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Seasonal patterns and calendar anomalies in the commodity market for natural resources

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ABSTRACT

This study investigates whether a wide range of 25 anomalies documented in the finance literature with regard to equities exist in nine natural resources that include precious metals and energy commodities (gold, silver, palladium, platinum, copper, zinc and energy-based resources: oil, heating oil, and natural gas). Using daily, weekly and monthly data for 1986 to 2018, we find evidence of the existence of many of these anomalies in the commodity market. The results, in many cases, are particularly significant after the earlier periods of the 2000s, during the financialization of commodities era when many international portfolio and hedge fund managers, as well as retail investors, increased their exposure to commodities. Our results are robust for different estimation procedures and subsamples.

1. Introduction

The objective of this study is to test for any existence of non-random movements in the commodity market for natural resources that include precious metals and energy commodities. Specifically, we focus on the price movements of copper, gold, silver, palladium, platinum, zinc, oil, heating oil and natural gas, and examine the distribution of their returns with respect to different events documented in the financial literature. To accomplish this task, we use daily, weekly and monthly data for January 1986 to July 2018, and test the existence of calendar and seasonal patterns in returns and variance in these commodities.

The research is motivated by the relatively scarce literature on the existence of seasonal patterns in precious metals and energy-based commodities. While there is research dealing with seasonality in equities, bonds and currencies (e.g., Arumugam, 1999; Coutts et al., 2000; Bialkowski et al., 2012; Gavriilidis et al., 2016; Kumar and Pathak, 2016), little is known about the effect of seasonality on precious metals and energy-based commodities. Most previous studies were generally limited to and focused on examining only a partial group of calendar anomalies (e.g., Borowski and Łukasik, 2017)[1] with a major focus on gold and its diversification benefits.[2] In contrast, the present study examines a much broader array of calendar anomalies and seasonal patterns and their effect on a wider variety of precious metals and other natural resources. Thus, one contribution of this paper is that it investigates the impact of 25 calendar anomalies, several of which have only recently been identified, and examines their effect on various natural resource commodities. In addition, our examination contributes to the debate on the implications of the "financialization" of commodities. This issue is important given the increasing tendency of investors to expose their portfolios to financial vehicles related to such commodities for speculative, hedging and investment purposes. Consequently, there is much more interest in understanding the extent to

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[1] Borowski and Łukasik (2017) use data for 1995–2015 and test for the existence of monthly effect, day-of-the-week effect and weekend effect for gold, silver, platinum, copper and palladium. Their results indicate monthly seasonality during September for palladium, and a weekend effect for gold and copper.

[2] See, e.g., Hillier et al. (2006); Lucey and Li (2015); Pierdzioch et al. (2016); Vigne et al. (2017); Tweneboah and Alagidede (2018).

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which the anomalies detected in equities are also evident in commodities.

The anomalies tested here are divided into three categories. The first includes ten anomalies: the January effect, the Halloween effect, the October effect, the Other January effect, the seasonal affective disorder effect, the turn-of-the-month effect, the day-of-the-week effect, the lunar cycle effect, the week-of-the-year effect and the within-the-month effect.[3] The second category includes eight holidays during which American exchanges are closed: Thanksgiving, Christmas, Presidents Day, Independence Day, Memorial Day, New Year's Day, Labor Day and Good Friday. The third category includes seven secular as well as non-secular (or ethnic) holidays celebrated in the US during which the stock exchange is still open: St. Patrick's Day, Valentine's Day, Yom Kippur and the Jewish High Holiday period, Diwali, the Chinese New Year and Friday the 13th.[4] Actually, the last day is not a holiday, but is regarded in Western superstition as an unlucky day. Table 1 lists these holidays and events.

This study differs from previous works in the literature in several ways. First, we cover a range of precious metals and energy-based commodities that have recently become part of the portfolios of both households and institutional investors. Second, we use a lengthy sample period that covers 1986 to 2018. Third, we utilize sound econometric methods that include not only OLS regressions but also maximum likelihood estimations that allow us to estimate the GARCH models (Bollerslev, 1986) not only for patterns in returns, but also in volatility. Fourth, we cover a wide range of calendar and seasonal anomalies detected in the finance literature.

Table 2 describes the results for each anomaly briefly. This table is followed by more complete results that appear in the subsequent tables. The overall picture that emerges shows that many of the anomalies examined here do exist and seem to be more evident in the period following 2004. One possible explanation for these patterns can be the development of precious metals- and energy-based financial products (in the form of ETFs, futures contracts, ETNs and derivatives) that have become a popular asset class for many funds and portfolio managers. Studies report that this line of products has resulted in the increased inclusion of commodities in investors' portfolios, and in turn, has increased their exposure to financial market movements.[5] In addition, commodity prices have become more correlated with each other (Tang and Xiong, 2012; Bhatia et al., 2018). Thus, results so far may indicate that special attention should be paid to calendar anomalies when adding such commodities to investors' portfolios.

The underlying mechanism capable of explaining part of the abnormal returns observed in the commodity market can be attributed to investor mood. This explanation is based on the psychological contention that an improvement in investor mood reduces risk aversion, making people willing to tolerate more risk (e.g., Forgas, 1995; Loewenstein et al., 2001). The role of emotions in economic behavior and financial decision-making has attracted much attention in recent years. Many non-economic conditions such as the amount of daylight (Kamstra et al., 2003), weather (Bassi et al., 2013), air pollution (Levy and Yagil, 2011; Leopri, 2016) and approaching holidays (Bergsma and Jiang, 2016) are often invoked as possible mechanisms through which variations in mood could take place, and consequently affect security prices.

Table 1
List of the seasonal and regularities tested.

Seasonal Patterns	Holidays -Exchanges are Closed	Events/Holidays -Exchanges are Open
January effect	Christmas	St. Patrick's Day
October effect	New Year's Day	Yom Kippur
Halloween	Thanksgiving	High Holidays
The other January effect	Presidents Day	Valentine's Day
Seasonal affective disorder	Independence Day	Friday the 13th
Turn-of-the-month	Memorial Day	Chinese New Year
Day-of-the-week effect	Labor Day	Diwali
Lunar cycle effect	Good Friday	
Week-of-the-year effect		
Within-the-month effect		

Notes: The table demonstrates the seasonal patterns, holiday and events tested in this study. Overall, the number of events considered is 25.

Corroborative support for this contention is evident in the positive abnormal returns obtained around joyful holidays such as the Christmas, Independence Day and New Year's Day (e.g., Table A3). Indeed, the literature has established that holidays are associated with a positive mood (e.g., Qadan and Kliger, 2016).[6] In addition, we observe negative returns during the fall, which is linked to the depression caused by shorter days in the fall and winter (Kamstra et al., 2003 – Table 10), and find strong negative returns around Yom Kippur and the High Holidays (Table A12). According to the Jewish faith, the former is a solemn day of fasting and repentance for past misdeeds, and is a time to reflect on one's sins and ask God's forgiveness so as to begin the next year with a clean slate. Hence, it is associated with a somber mood.[7]

To conclude, when investors experience a good (bad) mood, they are more (less) willing to expose their portfolios to risky assets. Given that precious metals and energy futures meet this definition, investors will include (drop) such commodities in (from) their portfolios under such conditions.

The results of this study also raise some questions regarding the efficiency of the commodity market, mainly in light of the increased evidence of the weakening of calendar anomalies in recent years. Indeed, the literature has documented this decline and suggested several factors contributing to it. Schwert (2003) argues that anomalies documented in the finance literature often seem to disappear, reverse or attenuate post academic publication. In parallel, and more specifically in the natural resources domain, the accelerated inclusion of commodities in investors' portfolios – recently called the financialization of commodities – has increased the attention to and trading volume of such natural resources-based products (Tang and Xiong, 2012).[8] Marquering et al. (2006) note that increased attention and trading volume are the most common explanations for the decrease in and disappearance of calendar anomalies. Nevertheless, our results indicate that many of the anomalies studied in previous financial works still

[3] The January effect (Ariel, 1990), the Halloween effect (e.g., Bouman and Jacobsen, 2002), the October effect (Zhang and Jacobsen, 2012), the Other January effect (Cooper et al., 2006), the seasonal affective disorder effect (Kamstra et al., 2003), the turn-of-the-month effect (Lakonishok and Smidt, 1988), the day-of-the-week effect (e.g., Cross, 1973; French, 1980; Keim and Stambaugh, 1984), the lunar cycle effect (Yuan et al., 2006) and the week-of-the-year effect (Levy and Yagil, 2012).

[4] St. Patrick's Day and Yom Kippur (Frieder and Subrahmanyam, 2004), Valentine's Day (Qadan and Aharon, 2018), Diwali and Chinese New Year (Chan et al., 1996), and Friday the 13th (Kolb and Rodriguez, 1987; Dyl and Maberly, 1988; and Lucey, 2001).

[5] Recent information concerning investing and the evolvement of commodity holdings appears in Chapter 4 of the 2018 Investment Company Fact Book: http://www.icifactbook.org/.

[6] Smith and Puczkó (2008) depict holidays as "a state of temporary happiness in which we are on a short-lived 'high'" (p. 42).

[7] Frieder and Subrahmanyam (2004) investigate daily market returns and volume behavior around the Jewish High Holidays, namely Rosh Hashanah and Yom Kippur. They found that despite the fact that Jews constitute only 2% of the US population, they have a significant effect on the US market.

[8] As of August 2018, the average daily trading volume for the most popular precious metal ETFs since their inception in terms of millions of shares is 11.5, 9.7, 0.09, 0.06, and 0.004, respectively, for SLV (silver), GLD (gold), PALL (palladium), PPLT (platinum), and CPER (copper).

Table 2
Summary of results.

	Anomaly/Effect	Main Findings	Notes
Panel A–Seasonal and Calendar Anomalies			
1.	**January**	Overall, positive tendency; strong for gold, silver and platinum, but negative tendency for energy-based futures.	Table 4
2.	**Halloween**	Except for energy futures and gold, it is present in the rest of the metals.	Table 5
3.	**October**	Negative tendency only in silver, oil and heating oil.	Table 6
4.	**TOM**	Significant for silver, platinum, palladium and copper.	Table 7
5.	**Week-of-the-year**	Negative returns on $Week_{43}$ for oil and heating oil.	Table 8
6.	**Lunar Cycle**	Negative but insignificant tendency in commodities, but only copper is correlated with full moons.	Table 9
7.	**SAD**	The effect is present and significant. Metals are negatively correlated with FALL, and positively correlated with SAD.	Table 10
8.	**Day-of-the-week**	Insignificant tendency for negative returns on Mondays, but significant positive returns on Fridays.	Table 11
9.	**Other Jan. Effect**	Insignificant tendency but the number of positive Januaries for palladium, platinum, and silver is significantly higher than negative Januaries.	Table 12
10.	**Within-the-Month**	Positive tendency in all commodities, and significant in gold, copper, silver, zinc and oil.	Table 13
Panel B: Holidays when Exchange Markets are Closed			
	Anomaly/Effect	Main Findings	Notes
1.	**Independence Day**	Significant and positive returns in the majority of the commodities in the days preceding this occasion.	Table A2
2.	**Christmas**	Positive return tendency for the majority of the commodities; much significant in gold, silver, palladium and platinum.	Table A3
3.	**Good Friday**	Significant and positive returns mainly in precious metals one day after.	Table A4
4.	**New Year's Day**	Positive return for the majority of the commodities, much significant in gold, silver palladium and platinum.	Table A5
5.	**Labor Day**	No clear patterns are detected	Table A6
6.	**Memorial Day**	Significant negative returns in gold, silver, copper and platinum in the days following the holiday.	Table A7
7.	**Thanksgiving**	No clear patterns are detected.	Table A8
8.	**Presidents Day**	Approaching the holiday is associated with positive returns mainly for the precious metals for the period after 2004.	Table A9
Panel C: Holidays when Exchange Markets are Open			
	Anomaly/Effect	Our Main Findings	Notes
1.	**St. Patrick's Day**	Copper and zinc tend to be positive.	Table A10
2.	**Friday the 13**th	Regular Fridays tend to be positive, but Friday the 13ths have insignificant returns.	Table A11
3.	**Rosh Hashanah**	Significant negative returns almost in all commodities.	Table A12 (Panel- A)
4.	**Yom Kippur and High Holidays (HH)**	The day before Yom Kippur is associated with strong negative returns. HH days are generally with a negative sign.	Table A12 (Panel- B)
5.	**Valentine's Day**	Negative tendency in gold returns; no clear patterns in the rest.	Table A13
6.	**Chinese New Year**	Tendency for positive returns on the first day and day before.	Table A14
7.	**Diwali Holiday**	No significant returns, but reduced volatility in returns.	Table A15

Notes: Halloween is the "sell in May and go away" effect; TOM is the turn-of-the-month effect, and SAD is the seasonal affective disorder.
Notes: The table demonstrates the seasonal patterns and holiday events tested in this study. Overall, the number of events tested is 25. For each event, we summarize the main findings. The third column in each panel refers the reader to the relevant table in which the full results are reported.

exist, and they still challenge the weak form of market efficiency.

The prices of natural resources and their volatility are very important economic variables. Therefore, it is important to understand that the prices of natural resources are affected not just by economic (or rational) factors, but also by irrational factors such as seasonal affective disorder, optimism, pessimism or happiness driven by non-financial events (e.g., daylight, sunless days, somber holidays, approaching holidays, etc.). Hence, understanding the role of calendar and seasonal patterns in influencing the prices of natural resources has major implications for a wide range of issues such as portfolio management, hedging strategies, investment decisions made by corporations and academic research.

From a practical point of view, investors as well as portfolio managers could utilize our empirical results to rebalance their portfolios and manage their risk in a much more informed manner. Alternatively, market participants can exploit these calendar anomalies to improve their investment strategies. Similarly, financial institutions and policy makers can use the empirical findings to improve their forecasts about any expected trends in the behavior of natural resources. From an academic point of view, researchers should be aware of such seasonal patterns when trying to accurately predict the returns and volatility of natural resources in periods of elevated mood.

A further implication that follows directly from those above indicates that the increased inclusion of commodities in investors' portfolios can possibly maintain the dependence between commodities and the equity market, because retail investors are those who are more likely to be affected by sentiment (e.g., Lee et al., 1991).

Finally, the study is confined to the US market because the US market is the largest one in terms of market capitalization and liquidity. In addition, it has been characterized in the literature as the driver of market movements worldwide. One limitation of this paper is that we concentrate on events that take place in the US with no evidence in hand about the real involvement of US traders relative to those from the rest of the world. Though we do not have any evidence regarding the proportion of US investors in the commodities studied here, we base our assumption on prior works demonstrating that price discovery in futures markets takes place mainly in the US, which is the dominant market for commodities (e.g., Gannon, 2005; Antonakakis et al., 2016; Yoon et al., 2018).

The remainder of this study proceeds as follows. Section 2 describes the data, Section 3 explains our empirical procedure and discusses the empirical findings, while Section 4 summarizes.

