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U.S. equity and commodity futures markets: Hedging or financialization?☆

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ABSTRACT

In this paper, we investigate the hedging versus the financialization nature of commodity futures vis-à-vis the equity market using a ARMA filter-based correlation approach. Our results suggest that while gold futures are typically seen as a hedge against unfavorable fluctuations in the stock market, the majority of commodity futures appears to be treated as a separate asset class in line with their increasing financialization. Our results are robust to the presence of inflation, highlight the hedging role played by fuel (energy) commodity futures in the nineties, and reveal that the commodity financialization boosted since the 2000s. We also show that gold futures are partially a safe haven for equity investments in the short-term, but not in the mid-term. Finally, we uncover some hedging (financialization) of crude oil futures associated to global demand (oil supply) shocks.

1. Introduction

Fluctuations in commodity prices have important economic implications and are typically seen as predictors of future economic activity (Fernandez-Perez et al., 2017; Hamilton, 2011).[1] In recent years, there has been a vast amount of work that looks at the dynamic relationship between macroeconomic aggregates and the commodity prices including particularly crude oil prices (Hamilton, 2003) or at the linkages between equity and commodity prices. Yet, with a few exceptions, the analysis has been confined to the crude oil asset given its crucial role in economic activity and industrial production.[2]

From the perspective of policymakers and practitioners, the degree of stock market integration is of paramount importance as a way of better understanding the benefits of portfolio diversification

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[1] Fernandez-Perez et al. (2017) argue that when commodity inventories are high (low), the slope of commodity futures' term structure is positive (negative), futures prices are expected to fall (rise) with maturity, and markets are contangoed (backwardated). They find that commodity portfolios that capture contango and backwardation features display predictability for future business cycle conditions.

[2] See Killian (2009), Arouri et al. (2011), Narayan and Sharma (2011), Creti et al. (2013), Bekiros et al. (2016), Bekiros et al. (2017), Reboredo and Ugolini (2017), Zhang (2017), Zhang et al. (2017) and Junttila et al. (2018). For recent studies looking at the topic from various perspectives, see also Aromi and Clements (2019), Batten et al. (forthcoming), Clements et al. (2019), Tiwari et al. (2019), Wang and Wang (2019).

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across asset classes.[3] Specifically , an increase in stock market integration might reduce diversification benefits, thus, pushing investors to commodity markets. Moreover, the presence of trade (Frankel and Rose, 1998; Pentecote et al., 2015), monetary (Bekaert et al., 2013) and financial (Aloui et al., 2011; Baele et al., 2004) links has a strong influence on (stock) market integration. This could lead to important shock and return spillovers during periods of crises, which reduce investors' appetite for diversification in stock markets only.[4] Recent studies assessing equity and stock market integration or co-movement also show that their integration is rather weak or, at most, moderate, which motivates stock investors to allocate funds to commodities.[5]

In this context, the study by Baur and Lucey (2010) reports that gold is a good hedge against stock return variations. Arouri et al. (2010) argue that not only oil, but also major precious metals, such as gold, display low correlation with stock returns and can be included in a well-diversified portfolio of stocks.[6]

As for the studies on commodity financialization, the hedging properties of gold have been documented by Baur and Lucey (2010). Prokopczuk and Wese Simen (2013) rely on a panel of commodity option prices to construct synthetic variance swaps. The authors show an increasing co-movement between bonds, commodities and equity variance swap returns, which is consistent with a rising integration of the variance swap markets.[7]

The current article contributes to the existing literature on equity-commodity futures market linkages along four dimensions. First, instead of nominal returns, we use inflation-adjusted real returns unlike many previous studies. This choice helps us to focus on the real component of the financial time series under consideration. Second, in order to retrieve evidence consistent with either hedging behavior or financialization of commodities, we estimate the best data-generating process for real equity market and commodity futures returns. Then, we compute the correlation between unexpected variations (i.e. shocks) in real equity market returns and unexpected variations in real commodity futures returns. Third, we look at a wide range of commodity futures and investigate whether the empirical evidence supports the existence of hedging or financialization across these assets. Fourth, we highlight the importance of the increasing integration of commodity markets and stock markets, and evaluate the role played by commodity futures in portfolio diversification.

We show strong evidence of financialization of commodities, thus, a positive correlation between shocks to equity market returns and shocks to commodity futures returns. However, shocks are negatively (albeit insignificantly) correlated for gold futures. As a result, this commodity can partially be seen as a safe haven for stock investors. This finding corroborates the study of Baur and Lucey (2010) and is close in spirit with the work of Batten et al. (2010).

Our results are robust no matter we measure returns in real terms or nominal terms, suggesting that inflation does not change the investment strategy of stock market participants in what concerns commodity futures. Additionally, when we split the sample period into two sub-samples, the empirical evidence shows that: (i) in the nineties, fuel (energy) commodities, such as crude oil, were a good hedge against unfavorable stock market fluctuations; and (ii) financialization of commodities has become especially relevant since the 2000s. Moreover, we consider returns spanning from 1-month and 5-year horizons and find that commodities exhibit different degrees of financialization at the various time horizons under analysis. For gold, we show that it can be partially used as a hedge against undesirable short-term variations in the stock market, but not against unfavorable mid-term fluctuations.

Our main results are checked for robustness within a dynamic framework using the state-of-the-art methodology of rotational conditional correlations (Noureldin et al., 2014). We show that our broad conclusions still hold even the time-varying nature of the multivariate relations between assets is taken into account and the heteroskedasticity of real returns (and also random shocks) are eliminated. Finally, while further looking at the specific relationship between equity and oil returns, our results support the presence of some hedging of crude oil vis-à-vis unfavorable equity market fluctuations that are explained by global demand shocks. They also suggest some financialization of crude oil due to oil supply shocks.

The rest of this paper is structured as follows: Section 2 describes the data and its detailed descriptive statistics. Section 3 presents the main empirical analysis. Section 4 provides sensitivity analysis and performs robustness tests to previous findings via several alternative approaches. Finally, Section 5 concludes.

2. Statistical data properties

We use monthly data over the period December 1988 (the earliest date available for all series under consideration)–December 2017 for three-month futures prices of eleven commodities (cocoa, coffee, copper, corn, cotton, crude oil, gold, heating oil, platinum, silver, and wheat) which are traded in New York Mercantile Exchange (NYMEX) and the Chicago Board of Trade (CBOT).[8] We also gather data for the S&P/Goldman Sachs Commodity Index (SP/GSCI) which is an industry benchmark of the commodity futures market.

The S&P500 index captures the behavior of the U.S. equity market, as it represents the leading financial market in the world based

[3] On the one hand, Bekaert and Harvey (2003) and Lehkonen (2015) emphasize that stock market integration through liberalization may enhance economic development via risk sharing and portfolio allocation. On the other hand, stock market integration can be considered from a geographical perspective, and not only discount rates and expected earnings growth, but also returns and volatility are influenced by market performance, macroeconomic fundamentals and other drivers. See Bekaert et al. (2002), Bekaert et al. (2013), Eiling and Gerard (2015), Boubaker et al. (2016), Valdes et al. (2016) and Sehgal et al. (2017).

[4] Prokopczuk (2011a) finds that "crisis-conscious" investors adopt less extreme stock portfolio positions than "crisis-ignorant" investors, thus, outperforming in terms of expected returns and utility. For an assessment of the role of risk premium in predicting implied volatility, see also Prokopczuk and Wese Simen (2014). Gozgor et al. (2016) note that risk perceptions and financial market uncertainty are two key drivers of commodity market volatility transmission, albeit their effects are time-varying.

[5] As reported in Roll (2013), Bekiros et al. (2016) and Gorton and Rouwenhorst (2016), this can be explained by the fact that the degree of synchronization and the cyclical pattern of stock and commodity markets are not similar, and their correlation also tends to be low.

[6] Batten et al. (2010) find that precious metals exhibit distinct characteristics to be considered as a single class of assets, which would lead to different optimal portfolios. Lahiani et al. (2013) uncover three levels of sensitivity of agricultural commodities to past return and volatility shocks: (i) a very low sensitivity (e.g. corn and cotton); (ii) an average sensitivity (e.g. wheat); and (iii) a high sensitivity (e.g. sugar).

[7] Similarly, Arouri et al. (2015) use data for China and find significant return and volatility effects between gold and stock prices, with past gold returns systematically forecasting stock returns. Nguyen et al. (2015) show evidence of asymmetry in the causal relationship between the U.S. equity returns and the returns of energy, metal and agricultural commodity futures. Maghyereh et al. (2017) argue that gold is not a good hedge against equity fluctuations, but it is still good for portfolio diversification.

[8] Prokopczuk (2011b) focuses on pricing and hedging of freight futures contracts traded on the International Maritime Exchange. The author highlights that cost-of-carry valuation is not possible in this futures market, because freight services are non-storable. This is in sharp contrast with the majority of commodity markets. Fernandez-Perez et al. (2017) find that commodity pricing models capturing both backwardation and contango phases display strong predictive power. Hammoudeh et al. (2014) investigate the impact of changes in energy prices on the distribution of CO_2 emission allowance prices by means of a quantile regression framework.

on the market capitalization and trading volume.[9] The vast majority of works in this field also consider this market as the benchmark or include it in cross-country comparisons (Killian, 2009; Nguyen et al., 2015).[10] Alternatively, we use a broader measure of stock market index and construct equity returns from the MSCI World Price Index.[11]

Following Hammoudeh et al. (2015) and Nguyen et al. (2015), we account for the effect of inflation. Thus, we compute real returns by applying a simple Fisher equation to nominal returns and using the seasonally adjusted U.S. Consumer Price Index to calculate inflation. All data are retrieved from Bloomberg and the Morgan Stanley Capital International (MSCI).

Since we are using monthly data (instead of daily), we consider percentage changes in prices for both commodity futures returns and equity returns. Table 1 presents some descriptive statistics for monthly nominal and real returns of the commodity futures and equity returns. Average monthly real (nominal) equity returns are 0.5% (0.7%) in the case of the S&P500 index and 0.3% (0.5%) for the MSCI World index. Crude oil, heating oil, and silver display the largest monthly average commodity futures returns whereas cotton, corn and wheat have the lowest monthly average commodity futures returns. In what concerns the volatility of the returns as proxied by the unconditional standard deviation, crude oil, heating oil, and coffee returns are the most volatile while gold is the least volatile. This is also validated by the Garman and Klass (1980) volatility measure which uses opening-highest-lowest-closing prices in a month to approximate volatility. In addition, it indicates that silver is also one of the highest volatile commodities in our sample period.[12] Additionally, returns are negatively skewed only for equity and platinum and positively skewed for other commodity futures. Platinum futures returns exhibit the highest kurtosis, whereas cotton futures returns have the lowest kurtosis. Skewness and kurtosis coefficients indicate that return series are far from normally distributed. The Jarque-Bera test (J-B) rejects the null hypothesis of normality for all return series.

