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Essays on Commodity Futures Markets

by

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Chapter 3: Are there common factors in commodity futures returns?

Chapter 1: Introduction

The developments in the commodity markets over the last years have attracted the interest of both academics and market participants. In the mid-2000s, both spot and futures prices of a broad set of commodities began to surge after nearly three decades of low and declining prices. The period 2003-2008 has been characterized as a *commodity boom* because it has witnessed a spectacular and simultaneous increase in the prices of the three major commodity groups (energy, metals, and agriculture, see Figure 1.1). At the same time, investments in commodities have grown rapidly mainly via commodity futures and index funds. The total value of the commodity index-related instruments purchased by institutional investors increased from an estimated $15 billion in 2003 to at least $200 billion in mid-2008 (CFTC, Staff Report, 2008). This phenomenon is usually referred to as the *financialization* of the commodity futures markets.

Commodities have attracted the attention of both individual and institutional investors because they are considered to form an alternative asset class. A number of empirical studies find that commodities exhibit low or even negative correlation with stocks and bonds over certain periods of time and hence diversification benefits are expected to emerge (e.g., Erb and Harvey, 2006, Gorton and Rouwenhorst, 2006). Nevertheless, the recent literature documents that, over the last years, commodities have become more correlated with other financial assets and with each other. This is mainly attributed to the increased presence of index traders in the commodity markets (e.g., Tang and Xiong, 2010). This evidence questions whether diversification benefits from commodity investing hold in practice. Moreover, it motivates investigating whether they are any common factors that explain the cross-section of commodity futures expected returns.

The well-documented increased investment activity in the futures markets in conjunction with the widespread ascent of commodity prices over the same period has also stimulated the public attention to commodities markets. There is a heated debate in policy circles about whether speculation by index traders caused the price surge.[1] This argument has been driving policy efforts to regulate the commodity futures markets.

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[1] In fact, two opposing views are competing. The first one argues that fundamentals, such as the weakening of the dollar or the increasing global demand, sufficiently explain the price movements (e.g., Alquist and Gervais, 2011), while the other stressing excessive speculation by index investors (e.g., Tang and Xiong, 2010).

Among others, it has revived the discussion about whether futures margin requirements should be regulated and used as a policy tool to restrict speculation and drive down the commodity prices. However, the impact of margin changes on vital characteristics of the commodity futures markets is unexplored and this calls for further research in this vein.

Overall, despite the pivotal importance of commodities for the economy and the capital markets, many issues remain open to discussion. Motivated by the recent developments in the commodity futures markets, this thesis examines the following three distinct questions. First, it investigates whether investors should include commodities in a typical portfolio that already contains stocks, bonds and cash. Second, it studies whether there are any common factors that explain the cross-section of commodity futures expected returns. Finally, it explores whether and how changes in the margin requirements affect the commodity futures markets.

The *first paper* (Chapter 2) investigates whether an investor is made better off by including commodities in a portfolio that consists of traditional asset classes, namely stocks, bonds and cash. The previous literature has provided unanimous evidence that incorporating commodities in the asset menu improves the risk-return profile of investors' portfolios (e.g., Jensen et al., 2000, Idzorek, 2007, Conover et al., 2010). However, their conclusions have been reached in a mean-variance (MV) in-sample setting. This approach is subject to three shortcomings though. First, the Markowitz, MV, setting may not reflect accurately the gains from investing in commodities since it is founded on rather restrictive assumptions. Second, most studies assess the diversification benefits of investing in commodities by eyeballing the relative position of the efficient frontiers; the comparison of the relative position of efficient frontiers should be set within a statistical framework. Third, all previous studies investigate the benefits of investing in commodities within an in-sample setting. In principle, the portfolio choice should be examined in an out-of-sample setting given that at any given point in time, the investor decides on the portfolio weights and the portfolio returns to be realised over the investment horizon is uncertain.

In light of these shortcomings, the first paper takes a more general approach to examining whether commodities should be included in an investor's portfolio. First, it revisits the posed question within an in-sample setting by employing mean-variance and non-mean-variance spanning techniques (see Huberman and Kandel, 1987, and DeRoon and Nijman, 2001, for MV spanning, and DeRoon et al., 1996, for generalized non-MV spanning tests). Second, the question under scrutiny is examined by employing an out-of-sample setting. In line with DeMiguel et al. (2009) and Kostakis et al. (2011), static one-period optimal portfolios are formed at any point in time by taking into account the higher order moments of the portfolio returns distribution and their performance under a number of performance measures is evaluated.

Regarding the empirical findings of the first paper, under the in-sample setting, commodities are beneficial only to non mean-variance investors. However, these benefits are not preserved out-of-sample. These findings challenge the alleged diversification benefits of commodities and are robust across a number of performance evaluation measures, utility functions and datasets. The results hold even when transaction costs are considered and across various sub-periods. The only exception appears over the recent commodity boom period. This comes to no surprise though given the unprecedented and simultaneous increase in commodity prices that takes place then.

The *second paper* (Chapter 3) examines whether there are any systematic factors that explain the cross-section of commodity futures expected returns. There is an extensive literature which addresses this task for traditional asset classes like equities. However, not much empirical research has been undertaken to investigate this issue for the cross-section of commodity futures returns.

The commodity asset pricing literature can be divided in two strands. The first strand uses traditional asset pricing models, designed to price *any* asset under the stochastic discount factor (SDF) framework. To the best of our knowledge, the related studies investigate only the performance of the traditional Capital Asset Pricing Model (CAPM) and Consumption CAPM (CCAPM) (see Dusak, 1973, Bodie and Rosansky, 1980, for evidence on the CAPM and Breeden, 1980, Jagannathan, 1985, and DeRoon and Szymanowska, 2010, for evidence on the CCAPM). The implementation of only a small number of SDF-based models calls for further research in this vein. The second strand argues that the expected return of any given commodity futures is driven by commodity-specific factors. Motivated by the hedging pressure hypothesis of Cootner (1960), the respective theoretical models allow both systematic factors and hedging pressure to affect *individual* commodity futures premiums (see Stoll, 1979, Hirschleifer, 1988, 1989, De Roon et al., 2000). On the other hand, Gorton et al. (2012), based on the theory of storage (Kaldor, 1939, Working, 1949, Brennan, 1958), focus on the relationship between the inventory levels of the commodities in the economy and their respective commodity futures expected returns. However, all the previous studies identify the link between the commodity-specific variables and *individual* commodity futures expected returns rather than evaluating them within a cross-sectional asset pricing setting. Hence, this issue remains open to discussion.

Building on the existing literature, the second paper investigates comprehensively whether there are any factors that explain the cross-sectional variation in commodity futures expected return. First, a number of macro and equity-motivated tradable factor asset pricing models, which have been traditionally used or proved successful to price the cross-section of equities, are implemented. The macro-factor models specify directly the functional form for the SDF using macroeconomic (i.e. aggregate) variables. In this category, this paper examines whether a monetary, a leverage, or a foreign exchange rate factor explains the cross-section of commodities returns (see Balvers and Huang, 2009, Adrian et al., 2011, and Lustig et al., 2011, respectively). Next, the most popular tradable factor models, which have been successfully used in the equity asset pricing literature, are implemented (Fama-French, 1993, Carhart, 1997, and Pastor and Stambaugh, 2003, liquidity factor). The motivation for examining these common factor models is that it is not clear a priori whether equity and commodity markets are integrated (e.g., Bessembinder, 1992, Bakshi et al., 2011, Hong and Yogo, 2012). Second, commodity-specific factors are constructed based on the hedging pressure and storage theories, and evaluated in a cross-sectional setting. Third, Principal Component factor models which do not require á priori specification of factors are implemented (Cochrane, 2011). The second paper presents unanimous evidence that none of the employed models and factors prices the cross-section of commodity futures returns. The results survive all robustness tests and reveal that the commodity futures markets are segmented from the equities market and they are significantly heterogeneous per se.

The *third paper* (Chapter 4) investigates comprehensively the effect of margin changes on the commodity futures markets. The recent commodity boom and the Dodd–Frank Act have revived the discussion about whether margins should be regulated and used as a policy tool to restrict speculation and drive down the commodity prices. Understanding how the margin changes affect the commodity market is a prerequisite prior to their regulation.

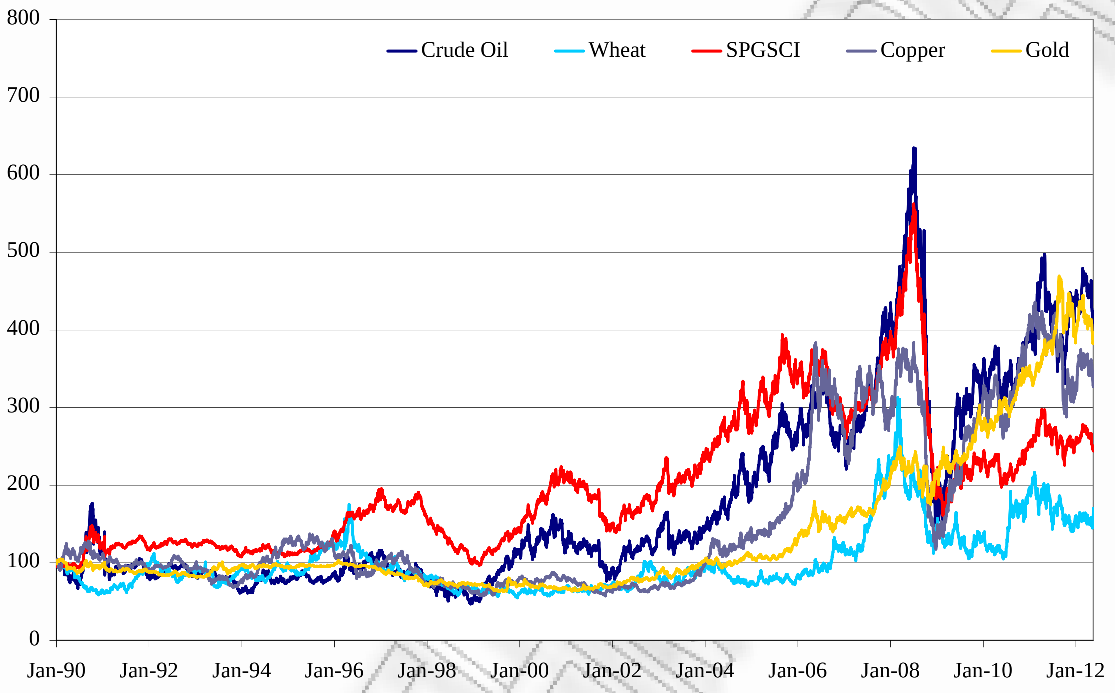
The existing literature on the effects of margin changes on the commodity futures markets is limited and can be classified into two main categories. The first category includes the studies that examine the margin effect on market activity. This literature documents an inverse relation between margin changes and open interest (see e.g., Hardouvelis and Kim, 1995, Adrangi and Chatrath, 1999, Hedegaard, 2011). The second category includes the studies that examine the relationship between margin requirements and volatility. The existing evidence is mixed; the effect is either positive (Hardouvelis and Kim, 1995, 1996), negative (Ma et al., 1993) or insignificant (Fishe et al., 1990).

The third paper extends the prior literature by investigating the margin effect on characteristics of the commodity markets that stand in the core of the debate about whether margins should be regulated or not. First, motivated by the theoretical models of Gârleanu and Pedersen (2011) and Acharya et al. (2011), it examines the effect of margin changes on the commodity futures prices and returns. A regulator aims at maintaining low commodity futures prices given that price increases harm the commodity consumers. Second, it studies the effect of margin changes on the functioning of the commodity futures markets as a risk transfer mechanism between hedgers and speculators. This is also of importance to the regulator since the main purpose of the futures markets is to provide a mechanism for sharing risk (e.g., Working, 1962). Third, it explores the effect of margin changes on the price stability by considering the effect on the volatility and the market liquidity of individual contracts. These two concepts are closely related; low market liquidity leads to a less stable market with increased volatility. Both price stabilization and increases in liquidity yield welfare gains and hence are of interest to the regulators (e.g., Massel, 1969, Huang and Wang, 2010). In addition, higher liquidity engenders a higher degree of informational efficiency (Chordia et al., 2008) and facilitates risk sharing (Cuny, 1993).

The third paper documents that changes in the margin requirements coincide with positive (negative) changes in prices (returns). Moreover, margin increases can harm the risk sharing function, primary objective of the commodity futures contracts, for grains and metal futures. There is a positive association between margin changes and volatility, whereas the market liquidity of the individual contracts/groups is not affected by margin changes. In the case the margin impact of positive and large margin changes is assessed separately, we find that the market liquidity in some markets (grains, softs and energy) decreases. These results have implications for the regulation of margin requirements in the commodity futures markets.

Figure 1.1. Commodity prices over the period January 1990-May 2012

This figure depicts price appreciations of four individual commodity futures, crude oil, wheat, copper, gold, and one commodity index, the S&P GSCI, over the period January 1990 to May 2012. In each case, the prices are normalized to be 100 in January 1990.



Chapter 2: Should investors include commodities in their portfolios after all? New evidence

Abstract

In this chapter, we investigate whether an investor is made better off by including commodities in a portfolio that consists of traditional asset classes. First, we revisit the posed question within an in-sample setting by employing mean-variance and non-mean-variance spanning tests. Then, we form optimal portfolios by taking into account the higher order moments of the portfolio returns distribution and evaluate their out-of-sample performance. Under the in-sample setting, we find that commodities are beneficial only to non mean-variance investors. However, these benefits are not preserved out-of-sample. Our findings challenge the alleged diversification benefits of commodities and are robust across a number of performance evaluation measures, utility functions and datasets. The results hold even when transaction costs are considered and across various sub-periods. Not surprisingly, the only exception appears over the 2005-2008 unprecedented commodity boom period.

2.1. Introduction

Investments in commodities have grown rapidly over the last years mainly via commodity futures and commodity index funds. It is estimated that "*...inflows into commodity investments during 2009 will be a record $60 billion, topping $51 billion from 2006...*" (Wall Street Journal, January 4, 2010) with the prospect being that they will increase further. Furthermore, Stoll and Whaley (2010) estimate the total commodity index investment in the U.S. to be about $174 billion in 2009. The common perception is that the popularity of investing in commodities lies in the fact that, from a theoretical point of view, commodities form an alternative asset class; their returns are expected to show small or even negative correlation with the returns of assets that belong to traditional asset classes like stocks and bonds.[2] This is because the factors that drive commodity prices

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[2] "… according to a survey of more than 300 attendees at Barclays Capital's fifth annual US Commodities Investor Conference…63% of those surveyed indicated they plan to increase their commodity exposure over

(e.g., weather and geopolitical conditions, supply constraints in the physical production, and event risk) are distinct from those that determine the value of stocks and bonds (see also Geman, 2005, for a discussion). Moreover, in contrast with stocks and bonds, commodities serve as an inflation hedge (e.g., Bodie, 1983). In fact, a number of empirical studies confirm this type of correlation over certain periods of time (see Bodie and Rosansky, 1980, Erb and Harvey, 2006, Gorton and Rouwenhorst, 2006, Geman and Kharoubi, 2008, Büyükşahin et al., 2010, Chong and Miffre, 2010). Consequently, diversification benefits, i.e. reduction of risk for any given level of expected return, may emerge.[3] However, there is evidence that the growing presence of index funds in commodities markets integrates the commodity markets with the stock and bond markets (Silvennoinen and Thorp, 2010, Tang and Xiong, 2010). This calls into question the diversification benefits of commodities.[4] This paper revisits the common perception on the diversification role of commodities by investigating the benefits of investing in commodities in a more general setting than the one that the previous literature has adopted so far.

There are already a number of papers that examine whether incorporating commodities in the asset menu improves the risk-return profile of investors' portfolios. Bodie and Rosansky (1980), Fortenbery and Hauser (1990), and Conover et al. (2010) find that investors can reduce risk without sacrificing return by switching from a stock portfolio to a portfolio with stocks and commodities over the periods 1950-1976, 1976-1985, and 1970-2007, respectively. Georgiev (2001) performs a similar analysis over the period 1995-2005 and finds an increase in the Sharpe ratio. In addition, a number of studies investigate the role of commodities under the Markowitz (1952) mean-variance (MV) static asset allocation setting and reach similar conclusions. Ankrim and Hensel (1993) study the diversification benefits of investing in commodities over the period 1972-

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the next three years.” (Barclays press release, December 2009, http://www.barcap.com/About+Barclays+Capital/Press+Office).

[3] The appeal of investing in commodities may also be attributed to the evidence that profitable trading strategies with commodities can be constructed. A number of studies find that commodity returns can be predicted by a number of variables (see e.g., Hong and Yogo, 2012, and references therein), and profitable momentum and term structure strategies can be implemented (see for instance, Erb and Harvey, 2006, Gorton et al., 2012, Miffre and Rallis, 2007, Fuertes et al., 2010, Szakmary et al., 2010). Chng (2009) reports also evidence that linkages across commodity futures that differ in the underlying asset can be used for profitable trading purposes. Interestingly though, Marshall et al. (2008) find that tenchical trading does not yield economically significant profits once these are adjusted for data-snooping.

[4] The evidence on markets integration is mixed though. Chong and Miffre (2010) and Büyükşahin et al. (2010) find that commodity and equity markets have become more segmented over the years in contrast to the findings of Tang and Xiong (2010) and Silvennoinen and Thorp (2010).

1990, and conclude that expanding the investable universe with commodities improves the risk/return trade-off of optimal portfolios for any given risk tolerance coefficient. Satyanarayan and Varangis (1996) and Abanomey and Mathur (1999) examine whether the efficient frontier changes when commodity futures are incorporated into international assets universes over the periods 1970-1992 and 1970-1995, respectively. They find that the inclusion of commodities shifts the efficient frontier upwards. Anson (1999) addresses the same question from another perspective. He forms optimal portfolios by maximising a quadratic expected utility for a range of risk aversion coefficients over the period 1974-1997. He concludes that adding commodities to a portfolio of stocks and bonds increases the Sharpe ratio of optimal portfolios. Jensen et al. (2000) also find that including commodities in a traditional asset universe improves the risk-return profile of the efficient portfolios over the period 1973-1997. Idzorek (2007) performs a similar empirical analysis over the period 1970-2005 and reaches similar conclusions.

Therefore, the above mentioned literature has provided unanimous evidence that the investor is better off by including commodities in her portfolio. However, this conclusion has been reached in a MV setting by comparing the position of the efficient frontiers corresponding to the without-commodities universe and the expanded one that includes commodities, respectively.[5] This approach is subject to three shortcomings though. First, the Markowitz setting may not reflect accurately the gains from investing in commodities since it is founded on two assumptions, i.e. that either the distribution of the asset returns is normal or investor's preferences are described by a quadratic utility function. Neither of these two conditions is expected to hold. In particular, there is ample empirical evidence that asset returns are not distributed normally, especially for relatively short horizons (see e.g., Peiro, 1999, for stock indexes, and Gorton and Rouwenhorst, 2006, Kat and Oomen, 2007a, for commodity futures). In the case where the non-normality of returns is not taken into account in the optimal portfolio formation process, then there is a utility loss (Jondeau and Rockinger, 2006). This is because a risk averse investor has a preference for positive skewness and dislikes high kurtosis, and therefore

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[5] You and Daigler (2010) consider the impact of introducing commodities in investors' portfolios on higher order moments. To this end, they compare the skewness and kurtosis of a portfolio consisting of stock index, interest rate, foreign exchange futures and commodity futures with these of a single asset portfolio (stock or commodity index). Given that their reduced and augmented asset universes under comparison differ from the ones employed in our study, no direct comparison between the two studies can be drawn. Interestingly, they find that the out-of-sample Sharpe ratio of the tangent portfolio is less than the in-sample one.

one should consider these moments in the portfolio choice process. Furthermore, a quadratic utility function exhibits negative marginal utility after a certain finite wealth level and increasing absolute risk aversion with respect to wealth; both these features are not consistent with rational behaviour. The second shortcoming is that the previously mentioned commodity papers assess the diversification benefits of investing in commodities by inspecting visually the relative position of efficient frontiers; the comparison of the relative position of efficient frontiers should be set within a statistical framework. Third, all previous studies investigate the benefits of investing in commodities within an in-sample setting.[6] In principle, the portfolio choice should be examined in an out-of-sample setting given that at any given point in time, the investor decides on the portfolio weights and the portfolio returns to be realised over the investment horizon is uncertain.

In light of the previously mentioned shortcomings, we take a more general approach to examining whether commodities should be included in an investors' portfolio. In particular, we consider an investor who allocates funds between equities, bonds, a risk-free asset and commodities in a standard static asset allocation context and make the following five contributions to the existing literature. First, we revisit the posed question within an in-sample setting that has also been employed by the previous literature in order to draw direct comparison with previous findings. The novelty though is that we employ rigorous tests that take into account the higher moments of the asset returns distributions instead of eyeballing the relative position of the efficient frontiers based on the traditional and the traditional augmented with commodities asset universes, respectively. To this end, we apply the regression-based spanning techniques to test for spanning when investor preferences are described by utility functions that are consistent with the MV setting, as well as, a more general non-MV one (see e.g., Huberman and Kandel, 1987, and DeRoon and Nijman, 2001, for MV spanning, and DeRoon et al., 1996, for generalized non-MV spanning tests).[7]

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[6] To the best of our knowledge, the papers by Abanomey and Mathur (1999) and You and Daigler (2009) are the only exceptions. They compare the out-of-sample performance of MV portfolios obtained from two asset universes: one that does not include commodities and one that is augmented with commodities. This may not be the optimal portfolio though for a non-MV investor. Moreover, in the latter paper, no portfolio rebalancing is allowed as new information becomes available. Our approach takes care of these two points among its other purposes.

[7] Huang and Zhong (2011), Nijman and Swinkels (2008), Scherer and He (2008), and Galvani and Plourde (2010) have also applied spanning techniques to assess the diversification benefits of investing in commodities. However, their analysis is placed under a MV setting.

Second, we examine the question under scrutiny by employing an *out-of-sample* setting. In line with DeMiguel et al. (2009) and Kostakis et al. (2011), we form static one-period optimal portfolios at any point in time, calculate their corresponding realised returns and evaluate their performance under a number of performance measures. Third, we construct optimal portfolios by taking into account the higher order moments of the returns distributions of the involved assets. To this end, direct utility maximization is performed (e.g., Cremers et al., 2005, Adler and Kritzman, 2007, Sharpe, 2007). The appeal of this approach compared to the MV optimization applied by previous studies is that it yields optimal portfolios by maximizing the expected utility of the investor for any assumed type of returns distribution and description of her preferences.

Fourth, we study the posed question by considering alternative ways of investing in commodities (see also Abanomey and Mathur, 1999, You and Daigler, 2009, 2010, for a similar approach). To this end, we consider the two most popular commodity indexes, namely the S&P Goldman Sachs Commodity Index (S&P GSCI) and the Dow Jones-UBS Commodity Index (DJ-UBSCI), as well as individual commodity futures contracts written on different types of commodities. The previous literature on asset allocation with commodities assumes that the investor can invest only in commodity indexes. In practice, this is not the case; instead investors follow different strategies represented by the available menu of futures written on individual commodities. Most importantly, the use of alternative individual commodity instruments will serve as a robustness test to the subsequently reported findings. This is because commodities present a significant heterogeneity in terms of their risk-return characteristics that commodity indexes fail to capture (Erb and Harvey, 2006, Kat and Oomen, 2007a). Moreover, the use of a commodity index may bias results in the case where the index overweights a particular commodity sector.

Finally, we employ a rich dataset spanning the period January 1989 to December 2009. This includes bearish and bullish regimes in commodity prices, the 2005-2008 commodity boom, the recent 2007-2009 subprime credit crisis, as well as the increasing presence of index investors in commodities markets and the potential markets integration. Hence, this allows exploring the effect of all these events within a commodities asset allocation setting.

We conduct a number of tests in order to check the robustness of the obtained results. First, we employ various utility/value functions and degrees of risk aversion that describe the preferences of the individual investor. This is because the formation of optimal portfolios is investor specific. In particular, exponential and power utility functions, as well as, the disappointment aversion setting introduced by Gul (1991) are adopted. The latter takes into account behavioural characteristics in investor's preferences. Second, we use a number of performance measures (Sharpe ratio, opportunity cost, portfolio turnover and risk-adjusted returns net of transaction costs) to compare the performance of the optimal portfolio based on traditional and augmented with commodities opportunity sets, respectively. This enables us to take into account the impact of the higher order moments as well as that of transaction costs on performance evaluation. Third, we calculate the optimal portfolios by also maximising the expected utility approximated by its second order (truncated) Taylor series expansion. This serves to check whether the in-sample diversification benefits of commodity investing in a MV framework reported by previous studies still show up in an out-of-sample setting. Fourth, we also consider enhanced commodity indexes designed to provide a greater risk-adjusted performance to S&P GSCI and DJ-UBS CI. Finally, we study the stability of the results over various sub-samples and assess the impact of the 2005-2008 commodity boom period as well as that of the recent 2007-2009 credit crisis.

The rest of the paper is structured as follows. Section 2.2 describes the dataset. Section 2.3 outlines the tests for spanning and discusses the results. Section 2.4 sets the asset allocation framework and then compares the out-of-sample performance of optimal portfolios that contain commodities with that of those that do not contain commodities. Section 2.5 investigates whether the results are robust under a MV setting and Section 2.6 conducts a number of further robustness tests. We summarise results in the last section.

2.2. The dataset

The dataset consists of monthly closing prices of a number of indexes and commodity futures provided by Bloomberg. We employ the S&P 500 total return index, Barclays U.S. Aggregate Bond Index and the Libor one-month rate to proxy the equity market, bond market and the risk-free rate, respectively. To get exposure to the commodity asset class, we use separately various well followed commodity futures indexes, as well as individual commodity futures contracts. In particular, we employ the S&P GSCI and DJ-

UBSCI total return indexes and five individual futures contracts on Crude oil (NYMEX), Cotton (NYBOT), Copper (COMEX), Gold (COMEX) and Live cattle (CME). The dataset for all assets spans the period from January 1989 to December 2009 with the exception of DJ-UBSCI that covers the period from January 1991 to December 2009 due to data availability constraints.

Commodity indexes represent passive investment strategies in a number of the shortest expiry commodity futures. The S&P GSCI was launched in January 1991 with historical data backfilled by index providers since January 1970. The index currently invests in twenty four commodities classified into five groups (energy, precious metals, industrial metals, agricultural and livestock) and is heavily concentrated on the energy sector (almost 70% of the total index value). The DJ-UBSCI was launched in July 1998 with historical data beginning on January 1991. The index invests in nineteen commodities from the energy, precious metals, industrial metals, agricultural and livestock sectors. In contrast to the S&P GSCI, the DJ-UBSCI relies on two important rules to ensure diversification: the minimum and the maximum allowable weight for any single commodity is 2% and 15%, respectively, and the maximum allowable for any sector is 33% (for a detailed description of the commodity indexes see for instance Geman, 2005, Erb and Harvey, 2006). Both employed indexes are the most popular within the large universe of existing commodity indexes (Stoll and Whaley, 2010, Tang and Xiong, 2010).

In the case of the five considered individual commodity futures contracts, we select each one of them on the grounds that each underlying commodity is a representative of the commodity sector that it corresponds to (energy, industrial metals, precious metals, agriculture and livestock). In particular, crude oil is the world's most actively traded commodity. Futures contracts on light sweet crude oil (WTI) are traded on NYMEX. They are the world's largest-volume futures contract on a physical commodity. Each futures contract has 1,000 barrels contract size and its price is quoted in U.S. dollars per barrel. Copper is the world's third most widely used metal and is primarily used in the infrastructure and construction industries. Therefore, its price is considered to reflect the current state of the world economy. The contract size is 25,000 pounds and its price is quoted in US cents per pound. Next, cotton futures have been traded in New York since 1870. They have been used by the domestic and global cotton industries to price and hedge transactions. The NYBOT cotton futures contract specifies delivery of 50,000 pounds net weight upon expiry and its price is quoted in terms of U.S. cents per pound. Gold has been a traditional investment vehicle since it serves as a hedge against inflation and a safe haven in periods of market crises (see e.g., Baur and McDermott, 2010). Each gold futures contract (traded on COMEX) has a contract size of 100 troy ounces and its price is quoted in U.S. dollars and cents per troy ounce. Finally, the livestock futures market serves mainly commodity merchandisers, producers, and processors. The live cattle futures contract has 40,000 pounds contract size and its price is quoted in U.S. cents per pound. The Bloomberg generic shortest futures series is used for each one of the five commodity futures. Bloomberg creates continuous time series of future prices by rolling over from the shortest series to the next shortest as the shortest approaches maturity (for a description on generic contracts, see also Chantziara and Skiadopoulos, 2008).

Table 2.1 reports the descriptive statistics for the various asset classes and the pairwise correlations (Panels A and B, respectively) over the period from January 1989 to December 2009 (the only exception is DJ-UBSCI, with data available from January 1991). At this point, few words of caution are in order. Futures contracts are zero-investment instruments, i.e. they do not require initial investment and therefore their respective returns are considered to be excess returns (over the risk-free rate). Therefore, to compare the rate of return on commodity futures with those on stocks and bonds, we approximate the return on a futures position with the sum of the percentage change in the futures prices and the risk-free rate of return (see e.g., Bodie and Rosansky, 1980; Fortenbery and Hauser, 1990). In the case of the commodity indexes (S&P GSCI and DJ-UBSCI), we compare the returns on stocks and bonds with the respective returns on total return indexes.

We can see that the monthly average return on commodity indexes is lower than that of stocks and bonds and exhibits greater standard deviation. As a result, the Sharpe ratio is considerably greater for bonds and stocks than commodity indexes. The reported evidence is consistent with previous studies, which support that the stand-alone performance of commodity indexes is inferior to other asset classes (see e.g., Jensen et al., 2000). Individual commodity futures are outperformed by stocks (with the exception of crude oil and gold) and bonds in terms of risk-adjusted returns. The Jarque-Bera test rejects the null hypothesis that the commodity asset returns are distributed normally (at a 5% significance level). The pairwise correlations of commodity futures with the traditional asset classes are low. This indicates the potential diversification benefits of commodities. In addition, the correlation among the individual commodities is low. This is in line with the findings reported by Erb and Harvey (2006) and supports the notion that there is a certain degree of heterogeneity among the various commodities. Hence, it is hard to accept the concept of an "average" commodity captured by a single commodity index.

2.3. In-sample benefits of commodities: Testing for spanning

The concept of spanning was first introduced by Huberman and Kandel (1987) and was initially restricted to a MV framework. In brief, the literature on MV spanning analyzes the effect that the introduction of additional risky assets (termed test assets) has on the MV frontier of a set of benchmark assets (see DeRoon and Nijman, 2001, for a review). MV spanning occurs when the MV frontier derived from the augmented investment opportunity set (benchmark assets plus the test ones) coincides with the frontier of the benchmark assets. This implies that the MV investors cannot improve their risk/return trade-off by adding the test assets, regardless of their risk aversion level.[8] In this section, we investigate the economic benefits from investing in various commodity products by means of tests for spanning, without restricting ourselves in an MV framework though. To this end, we follow DeRoon et al., (1996, 2003) and analyse the concept of spanning by means of the stochastic discount factor (SDF) that sets the ground for the ensuing discussion of spanning tests within a non-MV framework.

2.3.1. Definition of spanning: The stochastic discount factor approach

Let an investor who considers a set of K benchmark assets (stocks, bonds, and the risk-free asset) with R_{t+1} be the $(K\times 1)$ vector of the respective gross returns. Asset pricing theory dictates that there exists a SDF, M_{t+1}, such that

$$E\left[M_{t+1}R_{t+1}\,|\,I_t\right]=\iota_K \qquad (2.1)$$

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[8] If the two frontiers have only one point in common, this is known as intersection. In this case, there is only one value of the risk aversion coefficient for which mean-variance investors can not improve their risk/return trade-off by including the test assets in their investment set.

where I_t denotes the information available at time t and ι_K a K-dimensional unit vector. The SDF is derived from the first order conditions of a portfolio choice problem where the investor maximizes the expected utility of her terminal wealth (DeRoon and Nijman, 2001). In this case, the SDF is proportional to the first derivative of the assumed utility function of wealth, given the investor's optimal portfolio choice w^*:

$$M_{t+1} = \lambda U'(w^* R_{t+1}) \tag{2.2}$$

where λ is a constant and w^* the $(K\times 1)$ vector of optimal portfolio weights (see also DeRoon, et al., 2003). Equation (2.2) shows that the SDF varies across investors who have different utility functions or the same utility function with different risk aversion coefficients.

The investor has to decide whether she will incorporate a set of test assets (in our case one commodity asset), with gross return R^{test}_{t+1}, in the initial K-asset universe. Let M be a set of SDFs that price the K benchmark assets, i.e. for each M_{t+1} that belongs to M, equation (2.1) holds. DeRoon et al. (1996, Proposition 1, page 6) show that the returns R^{test}_{t+1} of the test asset are M-spanned by the returns R_{t+1} of the benchmark assets if and only if

$$\hat{R}^{test}_{t+1} = proj\left(R^{test}_{t+1} \,\middle\|\, \left[M \cup \left\{w'R_{t+1} : w \in W\right\}\right]\right) = w'R_{t+1} \text{ for some } w \in W \tag{2.3}$$

where $w \in W = \left\{w \in \mathbb{R}^k : w'\iota_k = 1\right\}$. Proposition 1 yields the following testable hypothesis: the new asset is M-spanned by the benchmark assets if and only if the return of the new asset can be written as the return of a portfolio of the benchmark assets, and a zero-mean error term, ε_{t+1}, i.e.

$$H_0 : R^{test}_{t+1} = w'R_{t+1} + \varepsilon_{t+1} \tag{2.4}$$

where ε_{t+1} is orthogonal to the set M of the pricing kernels under consideration.

2.3.2. Mean-variance spanning tests

First, we test for MV spanning. Hansen and Jagannathan (1991) show that the SDFs associated with MV optimizing behavior have the lowest variance among all admissible ones (that price correctly a set of asset returns) and are linear in asset returns. Hence, equation (2.3) can be estimated by the following linear regression

$$R_{t+1}^{test} = \alpha + \beta R_{t+1} + \varepsilon_{t+1} \qquad (2.5)$$

The null hypothesis for spanning is (see also Huberman and Kandel, 1987)

$$H_0 : \alpha = 0 \ and \ \beta \iota_k = 1 \qquad (2.6)$$

Since in our case the *K*-benchmark asset universe includes also the risk-free asset, the test for MV spanning is reformulated in excess returns terms.[9] To fix ideas, define α_J to be the intercept in the regression of the test asset's excess returns on the excess returns of the *K* benchmark assets, i.e.

$$R_{t+1}^{test} - R_t^f = \alpha_J + \beta\left(R_{t+1} - R_t^f i_K\right) + \varepsilon_{t+1} \qquad (2.7)$$

with R^f being the risk-free rate of return and $E\left(\varepsilon_{t+1}\right) = E\left(\varepsilon_{t+1} R_{t+1}\right) = 0$. In Appendix A, we derive the equivalence between the intercepts of equations (2.5) and (2.7), i.e.

$$\alpha_J = \alpha - R_t^f \left(1 - \beta i_K\right) \qquad (2.8)$$

Given the regression model in equation (2.7), imposing the spanning constraints of equation (2.6) yields $\alpha_J = 0$, i.e.

$$H_0 : \alpha_J = \alpha - R_t^f \left(1 - \beta i_K\right) = 0 \qquad (2.9)$$

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[9] From a financial theory perspective, it is legitimate to use the risk-free rate as a regressor in equation (2.5). However, from an econometric perspective, this is an unattractive regressor given its persistency and therefore the stated reformulation is preferred. Notice also that in the case that the risk-free asset is included in the set of benchmark assets, testing for spanning is equivalent to testing for intersection. This can be easily perceived by means of the MV efficient frontier. In the case where there is a risk-free asset, two mutual fund separation theorem holds, i.e. the efficient frontier is linear and constructed by combining the risk-free asset with the tangency portfolio. Hence, testing for spanning amounts to testing whether the two linear frontiers, that of the test and benchmark assets and the one that includes only benchmark assets, are the same. This is equivalent to testing whether the tangency portfolios are the same, i.e. testing for intersection.

Notice that in the case of the excess returns formulation, the hypothesis of spanning amounts to testing only the intercept term. The slope coefficients of the risky assets do not need to add up to one since they multiply only the excess returns of the *(K-1)* risky assets; the missing allocation is filled by the investment in the risk-free asset (see also Huberman and Kandel, 1987, Scherer and He, 2008).

2.3.3. Non mean-variance spanning tests

Next, we outline the test for spanning in the non–MV case. Let investors' preferences be described by a non-MV utility function *U(·)*, i.e. not a quadratic one. Consequently, the set *M* of pricing kernels under consideration includes the MV linear SDFs as well as the SDFs of the assumed non-MV utility function that correspond to different risk aversion coefficients. Equation (2.2) implies that any given value for the risk aversion coefficient imposes a different SDF that should be included in the set *M*. Therefore, in the case where a non-MV utility function is considered, the test for spanning should be carried out by examining whether the relative restrictions hold for *any* value of risk aversion. For the purposes of our study, we employ a wide range of risk aversion coefficients for each non-MV utility function $U_i(\cdot)$ of interest with $i=1,2,\ldots,n$ corresponding to the *i*th risk aversion value. Following the approach suggested by DeRoon et al. (1996, 2003), we estimate equation (2.3) by projecting the excess returns of the test assets on the set *M* of SDFs, i.e.:

$$R^{test}_{t+1} = \alpha + \beta R_{t+1} + \sum_{i=1}^{n} \gamma_i U_i{}'\left(w_i^{*\prime} R_{t+1}\right) + \varepsilon_{t+1} \qquad (2.10)$$

and test jointly for spanning in the MV and non-MV case by evaluating the restrictions

$$H_0 : \beta \iota_k = 1 \; and \; \alpha = \gamma_i = 0 \, \forall i \qquad (2.11)$$

Again, the test for non-MV spanning is reformulated in excess returns terms and the following linear regression equation is estimated (see Appendix B):

$$R^{test}_{t+1} - R^f_t = \alpha_J + \beta\left(R_{t+1} - R^f_t i_K\right) + \sum_{i=1}^{n} \gamma_i U_i{}'\left(w_i^{*\prime} R_{t+1}\right) + \varepsilon_{t+1} \qquad (2.12)$$

Hence, the restrictions that need to hold for the joint existence of MV and non-MV spanning, become[10]

$$H_0 : \alpha_J = 0 \text{ and } \gamma_i = 0 \, \forall i \tag{2.13}$$

From an implementation point of view, the restrictions in (2.9) and (2.13) are tested by Wald test (see e.g., DeRoon and Nijman, 2001). We correct the standard errors of the estimators by the Newey and West (1987) method to account for the presence of autocorrelation and heteroskedasticity in the residual term. Moreover, to perform the regression in equation (2.12), we need to estimate the unobserved regressors (i.e. the marginal utilities). To this end, we make an assumption about the utility function and estimate the optimal portfolio weights. In particular, we consider an investor whose preferences are described by either an exponential utility function or a power utility function, for different levels of risk aversion. The negative exponential utility function is defined as:

$$U(W) = -\boldsymbol{exp}\left\{-\eta W\right\} / \eta, \;\; \eta > 0 \tag{2.14}$$

where η is the coefficient of absolute risk aversion (ARA). The power utility function is defined as

$$U(W) = \frac{W^{1-\gamma} - 1}{1-\gamma}, \;\; \gamma \neq 1 \tag{2.15}$$

where γ is the coefficient of relative risk aversion (RRA).

We estimate the optimal portfolio weights by applying the Generalized Method of Moments (GMM, see e.g., Cochrane, 2005). The moment conditions generated by the SDFs of interest need to be defined. Given the assumed non-MV utility function, equations (2.1) and (2.2) imply that the returns on the K benchmark assets should satisfy the following conditions:

$$E\left[\lambda_i U_i'\left(w_i^{*\prime} R_{t+1}\right) R_{t+1} \mid I_t\right] = \iota_K \quad \forall i \tag{2.16}$$

Let the parameter vector $\Theta_i = [\lambda_i \;\; w_i^*]$ that corresponds to the *ith* value of risk aversion, *i=1,2,..,n*. Define the errors, $u_{t+1}\left(\Theta_i\right)$:

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[10] Notice that α_J can be interpreted as Jensen's alpha only under the MV setting.

$$u_{t+1}\left(\Theta_i\right) = \lambda_i U_i'\left(w_i^{*\prime} R_{t+1}\right) R_{t+1} - \iota_K \tag{2.17}$$

Then, for a sample of size *T*, the moment conditions $g_T\left(\Theta_i\right)$ are defined as the sample mean of the errors $u_{t+1}\left(\Theta_i\right)$ i.e.

$$g_T(\Theta_i) \equiv \frac{1}{T}\sum_{t=1}^{T} u_t\left(\Theta_i\right) = E_T\left[u_t\left(\Theta_i\right)\right] = E_T\left[\lambda_i U_i'\left(w_i^{*\prime} R_t\right) R_t - \iota_K\right] \tag{2.18}$$

By definition, the SDF (for each *i*) should price each one of the three benchmark assets. This provides us with three moment conditions in order to estimate Θ_i. We obtain the GMM estimate of Θ_i by minimizing the quadratic function

$$J_T(\Theta_i) = g_T(\Theta_i)' W g_T(\Theta_i) \tag{2.19}$$

where *W* is a positive definite weighting matrix. We set *W* equal to the identity matrix *I* since the number of unknowns equals the number of moment conditions.

2.3.4. Results and discussion

This section tests the spanning hypothesis when a commodity asset is included in a traditional asset universe, consisting of stocks, bonds and the risk-free asset. We conduct the analysis using either a commodity index or a futures contract written on an individual commodity in order to proxy the commodity investment vehicle. To this end, we employ the S&P GSCI and DJ-UBSCI as well as individual commodity future contracts written on crude oil, cotton, copper, live cattle and gold, separately.

Table 2.2 reports the Wald test statistics and the respective *p*-values for testing the null hypothesis that there is spanning. We test the following hypotheses separately: only MV spanning, MV and non-MV spanning jointly (MV & exponential, MV & power), as well as only non-MV spanning (exponential, power). We use risk aversion coefficients for a range of values (ARA, RRA=2,4,6,8,10) to conduct the non-MV spanning tests (equation (2.12)). We can see that the null hypothesis of MV spanning cannot be rejected at a 5% significance level. This holds for either one for the two commodity indexes and for every individual commodity futures. Therefore, the results suggest that under a MV setting, the performance of traditional portfolios, consisting of stocks, bonds and cash cannot be significantly improved by investing in commodities. These findings are in line with those reported by DeRoon et al. (1996) and Scherer and He (2008), and in contrast to Galvani and Plourde (2010) who test the spanning hypothesis using a different dataset from ours (individual energy futures and energy stocks) over the period 1990-2008.

On the other hand, in the non-MV case, we can see that the spanning hypothesis is rejected for the two commodity indexes and the majority of individual commodity contracts regardless of the assumed non-MV utility function; the only exceptions occur for futures on cotton (for the assumed exponential utility function) and live cattle. Results hold regardless of whether testing is carried out for joint MV and non-MV spanning or for only non-MV spanning. These findings are again in line with DeRoon et al. (1996); they find that commodity futures do not offer any added value to investors with utility functions consistent with the MV setting, while they do in the case where spanning is tested under a non-MV setting.

2.4. Out-of-sample benefits of commodities

Next, we investigate whether the (non-MV) in-sample diversification benefits provided by commodities are preserved in an out-of-sample setting, too. To this end, we calculate optimal portfolios separately for an asset universe that includes "traditional" asset classes (stock, bond, risk-free asset) and an "augmented" one that also includes commodities. Next, we evaluate their relative performance in an out-of-sample setting which is the ultimate test given that at any given point in time, the investor decides on the portfolio weights; the portfolio returns to be realised over the investment horizon are uncertain.

2.4.1. The asset allocation setting

Let a myopic investor with fixed initial wealth W_t who faces an asset universe of N assets that pay off at time $t+1$. Her utility function $U(W_{t+1})$ is assumed to be continuous, increasing, concave and differentiable. Let w_i be the weight of wealth invested in the risky asset i over the next period. We construct the optimal portfolio at time t by maximizing the investor's expected utility of wealth at time *t+1* with respect to the portfolio weights, i.e.

$$\max_{w_i} E[U(W_{t+1})], \quad s.t \quad \sum_{i=1}^{N} w_i = 1 \tag{2.20}$$

Let also $r_{i,t+1}$ be the simple rate of return on the individual asset *i* and $r_{p,t+1}$ the portfolio return. Without loss of generality, we assume that the initial wealth is normalized to one, i.e. $W_t = 1$. The end-of-period wealth is given by:

$$W_{t+1} = W_t(1+\sum_{i=1}^{N} w_i r_{i,t+1}) = 1+\sum_{i=1}^{N} w_i r_{i,t+1} = 1+r_{p,t+1} \tag{2.21}$$

To solve the expected utility maximization problem, an assumption about the utility function of the investor needs to be made. First, we assume that the preferences of the investors are described either by the negative exponential or the power utility function (equations (2.14) and (2.15), respectively) that are commonly used in the finance literature. To ensure the robustness of our results, we use various levels of absolute and relative risk aversion (ARA, RRA=2, 4, 6, 8, 10).

In addition, we consider the disappointment aversion (DA) setting introduced by Gul (1991) to capture behavioral characteristics in investors' preferences. In particular, this framework has been employed in recent asset allocation studies so as to capture the presence of loss aversion (see e.g., Ang et al., 2005, Driessen and Maenhout, 2007, Kostakis et al., 2011), i.e. the fact that investors are more sensitive to reductions in their financial wealth than to increases relative to a reference point. The advantage of Gul's (1991) DA setting over other behavioral models is that it is founded on formal decision theory that retains all assumptions and axioms underlying expected utility theory but the independence axiom that is replaced by a weaker one to accommodate the Allais paradox. In line with Driessen and Maenhout (2007) and Kostakis et al. (2011), we employ a DA value function based on a power utility function, i.e.

$$U(W) = \begin{cases} \dfrac{W_T^{1-\gamma}-1}{1-\gamma} & \text{if } W_T > \mu_W \\ \dfrac{W_T^{1-\gamma}-1}{1-\gamma} - \left(\dfrac{1}{A}-1\right)\left[\dfrac{\mu_W^{1-\gamma}-1}{1-\gamma} - \dfrac{W_T^{1-\gamma}-1}{1-\gamma}\right] & \text{if } W_T \le \mu_W \end{cases} \tag{2.22}$$

where γ denotes the RRA coefficient that controls the loss function in each region, $A \leq 1$ is the coefficient of DA that controls the relative steepness of the value function in the region of gains versus the region of losses and μ_W is the reference point relative to which gains or losses are measured; the investor gets disappointed in the case where her wealth drops below the reference point. Notice that the loss aversion decreases as *A* increases; *A*=1 corresponds to the case of the standard power utility function where there is no loss aversion. In accordance with Driessen and Maenhout (2007), we employ two values for *A*=0.6, 0.8. Furthermore, we set μ_W equal to the initial wealth invested at the risk-free rate, i.e. $\mu_W = W_t(1+r_f)$. This choice of the reference point is in line with Barberis et al. (2001) and implies that the investor uses the risk-free rate as a benchmark to code a gain or a loss. In fact, this is a realistic assumption. Veld and Veld-Merkoulova (2008) conduct a study on investors' behavior and find that a significant portion of investors use the risk-free rate as a reference point to distinguish between losses and gains. [11]

2.4.2. Calculating the optimal portfolio

We implement the optimization problem in equation (2.20) by performing direct utility maximization defined as the following non-linear optimization problem:

$$\max_{w_i} E[U(W_{t+1})] = \int .....\int U[W_t(1+\sum_{i=1}^{N} w_i r_i)]dF(r_1...r_N), \quad s.t \sum_{i=1}^{N} w_i = 1 \qquad (2.23)$$

where $F(r_1...r_N)$ is the joint cumulative distribution function (CDF) of the *N* returns at time *t*+1. Direct utility maximization provides a more general asset allocation setting compared with the Markowitz MV one since it takes into account the higher order moments of the joint CDF as well. On the other hand, the joint CDF needs to be estimated; this requires assuming either a specific estimator or a parametric form for the CDF leading to an estimation error. To circumvent this, we estimate optimal portfolios by applying the full scale optimization method proposed by Cremers et al. (2005) and Adler and Kritzman (2007). This is a non-parametric technique based on a numerical grid search procedure that uses as many asset mixes as necessary to identify the weights that

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[11] Notice that the DA function is not globally differentiable and hence it cannot be employed neither in the spanning tests described in Section 3 nor in the Taylor series approach that will be presented in Section 5.

yield the highest expected utility. The method requires no assumptions about the joint CDF of returns or potential estimators. On the other hand, the absence of simplifying assumptions comes at the cost of computational burden.

