
GI1	0.4	9.0	3.0	3.5	0.3	4.0	4.3	1.0	26.2	17.8	0.8	1.0	0.5	2.3	0.5	1.1	1.8	4.9	1.9	5.6	0.1	3.0	0.5	1.3	5.0	0.2	73.8	15.5
WTI	0.8	7.0	3.3	4.3	0.2	5.4	6.9	0.2	24.2	35.6	0.0	0.1	0.0	0.8	0.0	0.9	0.6	0.8	1.6	1.9	0.0	1.8	0.7	0.5	1.9	0.4	64.4	−17.7
NG	0.0	0.4	0.0	0.0	0.1	0.2	0.1	0.6	2.7	0.1	85.0	0.9	0.7	3.4	0.1	1.1	0.0	1.1	0.1	0.1	0.1	1.3	0.6	0.0	1.3	0.0	15.0	−7.2
ZS	0.9	2.1	1.1	1.0	0.6	1.1	0.5	2.6	1.7	0.1	0.5	46.1	8.2	14.5	1.0	0.9	6.1	3.4	0.9	2.3	0.3	1.4	0.0	0.1	2.4	0.0	53.9	−8.3
W	0.4	0.5	0.9	0.8	0.5	0.6	0.2	0.2	1.0	0.0	0.4	9.1	51.0	15.1	2.4	0.9	3.0	3.0	1.6	1.0	0.4	3.2	0.0	1.5	2.0	0.2	49.0	−10.7
C	1.3	3.2	2.1	2.2	0.1	2.7	2.3	0.4	3.3	0.8	1.5	11.7	11.0	37.2	1.5	0.4	3.1	3.3	1.2	2.7	0.0	3.0	0.0	1.7	3.2	0.1	62.8	1.7
KC	0.3	1.2	1.8	0.7	0.6	1.1	0.4	1.2	1.4	0.1	1.1	1.6	3.2	2.9	67.7	2.0	1.6	2.5	3.0	2.7	0.4	0.5	0.0	0.2	1.7	0.0	32.3	−17.2
SB	0.5	2.1	0.9	1.5	0.6	2.6	2.1	0.2	2.8	1.6	0.8	1.3	1.2	0.7	1.9	64.5	3.2	4.8	1.8	0.9	0.5	1.6	0.9	0.0	1.1	0.0	35.5	−15.7
CT	0.5	3.4	1.6	2.8	0.8	2.1	1.4	0.1	3.3	0.8	0.0	6.3	2.8	4.0	0.8	2.4	47.8	2.9	2.4	6.1	0.6	3.3	0.9	0.5	2.3	0.1	52.2	−12.6
AL	0.8	7.7	3.0	3.0	0.7	3.3	1.7	1.9	6.0	0.7	0.4	2.3	1.9	2.9	1.1	2.4	2.0	32.2	2.7	9.6	1.1	3.6	0.3	1.3	7.2	0.3	67.8	2.5
SI	0.1	4.2	1.5	3.1	0.8	3.1	1.8	0.1	2.7	1.7	0.0	0.7	1.2	1.2	1.6	1.0	1.9	3.1	37.2	6.6	15.2	3.2	2.1	0.2	5.3	0.3	62.8	2.5
COOP	0.0	6.8	1.5	2.1	0.4	2.1	0.9	0.2	7.6	1.9	0.0	1.8	0.7	2.6	1.1	0.5	4.6	10.6	6.4	35.8	2.8	2.2	0.4	0.5	6.0	0.3	64.2	−4.0
GOLD	4.3	0.1	0.1	0.1	0.1	0.0	0.4	1.6	0.1	0.0	0.1	0.2	0.4	0.0	0.3	0.4	0.7	1.9	22.3	4.3	54.4	3.5	2.8	0.1	1.8	0.0	45.6	−13.2
EUR	1.0	5.2	4.3	5.7	0.5	6.3	4.7	0.4	3.7	1.6	0.5	0.9	2.0	2.6	0.2	0.8	2.3	3.6	2.8	2.0	2.1	32.3	1.2	5.0	7.9	0.4	67.7	−2.9
JPY	0.6	3.9	0.9	0.9	0.1	0.9	0.6	0.1	1.3	1.4	0.5	0.0	0.0	0.0	0.0	0.9	1.4	0.7	3.9	0.8	3.7	2.7	70.9	1.1	2.0	0.4	29.1	−15.2
GBP	0.7	3.3	5.7	13.8	0.5	8.2	11.9	1.0	1.8	0.5	0.0	0.1	1.1	1.6	0.1	0.0	0.4	1.5	0.2	0.5	0.1	5.6	0.5	36.5	3.2	1.0	63.5	−21.0
CAD	2.0	11.5	5.0	4.1	1.6	5.3	3.6	2.1	5.0	1.4	0.4	1.4	1.0	2.3	0.6	0.4	1.2	5.9	3.8	4.4	0.9	6.5	0.7	2.3	26.3	0.3	73.7	11.7
CNY	1.6	2.1	2.3	5.4	1.3	3.3	3.3	0.5	0.5	0.8	0.0	0.1	0.2	0.1	0.0	0.0	0.1	0.6	0.6	0.7	0.0	1.0	0.4	2.0	0.7	72.3	27.7	−17.6
	60.3	119.2	109.1	119.4	27.9	124.5	111.9	33.3	89.3	46.7	7.7	45.5	38.3	64.5	15.1	19.8	39.6	70.3	65.3	60.2	32.3	64.8	13.9	42.5	85.4	10.2	TOTAL	58.3
Panel E: Realized Skewness (std)																												
USA	37.4	8.7	9.9	9.1	4.1	9.9	5.6	5.0	0.5	0.2	0.1	0.6	0.2	0.0	0.0	0.0	0.5	0.7	0.1	1.4	0.0	0.8	1.0	1.7	1.7	0.5	62.6	−8.8
CAN	6.7	28.7	6.7	5.9	3.2	6.9	6.0	2.1	4.0	3.0	0.3	0.5	0.0	0.0	0.9	0.4	1.0	3.0	3.2	4.3	1.1	2.2	0.1	0.7	8.2	0.6	71.3	15.9
GER	6.1	5.3	22.9	11.7	3.6	17.9	12.0	3.0	1.2	0.7	0.2	0.1	0.0	0.0	0.6	0.1	0.5	1.7	0.8	1.2	0.4	3.9	0.3	3.0	1.8	0.9	77.1	30.1
UK	5.9	5.0	12.4	24.2	3.1	15.0	10.8	2.8	2.3	1.5	0.3	0.0	0.0	0.0	0.2	0.1	0.3	1.0	0.8	1.2	0.6	4.0	0.1	5.5	2.0	0.9	75.8	24.0
CHI	5.0	5.0	7.2	5.8	45.5	4.9	4.1	3.0	0.9	1.3	0.9	0.1	0.1	0.1	0.4	0.6	0.6	1.3	2.3	2.0	0.9	1.7	0.0	0.9	2.2	3.3	54.5	−12.0
FRA	5.8	5.3	17.2	13.6	2.4	22.0	13.2	2.2	1.7	0.9	0.4	0.1	0.0	0.0	0.3	0.1	0.3	1.4	0.7	1.2	0.5	4.4	0.2	3.4	1.8	0.9	78.0	33.2
ITA	3.9	5.5	13.7	11.6	2.3	15.7	26.1	1.4	1.7	0.8	0.6	0.1	0.0	0.0	0.3	0.2	0.2	1.6	0.6	1.1	0.1	5.7	0.1	3.9	2.1	0.6	73.9	12.0
JAP	6.5	3.6	6.3	5.5	3.2	4.8	2.6	48.4	2.0	1.6	0.8	1.4	0.1	0.0	0.6	0.8	0.0	1.8	1.4	2.6	0.2	0.6	0.5	1.0	0.9	2.7	51.6	−12.8
GI1	0.4	4.5	1.7	3.1	0.6	2.5	2.1	1.3	32.3	22.1	3.0	1.3	0.3	0.6	1.3	1.5	1.1	3.1	2.5	5.2	0.9	2.1	0.1	2.2	3.6	0.8	67.7	18.2
WTI	0.2	4.3	1.3	2.5	1.1	1.6	1.3	1.4	27.6	40.3	2.0	0.5	0.0	0.1	1.0	1.3	1.2	1.4	1.8	3.4	0.4	0.7	0.0	1.8	2.3	0.5	59.7	−4.5
NG	0.2	0.8	0.6	0.9	1.4	1.2	1.5	1.2	6.3	3.5	68.9	1.5	0.5	0.1	0.7	0.6	0.1	1.9	1.6	0.5	1.2	1.6	0.7	1.5	0.7	0.3	31.1	−11.9
ZS	1.0	1.0	0.4	0.0	0.1	0.4	0.3	1.6	2.2	0.7	1.3	57.1	8.2	16.9	1.0	0.6	4.8	0.9	0.1	0.4	0.0	0.1	0.2	0.4	0.1	0.5	42.9	1.3
W	0.4	0.1	0.0	0.0	0.1	0.0	0.0	0.2	0.5	0.0	0.5	9.8	68.6	15.3	0.6	0.1	1.3	0.4	0.1	0.0	0.2	0.8	0.3	0.6	0.1	0.1	31.4	−4.6
C	0.0	0.1	0.1	0.1	0.2	0.0	0.0	0.0	1.0	0.1	0.1	18.0	13.5	60.6	1.4	0.0	1.8	0.5	0.1	0.0	0.0	0.4	0.3	0.1	0.0	1.4	39.4	−0.2
KC	0.0	2.1	1.9	0.7	0.9	1.1	0.8	1.0	2.6	1.6	0.9	1.1	0.7	1.6	66.0	2.4	0.1	3.9	2.3	4.6	0.4	1.2	0.0	0.2	1.4	0.6	34.0	−13.1
SB	0.0	1.1	0.2	0.2	1.0	0.4	0.5	1.2	3.4	2.4	0.7	0.8	0.1	0.0	2.7	74.7	0.8	4.1	0.2	2.6	0.1	0.4	0.6	0.1	1.0	0.5	25.3	−9.5

(*continued on next page*)

Table 3 (*continued*)

