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Time-series and cross-sectional momentum and contrarian strategies within the commodity futures markets

Enrique Benavides Rosales[1]*

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*Corresponding author: Enrique Benavides Rosales, Essex Business School, University of Essex, Colchester, UK
E-mail: e.bdes@hotmail.com

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David McMillan, University of Stirling, UK

Additional information is available at the end of the article

Abstract: The aim within this paper is to analyze the difference between momentum and contrarian portfolios constructed under the cross-sectional and time-series analysis, within the commodity futures markets. The returns indicate that the contrarian portfolios are the most profitable, as well as it's observed that they perform better within the cross-sectional analysis. The correlation of the best portfolios within other markets is also examined, and the results confirm that they are indeed a good investment tool for diversifying a portfolio with different assets. Within a pre- and post-2008 global crisis point of view, the findings suggest that, for the contrarian portfolios, the results are stronger during the pre-crisis period, although during the post-crisis period the portfolios preserve the positive returns. Additionally, it's perceived that the first and second subsequent years after a crash or crisis year are usually highly profitable within the cross-sectional and time-series contrarian portfolios.

Subjects: Economic Psychology; Investment & Securities; Risk Management

Keywords: momentum; contrarian; time-series; cross-sectional; commodities

ABOUT THE AUTHOR

My main research activities are focused on behavioral finance and portfolio management. The research reported in this paper is a clear example of these two subjects, and the idea behind this research is that there's very few papers and information regarding momentum and contrarian strategies within the commodity futures markets. Also important to note, there are virtually no researches on the contrast between cross-sectional and time-series within the momentum and contrarian strategies on the commodity markets. Exclusively because of this reason, I found it significant to research these topics altogether, as it could be used for further examination, as well as a complement for existing literature on these topics.

PUBLIC INTEREST STATEMENT

The present study has as an aim to examine and analyze the difference between momentum and contrarian (reversal) portfolios constructed under the cross-sectional and time-series analysis, within the commodity futures markets.

Momentum and contrarian are two investment strategies which are constructed based on equities' past performances. Momentum suggests that winning equities will continue to win on the short term, while losing equities will continue to lose. On the other hand, reversal suggests that winning equities will underperform on the medium and long term, while losing equities will over perform.

Within the investment strategies, there are two types of analyses for constructing the portfolios. Cross-sectional analysis, on one hand, focuses on the relative performance of assets over some prior period, whereas that time-series analysis focuses on the absolute performance of the assets.

It's revealed that the contrarian portfolios perform better than the momentum portfolios, especially after the subsequent years of a crash or crisis.

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1. Introduction

The commodity futures market has witnessed a tremendous popularity increase in the past years, after being trapped in a bearing market for about 25 years. This increase in popularity, which coincides with the beginning of the new millennium, also brought an increase in prices and volatility to the commodities market. Moreover, because of the recent and sudden increase in popularity of the commodity futures, there has been a huge inflow of institutional funds into the commodity futures markets in the past years, which in the financial literature is referred to as financialization of commodities. This financialization of the commodity markets, which began in the early 2000s, has been in an extreme cycle ever since, with a huge increase in the prices during some periods, but also a huge decrease in such prices during other periods. From early 2000 up to 30 June 2008, investment inflows to various commodity futures indices totaled roughly $200 billion dollars (Cheng & Xiong, 2014).

There are many reasons why commodities are seen as a great financial tool, and it's not only because of the positive excess returns they generally provide (Erb & Harvey, 2006; Jensen, Johnson, & Mercer, 2002), but also, and in great measure, because of the great diversification benefits they offer within an equity portfolio (Conover, Jensen, Johnson, & Mercer, 2010; Gorton & Rouwenhorst, 2006; Jensen, Johnson, & Mercer, 2000; Miffre & Rallis, 2007). Another reason whereby investors and hedge funds have been attracted to commodity investments is because commodity futures provide inflation hedge for equity portfolios (Bodie & Rosansky, 1980; Conover et al., 2010; Greer, 1978), although on the other hand, according to Erb and Harvey (2006), commodities are an inconsistent hedge against unexpected inflation. Furthermore, investors seek commodity futures because they offer leverage, due to nearby contracts being usually cheap and liquid to trade, as well as not being subject to short-selling restrictions[1] (Miffre & Rallis, 2007).

Momentum and reversal, with the latter being also known as "contrarian," are two of the most well-known and studied past performance-based investment strategies, from the time they were published by Jegadeesh and Titman (1993) and De Bondt and Thaler (1985), respectively. The momentum strategy consists in buying recent outperforming (winning) stocks and selling recent underperforming (losers) stocks.[2] The reversal strategy, on the contrary, is undertaken by buying assets that underperformed (lost) in the distant past and selling assets that outperformed (won) in the distant past. According to Fama (1998), momentum is the "premier unexplained anomaly," and since then many papers have tried explaining momentum but have failed to give an explanation to it. Reversal, on the other hand, is believed to be explained by the Fama–French three-factor model (Fama & French, 1996), although according to McLean (2005, p. 22), "once the seasonality of the long-term reversals is taken into account the Fama–French three-factor model no longer explains reversals."

A wide variety of papers, related to the momentum and reversal strategies, have been published since De Bondt and Thaler introduced the contrarian strategy in 1985, although the majority of these are mainly focused on the relative performance of assets over some prior period (cross-section strategy), while few are focused on the absolute performance of the asset (time-series strategy). Moskowitz, Ooi, and Pedersen (2012) analyze the momentum strategy within different markets (commodity futures market included) using time-series, whereas Bird, Gao, and Yeung (2016) compare the time-series and the cross-sectional strategies in momentum within 24 markets. In past papers, it's been observed, that the contrarian (reversal) strategy doesn't perform well within the commodity futures markets, whereas the momentum strategy usually has positive performances (Bianchi, Drew, & Fan, 2015; Miffre & Rallis, 2007).

Moskowitz et al. (2012) notice that the time-series momentum portfolios perform better during extreme markets. With time-series, the number of assets included in the winning and losing portfolios vary with the state of the market, while the cross-sectional momentum, on the other hand, digs deeper to select winning assets when markets are weak and deeper to select losing assets when markets are strong (Bird et al., 2016).

First and foremost, in this study, the time-series and cross-sectional momentum, as well as the time-series and cross-sectional contrarian strategies within the commodity futures market, will be analyzed and afterward, the results will be compared one with the other in order to identify which strategy and analysis perform better. Secondly, the results will be examined and analyzed from a pre- and post-2008 crisis perspective. This pre- and post-crisis period analysis is important within the research because it's essential to realize if there's any pattern or behavior within the investment strategies before and after crises years. According to the observations made by Moskowitz et al. (2012), the post-period crisis portfolios should display strong positive returns after the 2008 crisis, especially within the time-series momentum.

The motivation behind this study is mainly because of the recent growing interest in commodities and its markets, as well as in the behavioral finance literature. Moreover, the recent increase in the importance of the commodity futures markets as a financial diversification tool on investment portfolios, as well as to the small number of papers focused on this topics, in contrast with papers focused on other asset markets and other financial literatures, give an aggregated value to this study because of the uncommon combination of these subjects. Also, the importance of the momentum and contrarian strategies within the behavioral finance literature is one of the motivations behind this study. Besides, there are virtually no papers that compare the time-series and cross-sectional analyses within the commodity markets from a before and after 2008 global crisis perspective, so for this reason, it's attractive to additionally analyze all these topics within this perspective.

Two papers being used in this study and that are considered fundamental within the research are "Combining momentum with reversal in commodity futures" by Bianchi et al. (2015) and "Momentum strategies in commodity futures markets" by Miffre and Rallis (2007). These two papers mainly focus on momentum and reversal on the commodity futures markets, however, for the construction of the portfolios on their study, they only employ the cross-sectional analysis. As for the time-series analysis, the methodology used in this study is the same used on the paper by Moskowitz et al. (2012), which is one of the first papers to use time-series momentum within the momentum strategy.

This paper aims to evaluate and compare the cross-sectional and time-series analyses within the momentum and reversal strategies in the commodity futures markets. Moreover, an analysis is performed so to appreciate if there's existence of a January effect on the portfolios. Furthermore, the results will, as well, be analyzed within a pre and post 2008 crisis perspective. The latter is a very significant part of this study since virtually no previous paper has examined the time-series and cross-sectional momentum strategies employing the 2008 crisis as a perspective to compare the results of the study.

Furthermore, the main purpose of this study is to evaluate whether the momentum and contrarian strategies are feasible within the commodity futures market and whether if the different type of analyses, cross-sectional and time-series, along with the pre and post crises periods, play a significant role on the variance of the returns.

This paper proceeds as follows. Section 2 presents the literature review, which accounts for previously published papers and articles related to the topics that will be presented, evaluated and discussed in this paper. Section 3 presents the data used to obtain the commodity futures returns and subsequently the winner and loser portfolios, as well as it outlines the methodology, which describes how the winner and loser portfolios were created. Section 4 presents the findings obtained, as well as the analyses of the results and their implications. Lastly, Section 5 presents the conclusion of the study, in which the research findings are summarized and the contributions made by this study are emphasized.

2. Literature review

Commodities, for over a hundred years in the United States and even more in other parts of the World, have been traded on markets and available for investors, but still nowadays, it's not as popular and recognized as other asset markets such as the stock and bond markets. During the 1980s and 1990s, several papers, regarding the importance of the commodity futures markets, were published and contributed to a huge inflow of investments towards these markets, especially since the early 2000s, when the commodity futures markets became a popular market within hedge funds and investors.

In past recent years, investors have encountered the commodity futures markets as perfect fits for their investment portfolios. According to Erb and Harvey (2006), since 1969, the compound annualized return of the GSCI is equal to 12.2%, which compares favorably to the compound annualized return of the S&P 500, which equals 11.2%. This positive return, accompanied by the fact that commodities have a low and even negative correlation with most equity markets (Conover et al., 2010), make the commodity futures an even more attractive option for the investors. Incorporating commodities into an investment portfolio brings with it many sorts of benefits, especially diversification benefits. These benefits are more than just a low correlation between commodities and other assets, which results from the entirely different factors that affect commodities, to those that affect other assets. Some benefits that come within investing in commodities are the cheap futures contracts and the liquidity of such contracts, as well as the inflation hedge commodities offer. This last benefit is the most discussed and controversial benefit within the commodities literature, since according to several papers (Bodie & Rosansky, 1980; Conover et al., 2010; Fuertes, Miffre, & Rallis, 2010; Gorton & Rouwenhorst, 2006; Greer, 1978; Miffre & Rallis, 2007), commodities are an effective inflation hedge and generate positive returns during large inflation periods, whereas other assets are negatively affected by this inflation volatility. Just as Conover et al. (2010) observe, the low correlation between commodities and other assets seems to be driven by the unique performance of the commodity futures contracts during high inflationary periods. Throughout these high inflationary and high-interest rates periods, which negatively affect assets, the increase in the commodity futures prices is a common occurrence, although by taking long positions on these futures, an inflation hedge on asset portfolios can be achieved.

Erb and Harvey (2006), on the other hand, found that not all commodity futures are good inflation hedges, as well as that because of the different composition between that of a commodity futures index and an inflation index, commodity futures cannot be a good, effective inflation hedge. Similarly, Gabriel (2015) and Goldberg (2015) assert the negative side of commodities, in which they analyze the implications the paper from Gorton and Rouwenhorst (2006) had on the commodities market, since it had a huge positive impact within the commodity futures market, as many investors began to invest on this market. Gorton and Rouwenhorst (2006) estimate that commodity futures, during the period of July 1959 to December 2004, returned an annualized 10.5% on average. However, Goldberg (2015) establishes that from January 2005 to October 2015, the S&P GSCI and the Bloomberg Commodity Index, lost, on average, 6.5 and 4.7% per annum, respectively. Also, according to Goldberg (2015), the paper from Gorton and Rouwenhorst (2006) carries the mistake of including an equal-weighted basket of 35 commodities. As stated by Goldberg (2015), it isn't optimal to provide the same equal weight to lightly traded commodities than to commodities such as gold, silver, and crude oil because then the results could be biased. Moreover, the author establishes that another reason for the commodities market to be currently weak is that since 2005, there have been too many investments in such market. The impact the paper by Gorton and Rouwenhorst (2006) had on the commodity markets can be supported by the assessment made by Goldberg (2015) in which he states that by the end of 2005, exchange-traded products that tracked commodities held nearly $5 billion dollars. About 5 years later, the amount held by these tracking products escalated up to $125 billion, while at the end of 2013 the total was roughly $300 billion dollars.

Although the commodities are of an extreme variability nature, especially since their financialization, they are still considered as a good investment alternative. The increase in the level of volatility of commodities since the 2000s, are due to an increased financial investment in commodity markets and also due to fundamental factors. Furthermore, the extreme volatility in the commodity market since the 2008 crisis has been observed before, during the Great Depression and the 1970s

(Dwyer, Gardner, & Williams, 2011). In spite of the fact that the commodity markets suffer from extreme volatility, the recent increase in the equity markets volatility, make the commodity investments even more attractive because of the low correlation among both markets. The recent commodity desirability can be noticed on the CFTC staff report (2008) which establishes that, within institutional holdings, there's an estimated increase from $15 billion in 2003 to more than $200 billion in 2008 (CFTC 2008 staff report, cited in Basak & Pavlova, 2015).

