Performance evaluation of commodity investments

Dimitrios I. Vortelinos*and Hanxiong Zhang †

March 30, 2016

Abstract

This paper extends a still ongoing debate on whether the choice of the performance measure influences the evaluation of investments by investigating the daily returns of 10 spots-based commodities and 16 futures-based commodities. We find that the choice of performance measures and samples do affect the rankings of commodity investments. There are commodities that show substantial changes in ranking if the performance measure is changed from the Sharpe ratio to an alternative measure. Our findings are robust in 6 unequal length subsamples, which reflect different market conditions. Given that a large number of commodity traders use margin trading and the volatility of commodity is very high, we argue that the use of multi performance measures, high frequency data, and multi market condition subsamples could has a positive influence on the commodity investment.

Keywords: Investment evaluation; Sharpe ratio; Commodities; Spot; Futures.

JEL Classification: C10; D81; G11; G29.

*Corresponding author. Lincoln Business School, University of Lincoln, UK. Contact at dvortelinos@lincoln.ac.uk, 0044-1522-835634 (tel.).

†Lincoln Business School, University of Lincoln, UK. Contact at hzhang@lincoln.ac.uk, 0044-1522-835639 (tel.).

1 Introduction

In this paper we extend a still ongoing debate on whether the choice of the performance measure influences the evaluation of investments by investigating the daily returns of 10 spots-based commodities and 16 futures-based commodities. This research question is interesting for a variety of audiences. For investment practitioners, they can select any measure they think can marketing their financial products best to investors. They can even turn to the simplest and most popular performance measure on the purpose of selecting the best investments within a set of given alternatives (Auer, 2015). For regulators, they can assess how practitioners should best present financial performances without misleading the information users. Researchers could gain insight into effectiveness of the existing performance measures which, in turn, enable them to develop more sophisticated performance measures accordingly.

The Sharpe ratio, defined as the mean excess return over the standard deviation of the returns generated by the investment (Sharpe, 1966), is the simplest and most popular performance measure for the financial investment industry. Sharpe ratio is competent only for normally distributed investment returns. Unfortunately, it is quite common to observe that investment returns are non-normally distributed (Eling and Schuhmacher, 2007). Even worse, Sharpe ratio is prone to manipulation and suffers from a number of technical biases. For example, some option-based strategies that maximize the Sharpe ratio but do not necessarily add value to the investor (Goetzmann et al., 2007). Under certain conditions, a very high return in a prospective period is penalized by a lower realization of the Sharpe ratio, because, intuitively, an investor would expect the Sharpe ratio to increase in such a situation (Schuster and Auer, 2012). Alternatively, one can rise the Sharpe ratio by generating an extremely negative excess return (Auer, 2013). Consequently, a large number of alternative performance measures emerged for the purpose of overcoming the limitations of Sharpe ratio.

Pedersen and Rudholm-Alfvin (2003), Eling and Schuhmacher (2007) and Eling (2008) examine the Sharpe ratio with a number of alternative performance measures (reward-to-risk ratios based on drawdowns, partial moments, and the Value at Risk (VaR)) through a variety of asset class datasets, and surprisingly find almost identical rank orderings across investments. These findings quickly stimulate further theoretical and empirical investigations.

From a theoretical perspective, Schuhmacher and Eling (2011) and Schuhmacher and Eling (2012) argue that if investment returns meet the location and scale (LS) condition of Sinn (1983) and Meyer (1987), the Sharpe ratio, adequately defined drawdown-based performance measure and certain performance measures based on partial moment, the VaR and other risk quantities yield identical rankings. Given that the location and scale (LS) condition is not satisfied by cross-sectionally different levels of skewness and kurtosis in financial investment returns data (Agarwal and Naik, 2004), it cannot sufficiently interpret the empirically observable ranking similarities (Auer and Schuhmacher, 2013).

From an empirical perspective, the findings are mixed. For example, Zakamouline (2011) reinvestigates the findings of Eling and Schuhmacher (2007) using one of their German hedge fund datasets. Through calculating the maximum upgrade, maximum downgrade, mean absolute change, and standard deviation of the change in the rankings, Zakamouline (2011) argues that a high rank correlation coefficient does not necessarily yield almost identical fund ranking orders, given that there are funds that show substantial changes in ranking if the performance measure is changed from the Sharpe ratio to an alternative measure. Ornelas et al. (2012) reinvestigate the findings of Eling (2008) using the US mutual fund dataset, and suggest that different performance measures do not yield similar rankings if their mean excess returns (numerators) are different. On the contrary, Eling et al. (2011) find that the choice of performance measure does not matter when they are tailored to a moderate investment style. However, when they are applied to investigate aggressive investment styles, rank correlations with the Sharpe ratio decrease significantly. Auer and Schuhmacher (2013) find that the adequately defined drawdown-based performance measures yields hedge fund rankings not too different from those shown with the Sharpe ratio when investors are primarily interested in picking the best investments and when a long return sample is applied to calculate performance measure estimates. While, the rankings are not strictly identical when small return sample is employed to evaluate hedge funds. Beyond the mutual fund and hedge fund datasets, Auer (2015) finds that the Sharpe ratio and 12 alternative performance measures based on drawdowns, partial moments, and the VaR yield almost identical rank orderings across 30 futures-based commodity investments. Auer (2015) also argues that his empirical findings are robust in several dimensions, for instance, the dataset, the time period, the return calculation method and the performance measure parametrization.

This paper contributes to the literature from several perspectives. First, we are the first to study whether the choice of the performance measure influences the evaluation of spots-based commodity investments. Even though Auer (2015) provides deep insight into 30 futures-based commodity investments, commodity investments remain under-studied relative to stocks, bonds, even mutual funds and hedge funds. In particular, it remains unclear whether Auerâs (2015) findings are justified by the spots-based commodity investments. Investment returns in the spots and futures market differ from one another as a result of the disparity in the timing of delivery of the underlying goods. Buying or selling of the physical commodities for immediate delivery occur at a price that both buyer and seller will refer to is the spots-based commodity price. In contrast, the price for the purchases or sales of future obligations to make or take delivery rather than the physical commodities is futures-based commodity price. The costs associated with carrying the physical commodities until the agreed delivery date is the cost to carry. When the market is in equilibrium, future price is the sum of spot price and total carrying costs (including dividend, convenience yield, storage cost, and cost of money). Futures-based commodity prices are regarded as more volatile than spots-based commodity prices due to lower trading costs and ease of shorting. Although conventional wisdom argues that futures markets perform the function of price discovery, the empirical findings are mixed (Silvapulle and Moosa, 1999; Pindyck, 2001; Garner, 2012).

Second, contrast to existing literature (Auer and Schuhmacher, 2013; Auer, 2015), which investigate the ranking similarities over time by simply splitting full investment returns sample into a number of equal length subsamples. We divide the full sample into 6 unequal length subsamples according to the market conditions as defined in literature, namely, 1 growth subsample and 5 crisis subsamples. The rationale for distinguishing market conditions is driven by the fact that there is an increase in the correlation between investment assets during volatile periods (Loretan and English, 2000; Ang and Bekaert, 2002). Amira et al. (2011) argues that the increase in the correlation is driven by the historical return and the market direction rather than the volatility. If the returns sample is typically recession, then not only may the estimated volatilities be too high, but, perhaps the estimated ranking correlations will be higher than average. However, it remains unclear whether the market conditions influences the choice of performance measure.

Third, contrast to the majority of literature (Eling and Schuhmacher, 2007; Eling, 2008; Eling et al., 2011; Zakamouline, 2011; Auer and Schuhmacher, 2013; Auer, 2015)[1], we use daily data instead of monthly data. This is because daily data react much quicker to the arrival of new information and thereby yield greater precision in the estimates of the investment risk (Burghardt and Walls, 2011). For monthly data, even fairly large changes in market conditions would require longer time to detect. Considered that commodities' high volatility and a large number of commodity investors use margin trading, investors might be kicked out from the market even in the case of monthly return is zero. Therefore, daily data is superior to the monthly data in quantifying the investment risk.

Overall, our empirical findings suggest that the choice of performance measure matters for both of spots- and futures-based commodity investment, which is roughly in line with Ornelas et al. (2012) and Zakamouline (2011) but contrast to Auer and Schuhmacher (2013) and others, especially Auer (2015).

The reminder of the paper is organized as follows: Section 2 describes main features of our data. Section 3 presents empirical methodology. Section 4 shows the empirical results and robustness checks. Section 5 concludes the paper.

2 Data

In this paper, we use a dataset consisting of daily data for 10 spots-based commodities and 16 futures-based commoditiesâ prices over the sample from 1st September 1998 through 22nd August 2014. All commodity prices are denominated in US Dollar. Our spots-based commodities dataset covers 10 metal commodities (zinc, tin, silver, platinum, palladium, nickel, lead, copper, gold, aluminum). Our futures-based commodities dataset includes 5 energy commodities (natural gas, heating oil, gasoline, crude oil,

[1]Ornelas et al. (2012) use both monthly and daily data to study the choice of performance measure for ranking of US mutual funds. The rest of relevant literature use monthly data only.

and Brent crude oil) and 11 soft commodities (wool, wheat, sugar, soybeans, rubber, rice, oat, cotton, corn, coffee, cocoa). We obtain the real-time commodities prices from the Trading Economics. The selection of spots- and futures-based commodities are determined by the availability of data at the Trading Economics. We calculate the daily investment return as equation (1).

$$r_t = lnP_t - lnP_{t-1} \tag{1}$$

where, P_t is the spot price of commodity on day t, ln denotes for natural log. We calculate the excess returns of these commodity investments using the daily 10-year US government bond yield as a proxy for the daily risk-free rate instead of the 1-month Treasury bill rate as in Auer and Schuhmacher (2013) and Auer (2015). This is because the typical commodity traders in particular oil producers, usually have a much longer investment horizon and higher opportunity cost than the typical mutual fund investors. Our sample size is roughly comparable to Auer (2015), which uses monthly futures-based commodity data over the sample from January 2002 to September 2013.

2.1 Data description

In this subsection, there is a short description of each of commodities.

2.1.1 Energy commodities

Energy commodities have been recently researched by Doran and Ronn (2008). The time series properties of crude oil were examined in Sevi (2015). In the present study, Brent crude oil, crude oil, gas, gasoline and heating oil are the energy commidities evaluated.

Natural gas price is measured in USD/MMBtu. MMBtu equals to 1 million BTU (British thermal unit) and is standardized to 28.263682 m3 of natural gas at defined temperature and pressure. Natural gas accounts for almost a quarter of United States energy consumption, and the NYMEX Division natural gas futures contract is widely used as a national benchmark price. The futures contract trades in units of 10,000 million British thermal units (mmBtu). The price is based on delivery at the Henry Hub in Louisiana, the nexus of 16 intra- and interstate natural gas pipeline systems that draw supplies from the regionâs prolific gas deposits. The pipelines serve markets throughout the U.S. East Coast, the Gulf Coast, the Midwest, and up to the Canadian border.

Heating oil price is measured in USD/GAL. A gallon is 231 cubic inches or approximately 3.785 liters for liquids. It is also known as No. 2 fuel oil, accounts for about 25% of the yield of a barrel of crude, the second largest âcutâ after gasoline. The heating oil futures contract trades in units of 42,000 gallons (1,000 barrels) and is based on delivery in New York harbor, the principal cash market trading center. Options on futures, calendar spread options contracts, crack spread options contracts, and average price options contracts give market participants even greater flexibility in managing price risk. The heating oil futures contract is also used to hedge diesel fuel and jet fuel, both of which trade in the cash market at an often stable premium to NYMEX Division New York harbor heating oil futures.

Gasoline (US dollars per gallon) is the largest single volume refined product sold in the United States and accounts for almost half of national oil consumption. The NYMEX Division New York harbor unleaded gasoline futures contract and reformulated gasoline blend stock for oxygen blending (RBOB) futures contract trade in units of 42,000 gallons (1,000 barrels). They are based on delivery at petroleum products terminals in the harbor, the major East Coast trading center for imports and domestic shipments from refineries in the New York harbor area or from the Gulf Coast refining centers.

Crude oil price is measured in US Dollar per BBL. BBL is defined as 42 US gallons, which is about 159 litres or 35 imperial gallons, and it can also be defined in those units, depending on the context. Crude oil is the worldâs most actively traded commodity, and the NYMEX Division light, sweet crude oil futures contract is the worldâs most liquid forum for crude oil trading, as well as the worldâs largest-volume futures contract trading on a physical commodity. Because of its excellent liquidity and price transparency, the contract is used as a principal international pricing benchmark. The contract trades in units of 1,000 barrels, and the delivery point is Cushing, Oklahoma, which is also accessible to the international spot markets via pipelines.

Brent crude oil (USD/BBL) is sourced from the North Sea. The name âBrentâ comes from the naming policy of Shell Oil, which originally named all of its fields after birds (in this case the Brent Goose). Oil production from Europe, Africa and the Middle East flowing West tends to be priced relative to this oil, i.e. it forms a benchmark. However, large parts of Europe now receive their oil from the former Soviet Union especially through Russia.

2.1.2 Metals

Precious metals have been recently researched in Caporin, Ranaldo and Velo (2015). Recently, the time series properties of gold were investigated in Kristjanpoller and Minutolo (2015). In the present paper, aluminium, copper, gold, lead, nickel, palladium, platinum, silver, tin and zinc are the metals researched.

Aluminium price is measured in USD/LB. Roman libra (LB), also knwon as libra pondo or pound, is 0.45359237 kilograms. Aluminium is a lightweight, corrosion resistant metal used mainly in aerospace applications, as a construction material, in packaging, automobiles and railroad cars. Resources of bauxites, the raw material for aluminum are only located in seven areas: Western and Central Africa (mostly, Guinea), South America (Brazil, Venezuela, Suriname), the Caribbean (Jamaica), Oceania and Southern Asia (Australia, India), China, the Mediterranean (Greece, Turkey) and the Urals (Russia). Aluminum futures and options contracts provide price transparency to the U.S. aluminum market, valued at about $35 billion per year in products and exports.