	Stocks								Commodities													Foreign Exchange						
	USA	CAN	GER	UK	CHI	FRA	ITA	JAP	GI1	WTI	NG	ZS	W	C	KC	SB	CT	AL	SI	COOP	GOLD	EUR	JPY	GBP	CAD	CNY	FROM	NET
CT	1.0	2.5	1.6	0.9	1.0	1.0	0.4	0.1	2.5	2.1	0.1	5.9	1.3	2.1	0.0	0.8	70.9	0.3	1.1	2.2	0.1	0.2	0.1	0.0	1.4	0.4	29.1	−11.3
AL	0.8	4.3	3.1	1.6	1.2	2.7	2.5	1.5	3.9	1.5	1.1	0.7	0.2	0.3	2.4	2.3	0.1	41.0	3.6	13.6	1.5	3.6	0.0	0.5	4.7	1.2	59.0	−2.4
SI	0.2	4.2	1.3	1.3	1.9	1.2	0.8	1.1	3.0	1.7	1.1	0.1	0.2	0.1	1.3	0.1	0.6	3.4	38.3	6.6	20.2	3.6	2.0	0.2	4.6	1.0	61.7	5.9
COOP	1.4	5.6	1.9	1.9	1.7	2.0	1.6	2.0	6.0	3.2	0.3	0.3	0.0	0.0	2.6	1.3	1.1	12.5	6.4	37.6	1.8	1.6	0.0	0.1	5.4	1.7	62.4	3.9
GOLD	0.1	1.8	0.8	1.1	0.9	1.0	0.3	0.3	1.5	0.6	1.1	0.0	0.2	0.0	0.3	0.1	0.0	1.8	24.9	2.4	47.0	5.2	3.2	0.9	3.8	0.8	53.0	−9.1
EUR	0.7	2.7	6.0	5.8	1.3	7.0	7.6	0.5	2.2	0.6	0.8	0.0	0.4	0.2	0.6	0.2	0.1	3.1	3.3	1.5	3.8	35.1	0.7	8.6	5.0	2.1	64.9	0.7
JPY	2.8	0.8	1.8	1.1	0.3	1.6	0.8	1.0	0.4	0.2	0.8	0.3	0.3	0.5	0.1	1.3	0.1	0.3	3.9	0.2	4.8	1.6	72.2	0.1	1.3	1.2	27.8	−15.7
GBP	1.9	1.1	5.6	9.8	0.8	6.7	6.5	0.9	3.0	1.9	0.9	0.3	0.4	0.1	0.1	0.1	0.0	0.6	0.2	0.1	0.8	10.5	0.0	43.1	2.3	2.3	56.9	−14.4
CAD	1.9	10.6	3.1	3.2	1.8	3.2	3.1	0.7	4.1	2.2	0.6	0.1	0.1	0.0	0.7	0.5	0.7	4.3	4.4	5.3	3.0	5.3	0.6	2.0	36.7	2.0	63.3	−1.6
CNY	0.8	1.3	2.3	2.2	4.3	2.5	1.4	3.2	1.5	0.7	0.2	0.6	0.0	1.0	0.5	0.4	0.3	1.7	1.5	2.6	0.9	3.6	0.9	3.2	3.1	59.1	40.9	−13.2
	53.9	87.2	107.2	99.8	42.5	111.2	85.8	38.8	85.9	55.2	19.2	44.1	26.8	39.2	20.9	15.7	17.8	56.6	67.6	66.3	44.0	65.6	12.0	42.6	61.7	27.7	TOTAL	53.7
Panel F: Realized Kurtosis (std)																												
USA	83.6	5.6	0.6	0.3	0.6	0.4	0.5	0.5	0.5	0.1	0.8	0.3	0.3	0.0	0.1	0.7	0.2	0.0	0.0	0.3	1.3	1.1	1.0	0.4	0.8	0.1	16.4	−1.7
CAN	5.1	76.1	1.4	1.7	0.9	1.2	0.0	1.2	2.6	1.8	1.3	0.2	0.0	0.1	0.0	0.0	0.0	1.1	0.6	0.4	2.1	0.1	0.1	0.2	1.5	0.2	23.9	−1.4
GER	0.2	0.8	43.5	8.4	0.0	29.3	13.2	0.0	0.9	0.1	0.0	0.0	0.0	0.2	0.1	0.1	0.1	0.2	0.0	0.0	0.1	0.3	0.2	1.4	0.7	0.1	56.5	9.3
UK	0.2	1.3	11.1	57.0	0.0	11.9	6.9	0.2	2.3	0.2	0.0	1.1	0.6	1.5	0.1	0.0	0.0	0.0	0.4	0.0	1.1	0.3	0.0	1.8	1.9	0.0	43.0	−1.3
CHI	0.6	1.0	0.1	0.1	90.2	0.0	0.2	1.8	0.2	0.2	0.0	0.8	0.3	0.6	0.6	2.2	0.0	0.2	0.1	0.2	0.0	0.0	0.0	0.1	0.4	0.3	9.8	0.5
FRA	0.1	0.6	27.8	8.7	0.0	41.4	14.5	0.2	1.2	0.3	0.1	0.1	0.0	0.7	0.0	0.1	0.0	0.0	0.0	0.0	0.6	0.8	0.5	1.0	1.1	0.4	58.6	16.5
ITA	0.3	0.0	16.0	6.4	0.1	18.4	52.6	0.5	0.7	1.2	0.0	0.0	0.0	0.1	0.3	0.1	0.0	0.3	0.0	0.0	0.7	0.3	0.2	0.7	0.7	0.4	47.4	−2.4
JAP	0.5	1.3	0.0	0.3	1.7	0.4	0.9	84.9	0.9	0.0	0.6	0.1	0.3	0.6	0.0	0.0	0.2	0.5	1.8	0.0	0.5	0.8	0.9	1.2	0.0	1.5	15.1	−1.4
GI1	0.3	2.0	1.2	2.3	0.1	1.6	0.8	0.6	57.5	23.7	0.4	0.2	0.0	0.0	0.1	0.0	1.1	0.2	2.6	0.7	4.2	0.0	0.1	0.0	0.2	0.0	42.5	5.7
WTI	0.1	1.5	0.1	0.2	0.1	0.4	1.5	0.0	26.2	63.4	1.0	0.0	0.0	0.5	0.1	0.1	0.4	0.2	1.4	0.3	2.5	0.0	0.0	0.0	0.0	0.0	36.6	−1.3
NG	0.8	1.4	0.0	0.0	0.0	0.1	0.1	0.6	0.5	1.3	83.8	0.7	1.0	0.0	2.3	0.9	0.0	3.0	0.3	0.2	0.4	0.0	0.4	0.2	0.2	1.8	16.2	−0.4
ZS	0.3	0.3	0.4	1.7	1.0	0.7	0.2	0.2	0.4	0.0	0.7	86.5	0.8	2.1	0.0	1.5	0.1	0.0	0.0	0.7	0.1	0.1	0.0	0.7	1.1	0.2	13.5	−2.3
W	0.3	0.0	0.0	0.8	0.2	0.0	0.0	0.3	0.0	0.0	1.0	0.7	83.7	8.3	1.3	0.1	0.0	0.1	0.8	0.4	0.8	0.1	0.0	0.9	0.0	0.2	16.3	0.0
C	0.1	0.2	0.4	2.2	0.6	1.4	0.2	0.5	0.0	0.6	0.0	2.0	8.0	80.8	0.6	0.1	0.0	0.6	0.2	0.0	0.0	0.1	0.3	0.5	0.5	0.0	19.2	0.1
KC	0.1	0.0	0.1	0.1	0.7	0.0	0.5	0.0	0.3	0.2	2.4	0.0	1.4	0.7	88.4	0.3	0.7	0.3	0.3	0.0	1.3	0.2	0.0	0.4	0.1	1.5	11.6	−1.6
SB	0.8	0.0	0.1	0.1	2.2	0.2	0.1	0.0	0.0	0.1	0.9	1.6	0.1	0.3	0.3	88.9	0.0	0.5	0.0	0.1	0.3	0.1	0.2	1.4	0.3	1.3	11.1	−0.8
CT	0.2	0.0	0.3	0.0	0.0	0.1	0.0	0.3	1.7	0.6	0.0	0.2	0.0	0.0	0.7	0.0	93.0	0.6	0.0	0.5	0.0	0.0	0.0	0.1	0.1	1.7	7.0	−1.3
AL	0.0	1.3	0.3	0.0	0.2	0.0	0.5	0.6	0.3	0.3	3.1	0.4	0.5	0.7	0.3	0.5	0.5	86.5	0.5	2.5	0.3	0.1	0.1	0.1	0.2	0.1	13.5	−2.0
SI	0.0	0.6	0.0	0.5	0.1	0.0	0.0	1.5	3.1	1.5	0.3	0.0	0.7	0.1	0.2	0.0	0.0	0.3	68.9	0.5	20.4	0.8	0.1	0.1	0.1	0.5	31.1	−1.1
COOP	0.3	0.5	0.1	0.0	0.2	0.0	0.0	0.0	1.2	0.4	0.2	0.7	0.4	0.0	0.0	0.1	0.5	2.6	0.7	91.3	0.1	0.0	0.2	0.0	0.3	0.2	8.7	−1.1
GOLD	1.0	1.7	0.4	1.3	0.0	1.0	1.0	0.3	4.5	2.4	0.3	0.0	0.6	0.4	0.8	0.2	0.0	0.0	18.3	0.0	61.8	1.5	0.3	1.0	0.6	0.3	38.2	2.6
EUR	1.1	0.1	0.7	0.9	0.8	1.8	1.0	1.9	0.2	0.1	0.1	0.1	0.2	0.3	0.3	0.7	0.0	0.6	1.2	0.0	2.2	79.6	0.1	3.5	1.2	1.3	20.4	−8.4
JPY	1.1	0.1	0.5	0.2	0.1	1.2	0.3	0.3	0.2	0.0	0.4	0.0	0.1	1.0	0.0	0.2	0.0	0.0	0.1	0.2	0.3	0.1	91.4	1.1	0.3	0.5	8.6	−2.4
GBP	0.4	0.2	2.6	2.6	0.1	1.9	1.1	0.8	0.0	0.0	0.2	0.6	0.8	0.5	0.3	1.2	0.1	0.1	0.1	0.0	0.1	3.5	1.0	81.2	0.2	0.3	18.8	−1.4
CAD	0.8	1.7	1.3	2.8	0.4	2.2	1.0	0.0	0.3	0.0	0.2	1.1	0.0	0.4	0.1	0.1	0.1	0.2	0.2	0.3	0.8	0.0	0.0	0.3	85.1	0.5	14.9	−1.7
CNY	0.1	0.2	0.1	0.0	0.2	0.7	0.7	1.5	0.0	0.0	1.9	0.2	0.2	0.0	1.5	1.1	1.6	0.0	0.6	0.2	0.4	1.5	0.4	0.3	0.5	85.9	14.1	−0.8
	14.7	22.5	65.7	41.7	10.3	75.2	45.1	13.6	48.2	35.3	15.8	11.3	16.3	19.2	10.1	10.3	5.7	11.6	30.1	7.6	40.7	12.0	6.1	17.5	13.2	13.3	TOTAL	23.6

We estimate forecast error variance decompositions for the system. Shadowed columns correspond to commodity markets series.

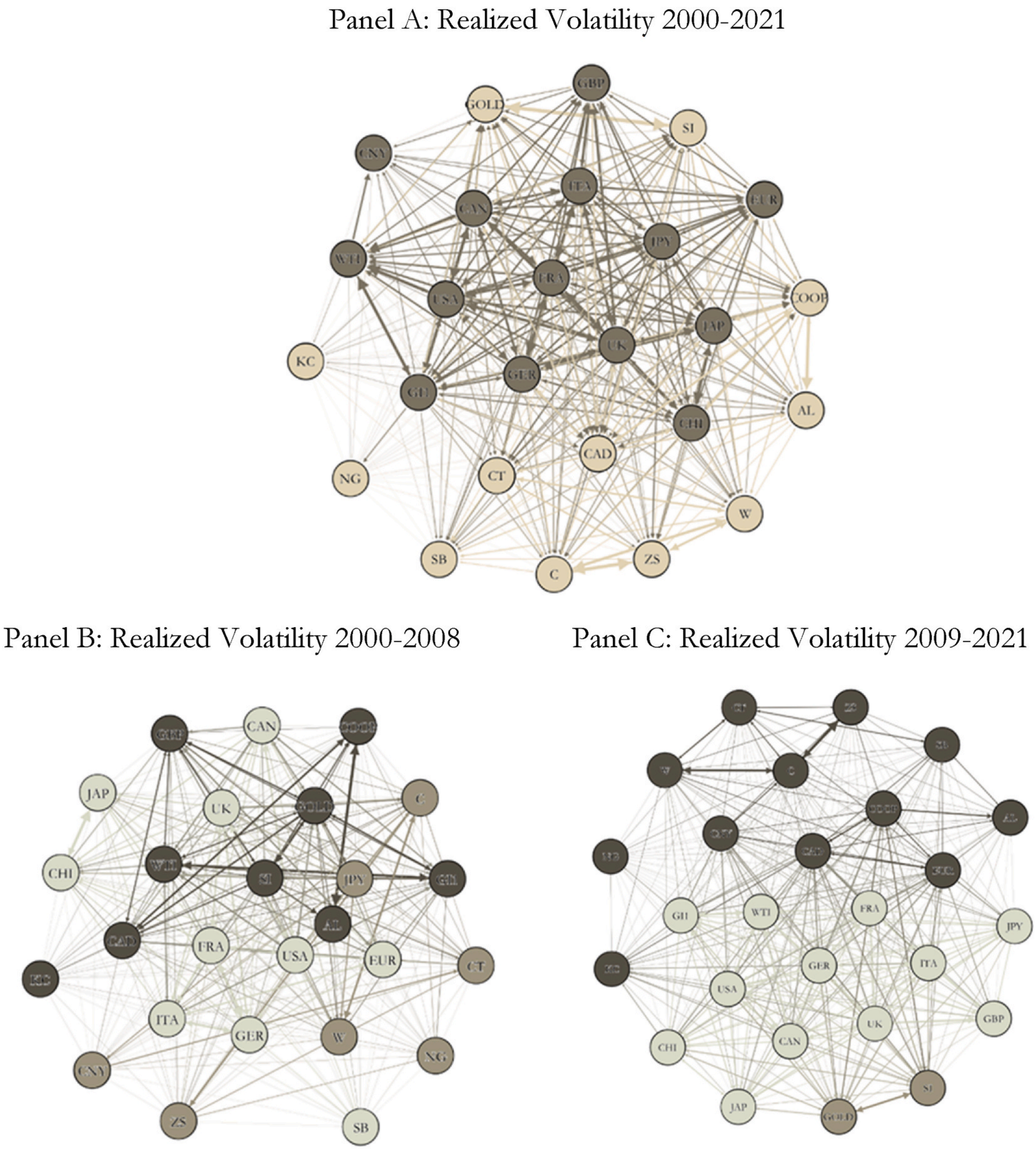

Fig. 1. Network representation of the global financial markets.