Although the commodity markets popularity has been on a constant rise in recent years, still many investors and authors don't trust and rely on this asset class as of a variety of reasons. Nevertheless, recent papers and researches have made clear the advantages and benefits of including commodities on an investment portfolio, ever since its financialization in the early 2000s. Likewise, a recently expanding subject, behavioral finance, is easing to understand and trust more on the commodity futures markets.

Behavioral finance, a relatively new field within the finance literature, seeks to study the influence of psychological and cognitive factors on the people's and institution's behavior, and how these affect the financial markets. This financial subject is also of great interest because it helps explain why people tend to make irrational decisions, as well as why and how financial markets may be inefficient (Sewell, 2007). Within the behavioral finance literature, there are two studies that revolutionized and introduced a new perspective on this subject, which will be essential for the research and analysis of this paper. Both papers, "Does the stock market overreact?" (De Bondt & Thaler, 1985) and "Returns to buying winners and selling losers: Implications for stock market efficiency" (Jegadeesh & Titman, 1993), not only have served, since then, as base and foundation for many studies in past years, but have also consolidated the behavioral finance subject. Sewell (2007) distinguishes that the paper published by De Bondt and Thaler (1985), in which they observe and analyze reversals on the stock markets, is, theoretically, the foundation of behavioral finance.

The momentum and contrarian (reversal) strategies are two of the most distinguished and extensively documented behavioral finance strategies, which have been studied and analyzed primarily in the stock markets, as well as in other asset markets. Furthermore, momentum and reversal are regarded as financial anomalies, as these two strategies are difficult to explain, with rational agents and frictionless markets, within the standard asset-pricing paradigm (Vayanos & Woolley, 2010).

In 1993, Jegadeesh and Titman introduced the momentum strategy, in which they find a tendency in which by buying stocks with good recent past performance and selling stocks that performed poorly during the same past period, such stocks would continue to overperform and underperform, respectively, thus generating significant positive returns over a maximum 1 year holding period. The formation and holding periods they mainly utilize are the 3, 6, 9, and 12 months, although they, as well, examine longer holding periods. The authors find significant positive returns within most of the portfolios, with formation and holding periods of maximum 12 months. The most significant returns they obtain are within the stocks selected based on their past 6-month returns and subsequently holding the portfolio for 6 more months. This last strategy returns 12.01% per annum on average. They also encounter that part of the abnormal returns produced during the following year after the portfolio formation, dissipates during the following 2 years.

The importance of the paper by Jegadeesh and Titman (1993) is huge within the behavioral finance literature, as it became a groundwork in this subject, leading a variety of authors to analyze this strategy within numerous and different perspectives, securities, assets, markets, etc. Nowadays, there are many papers that focus on the momentum subject, but with subtle differences regarding the 1993 paper by Jegadeesh and Titman, which analyzes momentum only within the stocks market, as well as by only using the cross-sectional analysis. Recent papers motivated on the momentum subject, are expanding and improving the original analysis, by examining different asset markets, as well as by evaluating momentum thru employing the time-series analysis. As Fama

(1998) stated, momentum remains the "premier unexplained anomaly" and up until today still is, as no author has found a concrete explanation to the momentum anomaly.

De Bondt and Thaler (1985) introduced the reversal strategy theory, with the aim to investigate whether people's "overreaction" to unexpected and dramatic news or events, affects stock prices in some way. This strategy, same as with the momentum strategy, became a pillar of the behavioral finance literature and has been, since then, thoroughly studied and analyzed along with the momentum strategy, because of their associated findings. The findings made by De Bondt and Thaler (1985) are still of great interest to the academia, because of their uniqueness and singularity. They observe that by buying the stocks that underperformed the most in past years, and by selling the stocks that over performed in the same period of past years, there will be significant positive returns, since they found that the stocks that underperformed in past years will reverse in the long run (3–5 years) and will have good returns, while on the other hand, the stocks that over perform in that same period, will underperform in the next 3–5 holding period years. Consistent with the "overreaction" they were originally studying, their research suggests that most people "overreact" to two type of news: the unexpected and dramatic news. People's behavior is fundamental for understanding how such behavior affects the stock market. Their results indicate that 36 months after the portfolio formation, the losing portfolios earns, on average, up to 25% more than the winner portfolios, despite the fact that the winner portfolios are riskier. They also accomplished to realize a January effect on the "loser" portfolios, since they have large positive excess returns every January for as long as 5 years after the formation of such portfolios. Opposed to the momentum anomaly, reversal, on the contrary, can be explained by the Fama–French three-factor model according to Fama and French (1996). Although on the other hand, McLean (2005) states that the Fama–French three-factor model cannot explain reversals once the seasonality of the reversal portfolio is taken into consideration.

On their study, Bianchi et al. (2015) examine the profitable trading strategies that momentum and reversal offer, within the commodity futures markets, by separately and jointly analyzing the portfolios. They observe that the single-sort momentum strategies, on average, return 11.14% per annum, while the double-sort strategy, which combines momentum and reversal strategies, returns, on average, 20.24% per annum, which significantly outperforms, by nearly the double, the single-sort momentum strategies. They also identify that because the double-sort strategy appears to be related to global funding liquidity, it may be utilized as a portfolio diversification tool, which makes it an even more exciting strategy.

Contrariwise, the excitement on the momentum and reversal strategies is not shared by everyone. Miffre and Rallis (2007) encounter that the momentum strategy in the commodity markets is significantly profitable, with a 9.38% average return a year; whereas the reversal strategy is not profitable at all, yielding a −2.64% per year. As a result, the loser portfolios keep losing not only on the short horizon but also on the long horizon. Similarly, Baltzer, Jank, and Smajlbegovic (2014), as well as Daniel and Moskowitz (2014), exhibit on their respective papers, the failed momentum strategies following financial crises or market crashes. Baltzer et al. (2014) observes that during the 1965–2012 period, a strategy of buying past winning stocks and, likewise, selling past losing stocks yielded, on average, 8.82% per year in the US and 9.97% in Germany; nonetheless, during the period of April–September 2009, just after the 2008 crisis breakout, the same double-sort strategy (buying past winning stocks and selling past losing stocks) would return a cumulative −50.77% in the US and −42.01% in Germany. In addition, Daniel and Moskowitz (2014) examine the momentum strategy following market declines, as well as when market volatility is high. They determine that the momentum crashes (unusual sequence of persistent negative returns) cannot be accurately forecasted and also establish their occurrence across most asset markets, including the commodity markets. Additionally, they show that "the low ex-ante expected returns in panic states are consistent with a conditionally high premium attached to the option-like payoffs of past losers" (Daniel & Moskowitz, 2014).

Two major limitations observed within these strategies are that they have not been evaluated within the commodity market as much as within other markets, as well as that they have been primarily studied within the cross-sectional analysis and not within the time-series analysis. Moskowitz et al. (2012) are one of the first authors to analyze the momentum strategy within the commodity futures markets, using time-series analysis, instead of the usual cross-sectional. The findings considered the most significant in their paper are the better performance of the time-series momentum during extreme markets, the 12-month formation period as the best predictor, and the existence of momentum during the first year, but a reversal afterward. The latter observations are significant since they will be employed in this study. The fact that there's an observed reversion after 12 months by Moskowitz et al. (2012), as well as by Bianchi et al. (2015), who not only observe a reversion after 12 months, but also identify a reversal after 12–30 months and subsequently a trend up again from 30 to 60 months; encourage this research to seek reversions after 12 months, instead of the usual 36 months noted by De Bondt and Thaler (1985).

Although it's clear that some recent papers have mix opinions on whether the momentum and reversal strategies yield significant results, still the majority of papers agree on the importance and significant positive returns these strategies generate, especially when combined. Both papers have, undoubtedly, penetrated within the main financial literature and become the foundation for many studies within the finance community.

The paper by Bird et al. (2016) is one of few papers in which there's a comparison, within the momentum strategy, between time-series, as seen in the paper by Moskowitz et al. (2012), and cross-sectional analysis, as observed in the study of Jegadeesh and Titman (1993). On their study, they seek for momentum across 24 markets by means of both type of analyses, and they find that both analyses produce positive and significant profits, although time-series is clearly superior to the cross-sectional analysis.

The main difference between time-series analysis and cross-sectional analysis is the number of stocks included within the winner and loser portfolios. The number of stocks incorporated in these portfolios varies depending on the performance and condition of the market. This state of the market has a direct repercussion on the analyses since cross-sectional momentum will dig deeper to select the winning stocks, that will constitute the portfolio when markets are not performing well; as well as it will dig deeper to select losing stocks whenever markets are doing good. As Bird et al. (2016) stated, "the information in the momentum signals is concentrated in the tails of the return distribution, it is not that surprising that momentum is best implemented using time-series momentum." In addition, according to Baltas and Kosowski (2013), time-series momentum strategies perform solidly and likewise, they help to improve the performance of numerous hedge funds.

Regarding the cross-sectional and time-series analysis, the meaningful superiority of the time-series is widely accepted within the majority of papers, although cross-sectional is easier to use and still gives positive returns with a relative small gap in relation to the yields returned by the time-series analysis. Furthermore, because of the recent use of the time-series analysis within the momentum strategy, not many papers focus on this type of analysis.

3. Methodology

The data being used in this study derives from *Datastream International* and it comprises settlement prices on the 24 US commodity futures contracts included in the S&P GSCI for 2016. The index contemplates 6 energy commodities, which compose 63.05% of the RPDW[3] of the S&P GSCI, and 18 non-energy commodities, which compose the remaining 36.95% of the RPDW (S&P Dow & Jones Indices, 2016). The 6 energy futures that are included in this sub-index are WTI crude oil, heating oil, unleaded (RBOB) gasoline, Brent crude oil, gas oil, and natural gas. The 18 non-energy futures included in the index are sub-divided in four further sub-indices which are agriculture, livestock, industrial metals, and precious metals. The commodities included in the agriculture sub-index are wheat (Chicago and Kansas), corn, soybeans, coffee, sugar, cocoa, and cotton. Within the livestock sub-index, the commodities being included are lean hogs, live cattle and feeder cattle. Within industrial metals, the index considers aluminum, copper, lead, nickel, and zinc. Lastly, within precious metals, gold, and silver are the enclosed commodities.

It's important to note that within the commodity futures data collection, there are two major financial databases from where to obtain the data. *Datastream International*, which is the database being used in this study, contains the Standard and Poor's Goldman Sachs Commodity Index (S&P GSCI), while on the other hand, *Bloomberg* incorporates the Dow-Jones UBS Commodity Index (DJ-UBSCI). Initially, it was considered to carry on a comparison between the outcomes observed on both databases, however in prior studies, it has been found that there's no evidence of a significant difference between results on both databases, therefore it was determined to analyze only the S&P GSCI (Bianchi et al., 2015). The commodity settlement prices retrieved from *Datastream International* are the monthly prices, from which the monthly futures returns are subsequently obtained.

The data-set in this study spans the period between January 2000 and December 2015. The reason this data-set span is preferred over other periods and spans is not only because it includes the last full year (2015), but also because it is easier and reasonable while analyzing the results from a pre and post 2008 crisis perspective since 2008 is virtually in the middle of the data span.

This study uses the monthly spot prices of the 24 commodities that make up the S&P GSCI, which tracks the price of the nearby futures contracts, to compute the futures returns that will be used to construct the winner and loser portfolios according to such returns. To compute the futures returns, the approach utilized is the same as the one used by Miffre and Rallis (2007), which consists of computing the change in the logarithms of the settlement prices. Within both analyses, time-series and cross-sectional, the change in the logarithms of the settlement prices is employed so to obtain the commodities futures returns that are used to construct the portfolios. The monthly returns obtained through the latter method, match with the monthly total returns of the commodities comprising the S&P GSCI, which as a matter of fact, measures commodity futures that are rolled forward from the fifth to the ninth business day of each month (S&P GSCI Commodity Index Components, Weights, Index Levels and Construction, 2016).

Within the cross-sectional and time-series analyses, the past period over which to measure the commodities returns – the formation period – is of huge importance within the momentum and reversal literature. The formation periods in the momentum literature usually consist of short-term periods, as for example the 3-, 6-, and 12-month formation periods. On the other hand, within the reversal literature, it is notoriously known that the formation periods are usually longer than the ones observed in momentum. For reversals, common formation periods are between the 3- and 5-year formation periods. However, in recent papers there have been indications of a reversal in the commodity markets after only 12 months and not after 36 or 60 months.[4] These recent findings encouraged to look for momentum as well as for reversals after only 12 months. In this study, the formation periods (J) to examine are of 6, 12 and 24-months. Similarly, the holding periods (K) are the same as the prior formation periods, meaning that there are 9 possible combinations of formation (J) and holding periods (K) for each analysis.