Copper (USD/MT) is another metal important fot international markets. Chile accounts for over one third of world's copper production followed by China, Peru, United States, Australia, Indonesia, Zambia, Canada and Poland. Major exporters of copper ores and concentrates are Chile, Peru, Indonesia, Australia , Canada, Brazil, Kazakhstan, United States, Argentina and Mongolia. The biggest importers of copper are China, Japan, India, South Korea and Germany. Copper market participants use the COMEX Division of high-grade copper futures and options to mitigate price risk. Copper is the world's third most widely used metal, after iron and aluminum, and is primarily used in highly cyclical industries such as construction and industrial machinery manufacturing. Profitable extraction of the metal depends on cost-efficient high-volume mining techniques, and supply is sensitive to the political situation particularly in those countries where copper mining is a government-controlled enterprise.

Gold price is measured in USD/t oz. The biggest producers of gold are China, Australia, United States, South Africa, Russia, Peru and Indonesia. The biggest consumers of gold jewelry are India, China, United States, Turkey, Saudi Arabia, Russia and UAE. Gold Futures are available for Trading in the Commodity Exchange (COMEX) which merged with the New York Mercantile exchange in 1994 and became the division responsible for metals trading. Half of the gold consumption in the world is in jewelry, 40% in investments, and 10% in industry. However, Gold is not only a precious metal but also a commodity vital for many industries. Gold is an excellent conductor of electricity, is extremely resistant to corrosion, and is one of the most chemically stable of the elements, making it critically important in electronics and other high-tech applications.

Lead (USD/MT) is a soft, malleable, ductile, bluish-white, dense metallic element, extracted from galena and found in ore with zinc, silver and copper. 80 percent of modern lead usage is in the production of batteries. Lead is also often used to line tanks that store corrosive liquids and as a shield against X and gamma-ray radiation. The biggest producers of lead are Australia, China and USA, followed by Peru, Canada, Mexico, Sweden, Morocco, South Africa and North Korea. Lead Futures are available for trading in The London Metal Exchange (LME). The standard contact has a size of 25 tonnes.

Nickel (USD/MT) is mainly used in the production of stainless steel and other alloys and can be found in food preparation equipment, mobile phones, medical equipment, transport, buildings, power generation. The biggest producers of nickel are Russia, Canada, New Caledonia, Australia, Indonesia, Cuba, China, South Africa, Dominican Republic, Botswana, Columbia, Greece and Brazil. Nickel futures are available for trading in The London Metal Exchange (LME). The standard contact has a weight of 6 tonnes.

Palladium (USD/t oz.) is a soft silver-white metal used mostly in the production of catalytic converters, electronics, dentistry, medicine, hydrogen purification, chemical applications, groundwater treatment and jewelry. The biggest producers of palladium are by fat Russia and South Africa followed by United States, Canada and Zimbabwe. Palladium Futures are available for trading in London Platinum and

Palladium Market and on the New York Mercantile Exchange. The standard contact weights 100 troy ounces.

Platinum (USD/t oz.) is among the world's scarcest metals. Supplies of platinum are concentrated in South Africa, which accounts for approximately 80% of supply; Russia, 11%; and North America, 6%. Because of the metal's importance as an industrial material, its relatively low production, and concentration among a few suppliers, prices can be volatile. For this reason, it is often considered attractive to investors.

Silver price is measured in US cents/t oz. Troy ounce (t oz) is a mass unit of troy weight system, is commonly used in measuring silver and other precious metals. 1 troy ounce is equal to 31.1034768 grams, or 1/12 per troy pound. In fact, the London silver fixing prices are fixed based on the unit of troy ounce; therefore, the silver prices of this website use the unit of troy ounce. Silver is a precious metal that plays a role in investment portfolios. The largest industrial users of silver are the photographic, jewelry, and electronic industries. The biggest producer of silver are: Mexico, Peru and China followed by Australia, Chile, Bolivia, United States, Poland and Russia.

Tin (USD/MT) is a silvery, malleable metal mainly used in the production of solder and to coat other metals to prevent corrosion. The biggest producers of tin are China, Malaysia, Indonesia, Peru, Thailand, Bolivia and Belgium. Tin Futures are available for trading in The London Metal Exchange (LME). The standard contact weights 5 tonnes.

Zinc price is measured in USD/MT; whereas, MT is an alternative term for tonne, a measurement of mass equal to one thousand kilograms. Zinc is a lightweight and corrosion-resistant metal. It is often used in die-casting alloys, castings, brass products, sheeting products, chemicals, medicine, paints and batteries. The biggest producers of zinc are. China, Peru, Australia, United States, Canada, India and Kazakhstan. Zinc Futures are available for trading in The London Metal Exchange (LME). The standard contact weights 25 tonnes.

2.1.3 Soft commodities

Not many papers have recently researched soft commodities. Here, cocoa, coffee, corn, cotton, oat, rice, rubber, soybeans, sugar, wheat and wool are researched.

Cocoa price is measured in US dollar (USD) per metric tonne (MT). The biggest producers of cocoa in the world are Cote d'Ivoire (34% of total in 2009/10 fiscal year), Ghana (17%), Indonesia (15%), Nigeria, Cameroon, Ecuador and Brazil. Cocoa has a wide variety of uses, from chocolate to cocoa butter to coloring agents for food products. Although cocoa is one of the world's smallest soft commodity markets, it has global implications on cocoa importers and exporters, food and candy producers, and the retail industry. The size of each contract is 10 metric tons and its commodity code is CJ. It is financially settled, and the final settlement price will be set at the value of New York Board of Trade cocoa futures contract on the termination day of the contract month, or as specified by the NYMEX Board of Directors.

Coffee price is measured in US cents per lb. Brazil is the biggest producer and exporter of coffee in the world; 33% of total production from September 2010 to August 2011. Colombia, India, Indonesia, Guatemala, Ethiopia, Mexico are also major producers. Coffee futures contracts that trade on the Inter Continental Exchange (ICE) are the world benchmark for Arabica coffee. The word "coffee" is believed to be come from Kaffe, Ehtiopia, where coffee originated in the 9th century. Derived from the coffee bean, it was not well-received, and at one time was even banned in Turkey and Egypt. The demand for coffee gradually increased until it has become one of the most popular beverages in the world.

Corn (USD/BU) is important for international trade and financial markets. Corn Futures are available for Trading in The Chicago Board of Trade (CBOT®) which was established in 1848 and is a leading futures and futures-options exchange. More than 3,600 CBOT member/stockholders trade 50 different futures and options products at the CBOT by open auction and electronically.

Cotton price is measured in US cents per lb. The biggest producers of cotton in the world are China (26% of total production in 2010/11 fiscal year) and India (22%), followed by United States, Pakistan, Brazil, Australia and Uzbekistan. The United States is the biggest exporter of cotton (40% of total exports). India, Australia, Brazil and Uzbekistan also have a big share in the cotton trade. Cotton, a soft fiber that grows around the cotton plant, is the world's most widely-used natural fiber for clothing.To maximize the needs of the cotton market, the New York Mercantile Exchange has made available a cocoa futures contract for trading on the CME Globex® trading platform and for clearing through NYMEX ClearPort® clearing. The size of each contract is 50,000 pounds and its commodity code is TT. It is financially settled, and the final settlement price shall be set at the value of the New York Board of Trade cotton futures contract on the termination day of the contract month, or as specified by the Board of Directors.

Oat price is measured in US cents (USX) per Bushel; whereas for oat, bushel is 32 lb or 14.5150 kilograms (Kgs). Oat is a species of cereal grain used mainly as a livestock feed and for human consumption. The biggest producers of oat are: European Union, Russia, Canada, Australia and United States. Oat Futures are available for trading in the Chicago Mercantile Exchange. The standard contract has 5,000 bushels, the equivalent 86 metric tons.

Rice is measured in USD per CWT; whereas, CWT is entitled hundredweight that equals to 100 pounds. China is the biggest producer of rice in the world (30% of total production in 2010/11 fiscal year), followed by India (21%), Indonesia (8%), Bangladesh (7%), Vietnam and Thailand. Biggest exporters of rice include Thailand (30% of total exports), Vietnam (20%), India (11%) and the United States (10%). The biggest consumer of rice is China, followed by India, Indonesia, Bangladesh and Vietnam. Rice Futures are available for Trading in The Chicago Board of Trade (CBOT®) which was established in 1848 and is a leading futures and futures-options exchange. More than 3,600 CBOT member/stockholders trade 50 different futures and options products at the CBOT by open auction and electronically.

Natural rubber price is measured in Malaysian ringgit (MYR) per kilogram (Kg). Rubber is a high resilience, extremely waterproof and stretchable material. Is used extensively in many applications and products, either alone or in combination with other materials. The biggest producers of rubber are China, Indonesia, Malaysia and Thailand. Others include: Papua New Guinea, Philippines, Singapore, Sri Lanka, Thailand, Vietnam, Cambodia and India. Rubber Futures are available for trading in Tokyo Commodity Exchange (TOCOM) and Malaysian Rubber Exchange.

Soybeans price is measured in USD/BU. The United States, Brazil, Argentina and Paraguay are the biggest producers and exporters of soybeans in the world, concentrating 85% of total production and 94% of total exports in 2010/11 fiscal year. China is the biggest importer of soybeans (60% of total imports) followed by the European Union, Mexico, Japan and Taiwan. Soybeans Futures are available for Trading in The Chicago Board of Trade (CBOT®) which was established in 1848 and is a leading futures and futures-options exchange. More than 3,600 CBOT member/stockholders trade 50 different futures and options products at the CBOT by open auction and electronically.

Sugar price is measured in US cents/LB. The biggest producer and exporter of sugar in the world is Brazil (23% of total production and 50% of total exports in the 2010/11 fiscal year). A significant amount of sugar is also produced in India, China, Thailand and the United States. Sugar futures contracts are available for trading in the New York Mercantile Exchange. The size of each contract is 112,000 pounds. Sugar was first thought to have been produced in Polynesia and later India, around 500 BC. It is primarily derived from sugar-cane, but other sugar sources include sugar beets, the date palm, sorghum, and the sugar maple. Sugar No. 11 is an extremely popular global sugar product. It is used in food and candy, rum, and even the fuel additive ethanol.

Wheat price is measured in USD/BU; whereas, BU is 1 bushel of wheat or soybeans = 60 pounds (77.2 Kg./hl.). The European Union, China, India, United States and Russia are the biggest producers of wheat in the world. THe United States is the biggest exporter of wheat (27% of total exports in 2010/11 fiscal year), followed by the European Union (17%), Australia (14%) and Canada (13%). Wheat Futures are available for Trading in The Chicago Board of Trade (CBOT®) which was established in 1848 and is a leading futures and futures-options exchange. More than 3,600 CBOT member/stockholders trade 50 different futures and options products at the CBOT by open auction and electronically.

Wool price is measured in Australian dollar (AUD) per 100 kilograms (Kg). Wool is the textile fiber obtained mostly from sheeps. The biggest producers of wool are: Australia, New Zealand, China and the United States. Wool Futures are available for trading in the Australian Wool Exchange. The standard contract is 20 farm bales, the equivalent of 2,500 kilograms.

2.2 Subsamples

Given that empirical findings may merely be a sample-specific phenomenon, we divide our full sample (from 1st September 1998 to 22nd August 2014) into 6 unequal length subsamples according to the market conditions as suggested in literature. These are:

(1) Argentina crisis sub-sample: December 1, 2001 - November 30, 2002: In this period, international markets were affected by the Argentine crisis, since the government of Argentina declared itself unable to pay its debts in December 2001 (Cho et al., 2015).

(2) Growth sub-sample: December 1, 2002 - August 31, 2008: This was a economic growth period with low inflation and expended international trade and financial flows particularly for the emerging and developing world.[2]

(3) Lehman Brothers crisis sub-sample: September 1, 2008 - December 7, 2010: This period starts with the expansion of the FED and ECB balance sheet, because of liquidity issues that seized financial markets following the collapse of Lehman Brothers (Cukierman, 2013).

(4) EU crisis sub-sample: December 8, 2010 - April 4, 2011: This period starts with the begging of the EU debt crisis and ends with the most influential period of the EU debt crisis (Cho et al., 2015).

(5) Greek crisis sub-sample: April 5, 2011 - March 31, 2012: This period starts after the end of the EU debt crisis up to the end of the Greek sovereign crisis. The ECB's rate of expansion of its balance sheet was accelerated by a 70.88% per annum (Cukierman, 2013).

(6) Post crisis sub-sample: April 1, 2012 - December 31, 2014: This period starts after the end of the Greek sovereign crisis up to the end of the sample. It can be considered as the ex-post crisis period, for the purposes of the present study.

In line with Auer (2015), Table 1 presents the minimum, maximum, mean, standard deviation, skewness, kurtosis, and the results of Jarque and Bera (1987) test for normality for the resulting excess returns for each commodity over the full sample and the 6 subsamples, respectively.

[Insert Table 1 about here]

Focusing on the full sample first, Table 1 suggests that the highest daily losses and gains are in the energy sector. For example, natural gas experiences a maximum daily loss (gain) of over 28.9% (37.8%). Brent oil (Cotton) shows the highest (lowest) mean excess returns, with a value of 0.0504% (-0.00278%). With 4.21% (0.98%), standard deviations take their highest (lowest) values for Natural Gas (Wool). With a few exceptions of Natural Gas, Coffee, Rice, Wheat and Wool, all excess return distributions are negatively skewed which suggests that there is a higher chance of achieving high negative excess returns than large positive ones. Apart from Corn, Cotton and Aluminum, all the rest of commodities report kurtosis values of larger than 3 indicate heavier tails and/or more peaked distribution than with a normal distribution. Furthermore, the null hypothesis of normally distributed excess returns is rejected for all

[2] Source: NBER Business Cycles available at http://www.nber.org/cycles/

commodities at the conventional significance level. The findings so far are roughly consistent with Auer (2015), although he uses futures-based monthly commodity indices. With a few exceptions, for example, the null hypothesis of normally distributed excess returns is not rejected for all commodities throughout the 6 subsamples, the findings of the subsamples are roughly consistent with the full sample.

3 Methodology

In order to make our empirical findings comparable to literature, Table 2 presents the 13 most widely used performance measures with their names, original developers, and basic formulas. With the exception of Upside potential ratio, all the performance measures use the mean excess return to proxy the reward measure (numerator). Given that the performance measures are mainly differ in terms of risk measure (denominator), we divide the 13 performance measures into four groups according to the method used to quantify risk as in Auer (2015).