2. Data and descriptive statistics

Our data consist of daily, weekly and monthly futures prices for copper, gold, silver, palladium, platinum, zinc, oil, heating oil, and natural gas retrieved from the New York Mercantile Exchange (NYMEX).[9] The data sets come from Factset, and the sample covers the period of January 1986 to July 17, 2018. More specifically, data for gold, silver and oil are available since January 1986; for palladium and platinum data are available since April 1986; for heating oil since July 1986; for copper since December 1986; for natural gas since April 1990; and for zinc, the data are available since July 1997.

In keeping with earlier empirical studies of futures, we use only the nearby futures contracts, namely, contracts that are closest to the spot delivery month, but not the delivery month itself. Information about holiday dates and hours of daylight, seasons, moon phases and latitude comes from https://www.timeanddate.com/.

The related empirical literature dates the start of the financialization of commodity futures to around 2004 (e.g., Buyuksahin et al., 2010; Boons et al., 2014; Hamilton and Wu, 2015, among others), and some of these works explicitly test for and confirm a structural break around 2004. We validate these findings using the structural break tests of Chow (1960) and that of Bai and Perron (1998). The findings appear in Table A1 in the online appendix, and support the premise that the commodity market experienced a structural break around 2004. As depicted in Fig. 1, for most cases there is a significant increase in the dynamic correlation between the commodities of interest and the S&P 500 returns in the period following 2004.

Accordingly, and for the sake of robustness, we divide the entire sample (1986–2018) into two periods reflecting the time before and during the financialization of commodities. The first period is between 1986 and December 2003 (henceforth, P_1), while the second is between 2004 and 2018 (henceforth, P_2). The total sample period will be denoted as $P_1 + P_2$. Another justification for this division is the claim raised in Schwert (2003) that anomalies documented and analyzed in the academic literature often seem to disappear, reverse, or attenuate post academic publication. Hence, it is interesting to determine how already documented anomalies behave in light of this claim.

According to Table 3, the sample size of daily returns ranges from 5269 for zinc to 8180 observations for gold and silver. The mean returns for contracts during the entire sample range from 0.01% for copper and zinc to 0.027% for palladium. The standard deviation of the daily returns ranges from 1.018% for gold to 1.957% for palladium. As demonstrated in Table 3, most of the commodities' returns are characterized by a combination of high kurtosis and negative skewness, regardless of the time period tested. Such statistics imply a greater chance of extremely negative returns due to heavy tails (a leptokurtic shape). The properties of these returns series differ from normal distribution, so we reject the JB (Jarque-Bera, 1987) test in each commodity.

Since the study uses time series data, we verify that our first differences data are stationary using both the augmented Dickey-Fuller (ADF, 1979)and Phillips-Perron (1988, PP) tests. We conducted two augmented Dickey-Fuller tests, one with a constant and the other with a constant and linear time trend. We also used the Phillips-Perron (1988) (PP) parametric test in two similar forms. The results, not presented here, demonstrated a statistically significant rejection of the null hypothesis of non-stationarity, suggesting that the variables as incorporated in the models were stationary.

As capital markets frequently experience extreme events such as financial crises, a speedy recovery from negative shocks, and changes in the regulatory environment, it is important to ensure that our findings are robust and not biased because of outliers. For this purpose, we conduct the sign test for many of the anomalies studied here. This test is completely free from the effect of outliers. For example, if we want to investigate whether Fridays affect returns and we assume that Fridays are generally associated with positive returns, we count the number of trading days ending with positive returns on Fridays. We then divide it by the total number of Fridays in the sample. Then, we test whether the resulting ratio is statistically different from 0.5 – a coin toss probability.

3. Empirical results and discussion

3.1. Calendar anomalies

In this section, we present each anomaly in detail, construct a relevant model, and discuss the results.[10] Our starting point is founded upon the premise that commodity prices are efficient, meaning that in an efficient market we should not reject the null hypothesis that each anomaly is absent. In the following subsections, we discuss each anomaly, our empirical approach and the results of our tests separately.

Primarily, our empirical analysis is based on two different, if somewhat related, approaches. The first is essentially descriptive and displays the average of the returns on the occasions of interest. Practically, we capture the mean of the returns on the anomaly of interest directly by regressing the returns of the commodity against a dummy variable that reflects that anomaly, “ANM”. That is,

$$R_t = \alpha + \beta_1 ANM_t + \varepsilon_t \tag{a}$$

In order to assess the contribution of the financialization of commodities to the anomalies studied here, we introduce two additional dummy variables; the first (D < 2004) refers to the period between 1986 and 2003, and the second (D ≥ 2004) refers to the period after 2004. Thus, the model reads as follows.

$$R_t = \alpha + \beta_1 ANM_t(D < 2004) + \beta_2 ANM_t(D \geq 2004) + v_t \tag{b}$$

The second analysis is more rigorous and utilizes models such as OLS (with the Newey–West (1987) procedure) as well as maximum likelihood estimations (MLE) that account for serial correlation and heteroscedasticity. This approach yields the following specification that distinguishes between the period before and after 2004.

$$R_t = \alpha + \beta_1 ANM_t(D < 04) + \beta_2 ANM_t(D \geq 04) + \sum_i^K \gamma_i R_{t-i} + u_t \tag{c}$$

We set K (the lag-length of the VAR) using the Schwarz Bayesian information criterion. Generally speaking, specification (b) and (c) provide us with very similar results. Hence, for brevity, we will present the results using the third specification. Regarding the conditional variance, the equation is given by:

$$\sigma_t^2 = w_0 + w_1 u_{t-1}^2 + w_2 \sigma_{t-1}^2 + w_3 ANM_t(D < 04) + w_4 ANM_t(D \geq 04). \tag{d}$$

The variance equation suggested above allows us to assess the contribution of the examined anomaly to the conditional variance. We incorporated two dummy variables in it; the first captures the anomaly, and the second captures the period of time. Consequently, w_3 quantifies the contribution of the anomaly examined to the variance for the period before 2004, while w_4 assesses the anomaly's contribution for the period after 2004.[11]

3.1.1. The January effect

The January effect, sometimes known as the turn-of-the-year effect, maintains that returns in January tend to be higher than returns in

[9] On August 1994, the NYMEX and Commodity Exchange (COMEX) merged under the NYMEX. In 2008, the NYMEX became a part of the Chicago Mercantile Exchange (CME) Group.

[10] Again, for convenience purposes, Table 2 presents a summary of the overall results of the study.

[11] For each estimation we tested the null hypothesis H_0: $\omega_1 + \omega_2 \geq 1$ against the alternative one H_1: $\omega_1 + \omega_2 < 1$. The results for the vast majority of cases tested indicated the rejection of the H_0 hypothesis, implying the non-negativity and stationarity of the variance process.

other months mainly for small firms (e.g., Ariel, 1990; Agnani and Aray, 2011; Lynch et al., 2014). If the commodity market is efficient, we should not observe any significant difference in returns between January and other months of the year. To test whether such efficiency holds, we estimate Eq. (1):

$$R_t = \sum_{j=1}^{12} \alpha_j D_{j,t} + \sum_{i=1}^{K} \gamma_i R_{t-i} + u_t, \tag{1}$$

where R_t denotes the monthly rate of change in the security's price, $\alpha_1 \ldots \alpha_{12}$, are the coefficients of dummy variables for each calendar month, and u_t is the error term. The null hypothesis postulates that the mean returns of each month as captured by the alpha coefficients ($\alpha_1 \ldots \alpha_{12}$) should not differ from zero.

Given that the January effect may be one of the most familiar anomalies, one might expect that such familiarity would lead to a decline in the anomaly. Indeed, many empirical works (e.g., Gu, 2003)

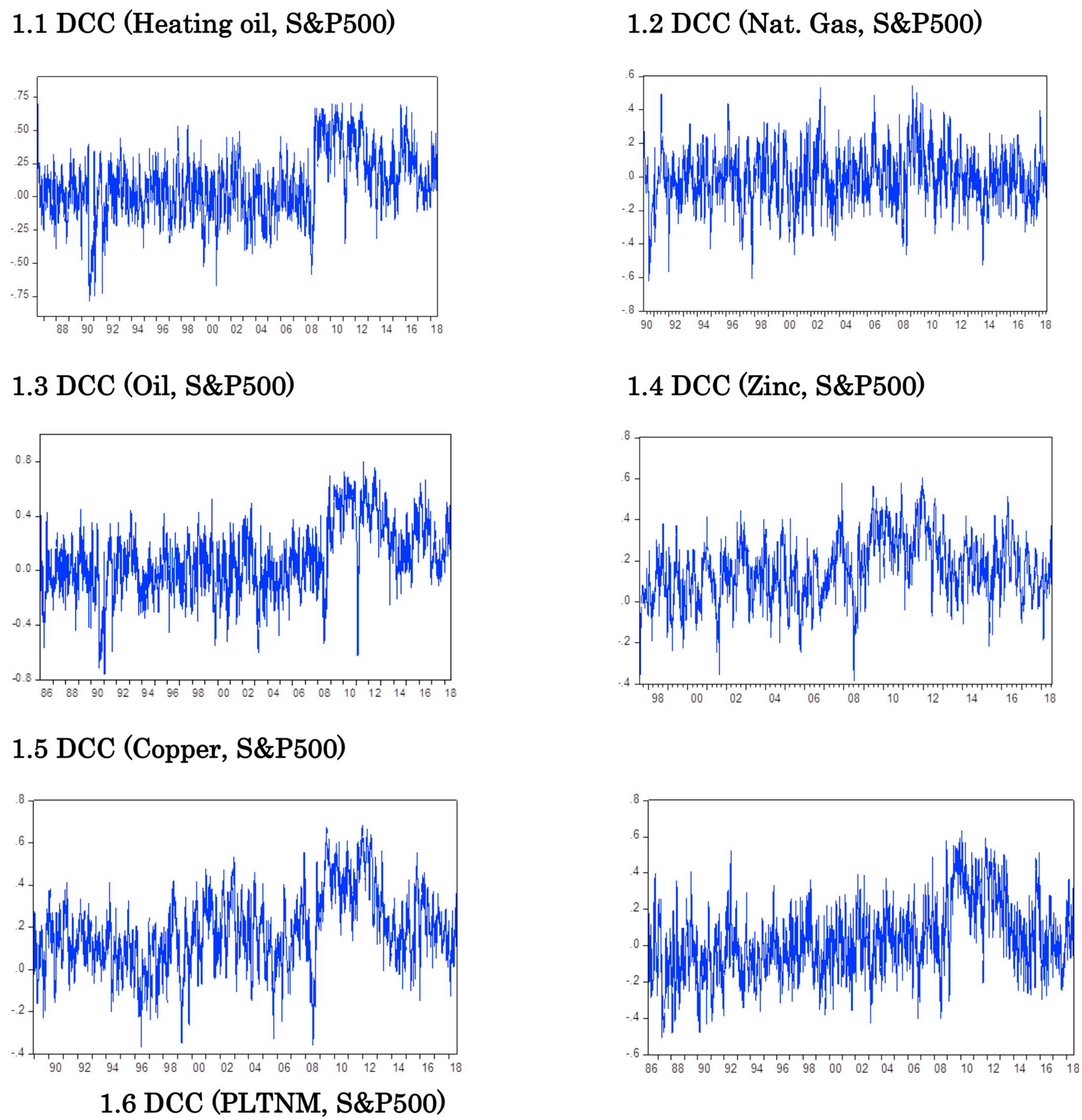
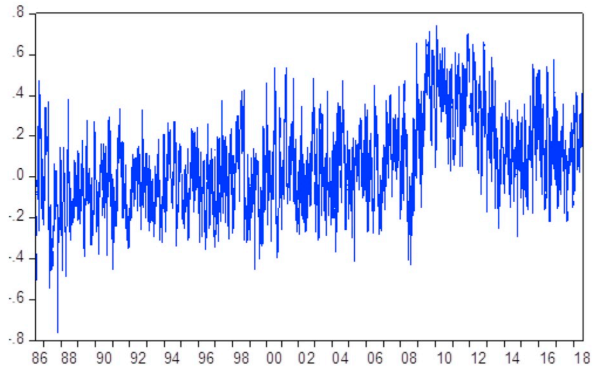
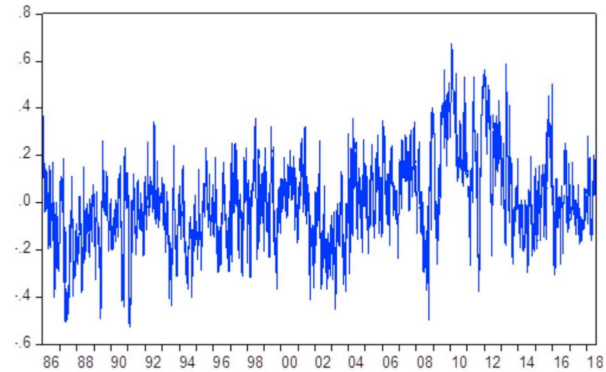


Fig. 1. Dynamic Conditional Correlations between the S&P500 and Natural Resources Futures ReturnsNotes
The figures depict the dynamic conditional correlation (DCC) between the market returns, proxied by the S&P 500, and other futures returns for 1986–2018. In many cases, we can easily observe that during early 2004 the DCC started increasing, indicating a major strengthening in the movements between the capital market and commodity prices. Corroborating evidence using the Chow Break Point Test (1960)and the Bai and Perron (1998) Test is presented in the online appendix inTable A1.

1.7 DCC (PLDM, S&P500)



1.8 DCC (Silver, S&P500)



1.9 DCC (GOLD, S&P500)

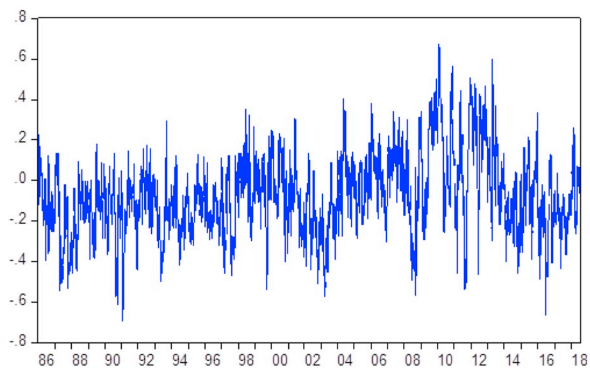


Fig. 1. (*continued*)

indicate that the January effect has weakened in the US. However, our findings present a contradictory picture. Examining the results in Table 4 reveals that this anomaly has not disappeared at all, and that the tendency for positive returns during January is evident across the different sample periods. Specifically, there are significant positive returns for gold, silver and platinum during P_2.

Gold and silver are naturally more familiar to investors and consequently, they may also be considered the more efficient markets. Therefore, we might expect the January effect to have little impact on them because we would expect investors to exploit the anomaly first in the precious metals markets with which they are familiar. However, our results imply that returns in the precious metals markets follow a seasonal pattern, which violates the assumption of a weak form of market efficiency. Similar results with respect to the monthly returns of precious metals are reported in Borowski and Łukasik (2017). This anomaly is also quite evident when considering the Other January effect. As will be discussed later in Subsection 3.1.9, the findings there indicate that the number of positive Januarys (in terms of returns) is significantly higher than that of negative Januarys, meaning that our results are not affected by outliers.