One main difference within the cross-sectional and time-series analysis lies heavily on the cut-off points that identify stocks as either winners or losers. For the cross-sectional momentum, the stocks are ranked on basis of their performance over the past *J* months. Meanwhile, winner stocks are identified as those that rank in the top 20% of the distribution (top 5 commodities), while the loser stocks are those that rank in the bottom 20% of the distribution (bottom 5 commodities). The reason the cut-off point for the cross-sectional momentum is fixed in 40% (20% on the top quintile and 20% in the bottom quintile) is because the performance of the strategies degrades as the cut-off points increase and subsequently more assets are included in the winner and loser portfolios (Bird et al., 2016). Since the paper of Bird et al. (2016) focuses on stocks and this paper focuses on commodities, the difference on the number of assets in such markets is immense, since in the stock markets there could be hundreds if not thousands of stocks, while in the commodity markets the number of commodities they could include are much less. The small number of commodities in the S&P GSCI (24 commodities included in this paper) does not allow a smaller cut-off point to be used because then the analysis would depend on too few commodities, and the analysis would be very volatile and unsteady.

On the other hand, because the cut-off for the time-series momentum is in absolute numbers, the selection of commodities on the winner and loser portfolios don't rely on quantiles, but instead a method in which all commodities above a certain return are included in the winner portfolios, while commodities below a certain return are incorporated in the loser portfolios. Moskowitz et al. (2012) use absolute cut-off points, meaning that all stocks with positive returns are placed on the winner portfolios and all stocks with negative returns are contained in the loser portfolios. In this paper, an analysis was made by using the same cut-off points as Moskowitz et al. (2012), as well as cut-off points of 1 and −1%, for the winner and loser portfolios respectively, up to cut-off points of 8 and −8%. It was found that the more the cut-off points increased, the more the months without commodities in certain periods were visible. The cut-offs selected for the research in this paper is 1% for the winner commodities and −1% for the loser portfolios. The 1 and −1% cut-off points were selected due to the fact that nearly all months have at least 1 commodity within all formation periods analyzed. The reason for which this study doesn't follow the same methodology as Moskowitz et al. (2012) regarding the time-series cut-offs, is because the inclusion of all commodities on the portfolios is not ideal according to Bird et al. (2016). For this very reason, just as with the cross-sectional momentum, a balance is pursued so to not to include all 24 commodities within the winner and loser portfolios using the time-series analysis, but also taking care of not to include very few assets, because that could bias the results, thus generating inaccurate results.

The construction of the winner and loser portfolios start with the data collection which, in this study, is the compilation of the monthly settlement prices of the 24 US commodity futures contracts encompassed in the S&P GSCI by 2016. The period to analyze comprises from January 2000 up to December 2015.

Once the prices are obtained, the monthly returns of these settlement prices are computed by calculating the change in the logarithms of such prices. After the returns for all commodities in the data span are obtained, then it is proceeded to calculate the top and bottom 20% of the commodities, within the index, for each month of the span being analyzed, so to obtain the winner and loser commodities that will be incorporated in such portfolios, in accordance with the cross-sectional analysis. With this data, the winner and loser portfolios are constructed by obtaining the average monthly return of the 5 commodities included on each of the two portfolios. The average depends on the formation periods examined (6, 12, and 24-months) since the winner and loser portfolios have different commodities included once the formation periods are taken into account.

Conversely, for obtaining the winner and loser commodities that will be fundamental on constructing the portfolios correlated to the time-series analysis, more work and process is needed. The first step is to obtain the average monthly returns of the commodities according to the formation periods. Within the winning commodities, the commodities with monthly returns larger than 1% are selected, whereas that for selecting the loser commodities, commodities with yields smaller than −1% are selected once they are averaged with respect to the formation periods. Within the time-series analysis, the average, when assembling the winner and loser portfolios within both analyses, is obtained by the total sum of the returns of the commodities according to the formation period, and then it's divided by the total number of commodities within the whole formation period selected, so to obtain the average monthly return for the winner and loser portfolios.

It's imperative to note that for each formation period, the process for selecting the winner and loser commodities for the portfolios is different since the commodities differ according to the total number of prior periods that are being analyzed. The commodities in the winner portfolio for March

2005, for example, are not going to be the same if the formation period is 6 months than if it is 12 months; regardless of whether it's a cross-sectional or time-series analysis. Likewise, the number of commodities differ between a cross-sectional and the time-series portfolios.

The weighting scheme used in this study corresponds to an equal weight scheme, which depends directly on the number of commodities being considered. The reason this weighting scheme is being used and not a market value weight or a volatility weight scheme is due to the latter two being very time consuming to perform and the results not being that different.

Once the monthly winner and loser commodities are selected within each analysis, regarding the formation periods, the next step is to construct the winner and loser portfolios regarding the holding periods.

Within each analysis, there are 9 possibilities of portfolios ($J \times K$) constructed depending on the formation periods (J) and holding periods (K). The possible strategies are 6 × 6, 6 × 12, 6 × 24, 12 × 6, 12 × 12, 12 × 24, 24 × 6, 24 × 12 and 24 × 24. On each portfolio, the commodities to hold are the ones that were selected before, according to the formation periods. Afterward, each winner and loser monthly portfolio are held for the number of months regarding the holding period to analyze, depending on the formation periods they were assembled on.

For the construction of the single-sort momentum and contrarian portfolios, the total return of the winner and loser portfolios are subtracted from each other. In the case of the single-sort momentum portfolio, the monthly yield of the winner portfolio is subtracted with the return of the loser portfolio of the same month (winner − loser). On the other hand, for the contrarian portfolios, the process is inverted, implicating that the return of the loser portfolio is being subtracted by the return of the winner portfolio.

Furthermore, yearly returns are calculated so to analyze the returns per year and be able to perform stronger and better analyses on each investment strategy within the different formation and holding periods. Besides, it simplifies the pre and post 2008 global crisis analysis, not only within the commodity futures market but also within the comparison between the two different analysis (time-series and cross-sectional).

4. Findings

In this section of the study, the perceived findings are analyzed and examined in detail. Within the results, it can be perceived that the formation portfolios are in accordance from what it's expected from them according to the literature on these subjects, as the winner portfolios have large returns during the formation periods, while on the other hand, the loser portfolios have huge losses. Once the formation portfolios are constructed, the next step is to assemble the winner and loser portfolios by using the commodities included in the formation portfolios, but this time, by holding the portfolios for a specific period. Afterward, the next step is to construct the momentum and contrarian portfolios, as well as to calculate the yearly returns of all the portfolios.

It is important to note that at the beginning, it was intended to use, for momentum, the 6 × 6, 6 × 12, 12 × 6, 12 × 12 ($J \times K$) portfolios; whereas for the reversal (contrarian) portfolios, these were the original portfolios: 12 × 12, 12 × 24, 24 × 12, 24 × 24. However, because of the findings made on the rest of the portfolios[5] not included in the original sample, the subsequent decision was to include all of the ($J \times K$) portfolios for both strategies, since the results obtained are of great importance and significance for the study.

Some of the results achieved are just as expected, while some others are surprising and unpredicted. The first analysis in this study focuses on the average annual returns of the four portfolios within the two type of analysis, cross-sectional and time-series, and their respective formation and holding period ($J \times K$) portfolios. From Tables 1–4, the average annual yield for each portfolio can be

Table 1. Data statistics of the winner and loser portfolios within the cross-sectional analysis

	6 months FP			12 months FP			24 months FP			Average
	6 months HP	12 months HP	24 months HP	6 months HP	12 months HP	24 months HP	6 months HP	12 months HP	24 months HP	
Winner										
Annualized arithmetic mean (%)	2.6511	−2.2738	−1.7843	−4.3581	−3.8999	−2.3403	−6.2665	−5.4939	−2.6315	−2.9330
Annualized volatility (%)	3.4550	1.9613	1.2711	3.2143	1.9520	1.2393	2.6113	1.8939	1.3148	2.1014
t-statistics	0.9779	0.5481	0.5648	0.4534	0.4310	0.5200	0.3178	0.3322	0.5038	0.5166
Reward/risk ratio	0.7673	−1.1593	−1.4037	−1.3558	−1.9979	−1.8885	−2.3998	−2.9009	−2.0015	−1.5933
Skewness	−0.9860	−0.7069	0.2037	−1.6590	−0.7701	0.1758	−0.5549	−0.5222	0.0521	−0.5297
Kurtosis	2.3639	0.4755	−0.4666	6.4404	0.5214	−0.6309	1.3748	0.5606	−0.6406	1.1109
% of positive months	57.2917	50.0000	40.1042	47.3958	46.3542	43.7500	42.1875	40.6250	42.7083	45.6019
Min return with 95% prob	−3.0318	−5.4998	−3.8751	−9.6452	−7.1108	−4.3787	−10.5616	−8.6090	−4.7942	−6.3896
Value of portfolio (%)	96.9682	94.5002	96.1249	90.3548	92.8892	95.6213	89.4384	91.3910	95.2058	93.6104
95% VaR	3.0318	5.4998	3.8751	9.6452	7.1108	4.3787	10.5616	8.6090	4.7942	6.3896
99% VaR	5.3864	6.8364	4.7413	11.8358	8.4411	5.2232	12.3412	9.8997	5.6902	7.8217
Loser										
Annualized arithmetic mean (%)	7.5783	5.4654	5.3234	7.3589	6.2524	6.1917	8.4210	7.5108	7.2850	6.8208
Annualized volatility (%)	2.9023	1.9824	1.2820	2.9757	2.0540	1.2046	2.6335	1.6174	1.1303	1.9758
t-statistics	0.6377	0.7743	0.7733	0.6617	0.7094	0.6931	0.5644	0.5948	0.5944	0.6670
Reward/risk ratio	2.6112	2.7570	4.1523	2.4730	3.0440	5.1401	3.1977	4.6436	6.4449	3.8293
Skewness	−0.4009	−0.2976	0.1332	0.1401	0.1370	0.1920	−0.1858	0.1388	0.3050	0.0180
Kurtosis	1.1040	0.3308	−0.2894	0.9650	0.1769	−0.3597	0.7887	0.7766	−0.2767	0.3573
% of positive months	61.9792	60.9375	59.3750	61.9792	60.4167	65.1042	61.4583	68.7500	67.1875	63.0208
Min return with 95% prob	2.8045	2.2046	3.2146	2.4643	2.8738	4.2104	4.0893	4.8503	5.4257	3.5709
Value of portfolio (%)	102.8045	102.2046	103.2146	102.4643	102.8738	104.2104	104.0893	104.8503	105.4257	103.5709
95% VaR	−2.8045	−2.2046	−3.2146	−2.4643	−2.8738	−4.2104	−4.0893	−4.8503	−5.4257	−3.5709
99% VaR	−0.8267	−0.8536	−2.3409	−0.4364	−1.4740	−3.3894	−2.2946	−3.7481	−4.6554	−2.2244

Table 2. Data statistics of the momentum and contrarian portfolios within the cross-sectional analysis

	6 months FP			12 months FP			24 months FP			Average
	6 months HP	12 months HP	24 months HP	6 months HP	12 months HP	24 months HP	6 months HP	12 months HP	24 months HP	
Momentum										
Annualized arithmetic mean (%)	−4.9272	−7.7391	−7.1077	−11.7170	−10.1523	−8.5320	−14.6875	−13.0047	−9.9165	−9.7538
Annualized volatility (%)	1.9329	1.5086	0.9696	2.5210	1.5842	0.9662	2.3393	1.7065	1.0921	1.6245
t-statistics	0.3311	0.1856	0.2046	0.0894	0.1153	0.1543	0.0473	0.0652	0.1196	0.1458
Reward/risk ratio	−2.5492	−5.1300	−7.3304	−4.6478	−6.4083	−8.8304	−6.2785	−7.6206	−9.0806	−6.4306
Skewness	0.0661	−0.0044	0.0598	−0.5951	−0.2419	0.4718	−0.2107	−0.3248	0.1749	−0.0671
Kurtosis	0.0091	0.3690	−0.0956	0.7155	−0.2655	0.4562	−0.0724	0.1097	−0.4283	0.0886
% of positive months	42.7083	32.8125	27.0833	32.8125	31.2500	20.3125	29.6875	25.0000	23.4375	29.4560
Min return with 95% prob	−8.1065	−10.2206	−8.7026	−15.8636	−12.7582	−10.1213	−18.5354	−15.8117	−11.7128	−12.4258
Value of portfolio (%)	91.8935	89.7794	91.2974	84.1364	87.2418	89.8787	81.4646	84.1883	88.2872	87.5742
95% VaR	8.1065	10.2206	8.7026	15.8636	12.7582	10.1213	18.5354	15.8117	11.7128	12.4258
99% VaR	9.4237	11.2487	9.3634	17.5817	13.8378	10.7797	20.1296	16.9746	12.4570	13.5329
Reversal										
Annualized arithmetic mean (%)	4.9272	7.7391	7.1077	11.7170	10.1523	8.5320	14.6875	13.0047	9.9165	9.7538
Annualized volatility (%)	1.9329	1.5086	0.9696	2.5210	1.5842	0.9662	2.3393	1.7065	1.0921	1.6245
t-statistics	0.8044	0.5444	0.5917	0.2990	0.3751	0.4778	0.1760	0.2333	0.3878	0.4322
Reward/risk ratio	2.5492	5.1300	7.3304	4.6478	6.4083	8.8304	6.2785	7.6206	9.0806	6.4306
Skewness	−0.0661	0.0044	−0.0598	0.5951	0.2419	−0.4718	0.2107	0.3248	−0.1749	0.0671
Kurtosis	0.0091	0.3690	−0.0956	0.7155	−0.2655	0.4562	−0.0724	0.1097	−0.4283	0.0886
% of positive months	57.2917	67.1875	72.9167	67.1875	68.7500	79.6875	70.3125	75.0000	76.5625	70.5440
Min return with 95% prob	1.7479	5.2577	5.5128	7.5703	7.5465	6.9427	10.8396	10.1977	8.1203	7.0817
Value of portfolio (%)	101.7479	105.2577	105.5128	107.5703	107.5465	106.9427	110.8396	110.1977	108.1203	107.0817
95% VaR	−1.7479	−5.2577	−5.5128	−7.5703	−7.5465	−6.9427	−10.8396	−10.1977	−8.1203	−7.0817
99% VaR	−0.4307	−4.2296	−4.8520	−5.8523	−6.4668	−6.2843	−9.2454	−9.0347	−7.3760	−5.9746