[Insert Table 2 about here]

In financial investment industry, Sharpe ratio is the most frequently used and simplest performance measure (Eling and Schuhmacher, 2007; Auer, 2013; Auer, 2015). However, Sharpe ratio will underestimate risk and overestimate performance in an asymmetric return distribution (Eling and Schuhmacher, 2007). It is also prone to manipulation and suffers from a number of technical biases (Auer, 2013; Auer and Schuhmacher, 2013).

There are 5 drawdown-based performance measures, namely, Calmar ratio, Sterling ratio, Burke ratio, Pain ratio and Martin ratio. All the drawdown-based performance measures use the worst-case scenarios to quantify the risk. Specifically speaking, the Calmar ratio quantify risk by calculating the largest negative cumulative excess return. The Sterling and Burke ratios use the mean and the square root of the sum of squares of the k-th largest negative cumulative excess return to estimate the risk measure. Burke ratio is more sensitive to the outliers than the Sterling ratio (Auer and Schuhmacher, 2013). The Pain ratio and Martin ratio quantify risk by calculating the mean of the percentage decreases from the previous peak and the square root of the mean of the squared percentage decreases from the previous peak (Auer, 2015). Drawdown-based performance measures are poplar because these ratios illustrate what the commodity trading advisors are supposed to do best, continually accumulating gains while consistently limiting losses (Lhabitant, 2004; Eling and Schuhmacher, 2007). For the Sterling and Burke ratios, we choose the 5 largest drawdowns (k=5).

There are 4 partial moments-based performance measures, namely, Omega ratio, Sortino ratio, Kappa 3 ratio and Upside potential ratio. Differ from the rest ratios, the Upside potential ratio use the Higher Partial Moment (HPM) of order one rather than mean excess return to proxy the reward measure (numerator). However, all the partial moments-based performance measures use different order of Lower

Partial Moment (LPM) to quantify risk. LPMs take into account only negative deviations from a minimal acceptable excess return (which could be the risk-free rate, or cost of capital). The LPMs of order 0 meant for shortfall probability, LPM of order 1 can be explained as expected shortfall, and LPM of order 2 as semi-variance. The Omega, Sortino and Kappa 3 ratios use LPMs of order 1, 2 and 3, respectively. The Upside potential ratio use the LPM of order 2 (Eling and Schuhmacher, 2007).

There are 3 Value at Risk (VaR)-based performance measures. VaR quantifies the maximum loss of an investment within a given probability of $1a$ in a certain period. The conditional VaR has the advantage of meeting certain plausible axioms. When returns are not normally distributed, the Cornish-Fisher expansion could be applied to consider skewness and kurtosis in estimating the Modified Sharpe ratio (Artzner et al., 1999; Favre and Galeano, 2002; Auer, 2015). For VaR-based measures, we use a significance level of a=5%.

Given that negative mean excess returns may yield biased Sharpe ratio, we calculate the Sharpe ratio as $\mu/\sigma^{\mu/abs(\mu)}$(Auer, 2015). For positive excess returns, the formula is same to the standard Sharpe ratio μ/σ. In the case of an negative excess return, our adjusted Sharpe ratio yields $\mu\sigma$. Throughout the paper, we use this adjustment for the Sharpe ratio and analogously for the rest 12 performance measures.

4 Empirical results

4.1 Main results

In our empirical investigation, we take the perspective of a commodity trader who has access to the datasets presented in Section 2 and is interested in identifying the best commodity investment by evaluating a commodities ranking based on historical performance.

Firstly, Table 3 presents the rankings generated from each of our performance measures as well as a mean ranking across all measures. The 10 spots-based commodities are ranked from best (1) to worst (10), and the 16 futures-based commodities are ranked from best (1) to worst (16) according to the calculated values. Contrast to Auer (2015), Table 3 suggests the 13 performance measures do not yield almost identical fund ranking orders, given that there are spots-based daily commodities that show substantial changes in ranking if the performance measure is changed from the Sharpe ratio to an alternative measure. Take the full-sample for example, the classical Sharpe ratio rank Gold as the best (1) sports-based commodity investment but the partial moments-based Upside potential ratio rank it as the worst (10) investment. Similarly, the Sharpe ratio view Coffee as the 3rd worst (14) futures-based commodity investment but the Upside potential ratio view it as the best (1) investment. The ranking difference is further confirmed by the mean rankings presented in the rightest column of the table. In particular, the Sharpe ratio rank Copper as the 3rd best spots-based commodity investment. However, the mean rankings of Copper across the 13 performance measures is 9. The ranking difference is quite substantial, given that there is only 10 spots-based commodities. The similar findings also shown in the subsamples.

Throughout the 6 subsamples, Table 3 suggests that the performances of commodities are time varying even based on a given performance measure. For instance, the Sharpe ratio rank Coffee as the 4th (4) best futures-based commodity investment in the Argentina crisis subsample, the 3rd (14) worst in the Growth subsample, and the 2nd (2) best in the Greek crisis subsample. The similar findings also shown in the rest commodities.

[Insert Table 3 about here]

Kendall'sτ Spearman's ρ

Table 4 displays Kendallâs 'sτ and Spearmanâs 's ρ rank correlation coefficients between the rankings according to the classic Sharpe ratio and the alternative performance measures listed in the first column. Table 4 suggests that the classic Sharpe ratio reports very high and statistically significant positive correlation with respect to the drawdowns-based performance measures (Calmar, Sterling, Burke, Pain and Martin), which is roughly consistent with the findings of Auer and Schuhmacher (2013) and Auer (2015). Take the spots-based commodities in the full sample for example, the correlations vary from 0.6889 (Calmar ratio) to 1 (Martin ratio); and from 0.8788 (Calmar ratio) to 1 (Martin ratio) according to Kendallâs 'sτ and Spearmanâs 's ρ respectively. However, the rank correlations between Sharpe ratio and the rest performance measures shrink substantially. In particular, the rank correlation between Sharpe ratio and the Upside potential ratio turns to negative, -0.3333 and -0.3939, but statistically insignificant at the conventional significant level according to Kendallâs 'sτ and Spearmanâs 's ρ respectively, which is a clear contrast to Auer (2015). The futures-based commodities report very similar findings, although the correlation between Sharpe ratio and Upside potential ratio is still positive, 0.0333 (Kendallâs 'sτ) and 0.0765 (Spearmanâs 's ρ).

The sign and magnitude of the ranking correlations between Sharpe ratio and alternative performance measures are time varying throughout the 6 subsamples. Take the futures-based commodity for example, the ranking correlation between Sharpe ratio and Upside potential ratio ranging from -0.5706 (Post crisis subsample) to 0.4353 (the EU crisis subsample) according to the Spearmanâs 's ρ. Similarly, the rank correlations between Sharpe ratio and Conditional VaR fluctuate between 0.6441 (the Lehman Brothers crisis subsample) to -0.2912 (the EU crisis subsample). The similar findings hold for Kendallâs 'sτ. It implies that the numerator (mean excess return) of performance measures could substantially influence the investment evaluations (Ornelas et al., 2012).

[Insert Table 4 about here]

To further address the criticism of Zakamouline (2011) and Ornelas et al. (2012) that high rank correlations does not necessarily yield almost identical ranking orders. Table 4 also presents the descriptive statistics for the differences in ranks, namely, minimum differences (Min), maximum differences

(Max), mean absolute differences (MAD), and standard deviation of the absolute differences (SDAD), generating when the performance measure is replaced from the Sharpe ratio by an alternative performance measure. Turning to the ranking differences (the difference between Sharpe ratio rank and the 12 alternative performance measures), Table 4 further suggests that the choice of performance measures matters. This is because some commodities experience substantial changes in the ranking when an alternative performance measure is applied instead of the classic Sharpe ratio. This finding is roughly in line with Zakamouline (2011). For example, there is one spots-based (futures-based) commodity that moves down 6 (13) places and another one that moves up 9 (12) places when we use Upside potential ratio instead of the Sharpe ratio. On average, a commodity moves 4.2 (4.75) places in the ranking when one utilizes this alternative performance measure. The findings in the subsamples are roughly consistent with the full sample.

Given that investors are primarily interested in identifying the best investment (Auer and Schuhmacher, 2013), Table 5 presents the ranking difference statistics for the 5 commodities with the highest Sharpe ratio. In the full sample, there is one spots-based (futures-based) commodity that moves up 9 (12) places when we use the Upside potential ratio instead of the Sharpe ratio. Furthermore, drawdown-based performance measures could generate rankings significantly differ to the Sharpe ratio even in a very long sample. For instance, there is one spots-based (futures-based) commodity that moves down 2 (4) places and another one that moves up 1 (13) places when we use the Pain ratio instead of the Sharpe ratio, which is a clear contrast to Auer and Schuhmacher (2013) and Auer (2015). This findings still holds in the 6 subsamples. Our results confirm that high ranking correlation does not necessarily yield almost identical ranking orders.

The findings of subsamples suggest that the general market direction (recession or boom) is insufficient to explain the time varying commodity performances, either spots- or futures-based. This is partially because commodity prices are no longer simply determined by the demand and supply of market fundamentals. Especially, the continuing financialization of the commodity market since the early 2000s has caused increasing price volatility of non-energy commodities (Tang and Xiong, 2012; Auer, 2015). Overall, our findings imply the evaluation of commodities are not only sensitive to the choice of performance measures but also the selection of samples.

[Insert Table 5 about here]

One possible explanation for the general competing results between this paper and Auer (2015) may lie within the frequency of commodity returns. Daily data react much quicker to the arrival of new information and thereby yield greater precision in the estimates of the investment risk (Burghardt and Walls, 2011). For monthly data, even fairly large changes in market conditions would require longer time to detect.

5 Concluding remarks

Departing from literature especially Auer (2015), we find that the choice of performance measure does affect the rankings of commodity investments. Our findings are robust in 6 unequal length subsamples, which reflect different market conditions as defined in literature. The ranking correlations between the Sharpe ratio and the drawdown-based performance measures are very high throughout subsamples, this is in line with Auer (2015). However, such high ranking correlation does not generate high ranking similarity. Furthermore, the sign and magnitude of correlations between the Sharpe ratio and the rest performance measures in particular the Upside potential ratio, experience substantial changes over time. So, our finding is a clear contrast to Auer (2015) for the futures-based commodity investment but generally in line with Ornelas et al. (2012) and Zakamouline (2011) for mutual fund and hedge fund datasets.

Relative to Auer (2015), a possible reason for us to get different findings might be that we use daily data instead of monthly data. And daily data is more sensitive than monthly data in quantifying the investment risk.

Given that a large number of commodity traders use margin trading and the volatility of commodity is very high, we argue that the use of multi performance measures, high frequency intraday data, multi size subsamples could has a positive influence on the commodity investment. This refinement is left for future research.

References

[1] Agarwal, V., Naik, N. (2004). Risk and portfolio decisions involving hedge funds. Review of Financial Studies, 17, 63-98.

[2] Amira, K., Taamouti, A. and Tsafack, G. (2011). What drives international equity correlations? Volatility or market direction? Journal of International Money and Finance, 30(6), 1234-1263.

[3] Ang, A. and Bekaert, G. (2002). International asset allocation with regime shifts. Review of Financial Studies, 15(4), 1137-1187.

[2] Artzner, P., Delbaen, F., Eber, J.-M. and Heath, D. (1999). Coherent measures of risk. Mathematical Finance, 9(3), 203-228.

[5] Auer, B. (2013). The low return distortion of the Sharpe ratio. Financial Markets and Portfolio Management, 27(3), 203-228.

[6] Auer, B. (2015). Does the choice of performance measure influence the evaluation of commodity investments? International Review of Financial Analysis, 38, 142-150.

[7] Auer, B., Schuhmacher, F. (2013). Robust evidence on the similarity of Sharpe ratio and drawdown-based hedge fund performance rankings. Journal of International Financial Markets, Institutions and Money, 24, 153-165.

[8] Burghardt, G. and Walls, B. (2011). *Managed Futures for Institutional Investors: Analysis and Portfolio Construction*. New Jersey: Wiley.

[9] Burke, G. (1994). A sharper Sharpe ratio. Futures, 23(3), 56.

[10] Caporin, M., Ranaldo, A., Velo, G. (2015). Precious metals under the microscope: A high-frequency analysis. Quantitative Finance, 15(5), 743-759.

[11] Cho, S., Hyde, S. and Nguyen, N. (2015) Time-varying regional and global integration and contagion: Evidence from style portfolios. International Review of Financial Analysis, 42, 109-131.

[12] Cukierman, A. (2013). Monetary policy and institutions before, during, and after the global financial crisis. Journal of Financial Stability, 9, 373-384.

[13] Doran, J.S., and Ronn, E.I. (2008). Computing the market price of volatility risk in the enrgy commodity markets. Journal of Banking and Finance, 32(12), 2541-2552.

[14] Dowd, K. (2000). Adjusting for risk: An improved Sharpe ratio. International Review of Economics and Finance, 9, 209-222.

[15] Eling, M. (2008). Does the measure matter in the mutual fund industry? Financial Analysts Journal, 64(3), 54-66.

[16] Eling, M., Farinelli, S., Rossello, D. and Tibiletti, L. (2011). One-size or tailor-made performance ratios for ranking hedge funds? Journal of Derivatives and Hedge Funds, 16(4), 267-277.

[17] Eling, M., and Schuhmacher, F. (2007). Does the choice of performance measure influence the evaluation of hedge funds? Journal of Banking and Finance, 31(9), 2632-2647.

[18] Favre, L. and Galeano, J.-A. (2002). Mean-modified Value-at-Risk optimization with hedge funds. The Journal of Alternative Investments, 5(2), 21-25.

[19] Garner, C. (2012). *A Trader's First Book on Commodities: An Introduction to the World's Fastest Growing Market*. 2 edn. New Jersey: Pearson Education.

[20] Goetzmann, W., Ingersoll, J., Spiegel, M., and Welch, I. (2007). Portfolio performance manipulation and manipulation-proof performance measures. Review of Financial Studies, 20(5), 1503-1546.

[21] Gregoriou, G., Gueyie, J.P. (2003). Risk-adjusted performance of funds of hedge funds using a modified Sharpe ratio. Journal of Wealth Management, 6, 77-83.

[22] Jarque, C. M. and Bera, A. K. (1987) A test for normality of observations and regression residuals. International Statistical Review / Revue Internationale de Statistique, 55(2), 163-172.