3.1.2. The Halloween effect

The Halloween effect postulates that stock returns tend to be lower during summer and fall months (specifically, May to October) than during winter and spring months (e.g., Bouman and Jacobsen, 2002). This seasonal effect still arouses debate among scholars. Degenhardt and Auer (2018) maintain that the Halloween effect has become gradually weaker in the stock market but much stronger in the futures market. Dzhabarov et al. (2018) state that although the Halloween effect may have weakened slightly in recent years, it still exists in international equity index futures markets. On the other hand, Dichtl and Drobetz (2015) report that the Halloween effect has weakened substantially or even diminished in recent years across different financial markets. In the context of the Japanese market, Maberly and Pierce (2003) suggest that the Halloween effect was evident mainly in the years before 1986, whereas post-1986, it disappeared.

To test for the existence and stability of the Halloween effect, we estimate the following model.

$$R_t = \alpha + \beta \cdot HLW_t + \sum_{i=1}^{K} \gamma_i R_{t-i} + u_t \tag{2}$$

where R_t denotes the return of the future on day t, HLW is a calendar dummy variable, and u_t is the disturbance term. Accordingly, the coefficient β estimates the magnitude of the difference between the mean returns of the summer and fall months and the mean returns during the rest of the year.

Table 5 presents the findings regarding the Halloween effect for each of the commodities. The simple specification, reported in Panel A, shows that the sign of the beta coefficients, which captures the Halloween effect, is negative and confirms the existence of such an anomaly in the natural resources commodities, mainly in silver, platinum, palladium and copper. Panel B tracks the stability of the HLW anomaly for the periods before and after 2004, and reveals a similar pattern to that reported above, meaning, a negative tendency in returns between May and October. Except for the energy-based commodities, the negative sign is maintained, and is statistically significant for platinum and palladium. Regardless of the period considered, the Halloween effect does not exist at all for gold and oil. For platinum and palladium, the major significant results occur in the P_2 period (2004–2018).

Panel C of the table provides the maximum likelihood estimation

Table 3
Descriptive statistics for the key variables.

$P_1 + P_2$ - Full Sample: 1986–2018	Data start	Mean%	Med%	Max%	Min%	S.D%	Skew	Kurt	#Obs
ΔGold	Jan. 1986	0.016	0.000	8.887	−9.821	1.018	−0.233	10.310	8178
ΔSilver	Jan. 1986	0.012	0.047	12.196	−19.546	1.809	−0.746	10.439	8180
ΔPLDM	April 1986	0.027	0.061	15.253	−13.383	1.957	−0.168	8.630	7977
ΔPLTNM	April 1986	0.008	0.049	12.716	−27.192	1.427	−1.120	22.825	8094
ΔCopper	Dec. 1986	0.011	0.000	11.644	−11.709	1.688	−0.291	7.378	7433
ΔZinc	July 1997	0.010	0.000	20.990	−31.689	2.060	−0.961	26.046	5269
ΔOil	Jan 1986	0.012	0.036	16.410	−40.048	2.446	−0.689	16.452	8184
ΔNat. Gas	April 1990	0.007	0.000	32.435	−37.575	3.415	0.135	11.116	7109
ΔHt.Oil	July 1986	0.022	0.042	13.994	−39.094	2.308	−1.258	21.371	8058
ΔGold		0.005	0.000	8.887	−7.733	0.876	0.016	12.652	4518
ΔSilver		0.001	0.000	9.634	−12.803	1.512	−0.311	8.595	4520
ΔPLDM		0.014	0.039	15.253	−12.804	1.918	0.152	10.739	4321
ΔPLTNM		0.015	0.034	12.716	−27.192	1.413	−1.638	37.281	4436
ΔCopper		−0.005	0.000	7.022	−11.011	1.494	−0.310	6.690	3774
ΔZinc		−0.028	0.000	7.014	−12.573	1.304	−0.675	11.732	1609
ΔOil		0.005	0.000	14.033	−40.048	2.536	−1.185	21.583	4524
ΔNat. Gas		0.039	0.000	32.435	−37.575	3.678	−0.222	12.673	3449
ΔHt.Oil		0.021	0.056	13.994	−39.094	2.474	−1.789	26.646	4398
P_2 - Period$_2$: 2004–2018									
ΔGold		0.030	0.040	8.625	−9.821	1.170	−0.367	8.322	3660
ΔSilver		0.026	0.106	12.196	−19.546	2.120	−0.907	9.657	3660
ΔPLDM		0.042	0.083	10.019	−13.383	2.002	−0.503	6.518	3656
ΔPLTNM		0.000	0.067	7.457	−9.603	1.444	−0.531	6.751	3658
ΔCopper		0.027	0.044	11.644	−11.709	1.868	−0.283	7.188	3659
ΔZinc		0.026	0.012	20.990	−31.689	2.315	−0.936	22.998	3660
ΔOil		0.020	0.081	16.410	−13.065	2.331	0.107	7.228	3660
ΔNat. Gas		−0.022	−0.080	26.771	−14.893	3.147	0.658	7.698	3660
ΔHt.Oil		0.023	0.027	10.403	−19.728	2.091	−0.164	7.092	3660

Notes: The table reports the descriptive statistics for the first difference data (returns) of the commodities addressed in this study. The periods considered are the entire sample (1986:2018), and two sub-periods - before the financialization period - P_1 (1986: 2003) and during the financialization period - P_2 (2004:2018). ΔX denotes the rate of change in the price of commodity X.

results. The β coefficients for palladium are significantly negative but are positive for natural gas. As the variance equation indicates, in the majority of the futures considered, during the HLW period before 2004, the conditional variance used to be lower. However, in the period following 2004, the picture has changed with a clear tendency for greater volatility. One explanation for this finding may be that commodity prices have become more correlated with each other and with capital market fluctuations (Tang and Xiong, 2012; Bhatia et al., 2018). The estimated variance equation is. $\sigma_t^2 = w_0 + w_1 u_{t-1}^2 + w_2 \sigma_{t-1}^2 + w_3 HLW_t(D < 04) + w_4 HLW_t(D \geq 04)$.

3.1.3. The October effect

The October effect, which is also called the Mark Twain effect, refers to the documented observation that stock returns in October are consistently lower than in other months (e.g., Zhang and Jacobsen, 2012). To test for the existence of such an effect, we suggest the following model that includes the *OCT* dummy variable that receives the value of 1 for Octobers, and 0 otherwise. Eq. (3) reads as follows.

$$R_t = \alpha + \beta \cdot OCT_t + \sum_{i=1}^{K} \gamma_i R_{t-i} + u_t. \tag{3}$$

If the commodity market is efficient, the beta should be very close to zero, meaning an absence of any seasonal pattern in October. The overall results in Table 6 reveal negative daily returns during October months. However, the only cases where this negative coefficient is significant is in silver, oil and heating oil prices during the full time period and during the pre-financialization period (P_1).

During the financialization period, the significance of these negative returns disappears. In Panel C of the table, we use a maximum likelihood estimation, and the same results hold. In addition, October's contribution to the conditional variance for the period before 2004, captured by the dummy OCT × (D < 04), is negative for the majority of the sampled securities. However, the picture changes slightly toward a positive contribution for the period after 2004. To summarize, while there is evidence that there are consistently negative and significant returns during October in stocks (e.g., Degenhardt and Auer, 2018), such a phenomenon is hard to find in precious metals and energy-based commodities. This finding may imply that these markets are relatively efficient with respect to the October effect. The MLE results for the full sample without distinguishing between periods appear in Table A29 in the online appendix, and indicate less volatility in October for silver and palladium.

3.1.4. Turn-of-the-month effect

According to the turn-of-the-month anomaly (TOM), market returns are higher during the first few trading days in each month (e.g., Agrawal and Tandon, 1994; Lakonishok and Smidt, 1988; McConnell and Xu, 2008). Following Lakonishok and Smidt (1988) and similar to our empirical steps described above, we define TOM as a dummy variable that receives the value of 1 on the trading days falling on the last trading day of the last week of each month and the consecutive three trading days of the first week of the following month, and 0 otherwise. The null hypothesis, according to which the commodity market is efficient, postulates that one should not observe such a pattern around the beginning of each month. The model used reads as follows:

$$R_t = \alpha + \beta \cdot TOM_t + \sum_{i=1}^{K} \gamma_i R_{t-i} + u_{it}. \tag{4}$$

Table 4
The January effect (monthly data).

OLS	Period	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	R_{t-1}
Gold	P_1+P_2	**2.131c**	1.519	1.606	0.219	−1.151	**−2.214c**	**2.273b**	−1.455	1.105	−1.914	0.114	1.101	−0.089
	P_1	−1.277	0.082	−1.335	0.973	0.035	−0.015	−0.131	0.086	1.989	−0.643	0.164	0.786	−0.03
	P_2	**2.912b**	**2.215c**	−0.19	0.582	−1.064	−0.496	0.606	2.194	0.818	−0.236	1.615	0.251	−0.148c
Silver	P_1+P_2	0.715	0.95	−0.852	0.757	−0.443	−0.207	0.193	0.99	1.433	−0.402	0.779	0.494	−0.097c
	P_1	−0.11	−0.982	1.543	1.036	−0.646	−0.91	1.754	**−3.40a**	2.812	**−3.44a**	−0.95	**2.646c**	−0.102
	P_2	**4.721b**	**4.453b**	1.612	−0.752	−1.732	**−3.77c**	**2.98b**	1.033	−1.158	0.116	1.417	−0.687	−0.076
PLDM	P_1+P_2	**2.699b**	2.519	1.994	0.355	−1.379	−0.926	2.013	**−3.04b**	−1.637	0.457	0.207	**3.193b**	−0.025
	P_1	2.514	1.567	1.158	−1.379	−0.255	0.846	1.412	**−4.41a**	−0.832	−0.82	−1.442	**4.117c**	0.003
	P_2	2.847	3.604	3.005	2.374	−2.538	−3.013	2.624	−1.336	−2.612	2.046	2.299	2.279	−0.058
PLTNM	P_1+P_2	**2.63b**	**2.998a**	−0.223	0.43	0.417	**−1.30c**	0.918	−0.243	**−3.16c**	−0.384	0.892	−0.456	0.005
	P_1	−0.089	**2.62a**	0.887	0.614	1.755	−0.973	1.06	−0.386	−1.519	−0.054	1.701	−1.207	−0.111c
	P_2	**5.313a**	3.074	−1.445	0.394	−1.052	−1.373	0.654	0.073	−5.358	−0.578	−0.013	0.54	0.089
Copper	P_1+P_2	0.187	1.764	1.194	1.101	−1.761	0.247	**2.44b**	−0.329	−1.813	−1.35	0.821	−0.339	0.065
	P_1	−0.218	−0.12	0.1	0.008	−1.851	−0.215	1.602	0.793	**−2.75b**	−0.864	1.442	−1.514	−0.111
	P_2	0.160	**3.654b**	1.827	1.922	−1.95	0.563	**3.26c**	−1.624	−0.571	−2.313	0.34	1.100	0.182
Zinc	P_1+P_2	0.738	**1.721c**	−1.307	1.907	−1.878	−1.936	**3.424a**	−0.3	−1.332	−0.144	1.29	0.669	0.018
	P_1	0.797	−0.284	−0.881	1.419	**−4.087a**	0.643	1.923	0.19	**−4.18b**	−1.444	0.612	−3.187	−0.04
	P_2	0.605	**2.534b**	−1.525	2.105	−0.993	**−3.049c**	**4.132a**	−0.526	0.123	0.383	1.586	2.212	0.034
Oil	P_1+P_2	−0.343	0.748	**2.834c**	**3.13b**	−0.096	0.442	0.204	2.154	1.025	**−3.01c**	**−2.77c**	0.38	0.122c
	P_1	−0.059	−1.74	2.382	2.7	0.166	−0.914	0.364	4.453	2.57	**−3.52b**	−3.111	1.149	0.054
	P_2	−0.492	**3.635b**	2.757	3.491	−0.585	2.062	−0.226	−0.786	−0.502	−2.046	−2.415	−0.55	0.216b
Ht.	P_1+P_2	−1.189	−0.228	0.962	1.454	−1.67	1.008	1.482	**4.45a**	2.415	−2.435	−1.357	0.687	−0.05
Oil	P_1	−2.372	−3.32	0.454	0.064	**−3.59b**	0.114	2.362	**6.02b**	**4.82c**	−2.247	−0.985	3.11	−0.122
	P_2	0.632	2.994	0.98	2.98	0.196	1.69	0.279	2.714	−0.296	−2.292	−1.853	−1.997	0.053
Nat.	P_1+P_2	**−6.53b**	−3.227	3.343	2.343	1.779	0.226	−3.666	−1.222	**9.29a**	**6.18b**	−1.355	−4.936	−0.021
Gas	P_1	−9.192	−0.232	4.799	3.242	1.729	−1.627	−5.274	3.48	**10.96a**	**7.67b**	−2.797	−4.812	−0.023
	P_2	−4.24	**−5.83c**	2.086	1.569	1.826	1.957	−2.062	−5.93	**7.63c**	4.695	0.094	−5.047	−0.021

Notes: The table presents the monthly average return (in %) for each commodity using the model $R_t = a_1D_{1t} + a_2D_{2t} + ...+a_{12}D_{12t} + \beta R_{t-1} + u_t$. R is the monthly return, "Di" is a dummy variable that captures month i (i = 1..12), and u_t is the error term. The results are reported with respect to three periods; P_1 (1986–2003), P_2 (2004–2018) and P_1+P_2 (the entire sample). Except for the energy futures, the January effect seems to exist significantly in most of the commodities tested. The small letters "a," "b" and "c" indicate significance at the 1%, 5% and 10% levels, respectively.

Table 5
The Halloween effect (daily data).