Table 3. Data statistics of the winner and loser portfolios within the time-series analysis

	6 months FP			12 months FP			24 months FP			Average
	6 months HP	12 months HP	24 months HP	6 months HP	12 months HP	24 months HP	6 months HP	12 months HP	24 months HP	
Winner										
Annualized arithmetic mean (%)	1.0048	1.9375	1.6388	3.1524	1.4182	0.5011	0.0180	−1.7543	−0.2339	0.8536
Annualized volatility (%)	2.5672	1.8104	1.2047	2.9950	2.0470	1.2123	2.9411	1.8555	1.0905	1.9693
t-statistics	0.8286	0.9065	0.8730	0.9822	0.8590	0.7644	0.7581	0.5887	0.6938	0.8060
Reward/risk ratio	0.3914	1.0702	1.3603	1.0526	0.6928	0.4133	0.0061	−0.9455	−0.2145	0.4252
Skewness	−1.4871	−0.2328	0.1362	−0.4733	0.0497	0.2634	−0.7097	−0.3488	0.0162	−0.3096
Kurtosis	5.0784	0.7484	−0.1201	1.2245	0.2822	−0.2890	1.8308	0.0885	−0.5114	0.9258
% of positive months	55.7292	56.2500	49.4792	53.6458	54.6875	50.0000	50.0000	44.2708	40.6250	50.5208
Min return with 95% prob	−3.2179	−1.0404	−0.3428	−1.7739	−1.9488	−1.4929	−4.8197	−4.8063	−2.0276	−2.3856
Value of portfolio (%)	96.7821	98.9596	99.6572	98.2261	98.0512	98.5071	95.1803	95.1937	97.9724	97.6144
95% VaR	3.2179	1.0404	0.3428	1.7739	1.9488	1.4929	4.8197	4.8063	2.0276	2.3856
99% VaR	4.9674	2.2742	1.1638	3.8150	3.3438	2.3191	6.8240	6.0708	2.7708	3.7277
Loser										
Annualized arithmetic mean (%)	7.4418	5.1252	4.4669	6.3216	4.6142	6.8155	6.3936	6.1567	6.4592	5.9772
Annualized volatility (%)	2.7902	1.8426	1.2304	3.1236	2.1042	1.2775	2.8669	1.5918	1.2630	2.0100
t-statistics	0.6454	0.7999	0.8523	0.7391	0.8457	0.6331	0.7078	0.6968	0.6639	0.7316
Reward/risk ratio	2.6671	2.7816	3.6304	2.0238	2.1928	5.3350	2.2301	3.8678	5.1141	3.3159
Skewness	−0.7352	−0.4889	0.2638	−0.7488	−0.5991	0.4431	0.0515	0.6843	0.7015	−0.0475
Kurtosis	2.1318	0.6584	−0.7769	2.7217	3.6840	−0.2913	2.0959	0.6478	0.6846	1.2840
% of positive months	59.3750	57.8125	54.1667	54.1667	53.6458	56.2500	46.3542	46.8750	47.3958	52.8935
Min return with 95% prob	2.8523	2.0945	2.4430	1.1838	1.1530	4.7142	1.6780	3.5385	4.3817	2.6710
Value of portfolio (%)	102.8523	102.0945	102.4430	101.1838	101.1530	104.7142	101.6780	103.5385	104.3817	102.6710
95% VaR	−2.8523	−2.0945	−2.4430	−1.1838	−1.1530	−4.7142	−1.6780	−3.5385	−4.3817	−2.6710
99% VaR	−0.9508	−0.8388	−1.6045	0.9449	0.2810	−3.8436	0.2758	−2.4537	−3.5209	−1.3012

Table 4. Data statistics of the momentum and contrarian portfolios within the time-series analysis

	6 months FP			12 months FP			24 months FP			Average
	6 months HP	12 months HP	24 months HP	6 months HP	12 months HP	24 months HP	6 months HP	12 months HP	24 months HP	
Momentum										
Annualized arithmetic mean (%)	−6.4369	−3.1877	−2.8280	−3.1692	−3.1960	−6.3144	−6.3756	−7.9110	−6.6931	−5.1236
Annualized volatility (%)	2.0942	1.3499	0.9312	2.7150	1.9378	1.2438	2.7014	1.8208	1.2872	1.7868
t-statistics	0.2418	0.4348	0.4537	0.4565	0.4440	0.2520	0.2862	0.2092	0.2422	0.3356
Reward/risk ratio	−3.0738	−2.3613	−3.0370	−1.1673	−1.6493	−5.0768	−2.3601	−4.3448	−5.1999	−3.1412
Skewness	−0.0764	0.0420	−0.2056	0.0452	−0.1192	−0.3207	−0.4462	−0.2838	0.0662	−0.1443
Kurtosis	−0.1368	0.1368	0.6920	0.0498	0.9296	1.2246	0.6397	−0.0196	−0.8698	0.2940
% of positive months	39.5833	44.7917	40.6250	47.3958	43.7500	31.7708	46.3542	37.5000	36.9792	40.9722
Min return with 95% prob	−9.8815	−5.4082	−4.3597	−7.6350	−6.3834	−8.3603	−10.8190	−10.9059	−8.8103	−8.0626
Value of portfolio (%)	90.1185	94.5918	95.6403	92.3650	93.6166	91.6397	89.1810	89.0941	91.1897	91.9374
95% VaR	9.8815	5.4082	4.3597	7.6350	6.3834	8.3603	10.8190	10.9059	8.8103	8.0626
99% VaR	11.3086	6.3281	4.9943	9.4853	7.7041	9.2079	12.6600	12.1468	9.6875	9.2803
Reversal										
Annualized arithmetic mean (%)	6.4369	3.1877	2.8280	3.1692	3.1960	6.3144	6.3756	7.9110	6.6931	5.1236
Annualized volatility (%)	2.0942	1.3499	0.9312	2.7150	1.9378	1.2438	2.7014	1.8208	1.2872	1.7868
t-statistics	0.6576	0.9752	0.9877	0.9781	0.9749	0.6719	0.6916	0.5602	0.6443	0.7935
Reward/risk ratio	3.0738	2.3613	3.0370	1.1673	1.6493	5.0768	2.3601	4.3448	5.1999	3.1412
Skewness	0.0764	−0.0420	0.2056	−0.0452	0.1192	0.3207	0.4462	0.2838	−0.0662	0.1443
Kurtosis	−0.1368	0.1368	0.6920	0.0498	0.9296	1.2246	0.6397	−0.0196	−0.8698	0.2940
% of positive months	60.4167	55.2083	59.3750	52.6042	56.2500	68.2292	53.6458	62.5000	63.0208	59.0278
Min return with 95% prob	2.9924	0.9672	1.2964	−1.2966	0.0086	4.2686	1.9323	4.9161	4.5759	2.1845
Value of portfolio (%)	102.9924	100.9672	101.2964	98.7034	100.0086	104.2686	101.9323	104.9161	104.5759	102.1845
95% VaR	−2.9924	−0.9672	−1.2964	1.2966	−0.0086	−4.2686	−1.9323	−4.9161	−4.5759	−2.1845
99% VaR	−1.5652	−0.0472	−0.6618	3.1468	1.3120	−3.4209	−0.0913	−3.6752	−3.6987	−0.9668

observed. For the winner portfolio, the average annualized arithmetic mean equals −2.9330%, while for the loser portfolio the annual yield, on average, is equal to 6.8208%. The return of the momentum portfolio, obtained by taking a long position on past winners (portfolio of commodities with high past returns) and a short position on past losers, equals −9.7538%. On the other hand, the reversal portfolio, which sells (long) past winners and buys (short) past losers, performs exceedingly well, with a yield equivalent to 9.7538%.

Moreover, it can be perceived that regarding the winner and momentum portfolios, the smaller the formation period, the less negative the returns; as well as that the larger the formation period, the more negative the returns. As for the loser and contrarian portfolios, it works the other way around, since the larger the formation period, the larger the returns, as well as that the smaller the holding period, the larger the return. Also, within the contrarian portfolio, the smallest return, on average, equals 4.9272% for the 6×6 strategy, whereas the largest return is 14.6875%, generated on the 24×6 strategy.

As for the portfolios created by means of the time-series analysis, the results are very similar, in context, to those observed on the cross-sectional analysis portfolios. The average annual yield for the winner portfolio equals 0.8536%, while for the loser portfolio is 5.9772%. In contrast with the cross-sectional portfolios, the winner time-series portfolio has, on average, a positive return, while the winner cross-sectional portfolio has a negative return. Regarding the loser portfolio, the yearly average return in the time-series portfolio is −0.8436% smaller, than the return of the cross-sectional portfolio. Likewise, regarding the momentum and contrarian portfolios, the contrarian portfolio has better returns than the momentum portfolio. The average annual return of the momentum time-series portfolio equals −5.1236%, while the average return for the contrarian time-series portfolio equals 5.1236% per annum. The results by ($J \times K$) strategies differ among the portfolios, but it can be observed that in the winner portfolio, only the 24×12 and 24×24 have negative yields, whereas the rest of the strategies are positive, although on average, with returns close to 1%. The loser portfolio, in contrast, has, on average, only positive returns, with yields in the range of 4.4669 and 7.4418%.

With regard to the influence of the size of the formation and holding periods on the portfolios, there's no clear influence of this subject within the winner and loser time-series portfolios, since the returns vary within the whole sample, as it can be seen from Tables 1–4; although for the reversal time-series portfolios, a slight improvement can be observed in the 24-month formation period with respect to the 6 and 12-month formation periods; whereas for the momentum time-series, there are better average returns within the 6 and 12-month formation periods.

The findings suggest that the returns of the portfolios constructed under the momentum strategy are better when performed under the time-series analysis, than within the cross-sectional analysis. This finding agrees with the hypothesis made by Moskowitz et al. (2012), although regarding the contrarian portfolios, the original[6] cross-sectional analysis produces better yields than the time-series analysis.