[23] Kaplan, P., Knowles, J. (2004). Kappa: A generalized downside risk-adjusted performance measure. Journal of Performance Management, 8(3), 42-54.

[24] Keating, C., Shadwick, W. (2002). A universal performance measure. Journal of Performance Measurement, 6, 59-84.

[25] Kestner, L. (1996). Getting a handle on true performance. Futures, 25, 44-46.

[26] Kristjanpoller, W., and Minutolo, M.C. (2015). Gold price volatility: A forecasting approach using the Artificial Neural Network-GARCH model. Expert Systems with Applications, 42(20), 7245-7251.

[27] Lhabitant, F. S. (2004) *Hedge Funds: Quantitative Insights*. Chichester: Wiley.

[28] Loretan, M. and English, W. B. (2000) Evaluating 'correlation breakdowns' during periods of market volatility. International Finance Discussion Papers No. 658, Board of Governors of Federal Reserve System.

[29] Martin, P., McCann, B. (1998). *The investor's guide to fidelity funds: Writing strategies for mutual fund investing*. 2nd Ed. Redmond: Venture Catalyst Inc.

[30] Ornelas, J. R. H., Silva Jï¿œnior, A. F., and Fernandes, J. L. B. (2012). Yes, the choice of performance measure does matter for ranking of us mutual funds. International Journal of Finance & Economics, 17(1), 61-72.

[31] Pedersen, C. S., and Rudholm-Alfvin, T. (2003). Selecting a risk-adjusted shareholder performance measure. Journal of Asset Management, 4(3), 152-172.

[32] Pindyck, R. S. (2001) The dynamics of commodity spot and futures markets : A primer. The Energy Journal, 22(3), 1-29.

[33] Schuster, M. and Auer, B. R. (2012). A note on empirical Sharpe ratio dynamics. Economics Letters, 116(1), 124-128.

[34] Sevi, B. (2015). Explaining the convenience yield in the WTI crude oil market using realized volatility and jumps. Economic Modelling, 44, 243-251.

[35] Sharpe, W. (1966). Mutual fund performance. Journal of Business, 39(1), 119-138.

[36] Silvapulle, P. and Moosa, I. A. (1999). The relationship between spot and futures prices: Evidence from the crude oil market. Journal of Futures Markets, 19(2), 175-193.

[37] Sortino, F., van der Meer, R. (1991). Downside risk. Journal of Portfolio Management, 17, 27-31.

[38] Sortino, F., van der Meer, R., Plantinga, A. (1999). The Dutch triangle. Journal of Portfolio Management, 26, 50-57.

[39] Young, T. (1991). Calmar ratio: A smoother tool. Futures, 20, 40.

[40] Zakamouline, V. (2011). The performance measure you choose influences the evaluation of hedge funds. Journal of Performance Measurment 15(3), 48-64.

[41] Zephyr Associates (2006). Pain ratio. StatFacts Online Documentation.

Tables

Table 1A. Descriptive statistics of daily excess returns - Full sample							
	Minimum	*Maximum*	*Mean*	*Std. deviation*	*Skewness*	*Kurtosis*	*JB test*
Panel A. Spot commodities							
Aluminium	-0.0826	0.0607	9.91e-5	0.0137	-0.2442	2.50	6.24**
Copper	-0.1036	0.1173	3.51e-4	0.0171	-0.1265	4.47	15.44**
Gold	-0.1016	0.0738	3.70e-4	0.0113	-0.3434	6.27	23.08***
Lead	-0.1320	0.1301	3.47e-4	0.0208	-0.2229	3.62	14.90**
Nickel	-0.1836	0.1331	3.67e-4	0.0237	-0.1425	3.77	10.31**
Palladium	-0.1786	0.1584	2.76e-4	0.0216	-0.2979	6.35	28.01***
Platinum	-0.1027	0.0822	3.08e-4	0.0143	-0.4563	4.35	11.14**
Silver	-0.1518	0.1081	3.43e-4	0.0193	-0.9573	7.51	22.40***
Tin	-0.1145	0.1539	3.36e-4	0.0172	-0.2349	6.89	34.14***
Zinc	-0.1147	0.0961	1.97e-4	0.0188	-0.2239	3.11	14.71**
Panel B. Futures commodities							
Brent	-0.1363	0.1350	5.04e-4	0.0216	-0.0806	3.21	10.23**
Cocoa	-0.1928	0.1938	1.56e-4	0.0190	-0.2116	13.95	43.04***
Coffee	-0.2324	0.2257	9.89e-5	0.0238	0.4436	13.61	21.62***
Corn	-0.1211	0.1089	1.85e-4	0.0193	-0.1443	2.99	13.88**
Cotton	-0.1024	0.1000	-2.78e-5	0.0198	-0.0097	2.12	13.00**
Crude oil	-0.1709	0.1641	4.67e-4	0.0238	-0.2803	5.01	13.68**
Gas	-0.2890	0.3781	1.77e-4	0.0421	0.4831	9.12	25.61***
Gasoline	-0.2487	0.2441	2.92e-4	0.0262	-0.0531	6.91	14.62**
Heating oil	-0.1518	0.1032	3.78e-4	0.0218	-0.2588	3.29	27.61***
Oat	-0.2450	0.2371	2.81e-4	0.0247	-0.2069	18.10	42.98***
Rice	-0.2445	0.2808	7.77e-5	0.0178	0.2597	27.90	17.21**
Rubber	-0.0783	0.0752	1.79e-4	0.0093	-0.8467	7.77	22.21***
Soybeans	-0.1341	0.0761	1.48e-4	0.0164	-0.6421	5.41	11.29**
Sugar	-0.1266	0.1685	1.72e-4	0.0218	-0.0190	3.64	9.19**
Wheat	-0.2011	0.2259	1.74e-4	0.0215	0.0807	10.22	18.76**
Wool	-0.1348	0.1326	1.45e-4	0.0098	0.5113	54.84	279.23***

Notes. Table 1A reports the descriptive statistics (minimum, maximum, mean, standard deviation, skewness, kurtosis and JB test statistic) of the daily excess returns of all commodities in the Full sample

Table 1B. Descriptive statistics of daily excess returns - *Argentina crisis*							
	Minimum	*Maximum*	*Mean*	*Std. deviation*	*Skewness*	*Kurtosis*	*JB test*
Panel A. Spot commodities							
Aluminium	-0.0241	0.0520	-3.54e-5	9.43e-3	0.8322	3.31	1.67
Copper	-0.0308	0.0471	2.25e-4	0.0103	0.4731	1.44	1.06
Gold	-0.0264	0.0272	5.71e-4	7.87e-3	-0.0162	1.45	2.03
Lead	-0.0490	0.0304	-2.35e-4	0.0120	-0.1650	0.6284	1.03
Nickel	-0.0645	0.0883	1.36e-3	0.0198	0.2042	1.48	0.8887
Palladium	-0.0769	0.1285	-1.08e-3	0.0184	1.02	11.64	14.29**
Platinum	-0.0396	0.0369	7.47e-4	0.0112	-0.4888	1.32	1.76
Silver	-0.0399	0.0293	-2.31e-4	0.0107	-0.5641	1.10	2.15
Tin	-0.0675	0.0298	1.44e-4	0.0121	-1.00	4.45	4.63*
Zinc	-0.0353	0.0357	1.62e-4	0.0111	0.0831	1.13	3.13
Panel B. Futures Commodities							
Brent	-0.0663	0.0819	1.11e-3	0.0207	0.2431	1.45	2.29
Cocoa	-0.0837	0.0563	8.87e-4	0.0168	-0.9908	5.50	16.29**
Coffee	-0.0680	0.1042	1.89e-4	0.0245	0.3790	1.64	1.72
Corn	-0.0697	0.0565	6.54e-4	0.0148	-0.1017	3.29	4.77*
Cotton	-0.0868	0.0842	1.25e-3	0.0235	0.2091	1.39	2.35
Crude oil	-0.0622	0.0995	1.24e-3	0.0221	0.1922	1.29	1.91
Gas	-0.1967	0.1589	3.19e-3	0.0428	0.2385	2.55	3.66*
Gasoline	-0.0881	0.0790	3.80e-4	0.0273	-0.3748	0.4472	3.99*
Heating oil	-0.0800	0.0904	2.77e-4	0.0259	-0.3690	0.9578	6.80**
Oat	-0.1707	0.0602	-3.89e-4	0.0245	-1.99	10.76	9.25**
Rice	-0.0748	0.0764	6.66e-5	0.0193	0.0440	2.85	3.01
Rubber	-0.0193	0.0269	2.06e-3	8.11e-3	0.1317	0.2361	1.35
Soybeans	-0.0405	0.0510	7.83e-4	0.0129	-0.1040	1.16	1.39
Sugar	-0.1266	0.0954	7.96e-4	0.0251	-0.1482	2.60	0.5554
Wheat	-0.0464	0.0469	1.35e-3	0.0135	0.3283	1.08	2.33
Wool	-0.1348	0.1326	1.96e-3	0.0178	1.01	28.53	89.69***

Notes. Table 1B reports the descriptive statistics (minimum, maximum, mean, standard deviation, skewness, kurtosis and *JB* test statistic) of the daily excess returns of all commodities in the *Argentinacrisis* subsample.

Table 1C. Descriptive statistics of daily excess returns - *Growth*							
	Minimum	*Maximum*	*Mean*	*Std. deviation*	*Skewness*	*Kurtosis*	*JB test*
Panel A. Spot Commodities							
Aluminium	-0.0826	0.0531	4.36e-4	0.0141	-0.3964	2.83	6.25**
Copper	-0.1036	0.1155	1.02e-3	0.0180	-0.1646	3.51	7.40**
Gold	-0.0628	0.0406	6.41e-4	0.0113	-0.6684	2.86	11.05**
Lead	-0.1015	0.1063	9.59e-4	0.0227	-0.1645	2.11	8.06**
Nickel	-0.1836	0.1054	6.61e-4	0.0255	-0.2781	3.18	5.75**
Palladium	-0.1242	0.1059	9.47e-5	0.0220	-0.4285	4.53	23.76***
Platinum	-0.1027	0.0822	3.78e-4	0.0161	-0.6823	4.96	16.82**
Silver	-0.1461	0.1081	6.82e-4	0.0231	-0.9210	5.63	18.80**
Tin	-0.1145	0.1118	1.02e-3	0.0177	-0.4537	5.49	21.24***
Zinc	-0.0980	0.0771	5.22e-4	0.0210	-0.2700	2.09	8.99**
Panel B. Futures commodities							
Brent	-0.0848	0.1030	1.00e-3	0.0204	0.0493	1.52	3.15
Cocoa	-0.1928	0.1938	3.34e-4	0.0214	-0.5228	20.16	58.69***
Coffee	-0.0879	0.1297	4.09e-4	0.0205	0.1210	2.29	5.70**
Corn	-0.0722	0.0868	5.52e-4	0.0190	0.0591	1.27	6.25**
Cotton	-0.0757	0.0893	1.87e-4	0.0190	-0.0493	1.89	9.86**
Crude oil	-0.1225	0.0841	9.72e-4	0.0216	-0.3055	1.95	2.91
Gas	-0.2392	0.2634	4.51e-4	0.0430	0.2401	5.13	17.71**
Gasoline	-0.2487	0.1815	3.28e-4	0.0301	-0.2949	4.92	5.13**
Heating oil	-0.0970	0.1032	3.84e-4	0.0225	-0.0360	1.70	10.42**
Oat	-0.1127	0.0882	2.03e-4	0.0193	-0.2406	2.89	14.59**
Rice	-0.2445	0.1618	1.02e-3	0.0184	-1.11	26.49	20.31***
Rubber	-0.0387	0.0277	7.09e-4	7.55e-3	-0.5213	2.22	8.08**
Soybeans	-0.1338	0.0761	2.88e-4	0.0190	-0.6471	3.86	9.73**
Sugar	-0.1000	0.1685	4.35e-4	0.0214	0.1759	4.68	6.81**
Wheat	-0.0811	0.0847	3.63e-4	0.0193	0.0849	1.91	8.52**
Wool	-0.1117	0.1046	-2.11e-4	9.29e-3	-0.5970	60.91	246.30***

Notes. Table 1C reports the descriptive statistics (minimum, maximum, mean, standard deviation, skewness, kurtosis and *JB* test statistic) of the daily excess returns of all commodities in the *Growth* subsample.

Table 1D. Descriptive statistics of daily excess returns - *Lehman Brothers*							
	Minimum	*Maximum*	*Mean*	*Std. deviation*	*Skewness*	*Kurtosis*	*JB test*
Panel A. Spot Commodities							
Aluminium	-0.0755	0.0607	-2.01e-4	0.0193	-0.3583	0.7862	0.6167
Copper	-0.1032	0.1173	2.79e-4	0.0263	-0.1810	1.68	2.55
Gold	-0.0714	0.0687	8.95e-4	0.0149	0.0751	3.48	7.61**
Lead	-0.1320	0.1301	3.19e-4	0.0318	-0.2987	1.43	1.39
Nickel	-0.1374	0.1331	2.98e-4	0.0318	-0.0397	2.23	2.92
Palladium	-0.1786	0.1092	1.56e-3	0.0281	-0.6653	4.56	5.58**
Platinum	-0.0594	0.0464	7.49e-4	0.0133	-0.4025	1.83	1.69
Silver	-0.1248	0.0597	2.05e-3	0.0220	-0.8719	3.03	3.87*
Tin	-0.0994	0.1539	3.83e-4	0.0257	0.1149	3.81	6.37**
Zinc	-0.1147	0.0961	4.20e-4	0.0282	-0.2330	0.7421	0.6167
Panel B. Futures commodities							
Brent	-0.1113	0.1350	-3.65e-4	0.0274	0.1842	2.59	3.36
Cocoa	-0.0970	0.0880	1.53e-4	0.0204	-0.2236	3.03	8.38**
Coffee	-0.0827	0.0594	1.39e-3	0.0185	-0.0116	1.01	1.34
Corn	-0.1211	0.1089	2.04e-5	0.0266	-0.2656	2.60	5.96**
Cotton	-0.0750	0.0904	1.19e-3	0.0242	-0.0636	1.21	4.96
Crude oil	-0.1283	0.1641	-4.35e-4	0.0340	0.1278	3.55	8.13**
Gas	-0.2553	0.2839	-1.03e-3	0.0471	0.8426	9.18	8.97**
Gasoline	-0.1115	0.0676	1.10e-3	0.0206	-0.4810	1.97	2.27
Heating oil	-0.0997	0.0891	1.46e-3	0.0201	-0.0029	4.48	13.96**
Oat	-0.0866	0.1268	4.59e-4	0.0262	0.3695	2.53	5.87**
Rice	-0.0602	0.0427	-4.88e-4	0.0170	-0.0512	-0.0114	1.01
Rubber	-0.0579	0.0445	5.67e-4	0.0112	-1.63	7.87	23.04***
Soybeans	-0.1341	0.0620	7.23e-4	0.0170	-0.9119	7.84	5.41**
Sugar	-0.1166	0.1073	1.20e-3	0.0281	-0.3328	1.24	0.5195
Wheat	-0.0995	0.1254	-6.59e-5	0.0278	0.2206	2.17	4.17*
Wool	-0.0768	0.0523	2.82e-4	0.0091	-0.7876	19.18	105.01***

Notes. Table 1D reports the descriptive statistics (minimum, maximum, mean, standard deviation, skewness, kurtosis and *JB* test statistic) of the daily excess returns of all commodities in the *LehmanBrothers* subsample.