Global Financial Crisis (GFC) of 2007–2008. Bad volatility is more persistent than good volatility. Kurtosis spillovers are considerably lower although they have been increasing since July 2015. Two periods of important increases in spillovers are identified, the first around the GFC and the second at the beginning of the Covid-19 pandemic.

From a theoretical point of view, our results can be explained by the recent literature on decision making that has shown that if decision makers are risk averse, higher order risk attitudes such as prudence and temperance determine to a great extend economic behavior (Trautmann and van de Kuilen, 2018) and by the experimental literature on higher order risk measures, which has shown the importance and strength of prudence (Harvey and Sidique, 2000; De Roon and Karehnke, 2018). By highlighting the differences in terms of spillovers between different risk measures, our results provide empirical support for the literature in asset pricing that attempts to augment the traditional variance-mean portfolio optimization framework by incorporating higher order moments (Mencía and Sentana, 2009; Briec et al., 2007; Briec and Kerstens, 2010; Cvitanic et al., 2008; Harvey et al., 2010), or the to the models that emphasize the role of 'rare' jump shocks, 'disasters', and tail events in the explanation of market crashes (Barro, 2006; Bates, 2012) and market anomalies (Santa-Clara and Yan, 2010; Benzoni et al., 2011; Bollerslev and Todorov, 2011; Gabaix, 2012; Drechsler, 2013; Wachter, 2013). In short, this literature claims that agents experience aversion towards negatively skewed returns, which obeys the fact that many investors are willing to give part of their average return in exchange for a decreased probability of experiencing negative, large and unexpected jumps in their wealth, which would certainly deteriorate their wealth and consumption. We show that,

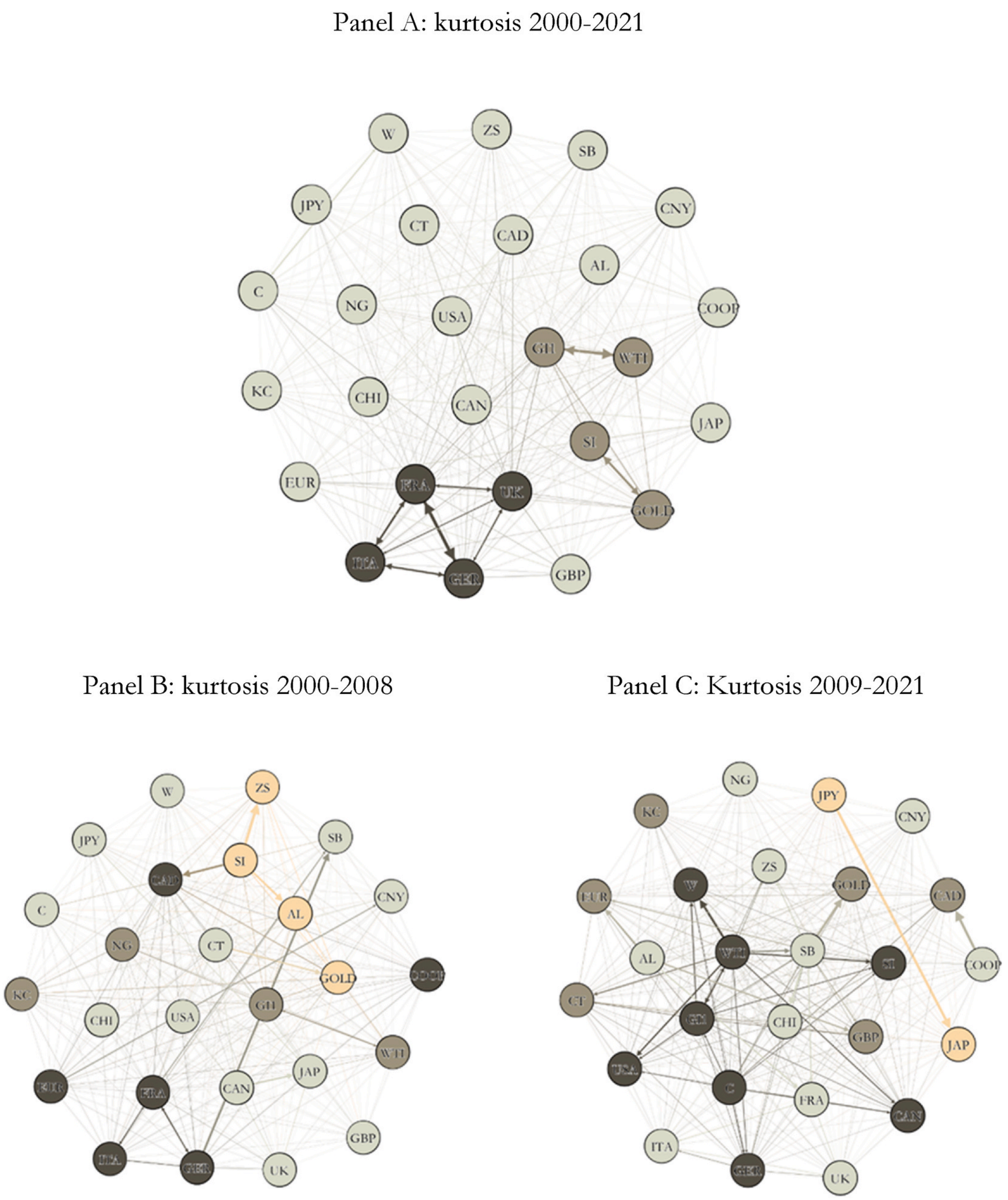

Fig. 2. Network representation of the global financial markets.

in this case, cross-spillovers estimated using only the estimated volatility of the assets depicts and incomplete panorama or risk in global commodity markets.

The remainder of the paper is structured as follows: Section 2 introduces the econometric methods used in this paper. Section 3 presents the data. Section 4 describes our main empirical results, and finally, the last section concludes.

2. Methodology

We estimate connectedness statistics as proposed by Diebold and Yilmaz (2012, 2014), but given the frequency of our measures and the number of cross sectional units we resort to the recent proposal by Demirer et al. (2018) to reduce the parameter space dimension of the original Vector Autoregression (VA)R system, as to make estimation feasible. Unlike the previous literature our VAR system is used to describe the relationship not only across (realized) volatilities, but also between realized semivariances (good and bad), realized skewness, sign jump variations, realized kurtosis and skewness.

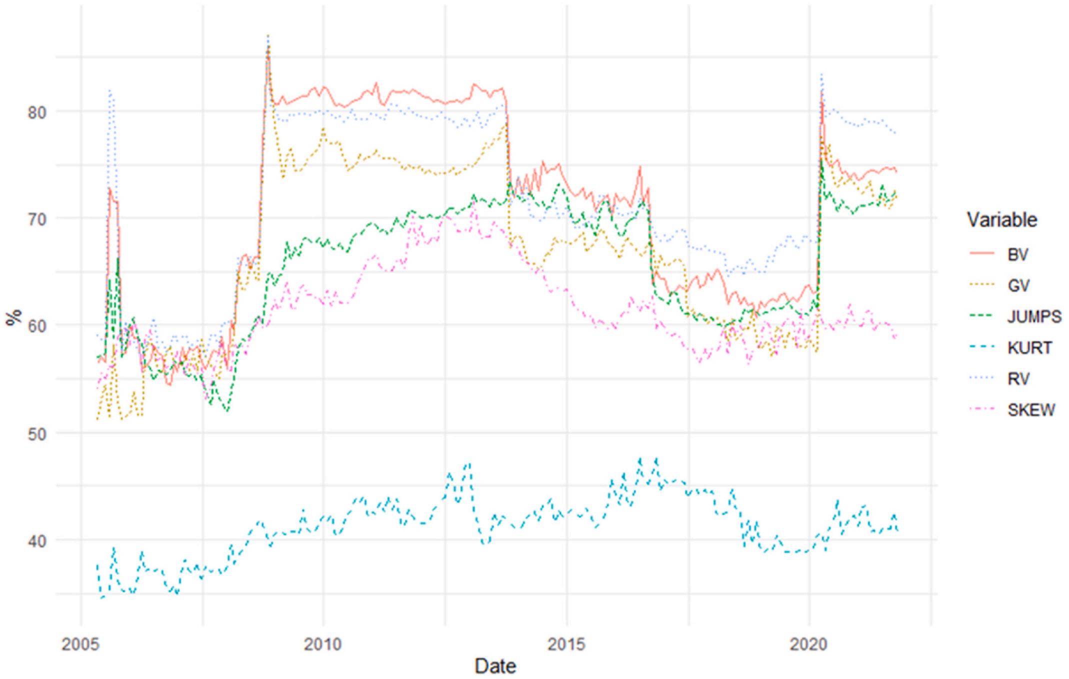

Fig. 3. Total dynamic spillover indices.

2.1. Spillovers statistics

The spillover indices are built upon a VAR with N variables that comprises stock, FX and commodity indicators. These statistics are constructed by means of the associated forecast error variance decomposition (FEVD). The errors are estimated from the moving average representation of the VAR following equations (1) and (2):

$$X_t = \Theta(L)\varepsilon_t, \tag{1}$$

$$X_t = \sum_{t=0}^{\infty} A_i \varepsilon_{t-i}, \tag{2}$$

where X_t is a matriz $T \times N$, $\Theta(L) = (I - \varphi(L))^{-1}$, ε_t is a vector of independently and identically distributed disturbances with zero mean, and Σ covariance matrix, $A_i = \varphi A_{i-1} + \varphi A_{i-2} + \ldots + \varphi A_{i-p}$ is the parameters' matrix, p is the number of lags in the estimation, and T is the number of time periods. To estimate the FEVD from the h-step ahead forecast, first we need to identify the structural perturbations to the VAR system. This can be achieved by imposing restrictions on the MA parameters. Following Diebold and Yilmaz's (2012) suggestion, we use the proposal of Koop et al. (1996) and Pesaran and Shin (1998), namely the generalized VAR for the construction of the FEVD.

The errors in the FEVD can be divided into *own variance* shares and *cross variance* shares. The former are the fractions of the errors that are associated to a shock to x_i on itself, while the latter are the portion of the shocks on x_i related to the rest of the variables in the system. Thus, the h-step ahead FEVD can be defined as:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i\right)}, \tag{3}$$

where σ_{jj} is the standard deviation of the j-th equation, e_i is a selection vector, with ones in the i-th element and zero otherwise, and Σ is the variance matrix of ε_t. To guarantee that the sum of each row is 1, $\sum_{j=1}^{N} \widetilde{\theta}_{ij}(H) = 1$, each entry of the variance decomposition must be normalized as follows:

$$\widetilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)}. \tag{4}$$

where $\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}(H) = N$.