The fact that the reversal signal is stronger and more significant than the momentum signal can be described as unexpected for some, but at the same time as informative. When observing within Tables 5 and 6 the returns of the portfolios during the holding periods of both, the winner and loser portfolios, it can be perceived that most of the returns are negative for both portfolios during most of the sample period. An explanation for this can be that because of the individual returns of the commodities per month and their huge volatility, during one month they enjoy a large positive return, while on the next month, they finish up with a huge negative return. Furthermore, because of this reason, it was inferred and later confirmed that the larger the holding period, the smaller the return of the portfolios; because the larger the holding period, the larger the probability that the variability of the commodities and the portfolios diminish, thus generating small loses and returns.[7]

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Table 5. Returns per annum and per (*J* × *K*) strategy within the cross-sectional portfolios

	6 months HP				12 months HP				24 months HP			
	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)
6 months FP												
2000	3.2305	0.5776	2.6529	−2.6529	−21.1087	−4.0656	−17.0431	17.0431	−11.7046	1.1377	−12.8423	12.8423
2001	−19.7200	−14.8542	−4.8658	4.8658	−4.0362	−0.5492	−3.4870	3.4870	5.8147	10.3337	−4.5190	4.5190
2002	25.4044	35.0178	−9.6134	9.6134	10.8599	26.2124	−15.3525	15.3525	12.9401	21.7214	−8.7813	8.7813
2003	15.3664	19.8320	−4.4656	4.4656	7.1331	23.2533	−16.1203	16.1203	9.1738	16.5771	−7.4032	7.4032
2004	34.6151	15.6138	19.0013	−19.0013	11.4529	9.4865	1.9664	−1.9664	13.0681	14.7491	−1.6809	1.6809
2005	30.5546	23.2389	7.3157	−7.3157	12.8370	15.4124	−2.5754	2.5754	12.2278	18.0001	−5.7723	5.7723
2006	6.9950	14.3721	−7.3771	7.3771	7.0414	21.2077	−14.1663	14.1663	−3.6712	16.7104	−20.3816	20.3816
2007	23.4849	29.0476	−5.5627	5.5627	2.2103	8.4302	−6.2199	6.2199	−17.7573	−7.8518	−9.9054	9.9054
2008	−59.1068	−41.4445	−17.6623	17.6623	−39.4030	−19.4845	−19.9184	19.9184	−13.4498	3.4079	−16.8577	16.8577
2009	45.7245	44.6906	1.0340	−1.0340	18.0590	34.7658	−16.7068	16.7068	19.6052	26.7442	−7.1390	7.1390
2010	30.7543	44.9192	−14.1649	14.1649	17.7761	25.5209	−7.7448	7.7448	1.1943	6.6800	−5.4856	5.4856
2011	−9.1195	−13.9751	4.8556	−4.8556	−15.5530	−11.9765	−3.5765	3.5765	−12.0895	−8.2245	−3.8650	3.8650
2012	−9.6714	2.8155	−12.4868	12.4868	−9.7888	−1.9634	−7.8253	7.8253	−6.6738	2.2396	−8.9134	8.9134
2013	−1.5873	−0.3937	−1.1937	1.1937	3.3105	1.3977	1.9128	−1.9128	−13.0269	−10.1517	−2.8752	2.8752
2014	−38.4802	−18.7908	−19.6894	19.6894	−27.4750	−18.9155	−8.5594	8.5594	−19.3517	−16.2554	−3.0963	3.0963
2015	−36.0264	−19.4134	−16.6130	16.6130	−9.6957	−21.2863	11.5905	−11.5905	−4.8479	−10.6431	5.7953	−5.7953
12 months FP												
2000	−0.7707	6.9696	−7.7403	7.7403	−18.1096	1.8318	−19.9414	19.9414	−9.9417	5.3745	−15.3161	15.3161
2001	−19.9399	−12.2071	−7.7329	7.7329	−7.8564	5.2642	−13.1205	13.1205	4.8935	12.0580	−7.1645	7.1645
2002	5.7483	32.5222	−26.7739	26.7739	7.1481	28.2532	−21.1050	21.1050	9.4186	22.9155	−13.4969	13.4969
2003	12.0294	20.5383	−8.5089	8.5089	9.7631	15.8162	−6.0531	6.0531	12.6505	14.5053	−1.8548	1.8548
2004	1.1775	18.3452	−17.1677	17.1677	10.8212	12.5281	−1.7068	1.7068	16.9472	14.0742	2.8730	−2.8730
2005	10.4499	14.6196	−4.1697	4.1697	13.2022	16.2015	−2.9993	2.9993	8.5670	18.2298	−9.6628	9.6628
2006	8.2331	20.5471	−12.3140	12.3140	−1.2542	21.8512	−23.1054	23.1054	−4.8977	14.4733	−19.3710	19.3710
2007	17.9448	23.4559	−5.5111	5.5111	−1.9830	16.1536	−18.1366	18.1366	−17.1884	−1.9712	−15.2172	15.2172
2008	−75.4876	−35.4544	−40.0332	40.0332	−40.7794	−14.8170	−25.9624	25.9624	−14.5180	6.6596	−21.1776	21.1776
2009	13.7569	51.2445	−37.4877	37.4877	17.2478	34.7204	−17.4726	17.4726	16.8500	26.5248	−9.6748	9.6748
2010	29.3633	48.2788	−18.9155	18.9155	20.0493	26.8883	−6.8390	6.8390	1.4358	10.0770	−8.6412	8.6412
2011	−23.2312	−26.4612	3.2300	−3.2300	−18.9071	−17.9849	−0.9222	0.9222	−16.3402	−9.1263	−7.2139	7.2139

(Continued)

Table 5. (*Continued*)

	6 months HP				12 months HP				24 months HP			
	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)
12 months FP												
2012	−11.7969	−0.1754	−11.6215	11.6215	−11.4285	−4.6293	−6.7992	6.7992	−7.3842	2.8365	−10.2207	10.2207
2013	−1.8609	1.8273	−3.6882	3.6882	−3.1241	0.1592	−3.2834	3.2834	−14.6880	−10.9107	−3.7774	3.7774
2014	−15.4459	−11.3459	−4.1000	4.1000	−23.9285	−12.0405	−11.8880	11.8880	−16.6192	−11.5741	−5.0450	5.0450
2015	−19.8997	−34.9627	15.0630	−15.0630	−13.2598	−30.1577	16.8979	−16.8979	−6.6299	−15.0789	8.4489	−8.4489
24 months FP												
2000	−5.4958	1.9736	−7.4694	7.4694	−19.1735	−2.3034	−16.8702	16.8702	−9.4739	3.9476	−13.4216	13.4216
2001	−33.1575	−2.0314	−31.1260	31.1260	−12.4204	6.8800	−19.3004	19.3004	4.7587	13.3015	−8.5428	8.5428
2002	8.1578	30.1287	−21.9709	21.9709	10.0007	21.0396	−11.0389	11.0389	5.6048	21.0857	−15.4809	15.4809
2003	18.0505	19.0578	−1.0073	1.0073	9.5904	19.2411	−9.6507	9.6507	9.1034	15.2545	−6.1511	6.1511
2004	−0.212	16.5333	−16.7461	16.7461	6.4693	8.8987	−2.4294	2.4294	15.0109	13.9666	1.0443	−1.0443
2005	2.4417	10.4464	−8.0047	8.0047	13.6991	13.2943	0.4049	−0.4049	18.5862	19.6314	−1.0452	1.0452
2006	2.2666	23.4429	−21.1763	21.1763	−4.5214	20.9845	−25.5059	25.5059	−2.6200	23.4208	−26.0408	26.0408
2007	−15.0938	22.6486	−37.7423	37.7423	−25.2634	11.3883	−36.6517	36.6517	−26.4530	0.3124	−26.7654	26.7654
2008	−52.5132	−22.9300	−29.5832	29.5832	−35.6333	−3.3615	−32.2717	32.2717	−13.0528	7.8024	−20.8552	20.8552
2009	10.0065	49.5616	−39.5551	39.5551	8.5052	34.7767	−26.2716	26.2716	17.4088	21.1382	−3.7294	3.7294
2010	31.6328	39.8807	−8.2479	8.2479	22.6597	28.7096	−6.0500	6.0500	2.9346	6.9291	−3.9945	3.9945
2011	−29.3663	−17.0928	−12.2735	12.2735	−21.8838	−8.0185	−13.8653	13.8653	−19.7982	−3.5431	−16.2552	16.2552
2012	−8.6916	6.0900	−14.7816	14.7816	−16.7590	1.1301	−17.8891	17.8891	−14.9622	5.1512	−20.1134	20.1134
2013	−0.1288	1.3225	−1.4513	1.4513	2.9363	7.7206	−4.7844	4.7844	−11.0938	−7.6556	−3.4382	3.4382
2014	−14.0812	−8.7994	−5.2818	5.2818	−16.8268	−12.9333	−3.8935	3.8935	−13.4173	−10.5455	−2.8717	2.8717
2015	−14.0783	−35.4959	21.4176	−21.4176	−9.2815	−27.2746	17.9931	−17.9931	−4.6407	−13.6373	8.9966	−8.9966

Table 6. Returns per annum and per ($J \times K$) strategy within the time-series portfolios

	6 months HP				12 months HP				24 months HP			
	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)
6 months FP												
2000	−6.7229	2.9847	−9.7077	9.7077	−19.0528	−1.8316	−17.2212	17.2212	−9.5774	−0.1698	−9.4076	9.4076
2001	−12.3146	−11.1807	−1.1338	1.1338	0.0704	0.5411	−0.4707	0.4707	6.6391	8.4881	−1.8490	1.8490
2002	15.9992	35.2807	−19.2815	19.2815	12.4305	22.3070	−9.8765	9.8765	15.5384	20.1532	−4.6149	4.6149
2003	19.0243	18.1890	0.8353	−0.8353	15.9442	23.6673	−7.7232	7.7232	14.1939	16.7443	−2.5504	2.5504
2004	8.4662	12.9600	−4.4938	4.4938	14.3515	8.3927	5.9588	−5.9588	16.3036	11.7138	4.5899	−4.5899
2005	15.5315	28.2326	−12.7011	12.7011	17.3886	15.0510	2.3375	−2.3375	14.6918	17.1568	−2.4650	2.4650
2006	12.5288	15.4050	−2.8761	2.8761	12.4288	23.7523	−11.3235	11.3235	10.4939	18.1573	−7.6635	7.6635
2007	18.9821	26.6061	−7.6240	7.6240	10.0661	6.3910	3.6751	−3.6751	−9.6815	−9.5592	−0.1223	0.1223
2008	−48.3922	−48.2013	−0.1909	0.1909	−27.2360	−22.3861	−4.8499	4.8499	−3.2168	1.9711	−5.1879	5.1879
2009	16.8694	35.3236	−18.4542	18.4542	18.9639	26.4437	−7.4798	7.4798	17.2708	22.6879	−5.4170	5.4170
2010	25.7761	45.2554	−19.4793	19.4793	22.7056	25.1580	−2.4523	2.4523	6.4509	5.5662	0.8847	−0.8847
2011	−12.5630	−7.8629	−4.7001	4.7001	−9.4896	−10.6561	1.1665	−1.1665	−9.3666	−7.3864	−1.9802	1.9802
2012	−6.6777	3.0527	−9.7304	9.7304	−8.0286	−1.5567	−6.4719	6.4719	−5.4014	−0.3449	−5.0565	5.0565
2013	−2.1373	−0.3682	−1.7691	1.7691	3.4812	−0.5927	4.0739	−4.0739	−15.4854	−10.8432	−4.6423	4.6423
2014	−19.0558	−14.9545	−4.1013	4.1013	−25.4139	−16.4080	−9.0059	9.0059	−18.8275	−14.7309	−4.0966	4.0966
2015	−9.2368	−21.6541	12.4173	−12.4173	−7.6096	−16.2696	8.6600	−8.6600	−3.8048	−8.1348	4.3300	−4.3300
12 months FP												
2000	−0.2189	20.8338	−21.0527	21.0527	−15.1207	12.2604	−27.3811	27.3811	−10.0110	14.7087	−24.7197	24.7197
2001	−5.8515	−12.0246	6.1731	−6.1731	8.1409	2.9753	5.1655	−5.1655	9.2583	10.6698	−1.4115	1.4115
2002	25.7385	40.9076	−15.1691	15.1691	17.7242	22.3040	−4.5798	4.5798	5.3505	21.5426	−16.1921	16.1921
2003	14.2121	4.2190	9.9931	−9.9931	16.1896	3.6308	12.5588	−12.5588	13.9574	3.3238	10.6336	−10.6336
2004	3.5811	19.7359	−16.1548	16.1548	10.5625	11.6512	−1.0887	1.0887	16.7297	15.0230	1.7068	−1.7068
2005	24.7258	16.3280	8.3978	−8.3978	21.7013	19.8608	1.8405	−1.8405	14.4897	17.9741	−3.4844	3.4844
2006	9.7300	16.9402	−7.2102	7.2102	10.0868	12.8425	−2.7556	2.7556	9.3235	11.5262	−2.2028	2.2028
2007	24.9408	24.4369	0.5039	−0.5039	8.2629	22.9245	−14.6616	14.6616	−9.6271	16.6052	−26.2323	26.2323
2008	−43.8824	−67.8376	23.9552	−23.9552	−26.5463	−27.0055	0.4592	−0.4592	−3.0342	3.6683	−6.7025	6.7025
2009	32.0131	30.8490	1.1641	−1.1641	13.7305	23.3124	−9.5819	9.5819	16.4787	24.2459	−7.7673	7.7673
2010	28.2775	39.8533	−11.5758	11.5758	22.6506	19.2669	3.3837	−3.3837	5.3824	3.7011	1.6813	−1.6813

(*Continued*)

Table 6. (*Continued*)