Table 1 also presents results of conventional stationarity tests to our return series. Augmented Dickey-Fuller (ADF) tests reject the null hypothesis of a unit root for all return series at the 1% significance level. Similarly, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test can not reject the stationarity of returns.

Finally, we examine the presence of serial correlation and heteroscedasticity via Ljung-Box Q-test and ARCH-LM test, respectively, using up to 10 lags. Except for wheat, all series exhibit an ARCH behavior and many are serially correlated up to some extent.

3. Hedging or financialization?

3.1. Econometric framework

The investment in commodities (futures) is typically advised because of three main potential benefits:[13] i) the overall low correlation between commodities and other asset classes, most notably equities; ii) relatively large returns (of the same order of magnitude of equity returns); and iii) a positive correlation with inflation. Not surprisingly, fund managers have been devoting a share of their portfolios to commodity-related products as part of a long-term diversification strategy. Thus, if shocks to commodity futures are *negatively* correlated with shocks to equity returns, investors will be able to use commodities to *hedge* against unfavorable states affecting their equity holdings.[14] However, the large capital inflows from financial investors into commodity-related financial products have also suggested an increase in the behavior of commodities as a financial asset class. In this context, shocks to commodity futures will be *positively* correlated with shocks to equity returns, reflecting the increased *financialization* of commodity markets.

Our study attempts to shed some light on these two lines of arguments. In the *first step*, we experiment with several specifications in the ARMA class as in Eqs. (1)– (2) and perform standard Box-Jenkins selection procedures to uncover the best data-generating processes governing equity and commodity futures returns.

$$EqRet_t = \mu + \sum_{i=1}^{T_1} \nu_i EqRet_{t-i} + \eta_t + \sum_{j=1}^{T_2} \xi_j \eta_{t-j} \tag{1}$$

$$ComFutRet_t = \mu + \sum_{i=1}^{T_3} \nu_i ComFutRet_{t-i} + \tau_t + \sum_{j=1}^{T_4} \xi_j \tau_{t-j} \tag{2}$$

where $EqRet_t$ denotes equity returns in real terms; $ComFutRet_t$ stands for commodity futures returns in real terms; η_t and τ_t are the time t innovations; μ is the constant; ν_i is the auto-regressive coefficient of order i; and ξ_j is the moving average coefficient of order j. Since we use rolling futures contracts with 3 months to maturity, T_i is set, at most, at 3.

In the *second step*, we extract the shock component of equity returns (η_t) and commodity futures returns (τ_t) by using the residuals of the estimated data-generating processes. *Finally*, we compute the correlations between equity return shocks and commodity futures shocks to investigate the relationship between the two and to assess whether it uncovers the existence of hedging or financialization patterns in commodities.

From a conceptual point of view, our approach is similar to that used by Baur and Lucey (2010). When investigating the potential of

[9] We consider the spot price of the S&P500 index, whereas we use futures prices for commodities. This choice is dictated by: *i*) liquidity; and *ii*) practicality. For example, exchange traded funds (ETF) that are tracking the S&P500 index are one of the most liquid assets in financial markets. In particular, SPDR S&P500 is the ETF with second highest trading volume in the world (with $20.37 billion daily average, as of 2019; see https://finance.yahoo.com/news/guide-10-most-heavily-traded-150003490.html). This means that the trading costs of the S&P500 index are extremely low. In the case of commodities, not all of them have funds that track their prices. Therefore, from a technical point of view, a cash investment in the spot market is not possible. Moreover, physically buying/selling such commodities in the spot market is not practical for several reasons (e.g. illiquidity, logistics and shipping and storing costs), which makes it impossible to include them in financial portfolios. Therefore, we use commodity futures instead, as these are highly liquid and can be easily bought/sold. Finally, we note that time differences do not create any problem in our context. Specifically, we consider the dynamics of both commodity futures and equity *returns*. Even though spot and futures prices can be different, they react to new information in a similar fashion. Therefore, there is a very high correlation between their returns, since they capture the response to shocks in the same financial assets.

[10] As a robustness check, we also consider correlations between returns of the S&P500 and the DJI Europe, the DJI Asia-Pacific and the DJI Canada equity market indices, which stand at 0.84, 0.73 and 0.78 respectively. This shows that S&P500 is a good representative of the performance of global equity markets.

[11] Sample data can be made entirely available upon request addressed to the corresponding author.

[12] In line with the work of Fabozzi et al. (2017), the volatility measure of Garman and Klass (1980) is estimated by the following expression: $0.5 \times [\log(H_t) - \log(L_t)]^2 - (2\log(2) - 1) \times [\log(C_t) - \log(O_t)]^2$ where H_t, L_t, C_t, O_t are highest, lowest, closing and opening price in month t, respectively. For each time series under consideration, we estimate this measure at the monthly frequency and, then, take the monthly average to represent volatility. We cannot estimate it for the GSCI since its monthly highest and lowest values are not available for more than half of our sample period.

[13] Throughout the paper, the term " investment in commodity (futures)" refers to taking a long position in a given futures contract.

[14] We highlight that if we considered the *nominal* commodity futures returns and the *nominal* equity returns, then, a correlation between the two variables smaller than unity would be enough for the benefits of diversification to take place. In fact, irrespective of whether the correlation was negative or positive, as long as it is was less than unity, risk diversification would occur. However, in order to be able to distinguish between financialization and hedging behaviors, we need to compute the correlation between the *unexpected component* of commodity futures returns and the *unexpected component* of equity returns.

Table 1
Descriptive statistics.

	S&P500	MSCI-World	Crude Oil	Heating Oil	Copper	Gold	Platinum	Silver	Wheat	Cocoa	Coffee	Corn	Cotton	GSCI
Panel A: descriptive statistics of nominal monthly returns														
Mean	0.007	0.005	0.007	0.008	0.005	0.004	0.004	0.006	0.003	0.004	0.004	0.003	0.003	0.004
Median	0.011	0.01	0.007	0.008	0.002	0.002	0.001	0	−0.001	0	−0.008	−0.001	0.005	0.006
Max	0.112	0.111	0.383	0.377	0.31	0.162	0.271	0.282	0.409	0.31	0.412	0.262	0.259	0.211
Min	−0.169	−0.19	−0.311	−0.277	−0.361	−0.186	−0.312	−0.279	−0.255	−0.232	−0.247	−0.212	−0.21	−0.278
Std dev	0.041	0.042	0.082	0.086	0.069	0.045	0.059	0.08	0.076	0.08	0.096	0.071	0.07	0.059
Kurtosis	4.34	4.514	5.241	4.903	6.284	4.175	6.677	3.929	5.548	3.833	4.97	3.809	3.659	4.795
Skewness	−0.594	−0.608	0.189	0.39	0	0.127	−0.51	0.11	0.549	0.449	0.92	0.257	0.188	−0.142
J-B Stat	46.46***	54.7***	74.9***	61.33***	156.36***	20.95***	211.09***	13.2***	111.6***	21.72***	105.38***	13.34***	8.35***	47.87***
ADF Stat	−17.48***	−17.32***	−15.47***	−15.87***	−17.14***	−20.65***	−18.16***	−20.21***	−20.38***	−21.88***	−19.11***	−19.22***	−18.96***	−15.93***
KPSS Stat	0.11	0.053	0.08	0.07	0.12	0.17	0.16	0.1	0.06	0.06	0.05	0.06	0.03	0.1
LB-Q(1)	0.47	1.22	10.81***	7.9***	1.97	4.49**	0.15	2.78*	2.98*	9.37***	0.23	0.42	0.18	7.74***
LB-Q(5)	2.96	4.28	19.03***	16.32***	8.92	6.69	6.66	5.84	6.68	16.12***	8.74	10.02*	17.79***	8.56
LB-Q(10)	7.41	6.24	23.49***	28.23***	16.53*	13.16	18.36**	15.13	11.46	17.41*	9.87	13.46	34.82***	16.54*
ARCH-LM(1)	19.57***	24.75***	13.93***	18.36***	6.95***	17.18***	31.87***	16.96***	0.75	2.34	9.13***	19.28***	34.8***	13.96***
ARCH-LM(5)	37.86***	37.9***	25.31***	25.47***	12.45**	19.38***	39.44***	37.34***	4.58	13.67**	11.72**	27.44***	40.47***	18.56***
ARCH-LM(10)	40.55***	44.92***	30.43***	27.39***	19.53**	22.48**	68.52***	44.97***	7.88	27.36***	14.09	45.76***	44.51***	29.59***
Panel B: descriptive statistics of real monthly returns														
Mean	0.005	0.003	0.005	0.006	0.003	0.002	0.001	0.004	0.001	0.002	0.002	0.001	0.001	0.002
Median	0.008	0.009	0.005	0.006	0	−0.001	0	−0.002	−0.004	−0.003	−0.009	−0.003	0.002	0.004
Max	0.108	0.108	0.374	0.368	0.303	0.158	0.268	0.276	0.406	0.302	0.411	0.262	0.26	0.209
Min	−0.162	−0.183	−0.305	−0.27	−0.356	−0.179	−0.313	−0.28	−0.255	−0.231	−0.248	−0.214	−0.209	−0.271
Std Dev	0.041	0.042	0.081	0.086	0.068	0.045	0.058	0.08	0.076	0.08	0.096	0.071	0.07	0.058
Kurtosis	4.168	4.33	5.198	4.872	6.178	4.168	6.684	3.898	5.518	3.808	4.98	3.835	3.684	4.691
Skewness	−0.55	−0.567	0.204	0.401	0.03	0.189	−0.482	0.115	0.559	0.449	0.913	0.27	0.21	−0.115
J-B Stat	37.31***	44.31***	72.47***	60.13***	146.5***	21.88***	210.32***	12.46***	110.08***	21.17***	105.2***	14.34***	9.34**	42.25***
ADF Stat	−17.88***	−17.59***	−15.77***	−16.18***	−17.35***	−20.85***	−18.32***	−20.31***	−20.41***	−21.97***	−19.2***	−19.32***	−19.1***	−16.39***
KPSS Stat	0.12	0.05	0.07	0.07	0.12	0.17	0.16	0.1	0.06	0.06	0.05	0.06	0.03	0.1
LB-Q(1)	0.27	0.95	8.95***	6.31**	1.53	4.61**	0.07	2.86*	2.99*	9.56***	0.28	0.5	0.28	5.4**
LB-Q(5)	2.79	4.35	16.85***	14.58**	8.06	6.49	6.68	5.75	6.66	16.27***	8.96	9.77*	17.94***	6.11
LB-Q(10)	7.94	6.51	21.34**	26.36***	15.46	13.27	18.38**	14.81	11.69	17.61*	10.12	13.22	34.08***	14.18
ARCH-LM(1)	16.01***	21.51***	11.39***	15.48***	5.82**	26.13***	29.39***	17.32***	0.74	2.63	9.28***	18.44***	34.02***	9.59***
ARCH-LM(5)	36.21***	36.95***	23.08***	23.36***	12.17**	27.35***	39.35***	37.88***	4.56	14.34**	11.82**	27.2***	39.74***	14.74**
ARCH-LM(10)	39.02***	43.89***	28.16***	25.23***	19.35**	30.36***	67.82***	44.31***	7.61	28.32***	14.21	44.9***	43.9***	26.61***