Table 1E. Descriptive statistics of daily excess returns - *EU crisis*							
	Minimum	*Maximum*	*Mean*	*Std. deviation*	*Skewness*	*Kurtosis*	*JB test*
Panel A. Spot Commodities							
Aluminium	-0.0256	0.0272	1.21e-3	0.0115	0.0112	-0.34	0.4696
Copper	-0.0410	0.0326	5.24e-4	0.0136	-0.2278	0.53	0.4551
Gold	-0.0257	0.0188	5.84e-5	8.63e-3	-0.8300	1.08	3.09
Lead	-0.0468	0.0429	1.99e-3	0.0184	-0.3260	0.17	0.5318
Nickel	-0.0473	0.0438	6.82e-4	0.0182	-0.1743	0.18	0.7303
Palladium	-0.0717	0.0506	3.54e-4	0.0203	-0.7410	1.41	1.83
Platinum	-0.0453	0.0264	-5.48e-4	0.0147	-0.7921	0.71	1.17
Silver	-0.1407	0.0497	-4.17e-3	0.0313	-1.31	3.96	1.26
Tin	-0.0443	0.0390	2.72e-3	0.0141	-0.6751	1.79	2.02
Zinc	-0.0525	0.0409	5.22e-4	0.0181	-0.2555	0.4936	0.4807
Panel B. Futures commodities							
Brent	-0.0327	0.0348	3.08e-3	0.0133	-0.0273	0.8209	1.41
Cocoa	-0.0568	0.0649	-5.36e-4	0.0197	-0.2749	1.79	2.55
Coffee	-0.0631	0.0520	-2.25e-3	0.0201	-0.3359	0.7817	0.4489
Corn	-0.0583	0.0622	3.31e-3	0.0223	0.3453	0.9891	2.53
Cotton	-0.0408	0.0525	4.87e-3	0.0264	-0.2424	-1.33	4.63*
Crude oil	-0.0400	0.0858	2.21e-3	0.0172	1.47	6.03	2.84
Gas	-0.0567	0.0731	-7.40e-4	0.0247	0.1365	0.0076	0.3913
Gasoline	-0.0722	0.0456	-3.16e-4	0.0212	-0.5518	1.16	0.8419
Heating oil	-0.0583	0.0520	-2.77e-4	0.0171	-0.4811	2.19	3.75*
Oat	-0.0604	0.0620	1.63e-4	0.0210	0.0597	0.8310	0.5709
Rice	-0.0541	0.0582	-2.12e-4	0.0204	0.0858	0.2352	0.2348
Rubber	-0.0783	0.0752	1.32e-3	0.0193	-0.5479	6.65	8.57**
Soybeans	-0.0449	0.0452	-1.35e-3	0.0136	0.0114	1.61	0.7549
Sugar	-0.0575	0.0653	-2.22e-3	0.0229	0.4993	0.5598	1.10
Wheat	-0.0654	0.0691	1.15e-3	0.0207	-0.0331	1.79	0.5653
Wool	-0.0419	0.0890	3.68e-3	0.0136	3.16	20.45	27.83***

Notes. Table 1E reports the descriptive statistics (minimum, maximum, mean, standard deviation, skewness, kurtosis and *JB* test statistic) of the daily excess returns of all commodities in the *EU crisis* subsample.

Table 1F. Descriptive statistics of daily excess returns - *Greek crisis*							
	Minimum	*Maximum*	*Mean*	*Std. deviation*	*Skewness*	*Kurtosis*	*JB test*
Panel A. Spot commodities							
Aluminium	-0.0513	0.0580	-8.59e-4	0.0148	-0.0817	1.27	0.7005
Copper	-0.0782	0.0668	-3.64e-4	0.0192	-0.0336	2.21	3.18
Gold	-0.0587	0.0379	6.44e-4	0.0136	-0.9662	2.70	6.49**
Lead	-0.0711	0.0741	-1.24e-3	0.0225	-0.0763	0.9728	1.70
Nickel	-0.0775	0.0779	-1.39e-3	0.0223	-0.0434	1.02	1.42
Palladium	-0.0857	0.0686	-7.23e-4	0.0216	-0.1754	1.59	1.51
Platinum	-0.0361	0.0437	-2.11e-4	0.0131	0.1379	0.8292	1.35
Silver	-0.0744	0.0698	8.34e-5	0.0184	0.1485	2.03	2.16
Tin	-0.0878	0.0702	-1.27e-3	0.0218	-0.4453	1.78	3.70*
Zinc	-0.0579	0.0585	-7.15e-4	0.0189	-0.1149	0.49	0.5393
Panel B. Futures commodities							
Brent	-0.0591	0.0378	2.19e-4	0.0157	-0.3666	0.95	1.66
Cocoa	-0.0483	0.0758	-8.75e-4	0.0194	0.5386	1.44	3.96*
Coffee	-0.0674	0.0646	-1.69e-3	0.0173	-0.0115	2.20	8.41**
Corn	-0.0696	0.0643	-4.98e-4	0.0206	-0.3343	1.41	5.42**
Cotton	-0.1024	0.1000	-3.03e-3	0.0231	-0.1096	2.20	3.84*
Crude oil	-0.0853	0.0513	-8.27e-6	0.0201	-0.7217	2.09	4.11*
Gas	-0.0787	0.0927	-2.87e-3	0.0273	0.3580	1.31	2.78
Gasoline	-0.0720	0.0380	5.89e-5	0.0158	-0.6116	2.37	5.94**
Heating oil	-0.0380	0.0458	2.39e-4	0.0118	0.2486	1.46	7.53**
Oat	-0.0868	0.0750	-1.48e-4	0.0207	-0.0031	2.90	5.37**
Rice	-0.0477	0.0644	2.29e-4	0.0158	0.4020	1.02	1.37
Rubber	-0.0762	0.0433	-1.11e-3	0.0122	-1.04	6.81	9.24**
Soybeans	-0.0483	0.0451	8.73e-4	0.0152	-0.0362	0.60	2.69
Sugar	-0.0522	0.0678	-7.88e-4	0.0151	0.0671	2.18	0.1011
Wheat	-0.1050	0.0653	-1.19e-3	0.0243	-0.4718	1.46	1.24
Wool	-0.0420	0.0247	-5.10e-4	6.48e-3	-1.76	13.77	124.26***

Notes. Table 1F reports the descriptive statistics (minimum, maximum, mean, standard deviation, skewness, kurtosis and *JB* test statistic) of the daily excess returns of all commodities in the *Greek crisis* subsample.

Table 1G. Descriptive statistics of daily excess returns - *Post debt crisis*							
	Minimum	*Maximum*	*Mean*	*Std. deviation*	*Skewness*	*Kurtosis*	*JB test*
Panel A. Spot Commodities							
Aluminium	-0.0357	0.0459	-2.43e-5	0.0114	0.3771	0.8843	0.7646
Copper	-0.0394	0.0606	-2.84e-4	0.0111	0.1265	2.38	3.73*
Gold	-0.1016	0.0543	-4.20e-4	0.0109	-1.44	13.98	10.05**
Lead	-0.0311	0.0520	1.60e-4	0.0123	0.2316	0.8551	0.6091
Nickel	-0.0658	0.0602	8.04e-5	0.0150	0.1086	1.25	1.08
Palladium	-0.0568	0.0530	4.88e-4	0.0134	-0.2915	2.10	3.67*
Platinum	-0.0446	0.0439	-4.03e-4	0.0100	0.0173	1.58	1.83
Silver	-0.1518	0.0688	-6.37e-4	0.0148	-1.78	19.78	12.51**
Tin	-0.0594	0.0639	-4.69e-5	0.0135	0.0671	3.27	7.22**
Zinc	-0.0321	0.0461	2.60e-4	0.0112	0.1694	0.5265	0.5550
Panel B. Futures commodities							
Brent	-0.0462	0.0474	-3.58e-4	0.0113	-0.2288	1.84	2.24
Cocoa	-0.0477	0.0367	4.81e-4	0.0122	-0.0148	0.9295	3.31
Coffee	-0.2324	0.2257	1.86e-4	0.0290	0.8043	28.07	35.24***
Corn	-0.0869	0.0667	-8.68e-4	0.0166	-0.2523	3.45	5.58**
Cotton	-0.0995	0.0833	-4.81e-4	0.0163	-0.4638	4.37	7.97**
Crude oil	-0.0599	0.0900	-2.06e-4	0.0135	0.1272	4.48	3.73*
Gas	-0.2702	0.3781	1.05e-3	0.0399	1.34	29.28	27.89***
Gasoline	-0.0762	0.2441	-1.05e-3	0.0189	3.80	48.72	30.74***
Heating oil	-0.0553	0.0931	-8.31e-4	0.0116	0.3651	9.42	21.84***
Oat	-0.2450	0.2371	1.00e-4	0.0294	-0.9327	28.36	28.55***
Rice	-0.1109	0.0512	-2.25e-4	0.0118	-1.31	13.19	2.95
Rubber	-0.0434	0.0337	-1.24e-3	0.0111	-0.4704	1.35	5.48**
Soybeans	-0.1096	0.0761	-6.05e-4	0.0146	-1.41	11.43	10.06**
Sugar	-0.0399	0.1419	-2.99e-4	0.0127	2.51	25.58	10.27**
Wheat	-0.2011	0.2259	-2.95e-4	0.0281	0.2401	17.83	20.26***
Wool	-0.0460	0.0491	-3.06e-4	0.0078	0.0626	13.33	97.59***

Notes. Table 1G reports the descriptive statistics (minimum, maximum, mean, standard deviation, skewness, kurtosis and *JB* test statistic) of the daily excess returns of all commodities in the *Postdebtcrisis* subsample.

Table 2. Performance measures				
No.	Performance measure	Original proposal	Reward measure	Risk measure
Classic				
1	*Sharpe* ratio	Sharpe (1966)	μ	σ
Based on drawdowns				
2	*Calmar* ratio	Young (1991)	μ	MDD
3	*Sterling* ratio	Kestner (1996)	μ	$K^{-1}\sum_{k=1}^{K} CDD_k$
4	*Burke* ratio	Burke (1994)	μ	$\left[\sum_{k=1}^{K} CDD_k^2\right]^{1/2}$
5	*Pain* ratio	Zephyr Associates (2006)	μ	$T^{-1}\sum_{t=1}^{T} DDP_t$
6	*Martin* ratio	Martin and McCann (1998)	μ	$\left[T^{-1}\sum_{t=1}^{T} DDP_t^2\right]^{1/2}$
Based on partial moments				
7	*Omega* ratio	Keating and Shadwick (2002)	μ	LPM_1
8	*Sortino* ratio	Sortino and van der Meer (1991)	μ	$[LPM_2]^{1/2}$
9	*Kappa*3 ratio	Kaplan and Knowles (2004)	μ	$[LPM_3]^{1/3}$
10	*Upside potential* ratio	Sortino et al. (1999)	HPM_1	$[LPM_2]^{1/2}$
Based on Value at Risk (VaR)				
11	*Excess return on VaR*	Dowd (2000)	μ	VaR_a
12	*Conditional Sharpe* ratio	Agarwal and Naik (2004)	μ	$CVaR_a$
13	*Modified Sharpe* ratio	Gregoriou and Gueyie (2003)	μ	$MVaR_a$

Notes. Table 2 presents the investment performance measures applied in our study. $\mu = T^{-1}(R_1 + \cdots + R_T)$ and $\sigma = \left[T^{-1}\left\{(R_1-\mu)^2 + \cdots + (R_T-\mu)^2\right\}\right]^{1/2}$ are the mean and the standard deviation of the excess returns $R_t = r_t - r_{f,t},\ t = 1,...,T$ of a given commodity. $r_t = lnP_t - lnP_{t-1}$ is the daily natural log return, P_t is the daily commodity price. MDD denotes for the largest negative cumulative excess return; CDD_k is the k-th largest negative cumulative excess return that is not interrupted by a positive excess return; DDP_k denotes a negative cumulative excess return from the previous peak. k is the number of continuous drawdowns incorporated in the calculation. The signs of the drawdowns are dropped to generate positive risk measures. $HPM_m{=}T^{-1}\sum_{t=1}^{T} max\,(R_t,0)^m$ and $LPM_m{=}T^{-1}\sum_{t=1}^{T} max\,(-R_t,0)^m$ are higher and lower partial moments of order m. VaR_a denotes for the Value at Risk (VaR) at the a-quantile of the excess return distribution; $VaR_a{=}-(\mu+\sigma z_a)$. The conditional VaR is estimated as $CVaR_a{=}B^{-1}\sum_{R_t \le -VaR_a} -R_t$, B is the number of excess returns fulfilling the summation condition. The modified VaR ($MVaR_a$) is estimated as $MVaR_a{=}-\left[\mu+\sigma\left\{z_a+\left(z_a^2-1\right)\gamma/6+\left(z_a^3-3z_a\right)k/24-\left(2z_a^3-5z_a\right)\gamma^2/36\right\}\right]$, where z_a is the a-quantile of the standard normal distribution, γ and κ denote skewness and excess kurtosis of the excess return distribution (Auer, 2015).