2.4.3. Out-of-sample performance measures

To ensure the out-of-sample nature of our study, a “rolling-sample” approach is employed. Let the dataset consist of T monthly observations for each asset and K be the size of the rolling window to be used for the calculation of the portfolio weights, where $K \leq T$. Standing at any given point in time (month) t, we use the previous K observations to estimate the asset allocation weights that maximize expected utility. The estimated weights at time t are then used to compute the out-of-sample realised return over the period $[t,t+1]$. This process is repeated by incorporating the return for the next period and ignoring the earliest one, until the end of the sample is reached. To ensure the robustness of the obtained results, we use alternative rolling windows sizes of K=36, 48, 60, 72 monthly observations. This rolling-window approach allows deriving a series of T-K monthly out-of-sample optimal portfolio returns, given the preferences of the investor and length of the estimation window. The time series of realised portfolio returns is then used to evaluate the out-of-sample performance of the formed optimal portfolios.

Following DeMiguel et al. (2009) and Kostakis et al. (2011), we employ a number of performance measures, namely the Sharpe ratio (SR), opportunity cost, portfolio turnover and a measure of the portfolio risk-adjusted returns net of transaction costs. To fix ideas, let a specific strategy c. The estimate of the strategy’s SR_c is defined as the fraction of the sample mean of out-of-sample excess returns $\hat{\mu}_c$, divided by their sample standard deviation $\hat{\sigma}_c$.

$$\widehat{SR}_c = \frac{\hat{\mu}_c}{\hat{\sigma}_c} \tag{2.24}$$

To test whether the SRs of the two optimal portfolio strategies are statistically different, we use the statistic proposed by Jobson and Korkie (1981) and corrected by Memmel (2003).

However, the SR is suitable to assess the performance of a strategy only in the case where the strategy’s returns are normally distributed. Hence, we use next the concept of opportunity cost (Simaan, 1993) to assess the economic significance of the difference in performance of the two optimal portfolios based on the traditional and augmented with commodities asset universes, respectively. Let r_{wc}, r_{nc} denote the optimal portfolio realized returns obtained by an investor with the expanded investment opportunity set that includes commodities and the investment opportunity set restricted to the traditional asset classes, respectively. The opportunity cost θ is defined as the return that needs to be added to the portfolio return r_{nc} so that the investor becomes indifferent (in utility terms) between the two strategies imposed by the different investment opportunity sets, i.e.

$$E\left[U\left(1+r_{nc}+\theta\right)\right]=E\left[U\left(1+r_{wc}\right)\right] \tag{2.25}$$

Hence, a positive opportunity cost implies that the investor is better off in case of an investment opportunity set that allows commodity investing. Notice that the opportunity cost takes into account all the characteristics of the utility function and hence it is suitable to evaluate strategies even when the return distribution is not the normal one.

In addition, we use the portfolio turnover metric so as to quantify the amount of trading required to implement each one of the two strategies. The portfolio turnover PT_c for a strategy *c* is defined as the average absolute change in the weights over the *T-K* rebalancing points in time and across the *N* available assets i.e.

$$PT_c=\frac{1}{T-K}\sum_{t=1}^{T-K}\sum_{j=1}^{N}\left(\left|\,w_{c,j,t+1}-w_{c,j,t+}\right|\right) \tag{2.26}$$

where $w_{c,j,t}, w_{c,j,t+1}$ are the derived optimal weights of asset *j* under strategy *c* at time *t* and *t+1*, respectively; $w_{c,j,t+}$ is the portfolio weight before the rebalancing at time *t+1*; the quantity $\left|w_{c,j,t+1}-w_{c,j,t+}\right|$ shows the magnitude of trade needed for asset *j* at the rebalancing point *t+1*. The *PT* quantity can be interpreted as the average fraction (in percentage terms) of the portfolio value that has to be reallocated over the whole period.

Finally, we also evaluate the two investment strategies under the risk-adjusted, net of transaction costs, returns measure proposed by DeMiguel et al. (2009). To fix ideas, let *pc* be the proportional transaction cost and $r_{c,p,t+1}$ the realized portfolio return at *t+1* (before rebalancing). The evolution of the net of transaction costs wealth NW_c for strategy *c*, is given by:

$$NW_{c,t+1} = NW_{c,t}\left(1+r_{c,p,t+1}\right)\left[1-pc\times\sum_{j=1}^{N}\left(\left|w_{c,j,t+1}-w_{c,j,t+}\right|\right)\right] \tag{2.27}$$

Therefore, the return net of transaction costs is defined as

$$RNTC_{c,t+1} = \frac{NW_{c,t+1}}{NW_{c,t}} - 1 \tag{2.28}$$

The return-loss measure is calculated as the additional return needed for the strategy with the restricted opportunity set to perform as well as the strategy with the expanded opportunity set that includes commodity futures. Let μ_{wc}, μ_{nc} be the monthly out-of-sample mean of *RNTC* from the strategy with the expanded and the restricted opportunity set, respectively, and σ_{wc}, σ_{nc} be the corresponding standard deviations. Then, the return-loss measure is given by:

$$return - loss = \frac{\mu_{wc}}{\sigma_{wc}} \times \sigma_{nc} - \mu_{nc} \tag{2.29}$$

To calculate $NW_{c,t+1}$, we set the proportional transaction cost *pc* equal to 50 basis points per transaction for stocks and bonds (see DeMiguel et al., 2009, for a similar choice), 35 basis points for the commodity indexes and individual commodity futures contracts (based on discussion with practitioners in the commodity markets), and zero for the risk-free asset.[12]

2.4.4. Direct maximization: Results and discussion

This section discusses the results on the out-of-sample performance of the traditional and augmented with commodities portfolios formed by direct maximization of expected utility. Tables 2.3, 2.4 and 2.5 show the results for the cases where the preferences of the

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[12] To ensure the robustness of the obtained results, when individual commodity futures are considered, we have also employed alternative values for the level of transaction costs (see for instance Szakmary et al., 2010). The results remain qualitatively similar, i.e. the inclusion of commodity futures in the asset universe does not make the investor better off.

investor are described by an exponential utility, power utility, and DA value function, respectively. Investors access investment in commodities via the S&P GSCI and DJ-UBSCI commodity indexes, separately (Panels A and B, respectively). Results are reported for the four performance measures and various levels of (absolute/relative) risk and disappointment aversion, as well as different sample sizes of the estimation window. To assess the statistical significance of the superiority in SRs, the *p*-values of Memmel's (2003) test are reported within parentheses. The null hypothesis is that the SRs obtained from the traditional investment opportunity set and the expanded investment opportunity set that also includes commodities are equal. We can see that the optimal portfolios formed based on the traditional investment opportunity set yield greater SRs than the corresponding portfolio strategies based on the expanded investment opportunity set. Some exceptions occur where the optimal strategies that include commodities yield greater SRs than the ones that use the traditional opportunity set. However, the *p*-values of Memmel's (2003) test indicate that the differences in SRs are not statistically significant. Interestingly, we can see that for any given level of risk aversion, the SRs decrease as the size of the rolling window increases. This implies that the recently arrived information should be weighted more heavily (see also Kostakis et al., 2011, for a similar finding). An exception to this pattern occurs when the size of the rolling window increases from 60 months to 72 months; this is more pronounced for the S&P GSCI.

Regarding the opportunity cost, we can see that this is negative in most cases. The negative sign indicates that the investor is willing to pay a premium in order to replace the optimal strategy that includes investment in commodities with the optimal one that invests only in the traditional assets. This implies that the investor is better off when the traditional investment opportunity set is considered. These results are in accordance with the ones obtained under the SR despite the fact the distribution of the optimal portfolio returns deviates from normality (evidence is based on unreported results). Interestingly, in most cases, the opportunity cost decreases (in absolute terms) as the risk aversion increases. This implies that the investor becomes indifferent in utility terms between including and excluding commodities in her asset portfolio as she becomes more risk averse.

Furthermore, the portfolios that include only the traditional asset classes induce less portfolio turnover compared with the ones that also include commodities. Interestingly, we can see that in most cases the difference in the portfolio turnovers of the two strategies decreases as the risk aversion increases. This suggests that as the investor becomes more risk averse, she decreases her rebalancing activity since she is willing less to undertake an active bet. Finally, we can see that the return-loss measure that takes into account transaction costs is negative. The negative sign simply confirms the out-of-sample superiority of the portfolios that include only the traditional asset class, even after deducting the incurred transaction costs. We can see that the return-loss measure decreases (in absolute terms) as the risk aversion increases, just as was the case with the opportunity cost. These findings hold regardless of the commodity index, assumed utility/value function, degree of the investor's relative/absolute risk and disappointment aversion, and the employed size of the estimation window.

Tables 2.6 and 2.7 show the results when investors access investment in commodities via each one of the individual futures contracts, separately, and their preferences are described by an exponential / power utility and DA value function, respectively. Due to space limitations, results are reported for ARA, RRA=2,4,6. Results are similar to the ones obtained in the case where commodity indexes were considered, i.e. in most cases, optimal augmented portfolios that include commodity futures do not outperform the ones that do not. In particular, we can see that the optimal portfolios formed based on the traditional investment opportunity set yield greater SRs than the corresponding portfolio strategies based on the expanded with commodity futures opportunity set. Some exceptions occur in the case of crude oil, copper, and gold futures, i.e. greater SRs are delivered for the optimal strategies that include commodities. However, in most cases, the *p*-values of Memmel's (2003) test indicate that the differences in SRs are not statistically significant. These findings hold regardless of the selected commodity futures contract, assumed utility/value function, degree of the investor's relative/absolute risk and disappointment aversion, and the employed size of the estimation window.

Regarding the opportunity cost, we can see that this is negative in almost all cases. Few exceptions occur when gold futures are considered. In most cases, the opportunity cost decreases (in absolute terms) as the risk aversion increases. In addition, the portfolios that include only the traditional asset classes induce less portfolio turnover compared with the ones that also include individual commodity futures. Interestingly, we can also see that in most cases the difference in the portfolio turnovers of the two strategies decreases as the risk aversion increases. Finally, regarding the return-loss measure, the results are mixed. This measure is negative in almost all cases across the various levels of risk aversion when crude oil, cotton and live cattle are used as investment vehicle. Exceptions occur though in the case of metal futures (copper and gold) in more than half of the cases. This implies that even though portfolios based on an investment opportunity set that includes gold /copper futures have greater turnover than the ones based on the traditional opportunity set, the investors can still earn positive risk-adjusted return by investing in these commodities. In the case of DA preferences, especially when A=0.6, the out-of-sample superiority of the portfolios that include only the traditional asset classes is confirmed by all employed performance measures. Overall, the reported results under the out-of-sample setting are in contrast with the findings within an in-sample non-MV setting (Section 2.3.4) where it was found that commodities offer in-sample diversification benefits to investors with non-MV utility functions.

2.5. Out-of-sample benefits of commodities: Mean-variance analysis

In this section, we examine the out-of-sample potential benefits of including commodities in an investor's portfolio within a MV setting. This approach will shed light on whether the previously reported evidence, that challenges the diversification role of commodities, is due to the inclusion of the higher order moments of the returns distribution. To this end, we maximize a second order approximation of the expected utility rather than solving the direct maximization problem. Let the mean value of the future wealth, $\overline{W}_{t+1}$, defined by equation (2.21)

$$\overline{W}_{t+1} = E_t\left(W_{t+1}\right) = 1 + \sum_{i=1}^{N} w_i \mu_{i,t+1} = 1 + \mu_{p,t+1} \tag{2.30}$$

where $\mu_{i,t+1}$ denotes the mean rate of return on the individual asset i and $\mu_{p,t+1}$ the mean portfolio return. The expected utility expanded by an infinite Taylor series expansion around $\overline{W}_{t+1}$ is given by:

$$E[U(W_{t+1})] = E\left[\sum_{k=0}^{\infty} U^k\left(\overline{W}_{t+1}\right)\frac{[W_{t+1} - \overline{W}_{t+1}]^k}{k!}\right] \tag{2.31}$$

Under rather mild conditions of convergence (see e.g., Garlappi and Skoulakis, 2011, and references therein), the expected utility can be expressed in terms of all the central moments of the distribution of the end-of-period wealth and the *k* partial derivatives of the utility function, i.e.

$$E[U(W_{t+1})] = \sum_{k=0}^{\infty} \frac{U^k(\bar{W}_{t+1})}{k!} E\left[\left(W_{t+1} - \bar{W}_{t+1}\right)^k\right] \tag{2.32}$$

We choose *k*=2 that corresponds to the MV optimization proposed by Markowitz (1952). The second order Taylor series expansion can be written as:

$$E[U(W_{t+1})] \approx U(\bar{W}_{t+1}) + \frac{U^2(\bar{W}_{t+1})}{2!} E\left[\left(W_{t+1} - \bar{W}_{t+1}\right)^2\right] = U(\bar{W}_{t+1}) + \frac{U^2(\bar{W}_{t+1})}{2!} \sigma^2_{p,t+1} \tag{2.33}$$

where $\sigma^2_{p,t+1}$ denotes the variance of the portfolio returns. Under the negative exponential and power utility functions, equation (2.33) is formulated respectively as

$$E\left[U\left(W_{t+1}\right)\right] \approx -\frac{1}{\eta} \exp\left(-\eta \bar{W}_{t+1}\right) \left(1 + \frac{\eta^2}{2} \sigma^2_{p,t+1}\right) \tag{2.34}$$

and

$$E\left[U\left(W_{t+1}\right)\right] \approx \frac{\bar{W}_{t+1}^{1-\gamma} - 1}{1-\gamma} - \frac{\gamma}{2} \bar{W}_{t+1}^{-\gamma-1} \sigma^2_{p,t+1} \tag{2.35}$$

Equations (2.34) and (2.35) are maximised with respect to the portfolio weights to obtain the optimal portfolio choice; a grid search over possible values of the assets weights is performed. To implement the maximization, we estimate the means and variance-covariance matrix of the asset returns by their corresponding sample estimators.

Table 2.8 shows the results for the cases where the preferences of the investor are described by second order Taylor series expansions of a power utility function and she accesses investment in commodities either via S&P GSCI or via DJ-UBSCI. We can see that the performance of the MV optimal portfolios formed based on the traditional investment opportunity set is superior to the performance of the corresponding portfolio strategies based on the expanded investment opportunity set. The results hold for an exponential utility function, too (not reported). Similar finding are also obtained in the case where each one of the individual futures contracts is included in the traditional asset universe. Results are not reported due to space limitations. Exceptions occur only for the gold and copper futures contracts where the return-loss is positive for some levels of risk aversion. Therefore, the results obtained under the MV setting are qualitatively identical with the ones obtained under the more general direct utility maximisation setting that takes also into account the higher order moments. Hence, they confirm that the introduction of commodity instruments in a traditional portfolio is not beneficial for a utility-maximizer investor. In addition, they extend the evidence reported in Section 2.3, where commodities were found to span the returns of the traditional assets within an in-sample MV setting, to an out-of-sample one.

2.6. Further robustness tests

In this section we perform further tests to assess the robustness of the results reported in sections 2.3.4 and 2.4.4. First, we divide the sample to two sub-periods based on commodities' performance and repeat the previous analysis. Second, we examine the effect of the recent subprime crisis. Third, we study the robustness of the results by employing enhanced commodity indexes that exhibit superior risk-adjusted performance than the traditional benchmarks.[13]

2.6.1. Sub-sample analysis: The effect of the commodity boom

We apply the previously described analysis to two successive sub-periods: January 1989 to December 2004, and January 2005 to June 2008. The latter period has witnessed a spectacular and simultaneous increase in the commodity prices of three major commodity groups (energy, metals and agriculture) that has taken them to record highs in the recent history of commodities and hence has been termed as a commodity boom period (see e.g., Conceição and Marone, 2008, Helbling, 2008). Therefore, this sub-sample analysis will enable examining whether an investor should have included commodities in her portfolio during a period characterized by superior commodities' performance.

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[13] We also assess the out-of-sample performance of the traditional versus the expanded universe based portfolios by using a 1/*N* portfolio choice rule rather than an expected utility maximization rule; DeMiguel et al. (2009) find that this naïve diversification rule outperforms other more sophisticated ones in an out-of-sample setting. We find again that the inclusion of commodities in the asset universe does not make the investor better off just as was the case with the expected utility maximization.

Regarding the analysis over the 1989-2004 period, the results on spanning and the out-of-sample performance of the two asset universes are similar to the ones obtained over the 1989-2009 period. In particular, we find that the null hypothesis of MV spanning cannot be rejected for either one of the two commodity indexes or for any individual commodity contract at a 5% significance level. On the other hand, in the non-MV case, the spanning hypothesis is rejected for the two commodity indexes and the majority of individual commodity contracts, irrespectively of the assumed utility function. The only exceptions occur for the individual contracts written on cotton and live cattle, just as was the case in the whole-sample analysis. Panel A of Tables 2.9 and 2.10 shows the evaluation of the out-of-sample performance when the investor accesses commodities via commodity indexes and individual commodity futures, respectively, over 1989-2004; her preferences are described by a power utility function and direct utility maximization is performed (qualitatively similar results are obtained for the case of exponential utility and DA value function). We can see that the inclusion of commodities does not make the investor better off.

On the other hand, the results for the period 2005-June 2008 are in contrast with those found over the 1989-2009 period. The investor benefits from the inclusion of commodities in her asset universe. This is confirmed both by the MV and non-MV tests for spanning as well as by the out-of-sample analysis. In particular, Panel B of Tables 2.9 and 2.10 shows the out-of-sample performance over the 2005-June 2008 period. We can see that the expanded universe based strategies yield greater SRs than the corresponding strategies formed by the traditional opportunity set. However, the differences in SRs are not always statistically significant. Regarding the opportunity cost, we can see that this is positive in most cases. This implies that the investor is better off when commodity investment is allowed. Finally, the positive reported in most cases sign of the return-loss measure also confirms the out-of-sample superiority of the augmented with commodities portfolios even after deducting the incurred transaction costs. The only exceptions occur for cotton and live cattle futures.

The results obtained over the period 2005-June 2008 come to no surprise though since this is a commodity boom period. In fact, it is the longest and broadest of the post-World War II commodity boom period (Conceição and Marone, 2008); it affected more commodities and imposed larger prices increases (in real terms) than any other boom in the last sixty years. Moreover, these findings should be interpreted with caution. This is because commodity booms are rare events. In particular, this period is only one of the three booming periods in the history of commodities since 1950 (the other two occurred in early 1950s and 1970s, see Radetzki, 2006). Furthermore, the finding that the inclusion of commodities is beneficial to the investor over the booming period though interesting per se, does not hold over other "normal" periods of time as the 1989-2004 analysis has revealed. Therefore, the reported benefits of including commodities in investor's portfolios is the exception rather than the rule.

2.6.2. The effect of the subprime crisis

In this section, we assess the robustness of our results by examining whether an investor should have included commodities in her portfolio over the recent subprime crisis period. The motivation for undertaking this analysis stems from the fact that the empirical evidence on the diversification benefits of commodities over periods of market turbulence is mixed. On the one hand, there is a number of empirical papers that examine the pre-2008 era. Their findings imply that the diversification benefits of commodities are more pronounced over turbulent periods (see e.g., Gorton and Rouwenhorst, 2006, Kat and Oomen, 2007b, Chong and Miffre, 2010, Büyükşahin et al., 2010). On the other hand, Silvennoinen and Thorp (2010), Tang and Xiong, (2010), and Buyuksahin et al. (2010) find that the return correlations between commodities and equities have increased substantially during the recent subprime crisis. Our analysis of asset returns' rolling pairwise correlations (unreported results) also uncovers the latter pattern. We consider August 2007 as the beginning of the sub-prime debt crisis in line with Gorton (2009) and hence we repeat the previous analysis over the period from August 2007 until December 2009.

The unreported results are qualitatively similar to these obtained when the analysis was conducted over the whole sample period. In particular, we find that the null hypothesis of MV spanning cannot be rejected for either of the two commodity indexes or for any individual commodity contract. On the other hand, investors whose preferences are described by non-MV utility functions become better off when commodities were included in their portfolios. The only exceptions occur for the individual contracts written on cotton and live cattle, just as was the case in the whole-sample analysis.

Next, we assess the out-of-sample performance of the traditional and augmented with commodities portfolios formed by direct maximization of expected utility over the subprime crisis period. Again, the results are qualitatively similar as the ones obtained when the analysis was conducted over the whole sample period (Section 2.4.4); results are not reported due to space limitations. In particular, the inclusion of commodities in the asset universe does not make the investor better off. The only exception occurs when gold futures are considered. The results over the crisis period may be attributed to the fact that correlations tend to increase over periods with extreme market conditions and hence diversification benefits vanish. The findings on the diversification benefits of gold are in accordance with the evidence on its "safe haven" role in periods of crisis (Baur and McDermott, 2010).

2.6.3. Enhanced commodity indexes

In this section, we assess the robustness of the reported results by considering alternative commodity indexes that yield greater risk-adjusted returns than the traditional commodity benchmarks (S&P GSCI and DJ-UBSCI) that have been employed so far. To this end, we choose the Deutsche Bank Liquid Commodities Index (DBLCI) and the Merrill Lynch Commodity Index eXtra (MLCX). The dataset spans the periods from January 1989 to December 2009 for DBLCI and from June 1990 to December 2009 for MLCX. Both indexes belong to the class of the so-called "second generation" (or enhanced) commodity indexes constructed to ensure greater risk-adjusted performance compared to the "first generation" commodity indexes where the S&P GSCI and DJ-UBSCI belong to (see e.g., Fuertes et al., 2012). In fact, the SRs for MLCX and DBLCI are 0.43 and 0.37, respectively, whereas the respective figures for S&P GSCI and DJ-UBSCI are 0.16 and 0.19. Even though both indexes represent passive strategies just as the S&P GSCI and DJ-UBSCI, they exhibit significant differences in their composition and rolling procedures. In particular, DBLCI and MLCX track the performance of six and eighteen commodities, respectively, in the energy, precious metals, industrial metals, and grain sectors. In addition, MLCX rolls from the second-to-the third month contract rather than the nearby to the next nearby contract as the S&P GSCI and DJ-UBSCI do so that to profit from a positive roll yield.

We perform the spanning tests and the out-of-sample analysis. Under the in-sample spanning setting, the (unreported) results are qualitatively similar as the ones obtained for S&P GSCI and DJ-UBSCI (Section 2.3.4). In particular, we find that the null hypothesis of MV spanning cannot be rejected for both commodity indexes whereas in the non-MV case, the spanning hypothesis is rejected regardless of the assumed utility function and commodity index under scrutiny. Regarding the out-of-sample analysis, Table 2.11 reports the performance evaluation when investor's preferences are described by a power utility function. We find qualitatively similar results to the case of exponential utility and DA value function; the detailed results are not reported due to space limitations. We can see that the results are in line with those obtained for S&P GSCI and DJ-UBSCI (Section 2.4.4) i.e. again the inclusion of commodities does not make the investor better off. The results hold even after deducting the transaction costs.

2.7. Conclusions

This paper investigates whether an investor is made better off by including commodities in a portfolio that consists of traditional asset classes, namely stocks, bonds and cash. To this end, we take a more general approach than the mean-variance (MV) in-sample setting followed by the previous literature. In particular, we depart from the previous literature in two aspects. First, we revisit the posed question within an in-sample setting by employing rigorous spanning tests that are consistent with MV as well as non-MV preferences. Second, we study the diversification benefits of commodities within an out-of-sample static non-MV framework. To this end, we form optimal portfolios under the traditional and augmented with commodities asset universes, separately, by taking into account the higher order moments of returns distribution. Next, we evaluate their comparative performance. To check the robustness of the obtained results, we consider alternative ways of investing in commodities and various utility/value functions that describe the preferences of the individual investor. Furthermore, we employ a number of performance measures and take into account the presence of transaction costs. Finally, we investigate whether our findings are robust under the popular MV setting, as well as over various sub-periods and for the case where enhanced commodity indexes are considered.

We find that within the in-sample setting, commodities do not yield added value to MV investors while they do to the non-MV ones. Therefore, commodities offer in-sample diversification benefits only in the case where higher order moments are taken into account. However, these benefits are not preserved in the out-of-sample framework. In the vast majority of the cases, the optimal portfolios that include only the traditional asset classes have superior performance.

Given that the out-of-sample setting is the ultimate test for addressing the primary question of this paper, our results challenge the common belief that commodities should be included in investor's portfolios. Most importantly, the findings are robust given that they hold regardless of the performance measure, specification of utility function and commodity instrument that is used as investment vehicle (gold is the only exception). Furthermore, the superiority of the traditional portfolios is confirmed even under the presence of transaction costs. We reach similar conclusions under a MV setting as well as over various sub-periods including the subprime crisis period. The only exception appears over the 2005-2008 commodity boom period. This comes to no surprise though given the unprecedented and simultaneous increase in commodity prices that takes place then. Therefore, the reported benefits of including commodities in investor's portfolios are the exception rather than the rule. Our findings are consistent with the empirical evidence on the increasing financialization of commodities that is expected to deteriorate the diversification benefits of commodities.

Future research should look at the benefits of commodities within a dynamic asset allocation context. Hong and Yogo (2012) find that expected commodity returns have negative conditional correlation with expected stock and bond returns. This implies that commodities may be useful to investors for intertemporal hedging. However, such an exercise should take into account all commodity related factors that affect the dynamics of the investment opportunity set (see e.g., Schwartz and Trolle, 2009, and references therein).[14] This is well beyond the scope of the current paper but deserves to become a topic for future research.

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[14] To the best of our knowledge, Dai (2009) is the only study that studies the intertemporal hedging benefits of investing in commodities. However, his analysis uses a single factor model for the dynamics of commodity prices.

Table 2.1. Descriptive statistics

Entries report the descriptive statistics for the alternative asset classes used in this study. The dataset spans the period from January 1989 to December 2009, with the exception of DJ-UBSCI that covers the period from January 1991 to December 2009. Panel A reports the summary statistics: annualized mean returns, standard deviatios and Sharpe Ratios as well as skewness and kurtosis figures. The *p*-values of Jarque-Bera test are also reported. The null hypothesis is that the distribution of returns is normal. Panel B shows the correlation matrix of the assets under consideration.

Panel A: Summary statistics

	Average return	**Standard deviation**	**Sharpe ratio**	**Skewness**	**Kurtosis**	**JB p-value**
S&P 500 Total Return	10.0%	14.9%	0.37	-0.65	4.31	0.000
Barclays Aggregate Bond Index	7.2%	3.9%	0.69	-0.26	3.54	0.062
S&P GSCI Total Return Index	8.0%	21.4%	0.16	-0.12	5.30	0.000
DJ-UBSCI Total Return Index	6.8%	14.5%	0.19	-0.57	6.24	0.000
Cotton (NYBOT)	10.1%	29.4%	0.19	-0.10	3.68	0.092
Crude Oil (NYMEX)	17.3%	33.3%	0.38	0.44	5.60	0.000
Gold (COMEX)	10.3%	14.9%	0.39	0.23	4.82	0.000
Copper (COMEX)	11.8%	26.9%	0.27	0.12	5.88	0.000
Live Cattle (CME)	6.5%	16.1%	0.13	-0.29	5.13	0.000
Libor 1-month	4.5%	0.7%		0.07	2.64	0.420

Panel B: Correlation matrix

S&P 500 Total Return	1.00								
Barclays Aggregate Bond Index	0.19	1.00							
S&P GSCI Total Return Index	0.08	0.01	1.00						
DJ-UBS Total Return Index	0.23*	0.07	0.90*	1.00					
Cotton (NYBOT)	0.19*	0.04	0.07	0.22*	1.00				
Crude Oil (NYMEX)	-0.02	-0.06	0.88*	0.73*	0.00	1.00			
Gold (CMX)	-0.07	0.15**	0.24*	0.39*	0.07	0.20*	1.00		
Copper (NYMEX)	0.27*	-0.10	0.32*	0.52*	0.18*	0.25*	0.23*	1.00	
Live Cattle (CME)	0.06	-0.07	0.06	0.09	0.05	-0.03	-0.04	0.04	1.00

* Significant at 1%.
** Significant at 5%.

Table 2.2. Testing for spanning

Entries report the Wald test statistics and respective *p*-values for the null hypothesis that a set of benchmark assets consisting of stocks, bonds and the risk-free asset spans a given test asset from the commodities market. The first column reports results for the null hypothesis that there is mean-variance spanning. The next column reports results for the null hypothesis that there is both mean-variance and exponential utility spanning with risk aversion coefficient ranging from 2 to 10. The third column reports results for the null hypothesis that there is spanning only for investors with exponential utility function. The forth column reports results for the null hypothesis that there is both mean-variance and power utility spanning with risk aversion coefficient ranging from 2 to 10. The last column presents the respective results when only power utility function is considered. The initial set of assets is the S&P 500 Total Return Index, Barclays Aggregate Bond Index and Libor 1-month. Results are based on monthly observations from Jan. 1989 –Dec. 2009 for S&P GSCI and Jan. 1991-Dec. 2009 for DJ-UBSCI. All test statistics are based on a Newey-West covariance matrix with five lags.

Test asset	**Mean - variance (MV)**	**MV & Exponential**	**Exponential**	**MV & Power**	**Power**
S&P GSCI	0.23	23.41	14.39	72.58	70.95
	(0.631)	*(0.001)*	*(0.013)*	*(0.000)*	*(0.000)*
DJ-UBSCI	0.06	29.94	28.67	79.63	79.62
	(0.800)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
Crude Oil	2.67	39.80	13.72	91.50	87.62
	(0.102)	*(0.000)*	*(0.017)*	*(0.000)*	*(0.000)*
Cotton	0.33	6.58	5.42	27.12	27.09
	(0.563)	*(0.361)*	*(0.367)*	*(0.000)*	*(0.000)*
Copper	0.99	25.81	18.40	60.06	55.92
	(0.320)	*(0.000)*	*(0.003)*	*(0.000)*	*(0.000)*
Gold	2.06	17.26	12.85	46.81	42.73
	(0.151)	*(0.008)*	*(0.025)*	*(0.000)*	*(0.000)*
Live Cattle	0.85	3.77	1.89	4.67	3.61
	(0.358)	*(0.708)*	*(0.864)*	*(0.587)*	*(0.607)*

Table 2.3. Direct maximization: Commodity indexes and exponential utility function

Entries report the performance measures (annualized Sharpe Ratio, annualized Opportunity Cost, Portfolio Turnover, annualized Return-Loss) for the case where the expected utility is maximized under an exponential utility function. The *p*-values of Memmel's (2003) test are also reported within parentheses; the null hypothesis is that the SR obtained from the traditional investment opportunity set is equal to that derived from the expanded set that includes commodities. Results are reported for different sizes of the rolling window (*K*=36,48,60,72 observations) and different degrees of absolute risk aversion (*ARA*=2,4,6,8,10). Investors access investment in commodities either via S&P GSCI (Panel A) or DJ-UBSCI (Panel B). Results are based on monthly observations from Jan. 1989 to Dec. 2009 for S&P GSCI and from Jan. 1991 to Dec. 2009 for DJ-UBSCI.

		ARA=2		**ARA=4**		**ARA=6**		**ARA=8**		**ARA=10**	
		Expanded	**Traditional**	**Expanded**	**Traditional**	**Expanded**	**Traditional**	**Expanded**	**Traditional**	**Expanded**	**Traditional**
Panel A: S&P GSCI (1989-2009)											
K=36	Sharpe Ratio	0.30	0.49	0.36	0.57	0.39	0.59	0.40	0.59	0.40	0.58
	(p-value)	*(0.151)*		*(0.075)*		*(0.064)*		*(0.589)*		*(0.082)*	
	Opp. Cost	-6.00%		-6.24%		-5.04%		-4.32%		-3.24%	
	Port.Turnover	82.75%	56.28%	73.42%	53.09%	69.46%	53.78%	60.45%	52.32%	61.28%	52.91%
	Return-Loss	-5.40%		-5.14%		-4.24%		-3.60%		-2.82%	
K=48	Sharpe Ratio	0.21	0.34	0.31	0.44	0.35	0.47	0.34	0.44	0.31	0.42
	(p-value)	*(0.239)*		*(0.180)*		*(0.176)*		*(0.176)*		*(0.160)*	
	Opp. Cost	-5.40%		-4.08%		-2.76%		-1.80%		-1.44%	
	Port.Turnover	71.34%	44.77%	57.03%	40.12%	49.38%	37.64%	50.19%	42.20%	48.86%	40.51%
	Return-Loss	-4.32%		-3.52%		-2.68%		-2.08%		-1.87%	
K=60	Sharpe Ratio	0.03	0.16	0.15	0.27	0.17	0.26	0.19	0.28	0.18	0.25
	(p-value)	*(0.211)*		*(0.184)*		*(0.201)*		*(0.199)*		*(0.277)*	
	Opp. Cost	-7.44%		-4.68%		-3.12%		-2.52%		-0.14%	
	Port.Turnover	71.74%	38.00%	53.32%	35.70%	47.76%	35.19%	40.16%	35.56%	40.81%	35.12%
	Return-Loss	-5.05%		-3.58%		-2.51%		-1.87%		-1.30%	
K=72	Sharpe Ratio	0.11	0.25	0.31	0.38	0.33	0.38	0.36	0.37	0.37	0.40
	(p-value)	*(0.219)*		*(0.317)*		*(0.348)*		*(0.460)*		*(0.412)*	
	Opp. Cost	-8.64%		-3.96%		-2.64%		-1.20%		-1.44%	
	Port.Turnover	65.49%	32.74%	42.48%	26.24%	37.89%	27.05%	32.59%	28.45%	33.31%	28.67%
	Return-Loss	-5.01%		-2.48%		-1.62%		-0.66%		-0.82%	
Panel B: DJ-UBSCI (1991-2009)											
K=36	Sharpe Ratio	0.47	0.45	0.50	0.54	0.48	0.55	0.47	0.55	0.47	0.52
	(p-value)	*(0.473)*		*(0.400)*		*(0.323)*		*(0.285)*		*(0.361)*	
	Opp. Cost	-0.12%		-2.64%		-2.88%		-2.88%		-2.52%	
	Port.Turnover	82.47%	57.13%	78.45%	56.12%	75.94%	58.28%	68.02%	57.29%	69.17%	58.17%
	Return-Loss	-0.91%		-1.97%		-2.20%		-2.03%		-1.37%	
K=48	Sharpe Ratio	0.38	0.37	0.41	0.49	0.43	0.52	0.40	0.48	0.39	0.46
	(p-value)	*(0.523)*		*(0.329)*		*(0.280)*		*(0.285)*		*(0.307)*	
	Opp. Cost	-0.84%		-3.60%		-3.12%		-2.16%		-1.80%	
	Port.Turnover	72.89%	42.64%	65.43%	39.67%	57.82%	39.34%	55.96%	45.56%	54.50%	43.76%
	Return-Loss	-1.27%		-2.82%		-2.65%		-2.01%		-1.62%	
K=60	Sharpe Ratio	-0.07	0.08	0.04	0.21	0.06	0.21	0.10	0.23	0.08	0.21
	(p-value)	*(0.230)*		*(0.147)*		*(0.149)*		*(0.187)*		*(0.187)*	
	Opp. Cost	-8.40%		-7.20%		-4.56%		-3.12%		-2.40%	
	Port.Turnover	69.17%	36.95%	61.69%	36.13%	54.95%	36.78%	39.37%	34.51%	42.55%	35.29%
	Return-Loss	-5.24%		-4.96%		-3.70%		-2.43%		-2.17%	
K=72	Sharpe Ratio	-0.10	0.00	0.05	0.18	0.05	0.19	0.06	0.18	0.06	0.22
	(p-value)	*(0.321)*		*(0.231)*		*(0.213)*		*(0.213)*		*0.151*	
	Opp. Cost	-8.88%		-7.20%		-5.28%		-3.60%		-3.72%	
	Port.Turnover	60.87%	33.26%	45.41%	25.71%	41.28%	27.21%	39.61%	29.40%	34.33%	28.40%
	Return-Loss	-3.76%		-3.85%		-3.31%		-2.41%		-2.37%	

Table 2.4. Direct maximization: Commodity indexes and power utility function

Entries report the performance measures (annualized Sharpe Ratio, annualized Opportunity Cost, Portfolio Turnover, annualized Return-Loss) for the case where the expected utility is maximized under a power utility function. The *p*-values of Memmel's (2003) test are also reported within parentheses; the null hypothesis is that the SR obtained from the traditional investment opportunity set is equal to that derived from the expanded opportunity set that includes commodities. Results are reported for different sizes of the rolling window (*K*=36,48,60,72 observations) and different degrees of relative risk aversion (*RRA*=2,4,6,8,10). Investors access investment in commodities either via S&P GSCI (Panel A) or DJ-UBSCI (Panel B). Results are based on monthly observations from Jan. 1989 to Dec. 2009 for S&P GSCI and from Jan. 1991 to Dec. 2009 for DJ-UBSCI.

		RRA=2		**RRA=4**		**RRA=6**		**RRA=8**		**RRA=10**	
		Expanded	**Traditional**	**Expanded**	**Traditional**	**Expanded**	**Traditional**	**Expanded**	**Traditional**	**Expanded**	**Traditional**
Panel A: S&P GSCI (1989-2009)											
K=36	Sharpe Ratio	0.30	0.49	0.35	0.57	0.38	0.59	0.39	0.59	0.40	0.58
	(p-value)	*(0.147)*		*(0.075)*		*(0.065)*		*(0.062)*		*(0.077)*	
	Opp. Cost	-6.12%		6.12%		4.80%		4.08%		3.24%	
	Port.Turnover	82.96%	56.57%	73.68%	53.48%	69.43%	53.75%	65.61%	55.01%	60.96%	52.43%
	Return-Loss	-5.48%		5.15%		4.23%		3.57%		2.89%	
K=48	Sharpe Ratio	0.20	0.34	0.30	0.44	0.35	0.47	0.33	0.44	0.31	0.42
	(p-value)	*(0.229)*		*(0.180)*		*(0.178)*		*(0.156)*		*(0.138)*	
	Opp. Cost	-5.76%		3.96%		2.40%		1.68%		1.56%	
	Port.Turnover	71.75%	44.66%	57.22%	39.61%	49.68%	37.72%	48.67%	38.88%	48.40%	40.22%
	Return-Loss	-4.48%		3.55%		2.68%		2.27%		2.01%	
K=60	Sharpe Ratio	0.03	0.17	0.15	0.27	0.16	0.26	0.17	0.25	0.17	0.24
	(p-value)	*(0.206)*		*(0.182)*		*(0.203)*		*(0.227)*		*(0.241)*	
	Opp. Cost	-7.80%		4.68%		2.64%		1.80%		1.68%	
	Port.Turnover	71.47%	37.58%	52.99%	34.89%	47.52%	34.75%	42.64%	34.47%	40.30%	34.75%
	Return-Loss	-5.12%		3.63%		2.53%		1.84%		1.44%	
K=72	Sharpe Ratio	0.11	0.25	0.31	0.38	0.33	0.38	0.34	0.38	0.36	0.39
	(p-value)	*(0.220)*		*(0.318)*		*(0.203)*		*(0.367)*		*(0.408)*	
	Opp. Cost	-9.84%		4.20%		2.64%		1.80%		1.44%	
	Port.Turnover	65.30%	32.81%	43.23%	26.62%	38.17%	27.08%	34.50%	27.48%	31.88%	28.36%
	Return-Loss	-4.97%		2.50%		2.53%		1.19%		0.81%	
Panel B: DJ-UBSCI (1991-2009)											
K=36	Sharpe Ratio	0.47	0.46	0.49	0.53	0.48	0.55	0.47	0.54	0.47	0.52
	(p-value)	*(0.519)*		*(0.403)*		*(0.331)*		*(0.306)*		*(0.359)*	
	Opp. Cost	0.12%		2.40%		2.52%		2.52%		2.28%	
	Port.Turnover	82.73%	57.40%	78.76%	56.47%	76.04%	58.20%	72.83%	60.22%	68.68%	57.61%
	Return-Loss	1.01%		1.95%		2.16%		1.89%		1.39%	
K=48	Sharpe Ratio	0.39	0.38	0.42	0.48	0.43	0.52	0.40	0.48	0.39	0.47
	(p-value)	*(0.525)*		*(0.338)*		*(0.280)*		*(0.283)*		*(0.293)*	
	Opp. Cost	0.84%		3.48%		2.76%		1.68%		1.80%	
	Port.Turnover	72.50%	42.46%	65.30%	39.00%	58.01%	39.38%	56.80%	41.88%	54.82%	43.37%
	Return-Loss	1.24%		2.78%		2.67%		2.18%		1.73%	
K=60	Sharpe Ratio	0.07	0.08	0.04	0.21	0.06	0.21	0.07	0.21	0.09	0.20
	(p-value)	*(0.228)*		*(0.152)*		*(0.151)*		*(0.170)*		*(0.203)*	
	Opp. Cost	8.64%		7.32%		4.32%		2.76%		2.16%	
	Port.Turnover	68.38%	36.45%	61.33%	35.19%	55.06%	36.24%	46.86%	35.74%	42.39%	34.88%
	Return-Loss	5.16%		4.92%		3.73%		2.77%		2.07%	
K=72	Sharpe Ratio	0.09	0.00	0.04	0.17	0.04	0.19	0.05	0.20	0.07	0.21
	(p-value)	*(0.320)*		*(0.235)*		*(0.185)*		*(0.171)*		*(0.176)*	
	Opp. Cost	9.72%		7.44%		5.04%		3.96%		3.36%	
	Port.Turnover	61.04%	33.37%	45.89%	26.15%	41.43%	27.23%	37.13%	28.27%	33.29%	28.18%
	Return-Loss	3.77%		3.82%		3.29%		2.69%		2.17%	

Table 2.5. Direct maximization: Commodity indexes and disappointment aversion value function

Entries report the performance measures (annualized Sharpe Ratio, annualized Opportunity Cost, Portfolio Turnover, annualized Return-Loss) for the case where the expected utility is maximized under a disappointment aversion value function. The *p*-values of Memmel's (2003) test are also reported within parentheses; the null hypothesis is that the SR obtained from the traditional investment opportunity set is equal to that derived from the expanded opportunity set that includes commodities. Results are reported for different sizes of the rolling window (*K*=36,48,60,72 observations), degrees of relative risk aversion (*RRA*=2,4,6,8,10) and values of the disappointment aversion parameter (*A*=0.6,0.8). Investors access investment in commodities either via S&P GSCI (Panels A and B) or DJ-UBSCI (Panels C and D). Results are based on monthly observations from Jan. 1989 to Dec. 2009 for S&P GSCI and from Jan. 1991 to Dec. 2009 for DJ-UBSCI.

		RRA=2		**RRA=4**		**RRA=6**		**RRA=8**		**RRA=10**	
		Expanded	**Traditional**	**Expanded**	**Traditional**	**Expanded**	**Traditional**	**Expanded**	**Traditional**	**Expanded**	**Traditional**
Panel A: S&P GSCI (A=0.6)											
K=36	Sharpe Ratio	0.39	0.59	0.34	0.50	0.38	0.49	0.38	0.46	0.38	0.44
	(p-value)	*(0.071)*		*(0.100)*		*(0.196)*		*(0.253)*		*(0.310)*	
	Opp. Cost	-6.00%		-4.92%		-3.36%		-2.40%		-2.16%	
	Port.Turnover	72.33%	52.51%	63.87%	50.69%	53.58%	46.80%	50.60%	41.18%	43.68%	37.50%
	Return-Loss	-4.34%		-3.13%		-1.85%		-1.46%		-1.06%	
K=48	Sharpe Ratio	0.34	0.47	0.29	0.35	0.24	0.27	0.22	0.25	0.20	0.23
	(p-value)	*(0.147)*		*(0.278)*		*(0.355)*		*(0.407)*		*(0.384)*	
	Opp. Cost	-3.84%		-2.16%		-1.92%		-1.56%		-1.44%	
	Port.Turnover	62.51%	45.72%	59.78%	47.47%	47.36%	45.69%	44.85%	39.33%	40.26%	40.26%
	Return-Loss	-3.02%		-1.53%		-0.78%		-0.67%		-0.69%	
K=60	Sharpe Ratio	0.26	0.30	0.16	0.17	0.14	0.14	0.12	0.12	0.10	0.09
	(p-value)	*(0.370)*		*(0.446)*		*(0.499)*		*(0.497)*		*(0.474)*	
	Opp. Cost	-2.64%		-2.04%		-1.80%		-1.44%		-0.96%	
	Port.Turnover	67.82%	59.96%	56.55%	55.50%	47.48%	41.79%	39.33%	32.05%	32.69%	26.44%
	Return-Loss	-1.24%		-0.55%		-0.57%		-0.65%		-0.52%	
K=72	Sharpe Ratio	0.42	0.39	0.28	0.28	0.26	0.27	0.26	0.27	0.26	0.26
	(p-value)	*(0.390)*		*(0.489)*		*(0.471)*		*(0.459)*		*(0.491)*	
	Opp. Cost	-1.08%		-1.92%		-1.56%		-1.20%		-0.96%	
	Port.Turnover	53.62%	66.87%	51.20%	53.45%	42.10%	38.76%	32.01%	28.59%	25.60%	23.45%
	Return-Loss	0.66%		-0.30%		-0.61%		-0.68%		-0.60%	
Panel B: S&P GSCI (A=0.8)											
K=36	Sharpe Ratio	0.34	0.58	0.36	0.57	0.36	0.56	0.38	0.56	0.40	0.56
	(p-value)	*(0.066)*		*(0.061)*		*(0.051)*		*(0.077)*		*(0.108)*	
	Opp. Cost	-7.32%		-5.88%		-5.04%		-3.72%		-3.00%	
	Port.Turnover	81.37%	61.79%	74.20%	56.33%	68.32%	56.81%	60.87%	51.57%	53.80%	46.31%
	Return-Loss	-5.72%		-4.47%		-3.71%		-2.86%		-2.18%	
K=48	Sharpe Ratio	0.34	0.45	0.35	0.48	0.32	0.41	0.29	0.38	0.28	0.36
	(p-value)	*(0.210)*		*(0.169)*		*(0.201)*		*(0.192)*		*(0.227)*	
	Opp. Cost	-1.32%		-3.24%		-1.68%		-1.80%		-1.44%	
	Port.Turnover	62.51%	47.07%	54.95%	46.49%	54.58%	48.50%	51.63%	47.68%	46.33%	44.28%
	Return-Loss	-2.60%		-2.71%		-1.80%		-1.47%		-1.08%	
K=60	Sharpe Ratio	0.14	0.32	0.19	0.30	0.18	0.26	0.17	0.23	0.16	0.21
	(p-value)	*(0.119)*		*(0.190)*		*(0.238)*		*(0.277)*		*(0.319)*	
	Opp. Cost	-6.00%		-3.36%		-2.28%		-1.92%		-1.56%	
	Port.Turnover	56.64%	33.53%	53.22%	40.14%	47.12%	41.08%	42.89%	40.35%	40.61%	37.38%
	Return-Loss	-5.07%		-2.66%		-1.64%		-1.15%		-0.90%	
K=72	Sharpe Ratio	0.27	0.38	0.37	0.42	0.35	0.38	0.35	0.36	0.33	0.35
	(p-value)	*(0.237)*		*(0.363)*		*(0.399)*		*(0.444)*		*(0.413)*	
	Opp. Cost	-4.68%		-2.52%		-1.92%		-1.56%		-1.44%	
	Port.Turnover	45.63%	25.52%	38.38%	28.36%	37.43%	32.95%	35.98%	36.38%	33.82%	30.93%
	Return-Loss	-3.46%		-1.54%		-0.95%		-0.57%		-0.72%	

Table 2.5. Direct maximization: Commodity indexes and disappointment aversion value function (cont'd)

Entries report the performance measures (annualized Sharpe Ratio, annualized Opportunity Cost, Portfolio Turnover, annualized Return-Loss) for the case where the expected utility is maximized under a disappointment aversion value function. The *p*-values of Memmel's (2003) test are also reported within parentheses; the null hypothesis is that the SR obtained from the traditional investment opportunity set is equal to that derived from the expanded opportunity set that includes commodities. Results are reported for different sizes of the rolling window (*K*=36,48,60,72 observations), degrees of relative risk aversion (*RRA*=2,4,6,8,10) and values of the disappointment aversion parameter (*A*=0.6,0.8). Investors access investment in commodities either via S&P GSCI (Panels A and B) or DJ-UBSCI (Panels C and D). Results are based on monthly observations from Jan. 1989 to Dec. 2009 for S&P GSCI and from Jan. 1991 to Dec. 2009 for DJ-UBSCI.