	6 months HP				12 months HP				24 months HP			
	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)
12 months FP												
2011	−11.2991	−3.8707	−7.4284	7.4284	−8.5727	−18.3052	9.7325	−9.7325	−7.8942	−4.1206	−3.7737	3.7737
2012	−14.7771	4.9575	−19.7347	19.7347	−13.6716	−3.8566	−9.8149	9.8149	−9.6904	0.1806	−9.8710	9.8710
2013	1.1134	−3.4750	4.5883	−4.5883	−4.5332	−0.3134	−4.2198	4.2198	−18.9717	−10.7800	−8.1917	8.1917
2014	−15.2380	−10.8203	−4.4176	4.4176	−22.4285	−10.9139	−11.5147	11.5147	−15.9816	−10.8172	−5.1645	5.1645
2015	−22.6273	−19.8876	−2.7397	2.7397	−15.4856	−16.8075	1.3220	−1.3220	−7.7428	−8.4038	0.6610	−0.6610
24 months FP												
2000	3.5251	6.6883	−3.1632	3.1632	−17.8069	−0.2636	−17.5433	17.5433	−9.8566	6.5706	−16.4272	16.4272
2001	−32.3561	−17.2760	−15.0801	15.0801	−12.5557	0.9198	−13.4755	13.4755	2.3681	12.7964	−10.4283	10.4283
2002	16.1780	30.4059	−14.2279	14.2279	7.7050	21.2509	−13.5459	13.5459	−5.0785	21.7862	−26.8647	26.8647
2003	12.7979	−3.5378	16.3357	−16.3357	5.9700	12.8002	−6.8302	6.8302	7.1743	9.6818	−2.5076	2.5076
2004	8.7364	6.3216	2.4148	−2.4148	14.4498	4.0947	10.3550	−10.3550	17.8617	7.4729	10.3888	−10.3888
2005	24.9558	−2.1433	27.0991	−27.0991	24.3107	−0.6782	24.9888	−24.9888	19.2360	3.3815	15.8544	−15.8544
2006	4.3123	11.7014	−7.3892	7.3892	6.8756	14.0878	−7.2122	7.2122	8.0178	21.9439	−13.9261	13.9261
2007	26.8600	26.0831	0.7769	−0.7769	5.3554	1.1937	4.1617	−4.1617	−12.1092	−8.8177	−3.2915	3.2915
2008	−51.4430	−18.2193	−33.2237	33.2237	−34.2874	9.0297	−43.3171	43.3171	−6.9061	14.4200	−21.3260	21.3260
2009	11.9720	48.9373	−36.9653	36.9653	9.9504	32.5713	−22.6209	22.6209	14.1705	22.4764	−8.3059	8.3059
2010	33.7962	36.2777	−2.4816	2.4816	23.6342	24.0225	−0.3883	0.3883	5.7873	6.2041	−0.4168	0.4168
2011	−13.1150	−8.7618	−4.3532	4.3532	−9.4399	−3.8140	−5.6259	5.6259	−8.1818	−0.9937	−7.1881	7.1881
2012	−4.0460	17.6588	−21.7047	21.7047	−9.2694	8.2649	−17.5343	17.5343	−7.1939	12.9622	−20.1561	20.1561
2013	−1.8950	1.7207	−3.6158	3.6158	−3.5504	5.2886	−8.8390	8.8390	−5.3677	−7.1507	1.7830	−1.7830
2014	−26.8774	−10.7249	−16.1525	16.1525	−27.8292	−12.3427	−15.4865	15.4865	−17.8743	−10.4284	−7.4459	7.4459
2015	−13.1134	−22.8339	9.7205	−9.7205	−11.5806	−17.9179	6.3373	−6.3373	−5.7903	−8.9590	3.1687	−3.1687

Table 7. Monthly average return within the cross-sectional portfolios

	6 months HP				12 months HP				24 months HP			
	Winner (%)	**Loser (%)**	**Momentum (%)**	**Reversal (%)**	**Winner (%)**	**Loser (%)**	**Momentum (%)**	**Reversal (%)**	**Winner (%)**	**Loser (%)**	**Momentum (%)**	**Reversal (%)**
6 months FP												
January	1.2218	1.5863	−0.3645	0.3645	−0.3549	0.7821	−1.1371	1.1371	−0.3204	0.7357	−1.0561	1.0561
February	1.0771	1.4513	−0.3743	0.3743	−0.1535	0.7905	−0.9440	0.9440	−0.2456	0.6827	−0.9283	0.9283
March	0.8071	0.5229	0.2842	−0.2842	−0.1922	0.5824	−0.7746	0.7746	−0.0437	0.3845	−0.4282	0.4282
April	0.7647	0.6200	0.1447	−0.1447	0.0921	0.4800	−0.3879	0.3879	0.1063	0.4123	−0.3060	0.3060
May	−0.0103	−0.2533	0.2429	−0.2429	−0.4251	0.2117	−0.6367	0.6367	−0.4048	0.1627	−0.5675	0.5675
June	−0.2725	0.1792	−0.4517	0.4517	0.0918	0.1031	−0.0114	0.0114	0.0684	0.3404	−0.2720	0.2720
July	−0.7303	−0.1754	−0.5550	0.5550	−0.0537	0.2671	−0.3209	0.3209	0.0487	0.1828	−0.1341	0.1341
August	−0.6116	−0.2342	−0.3773	0.3773	0.1274	0.2887	−0.1613	0.1613	0.0298	0.3396	−0.3098	0.3098
September	−0.3984	0.4859	−0.8843	0.8843	−0.2635	0.2543	−0.5178	0.5178	−0.2399	0.2835	−0.5234	0.5234
October	−0.2919	0.9073	−1.1992	1.1992	−0.5365	0.5565	−1.0929	1.0929	−0.3875	0.7917	−1.1792	1.1792
November	0.4678	1.4803	−1.0125	1.0125	−0.2057	0.5965	−0.8022	0.8022	−0.1707	0.5380	−0.7088	0.7088
December	0.6278	1.0080	−0.3802	0.3802	−0.3999	0.5524	−0.9523	0.9523	−0.2249	0.4695	−0.6943	0.6943
Best month	1.2218	1.5863	0.2842	1.1992	0.1274	0.7905	−0.0114	1.1371	0.1063	0.7917	−0.1341	1.1792
	January	January	March	October	August	February	June	January	April	October	July	October
12 months FP												
January	−0.3069	1.6130	−1.9199	1.9199	−0.3602	0.5693	−0.9295	0.9295	−0.2843	0.6037	−0.8880	0.8880
February	−0.7160	1.2506	−1.9666	1.9666	−0.5499	0.7114	−1.2612	1.2612	−0.2771	0.6020	−0.8791	0.8791
March	−0.9038	0.8399	−1.7437	1.7437	−0.6170	0.7833	−1.4003	1.4003	−0.2671	0.4733	−0.7403	0.7403
April	−0.4323	0.6051	−1.0373	1.0373	−0.2675	0.8337	−1.1011	1.1011	−0.1126	0.5717	−0.6843	0.6843
May	−0.4379	−0.3280	−0.1099	0.1099	−0.1073	0.4078	−0.5151	0.5151	−0.1470	0.3597	−0.5067	0.5067
June	−1.0705	0.3093	−1.3798	1.3798	−0.2870	0.5634	−0.8503	0.8503	−0.1332	0.5470	−0.6802	0.6802
July	−0.5124	0.1718	−0.6842	0.6842	−0.1691	0.5092	−0.6783	0.6783	−0.0232	0.5782	−0.6014	0.6014
August	−0.2773	−0.0859	−0.1914	0.1914	−0.3706	0.3572	−0.7278	0.7278	−0.2302	0.5142	−0.7445	0.7445
September	−0.3065	0.5945	−0.9009	0.9009	−0.3222	0.2301	−0.5523	0.5523	−0.2231	0.4049	−0.6280	0.6280
October	0.0280	0.7262	−0.6982	0.6982	−0.1624	0.2796	−0.4421	0.4421	−0.1482	0.5941	−0.7423	0.7423

(*Continued*)

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Table 7. (*Continued*)

	6 months HP				12 months HP				24 months HP			
	Winner (%)	**Loser (%)**	**Momentum (%)**	**Reversal (%)**	**Winner (%)**	**Loser (%)**	**Momentum (%)**	**Reversal (%)**	**Winner (%)**	**Loser (%)**	**Momentum (%)**	**Reversal (%)**
12 months FP												
November	0.2078	0.9451	−0.7373	0.7373	−0.3566	0.4569	−0.8134	0.8134	−0.1998	0.4951	−0.6949	0.6949
December	0.3695	0.7172	−0.3477	0.3477	−0.3302	0.5506	−0.8808	0.8808	−0.2947	0.4478	−0.7425	0.7425
Best month	0.3695	1.6130	−0.1099	1.9666	−0.1073	0.8337	−0.4421	1.4003	−0.0232	0.6037	−0.5067	0.8880
	December	January	May	February	May	April	October	March	July	January	May	January
24 months FP												
January	−0.4366	1.5393	−1.9760	1.9760	−0.5548	0.9085	−1.4633	1.4633	−0.3196	0.8218	−1.1414	1.1414
February	−0.3200	1.4195	−1.7396	1.7396	−0.5795	0.8442	−1.4238	1.4238	−0.1522	0.7015	−0.8537	0.8537
March	−0.5734	0.2762	−0.8496	0.8496	−0.3206	0.4932	−0.8138	0.8138	−0.0919	0.4998	−0.5917	0.5917
April	−0.8035	0.9608	−1.7643	1.7643	−0.2520	0.8176	−1.0696	1.0696	0.0002	0.6836	−0.6834	0.6834
May	−0.5682	−0.1464	−0.4218	0.4218	−0.2319	0.4729	−0.7048	0.7048	−0.1822	0.4564	−0.6385	0.6385
June	−0.7484	0.5330	−1.2815	1.2815	−0.3657	0.7017	−1.0674	1.0674	−0.2297	0.7164	−0.9461	0.9461
July	−0.8620	−0.1683	−0.6938	0.6938	−0.4300	0.4468	−0.8768	0.8768	−0.0998	0.5788	−0.6785	0.6785
August	−0.7401	0.2843	−1.0243	1.0243	−0.4686	0.5830	−1.0515	1.0515	−0.1645	0.5005	−0.6650	0.6650
September	−0.6494	0.8880	−1.5374	1.5374	−0.4813	0.5385	−1.0198	1.0198	−0.3111	0.4939	−0.8049	0.8049
October	−0.3653	1.1893	−1.5547	1.5547	−0.7422	0.4912	−1.2333	1.2333	−0.4057	0.5589	−0.9646	0.9646
November	−0.1335	1.0905	−1.2241	1.2241	−0.7008	0.4806	−1.1814	1.1814	−0.4195	0.5534	−0.9729	0.9729
December	−0.0659	0.5547	−0.6206	0.6206	−0.3665	0.7326	−1.0992	1.0992	−0.2556	0.7201	−0.9757	0.9757
Best month	−0.0659	1.5393	−0.4218	1.9760	−0.2319	0.9085	−0.7048	1.4633	0.0002	0.8218	−0.5917	1.1414
	December	January	May	January	May	January	May	January	April	January	March	January

Table 8. Monthly average return within the time-series portfolios

	6 months HP				12 months HP				24 months HP			
	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)
6 months FP												
January	0.6364	1.3828	−0.7464	0.7464	0.2882	0.7893	−0.5012	0.5012	0.1536	0.6047	−0.4511	0.4511
February	0.3296	1.1917	−0.8621	0.8621	−0.0025	0.8872	−0.8897	0.8897	−0.0775	0.7880	−0.8655	0.8655
March	−0.1109	0.4235	−0.5343	0.5343	0.1008	0.2952	−0.1944	0.1944	0.0990	0.5005	−0.4016	0.4016
April	0.0413	0.6341	−0.5927	0.5927	0.3079	0.6756	−0.3676	0.3676	0.3181	0.2833	0.0348	−0.0348
May	−0.7069	0.1220	−0.8289	0.8289	0.3865	0.3279	0.0585	−0.0585	0.2242	0.1863	0.0379	−0.0379
June	−0.0973	0.2160	−0.3133	0.3133	0.3976	0.0802	0.3174	−0.3174	0.3248	0.1401	0.1847	−0.1847
July	−0.6248	0.1469	−0.7717	0.7717	0.0292	0.1641	−0.1349	0.1349	0.2182	0.0361	0.1821	−0.1821
August	0.0890	−0.0996	0.1886	−0.1886	0.1036	0.4753	−0.3717	0.3717	0.1231	0.4177	−0.2947	0.2947
September	0.1842	0.7593	−0.5751	0.5751	0.0545	0.3985	−0.3439	0.3439	−0.0071	0.2486	−0.2557	0.2557
October	−0.1632	0.6662	−0.8294	0.8294	−0.1053	0.3599	−0.4651	0.4651	−0.1383	0.5750	−0.7133	0.7133
November	0.9094	1.3299	−0.4205	0.4205	0.3001	0.4593	−0.1592	0.1592	0.2220	0.3614	−0.1394	0.1394
December	0.5180	0.6692	−0.1512	0.1512	0.0769	0.2127	−0.1358	0.1358	0.1787	0.3250	−0.1463	0.1463
Best month	0.9094	1.3828	0.1886	0.8621	0.3976	0.8872	0.3174	0.8897	0.3248	0.7880	0.1847	0.8655
	November	January	August	February	June	February	June	February	June	February	June	February
12 months FP												
January	0.9042	1.1894	−0.2852	0.2852	0.5220	0.1431	0.3789	−0.3789	0.2169	0.3351	−0.1182	0.1182
February	0.1601	0.9576	−0.7975	0.7975	0.0700	0.3806	−0.3106	0.3106	−0.0195	0.5279	−0.5474	0.5474
March	−0.0991	0.4502	−0.5492	0.5492	−0.0454	0.2892	−0.3347	0.3347	0.0223	0.4248	−0.4025	0.4025
April	−0.0791	−0.4401	0.3609	−0.3609	−0.0098	−0.2883	0.2785	−0.2785	−0.1229	0.4506	−0.5735	0.5735
May	−0.3541	−0.1380	−0.2162	0.2162	0.1746	0.5536	−0.3790	0.3790	−0.0356	0.7219	−0.7575	0.7575
June	−0.4322	0.1648	−0.5970	0.5970	−0.0376	0.4609	−0.4985	0.4985	0.0433	0.4683	−0.4250	0.4250
July	0.0394	0.0212	0.0181	−0.0181	−0.0622	0.4003	−0.4624	0.4624	0.1614	0.5660	−0.4046	0.4046
August	0.9662	−0.3608	1.3270	−1.3270	0.3421	0.1139	0.2282	−0.2282	0.0938	0.5263	−0.4324	0.4324
September	0.0271	0.6702	−0.6430	0.6430	−0.0718	0.5693	−0.6411	0.6411	−0.0691	0.6345	−0.7036	0.7036
October	0.2529	0.8768	−0.6239	0.6239	0.1677	0.5596	−0.3919	0.3919	−0.0355	0.7020	−0.7376	0.7376
November	1.0797	2.3400	−1.2603	1.2603	0.3167	1.2586	−0.9419	0.9419	0.1527	1.0559	−0.9032	0.9032