Table 3A. Investment rankings - Full sample

	Classic	Based-on-drawdowns					Based-on-partial-moments				Based-on-the-Value-at-Risk			
Sample	*Sharpe*	*Calmar*	*Sterling*	*Burke*	*Pain*	*Martin*	*Omega*	*Sortino*	*Kappa3*	*Upside*	*Excess*	*Conditional*	*Modified*	*Mean*
Panel A. Spot commodities														
Aluminium	10	9	10	10	10	10	10	10	10	9	10	8	8	8
Copper	3	1	2	2	4	3	4	2	2	6	4	9	9	9
Gold	1	2	1	1	1	1	1	1	1	10	1	1	1	1
Lead	6	6	6	6	6	6	6	6	6	2	6	2	2	2
Nickel	7	5	7	7	7	7	7	5	5	1	5	4	4	4
Palladium	8	8	8	8	8	8	8	8	8	3	9	3	3	3
Platinum	2	4	3	3	3	2	2	7	7	8	2	5	5	5
Silver	5	7	5	5	5	5	5	4	4	4	3	7	7	7
Tin	4	3	4	4	2	4	3	3	3	7	7	10	10	10
Zinc	9	10	9	9	9	9	9	9	9	5	8	6	6	6
Panel B. Futures commodities														
Brent	1	1	1	1	2	1	2	1	1	4	1	1	1	1
Crude oil	10	11	8	9	9	11	9	10	10	12	11	12	12	12
Gas	15	13	13	13	15	13	15	14	14	7	14	9	9	9
Gasoline	8	4	10	8	8	8	8	8	8	11	6	3	3	3
Heat oil	16	16	16	16	16	16	16	16	16	10	15	10	10	10
Cocoa	2	2	3	2	4	3	4	2	2	3	3	2	2	2
Coffee	14	14	15	14	13	14	14	13	12	1	13	16	16	15
Corn	7	5	7	7	7	7	7	5	4	2	7	4	4	4
Cotton	4	3	4	3	3	4	5	3	3	5	2	7	7	7
Oat	6	7	5	6	6	6	6	4	5	6	8	8	8	8
Rice	13	15	14	15	14	15	13	15	15	13	16	13	13	16
Rubber	3	6	6	5	5	2	3	7	7	15	4	5	5	5
Soybeans	9	9	9	10	10	9	10	12	13	14	5	11	11	11
Sugar	12	12	12	12	12	12	12	11	11	8	10	14	14	14
Wheat	11	10	11	11	11	10	11	9	9	9	12	15	15	13
Wool	5	8	2	4	1	5	1	6	6	16	9	6	6	6

Notes. Table 3A reports the investment rankings of the Spot and Futures commodities in the Full sample.

Table 3B. Investment rankings - Argentina crisis sub-sample														
	Classic	Based-on-drawdowns					Based-on-partial-moments				Based-on-the-Value-at-Risk			
Sample	*Sharpe*	*Calmar*	*Sterling*	*Burke*	*Pain*	*Martin*	*Omega*	*Sortino*	*Kappa3*	*Upside*	*Excess*	*Conditional*	*Modified*	*Mean*
Panel A. Spot commodities														
Aluminium	10	10	10	10	10	10	10	10	10	9	10	5	5	10
Copper	5	5	5	5	6	5	5	7	7	7	8	6	6	8
Gold	1	3	1	1	1	1	1	4	4	10	1	7	7	3
Lead	7	7	7	7	7	7	7	6	6	5	6	2	2	2
Nickel	2	1	2	2	2	3	2	1	1	1	3	8	8	4
Palladium	4	4	4	4	4	4	4	2	2	2	4	9	9	6
Platinum	3	2	3	3	3	2	3	3	3	3	2	1	1	1
Silver	6	6	6	6	5	6	6	5	5	8	5	3	3	5
Tin	9	9	9	9	9	9	9	9	9	4	7	4	4	7
Zinc	8	8	8	8	8	8	8	8	8	6	9	10	10	9
Panel B. Futures commodities														
Brent	7	3	6	6	7	6	8	7	7	8	8	14	14	11
Crude oil	9	9	9	9	6	9	5	8	8	11	4	7	7	7
Gas	15	14	15	15	15	15	15	15	15	7	15	8	9	15
Gasoline	10	10	10	10	10	10	10	11	11	14	10	4	4	4
Heat oil	8	7	8	7	8	7	9	6	6	5	6	3	3	3
Cocoa	6	8	7	8	9	8	7	5	5	6	9	15	15	12
Coffee	4	4	4	4	4	4	4	3	2	1	3	1	1	2
Corn	13	12	12	12	12	12	13	13	13	2	13	6	6	8
Cotton	14	13	14	14	14	14	14	14	14	3	14	16	16	14
Oat	12	15	13	13	13	13	12	12	12	9	12	9	8	13
Rice	16	16	16	16	16	16	16	16	16	10	16	10	10	16
Rubber	1	1	2	1	2	1	1	2	3	16	1	11	11	5
Soybeans	5	6	5	5	5	5	6	9	9	15	5	12	12	10
Sugar	11	11	11	11	11	11	11	10	10	4	11	5	5	6
Wheat	3	2	3	3	3	3	3	4	4	13	2	13	13	9
Wool	2	5	1	2	1	2	2	1	1	12	7	2	2	1

Notes. Table 3B reports the investment rankings of the Spot and Futures commodities in the Argentina crisis sub-sample.

Table 3C. Investment rankings - Growth sub-sample

	Classic	Based-on-drawdowns					Based-on-partial-moments				Based-on-the-Value-at-Risk			
Sample	*Sharpe*	*Calmar*	*Sterling*	*Burke*	*Pain*	*Martin*	*Omega*	*Sortino*	*Kappa3*	*Upside*	*Excess*	*Conditional*	*Modified*	*Mean*
Panel A. Spot commodities														
Aluminium	5	5	5	5	5	5	5	8	8	9	5	7	7	7
Copper	3	1	1	1	3	1	3	2	2	6	4	9	9	8
Gold	2	2	3	3	2	2	2	4	4	10	1	3	3	2
Lead	4	4	4	4	4	4	4	3	3	2	3	10	10	10
Nickel	7	8	8	7	8	7	7	6	6	1	8	2	2	3
Palladium	10	10	10	10	10	10	10	10	10	5	10	8	8	9
Platinum	9	9	9	9	9	9	9	9	9	8	9	4	4	4
Silver	6	6	6	6	6	6	6	5	5	3	7	6	6	6
Tin	1	3	2	2	1	3	1	1	1	7	2	1	1	1
Zinc	8	7	7	8	7	8	8	7	7	4	6	5	5	5
Panel B. Futures commodities														
Brent	3	2	3	3	3	3	3	2	2	5	3	14	14	8
Crude oil	11	11	8	10	7	11	8	10	10	14	15	8	8	12
Gas	8	7	7	8	9	8	9	7	8	7	9	9	9	11
Gasoline	5	4	6	5	6	5	6	5	5	8	4	10	10	9
Heat oil	16	14	16	16	16	16	16	16	16	13	12	11	11	16
Cocoa	4	3	4	4	4	4	4	4	3	3	2	3	3	3
Coffee	14	16	14	15	15	15	13	9	7	1	16	15	15	15
Corn	13	15	13	13	13	13	15	13	13	2	14	4	4	4
Cotton	10	6	10	11	10	10	11	8	9	4	8	16	16	13
Oat	15	12	15	14	14	14	14	15	15	11	11	7	7	7
Rice	2	5	1	2	2	2	2	1	1	12	5	1	1	1
Rubber	1	1	2	1	1	1	1	3	4	15	1	2	2	2
Soybeans	12	9	12	12	12	12	12	14	14	10	7	5	5	5
Sugar	7	8	9	7	8	7	7	6	6	6	10	12	12	10
Wheat	9	10	11	9	11	9	10	12	11	9	6	13	13	14
Wool	6	13	5	6	5	6	5	11	12	16	13	6	6	6

Notes. Table 3C reports the investment rankings of the Spot and Futures commodities in the Growth sub-sample.

Table 3D. Investment rankings - Lehman Brothers sub-sample														
	Classic	Based-on-drawdowns					Based-on-partial-moments				Based-on-the-Value-at-Risk			
Sample	*Sharpe*	*Calmar*	*Sterling*	*Burke*	*Pain*	*Martin*	*Omega*	*Sortino*	*Kappa3*	*Upside*	*Excess*	*Conditional*	*Modified*	*Mean*
Panel A. Spot commodities														
Aluminium	8	6	10	8	8	8	9	10	10	8	6	8	8	8
Copper	7	8	7	7	7	7	7	9	9	6	9	9	9	10
Gold	2	2	2	2	2	2	2	3	3	9	4	1	1	1
Lead	9	9	9	9	9	9	8	7	7	1	8	6	6	6
Nickel	10	10	8	10	10	10	10	8	8	2	10	7	7	7
Palladium	4	3	3	3	3	4	3	2	2	3	3	4	4	4
Platinum	3	4	4	4	4	3	4	4	4	10	2	2	2	2
Silver	1	1	1	1	1	1	1	1	1	5	1	3	3	3
Tin	5	5	5	6	5	5	5	6	6	7	7	10	10	9
Zinc	6	7	6	5	6	6	6	5	5	4	5	5	5	5
Panel B. Futures commodities														
Brent	12	12	13	12	13	12	13	13	13	7	12	14	14	14
Crude oil	14	14	14	14	14	14	14	14	14	12	14	8	8	9
Gas	1	2	2	2	2	2	2	2	2	11	1	3	3	3
Gasoline	16	16	16	16	16	16	16	16	16	8	16	10	10	15
Heat oil	5	3	3	4	5	5	6	3	3	4	4	11	11	10
Cocoa	13	13	12	13	12	13	12	12	12	3	13	15	15	13
Coffee	10	11	10	10	10	10	10	6	6	1	10	16	16	11
Corn	3	4	4	3	4	4	5	4	4	9	3	5	5	5
Cotton	2	1	1	1	1	1	1	1	1	10	2	1	1	1
Oat	11	9	11	11	11	11	11	11	11	6	11	12	12	12
Rice	9	7	9	9	9	9	9	10	10	14	7	4	4	4
Rubber	4	6	8	8	6	3	3	8	8	15	5	9	9	8
Soybeans	6	8	7	6	7	6	7	7	7	13	6	6	6	6
Sugar	7	5	6	5	8	7	8	5	5	2	8	2	2	2
Wheat	15	15	15	15	15	15	15	15	15	5	15	13	13	16
Wool	8	10	5	7	3	8	4	9	9	16	9	7	7	7

Notes. Table 3D reports the investment rankings of the Spot and Futures commodities in the Lehman Brothers sub-sample.

Table 3E. Investment rankings - EU crisis sub-sample

	Classic	Based-on-drawdowns					Based-on-partial-moments				Based-on-the-Value-at-Risk			
Sample	*Sharpe*	*Calmar*	*Sterling*	*Burke*	*Pain*	*Martin*	*Omega*	*Sortino*	*Kappa3*	*Upside*	*Excess*	*Conditional*	*Modified*	*Mean*
Panel A. Spot commodities														
Aluminium	4	2	2	2	2	3	4	4	4	7	4	10	10	5
Copper	5	5	5	5	5	6	5	7	7	8	6	3	3	4
Gold	10	10	10	10	10	10	10	10	10	10	10	9	9	10
Lead	3	3	3	3	4	4	2	3	3	1	3	2	2	2
Nickel	6	6	6	6	6	5	6	5	5	5	7	5	5	6
Palladium	9	9	9	9	9	9	9	9	9	3	9	7	7	8
Platinum	7	8	8	8	7	7	7	6	6	9	5	8	8	9
Silver	2	4	4	4	3	2	3	2	1	4	1	4	4	3
Tin	1	1	1	1	1	1	1	1	2	2	2	1	1	1
Zinc	8	7	7	7	8	8	8	8	8	6	8	6	6	7
Panel B. Futures commodities														
Brent	2	2	2	2	2	2	2	3	3	5	2	14	14	2
Crude oil	12	12	11	12	12	12	11	12	12	12	12	5	5	14
Gas	6	8	8	6	6	7	7	6	6	15	4	1	1	3
Gasoline	4	5	3	4	4	5	3	4	4	3	3	6	6	5
Heat oil	3	3	5	3	3	3	4	2	2	1	1	7	7	6
Cocoa	5	4	4	5	5	4	5	5	5	9	8	15	15	7
Coffee	11	11	12	11	11	11	12	11	11	4	11	16	16	13
Corn	14	13	14	14	14	14	14	13	13	10	13	4	4	12
Cotton	13	14	13	13	13	13	13	14	14	14	14	3	3	11
Oat	16	16	16	16	16	16	16	16	16	8	16	8	8	16
Rice	15	15	15	15	15	15	15	15	15	11	15	9	9	15
Rubber	9	10	10	10	7	9	6	8	8	7	9	2	2	4
Soybeans	7	7	9	8	9	6	8	9	9	16	7	10	10	9
Sugar	8	6	6	7	8	8	9	7	7	13	6	11	11	8
Wheat	10	9	7	9	10	10	10	10	10	6	10	12	12	10
Wool	1	1	1	1	1	1	1	1	1	2	5	13	13	1

Notes. Table 3E reports the investment rankings of the Spot and Futures commodities in the EU crisis sub-sample.