		RRA=2		**RRA=4**		**RRA=6**		**RRA=8**		**RRA=10**	
		Expanded	**Traditional**	**Expanded**	**Traditional**	**Expanded**	**Traditional**	**Expanded**	**Traditional**	**Expanded**	**Traditional**
Panel C: DJ-UBS CI (A=0.6)											
K=36	Sharpe Ratio	0.48	0.56	0.43	0.48	0.44	0.45	0.43	0.41	0.41	0.39
	(p-value)	*(0.301)*		*(0.381)*		*(0.474)*		*(0.533)*		*(0.553)*	
	Opp. Cost	-4.44%		-3.48%		-3.12%		-2.76%		-2.28%	
	Port.Turnover	81.75%	52.83%	66.82%	49.72%	57.04%	45.80%	53.27%	39.70%	46.75%	35.60%
	Return-Loss	-2.71%		-1.64%		-0.98%		-0.91%		-0.78%	
K=48	Sharpe Ratio	0.38	0.52	0.35	0.40	0.31	0.34	0.31	0.33	0.28	0.31
	(p-value)	*(0.177)*		*(0.358)*		*(0.398)*		*(0.454)*		*(0.404)*	
	Opp. Cost	-4.56%		-2.16%		-2.52%		-1.92%		-1.80%	
	Port.Turnover	72.58%	48.80%	60.64%	49.12%	53.57%	45.51%	48.05%	37.77%	42.91%	31.80%
	Return-Loss	-3.58%		-1.46%		-1.06%		-0.86%		-1.00%	
K=60	Sharpe Ratio	0.09	0.27	0.07	0.14	0.07	0.10	0.05	0.08	0.04	0.05
	(p-value)	*(0.086)*		*(0.311)*		*(0.423)*		*(0.419)*		*(0.467)*	
	Opp. Cost	-5.04%		-2.52%		-2.04%		-1.92%		-1.20%	
	Port.Turnover	74.40%	59.87%	50.87%	55.57%	42.67%	41.29%	39.19%	31.83%	32.42%	26.41%
	Return-Loss	-4.06%		-1.10%		-0.68%		-0.82%		-0.60%	
K=72	Sharpe Ratio	0.12	0.26	0.03	0.17	0.01	0.16	0.02	0.16	0.02	0.15
	(p-value)	*(0.178)*		*(0.163)*		*(0.177)*		*(0.183)*		*(0.203)*	
	Opp. Cost	-4.08%		-3.36%		-2.76%		-2.16%		-1.68%	
	Port.Turnover	56.06%	67.19%	50.07%	52.87%	43.28%	38.32%	34.03%	28.19%	27.90%	23.27%
	Return-Loss	-4.08%		-1.87%		-1.59%		-1.42%		-1.20%	
Panel D: DJ-UBS CI (A=0.8)											
K=36	Sharpe Ratio	0.47	0.55	0.48	0.53	0.45	0.52	0.46	0.50	0.46	0.50
	(p-value)	*(0.329)*		*(0.361)*		*(0.319)*		*(0.390)*		*(0.397)*	
	Opp. Cost	-3.72%		-3.36%		-3.24%		-2.76%		-2.76%	
	Port.Turnover	88.25%	65.14%	81.67%	61.20%	74.19%	62.28%	66.11%	55.31%	60.18%	48.72%
	Return-Loss	-2.75%		-2.04%		-1.75%		-1.25%		-1.20%	
K=48	Sharpe Ratio	0.39	0.49	0.42	0.52	0.40	0.46	0.37	0.43	0.37	0.42
	(p-value)	*(0.280)*		*(0.256)*		*(0.341)*		*(0.341)*		*(0.373)*	
	Opp. Cost	-4.56%		-3.60%		-1.44%		-2.16%		-1.68%	
	Port.Turnover	71.88%	47.63%	63.99%	49.55%	61.77%	52.65%	59.83%	51.40%	53.13%	46.68%
	Return-Loss	-3.42%		-2.74%		-1.56%		-1.30%		-0.98%	
K=60	Sharpe Ratio	0.01	0.27	0.06	0.26	0.07	0.22	0.08	0.20	0.07	0.17
	(p-value)	*(0.070)*		*(0.083)*		*(0.132)*		*(0.199)*		*(0.240)*	
	Opp. Cost	-9.60%		-5.52%		-3.12%		-2.28%		-1.92%	
	Port.Turnover	68.66%	33.40%	60.86%	41.30%	50.39%	40.60%	43.63%	39.96%	40.27%	36.73%
	Return-Loss	-7.45%		-4.66%		-2.98%		-1.88%		-1.42%	
K=72	Sharpe Ratio	0.04	0.19	0.08	0.23	0.05	0.21	0.05	0.20	0.05	0.19
	(p-value)	*(0.221)*		*(0.163)*		*(0.153)*		*(0.172)*		*(0.171)*	
	Opp. Cost	-7.56%		-5.04%		-3.60%		-3.12%		-2.76%	
	Port.Turnover	52.52%	24.21%	44.12%	28.07%	39.77%	32.86%	37.56%	36.50%	35.88%	31.15%
	Return-Loss	-4.66%		-3.57%		-2.63%		-1.92%		-1.75%	

Table 2.6. Direct maximization: Individual commodity futures and exponential and power utility function

Entries report the performance measures (annualized Sharpe Ratio, annualized Opportunity Cost, Portfolio Turnover, annualized Return-Loss) for the case where the expected utility is maximized under exponential (Panel A) and power (Panel B) utility function. The *p*-values of Memmel's (2003) test are also reported within parentheses; the null hypothesis is that the SR obtained from the traditional investment opportunity set is equal to that derived from the expanded set that includes commodities. Results are reported for different sizes of the rolling window (*K*=36,48,60,72 observations) and different degrees of absolute/relative risk aversion (*ARA,RRA*=2,4,6). Investors access investment in commodities via the selected individual commodity futures contracts. Results are based on monthly observations from Jan. 1989 to Dec. 2009.

Panel A: Exponential utility

		ARA=2						**ARA=4**						**ARA=6**					
		Crude Oil	**Copper**	**Cotton**	**Gold**	**Live Cattle**	**Traditional**	**Crude Oil**	**Copper**	**Cotton**	**Gold**	**Live Cattle**	**Traditional**	**Crude Oil**	**Copper**	**Cotton**	**Gold**	**Live Cattle**	**Traditional**
K=36	Sharpe Ratio	0.39	0.49	0.19	0.75	0.25	0.49	0.50	0.57	0.31	0.69	0.41	0.57	0.56	0.61	0.38	0.69	0.45	0.59
	(p-value)	*(0.332)*	*(0.499)*	*(0.054)*	*(0.091)*	*(0.049)*		*(0.349)*	*(0.491)*	*(0.029)*	*(0.279)*	*(0.079)*		*(0.435)*	*(0.454)*	*(0.033)*	*(0.274)*	*(0.079)*	
	Opp. Cost	-4.44%	-0.72%	-10.44%	8.04%	-6.36%		-3.36%	-2.40%	-7.68%	0.48%	-4.20%		-2.16%	-1.80%	-5.64%	-0.60%	-3.24%	
	Port.Turnover	77.24%	78.80%	92.65%	81.33%	92.27%	56.28%	64.61%	71.93%	74.28%	78.54%	73.88%	53.09%	61.50%	69.47%	66.71%	75.64%	67.33%	53.78%
	Return-Loss	-3.44%	-0.97%	-8.00%	5.01%	-6.71%		-2.12%	-1.14%	-6.04%	1.12%	-4.07%		-0.98%	-0.52%	-4.31%	0.86%	-2.93%	
K=48	Sharpe Ratio	0.35	0.42	0.07	0.57	0.23	0.34	0.44	0.51	0.22	0.54	0.31	0.44	0.49	0.47	0.30	0.54	0.36	0.47
	(p-value)	*(0.476)*	*(0.377)*	*(0.034)*	*(0.139)*	*(0.210)*		*(0.497)*	*(0.387)*	*(0.014)*	*(0.310)*	*(0.125)*		*(0.459)*	*(0.413)*	*(0.017)*	*(0.346)*	*(0.110)*	
	Opp. Cost	-2.64%	-0.60%	-8.28%	5.52%	-3.60%		-2.16%	-2.04%	-5.64%	-2.52%	-3.60%		-1.44%	-2.64%	-3.96%	-3.00%	-2.52%	
	Port.Turnover	68.44%	65.75%	70.84%	71.99%	75.16%	44.77%	51.38%	57.88%	52.57%	65.73%	58.74%	40.12%	43.62%	53.20%	46.30%	59.41%	49.40%	37.64%
	Return-Loss	-1.07%	0.65%	-7.18%	3.98%	-3.93%		-0.79%	0.14%	-4.91%	0.75%	-3.41%		-0.31%	-0.36%	-3.50%	0.09%	-2.53%	
K=60	Sharpe Ratio	0.22	0.26	0.02	0.48	0.09	0.16	0.31	0.31	0.18	0.44	0.21	0.27	0.30	0.34	0.20	0.40	0.21	0.26
	(p-value)	*(0.396)*	*(0.353)*	*(0.152)*	*(0.056)*	*(0.317)*		*(0.421)*	*(0.428)*	*(0.134)*	*(0.194)*	*(0.270)*		*(0.385)*	*(0.342)*	*(0.157)*	*(0.208)*	*(0.251)*	
	Opp. Cost	-6.00%	-5.88%	-5.28%	6.00%	-3.84%		-4.08%	-5.28%	-3.00%	-2.76%	-2.64%		-3.00%	-2.88%	-2.04%	-2.28%	-2.04%	
	Port.Turnover	64.42%	69.21%	61.54%	72.48%	63.14%	38.00%	46.32%	55.12%	45.18%	60.23%	48.58%	35.70%	40.71%	47.48%	40.25%	53.57%	44.16%	35.19%
	Return-Loss	-0.37%	0.52%	-4.61%	5.61%	-3.08%		-0.30%	-0.51%	-2.54%	2.04%	-2.04%		0.06%	0.39%	-1.60%	1.38%	-1.53%	
K=72	Sharpe Ratio	0.28	0.45	0.10	0.55	0.08	0.25	0.39	0.49	0.28	0.48	0.27	0.38	0.41	0.50	0.31	0.45	0.31	0.38
	(p-value)	*(0.431)*	*(0.201)*	*(0.167)*	*(0.053)*	*(0.093)*		*(0.484)*	*(0.289)*	*(0.160)*	*(0.287)*	*(0.112)*		*(0.436)*	*(0.269)*	*(0.175)*	*(0.341)*	*(0.161)*	
	Opp. Cost	-6.00%	-1.20%	-4.92%	6.48%	-5.52%		-4.80%	-3.12%	-2.88%	-6.12%	-2.88%		-3.60%	-2.64%	-2.04%	-6.60%	-1.80%	
	Port.Turnover	59.25%	61.72%	47.54%	64.28%	59.16%	32.74%	37.13%	42.21%	32.82%	51.82%	38.00%	26.24%	33.94%	39.81%	31.88%	45.44%	36.58%	27.05%
	Return-Loss	-0.85%	3.04%	-4.29%	5.50%	-5.53%		-0.91%	0.90%	-2.44%	0.43%	-3.03%		-0.33%	0.83%	-1.60%	-0.09%	-1.82%	

Panel B: Power utility

		RRA=2						**RRA=4**						**RRA=6**					
		Crude Oil	**Copper**	**Cotton**	**Gold**	**Live Cattle**	**Traditional**	**Crude Oil**	**Copper**	**Cotton**	**Gold**	**Live Cattle**	**Traditional**	**Crude Oil**	**Copper**	**Cotton**	**Gold**	**Live Cattle**	**Traditional**
K=36	Sharpe Ratio	0.38	0.49	0.20	0.75	0.26	0.49	0.50	0.56	0.31	0.69	0.41	0.57	0.56	0.61	0.38	0.69	0.45	0.59
	(p-value)	*(0.320)*	*(0.489)*	*(0.055)*	*(0.096)*	*(0.049)*		*(0.345)*	*(0.485)*	*(0.029)*	*(0.278)*	*(0.079)*		*(0.429)*	*(0.459)*	*(0.033)*	*(0.276)*	*(0.080)*	
	Opp. Cost	-4.80%	-0.84%	-10.80%	7.92%	-6.48%		-3.48%	-2.40%	-7.92%	0.36%	-4.32%		-2.28%	-1.56%	-5.64%	-0.60%	-3.24%	
	Port.Turnover	78.26%	79.35%	92.61%	49.30%	92.32%	56.57%	65.67%	72.75%	74.62%	77.41%	74.46%	53.48%	61.58%	69.86%	66.47%	75.59%	67.59%	53.75%
	Return-Loss	-3.63%	-1.15%	-7.99%	4.91%	-6.78%		-2.19%	-1.22%	-6.10%	1.18%	-4.11%		-1.03%	-0.58%	-4.33%	0.85%	-2.98%	
K=48	Sharpe Ratio	0.35	0.42	0.07	0.58	0.23	0.34	0.43	0.50	0.21	0.54	0.31	0.44	0.48	0.51	0.29	0.54	0.36	0.47
	(p-value)	*(0.486)*	*(0.375)*	*(0.034)*	*(0.139)*	*(0.140)*		*(0.495)*	*(0.396)*	*(0.014)*	*(0.312)*	*(0.125)*		*(0.459)*	*(0.419)*	*(0.017)*	*(0.347)*	*(0.115)*	
	Opp. Cost	-3.12%	-0.84%	-8.52%	5.40%	-3.72%		-2.28%	-2.28%	-5.76%	-3.96%	-3.72%		-1.44%	-2.64%	-3.96%	-3.60%	-2.52%	
	Port.Turnover	68.82%	65.53%	71.15%	71.92%	75.03%	44.66%	51.05%	57.92%	52.43%	65.25%	58.48%	39.61%	43.85%	53.05%	46.78%	59.50%	49.69%	37.72%
	Return-Loss	-1.21%	0.67%	-7.25%	3.96%	-3.91%		-0.88%	0.00%	-4.96%	0.71%	-3.47%		-0.31%	-0.41%	-4.33%	0.08%	-2.51%	
K=60	Sharpe Ratio	0.22	0.27	0.02	0.48	0.09	0.17	0.30	0.31	0.17	0.44	0.21	0.27	0.30	0.33	0.19	0.40	0.21	0.26
	(p-value)	*(0.394)*	*(0.344)*	*(0.145)*	*(0.057)*	*(0.314)*		*(0.426)*	*(0.439)*	*(0.130)*	*(0.196)*	*(0.267)*		*(0.383)*	*(0.350)*	*(0.160)*	*(0.207)*	*(0.261)*	
	Opp. Cost	-9.12%	-8.52%	-5.52%	5.28%	-4.32%		-4.92%	-6.24%	-3.12%	-4.92%	-2.76%		-3.36%	-3.12%	-2.04%	-2.76%	-2.04%	
	Port.Turnover	64.20%	67.66%	61.76%	72.10%	63.23%	37.58%	45.28%	55.05%	44.73%	59.93%	47.61%	34.89%	40.31%	47.24%	40.17%	53.68%	44.22%	34.75%
	Return-Loss	-0.36%	0.67%	-4.74%	5.57%	-3.16%		-0.36%	-0.70%	-2.61%	1.95%	-2.08%		0.07%	0.30%	-1.61%	1.37%	-1.51%	
K=72	Sharpe Ratio	0.28	0.45	0.10	0.55	0.08	0.25	0.39	0.49	0.28	0.48	0.26	0.38	0.41	0.49	0.31	0.45	0.31	0.38
	(p-value)	*(0.434)*	*(0.207)*	*(0.168)*	*(0.056)*	*(0.091)*		*(0.481)*	*(0.300)*	*(0.161)*	*(0.290)*	*(0.109)*		*(0.429)*	*(0.275)*	*(0.175)*	*(0.344)*	*(0.165)*	
	Opp. Cost	-10.80%	-8.64%	-5.04%	5.64%	-5.64%		-6.12%	-4.80%	-2.88%	-10.68%	-2.88%		-4.32%	-3.36%	-2.04%	-9.24%	-1.68%	
	Port.Turnover	59.38%	62.50%	48.00%	65.28%	59.21%	32.81%	37.95%	42.90%	33.09%	52.80%	38.66%	26.62%	33.79%	40.30%	31.96%	45.98%	36.14%	27.08%
	Return-Loss	-0.89%	2.89%	-4.29%	5.38%	-5.57%		-0.91%	0.74%	-2.44%	0.35%	-3.08%		-0.28%	0.75%	-1.61%	-0.14%	-1.80%	

Table 2.7. Direct maximization: Individual commodity futures and disappointment aversion value function

Entries report the performance measures (annualized Sharpe Ratio, annualized Opportunity Cost, Portfolio Turnover, annualized Return-Loss) for the case where the expected utility is maximized under a disappointment aversion value function. The *p*-values of Memmel's (2003) test are also reported within parentheses; the null hypothesis is that the SR obtained from the traditional investment opportunity set is equal to that derived from the expanded set that includes commodities. Results are reported for different sizes of the rolling window (*K*=36,48,60,72 observations), degrees of relative risk aversion (*RRA*=2,4,6) and values of the disappointment aversion parameter (Panel A for *A*=0.6 and Panel B for *A*=0.8). Investors access investment in commodities via the selected individual futures contracts. Results are based on monthly observations from Jan. 1989 to Dec. 2009.

		RRA=2						**RRA=4**						**RRA=6**					
		Crude Oil	**Copper**	**Cotton**	**Gold**	**Live Cattle**	**Traditional**	**Crude Oil**	**Copper**	**Cotton**	**Gold**	**Live Cattle**	**Traditional**	**Crude Oil**	**Copper**	**Cotton**	**Gold**	**Live Cattle**	**Traditional**
Panel A: A=0.6																			
K=36	Sharpe Ratio	0.49	0.61	0.38	0.69	0.49	0.59	0.54	0.56	0.37	0.64	0.44	0.50	0.54	0.55	0.37	0.57	0.46	0.49
	(p-value)	*(0.264)*	*(0.472)*	*(0.027)*	*(0.262)*	*(0.138)*		*(0.385)*	*(0.382)*	*(0.068)*	*(0.186)*	*(0.239)*		*(0.357)*	*(0.376)*	*(0.082)*	*(0.292)*	*(0.346)*	
	Opp. Cost	-4.68%	-3.00%	-5.40%	-0.96%	-2.52%		-2.28%	-3.24%	-0.84%	-1.80%	-1.92%		-1.92%	-4.32%	-2.88%	-3.60%	-1.20%	
	Port.Turnover	72.41%	70.67%	67.02%	78.44%	68.29%	52.51%	62.97%	67.23%	65.22%	71.91%	61.39%	50.69%	57.03%	58.51%	56.45%	65.46%	51.18%	46.80%
	Return-Loss	-2.58%	-0.90%	-4.27%	0.56%	-2.42%		-0.24%	-0.33%	-2.66%	0.80%	-1.41%		-0.30%	-0.51%	-1.92%	-0.23%	-0.72%	
K=48	Sharpe Ratio	0.44	0.46	0.37	0.49	0.37	0.47	0.37	0.39	0.26	0.29	0.29	0.35	0.33	0.35	0.19	0.28	0.23	0.27
	(p-value)	*(0.418)*	*(0.530)*	*(0.060)*	*(0.468)*	*(0.109)*		*(0.423)*	*(0.405)*	*(0.056)*	*(0.376)*	*(0.220)*		*(0.322)*	*(0.334)*	*(0.078)*	*(0.474)*	*(0.279)*	
	Opp. Cost	-3.24%	-5.04%	-2.64%	-4.80%	-2.64%		-1.92%	-3.60%	-2.04%	-3.84%	-1.68%		-1.56%	-3.12%	-1.56%	-5.16%	-1.80%	
	Port.Turnover	62.26%	68.15%	60.41%	71.38%	61.71%	45.72%	55.19%	61.02%	57.52%	70.67%	52.26%	47.47%	50.22%	52.27%	50.40%	64.64%	45.57%	45.69%
	Return-Loss	-1.47%	-1.64%	-2.36%	-1.08%	-2.49%		-0.27%	-0.47%	-1.64%	-0.54%	-1.24%		-0.01%	-0.19%	-1.16%	-1.05%	-0.79%	
K=60	Sharpe Ratio	0.25	0.24	0.20	0.31	0.27	0.30	0.19	0.20	0.12	0.21	0.16	0.17	0.16	0.19	0.08	0.17	0.13	0.14
	(p-value)	*(0.377)*	*(0.395)*	*(0.058)*	*(0.468)*	*(0.363)*		*(0.434)*	*(0.446)*	*(0.166)*	*(0.409)*	*(0.428)*		*(0.431)*	*(0.390)*	*(0.130)*	*(0.421)*	*(0.492)*	
	Opp. Cost	-5.04%	-8.16%	-2.76%	-6.12%	-1.92%		-3.24%	-4.44%	-1.44%	-4.80%	-1.80%		-2.88%	-3.24%	-1.20%	-4.20%	-1.44%	
	Port.Turnover	65.18%	79.25%	67.86%	83.60%	66.05%	59.96%	56.73%	58.33%	58.62%	70.15%	55.14%	55.50%	48.75%	46.22%	47.74%	54.86%	45.87%	41.79%
	Return-Loss	-1.45%	-2.14%	-2.06%	-0.91%	-0.92%		-0.23%	-0.42%	-0.88%	-0.52%	-0.38%		-0.58%	-0.43%	-0.90%	-0.78%	-0.41%	
K=72	Sharpe Ratio	0.34	0.41	0.35	0.35	0.37	0.39	0.26	0.33	0.25	0.24	0.24	0.28	0.22	0.31	0.23	0.23	0.21	0.27
	(p-value)	*(0.375)*	*(0.458)*	*(0.312)*	*(0.424)*	*(0.399)*		*(0.452)*	*(0.401)*	*(0.315)*	*(0.406)*	*(0.259)*		*(0.369)*	*(0.388)*	*(0.224)*	*(0.422)*	*(0.175)*	
	Opp. Cost	-4.08%	-4.92%	-1.32%	-7.44%	-1.44%		-3.12%	-4.08%	-0.96%	-5.64%	-2.16%		-2.88%	-3.24%	-0.84%	-3.96%	-1.68%	
	Port.Turnover	50.72%	59.11%	58.09%	78.79%	47.00%	66.87%	47.41%	49.76%	54.29%	63.10%	53.10%	53.45%	42.58%	39.80%	44.29%	49.36%	43.48%	38.76%
	Return-Loss	-0.84%	-0.14%	-0.41%	-1.62%	0.11%		-0.53%	-0.16%	-0.40%	-1.44%	-0.75%		-1.10%	-0.72%	-0.61%	-1.36%	-0.93%	
Panel B:A=0.8																			
K=36	Sharpe Ratio	0.47	0.54	0.25	0.72	0.37	0.58	0.53	0.59	0.34	0.67	0.44	0.57	0.57	0.59	0.38	0.65	0.46	0.56
	(p-value)	*(0.287)*	*(0.434)*	*(0.015)*	*(0.212)*	*(0.048)*		*(0.395)*	*(0.470)*	*(0.021)*	*(0.274)*	*(0.094)*		*(0.493)*	*(0.452)*	*(0.029)*	*(0.283)*	*(0.346)*	
	Opp. Cost	-5.16%	-3.12%	-10.20%	2.28%	-5.52%		-3.12%	-2.64%	-6.24%	-0.84%	-3.24%		-2.16%	-2.76%	-4.92%	-2.16%	-1.20%	
	Port.Turnover	70.36%	79.16%	83.24%	89.38%	85.69%	61.79%	64.83%	71.04%	70.53%	84.70%	76.75%	56.33%	61.79%	66.18%	61.87%	76.61%	51.18%	56.81%
	Return-Loss	-3.05%	-1.82%	-7.67%	1.63%	-5.16%		-1.33%	-0.73%	-4.74%	0.55%	-3.05%		-0.43%	-0.42%	-3.25%	0.45%	-0.72%	
K=48	Sharpe Ratio	0.41	0.44	0.21	0.56	0.29	0.45	0.47	0.50	0.33	0.53	0.37	0.48	0.45	0.47	0.29	0.48	0.33	0.41
	(p-value)	*(0.424)*	*(0.494)*	*(0.012)*	*(0.297)*	*(0.099)*		*(0.486)*	*(0.459)*	*(0.025)*	*(0.372)*	*(0.169)*		*(0.400)*	*(0.388)*	*(0.029)*	*(0.329)*	*(0.158)*	
	Opp. Cost	-3.84%	-4.44%	-6.60%	-0.96%	-4.68%		-2.28%	-3.60%	-3.48%	-3.72%	-2.64%		-1.32%	-2.52%	-2.76%	-2.64%	-1.80%	
	Port.Turnover	57.52%	64.40%	58.16%	70.52%	63.90%	47.07%	46.85%	58.74%	52.15%	65.13%	56.37%	46.49%	48.17%	55.51%	50.82%	62.50%	55.03%	48.50%
	Return-Loss	-1.70%	-1.26%	-5.54%	0.91%	-4.12%		-0.54%	-0.69%	-2.93%	-0.06%	-2.71%		0.19%	0.01%	-2.11%	0.21%	-1.56%	
K=60	Sharpe Ratio	0.25	0.27	0.21	0.47	0.23	0.32	0.28	0.31	0.22	0.39	0.23	0.30	0.27	0.32	0.20	0.34	0.20	0.26
	(p-value)	*(0.360)*	*(0.423)*	*(0.095)*	*(0.246)*	*(0.189)*		*(0.465)*	*(0.466)*	*(0.121)*	*(0.302)*	*(0.190)*		*(0.458)*	*(0.373)*	*(0.143)*	*(0.320)*	*(0.230)*	
	Opp. Cost	-7.56%	-10.44%	-3.60%	-1.80%	-3.12%		-4.32%	-5.28%	-2.16%	-4.08%	-2.28%		-3.12%	-3.12%	-1.56%	-3.48%	-2.52%	
	Port.Turnover	49.91%	57.11%	45.14%	63.49%	48.14%	33.53%	43.38%	52.40%	44.10%	58.46%	47.95%	40.14%	41.98%	47.56%	44.08%	52.78%	46.00%	41.08%
	Return-Loss	-2.76%	-2.67%	-3.12%	1.57%	-2.80%		-0.82%	-0.74%	-1.65%	0.65%	-1.78%		-0.26%	0.08%	-1.19%	0.27%	-1.22%	
K=72	Sharpe Ratio	0.31	0.42	0.27	0.51	0.26	0.38	0.40	0.48	0.33	0.45	0.34	0.42	0.39	0.46	0.32	0.39	0.31	0.38
	(p-value)	*(0.365)*	*(0.417)*	*(0.122)*	*(0.250)*	*(0.106)*		*(0.459)*	*(0.362)*	*(0.121)*	*(0.431)*	*(0.150)*		*(0.481)*	*(0.335)*	*(0.165)*	*(0.480)*	*(0.141)*	
	Opp. Cost	-7.68%	-7.08%	-3.24%	-2.52%	-3.36%		-4.08%	-3.84%	-2.16%	-7.56%	-1.92%		-3.00%	-3.60%	-1.44%	-6.96%	-2.52%	
	Port.Turnover	45.09%	46.86%	34.71%	56.49%	43.52%	25.52%	34.48%	39.92%	34.10%	46.72%	36.20%	28.36%	34.70%	38.20%	35.67%	44.65%	36.65%	32.95%
	Return-Loss	-2.79%	-0.72%	-2.91%	0.95%	-3.36%		-0.98%	0.01%	-1.78%	-0.81%	-1.74%		-0.43%	0.14%	-1.11%	-0.93%	-1.34%	

Table 2.8. Mean-variance optimization: Commodity indexes and Taylor series expansion of power utility function

Entries report the performance measures (annualized Sharpe Ratio, annualized Opportunity Cost, Portfolio Turnover, annualized Return-Loss) for the case where the expected utility is maximized under a second order Taylor series expansion of power utility function. The *p*-values of Memmel's (2003) test are also reported within parentheses; the null hypothesis is that the SR obtained from the traditional investment opportunity set is equal to that derived from the expanded set that includes commodities. Results are reported for different sizes of the rolling window (*K*=36,48,60,72 observations) and different degrees of relative risk aversion (*RRA*=2,4,6,8,10). Investors access investment in commodities either via S&P GSCI (Panel A) or DJ-UBSCI (Panel B). Results are based on monthly observations from Jan. 1989 to Dec. 2009 for S&P GSCI and from Jan. 1991 to Dec. 2009 for DJ-UBSCI.

		RRA=2		**RRA=4**		**RRA=6**		**RRA=8**		**RRA=10**	
		Expanded	**Traditional**	**Expanded**	**Traditional**	**Expanded**	**Traditional**	**Expanded**	**Traditional**	**Expanded**	**Traditional**
Panel A: S&P GSCI (1989-2009)											
K=36	Sharpe Ratio	0.31	0.49	0.38	0.59	0.39	0.60	0.41	0.60	0.42	0.59
	(p-value)	*-0.155*		*-0.084*		*-0.063*		*-0.067*		*-0.066*	
	Opp. Cost	-5.88%		-6.36%		-5.76%		-3.84%		-4.08%	
	Port.Turnover	81.25%	55.01%	71.89%	52.42%	68.55%	52.99%	65.97%		61.80%	53.24%
	Return-Loss	-5.31%		-5.13%		-4.47%		-3.95%		-3.14%	
K=48	Sharpe Ratio	0.21	0.33	0.30	0.44	0.38	0.49	0.38	0.48	0.33	0.42
	(p-value)	*-0.258*		*-0.166*		*-0.184*		*-0.174*		*-0.171*	
	Opp. Cost	-5.16%		-4.68%		-3.36%		-2.64%		-2.16%	
	Port.Turnover	70.84%	44.62%	57.92%	40.37%	49.15%	37.86%	47.11%	37.93%	48.79%	41.34%
	Return-Loss	-4.11%		-3.80%		-2.66%		-2.14%		-1.76%	
K=60	Sharpe Ratio	0.02	0.16	0.16	0.28	0.19	0.28	0.21	0.28	0.20	0.25
	(p-value)	*-0.221*		*-0.177*		*-0.201*		*-0.238*		*-0.283*	
	Opp. Cost	-7.32%		-5.04%		-3.60%		-2.64%		-2.04%	
	Port.Turnover	72.53%	38.18%	52.35%	33.15%	49.33%	37.42%	44.11%	35.21%	41.16%	35.79%
	Return-Loss	-5.00%		-3.81%		-2.49%		-1.77%		-1.20%	
K=72	Sharpe Ratio	0.10	0.24	0.29	0.37	0.34	0.40	0.33	0.38	0.35	0.39
	(p-value)	*-0.221*		*-0.274*		*-0.339*		*-0.345*		*-0.155*	
	Opp. Cost	-8.16%		-4.08%		-2.88%		-2.28%		-1.80%	
	Port.Turnover	66.71%	32.79%	43.27%	25.31%	36.51%	26.59%	35.26%	27.73%	32.73%	28.64%
	Return-Loss	-5.09%		-2.95%		-1.68%		-1.27%		-0.95%	
Panel B: DJ-UBSCI (1991-2009)											
K=36	Sharpe Ratio	0.47	0.45	0.51	0.55	0.49	0.56	0.48	0.55	0.48	0.55
	(p-value)	*-0.473*		*-0.404*		*-0.318*		*-0.298*		*-0.308*	
	Opp. Cost	0.00%		-2.52%		-3.60%		-3.24%		-3.00%	
	Port.Turnover	82.40%	55.71%	75.74%	55.43%	75.96%	57.45%	71.60%	59.06%	68.57%	58.61%
	Return-Loss	-0.96%		-1.88%		-2.32%		-1.99%		-1.63%	
K=48	Sharpe Ratio	0.38	0.37	0.41	0.49	0.46	0.54	0.45	0.52	0.41	0.47
	(p-value)	*-0.475*		*-0.331*		*-0.301*		*-0.300*		*-0.342*	
	Opp. Cost	-0.72%		-3.48%		-3.48%		-2.88%		-2.28%	
	Port.Turnover	73.54%	42.50%	64.18%	40.06%	57.64%	39.67%	53.26%	40.87%	54.58%	44.96%
	Return-Loss	-1.27%		-2.77%		-2.49%		-2.03%		-1.42%	
K=60	Sharpe Ratio	-0.07	0.07	0.03	0.22	0.10	0.24	0.11	0.24	0.11	0.22
	(p-value)	*-0.233*		*-0.119*		*-0.149*		*-0.162*		*-0.199*	
	Opp. Cost	-8.04%		-7.44%		-4.92%		-3.60%		-2.40%	
	Port.Turnover	69.57%	37.14%	60.44%	33.23%	55.56%	39.36%	48.50%	37.13%	43.34%	36.28%
	Return-Loss	-5.11%		-5.64%		-3.65%		-2.82%		-2.05%	
K=72	Sharpe Ratio	-0.10	-0.01	0.04	0.18	0.08	0.22	0.07	0.21	0.09	0.22
	(p-value)	*-0.324*		*-0.209*		*-0.183*		*-0.165*		*-0.170*	
	Opp. Cost	-8.28%		-7.08%		-5.16%		-4.20%		-3.36%	
	Port.Turnover	61.46%	33.24%	45.85%	24.55%	39.79%	26.45%	37.99%	28.65%	33.80%	25.34%
	Return-Loss	-3.73%		-4.30%		-3.30%		-2.75%		-2.22%	

Table 2.9. Sub-sample analysis for commodity indexes and power utility function

Entries report the performance measures (annualized Sharpe Ratio, annualized Opportunity Cost, Portfolio Turnover, annualized Return-Loss) for the case where the entire sample is divided to two sub-samples based on the commodities' performance, pre-2005 (Panel A) and post-2005 period (Panel B), and the expected utility is maximized under a power utility function. The *p*-values of Memmel's (2003) test are also reported within parentheses; the null hypothesis is that the SR obtained from the traditional investment opportunity set is equal to that derived from the expanded set that includes commodities. Results are reported for different sizes of the rolling window (*K*=36,48 observations) and different degrees of relative risk aversion (*RRA*=2,4,6,8,10). Investors access investment in commodities either via S&P GSCI or DJ-UBSCI. Results are based on monthly observations from Jan. 1989 to Jun. 2008 for S&P GSCI and from Jan. 1991 to Jun. 2008 for DJ-UBSCI.

Panel A: Pre-2005 period

S&P GSCI (1989-2004)

		RRA=2		RRA=4		RRA=6		RRA=8		RRA=10	
		S&P GSCI	**Traditional**	**S&P GSCI**	**Traditional**	**S&P GSCI**	**Traditional**	**S&P GSCI**	**Traditional**	**S&P GSCI**	**Traditional**
K=36	Sharpe Ratio	0.30	0.64	0.36	0.70	0.39	0.69	0.39	0.68	0.40	0.68
	(p-value)	*(0.028)*		*(0.018)*		*(0.020)*		*(0.020)*		*(0.027)*	
	Opp. Cost	-9.12%		-8.04%		-6.12%		-5.28%		-4.32%	
	Port.Turnover	80.60%	51.04%	74.53%	51.27%	71.87%	52.90%	66.30%	52.42%	61.31%	49.12%
	Return-Loss	-9.39%		-7.82%		-6.24%		-5.38%		-4.46%	
K=48	Sharpe Ratio	0.42	0.54	0.51	0.64	0.55	0.66	0.50	0.62	0.47	0.60
	(p-value)	*(0.247)*		*(0.215)*		*(0.202)*		*(0.155)*		*(0.125)*	
	Opp. Cost	-3.48%		-2.52%		-1.32%		-0.84%		-1.08%	
	Port.Turnover	62.21%	38.17%	52.43%	35.26%	46.46%	32.90%	46.60%	34.12%	47.46%	36.97%
	Return-Loss	-4.42%		-3.47%		-2.80%		-2.56%		-2.32%	

DJ-UBSCI (1991-2004)

		RRA=2		RRA=4		RRA=6		RRA=8		RRA=10	
		DJUBSCI	**Traditional**	**DJUBSCI**	**Traditional**	**DJUBSCI**	**Traditional**	**DJUBSCI**	**Traditional**	**DJUBSCI**	**Traditional**
K=36	Sharpe Ratio	0.54	0.62	0.53	0.68	0.50	0.66	0.49	0.65	0.50	0.63
	(p-value)	*(0.306)*		*(0.177)*		*(0.155)*		*(0.159)*		*(0.208)*	
	Opp. Cost	-1.92%		-3.60%		-3.12%		-3.36%		-3.24%	
	Port.Turnover	83.69%	50.90%	81.59%	54.97%	78.65%	58.92%	75.58%	59.18%	70.74%	55.73%
	Return-Loss	-3.65%		-4.42%		-4.07%		-3.59%		-2.84%	
K=48	Sharpe Ratio	0.62	0.63	0.70	0.75	0.68	0.77	0.62	0.72	0.60	0.70
	(p-value)	*(0.378)*		*(0.382)*		*(0.296)*		*(0.261)*		*(0.263)*	
	Opp. Cost	-0.02%		-1.08%		-1.08%		-0.60%		-1.32%	
	Port.Turnover	64.97%	33.28%	60.62%	33.45%	54.90%	34.34%	57.01%	37.51%	56.56%	41.02%
	Return-Loss	-0.27%		-2.53%		-2.86%		-2.79%		-2.29%	

Panel B: Post-2005 period

		RRA=2			RRA=4			RRA=6			RRA=8			RRA=10		
		S&PGSCI	**DJUBS**	**Traditional**	**S&PGSCI**	**DJUBS**	**Traditional**	**S&PGSCI**	**DJUBS**	**Traditional**	**S&PGSCI**	**DJUBS**	**Traditiona**	**S&PGSCI**	**DJUBSCI**	**Traditional**
K=36	SharRatio	0.52	0.78	0.13	0.47	0.78	0.19	0.49	0.73	0.28	0.49	0.69	0.28	0.48	0.68	0.26
	(p-value)	*(0.267)*	*(0.158)*		*(0.291)*	*(0.149)*		*(0.314)*	*(0.181)*		*(0.298)*	*(0.186)*		*(0.283)*	*(0.174)*	
	Opp. Cost	6.84%	14.76%		2.04%	8.76%		0.48%	4.32%		0.00%	3.12%		0.00%	2.76%	
	PortTurnover	75.21%	63.27%	65.94%	60.45%	59.38%	53.27%	54.88%	63.48%	50.80%	59.95%	61.53%	60.16%	56.88%	60.57%	60.03%
	Ret-Loss	5.01%	9.57%		3.17%	7.69%		2.07%	4.95%		1.87%	4.26%		1.79%	3.82%	
K=48	SharRatio	0.26	0.52	0.00	0.14	0.32	-0.03	0.19	0.32	0.01	0.18	0.32	0.01	0.19	0.33	0.04
	(p-value)	*(0.334)*	*(0.212)*		*(0.360)*	*(0.258)*		*(0.331)*	*(0.255)*		*(0.324)*	*(0.235)*		*(0.328)*	*(0.242)*	
	Opp. Cost	-0.24%	9.00%		-1.92%	0.72%		-0.96%	0.12%		-0.84%	0.72%		-0.72%	0.84%	
	PortTurnover	70.48%	62.14%	34.23%	48.45%	55.79%	27.56%	38.16%	46.76%	29.90%	35.98%	40.69%	35.03%	34.50%	36.58%	33.81%
	Ret-Loss	1.60%	5.82%		0.71%	3.03%		1.18%	2.43%		1.25%	2.69%		0.97%	2.29%	

Table 2.10. Sub-sample analysis for individual commodity futures and power utility function

Entries report the performance measures (annualized Sharpe Ratio, annualized Opportunity Cost, Portfolio Turnover, annualized Return-Loss) for the case where the entire sample is divided to two subsamples based on the commodities' performance, pre-2005 (Panel A) and post-2005 period (Panel B), and the expected utility is maximized under a power utility function. The *p*-values of Memmel's (2003) test are also reported within parentheses; the null hypothesis is that the SR obtained from the traditional investment opportunity set is equal to that derived from the expanded set that includes commodities. Results are reported for different sizes of the rolling window (*K*=36,48 observations) and different degrees of relative risk aversion (*RRA*=2,4,6). Investors access investment in commodities via the selected individual commodity futures contracts. Results are based on monthly observations from Jan. 1989 to Jun. 2008.

		RRA=2						**RRA=4**						**RRA=6**					
		Crude Oil	**Copper**	**Cotton**	**Gold**	**Live Cattle**	**Traditional**	**Crude Oil**	**Copper**	**Cotton**	**Gold**	**Live Cattle**	**Traditional**	**Crude Oil**	**Copper**	**Cotton**	**Gold**	**Live Cattle**	**Traditional**
Panel A: Pre-2005 period (1989-2004)																			
K=36	Sharpe ratio	0.33	0.54	0.24	0.67	0.36	0.64	0.46	0.62	0.36	0.68	0.52	0.70	0.53	0.65	0.44	0.69	0.55	0.69
	(p-value)	*(0.078)*	*(0.320)*	*(0.024)*	*(0.393)*	*(0.053)*		*(0.078)*	*(0.356)*	*(0.015)*	*(0.464)*	*(0.105)*		*(0.137)*	*(0.416)*	*(0.023)*	*(0.499)*	*(0.116)*	
	Opp. Cost	-9.24%	-2.04%	-13.68%	1.80%	-7.56%		-6.36%	-2.40%	-9.84%	-0.60%	-4.68%		-4.08%	-1.08%	-6.72%	-0.24%	-3.36%	
	Port.Turnover	76.83%	80.80%	90.38%	81.44%	88.25%	51.04%	66.14%	71.75%	76.97%	77.59%	72.86%	51.27%	63.15%	70.22%	68.76%	77.02%	66.67%	52.90%
	Return-Loss	-8.69%	-3.55%	-10.90%	-0.20%	-8.06%		-5.70%	-2.42%	-7.99%	-1.27%	-4.58%		-3.46%	-1.47%	-5.43%	-0.92%	-3.14%	
K=48	Sharpe ratio	0.39	0.45	0.21	0.48	0.43	0.54	0.55	0.58	0.38	0.57	0.51	0.64	0.61	0.59	0.46	0.59	0.55	0.66
	(p-value)	*(0.217)*	*(0.321)*	*(0.023)*	*(0.343)*	*(0.258)*		*(0.268)*	*(0.359)*	*(0.014)*	*(0.282)*	*(0.172)*		*(0.321)*	*(0.320)*	*(0.019)*	*(0.274)*	*(0.153)*	
	Opp. Cost	-4.56%	-2.40%	-10.44%	-1.44%	-3.24%		-1.92%	-1.92%	-6.72%	-1.92%	-3.60%		-0.84%	-2.16%	-4.56%	-1.68%	-2.52%	
	Port.Turnover	63.57%	63.09%	68.56%	69.10%	68.94%	38.17%	45.12%	53.17%	49.66%	59.56%	54.56%	35.26%	38.61%	48.48%	43.66%	52.40%	46.03%	32.90%
	Return-Loss	-5.29%	-3.49%	-9.61%	-2.79%	-4.16%		-2.41%	-2.23%	-6.10%	-2.53%	-3.73%		-1.28%	-2.23%	-4.19%	-2.23%	-2.77%	
Panel B: Post-2005 period (2005-June 2008)																			
K=36	Sharpe ratio	1.24	1.04	0.19	1.42	-0.02	0.13	1.14	0.89	0.20	1.38	0.06	0.19	1.13	0.89	0.28	1.29	0.16	0.28
	(p-value)	*(0.053)*	*(0.114)*	*(0.459)*	*(0.031)*	*(0.316)*		*(0.049)*	*(0.165)*	*(0.495)*	*(0.035)*	*(0.294)*		*(0.046)*	*(0.180)*	*(0.498)*	*(0.049)*	*(0.285)*	
	Opp. Cost	34.44%	33.48%	-1.44%	35.64%	-4.32%		17.52%	10.44%	-2.40%	25.68%	-3.72%		11.64%	4.20%	-2.28%	16.32%	-2.76%	
	Port.Turnover	67.82%	59.35%	86.75%	60.67%	85.59%	65.94%	52.93%	67.26%	55.20%	58.60%	67.60%	53.27%	44.24%	62.20%	45.85%	59.92%	62.74%	50.80%
	Return-Loss	16.77%	13.49%	-0.33%	19.83%	-3.90%		13.20%	8.74%	-0.63%	16.61%	-3.07%		11.04%	6.85%	-0.42%	12.73%	-2.52%	
K=48	Sharpe ratio	1.12	1.02	-0.08	1.39	-0.10	0.00	0.91	0.85	-0.08	1.31	-0.12	-0.03	0.87	0.82	-0.01	1.19	-0.06	0.01
	(p-value)	*(0.044)*	*(0.104)*	*(0.410)*	*(0.031)*	*(0.382)*		*(0.045)*	*(0.117)*	*(0.411)*	*(0.029)*	*(0.362)*		*(0.043)*	*(0.116)*	*(0.449)*	*(0.023)*	*(0.379)*	
	Opp. Cost	32.52%	33.36%	-1.80%	37.68%	-4.08%		13.68%	12.00%	-0.84%	26.40%	-3.72%		9.00%	5.64%	-0.36%	17.04%	-2.52%	
	Port.Turnover	66.39%	53.49%	49.64%	59.03%	67.97%	34.23%	49.38%	59.22%	35.83%	52.63%	48.55%	27.56%	39.20%	52.92%	32.67%	51.68%	39.44%	29.90%
	Return-Loss	14.67%	13.15%	-2.15%	19.04%	-3.55%		11.17%	9.99%	-1.13%	16.92%	-2.59%		9.39%	8.04%	-0.51%	13.31%	-1.68%	

Table 2.11. Enhanced commodity indexes and power utility function

Entries report the performance measures (annualized Sharpe Ratio, annualized Opportunity Cost, Portfolio Turnover, annualized Return-Loss) for the case where the expected utility is maximized under a power utility function. The *p*-values of Memmel's (2003) test are also reported within parentheses; the null hypothesis is that the SR obtained from the traditional investment opportunity set is equal to that derived from the expanded set that includes commodities. Results are reported for different sizes of the rolling window (*K*=36,48,60,72 observations) and different degrees of relative risk aversion (*RRA*=2,4,6,8,10). Investors access investment in commodities either via DBLCI or MLCX. Results are based on monthly observations from Jan. 1989 to Dec. 2009 for DBLCI and from Jun. 1990 to Dec. 2009 for MLCX.