Notes: This table presents descriptive statistics for monthly nominal returns (Panel A) and real returns (Panel B). The null hypothesis of Jarque-Berra (J-B) test is returns are normally distributed. The null hypothesis of the Augmented Dicky-Fuller (ADF) test is the existence of a unit root. The null hypothesis of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is the stationarity of returns. The null hypothesis of the Ljung–Box Q (LB-Q) test is returns are not autocorrelated. The null hypothesis of ARCH-LM test is the absence of ARCH effect. In both panels, *, ** and *** denote 10%, 5% and 1% significance level.

gold as an investment, the authors distinguish between a hedge and a diversifier. The former denotes an asset that is either negatively correlated or uncorrelated with another asset, while the latter corresponds to the case of a positive correlation. They also consider the case of a third type of asset, namely, the safe haven, which is an asset that is negatively correlated with another asset in times of financial stress.

Our method follows the same reasoning except that we specifically focus on the correlation between unexpected variations of equity returns and commodity futures returns, which is in the same spirit of the finance theory. Indeed, the correlation between equity returns and commodity futures returns *per se* does not distinguish between the systematic and the idiosyncratic components of these variables. This implies that such correlation may simply be due to the dynamics of a third factor, which spuriously generates the linear association. In contrast, the correlation between *shocks* to equity returns and *shocks* to commodity futures returns solely captures the co-movement among their idiosyncratic components, which, in finance, lays at the heart of investors' behavioral decisions.

For instance, the property of gold as a good hedge against unfavorable inflation fluctuations comes from the fact that shocks to gold returns tend to be negatively correlated with inflation shocks. Thus, when inflation unexpectedly rises, the price of gold tends to increase unexpectedly too. This implies that by, holding a larger fraction of their portfolio in the form of gold assets, investors are compensated for higher than expected inflation. Along the same line, Longin and Solnik (1995) use an explicit modeling of the conditional correlation between international stock markets, and find that: (i) it has increased over time; and (ii) it rises during periods of large conditional market volatility. Using multivariate extreme value theory, Longin and Solnik (2001) further show that such correlation increases in bear markets, but not in bull markets.

3.2. Empirical results

Panel A of Table 2 provides a summary of the fitted data-generating processes. It can be seen that equity market returns are best described as an ARMA(1,1) process.[15]

As for different commodity futures returns, they are tracked well by alternative ARMA(p,q) processes.[16] For example, ARMA(2,3) provides a good characterization of the returns of many commodity futures, such as crude oil, heating oil, platinum and cocoa. Another ARMA process, ARMA (3,3) describes well the dynamics of commodities, such as silver, corn and cotton. MA processes characterize the patterns of gold futures, while copper and wheat futures are described by an AR(2) process. These fitted-models suggest that the level of current copper and wheat observations depends on the level of their 2 months lagged observations only. For copper, if we observe a high positive return this month, we will expect that its return over the next two months will also be positive due to the positive second-order auto-regressive coefficient. For wheat, a high positive return this month is likely to be followed by a negative return over the next months due to the negative and significant auto-regressive parameter.

Other assets' returns (except for gold), cannot be modeled with their lagged observations only. Their returns at time t are also effected by shocks that have taken place before time t. For example, if we observe a negative crude oil shock, we would expect that it affects the returns not only when it takes place, but also in the near future. Regarding gold, observed returns are defined by a deterministic trend and the weighted previous shocks, emphasizing the lingering effects of random shocks to the gold on its future price levels.

Panel B of Table 2 shows the normality, autocorrelation and heteroscedasticity characteristics of residual series. Once the filtering approach is applied, the serial correlation completely disappears from all series. Although normality is still rejected, the considerable decrease in J-B test statistics of all series is an indicator of residuals being closer to a normal distribution than real returns. Similarly, the ARCH effect is still observed in residuals (except for wheat futures returns), with however a significant decrease compared to returns series, as evidenced by coffee, copper and crude oil futures residuals.

Panel C of Table 2 provides a summary of the correlations between shocks to real equity returns and shocks to real commodity futures returns. Our results suggest that while they are relatively low, the correlations are statistically significant for a large number of commodity futures returns. The point estimates are positive except for gold futures where the correlation with equity returns is negative, albeit insignificant. Finally, there is a wide degree of variation in the correlations, which are reasonably large for copper (0.331), cotton (0.245) wheat (0.175), platinum (0.137) and crude oil (0.131).

All in all, this evidence suggests that while gold can be typically used as a hedge against unfavorable variation in equity markets up to some extent (as corroborated by the negative correlation), most of the other commodity futures display a behavior that is consistent with financialization (as reflected in the positive correlation). Indeed, when considering the SP/GSCI index, the correlation of its unexpected component with shocks to equity market returns is positive and significant (0.188), which shows that commodities are increasingly taken into account by investors when designing their asset portfolios.[17]

4. Sensitivity analysis and robustness tests

4.1. Accounting for the effect of inflation

We also measure returns in nominal terms in order to control for the importance of inflation. In this context, the majority of the empirical research on the hedging properties of gold have relied on VAR and co-integration models (Kolluri, 1981; Moore, 1990). Amenc et al. (2009) emphasize the inflation-hedging properties of commodities and their relevance for long-term investors.

Panel A of Table 3 reports the fitted data-generating processes for nominal returns and shows that, for the majority of the assets under consideration, they are very similar to those we found for real returns (Table 2). For example, nominal heating oil, copper, gold,

[15] In the strong form of market efficiency, there is an instantaneous dissemination of new information into prices. Therefore, prices can only depend on future events but, since the future cannot be predicted, prices are assumed follow a random walk process. In the case of the weak-form of the efficient market hypothesis, if stock prices follow an ARMA process, then, they are not efficient, as future price changes depend on lagged returns and past random shocks. Since the weak-form of efficiency does not hold, we also reject the semi-strong or strong forms of efficiency. Stock markets display this type of behavior for various reasons. For instance, seasonality may affect investor behavior/sentiment in stock markets (e.g. the ' January' effect, the ' sell in May and go away' strategy, or the ' Halloween' effect).

[16] Due to their nature, commodity supply or demand also depends heavily on external factors (e.g. weather conditions). This might impair the strong form of commodity market efficiency. For example, energy commodity prices experience increases in Winter (due to rises in demand) and price decreases in the Summer (due to falls in demand). Similarly, agricultural commodities tend to display specific price cycles.

[17] As an alternative approach, we let the lags of the ARMA(p,q) modeling framework to take values up to 4. In the new scheme, the main conclusions regarding autocorrelation, normality and heteroscedasticity of ARMA residuals remain unchanged. Additionally, the correlation structure does not alter, with the exception of silver where it is still positive but loses some statistical significance. For some assets, the optimal lag selection slightly changes. For other time series, the non-seasonal moving average polynomial is non-invertible, which means that the model extension to the fourth lag is not feasible. These results are available from the authors upon request.

Table 2
The linkage between real equity returns and real commodity futures returns.

	μ	ν_1	ν_2	ν_3	ξ_1	ξ_2	ξ_3
Panel A: ARMA estimated data-generating processes for monthly real equity returns and real commodity futures returns							
S&P500	0.010**	−0.856***		0.903***			
	(2.26)	(−18.07)		(20.50)			
Crude oil	0.016	−0.289***	−0.980***		0.449***	1.048***	0.175***
	(1.51)	(−40.95)	(−151.06)		(9.26)	(62.06)	(3.53)
Heating oil	0.008	0.298***	−0.901***		−0.167***	0.963***	0.125**
	(0.96)	(15.92)	(−70.01)		(−3.51)	(52.60)	(2.54)
Copper	0.003	0.058	0.122**				
	(0.71)	(1.20)	(2.47)				
Gold	0.002				−0.124***		
	(1.04)				(−2.59)		
Platinum	0.003	−0.177*	−0.834***		0.193*	0.886***	0.096**
	(0.49)	(−1.87)	(−10.27)		(1.81)	(12.41)	(2.02)
Silver	0.001***	0.676***	−0.577***	0.850***	−0.776***	0.617***	−0.841***
	(6.42)	(6.68)	(−4.88)	(11.07)	(−7.18)	(4.45)	(−10.00)
Wheat	0.001	−0.100**	−0.086				
	(0.31)	(−1.98)	(−1.60)				
Cocoa	0.001**	0.216	0.727***		−0.387*	−0.643**	0.029
	(2.57)	(1.07)	(3.58)		(−1.85)	(−2.53)	(0.42)
Coffee	0.003	0.127	−0.604***		−0.152	0.754***	
	(0.36)	(0.92)	(−4.60)		(−1.27)	(6.87)	
Corn	0.000	0.847***	−0.083	−0.600***	−0.923***	0.234	0.528**
	(0.03)	(3.73)	(−0.25)	(−2.82)	(−3.72)	(0.66)	(2.21)
Cotton	0.001	0.479***	0.447***	−0.737***	−0.535***	−0.311*	0.752***
	(0.35)	(3.06)	(2.89)	(−6.37)	(−3.21)	(−1.65)	(5.72)
GSCI	0.004	−1.146***	−0.800***	0.131***	1.291***	0.945***	
	(0.39)	(−20.86)	(−12.64)	(2.96)	(33.17)	(26.51)	
MSCI-World	0.006	0.235	−0.267	−0.728***	−0.192	0.223	0.791***
	(−1.39)	(0.92)	(−1.08)	(−2.88)	(−0.83)	(0.99)	(3.39)