Panel A: $\boldsymbol{R_t = \alpha + \beta \cdot HLW_t + u_t}$

	Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht. Oil	Nat Gas
α	0.022	0.052c	0.046b	0.085a	0.043	0.041	0.012	0.004	−0.083
HLW	−0.014	**−0.079b**	**−0.075b**	**−0.115a**	**−0.065c**	−0.063	−0.001	0.034	**0.177b**

Panel B: $\boldsymbol{R_t = \beta_0 + \beta_1 HLW_t \cdot (D < 2004) + \beta_2 HLW_t + \cdot (D \geq 2004)\gamma_1 R_{t-1} + u_t}$

	Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht. Oil	Nat Gas
α	0.023	0.053b	0.045b	0.080a	0.044	0.045	0.013	0.004	−0.086
HLW × (D < 04)	−0.013	**−0.084b**	−0.043	**−0.099b**	−0.069	**−0.108c**	0.015	0.053	**0.220b**
HLW × (D ≥ 04)	−0.014	−0.076	**−0.109a**	**−0.117b**	−0.064	−0.054	−0.024	0.014	0.147
R_{t-1}	−0.012	−0.022	0.027	0.073a	−0.050a	−0.116a	−0.018	−0.024	−0.030b
R^2	0.000	0.001	0.001	0.006	0.003	0.013	0.000	0.000	0.001
F-STAT	0.565	2.755b	4.634a	16.93a	7.319a	24.79a	0.983	1.903	3.879a

Panel C: ML Estimation

	Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht.Oil	Nat. Gas
α	0.001	−0.002	0.022	0.056b	0.010	−0.007	0.013	0.004	−0.028
HLW × (D < 04)	−0.017	−0.038	−0.037	**−0.068c**	−0.015	−0.056	0.015	0.050	**0.164b**
HLW × (D ≥ 04)	0.012	0.000	−0.051	−0.044	−0.019	0.015	−0.024	0.013	0.043
R_{t-1}	−0.013	−0.020b	0.030a	0.068a	−0.034a	−0.038a	−0.018	−0.005	−0.034a
ω_0	0.003a	0.020a	0.023a	0.086a	0.019a	0.005a	5.982a	0.080a	0.050a
ARCH(w_1)	0.040a	0.041a	0.059a	0.109a	0.041a	0.035a	0.15a	0.088a	0.077a
GARCH(w_2)	0.958a	0.953a	0.931a	0.872a	0.952a	0.963a	0.6a	0.901a	0.919a
HLW × (D < 04)	**−0.002a**	**−0.004c**	**−0.007a**	**−0.021a**	−0.003	**0.005b**	0.000	**−0.016b**	**0.138a**
HLW × (D ≥ 04)	0.001	**0.008b**	−0.002	0.008	0.001	**0.007b**	0.000	**−0.025a**	**0.061a**
QLB(5)	3.490	8.616	8.792	12.48b	2.017	4.254	15.34a	2.398	9.347c
QLB(10)	9.351	12.55	10.22	21.56b	14.31	11.64	25.96a	7.795	16.26c
w1 + w2	0.998	0.994	0.99	0.981	0.993	0.998	0.75	0.989	0.996

Table 6
The October effect (daily data).

Panel A: $R_t = \alpha + \beta \cdot OCT_t + u_t$

	Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht.Oil	Nat Gas
α	0.02c	0.022	0.01	0.027	0.018	0.01	0.025	0.035	−0.018
OCT	−0.044	**−0.114c**	−0.026	−0.005	−0.084	−0.018	**−0.154c**	**−0.150c**	**0.288b**

Panel B: $R_t = \alpha + \beta_1 OCT_t \cdot (D < 04) + \beta_2 OCT_t \cdot (D \geq 04) + \gamma_1 R_{t-1} + u_t$

	Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht.Oil	Nat Gas
α	0.019c	0.022	0.009	0.025	0.018	0.011	0.025	0.035	−0.018
OCT × (D < 04)	−0.051	**−0.195a**	0.000	−0.059	−0.046	−0.085	**−0.179c**	**−0.160c**	**0.362c**
OCT × (D ≥ 04)	−0.033	−0.012	−0.056	0.068	−0.134	0.010	−0.126	−0.141	0.229
R_{t-1}	−0.012	−0.022	0.028	0.074a	−0.050a	−0.116a	−0.018	−0.024	−0.029b
R^2	0.000	0.001	0.000	0.005	0.002	0.013	0.000	0.001	0.001
F-STAT	0.856	2.858b	2.292c	15.12a	7.016a	24.21a	1.801	2.588c	3.532b

Panel C: MLE Results

	Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht.Oil	Nat. Gas
α	−0.001	−0.005	−0.000	0.022	0.006	−0.016	0.036c	0.028	0.008
OCT × (D < 04)	−0.022	**−0.158b**	0.003	0.030	−0.038	−0.005	−0.120	−0.082	0.368
OCT × (D ≥ 04)	0.008	0.032	−0.008	0.044	−0.065	0.038	−0.090	−0.025	0.154
R_{t-1}	−0.012	−0.020b	0.031a	0.068a	−0.034a	−0.037a	−0.006	−0.005	−0.034a
ω_0	0.002a	0.020a	0.020a	0.082a	0.020a	0.009a	0.044a	0.065a	0.118a
ARCH(w_1)	0.040a	0.040a	0.059a	0.110a	0.042a	0.035a	0.069a	0.088a	0.079a
GARCH(w_2)	0.959a	0.953a	0.931a	0.873a	0.951a	0.962a	0.924a	0.902a	0.913a
OCT × (D < 04)	−0.001	**−0.026a**	**−0.010b**	**−0.043a**	**−0.015c**	0.003	−0.020	0.008	**0.431a**
OCT × (D ≥ 04)	**0.014a**	**0.049a**	0.015	−0.001	0.011	0.003	−0.007	−0.008	**0.302a**
QLB(5)	3.403	9.016	8.448	12.26b	1.961	4.129	5.827	2.232	9.641c
QLB(10)	9.510	12.63	9.857	21.88b	14.03	11.54	11.03	7.448	15.44
w1 + w2	0.999	0.993	0.99	0.983	0.993	0.997	0.993	0.99	0.992

Notes: Panels A and B illustrates the OLS regression results, and Panel C reports those of the maximum likelihood model. OCT_t is a dummy variable that captures the October period. Most of the results indicate a negative tendency in returns during October, but they are statistically insignificant. $R_t = \alpha + \beta_1 OCT_t \cdot (DM < 2004) + \beta_2 OCT_t \cdot (DM \geq 2004) + \sum_i^K \gamma_i R_{t-i} + u_t$. The variance equation is $\sigma_t^2 = w_0 + w_1 u_{t-1}^2 + w_2 \sigma_{t-1}^2 + w_3 OCT_t (D < 04) + w_4 OCT_t (D \geq 04)$.

Table 7 presents the results obtained. In line with former studies documenting such an effect in equity prices (e.g., Cadsby and Ratner, 1992; Lakonishok and Smidt, 1988; Kunkel, Compton and Beyer, 2003), the TOM effect exists more significantly in the less familiar commodities such as platinum, palladium and copper. Heating oil and natural gas, however, provide significant negative returns.

Moreover, the TOM effect is much more significant in the period after the financialization structural break as evident by the statistically significant TOM × (D ≥ 04) coefficients. The results are robust in both procedures used – the OLS (Panel B of the table) as well as in the GARCH(1,1) specification (Panel C). Finally, the conditional variance for gold, silver, copper, zinc and heating oil is greater on TOM for the period after 2004 as evident by the statistically significant TOM ≥ 04 in the variance equation.

3.1.5. Week-of-the-year effect

A relatively recent anomaly documented by Levy and Yagil (2012) indicates that in $Week_{43}$, which starts on October 22 and ends on October 28, equity markets exhibit negative returns. In addition, during $Week_{44}$ of the year, which starts on October 29 and ends on November 4, market returns are consistently positive. In line with Levy and Yagil (2012), we defined two dummy variables that correspond to $Week_{43}$ and $Week_{44}$. The models employed are presented in Eq. (5)- (6), respectively:

$$R_t = \alpha_0 + \delta_1 Week_{43} + \delta_2 R_{t-1} + \varphi_{it}. \tag{5}$$

$$R_t = \alpha_0 + \gamma_1 Week_{44} + \gamma_2 R_{t-1} + \upsilon_{it}. \tag{6}$$

$Week_{43}$ and $Week_{44}$ are dummy variables that capture these weeks, respectively. Table 8 presents the findings. The returns on commodities in $Week_{43}$ ($Week_{44}$) are generally negative (positive), but there is no indication of consistent significance except for oil and heating oil (Panel A). $Week_{44}$ returns are significant and positive only for natural gas during the full sample (Panel A of Table 8.2). The MLE results in panel C indicate negative returns for palladium, platinum and oil for the period 1986–2003. Overall, there is no clear evidence for the week-of-the-year effect neither in mean return nor in variance.

3.1.6. The lunar cycle effect

Yuan et al. (2006) provide evidence that market index returns are correlated with the lunar cycle, such that stock returns are lower on the days near full moons (FM) than on other days. Floros and Tan (2013) report that this anomaly exists in emerging markets, but is weak in the US. Lucey (2010) addresses this effect in precious metals (gold, silver and platinum) for 1998 to September 2007, and reports that the lunar cycle effect is more pronounced in silver than gold, with very little evidence for an effect in platinum.

To test if such an anomaly also exists in other commodities, we define FM using three different windows of time. The first full moon dummy variable (FM_1) captures the full moon day itself; the second dummy captures a window of (−3, +3) days around full moon days (FM_3), and the last one (FM_7) captures (−7, +7) days around them.

The results in Table 9 show that the precious metals market is efficient regardless of the sample period considered. In fact, in Panels A (FM1) and C (FM3) the FM_i coefficients are generally negative. Despite the fact that they are statistically insignificant, the negative tendency is noticeable. The only exception is copper, which exhibits positive returns for FM_3 and FM_7. As Panel C of the table illustrates, there is a clear

Table 7
Turn-of-the-month effect (TOM, daily data).

Panel A: $\boldsymbol{R_t = \alpha + \beta \cdot TOM_t + u_t}$									
	Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht. Oil	Nat Gas
α	0.015	−0.009	−0.016	0.000	−0.002	0.000	0.012	0.041	0.054
TOM	−0.000	**0.111b**	**0.131a**	**0.138b**	0.069	0.045	−0.002	**−0.104c**	**−0.247b**
Panel B: Panel B: $\boldsymbol{R_t = \alpha + \beta_1 TOM_t \cdot (D < 04) + \beta_2 TOM_t \cdot (D \geq 04) + \gamma_1 R_{t-1} + u_t}$									
	Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht. Oil	Nat Gas
α	0.015	−0.009	−0.016	−0.000	−0.003	−0.000	0.012	0.042	0.052
TOM × (D < 04)	−0.024	**0.107c**	**0.124a**	0.090	0.001	−0.107	0.014	**−0.210c**	−0.163
TOM × (D ≥ 04)	0.031	0.124	**0.132b**	**0.185b**	**0.143c**	0.120	−0.017	0.021	**−0.306b**
R_{t-1}	−0.012	−0.023	0.026	0.074a	−0.050a	−0.117a	−0.018	−0.025	−0.028c
R^2	0.000	0.001	0.002	0.006	0.003	0.014	0.000	0.001	0.001
F-STAT	0.825	3.104b	5.508a	17.11a	7.873a	25.19a	0.912	3.777b	3.992a
Panel C- ML Estimation									
	Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht. Oil	Nat. Gas
α	0.000	−0.033c	−0.015	0.006	−0.005	−0.006	0.026	0.033	0.050
TOM × (D < 04)	**−0.043c**	**0.091b**	0.057	0.079	0.010	−0.059	0.018	−0.070	−0.148
TOM × (D ≥ 04)	0.035	**0.107c**	**0.117b**	**0.127b**	0.089	−0.000	−0.028	−0.013	**−0.255b**
R_{t-1}	−0.013	−0.020b	0.030a	0.067a	−0.035a	−0.037a	−0.004	−0.005	−0.029a
ω_0	0.001	0.029a	0.024a	0.097a	0.010b	0.004	0.062a	0.040a	0.408a
ARCH(w_1)	0.041a	0.042a	0.060a	0.109a	0.042a	0.034a	0.069a	0.090a	0.074a
GARCH(w_2)	0.957a	0.949a	0.930a	0.872a	0.950a	0.961a	0.926a	0.898a	0.910a
TOM < 04	0.005	**−0.043a**	**−0.026b**	**−0.130a**	**0.037c**	0.021	**−0.120a**	**0.213a**	**−1.074a**
TOM ≥ 04	**0.021a**	**0.047b**	−0.005	0.004	**0.064a**	**0.067a**	**−0.099a**	**0.134a**	**−1.151a**
QLB(5)	3.251	8.553	8.446	12.93b	2.088	4.568	5.624	2.158	8.318
QLB(10)	9.803	12.56	9.740	23.03b	14.13	12.00	10.77	7.372	14.34
w1 + w2	0.998	0.991	0.99	0.981	0.992	0.995	0.995	0.988	0.984

Notes: TOM_t is a dummy variable that receives the value of 1 on the trading days falling on the last trading day of the last week of each month and the consecutive three trading days of the first week of the following month, and 0 otherwise. According to this anomaly, market returns are higher during the first few trading days in each month (e.g., Lakonishok and Smidt, 1988; McConnell and Xu, 2008). Most of the results verify a significant positive β coefficient. The small letters "a," "b" and "c" denote significance at the 1%, 5% and 10% levels, respectively. The mean equation is $R_t = \alpha + \beta_1 TOM_t(DM < 04) + \beta_2 TOM_t(DM \geq 04) + \gamma_1 R_{t-1} + u_t$, whereas the variance equation is.$\sigma_t^2 = w_0 + w_1 u_{t-1}^2 + w_2 \sigma_{t-1}^2 + w_3 TOM_t(D < 04) + w_4 TOM_t(D \geq 04)$.

tendency for less volatility on FM days as evident in the coefficients of FM > 04 and FM < 04 for silver, oil, heating oil and natural gas. Thus, the overall findings suggest that such an anomaly does not exist in precious metals. Finally, the FM contribution to conditional variance differs between commodities but seems to be associated with less influence for the period before 2004. Anyway, in most cases, FM is not statistically significant in the variance part. See also Table A29 in the online appendix.

3.1.7. The SAD effect

Our next hypothesis deals with the seasonal affective disorder (SAD) effect (Kamstra et al., 2003). SAD refers to the seasonal variation in stock returns, which is linked to the depression caused by shorter days in the fall and winter. Kamstra et al. (2003) conjecture that risk-averse investors begin to avoid risky securities in the fall as the length of the day shortens. Their avoidance of such securities has an immediate negative influence on stock prices, contributing to lower contemporaneous returns and higher expected future returns.

Following Kamstra et al. (2003) and Garrett et al. (2005), we use the model described in Eq. (7) to test for any potential impact of the winter blues:

$$R_t = \alpha + \beta_{SAD} SAD_t + \beta_{FALL} FALL_t + \beta_{MON} MON_t + \beta_{TAX} TAX_t + \sum_{j=1}^{p} c_j R_{t-j} + u_t, \tag{7}$$

where R_t is the daily return on day t; α is an intercept; and SAD_t equals $H_t - 12$ for trading days in the fall and winter, and 0 otherwise. H_t is the amount of time between sunrise and sunset,[12] and $(H_t - 12)$ denotes the length of the night relative to the annual average length of the night. $FALL_t$ is an interactive dummy variable that receives "SAD_t" for days of the year in the fall season (September 21 to December 20 in the northern hemisphere), and zero otherwise. MON_t is a dummy variable that receives the value of 1 on Mondays (or the first trading day following a long weekend) and 0 otherwise; and Tax_t is a tax-loss selling dummy variable that takes the value of 1 for the day prior to and the four days following the start of a tax year and 0 otherwise. To control for autocorrelation in u_t, we include past lags of the dependent variable $\sum_{j=1}^{p} c_j R_{t-j}$. Therefore, if the *SAD* effect truly exists in the precious metals market, we expect that SAD will have a positive coefficient, and *FALL* should be negative. On the other hand, if the market is efficient, such relationships should not hold, and the beta coefficients for both *SAD* and *FALL* will be no different from zero (i.e., insignificant).