		RRA=2		**RRA=4**		**RRA=6**		**RRA=8**		**RRA=10**	
		Expanded	**Traditional**	**Expanded**	**Traditional**	**Expanded**	**Traditional**	**Expanded**	**Traditional**	**Expanded**	**Traditional**
Panel A: DBLCI (1989-2009)											
K=36	Sharpe Ratio	0.32	0.49	0.41	0.57	0.44	0.59	0.48	0.59	0.51	0.58
	(p-value)	*(0.222)*		*(0.212)*		*(0.212)*		*(0.265)*		*(0.339)*	
	Opp. Cost	-5.76%		-6.00%		-5.52%		-4.32%		-3.48%	
	PortTurnover	77.58%	56.57%	70.62%	53.48%	66.30%	53.75%	62.40%	55.01%	59.33%	52.43%
	Return-Loss	-4.90%		-3.97%		-3.23%		-2.15%		-1.46%	
K=48	Sharpe Ratio	0.34	0.34	0.40	0.44	0.41	0.47	0.40	0.44	0.39	0.42
	(p-value)	*(0.497)*		*(0.412)*		*(0.367)*		*(0.398)*		*(0.421)*	
	Opp. Cost	-2.28%		-3.84%		-3.60%		-3.00%		-2.52%	
	PortTurnover	68.41%	44.66%	55.99%	39.61%	48.48%	37.72%	46.65%	38.88%	46.39%	40.22%
	Return-Loss	-1.32%		-1.85%		-1.76%		-1.22%		-0.91%	
K=60	Sharpe Ratio	0.17	0.17	0.21	0.27	0.23	0.26	0.24	0.25	0.25	0.24
	(p-value)	*(0.496)*		*(0.369)*		*(0.420)*		*(0.470)*		*(0.470)*	
	Opp. Cost	-7.44%		-7.20%		-5.04%		-3.84%		-3.00%	
	PortTurnover	67.93%	37.58%	50.60%	34.89%	44.12%	34.75%	40.82%	34.47%	38.67%	34.75%
	Return-Loss	-1.79%		-2.37%		-1.32%		-0.77%		-0.38%	
K=72	Sharpe Ratio	0.26	0.25	0.34	0.38	0.36	0.38	0.37	0.38	0.40	0.39
	(p-value)	*(0.522)*		*(0.411)*		*(0.435)*		*(0.465)*		*(0.474)*	
	Opp. Cost	-8.52%		-8.64%		-6.24%		-4.68%		-3.60%	
	PortTurnover	59.88%	32.81%	43.91%	26.62%	36.21%	27.08%	32.45%	27.48%	30.16%	28.36%
	Return-Loss	-1.44%		-2.08%		-1.24%		-0.80%		-0.41%	
Panel B: MLCX (1990-2009)											
K=36	Sharpe Ratio	0.40	0.48	0.48	0.55	0.49	0.56	0.50	0.55	0.51	0.54
	(p-value)	*(0.372)*		*(0.365)*		*(0.339)*		*(0.371)*		*(0.432)*	
	Opp. Cost	-3.96%		-5.04%		-5.16%		-4.20%		-3.24%	
	PortTurnover	78.42%	57.53%	75.93%	56.65%	72.08%	57.58%	67.25%	59.16%	62.48%	56.43%
	Return-Loss	-2.87%		-2.42%		-2.13%		-1.42%		-0.89%	
K=48	Sharpe Ratio	0.51	0.38	0.48	0.47	0.50	0.50	0.46	0.46	0.45	0.44
	(p-value)	*(0.269)*		*(0.464)*		*(0.498)*		*(0.498)*		*(0.488)*	
	Opp. Cost	2.28%		-2.76%		-3.00%		-2.88%		-2.28%	
	Port.Turnover	67.62%	43.03%	60.12%	40.71%	51.72%	39.97%	49.52%	41.86%	49.72%	43.35%
	Return-Loss	1.87%		-0.86%		-0.89%		-0.61%		-0.46%	
K=60	Sharpe Ratio	0.25	0.15	0.29	0.28	0.30	0.27	0.30	0.27	0.32	0.26
	(p-value)	*(0.320)*		*(0.471)*		*(0.431)*		*(0.401)*		*(0.352)*	
	Opp. Cost	-5.40%		-5.40%		-3.84%		-3.24%		-2.40%	
	PortTurnover	63.68%	63.68%	50.07%	35.63%	45.74%	36.33%	41.78%	35.51%	37.84%	34.49%
	Return-Loss	-0.87%		-0.79%	-	-0.22%		-0.02%		-0.02%	-
K=72	Sharpe Ratio	0.17	0.09	0.24	0.27	0.26	0.29	0.27	0.30	0.29	0.31
	(p-value)	*(0.352)*		*(0.431)*		*(0.418)*		*(0.432)*		*(0.461)*	
	Opp. Cost	-10.80%		-9.72%		-7.20%		-5.40%		-4.32%	
	PortTurnover	63.35%	32.61%	45.75%	26.77%	37.88%	28.15%	33.56%	28.59%	30.52%	28.29%
	Return-Loss	-0.32%		-2.05%		-1.47%		-1.06%		-0.76%	

Appendix A: Mean-variance spanning tests in excess returns

In the case where the initial *K*-benchmark asset universe includes also the risk-free asset, we modify the test for MV spanning to formulate it in excess returns terms. In particular, subtracting the risk-free rate from both sides of (2.5), yields

$$R_{t+1}^{test} - R_t^f = \alpha + \beta R_{t+1} - R_t^f + \varepsilon_{t+1} \Rightarrow R_{t+1}^{test} - R_t^f = \alpha + \beta R_{t+1} - \left(R_t^f\left(1-\beta\iota_K\right) + R_t^f \beta\iota_K\right) + \varepsilon_{t+1} \Rightarrow$$

$$R_{t+1}^{test} - R_t^f = \left[\alpha - R_t^f\left(1-\beta\iota_K\right)\right] + \beta\left(R_{t+1} - R_t^f \iota_K\right) + \varepsilon_{t+1} \qquad \text{(A.1)}$$

Let α_J denote the intercept in the regression of the test asset's excess returns on the excess returns of the *K* benchmark assets (see equation (2.7)). Equation (A.1) establishes the equivalence between the intercepts of equations (2.5) and (2.7), i.e. $\alpha_J = \alpha - R_t^f\left(1-\beta i_K\right)$. Given that the restrictions in the case where the test is formulated in gross returns are $\alpha = 0$ and $\beta i_K = 1$, the equivalent restriction in excess returns is that $\alpha_J = 0$.

Appendix B: Non mean-variance spanning tests in excess returns

In the case where the initial *K*-benchmark asset universe includes also the risk-free asset, we formulate the test for non- MV spanning in terms of excess returns. In particular, subtracting the risk-free rate from both sides of (10) yields

$$R_{t+1}^{test} - R_f = \alpha + \beta R_{t+1} - R_f + \sum_{i=1}^{n} \gamma_i U_i'\left(w_i^{*\prime} R_{t+1}\right) + \varepsilon_{t+1} \Rightarrow$$

$$R_{t+1}^{test} - R_f = \alpha + \beta R_{t+1} - \left(R_f\left(1-\beta\iota_K\right) + R_f \beta\iota_K\right) + \sum_{i=1}^{n} \gamma_i U_i'\left(w_i^{*\prime} R_{t+1}\right) + \varepsilon_{t+1} \Rightarrow$$

$$R_{t+1}^{test} - R_f = \left[\alpha - R_f\left(1-\beta\iota_K\right)\right] + \beta\left(R_{t+1} - R_f \iota_K\right) + \sum_{i=1}^{n} \gamma_i U_i'\left(w_i^{*\prime} R_{t+1}\right) + \varepsilon_{t+1} \qquad \text{(B.1)}$$

Let α_J again denote the intercept in the regression (B.1), i.e. $\alpha_J = \alpha - R_f\left(1-\beta\iota_K\right)$. In the case where the test is formulated in gross returns the constraints are $\alpha = \gamma_i = 0 \ \forall i$ and $\beta i_K = 1$. Hence, the equivalent restriction in excess returns is that $\alpha_J = \gamma_i = 0 \ \forall i$.

Chapter 3: Are there common factors in commodity futures returns?

Abstract

We explore whether there are any common factors in the cross-section of commodity futures expected returns. We test a number of asset pricing models which have proved successful for equities, as well as models motivated by commodity pricing theories. We also consider a Principal Components factor model which does not require à priori specification of factors. We find that none of the models is successful. In addition, the factors that affect the time series of commodity futures returns differ across commodities. Our results imply that commodity markets are segmented from the equities market and they are significantly heterogeneous per se.

3.1. Introduction

The primary goal of the literature in asset pricing is to develop a model which explains (i.e. prices) the *cross-section* of the assets expected returns by means of a small set of common factors. There is an extensive literature which addresses this task for traditional asset classes like equities. The empirical evidence is universal in that there are at least three well-accepted factors (size, value, and momentum, see Fama and French, 1993, Carhart, 1997, Campbell, 2000) which price the cross-section of equities. However, not much empirical research has been undertaken to investigate whether there is one or more asset pricing models which may explain the cross-section of commodity futures expected returns. We fill this void.

The answer to the asset pricing question in the case of commodities is challenging from an academic standpoint given that commodities are alleged to form an alternative asset class (Gorton and Rouwenhorst, 2006). Therefore, the factors which price the traditional asset classes may not price commodities. In addition, commodities are notorious for their heterogeneous structure (Erb and Harvey, 2006, Kat and Oomen, 2007b). This makes harder the identification of a set of systematic factors which may price the common variation of commodity returns. The detection of an appropriate asset pricing commodity model is also of particular importance to practitioners. Institutional investors have increased their portfolio allocations to commodities over the last years (see Chapters 1 and 2). Therefore, they need to have reliable asset pricing models to evaluate their risk-adjusted performance.

The commodity asset pricing literature can be divided in two strands. The first strand uses asset pricing models which are designed to price *any* asset under the stochastic discount factor (SDF) paradigm (Campbell, 2000, Cochrane, 2005). Dusak (1973) and Bodie and Rosansky (1980) investigate the performance of the Capital Asset Pricing Model (CAPM) and Breeden (1980) examines the performance of the Consumption CAPM (CCAPM). However, these papers examine the pricing ability of the models for individual commodities rather than for the cross-section of commodities. To the best of our knowledge, Jagannathan (1985) and DeRoon and Szymanowska (2010) are the only studies which explore the cross-sectional validity of a theoretically sound model (CCAPM). The former study rejects the CCAPM using monthly data, whereas the latter finds that the CCAPM explains commodity futures returns (only) for quarterly horizons. The mixed empirical evidence and the usage of a small number of SDF-based models call for further research in this vein.

The second strand argues that the expected return of any given commodity futures is driven by factors specific to the commodities markets. This is because there are non-marketable sources of risks in these markets for which no marketable claims can be issued. The relative positions of hedgers to speculators in the commodity futures markets (hedging pressure) and the level of inventories emerge as relevant variables. Motivated by the hedging pressure theory of Cootner (1960), the models of Stoll (1979), Hirschleifer (1988, 1989), and De Roon et al. (2000) allow both systematic factors and hedging pressure to affect *individual* commodity futures premiums. Carter et al. (1983) and Bessembinder (1992) provide further empirical evidence on this direction. On the other hand, Gorton et al. (2012), based on the theory of storage (Kaldor, 1939, Working, 1949, Brennan, 1958), focus on the relationship between the commodities inventory levels and their respective commodity futures expected returns. Acharya et al. (2011) provide a unified setting where the hedging pressure and the inventories interact due to limits in capital movements and they determine the futures risk premiums. However, all the above mentioned studies again identify the linkage between the proposed commodity-specific variables and *individual* commodity futures expected returns rather than evaluating them as *systematic* factors within a cross-sectional asset pricing setting. Therefore, the question whether there is an asset pricing model that may price commodity futures returns is left unanswered within the second strand, too.

Building on the previously discussed literature, we investigate comprehensively whether there are any factors which explain the *cross-sectional* variation in commodity futures expected returns. We begin our research by testing a number of popular asset pricing models which fall within two categories: the macro-factor and the equity-motivated tradable factor models. The macro-factor models specify directly the functional form for the SDF using macroeconomic (i.e. aggregate) variables. First, we implement the CAPM and CCAPM models. Then, we test the Money-CAPM and Money-CCAPM (MCAPM, MCCAPM) models of Balvers and Huang (2009) which augment the CAPM and CCAPM models by the growth rate of the money supply in the economy. The application of these models to the commodity markets is motivated by the evidence that the monetary policy affects the returns of individual commodity futures (Frankel and Hardouvelis, 1985, Barsky and Kilian, 2001, Frankel, 2008, and Anzuini et al., 2010). Next, we test the leverage model of Adrian et al. (2011) which uses the broker dealers' leverage as a state variable. This state variable is also an appealing candidate pricing factor for commodity futures returns given the importance of broker dealers for commodity futures markets.[1] Also, the models of Etula (2010) and Acharya et al. (2011) predict a negative relationship between the broker dealers' leverage and the individual commodity futures risk premium. Finally, we adopt an international-CAPM setting and examine whether an aggregate foreign exchange factor is priced in the cross-section of commodity futures returns (see e.g., Dumas and Solnik, 1993, DeSantis and Gerald, 1998). The application of this model is motivated by the evidence that the exchange rate risk affects the returns of the individual commodity futures (Erb and Harvey, 2006). We proxy the aggregate risk factor by using the Lustig et al. (2011) traded factor. To the best of our knowledge, no study has examined whether a monetary, a leverage, or a foreign exchange rate factor explains the cross-section of commodity futures expected returns even though

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[1] To a large extent, broker dealers are the marginal investor on the speculative side of the commodity derivatives market in the over-the-counter (OTC) transactions. The high degree of financial intermediation required to channel capital to commodity markets as well as the vast size of the OTC transactions (about 90% of the size of investments in commodities, Etula, 2010) further supports the importance of the broker-dealers' risk-bearing capacity for the determination of commodity futures premiums.

these have been proven successful in pricing equities and they play an important role in commodity futures markets, too.

We find that none of the macro-factor models prices commodity futures successfully. Therefore, we examine the equity-motivated tradable factor models. We employ the factors which have been commonly and successfully used in the equity asset pricing literature (Fama-French, 1993, Carhart, 1997, and Pastor and Stambaugh, 2003, liquidity factor). Under the law of one price, free portfolio formation, and provided that markets are not-segmented, these empirically successful factors for the equity market should price the cross-section of commodity futures, too (Cochrane, 2005, Theorem, page 64). However, it is not clear à priori whether the equity and the commodity markets are integrated. Bessembinder (1992) and Bessembinder and Chan (1992) find that certain commodity markets are segmented from other asset markets. The evidence in Erb and Harvey (2006) also indicates that the Fama-French (1993) factors do not drive the returns of individual commodity futures. Gorton and Rouwenhorst (2006) regard the low correlations of commodities with other asset classes as evidence for market segmentation. On the other hand, Tang and Xiong (2010) argue that the increase of investments in commodities via commodity indexes (financialization of commodities) tends to integrate the equity with the commodity markets. Bakshi et al. (2011) and Hong and Yogo (2012) find that there are common variables which predict commodity futures and equity returns. This is a necessary but not a sufficient condition for market integration though (Bessembinder and Chan, 1992).

We find that the equity-motivated tradable factors models cannot price the commodity futures either. This finding in conjunction with Cochrane's (2005) theorem implies that the commodity futures markets are segmented from the equity markets. Consequently, then we focus on commodity-specific factors. We construct theoretically sound commodity-specific factors by relying on the two main theories for the determination of commodity returns (hedging pressure and theory of storage). Then, we explore whether these factors price the cross-section of commodity futures. Basu and Miffre (2012) also construct various factor-mimicking portfolios associated with the hedging pressure and investigate whether these explain the cross section of commodity futures. They find mixed results regarding the significance of the price of risk of the hedging pressure factor depending on the assumptions made for its construction. On the other hand, Gorton et al. (2012) find that the level of inventories of individual commodities is informative about the respective futures risk premiums. However, they do not test whether an inventory factor prices the cross-section of commodities. Surprisingly, we find that the commodity-specific factors fail in pricing commodity futures, too. This implies that there is no common risk factor structure in the cross-section of commodity futures risk premiums. We verify the heterogeneous structure of commodity futures markets by showing that there is none of the macro, equity-motivated, and commodity-specific factors that can explain the *time series* of *all* commodity futures returns.

As a final step, we implement a principal components (PCs) factor model in the spirit of Connor and Korajczyk (1986) and Cochrane (2011). The model does not require à priori specification of factors and it enables detecting the presence of *any* factor that may be used as a candidate for pricing commodity returns. We find that the PC model performs also poorly. Moreover, the results from the PC model confirm that the commodities futures market is segmented itself. This explains the failure of the previously employed factors.

We use a representative cross-section of 22 individual commodity futures contracts over the period January 1989-December 2010. The employed contracts represent the four main commodity categories (energy, metals, agriculture, and livestock). Moreover, this time period incorporates bull and bear regimes in commodity prices as well as the 2003-2008 commodity boom period and the recent 2007-2009 financial crisis.[2] We estimate the various asset pricing models by using the Fama-MacBeth (1973) two-pass approach for both monthly and quarterly horizons. We perform a number of further robustness tests in terms of the dataset, the estimation approach, and the measurement of the inputs of certain pricing models. Again, we find unanimous evidence that none of the employed factors accounts for the cross-sectional variation of the commodity futures expected returns.

The rest of the paper is structured as follows. Section 3.2 describes the datasets. Sections 3.3 and 3.4 review the employed macro and equity-motivated tradable factors asset pricing models and describe the construction of the commodity-specific factors, respectively. Sections 3.5 and 3.6 outline the econometric estimation of the asset pricing models and discuss the results on their performance, respectively. Section 3.7 provides further robustness tests. Section 3.8 describes the Principal Component Analysis (PCA)

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[2] The period 2003-2008 has witnessed a spectacular and simultaneous increase in the commodity prices of the three major commodity groups (energy, metals, and agriculture) which has taken all of them to record highs in the recent history of commodities. Hence, it has been termed a commodity boom period (see e.g., Helbling, 2008).

factor models and discusses results. Section 3.9 concludes and discusses the implications of our research.

3.2. The dataset

We use data on 22 individual commodity futures contracts, provided by Bloomberg. Our sample is balanced and it extends from January 1989 to December 2010.[3] Table 3.1 describes the available commodity futures data, the delivery date for each one of the employed commodities as well as the exchanges where the individual contracts are traded.

For each underlying commodity, we create a continuous time series of monthly and quarterly futures percentage returns. In particular, to calculate the monthly returns, we hold the first nearby contract until the beginning of the delivery month and then we roll over our position to the contract with the following delivery month which then becomes the nearest-to-maturity contract**.** Notice that we compute the monthly futures returns using the successive monthly prices of a contract for a given delivery date, i.e. we do not compute returns by using prices across contracts with different delivery dates. Hence, the returns reflect a strategy of closing the position in the near contract and opening a position in the second nearest contract at the beginning of the delivery month (see for a similar approach, Bessembinder and Chan, 1992, De Roon and Szymanowska, 2010, Fuertes et al., 2010, Gorton et al., 2012). Next, we construct the time series of quarterly futures returns by compounding the respective monthly figures for each underlying commodity. Table 3.2 presents the descriptive statistics for the constructed series of monthly and quarterly commodity futures returns over the period January 1989-December 2010. The average return varies across commodities; the greatest average returns are earned by energy, copper and palladium futures, both for the monthly and quarterly frequencies. These contracts, along with the platinum futures, outperform the other contracts also in terms of the risk-adjusted performance, i.e. the Sharpe ratio figures.

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[3] We have also conducted the analysis by employing a larger sample that spans the period 1975-2010. Due to data availability constraints, this extended sample is unbalanced, i.e. the starting date and the number of observations vary across commodities. The earliest starting date is January 1975 which delivers observations for 15 out of the 22 commodity futures contracts; the rest of the contracts enter the sample gradually. The results remain qualitatively similar to these obtained from the analysis on the balanced dataset, and hence we do not report them.

We also use a number of additional variables in the subsequent asset pricing tests. We obtain the market excess return, value, size, and momentum factors from Kenneth French's website. Regarding the market excess return, we proxy it by the value-weighted return on all NYSE, AMEX, and NASDAQ stocks minus the one-month Treasury bill rate. The use of a stock index as a proxy for the market portfolio is justified from a theoretical point of view despite the fact that commodity futures are traded as well. This is because when one takes all futures contracts together these net out to zero; there is a long position for every short position (for an argument along these lines, see Black, 1976). This choice is also in line with Dusak (1973) who chooses the S&P 500 to proxy the market portfolio for the purposes of testing whether the CAPM holds in commodity markets. Alternatively, we use the S&P GSCI commodity excess return index obtained from Bloomberg, and we also construct a hybrid stock-commodity index to proxy the market excess return; we present the arguments in favour of its construction in Section 3.7.2. We obtain the time series data on the Pastor-Stambaugh (2003) liquidity, Lustig et al. (2011) foreign exchange, and Adrian et al. (2011) leverage factors from Robert Stambaugh‘s, Hanno Lustig's and Tyler Muir's websites, respectively. Given that the liquidity and the foreign exchange factors are tradable factors, we obtain the quarterly observations by compounding the monthly observations; the leverage factor is available only for quarterly horizons.

To measure the real consumption per capita growth variable, we use the seasonally adjusted aggregate nominal consumption expenditure on nondurables and services from the National Income and Product Accounts (NIPA) Tables 2.3.5 and 2.8.5 (quarterly and monthly frequency data, respectively). We obtain population numbers from NIPA Tables 2.1 and 2.6 and price deflator series from NIPA Tables 2.3.4 and 2.8.4 to construct the time series of per capita real consumption figures for the monthly and quarterly horizons, respectively. The money growth is based on the time series of the seasonally adjusted nominal M2 that is available from the Federal Reserve Bank of St. Louis. Alternatively, we use weekly data on the primary dealers' repos obtained from the Federal Reserve Bank of New York to measure the money growth. These are available only for the period January 1998-December 2010. The observation which is closest to the beginning of the month and beginning of the quarter is recorded. The long and short hedging positions of large traders are reported by the U.S. Commodity Futures Trading Commission (CFTC) for each commodity contract on a weekly basis. These are traders who own or control positions in a commodity futures market above a specific threshold specified by CFTC.

3.3. Asset pricing models: Macro and equity-motivated tradable factors

In this section, we investigate whether models that include aggregate and equity-motivated tradable factors can explain the common variation of commodity futures expected returns. The set of aggregate factor models consists of the CAPM, CCAPM, MCAPM, MCCAPM, leverage factor model, and the International CAPM. The set of the equity-motivated tradable factors comprises the Fama-French (1993), Carhart (1997), and Pastor and Stambaugh (2003).

3.3.1. CAPM and CCAPM

First, we consider the popular one-factor CAPM and CCAPM asset pricing models. The CAPM dictates that the expected return of any asset *i* is given by

$$E\left(r_{i,t+1}\right)=\beta_{i,MKT}E\left(r_{M,t+1}\right) \tag{3.1}$$

where $r_{M,t+1}, r_{i,t+1}$ are the excess returns of the market portfolio and an asset *i*, respectively, $\beta_{i,MKT}=Cov\left(r_{i,t+1},r_{M,t+1}\right)/Var\left(r_{M,t+1}\right)$ is the market beta, and E[.] is the expectation operator.

According to the standard consumption-based asset pricing model (CCAPM, Breeden, 1979), assuming a constant relative risk aversion utility function, the risk premium of any asset *i* depends linearly on its exposure to consumption risk, i.e. the covariance of the return on the asset *i* with the contemporaneous aggregate consumption growth

$$E\left(r_{i,t+1}\right)=\beta_{i,CON}\lambda_{CON} \tag{3.2}$$

where λ_{CON} denotes the market price for consumption risk, and $\beta_{i,CON}=Cov\left(r_{i,t+1},g_{t+1}\right)/Var\left(g_{t+1}\right)$ is the consumption beta, where $g_{t+1}=\left(\left(c_{t+1}/c_{t}\right)-1\right)$ denotes the percentage change in consumption. In principle, the CCAPM is expected to explain the cross-sectional variation of commodity returns because their prices are related to aggregate consumption. Increased consumption expenditures result in greater demand for energy and agricultural products, as well as for industrial metals and thus increases in their prices. Breeden (1980) finds evidence for differences between the estimated market and consumption betas.

3.3.2. Balvers and Huang (2009) model

The question whether monetary policy is a systematic factor that prices the cross-section of commodities has not been addressed by the previous literature. We fill this void by adopting the theoretical framework of Balvers and Huang (2009) which adds the growth of the money supply to the traditional CAPM and CCAPM setting. The intuition is that the presence of money helps transactions and hence decreases transaction costs. Therefore, the money supply growth affects the adjusted for transaction costs marginal utility of wealth and therefore the SDF of the representative agent. The beta formulations for the *i*th asset's expected excess return for the MCAPM and MCCAPM are given by the following equations, respectively:

$$E\left(r_{i,t+1}\right)=\beta_{i,MKT}\lambda_{MKT}+\beta_{i,MG}\,\lambda_{MG} \tag{3.3}$$

$$E\left(r_{i,t+1}\right)=\beta_{i,CON}\lambda_{CON}+\beta_{i,MG}\lambda_{MG} \tag{3.4}$$

where λ_{MG} denotes the market price of risk associated with money growth and $\beta_{i,MG}$ is the respective sensitivity of asset *i* on money growth factor.

We proxy the money growth by two alternative measures of the money supply in the economy. The first is the M2 growth, provided by the Federal Reserve Bank of St. Louis. The money stock M2, the traditional measure of the liabilities of deposit-taking banks, has been commonly considered to be the standard measure of the money supply. Adrian and Shin (2009) argue though that M2 is indicative of the money available in the economy only in a bank-based financial system where the commercial banks are the dominant suppliers of credit. However, nowadays, their role has been superseded by market-based institutions (termed broker dealers). Broker dealers are leveraged financial institutions whose importance in the supply of credit has increased recently with the growth of securitization and the changing nature of the traditional bank-based financial system towards one based on the capital markets (market-based system, Adrian and Shin, 2008). In contrast to the deposit-funded banks, broker dealers use repos to finance their short-term liabilities and thus creating money in the economy. Consequently, in a market based system, M2 is not indicative of the money available in the economy. Therefore, we use the time series of the primary broker dealers' repos growth as a second measure of the money supply growth in the economy.[4]

3.3.3. Commodity futures returns and financial intermediaries

Next, we explore whether a factor that is constructed from data obtained from broker dealers' balance sheets explains the cross-section of commodity returns. The motivation for doing so stems from Adrian et al. (2011) who find that the leverage of broker-dealers explains the cross-section of equity returns. Also Etula (2010) shows that the broker dealers' leverage affects the SDF of the representative agent in a setting where households interact with broker dealers. The limits to hedging model of Acharya et al. (2011) delivers a similar prediction. The intuition is that the leverage reflects the ease of access to capital. The greater the leverage, the easier is for broker dealers to meet the hedging demand of producers and therefore the lower the required futures risk premium.

We adopt the Adrian et al. (2011) intertemporal CAPM setting and examine whether shocks to broker-dealers' financial leverage explain the cross-sectional variation in commodity futures expected returns. The leverage factor is obtained from Tyler Muir's website. This is constructed by using the balance sheet data of broker dealers obtained from the Federal Reserve's Flow of Funds database. This reports quarterly the aggregate values of financial assets and liabilities for all U.S. securities broker dealers. Within this setting, the expected excess return of asset *i* is given by

$$E\left(r_{i,t+1}\right)=\beta_{i,f}\lambda_{f}+\beta_{i,Lev}\lambda_{Lev} \tag{3.5}$$

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[4] According to Federal Reserve Bank of New York, the Primary Dealers serve as trading counterparties of the New York Fed in its implementation of monetary policy, i.e. they participate in the open market operations to implement the decisions of the Federal Open Market Committee (FOMC). In addition, they provide the New York Fed's trading desk with useful market information and analysis for the purposed of formulating and implementing the monetary policy. Primary dealers are also required to participate in all auctions of U.S. government debt and act as market makers for the New York Fed when it transacts on behalf of its foreign official account-holders.

where λ_f denotes the $(K \times 1)$ vector of risk premiums on some assumed factors *f*, λ_{Lev} is the risk premium associated with the leverage factor, $\beta_{i,f}$ is the $(K \times 1)$ vector of betas of the factors *f* for asset *i*, and $\beta_{i,Lev}$ is the beta of the leverage factor for asset *i*. The factor sensitivities are defined by the following multi-factor linear model

$$r_{i,t+1} = a_i + \beta'_{i,f} f_{t+1} + \beta_{i,Lev} Lev_{t+1} + e_{i,t+1} \tag{3.6}$$

where f_{t+1} denotes the vector containing the realization of the assumed additional factors and Lev_{t+1} denotes the leverage factor.

3.3.4. Commodity futures returns and foreign exchange risk

Finally, we consider a risk factor that takes into account the exposure of commodity futures to the foreign exchange rate risk. Erb and Harvey (2006) provide significant evidence on the relationship between commodity futures and the exchange rate risk by using data on the S&P GSCI and individual energy and precious metals futures contracts. Given that most commodities are priced in U.S. dollars, the fluctuations in the U.S. dollar exchange rate with respect to other currencies affect both the demand and the supply of commodities. For instance, a depreciation of the U.S. currency makes the commodities more attractive to the non-US consumers and hence it increases their prices as global demand rises. On the supply side, the declining profits in local currency for producers outside the dollar area might drive them to reduce their production to bump prices up. In addition, a decline in the effective value of the dollar also reduces the returns on the dollar-denominated financial assets which may make the commodities a more attractive class of "alternative assets" to foreign investors.

We adopt the international-CAPM setting (see for instance, Dumas and Solnik, 1993, DeSantis and Gerald, 1998). In this setting, any investment for a non-US investor in a commodity is a combination of an investment in the performance of the commodity and an investment in the performance of the domestic currency relative to the US dollar. The premium for the exposure to the exchange rate risk is aggregated over investors from different countries. The beta formulation for the *i*th asset's expected excess return is given by

$$E\left(r_{i,t+1}\right) = \beta'_{i,f}\lambda_f + \beta_{i,fx}\lambda_{fx} \tag{3.7}$$

where λ_f denotes the $(K \times 1)$ vector of risk premiums of any other assumed factors *F*, λ_{fx} is the foreign exchange risk premium, $\beta_{i,f}$ is the $(K \times 1)$ vector of the betas of factors *f* for asset *i*, and $\beta_{i,fx}$ is the beta of the foreign exchange factor for asset *i*. The factor sensitivities are defined by

$$r_{i,t+1} = a_i + \beta'_{i,f} f_{t+1} + \beta_{i,fx} FX_{t+1} + e_{i,t+1} \tag{3.8}$$

where *f* is the vector containing the realization of the assumed additional factors and FX is the aggregate foreign exchange factor. We proxy the risk factor by using the Lustig et al. (2011) traded factor. This factor is based on the popular carry trade strategy which borrows in currencies with low interest rates and invests in currencies with high interest rates (see also Menkhoff et al., 2012, for an analysis of the carry trade strategy and for proposing a related volatility factor to the Lustig et al., 2011, factor).

3.3.5. Equity-motivated tradable factors

We employ the factor mimicking factors of Fama-French (1993), Carhart (1997), and Pastor and Stambaugh (2003) which have been found to explain the cross-section of expected stock returns. Cochrane (2005) provides the theoretical foundation for applying these equity factors to the commodity futures markets. Given that these equity-motivated factors are found to price equities successfully, they should also price the cross-section of commodity futures provided that the law of one price holds, portfolios can be freely formed, and markets are not-segmented. Integration of the equity and commodity futures markets implies that the expected return of equities should equal the expected return of the commodity futures provided that the systematic risk is the same in the two markets (Bessembinder, 1992).

Fama and French (1993) find that a three factor model consisting of a broad stock market beta and betas on two mimicking portfolios related to size and book-to-market equity ratios, respectively, explain the common variation in equity returns. The beta formulation for the *i*th asset's expected excess return is given by

$$E\left(r_{i,t+1}\right)=\beta_{i,MKT}\lambda_{MKT}+\beta_{i,SMB}\lambda_{SMB}+\beta_{i,HML}\lambda_{HML} \qquad (3.9)$$

where $\lambda_{MKT},\lambda_{SMB},\lambda_{HML}$ denote the risk premiums on the market, value and size factors, respectively, and $\beta_{i,MKT}$, $\beta_{i,SMB},\beta_{i,HML}$ denote the respective sensitivities of asset *i*, derived from the assumed multi-factor linear model

$$r_{i,t+1}=a_i+\beta_{i,MKT}r_{M,t+1}+\beta_{i,SMB}SMB_{t+1}+\beta_{i,HML}HML_{t+1}+e_{i,t+1} \qquad (3.10)$$

where $r_{M,t+1},SMB_{t+1},HML_{t+1}$ denote the market, size, and value factors, respectively. The SMB and HML factors are the payoffs on long-short portfolios constructed by sorting stocks according to the market capitalization and book-to-market ratio, respectively.

Carhart (1997) extends the Fama-French (1993) model by including a momentum factor. The beta formulation for the *i*th asset's expected excess return is given by

$$E\left(r_{i,t+1}\right)=\beta_{i,MKT}\lambda_{MKT}+\beta_{i,SMB}\lambda_{SMB}+\beta_{i,HML}\lambda_{HML}+\beta_{i,MOM}\lambda_{MOM} \qquad (3.11)$$

where λ_{MOM} denotes the risk premium on the momentum factor and β_i^{MOM} denotes the respective sensitivity of asset *i* defined by the following assumed multi-factor linear model

$$r_{i,t+1}=a_i+\beta_{i,MKT}r_{M,t+1}+\beta_{i,SMB}SMB_{t+1}+\beta_{i,HML}HML_{t+1}+\beta_{i,MOM}MOM_{t+1}+e_{i,t+1} \qquad (3.12)$$

where MOM_{t+1} denotes the momentum factor. The *MOM* factor is the payoff on long-short spreads constructed by sorting stocks according to the previous year return data.
Next, we use a risk factor related to market liquidity, i.e. whether financial assets can be traded quickly and at low cost to check whether it prices commodity futures returns. Liquidity risk is defined as the change of a common liquidity factor over time. Marshall et al. (2011) find evidence of commonality in liquidity across commodity markets during 1997-2003. Moreover, they find that changes in the stock market liquidity are positively related to changes in the individual commodities liquidity. In the presence of a liquidity factor, the beta formulation for the *i*th asset's expected excess return is given by

$$E\left(r_{i,t+1}\right)=\beta'_{i,f}\lambda_f+\beta_{i,L}\lambda_L \qquad (3.13)$$

where λ_f denotes the $(K \times 1)$ vector of risk premiums of any other assumed factors *F*, λ_L is the liquidity risk premium, $\beta_{i,f}$ is the $(K \times 1)$ vector of the betas of factors *f* for asset *i*, and $\beta_{i,L}$ is the beta of the liquidity factor for asset *i*. The factor sensitivities are defined by

$$r_{i,t+1} = a_i + \beta'_{i,f} f_{t+1} + \beta_{i,L} L_{t+1} + e_{i,t+1} \tag{3.14}$$

where *f* is the vector that contains the realization of the assumed additional factors and L is the liquidity factor. We proxy the liquidity factor by using the Pastor and Stambaugh (2003) traded factor which has been found to explain the cross-section of equity returns.

3.4. Commodity-specific factors: Construction

In this section, we construct three zero-cost commodity-specific factors: one hedging pressure and two inventory-related factors. Their construction is motivated by the hedging pressure hypothesis (Cootner, 1960) and the theory of storage (Kaldor, 1939, Working, 1949, Brennan, 1958), respectively. At each portfolio formation date (first day of the month or quarter), we rank all available commodity futures based on a particular attribute and construct distinct portfolios on the basis of this rank. Then, on the first day of the following month or quarter, we calculate the mimicking portfolio return for the factor as the difference between the return on the portfolios with the highest and the lowest attribute, respectively. We rebalance the portfolios every month and quarter throughout the sample.

3.4.1. Hedging-pressure risk factor

Let the hedging pressure $HP_{i,t}$ for any commodity *i* at time *t* defined as the number of short hedgers minus the number of long hedgers divided by the total number of hedgers in the respective commodity market, i.e.:

$$HP_{i,t} = \frac{\#\,of\ \ short\ hedge\ positions_{i,t}\ \text{-}\#\,of\ \ long\ hedge\ positions_{i,t}}{Total\ \ \#\,of\ hedge\ positions_{i,t}} \tag{3.15}$$

According to the hedging pressure hypothesis (Cootner, 1960) futures markets provide a risk transfer mechanism whereby risk averse speculators demand compensation to take (either long or short) futures positions to share the price risk with hedgers. If $HP_{i,t} > 0$ (<0), the expected return from a long position on the corresponding *i* futures is positive (negative). This is because hedgers are net short (long) and they have to offer a positive risk premium in order to entice speculators to take the respective long (short) position in the futures contract.

We use this theoretical implication to construct a zero-cost portfolio which mimics this strategy. At each point in time *t*, we use the available data on the positions of traders reported by CFTC and we estimate the hedging pressure for each futures contract. We construct a HML_{HP} (high minus low HP) risk factor by going long in the portfolio of commodities which have a positive HP and short in a portfolio consisting of commodities with a negative HP. To determine the two portfolios, at each point of time *t*, we rank the futures contracts based on the respective calculated hedging pressure figures. Then, we form two equally-weighted portfolios, H and L, and derive their next period (*t+1*, i.e. post-ranking) excess return. We construct the two portfolios by using the following two alternative methods:

a. Portfolio H contains the commodities with positive HP whereas portfolio L contains those with negative HP.
b. Portfolio H contains the five commodities with the highest positive HP whereas portfolio L contains those five with the lowest negative HP. In the cases where we observe less than five contracts that exhibit positive or negative HP, we use the number of available contracts with these features.

3.4.2. Inventory-related risk factors

Next, we examine whether an aggregate measure of the level of inventories may explain the cross-section of commodity futures returns. Gorton et al. (2012) find that a low inventory level for an individual commodity is associated with a high risk premium for the futures written on that commodity. The intuition is that the low inventory commodities should earn a greater risk premium due to the risk of a stock out as a result of a high demand for the commodity in the future. However, they do not investigate whether a market wide measure of inventories prices the cross-section of commodity futures.

The construction of an inventory risk factor is not feasible because there are a number of constraints which do not allow compiling a comprehensive dataset of inventories. First, there is not a common source that provides these data. As a result, the data are not recorded with the same frequency across the different sources. Second, there is a notorious difficulty in measuring inventories accurately because commodities are produced, consumed, and traded internationally. For instance, the crude oil inventories should include not only the physical stocks held at a given delivery point but also these held at international locations which could be economically shipped to this location, as well as government stocks. Obviously, the aggregation of these quantities is not always feasible. Given the difficulties in constructing an inventory factor, we construct inventory-related factors by using attributes that reflect the level of inventories. These attributes are the basis and the prior futures returns which are readily available and do not suffer from measurement errors.[5]

A. Basis risk factor: Construction

According to the theory of storage, the sign of the futures basis depends on the magnitude of the convenience yield, i.e. a high (low) convenience yield delivers a positive (negative) basis. Moreover, the theory predicts a negative relation between the convenience yield and the level of inventories. Therefore, a positive (negative) basis indicates low (high) inventories for any given commodity. Gorton et al. (2012) document that for any given commodity, the low inventory months are associated with a high and positive basis. They also find that a portfolio consisting of commodities with a high basis outperforms the one consisting of commodities with a low basis (for additional evidence on the relationship between the basis and futures excess returns, see Fama and French, 1987, Gorton and Rouwenhorst, 2006, Yang, 2011).

Based on the above theoretical rationale and the related empirical evidence, we construct at each point in time t, a zero-cost HML_B (high minus low basis) basis risk factor

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[5] The basis is calculated for each commodity as $\left(F_1 - F_2\right)/F_1$ where F_1 denotes the nearest futures contract, and F_2 the next nearest futures contract.

by going long in the portfolio of commodities which have a positive basis and going short in a portfolio comprised of commodities with a negative basis. To determine the two portfolios at each point of time *t*, we calculate the basis for each futures contract and rank the futures based on the respective calculated basis figures. Then, we form two equally-weighted portfolios, H and L, and derive their next period (*t+1*, i.e. post-ranking) excess returns. We construct portfolios H and L by using the following two alternative methods:

a. Portfolio H contains the commodities with positive basis (High Basis Portfolio) whereas portfolio L contains those with negative basis (Low Basis Portfolio).
b. Portfolio H contains the five commodities with the highest positive basis (High Basis Portfolio) whereas portfolio L contains those five with the lowest negative figures (Low Basis Portfolio). In the cases where we observe less than five contracts that exhibit positive or negative basis, we use the number of available contracts with these features.

B. Momentum risk factor: Construction

Gorton et al. (2012) find evidence for a momentum in individual commodity futures excess returns which can be explained by the time-series variation of the respective inventory level. They argue that an unexpected increase in prices due to a negative shock to inventories is followed by a temporary period of high expected futures returns for that commodity. This momentum phenomenon can be attributed to the slow adjustment process of inventories. These can be restored through the time-consuming process of new production. Consequently, the limited supply cannot meet the demand for this commodity over a period of time. Therefore, deviations of inventories from normal levels are expected to be persistent.

The evidence presented by Gorton et al. (2012) implies that an investor would gain positive excess return if she goes long in commodities that exhibit a high prior 12-month average return and short in the commodities with a low prior 12-month average return. Hence, we construct a zero-cost portfolio HML_M (high minus low momentum) risk factor by going long in the portfolio of commodities with a positive prior 12-month average return and going short in a portfolio comprised of commodities with a negative prior 12-month average return. To determine the two portfolios, at each point of time *t*, we calculate the prior average 12-month futures return for every contract, and rank them based on the respective figures. Then, we form two equally-weighted portfolios, H and L, and derive their next period (*t+1*, i.e. post-ranking) excess return. We construct the two portfolios by using the following two alternative methods:

a. Portfolio H contains the commodities with positive prior 12-month average return (High Momentum Portfolio) whereas portfolio L contains those with negative prior 12-month average return (Low Momentum Portfolio).

b. Portfolio H contains the five commodities with the highest positive prior 12-month average return (High Momentum Portfolio), whereas portfolio L contains those five with the lowest negative figures (Low Momentum Portfolio). In the cases where we have less than five contracts which exhibit positive or negative 12-month average prior average futures return, we use the number of available contracts with these features.

Table 3.5 reports the descriptive statistics of the returns of the commodity-specific factor mimicking portfolios and their constituents. For each employed attribute, we consider both construction methods for the mimicking portfolios (HP/Basis/Momentum factor (a) and (b), respectively). Results are reported for monthly and quarterly horizons (panels A and B, respectively). We can see that the hedging pressure hypothesis is not verified in all cases because both the long and short portfolios earn positive returns. In addition, the mean return on $\mathrm{HML}_{\mathrm{HP}}$ is barely positive and statistically insignificant from zero. Hence, the sorting process based on HP is not informative about the futures risk premiums. This implies that the hedging pressure theory does not hold (for similar evidence, see also Gorton et al., 2012). On the other hand, the returns of the basis and the momentum risk factors are consistent with the theoretical predictions in all cases. A positive (negative) basis and high (low) prior futures returns are associated with positive (negative) future returns. In addition, the mean returns on HML_B and HML_M are positive and significant. These findings suggest that the basis and the prior-futures returns constitute meaningful sorting criteria.

3.5. Estimation methodology

We employ the standard Fama-MacBeth (1973) two-pass approach to estimate the various asset pricing models. The process can be described as follows. Let a *K*-factor asset pricing model:

$$E(r_i) = \beta_i' \lambda, \;\; i = 1, 2, ..., N. \tag{3.16}$$

where r_i denotes the $(T \times 1)$ vector of excess returns for asset *i*, λ is the $(K \times 1)$ vector of factor risk premiums, and β_i is the $(K \times 1)$ vector of betas for asset *i*. The first pass estimates the factor betas by rolling time series regressions of each commodity futures' excess return on the vector *f* of risk factors, i.e.:

$$r_{i,t} = a_i + \beta_i' f_t + e_{i,t}, \;\; t = 1, 2, ..., T \; for \; each \; i \tag{3.17}$$

In line with Fama-MacBeth (1973), we estimate the beta coefficients using a rolling window of 60 monthly observations. In the second pass, we use the estimated betas from the first step and run a cross-sectional regression at each time *t*,

$$r_i = \lambda_{0i} + \beta_i' \lambda + e_i, \;\; i = 1, 2, ..., N \; for \; each \; t \tag{3.18}$$

Then, we estimate λ as the average of the cross-sectional estimates and obtain their corresponding average *t*-statistics and average R^2's.

We use a cross-section of twenty two individual commodity futures returns as test assets. This is in contrast to the previous literature on testing asset pricing models on equities data which uses portfolios rather than individual equities. Equities are formed in portfolios to mitigate the errors-in-variables (EIV) problem caused by using estimated betas as independent variables in the second pass of the Fama-MacBeth estimation procedure. In our case, forming commodities in portfolios is not possible due to the limited number of available commodity futures. Moreover, the portfolio formation research approach is subject to a number of limitations. The formation of assets in portfolios is arbitrary and may lead to data-snooping (Lo and MacKinlay, 1990); different results on the significance of the factors may be obtained depending on the criteria used in portfolio formation, and/or the number of portfolios employed in the cross-sectional analysis. Furthermore, the portfolio formation method may mask important features of the individual assets. This is particularly important in the case of commodities given their heterogeneity (Erb and Harvey, 2006, Kat and Oomen, 2007b). To address the EIV problem, we use Shanken's (1992) adjustment for the standard errors of the risk premium estimators.

3.6. Testing the asset pricing models: Results and discussion

3.6.1. Macro-factor models

Regarding the performance of the macro-factor asset pricing models, Table 3.6 reports the (average) constant coefficients, risk premiums, *t*-statistics, Shanken's (1992) adjusted *t*-statistics, R^2 and adjusted R^2 obtained from implementing CAPM, CCAPM, MCAPM, MCCAPM, and Adrian et al. (2011) models for monthly and quarterly futures returns (panels A and B, respectively).