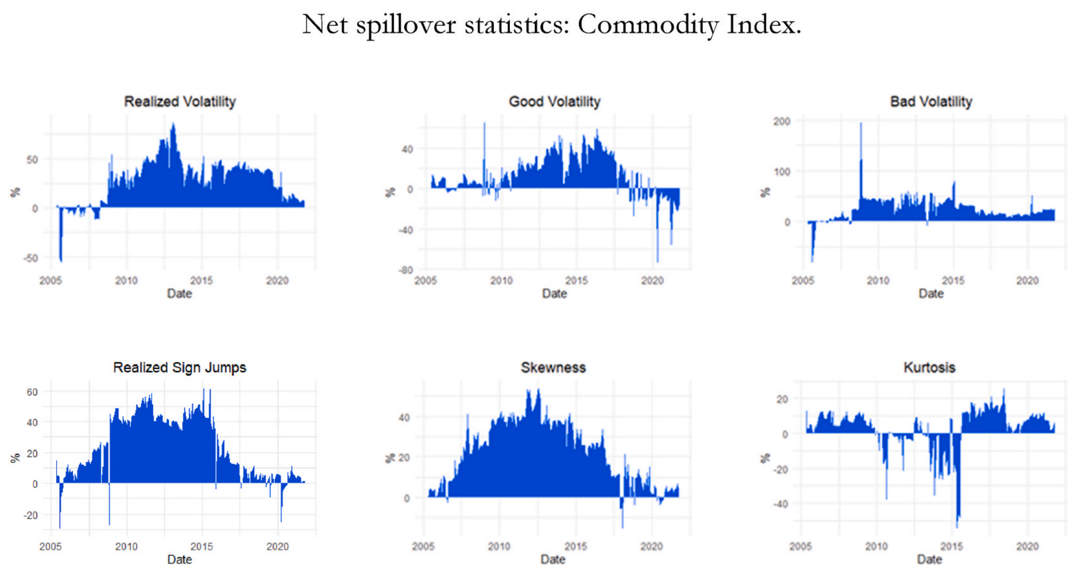

Fig. 4. Net spillover statistics: Commodity Index.

With the normalized variance decomposition, a total spillover index can be calculated as:

$$C(H) = \frac{\sum_{i,j=1,\ i\neq j}^{N} \widetilde{\theta}_{ij}(H)}{N} \times 100. \tag{5}$$

This index measures the percentage of the forecasted variance series that can be explained by cross-spillovers. It can be extended to a *directional spillover* index, in which the effect of a shock from all other variables j on the variable x_i is given by:

$$C_{i\leftarrow j}(H) = \frac{\sum_{j=1,\ i\neq j}^{N} \widetilde{\theta}_{ij}(H)}{N} \times 100, \tag{6}$$

conversely, the effect of a shock from x_i on all other markets j is given by:

$$C_{i\rightarrow j}(H) = \frac{\sum_{j=1,\ i\neq j}^{N} \widetilde{\theta}_{ji}(H)}{N} \times 100, \tag{7}$$

with the two directional spillover indices one constructs a *net spillover* index, given by:

$$C_i(H) = C_{i\rightarrow j}(H) - C_{i\leftarrow j}(H). \tag{8}$$

The net spillover index is a measure of the effect related to a shock in the variable x_i on the rest of the system. Therefore, each variable will act either as a *net receiver* or as a *net transmitter* of shocks in each t. It is also possible to construct a *net pairwise spillover* statistic, which accounts for the net spillover effect of variable x_i on x_j, where $i \neq j$. The net pairwise index is defined as follows:

$$C_{ij}(H) = \frac{\widetilde{\theta}_{ji}(H) - \widetilde{\theta}_{ij}(H)}{N} \times 100. \tag{9}$$

It is also possible to present the information contained in the variance of the forecasted error by networks. Nodes and edges constitute network graphs. In the results section the placement of nodes in the network is determined by the Force Atlas2 algorithm developed by Jacomy et al. (2014). This algorithm encounters a steady-state balance between forces of transmission and reception. Color intensity represents the degree of connectedness between the corresponding markets. Darker color segments correspond to more connected markets.

2.1.1. Least Absolute Shrinkage and Selection Operator (LASSO)

LASSO was proposed by Demirer et al. (2018) in the context of VAR systems for financial connectivity. These authors highlight that in applications that study connectivity across numerous markets or asset classes the VAR system requires estimation on a large dimensional space, without losing excessive degrees of freedom (to the point of making the estimation unfeasible). By using shrinkage or through model comparison and selection (using traditional AIC or BIC criteria) this can be achieved. LASSO blends the two approaches.

Consider an ordinary regression by least squares:

$$\widehat{\beta} = \underset{\beta}{\operatorname{argmin}} \sum_{t=1}^{T} \left(y_t - \sum_{i}^{N} \beta_i x_{it} \right)^2, \tag{10}$$

subject to the restriction

$$\sum_{i=1}^{K} |\beta_i|^q \le c, \tag{11}$$

which can be also presented as a penalized estimation problem as follows:

$$\widehat{\beta} = \underset{\beta}{\operatorname{argmin}} \left[\sum_{t=1}^{T} \left(y_t - \sum_{i}^{N} \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} |\beta_i|^q \right], \tag{12}$$

Concave penalty functions non-differentiable at the origin produce selection, whereas smooth convex penalties generate shrinkage. Thus, penalized estimation blend selection and shrinkage. The LASSO solves the penalized regression problem with $q = 1$. Hence it shrinks and selects. In addition, it requires only one minimization, and it uses the smallest q for which the minimization problem is convex.

The Adaptive Elastic net is an extension of LASSO due to Zou and Zhang (2009), which on top of shrinking and selecting, presents the 'oracle property'. In the implementation of the Adaptive Elastic net in this proposal, following Demirer et al. (2018) is necessary to solve

$$\widehat{\beta}_{AEnet} = \operatorname{argmin}_{\beta} \left[\sum_{t=1}^{T} \left(y_t - \sum_{i}^{N} \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} w_i \left(\frac{1}{2} |\beta_i| + \frac{1}{2} \beta_i^2 \right) \right], \tag{13}$$

where $w_i = 1/\left|\widehat{\beta}_{i,\ OLS}\right|$ and λ is selected equation-by-equation by 10-fold cross validation for different values of λ . The adaptive elastic net penalty weights the average by the inverse of OLS parameter estimates, and by doing so shrinks the smallest OLS coefficients toward zero.

2.2. Realized statistics

The N series included in the VAR representation are generally returns or volatilities. In both cases spillover statistics constructed upon the FEVD of the system refer to second order risks faced by financial investors. We expand this traditional analysis by allowing different moments and statistics to be considered as our work unit. We estimate monthly-realized variances of log asset prices Y (see Andersen et al., 2011) as follows:

$$RV = \sum_{j=1}^{n} \left(Y_{t_j} - Y_{t_{j-1}} \right)^2, \tag{14}$$

where $0 = t_0 < t_1 < \ldots < t_n = 1$ are the times at which prices are available, in our case on a daily frequency. This has been proved to be a useful methodology to estimate and forecast conditional variances for risk management and asset pricing. We also estimate realized-semivariances proposed by Barndorff-Neilsen et al. (2010), as:

$$\begin{aligned} RS^- &= \sum_{j=1}^{n} r_{t_j}^2 \, 1_{r_{t_j} \le 0} \\ RS^+ &= \sum_{j=1}^{n} r_{t_j}^2 \, 1_{r_{t_j} > 0} \end{aligned} \tag{15}$$

where $r_{t_j} = Y_{t_j} - Y_{t_{j-1}}$. Using equation (15) is possible to estimate a measure of the realize jump variations as $RJ = RS^+ - RS^-$. (standardized) realized skewness and realized kurtosis in our framework are estimated as:

$$RS = \sum_{j=1}^{n} \frac{\left(r_{t_j}\right)^3}{\sqrt{RV}}, \tag{16}$$

$$RK = \sum_{j=1}^{n} \frac{\left(r_{t_j}\right)^4}{\sqrt{RV}}, \tag{17}$$

With these six measures we estimated separate VAR systems and constructed spillovers and connectedness statistics and networks aiming to analyze spillovers at different moments of the return distributions.

3. Data

Our data set consists of daily closing prices in future markets from eight stock markets, thirteen commodity markets, and five exchange rate markets from January 4, 2000, to October 31, 2021. All the data were collected from Bloomberg. The following stock markets indices are included in the study: SP (the USA), MXCAIndex (Canada), MXDEIndex (Germany), MXGBIndex (the UK), MXCNIndex (China), MXFRIndex (France), MXITIndex (Italy), and MXJPIndex (Japan). The exchange rate markets are represented by five of the most traded currencies per US dollar: Canadian Dollar (CAD), Chinese Yuan (CNY), Euro (EUR), the Japanese Yen (JPY) and the Pound sterling (GBP). Finally, the commodity markets used include: GI1COMBIndex (commodity index), CL1Comdty (WTI Oil), NG1Comdty (Natural Gas), S1Comdty (Soy), Wheat, Corn, Coffee, Sugar, Cotton, Aluminum, Silver, HG1Comdty (Copper), and GC1Comdty (Gold).

We work with monthly moments (estimated based on daily frequency data) seeking to identify relatively persistent shocks in the market and reduce the noise presented by intraday data. The span period of the data allows us to evaluate the effect of the global financial crisis on the dynamic interactions between different markets.

4. Results

4.1. Univariate summary statistics

Our main results are reported in Tables 1–3 and Figs. 1–4. Table 1 shows the univariate summary statistics for the markets in our sample. The average monthly realized volatility (panel A), positive and negative realized semivariances (B and C), alongside the average realized sign jump variation (panel D), realized skewness (E) and realized kurtosis (F) are shown in Table 1 for two sub-samples: The first running from January 2000 to December 2008 and the second from January 2009 to October 2021 (before and after the GFC). Descriptive statistics for the whole sample are also shown.

The shadowed columns correspond to statistics for commodity future prices, on which we emphasize in this study. Realized volatilities are considerably larger for commodities than for stock markets and currencies both before and after the GFC, as shown in Panels A, B, and C. Interestingly, though, realized volatilities of the commodity index are comparable to those of major stock markets, showing that considerable diversification opportunities are available within commodity markets. In other words, while individual commodities in future markets are highly volatile when compared to assets from more traditional classes, weighted baskets of commodities offer investors the advantage of a considerably lower return variation. Within commodity markets, energy markets (oil and natural gas) exhibit the highest realized volatilities. As expected, realized bad volatilities are higher than realized good volatilities for most assets. Jumps are negative on average for most asset returns. However, jumps are positive and high on average for natural gas. This is consistent with the fact that, unlike the rest of the assets, natural gas presents higher realized good volatility than bad volatility.

As expected, kurtosis for all asset returns is significantly higher than three, indicating fat tails in their distributions.

4.2. Static spillovers

Table 2 presents the spillovers between the realized variances of the markets in our sample in panel A and between the realized semi-variances, positive and negative, in panels B and C, respectively. The percentage of the variation of the forecast error (1 month ahead) explained by each market in the sample is reported in rows. Results in panel A show that stock markets are the main spillover transmitters when realized variances are considered. All of the stock markets in our sample are net volatility transmitters and the values of their net positions are large except for the Chinese market. The four main transmitters are the stock markets of UK, France, Canada, and the US. All commodities are net spillover receivers, except for the aggregate commodity index which, in fact, has a large transmitter position. This interesting result indicates that when traditional realized volatility measures are used as indicators of risk, spillover indexes support the commodity financialization hypothesis that commodity prices are considerably driven by traditional financial markets. Currencies (except for JPY and CAD) are also net volatility receptors.

Results in Panel B, show that when only good volatility spillovers are considered, stock markets are also net transmitters. An important difference is observed among commodity markets, however, as Gold and Silver become volatility transmitters as well. In fact, their net position is larger than the net position of the global commodity index. Regarding currencies, the JPY remains as a spillover transmitter while the CAD becomes a net volatility receiver, as alongside all other currencies.

When bad volatility spillovers are considered, stock markets, the global commodity index, copper, the EUR, and the CNY appear to be net volatility transmitters. All other securities are spillover receivers. Summing-up, when realized volatility measures are considered, stock markets and the aggregate commodity index are the only markets which consistently appear to be volatility transmitters. Most commodities and currencies are net volatility receivers. These results provide support to the commodity financialization hypothesis.