	S&P500	Crude oil	Heating oil	Copper	Gold	Platinum	Silver	Wheat	Cocoa	Coffee	Corn	Cotton	GSCI	MSCI-World
Panel B: time series characteristics of ARMA-filtered monthly real residuals														
J-B Stat	34.83***	38.24***	43.96***	118.96***	20.57***	181.96***	24.03***	119.5***	13.54***	100.64***	24.41***	8.73**	23.05***	32.5***
LB-Q(1)	0.02	0.01	0	0	0	0	0.02	0	0	0.01	0.11	0.21	0	0
p-Value	(0.885)	(0.941)	(0.944)	(0.991)	(0.944)	(0.985)	(0.894)	(0.947)	(0.997)	(0.927)	(0.744)	(0.646)	(1.000)	(0.977)
LB-Q(5)	1.58	4.95	3.12	0.47	1.54	1.29	1.38	1.07	0.57	0.12	2.31	6.83	0.9	1.95
p-Value	(0.904)	(0.421)	(0.681)	(0.993)	(0.908)	(0.936)	(0.927)	(0.957)	(0.989)	(1.000)	(0.804)	(0.233)	(0.970)	(0.856)
LB-Q(10)	6.50	8.96	14.04	7.18	8.82	7.97	4.94	5.74	2.57	1.56	9.23	10.54	7.38	5.36
p-Value	(0.772)	(0.536)	(0.171)	(0.709)	(0.550)	(0.632)	(0.895)	(0.837)	(0.990)	(0.999)	(0.510)	(0.250)	(0.689)	(0.866)
ARCH-LM(1)	16.46***	3.64*	7.54***	3.97**	16.38***	26.32***	15.95***	0.32	3.02*	8.14***	22.51***	23.33***	7.09***	19.31***
p-Value	(0.001)	(0.056)	(0.006)	(0.046)	(0.001)	(0.001)	(0.001)	(0.573)	(0.082)	(0.004)	(0.001)	(0.001)	(0.008)	(0.001)
ARCH-LM(5)	35.11***	13.96**	16.70***	9.41*	20.05***	36.63***	38.90***	3.82	17.10***	10.75*	24.94***	26.41***	10.90*	34.53***
p-Value	(0.001)	(0.016)	(0.005)	(0.094)	(0.001)	(0.001)	(0.001)	(0.575)	(0.004)	(0.057)	(0.001)	(0.001)	(0.053)	(0.001)
ARCH-LM(10)	36.96***	18.76**	18.00*	17.23*	22.86**	61.30***	44.63***	7.43	31.33***	12.90	40.30***	30.85***	25.02***	40.57***
p-Value	(0.001)	(0.043)	(0.055)	(0.069)	(0.011)	(0.001)	(0.001)	(0.684)	(0.001)	(0.229)	(0.001)	(0.001)	(0.005)	(0.001)

	Crude oil	Heating oil	Copper	Gold	Platinum	Silver	Wheat	Cocoa	Coffee	Corn	Cotton	GSCI
Panel C: Correlation between monthly real equity residuals (shocks) and real commodity futures residuals (shocks)												
S&P500	0.131**	0.126**	0.331***	−0.041	0.137**	0.123**	0.175***	0.052	0.109**	0.168***	0.245***	0.188***
p-Value	(0.015)	(0.019)	(0.001)	(0.442)	(0.011)	(0.021)	(0.001)	(0.335)	(0.043)	(0.002)	(0.000)	(0.000)
MSCI-W	0.206***	0.171***	0.343***	0.071	0.277***	0.219***	0.195***	0.102*	0.130**	0.193***	0.260***	0.278***
p-Value	(0.000)	(0.001)	(0.000)	(0.187)	(0.000)	(0.000)	(0.000)	(0.057)	(0.015)	(0.000)	(0.000)	(0.000)

Notes: Panel A presents the coefficients for the estimated best-fitting ARMA(p,q) models for monthly real returns. Panel B displays the time-series characteristics of the residuals obtained from these estimations. Panel C shows correlations between equity residuals and commodity futures residuals. In Panel A, values in parentheses are Newey-West *t*-statistics, whereas they refer to *p*-values in Panels B and C. In all panels, *, ** and *** denote 10%, 5% and 1% significance level.

Table 3
The linkage between nominal equity returns and nominal commodity futures returns.

	μ	ν_1	ν_2	ν_3	ξ_1	ξ_2	ξ_3
Panel A: ARMA estimated data-generating processes for monthly nominal equity returns and nominal commodity futures returns							
S&P500	0.016***	−0.072**	−0.133***	−0.862***	0.136***	0.107***	0.971***
	(3.17)	(−2.12)	(−3.72)	(−34.92)	(4.17)	(3.19)	(34.90)
Crude oil	0.006	0.176***					
	(1.36)	(4.28)					
Heating oil	0.012	0.300***	−0.903***		−0.155***	0.959***	0.139***
	(1.38)	(16.08)	(−71.3)		(−3.27)	(52.74)	(2.84)
Copper	0.004	0.065	0.127***				
	(1.16)	(1.36)	(2.60)				
Gold	0.004**				−0.124***		
	(2.02)				(−2.77)		
Platinum	0.008	−0.188**	−0.830***		0.210**	0.881***	0.104**
	(1.08)	(−1.98)	(−10.02)		(1.96)	(11.91)	(2.22)
Silver	0.013	−0.296***	−0.864***		0.215**	0.834***	
	(1.48)	(−2.97)	(−11.16)		(2.02)	(10.16)	
Wheat	0.024**	−1.842***	−0.905***		1.777***	0.677***	−0.166***
	(2.05)	(−120.90)	(−58.47)		(31.85)	(6.31)	(−3.01)
Cocoa	0.001***	0.253*	0.686***		−0.412**	−0.588***	
	(2.80)	(1.67)	(4.62)		(−2.33)	(−3.39)	
Coffee	0.006	0.128	−0.602***		−0.152	0.750***	
	(0.69)	(0.91)	(−4.46)		(−1.25)	(6.65)	
Corn	0.005	0.215***	−0.816***		−0.252***	0.967***	−0.032
	(0.71)	(3.90)	(−15.58)		(−3.95)	(33.68)	(−0.60)
Cotton	0.003	0.486***	0.455***	−0.740***	−0.538***	−0.320*	0.754***
	(0.84)	(3.18)	(3.02)	(−6.46)	(−3.33)	(−1.73)	(5.78)
GSCI	0.009	−1.123***	−0.770***	0.155***	1.291***	0.947***	
	(0.94)	(−21.11)	(−12.64)	(3.61)	(33.99)	(27.38)	
MSCI World	0.009**	0.343	−0.499**	−0.499*	−0.281	0.454*	0.612***
	(2.06)	(1.22)	(−2.08)	(−1.79)	(−1.03)	(1.88)	(2.23)

	Crude oil	Heating oil	Copper	Gold	Platinum	Silver	Wheat	Cocoa	Coffee	Corn	Cotton	GSCI
Panel B: correlation between monthly nominal equity residuals (shocks) and nominal commodity futures residuals (shocks)												
S&P500	0.141***	0.132**	0.335***	−0.056	0.138**	0.082	0.164***	0.05	0.116**	0.189***	0.262***	0.202***
p-Value	(0.008)	(0.014)	(0.001)	(0.294)	(0.011)	(0.126)	(0.002)	(0.353)	(0.031)	(0.001)	(0.001)	(0.001)
MSCI World	0.173***	0.152***	0.362***	0.082	0.262***	0.207***	0.179***	0.080	0.140***	0.181***	0.274***	0.264***
p-Value	(0.001)	(0.005)	(0.000)	(0.129)	(0.000)	(0.000)	(0.001)	(0.138)	(0.009)	(0.001)	(0.000)	(0.000)

Notes: Panel A presents the coefficients for the estimated best-fitting ARMA(p,q) models for monthly nominal returns. Panel B shows the correlations between equity residuals and commodity futures residuals obtained from these estimations. In Panel A, values in parentheses are Newey-West *t*-statistics, whereas they refer to *p*-values in Panel B. In both panels, *, ** and *** denote 10%, 5% and 1% significance level.

platinum, coffee, cotton and S&P GSCI index residuals are still represented best by the exact ARMA processes fitted to the corresponding real residuals.

Panel B of Table 3 summarizes the correlations between shocks to nominal equity returns and shocks to nominal commodity futures returns. Again, the empirical evidence shows that these correlations are typically small in magnitude, but statistically significant for the majority of commodity futures. Additionally, we confirm the existence of a negative, albeit insignificant correlation in the case of gold futures, reflecting the property of gold as a hedge against unfavorable stock market news up to some extent. This corroborates the findings of Baur and Lucey (2010) and is in line with the work of Batten et al. (2010). Yet, for most of the other commodity futures returns which display a significant correlation with equity market returns, this correlation is positive. For instance, the correlation between shocks to positive equity market returns and shocks to nominal SP/GSCI returns is 0.20 and significant at the 1% level. It is also particularly large in the case of copper (0.335), cotton (0.262), and corn (0.189). This corroborates the presence of financialization in these specific commodities.

4.2. Sub-sample periods

Bekiros et al. (2015) estimate the dependence structure on the 20 asset-mining sector portfolios from the Australian Securities Exchange using vine copulas and minimum risk portfolios. They find a complex dependence pattern with some results pointing to convergence on some stocks in a portfolio optimization exercise. Using a dynamic equicorrelation GARCH model, Sensoy et al. (2015) find evidence of convergence for precious and industrial metal commodity futures since mid-2000s, whereas agricultural commodity futures did not seem to be correlated over the period 1997–2013. Interestingly, physical supply/demand balances - instead of global financial conditions - are the main driving forces of commodity futures prices.