(*Continued*)

Table 8. (*Continued*)

	6 months HP				12 months HP				24 months HP			
	Winner (%)	**Loser (%)**	**Momentum (%)**	**Reversal (%)**	**Winner (%)**	**Loser (%)**	**Momentum (%)**	**Reversal (%)**	**Winner (%)**	**Loser (%)**	**Momentum (%)**	**Reversal (%)**
12 months FP												
December	0.6873	0.5904	0.0970	−0.0970	0.0519	0.1734	−0.1216	0.1216	0.0932	0.4021	−0.3090	0.3090
Best month	1.0797	2.3400	1.3270	1.2603	0.5220	1.2586	0.3789	0.9419	0.2169	1.0559	−0.1182	0.9032
	November	November	August	November	January	November	January	November	January	November	January	November
24 months FP												
January	−0.0535	1.1188	−1.1723	1.1723	−0.0615	0.4179	−0.4795	0.4795	−0.1756	0.5743	−0.7498	0.7498
February	0.1754	1.1445	−0.9692	0.9692	−0.0126	0.6800	−0.6926	0.6926	−0.0079	0.9760	−0.9839	0.9839
March	0.3079	0.1361	0.1718	−0.1718	−0.1827	0.6274	−0.8100	0.8100	−0.0168	0.8056	−0.8224	0.8224
April	0.5282	0.6267	−0.0985	0.0985	0.1245	0.9613	−0.8368	0.8368	0.1788	0.6604	−0.4817	0.4817
May	−0.1454	0.3998	−0.5452	0.5452	−0.1124	0.6578	−0.7703	0.7703	−0.0606	0.5470	−0.6076	0.6076
June	−0.3894	0.6012	−0.9907	0.9907	−0.2972	0.9066	−1.2038	1.2038	−0.0864	0.7902	−0.8765	0.8765
July	−0.2700	0.0023	−0.2724	0.2724	−0.1690	0.2870	−0.4560	0.4560	0.0316	0.5130	−0.4814	0.4814
August	0.0809	−0.4276	0.5085	−0.5085	−0.1093	0.3019	−0.4112	0.4112	0.2081	0.3853	−0.1772	0.1772
September	−0.4917	0.8025	−1.2942	1.2942	−0.2164	0.4234	−0.6398	0.6398	0.0009	0.1758	−0.1749	0.1749
October	−0.0435	0.6358	−0.6794	0.6794	−0.2113	0.2071	−0.4184	0.4184	−0.0666	0.2507	−0.3173	0.3173
November	0.1438	1.0378	−0.8939	0.8939	−0.3249	0.3522	−0.6771	0.6771	−0.2384	0.3386	−0.5769	0.5769
December	0.1754	0.3156	−0.1402	0.1402	−0.1814	0.3340	−0.5154	0.5154	−0.0011	0.4423	−0.4434	0.4434
Best month	0.5282	1.1445	0.5085	1.2942	0.1245	0.9613	−0.4112	1.2038	0.2081	0.9760	−0.1749	0.9839
	April	February	August	September	April	April	August	June	August	February	September	February

Another reason that could explain these results can be found in the study by Gabriel (2015), in which he analyzes the negative impact the paper from Gorton and Rouwenhorst (2006) had on the commodities market, since after its publication, many investors favored the commodity markets more than ever and caused the market to have lower and even negative returns. Since in the majority of months, and therefore in most of the years, the returns are negative for both, the winner and loser portfolios within both strategies, the momentum results are also negative, while the reversal yields are significantly positive.

A further analysis of the results, which can be observed in Table 5, shows that they exhibit a January effect on most of the loser and contrarian portfolios on the cross-sectional analysis, just as within the paper by De Bondt and Thaler (1985), where they also perceive a January effect within these two portfolios.[8]

On the other hand, on Table 6 it can be observed that there's no indication of a January effect on the time-series analysis and that in fact, the months with the best returns within the loser and reversal portfolios are February and November. Regarding the winner and momentum portfolios, there's no January effect and there's no indication of any monthly seasonality effect.

Concerning the risk (standard deviation) for the contrarian portfolios,[9] the Sharpe ratio[10] is useful to understand how good the returns are in contrast with the risk each portfolio carries. The contrarian cross-sectional portfolio has a Sharpe ratio equal to 6.4306 which is extremely good, considering that a ratio of 3 is usually considered as excellent. On the other hand, the contrarian time-series portfolio carries an average Sharpe ratio of 3.1412, which is excellent even when considering that it's almost half the cross-sectional portfolio's Sharpe ratio.

When analyzing the average annual results, clearly the best investment strategy is to invest, in order, on the contrarian cross-sectional, loser cross-sectional, loser time-series and contrarian time-series portfolios. When analyzing further, the best strategies are located within the cross-sectional analysis and these are the $CON_{24\times6}$, $CON_{24\times12}$, $CON_{24\times6}$, and $CON_{24\times12}$; all of them returning, on average, at least 10% per annum.

In this study, in addition to calculating and analyzing returns and risks, other indicators like skewness and kurtosis are also examined. In statistics, skewness measures symmetry, whereas kurtosis measures "fat-tails." On one hand, skewness is very close to zero in all portfolios, although in almost half of them they're slightly negative and in the other half they're positive. When skewness is zero it means that the returns follow a normal distribution, while the negative skewness means that the left tail is longer than the right tail. When observing the results, it's visible that nearly all portfolios have kurtosis less than 3, which means that basically all the portfolios have thinner tails than a normal distribution (fewer outliers).

Table 9. Correlation matrix/correlation between the best strategies and indexes

Analysis	Best strategy	Index					Average
		S&P GSCI	S&P 500	T-bond	US FX	MSCI emerging markets	
Cross-sectional	MOM 6 × 6	0.5556	0.2304	0.2454	−0.2594	0.3060	0.2156
	CON 24 × 6	0.2080	−0.3340	−0.0634	−0.3605	0.2539	−0.0592
Time-series	MOM 6 × 24	−0.0437	0.0706	0.0103	−0.0952	0.1116	0.0107
	CON 24 × 12	−0.4388	−0.4164	−0.1917	0.1999	−0.3779	−0.2450
	Average	0.0703	−0.1124	0.0002	−0.1288	0.0734	−0.0195

Table 10. Yearly returns per ($J \times K$) strategy within the pre and post 2008 crisis cross-sectional portfolios

	6 months HP				12 months HP				24 months HP			
	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)
6 months FP												
'00 - September.'08 Avg	7.7892	8.9124	−1.1232	1.1232	−1.6421	8.1611	−9.8032	9.8032	0.3916	10.0676	−9.6760	9.6760%
October. '08 - '15 Avg	−3.5499	5.9683	−9.5182	9.5182	−3.0362	2.2119	−5.2480	5.2480	−4.4104	−0.4024	−4.0080	4.0080%
12 months FP												
'00 - September.'08 Avg	−3.9625	9.9437	−13.9062	13.9062	−3.6389	10.8453	−14.4843	14.4843	0.3185	11.4340	−11.1155	11.1155%
October. '08 - '15 Avg	−4.8356	4.2392	−9.0748	9.0748	−4.2149	0.7092	−4.9241	4.9241	−5.5491	−0.1351	−5.4140	5.4140%
24 months FP												
'00 - September.'08 Avg	−8.5864	11.1805	−19.7669	19.7669	−6.6900	10.1989	−16.8889	16.8889	−0.1330	12.8657	−12.9987	12.9987%
October. '08 - '15 Avg	−3.4665	5.0907	−8.5572	8.5572	−4.0504	4.2664	−8.3168	8.3168	−5.6470	0.5497	−6.1967	6.1967%

Table 11. Yearly average return of the pre and post 2008 crisis cross-sectional portfolios

	Winner (%)	Loser (%)	Momentum (%)	Contrarian (%)
'00 - September.'08	−1.7948	10.4010	−12.1959	12.1959
October. '08 – '15	−4.3067	2.4998	−6.8064	6.8064

Another evaluation being made in the research is on the number of months with positive returns within each strategy and its portfolios. The percentage of months with positive returns suggests that the winner and loser portfolios have many months with similar returns, especially within short formation periods. The momentum strategy portfolios from both analyses don't have any portfolio with at least 50% of months with positive returns, although it's clear that the time-series momentum portfolios have, in average, a higher percentage of months with positive returns than the cross-sectional momentum portfolios. Meanwhile, there's no portfolio within the contrarian portfolios with a 50% or less of months with positive returns. Besides, the cross-sectional portfolios offer better returns and more profitable months than the time-series portfolios within the reversal strategy, with up to 75% of the months being positive within the $CON_{24\times12}$ strategy.

Value at Risk (VaR) is also being considered in the study because it is one of the most important risk measures within finance, which summarizes the predicted maximum loss over a specific horizon within a given confidence level. The two most popular confidence levels, and both utilized in this paper, are the 95 and 99% confidence levels. The results obtained on the VaR calculation make the contrarian portfolios appear even better as an investment strategy since the VaR for these portfolios are nearly all negative, indicating that the portfolios have a high probability of making a profit. In general, within VaR, the cross-sectional portfolios offer better results for the contrarian portfolios than for the time-series portfolios.

Also important for the study, *t*-statistics indicate whether the observed results are simply by chance or not. Almost all of the *t*-stats obtained are very high, with many of them being close to 1, although there are three portfolios with an average *t*-stat smaller than 10%,[11] meaning that these three portfolios are significant at the 10% (0.10) significance level. The rest of the portfolios, which are all above 0.10, are not significant at any level, implying that the probability of the observed results being due to random chance is high.

Within the investments literature, the diversification of assets is one of the most important and significant topics. The approach for identifying if an asset is a good diversification tool, is by observing at its correlation with other assets or indexes. In Table 7,[12] the correlation between the best[13] momentum and reversal portfolios within both, the cross-sectional and time-series analysis; and the S&P GSCI, S&P 500, T-bond, US FX[14] and MSCI Emerging Markets Index (MSCI, 2012), can be observed. The cross-sectional momentum portfolio is the only portfolio that has a correlation larger than 0.5, although this moderate positive correlation only occurs with the S&P GSCI. In the rest of the portfolios, the correlations oscillate between 0.3060 and −0.4388, having, most of them, weak positive or negative correlation between the assets and indexes considered. The S&P GSCI, T-bond and MSCI Emerging Markets Index are the only assets and indexes in this study that have, on average, a positive correlation with the portfolios constructed under the two analyses, although they are very close to zero, which means that they have weak correlations with the portfolios. Both reversal portfolios have, on average, negative correlations with the assets and indexes, which makes them a good diversification tool within a portfolio involving any or all of these four assets or indexes, although in general, the correlation coefficients indicate that all portfolios in this study are good diversification tools within investment portfolios.