Remarkably different results are obtained once higher-order measures of risk are introduced to the analysis. For instance, when sign jump variations are considered, various stock markets turn into net volatility receivers. In fact, Japan, China, and the US stock markets exhibit negative net positions as shown in panel A of Table 3. At the same time, more commodity markets become spillover transmitters, the global commodity index, corn, aluminum, and silver. Among currencies, only the JPY has a positive net position. Results when skewness is used as the risk measure are similar to those obtained when sign jumps are used, as seen in panel B of Table 3. Results when kurtosis is considered also show several net receiver positions for important stock markets, like the US, Canada, the UK, Italy, and Japan. The aggregate commodity index and gold are the only two commodity markets in having a positive net position, and all currencies are net receivers of risk spillovers (Table 3, Panel C).

Comparing volatility and skewness spillovers, we have that WTI seems to receive more shocks when we look at volatilities than when we look at skewness. Moreover, WTI seems rather isolated from shocks in other commodities, except for the commodity index, when we estimate volatility spillovers, but when we look at skewness, WTI is more integrated with other commodity markets, like cooper, and to some extent natural gas, aluminum and silver. Natural gas is mainly a receiver of shocks from WTI during the sample period. Although, soybean receives larger shocks from almost all other markets in skewness than in volatility, it is very sensitive to other market shocks in the two cases. While some commodities like coffee and cotton, increase considerably their dependency on other markets when we analyze the skewness spillovers, some others like wheat depict an opposite pattern, which is convenient in terms of portfolio diversification during market distress episodes. Aluminum, silver and gold are equally sensitive according to the two measures of spillovers.

In terms of financial stability is worth emphasizing the role of natural gas, sugar, or cooper, as markets generating skewness spillovers. Interestingly, gold does not produce large skewness spillovers compared to its volatility spillovers.

In synthesis, average spillover calculations clearly show that results vary widely when different risk measures are adopted. Under traditional metrics, such as realized (good, bad, total) volatilities, stock markets appear to be the dominant source of risk spillovers to commodity and currency markets. However, when other risk proxies are used, results change significantly, especially when higher-order measures are considered. Importantly, the US stock market becomes a net volatility receiver when higher-order moments are considered. Additionally, the aggregate commodity index is, under all risk measures, a net volatility transmitter. Individual commodities tend to be more integrated with other commodities and also with stocks in skewness than in volatility.

4.3. Network analysis

Different moments measure distinct faces of risk which ideally should be addressed from an integrated perspective by portfolio managers and energy firms. However, such asymmetries are overlooked by traditional risk analysis based solely on the analysis of volatility. For instance, while variances and kurtosis are related to symmetric risks, skewness speaks directly on the probability of market crashes, which is asymmetric by its very nature. The sorts of asymmetries that we seek to emphasize are better explained graphically, using networks. We use the algorithm developed by Jacomy et al. (2014) to represent our findings regarding the propagation of risk beyond the variance.

Fig. 1 shows risk clusters that correspond to total realized volatility. Panel A corresponds to the whole sample period's network, while panels B and C correspond to the network before and after the GFC, respectively. In all three panels the central role of stock markets in the network is evident. Most asset securities are linked to the network through these central nodes. The network is dense in the sense that most assets are well connected to one another. Connections are clearly stronger within asset classes, but strong connections are also observed between different asset classes. For instance, stock and currency markets appear to be very well integrated. Additionally, some assets appear in clusters in which most other participants belong to a different asset class. Most commodities connect with currencies through their relationship with stock markets. Among commodities, aggregate commodity index is the most linked to traditional financial markets. Interestingly, commodity markets are not intensively linked to one another. This result indicates that diversification opportunities exist within commodity markets.

Some notable differences are observed for the networks representing market interconnections before and after the GFC (Fig. 1, panels B and C). Before the GFC, market interconnections were weaker. Importantly, panel B indicates that commodity markets were far less connected with the other two asset classes. After the GFC, in contrast, the density of the network increased significantly, as shown in panel C. This fact also goes in line with the phenomenon financialization in commodity markets, which postulates that the dynamics of commodity and traditional financial markets are increasingly linked. Before the GFC, commodity markets were more strongly connected with currency markets than with stock markets. On the contrary, after the GFC the opposite is observed. This result can explain the process of "decoupling" that currencies from many commodity-producer countries have experienced from commodity price variations over the last decade. Intensities of realized volatility transmission have also changed. Notably, intensities of transmission between pairs of assets including at least one commodity are stronger after the GFC, showing once more that commodity markets are gaining an important participation in global investment portfolios.

Network results vary not only when the sample is split before and after the GFC, but also when alternative risk measures are considered. Panels A, B, and C of Fig. 2 present the total sample, before and after the GFC networks for kurtosis. These three networks are less dense than those constructed for total realized volatility. For instance, while stock markets continue to play a major role when the total sample is used (panel A), interconnections are weaker. Cluster members are also different, becoming relatively more important within the network those conformed by European stock markets and by some commodity markets (the aggregate commodity index, gold, silver, and the WTI).

Altogether, results show that the network became more interconnected after the GFC, while commodity markets gained importance within the network. This result, which holds regardless of the risk measure that is used for calculating spillovers, supports the commodity financialization hypothesis proposing that commodity markets have become an additional asset class that is strongly connected with traditional financial markets. However, cluster formation, network density, and intensity of spillover transmission between and within clusters critically depends on the specific risk measure used in the computation of spillovers.

4.4. Dynamic spillovers

The growing literature on volatility spillovers has shown that spillover direction and intensity vary over time significantly. Similar results are reached when different risk spillover measures are considered, as shown by Fig. 3. Note that, while all graphs exhibit high-time variation and show that volatility spillovers spike around the GFC and at the beginning of the covid19 pandemic, global financial risk profile is in various aspects dissimilar whether we focus on realized volatility, skewness, or other moments of the series under analysis. For instance, realized bad volatility presents more persistence than realized good volatility. The incremental trend in terms of the realized jump variation peaks significantly later than the recorded peak dates in realized good and bad volatilities. In fact, sign jumps spiked at the beginning of the covid-19 pandemic, showing that this measure of risk responds more strongly to (real and financial) uncertainty shocks than realized volatilities. Skewness and kurtosis spillovers, on the contrary, do not exhibit spillover peaks during the pandemic.

Spillovers between securities also present high time-variation. We focus here on showing the dynamics followed by the net spillover index for commodities, over the time. Fig. 4 depicts net spillovers from the commodity index to the rest of the system for the whole sample period. Each of the six panels in the figure presents a different risk measure. Panel A, total realized volatility, shows that the aggregate commodity index has been a net spillover transmitter most of the time according to this risk measure. However, the magnitude of the net position is relatively low. Interestingly, it presented a net spillover receiver position all the time before the GFC. Right after the GFC, its net position changed, because of the financialization of commodity markets. Notable differences are observed when good and bad volatility measures are considered. Panel B shows that when good volatility is used, the net position of the aggregate commodity index varies more over time than when total volatility is considered. For instance, for the last three years the commodity index has been a net volatility receptor when the good volatility measure is considered. On the contrary, panel C shows that this index is a net volatility transmitter most of the time, especially during times of financial distress. However, while spillover transmission to the rest of the system was high during the GFC and during the European debt crisis, during the covid-19 pandemic bad volatility transmission from this index to the rest of the system has been relatively low. Net spillovers to the system when sign jump is considered (panel D) behave similarly to bad volatility transmission. Under skewness, the commodity index is an important net spillover transmitter to the rest of the system. In fact, it presents a positive and relatively high magnitude of transmission for the whole sample, especially during times of financial stress. Finally, under kurtosis time variation in the net position is higher and the magnitude of spillovers is lower. However, most of the time the commodity index appears to be a net volatility receiver.

High time-variability and significant differences in net spillover indexes are also found when individual commodities or other assets are considered. Appendix 1 shows graphs for spillover indexes under the six different risk definitions for all other assets included in this study.

Appendix 2 also presents robustness results obtained when six other commodity indexes were used, namely the Deutsche Bank Liquid Commodity Index, the S&P Goldman Sachs Commodity Index, the UBS Bloomberg Index, the DCI BNP Paribas Enhanced Index, the BNP Paribas Oscillator Commodities, and the Morningstar Commodity Index. Results are qualitatively identical to those discussed in this section of the paper.

5. Conclusions

We show that volatility spillovers, frequently used in the literature to understand the sources of risk in international financial markets, including commodity markets, are not sufficient to fully characterize risk transmission on such markets. To complement this literature, with a focus on commodity markets, we estimate skewness, kurtosis, sign jumps and semi-volatility spillovers. Our main conclusion is that the main givers and receivers of shocks change depending on the definition of risk that we use, which has important implications for asset pricing and policymaking, especially regarding financial stability issues for commodity-dependent economies.

We show that similar results are obtained for the three realized volatility measures that we use, but significant differences emerge when jumps and higher order risk measures are considered. When realized volatility is considered, stock markets are the main spillover transmitters while commodities and exchange rates are net spillover receivers. In fact, all stock markets are net spillover transmitters to the system, while all commodities except for the commodity index and all currencies except for the Japan and the Canada currencies are net spillover receivers. When realized good volatility is considered, all stock markets continue to be net spillover transmitters. However, more commodities become volatility transmitters as well (the aggregate commodity index, gold, and silver). In the case of realized bad volatility, all stock markets, the aggregate commodity index, copper, the Euro, and the Yuan are net volatility transmitters. All other securities are net volatility receivers. Results from sign jumps are quite different. For instance, several stock markets which were volatility transmitters under realized volatility measures become volatility receivers, such as the stock markets from the US, Japan, and China. Results for commodities and exchange rates are mixed. Interestingly, the global commodity index continues to be an important volatility transmitter, while corn, aluminum, and silver become volatility transmitters as well. When we compared volatility and skewness spillovers, most commodity markets seem to be more integrated with other commodity markets than previously thought. The cases of natural gas, soybean and cotton are worth mentioning.

Our results also indicate that risk spillovers vary importantly over time. One notable feature is that commodity markets have been gaining importance as a new asset class within global financial markets since the GFC. Their degree of connectedness has significantly increased, as well as their spillover transmission to the rest of the system. These results are consistent with the commodity financialization hypothesis.

Our results provide empirical support for theoretical asset pricing models that conduct the optimization required for portfolio balancing in the mean-variance-skewness space (instead of the traditional mean-variance or the mean-variance-kurtosis spaces) by showing that risk diversification opportunities vary greatly when one considers variance or skewness as the fundamental proxy for risk, but also by showing that kurtosis does not propagate as much as skewness, and therefore the latter merits a more significant consideration in risk analysis than the former.

Credit author statement

All authors contributed equally to the article.

Financial disclosure

I certify that no party having a direct interest in the results of the research supporting this article has or will confer a benefit on me or on any organization with which I am associated AND, if applicable, I certify that all financial and material support for this research (eg, NIH or NHS grants) and work are clearly identified in the title page of the manuscript.

Appendix 1

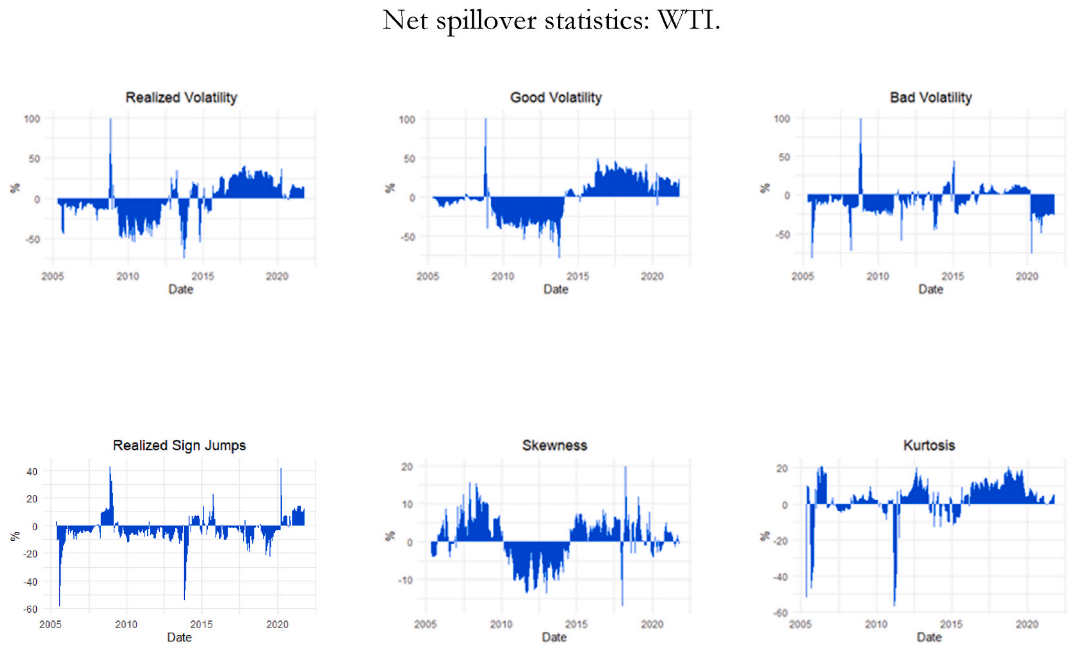

Fig. 5. Net spillover statistics: WTI.