Given that the use of commodity futures might have changed over time, we split the sample into two sub-periods: December 1988–December 1999 and January 2000–December 2017.[18] The obvious

[18] Baur and Lucey (2010) identify bull-bear equity market periods. Along the same line, our sample includes the following bull and bear equity market episodes: *1* December 1988–May 1990 (bull market); *2* May 1990–October 1990 (bear market); *3* October 1990–March 2000 (bull market); *4* March 2000–March 2003 (bear market); *5* March 2003–October 2007 (bull market); *6* October 2007–March 2009 (bear market); and *7* March 2009–December 2017 (bull market). Thus, we re-estimate our models for these specific periods. As the number of observations included in episodes 1 and 2 is small, we focus on episodes 3 to 7. The main observation is that gold has not been significantly positively correlated with the S&P500 index in any phase. In sub-periods 3 (bull), 4 (bear), 6 (bear) and 7 (bull), gold is negatively (albeit insignificantly) correlated with it, which categorizes it as a diversifier according to the definition of Baur and Lucey (2010). We also find that the financialization effect on other commodities starts kicking in over the last decade. For instance, in period 6 (bear) and 7 (bull), correlations between commodities and the S&P500 become positive. This is particularly significant in the case of period 7 (i.e. the last period of our sample), where almost all commodities (except gold) show highly significant positive correlations with the stock market. All in all, the main conclusions of our study hold in non-crisis or boom periods. For brevity, these results are not reported in the paper, but they are available from the authors upon request.

caveat of this exercise is that it drops a substantial amount of information, thus, making the estimation of the data-generating processes less accurate and more prone to error.

In Panel A of Table 4, we present the empirical evidence for the estimated data-generating processes using data from December 1988 until December 1999. As can be seen, there are some notable differences vis-à-vis the results reported in Table 2 (i.e., where we considered the full sample period). For instance, the returns on the S&P500 index, the heating oil, cocoa and coffee futures are captured well by an ARMA(3,3) model. The returns on the platinum futures are described by a pure MA process.

Panel B of Table 4 reports the correlations between shocks to real equity returns and shocks to real commodity futures returns. We find that, in general, investors did not seem to use commodity futures to hedge against unfavorable fluctuations in their portfolios of stocks over the period of 1990: 1–1999:12. Indeed, the correlations between the shocks are not significant for any of the commodities under consideration except the crude oil. Two important results should be highlighted. First, shocks to gold futures returns are still negatively correlated with shocks to equity market returns, yet this correlation is not statistically significant. Second, shocks to crude oil and heating oil futures are negatively correlated with shocks to equity market returns, and in the case of crude oil, this negative correlation is significant. As a result, fuel (energy) commodity futures appear to be a good risk-hedge for stocks in the first sub-sample period.[19]

The estimated data-generating processes based on data for the period January 2000–December 2017 are reported in the Panel A of Table 5. The returns on some of the assets, such as heating oil and copper, appear to be proxied well by the pure AR model. In the case of the gold, cocoa, corn, cotton and the S&P GSCI index, returns are well described by an ARMA(3,3) process.

Panel B of Table 5 presents the correlations between shocks to real equity returns and shocks to real commodity futures returns. We can see that commodities have become more important for investors since the 2000s, which is in line with the idea that financialization of these assets increased relevance over time. In fact, the correlation between the shocks to real returns on the S&P500 and the shocks to real returns on the SP/GSCI index is positive (0.25) and statistically significant at the 1% level. Moreover, when compared to the first sub-sample period, the correlation between commodity futures returns and equity market returns is positive and significant for a larger number of commodities. This is especially the case of crude oil, heating oil, copper, cotton, platinum, silver, wheat and coffee.

In the case of crude oil, it is interesting to note that while the correlation is negative and significant in the nineties, it shifted to (significantly) positive since the 2000s. Therefore, investors used this commodity to protect their investments in stocks from unfavorable fluctuations, but nowadays it gained a renewed importance in portfolios due to the increase in financialization. Additionally, gold and cocoa are the only two commodities that display an insignificant correlation with equities. Thus, the hedging property of gold emerges when the sample period is long enough to account for both the stock market and the gold price cycles, which are typically long.[20]

4.3. Different time horizons

We now assess the hedging versus the financialization properties of commodities at different time horizons. Baur and Lucey (2010) show that gold offers a significant safe haven opportunity for stocks in the short-term. However, over the long-term, this characteristic tends to erode. In our case, that would imply that the negative correlation between shocks to real equity market returns and shocks to real gold futures returns would be larger (in magnitude) at shorter horizons and smaller (in magnitude) at longer horizons.

To investigate this hypothesis, we start by computing equity market and commodity futures returns at different rolling windows, namely, buy-and-hold investment strategies over the 1-quarter, 1-year and 5-year horizons. Then, we estimate the best data-generating process for these returns to extract their unexpected components. Finally, we compute the correlation between these shocks and the shocks to the various commodity futures returns.

For concision purposes, Panel A of Table 6 only reports the data-generating processes for real equity returns at different time horizons.[21] We do not find relevant differences among them: ARMA processes characterize well equity returns, with the exception of 1-quarter equity returns that seen to be described by an MA process.

Panel B of Table 6 presents the estimated correlations. We find that the correlation between shocks to the returns on the S&P500 and shocks to the returns on the SP/GSCI index are positive and statistically significant across the various time horizons. Its largest value is achieved at the 1-year horizon (0.206), which implies that financialization is particularly relevant for investors considering this time horizon.

In line with our previous results, gold is the only commodity futures that consistently displays a negative correlation with equity market returns, which corroborates the idea that it has relevant hedging properties. Except for the 1-year holding period, all correlations are negative, albeit insignificant. This finding indicates that gold might be a good hedge for short-term equity market fluctuations, but not in the mid-term. It is also in accordance with the work of Baur and Lucey (2010), who provide evidence corroborating the importance of gold as a safe haven for stocks over relatively short horizons.

We can also see that the correlation is: (i) always positive and significant in the case of copper, platinum, silver, wheat, corn and cotton, which implies that financialization is especially important for these commodities no matter the time horizon under consideration; (ii) the correlation between shocks to cocoa futures returns and shocks to equity returns is not significant across the different time horizons analyzed, suggesting that this commodity has not been financialized yet and still provides diversification opportunities.

4.4. Dynamic conditional correlations

Even though we filter our return series with ARMA processes, one might concern that the ARCH effect still present in the series might lead to wrong conclusions since the ARMA model is not conditionally

[19] We highlight that even though correlation is not a perfect measure of hedge effectiveness, the fundamentals of hedging theory still rely on this concept. In seminal studies, this referred in the context of the Markowitz's (1952) and Sharpe's (1964) Portfolio Theory, where portfolio risk directly depends on the correlation of the asset returns within the portfolio. In modern times, its importance has been emphasized in hedging operations using derivatives products when the spot position to be hedged does not have a direct derivative product written on it. For example, until the last decade, the airline industry used crude oil derivatives to hedge itself against jet fuel price fluctuations. The reason is that, back then, jet fuel did not have any derivatives contract (or the market was extremely illiquid), but its price was highly correlated with crude oil prices.

[20] In the spirit of Baur and Lucey (2010), these results would be consistent with the idea that increasing financialization is associated with a strengthening of both hedging/speculation and diversification/index investment), that is, the correlations increase in magnitude along with increasing financialization.

[21] The best-suited specification models for commodity futures can be made entirely available upon request to the corresponding author.

Table 4
The linkage between real equity returns and real commodity futures returns - 1988:12–1999:12.

	μ	ν_1	ν_2	ν_3	ξ_1	ξ_2	ξ_3
Panel A: ARMA estimated data-generating processes for monthly real equity returns and real commodity futures returns							
S&P500	0.005	0.409	-0.567^{***}	0.694^{***}	-0.549^{*}	0.763^{***}	-0.833^{***}
	(0.60)	(1.18)	(−4.79)	(2.32)	(−1.76)	(8.74)	(−2.70)
Crude oil	0.001	0.890^{***}			-0.705^{***}	-0.295^{***}	
	(0.83)	(14.85)			(−7.48)	(−3.55)	
Heating oil	0.015	-1.077^{***}	-1.105^{***}	−0.158	1.341^{***}	1.421^{***}	0.501^{**}
	(0.75)	(−5.41)	(−6.04)	(−0.79)	(6.52)	(7.38)	(2.37)
Copper	−0.002	1.340^{***}	-0.854^{***}		-1.488^{***}	0.987^{***}	0.009
	(−0.69)	(62.23)	(−64.82)		(−18.15)	(7.60)	(0.10)
Gold	−0.010	-0.950^{***}	-0.216^{**}		0.910^{***}		
	(−1.61)	(−9.79)	(−2.44)		(15.91)		
Platinum	−0.003				-0.250^{*}		
	(−1.30)				(−1.66)		
Silver	−0.004	-1.763^{***}	-0.816^{***}		1.732^{***}	0.540^{***}	-0.234^{**}
	(−0.23)	(−74.56)	(−39.69)		(20.55)	(3.14)	(−2.29)
Wheat	−0.008	-0.608^{***}	-0.938^{***}		0.646^{***}	1.001^{***}	
	(−0.61)	(−50.98)	(−66.16)		(24.06)	(34.38)	
Cocoa	−0.001	0.934^{***}	-0.873^{***}	0.658^{***}	-1.030^{***}	1.068^{***}	-0.819^{***}
	(−0.21)	(8.20)	(−13.07)	(7.26)	(−10.08)	(16.20)	(−8.69)
Coffee	0.007	-0.537^{***}	-0.416^{***}	-0.653^{***}	0.682^{***}	0.682^{***}	0.999^{***}
	(0.21)	(−10.73)	(−10.20)	(−17.13)	(22.06)	(18.56)	(25.58)
Corn	−0.007	-1.091^{***}	−0.136		0.999^{***}		
	(−0.66)	(−12.38)	(−1.55)		(47.84)		
Cotton	−0.003	0.748^{***}	-0.734^{***}	-0.130^{*}	-0.899^{***}	0.999^{***}	
	(−0.49)	(8.53)	(−9.16)	(−1.82)	(−19.95)	(22.92)	
GSCI	−0.001	0.372^{*}	0.413^{**}		−0.263	-0.737^{***}	
	(−1.22)	(1.69)	(2.00)		(−1.48)	(−4.25)	
MSCI World	0.004^{*}	1.017^{***}	−0.323	−0.428	-1.154^{***}	0.505	0.333
	(1.77)	(3.12)	(−0.68)	(−1.32)	(−3.42)	(0.96)	(0.91)

	Crude oil	Heating oil	Copper	Gold	Platinum	Silver	Wheat	Cocoa	Coffee	Corn	Cotton	GSCI
Panel B: correlation between monthly real equity residuals and real commodity futures residuals												
S&P500	-0.156^{*}	−0.127	0.036	−0.105	0.037	0.101	0.056	0.074	0.01	0.14	0.04	−0.097
p-Value	(0.074)	(0.147)	(0.679)	(0.230)	(0.677)	(0.249)	(0.520)	(0.400)	(0.913)	(0.110)	(0.645)	(0.271)
MSCI World	−0.130	−0.108	0.067	−0.074	0.145^{*}	0.081	0.014	−0.062	0.004	0.092	0.075	−0.075
p-Value	(0.137)	(0.219)	(0.448)	(0.397)	(0.096)	(0.356)	(0.870)	(0.478)	(0.961)	(0.295)	(0.390)	(0.396)

Notes: Panel A presents the coefficients for the estimated best-fitting ARMA(p,q) models for monthly real returns from December 1988 to December 1999. Panel B shows the correlations between equity residuals and commodity futures residuals obtained from these estimations. In Panel A, values in parentheses are Newey-West *t*-statistics, whereas they refer to *p*-values in Panel B. In both panels, *, ** and *** denote 10%, 5% and 1% significance level.

heteroscedastic, i.e. it does not take into account volatility clustering. On top of that, splitting the time sample might not be realistic considering the dynamic structure of financial markets.