First, we can see that both the traditional CAPM and CCAPM perform poorly. Both models have low explanatory power for the cross-sectional variation of commodity futures returns. The CAPM delivers an adjusted R^2 of 6.82% and 4.76% for monthly and quarterly horizons, respectively, whereas the CCAPM delivers an adjusted R^2 of 5.01% and 2.09% for monthly and quarterly horizons, respectively. Moreover, both models yield insignificant risk premiums. Their average pricing errors (pricing error λ_0 in equation (3.18)) are low and statistically insignificant. This is attributed to the high standard deviation of the cross-sectional α estimates which indicates the instability of the models.

The poor performance of the CAPM and CCAPM is in line with the previous evidence on their performance in equities (Mehra and Prescott, 1985, Campbell, 2000) and commodity futures (Jagannathan, 1985) markets. Interestingly, the evidence on the performance of the CCAPM differs partially from the findings of DeRoon and Szymanowka (2010) who find significant risk premium and high explanatory power for the CCAPM only at the quarterly returns. This divergence of results may be attributed to the different datasets employed in the two studies and the differences in the implementation of the Fama-MacBeth approach. DeRoon and Szymanowka (2010) study an unbalanced dataset over the period 1968-2004 and estimate a full sample rather than a rolling beta in the first step Fama-MacBeth time series regression as we do.

Regarding the performance of the MCAPM and MCCAPM models, in the case where we implement them by using the M2 growth (MCAPM(a) and MCCAPM(a) models, respectively), the explanatory power of the two models increases compared to that delivered by the traditional asset pricing models, yet it is still too low (e.g., in the monthly frequency, the adjusted R^2 for the CAPM increases from 6.82% to 10.64% for the MCAPM(a)). In addition, the monetary factor's risk premium is statistically insignificant. Qualitatively similar conclusions are drawn in the case where we proxy the money growth by the primary dealers' repo growth (MCAPM(b) and MCCAPM(b) models, respectively). Notice that in this case, the analysis covers only the period January 1998-December 2010 and is conducted by employing only the monthly frequency data. We do not use the quarterly frequencies because the application of the Fama-MacBeth first step rolling beta estimation would require a longer time series. These findings do not contradict the evidence provided by previous studies that the monetary policy affects the returns of *individual* commodity futures. Instead, our results show that the monetary factor does not represent a priced risk factor for the *cross-section* of the commodity futures returns.

Next, we augment the CAPM with the innovations in the broker-dealers' financial leverage (LevCAPM) to examine whether the leverage factor explains the cross-sectional variation in commodity futures returns. Notice that in this case, the analysis and the reported results refer only to the quarterly frequency because only quarterly data for the aggregate leverage of broker-dealers are available. We can see that the price of risk for the leverage shocks is statistically insignificant and the explanatory power of the hybrid model is low (adjusted R^2=8.69%) whereas the pricing error is insignificant. Similar conclusions are drawn when we augment the CAPM with the Lustig et al. (2011) foreign exchange risk factor (FXCAPM). The explanatory power of the model increases compared to that delivered by the traditional asset pricing models, yet it is still too low (e.g., in the monthly frequency, the adjusted R^2 for the CAPM increases from 6.82% to 9.76% for the FXCAPM). However, the statistical insignificance of the risk premium indicates the foreign exchange risk factor does not price the cross section of commodity futures returns.

A final remark is in order which highlights the inability of the monetary and leverage factor models to price commodity futures compared to equities. The adjusted R^2's obtained from these models are small compared with the ones obtained from their application to equity portfolios. The application of the MCAPM (MCCAPM) in Balvers and Huang (2009) over the quarterly horizons for the period 1959-2010 yields R^2's in the range 11% - 64% (25% - 58%) depending on the type of equity portfolio being priced. Similarly, the application of the leverage factor of Adrian et al. (2011) over the quarterly horizons for the period 1968-2009 yields R^2's in the range 24%- 75%.

3.6.2. Equity-motivated tradable factor models

Next, we examine the tradable Fama-French (1993, FF), Carhart (1997), and Pastor and Stambaugh (2003) factors which have been commonly used in the equity asset pricing literature. Table 3.7 summarizes the results. In the case of the FF model, the explanatory power in adjusted R^2 terms increases compared to the CAPM (18.41% for monthly and 9.37% for quarterly data) even though the prices of risk associated with the value and size factors are statistically insignificant. Similarly, in the case of the Carhart model, the goodness-of-fit increases further (the adjusted R^2 is 24.82% and 16.63% for the monthly and quarterly horizons, respectively), yet the risk premiums are statistically insignificant again regardless of the horizon. To determine whether the liquidity risk is priced in the cross-section of commodity futures returns, we augment the FF and Carhart models with the Pastor and Stambaugh (2003) factor (LFF, LCarhart model, respectively). The goodness-of-fit improves as we switch from the hybrid LFF model to the five factors LCarhart model (adjusted R^2 of 28.70% for the monthly frequency data). However, the risk-premium of the liquidity factor as well as these of the other risk factors is insignificant in all cases.

The results highlight the inability of the traditional equity-motivated tradable factors models to explain the cross-section of commodity futures returns and extend the empirical evidence provided by Erb and Harvey (2006). Our findings imply that either the equity and commodity markets are segmented, or that arbitrage opportunities exist. The former implication is consistent with Bessembinder (1992) and Bessembinder and Chan (1992) who find that some agricultural markets are segmented from the equity and foreign exchange markets.

3.6.3. Commodity-specific risk factors models

In this section, we investigate whether the constructed commodity-specific factors described in Section 3.4 price the cross-section of commodity futures expected returns. Table 3.8 summarizes the results. First we augment the CAPM with the hedging pressure factor $\mathrm{HML}_{\mathrm{HP}}$ (HP-CAPM). Panel A reports the results for monthly and quarterly frequencies. Notice that we have constructed two distinct $\mathrm{HML}_{\mathrm{HP}}$ factors (HP factor (a) and (b) under the assumptions (a) and (b) in Section 3.4.1, respectively). We can see that the HP-CAPM has low, albeit increased compared to the regular CAPM, explanatory power for the cross-section of commodity futures returns (the adjusted R^2 is almost 14.80% for the quarterly data). Yet, it yields insignificant risk premiums. These findings hold regardless of the hedging pressure risk factor under examination and the frequency of the data.

Next, we examine whether the constructed inventory-related factor prices the cross-section of commodity futures returns. To this end, we augment the CAPM with either the inventory-related factors, HML_B or HML_M (basis and momentum factors, respectively), that we constructed in Section 3.4.2 (Basis-CAPM and FutMom-CAPM, respectively). Panels B and C report the results on HML_B and HML_M , respectively. Results are reported for the two distinct HML_B factors ((Basis Factor (a) and (b)) and the two distinct HML_M factors (Momentum Factor (a) and (b)) described in Section 3.4.2. The two-factor Basis-CAPM and FutMom-CAPM have low, albeit increased relative to the CAPM, explanatory power for the cross-section of commodity futures returns. Yet, the models yield insignificant risk premiums for all factors and frequencies just as was the case with the hedging pressure factors. Overall, the commodity-specific factor models cannot price the cross-section of commodities either.[6] This implies that the commodity

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[6] Yang (2011) and Asness et al. (2011) are two recent studies that also construct basis and momentum commodity-specific factors. Yang (2011) constructs a basis factor similar to ours and finds that it prices tests assets by using a two factor CAPM-basis model. However, the test assets in his study are five portfolios of commodity futures constructed by sorting commodities according to their basis values, i.e. the same criterion employed to construct the basis factor. This is a tautology and hence this factor ought to price his basis-sorted portfolios by construction. In addition, since the test assets are only five portfolios, there are only two degrees of freedom in the performed tests. Asness et al. (2011) construct value and momentum factors by averaging information across eight markets including the commodity futures one. They find that these factors price a cross-section of test assets consisting of the assets of all employed markets. However, the fact that their factors price the full universe of all eight markets simultaneously does not imply that they price any given asset class separately. This is the challenge we address by investigating the presence of any common factors for the commodity futures cross-section only.

futures market is segmented itself. In the next section, we explore further the heterogeneity of the commodity futures markets.

3.6.4. Heterogeneity in commodity futures markets

Apart from the equity and commodity futures markets segmentation, the previously reported evidence that none of the employed factors prices the cross-section of commodities may also be attributed either to a possible non-significance of the factor betas (see for a similar approach, Dusak, 1973, Bodie and Rosansky, 1980) and/or a heterogeneous cross-section of commodity futures. To this end, first we examine the significance of the estimated rolling factor factor betas obtained from the first step of the Fama-MacBeth approach. We undertake this exercise for every asset pricing model and every commodity. Unreported results show that in most cases the rolling betas are significantly different from zero. Therefore, the insignificant risk premia cannot be attributed to insignificant rolling betas.

Next, we examine whether the insignificant risk premia can be attributed to a heterogeneous cross-section of commodity futures. To this end, we estimate single factor models for each commodity futures time series returns at the monthly and quarterly frequency, using in turn each of the 16 factors we have previously employed. We opt for a system-based estimation to take into account potential correlations in the models' residuals across commodity futures. To this end, we estimate the single factor models by the Generalized Method of Moments (GMM). Table 3.9 shows the estimated factor coefficients for every model and every commodity futures for the monthly (panel A) and quarterly (panel B) horizons. We can see that there is no factor for which all commodities futures returns are significantly exposed (sensitive) to over the full sample period. For each factor employed, different sets of commodities yield significant betas, highlighting the heterogeneity of their returns' nature (for similar evidence see also Erb and Harvey, 2006, Kat and Oomen, 2007b). The reported evidence on the heterogeneity of commodity futures explains the lack of common factors in the cross-section of commodity futures returns and may be attributed to the fact that the drivers of their returns differ across the various commodity categories. This finding is also in line with the predictions of the theoretical models of Stoll (1979), Hirschleifer (1988, 1989), and De Roon et al. (2000)

which imply that the commodity-specific factors can explain only the individual commodity futures expected returns.

3.7. Further robustness tests

In this section we perform further tests to assess the robustness of the results reported in Section 3.6. First, we employ GMM to estimate the various asset pricing models as an alternative estimation method to the Fama-MacBeth approach. Second, we use alternative proxies for the market portfolio whenever the measurement of the market portfolio is required. Third, we re-estimate the asset pricing models by using a larger cross-section of commodity futures returns.

3.7.1. GMM estimation of the alternative asset pricing models

The advantage of the GMM compared to the Fama-MacBeth two-step procedure is that it estimates the model parameters in a single pass thereby avoiding the errors in variables problem (Jagannathan et al., 2010). We estimate all models by employing the two-step Generalized Method of Moments (GMM). To fix ideas, assume that the returns on the *N* commodity contracts are generated by a *K*-factor linear factor model

$$R_t = a + Bf_t + e_t \tag{3.19}$$

where R_t is the $(N \times 1)$ vector of the (excess) returns of the respective *N* commodity contracts, *B* is the $(N \times K)$ matrix of factor loadings, and f_t is the $(K \times 1)$ vector of the realizations of the *K* risk factors. The expected returns of the assumed contracts are given by the following linear asset pricing model:

$$E(R_t) = B\lambda_f \tag{3.20}$$

where λ_f is the $(K \times 1)$ vector of the factors risk premiums. Define $\theta = [\,\alpha, B, \lambda_F\,]$ the vector of the unknown parameters to be estimated and x_t the vector of the variables observed in the *t*th period. Using a sample of size *T*, the GMM estimate of θ is obtained by minimizing the quadratic function:

$$J_T(\theta) = g_T(\theta)' W g_T(\theta) \tag{3.21}$$

where $g_T(\theta)$ are the respective moment conditions defined as follows:

$$g_T(\theta) = E\left(g\left(x_t, \theta\right)\right) = \begin{bmatrix} E\left(R_t - a - Bf_t\right) \\ E\left(R_t - B\lambda_f\right) \\ E\left[\left(R_t - a - Bf_t\right) \otimes f_t\right] \end{bmatrix} = \begin{bmatrix} 0_N \\ 0_N \\ 0_{NxK} \end{bmatrix} \tag{3.22}$$

The two stage GMM yields asymptotically efficient estimates of θ because it uses an optimal weighting matrix *W* in equation (3.21) calculated as

$$W = S^{-1},\ S = \sum_{j=-\infty}^{\infty} E\left[g\left(x_t, \theta\right) g\left(x_t, \theta\right)'\right] \tag{3.23}$$

(Hansen, 1982, Cochrane, 2005). We estimate *S* using the heteroscedasticity and autocorrelation consistent covariance matrix estimator (HAC) described in Newey and West (1987) to account for autocorrelation and heteroskedasticity in the error terms of the asset pricing model.

Tables 3.10 and 3.11 report the GMM estimated risk premiums and the associated *t*-statistics of the macro (panel A), equity-motivated tradable (panel B), and commodity specific factors, respectively. We conduct the analysis both for monthly and quarterly frequency data. The GMM estimation yields insignificant risk premiums in all cases. The only exception occurs in the case of the commodity-specific factors in the monthly horizons where a significant risk premium is obtained in the case of the basis risk factor (b) (*t*-stat=2.146). These results are in accordance with these obtained by the Fama-MacBeth approach and confirm the inadequacy of the examined asset pricing models to explain the cross section of the commodity futures returns.

3.7.2. Alternative proxies for the market portfolio

In the previous sections, we used a broad stock index (that includes the NYSE, AMEX and NASDAQ stocks) to proxy the market portfolio. The measurement of the market portfolio is a prerequisite for the implementation of the asset pricing models that require it as an input. Therefore, the results on the estimated risk premiums depend on how the market portfolio is measured. In the case where one considers the question of asset pricing for commodities, one may argue that a stock index does not proxy the market portfolio satisfactorily on both theoretical and practical grounds. From a theoretical point of view, in a CAPM context, the market portfolio lies on the efficient frontier. A number of empirical studies find that commodities exhibit low or even negative correlation with traditional asset classes (e.g., stocks) over certain periods of time (Bodie and Rosansky, 1980, Erb and Harvey, 2006, Gorton and Rouwenhorst, 2006). Therefore, commodities should be included in any efficient portfolio because they yield diversification benefits and hence improve investment opportunities (in Chapter 2, it is reported though that this improvement does not hold in an out-of-sample setting). From a practical point of view, investments in commodities via commodity funds written on commodity indexes (e.g., exchange-traded funds) have grown over the last years with the institutional investors increasing their portfolio allocations to commodities. In the case where one trades commodities via index funds written on commodity indexes, Black’s (1976) theoretical argument against the inclusion of commodities in the market portfolio does not apply any longer.

Consequently, in this section we re-estimate the asset pricing models which require the market portfolio as an input by using alternative proxies for the market portfolio. We proxy the market portfolio by the popular commodity index S&P GSCI, as well as by a hybrid, equally-weighted, index which contains both stocks and commodities (for a similar choice, see Carter et al., 1983).[7] Table 3.12 reports results in the case where we estimate the CAPM, MCAPM, LevCAPM, and extensions of the CAPM which include commodity-specific factors (hedging pressure, basis, 12-months prior futures return momentum) by using the S&P GSCI, and a hybrid, equally-weighted, index comprised of

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[7] The S&P GSCI was launched in January 1991 with historical data backfilled by index providers since January 1970. The index invests in twenty four commodities classified into five groups (energy, precious metals, industrial metals, agricultural, and livestock) and is heavily concentrated (almost 70% of the total index value) on the energy sector.

the employed so far stock index and the S&P GSCI (panels A and B, respectively) as alternative proxies for the market portfolio. We apply the Fama-MacBeth two-pass approach and conduct the analysis for monthly and quarterly frequencies.

We can see that the risk premiums of all factors are insignificant regardless of the alternative proxy of the market portfolio in almost all cases. This evidence is in accordance with the results obtained in the case where we proxied the market portfolio by the stock index. The only exception appears in the case where the hybrid index and the basis factor (a) are considered; the risk premium for the basis risk factor(a) is marginally significant in the quarterly frequency (Shanken's *t*-stat=1.988). As a robustness test of this particular case, we also estimate the model by using GMM. The (unreported) results do not support the significance of the basis factor any longer. Overall, the further robustness tests confirm the conclusions of the previous section that there are no common factors which price the cross-section of commodity futures expected returns.

3.7.3. Extended commodity futures dataset

We estimate all asset pricing models described in Sections 3.3 and 3.4 by using an extended dataset of commodity futures which includes both the nearest and the second nearest commodity futures contracts. This choice of maturities is dictated by the fact that these are the most liquid maturities (see for a similar choice, De Roon and Szymanowska, 2010); unreported results show that the volume of traded commodity futures drops significantly from the third nearest maturity onwards. We create the futures returns for the second-nearest-to-maturity futures contracts by following a similar approach as the one described in Section 3.2. We hold the second nearby contract until the beginning of the delivery month for the shortest contract. Then, we roll over our position to the contract with the following delivery month which then becomes the second nearest to maturity contract. This approach ensures that we compute the monthly futures returns using the successive monthly prices of a contract for a *given* delivery date. We repeat the described process throughout the dataset for each one of the 22 assumed futures contract. This delivers a larger cross-section of 44 observations at each point of time. The Fama-MacBeth and GMM estimation results are qualitatively similar to these obtained when the analysis was conducted only for the shortest-to-maturity contracts; results are not reported due to space limitations. In particular, we find that neither the common factors nor the commodity-specific factors explain the cross-sectional variation in commodities' futures premiums.

3.8. Principal Components Analysis (PCA) models

The findings reported in the previous sections show that none of the postulated macro, equity-motivated, or commodity-related factors prices the cross-section of the commodity futures returns. In this section, we take an alternative approach to identify any factors which may explain the cross-section of commodity returns. In line with Connor and Korajczyk (1986) and Cochrane (2011), instead of positing *in advance* any candidate factors as we did in the previous sections, first we let the data to determine themselves the candidate factors. Then, we employ them as an input in the Fama-MacBeth two step regressions. To this end, we use the Principal Components Analysis (PCA) to investigate the factor structure of commodity futures returns.

PCA is a non-parametric statistical technique that converts a set of correlated variables into a set of uncorrelated variables termed principal components (PCs). We apply PCA to the correlation matrix of the twenty two commodity futures returns to identify the PCs that drive their common variation. To fix ideas, let λ_i, q_i be the respective *i*th eigenvalue and eigenvector of the correlation matrix of futures returns, for *i*=1,2,,,22. These eigenvectors are the weights by which we form the f_i's PCs as linear combination of the commodities excess returns, i.e.

$$f_{i,t} = q_i' r_{\iota,t} \tag{3.24}$$

$q_i = (q_{1i}, q_{2i}, ..., q_{22i})'$, $r_i = (r_1, r_2, ..., r_{22})'$. Equivalently, the commodity futures excess returns can be represented as a linear combination of the eigenvectors (termed also correlation loadings), i.e.

$$r_{i,t} = q_{1i} f_{1,t} + q_{2i} f_{2,t} + q_{3i} f_{3,t} + ... + q_{22i} f_{22,t} \tag{3.25}$$

These correlation loadings can also be extracted from a regression of commodities returns on the factors.

Equation (3.25) shows that the PCA yields PCs that can be interpreted as common factors that explain the systematic variation of commodity returns (PCA factor model). Therefore, they can be used as factors in the two steps Fama-MacBeth regressions to determine their respective risk premiums. To reduce the dimensionality of the problem, we retain a number of PCs that explain a sufficient amount of the total variation of the original variables. In particular, we retain the first five PCs; these explain 59.74% and 61.32% of the total variance of commodity futures returns in the monthly and quarterly horizons, respectively. The quite small amount of variance explained by the five factors PC model reflects the heterogeneity of commodity futures returns thus confirming the evidence reported in Section 3.6.4.

We implement five different versions of the PCA factor model by including one, two, three, four, and five PCs, respectively. Figure 1 shows the correlations loading for each one of the first five PCs when PCA is applied to monthly and quarterly returns. We can see that the first two PCs move the commodity futures returns to the same direction. The first PC also tends to have the same impact on commodities that belong to the same group. Table 3.13 reports the results on the significance of the risk premiums of the respective five factors. Results are reported for the monthly and quarterly horizons (panels A and B, respectively). The risk-premiums of the respective PCs are insignificant in almost all cases. In particular, in the monthly case, the risk premium of only the second PC is significant only in the case of the two factor PCA model. Unreported results show that this significance vanishes though once the second PC is employed as a stand-alone pricing factor. Similarly, in the case of the quarterly commodity futures returns, only the third factor prices the cross-section of commodity futures returns. This holds for the three, four, and five PCA factor models. However, the third PC explains only a minor fraction of the total variation of commodity futures returns as a stand-alone factor (about 10%). Moreover, it lacks any economic interpretation. Unreported results show that the pairwise correlations of the third PC with the risk factors employed in the previous sections are insignificant in almost all cases. In the few cases where these are significant, their magnitude is small and does not exceed 0.35.

Finally, we conduct two further robustness tests of the PCA model. First, we explore the performance of the PCA model over the 2004-2008 commodity boom period characterized by the significant and simultaneous increase of commodity prices across the various commodity categories. Tang and Xiong (2010) confirm that the correlations across commodities which are included in the popular commodity index become stronger over this period and they find that this is attributed to the presence of index traders in the commodity markets. Unfortunately, the construction of an "investment flow by index traders" factor which may price commodity futures is not possible because the data on the positions of commodity index traders are available by CFTC only from 2006 onwards. Yet, we find that the PCA model performs poorly again despite the documented increase in correlations among commodities.

Second, we test whether the heterogeneity of the commodity futures which affects the performance of the PCA model may be attributed to a particular sector of commodities (energy, grains, softs, livestock, metals). To this end, we examine the percentage of the variance explained by the first five PCs by removing and replacing one by one the commodity categories and applying PCA to the remaining ones. We find that the percentage of the explained variance remains quite small; the greatest explained amount is 70% of the total variance for the case where the softs are removed from the original sample. Therefore, the documented heterogeneity of commodity returns can not be attributed to a particular commodities category. Instead, it is a universal characteristic of the commodity futures universe.

In brief, the evidence on the poor performance of the PC factor models can be attributed to the heterogeneity of the commodity futures markets. In addition, it supports the conclusions drawn from the previous analysis in that none of the employed macro factors, equity-motivated tradable factors and commodity-specific factors can explain the cross-section of commodity futures returns.

3.9. Conclusions

Despite the pivotal importance of commodities for the economy and capital markets, not much empirical research has been devoted to investigate whether there is one or more asset pricing models which may explain (price) the cross-section of commodity futures expected returns. This paper addresses this question comprehensively. We implement a number of macro and equity-motivated tradable factor asset pricing models which have been traditionally used or proved successful to price the cross-section of equities. In addition, we construct theoretically sound commodity-specific factors and we evaluate them in a cross-sectional setting. Finally, we examine the performance of various versions of a principal components (PC) asset pricing model which does not postulate in advance any candidate factors but it rather lets the data to determine them. We also conduct a number of further robustness tests. We find that none of the employed factors prices the cross-section of commodity futures. This evidence is corroborated by the PC model. Moreover, we find that the commodity futures markets are significantly heterogeneous. These results survive all robustness tests.

Our analysis has the following implications. First, some of the popular factor models which have been found to price the cross-section of stock returns should not be used to evaluate the risk-adjusted performance of investments in commodity futures. Second, the inability of these models to price commodity futures may be due to the fact that equity and commodity markets are segmented and/or that there exist arbitrage opportunities in the economy and/or there are market frictions. The absence of any common-factors in the cross-section of commodity futures may also be explained by its heterogeneous structure. Third, the results that the commodity-specific factors are not priced either confirm that the commodity market is segmented itself. Our findings confirm the predictions of the theoretical models of Stoll (1979), Hirschleifer (1988, 1989) De Roon et al. (2000), and Acharya et al. (2011). These show that in the presence of non-marketable risks, the equilibrium commodity futures expected returns are solely determined by the individual characteristics of the corresponding commodity contracts.

Table 3.1. Commodity Futures Contracts

The table reports the futures exchange and delivery months for each one of the 22 commodity futures contracts employed in this study.

Commodity Futures Contract	Exchange	Delivery months
Grains & Oilseeds		
Corn	Chicago Board of Trade	3,5,7,9,12
Wheat	Chicago Board of Trade	3,5,7,9,12
Kansas Wheat	Kansas City Board of Trade	3,5,7,9,12
Soybeans	Chicago Board of Trade	1,3,5,7,8,9,11
Soybean Meal	Chicago Board of Trade	1,3,5,7,8,9,10,12
Soybean Oil	Chicago Board of Trade	1,3,5,7,8,9,10,12
Oats	Chicago Board of Trade	3,5,7,9,12
Softs		
Cocoa	New York Board of Trade	3,5,7,9,12
Coffee	New York Board of Trade	3,5,7,9,12
Cotton	New York Board of Trade	3,5,7,10,12
Sugar	New York Board of Trade	3,5,7,10
Livestock		
Live Cattle	Chicago Mercantile Exchange	2,4,6,8,10,12
Lean Hogs	Chicago Mercantile Exchange	2,4,5,6,7,8,10,12
Feeder Cattle	Chicago Mercantile Exchange	1,3,4,5,8,9,10,11
Frozen Pork Bellies	Chicago Mercantile Exchange	2,3,5,7,8
Energy		
Crude Oil	New York Mercantile Exchange	All
Heating Oil	New York Mercantile Exchange	All
Metals		
Gold	Commodity Exchange, Inc.	2,4,6,8,10,12
Silver	Commodity Exchange, Inc.	1,3,5,7,9,12
Copper	Commodity Exchange, Inc.	All
Platinum	New York Mercantile Exchange	1,4,7,10
Palladium	New York Mercantile Exchange	3,6,9,12

Table 3.2. Descriptive Statistics

The table reports the descriptive statistics for the 22 individual commodity futures used in this study. The dataset spans the period January 1989-December 2010. Panel A reports the summary statistics for the annualized mean returns (in % terms), standard deviations (in % terms) and Sharpe ratios for the monthly horizons. Panel B reports the respective figures for the quarterly horizons.

	Monthly Frequency			**Quarterly Frequency**		
Futures Contract	**Av. Return**	**St. Deviation**	**Sharpe Ratio**	**Av. Return**	**St. Deviation**	**Sharpe Ratio**
Corn	-4.73**	25.48	-0.19	-5.14**	27.08	-0.19
Wheat	-3.93**	26.50	-0.15	-4.55*	26.14	-0.17
Kansas Wheat	-3.30*	31.69	-0.10	-4.60	33.46	-0.14
Soybeans	3.89**	24.89	0.16	3.04	24.86	0.12
Soybean Meal	8.47**	26.26	0.32	7.91**	27.10	0.29
Soybean Oil	1.30	26.30	0.05	-0.09	23.99	0.00
Oats	-5.10**	30.90	-0.17	-5.00	32.02	-0.16
Cocoa	-2.07	29.47	-0.07	-3.23	24.95	-0.13
Coffee	-0.16	39.17	0.00	-0.21	45.25	0.00
Cotton	-0.91	26.42	-0.03	-2.91	22.88	-0.13
Sugar	9.45**	31.59	0.30	8.78**	32.46	0.27
Live Cattle	0.88	12.56	0.07	0.71	13.07	0.05
Lean Hogs	-4.23**	23.31	-0.18	-4.08*	22.74	-0.18
Feeder Cattle	2.38**	12.71	0.19	2.24	13.43	0.17
Frozen Pork Bellies	0.14	33.41	0.00	-0.58	29.78	-0.02
Crude Oil	14.53**	33.07	0.44	16.65**	41.02	0.41
Heating Oil	11.91**	33.41	0.36	13.61**	39.95	0.34
Gold	2.89**	15.12	0.19	2.28**	12.37	0.18
Silver	6.17**	26.40	0.23	4.01*	22.41	0.18
Copper	11.51**	27.30	0.42	12.21**	30.03	0.41
Platinum	7.92**	20.86	0.38	8.30**	21.08	0.39
Palladium	13.55**	34.22	0.40	13.88**	36.82	0.38

*   Significant at 10%.
** Significant at 5%.

Table 3.3. List of the various employed asset pricing models

The table describes the various asset pricing models employed in this study.

Macro factor models
CAPM
CCAPM
CAPM and money growth factor (MCAPM)
CCAPM and money growth factor (MCCAPM)
CAPM and Leverage factor (LevCAPM)
CAPM and FX factor (FXCAPM)

Equity-motivated tradable factor models
Fama-French three-factor model (FF)
Carhart four-factor model
Fama-French three-factor model and Liquidity factor (LFF)
Carhart four-factor model and Liquidity factor (LCarhart)

Commodity-specific factor models
CAPM and HP risk factor (HP-CAPM)
CAPM and Basis risk factor (Basis-CAPM)
CAPM and Momentum risk factor (FutMom-CAPM)

Table 3.4. Description of the risk factors

The table describes the set of risk factors employed in this study; panel A includes the macro and equity-motivated tradable factors, and panel B describes the commodity-specific factors.

Risk Factor	Definition
Panel A: Macro and tradable factors	
Stock Market index	The value-weighted return on all NYSE, AMEX, and NASDAQ stocks.
Commodity market index	The S&P GSCI excess return index.
Hybrid Index	An equally weighted index of the Stock Market index and the S&P GSCI.
Consumption growth	The percentage change in the seasonally-adjusted aggregate real per capita consumption expenditures on non-durable goods and services.
Value factor	The difference between the return of a portfolio of high book-to-market stocks and the return of a portfolio of low book-to-market stocks.
Size factor	The difference in the return of a portfolio of small capitalization stocks and the return of a portfolio of large capitalization stocks.
Momentum factor	The difference in the return of a portfolio of stocks with high 1-year prior return and the return of a portfolio of stocks with low prior 1-year return.
Money growth (a)	The percentage change in the seasonally-adjusted M2 money stock.
Money growth (b)	The primary dealer repo growth.
Liquidity factor	The difference between the return of a portfolio of stocks with high liquidity betas and the return of a portfolio of stocks with low liquidity betas.
Leverage factor	The shocks in the financial log leverage of broker dealers, where leverage is defined as the ratio of broker-dealer total assets to broker-dealer equity.
FX factor	The difference between the return of a portfolio of high interest rate currencies and the return of portfolio of low interest rate currencies.
Panel B: Commodity-related factors	
Hedging-Pressure factor (a)	The difference between the return of a portfolio of commodity futures with positive hedging pressure and the return of a portfolio of futures with negative hedging pressure.
Hedging-Pressure factor (b)	The difference between the return of a portfolio of the five commodity futures with the highest positive hedging pressure and the return of a portfolio of the five futures with the lowest negative hedging pressure.
Basis factor (a)	The difference between the return of a portfolio of commodity futures with positive basis and the return of a portfolio of futures with negative basis.
Basis factor (b)	The difference between the return of a portfolio of the five commodity futures with the highest positive basis and the return of a portfolio of the five futures with the lowest negative basis.
Momentum factor (a)	The difference between the return of a portfolio of commodity futures with positive prior 12-month return and the return of a portfolio of futures with negative prior 12-month return.
Momentum factor (b)	The difference between the return of a portfolio of the five commodity futures with the highest positive prior 12-month return and the return of a portfolio of the five futures with the lowest negative prior 12-month return.

Table 3.5. Characteristics of the commodity-specific factor mimicking portfolios

Entries report the mean and the standard deviation of the returns of the commodity-specific factor mimicking portfolios and their constituents. At each portfolio formation date, we rank all available commodity futures based on a particular attribute and construct distinct portfolios based on this rank. Then, on each month, we calculate the mimicking factor portfolio return as the difference between the return on the portfolios with the highest and lowest attribute, respectively. The employed attributes are the hedging pressure, the basis, and the prior 12-months return. We consider two different construction methods for the mimicking portfolios (HP/Basis/Momentum factor (a) and (b), respectively). In each case, we report the annualized mean and standard deviation, both for the distinct portfolios and their difference; the *t*-statistic for the difference is also reported. The test assets are the 22 individual commodity futures and the dataset spans the period January 1989-December 2010. Results are reported for monthly and quarterly data (panels A and B, respectively).

	Panel A: Monthly Frequency		*Panel B: Quarterly Frequency*	
	Mean	St. Deviation	Mean	St. Deviation
HP factor (a)				
Long Portfolio (HP^{+})	3.86%	14.05%	3.70%	13.54%
Short Portfolio (HP^{-})	2.64%	14.48%	2.24%	15.04%
HML_{HP}	1.22%	14.91%	1.46%	15.47%
t-stat	*(0.383)*		*(0.441)*	
HP factor (b)				
Long Portfolio (HP^{+})	4.36%	17.23%	6.77%	16.83%
Short Portfolio (HP^{-})	2.05%	15.21%	2.85%	14.92%
HML_{HP}	2.31%	20.12%	3.93%	20.17%
t-stat	*(0.538)*		*(0.908)*	
Basis factor (a)				
Long Portfolio (Basis^{+})	10.98%	16.90%	9.58%	16.69%
Short Portfolio (Basis^{-})	-0.46%	12.94%	-0.36%	12.96%
HML_{B}	11.44%	14.87%	9.94%	14.95%
t-stat	*(3.604)*		*(3.100)*	
Basis factor (b)				
Long Portfolio (Basis^{+})	7.63%	18.74%	7.16%	17.96%
Short Portfolio (Basis^{-})	-3.97%	15.56%	-4.28%	16.02%
HML_{B}	11.60%	18.89%	11.44%	20.00%
t-stat	*(2.874)*		*(2.669)*	
Momentum factor (a)				
Long Portfolio (Mom^{+})	8.71%	14.04%	8.57%	15.14%
Short Portfolio (Mom^{-})	-4.59%	16.27%	-2.83%	12.49%
HML_{M}	13.30%	17.76%	11.40%	15.89%
t-stat	*(3.505)*		*(3.345)*	
Momentum factor (b)				
Long Portfolio (Mom^{+})	10.11%	20.42%	8.44%	21.49%
Short Portfolio (Mom^{-})	-4.67%	18.84%	-2.75%	14.86%
HML_{M}	14.78%	25.58%	11.19%	23.49%
t-stat	*(2.705)*		*(2.221)*	

Table 3.6. Macro-factor models

Entries report the results for the set of macro-factor models employed in this study. We examine the CAPM, CCAPM, MCAPM, MCCAPM, LevCAPM and, FXCAPM. We proxy the monetary factor using a traditional measure of money supply, M2 growth (MCAPM (a) and MCCAPM (a)), as well as a recently proposed one, the primary dealers' repo growth (MCAPM (b) and MCCAPM (b)). We employ the two-pass Fama-MacBeth (1973) approach to estimate the various asset pricing models. Results are reported for monthly and quarterly frequency data (panels A and B, respectively). In each case, we report the constant coefficients, risk premiums, *t*-statistics, Shanken's (1992) adjusted t-statistics, R^2 and adjusted R^2. The test assets are the 22 individual commodity futures and the dataset spans the period January 1989-December 2010. Due to data availability constraints, when the primary dealers' data are considered, the dataset spans the period January 1998-December 2010, and the reported results refer only to monthly frequency. In addition, when the leverage factor is considered, the reported results refer only to quarterly frequency.

	Panel A: Monthly Frequency							***Panel B: Quarterly Frequency***					
	CAPM	**CCAPM**	**MCAPM (a)**	**MCAPM (b)**	**MCCAPM (a)**	**MCCAPM (b)**	**FXCAPM**	**CAPM**	**CCAPM**	**MCAPM (a)**	**MCCAPM (a)**	**LevCAPM**	**FXCAPM**
Constant	0.004	0.003	0.004	0.003	0.001	0.004	0.003	0.009	0.015	0.005	0.003	0.011	0.012
t-stat	*(1.451)*	*(1.278)*	*(1.764)*	*(0.718)*	*(0.532)*	*(0.876)*	*(1.251)*	*(0.586)*	*(0.978)*	*(0.307)*	*(0.181)*	*(0.716)*	*(0.748)*
Shanken's t-stat	*(1.451)*	*(1.277)*	*(1.726)*	*(0.664)*	*(0.524)*	*(0.838)*	*(1.248)*	*(0.585)*	*(0.977)*	*(0.290)*	*(0.172)*	*(0.665)*	*(0.726)*
Market Return	0.000		-0.004	0.015			-0.002	0.006		0.004		-0.002	0.016
t-stat	*(0.022)*		*(-0.548)*	*(1.669)*			*(-0.238)*	*(0.172)*		*(0.131)*		*(-0.059)*	*(0.510)*
Shanken's t-stat	*(0.022)*		*(-0.538)*	*(1.583)*			*(-0.238)*	*(0.172)*		*(0.125)*		*(-0.055)*	*(0.499)*
Consumption growth		0.000			0.000	-0.001			0.000		0.000		
t-stat		*(0.211)*			*(-0.539)*	*(-0.796)*			*(0.156)*		*(0.006)*		
Shanken's t-stat		*(0.211)*			*(-0.532)*	*(-0.767)*			*(0.155)*		*(0.006)*		
Money growth			-0.001	0.019	-0.001	0.016				-0.003	-0.002		
t-stat			*(-1.093)*	*(1.358)*	*(-0.981)*	*(1.146)*				*(-0.959)*	*(-0.909)*		
Shanken's t-stat			*(-1.074)*	*(1.280)*	*(-0.969)*	*(1.110)*				*(-0.920)*	*(-0.876)*		
FX factor							-0.002						-0.004
t-stat							*(-0.386)*						*(-0.140)*
Shanken's t-stat							*(-0.385)*						*(-0.136)*
Leverage factor												-0.033	
t-stat												*(-1.063)*	
Shanken's t-stat												*(-1.006)*	
R-squared	11.25%	9.54%	19.15%	17.18%	18.79%	16.57%	18.36%	9.30%	6.75%	17.46%	15.65%	17.38%	17.82%
Adj-R-squared	6.82%	5.01%	10.64%	8.47%	10.24%	7.79%	9.76%	4.76%	2.09%	8.77%	6.77%	8.69%	9.17%

Table 3.7. Equity-motivated tradable factor models

Entries report the results for the set of tradable factor models employed in this study. We examine the Fama-French (FF), Carhart, and liquidity factor models (LFF, LCarhart). We employ the two-pass Fama-MacBeth (1973) approach to estimate the various asset pricing models. Results are reported for monthly and quarterly frequency data (Panel A and Panel B, respectively). In each case, we report the constant coefficients, risk premiums, *t*-statistics, Shanken's (1992) adjusted *t*-statistics, R^2 and adjusted R^2. The test assets are the 22 individual commodity futures and the dataset spans the period January 1989 to December 2010.

	Panel A: Monthly Frequency				*Panel B: Quarterly Frequency*			
	FF	**Carhart**	**LFF**	**LCarhart**	**FF**	**Carhart**	**LFF**	**LCarhart**
Constant	0.006	0.006	0.005	0.004	0.009	0.014	0.009	0.014
t-stat	*(2.681)*	*(2.530)*	*(2.036)*	*(1.731)*	*(0.612)*	*(1.070)*	*(0.653)*	*(1.057)*
Shanken's t-stat	*(2.669)*	*(2.494)*	*(2.004)*	*(1.668)*	*(0.501)*	*(0.860)*	*(0.466)*	*(0.761)*
Market Factor	-0.002	-0.001	0.001	0.004	0.031	0.013	0.030	0.018
t-stat	*(-0.302)*	*(-0.193)*	*(0.172)*	*(0.456)*	*(0.774)*	*(0.277)*	*(0.792)*	*(0.384)*
Shanken's t-stat	*(-0.301)*	*(-0.191)*	*(0.170)*	*(0.442)*	*(0.651)*	*(0.227)*	*(0.591)*	*(0.284)*
Size Factor	-0.002	-0.003	-0.003	-0.004	0.022	0.024	0.030	0.029
t-stat	*(-0.393)*	*(-0.566)*	*(-0.525)*	*(-0.768)*	*(0.634)*	*(0.671)*	*(0.884)*	*(0.818)*
Shanken's t-stat	*(-0.391)*	*(-0.559)*	*(-0.518)*	*(-0.745)*	*(0.528)*	*(0.548)*	*(0.645)*	*(0.601)*
Value Factor	-0.002	-0.001	-0.003	-0.003	0.041	0.032	0.036	0.030
t-stat	*(-0.229)*	*(-0.070)*	*(-0.441)*	*(-0.391)*	*(1.094)*	*(0.934)*	*(0.987)*	*(0.858)*
Shanken's t-stat	*(-0.228)*	*(-0.069)*	*(-0.435)*	*(-0.379)*	*(0.921)*	*(0.777)*	*(0.733)*	*(0.646)*
Momentum Factor		0.007		0.009		-0.065		-0.056
t-stat		*(0.681)*		*(0.901)*		*(-1.360)*		*(-1.209)*
Shanken's t-stat		*(0.672)*		*(0.873)*		*(-1.120)*		*(-0.901)*
Liquidity Factor			0.005	0.004			0.044	0.044
t-stat			*(0.637)*	*(0.531)*			*(1.403)*	*(1.288)*
Shanken's t-stat			*(0.628)*	*(0.514)*			*(1.051)*	*(0.967)*
R-squared	30.06%	39.14%	37.62%	45.68%	22.32%	32.51%	30.02%	40.22%
Adj-R-squared	18.41%	24.82%	22.94%	28.70%	9.37%	16.63%	13.56%	21.54%

Table 3.8. Commodity-specific factor models

Entries report the results in the cases where commodity-specific factors are added to the traditional CAPM. We consider both hedging-pressure (panel A) and inventory-related risk factors proxied by the basis and 12-month prior return (panels B and C, respectively). We consider two different construction methods of the mimicking portfolios (risk factors) (HP/Basis/Momentum factor (a) and (b), respectively). The constant coefficients, risk premiums, *t*-statistics, Shanken's (1992) adjusted *t*-statistics, R^2 and adjusted R^2 are reported for monthly and quarterly frequencies. The test assets are the 22 individual commodity futures and the dataset spans the period January 1989-December 2010.

Panel A: HP factor

	Monthly Frequency		**Quarterly Frequency**	
	HP factor (a)	**HP factor (b)**	**HP factor (a)**	**HP factor (b)**
Constant	0.003	0.004	0.004	0.003
t-stat	*(1.312)*	*(1.575)*	*(0.280)*	*(0.217)*
Shanken's t-stat	*(1.311)*	*(1.575)*	*(0.266)*	*(0.205)*
Market Factor	0.001	0.000	0.011	0.010
t-stat	*(0.095)*	*(0.064)*	*(0.357)*	*(0.312)*
Shanken's t-stat	*(0.095)*	*(0.064)*	*(0.343)*	*(0.300)*
HP Factor	0.001	0.000	0.023	0.033
t-stat	*(0.241)*	*(0.058)*	*(0.889)*	*(1.191)*
Shanken's t-stat	*(0.240)*	*(0.058)*	*(0.858)*	*(1.156)*
R-squared	21.54%	20.93%	22.92%	22.97%
Adj-R-squared	13.28%	12.61%	14.81%	14.87%

Panel B: Basis factor

	Basis factor (a)	**Basis factor (b)**	**Basis factor (a)**	**Basis factor (b)**
Constant	0.003	0.003	0.009	0.006
t-stat	*(1.552)*	*(1.195)*	*(0.597)*	*(0.401)*
Shanken's t-stat	*(1.540)*	*(1.172)*	*(0.547)*	*(0.397)*
Market Factor	-0.001	0.001	-0.003	0.001
t-stat	*(-0.172)*	*(0.120)*	*(-0.103)*	*(0.049)*
Shanken's t-stat	*(-0.171)*	*(0.118)*	*(-0.097)*	*(0.048)*
Basis Factor	-0.005	0.011	-0.032	0.014
t-stat	*(-0.837)*	*(1.330)*	*(-1.624)*	*(0.383)*
Shanken's t-stat	*(-0.832)*	*(1.309)*	*(-1.552)*	*(0.380)*
R-squared	21.27%	20.73%	15.05%	16.14%
Adj-R-squared	12.98%	12.38%	6.11%	7.32%

Panel C: Momentum factor

	Momentum factor (a)	**Momentum factor (b)**	**Momentum factor (a)**	**Momentum factor (b)**
Constant	0.004	0.004	0.011	0.006
t-stat	*(2.072)*	*(2.059)*	*(0.801)*	*(0.495)*
Shanken's t-stat	*(2.037)*	*(2.049)*	*(0.765)*	*(0.419)*
Market Factor	-0.004	-0.004	0.010	-0.002
t-stat	*(-0.556)*	*(-0.470)*	*(0.296)*	*(-0.073)*
Shanken's t-stat	*(-0.548)*	*(-0.468)*	*(0.286)*	*(-0.065)*
Momentum Factor	0.008	0.004	0.024	0.073
t-stat	*(1.038)*	*(0.370)*	*(0.594)*	*(1.613)*
Shanken's t-stat	*(1.024)*	*(0.369)*	*(0.571)*	*(1.414)*
R-squared	22.93%	22.84%	21.77%	22.21%
Adj-R-squared	14.82%	14.72%	13.53%	14.02%

Table 3.9. GMM results for one factor asset pricing models

Entries report the factors betas obtained by estimating single factor models for each commodity futures time series returns, using in turn each of the 16 macro, equity motivated, and commodity-specific factors described in Sections 3.3 and 3.4. All models are estimated by GMM. Results are reported for monthly and quarterly data (panels A and B, respectively). The Newey-West standard errors are used to correct for autocorrelation and heteroscedasticity. One, two, and three asterisks indicate that the estimated betas are statistically significant at 10%, 5%, and 1% level, respectively. The test assets are the 22 individual commodity futures and the dataset spans the period January 1989-December 2010.