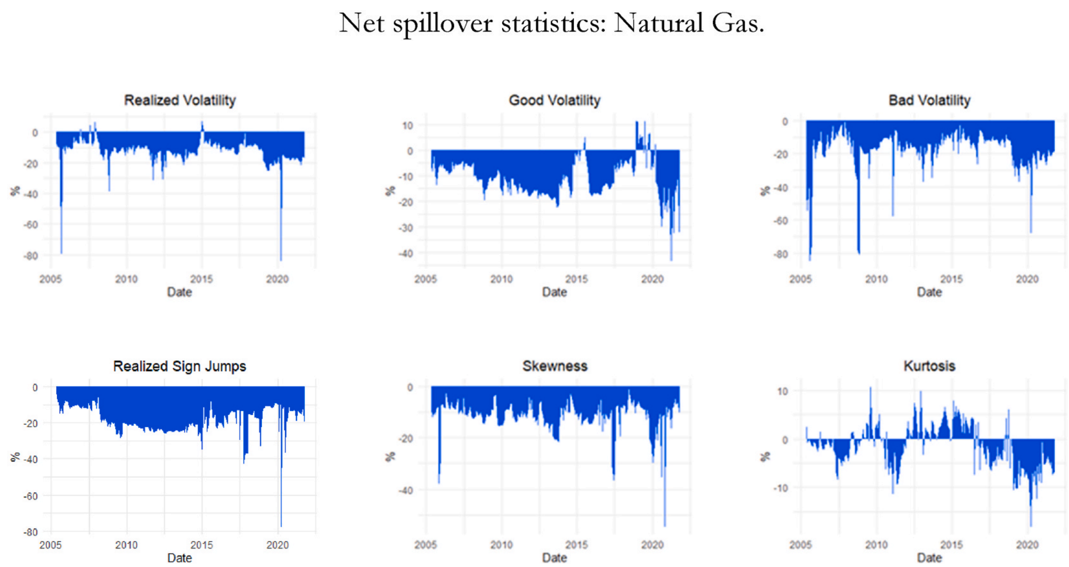

Fig. 6. Net spillover statistics: Natural Gas.

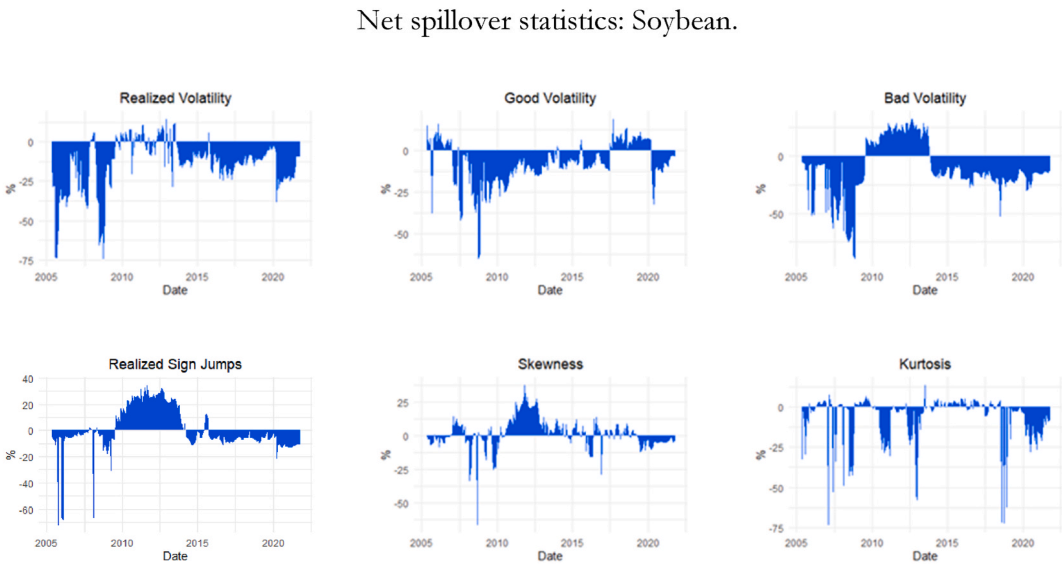

Fig. 7. Net spillover statistics: Soybean.

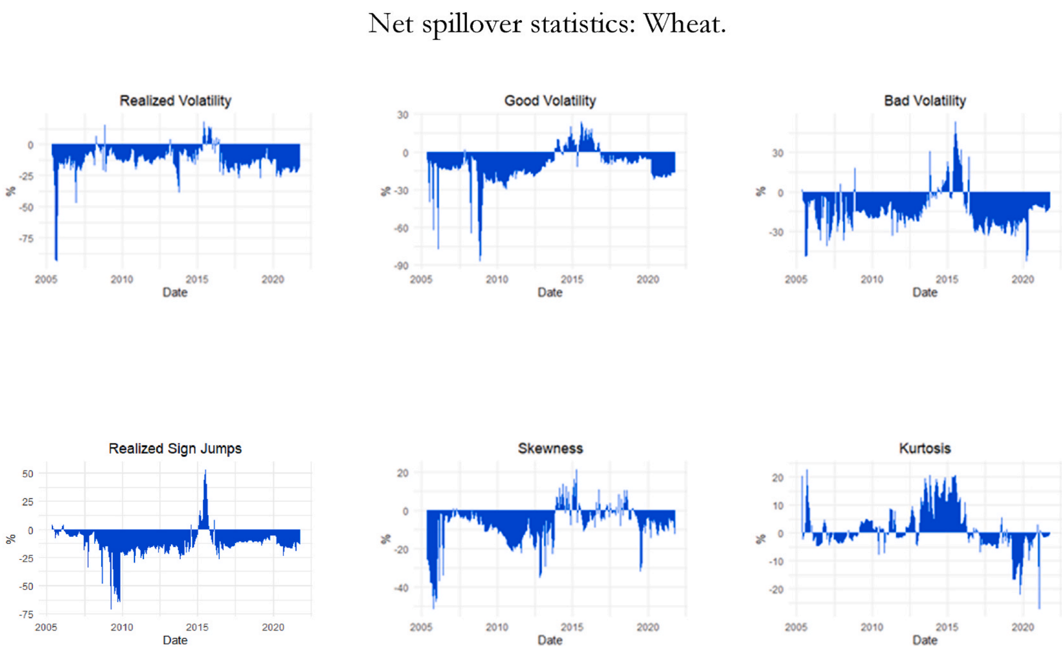

Fig. 8. Net spillover statistics: Wheat.

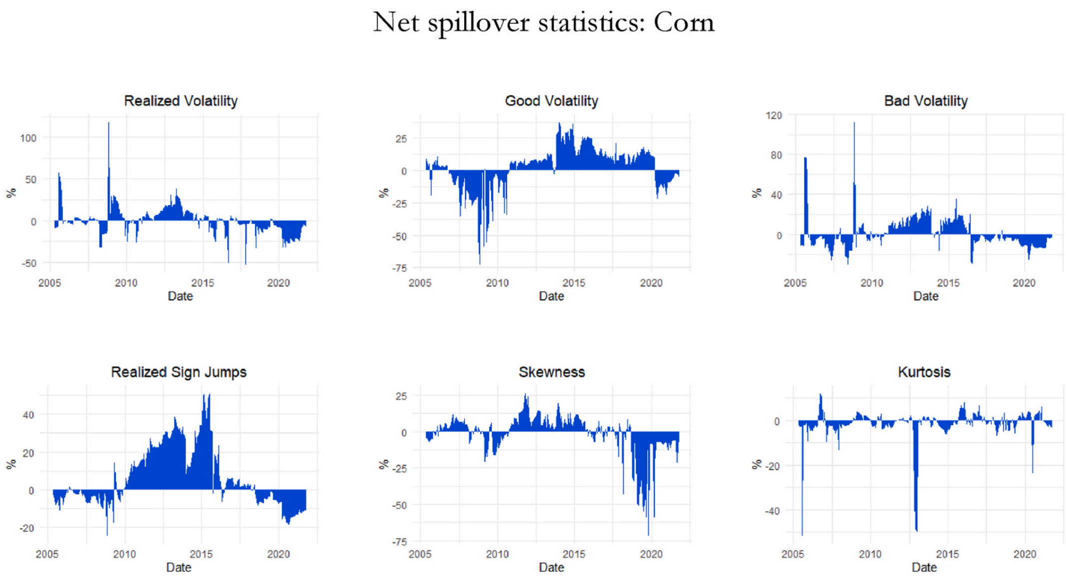

Fig. 9. Net spillover statistics: Corn.

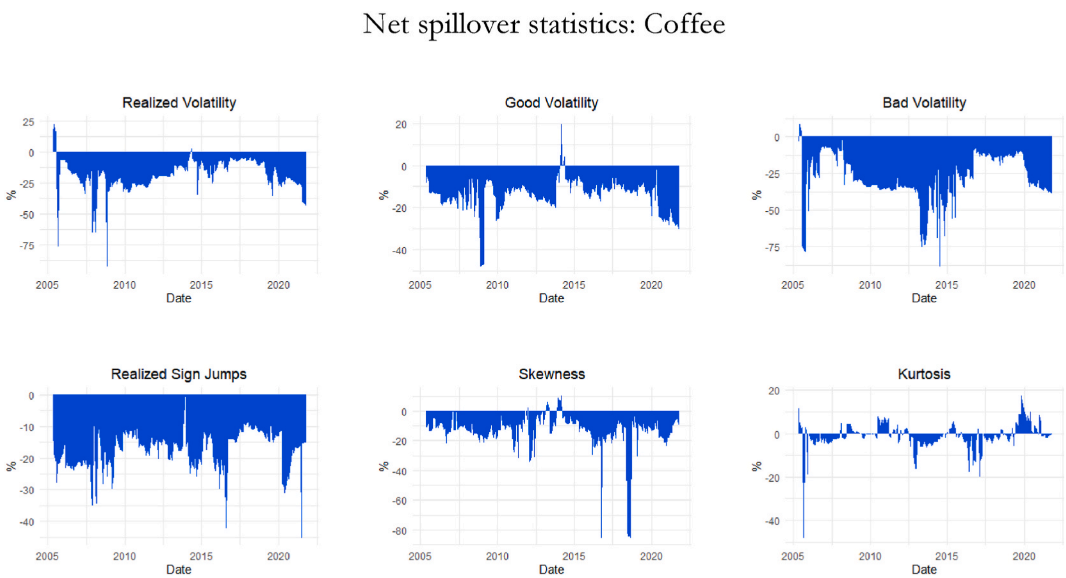

Fig. 10. Net spillover statistics: Coffee.