In this sub-section, we employ the state-of-the-art methodology of rotational dynamic conditional correlation (RCC) of Noureldin et al. (2014) on ARMA-filtered residuals to deal with the abovementioned concerns. This approach focuses on conditional correlations of GARCH filtered series, and therefore, the heteroscedasticity effect is removed. Moreover, it allows us to estimate a time-varying correlation coefficient without consuming any initial data unlike the case of rolling window estimations and, due to its dynamic nature, we do not need to split the sample with a cutoff date.[22]

For concision purposes, in Fig. 1, we drive our attention to dynamic correlations between the equity market and gold futures and between the equity market and the GSCI index. The upper subfigure shows that gold has been and still is an hedge for the equity market, as reflected in their negative correlation. In fact, the only period when the correlation between the two assets was positive was around mid-2012. However, this period is short and the negative correlation has been preserved since then.

Additionally, the lower sub-figure provides strong evidence of commodity financialization, especially since the Global Financial Crisis (GFC). Prior to this event, dynamic correlations between equity and the GSCI index hover around zero. However, at the onset of the GFC, the correlation immediately jumps and even reaches 0.8 in 2012 (i.e., around the same time the correlation between gold futures and the equity market becomes positive). This picture seems to be a manifestation of a “new normal” era where equity markets and commodity markets are highly integrated in the global financial system.

4.5. Further discussion on the relationship between equity and oil returns

Over recent years, changes in supply due to energy substitution and fracking and in demand due to green energy initiatives such as the use of cleaner coal in coastal Chinese cities have transformed energy markets. These structural factors have potentially changed the relationship between equity and oil returns. Moreover, the recent tendency for equity prices to display a positive co-movement with oil prices is somewhat surprising, as oil price declines (such as those observed since mid-2014) have been seen as good news for net oil-importing countries, such as the U.S. or China.

One plausible explanation for such positive co-movement is the response of equity and oil prices to a common factor, namely, a

[22] Technical details of the methodology are provided in Sensoy et al. (2014). Noureldin et al. (2014) show that this dynamic conditional correlation (DCC) structure model is more flexible than the correlation targeting scalar DCC model of Engle (2002). Aielli (2013) also stress a bias problem in the DCC model of Engle (2002) compared to the RCC model of Noureldin et al. (2014). This is another important advantage of the latter compared to the former.

Table 5
The linkage between real equity returns and real commodity futures returns - 2000:1–2017:12.

	μ	ν_1	ν_2	ν_3	ξ_1	ξ_2	ξ_3
Panel A: ARMA estimated data-generating processes for monthly real equity returns and real commodity futures returns							
S&P500	0.006	−1.291***	−0.813***		1.339***	0.815***	
	(0.67)	(−19.51)	(−15.31)		(17.57)	(12.30)	
Crude oil	0.011	0.247***	−0.904***		−0.280***		
	(1.21)	(12.33)	(−53.94)		(−14.92)	0.999***	
Heating oil	0.006	0.109				(59.84)	
	(1.11)	(1.63)					
Copper	0.005	0.085	0.161**				
	(1.08)	(1.27)	(2.40)				
Gold	0.012**	0.110	−0.001	−0.839***	−0.231*	0.006	0.888***
	(2.22)	(0.92)	(−0.01)	(−7.44)	(−1.74)	(0.04)	(6.57)
Platinum	0.008	0.025	−0.845***	0.164***	0.054***	1.001***	
	(0.82)	(0.51)	(−31.47)	(3.09)	(3.03)	(64.72)	
Silver	0.006	1.064***	−0.936***		−1.105***	0.999***	
	(1.13)	(73.56)	(−75.62)		(−69.28)	(61.92)	
Wheat	0.017	−1.876***	−1.071***	−0.190***	1.780***	0.780***	
	(0.78)	(−13.07)	(−5.83)	(−2.64)	(13.79)	(5.93)	
Cocoa	0.005	0.698***	0.101	−0.697***	−0.910***	0.130	0.583***
	(0.99)	(4.41)	(0.44)	(−4.87)	(−4.85)	(0.46)	(3.13)
Coffee	0.001	0.904***			−1.066***	0.297***	−0.172***
	(1.41)	(23.52)			(−12.76)	(3.03)	(−2.61)
Corn	0.002	0.943***	0.736***	−0.909***	−1.012***	−0.674***	0.884***
	(1.51)	(14.61)	(6.20)	(−13.85)	(−12.20)	(−4.60)	(10.81)
Cotton	0.003	0.388***	0.513***	−0.746***	−0.459***	−0.394***	0.840***
	(0.49)	(4.66)	(6.41)	(−10.05)	(−5.08)	(−4.13)	(11.28)
GSCI	0.005	0.109	−0.772***	0.490	0.039	0.852***	−0.366
	(0.68)	(0.29)	(−5.40)	(1.35)	(0.10)	(5.16)	(−0.89)
MSCI World	0.001	0.571***			−0.450**	−0.126*	0.174***
	(0.29)	(2.53)			(−2.00)	(−1.68)	(2.86)

	Crude oil	Heating oil	Copper	Gold	Platinum	Silver	Wheat	Cocoa	Coffee	Corn	Cotton	GSCI
Panel B: correlation between monthly real equity residuals and real commodity futures residuals												
S&P500	0.231***	0.209***	0.410***	0.029	0.164**	0.199***	0.203***	0.063	0.200***	0.171**	0.285***	0.249***
p-Value	(0.001)	(0.002)	(0.001)	(0.675)	(0.016)	(0.003)	(0.003)	(0.360)	(0.003)	(0.012)	(0.000)	(0.000)
MSCI World	0.310***	0.286***	0.444***	0.134*	0.273***	0.295***	0.233***	0.133*	0.235***	0.196***	0.335***	0.346***
p-Value	(0.000)	(0.000)	(0.000)	(0.051)	(0.000)	(0.000)	(0.001)	(0.051)	(0.000)	(0.004)	(0.000)	(0.000)

Notes: Panel A presents the coefficients for the estimated best-fitting ARMA(p,q) models for monthly real returns from January 2000 to December 2017. Panel B shows the correlations between equity residuals and commodity futures residuals obtained from these estimations. In Panel A, values in parentheses are Newey-West *t*-statistics, whereas they refer to *p*-values in Panel B. In both panels, *, ** and *** denote 10%, 5% and 1% significance level.

weakening of global aggregate demand, which has a negative impact on both corporate profits and oil demand (Bernanke, 2016).

To investigate this issue, we apply a decomposition suggested by Hamilton (2014), who estimates an equation relating oil price changes ($\Delta p_{oil,t}$) with copper price changes ($\Delta p_{copper,t}$), changes in the trade-weighted index of the U.S. dollar ($\Delta p_{USD,t}$) and changes in the 10-year government bond yield ($\Delta r_{10y,t}$), that is:

$$\Delta p_{oil,t} = \alpha_1 + \alpha_2 \Delta p_{copper,t} + \alpha_3 \Delta p_{USD,t} + \alpha_4 \Delta r_{10y,t} + \eta_t \tag{3}$$

where η_t is the disturbance term.

Additionally, we follow Bernanke (2016) and estimate an augmented version of Hamilton's (2014) equation by adding the percentage change in the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) (ΔVIX_t) to the set of controls. This variable measures the volatility of stock market index and can be thought as a proxy for global risk aversion and uncertainty. It is also an indicator of market integration due to the co-movement implied by the global financial cycle (Rey, 2015). Thus, the premise is that if periods of high risk aversion and uncertainty are associated with lower investors' exposure to both commodities and equities, then, heightened volatility may be the common factor behind the positive co-movement between the two assets.

In this context, we estimate:

$$\Delta p_{oil,t} = \beta_1 + \beta_2 \Delta p_{copper,t} + \beta_3 \Delta p_{USD,t} + \beta_4 \Delta r_{10y,t} + \beta_5 \Delta VIX_t + v_t \tag{4}$$

where v_t is the disturbance term.

Oil price corresponds to the West Texas Intermediate (WTI) spot crude oil price series (*WTISPLC*) and is obtained from the Federal Reserve Economic Data (FRED) of the Federal Reserve Bank of St. Louis. Data for copper prices, long-term interest rates, the U.S. Dollar value and the VIX index are sourced from Bloomberg. All variables are expressed in logs of first-differences, except for changes in the 10-year government bond yield which are computed in first-differences.

We obtain the following relationships:

$$\Delta p_{oil,t} = \underset{(0.00)}{0.004} + \underset{(0.12)}{0.398^{***}} \Delta p_{copper,t} - \underset{(0.35)}{1.155^{***}} \Delta p_{USD,t} + \underset{(0.02)}{0.040^{**}} \Delta r_{10y,t}, \bar{R}^2 = 0.207$$

and

$$\Delta p_{oil,t} = \underset{(0.00)}{0.002} + \underset{(0.12)}{0.411^{***}} \Delta p_{copper,t} - \underset{(0.35)}{1.231^{***}} \Delta p_{USD,t} + \underset{(0.02)}{0.047^{***}} \Delta r_{10y,t} + \underset{(0.03)}{0.013} \Delta VIX_t, \bar{R}^2 = 0.223,$$

where values in parentheses are Newey-West standard errors with an adjustment up to 12 lags, and *, ** and *** denote 10%, 5% and 1% significance level.