Looking at the results in Table 10, the *FALL* coefficient is generally significant and negative, while the SAD coefficient is significant and positive (except for copper). Our results indicate that returns increase during the SAD months, consistent with the notion that investors who suffer from SAD require higher returns to be induced to hold risky assets. The negative coefficients on the *FALL* variable indicate that returns respond asymmetrically around the winter solstice, suggesting that investors sell risky assets as they become more risk averse in the fall and

[12] We follow Kamstra et al. (2003) and Garret et al. (2005) in calculating the parameters. The day of the year receives values from 1 to 365 (366 in a leap year).

Table 8
The week-of-the-year effect (weekly data).

Table 8.1: WEEK 43

A: Simple Differences (1986–2018) Panel A: $R_t = \alpha + \beta \cdot Week43_t + u_t$

	Gold	Silver	PLDM	PLTNM	CPR	ZINC	OIL	Ht. Oil	Nat. Gas
α	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.001	0.000
Week43	−0.005	−0.006	−0.006	−0.004	−0.007	−0.006	**−0.021b**	**−0.016c**	0.011

B: OLS Estimation $\boldsymbol{R_t = \alpha + \beta_1 WK43_t \cdot (D < 04) + \beta_2 WK43_t \cdot (D \geq 04) + \gamma_1 R_{t-1} + u_t}$

	Gold	Silver	PLDM	PLTNM	CPR	ZINC	OIL	Ht. Oil	Nat. Gas
α	0.000c	0.000	0.001	0.000	0.000	0.000	0.000	0.001	0.000
WK43(< 04)	−0.001	−0.000	−0.004	0.000	0.000	−0.002	−0.026	−0.022	0.019
WK43(≥04)	−0.009	−0.013	−0.008	−0.011	−0.015	−0.009	−0.013	−0.006	0.003
R_{t-1}	0.003	−0.007	−0.021	−0.031	0.002	−0.065c	−0.062b	−0.079b	−0.045c
R^2	0.002	0.001	0.001	0.002	0.002	0.005	0.007	0.009	0.003
F-STAT	0.921	0.561	0.475	1.205	0.878	1.810	4.287a	5.041a	1.334

C: Maximum Likelihood Estimation

	Gold	Silver	PLDM	PLTNM	CPR	ZINC	OIL	Ht. Oil	Nat. Gas
α	0.000	−0.000	0.001	0.000	−0.000	−0.000	0.000	0.000	0.000
WK43(< 04)	0.001	0.001	0.002	0.004	−0.000	−0.003	−0.016	−0.016	0.018
WK43(≥04)	−0.005	−0.008	0.003	0.001	−0.005	−0.010	−0.012	−0.007	−0.012
R_{t-1}	−0.009	−0.025	−0.034	−0.041	−0.014	−0.019	−0.047c	−0.063b	−0.060b
ω_0	0.000a	0.000a	0.000a	0.000a	0.000a	0.000b	0.000a	0.000a	0.000a
ARCH(w_1)	0.070a	0.077a	0.079a	0.083a	0.059a	0.058a	0.079a	0.209a	0.114a
GARCH(w_2)	0.904a	0.910a	0.896a	0.881a	0.920a	0.933a	0.883a	0.588a	0.773a
WK43(< 04)	**−0.000a**	**−0.000a**	−0.000	**−0.000a**	−0.000	−0.000	**−0.000b**	0.000	**0.005b**
W4K3(≥04)	**0.000b**	0.000	0.000	0.000	0.000	0.000	**−0.000b**	**−0.001a**	0.001
QLB(5)	1.362	10.04c	14.62b	9.643c	3.103	1.961	3.394	1.048	5.906
QLB(10)	3.988	14.58	21.42b	16.55c	5.878	9.874	12.06	6.490	10.01
w1 + w2	0.974	0.987	0.975	0.964	0.979	0.991	0.962	0.797	0.887

Table 8.2: WEEK 44

A: $R_t = \alpha + \beta \cdot Week44_t + u_t$

	Gold	Silver	PLDM	PLTNM	CPR	ZINC	OIL	Ht. Oil	Nat. Gas
α	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.001	−0.000
Week44	0.000	−0.004	0.003	**−0.009c**	−0.000	0.009	−0.007	−0.012	**0.030b**

B: OLS Estimation $\boldsymbol{R_t = \alpha + \beta_1 WK44_t \cdot (D < 04) + \beta_2 WK44_t \cdot (D \geq 04) + \gamma_1 R_{t-1} + u_t}$

	Gold	Silver	PLDM	PLTNM	CPR	ZINC	OIL	Ht. Oil	Nat. Gas
α	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.001	−0.000
WK44(< 04)	−0.003	−0.009	−0.000	**−0.016b**	−0.001	0.000	−0.014	−0.015	0.045
WK44(≥04)	0.005	0.001	0.009	−0.001	0.000	0.013	−0.001	−0.012	0.016
R_{t-1}	0.004	−0.007	−0.020	−0.032	0.003	−0.063	−0.065b	−0.082b	−0.046c
R^2	0.001	0.001	0.001	0.004	0.000	0.006	0.005	0.008	0.006
F-STAT	0.391	0.377	0.448	2.153c	0.015	2.076	2.869b	4.564a	3.061b

C: Maximum Likelihood Estimation

	Gold	Silver	PLDM	PLTNM	CPR	ZINC	OIL	Ht. Oil	Nat. Gas
α	0.000	−0.000	0.001	0.000	0.000	−0.000	0.000	0.000	−0.000
WK44(< 04)	−0.002	−0.005	**−0.006b**	**−0.010b**	−0.001	0.000	**−0.021c**	−0.016	**0.053b**
WK44(≥04)	0.006	0.003	0.010	0.002	0.000	0.013	0.008	−0.001	0.015
R_{t-1}	−0.011	−0.025	−0.001	−0.039	0.002	−0.018	−0.051c	−0.074a	−0.063b
ω_0	0.000a	0.000a	0.000a	0.000a	0.001	0.000b	0.000a	0.000a	0.000a
ARCH(w_1)	0.071a	0.079a	0.193a	0.086a	0.15	0.060a	0.078a	0.075a	0.124a
GARCH(w_2)	0.905a	0.909a	0.574a	0.876a	0.6c	0.932a	0.883a	0.906a	0.760a
W44(< 04)	**−0.000b**	**−0.000a**	**−0.001a**	−0.000	0.000	−0.000	−0.000	**0.000b**	**0.004c**
W44(≥04)	**0.000b**	**0.000c**	0.000	**0.000c**	0.000	−0.000	−0.000	0.000	0.002

(continued on next page)

Table 8 (*continued*)

Table 8.1: WEEK 43

A: Simple Differences (1986–2018) Panel A: $R_t = \alpha + \beta{\cdot}Week43_t + u_t$

	Gold	Silver	PLDM	PLTNM	CPR	ZINC	OIL	Ht. Oil	Nat. Gas
QLB(5)	1.623	9.959c	11.87b	9.983c	3.500	2.236	3.174	2.269	5.845
QLB(10)	4.467	14.62	18.54b	16.87c	8.709	9.471	11.28	6.066	10.05
w1 + w2	0.976	0.988	0.767	0.962	0.75	0.992	0.961	0.981	0.884

Notes: Panel A reports average returns on Week43 (WK43), Panel B report the OLS and the MLE specifications. According to this anomaly (Levy and Yagil, 2012), negative excessive returns detected in $Week_{43}$ (starts on October 22 and ends on October 28), but excessive positive returns occur in $Week_{44}$ of the year (starts on October 29 and ends on November 4). $Week_{43t}$ and $Week_{44t}$ are dummy variables that equal 1 for the 43rd and 44th weeks of the year, respectively, and 0 otherwise. The small letters "a," "b" and "c" indicate significance at the 1%, 5% and 10% levels, respectively. QLB is the Q-statistic developed by Ljung and Box (1978) to test for the hypothesis of no serial correlation in the squared residuals at the k-th lagged order. Table 8.2 reports the corresponding estimations for Week44 (WK44).

then begin to resume risky holdings when the hours of daylight increase again. Overall, the results accord with those of Kamstra et al. (2003) who find similar coefficients in stock returns. Note also that the relationships become much more significant during the financialization of commodities period (P_2), while during P_1 they are evident only in palladium. The results hold true not only for the OLS specification in Panel A, but also for the MLE one, as depicted in Panel B. The finding is interesting because according to Kamstra et al., investors become more risk averse in the fall. Therefore, we could have anticipated that they might shift their investments towards precious metals as part of their risk aversion during this time.

3.1.8. Day-of-the-week effect

A well-known anomaly in daily prices is the day-of-the-week effect or the weekend effect. This effect is one of the most documented anomalies in the financial research and has been detected globally in equity, bond, futures and currency markets (e.g., Cross, 1973; Keim and Stambaugh, 1984). However, Olson et al. (2010) show that such an effect is probably in its last stages and close to disappearing in seven major U.S. stock market index returns.

Generally, the literature has documented positive returns in stocks and indices on Fridays and negative returns on Mondays. Cross (1973) was the first to reveal that Mondays exhibit lower returns on average (−0.18% and negative), while Fridays tend to be associated with higher returns (+0.12% and positive). French (1980) also documents a negative return on average using S&P returns. Following prior works, we test the null hypothesis that the mean returns across the days of the week are equal by using the following OLS regression (with the HAC correction method) described in Eq. (8):

$$R_{i,t} = \sum_{i=2}^{6} \beta_i D_{i,t} + \sum_{k=1}^{K} \gamma_i R_{t-k} + u_t \tag{8}$$

where $R_{i,t}$ is the daily return of metal i on day t; $D_{i,t}$ is a dummy variable that receives the value of 1 if the ith day falls on day t (i = 2,3,..,6). If the expected return is the same for each day of the week, the estimates of β_2 through β_6 should be close to zero. In other words, we are testing the joint hypothesis that all β_i coefficients are jointly not significantly different from zero.

The results are reported in Table 11. They clearly indicate that Fridays are associated with positive returns, which are statistically significant in gold, palladium and copper prices, mainly for the period after the start of the financialization of commodities (P_2). Borowski and Łukasik (2017) report a positive but weak tendency for positive returns on Fridays in gold, copper and silver. Regarding Mondays, the overall results point to negative coefficients that are statistically significant only for zinc and heating oil, and insignificant for the rest of the products.

In order to insure that our results are not driven by outliers, we utilize the sign test. Despite the insignificant coefficients on Monday, the sign test results, available in the online appendix (Table A16), indicate a significant tendency toward negative Mondays mainly for copper, oil, natural gas and heating oil. In addition, the table indicates a significant tendency toward positive Fridays for gold, palladium, copper, and oil. In these cases, the number of positive Fridays exceeds that of negative ones.

3.1.9. The Other January effect

According to Cooper et al. (2006), the other January effect, sometimes known as the "January barometer," is related to the documented observation that stock market performance in January predicts market returns over the following 11 months. This effect predicts that if the January returns are positive, the returns for the next 11 months will be positive as well, but if January concludes with negative returns, the returns in the following 11 months will be negative as well.

Table 12 reports the results for each commodity. The returns for the 11 months following a positive January tend to be positive, but they are statistically insignificant. In addition, the returns for the 11 months following a negative January also are no different from zero. The only significant result presented in the table is the relatively high number of positive January months for silver (20 vs. only 12 negative Januarys), platinum (23 vs. 9) and palladium (25 positive Januarys vs. only 7 negative Januarys).

3.1.10. Within-the-month effect/time-of-the month

According to this anomaly, positive rates of returns occur only in the first half of the month (Ariel, 1987; Kim and Park, 1994). Using a similar approach, other works suggest dividing the whole month into three parts (Kohers and Patel, 1999; Cadsby and Torbey, 2003). Doing so results in abnormal returns in the first part, but a decreasing trend in the second, and in third part returns are either very low or negative. Table 13 presents results demonstrating that the time-of-the-month effect does exist mainly in copper, gold, silver, zinc and oil. According to these findings, the coefficients of the returns in the second half of each month are positive and significant mainly for the period after 2004. However, for the less familiar commodities, such as platinum and palladium, the returns in the second half of each month are positive and significant. The results hold true for the maximum likelihood specification depicted in Panel B of the table. Furthermore, the sign test also provides corroborating evidence. As reported in Table A18 in the online appendix, for 2004 to 2018 the number of positive times during which the trading days in the second half of the month resulted in positive returns was significantly higher than the positive days in the first half of the months. To wit, for 2004 to 2018, there were 1698 days that fell in the first half in each month (835 + 863), 835 of which were positive, and 863 of which were negative. Statistically, there is no difference and the results seem no different from a coin toss. On the other hand, we find that 1058 days in the second half of the months considered ended

Table 9
The full moon (FM) effect (daily data).

Panel A: FM_1

A1: $R_t = \alpha + \beta \cdot FM_{1t} + u_t$

	Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht. Oil	Nat Gas
α	0.016	0.013	0.009	0.032	0.006	0.003	0.007	0.015	0.004
FM1	−0.027	−0.039	−0.054	−0.165	0.116	0.147	0.121	0.171	0.090

A2: $R_t = \alpha + \beta_1 \cdot FM_{1t}(D < 04) + \beta_2 FM_{1t}(D \geq 04) + \gamma_1 R_{t-1} + u_t$

	Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht. Oil	Nat Gas
α	0.017	0.014	0.009	0.030	0.006	0.004	0.007	0.016	0.004
FM1 < 04	−0.039	**−0.197c**	−0.110	**−0.356c**	0.139	0.012	0.111	0.292	0.215
FM1 ≥ 04	−0.011	0.158	0.018	0.069	0.106	0.186	0.141	0.028	−0.027
R_{t-1}	−0.012	−0.022	0.028	0.074a	−0.050a	−0.116a	−0.018	−0.024	−0.029b
R^2	0.000	0.000	0.001	0.006	0.002	0.013	0.000	0.001	0.001
F-STAT	0.518	2.313c	2.445c	16.55a	6.778a	24.45a	1.125	2.442c	2.193c

A3: Maximum Likelihood Estimation

	Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht.Oil	Nat. Gas
α	−0.002	−0.014	0.002	0.050	0.006	−0.020	0.026	0.021	0.024
FM1 < 04	−0.043	−0.114	**−0.202b**	**−0.274b**	0.139	0.191	−0.050	0.059	0.330
FM1 ≥ 04	−0.023	0.171	0.069	0.067	0.105	0.124	0.075	0.060	−0.062
R_{t-1}	−0.012	−0.020c	0.031a	0.070a	−0.050	−0.037a	−0.006	−0.005	−0.034a
ω_0	0.001a	0.024a	0.019a	2.801a	2.841a	0.014a	0.046a	0.072a	0.128a
ARCH(w_1)	0.040a	0.040a	0.061a	0.052a	0.15a	0.034a	0.068a	0.087a	0.079a
GARCH(w_2)	0.958a	0.952a	0.928a	0.578a	0.6a	0.962a	0.926a	0.902a	0.914a
FM1 < 04	0.012	**−0.183a**	0.068	**−0.245a**	0.000	**−0.190a**	−0.043	−0.083	**0.691b**
FM1 ≥ 04	**0.063a**	**0.123c**	0.077	**−0.427a**	0.000	−0.020	**−0.267b**	**−0.269b**	−0.207
QLB(5)	3.473	8.376	8.113	19.63a	1.608	4.712	5.668	2.145	9.586c
QLB(10)	9.804	12.26	9.527	35.29a	18.53b	12.09	10.66	7.299	16.05c
w1 + w2	0.998	0.992	0.989	0.63	0.75	0.996	0.994	0.989	0.993