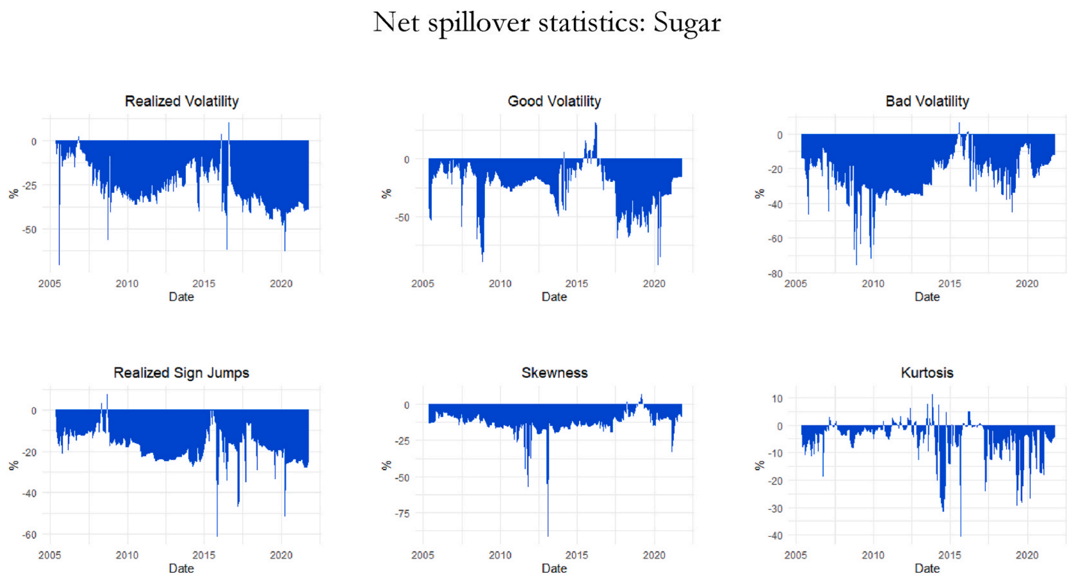

Fig. 11. Net spillover statistics: Sugar.

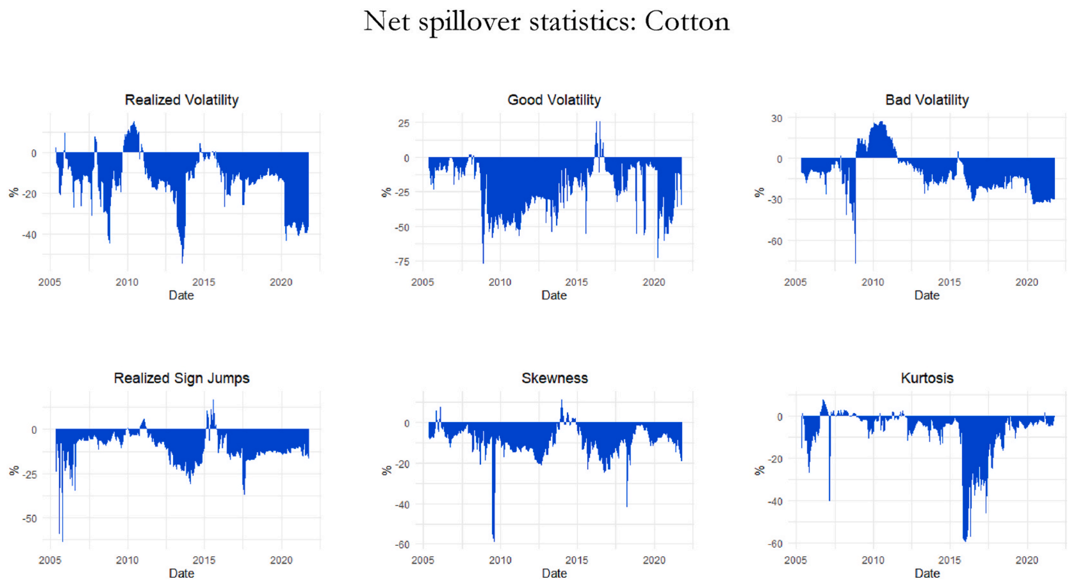

Fig. 12. Net spillover statistics: Cotton.

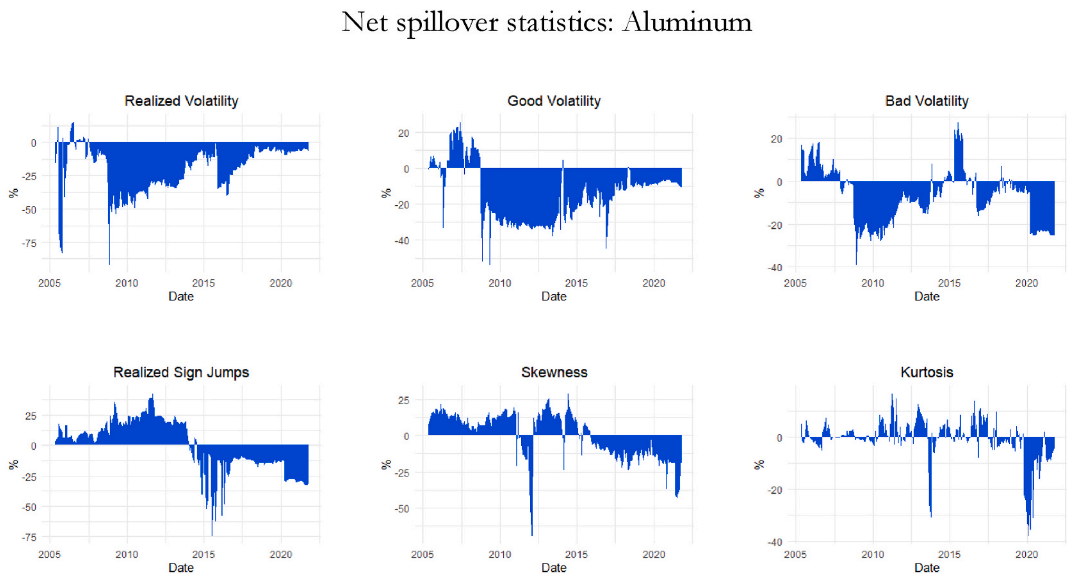

Fig. 13. Net spillover statistics: Aluminum.

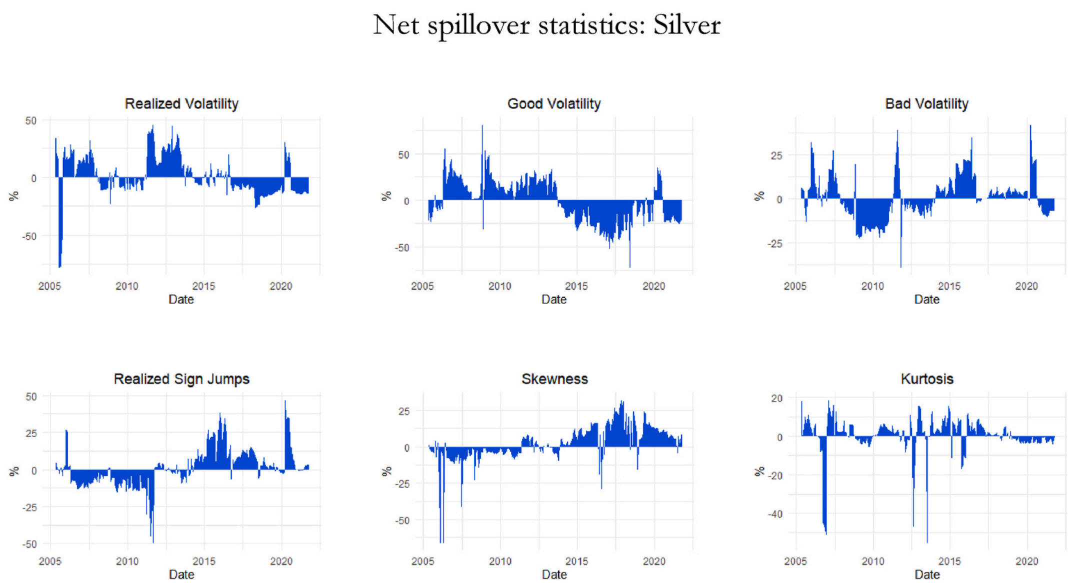

Fig. 14. Net spillover statistics: Silver.

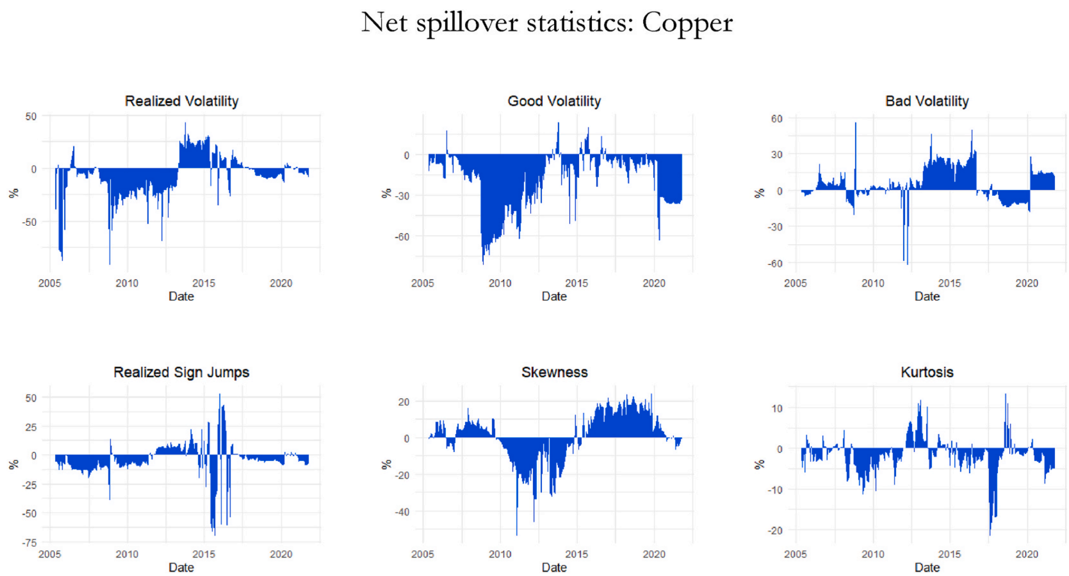

Fig. 15. Net spillover statistics: Copper.

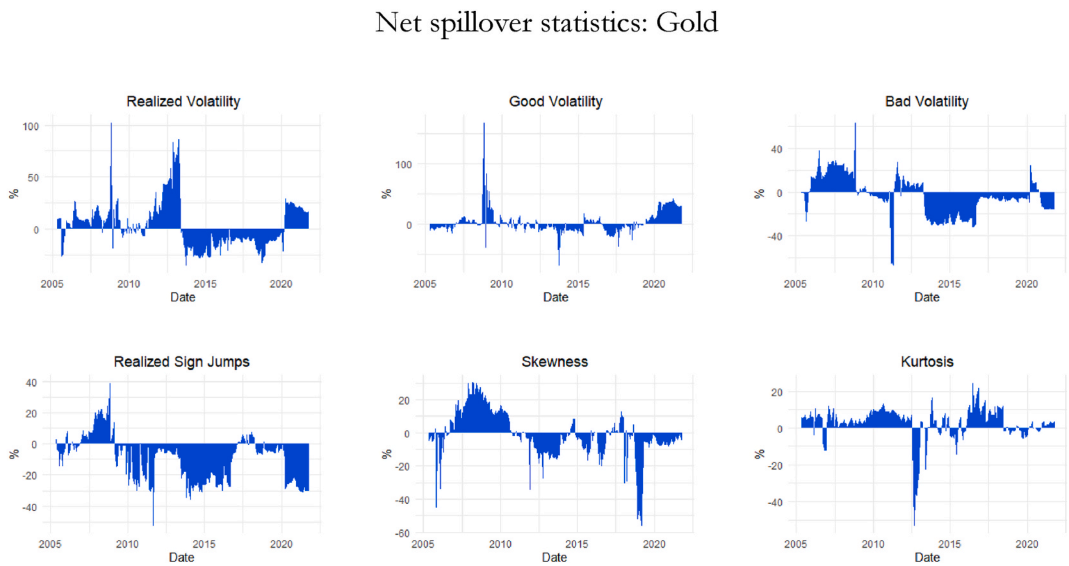

Fig. 16. Net spillover statistics: Gold.