All estimated coefficients are statistically significant, except for changes in the VIX index. Thus, oil prices display a positive and

Table 6
The linkage between real equity returns and real commodity futures returns - different time horizons.

	μ	ν_1	ν_2	ν_3	ξ_1	ξ_2	ξ_3
Panel A: ARMA estimated data-generating processes for real equity returns							
S&P500 (1 month)	0.010**	−0.856***			0.903***		
	(2.26)	(−18.07)			(20.50)		
S&P500 (1 quarter)	0.017**				0.944**	0.887**	
	(2.39)				(2.57)	(2.33)	
S&P500 (1 year)	0.016	0.015	0.051	0.715***	0.982***	0.956***	0.013
	(1.53)	(0.25)	(1.12)	(22.74)	(12.27)	(13.25)	(0.19)
S&P500 (5 years)	0.002	1.898***	−0.902***		−0.898***	−0.039	0.100*
	(1.08)	(26.64)	(−12.90)		(−10.46)	(−0.61)	(1.77)
MSCI-World (1 month)	0.006	0.235	−0.267	−0.728***	−0.192	0.223	0.791***
	(1.39)	(0.92)	(−1.08)	(−2.88)	(−0.83)	(0.99)	(3.39)
MSCI-World (1 quarter)	0.000	1.039***	−0.071		−0.050	−0.054*	−0.895***
	(1.63)	(20.41)	(−1.36)		(−1.53)	(−1.74)	(−27.77)
MSCI-World (1 year)	0.001***	0.999***	0.788***	−0.810***	0.050*	−0.950***	
	(2.59)	(43.36)	(30.50)	(−36.00)	(1.87)	(−32.31)	
MSCI-World (5 years)	0.004	1.680***	−0.697***		−0.654***	−0.049	0.169***
	(1.07)	(11.04)	(−4.69)		(−4.08)	(−0.75)	(3.04)

	Crude oil	Heating oil	Copper	Gold	Platinum	Silver	Wheat	Cocoa	Coffee	Corn	Cotton	GSCI
Panel B: correlation between real equity residuals and real commodity futures residuals												
S&P500 (1 month)	0.131**	0.126**	0.331***	−0.041	0.137**	0.123**	0.175***	0.052	0.109**	0.168***	0.245***	0.188***
p-Value	(0.015)	(0.019)	(0.001)	(0.442)	(0.011)	(0.021)	(0.001)	(0.335)	(0.043)	(0.002)	(0.001)	(0.001)
S&P500 (1 quarter)	0.070	0.075	0.306***	−0.022	0.143***	0.145***	0.173***	0.011	0.139**	0.162***	0.238***	0.139***
p-Value	(0.196)	(0.162)	(0.001)	(0.690)	(0.008)	(0.007)	(0.001)	(0.832)	(0.011)	(0.002)	(0.001)	(0.009)
S&P500 (1 year)	0.118**	0.108**	0.311***	0.042	0.166***	0.155***	0.184***	0.049	0.081	0.185***	0.260***	0.206***
p-Value	(0.031)	(0.047)	(0.001)	(0.438)	(0.002)	(0.004)	(0.001)	(0.368)	(0.137)	(0.001)	(0.001)	(0.001)
S&P500 (5 years)	0.187***	0.161***	0.207***	−0.020	0.130**	0.102*	0.136**	0.079	0.108*	0.148**	0.246***	0.197***
p-Value	(0.001)	(0.006)	(0.001)	(0.730)	(0.027)	(0.084)	(0.021)	(0.181)	(0.066)	(0.012)	(0.001)	(0.001)
MSCI-W (1 month)	0.206***	0.171***	0.343***	0.071	0.277***	0.219***	0.195***	0.102*	0.130**	0.193***	0.26***	0.278***
p-Value	(0.000)	(0.001)	(0.000)	(0.187)	(0.000)	(0.000)	(0.000)	(0.057)	(0.015)	(0.000)	(0.000)	(0.000)
MSCI-W (1 quarter)	0.125**	0.122**	0.333***	0.092*	0.263***	0.222***	0.177***	0.054	0.154***	0.187***	0.266***	0.211***
p-Value	(0.020)	(0.024)	(0.000)	(0.088)	(0.000)	(0.000)	(0.001)	(0.313)	(0.004)	(0.000)	(0.000)	(0.000)
MSCI-W (1 year)	0.155***	0.124**	0.341***	0.147***	0.323***	0.236***	0.197***	0.125**	0.133**	0.198***	0.293***	0.241***
p-Value	(0.004)	(0.022)	(0.000)	(0.007)	(0.000)	(0.000)	(0.000)	(0.022)	(0.014)	(0.000)	(0.000)	(0.000)
MSCI-W (5 years)	0.245***	0.214***	0.265***	0.061	0.264***	0.201***	0.176***	0.085	0.126**	0.177***	0.279***	0.264***
p-Value	(0.000)	(0.000)	(0.000)	(0.305)	(0.000)	(0.001)	(0.003)	(0.151)	(0.032)	(0.003)	(0.000)	(0.000)

Notes: Panel A presents the coefficients for the estimated best-fitting ARMA(p,q) models for real returns with different time horizons. Panel B shows the correlations between equity residuals and commodity futures residuals obtained from these estimations. In Panel A, values in parentheses are Newey-West *t*-statistics, whereas they refer to *p*-values in Panel B. In both panels, *, ** and *** denote 10%, 5% and 1% significance level.

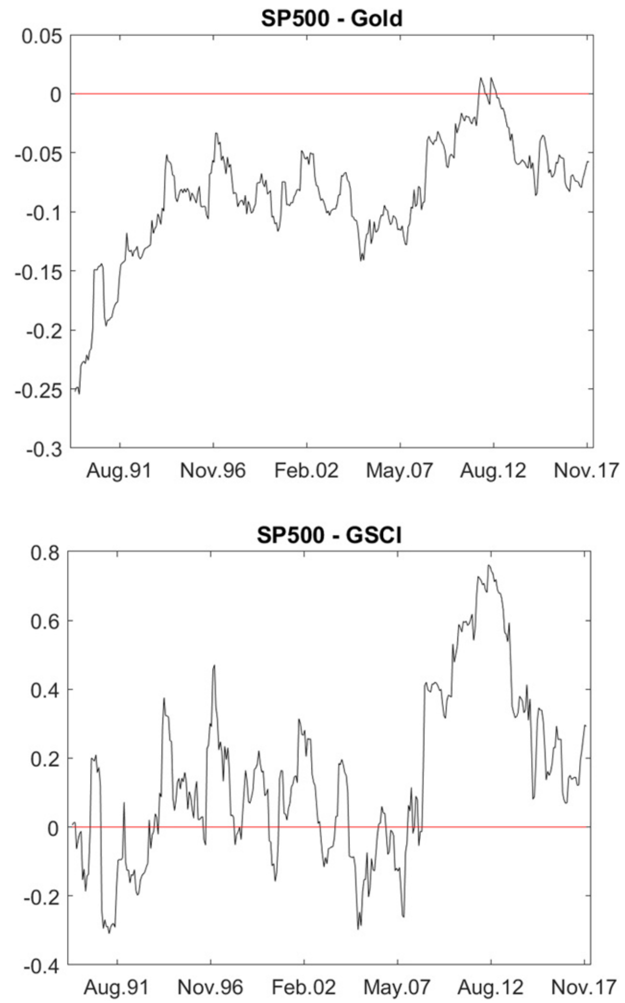

Fig. 1. Rotational dynamic conditional correlations between ARMA-filtered monthly real equity and commodity futures residuals.

significant link with copper prices and changes in the 10-year government bond yield and a negative and significant relationship with the value of the U.S. dollar. The predictive ability of the two models is confirmed by the adjusted $\bar{R}^2$ statistics: 20.7% and 22.3%, respectively.

Next, we use the value of the oil price predicted by the two equations to measure the impact of global demand on oil prices, under the assumption that the dynamics of commodity prices, copper prices, long-term interest rates, the U.S. dollar value and the VIX index mainly reflect shifts in investors' perceptions of global and U.S. demand or risk, and not so much oil supply shifts. More specifically, we re-estimate the two equations using data up to June 2014 and, then, use them to predict what the oil price would have been if the oil market was only hit by demand shocks.

Fig. 2 compares the actual decline of the crude oil price with the predicted decline as implied by the two model specifications. Between June 2014 and June 2017, the crude oil price fell by around 57%. The model by Hamilton (2014) predicts a decline of a bit less than 3.5%, while the model by Bernanke (2016) forecasts a decline in the crude oil price of close to 11%. Thus, comparing the actual and the predicted fall in oil prices, we find that between 6% and 20% of the oil price fall in recent times can be attributed to a weak global demand. This suggests that although a reasonable fraction of the positive relationship between oil and equity prices can be accounted for developments in global demand and risk appetite, a significant portion of such link is possibly due to the dynamics of oil supply.

In this context, we further analyze the potential drivers of the relationship between equity and commodity prices. *First* and similarly to Eqs. (1)–(2), we consider several specifications in the ARMA class and standard Box-Jenkins selection procedures to estimate the best data-generating process governing the growth rate of crude oil prices, and extract the shock component of this variable.

Second, we recover the residuals of the model by Hamilton (2014) and Bernanke (2016). These series can be interpreted as global oil demand shocks. Additionally, we estimate four simple models where changes in real oil prices (*WTI*) are regressed on changes of: *i*) the real foreign exchange value of the U.S. dollar (ΔFX_t);[23] *ii*) the U.S. industrial production ($\Delta IndustrialProd_t$); *iii*) the U.S. tight (or fracking) oil production ($\Delta TightOilProd_t$); and *iv*) the U.S. field production of crude oil ($\Delta FieldOilProd_t$). Data for the real foreign exchange value of the U.S. Dollar and the U.S. industrial production are obtained from Bloomberg, while data for the U.S. oil production are gathered from the U.S. Energy Information Administration (EIA).

Table 7 provides a summary of the estimated relationships. It shows that a higher crude oil price is associated with a fall in the real foreign exchange value of the U.S. dollar and a rise in industrial production, and these links are statistically significant. We also find that both tight (or fracking) oil and field crude oil production are associated with a fall in the crude oil price. However, only the latter has a significant impact.