Panel A: Monthly frequency

	Market return	Commodity market return	Consumption growth	Size factor	Value factor	Momentum factor	Liquidity factor	Money growth	FX factor	HP (a)	HP (b)	Basis (a)	Basis (b)	MOM (a)	MOM (b)
Corn	0.235*	0.276**	1.992	0.046	0.063	-0.106	0.053	-0.459	-0.151	0.285**	0.111	0.055	-0.068	-0.001	0.008
Wheat	0.281**	0.345	1.291	0.135	0.027	-0.144*	0.038	-0.379	0.001	0.096	0.025	-0.032	-0.130*	-0.086	-0.009
Kansas Wheat	0.190	0.308***	0.783	-0.047	-0.058	-0.101	-0.137	2.239	-0.104	0.267**	0.101	-0.182	-0.116	-0.280	-0.119
Soybeans	0.246*	0.321***	-0.427	0.023	0.116	-0.133	0.048	-2.061*	0.048	0.433***	0.179	0.056	0.071	0.097	0.073
Soybean Meal	0.163	0.285***	-0.323	0.100	0.082	-0.105	-0.010	-1.887	-0.040	0.436***	0.210**	0.066	0.059	0.094	0.081
Soybean Oil	0.324**	0.292**	0.104	-0.017	0.167	-0.182**	0.132	-2.104	0.177	0.405**	0.133	0.009	0.041	0.084	0.056
Oats	0.136	0.349**	1.961	-0.004	0.135	-0.030	0.088	0.533	0.040	0.736***	0.537***	0.077	-0.047	0.224	0.172
Cocoa	-0.016	0.183*	-4.459*	0.075	0.138	-0.024	0.035	-0.258	0.356*	0.260	0.095	-0.201*	-0.135	0.062	0.059
Coffee	0.320**	0.148	-0.449	-0.150	0.113	-0.312***	0.293	-3.100*	0.364	0.166	0.023	-0.097	0.056	-0.121	-0.052
Cotton	0.372**	0.278***	-1.308	-0.044	0.134	-0.209*	0.066	-3.725***	0.179	0.203	-0.049	0.205*	0.043	0.109	0.093
Sugar	0.095	0.176**	-0.648	0.044	0.200	-0.244**	0.164	-1.265	0.144	0.199	0.192	0.147	0.071	0.161	0.105
Livecattle	0.066	0.081*	1.212	0.100	0.029	0.005	0.016	-0.432	0.127	-0.157**	-0.122**	0.093	0.015	-0.115***	-0.089***
Lean Hogs	0.059	0.124*	1.774	0.089	0.168	-0.038	-0.152	-0.400	0.120	-0.265**	-0.202***	0.016	-0.081	-0.270***	-0.132*
Feeder cattle	0.071	0.081*	0.440	0.085	0.027	-0.025	0.007	-0.737	0.110	-0.189***	-0.138***	0.087	0.028	-0.134***	-0.091**
Frozen Pork Bellies	0.033	0.107	1.481	0.201	-0.076	0.112	0.014	3.043*	0.091	-0.134	-0.166	0.296*	0.139	-0.108	-0.014
Crude Oil	0.224	1.370***	-0.077	0.256	0.030	0.039	0.182	-4.097**	0.560*	-0.042	-0.138	0.102	0.204*	0.095	0.146
Heating Oil	0.216	1.392***	2.398	0.220	-0.034	0.140	0.232	-3.468*	0.480*	0.020	-0.104	0.109	0.212**	0.150	0.173
Gold	-0.038	0.160***	-2.000**	0.091	-0.054	0.065	0.127	0.028	-0.033	0.315***	0.279***	-0.106	0.056	0.141*	0.115**
Silver	0.238**	0.250***	-2.285	0.180	0.022	-0.035	0.303**	-1.580	0.063	0.612***	0.673***	-0.406***	-0.071	0.294**	0.206**
Copper	0.501***	0.465***	-0.061	0.152	0.242058*	-0.249***	0.282**	-4.319***	0.585**	0.271**	0.175	-0.105	-0.029	0.133	0.091
Platinum	0.182	0.294***	-0.919	0.076	0.006	-0.074	0.194	-1.526	0.161	0.370**	0.345***	0.041	0.132*	0.122	0.106
Palladium	0.397**	0.381	4.606*	0.589*	-0.246	0.066	0.078	-2.714	-0.019	0.394	0.512***	0.349	0.400***	0.201	0.155

Table 3.9. GMM results for one factor asset pricing models (cont'd)

Entries report the factors betas obtained by estimating single factor models for each commodity futures time series returns, using in turn each of the 16 macro, equity motivated, and commodity-specific factors described in Sections 3.3 and 3.4. All models are estimated by GMM. Results are reported for monthly and quarterly data (panels A and B, respectively). The Newey-West standard errors are used to correct for autocorrelation and heteroscedasticity. One, two, and three asterisks indicate that the estimated betas are statistically significant at 10%, 5%, and 1% level, respectively. The test assets are the 22 individual commodity futures and the dataset spans the period January 1989-December 2010.

Panel B: Quarterly frequency

Futures Contract	**Market return**	**Commodity market return**	**Consumption growth**	**Size factor**	**Value factor**	**Momentum factor**	**Liquidity factor**	**Money growth**	**Leverage**	**FX factor**	**HP (a)**	**HP (b)**	**Basis (a)**	**Basis (b)**	**MOM (a)**	**MOM (b)**
Corn	0.163	0.132	2.573	-0.007	-0.321**	0.285***	0.031	-1.362	0.274**	0.123	0.566***	0.453***	-0.013	0.061	0.400	0.271*
Wheat	0.241	0.080	0.191	0.095	-0.268	0.183	0.066	-2.954**	0.311***	0.212	0.117	0.113	0.076	-0.043	0.194	0.169
Kansas Wheat	0.066	0.068	3.409	0.089	-0.225	0.207	-0.281	-0.158	0.187	-0.007	0.247	0.039	0.066	-0.210	0.012	0.028
Soybeans	0.190	0.293*	1.193	0.242	-0.103	0.069	0.098	-3.051	-0.01786	0.245	0.606***	0.429***	0.064	0.079	0.029	0.073
Soybean Meal	0.160	0.268*	0.741	0.261	-0.068	0.014	-0.089	-2.024	-0.090	0.160	0.665***	0.461***	0.112	0.077	-0.083	0.013
Soybean Oil	0.188	0.269	1.783	0.298*	-0.106	0.087	0.408*	-4.320**	0.077	0.299	0.408**	0.281**	0.101	0.181	0.135	0.123
Oats	0.029	0.175	1.307	0.382	0.019	0.216	0.109	-0.637	0.243	0.186	0.712***	0.654***	0.061	0.127	0.288	0.183
Cocoa	-0.329**	0.102	-7.124*	0.071	0.025	0.117	0.331	-0.035	0.094	0.252	0.351**	0.217*	-0.217	-0.109	0.165	0.088
Coffee	0.378*	0.053	6.714*	0.109	-0.341	-0.101	0.189	-8.393**	0.131	0.604075*	0.304	0.115	-0.733	-0.748	0.096	0.289
Cotton	0.420**	0.199	0.755	0.039	-0.042	-0.056	0.119	-6.300***	-0.242	0.004	-0.087	-0.035	0.020	-0.046	0.215	0.145
Sugar	0.305	0.287*	-1.269	0.531	0.271	-0.320*	-0.138	-3.977**	-0.407***	0.065	0.234	0.167	0.507**	0.416***	0.283**	0.201*
Livecattle	0.116	0.186***	3.162	0.088	0.063	-0.055	0.015	-2.286**	0.050	0.206	-0.115*	-0.138***	0.165*	0.073	-0.151	-0.131
Lean Hogs	0.089	0.200**	5.238	0.142	0.070	0.074	-0.103	-1.734	0.246*	0.202	-0.243	-0.251**	0.045	0.107	-0.166	-0.139
Feeder cattle	0.099	0.189***	2.391	0.096	0.033	-0.081	-0.011	-2.261***	0.035	0.159	-0.190**	-0.222***	0.200**	0.108	-0.170*	-0.142*
Pork Bellies	0.033	0.133	4.022	0.189	-0.363	0.314	0.262	3.646**	0.166	0.409	-0.394**	-0.331***	0.124	0.159	-0.119	-0.145
Crude Oil	-0.173	1.494***	7.327	-0.506	0.224	0.252	0.635	-6.419*	-0.109	0.994399**	-0.536	-0.562	0.390	-0.162	0.101	0.348**
Heating Oil	-0.203	1.474***	8.628	-0.501	0.133	0.324	0.674*	-5.898*	-0.016	0.865236*	-0.621	-0.665*	0.536*	-0.028	0.071	0.319*
Gold	-0.092	0.126***	-1.393	-0.053	-0.019	0.040	0.208**	-1.025	-0.032	-0.026	0.259*	0.241**	-0.087	0.012	0.122*	0.126***
Silver	0.171	0.136	3.561	0.170	0.134	-0.132	0.432***	-3.047*	-0.063	0.110	0.606***	0.658***	-0.480**	-0.017	0.293*	0.247**
Copper	0.388	0.448***	1.484	0.114	0.335*	-0.387***	0.571**	-7.583**	-0.378***	0.747908*	0.138	0.193	-0.221	-0.051	0.206	0.263**
Platinum	0.280**	0.286**	5.618	0.331*	-0.174	-0.078	0.377*	-3.332	-0.203*	0.293	0.421**	0.350**	0.004	0.196*	0.432*	0.330***
Palladium	0.661***	0.202	14.039***	0.374	-0.258	-0.110	0.257	-5.300	0.062	-0.012	0.174	0.336	0.064	0.356**	0.439	0.371**

Table 3.10. GMM results for asset pricing models with macro and equity-motivated tradable factors

Entries report the results in the case where we employ the GMM method to estimate the macro and the equity-motivated tradable factor models employed in this study (panels A and B, respectively). The set of the macro factor models comrpises the CAPM, CCAPM, MCAPM, MCCAPM, the fx factor model (FXCAPM), and the leverage factor model (LevCAPM). The set of equity-motivated tradable factor models comprises the Fama-French (FF), Carhart, and liquidity factor models (LFF, LCarhart). We report the risk premiums and the respective *t* –statistics. The test assets are the 22 individual commodity futures and the dataset spans the period January 1989-December 2010.

Panel A: Macro factor models

	Monthly Frequency							**Quarterly Frequency**					
	CAPM	**CCAPM**	**MCAPM (a)**	**MCAPM (b)**	**MCCAPM (a)**	**MCCAPM (b)**	**FXCAPM**	**CAPM**	**CCAPM**	**MCAPM (a)**	**MCCAPM (a)**	**LevCAPM**	**FXCAPM**
Market Return	0.045		-0.017	0.037			0.007	0.227		-0.049		0.001	0.042
t-stat	*(1.452)*		*(-0.659)*	*(1.222)*			*(0.284)*	*(0.606)*		*(-0.934)*		*(0.023)*	*(0.885)*
Consumption growth		0.030			0.012	-0.020			0.006		0.012		
t-stat		*(0.017)*			*(0.029)*	*(-0.040)*			*(1.263)*		*(0.413)*		
Money growth			-0.006	0.165	-0.001	-0.084				-0.008	0.004		
t-stat			*(-1.716)*	*(1.716)*	*(-0.010)*	*(-0.034)*				*(-1.489)*	*(0.252)*		
FX factor							0.057						0.076
t-stat							*(1.435)*						*(1.430)*
Leverage factor												-0.165	
t-stat												*(-1.744)*	

Panel B: Tradable factor models

	FF	**Carhart**	**LFF**	**LCarhart**	**FF**	**Carhart**	**LFF**	**LCarhart**
Market return	-0.013	-0.016	-0.013	-0.015	0.042	0.045	0.051	0.068
t-stat	*(-0.319)*	*(-0.222)*	*(-0.455)*	*(-0.346)*	*(0.540)*	*(0.597)*	*(0.621)*	*(0.722)*
Size Factor	0.07	0.117	0.049	0.077	-0.138	-0.122	-0.175	-0.148
t-stat	*(1.549)*	*(0.743)*	*(1.800)*	*(1.142)*	*(-0.896)*	*(-1.181)*	*(-0.955)*	*(-0.917)*
Value Factor	0.056	0.039	0.034	0.017	0.011	0.022	0.008	0.048
t-stat	*(0.916)*	*(0.410)*	*(0.876)*	*(0.340)*	*(0.224)*	*(0.483)*	*(0.143)*	*(0.632)*
Momentum Factor		-0.125		-0.073		0.033		0.052
t-stat		*(-0.619)*		*(-0.885)*		*(0.452)*		*(0.558)*
Liquidity Factor			0.013	0.019			-0.006	-0.030
t-stat			*(0.606)*	*(0.615)*			*(-0.072)*	*(-0.410)*

Table 3.11. GMM results for asset pricing models with commodity-specific factors

Entries report the results in the case where we employ the GMM to estimate the asset pricing models that include the commodity-specific factors. We consider both hedging-pressure (panel A) and inventory-related risk factors proxied by the basis and 12-months prior return (panels B and C, respectively). We consider two different construction methods of the mimicking portfolios (risk factors) (HP/Basis/Momentum factor (a) and (b), respectively). Results are reported for monthly and quarterly data. In each case, we report the risk premiums and the respective *t* –statistics. The test assets are the 22 individual commodity futures and the dataset spans the period January 1989-December 2010.

Panel A: HP risk factor

	Monthly Frequency		**Quarterly Frequency**	
	HP (a)-CAPM	**HP (b)-CAPM**	**HP (a) -CAPM**	**HP (b)-CAPM**
Market Factor	0.080	0.062	0.190	0.194
t-stat	*(1.097)*	*(1.216)*	*(0.866)*	*(0.814)*
HP Factor	-0.040	-0.024	-0.087	-0.082
t-stat	*(-1.214)*	*(-1.154)*	*(-0.809)*	*(-0.785)*

Panel B: Basis risk factor

	Basis (a)-CAPM	**Basis (b)-CAPM**	**Basis (a)-CAPM**	**Basis (b)-CAPM**
Market Factor	-0.002	0.002	0.073	0.308
t-stat	*(-0.042)*	*(0.144)*	*(0.879)*	*(0.483)*
Basis Factor	0.155	0.055	0.122	-0.133
t-stat	*(0.668)*	*(2.146)*	*(1.162)*	*(-0.422)*

Panel C: Momentum risk factor

	FutMom (a)-CAPM	**FutMom (b)-CAPM**	**FutMom (a)-CAPM**	**FutMom (b)-CAPM**
Market Factor	-0.009	0.271	-0.316	-0.290
t-stat	*(-0.269)*	*(0.281)*	*(-0.311)*	*(-0.390)*
Momentum Factor	0.074	-0.378	0.589	0.303
t-stat	*(1.676)*	*(-0.258)*	*(0.293)*	*(0.419)*

Table 3.12. Alternative proxies for the market portfolio

Entries report the results in the case where we estimate the CAPM, MCAPM, LevCAPM, FXCAPM and extensions of the CAPM with commodity-specific factors (hedging pressure, basis, 12-months prior futures return momentum) using alternative proxies for the market portfolio. We consider the S&P GSCI commodity index (panel A) and a hybrid equally-weighted, index that consists of both stocks and commodities (panel B). Results are reported for monthly and quarterly data. In each case, we report the constant coefficients, risk premiums, *t*-statistics, Shanken's (1992) adjusted *t*-statistics, R^2 and adjusted R^2. The test assets are the 22 individual commodity futures and the dataset spans the period January 1989-December 2010.

Panel A: S&P GSCI

	Monthly Frequency										Quarterly Frequency									
	CAPM	**MCAPM(a)**	**MCAPM(b)**	**FXCAPM**	**HP(a)-CAPM**	**HP(b)-CAPM**	**Basis(a)-CAPM**	**Basis(b)-CAPM**	**Mom(a)-CAPM**	**Mom(b)-CAPM**	**CAPM**	**MCAPM (a)**	**Lev-CAPM**	**FXCAPM**	**HP(a)-CAPM**	**HP(b)-CAPM**	**Basis(a)-CAPM**	**Basis(b)-CAPM**	**Mom(a)-CAPM**	**Mom(b)-CAPM**
Constant	0.003	0.003	0.004	0.003	0.003	0.004	0.003	0.002	0.004	0.003	0.016	0.007	0.017	0.016	0.006	0.003	0.011	0.017	0.016	0.012
t-stat	*(1.170)*	*(1.234)*	*(0.962)*	*(1.170)*	*(1.141)*	*(1.548)*	*(1.269)*	*(1.041)*	*(1.565)*	*(1.422)*	*(1.111)*	*(0.462)*	*(1.262)*	*(1.111)*	*(0.533)*	*(0.295)*	*(0.835)*	*(1.239)*	*(1.221)*	*(0.952)*
Shanken's t-stat	*(1.166)*	*(1.214)*	*(0.949)*	*(1.166)*	*(1.135)*	*(1.545)*	*(1.247)*	*(1.032)*	*(1.552)*	*(1.418)*	*(1.106)*	*(0.426)*	*(1.150)*	*(1.105)*	*(0.450)*	*(0.246)*	*(0.714)*	*(1.145)*	*(1.061)*	*(0.810)*
Market factor	0.005	0.005	0.008		0.004	0.003	0.005	0.006	0.004	0.004	0.012	0.016	0.008		0.025	0.026	0.016	0.013	0.011	0.019
t-stat	*(1.052)*	*(1.036)*	*(0.960)*		*(0.900)*	*(0.720)*	*(1.048)*	*(1.243)*	*(0.738)*	*(0.859)*	*(0.425)*	*(0.528)*	*(0.274)*		*(0.846)*	*(0.893)*	*(0.566)*	*(0.462)*	*(0.362)*	*(0.646)*
Shanken's t-stat	*(1.052)*	*(1.033)*	*(0.958)*		*(0.899)*	*(0.720)*	*(1.046)*	*(1.241)*	*(0.737)*	*(0.858)*	*(0.424)*	*(0.509)*	*(0.264)*		*(0.793)*	*(0.828)*	*(0.533)*	*(0.449)*	*(0.342)*	*(0.605)*
Money growth		-0.001	0.009									-0.003								
t-stat		*(-1.064)*	*(0.647)*									*(-1.255)*								
Shanken's t-stat		*(-1.050)*	*(0.641)*									*(-1.183)*								
Leverage factor													-0.037							
t-stat													*(-1.173)*							
Shanken's t-stat													*(-1.092)*							
FX factor				0.005										0.012						
t-stat				*(1.052)*										*(0.425)*						
Shanken's t-stat				*(1.051)*										*(0.420)*						
HP Factor					-0.003	-0.002									0.044	0.058				
t-stat					*(-0.508)*	*(-0.345)*									*(1.675)*	*(1.958)*				
Shanken's t-stat					*(-0.507)*	*(-0.345)*									*(1.482)*	*(1.743)*				
Basis Factor							-0.007	0.006									-0.041	0.040		
t-stat							*(-1.192)*	*(0.647)*									*(-2.035)*	*(0.991)*		
Shanken's t-stat							*(-1.177)*	*(0.642)*									*(-1.867)*	*(0.931)*		
Momentum Factor									0.006	-0.003									0.045	0.073
t-stat									*(0.833)*	*(-0.274)*									*(1.150)*	*(1.551)*
Shanken's t-stat									*(0.828)*	*(-0.273)*									*(1.018)*	*(1.362)*
R-squared	13.93%	22.96%	21.45%	13.93%	24.26%	23.63%	23.75%	23.75%	24.74%	24.74%	17.68%	24.33%	25.24%	17.68%	29.30%	29.88%	22.84%	23.05%	28.98%	30.49%
Adj-R-squared	9.63%	14.85%	13.18%	9.63%	16.29%	15.59%	15.72%	15.72%	16.81%	16.81%	13.56%	16.37%	17.37%	13.56%	21.86%	22.50%	14.72%	14.95%	21.50%	23.17%

Table 3.12. Alternative proxies for the market portfolio (cont'd)

Entries report the results in the case where we estimate the CAPM, MCAPM, LevCAPM, FXCAPM and extensions of the CAPM with commodity-specific factors (hedging pressure, basis, 12-months prior futures return momentum) using alternative proxies for the market portfolio. We consider the S&P GSCI commodity index (panel A) and a hybrid equally-weighted, index that consists of both stocks and commodities (panel B). Results are reported for monthly and quarterly data. In each case, we report the constant coefficients, risk premiums, *t*-statistics, Shanken's (1992) adjusted *t*-statistics, R^2 and adjusted R^2. The test assets are the 22 individual commodity futures and the dataset spans the period January 1989-December 2010.

Panel B: Hybrid Index (50% Stock Market Index and 50% S&P GSCI)

	Monthly Frequency										**Quarterly Frequency**									
	CAPM	**MCAPM(a)**	**MCAPM(b)**	**FXCAPM**	**HP (a)-CAPM**	**HP (b)-CAPM**	**Basis(a)-CAPM**	**Basis(b)-CAPM**	**Mom(a)-CAPM**	**Mom(b)-CAPM**	**CAPM**	**MCAPM(a)**	**Lev-CAPM**	**FXCAPM**	**HP (a)-CAPM**	**HP (b)-CAPM**	**Basis(a)-CAPM**	**Basis(b)-CAPM**	**Mom(a)-CAPM**	**Mom(b)-CAPM**
Constant	0.002	0.003	0.003	0.002	0.002	0.003	0.002	0.002	0.003	0.003	0.012	0.006	0.015	0.012	0.001	-0.003	0.008	0.013	0.013	0.009
t-stat	*(0.979)*	*(1.203)*	*(0.757)*	*(0.979)*	*(0.827)*	*(1.151)*	*(1.088)*	*(0.845)*	*(1.367)*	*(1.257)*	*(0.852)*	*(0.406)*	*(1.206)*	*(0.852)*	*(0.124)*	*(-0.280)*	*(0.598)*	*(0.954)*	*(0.933)*	*(0.689)*
Shanken's t-stat	*(0.972)*	*(1.184)*	*(0.739)*	*(0.972)*	*(0.822)*	*(1.146)*	*(1.062)*	*(0.834)*	*(1.349)*	*(1.251)*	*(0.836)*	*(0.372)*	*(1.064)*	*(0.835)*	*(0.105)*	*(-0.224)*	*(0.492)*	*(0.916)*	*(0.836)*	*(0.600)*
Market factor	0.005	0.005	0.008		0.005	0.004	0.005	0.006	0.003	0.004	0.015	0.014	0.010		0.025	0.029	0.020	0.011	0.014	0.014
t-stat	*(1.315)*	*(1.378)*	*(1.426)*		*(1.212)*	*(1.063)*	*(1.324)*	*(1.548)*	*(0.855)*	*(1.043)*	*(0.662)*	*(0.623)*	*(0.417)*		*(1.108)*	*(1.237)*	*(0.860)*	*(0.522)*	*(0.607)*	*(0.619)*
Shanken's t-stat	*(1.311)*	*(1.369)*	*(1.418)*		*(1.208)*	*(1.061)*	*(1.312)*	*(1.540)*	*(0.851)*	*(1.041)*	*(0.654)*	*(0.590)*	*(0.385)*		*(0.994)*	*(1.067)*	*(0.757)*	*(0.510)*	*(0.566)*	*(0.566)*
Money growth		-0.001	0.010									-0.003								
t-stat		*(-0.961)*	*(0.725)*									*(-1.269)*								
Shanken's t-stat		*(-0.949)*	*(0.713)*									*(-1.193)*								
Leverage factor													-0.043							
t-stat													*(-1.422)*							
Shanken's t-stat													*(-1.294)*							
FX factor				0.005										0.015						
t-stat				*(1.315)*										*(0.662)*						
Shanken's t-stat				*(1.311)*										*(0.652)*						
HP Factor					-0.001	-0.001									0.040	0.058				
t-stat					*(-0.211)*	*(-0.099)*									*(1.464)*	*(1.862)*				
Shanken's t-stat					*(-0.210)*	*(-0.099)*									*(1.285)*	*(1.602)*				
Basis Factor							-0.008	0.006									-0.044	0.026		
t-stat							*(-1.294)*	*(0.692)*									*(-2.215)*	*(0.715)*		
Shanken's t-stat							*(-1.271)*	*(0.684)*									*(-1.988)*	*(0.693)*		
Momentum Factor									0.008	-0.001									0.039	0.066
t-stat									*(1.000)*	*(-0.102)*									*(1.025)*	*(1.412)*
Shanken's t-stat									*(0.990)*	*(-0.102)*									*(0.933)*	*(1.263)*
R-squared	14.17%	22.90%	21.69%	14.17%	24.49%	23.75%	23.78%	23.80%	25.16%	25.33%	16.60%	22.94%	23.88%	16.60%	28.57%	29.89%	22.08%	21.57%	26.87%	29.05%
Adj-R-squared	9.88%	14.78%	13.45%	9.88%	16.54%	15.72%	15.76%	15.78%	17.28%	17.47%	12.43%	14.83%	15.86%	12.43%	21.05%	22.51%	13.87%	13.31%	19.17%	21.58%

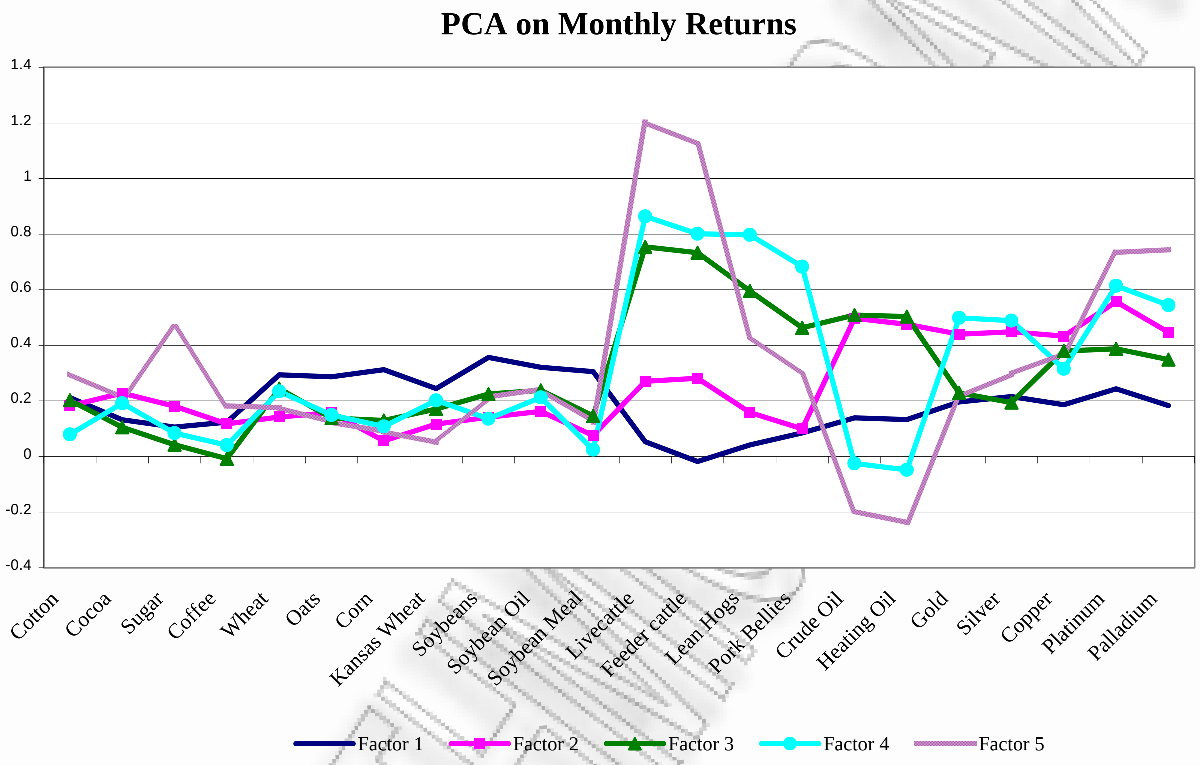
Table 3.13. Principal Components Analysis (PCA) factor models

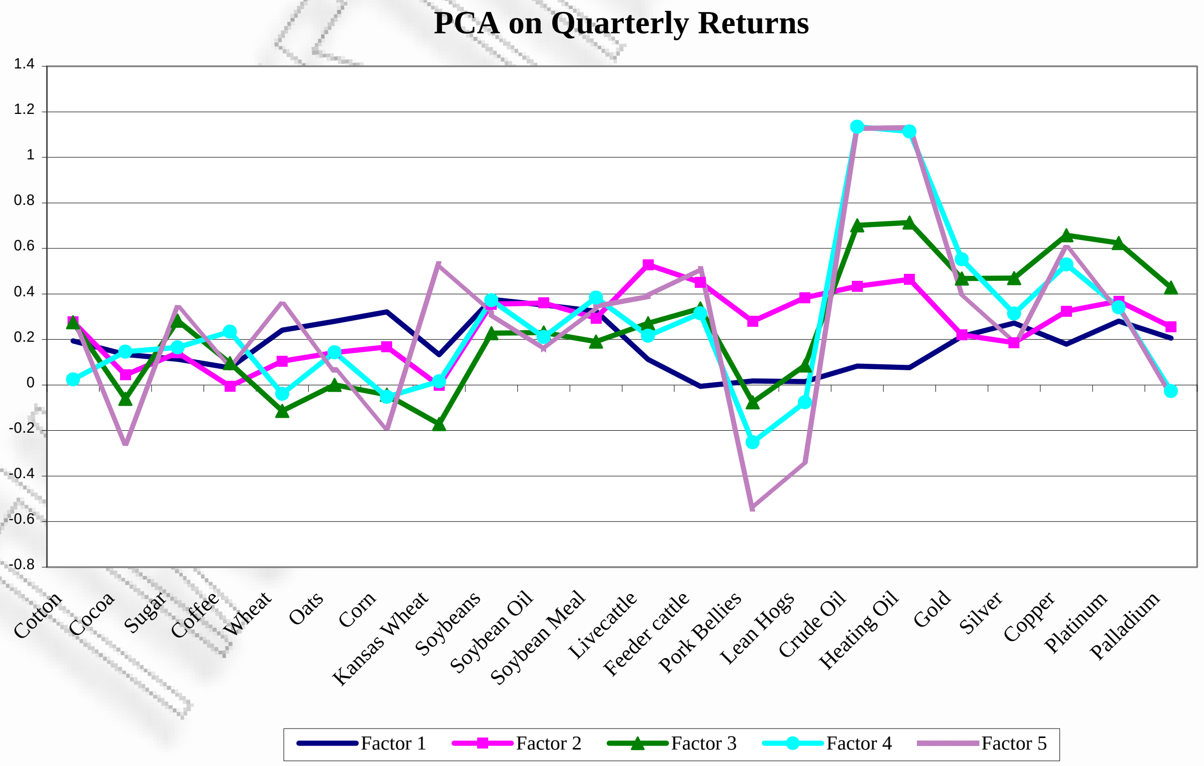
Entries report the results in the case where one, two, three, four and five PCA factor models are estimated. We employ the two-pass Fama-MacBeth (1973) approach to estimate the various PCA asset pricing models (one, two, three, four and five PCs models). Results are reported for monthly and quarterly data (panels A and B, respectively). In each case, we report the estimated constant coefficients, risk premiums, *t*-statistics, Shanken's (1992) adjusted *t*-statistics, R^2 and adjusted R^2. The test assets are the 22 individual commodity futures and the dataset spans the period January 1989-December 2010.

	Panel A: Monthly Frequency					***Panel B: Quarterly Frequency***				
	1 factor	**2 factors**	**3 factors**	**4 factors**	**5 factors**	**1 factor**	**2 factors**	**3 factors**	**4 factors**	**5 factors**
Constant	0.003	-0.002	0.002	0.002	-0.001	0.009	-0.002	-0.001	-0.004	-0.003
t-stat	*(1.205)*	*(-0.841)*	*(0.806)*	*(0.720)*	*(-0.215)*	*(0.665)*	*(-0.185)*	*(-0.090)*	*(-0.306)*	*(-0.221)*
Shanken's t-stat	*(1.204)*	*(-0.818)*	*(0.790)*	*(0.706)*	*(-0.210)*	*(0.657)*	*(-0.175)*	*(-0.077)*	*(-0.260)*	*(-0.185)*
Factor 1	0.001	0.003	0.001	0.001	0.003	0.004	0.007	0.008	0.008	0.008
t-stat	*(0.447)*	*(1.564)*	*(0.483)*	*(0.498)*	*(1.161)*	*(0.549)*	*(0.898)*	*(0.974)*	*(1.090)*	*(1.059)*
Shanken's t-stat	*(0.447)*	*(1.546)*	*(0.478)*	*(0.492)*	*(1.146)*	*(0.545)*	*(0.862)*	*(0.867)*	*(0.969)*	*(0.932)*
Factor 2		0.003	0.002	0.002	0.003		0.003	0.001	0.001	0.001
t-stat		*(2.332)*	*(1.260)*	*(1.301)*	*(1.824)*		*(0.691)*	*(0.166)*	*(0.307)*	*(0.195)*
Shanken's t-stat		*(2.312)*	*(1.250)*	*(1.291)*	*(1.806)*		*(0.675)*	*(0.157)*	*(0.288)*	*(0.183)*
Factor 3			-0.003	-0.002	-0.001			0.008	0.007	0.007
t-stat			*(-1.712)*	*(-1.567)*	*(-0.818)*			*(2.661)*	*(2.455)*	*(2.539)*
Shanken's t-stat			*(-1.696)*	*(-1.553)*	*(-0.809)*			*(2.623)*	*(2.412)*	*(2.494)*
Factor 4				0.000	0.000				-0.001	-0.001
t-stat				*(-0.305)*	*(-0.030)*				*(-0.428)*	*(-0.411)*
Shanken's t-stat				*(-0.305)*	*(-0.030)*				*(-0.422)*	*(-0.410)*
Factor 5					0.000					-0.002
t-stat					*(0.128)*					*(-0.769)*
Shanken's t-stat					*(0.127)*					*(-0.704)*
R-squared	13.56%	26.43%	38.59%	48.31%	55.79%	17.43%	29.39%	44.23%	53.57%	63.47%
Adj-R-squared	9.24%	18.69%	28.35%	36.15%	41.98%	13.30%	21.96%	34.93%	42.64%	52.06%

Figure 3.1. PCA analysis

The figure plots the correlation loadings (the eigenvalues) of the first five factors obtained from the Principal Components Analysis (PCA) for each one of the employed commodity futures contracts. Results are reported when PCA is applied to monthly and quarterly returns, separately.





Chapter 4: The effects of margin changes on the commodity futures markets

Abstract

The debate on the regulation of the commodity futures margins has been revived recently. This chapter assesses the effect of margin changes on the prices/returns, the sharing of risk between speculators and hedgers, and the price stability of the commodity futures markets. We find that margin increases restrict the rate at which prices increase. On the other hand, margin increases harm the risk sharing function and the market liquidity in certain markets. Margin changes also coincide with changes in volatility in the same direction. However, they constrain excessive speculation in some markets. The regulator should take the heterogeneity of commodity futures markets into account to set margins. The effect of margins may spillover across related markets though.

"…Government data confirm that oil speculators are driving the price increase …In the Dodd-Frank Wall Street Reform and Consumer Protection Act, we empowered your Commission with a number of new tools to rein in excessive speculation and prevent market failures ... Now is the time to exercise that authority…. Higher margin levels would reduce incentives for excessive speculation by requiring investors to back their bets with real capital…"

U.S. Senators letter sent to Gary Gensler, chairman of the Commodity Futures Trading Commission (CFTC), March 2011

"...Mr. President, if CFTC Chairman Gary Gensler doesn't act soon to implement rules that will cut down on speculation in the oil futures markets, then you should consider not reappointing him."

Senator Nelson, in his letter to President Obama, April 2012

4.1. Introduction

Traditionally, the futures exchanges use margins as a risk management tool because they are a payment that serves as a collateral deposit to eliminate credit risk (Telser 1981, Figlewski, 1984, Kahl et al., 1985, Gay et al., 1986, Fenn and Kupiec, 1993, Kroszner, 1999). However, the 2003-2008 commodity boom and the recent increased prices in energy markets have revived the discussion about whether the commodity futures margin requirements should be regulated so that they can also be used as a policy tool to restrict excessive speculation and drive down the commodity prices.[1] The argument in favor of regulating margins is that they can decrease prices by dampening the excessive speculation that destabilizes the market. On the other hand, the main argument against margins regulation is that it deprives the futures exchanges the ability to protect themselves and their members against credit risk. To the extent that the margin requirements in futures markets have performed well in preventing contractual defaults, further margin regulation can not be justified (see Gemmill, 1994, Bates and Craine, 1999, for the adequacy of margins in the case of default). In addition, the federal agencies question the allegation that low margins encourage undue speculation and lead to increased volatility (see Greenspan, 1990, for a similar view). They also express their concern that higher margins would harm the futures market liquidity and this would deter hedgers and speculators from sharing risk. This would undermine the role of the futures markets as a risk transfer mechanism between the hedgers and the speculators (see Markham, 1991, for a review of the debate on margin regulation).

Till recently, the futures exchanges had the discretion to set and change the margin rules. However, the Dodd–Frank Wall Street Reform and Consumer Protection Act signed into law on July 21, 2010, gives the authority to the U.S. Commodity Futures Trading Commission (CFTC) to establish the margin requirements so as to protect the

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[1] The period 2003-2008 is termed commodity boom because it has witnessed a spectacular and simultaneous increase in the commodity prices of the three major commodity groups (energy, metals, and agriculture) which has taken all of them to record highs in the recent history of commodities (see e.g., Helbling, 2008). There are two opposing views regarding the contribution of the speculative forces to the commodity boom. The first one attributes the rapid increase in overall commodity prices on institutional investors' embrace of commodities as an investable asset class (Tang and Xiong, 2010). The second view dismisses the idea that the commodity trading activity in futures exchanges may have affected commodity returns (e.g., Stoll and Whaley, 2010, Irwin and Saunders, 2011). This strand of literature argues that fundamentals such as the weakening of the dollar, tight supply, and increasing demand sufficiently explain the price movements (e.g., Frankel and Rose, 2010, Alquist and Gervais, 2011, Fattouh et al., 2012).

financial integrity of the futures markets, including the commodity futures markets. So far, the CFTC has not exercised this authority to set the margins, yet the view that the CFTC should use the margin rules as a policy tool to curb and discourage excessive speculation gains popularity.

We investigate comprehensively the effect of margin changes on certain features of the commodity futures markets that stand in the core of the debate about whether margins should be regulated or not. Understanding how the margin changes affect the commodity futures market is a prerequisite prior to the regulation of the margin requirements. To the best of our knowledge, the study of the margin effect on some of the features under scrutiny is novel. First, we examine the effect of margin changes on the commodity futures prices and returns. Commodity futures prices are related to the underlying commodity spot prices. In fact, the market participants use the shortest maturity commodity futures price to proxy the spot commodity price. A regulator aims at maintaining a low level of commodity futures price given that an increase in commodity prices creates inflation that harms the consumers and the producers who use commodities as an input in their production process. From a theoretical standpoint, Gârleanu and Pedersen (2011) and Acharya et al. (2011) develop a setting where hedgers and capital constrained speculators interact. Their models predict that in the case where the speculators are net long (short), increases in margins lead to decreases (increases) in the futures prices. To the best of our knowledge, Hedegaard (2011) is the only empirical study that investigates the effect of margin changes on 16 commodity futures returns. However, he investigates the margin effect by grouping all commodity contracts rather than examining the margin effect on each individual futures. This may mask the heterogeneity of different commodity contracts and groups (see Chapter 3 for evidence on this heterogeity). In addition, he examines the margin effect only over short horizons.

Second, we examine the effect of margin changes on the functioning of the commodity futures markets as a risk transfer mechanism between the hedgers and speculators. To the best of our knowledge, we are the first who investigate this effect. This is of importance to the regulator because one of the main purposes of the futures markets is to provide a mechanism for risk sharing (Johnson, 1960, Working, 1962). To address this question, we study the effect of the margin changes on the open interest corresponding to the total (i.e. the sum of long and short positions) speculative and hedging positions, separately. In the case where we find that an increase in margins coincides with a decrease in the hedgers total open interest, this will imply that the risk sharing role of futures markets is at risk; the hedgers may leave the futures markets either because they can not afford hedging or they can not find speculators to share their risk. The latter will be the case if we find that an increase in margins decreases the speculators open interest as well.

Third, we investigate the effect of margin changes on the price stability of the commodity futures market by considering the effect on the volatility and the market liquidity of the respective markets. Volatility and liquidity are closely related concepts. Brunnermeier and Pedersen (2009) define market liquidity as the asset’s ability to be traded easily at low cost; low market liquidity leads to a less stable market with increased volatility. In fact, the lack of liquidity has been blamed for exacerbating market crises in financial markets such as the stock market crash in 1987 and the current upheaval in the credit market. The issue of price stability is of particular importance to the regulators. Among others, Massell (1969) and Turnovsky (1974) show that price stabilization yields welfare gains. Similarly, increases in liquidity increase the social welfare (e.g., Huang and Wang, 2010). With regard to the futures markets, liquidity is a prerequisite for the well-functioning of the futures markets as a risk transfer mechanism. This is because the more liquid the market is, the easier is for hedgers and speculators to access it (see Cuny, 1993, and references therein). In addition, greater liquidity engenders a higher degree of informational efficiency (Chordia et al., 2008). This also helps the risk sharing role of futures markets because the agents base their decisions on current futures prices that reflect the full information, and hence they can trade at lower costs compared to markets that require extensive information search (see e.g., Chowdhury, 1991, Kahl et al, 1985). Finally, a highly liquid market obstructs market manipulation (Pashigian, 1986) and hence it promotes market transparency. The International Organization of Securities Commission (IOSCO, 2003, 2011) sets the market efficiency and transparency as two objectives that the regulator should be after. To the best of our knowledge, no previous study has examined the effect of margin changes on the market liquidity; the previous literature has only considered volatility as a measure of price stability (see e.g., Ma et al., 1993, Hardouvelis and Kim, 1995, 1996).

Fourth, we investigate whether the margin changes for an individual futures contract (target contract) affect the previously examined characteristics of the other contracts that belong to the same commodity group (cross-margin effects). This is also an issue of importance that should be taken into account by the margin regulators. It may well be the case that margin increases for the target contract make investors moving to other related markets, or alternatively, drive them out of that group entirely in fear that these increases will be extended to all related contracts (see Hardouvelis and Kim, 1995, for evidence on the metal futures markets).

To ensure the robustness of the obtained results and gain further insight on the effect of margin changes on the examined features of the commodity futures markets, we further classify the margin changes into (a) positive and negative margin changes, (b) large and small margin changes, and analyze their effect separately (for a similar approach, see e.g., Hardouvelis and Kim, 1995, Hedegaard, 2011). This analysis is also of importance to regulators. First, the policy circles are in favour of imposing higher regulated margin levels and therefore the effect of positive changes interest them most. Second, the exact magnitude of margin changes to be imposed by the regulator under the Dodd–Frank Act is to be decided and thus the effect of large margin changes on the commodity futures market should be studied.[2]

To assess the impact of margin changes on the variables of interest, we employ a large cross section of 20 individual commodity futures. We apply the event study methodology in line with Hardouvelis and Peristiani (1992) and Hardouvelis and Kim (1995). We identify the days of margin changes for each individual futures contract and we examine their effect on the variables of interest around these days.[3] We repeat the analysis by classifying the individual commodities in 5 distinct commodity groups, namely grains, softs, livestock, energy and metal groups. The analysis on the individual futures takes into account the heterogeneity of the different commodity contracts whereas the analysis on the groups gains statistical power because the contracts that belong in the same group share similar characteristics (for a similar approach see also Hardouvelis and

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[2] After the 1987 stock market crash, the Brady report recommended that great increases in futures margin requirements should be imposed as it is the case with the margins in the stock markets. In fact, it called for making margins equal across futures and stock markets. Till then, the issue of harmonization of the margin policy across markets is frequently raised.

[3] We should acknowledge that an endogeneity econometric issue may arise in the literature of the effect of margin changes. The margins in futures markets are set based on the market conditions (e.g., volatility, see Figlewski, 1984, Moser, 1992, Fenn and Kupiec, 1993). To address this endogeneity constraint, one should employ instrumental variables that are correlated with the independent variables (margin changes) and uncorrelated with the dependent variables. However, there is no theory in the margins literature that dictates the choice of these instrumental variables.

Kim, 1995). The previous empirical studies use only small data samples that included a few individual commodity futures contracts.

Our empirical analysis yields five main results. First, we find that changes in the margin requirements have a positive (negative) relationship with the commodity futures prices (returns). This implies that an increase in the margin requirements constrains the rate at which commodity futures prices increase. Second, we find that the speculators decrease their open interest positions more than hedgers do when faced margin increases. However, this does not impair the risk transfer mechanism in all commodities but grains and metals where hedgers also decrease their positions. Third, we find that there is a positive relationship between the margin changes and volatility. However, the liquidity of the individual contracts, as measured by the Amihud (2002) illiquidity ratio, is not affected by the margin changes. Fourth, we find that cross-margin effects exist in some cases, i.e. when a margin change occurs for a target contract, other related contracts that belong to the same group may also be affected. Finally, in the case where we examine the impact of positive and negative, as well as of large and small margin changes separately, we find that the previously examined market variables are more sensitive to margin increases and large margin changes. Interestingly, we document that in these cases, the liquidity of the market decreases for some commodity groups. Our results have implications for the regulation of margin requirements in the commodity futures markets.

The rest of the paper is structured as follows. The following section reviews the related literature. Section 4.3 describes the dataset. Section 4.4 describes the event study methodology and the effect of margin changes on the commodity futures markets. Section 4.5 examines whether cross-margin effects exist. Section 4.6 discusses the results of the robustness tests. The final section concludes and discusses the implications of our findings.

4.2. Related literature

4.2.1. Effect of margin changes on prices and returns

The models of Gârleanu and Pedersen (2011) and Acharya et al. (2011) show that changes in the margin requirements affect asset prices. Both models consider a setting where hedgers and speculators interact. The hedgers are more risk averse than the speculators whereas the speculators are capital constrained in the sense that they are restricted in their ability to deploy capital in the market to fund their activities. Given that the hedgers are assumed to be less capital constrained, both models show that the behavior of the capital-constrained speculators determines the price impact of the margin changes. This is because the margin requirements restrict the positions to be taken by the capital-constrained speculators and therefore their changes will affect them.

Gârleanu and Pedersen (2011) develop a Margin-CAPM model which predicts that an increase in the margin decreases (increases) the asset prices in the case where the speculators are net long (short) in aggregate. The intuition is that margin increases make the speculators' capital-constraints binding. Hence, the securities that suffer from margin hikes are riskier; they can not be easily funded due to speculators' capital constraints, their demand and, in turn, their prices drop. In addition, the speculators who already hold long positions in the capital-intensive securities may decide to close them, thus driving further down their prices (see also Brunnermeier and Pedersen, 2009). Similarly, Acharya et al. (2011) build partial equilibrium model of commodity markets in the presence of capital constrained speculators and they reach qualitatively similar conclusions regarding the effect of margin changes on futures prices. In their model, the capital-constrained speculators satisfy the hedging demand expressed by commodity producers. For the speculators to be enticed to take the respective long (short) positions in the futures market in order to meet this hedging demand, the futures price has to decrease (increase) as the margin requirements increase (see their Proposition 1, page 10).

Interestingly, both models accept that if the capital constraints are not binding (e.g., the speculators capital is high enough), then the margin changes will not affect the asset prices. Hedegaard (2011) examines the effect of margin changes for a group of 16 futures contracts. He finds that margin changes do not affect the futures prices and he concludes that the capital constraints may not be binding for commodity futures traders.

4.2.2. Effect of margin changes on the risk transfer mechanism

It is not clear à priori whether the margin requirements impose significant costs on the futures traders, and hence whether they affect their trading activity. In the case they do, they could undermine the risk transfer mechanism of the futures markets. On the one hand, Black (1976) and Anderson (1981) argue that the futures margin requirements are costless and the margin changes do not affect the behaviour of traders. This is because the margins in futures markets are relatively low, the amount can be posted in T-bills, and the investor earns interest on the deposited margin. On the other hand, Telser (1981) argues that margins impose significant costs on futures traders. These costs can be viewed either as opportunity costs because the deposited margin amount is no longer available for other purposes or as transaction costs because traders are forced to reallocate their financial resources in the case of margin changes. A number of theoretical studies show that there is a negative relationship between the margin requirements and the number of contracts demanded by the individual traders (Fishe and Goldberg, 1986, Hartzmark, 1986, Adrangi and Chatrath, 1999).

There is a number of papers that provide unanimous empirical evidence that margin changes affect the trading activity, and hence implying that they impose significant costs on traders. In particular, the literature documents an inverse relationship between the margin changes and open interest (Fishe and Goldberg, 1986, Hartzmark, 1986, Ma et al., 1993, Hardouvelis and Kim, 1995, Adrangi and Chatrath, 1999, Chatrath et al., 2001, Hedegaard, 2011). On the other hand, there is scarce empirical evidence on the impact of margin changes on the trading activity associated with the positions of different types of investors in the futures markets. Hartzmark (1986) examines wheat, pork bellies, feedercattle and U.S. Treasury bond markets, over the period July 1977-December 1981. He finds significant effects on the composition (i.e. the relative proportions) of the traders (hedgers and speculators) in the market in the case of margin changes. Kalavathi and Shanker (1991) find that increases in margin requirements lower the hedgers' positions in the S&P 500 index futures and thus reduce the hedging effectiveness of the futures contracts over the period 1982-1988. In the commodity futures markets, Adrangi and Chatrath (1999) and Chatrath et al. (2001) find that the margin changes are negatively associated with the positions held by all trader groups (speculators, hedgers, and small traders), with the hedgers being less affected than the rest of traders. However, their analysis is limited to a small number of commodity futures contracts (corn, soybean, gold and silver, from January 1986 to March 1995) and it is conducted by estimating time series regression models with bimonthly observations, i.e. they do not focus on margin changes events. In addition, they do not discuss whether margin changes affect the risk sharing mechanism among hedgers and speculators.