Appendix 2

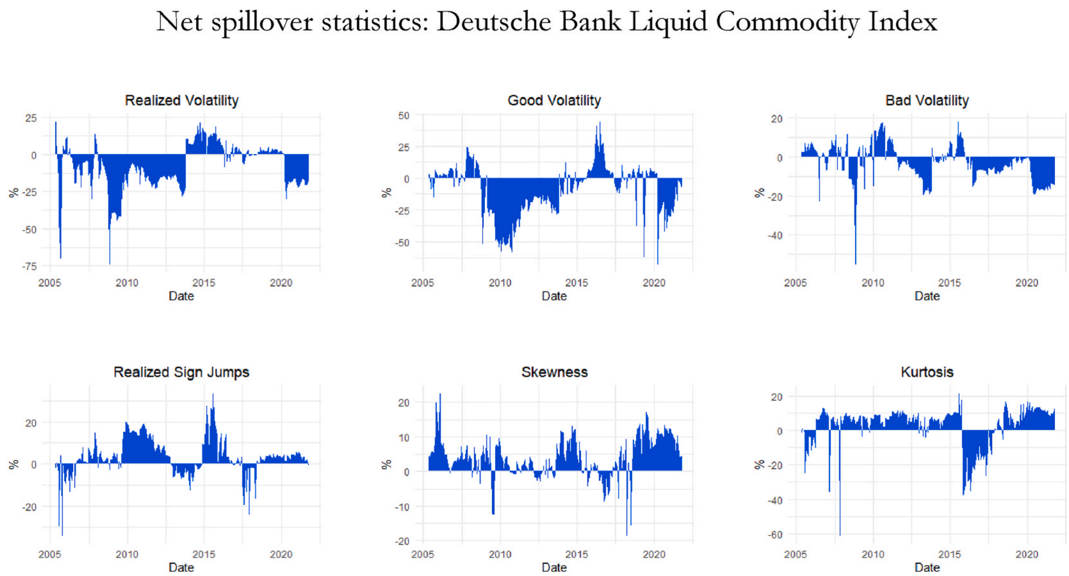

Fig. 17. Net spillover statistics: Deutsche Bank Liquid Commodity Index

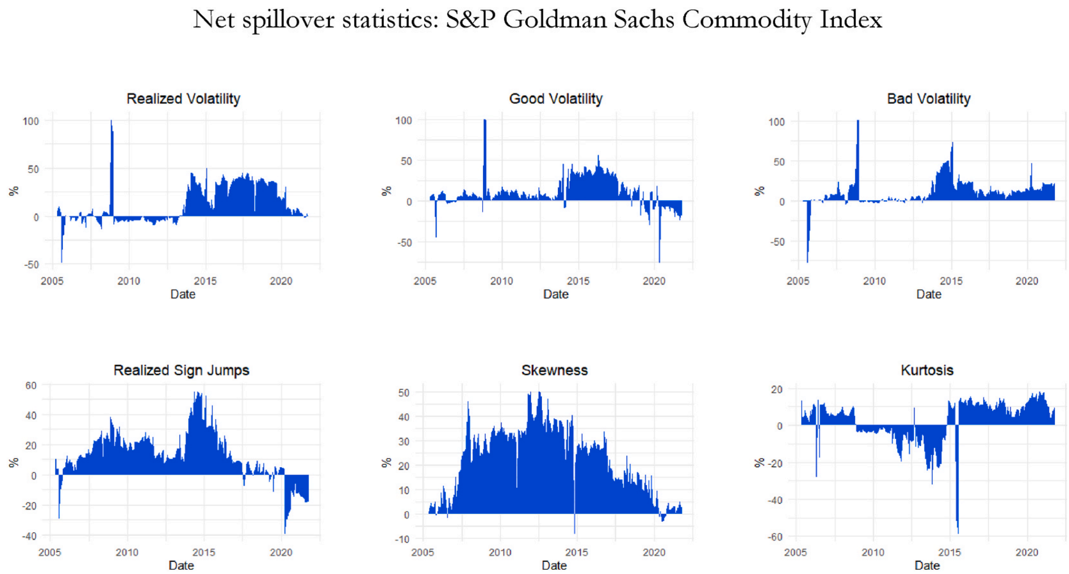

Fig. 18. Net spillover statistics: S&P Goldman Sachs Commodity Index

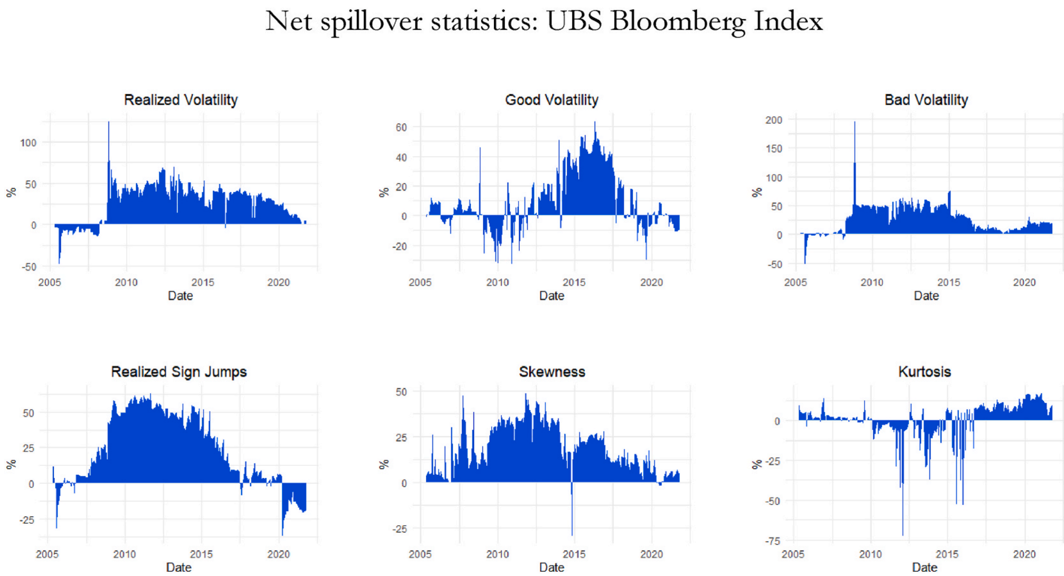

Fig. 19. Net spillover statistics: UBS Bloomberg Index

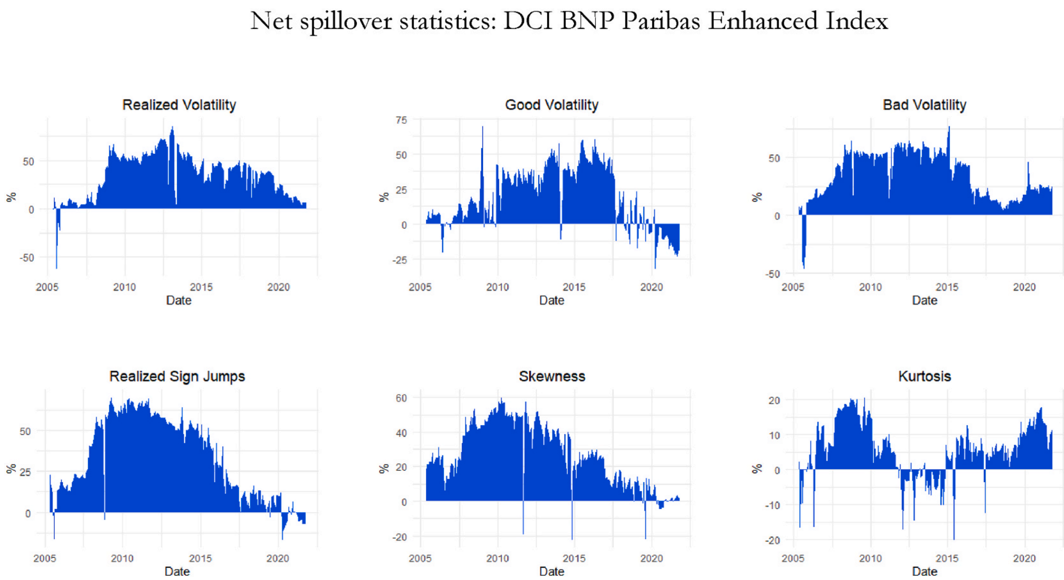

Fig. 20. Net spillover statistics: DCI BNP Paribas Enhanced Index.

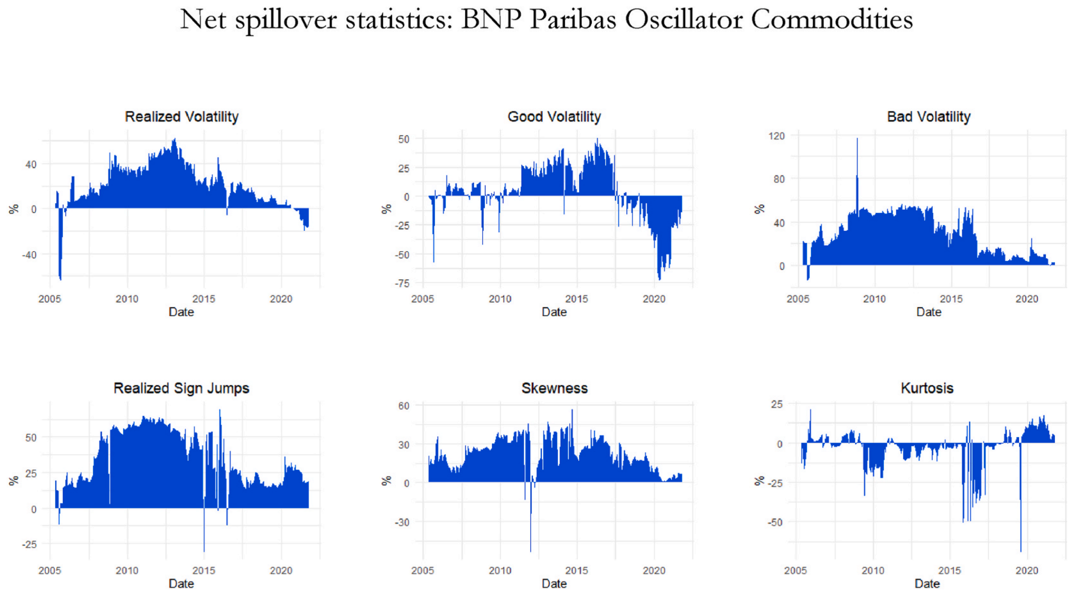

Fig. 21. Net spillover statistics: BNP Paribas Oscillator Commodities.

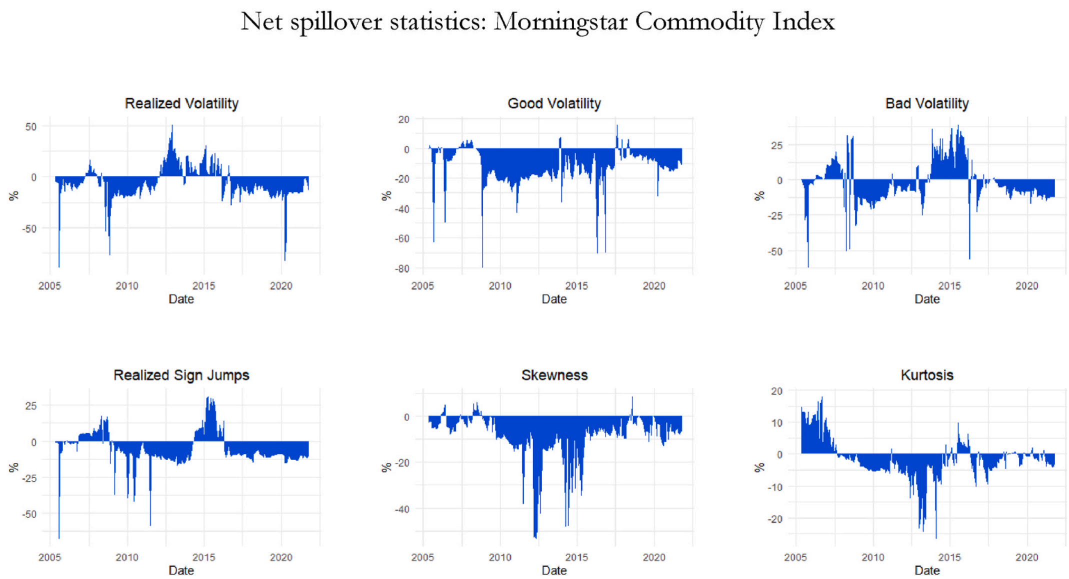

Fig. 22. Net spillover statistics: Morningstar Commodity Index

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