Having estimated these relationships between crude oil prices and some potential determinants, we also extract the residuals of the four model specifications. As these models capture the potential impact of exchange rate fluctuations, real economic activity and oil supply on the dynamics of oil prices, their residuals correspond to additional sources of unexpected variation (i.e., shocks) in crude oil returns.

Finally, we compute the correlations between shocks to equity returns (as proxied by S&P500 and MSCI World indices) and crude oil price shocks obtained by *i*) the best fitting ARMA process and *ii*) the six different models.

Table 8 summarizes the main findings. In Panel A, we provide the coefficients associated with an ARMA(3,1) process, which is estimated to be the best data-generating process of the spot crude oil price. In Panel B, we show that shocks to spot crude oil returns are not significantly correlated with shocks to equity returns. However, we also find evidence of: *i*) a negative correlation between equity return shocks and the residuals from the model of Hamilton (2014), albeit at the 10% significance level and for S&P500 returns only; *ii*) a positive and significant correlation between equity return shocks and residuals from models that include the U.S. tight (or fracking) oil production as the explanatory variable for the dynamics of real crude oil returns; and *iii*) a positive correlation between equity return shocks and residuals from the model that includes the U.S. field crude oil production as the driver of real crude oil returns, albeit at the 10% significance level and for MSCI World returns only.

All in all, these results suggest that some hedging properties of crude oil vis-à-vis unfavorable equity market fluctuations is explained by global demand shocks, where growth prospects about the Chinese economy are becoming more prominent (IMF, 2016). Additionally, some financialization of crude oil seems to be due to oil supply shocks, which are potentially related with declining technology costs of technology and the impact of innovation (Deloitte, 2015).

[23] Forbes (2002) shows that, for commodity firms, domestic currency devaluations have a positive effect on output growth and operating profit growth rates. However, as pointed out by Lozada (2002), the impact of devaluations on fixed capital investment and stock returns is only positive when the capital-labor ratio is low and the cost of capital does not substantially rise.

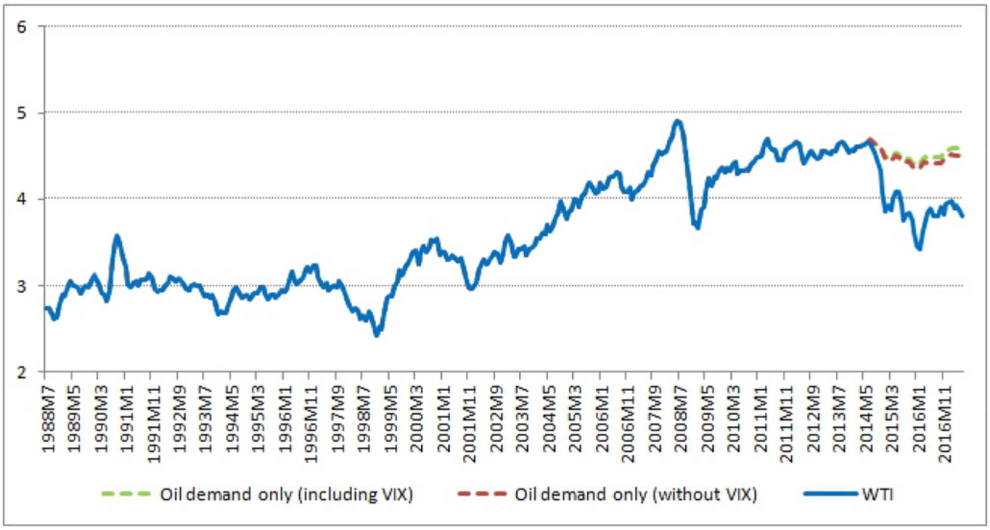

Fig. 2. WTI crude oil - estimated demand effect.

5. Conclusion

This paper uses a ARMA filter-based correlation and rotational dynamic conditional correlation approach to examine the role played by commodity futures in the diversification of equity portfolios. We consider a broad set of commodity futures and focus on the unexpected component of equity returns and commodity futures returns.

Our results show that although they are low, the correlations between shocks to equity returns and shocks to commodity futures returns are generally significant. Moreover, they are positive, which suggests the existence of financialization of commodities. The only exception is gold for which a negative correlation between shocks to equity and commodity returns is found. Gold can, thus, be considered as a hedge for equity investments. Similar findings are obtained when we measure returns in nominal terms, which shows that our results are robust once we control for the importance of inflation.

Considering two different sub-sample periods, we show that: (i) over the period of 1988: 12–1999:12, investors relied on fuel (energy) commodities, such as crude oil, to hedge against unfavorable fluctuations in the stock markets; and (ii) financialization of commodities has become more important since the 2000s.

When looking at various time horizons, we find that: (i) gold is particularly useful as a hedge against undesirable short-term (instead of mid-term) stock market variations; and (ii) different commodities display different degrees of financialization across the 1-month, 1-quarter, 1-year and 5-year horizons.

Finally, in the case of the specific link between equity and oil returns, we show some hedging of crude oil associated to global demand shocks, and financialization of crude oil at times of oil supply shocks.

Overall, the evidence provided in this paper has several implications for investors, portfolio managers, and policymakers. For investors, even though diversification benefits can still be obtained from commodity futures, they tend to be reduced with financialization, except for gold which continues to offer some stock hedging abilities. This finding can undoubtedly be explained by the unique characteristics of gold including, among others, its scarcity of supply and its role as a store of value and a hedge against inflation. This finding can undoubtedly be explained by the unique characteristics of gold including, among others, its scarcity of supply and its role as a store of value and a hedge against inflation. It is also worth noting that, in the context of consecutive crises (i.e., the global financial crisis of 2008–2009 and the European sovereign debt crisis of 2010–2012), subsequent quantitative easing policies, increasing economic uncertainty and international trade tensions (e.g. Brexit, growth slowdown and US-China trade war), some other factors are becoming increasingly important in driving up the price of gold. This further makes it a strategic asset for long-term returns and portfolio's performance enhancement. We should also notably mention the increasing demand for gold from ETFs (with a new record of 2855 tons in the third quarter of 2019) and from central banks (with 547 tons more on year-to-year basis added to reserves) (WGC, 2019). Thus, higher demand boosts gold prices if the supply side does not increase enough.

As for traders, they can exploit the design of profitable investment strategy positions based on crude oil hedging during periods characterized by global demand shocks and an amplification of the links between crude oil and equities during episodes of oil supply shocks. In what concerns producers, they should be increasingly aware of the lengthening of commodity cycle times and the more prominent role of growth prospects about China's growth, as well as the declining technology costs and the impact of innovation, when making decisions about future investments in the field. Finally, for government policymakers, the financialization of commodity markets, which increases links with stock markets, would require them to integrate the potential shock and volatility and transmission into their regulatory policy design, particularly in the presence of financial distress and crises.

Table 7
Other drivers of real oil prices.

	ΔFX_t	$\Delta IndustrialProd_t$	$\Delta TightOilProd_t$	$\Delta FieldOilProd_t$
WTI	−2.052	1.548	−0.276	−0.299
	(0.54)	(0.78)	(0.30)	(0.15)
$\overline{R}^2$	0.09	0.01	0.00	0.01

Notes: This table summarizes the estimation of four simple models where changes in real oil prices (*WTI*) are regressed on changes of: *i*) the real foreign exchange value of the U.S. Dollar (ΔFX_t); *ii*) the U.S. industrial production ($\Delta IndustrialProd_t$); *iii*) the U.S. tight (or fracking) oil production ($\Delta TightOilProd_t$); and *iv*) the U.S. field production of crude oil ($\Delta FieldOilProd_t$). Newey-West standard errors in parentheses. $\overline{R}^2$ corresponds to the adjusted R-square. *, ** and *** denote 10%, 5% and 1% significance level.

Table 8
The linkage between real equity returns and real crude oil returns.

	μ	ν_1	ν_2	ν_3	ξ_1	ξ_2	ξ_3
Panel A: ARMA estimated best data-generating process for monthly real WTI spot crude oil returns							
WTI	0.001	1.014***	−0.170**	−0.105**	−0.756***	–	–
	(0.98)	(7.67)	(−2.03)	(−1.99)	(−5.96)	–	–

	WTI	Hamilton (2014)	Bernanke (2016)	ΔFX_t	$\Delta IndustrialProd_t$	$\Delta TightOilProd_t$	$\Delta FieldOilProd_t$
Panel B: correlation between real equity residuals (shocks) and WTI spot crude oil residuals obtained by best fitting ARMA process and six alternative models							
S&P500	−0.0147	−0.0984*	−0.0871	−0.0767	0.0007	0.1296*	0.0051
p-Value	(0.784)	(0.069)	(0.115)	(0.153)	(0.989)	(0.058)	(0.925)
MSCI-World	0.0690	−0.0481	−0.0384	−0.0256	0.0844	0.1815***	0.0904*
p-Value	(0.199)	(0.376)	(0.488)	(0.635)	(0.116)	(0.008)	(0.0923)

Notes: Panel A reports the coefficients of the best fitting ARMA(p,q) model with the corresponding *t*-statistics provided in the parentheses below. Panel B presents the correlation coefficients between S&P500 and MSCI-World residuals (obtained by the best-fitting ARMA(p,q) models for real returns) and crude oil residuals obtained by *i*) best fitting ARMA process, and *ii*) six different models. Selected models are explained as follows. Hamilton (2014): the model where changes in nominal oil prices are regressed in changes in nominal copper prices, changes in the value of the U.S. Dollar and changes in the 10-year government bond yield; Bernanke (2016): the model where changes in nominal oil prices are regressed in changes in nominal copper prices, changes in the value of the U.S. Dollar, changes in the 10-year government bond yield and changes in the VIX index; ΔFX_t: the model where changes in real oil prices are regressed on changes of the real foreign exchange value of the U.S. Dollar; $\Delta IndustrialProd_t$): the model where changes in real oil prices are regressed on changes of the U.S. industrial production; $\Delta TightOilProd_t$: the model where changes in real oil prices are regressed on changes of U.S. tight oil production; and $\Delta FieldOilProd_t$: the model where changes in real oil prices are regressed on changes of US field production of crude oil. In Panel B, values in parentheses are *p*-values. In all panels, *, ** and *** denote 10%, 5% and 1% significance level.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2019.104660.

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