Panel B: FM_3
B1: Simple specification: $R_t = \alpha + \beta \cdot FM_{3t} + u_t$

		Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht.Oil
α	0.011	0.001	0.001	0.015	−0.009	0.001	0.010	0.011	0.013
FM3	0.020	0.044	0.029	0.047	**0.083c**	0.032	0.002	0.044	−0.026

B2: $R_t = \alpha + \beta_1 FM_{3t}(D < 04) + \beta_2 FM_{3t}(D \geq 04) + \gamma_1 R_{t-1} + u_t$

	Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht.Oil	Nat Gas
α	0.011	0.002	0.000	0.015	−0.010	0.000	0.011	0.012	0.014
FM3 < 04	0.021	0.026	0.014	0.021	**0.100c**	−0.080	−0.121	0.019	−0.057
FM3 ≥ 04	0.019	0.066	0.047	0.063	0.074	0.087	**0.158c**	0.073	0.000
R_{t-1}	−0.012	−0.022	0.028	0.074a	−0.051a	−0.116a	−0.018	−0.024	−0.029b
R^2	0.000	0.000	0.001	0.005	0.003	0.013	0.001	0.000	0.000
F-STAT	0.641	1.759	2.421c	15.13a	7.563a	24.78a	2.968b	1.897	2.101c

B3: Maximum Likelihood Estimation

	Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht. Oil	Nat. Gas
α	−0.014	−0.021	0.000	0.034c	−0.016	−0.015	0.029	0.020	0.028
FM3 < 04	**0.046b**	0.008	−0.020	−0.064	0.077	−0.048	−0.087	−0.028	0.093
FM3 ≥ 04	0.034	0.060	0.017	0.011	0.079	0.054	0.091	0.058	−0.072
R_{t-1}	−0.013	−0.019c	0.031a	0.068a	−0.035a	−0.037a	−0.006	−0.005	−0.033a
ω_0	0.003a	0.026a	0.024a	0.068a	0.016a	0.010b	0.064a	0.085a	0.107a
ARCH(w_1)	0.040a	0.040a	0.060a	0.111a	0.041a	0.034a	0.068a	0.087a	0.079a
GARCH(w_2)	0.958a	0.952a	0.930a	0.871a	0.952a	0.961a	0.926a	0.902a	0.913a
FM3 < 04	−0.004	**−0.030b**	−0.015	0.033	0.007	−0.006	**−0.077b**	−0.040	**0.272a**
FM3 ≥ 04	0.001	0.010	−0.016	**0.082a**	0.010	0.024	**−0.109a**	**−0.104a**	0.079
QLB(5)	3.692	8.665	8.164	12.66b	2.204	4.459	5.579	2.100	9.455c
QLB(10)	9.555	12.72	9.624	22.34b	15.07	11.85	10.53	7.188	15.87
w1 + w2	0.998	0.992	0.99	0.982	0.993	0.995	0.994	0.989	0.992

(*continued on next page*)

Table 9 (*continued*)

Panel A: FM_1									
A1: $R_t = \alpha + \beta \cdot FM_{1t} + u_t$									
	Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht. Oil	Nat Gas
Panel C: FM_7									
C1: Simple specification: $R_t = \alpha + \beta \cdot FM_{7t} + \varepsilon_t$	Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht.Oil	Nat Gas
α	0.024	0.028	0.020	0.030	−0.036	0.005	−0.003	0.002	−0.001
FM7	−0.017	−0.032	−0.025	−0.007	**0.094b**	0.007	0.030	0.038	0.017
C2: $R_t = \alpha + \beta_1 \cdot FM_{7t}(D < 04) + \beta_2 FM_{7t}(D \geq 04) + \gamma_1 R_{t-1} + \varepsilon_t$	Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht.Oil	Nat Gas
α	0.025	0.029	0.019	0.027	−0.039	0.003	−0.003	0.003	−0.000
FM7 < 04	−0.027	−0.051	−0.025	−0.015	**0.087b**	−0.015	−0.001	0.043	0.079
FM7 ≥ 04	−0.006	−0.009	−0.020	0.010	**0.115b**	0.024	0.072	0.030	−0.042
R_{t-1}	−0.012	−0.022	0.028	0.074a	−0.051a	−0.116a	−0.018	−0.024	−0.029b
R^2	0.000	0.000	0.000	0.005	0.003	0.013	0.000	0.000	0.001
F-STAT	0.795	1.791	2.317c	14.93a	8.637a	24.21a	1.302	1.833	2.426c
C3: Maximum Likelihood Estimation	Gold	Silver	PLTNM	PLDM	Copper	ZINC	OIL	Ht.Oil	Nat. Gas
α	−0.005	0.013	0.019	0.046c	−0.035	0.003	0.043	0.030	0.018
FM7 < 04	−0.006	**−0.072b**	−0.035	−0.048	**0.070c**	−0.015	−0.061	−0.026	0.083
FM7 ≥ 04	0.025	−0.019	−0.044	−0.027	**0.076c**	0.024	0.001	0.003	−0.033
R_{t-1}	−0.013	−0.019c	0.030a	0.068a	−0.035a	−0.116a	−0.006	−0.005	−0.034a
ω_0	0.003b	0.041a	0.026a	0.077a	0.019a	4.182a	0.061a	0.085a	0.094a
ARCH(w_1)	0.040a	0.039a	0.060a	0.112a	0.041a	0.15a	0.069a	0.088a	0.078a
GARCH(w_2)	0.958a	0.953a	0.930a	0.871a	0.952a	0.6a	0.925a	0.901a	0.914a
FM7 < 04	−0.002	**−0.045a**	−0.010	−0.000	−0.002	0.000	−0.028	−0.011	**0.150a**
FM7 ≥ 04	0.000	**−0.024b**	−0.011	0.022	0.001	0.000	**−0.045b**	**−0.053a**	0.049
QLB(5)	3.462	8.381	8.323	12.67b	2.050	24.3a	5.656	2.060	9.267c
QLB(10)	9.484	12.45	9.730	22.45b	14.45	34.12a	10.56	7.139	15.71
w1 + w2	0.998	0.992	0.99	0.983	0.993	0.75	0.994	0.989	0.992

Notes: FM is a dummy variable that receives the value of 1 for the full moon (FM) phase. For robustness, FM is measured in three different time windows. We use FM_1, FM_3 and FM_7 to capture the one day of a full moon, and [-3, +3] and [-7, +7] days before and after the full moon day including the full moon day itself, respectively. The small letters "a," "b" and "c" denote significance at the 1%, 5% and 10% levels, respectively. The variance equation is $\sigma_t^2 = w_0 + w_1 u_{t-1}^2 + w_2 \sigma_{t-1}^2 + w_3 FM_{it}(D < 04) + w_4 FM_{it}(D \geq 04)$, $i = 1,3,7$. QLB is the Q-statistic developed by Ljung and Box (1978) to test for the hypothesis of no serial correlation in the squared residuals at the k-th lagged order. "a," "b" and "c" indicate significance at the 1%, 5% and 10% levels, respectively.

with positive returns, and 904 with negative returns. In other words, roughly 54% of the cases were positive.

3.2. National and secular holidays – exchanges are closed

3.2.1. Independence Day

Independence Day is considered one of the happiest days of the holidays. As Table A2 illustrates, the positive sentiment associated with Independence Day actually precedes the holiday itself. While this effect is evident in all metals during the full sample period, recent evidence in the financialization period demonstrates that this positive sentiment is reduced with regard to the prices of gold, platinum and copper. Based on these findings, we maintain that most of metals studied here are still characterized by inefficiency, which can be exploited by investors. The sign test results reported in Table A19 lend support to our findings, and strengthen the premise that the results are not driven by outliers.

3.2.2. Christmas

One of the most compelling pieces of evidence for the existence of market inefficiency is the seasonality of returns around Christmas. As Table A3 indicates, commodities follow this trend and in fact confirm the hypothesis that the positive sentiment associated with Christmas will be accompanied by an increase in commodity prices. Note that the stock market is closed on Christmas itself, so the response in returns is captured on the first trading day after Christmas. In fact, during the full sample period, each of the metals studied here (excluding natural gas) is accompanied by positive returns on the first trading day after Christmas. Looking at each sub-period, one can see that the positive sentiment that prevails around holidays (Qadan and Aharon, 2018) is more prominent in the period of the financialization of commodities. The sign test results reported in Table A20 provide strong support for our story as evidenced in the large ratios reported on the days before and after Christmas. These findings suggest that the precious metals market is generally inefficient because it consistently yields significant positive returns around this holiday period.

3.2.3. Good Friday

Table A4 shows that similar to Christmas, Good Friday too is associated with positive sentiment. In the total sample period, gold, palladium and platinum exhibit significant and positive returns on the first trading day after Good Friday. Note that this finding is interesting in the context of positive sentiment. The first day of trading after Good Friday actually takes place on Monday. According to the literature, Mondays are associated with negative returns. Thus, the positive sentiment of the Good Friday holiday may overcome the negative tendency in returns on Mondays. As for the role of the financialization period, one can see that

Table 10
Estimation results of the SAD effect (daily data).

Panel A – OLS Estimation

Commodity	Sample Period	α	SAD	FALL	MON	TAX	R_{-1}
Gold	P_1+P_2	0.011	0.025c	−0.033c	−0.009	−0.029	−0.013
	P_1	0.014	0.000	−0.000	−0.042	−0.070	−0.031
	P_2	0.006	0.057b	−0.073b	0.037	0.012	−0.001
Silver	P_1+P_2	−0.002	0.052b	−0.058b	−0.026	0.118	−0.023
	P_1	0.004	0.006	0.003	−0.073	0.218	−0.037c
	P_2	−0.013	0.110a	−0.135a	0.039	−0.005	−0.016
PLADM	P_1+P_2	−0.005	0.099a	−0.087b	−0.057	−0.029	0.073a
	P_1	−0.006	0.083b	−0.069	−0.081	−0.005	0.089a
	P_2	−0.004	0.117a	−0.108b	−0.023	−0.000	0.055a
PLTNM	P_1+P_2	−0.014	0.065a	−0.082a	0.010	0.136	0.026
	P_1	0.014	0.026	−0.057c	0.010	−0.019	0.014
	P_2	−0.050	0.110a	−0.112a	0.011	0.326c	0.036c
Copper	P_1+P_2	0.019	0.031	−0.043	−0.082c	−0.040	−0.050a
	P_1	0.019	0.014	0.000	−0.203a	0.052	−0.018
	P_2	0.019	0.050	−0.092b	0.045	−0.141	−0.072a
Zinc	P_1+P_2	0.030	0.038	−0.013	−0.240a	−0.003	−0.116a
	P_1	−0.008	0.010	0.015	−0.198b	0.042	−0.041c
	P_2	0.048	0.049	−0.024	−0.259b	−0.016	−0.127a
Oil	P_1+P_2	0.084a	−0.023	−0.086c	−0.135c	0.247	−0.019
	P_1	0.074c	−0.056	−0.036	−0.113	0.542c	0.006
	P_2	0.097b	0.020	−0.154b	−0.162	−0.124	−0.057a
Ht. Oil	P_1+P_2	0.125a	−0.054	−0.019	−0.278a	−0.002	−0.025c
	P_1	0.113a	−0.053	0.000	−0.230b	−0.306	−0.015
	P_2	0.141a	−0.057	−0.044	−0.339a	0.364	−0.045b
Nat. Gas	P_1+P_2	0.126a	−0.242a	0.245a	−0.162	0.141	−0.031b
	P_1	0.186a	−0.364a	0.424a	−0.228	0.363	−0.015
	P_2	0.067	−0.127	0.072	−0.100	−0.071	−0.055a

Panel B – MLE

Commodity	Sample Period	α	SAD	FALL	MON	TAX	R_{-1}
Gold	P_1+P_2	−0.001	0.011	−0.020	−0.005	−0.106c	−0.013
	P_1	−0.010	−0.000	0.001	−0.009	−0.125b	−0.021
	P_2	0.019	0.043c	−0.080a	0.012	−0.030	−0.006
Silver	P_1+P_2	−0.020	0.038c	−0.055b	−0.042	0.181c	−0.021b
	P_1	−0.022	0.015	−0.011	−0.081c	0.229c	−0.043a
	P_2	−0.013	0.100b	−0.163a	0.043	−0.007	0.003
PLADM	P_1+P_2	0.020	0.056b	−0.065b	−0.071c	0.071	0.067a
	P_1	0.014	0.038	−0.044	−0.081c	0.117	0.081a
	P_2	0.031	0.077b	−0.088c	−0.065	−0.009	0.059a
PLTNM	P_1+P_2	−0.007	0.049a	−0.060a	−0.040	0.078	0.029a
	P_1	0.003	0.024	−0.034	−0.061	−0.061	0.027c
	P_2	−0.023	0.084a	−0.097a	−0.011	0.275c	0.029c
Copper	P_1+P_2	0.004	0.029	−0.027	−0.063	−0.145	−0.034a
	P_1	0.010	0.025	−0.024	−0.125b	−0.093	−0.023
	P_2	−0.005	0.036	−0.029	0.022	−0.212	−0.046a
Zinc	P_1+P_2	−0.018	0.026	0.017	−0.114b	−0.097	−0.038a
	P_1	−0.006	0.007	0.033	−0.192b	0.074	−0.029
	P_2	−0.009	0.036	0.005	−0.046	−0.215	−0.045a
Oil	P_1+P_2	0.052c	0.030	−0.082b	−0.082c	−0.045	−0.006
	P_1	0.056	−0.003	−0.081c	−0.093	0.085	0.016
	P_2	0.049	0.055	−0.068	−0.075	−0.161	−0.034b
Ht. Oil	P_1+P_2	0.097a	−0.053b	0.010	−0.224a	0.073	−0.006
	P_1	0.098a	−0.106a	0.053	−0.189a	0.023	0.002
	P_2	0.090b	−0.017	−0.010	−0.265a	0.126	−0.021
Nat. Gas	P_1+P_2	0.088b	−0.200a	0.234a	−0.085	−0.100	−0.035a
	P_1	0.124b	−0.328a	0.375a	−0.047	−0.300	−0.027c
	P2	0.058	−0.102	0.127	−0.118	0.054	−0.043b

Notes: The table reports the estimation results of the model $R_t = a + b_{SAD}SAD_t + b_{FALL}FALL_t + +b_{MON}MON_t + b_{TAX}TAX_t + \sum_{j=1}^{p} c_j R_{i,t-j} + u_t$, once using OLS (Panel A) and again using MLE (Panel B). SAD_t is (H_t −12) for trading days in the fall and winter, and zero otherwise. H_t is the amount of time between sunset and sunrise, and $(H_t - 12)$ denotes the length of the night relative to the annual average length of the night. MON_t is a dummy variable that captures Mondays (or the first trading day following a long weekend) and 0 otherwise; and Tax_t is a tax-loss selling dummy variable that takes the value of 1 for the day prior to and the four days following the start of a tax year and 0 otherwise. The results are consistent with a SAD-induced seasonal pattern in returns. Depressed and risk-averse investors avoid risky assets in the fall and resume their risky holdings in the winter. Thus, returns in the fall are lower than average and higher during winter months, when daylight becomes more plentiful. “a,” “b” and “c” denote significance at the 1%, 5% and 10% levels, respectively. Full MLE results appear in Table A29.