Table 3F. Investment rankings - Greek crisis sub-sample														
	Classic	Based-on-drawdowns					Based-on-partial-moments				Based-on-the-Value-at-Risk			
Sample	*Sharpe*	*Calmar*	*Sterling*	*Burke*	*Pain*	*Martin*	*Omega*	*Sortino*	*Kappa3*	*Upside*	*Excess*	*Conditional*	*Modified*	*Mean*
Panel A. Spot commodities														
Aluminium	3	1	2	2	3	2	4	4	4	9	5	6	6	6
Copper	8	9	8	8	8	8	8	8	8	7	8	4	4	4
Gold	5	6	1	5	4	5	3	5	5	8	3	3	3	3
Lead	4	3	5	4	5	4	5	3	3	1	4	7	7	7
Nickel	1	2	3	1	2	1	1	1	1	3	2	8	8	5
Palladium	7	5	6	7	7	7	7	7	7	2	7	2	2	2
Platinum	9	8	9	9	9	9	9	9	9	10	9	9	9	10
Silver	10	10	10	10	10	10	10	10	10	5	10	5	5	8
Tin	2	4	4	3	1	3	2	2	2	4	1	1	1	1
Zinc	6	7	7	6	6	6	6	6	6	6	6	10	10	9
Panel B. Futures commodities														
Brent	13	12	12	13	13	13	13	13	13	8	11	9	9	12
Crude oil	9	5	9	9	9	9	9	8	8	7	9	12	12	11
Gas	3	1	2	2	3	3	4	3	3	14	3	3	3	3
Gasoline	10	10	10	10	10	10	10	10	10	4	10	7	7	7
Heat oil	1	3	3	1	2	1	2	1	1	10	2	1	1	1
Cocoa	16	16	16	16	16	16	16	16	16	2	16	11	11	16
Coffee	2	2	4	3	4	2	3	2	2	3	1	15	15	8
Corn	15	15	15	15	15	15	15	15	15	11	15	10	10	15
Cotton	11	11	11	11	11	11	11	11	11	13	12	16	16	13
Oat	14	14	14	14	14	14	14	14	14	5	14	8	8	9
Rice	12	13	13	12	12	12	12	12	12	9	13	13	13	14
Rubber	4	9	5	5	5	4	5	4	4	15	4	4	4	4
Soybeans	6	7	6	6	6	6	6	7	7	6	6	2	2	2
Sugar	7	6	7	8	8	8	7	9	9	12	8	14	14	10
Wheat	8	4	8	7	7	7	8	6	5	1	7	5	5	6
Wool	5	8	1	4	1	5	1	5	6	16	5	6	6	5

Notes. Table 3F reports the investment rankings of the Spot and Futures commodities in the Greek sub-sample.

Table 3G. Investment rankings - Post-debt crisis sub-sample

	Classic	Based-on-drawdowns					Based-on-partial-moments				Based-on-the-Value-at-Risk			
Sample	*Sharpe*	*Calmar*	*Sterling*	*Burke*	*Pain*	*Martin*	*Omega*	*Sortino*	*Kappa3*	*Upside*	*Excess*	*Conditional*	*Modified*	*Mean*
Panel A. Spot commodities														
Aluminium	10	10	10	10	10	10	10	10	10	6	10	6	6	10
Copper	5	4	5	5	5	6	5	5	5	8	6	7	7	6
Gold	3	7	1	4	3	4	2	3	3	10	4	4	4	4
Lead	7	6	7	7	7	7	7	7	7	3	7	8	8	8
Nickel	8	8	8	8	8	8	8	8	8	1	8	5	5	5
Palladium	4	2	3	3	2	3	3	2	2	2	2	2	2	2
Platinum	2	1	4	1	4	2	4	4	4	9	3	1	1	1
Silver	1	5	2	2	1	1	1	1	1	7	1	3	3	3
Tin	9	9	9	9	9	9	9	9	9	4	9	9	9	9
Zinc	6	3	6	6	6	5	6	6	6	5	5	10	10	7
Panel B. Futures commodities														
Brent	8	8	9	8	10	8	10	10	10	12	6	12	12	13
Crude oil	6	5	4	5	6	5	7	7	7	7	2	1	1	1
Gas	15	15	15	15	15	15	15	15	15	4	15	7	7	8
Gasoline	4	3	6	4	5	3	5	5	5	6	3	2	2	3
Heat oil	9	9	10	9	9	9	9	9	9	5	8	4	4	4
Cocoa	13	11	13	13	13	13	13	14	14	8	12	13	13	15
Coffee	10	12	8	10	8	10	8	4	3	1	11	14	14	11
Corn	3	2	3	3	3	4	3	2	2	9	10	15	15	9
Cotton	2	4	2	2	2	2	2	3	4	14	4	16	16	7
Oat	16	16	16	16	16	16	16	16	16	2	16	8	8	12
Rice	12	13	12	12	12	12	12	13	13	11	9	6	6	6
Rubber	1	1	1	1	1	1	1	1	1	15	1	3	3	2
Soybeans	5	10	7	7	7	6	6	6	6	10	5	5	5	5
Sugar	11	6	11	11	11	11	11	11	11	13	13	9	9	14
Wheat	14	14	14	14	14	14	14	12	12	3	14	10	10	16
Wool	7	7	5	6	4	7	4	8	8	16	7	11	11	10

Notes. Table 3G reports the investment rankings of the Spot and Futures commodities in the Post debt crisis sub-sample.

Table 4A. Rank correlations and corresponding ranking difference statistics; Full sample														
		Rank correlations				Ranking differences								
		τ		p		*Min*		*Max*		*MAD*		*SDAD*		
		Spot	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	
Based-on-drawdowns	*Calmar*	0.6889	0.7833	0.8788	0.9265	-2	-4	2	3	1.20	1.25	0.7888	1.29	
	Sterling	0.9556	0.8333	0.9879	0.9500	-1	-3	1	3	0.2000	1.00	0.4216	1.10	
	Burke	0.9556	0.9000	0.9879	0.9765	-1	-2	1	2	0.2000	0.6250	0.4216	0.8062	
	Pain	0.9111	0.8667	0.9636	0.9559	-2	-4	1	2	0.4000	0.8750	0.6992	1.09	
	Martin	1.00	0.9167	1.00	0.9824	0	-2	0	2	0	0.5000	0	0.7303	
Based-on-partial-moments	*Omega*	0.9556	0.9000	0.9879	0.9647	-1	-4	1	2	0.2000	0.6250	0.4216	1.09	
	Sortino	0.7333	0.8000	0.8061	0.9324	-2	-2	5	4	1.00	1.25	1.56	1.18	
	Kappa3	0.7333	0.7667	0.8061	0.9147	-2	-3	5	4	1.00	1.38	1.56	1.36	
	Upside	-0.3333	0.0333	-0.3939	0.0765	-6	-13	9	12	4.20	4.75	2.44	4.22	
Based-on-the-Value-at-Risk	*Excess*	0.7333	0.7167	0.8788	0.9059	-2	-4	3	4	1.00	1.63	1.05	1.20	
	Conditional	0.1111	0.5833	0.1030	0.7706	-5	-6	6	4	3.40	2.50	1.90	1.93	
	Modified	0.1111	0.5833	0.1030	0.7706	-5	-6	6	4	3.40	2.50	1.90	1.93	
	Mean	-	-	-	-	-5	-6	6	3	3.40	2.50	1.90	1.83	

Notes. Table 4A reports the Kendall's (τ) and Spearman's (p) correlations between rankings for spot and futures commodities in the Full sample. The table also provides descriptive statistics of the differences in rankings.

Table 4B. Rank correlations and corresponding ranking difference statistics; Argentina crisis														
		Rank correlations				Ranking differences								
		τ		p		*Min*		*Max*		*MAD*		*SDAD*		
		Spot	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	
Based-on-drawdowns	*Calmar*	0.9111	0.8333	0.9636	0.9353	-1	-4	2	3	0.4000	1.125	0.6992	1.26	
	Sterling	1.00	0.9500	1.00	0.9912	0	-1	0	1	0	0.3750	0	0.5000	
	Burke	1.00	0.9500	1.00	0.9882	0	-1	0	2	0	0.3750	0	0.6191	
	Pain	0.9556	0.8833	0.9879	0.9676	-1	-3	1	3	0.2000	0.6250	0.4216	1.02	
	Martin	0.9556	0.9500	0.9879	0.9882	-1	-1	1	2	0.2000	0.3750	0.4216	0.6191	
Based-on-partial-moments	*Omega*	1.00	0.9333	1.00	0.9706	0	-4	0	1	0	0.5000	0	1.03	
	Sortino	0.7333	0.8667	0.8788	0.9588	-2	-2	3	4	1.00	0.8750	1.05	1.02	
	Kappa3	0.7333	0.8500	0.8788	0.9588	-2	-2	3	4	1.00	1.00	1.05	1.10	
	Upside	0.2000	-0.2833	0.2242	-0.4176	-5	-11	9	15	2.60	6.50	2.59	4.38	
Based-on-the-Value-at-Risk	*Excess*	0.7778	0.8000	0.8909	0.9029	-2	-5	3	5	1.00	1.13	0.9428	1.75	
	Conditional	-0.0667	0.1167	0.8909	0.0647	-5	-7	6	10	4.00	5.63	1.83	2.94	
	Modified	-0.0667	0.1333	-0.1515	0.0735	-5	-7	6	10	4.00	5.63	1.83	2.87	
	Mean	-	-	-	-	-5	-6	3	6	2.00	3.25	1.33	2.32	

Notes. Table 4B reports the Kendall's (τ) and Spearman's (p) correlations between rankings for spot and futures commodities in the Argentina crisis subsample. The table also provides descriptive statistics of the differences in rankings.

Table 4C. Rank correlations and corresponding ranking difference statistics; Growth														
		Rank correlations				Ranking differences								
		τ		p		*Min*		*Max*		*MAD*		*SDAD*		
		Spot	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	
Based-on-drawdowns	*Calmar*	0.8222	0.6667	0.9394	0.8382	-2	-4	2	7	0.6000	2.00	0.8433	1.75	
	Sterling	0.8667	0.8833	0.9515	0.9676	-2	-3	1	2	0.6000	0.7500	0.6992	0.9309	
	Burke	0.9111	0.9667	0.9636	0.9941	-2	-1	1	1	0.4000	0.2500	0.6992	0.4472	
	Pain	0.9556	0.8833	0.9879	0.9618	-1	-4	1	2	0.2000	0.7500	0.4216	1.06	
	Martin	0.8667	0.9833	0.9515	0.9971	-2	-1	2	1	0.4000	0.1250	0.8433	0.3416	
Based-on-partial-moments	*Omega*	1.00	0.9000	1.00	0.9706	0	-3	0	2	0	0.7500	0	0.8563	
	Sortino	0.7778	0.7667	0.8909	0.8882	-1	-5	3	5	1.00	1.50	0.9428	1.63	
	Kappa3	0.7778	0.7000	0.8909	0.8412	-1	-7	3	6	1.00	1.63	0.9428	2.09	
	Upside	-0.2000	-0.0833	-0.3091	-0.1412	-6	-13	8	14	4.20	5.25	2.10	4.73	
Based-on-the-Value-at-Risk	*Excess*	0.8222	0.5500	0.9394	0.7588	-2	-5	1	7	0.8000	2.63	0.6325	1.89	
	Conditional	0.0667	0.2167	0.1515	0.3294	-5	-9	6	11	3.00	4.25	2.36	3.34	
	Modified	0.0667	0.2167	0.1515	0.3294	-5	-9	6	11	3.00	4.25	2.36	3.34	
	Mean	-	-	-	-	-5	-9	6	5	2.60	3.25	2.32	2.86	

Notes. Table 4C reports the Kendall's (τ) and Spearman's (p) correlations between rankings for spot and futures commodities in the Growth subsample. The table also provides descriptive statistics of the differences in rankings.

Table 4D. Rank correlations and corresponding ranking difference statistics; Lehman Brothers														
		Rank correlations				Ranking differences								
		τ		p		*Min*		*Max*		*MAD*		*SDAD*		
		Spot	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	
Based-on-drawdowns	*Calmar*	0.8667	0.8500	0.9515	0.9529	-2	-2	1	2	0.6000	1.13	0.6992	0.8851	
	Sterling	0.8222	0.8333	0.9394	0.9471	-2	-3	2	4	0.6000	1.00	0.8433	1.15	
	Burke	0.9111	0.9000	0.9758	0.9647	-1	-2	1	4	0.4000	0.6250	0.5164	1.09	
	Pain	0.9556	0.8667	0.9879	0.9471	-1	-5	1	2	0.2000	0.8750	0.4216	1.26	
	Martin	1.00	0.9667	1.00	0.9941	0	-1	0	1	0	0.2500	0	0.4472	
Based-on-partial-moments	*Omega*	0.9111	0.8833	0.9758	0.9588	-1	-4	1	2	0.4000	0.8750	0.5164	1.02	
	Sortino	0.6889	0.8167	0.8545	0.9294	-2	-4	2	4	1.40	1.25	0.6992	1.24	
	Kappa3	0.6889	0.8167	0.8545	0.9294	-2	-4	2	4	1.40	1.25	0.6992	1.24	
	Upside	-0.3333	-0.1833	-0.5273	-0.3000	-8	-10	7	11	4.00	6.88	3.20	2.92	
Based-on-the-Value-at-Risk	*Excess*	0.7333	0.9500	0.8788	0.9882	-2	-2	2	1	1.20	0.3750	0.7888	0.6191	
	Conditional	0.4667	0.4500	0.6727	0.6441	-3	-6	5	6	1.80	3.25	1.55	2.21	
	Modified	0.4667	0.4500	0.6727	0.6441	-3	-6	5	6	1.80	3.25	1.55	2.21	
	Mean	-	-	-	-	-3	-5	4	5	1.80	2.25	1.40	1.88	

Notes. Table 4D reports the Kendall's (τ) and Spearman's (p) correlations between rankings for spot and futures commodities in the Lehman Brothers subsample. The table also provides descriptive statistics of the differences in rankings.

Table 4E. Rank correlations and corresponding ranking difference statistics; EU crisis														
		Rank correlations				Ranking differences							
		τ		p		*Min*		*Max*		*MAD*		*SDAD*	
		Spot	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*
Based-on-drawdowns	*Calmar*	0.8222	0.9000	0.9394	0.9794	-2	-2	2	2	0.6000	0.6250	0.8433	0.7188
	Sterling	0.8222	0.8667	0.9394	0.9559	-2	-3	2	2	0.6000	1.00	0.8433	0.9661
	Burke	0.8222	0.9667	0.9394	0.9941	-2	-1	2	1	0.6000	0.2500	0.8433	0.4472
	Pain	0.9111	0.9500	0.9636	0.9882	-2	-2	1	2	0.4000	0.2500	0.6992	0.6831
	Martin	0.9111	0.9667	0.9758	0.9941	-1	-1	1	1	0.4000	0.2500	0.5164	0.4472
Based-on-partial-moments	*Omega*	0.9556	0.9167	0.9879	0.9765	-1	-3	1	1	0.2000	0.6250	0.4216	0.8062
	Sortino	0.9111	0.9333	0.9636	0.9853	-1	-1	2	2	0.4000	0.5000	0.6992	0.6325
	Kappa3	0.8667	0.9333	0.9515	0.9853	-1	-1	2	2	0.6000	0.5000	0.6992	0.6325
	Upside	0.4222	0.2667	0.5636	0.4353	-6	-8	3	9	2.20	4.00	1.62	2.92
Based-on-the-Value-at-Risk	*Excess*	0.8667	0.8333	0.9515	0.9412	-2	-2	1	4	0.6000	1.00	0.6992	1.26
	Conditional	0.5556	-0.1667	0.6606	-0.2912	-2	-10	6	12	1.80	6.63	1.62	3.42
	Modified	0.5556	-0.1667	0.6606	-0.2912	-2	-10	6	12	1.80	6.63	1.62	3.42
	Mean	-	-	-	-	-1	-5	2	3	0.8000	1.50	0.6325	1.46

Notes. Table 4E reports the Kendall's (τ) and Spearman's (p) correlations between rankings for spot and futures commodities in the EU crisis subsample. The table also provides descriptive statistics of the differences in rankings.