4.2.3. Effect of margin changes on price stability

Regarding the effect of margin changes on price stability, the literature measures price stability by the exhibited volatility and it examines three alternative hypotheses (e.g., Fishe et al., 1990, Ma et al., 1993). The first hypothesis states that the increases in margins decrease volatility (i.e. increase price stability) because they drive out of the market the destabilizing speculators who increase the volatility. On the other hand, the second hypothesis argues that increases in margins increase volatility (i.e. decrease price stability) because they drive out of the market the speculators who provide liquidity (for a theoretical foundation of this argument, see Brunnermeier and Pedersen, 2009). The last hypothesis states that there is no relationship between changes in the margins and volatility because the two effects described in the first two hypotheses cancel out.

In the commodity futures markets, the prior empirical evidence regarding the margin effect on the volatility is mixed. Hartzmark (1986) and Fishe et al. (1990) do not find a consistent relationship between the margin changes and the volatility. Ma et al. (1993) examine the silver market and they find a strong negative impact of margin changes on volatility across various subperiods. On the other hand, Hardouvelis and Kim (1995, 1996) report a significant positive association between margins and volatility in metal futures. Adrangi and Chatrath (1999) and Chatrath et al. (2001) also report a high positive correlation coefficient between margin requirements and volatility. Interestingly, there is no previous study that examines the impact of margin changes on market liquidity using liquidity measures that are highly correlated with transaction costs.

4.3. The Dataset

We collect data on the maintenance margins for a representative cross-section of 20 individual commodity futures contracts. The employed contracts represent the five main commodity categories (energy, metals, grains, softs, and livestock) and provide a lengthy sample of margin changes that enable us to conduct our subsequent analysis. We obtain the data on margins from the individual exchanges where the employed commodity futures trade, namely the CME group and the ICE, as well as from the CFTC to fill in some of the years that the margin data are not directly available from the exchanges. We use the maintenance rather than the initial margins because the former are the same for hedgers and speculators and they are publicly-available for a greater number of contracts.

The sample is unbalanced, i.e. the starting date and the number of margin changes vary across commodities. In particular, the margin data cover the period 2000-2011 for livestock, 2003-2011 for grains and oilseeds, 2004-2011 for energy, copper and platinum contracts, 2008-2011 for gold and silver contracts, whereas the data on soft contracts start in mid 1990s.[4] The sample interval incorporates bull and bear regimes in commodity prices as well as the 2003-2008 commodity boom period and the recent 2007-2009 financial crisis.

Table 4.1 reports the first date of margin change, the average maintenance margin, the average number of days between margin changes, the total number of margin changes as well as the number of increases and decreases for each one individual futures contract as well as for the distinct commodity groups. In addition, we also report the average percentage increases and decreases. The dataset consists of 784 margin changes, of which 457 are increases and 327 are decreases. Margin changes do not occur on a regular basis (the average time between margin changes ranges from 38 to 156 days), yet the number of margin changes occurred is considered to be large enough compared to the frequency of margin changes in other markets. For instance, the Federal Reserve Board has changed the margin requirements in the stock markets only 23 times over the period 1934-1974, and margin requirements remain constant since 1974. We can also see that the average increase in margins ranges from 13.26% to 34.44% whereas the average decrease ranges from 11.90% to 27.48%, which indicates the magnitude of margin changes differ significantly among commodities. The margin changes on the energy sector seem to be of smaller size than other commodity groups, yet they occur more frequently.

We also obtain data on daily closing, opening, high and low futures prices for the individual commodity futures contracts from Bloomberg. To create continuous series of commodity futures daily returns, we hold the first nearby contract until the beginning of the delivery month and then we roll over our position to the contract with the following delivery month which then becomes the nearest-to-maturity contract. Notice that we compute daily futures returns using the successive daily prices of a contract for a given

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[4] The CME group provides data on energy (crude oil, heating oil, natural gas), copper and platinum contracts over the period 2009-2011. We obtain the margin data on these futures over 2004-2008 from the CFTC. In addition, we also obtain the data on gold and silver contracts for 2008 from the CFTC.

delivery date, i.e. we do not compute returns by using prices across contracts with different delivery dates. Hence, the returns reflect a strategy of closing the position in the near contract and opening a position in the second nearest contract at the beginning of the delivery month (see Chapter 3 and the references therein).

Finally, we use the data on the traders' positions as reported by the CFTC on a weekly basis. The Commitments of Traders (COT) reports provide a breakdown of the total open interest of all outstanding futures contracts for each distinct commodity futures contract into commercial (hedging) and non-commercial (speculative) positions.

4.4. The impact of margin changes on commodity futures markets

4.4.1. The Event Study Methodology

To assess the impact of margin changes on the variables of interest, we apply the event study methodology. We isolate the days where a margin change for each individual futures contract has occurred and we examine their impact on a number of features of the commodity futures market around these days. We consider a short and a long pre-event and post-event period. We examine the variables of interest over a pre-event period that consists of the last five (or twenty) trading days immediately before the margin change and a post-event period that consists of the five (or twenty) trading days immediately after the margin change. We investigate the impact of margin changes both on individual commodity futures contracts as well as on distinct groups including related contracts that belong to the same sector and share similar characteristics.

4.4.2. The margin effect on the commodity futures prices

First, we investigate whether the margin changes affect the prices and returns of commodity futures. According to the predictions of the models of Gârleanu and Pedersen (2011) and Acharya et al. (2011), we expect that in the case that the speculators are net long (short), there would be a negative (positive) relationship between the margin changes and the futures prices. Hence, first we examine the sign of the net speculative positions prior to the margin changes for each commodity futures contract and then formulate the respective hypothesis regarding the margin effect on futures returns. Let the net speculative positions $NSP_{i,t}$ for any commodity *i* at time *t* (just prior to the margin change) defined as the number of long speculators minus the number of short speculators divided by the total open interest in the respective commodity market, i.e.

$$NSP_{i,t} = \frac{Long\ SP_{i,t} - Short\, SP_{i,t}}{Total\, OI_{i,t}} \tag{4.1}$$

Table 4.2 presents the average NSP for each one of the assumed commodity futures contracts. We can see that, on average, the long speculative positions exceed the short ones prior to the margin change in almost all contracts. The only exceptions are the natural gas and the copper futures contracts. Hence, for the majority of individual futures contracts, the models of Gârleanu and Pedersen (2011) and Acharya et al. (2011) predict that the margin changes will have a negative effect on the commodity futures prices.

To assess the price impact of margin changes, we examine the effect both on the price level as well as on the price growth (i.e. the returns) for each commodity futures contract. To fix ideas, we run the following regressions:

$$\Delta Y_i = a_0 + a_1 \Delta \boldsymbol{ln} M_i + u_i \tag{4.2}$$

where $\Delta Y_i = \Delta \boldsymbol{ln} P_i$ or ΔR_i is the change in the average price level or the change in the average return, and $\Delta \boldsymbol{ln} M_i$ is the change in the average margin level before and after the margin change *i*. In particular, $\Delta \boldsymbol{ln} P_i \equiv \boldsymbol{ln} P_{A,i} - \boldsymbol{ln} P_{B,i}$, $P_{B,i}$ is the average price level before the margin change *i*, from business day -5 (or -20) to business day -1, $P_{A,i}$ is the average price level after the margin change *i*, from business day 0 to business day 5 (or 20), with day 0 being the day of the *i*th margin change for a given commodity futures contract; $\Delta R_i \equiv R_{A,i} - R_{B,i}$, $R_{B,i}$ is the geometric average daily futures return before the margin change *i*, from business day -5 (or -20) to business day -1, $R_{A,i}$ is the geometric average daily futures return after the margin change *i*, from business day 0 to business day 5 (or 20); $\Delta \boldsymbol{ln} M_i \equiv \boldsymbol{ln(} M_{A,i} / M_{B,i} \boldsymbol{)}$, $M_{B,i}$ is the average daily level of the maintenance margin before the margin change *i*, from business day -5 (or -20) to business day -1, $M_{A,i}$ is the average daily level of maintenance margin after the margin change *i*, from business day 0 to business day 5 (or 20).

Note that we calculate the average daily prices and returns by using the same expiry contracts in both the pre-event and post-event period to avoid incurring noise in our analysis due to the contracts rollover.[5] We estimate the regression models by ordinary least squares (OLS) first on the individual commodity futures contracts and then on each distinct commodity group. To this end, we assume that margin changes are independent over time for each individual contract and independent across contracts.

Table 4.3 reports the results in the case where we examine the price impact of margin changes. We assess the margin effect both on the price level as well as on the futures returns. Panels A and B report the results for the individual commodity futures contracts and for the distinct commodity groups, respectively. Overall, we can see that there is a positive (negative) association between margin changes and average futures prices (returns) in most cases. This evidence implies that margin increases decrease the rate at which futures prices increase. Livestock futures is the only exception where the margin effect on both futures prices and returns is negative. This evidence is more pronounced for the distinct commodity groups rather than the individual futures contracts and it is stronger over the longer rather than the shorter horizon.

Our results are in contrast to the predictions of the models of Gârleanu and Pedersen (2011) and Acharya et al. (2011) where margin increases lead to price drops. On the other hand, they are in line with the findings of Hedegaard (2011) that do not confirm the predictions of Gârleanu and Pedersen (2011) and Acharya et al. (2011) models either. He finds that changes in the maintenance margins do not affect the returns of 16 individual commodity futures contracts. His event study approach is structured differently than ours though. He investigates the impact of margin changes on the returns observed only on the first day after the margin change. Instead, we examine whether the difference in returns between the prior and post event periods can be attributed to the margin change. The choice of longer event periods is dictated by the fact that the effect of a margin

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[5] We derive qualitatively similar results when the margin change from day -1 to day 0 is employed as an independent variable in the regression model (4.2). We also derive qualitatively similar results, when the average figures are calculated using the shortest to maturity contract; this approach does not assume the same expiry contract during the pre and post event periods.

change on the asset price may not appear within a day but it may require a longer horizon for its action to take place.

4.4.3. The margin effect on the risk transfer mechanism of futures markets

In this section, we investigate whether margin changes affect the risk transfer mechanism of the commodity futures markets. We use the event study methodology to assess the differential impact of margin changes on the speculators and hedgers open interest, separately.

We employ data from the COT report compiled by the CFTC. First, we regress the change in the hedging open interest positions (HP) on the change in margins. In the case where we find that the hedgers positions are negatively affected by the margin changes, this would imply that an increase in the margin would make the hedgers exit the market. This would undermine the risk transferring role of futures markets. The fact that hedgers exit the market can be attributed to either that they can not afford the hedging costs or they can not find speculators to hedge their risk. To identify the explanation, we regress the change in the speculative open interest positions (SP) and the change in the ratio (SP/HP) positions on the change in margins, separately. For instance, assume that both speculative and hedging positions are negatively affected by the margin increases.[6] In this case, a negative (positive) effect on the (SP/HP) ratio would imply that the speculative positions are more (less) sensitive than the hedging positions. Evidence that the hedgers are more sensitive than the speculators indicates that the hedgers leave the market because they can not afford the hedging costs. On the other hand, evidence that the speculators are more sensitive indicates that the hedgers leave the market because they can not find speculators to hedge their risk. Interestingly, the models of Gârleanu and Pedersen (2011) and Acharya et al. (2011) assume that the speculators are more sensitive than hedgers to changes in margin requirements. To fix ideas, we estimate the following regression model:

$$\Delta \ln Pos_i = a_0 + a_1 \Delta \ln M_i + u_i, \qquad for\ \ Pos_i = HP_i, SP_i, SP_i / HP_i \qquad (4.3)$$

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[6] Unreported results confirm the well-documented by the previous literature negative relationship between margin changes and open interest for all commodity groups and for the majority of individual futures contracts. This is in line with the previously reviewed literature.

where $\Delta \boldsymbol{ln}\, Pos_i \equiv \boldsymbol{ln(}\, Pos_{A,i} \,/\, Pos_{B,i}\,\boldsymbol{)}$, $Pos_{B,i}$ is the average traders' positions before the margin change *i*, from business day -5 (or -20) to business day -1, $Pos_{A,i}$ is the average traders' positions after the margin change *i*, from business day 0 to business day 5 (or 20), with day 0 the day of the *i*th margin change for a given commodity futures contract. Note that the CFTC data are available on a weekly basis, recorded every Tuesday. This may not coincide with the date where a margin change occurs. To match the timing of a margin change with the corresponding change in traders' positions, we assign to each day falling in the interval from Tuesday to Monday the Tuesday value provided by the CFTC (for a similar approach with weekly data, see also Hardouvelis and Peristiani, 1992).

Table 4.4 reports the results from the regression described in equation (4.3) for the individual commodity futures returns and for the distinct commodity groups (panels A and B, respectively). Overall, we can see that the margin changes are negatively associated with the hedging positions in the grains and metals markets and have no association with the hedging positions in the other markets. This indicates that the margin increases impair the risk sharing function in the grains, a traditional hedging market, and metals markets. In these two markets, we can also see that there is a negative association of the margin changes with the speculative positions as well as with the SP/HP ratio. This indicates that the speculators are more sensitive to margin changes than hedgers. Therefore, the hedgers exit these two markets because they can not afford the increased costs as well as because they can not find a counterparty to share their price risk. The significance in results is mostly documented for the commodity groups rather than for the individual futures contracts.

The heterogeneity across individual contracts and groups regarding the margin effect on the hedging positions indicates that each futures contract/group should be examined individually by the regulatory agencies. In addition, these findings are consistent with the view that even though the margin changes may affect all trader groups, they would impose greater costs on speculators who are generally conceived as capital-constrained investors. The hedgers may also decrease their positions in response to margin increases but to a lesser extent because their motive to manage their risks dominates. Moreover, the hedgers are expected to be less capital-constrained investors than speculators; they are more risk averse and hence they are expected to hold more cash in their portfolios (Hardouvelis, 1990). Our results are consistent with the assumption of the theoretical models of Gârleanu and Pedersen (2011) and Acharya et al. (2011) that the speculators are more capital constrained than the hedgers and hence it is their trading activity that impacts asset prices. They are also in line with the findings of Adrangi and Chatrath (1999) and Chatrath et al. (2001).

4.4.4. The margin effect on the price stability

In this section, we investigate the effect of margin changes on the price stability of the commodity futures market. We use volatility as a measure of price stability (see e.g., Ma et al., 1993, Hardouvelis and Kim, 1995, 1996). We also examine the effect of margin changes on the market liquidity of the individual contracts. The recent literature and the 2007-2009 subprime credit crisis have revealed that market liquidity is an alternative way of signalling price stability because it is closely related with volatility (Brunnermeier and Pedersen, 2009, Huang and Wang, 2010).

A. The margin effect on the futures returns volatility

We regress the change in the average volatility on the change in the average margin requirement (Hardouvelis and Kim, 1995).

$$\Delta \mathbf{ln} Vol_i = a_0 + a_1 \Delta \mathbf{ln} M_i + u_i \tag{4.4}$$

where $\Delta \mathbf{ln} Vol_i \equiv \mathbf{ln(} Vol_{A,i} / Vol_{B,i} \mathbf{)}$, $Vol_{B,i}$ is the average daily returns volatility of commodity futures returns before the margin change *i*, from business day -5 (or -20) to business day -1, $Vol_{A,i}$ is the average daily returns volatility after the margin change *i*, from business day 0 to business day 5 (or 20), with day 0 the day of the ith margin change for a given commodity futures contract.

We measure the daily futures returns volatility by using three alternative volatility estimators to ensure the robustness of the obtained results. First, we employ two traditional variance measures that combine high, low, opening, and closing prices, namely the Garman and Klass (1980) and Rogers and Satchell (1991) estimators, $V_{GK,t}$ and $V_{RS,t}$, respectively. Both estimators are based on the assumption that the asset prices follow a Geometric Brownian Motion. They differ in that the Garman-Klass (GK) estimator assumes zero drift, whereas the Rogers-Satchell (RS) derive an estimator that does not depend on the assumption regarding the drift. Let O_t, C_t, H_t, and L_t denote the opening, closing, high, and low futures prices at day t, respectively.

$$V_{GK,t} = 0.5\left(\ln H_t - \ln L_t\right)^2 - \left(2\ln 2 - 1\right)\left(\ln C_t - \ln O_t\right)^2 \tag{4.5}$$

$$V_{RS,t} = \left(\ln H_t - \ln O_t\right)\left(\ln H_t - \ln C_t\right) + \left(\ln L_t - \ln O_t\right)\left(\ln L_t - \ln C_t\right) \tag{4.6}$$

In addition, we use the log range, defined as the difference between the asset's highest and lowest log prices at day t, i.e.

$$V_{R,t} = \left(\ln H_t - \ln L_t\right) \tag{4.7}$$

Alizadeah et al. (2002) propose the log range as a superior volatility proxy since it is indicative of the intraday price fluctuations. In addition, they argue against the inclusion of the opening and closing prices on the grounds that these prices are highly influenced by microstructure effects (see also Brown, 1990).

Table 4.5 reports the results from the regression in equation (4.4) for the individual commodity futures returns and for the distinct commodity groups (panels A and B, respectively). In the case of the individual commodity futures contracts, we observe a positive association between the margin changes and changes in volatility in more than half of the cases, mostly over the long event window; over the short event window, the reported results are not statistically significant in almost all cases. This implies that the margin changes for most commodity futures coincide with changes of similar direction in volatility over longer intervals of time. In the case of the grouped commodities, again we find a positive association between margin changes and volatility, especially when the long horizon is considered.

The evidence on the margin effect on volatility is in line with the findings of Hardouvelis and Kim (1995) in the metal futures market. This could be attributed to the fact that an increase in the margin drives the liquidity-providers speculators out of the market, thus causing an increase in the volatility of the futures contract. We shed further light on this issue by analyzing the margin effect on the futures contracts' liquidity in the next subsection.

B. The margin effect on the futures liquidity

We examine the effect of margin changes on the liquidity of the market. To this end, we use the Amihud's (2002) commonly used liquidity measure. Marshall et al. (2011) conduct a horse race among various liquidity proxies by focusing on the commodity futures markets. They conclude that the Amihud ratio has the largest correlation with high-frequency liquidity measures that represent actual commodity transaction costs. The Amihud illiquidity measure $ILL_{j,t}$ at day t of a given commodity j is defined as follows:

$$ILL_{j,t} = \frac{\left| r_{j,t} \right|}{DolVol_{j,t}} \tag{4.8}$$

where $r_{i,t}$ is the daily return of the commodity j on day t, $\left| \, . \, \right|$ denotes the absolute value; $DolVol_{j,t}$ is the dollar volume for commodity j on day t, i.e. the closing price on day t multiplied by the number of futures contracts traded during that date. The Amihud ratio gives the absolute (percentage) price change per dollar of daily trading volume; the greater the Amihud ratio, the greater the response of returns will be and hence the more illiquid the futures contract is considered to be.

To assess the impact of margin changes on contract's liquidity, we examine the change in the individual contract's illiquidity measure over two intervals, before and after the margin change. To this end, we regress the change in the average illiquidity on the change in the average margin requirement:

$$\Delta \mathbf{ln}\, ILL_i = a_0 + a_1 \Delta \mathbf{ln}\, M_i + u_i \tag{4.9}$$

where $\Delta \mathbf{ln}\, ILL_i \equiv \mathbf{ln}\left(ILL_{A,i} \,/\, ILL_{B,i} \right)$, $ILL_{B,i}$ is the average illiquidity before the margin change i, from business day -5 (or -20) to business day -1, $ILL_{A,i}$ is the average illiquidity after the margin change i, from business day 0 to business day 5 (or 20), with day 0 the day of the ith margin change for a given commodity futures contract.

Table 4.6 reports the results from the regression described in equation (4.9) for the individual commodity futures returns and for the distinct commodity groups (panels A and B, respectively). Overall, we can see that the margin changes do not affect the liquidity of the futures contracts in almost all cases. This holds both for the individual contracts as well as for the distinct commodity groups, regardless of the employed size of the event window. The evidence that increases in margins do not affect liquidity in conjunction with the previous finding that a change in margins negatively affects the speculative positions (Section 4.4.3), implies that the more sensitive speculative forces do not offer liquidity. Therefore, they can be considered as *excessive* speculation, i.e. in excess of the speculation needed to provide market liquidity. Hence, an increase in margins decreases the excessive speculation.

Our findings from the liquidity and volatility analysis suggest that the positive relation between the volatility and the margin changes can not be attributed to the changes in the market liquidity. A possible explanation for our finding may lie in the decision rules that the futures exchanges follow; exchanges raise (decrease) margins in anticipation of higher (lower) volatility for individual futures contracts. Therefore, the exchanges increase the margins of those contracts that are expected to show an increase in future volatility (for a similar explanation see Hardouvelis and Kim, 1995).

4.5. Cross-margin effects

In this section, we examine whether the margin changes for an individual futures contract affect the rest of the contracts that belong to the same commodity group (cross-margin effect). For each target contract and each margin change *i*, we create a benchmark set that includes the contracts that belong in the same commodity group and do not undergo a margin change during the event period (-20,20) of the *i*th margin change of the target contract (see Hardouvelis and Kim, 1995, for the concept of the benchmark groups). Then, we assess the impact of the margin changes for the target contract on the benchmark group. To this end, we estimate again the regression equations (4.2)-(4.4) and (4.9) where the independent variable is the margin changes for the target contract and the dependent variables are the previously examined characteristics of the benchmark group around these changes.

Table 4.7 reports the results when the effect of margin changes for the target contract on other related contracts is examined. We evaluate the change on the benchmark groups' prices (panel A), returns (panel B), hedging positions (panel C), speculative positions (panel D), volatility (panel E), and liquidity (panel F). Due to space limitations, the results are reported only for the long event window. We can see that cross-margin effects appear only in some cases. However, their magnitude and sign depend on the commodity group under scrutiny. This implies that the policymakers should take into account that margin changes in a futures contract may affect other related contracts as well as that the direction of the effect varies across groups.

In particular, we can see that a margin change in the target contract does not affect the prices and returns of the contracts that belong in the same group in most of the cases. The effect on the hedging positions depends on the commodity contract under scrutiny. In the case of softs, the change in margin for half of the target contracts coincides with positive changes in the hedging positions of other related contracts, indicating that the hedgers turn to other softs contracts when faced a margin increase. On the other hand, in the case of metals, the respective negative relationship for half of the contracts indicates that when the margin on the target contract increases, the hedgers leave the metals market completely. For the other target contracts, the changes in the margins have no effect on the hedging positions of the related futures. Regarding the effect on the speculative positions, changes in the margin of the target contract are negatively associated with the speculative positions for half of the target contracts that belong in grains, livestock and metal markets; for the other groups the results are insignificant. This finding, in conjunction with the finding in Section 4.4.3, implies that a margin increase for these target contracts decreases both the speculative positions for the target contract as well as for contracts that belong to the same group. Finally, we can see that, in most cases, the margin changes of the target contracts have no effect on the volatility and the liquidity of the other related contracts.

4.6. Robustness tests

We perform further tests to assess the robustness of the results reported in the previous sections. First, we classify the margin changes into positive and negative changes, and analyze their effect separately. Second, we differentiate the impact of large and small margin changes on the various dependent variables. Third, we examine the price impact of margin changes during the recent 2007-2009 liquidity crisis. Fourth, we revisit the margin effect on volatility by examining whether the results reported in Section 4.4.4 may be attributed to volatility persistence. In the first three cases, we conduct the analysis only for the distinct commodity groups due to the limited number of observations for the individual commodity futures that come up due to the distinction in categories of the margin changes.

4.6.1. The impact of positive and negative margin changes

We repeat the event study analysis described in the previous sections by examining separately the impact of margin increases and decreases on the corresponding values of the dependent variables. This differentiation will allow us to understand the impact of margin increases. This is of importance for regulatory purposes because the policy circles argue in favour of imposing higher margin requirements on commodity futures.

Table 4.8 reports the results for the distinct commodity groups. We assess the effect of positive and negative margin changes separately on futures prices (panel A), futures returns (panel B), hedging positions (panel C), speculative positions (panel D), speculative/hedging positions (panel E), volatility (panel F), and liquidity (panel G). Overall, we can see that there is an asymmetric reaction of each dependent variable to positive and negative margin changes; for most groups and market variables, the effect of margin increases is statistically significant whereas there is no effect caused by margin decreases. The direction of the effect of the margin increases on most dependent variable is the same with the one described in Sections 4.4.2-4.4.4, i.e. a margin increase coincides with increases (decreases) in futures prices (returns), decreases in the hedging positions (only for grains and metals) and the speculative positions with the speculative positions being more sensitive than the hedging ones, and increases in volatility. The results confirm the evidence reported over the full sample of margin changes that the risk sharing function of grains and metals futures markets is impaired when faced a margin increase.

On the other hand, the margin increases decrease the liquidity (only) in the case of softs and energy markets; for the other groups, there is no effect on the liquidity both for positive and negative margin changes. This implies that any margin increase in these markets could harm their liquidity, i.e. the liquidity-providers speculators leave the market when faced a margin change that restricts their trading activities. This is in contrast to the findings reported in Section 4.4.4 where we document that the margin changes do not affect the liquidity of each one of the distinct commodity groups. This indicates that examining the full sample of margin changes masks the asymmetric margin effect on market liquidity.

4.6.2. The impact of large and small margin changes

In this section, we partition the margin sample for each commodity group into two groups of large and small margin changes and assess separately their impact on the various dependent variables. The motivation for undertaking this analysis is to examine whether the results reported in the previous sections are sensitive to the magnitude of margin changes (for a similar approach see also Hardouvelis and Kim, 1995, Hedegaard, 2011). This is important for regulatory purposes because it will help deciding whether a large or small margin change should be imposed.

First, for each commodity group, we rank the margin changes across all futures contracts in the group based on their absolute changes and calculate their average value. Then, we classify the set of changes above the average in the large margin changes group and the set of changes below the average in the small margin changes group. Next, we assess the impact of large and small margin changes on the corresponding values of each dependent variable, separately.[7] Table 4.9 reports the results. We assess the effect of large and small margin changes separately on futures prices (panel A), futures returns (panel B), hedging positions (panel C), speculative positions (panel D), speculative/hedging positions (panel E), volatility (panel F), and liquidity (panel G). Overall, we can see that there is an asymmetric reaction of the dependent variables to large and small margin changes. For most groups and dependent variables, the effect of large margin changes is statistically significant whereas there is no significant effect caused by the small margin changes. The direction of the effect of large margin changes on every dependent variable is the same one obtained over the full sample of margin changes. Again the risk sharing function of grains and metal markets is impaired when faced large margin changes.

On the other hand, the large margin changes decrease the liquidity in the case of grains, softs and energy markets; for the other two groups, there is no effect on the liquidity both for large and small margin changes. This evidence implies that speculators

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[7] Qualitatively similar results are also derived when the two groups, large and small, are formed based on the median.

who provide liquidity in these markets decrease their positions when faced a large margin change. This is in contrast to the results reported in Section 4.4.4 where the margin changes do not affect the liquidity of the futures contracts. This indicates again that examining the full sample of margin changes masks the asymmetric effect of small and large changes on the market liquidity just as was the case with the effect of positive and negative margin changes. The margin effect depends on the magnitude of the changes; the commodity markets are more sensitive to large changes and so does the liquidity for some groups.

4.6.3. The 2007-2009 liquidity crisis and the price impact of margin changes

The results reported in Section 4.4.2 do not confirm the predictions of Gârleanu and Pedersen (2011) and Acharya et al. (2011) with regard to the effect of the margin changes on futures prices. A possible explanation for these findings may be that the margin increases may not make binding the capital-constraints of the speculators over the full sample period. It may well be the case that, in most examined cases, the speculators' capital is abundant so that there is no risk of breaching the capital constraints. We investigate this further being motivated by Brunnermeier and Pedersen's (2009) and Gârleanu and Pedersen's (2011) arguments that the paramount role of funding (i.e. margin) constraints becomes particularly salient during liquidity crisis periods compared to calmer periods.

In particular, we conduct a sub-sample analysis and examine the impact of margin changes on prices and returns during the recent liquidity crisis period (2007-2009). Table 4.10 reports the results. We can see that the positive association between margin changes and prices, previously reported for all groups but livestock over the full sample, holds now only for energy and metal futures; the other two groups (grains and softs) present insignificant results. However, the effect on the futures returns remains negative just as was over the full sample period, i.e. the margin increases coincide with negative changes in futures returns. The livestock futures is again the only exception where the margin increases coincide with decreases in prices. The results indicate that the predictions of the theoretical models can not be verified even during the liquidity crisis period where the speculators' capital constraints are expected to be binding.

4.6.4. The margin effect on the futures returns unexpected volatility

It is well-documented that the volatility of financial asset returns persists; high-volatility periods are apt to be followed by high-volatility periods, and similarly for low-volatility periods (see Ng and Pirrong, 1994, Pindyck, 2004, Chen et al., 2006, for evidence on the commodity futures returns). In this section, we estimate the shocks in volatility and examine the impact of margin changes on these quantities so as to check whether the previously documented positive relationship between changes in margins and volatility may be attributed to volatility persistence.

In line with Ang et al., 2006, for each individual futures contract and each margin change *i*, we fit an AR(1) model to the futures volatility series over the period (-20,20) and extract the residuals (volatility shocks). We estimate the volatility shocks for each one of the three volatility measures described in Section 4.4.4. Next, we regress the change in the average volatility shocks on the change in the average margin requirements (see equation (4.4)).

Table 4.11 reports the results. Panels A and B report the results for the individual commodity futures and the distinct commodity groups, respectively. The results remain qualitatively similar as those reported in Section 4.4.4, i.e. increases in margins coincide with increases in (unexpected) volatility. In the case of the individual commodity futures contracts, over the long event window, we observe a significant positive association between the margin changes and changes in volatility in more than half of the cases. This implies that the margin changes coincide with changes of similar direction in volatility, for most commodity futures over longer horizons. In the case of the grouped commodities analysis, the positive relationship is documented for all commodity groups, again only over the longer event window.

4.7. Conclusions

The recent commodity boom and the Dodd-Frank reform have revived the debate about whether the margin requirements should be regulated in the commodity futures markets. We contribute to this discussion and we investigate the impact of margin changes on the commodity futures prices/returns, the risk sharing mechanism, and the price stability of the commodity futures market. In light of the recent advances in the academic literature and the 2007-2009 liquidity crisis, we assess the price stability by using both the traditional volatility measure as well as the market liquidity measure. In addition, we also examine whether margin changes in one market affect the characteristics of all other futures markets that belong to the same commodity group (cross-margin effects). The effect of margin changes on these features is of interest to the regulator.

We find that changes in the margin requirements coincide with positive (negative) changes in prices (returns). Moreover, we find that the margin effect on the hedgers open interest is either negative (grains and metals) or insignificant (other commodity groups). In the former case, the margin impact on the speculators open interest is also negative and greater than that of the hedgers ones in all commodity markets. We also report a positive association between margin changes and volatility, whereas the market liquidity of the individual contracts/groups is not affected by margin changes. In the case where we examine the margin impact of positive and large margin changes separately, we find that the market liquidity in some markets (grains, softs and energy) decreases. Finally, we document cross-margin effects in a few cases.

Our findings have a number of implications for academics, market participants, and policy makers. The regulation of the margin requirements in the commodity futures markets has pros and cons. On the one hand, an increase in margins can help decreasing the rate at which commodity prices increase. This property of the margins is of particular importance over periods where the commodity prices rise. However, the margin increases harm the risk sharing function and the market liquidity in certain markets.[8] In addition, our results have implications for the effect of margin regulation on excessive speculation. The fact that we find that margin increases decrease the speculators' positions in the livestock and metals markets, yet they do not affect their market liquidity, implies that regulating the margins in these markets constrains excessive speculation. Finally, the policymakers should also take into account that the effect of margin changes varies across commodity groups and the margin effect on each one of them should be examined separately. Interestingly, changes in the margins of one commodity future may affect other related commodity futures that belong in the same commodity group.

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[8] This evidence is in line with the opinion expressed by Alan Greenspan, former Chairman of the Federal Reserve, during a Fed Policy Meeting in September 1996: "*I guarantee you that if you want to get rid of the bubble, whatever it is, that [raising margin requirements] will do it. My concern is that I am not sure what else it will do*."

Table 4.1. Commodity futures contracts and margin changes

The table describes the commodity futures contracts employed in this study and provides information regarding the margin changes for each one individual futures contract as well as for the distinct commodity groups. In particular, entries report for each individual futures contract the first date of margin change, the average maintenance margin, the average number of days between margin changes, the total number of margin changes as well as separately the number of increases and decreases. In addition, the average percentage increases and decreases are also reported.

Futures Contract	Exchange	Inception date	Average % Maint.Margin	Average # of days btw changes	Frequency of margin changes			Average margin change in %	
					Increases	Decreases	Total	Increases	Decreases
Grains & Oilseeds									
Corn	Chicago Board of Trade/ CME Group	24/11/2003	4.69%	69	25	16	41	21.27%	-17.88%
Wheat	Chicago Board of Trade/ CME Group	24/11/2003	5.60%	73	25	15	40	21.84%	-20.53%
Soybeans	Chicago Board of Trade/ CME Group	24/11/2003	4.48%	71	23	18	41	19.46%	-15.31%
Soybean Meal	Chicago Board of Trade/ CME Group	24/11/2003	4.79%	91	21	15	36	22.65%	-20.68%
Soybean Oil	Chicago Board of Trade/ CME Group	24/11/2003	3.80%	99	17	12	29	21.75%	-19.48%
Oats	Chicago Board of Trade/ CME Group	24/11/2003	5.24%	110	14	10	24	27.99%	-21.09%
			4.77%	86	125	86	211	22.49%	-19.16%
Softs									
Cocoa	New York Board of Trade/ ICE Futures US	14/1/1998	5.57%	120	24	18	42	25.89%	-23.11%
Coffee	New York Board of Trade/ ICE Futures US	18/12/1996	6.27%	68	44	34	78	24.34%	-20.10%
Cotton	New York Board of Trade/ ICE Futures US	3/1/1995	6.76%	104	37	23	60	34.44%	-27.48%
Sugar	New York Board of Trade/ ICE Futures US	1/5/1997	6.43%	117	29	16	45	26.22%	-19.93%
			6.26%	102	134	91	225	27.72%	-22.65%
Livestock									
Live Cattle	Chicago Mercantile Exchange/CME group	1/1/2000	2.34%	98	25	18	43	19.74%	-17.23%
Lean Hogs	Chicago Mercantile Exchange/CME group	1/1/2000	3.41%	156	14	13	27	16.71%	-11.90%
Feeder Cattle	Chicago Mercantile Exchange/CME group	1/1/2000	2.03%	89	25	22	47	24.14%	-17.01%
			2.59%	114	64	53	117	20.20%	-15.38%
Energy									
Crude Oil	New York Mercantile Exchange/CME Group	1/9/2004	6.30%	85	18	14	32	15.01%	-13.29%
Heating Oil	New York Mercantile Exchange/CME Group	1/9/2004	6.26%	59	25	21	46	14.62%	-12.92%
Natural Gas	New York Mercantile Exchange/CME Group	1/9/2004	9.29%	38	35	35	70	17.62%	-15.07%
			7.28%	61	78	70	148	15.75%	-13.76%
Metals									
Gold	Commodity Exchange, Inc./CME group	7/9/2008	4.00%	93	8	5	13	29.58%	-14.09%
Silver	Commodity Exchange, Inc./CME group	7/9/2008	7.46%	56	17	4	21	13.26%	-17.22%
Copper	Commodity Exchange, Inc./CME group	1/9/2004	6.46%	83	18	9	27	16.13%	-15.91%
Platinum	New York Mercantile Exchange/CME Group	1/9/2004	5.58%	94	13	9	22	26.34%	-21.31%
			5.88%	82	56	27	83	21.33%	-17.13%

Table 4.2. Net Speculative Positions around margin changes

Entries report the average net speculative positions for each commodity futures contract, as well as its standard deviation prior to the margin changes, based on weekly observations from the Commitment of Traders Report. The Net Speculative Positions, $NSP_{i,t}$, for any commodity *i* at time *t* is defined as the number of long speculators minus the number of short speculators divided by the total open interest in the respective commodity market, i.e.

$$NSP_{i,t} = \frac{Long\ SP_{i,t} - Short\ SP_{i,t}}{Total\ OI_{i,t}}$$

Futures Contract	Mean	Standard deviation
Wheat	0.0038	0.0807
Corn	0.1349	0.1265
Oats	0.2070	0.1719
Soybean	0.1382	0.1548
Soybean Oil	0.1073	0.1336
Soybean Meal	0.1055	0.1284
Cotton	0.1078	0.1980
Coffee	0.1276	0.1447
Cocoa	0.0789	0.1527
Sugar	0.1590	0.1033
Livecattle	0.1299	0.1099
Feedercattle	0.1235	0.1507
Leanhogs	0.1007	0.1456
Crude oil	0.0495	0.0469
Heating oil	0.0556	0.0514
Natural gas	-0.0678	0.0814
Gold	0.3625	0.0846
Silver	0.2303	0.0501
Copper	-0.0213	0.1147
Platinum	0.4855	0.1226

Table 4.3. Margin requirements and commodity futures prices/returns

Entries report the results when the price impact of margin changes is examined. First, we consider the effect on the commodiy futures prices and estimate the following regression model: $\Delta \boldsymbol{ln} P_i = a_0 + a_1 \Delta \boldsymbol{ln} M_i + u_i$,where $\Delta \boldsymbol{ln} P_i \equiv P_{A,i} - P_{B,i}$ $P_{B,i}$ $\left(P_{A,i}\right)$ is the average price level in the pre (post)-event period, $\Delta \boldsymbol{ln} M_i \equiv \boldsymbol{ln(} M_{A,i} / M_{B,i} \boldsymbol{)}$, $M_{B,i}$ $\left(M_{A,i}\right)$ is the average daily level of margin in the pre (post)-event period. Second, we consider the effect of margin changes on the commodity futures returns and estimate the following regression model: $\Delta R_i = a_0 + a_1 \Delta \boldsymbol{ln} M_i + u_i$ where $\Delta R_i \equiv R_{A,i} - R_{B,i}$, $R_{B,i}$ $\left(R_{A,i}\right)$ is the average geometric daily return in the pre-event (post-event) period. The coefficient estimates α_1 and the respective *t*-statistics in parentheses are reported for the individual commodity futures returns and for the distinct commodity groups (panels A and B, respectively). A pre-event and post-event period of five and twenty days is used.

Panel A: Individual Commodity Futures Contracts

	Regression model: $\Delta lnP_i = \alpha_0 + \alpha_1 \Delta lnM_i + u_i$		**Regression model: $\Delta R_i = \alpha_0 + \alpha_1 \Delta lnM_i + u_i$**	
	5-day horizon	*20-day horizon*	*5-day horizon*	*20-day horizon*
Corn	0.086	0.223	-0.001	0.001
	(2.665)	*(5.314)*	*(-0.147)*	*(0.173)*
Wheat	0.017	0.102	-0.033	-0.011
	(0.610)	*(2.655)*	*(-4.659)*	*(-4.035)*
Oats	-0.007	-0.024	-0.014	-0.015
	(-0.192)	*(-0.521)*	*(-1.057)*	*(-3.116)*
Soybeans	0.014	0.019	0.000	-0.002
	(0.498)	*(0.442)*	*(0.009)*	*(-0.577)*
Soybean Meal	0.037	0.056	0.009	-0.001
	(1.322)	*(1.429)*	*(1.060)*	*(-0.383)*
Soybean Oil	0.022	0.125	-0.020	-0.004
	(0.758)	*(2.914)*	*(-1.751)*	*(-0.608)*
Cocoa	-0.037	-0.022	0.008	-0.005
	(-1.315)	*(-0.516)*	*(0.819)*	*(-1.314)*
Coffee	0.024	0.119	-0.033	-0.021
	(1.125)	*(3.014)*	*(-4.044)*	*(-6.022)*
Cotton	0.014	0.071	-0.009	-0.005
	(1.119)	*(3.412)*	*(-2.183)*	*(-2.493)*
Sugar	-0.057	0.037	-0.009	-0.011
	(-1.516)	*(0.629)*	*(-0.930)*	*(-2.996)*
Live Cattle	-0.033	-0.003	-0.017	-0.002
	(-1.634)	*(-0.115)*	*(-4.315)*	*(-2.038)*
Lean Hogs	0.005	-0.093	0.001	0.000
	(0.146)	*(-1.472)*	*(0.089)*	*(-0.049)*
Feeder Cattle	-0.043	-0.044	-0.003	0.001
	(-2.990)	*(-2.477)*	*(-0.944)*	*(0.456)*
Crude Oil	0.081	0.243	-0.024	-0.013
	(1.525)	*(3.259)*	*(-1.870)*	*(-2.445)*
Heating Oil	0.087	0.248	-0.027	-0.011
	(2.284)	*(3.989)*	*(-2.096)*	*(-2.222)*
Natural Gas	0.158	0.391	-0.032	-0.007
	(4.035)	*(7.270)*	*(-3.204)*	*(-1.860)*
Gold	0.082	0.031	-0.008	-0.012
	(1.497)	*(0.528)*	*(-0.660)*	*(-3.214)*
Silver	-0.212	-0.203	-0.027	-0.026
	(-1.869)	*(-2.044)*	*(-0.762)*	*(-2.908)*
Copper	0.089	0.238	-0.011	-0.004
	(1.888)	*(3.305)*	*(-0.726)*	*(-0.577)*
Platinum	0.021	0.163	-0.008	-0.008
	(0.592)	*(3.076)*	*(-0.919)*	*(-1.655)*

Table 4.3. Margin requirements and commodity futures prices/ returns (cont'd)

Entries report the results when the price impact of margin changes is examined. First, we consider the effect on the commodiy futures prices and estimate the following regression model: $\Delta \boldsymbol{ln} P_i = a_0 + a_1 \Delta \boldsymbol{ln} M_i + u_i$,where $\Delta \boldsymbol{ln} P_i \equiv P_{A,i} - P_{B,i}$ $P_{B,i}$ $\left(P_{A,i}\right)$ is the average price level in the pre (post)-event period, $\Delta \boldsymbol{ln} M_i \equiv \boldsymbol{ln(} M_{A,i} / M_{B,i} \boldsymbol{)}$, $M_{B,i}$ $\left(M_{A,i}\right)$ is the average daily level of margin in the pre (post)-event period. Second, we consider the effect of margin changes on the commodity futures returns and estimate the following regression model: $\Delta R_i = a_0 + a_1 \Delta \boldsymbol{ln} M_i + u_i$ where $\Delta R_i \equiv R_{A,i} - R_{B,i}$, $R_{B,i}$ $\left(R_{A,i}\right)$ is the average geometric daily return in the pre (post)- event period. The coefficient estimates α_1 and the respective *t*-statistics in parentheses are reported for the individual commodity futures returns and for the distinct commodity groups (panels A and B, respectively). A pre-event and post-event period of five and twenty days is used.

Panel B: Distinct Commodity Futures Groups

	Regression model: $\Delta lnP_i=\alpha_0+\alpha_1\Delta lnM_i+u_i$		**Regression model: $\Delta R_i=\alpha_0+\alpha_1\Delta lnM_i+u_i$**	
	5-day horizon	***20-day horizon***	***5-day horizon***	***20-day horizon***
Grains Futures	0.032 *(2.547)*	0.091 *(5.164)*	-0.012 *(-3.111)*	-0.007 *(-4.251)*
Soft Futures	-0.001 *(-0.100)*	0.066 *(3.628)*	-0.012 *(-3.269)*	-0.010 *(-6.204)*
Livestock Futures	-0.035 *(-3.170)*	-0.023 *(-1.452)*	-0.010 *(-3.513)*	-0.001 *(-0.764)*
Energy Futures	0.129 *(4.621)*	0.342 *(7.954)*	-0.029 *(-4.379)*	-0.009 *(-3.293)*
Metal Futures	0.007 *(0.215)*	0.104 *(2.484)*	-0.011 *(-1.215)*	-0.010 *(-3.152)*

Table 4.4. Margin requirements and the effect on different traders positions

Entries report the results from the following regression model: $\Delta \boldsymbol{ln} Pos_i = a_0 + a_1 \Delta \boldsymbol{ln} M_i + u_i$ where $\Delta \boldsymbol{ln} M_i \equiv \boldsymbol{ln(} M_{A,i} \,/\, M_{B,i} \boldsymbol{)}$, $M_{B,i}$ $\left(M_{A,i}\right)$ is the average daily level of margin in the pre-event (post-event) period , $\Delta \boldsymbol{ln} Pos_i \equiv \boldsymbol{ln(} Pos_{A,i} \,/\, Pos_{B,i} \boldsymbol{)}$, $Pos_{B,i}$ $\left(Pos_{A,i}\right)$ is the average positions in the pre-event (post – event) period. We consider the change in hedging positions (HP), speculative positions(SP) and the ratio (SP/HP). The coefficient estimates α_1 and the respective *t*-statistics in parentheses are reported for the individual commodity futures and for the distinct commodity groups (panels A and B, respectively). A pre-event and post-event period of five and twenty days is used.