Table 11
The day-of-the-week effect (daily data).

Panel A: Simple Averages $R_t = \sum_{i=2}^{6} \mu_i D_{i,t} + u_t$

	Sample Period	MON	TUE	WED	THU	FRI
Gold	P_1+P_2	0.007	−0.016	−0.000	0.031	**0.059b**
	P_1	−0.031	−0.004	−0.011	0.035	0.033
	P_2	0.056	−0.032	0.012	0.025	**0.091b**
Silver	P_1+P_2	−0.010	−0.013	0.026	0.070	−0.014
	P_1	−0.060	−0.017	0.000	**0.155a**	−0.078
	P_2	0.051	−0.007	0.058	−0.032	0.064
PLDM	P_1+P_2	−0.017	0.035	−0.043	0.066	**0.092b**
	P_1	−0.050	0.098	−0.076	0.049	0.044
	P_2	0.021	−0.038	−0.005	0.085	**0.148b**
PLTNM	P_1+P_2	0.015	−0.022	−0.012	0.033	0.028
	P_1	0.025	−0.008	−0.002	0.033	0.026
	P_2	0.004	−0.039	−0.025	0.033	0.031
Copper	P_1+P_2	−0.063	−0.026	0.034	0.001	**0.103b**
	P_1	**−0.172a**	−0.028	0.092	0.021	0.051
	P_2	0.049	−0.023	−0.024	−0.018	**0.156b**
Zinc	P_1+P_2	**−0.185b**	0.100	0.086	0.004	0.020
	P_1	**−0.190b**	−0.048	0.021	0.109	−0.041
	P_2	**−0.182c**	**0.165c**	0.115	−0.040	0.048
Oil	P_1+P_2	−0.102	−0.071	0.064	0.068	**0.094c**
	P_1	−0.089	−0.099	0.049	0.052	0.109
	P_2	−0.119	−0.037	0.082	0.089	0.076
Ht. Oil	P_1+P_2	**−0.203a**	−0.029	**0.160a**	**0.146b**	0.018
	P_1	**−0.165c**	−0.098	**0.153b**	0.127	0.078
	P_2	**−0.250a**	0.052	**0.169b**	**0.169b**	−0.052
Nat. Gas	P_1+P_2	−0.118	0.107	0.039	−0.077	0.076
	P_1	−0.139	0.071	−0.022	0.080	0.197
	P_2	−0.098	0.140	0.097	**−0.225c**	−0.037

	Sample Period	MON	TUE	WED	THU	FRI	R_{t-1}
Gold	P_1+P_2	0.007	−0.016	−0.001	0.031	**0.06b**	−0.013
	P_1	−0.031	−0.005	−0.011	0.036	0.035	−0.032
	P_2	0.056	−0.032	0.012	0.025	**0.09b**	0.001
Silver	P_1+P_2	−0.012	−0.013	0.026	0.073	−0.013	−0.023
	P_1	−0.063	−0.019	0.00	**0.157a**	−0.073	−0.036c
	P_2	0.052	−0.007	0.058	−0.032	0.064	−0.014
PLDM	P_1+P_2	−0.025	0.037	−0.047	0.071	**0.09c**	0.075a
	P_1	−0.058	0.107	−0.087	0.06	0.043	0.092a
	P_2	0.015	−0.042	−0.004	0.085	**0.14b**	0.058a
PLTNM	P_1+P_2	0.013	−0.02	−0.013	0.032	0.029	0.028
	P_1	0.021	−0.003	−0.004	0.031	0.028	0.016
	P_2	0.003	−0.04	−0.024	0.034	0.03	0.043c
Copper	P_1+P_2	−0.058	−0.029	0.029	0.003	**0.104b**	−0.05a
	P_1	**−0.171a**	−0.032	0.084	0.024	0.054	−0.019
	P_2	0.061	−0.02	−0.027	−0.021	**0.16b**	−0.071a
Zinc	P_1+P_2	**−0.187b**	0.083	**0.099c**	0.012	0.024	−0.117a
	P_1	**−0.191b**	−0.056	0.02	0.102	−0.038	−0.042c
	P_2	**−0.185c**	**0.149c**	**0.137c**	−0.027	0.047	−0.127a
Oil	P_1+P_2	−0.102	−0.073	0.063	0.072	**0.096c**	−0.018
	P_1	−0.091	−0.099	0.05	0.055	0.109	0.007
	P_2	−0.117	−0.04	0.08	0.093	0.081	−0.055a
Ht. Oil	P_1+P_2	**−0.204a**	**−0.034**	**0.161a**	**0.151a**	0.023	−0.026c
	P_1	**−0.164c**	−0.101	**0.154b**	0.130	0.081	−0.015
	P_2	**−0.254a**	0.043	**0.171b**	**0.177b**	−0.046	−0.044b
Nat. Gas	P_1+P_2	−0.115	0.104	0.043	−0.077	0.074	−0.029b
	P_1	−0.137	0.07	−0.02	0.08	0.199	−0.01
	P_2	−0.100	0.138	0.105	**−0.223c**	−0.05	−0.054a

Notes: This panel reports the simple averages of the returns. The small letters “a,” “b” and “c” denote significance at the 1%, 5% and 10% levels, respectively. The sign test results appear in the online appendix Table A16.

Notes: The table reports the OLS (with the Newey–West (1987) procedure) estimation results of the following equation: $R_t = \sum_{i=2}^{6} \mu_i D_{i,t} + \gamma_j R_{t-j} + u_t$, where R_t is the daily return of the commodity; $D_{i,t}$ is a dummy variable that receives the value of 1 if the ith day falls on day t (i = 2,3,..,6). If the expected return is the same for each day of the week, the estimates of μ_2 through μ_6 should be close to zero. According to this anomaly, the distribution of commodity returns varies according to the day of the week. The findings show that on Fridays, the mean returns tend to be positive and significant, whereas on Mondays most of the returns are negative and insignificant except for copper, zinc and heating oil. The small letters “a,” “b” and “c” denote significance at the 1%, 5% and 10% levels, respectively. The sign test results appear in the online appendix Table A16.

Table 12
The other January effect (monthly data).

	Silver				Gold			
	Positive Januarys		Negative Januarys		Positive Januarys		Negative Januarys	
Sample Period	Next 11 Months Return	N	Next 11 Months Return	N	Next 11 Months Return	N	Next 11 Months Return	N
1986–2018	−3.40% (4.21%)	20	6.43% (8.82%)	12	3.00% (3.12%)	16	3.65% (3.78%)	16
1986–2003	−1.86% (4.50%)	10	0.26% (5.55%)	8	3.34% (4.45%)	7	1.26% (3.04%)	11
2004–2018	−5.27% (7.06%)	10	18.76% (21.47%)	4	3.06% (4.32%)	9	8.91% (9.18%)	5

	Palladium				Platinum			
	Positive Januarys		Negative Januarys		Positive Januarys		Negative Januarys	
Sample Period	Next 11 Months Return	N	Next 11 Months Return	N	Next 11 Months Return	N	Next 11 Months Return	N
1986–2018	10.06% (8.32%)	25	−5.60% (9.12%)	7	−2.06% (4.51%)	23	7.48% (6.09%)	9
1986–2003	6.44% (9.52%)	14	−11.14% (9.52%)	4	0.04% (4.89%)	10	8.39% (6.38%)	8
2004–2018	14.66% (13.88%)	11	1.80% (13.98%)	3	−3.84% (6.99%)	13	0.23%	1

	Copper				Zinc			
	Positive Januarys		Negative Januarys		Positive Januarys		Negative Januarys	
Sample Period	Next 11 Months Return	N	Next 11 Months Return	N	Next 11 Months Return	N	Next 11 Months Return	N
1986–2018	3.71% (10.57%)	16	4.28% (4.96%)	16	9.57% (9.54%)	13	0.84% (7.60%)	19
1986–2003	−1.85% (10.02%)	8	−1.60% (4.40%)	10	−0.28% (9.42%)	5	−3.06% (2.32%)	13
2004–2018	9.28% (17.63%)	8	14.07% (9.18%)	6	16.93% (13.78%)	8	9.29% (22.49%)	6

	Oil				Heat Oil			
	Positive Januarys		Negative Januarys		Positive Januarys		Negative Januarys	
Sample Period	Next 11 Months Return	N	Next 11 Months Return	N	Next 11 Months Return	N	Next 11 Months Return	N
1986–2018	3.07% (7.00%)	15	5.98% (10.17%)	17	2.96% (6.98%)	14	11.59% (10.40%)	18
1986–2003	1.12% (9.92%)	10	2.66% (11.21%)	8	−8.23% (3.96%)	5	14.92% (11.73%)	13
2004–2018	7.58% (6.42%)	5	8.93% (15.69%)	9	9.17% (9.62%)	9	2.91% (19.27%)	5

	Natural Gas			
	Positive Januarys		Negative Januarys	
Sample Period	Next 11 Months Return	N	Next 11 Months Return	N
1986–2018	4.83% (24.20%)	9	6.37% (7.64%)	23
1986–2003	31.08% (47.00%)	4	9.88% (10.76%)	14
2004–2018	−15.20%	5	0.90%	9

(*continued on next page*)

Table 12 (*continued*)

	Natural Gas			
	Positive Januarys		Negative Januarys	
Sample Period	Next 11 Months Return	N	Next 11 Months Return	N
	(17.11%)		(8.91%)	

Notes: The returns denote the mean of the excess returns of the 11-month holding period of each commodity. The returns for the 11 months following January are measured using: $R_{2,12} = (1 + R_{Feb})(1 + R_{Mar})...(1 + R_{Dec}) - 1$. “N” counts the number of January months in each positive and negative category. The values in parentheses are the standard errors of the of the estimates. Though returns are not significant for the months following January, one significant finding is the number of positive Januarys for silver, palladium and platinum.

except for gold, silver and platinum, the rest commodities do not exhibit statistically significant positive returns.

3.2.4. New Year's day

The findings in Table A5 also demonstrate positive returns around New Year's Day. Investors' anticipation of a fresh start to the year may be associated with optimism reflected in the positive returns. In the total sample period ($P_1 + P_2$), all commodities, but the natural gas, are associated with positive returns. Gold, palladium, platinum and oil are statistically significant. As the significance level of the abnormal returns indicates, these findings are more evident in the financialization period (P_2) than the prior period (P_1). Though we might expect that the financialization period would be characterized by more efficiency (i.e., insignificant returns), the empirical evidence here shows the opposite and contradicts the efficient market hypothesis. The literature argues that the more liquid the market the more efficient it should be. However, one possible “dark side” of liquidity is that it permits inefficiency, which is evident in the returns on metals with regard to calendar anomalies. In the same way, sometimes illiquid securities might not appear to be volatile because there are no transactions that can express the true degree of their volatility. In contrast, liquidity does reveal the true volatility of a stock. Similarly, the financialization period may act as an “alignment mechanism” (Aharon et al., 2017) that allows the appearance of abnormal returns around New Year's Day.

3.2.5. Labor Day

Excluding gold and platinum, which are associated with significant positive returns before Labor Day, the general results in Table A6 show that the precious metals market is mainly efficient. During the time window surrounding Labor Day we could not identify any significant

Table 13
Within-the-month effect (daily data).

Panel A: OLS									
	Gold	Silver	PLDM	PLTNM	Copper	Zinc	Oil	Ht.Oil	Nat. Gas
$HF_1(<04)$	0.004	0.036	**0.121a**	**0.077a**	0.002	−0.016	**0.112b**	−0.01	−0.018
$HF_2(<04)$	0.018	0.001	−0.064	−0.035	0.004	0.001	−0.062	0.074	0.108
$HF_1(\geq 04)$	−0.018	−0.01	0.067	0.038	0.049	−0.034	0.058	0.169	−0.21
$HF_2(\geq 04)$	**0.130a**	**0.230b**	0.077	0.049	**0.253a**	**0.542a**	**0.138c**	0.04	0.238
JAN	−0.081c	−0.198b	−0.108	−0.036	−0.117	−0.384b	−0.168	−0.164c	−0.126
R_{t-1}	−0.032b	−0.028	0.077a	0.01	−0.039a	−0.233a	0.002	−0.016	−0.011
Panel B-MLE	Gold	Silver	PLDM	PLTNM	CPR	ZINC	OIL	Ht.Oil	Nat. Gas
HF1(< 04)	−0.018	−0.018	**0.057c**	0.030	−0.019	−0.056	0.012	−0.006	−0.087
HF2 (< 04)	−0.005	**−0.053c**	−0.046	**−0.044c**	0.010	−0.008	−0.001	0.041	**0.186a**
HF1 (≥04)	0.029	0.044	0.064	0.022	−0.027	**−0.083b**	−0.019	0.029	−0.007
HF2 (≥04)	0.021	−0.030	0.030	−0.030	0.045	**0.092b**	**0.111a**	0.049	0.062
JAN	−0.024	0.102c	0.065	0.120a	−0.005	0.054	0.009	−0.097	−0.3b
R_{t-1}	−0.013	−0.022b	0.066a	0.028b	−0.034a	−0.038a	−0.007	−0.005	−0.034a
ARCH(w_1)	0.040a	0.042a	0.110a	0.059a	0.041a	0.033a	0.067a	0.087a	0.095a
GARCH(w_2)	0.958a	0.948a	0.871a	0.931a	0.951a	0.962a	0.927a	0.901a	0.882a
HF1(< 04)	**−0.005a**	**−0.022a**	**0.021b**	**−0.029a**	−0.011	**−0.033a**	**0.060a**	0.015	**−0.066a**
HF2(< 04)	**0.014a**	**0.084a**	**0.094a**	**0.091a**	**0.054a**	**0.080a**	−0.025	**0.123a**	**0.803a**
HF1 (≥04)	**0.020a**	**0.085a**	**0.094a**	**0.039a**	**0.050a**	**0.122a**	**−0.081a**	−0.026	0.006
HF2 (≥04)	0.001	**0.041a**	**0.058a**	**0.059a**	0.018	−0.010	0.029	**0.104a**	**0.579a**
QLB(5)	3.427	8.221	13.27b	8.688	1.940	4.263	5.741	1.807	8.478
QLB(10)	9.763	12.24	23.41a	9.964	14.54	11.82	10.77	7.065	15.35
w1 + w2	0.998	0.99	0.981	0.99	0.992	0.995	0.994	0.988	0.977

Notes: The table reports the OLS estimation results for the following equation: $R_t = \beta_1 HF_{1t}(D < 04) + \beta_2 HF_{2t}(D < 04) + \beta_3 HF_{1t}(D \geq 04) + \beta_4 HF_{2t}(D \geq 04) + \beta_5 JAN_t + \gamma_1 R_{t-1} + u_t$. HF_1 and HF_2 are dummy variables that capture the first and second half of the month, respectively. JAN is a dummy variable that captures the January month. The findings show that in the second half of the month, the returns on precious metals and energy-based futures are positive, and statistically significant for copper, gold, silver, zinc, and oil during P_2 (2004–2018). In contrast, for the first half of the month in the period after 2004, there is no clear tendency. The small letters “a,” “b” and “c” denote significance at the 1%, 5% and 10% levels, respectively. The results are mainly the same using the GARCH estimation method. In the period before 2004, HF1 periods are associated with less volatility. For the period after 2004, it seems that the variance is higher in HF1 compared with HF2. The related sign test results appear in the online appendix in. Table A18.

results. However, such insignificant returns may be due to a simple average of positive and negative returns. A closer look on sign test results reported in Table A23 reveals consistent picture. That is, the majority of the commodities fail to provide any significant amount of positive returns on the days before the Labor Day, except for platinum and copper. Overall, the picture indicates unpredictable patterns in prices around the Labor Day.