The second part of this study focuses on the pre and post 2008 global crisis analysis within the commodities market,[15] emphasizing the cross-sectional and time-series analyses on the momentum and contrarian strategies. Firstly, within the cross-sectional analysis,[16] the average annual

Table 12. Yearly returns per ($J \times K$) strategy within the pre and post 2008 crisis time-series portfolios

	6 months HP				12 months HP				24 months HP			
	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)	Winner (%)	Loser (%)	Momentum (%)	Reversal (%)
6 months FP												
'00 - September.'08 Avg	2.9576	9.2308	−6.2733	6.2733	3.5450	8.1791	−4.6341	4.6341	5.7689	9.1309	−3.3620	3.3620%
October. '08 - '15Avg	−1.3519	5.2825	−6.6344	6.6344	−0.0026	1.4395	−1.4421	1.4421	−3.3458	−1.1622	−2.1837	2.1837%
12 months FP												
'00 - September.'08 Avg	6.2287	7.3752	−1.1465	1.1465	5.1143	8.5137	−3.3994	3.3994	4.6944	12.4832	−7.7888	7.7888%
October. '08 - '15 Avg	−0.5605	5.0500	−5.6104	5.6104	−3.0427	−0.0922	−2.9505	2.9505	−4.5598	−0.0248	−4.5350	4.5350%
24 months FP												
'00 - September.'08 Avg	1.8815	4.4395	−2.5580	2.5580	−0.2059	5.9867	−6.1926	6.1926	2.1041	9.3329	−7.2288	7.2288%
October. '08 - '15 Avg	−2.2311	8.7521	−10.9832	10.9832	−3.6230	6.3620	−9.9849	9.9849	−3.0557	2.9908	−6.0465	6.0465%

return for the winner portfolio equals −1.7948%, for the loser portfolio 10.4010%, for the momentum portfolio −12.1959%, and for the reversal portfolio 12.1959%. On the other hand, within the time-series analysis,[17] the average returns per annum are 3.5654% for the winner portfolio, 8.2969% for the loser portfolio, −4.7315% for the momentum portfolio, and 4.7315% for the reversal portfolio. Just as with the average annual yield of the total sample, both, the pre and post 2008 crisis average annual returns for the momentum portfolios, are better within the time-series analysis than within the cross-sectional analysis. The contrarian cross-sectional portfolios perform the best, and even the contrarian cross-sectional post-crisis average annual yield is higher than both[18] contrarian time-series average annual yields.[19] In general, as expected, the pre-2008 crisis portfolios perform better than the post-2008 crisis portfolios, although the momentum portfolios constructed under both types of analyses perform better during the post-2008 crisis period than during the pre-2008 crisis period (Tables 12–14).

However, it's important to note that after the 2008 crisis, in 2009 and 2010, the winner and loser portfolios display large positive returns, but afterward, ever since 2011, these portfolios have had mostly negative returns, affecting, even more, the post-2008 crisis returns as a whole. Some of the numerous reasons that have negatively affected the commodity markets since 2011, are the global abundant supply and weak demand, the strengthening of the US dollar, and the cheapening of the oil (World Bank, 2015).

Within a more in depth analysis of the pre and post 2008 crisis, it can be observed that, usually, whenever there's a crisis like in 2001 and 2008, these years will have significant losses in both, the winner and loser portfolios, particularly when the formation and holding periods are short. When the

Table 13. Yearly average return of the pre and post 2008 crisis time-series portfolios

	Winner (%)	Loser (%)	Momentum (%)	Contrarian (%)
‘00 - September.‘08	3.5654	8.2969	−4.7315	4.7315
October. ‘08 - ‘15	−2.4192	3.1775	−5.5967	5.5967

Table 14. Returns of the assets and indexes used for calculating the correlation matrix

	Returns				
	T-bond (%)	GSCI (%)	S&P 500 (%)	BIS real effective exchange rate (%)	MSCI emerging markets (%)
2000	−22.0200	23.8456	−2.0613	7.6110	−30.6100
2001	0.2900	−37.8251	−18.9500	4.4594	−2.3700
2002	−24.0700	32.9413	−27.8230	−7.1542	−6.1700
2003	15.7700	10.2528	27.9053	−10.6043	55.8200
2004	1.4300	17.5309	4.3373	−2.4517	25.5500
2005	5.8400	32.9702	8.0332	3.6079	34.0000
2006	7.3600	0.4449	11.6498	−1.0985	32.1400
2007	−13.7900	34.1506	−4.2388	−7.4973	39.4200
2008	−50.4300	−55.8555	−51.2338	11.1193	−53.3300
2009	62.9500	40.7495	26.2575	−8.4026	78.5100
2010	−10.8000	18.5947	18.0361	−2.9862	18.8800
2011	−50.4700	2.0495	2.0235	2.9358	−18.4200
2012	−0.8700	0.2586	13.2339	−1.2885	18.2200
2013	61.6600	−2.2363	17.3863	4.0033	−2.6000
2014	−31.0100	−41.3567	11.2572	10.0709	−2.1900
2015	11.7700	−29.3886	2.4240	8.4095	−14.9200

formation and, especially, the holding periods are longer, the returns can even end up being positive.[20] During those years, momentum portfolios perform very poorly, especially when constructed by means of the cross-sectional analysis, since the returns of the winner portfolios are more negative than those of the loser portfolios, although the reversal portfolios perform really good, especially within longer formation periods, like in 2008, when the average returns for the $\mathrm{CON}_{24\times24}$ cross-sectional and time-series portfolios were 27.57 and 32.62%, respectively. Furthermore, during the next 1–2 years after the crisis year, it can be noticed that the winner portfolios, as well as the loser portfolios, perform extraordinarily, with significant yields. However, because of the higher yields of the loser portfolios, the momentum strategy is considered not a good investment option. On the other hand, the contrarian strategy presents itself as an optimal investment option for the next 1 and 2 years following a crash or crisis year, as it generates huge returns, like for example on the $\mathrm{CON}_{24\times6}$, where on 2009 it returns 39.5551% per annum within the cross-sectional portfolios and 39.9653% within the time-series portfolios.

5. Conclusion

This study examines the differences between cross-sectional and time-series within the momentum and reversal strategies, by means of using commodities as the assets in the portfolios. The results suggest that buying past loser commodities and shorting past winner commodities yields positive significant profits. The momentum strategy, on the other hand, is not the best of the strategies, since it produces mainly negative profits. Regarding the analyses, within the contrarian strategy, the cross-sectional analysis works better than the time-series, contrary to the time-series momentum, which performs better than the cross-sectional momentum, although these last two portfolio strategies still return negative yields. Volatility is very similar within the reversal and momentum portfolios within both analyses, but due to the statistically significant profits of the contrarian portfolios, the average Sharpe ratios for the cross-sectional and time-series contrarian portfolios are 6.4306 and 3.1412, respectively. It's worth mentioning that a portfolio with a Sharpe ratio of 3 offers a significant return on behalf of its bearing risk.

The results suggest that the best contrarian portfolios, regardless of the analysis, are those with a larger formation period, reflecting the observations made by De Bondt and Thaler (1985). On the other hand, when taking into account the holding periods, the portfolios returns differ from one analysis to the other.

The cross-sectional contrarian portfolios perform better within smaller holding periods, while, regarding the time-series contrarian portfolios, they perform better within larger holding periods. In general, the best portfolios in this study are the ones constructed following the contrarian strategy and especially when constructed under the cross-sectional analysis. The four portfolios with the best average annualized arithmetic means are the $\mathrm{CON}_{24\times6}$, $\mathrm{CON}_{24\times12,}$ $\mathrm{CON}_{12\times6}$, and $\mathrm{CON}_{12\times12}$. These portfolios return, on average, 14.6875, 13.0047, 11.7170 and 10.1523% per annum, respectively.

Regarding the time-series analysis, it performs better on momentum portfolios, as according to Moskowitz et al. (2012), and although its returns are negative, as with the cross-sectional analysis, it has a higher percentage of months with positive returns than its cross-sectional counterpart. The reason momentum doesn't perform well and has so many months and years with negative returns is because of the similar returns of both, the winner and loser portfolios. It's clear from the data that virtually every time (month or year) the winner portfolio has a negative return; the loser portfolios also have a negative return. Likewise, it can be observed that more than often the loser portfolio outperforms the winner portfolio. This last observation can be rationalized because of the process that a momentum portfolio follows for its construction, in which the winner portfolio is bought and the loser portfolio is shorted, the momentum portfolios are more prone to having negative returns than the contrarian portfolios, which are benefited whenever the loser portfolios outperform the winner portfolios.

Because of the high variability of the commodities from one month to the next one and also because of the way in which time-series portfolios are constructed, in which it analyzes the absolute performance of the asset, in contrast with the cross-sectional, which analysis the relative performance of assets over some period, time-series is prone to having months in which a portfolio has no assets. Even though the cut-off points for the time-series analysis were only of 1 and −1%, there are some months, especially within larger formation and holding periods, which have no commodities in one of its portfolios. This is more common during the years of crisis, in which some months during the year don't include commodities within the winner portfolio because there are no commodities with returns larger than 1%. Nonetheless, the time-series analysis follows that construction process so to not include "less" negative commodities in the winner portfolios, and instead only include the commodities that accomplish certain return, because then the return obtained should be more accurate. For this reason, the momentum and winner portfolios perform better under the time-series analysis than under the cross-sectional analysis, although it still produces negative yields.

Furthermore, there's existence of a January effect on the loser and contrarian portfolios within the cross-sectional analysis, just as the observation made by De Bondt and Thaler (1985), in which they observed the same phenomena within these two portfolios constructed via the cross-sectional analysis, although their observation is within the US stock market and the observation in this study is within the commodities market.

The weak and inexistent correlations found between the contrarian and momentum portfolios, and the S&P GSCI, S&P 500, T-bond, US FX, and MSCI Emerging Markets Index, supports the idea of the commodities being an appropriate tool as an investment diversification asset. This confirmation makes the contrarian portfolios look even better since they would improve the returns and lower the risk in a portfolio.

The period before the 2008 crisis, which in this study is the period between January 2000 and September 2008, produces mainly positive returns for the winner, loser, and contrarian portfolios within both, the cross-sectional and time-series analysis. However, after the crisis the winner portfolio returns mainly negative profits, whereas the loser and contrarian still yield positively, although they don't perform as well as during the pre-crisis period. There's also suggestions that after a crash in the market, like on 2001 and 2008, during the next 1 and 2 years, the yearly returns are highly significant. The latter suggests that the years following a crash or a crisis are ideal for investing on commodities portfolios under the contrarian strategy.

In general, the contrarian portfolios constructed under the cross-sectional analysis are the ideal portfolios, even during and after the crisis, since on average, they return about 9.7538% per annum. Time-series analysis proved to be the best option for momentum portfolio's construction, while on the other hand, cross-sectional analysis is the best within contrarian portfolios.

Commodities market has proved to be very volatile, but by using the correct strategies it can be beneficial within an investment portfolio. Buying the contrarian portfolios and shorting the momentum portfolios derives on a better investment opportunity than just investing on the contrarian portfolio, since the returns are virtually higher, even to the point of doubling the returns.

Concisely, this study provides the first study of cross-sectional and time-series within momentum and reversal, applied to the commodity markets. Furthermore, it analyzes the results generated within a pre and post 2008 crisis perspective. The findings reveal the profitability and superiority of the cross-sectional within the contrarian portfolios.

Some significant questions that remain are the impact of different weighting schemes when constructing the portfolios, the influence and effect that implementation and transaction costs have on these portfolios, as well as how a zero cut-off point on the time-series could affect the results. These questions are left for possible future analysis and research.

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Author details
Enrique Benavides Rosales[1]
E-mail: e.bdes@hotmail.com
[1] Essex Business School, University of Essex, Colchester, UK.

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Notes
1. Stocks, for example, are subject to short-selling restrictions.
2. In this paper, stocks are not used, but instead commodities are used.
3. RPDW: Reference Percentage Dollar Weights.
4. Observations made by Moskowitz et al. (2012), as well as by Bianchi et al. (2015).
5. Rest of the portfolios for momentum: 6 × 24, 12 × 24, 24 × 6, 24 × 12 and 24 × 24. Rest of the portfolios for the contrarian strategy: 6 × 6, 6 × 12, 6 × 24, 12 × 6, 24 × 6.
6. The paper by De Bondt and Thaler (1985) uses cross-sectional analysis for the whole study.
7. Within the cross-sectional analysis, the returns of the portfolios decrease when increasing the holding periods. This observation is not valid on the time-series analysis.
8. The paper by De Bondt and Thaler (1985) focuses on reversal portfolios, as well as in the cross-sectional analysis.
9. Here, only the Sharpe ratio of the contrarian portfolios are considered since the momentum portfolio has negative returns and its Sharpe ratio would be negative and not significant.
10. Sharpe ratio is also known as the reward/risk ratio.
11. $MOM_{12\times6}$, $MOM_{24\times6}$ and $MOM_{24\times12}$ within the cross-sectional analysis.
12. Sources: Datastream International, Bloomberg, and MSCI.
13. Best portfolio refers to the portfolio with the largest return.
14. US Dollar real effective exchange rate (REER).
15. The pre 2008 crisis period consists of January 2000 – September 2008, while on the other hand the post 2008 crisis data span is October 2008 – December 2015.
16. Results can be observed on Tables 8 and 9.
17. Results can be observed on Tables 10 and 11.
18. The pre and the post 2008 crisis contrarian time-series portfolios.
19. Contrarian cross-sectional average annual yield equals 6.8064%, while the contrarian time-series average annual yields for pre and post crisis portfolios is 4.7315 and 5.5967%, respectively.
20. Observation made on the loser portfolios with larger formation periods and larger holding periods within the time-series analysis.

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