Table 4F. Rank correlations and corresponding ranking difference statistics; Greek crisis														
		Rank correlations				Ranking differences								
		τ		p		*Min*		*Max*		*MAD*		*SDAD*		
		Spot	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	
Based-on-drawdowns	*Calmar*	0.7333	0.7000	0.8909	0.8853	-2	-4	2	5	1.20	1.50	0.6325	1.67	
	Sterling	0.6889	0.8833	0.8303	0.9588	-4	-4	2	2	1.20	0.7500	1.23	1.13	
	Burke	0.9556	0.9500	0.9879	0.9912	-1	-1	1	1	0.2000	0.3750	0.4216	0.5000	
	Pain	0.9111	0.9000	0.9758	0.9647	-1	-4	1	2	0.4000	0.6250	0.5164	1.09	
	Martin	0.9556	0.9833	0.9879	0.9971	-1	-1	1	1	0.2000	0.1250	0.4216	0.3416	
Based-on-partial-moments	*Omega*	0.9111	0.9333	0.9636	0.9706	-2	-4	1	1	0.4000	0.5000	0.6992	1.03	
	Sortino	0.9556	0.9500	0.9879	0.9853	-1	-2	1	2	0.2000	0.3750	0.4216	0.7188	
	Kappa3	0.9556	0.9333	0.9879	0.9765	-1	-3	1	2	0.2000	0.5000	0.4216	0.8944	
	Upside	0.2000	-0.2000	0.3091	-0.3088	-5	-14	6	11	2.80	6.25	1.99	4.20	
Based-on-the-Value-at-Risk	*Excess*	0.8222	0.9333	0.9394	0.9853	-2	-2	2	1	0.6000	0.5000	0.8433	0.6325	
	Conditional	0.0667	0.3333	0.0667	0.4265	-5	-6	7	13	3.40	3.75	2.07	3.32	
	Modified	0.0667	0.3333	0.0667	0.4265	-5	-6	7	13	3.40	3.75	2.07	3.32	
	Mean	-	-	-	-	-5	-5	4	6	2.80	1.88	1.32	1.93	

Notes. Table 4F reports the Kendall's (τ) and Spearman's (p) correlations between rankings for spot and futures commodities in the Greek crisis subsample. The table also provides descriptive statistics of the differences in rankings.

Table 4G. Rank correlations and corresponding ranking difference statistics; Post-debt-crisis														
		Rank correlations				Ranking differences								
		τ		p		*Min*		*Max*		*MAD*		*SDAD*		
		Spot	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*
Based-on-drawdowns	*Calmar*	0.6000	0.7833	0.7091	0.9029	-3	-5	4	5	1.60	1.25	1.58	1.65
	Sterling	0.8667	0.9000	0.9394	0.9676	-2	-2	2	2	0.6000	0.7500	0.8433	0.9309
	Burke	0.9111	0.9667	0.9758	0.9912	-1	-1	1	2	0.4000	0.2500	0.5164	0.5774
	Pain	0.8667	0.8833	0.9515	0.9676	-2	-3	2	2	0.4000	0.6250	0.8433	1.02
	Martin	0.9111	0.9667	0.9758	0.9941	-1	-1	1	1	0.4000	0.2500	0.5164	0.4472
Based-on-partial-moments	*Omega*	0.9111	0.9000	0.9636	0.9706	-1	-3	2	2	0.4000	0.6250	0.6992	0.9574
	Sortino	0.8667	0.8333	0.9515	0.9235	-2	-6	2	2	0.4000	1.13	0.8433	1.45
	Kappa3	0.8667	0.8167	0.9515	0.9000	-2	-7	2	2	0.4000	1.25	0.8433	1.69
	Upside	-0.3333	-0.4333	-0.5394	-0.5706	-7	-14	7	14	4.60	6.88	2.17	4.56
Based-on-the-Value-at-Risk	*Excess*	0.8667	0.7500	0.9515	0.8676	-2	-4	1	7	0.6000	1.50	0.6992	1.90
	Conditional	0.4667	0.0333	0.6606	0.0735	-4	-8	4	14	2.00	5.00	1.33	3.92
	Modified	0.4667	0.0333	0.6606	0.0735	-4	-8	4	14	2.00	5.00	1.33	3.92
	Mean	-	-	-	-	-3	-7	2	6	1.20	3.50	0.9189	2.16

Notes. Table 4G reports the Kendall's (τ) and Spearman's (p) correlations between rankings for spot and futures commodities in the Post-debt-crisis subsample. The table also provides descriptive statistics of the differences in rankings.

Table 5A. Ranking difference statistics for the Top 5 best commodities; Full sample								
	Full sample							
	Min		*Max*		*MAD*		*SDAD*	
	Spot	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*
Based-on-drawdowns								
Calmar	-2	-1	2	11	1.60	3.60	0.5477	4.34
Sterling	-1	-3	1	11	0.4000	3.40	0.5477	4.51
Burke	-1	-1	1	11	0.4000	3.00	0.5477	4.53
Pain	-2	-4	1	13	0.8000	4.20	0.8367	5.07
Martin	0	-1	0	11	0	2.40	0	4.83
Based-on-partial-moments								
Omega	-1	-4	1	13	0.4000	3.80	0.5477	5.36
Sortino	-1	-1	5	12	1.60	3.60	1.95	4.93
*Kappa*3	-1	-1	5	12	1.60	3.60	1.95	4.93
Upside	-1	1	9	12	4.40	6.40	3.13	4.88
Based-on-the-Value-at-Risk								
Excess	-2	-2	3	12	1.20	3.80	1.30	4.82
Conditional	0	0	6	7	3.40	2.60	2.61	2.70
Modified	0	0	6	7	3.40	2.60	2.61	2.70
Mean	0	0	6	7	3.40	2.60	2.61	2.70

Notes. Table 5A reports the descriptive statistics of the ranking differences for the 5 commodities (either spot or futures) with the highest Sharpe ratios. Min, Max, MAD and SDAD represent the minimum, maximum mean absolute and standard deviation absolute of the ranking differences, respectively. Results concern the Full sample.

Table 5B. Ranking difference statistics for the Top 5 best commodities; Argentina crisis and Growth subsamples																
	Argentina crisis								Growth							
	Min		*Max*		*MAD*		*SDAD*		*Min*		*Max*		*MAD*		*SDAD*	
	Spot	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*
Based-on-drawdowns																
Calmar	-1	-1	2	3	0.8000	1.00	0.8367	1.22	-2	-1	2	3	0.8000	1.20	1.10	1.10
Sterling	0	-1	0	1	0	0.4000	0	0.5477	-2	-1	1	1	0.8000	0.6000	0.8367	0.5477
Burke	0	0	0	0	0	0	0	0	-2	0	1	0	0.8000	0	0.8367	0
Pain	0	-1	1	1	0.2000	0.4000	0.4472	0.5477	0	0	0	1	0	0.2000	0	0.4472
Martin	-1	0	1	0	0.4000	0	0.5477	0	-2	0	2	0	0.8000	0	1.10	0
Based-on-partial-moments																
Omega	0	0	0	1	0	0.2000	0	0.4472	0	0	0	1	0	0.2000	0	0.4472
Sortino	-2	-1	3	4	1.60	1.60	1.14	1.34	-1	-1	3	2	1.40	0.8000	1.14	0.8367
Kappa3	-2	-2	3	4	1.60	2.00	1.14	1.22	-1	-1	3	3	1.40	1.20	1.14	1.10
Upside	-2	-3	9	15	2.80	9.60	3.56	4.28	-2	-1	8	14	4.60	6.00	2.41	5.70
Based-on-the-Value-at-Risk																
Excess	-1	-1	3	5	1.00	1.40	1.22	2.07	-1	-2	1	3	0.8000	1.20	0.4472	1.30
Conditional	-2	-3	6	10	4.00	6.00	2.35	4.42	0	-1	6	11	3.00	3.80	2.83	4.38
Modified	-2	-3	6	10	4.00	6.00	2.35	4.42	0	-1	6	11	3.00	3.80	2.83	4.38
Mean	-2	-2	3	6	2.20	3.60	0.4472	2.07	0	-1	6	5	2.60	2.40	2.79	1.95

Notes. Table 5B reports the descriptive statistics of the ranking differences for the 5 commodities (either spot or futures) with the highest Sharpe ratios. Min, Max, MAD and SDAD represent the minimum, maximum mean absolute and standard deviation absolute of the ranking differences, respectively. Results concern the Argentina crisis and Growth subsamples.

Table 5C. Ranking difference statistics for the Top 5 best commodities; Lehman Brothers and EU crises subsamples																
	Lehman Brothers								EU crisis							
	Min		*Max*		*MAD*		*SDAD*		*Min*		*Max*		*MAD*		*SDAD*	
	Spot	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*
Based-on-drawdowns																
Calmar	-1	-2	1	12	0.4000	3.60	0.5477	4.72	-2	-1	2	1	0.8000	0.4000	1.10	0.5477
Sterling	-1	-2	1	4	0.4000	1.80	0.5477	1.30	-2	-1	2	2	0.8000	0.8000	1.10	0.8367
Burke	-1	-1	1	4	0.6000	1.40	0.5477	1.52	-2	0	2	0	0.8000	0	1.10	0
Pain	-1	-1	1	2	0.4000	1.00	0.5477	0.7071	-2	0	1	0	0.8000	0	0.8367	0
Martin	0	-1	0	1	0	0.8	0	0.4472	-1	-1	1	1	0.6000	0.4000	0.5477	0.5477
Based-on-partial-moments																
Omega	-1	-1	1	2	0.4000	1.20	0.5477	0.4472	-1	-1	1	1	0.4000	0.4000	0.5477	0.5477
Sortino	-2	-2	1	4	1.00	1.80	0.7071	1.30	0	-1	2	1	0.4000	0.4000	0.8944	0.5477
Kappa3	-2	-2	1	4	1.00	1.80	0.7071	1.30	-1	-1	2	1	0.8000	0.4000	0.8367	0.5477
Upside	-1	-1	7	11	4.20	7.20	2.77	3.96	-2	-2	3	4	2.20	2.20	0.8367	1.30
Based-on-the-Value-at-Risk																
Excess	-1	-1	2	1	1.20	0.4	0.8367	0.5477	-1	-2	1	4	0.6000	2.00	0.5477	1.58
Conditional	-1	-1	5	6	1.80	3.20	1.92	2.17	-2	2	6	12	2.20	8.00	2.28	4.69
Modified	-1	-1	5	6	1.80	3.20	1.92	2.17	-2	2	6	12	2.20	8.00	2.28	4.69
Mean	-1	-1	4	5	1.60	2.80	1.52	1.64	-1	0	1	3	0.8000	1.20	0.4472	1.30

Notes. Table 5C reports the descriptive statistics of the ranking differences for the 5 commodities (either spot or futures) with the highest Sharpe ratios. Min, Max, MAD and SDAD represent the minimum, maximum mean absolute and standard deviation absolute of the ranking differences, respectively. Results concern the Lehman Brothers and EU crises subsamples.

Table 5D. Ranking difference statistics for the Top 5 best commodities; Greek and Post-debt crises subsamples																
	Greek crisis								Post-debt crisis							
	Min		*Max*		*MAD*		*SDAD*		*Min*		*Max*		*MAD*		*SDAD*	
	Spot	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*
Based-on-drawdowns																
Calmar	-2	-2	2	5	1.40	2.40	0.5477	1.82	-2	-1	4	5	2.40	1.80	1.52	1.92
Sterling	-4	-4	2	2	2.00	2.00	1.22	1.22	-2	0	2	2	1.20	0.8000	0.8367	1.10
Burke	-1	-1	1	1	0.4000	0.8000	0.5477	0.4472	-1	0	1	2	0.8000	0.4000	0.4472	0.8944
Pain	-1	-4	1	2	0.8000	1.60	0.4472	1.52	-2	0	2	2	0.8000	0.6000	1.10	0.8944
Martin	-1	0	1	0	0.4000	0	0.5477	0	-1	-1	1	1	0.6000	0.6000	0.5477	0.5477
Based-on-partial-moments																
Omega	-2	-4	1	1	0.8000	1.60	0.8367	1.34	-1	0	2	1	0.8000	0.4000	0.8367	0.5477
Sortino	-1	0	1	0	0.4000	0	0.5477	0	-2	-1	2	1	0.8000	0.8000	1.10	0.4472
Kappa3	-1	0	1	1	0.4000	0.2000	0.5477	0.4472	-2	-1	2	2	0.8000	1.00	1.10	0.7071
Upside	-3	1	6	11	3.20	8.60	1.64	4.34	-2	2	7	14	5.00	7.80	2.35	5.02
Based-on-the-Value-at-Risk																
Excess	-2	-1	2	1	1.20	0.4000	0.8367	0.5477	-2	-1	1	7	1.00	2.00	0.7071	2.92
Conditional	-2	0	7	13	3.20	2.80	2.28	5.72	-2	-2	2	14	1.60	6.00	0.5477	6.48
Modified	-2	0	7	13	3.20	2.80	2.28	5.72	-2	-2	2	14	1.60	6.00	0.5477	6.48
Mean	-2	0	4	6	2.60	1.20	1.14	2.68	-2	-1	2	6	1.40	2.60	0.5477	2.70

Notes. Table 5D reports the descriptive statistics of the ranking differences for the 5 commodities (either spot or futures) with the highest Sharpe ratios. Min, Max, MAD and SDAD represent the minimum, maximum mean absolute and standard deviation absolute of the ranking differences, respectively. Results concern the Greek and Post-debt crises subsamples.