3.2.6. Memorial Day

On this day, the public honors the memory of fallen US soldiers. Consequently, Memorial Day is one of very few holidays that may be associated with a negative mood. However, in an efficient market such negative sentiment should not hold consistently. As Table A7 indicates, the general results of the total sample period demonstrate significant negative returns, which support the negative sentiment and contradict the efficient market hypothesis. The negative sentiment in the precious metals market is evident before and after Memorial Day. Dividing the sample period into pre and during the financialization periods does not change the general direction. Corroborative evidence also comes from the sign test results depicted in Table A24 The table depicts the number of positive and negative trading days before and after Memorial Day. The picture that emerges show a clear tendency for negative returns on the days before and after this occasion in several commodities such as silver, gold, palladium and oil.

3.2.7. Thanksgiving and Black Friday

As Table A8 illustrates, the commodity market is essentially efficient around these events. Excluding heating oil and natural gas in the entire sample period, and platinum in the pre-financialization period, no commodity exhibit any significant returns. A support for these findings also appear in the sign test results (Table A25) which show consistent and insignificant results. Moreover, in the financialization period, none of the metals has any significant returns. Based on these findings, we can argue that the findings around Thanksgiving support the efficient market hypothesis.

The day following Thanksgiving Day in the United States is known as Black Friday, which in recent decades has been regarded as the beginning of America's Christmas shopping season. The findings on $t = +1$ indicate an unclear direction in the prices of precious metals.

3.2.8. Presidents Day

This is an official federal holiday in the US celebrated on the third Monday of February in honor of all persons who have served as president. The results presented in Table A9 are mixed. While the P_1 period shows negative returns on the first day following this holiday, the P_2 period provides a contradictory picture with relatively high and positive returns. Focusing on the days before the holiday, mainly for P_2, indicates that the lead-up to Presidents Day is associated with increased returns on some of these days that are statistically significant.

3.3. Ethnic holidays, superstitions, and secular events

The common feature of the events discussed here is that they take place when the exchanges are open. These events include St. Patrick's Day, Friday the 13th, the Jewish High Holidays (Rosh Hashanah and Yom Kippur), Valentine's Day, the Chinese New Year and Diwali Festival. Since these are non-economic events, one could argue that rational agents will not react differently on these days. Moreover, such events are more likely to be exploited by investors in light of their being recurring events and consequently can be forecasted in advance.

Given that the effect of such events may possibly be reflected in the price of commodities before and after the event day, we test a time window of three trading days around the event day. If the event takes place when the exchange is closed, the event date is defined as the first trading day after the event. To capture the possible effect of each event, and similar to the general approach we employed in testing the first group of events in the previous section, we use dummy variables. Each dummy variable receives the value of 1 on the days preceding and after the event as well as the day of event itself, and 0 otherwise.

3.3.1. St. Patrick's day

Frieder and Subrahmanyam (2004) document abnormal positive returns around St. Patrick's Day. More specifically, they find that the mean (median) returns for St. Patrick's Day are persistently above the mean (median) for the full sample. Hirsch (1987) also reports that St. Patrick's Day is associated with positive returns, although such returns are insignificant. Empirical evidence in papers dealing with seasonality around St. Patrick's Day are rare in the literature and all the more so in the context of the possible impact on the precious metals and energy market. As Table A10 indicates, only copper and zinc demonstrate significant positive returns in the entire sample period. These returns tend to occur one day before St. Patrick's Day. Note that in the case of gold, the returns on t-2 and t-3 are negative and significant in the pre-financialization period (P1) although they tend to be diminished during the financialization period (P2). Silver exhibits positive returns on $t + 3$, but similar to gold and other precious metals, such returns do not survive the financialization period. Overall, precious metals tend to be efficient but copper contradicts the efficient market hypothesis.

3.3.2. Friday the 13th

Stories concerning sorcery, black cats, witches, Halloween and other related topics continue to attract the interest of the general public, as witnessed by the popularity of recent books (Harry Potter) and movies (Saw I, II, …, VIII; Scream I, II, …, V). Based on this popularity, it seems natural to test whether such superstition has any impact on commodities. From an empirical perspective, Friday the 13th can proxy for such beliefs.

As previously discussed, many empirical studies have shown that average returns differ for each day of the week, although the underlying reasons remain unclear. In particular, Friday returns are usually larger than those on other days. Do returns on Friday the 13th differ from the returns of other Fridays? In fact, the empirical finance literature has addressed this topic, but left us with mixed evidence about abnormal returns on Friday the 13th compared with other Fridays (Kolb and Rodriguez, 1987; Dyl and Maberly, 1988; Lucey, 2001). To be clearer, our main hypothesis reads as follows:

$$H_0\text{: } E(R) \text{ on Friday the Thirteenth } = E(R) \text{ other Fridays}$$

$$H_1\text{: } E(R) \text{ on Friday the Thirteenth } < E(R) \text{ other Fridays}$$

The full sample data consist of 1619 trading days that fall on Fridays: 1564 cases are *regular* Fridays and 55 are Friday the 13th. The empirical evidence shown in Table A11 demonstrates that for all metals there is no indication of significant returns on Friday the 13th in any period tested. Nevertheless, Fridays are generally associated with positive returns. This tendency is particularly evident for P_2 (2004–2018).

3.3.3. Jewish holidays

Although the finance literature has examined various issues with regard to holidays, there is only limited research related to commodities such as precious metals and energy resources. We focus on the ten days of the Jewish High Holidays between Rosh Hashanah, the Jewish New Year, and Yom Kippur, the Day of Atonement. During this period of self-reflection, Jews are granted the opportunity to express regret for misdeeds, and ask for forgiveness, resulting in God's judging them favorably on Yom Kippur. Unlike other secular or religious holidays that are generally considered joyous or festive days, the focus of the High Holidays is on self-reflection and atonement, and the overall atmosphere among believers is somber (Kliger and Qadan, 2019).

There is earlier evidence about the non-typical performance of capital exchanges during this time period. Newspaper stories as early as September 19, 1915 have commented on the muted volume of trade on the London Stock Exchange resulting from the lack of Jewish traders on Rosh Hashanah (*The New York Times)*. Similarly, an article in the *Altoona Mirror* on September 27, 1935 noted the Wall Street saying, “Sell before Rosh Hashana, and buy before Yom Kippur.” Finally, on September 11, 2007, *The Wall Street Journal* explored the conventional explanation that traders sell prior to Rosh Hashanah “in advance of spending the holidays with family,” but indicated that other latent causes may be present.[13]

In this spirit, previous studies such as those of Frieder and Subrahmanyam (2004) and Loughran and Schultz (2004) report that on Yom Kippur the U.S. equity market is associated with reduced trading volume, especially for firms located in cities with a high percentage of Jewish residents (such as Boston, Los Angeles, Miami, and New York City).

The empirical results are reported in Table A12. In Panel A of the table, we report the estimation results (average returns) around Rosh Hashanah –the Jewish New Year. Regardless of the sample used, the returns are negative for all metals, and are statistically significant except for palladium. The energy commodities exhibit insignificant negative returns. The results hold true for the entire sample period and for Period 2 (2004–2018).

In Panel B of Table A12, we analyze the returns around Yom Kippur, because it is the most prominent of these ten days. According to the full sample, it appears that the anticipation of Yom Kippur is already embedded in the days preceding it. Such anticipation is reflected in the negative returns on the days preceding Yom Kippur. In addition, the general negative mood associated with such a holiday in some cases also spills over into the day after Yom Kippur. Nevertheless, shortly after this sequence of negative returns, there appear to be positive returns that may act as a correction after several down days.

The High Holidays (captured by $\text{Kippur}_{t\text{-}1}$ to $\text{Kippur}_{t\text{-}6}$ and presented in Panel B of the table) exhibit negative returns in most cases around the period and the subsequently positive returns that may balance the negative trend associated with such “days of awe.” Note also that the efficiency of the precious metals market has not changed essentially. This is an interesting result because we might have expected the financialization period in which overall market liquidity and attention to metals increased would also be accompanied by a more efficient market.

3.3.4. Valentine's day

Celebrated annually on February 14, Valentine's Day has become a worldwide romantic day and is a joyful day (Qadan and Aharon, 2018). Mood-based financial studies have established that happiness and an elevated mood are translated into a greater willingness to take risks (e.g., Lepori, 2015a, 2015b; Tausch and Zumbuehl, 2018). The results in Table A13 show that despite the positive sentiment that we expect to see, in each of the periods there is no unequivocal evidence of this possible effect. In fact, only gold and natural gas have negative abnormal returns in the overall sample period. For all other commodities, there is no evidence of excess returns. In addition, as reported in Table A31 in the online appendix, Valentine's Day is associated with less variance as evident in the significantly negative “VLNTN” dummy variable in the variance equation. Such lower conditional variance is associated with good mood is evident in the finance literature (Kliger and Qadan, 2016). Finally, and broadly speaking, the precious metals market is efficient.

3.3.5. Chinese New Year

Parallel to other holidays, the Chinese New Year has attracted extensive attention in the finance literature and is the main focus in several studies (e.g., Chan et al., 1996; Yen et al., 2001; Chong et al., 2005; Yuan and Gupta, 2014; Bergsma and Jiang, 2016). The Chinese New Year, also known as the Spring Festival in China, starts on the 23rd day of the twelfth lunar month of the Chinese calendar. According to tradition, people clean their homes to welcome the Spring Festival, put up red posters with poetic verses on their doors, and decorate their homes with red lanterns. It is also a time to reunite with relatives so many people visit their families at this time of the year. In the evening of the Spring Festival Eve, many people set off fireworks and firecrackers, hoping to banish bad luck and attract good fortune.

According to the United States Census Bureau,[14] as of 2017, the Chinese constitute about 1.3% of the total US population (relative to 1.9% for Jews). Given the importance of this holiday, we test for any impact of the Chinese New Year on the futures contracts of interest. As depicted in Table A14, we find significant abnormal returns on the day opening the Chinese New Year, and a tendency for positive returns on the days before, mainly for the period after 2004 (P_2).

In addition, as reported in Table A31 in the online appendix, we observe less variance on the three days before the New Year starts. One possible explanation for these findings is investors' mood. Bergsma and Jiang (2016) report that the period leading up to the Chinese New Year is associated with positive returns on the Chinese market. Hence, such a positive atmosphere in the local Chinese capital markets may spill over to the regional market that celebrate this holiday (Hong Kong, Singapore and Taiwan; Bergsma and Jiang, 2016) and then to commodity markets worldwide.

3.3.6. Diwali

The literature has included several studies focusing on the possible effect of Hindu holidays on capital markets (e.g., Chan et al., 1996; Mehta and Chander, 2009). One of these significant Hindu festivals is Diwali, the Festival of Lights. It is celebrated for five days on different dates each year depending on the position of the moon. According to tradition, on this day Rama returned to his people after 14 years of exile during which he fought and won a battle against the demons and their king, Ravana. The celebration of this festive holiday includes exchanges of gifts, fireworks and festive meals. People also try to pay off their old debts, make or buy new clothes and thoroughly clean their houses as part of the festival preparations. According to the United States Census Bureau, in 2017, Asian Indians, who are those who generally celebrate Diwali, constituted 1.1% of the total US population.

We find that in both the precious metals and energy-based futures, the Hindu holidays have no significant impact on futures returns. However, in the case of gold, silver, copper and zinc, there is a significant decrease in volatility during the Diwali holiday, which may correspond to a possible elevated mood during this period. An exception however, is natural gas in which there is greater volatility. The full results are depicted in Table A15 and Table A31 in the online appendix.

4. Summary

The growing popularity of incorporating natural resources into investors' portfolios over the last decade motivated us to examine whether calendar anomalies documented with regard to stock returns also exist in precious metals as well as other commodities. In addition, there is a relatively large literature on seasonality in stock returns, but much less research on the seasonality of returns in such commodities.

The overall findings challenge the efficient market hypothesis, and show that the day-of-the-week, Halloween effect, SAD effect, January effect, within-the-month effect, and turn-of-the-month effect impact the commodity markets for metals and energy. These effects are also evident around several holidays such as Christmas, New Year's Day, Independence Day, Yom Kippur and the High Holidays. Despite the

[13] Gaffen, D. September 11, 2007. *Days of awe, but not for stocks*. The Wall Street Journal.

[14] https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=ACS_17_5YR_DP05&src=pt.

increased liquidity in commodity markets and the contention that academic publications about these anomalies have tended to reduce their presence, the results are robust.

The findings of this study may have important implications for the pricing of natural resources in the commodity market. The results confirm that investors are not fully rational, and that commodity prices can be exposed to fluctuations in investor sentiment. As evident in this study, investors' emotional states such as happiness and optimism (as holidays approach), or pessimism (resulting from fewer hours of daylight or somber holidays) significantly affect price returns and volatility. Understanding these factors and their effects can help investors formulate better trading strategies. Specifically, investors can time their long and short positions to increase their abnormal returns.

To conclude, given that the vast majority of commodities analyzed in this study are used as raw materials in many industries, their price level and variability are important dimensions in the stability of the macroeconomic environment as well for the industries themselves. Policy makers and producers may find the evidence revealed here useful for their decision-making. Investors and portfolio managers may wish to keep an eye on this branch of literature, because they can use its findings to make practical decisions regarding their portfolios. Future research will reveal whether these anomalies are short-lived effects or persist over time.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.resourpol.2019.101435.

Notes: Panels A and B report the OLS (with the Newey–West (1987) procedure) estimation results of Eq. (2), while Panel C reports the maximum likelihood estimation. $\sigma_t^2 = w_0 + w_1 u_{t-1}^2 + w_2 \sigma_{t-1}^2 + w_3 HLW_t(D < 04) + w_4 HLW_t(D \geq 04)$. The small letters "a," "b" and "c" indicate significance at the 1%, 5% and 10% levels, respectively. QLB is the Q-statistic developed by Ljung and Box (1978) to test for the hypothesis of no serial correlation in the squared residuals at the k-th lagged order.

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Further reading

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