Panel A: Individual Commodity Futures Contracts

	$\Delta lnHP_i=\alpha_0+\alpha_1\Delta lnM_i+u_i$		$\Delta lnSP_i=\alpha_0+\alpha_1\Delta lnM_i+u_i$		$\Delta ln(SP_i/HP_i)=\alpha_0+\alpha_1\Delta lnM_i+u_i$	
	5day horizon	***20day horizon***	***5day horizon***	***20day horizon***	***5day horizon***	***20day horizon***
Corn	0.005	0.032	-0.034	-0.101	-0.039	-0.132
	(0.264)	*(0.902)*	*(-1.381)*	*(-2.319)*	*(-1.403)*	*(-2.525)*
Wheat	0.002	0.013	0.016	0.044	0.013	0.029
	(0.087)	*(0.427)*	*(0.419)*	*(0.933)*	*(0.466)*	*(0.900)*
Oats	-0.110	-0.164	-0.174	-0.342	-0.062	-0.161
	(-1.636)	*(-1.456)*	*(-1.962)*	*(-2.295)*	*(-0.633)*	*(-1.500)*
Soybeans	-0.038	-0.100	-0.048	-0.173	-0.011	-0.076
	(-1.177)	*(-1.951)*	*(-0.771)*	*(-2.653)*	*(-0.227)*	*(-1.385)*
Soybean Meal	-0.013	-0.067	-0.176	-0.382	-0.162	-0.314
	(-0.491)	*(-1.862)*	*(-2.579)*	*(-3.871)*	*(-2.800)*	*(-3.513)*
Soybean Oil	-0.044	-0.085	-0.052	-0.268	-0.011	-0.182
	(-1.706)	*(-1.886)*	*(-0.649)*	*(-2.444)*	*(-0.137)*	*(-1.713)*
Cocoa	0.011	-0.047	-0.190	-0.372	-0.685	-0.623
	(0.167)	*(-1.347)*	*(-3.121)*	*(-4.219)*	*(-0.679)*	*(-0.762)*
Coffee	0.044	0.058	-0.068	-0.124	-0.113	-0.612
	(1.804)	*(1.375)*	*(-1.372)*	*(-1.524)*	*(-2.444)*	*(-1.422)*
Cotton	-0.002	0.011	0.031	-0.036	0.034	-0.048
	(-0.139)	*(0.421)*	*(0.925)*	*(-0.824)*	*(1.163)*	*(-1.207)*
Sugar	0.007	0.015	0.029	0.077	0.022	0.065
	(0.275)	*(0.324)*	*(0.400)*	*(0.985)*	*(0.320)*	*(0.841)*
Live Cattle	0.003	-0.084	-0.134	-0.295	-0.136	-0.211
	(0.197)	*(-2.743)*	*(-4.973)*	*(-7.350)*	*(-5.193)*	*(-5.144)*
Lean Hogs	-0.009	0.032	0.001	-0.153	0.013	-0.181
	(-0.134)	*(0.230)*	*(0.010)*	*(-0.591)*	*(0.111)*	*(-0.773)*
Feeder Cattle	0.005	0.010	-0.041	-0.230	-0.046	-0.243
	(0.110)	*(0.136)*	*(-0.904)*	*(-2.694)*	*(-0.741)*	*(-2.156)*
Crude Oil	0.027	-0.016	0.062	0.001	0.034	0.017
	(1.300)	*(-0.481)*	*(1.292)*	*(0.020)*	*(0.652)*	*(0.217)*
Heating Oil	-0.018	-0.029	-0.196	-0.449	-0.177	-0.420
	(-0.523)	*(-0.732)*	*(-3.178)*	*(-4.535)*	*(-2.565)*	*(-4.390)*
Natural Gas	0.006	0.052	-0.091	-0.072	-0.097	-0.124
	(0.441)	*(1.672)*	*(-1.875)*	*(-1.328)*	*(-2.255)*	*(-2.333)*
Gold	-0.069	-0.188	-0.046	-0.229	0.022	-0.041
	(-1.679)	*(-1.919)*	*(-0.639)*	*(-2.089)*	*(0.303)*	*(-0.434)*
Silver	-0.084	-0.201	-0.171	-0.458	-0.085	-0.256
	(-1.837)	*(-4.398)*	*(-1.790)*	*(-5.922)*	*(-0.792)*	*(-3.842)*
Copper	-0.012	0.016	-0.140	-0.319	-0.128	-0.337
	(-0.319)	*(0.379)*	*(-1.970)*	*(-3.349)*	*(-1.905)*	*(-4.645)*
Platinum	-0.001	-0.113	-0.049	-0.262	-0.048	-0.149
	(-0.018)	*(-1.484)*	*(-0.623)*	*(-2.625)*	*(-0.664)*	*(-1.577)*

Table 4.4. Margin requirements and the effect on different traders positions (cont'd)

Entries report the results from the following regression model: $\Delta \boldsymbol{ln}\, Pos_i = a_0 + a_1 \Delta \boldsymbol{ln}\, M_i + u_i$ where $\Delta \boldsymbol{ln}\, M_i \equiv \boldsymbol{ln(}M_{A,i} / M_{B,i}\boldsymbol{)}$, $M_{B,i}$ $\left(M_{A,i}\right)$ is the average daily level of margin in the pre-event (post-event) period , $\Delta \boldsymbol{ln}\, Pos_i \equiv \boldsymbol{ln(}Pos_{A,i} / Pos_{B,i}\boldsymbol{)}$, $Pos_{B,i}$ $\left(Pos_{A,i}\right)$ is the average positions in the pre-event (post – event) period. We consider the change in hedging positions (HP), speculative positions (SP) and the ratio (SP/HP). The coefficient estimates α_1 and the respective *t*-statistics in parentheses are reported for the individual commodity futures and for the distinct commodity groups (panels A and B, respectively). A pre-event and post-event period of five and twenty days is used.

Panel B: Distinct Commodity Futures Groups

	Regression model: $\Delta lnHP_i=\alpha_0+\alpha_1\Delta lnM_i+u_i$		**Regression model:** $\Delta lnSP_i=\alpha_0+\alpha_1\Delta lnM_i+u_i$		**Regression model:** $\Delta ln(SP_i/HP_i)=\alpha_0+\alpha_1\Delta lnM_i+u_i$	
	5day horizon	***20day horizon***	***5day horizon***	***20day horizon***	***5day horizon***	***20day horizon***
Grains Futures	-0.025	-0.043	-0.068	-0.167	-0.042	-0.122
	(-1.951)	*(-2.062)*	*(-2.797)*	*(-4.769)*	*(-1.925)*	*(-4.094)*
Soft Futures	0.012	0.015	-0.027	-0.092	-0.104	-0.246
	(0.819)	*(0.830)*	*(-1.081)*	*(-2.620)*	*(-0.617)*	*(-1.934)*
Livestock Futures	0.003	-0.033	-0.088	-0.265	-0.091	-0.233
	(0.155)	*(-0.876)*	*(-3.006)*	*(-5.208)*	*(-2.767)*	*(-4.092)*
Energy Futures	0.003	0.027	-0.094	-0.137	-0.097	-0.164
	(0.234)	*(1.708)*	*(-2.882)*	*(-3.199)*	*(-3.072)*	*(-3.926)*
Metal Futures	-0.033	-0.089	-0.099	-0.316	-0.065	-0.227
	(-1.366)	*(-2.707)*	*(-2.506)*	*(-6.423)*	*(-1.680)*	*(-5.345)*

Table 4.5. Margin Requirements and volatility of daily futures returns

Entries report the results from the regression model: $\Delta \mathbf{ln} Vol_i = a_0 + a_1 \Delta \mathbf{ln} M_i + u_i$ where $\Delta \mathbf{ln} Vol_i \equiv \mathbf{ln(} Vol_{A,i} / Vol_{B,i} \mathbf{)}$, $Vol_{B,i}$ $\left(Vol_{A,i}\right)$ is the average daily volatility in the pre-event (post-event) period, $\Delta \mathbf{ln} M_i \equiv \mathbf{ln(} M_{A,i} / M_{B,i} \mathbf{)}$, $M_{B,i}$ $\left(M_{A,i}\right)$ is the average daily level of margin in the pre-event (post-event) period. The coefficient estimates α_1 and the respective *t*-statistics in parentheses are reported for the individual commodity futures and for the distinct commodity groups (panels A and B, respectively). A pre-event and post-event period of five and twenty days is used. Three different volatility proxies are employed: the Garman-Klass (GK, 1980) estimator, the Rogers-Satchell (RS,1991) estimator and the log-range.

Panel A: Individual Commodity Futures Contracts

Regression model: $\Delta lnVol_i = \alpha_0 + \alpha_1 \Delta lnM_i + u_i$

	GK estimator		***RS estimator***		***Logrange***	
	5-day horizon	***20-day horizon***	***5-day horizon***	***20-day horizon***	***5-day horizon***	***20-day horizon***
Corn	-0.147	0.265	-0.049	0.344	-0.252	0.158
	(-0.706)	*(1.980)*	*(-0.220)*	*(2.479)*	*(-1.208)*	*(1.149)*
Wheat	0.184	0.293	0.228	0.326	0.066	0.227
	(1.152)	*(3.568)*	*(1.317)*	*(3.957)*	*(0.424)*	*(2.659)*
Oats	-0.068	0.082	0.175	0.168	-0.256	0.018
	(-0.365)	*(0.494)*	*(0.816)*	*(0.920)*	*(-1.382)*	*(0.116)*
Soybeans	-0.230	0.226	-0.159	0.276	-0.209	0.169
	(-1.379)	*(1.971)*	*(-0.819)*	*(2.326)*	*(-1.222)*	*(1.429)*
Soybean Meal	-0.240	0.134	-0.160	0.162	-0.434	0.090
	(-1.306)	*(1.116)*	*(-0.870)*	*(1.260)*	*(-2.192)*	*(0.715)*
Soybean Oil	-0.246	0.026	-0.210	0.005	-0.250	0.027
	(-1.395)	*(0.177)*	*(-0.963)*	*(0.032)*	*(-1.370)*	*(0.183)*
Cocoa	0.106	0.191	0.228	0.244	-0.072	0.158
	(0.699)	*(1.862)*	*(1.562)*	*(2.365)*	*(-0.411)*	*(1.347)*
Coffee	0.059	0.241	0.143	0.261	-0.028	0.227
	(0.542)	*(2.706)*	*(1.250)*	*(2.940)*	*(-0.253)*	*(2.542)*
Cotton	0.101	0.127	0.205	0.133	0.053	0.113
	(0.974)	*(2.092)*	*(1.439)*	*(2.115)*	*(0.494)*	*(1.756)*
Sugar	0.126	0.351	0.188	0.426	0.028	0.281
	(0.757)	*(2.948)*	*(1.114)*	*(3.279)*	*(0.149)*	*(2.386)*
Live Cattle	0.542	0.240	0.619	0.210	0.422	0.270
	(3.795)	*(2.353)*	*(3.780)*	*(1.961)*	*(3.125)*	*(2.593)*
Lean Hogs	0.192	-0.083	0.308	-0.009	0.069	-0.154
	(0.682)	*(-0.500)*	*(0.869)*	*(-0.047)*	*(0.262)*	*(-0.944)*
Feeder Cattle	0.498	0.114	0.583	0.174	0.541	0.096
	(3.143)	*(0.972)*	*(3.520)*	*(1.373)*	*(3.191)*	*(0.818)*
Crude Oil	-0.220	0.417	-0.088	0.440	-0.410	0.388
	(-0.751)	*(2.043)*	*(-0.259)*	*(2.068)*	*(-1.484)*	*(1.938)*
Heating Oil	0.231	0.609	0.335	0.668	0.038	0.464
	(1.018)	*(3.957)*	*(1.311)*	*(4.245)*	*(0.160)*	*(3.002)*
Natural Gas	-0.042	0.306	-0.030	0.323	-0.047	0.266
	(-0.329)	*(3.465)*	*(-0.217)*	*(3.468)*	*(-0.353)*	*(3.107)*
Gold	0.130	0.496	0.159	0.471	-0.003	0.497
	(0.589)	*(1.800)*	*(0.640)*	*(1.664)*	*(-0.013)*	*(1.763)*
Silver	-0.198	0.389	-0.198	0.389	0.032	0.537
	(-0.442)	*(1.345)*	*(-0.442)*	*(1.345)*	*(0.073)*	*(1.934)*
Copper	0.388	0.781	0.398	0.813	0.319	0.725
	(1.349)	*(4.734)*	*(1.221)*	*(4.698)*	*(1.130)*	*(4.518)*
Platinum	-0.447	0.135	-0.359	0.192	-0.649	0.043
	(-1.804)	*(0.609)*	*(-1.277)*	*(0.852)*	*(-2.266)*	*(0.189)*

Table 4.5. Margin Requirements and volatility of daily futures returns (cont'd)

Entries report the results from the regression model: $\Delta \boldsymbol{ln} Vol_i = a_0 + a_1 \Delta \boldsymbol{ln} M_i + u_i$ where $\Delta \boldsymbol{ln} Vol_i \equiv \boldsymbol{ln(} Vol_{A,i} / Vol_{B,i} \boldsymbol{)}$, $Vol_{B,i}$ $\left(Vol_{A,i}\right)$ is the average daily volatility in the pre-event (post-event) period, $\Delta \boldsymbol{ln} M_i \equiv \boldsymbol{ln(} M_{A,i} / M_{B,i} \boldsymbol{)}$, $M_{B,i}$ $\left(M_{A,i}\right)$ is the average daily level of margin in the pre-event (post-event) period. The coefficient estimates α_1 and the respective *t*-statistics in parentheses are reported for the individual commodity futures and for the distinct commodity groups (panels A and B, respectively). A pre-event and post-event period of five and twenty days is used. Three different volatility proxies are employed: the Garman-Klass (GK, 1980) estimator, the Rogers-Satchell (RS, 1991) estimator and the log-range.

Panel B: Distinct Commodity Futures Groups

Regression model: $\Delta lnVol_i = \alpha_0 + \alpha_1 \Delta lnM_i + u_i$

	GK estimator		***RS estimator***		***Lograngе***	
	5-day horizon	***20-day horizon***	***5-day horizon***	***20-day horizon***	***5-day horizon***	***20-day horizon***
Grains Futures	-0.073	0.219	0.016	0.261	-0.176	0.161
	(-0.975)	*(4.304)*	*(0.195)*	*(4.907)*	*(-2.308)*	*(3.112)*
Soft Futures	0.100	0.200	0.196	0.227	0.016	0.177
	(1.647)	*(4.697)*	*(2.778)*	*(5.135)*	*(0.246)*	*(3.992)*
Livestock Futures	0.513	0.160	0.597	0.172	0.458	0.161
	(5.270)	*(2.368)*	*(5.490)*	*(2.383)*	*(4.715)*	*(2.363)*
Energy Futures	0.001	0.383	0.052	0.408	-0.077	0.323
	(0.006)	*(5.377)*	*(0.440)*	*(5.482)*	*(-0.705)*	*(4.648)*
Metal Futures	-0.049	0.461	-0.013	0.489	-0.133	0.436
	(-0.322)	*(4.034)*	*(-0.082)*	*(4.195)*	*(-0.851)*	*(3.804)*

Table 4.6. Margin requirements and Illiquidity

Entries report the results from the regression model: $\Delta \mathbf{ln}\, ILL_i = a_0 + a_1 \Delta \mathbf{ln}\, M_i + u_i$ where $\Delta \mathbf{ln}\, ILL_i \equiv \mathbf{ln(}\, ILL_{A,i} \,/\, ILL_{B,i}\, \mathbf{)}$, $ILL_{B,i}$ $\left(ILL_{A,i}\right)$ is the average value of Amihud (2002) illiquidity measure in the pre-event period (post –event) period, $\Delta \mathbf{ln}\, M_i \equiv \mathbf{ln(}\, M_{A,i} \,/\, M_{B,i}\, \mathbf{)}$, $M_{B,i}$ $\left(M_{A,i}\right)$ is the average daily level of margin in the pre-event (post-event) period. The coefficient estimates α_1 and the respective *t*-statistics in parentheses are reported for the individual commodity futures and for the distinct commodity groups (panels A and B, respectively). A pre-event and post-event period of five and twenty days is used.

Panel A: Individual Commodity Futures Contracts

Regression model: $\Delta lnILL_i=\alpha_0+\alpha_1\Delta M_i+u_i$

	5-day horizon	*20-day horizon*
Corn	-0.245	0.222
	(-0.652)	*(0.977)*
Wheat	0.101	0.524
	(0.229)	*(1.646)*
Oats	-0.050	0.756
	(-0.125)	*(1.395)*
Soybeans	-0.485	1.152
	(-0.526)	*(1.402)*
Soybean Meal	-1.615	-0.352
	(-1.503)	*(-0.372)*
Soybean Oil	-0.682	-0.263
	(-1.030)	*(-0.486)*
Cocoa	-0.476	0.148
	(-0.596)	*(0.153)*
Coffee	0.034	0.132
	(0.187)	*(0.687)*
Cotton	0.094	0.074
	(0.401)	*(0.208)*
Sugar	0.189	0.726
	(0.661)	*(2.122)*
Live Cattle	-0.038	1.414
	(-0.028)	*(0.954)*
Lean Hogs	-0.654	0.001
	(-0.597)	*(0.001)*
Feeder Cattle	0.403	0.313
	(1.257)	*(1.317)*
Crude Oil	-0.568	0.294
	(-0.611)	*(1.016)*
Heating Oil	-0.319	0.163
	(-0.471)	*(0.664)*
Natural Gas	-0.026	0.138
	(-0.050)	*(0.374)*
Gold	-0.189	-0.628
	(-0.733)	*(-1.297)*
Silver	-1.251	1.232
	(-1.137)	*(1.274)*
Copper	0.397	0.642
	(0.777)	*(2.699)*
Platinum	-0.691	-0.161
	(-1.611)	*(-0.619)*

Table 4.6. Margin requirements and Illiquidity (cont'd)

Entries report the results from the regression model: $\Delta \mathbf{ln}\, ILL_i = a_0 + a_1 \Delta \mathbf{ln}\, M_i + u_i$ where $\Delta \mathbf{ln}\, ILL_i \equiv \mathbf{ln(}\, ILL_{B,i} \,/\, ILL_{A,i} \,\mathbf{)}$, $Y_{A,i}$ is the average value of Amihud (2002) illiquidity measure in the pre-event period, $Y_{B,i}$ is the average value of Amihud (2002) illiquidity measure in the post –event period, $\Delta \mathbf{ln}\, M_i \equiv \mathbf{ln(}\, M_{B,i} \,/\, M_{A,i} \,\mathbf{)}$, $M_{A,i}$ $\left(M_{B,i}\right)$ is the average daily level of margin in the pre-event (post-event) period. The coefficient estimates α_1 and the respective *t*-statistics in parentheses are reported for the individual commodity futures and for the distinct commodity groups (panels A and B, respectively). A pre-event and post-event period of five and twenty days is used.

Panel B: Distinct Commodity Futures Groups

Regression model: $\Delta lnILL_i=\alpha_0+\alpha_1\Delta M_i+u_i$

	5-day horizon	*20-day horizon*
Grains Futures	-0.481 *(-1.680)*	0.361 *(1.490)*
Soft Futures	-0.002 *(-0.013)*	0.199 *(0.957)*
Livestock Futures	-0.086 *(-0.140)*	0.761 *(1.185)*
Energy Futures	-0.160 *(-0.405)*	0.205 *(0.857)*
Metal Futures	-0.367 *(-1.202)*	0.522 *(1.296)*

Table 4.7. Cross margin effects

Entries report the results the effect of margin changes on benchmark groups is examined. For each target contract and each margin change *i*, we create a benchmark group that includes the remaining contracts in the same commodity group that do not undergo a margin change during the event period (-20,20) of the ith margin change of the target contract. We examine the effect of the margin changes of the target contract on benchmark groups's prices (panel A), returns (panel B), hedging positions (panel C), speculative positions (panel D), volatility (panel E), liquidity (panel F). Due to space limitations, the results are reported only for the longer event window, i.e. (-20,20).

	Panel A	***Panel B:***	***Panel E:***	***Panel D:***	***Panel F***	***Panel G:***
	$\Delta P_i=\alpha_0+\alpha_1\Delta \ln M_i+u_i$	$\Delta R_i=\alpha_0+\alpha_1\Delta \ln M_i+u_i$	$\Delta \ln HP_i=\alpha_0+\alpha_1\Delta \ln M_i+u_i$	$\Delta \ln SP_i=\alpha_0+\alpha_1\Delta \ln M_i+u_i$	$\Delta \ln Vol_i=\alpha_0+\alpha_1\Delta \ln M_i+u_i$	$\Delta \ln ILL_i= \alpha_0+\alpha_1\Delta \ln M_i+u_i$
Corn	0.095	0.004	0.018	-0.189	0.155	-0.309
	(3.032)	*(1.767)*	*(0.468)*	*(-2.796)*	*(1.974)*	*(-0.664)*
Wheat	0.092	-0.002	0.03	-0.035	0.132	0.053
	(4.466)	*(-1.348)*	*(1.075)*	*(-0.725)*	*(2.024)*	*(0.205)*
Oats	-0.011	-0.002	-0.04	-0.105	0.092	0.656
	(-0.478)	*(-0.628)*	*(-1.392)*	*(-2.091)*	*(1.018)*	*(1.764)*
Soybeans	-0.042	0.003	-0.048	-0.187	-0.06	0.834
	(-1.088)	*(1.095)*	*(-1.007)*	*(-2.552)*	*(-0.600)*	*(1.765)*
SoybeanMeal	0.013	0.001	-0.004	-0.082	0.011	-0.244
	(0.420)	*(0.319)*	*(-0.093)*	*(-1.307)*	*(0.115)*	*(-0.515)*
Soybean Oil	0.092	-0.001	0.04	0.009	-0.097	0.03
	(2.043)	*(-0.401)*	*(0.836)*	*(0.114)*	*(-0.930)*	*(0.078)*
Cocoa	0.068	0.004	0.073	0.049	0.154	-0.857
	(1.722)	*(1.811)*	*(2.450)*	*(1.009)*	*(1.843)*	*(-2.340)*
Coffee	0.000	-0.001	0.019	-0.028	-0.005	-0.729
	(-0.008)	*(-0.447)*	*(0.769)*	*(-0.509)*	*(-0.083)*	*(-1.750)*
Cotton	-0.025	0.005	0.000	-0.061	-0.023	0.445
	(-1.199)	*(2.500)*	*(-0.017)*	*(-1.046)*	*(-0.361)*	*(0.533)*
Sugar	0.039	-0.001	0.065	-0.051	-0.061	0.259
	(1.223)	*(-0.637)*	*(2.322)*	*(-1.019)*	*(-0.676)*	*(0.186)*
Live Cattle	-0.067	-0.006	-0.091	-0.418	-0.052	-0.192
	(-2.635)	*(-2.452)*	*(-1.705)*	*(-5.985)*	*(-0.606)*	*(-0.416)*
Lean Hogs	0.005	-0.001	0.022	0.095	0.335	-0.501
	(0.167)	*(-0.411)*	*(0.103)*	*(0.442)*	*(1.515)*	*(-0.634)*
Feeder Cattle	0.016	0.000	0.036	-0.285	-0.170	0.400
	(0.568)	*(0.190)*	*(0.678)*	*(-3.769)*	*(-1.724)*	*(0.695)*
Crude Oil	0.103	0.002	0.011	0.017	0.272	-0.302
	(0.866)	*(0.143)*	*(0.218)*	*(0.148)*	*(1.174)*	*(-0.592)*
Heating Oil	0.038	-0.020	0.000	0.083	0.096	0.040
	(0.429)	*(-2.885)*	*(-0.013)*	*(0.957)*	*(0.516)*	*(0.115)*
Natural Gas	0.043	-0.006	0.034	-0.008	0.249	0.380
	(1.476)	*(-1.762)*	*(1.193)*	*(-0.140)*	*(2.200)*	*(1.453)*
Gold	-0.115	-0.009	-0.008	-0.119	0.668	0.429
	(-1.795)	*(-2.408)*	*(-0.097)*	*(-1.273)*	*(4.395)*	*(1.610)*
Silver	-0.013	-0.004	-0.147	-0.174	0.420	0.010
	(-0.215)	*(-1.658)*	*(-2.929)*	*(-3.021)*	*(3.128)*	*(0.185)*
Copper	-0.206	0.002	-0.233	-0.396	0.119	0.534
	(-2.356)	*(0.449)*	*(-1.307)*	*(-1.844)*	*(0.315)*	*(0.260)*
Platinum	-0.072	-0.003	-0.139	-0.136	0.263	0.437
	(-1.420)	*(-0.839)*	*(-1.947)*	*(-0.907)*	*(1.214)*	*(0.503)*

Table 4.8. The impact of margin increases and decreases

Entries report the results when the margin changes are further classified as increases and decreases and analyzed separately. For each commodity group, we examine the effect of margin changes on futures prices (panel A), futures returns (panel B), hedging positions (panel C), speculative positions (panel D), speculative/hedging positions (panel E), volatility (logrange, panel F), and liquidity (panel G). The coefficient estimates α_1 and the respective *t*-statistics in parentheses are reported. A pre-event and post-event period of five and twenty days is used.

	Panel A:		***Panel B:***		***Panel C:***		***Panel D:***		***Panel E:***		***Panel F:***		***Panel G:***	
	$\Delta \ln P_i=\alpha_0+\alpha_1\Delta \ln M_i+u_i$		$\Delta R_i=\alpha_0+\alpha_1\Delta \ln M_i+u_i$		$\Delta \ln HP_i=\alpha_0+\alpha_1\Delta \ln M_i+u_i$		$\Delta \ln SP_i=\alpha_0+\alpha_1\Delta \ln M_i+u_i$		$\Delta \ln(SP_i/HP_i)=\alpha_0+\alpha_1\Delta \ln M_i+u_i$		$\Delta \ln Vol_i=\alpha_0+\alpha_1\Delta \ln M_i+u_i$		$\Delta \ln ILL_i=\alpha_0+\alpha_1\Delta M_i+u_i$	
	5day horizon	***20day horizon***	***5day horizon***	***20day horizon***	***5day horizon***	***20day horizon***	***5day horizon***	***20day horizon***	***5day horizon***	***20day horizon***	***5day horizon***	***20day horizon***	***5day horizon***	***20day horizon***
Grains Futures														
Margin Increases	0.097	0.128	-0.030	-0.012	-0.047	-0.065	-0.108	-0.244	-0.007	-0.110	0.096	0.469	0.638	0.721
	(2.485)	*(2.990)*	*(-2.450)*	*(-3.498)*	*(-1.243)*	*(-1.985)*	*(-1.879)*	*(-2.493)*	*(-0.117)*	*(-2.184)*	*(0.431)*	*(4.012)*	*(0.791)*	*(1.419)*
Margin Decreases	-0.007	0.073	-0.011	-0.004	-0.015	-0.017	-0.055	-0.168	-0.093	-0.141	-0.361	0.180	-0.510	0.114
	(-0.301)	*(1.557)*	*(-1.461)*	*(-0.676)*	*(-0.461)*	*(-0.346)*	*(-0.770)*	*(-2.004)*	*(-1.676)*	*(-1.584)*	*(-1.973)*	*(1.178)*	*(-0.682)*	*(1.375)*
Soft Futures														
Margin Increases	0.000	0.090	-0.026	-0.008	-0.010	-0.006	-0.011	-0.089	0.165	0.107	0.432	0.437	0.199	0.780
	(-0.006)	*(2.159)*	*(-2.574)*	*(-2.429)*	*(-0.252)*	*(-0.168)*	*(-0.234)*	*(-2.121)*	*(0.338)*	*(0.304)*	*(2.974)*	*(4.779)*	*(0.463)*	*(1.922)*
Margin Decreases	-0.022	0.027	-0.009	-0.003	0.003	0.022	0.048	0.041	0.046	0.010	-0.147	-0.072	-0.113	-0.155
	(-1.302)	*(0.855)*	*(-1.555)*	*(-1.111)*	*(0.133)*	*(0.487)*	*(0.975)*	*(0.511)*	*(0.872)*	*(0.023)*	*(-1.032)*	*(-0.744)*	*(-0.397)*	*(-0.322)*
Livestock Futures														
Margin Increases	-0.076	-0.012	-0.014	-0.003	-0.060	-0.075	-0.181	-0.385	-0.120	-0.312	0.923	0.491	-0.860	0.549
	(-3.227)	*(-0.365)*	*(-2.513)*	*(-1.481)*	*(-1.737)*	*(-1.121)*	*(-3.737)*	*(-4.307)*	*(-2.032)*	*(-3.063)*	*(5.324)*	*(4.942)*	*(-0.835)*	*(1.542)*
Margin Decreases	-0.011	0.024	-0.009	-0.006	0.073	-0.001	0.095	-0.137	0.021	-0.139	-0.475	-0.177	0.427	0.887
	(-0.421)	*(0.648)*	*(-0.963)*	*(-1.648)*	*(0.807)*	*(-0.012)*	*(0.777)*	*(-0.836)*	*(0.157)*	*(-0.765)*	*(-1.418)*	*(-0.734)*	*(1.667)*	*(1.550)*
Energy Futures														
Margin Increases	0.194	0.402	-0.004	0.004	-0.035	0.064	-0.214	-0.168	-0.179	-0.205	0.231	0.469	0.856	0.698
	(3.409)	*(7.391)*	*(-0.281)*	*(0.674)*	*(-1.146)*	*(1.629)*	*(-3.076)*	*(-1.923)*	*(-2.618)*	*(-2.498)*	*(0.888)*	*(3.319)*	*(1.080)*	*(1.927)*
Margin Decreases	0.045	0.406	-0.035	-0.004	-0.057	0.048	-0.151	-0.122	-0.092	-0.216	-1.331	0.241	-0.327	-0.857
	(0.358)	*(3.828)*	*(-1.057)*	*(-0.564)*	*(-0.954)*	*(1.006)*	*(-0.898)*	*(-1.298)*	*(-0.567)*	*(-1.659)*	*(-2.726)*	*(1.169)*	*(-0.680)*	*(-1.026)*
Metal Futures														
Margin Increases	0.107	0.302	-0.038	-0.020	-0.045	-0.077	-0.134	-0.410	-0.092	-0.326	0.275	1.262	0.748	0.811
	(1.243)	*(3.671)*	*(-1.680)*	*(-3.006)*	*(-0.712)*	*(-1.941)*	*(-1.464)*	*(-4.555)*	*(-0.967)*	*(-4.369)*	*(0.774)*	*(6.983)*	*(1.134)*	*(1.101)*
Margin Decreases	0.048	0.076	0.000	0.010	0.105	0.071	0.057	-0.220	-0.047	-0.388	0.248	0.525	-0.335	-0.398
	(0.624)	*(0.528)*	*(0.001)*	*(0.942)*	*(1.395)*	*(0.479)*	*(0.341)*	*(-0.794)*	*(-0.335)*	*(-2.129)*	*(0.361)*	*(0.929)*	*(-0.213)*	*(-1.502)*

Table 4.9. The impact of large and small margin changes

Entries report the results when the margin changes are further classified into two groups of large and small according to the absolute size of the percentage change, and analyzed separately. For each commodity group, we examine the effect of margin changes on futures prices (panel A), futures returns (panel B), hedging positions (panel C), speculative positions (panel D), speculative/hedging positions (panel E), volatility (logrange, panel F), and liquidity (panel G). The coefficient estimates α_1 and the respective *t*-statistics in parentheses are reported. A pre-event and post-event period of five and twenty days is used.

	Panel A:		***Panel B:***		***Panel C:***		***Panel D:***		***Panel E:***		***Panel F:***		***Panel G:***	
	$\Delta lnP_i=\alpha_0+\alpha_1\Delta lnM_i+u_i$		$\Delta R_i=\alpha_0+\alpha_1\Delta lnM_i+u_i$		$\Delta lnHP_i=\alpha_0+\alpha_1\Delta lnM_i+u_i$		$\Delta lnSP_i=\alpha_0+\alpha_1\Delta lnM_i+u_i$		$\Delta ln(SP_i/HP_i)=\alpha_0+\alpha_1\Delta lnM_i+u_i$		$\Delta lnVol_i=\alpha_0+\alpha_1\Delta lnM_i+u_i$		$\Delta lnILL_i=\alpha_0+\alpha_1\Delta lnM_i+u_i$	
	5day horizon	*20day horizon*	*5day horizon*	*20day horizon*	*5day horizon*	*20day horizon*	*5day horizon*	*20day horizon*	*5day horizon*	*20day horizon*	*5day horizon*	*20day horizon*	*5day horizon*	*20day horizon*
Grains Futures														
Large changes	0.036	0.090	-0.013	-0.008	-0.027	-0.056	-0.067	-0.163	-0.040	-0.105	-0.166	0.150	-0.176	0.477
	(2.430)	*(4.304)*	*(-2.694)*	*(-4.026)*	*(-1.703)*	*(-2.087)*	*(-2.329)*	*(-3.650)*	*(-1.474)*	*(-2.858)*	*(-1.797)*	*(2.431)*	*(-1.107)*	*(1.953)*
Small changes	-0.006	0.077	-0.005	-0.003	-0.021	-0.010	-0.081	-0.200	-0.061	-0.167	-0.216	0.221	-0.895	-0.015
	(-0.220)	*(2.047)*	*(-0.598)*	*(-0.848)*	*(-0.716)*	*(-0.250)*	*(-1.457)*	*(-2.847)*	*(-1.259)*	*(-3.032)*	*(-1.257)*	*(1.963)*	*(-1.204)*	*(-0.026)*
Soft Futures														
Large changes	-0.006	0.122	-0.002	-0.017	0.031	0.040	-0.089	-0.172	-0.025	-0.075	0.050	0.146	0.269	0.648
	(-0.243)	*(3.409)*	*(-0.204)*	*(-5.726)*	*(0.735)*	*(1.081)*	*(-1.389)*	*(-2.647)*	*(-0.941)*	*(-1.903)*	*(0.669)*	*(2.814)*	*(0.710)*	*(2.036)*
Small changes	0.000	0.049	-0.014	-0.007	0.008	0.007	-0.016	-0.068	-0.521	-0.788	-0.144	0.297	-0.050	-0.125
	(-0.005)	*(2.203)*	*(-2.856)*	*(-3.736)*	*(0.767)*	*(0.321)*	*(-0.591)*	*(-1.474)*	*(-0.981)*	*(-1.715)*	*(-0.916)*	*(3.383)*	*(-0.228)*	*(-0.518)*
Livestock Futures														
Large changes	-0.038	-0.012	-0.011	-0.002	0.017	-0.011	-0.084	-0.257	-0.102	-0.248	0.448	0.134	-0.243	0.669
	(-1.945)	*(-0.453)*	*(-2.655)*	*(-1.677)*	*(0.801)*	*(-0.298)*	*(-2.637)*	*(-4.532)*	*(-2.586)*	*(-3.987)*	*(3.231)*	*(1.685)*	*(-0.283)*	*(1.328)*
Small changes	0.017	-0.027	-0.007	0.001	0.035	-0.001	-0.008	-0.114	-0.041	-0.112	0.175	-0.087	0.493	0.152
	(1.064)	*(-1.014)*	*(-1.215)*	*-0.582*	*(0.710)*	*(-0.006)*	*(-0.122)*	*(-0.979)*	*(-0.531)*	*(-0.831)*	*(0.903)*	*(-0.588)*	*(1.174)*	*(0.105)*
Energy Futures														
Large changes	0.135	0.328	-0.024	-0.007	-0.012	0.034	-0.130	-0.112	-0.118	-0.146	-0.140	0.326	0.284	0.447
	(4.178)	*(3.932)*	*(-2.504)*	*(-2.069)*	*(-0.844)*	*(1.837)*	*(-3.497)*	*(-2.335)*	*(-3.321)*	*(-3.160)*	*(-1.062)*	*(3.914)*	*(0.691)*	*(2.017)*
Small changes	0.106	0.384	-0.046	-0.012	0.047	0.004	0.002	-0.201	-0.044	-0.204	0.045	0.323	-0.383	-0.411
	(2.238)	*(3.109)*	*(-4.068)*	*(-2.651)*	*(1.794)*	*(0.128)*	*-0.036*	*(-2.440)*	*(-0.691)*	*(-2.527)*	*(0.209)*	*(2.497)*	*(-1.679)*	*(-0.845)*
Metal Futures														
Large changes	0.019	0.109	-0.012	-0.008	-0.027	-0.065	-0.085	-0.298	-0.068	-0.233	-0.041	0.406	-0.148	0.267
	(0.490)	*(2.130)*	*(-1.259)*	*(-2.425)*	*(-1.575)*	*(-1.934)*	*(-1.877)*	*(-4.178)*	*(-1.338)*	*(-4.287)*	*(-0.213)*	*(2.968)*	*(-0.414)*	*(0.774)*
Small changes	-0.069	0.003	0.010	-0.013	-0.086	-0.105	-0.135	-0.290	-0.028	-0.165	-0.585	0.414	-0.303	0.980
	(-0.930)	*(0.039)*	*(0.465)*	*(-1.573)*	*(-1.229)*	*(-1.673)*	*(-1.450)*	*(-2.274)*	*(-0.369)*	*(-1.881)*	*(-1.727)*	*(1.598)*	*(-1.870)*	*(0.873)*

Table 4.10. Margin requirements and futures prices during the liquidity crisis period (2007-2009)

Entries report the results when the price impact of margin changes is examined. First, we consider the effect on the commodiy futures prices and estimate the following regression model: $\Delta \boldsymbol{ln} P_i = a_0 + a_1 \Delta \boldsymbol{ln} M_i + u_i$,where $\Delta \boldsymbol{ln} P_i \equiv P_{A,i} - P_{B,i}$ $P_{B,i}$ $\left(P_{A,i}\right)$ is the average price level in the pre (post)-event period, $\Delta \boldsymbol{ln} M_i \equiv \boldsymbol{ln(} M_{A,i} / M_{B,i} \boldsymbol{)}$, $M_{B,i}$ $\left(M_{A,i}\right)$ is the average daily level of margin in the pre (post)-event period. Second, we consider the effect of margin changes on the commodity futures returns and estimate the following regression model: $\Delta R_i = a_0 + a_1 \Delta \boldsymbol{ln} M_i + u_i$ where $\Delta R_i \equiv R_{A,i} - R_{B,i}$, $R_{B,i}$ $\left(R_{A,i}\right)$ is the average geometric daily return in the pre-event (post-event) period. The coefficient estimates α_1 and the respective *t*-statistics in parentheses are reported for the for the distinct commodity groups. A pre-event and post-event period of five and twenty days is used.

	Regression model: $\Delta lnP_i = \alpha_0 + \alpha_1 \Delta lnM_i + u_i$		**Regression model: $\Delta R_i = \alpha_0 + \alpha_1 \Delta lnM_i + u_i$**	
	5-day horizon	***20-day horizon***	***5-day horizon***	***20-day horizon***
Grains Futures	-0.006	0.013	-0.021	-0.009
	(-0.236)	*(0.365)*	*(-2.159)*	*(-2.518)*
Soft Futures	0.015	-0.020	-0.010	-0.014
	(0.512)	*(-0.562)*	*(-1.100)*	*(-4.005)*
Livestock Futures	-0.037	-0.104	-0.002	0.002
	(-1.173)	*(-2.293)*	*(-0.231)*	*(0.363)*
Energy Futures	0.028	0.313	-0.041	-0.015
	(0.541)	*(4.690)*	*(-3.321)*	*(-3.594)*
Metal Futures	0.089	0.128	-0.021	-0.015
	(2.232)	*(2.183)*	*(-2.459)*	*(-3.460)*

Table 4.11. Margin Requirements and unexpected volatility

Entries report the results from the regression model: $\Delta Vol_i = a_0 + a_1 \Delta \mathbf{ln} M_i + u_i$ where $\Delta Vol_i \equiv Vol_{A,i} - Vol_{B,i}$, $Vol_{B,i}$ $\left(Vol_{A,i}\right)$ is the average daily volatility shocks in the pre-event (post-event) period, $\Delta \mathbf{ln} M_i \equiv \mathbf{ln(} M_{A,i} / M_{B,i} \mathbf{)}$, $M_{B,i}$ $\left(M_{A,i}\right)$ is the average daily level of margin in the pre-event (post-event) period. The volatility shocks are extracted from an AR(1) model, fitted over the period (-20,20) for each margin change. The coefficient estimates α_1 and the respective *t*-statistics in parentheses are reported for the individual commodity futures and for the distinct commodity groups (panels A and B, respectively). A pre-event and post-event period of five and twenty days is used. Three different volatility proxies are employed: the Garman-Klass (GK, 1980) estimator, the Rogers-Satchell (RS,1991) estimator and the log-range.

Panel A: Individual Commodity Futures Contracts

Regression model: $\Delta Vol_i=\alpha_0+\alpha_1\Delta lnM_i+u_i$						
	GK estimator		***RS estimator***		***Logrange***	
	5-day horizon	***20-day horizon***	***5-day horizon***	***20-day horizon***	***5-day horizon***	***20-day horizon***
Corn	-0.002	0.003	0.000	0.005	-0.006	0.003
	(-0.577)	*(2.138)*	*(0.021)*	*(2.717)*	*(-1.076)*	*(1.059)*
Wheat	0.001	0.005	0.002	0.006	-0.003	0.005
	(0.258)	*(3.127)*	*(0.485)*	*(4.020)*	*(-0.506)*	*(1.926)*
Oats	-0.002	0.002	0.002	0.005	-0.010	0.000
	(-0.480)	*(0.821)*	*(0.491)*	*(1.617)*	*(-1.507)*	*(-0.064)*
Soybeans	-0.003	0.002	-0.001	0.003	-0.006	0.003
	(-1.170)	*(1.743)*	*(-0.539)*	*(2.116)*	*(-1.383)*	*(1.126)*
Soybean Meal	-0.004	0.000	-0.004	-0.001	-0.005	0.000
	(-1.219)	*(-0.201)*	*(-1.037)*	*(-0.499)*	*(-1.044)*	*(0.124)*
Soybean Oil	-0.003	0.001	-0.002	0.002	-0.011	0.001
	(-1.147)	*(0.890)*	*(-0.653)*	*(1.087)*	*(-2.211)*	*(0.357)*
Cocoa	0.000	0.002	0.002	0.003	-0.004	0.002
	(0.071)	*(1.387)*	*(0.682)*	*(2.176)*	*(-0.755)*	*(0.682)*
Coffee	-0.002	0.003	-0.001	0.003	-0.006	0.006
	(-1.125)	*(2.098)*	*(-0.270)*	*(2.387)*	*(-1.563)*	*(2.426)*
Cotton	0.001	0.002	0.002	0.002	0.002	0.002
	(0.950)	*(2.310)*	*(1.512)*	*(2.298)*	*(0.959)*	*(1.879)*
Sugar	-0.001	0.003	0.001	0.005	-0.005	0.004
	(-0.348)	*(1.989)*	*(0.331)*	*(2.579)*	*(-0.936)*	*(1.405)*
Live Cattle	0.005	0.002	0.005	0.001	0.007	0.004
	(4.157)	*(2.578)*	*(4.079)*	*(1.857)*	*(3.686)*	*(3.300)*
Lean Hogs	0.002	-0.002	0.003	-0.001	0.000	-0.004
	(0.504)	*(-0.898)*	*(0.774)*	*(-0.365)*	*(0.027)*	*(-1.348)*
Feeder Cattle	0.004	0.001	0.005	0.002	0.006	0.001
	(3.105)	*(1.632)*	*(3.611)*	*(1.963)*	*(2.916)*	*(1.342)*
Crude Oil	-0.007	0.003	-0.004	0.004	-0.019	0.003
	(-1.271)	*(0.912)*	*(-0.667)*	*(1.231)*	*(-1.863)*	*(0.627)*
Heating Oil	0.004	0.007	0.006	0.008	0.001	0.013
	(1.055)	*(3.392)*	*(1.416)*	*(3.469)*	*(0.146)*	*(3.053)*
Natural Gas	-0.004	0.004	-0.004	0.005	-0.004	0.007
	(-1.229)	*(2.558)*	*(-1.095)*	*(2.585)*	*(-0.726)*	*(2.443)*
Gold	-0.003	0.006	-0.002	0.007	-0.010	0.009
	(-1.130)	*(2.245)*	*(-0.695)*	*(2.330)*	*(-1.691)*	*(2.027)*
Silver	-0.009	0.005	-0.009	0.005	-0.008	0.009
	(-0.799)	*(1.031)*	*(-0.799)*	*(1.031)*	*(-0.458)*	*(1.147)*
Copper	0.003	0.009	0.003	0.009	0.004	0.019
	(0.506)	*(4.484)*	*(0.483)*	*(4.258)*	*(0.382)*	*(4.752)*
Platinum	-0.004	0.003	-0.003	0.004	-0.010	0.003
	(-1.069)	*(1.599)*	*(-0.691)*	*(1.876)*	*(-1.737)*	*(0.824)*

Table 4.11. Margin Requirements and unexpected volatility (cont'd)

Entries report the results from the regression model: $\Delta Vol_i = a_0 + a_1 \Delta \boldsymbol{ln} M_i + u_i$ where $\Delta Vol_i \equiv Vol_{A,i} - Vol_{B,i}$, $Vol_{B,i}$ $\left(Vol_{A,i}\right)$ is the average daily volatility shocks in the pre-event (post-event) period, $\Delta \boldsymbol{ln} M_i \equiv \boldsymbol{ln(} M_{A,i} / M_{B,i} \boldsymbol{)}$, $M_{B,i}$ $\left(M_{A,i}\right)$ is the average daily level of margin in the pre-event (post-event) period. The volatility shocks are extracted from an AR(1) model, fitted over the period (-20,20) for each margin change. The coefficient estimates α_1 and the respective *t*-statistics in parentheses are reported for the individual commodity futures and for the distinct commodity groups (panels A and B, respectively). A pre-event and post-event period of five and twenty days is used. Three different volatility proxies are employed: the Garman-Klass (GK, 1980) estimator, the Rogers-Satchell (RS,1991) estimator and the log-range.

Panel B: Distinct Commodity Futures Groups

Regression model: $\Delta Vol_i = \alpha_0 + \alpha_1 \Delta ln M_i + u_i$

	GK estimator		*RS estimator*		*Logrange*	
	5-day horizon	*20-day horizon*	*5-day horizon*	*20-day horizon*	*5-day horizon*	*20-day horizon*
Grains Futures	-0.001	0.003	0.000	0.004	-0.006	0.003
	(-1.102)	*(4.394)*	*(0.067)*	*(5.323)*	*(-2.729)*	*(2.696)*
Soft Futures	0.000	0.002	0.001	0.003	-0.002	0.003
	(-0.027)	*(3.869)*	*(1.328)*	*(4.585)*	*(-0.923)*	*(3.270)*
Livestock Futures	0.004	0.001	0.005	0.001	0.006	0.002
	(5.138)	*(2.652)*	*(5.289)*	*(2.369)*	*(4.583)*	*(2.860)*
Energy Futures	-0.003	0.005	-0.001	0.006	-0.005	0.008
	(-1.114)	*(3.950)*	*(-0.559)*	*(4.133)*	*(-1.255)*	*(3.696)*
Metal Futures	-0.003	0.006	-0.002	0.007	-0.006	0.011
	(-0.927)	*(4.335)*	*(-0.696)*	*(4.474)*	*(-1.211)*	*(4.114)*

Chapter 5: Conclusions and avenues for future research

Motivated by the recent developments in the commodity markets, this thesis has addressed for the first time important research questions regarding the commodity futures markets. First, it has explored comprehensively whether an investor is made better off by including commodities in a portfolio that consists of the traditional asset classes (stocks, bonds and cash). Second, it has examined whether there are any systematic factors that explain (price) the cross-section of commodity futures expected returns. Third, it has investigated whether and how changes in margin requirements affect the commodity futures markets.

Regarding the *first* research question, the benefits of commodity investing are assessed by adopting a more general approach than the mean-variance (MV) in-sample setting followed by the previous literature. First, the posed question is revisited within an in-sample setting by employing rigorous spanning tests, consistent with MV as well as non-MV investors' preferences. Second, the diversification benefits of commodities are assessed within an out-of-sample framework. To this end, we form optimal portfolios both under the traditional and the augmented with commodities asset universe by taking into account the higher order moments of the returns distribution. Next, we evaluate their comparative performance. To ensure the robustness of the obtained results, alternative ways of investing in commodities and various utility/value functions that describe the investors' preferences are considered. Moreover, a number of performance measures that take also into account the presence of transaction costs are employed.

The results indicate that within the in-sample setting, commodities do not yield added value to MV investors while they do to the non-MV ones. This implies that commodities offer in-sample diversification benefits only in the case where higher order moments are taken into account. However, these benefits are not preserved in the out-of-sample framework; in the vast majority of the cases, the optimal portfolios that include only the traditional asset classes have superior performance. Given that the out-of-sample setting is the ultimate test for addressing the performance evaluation issue, these results challenge the common belief that commodities should be included in investors' portfolios. In fact, they are consistent with the empirical evidence on the increasing financialization of commodity markets that is expected to deteriorate the diversification benefits of commodities.

With respect to the *second* research question, the challenging asset pricing question for the commodity futures returns is comprehensively addressed. A number of macro and equity-motivated tradable factor asset pricing models, which have been traditionally used or proved successful to price the cross-section of equities, are implemented. In addition, theoretically sound commodity-specific factors are constructed and evaluated in a cross-sectional setting. Finally, the performance of principal components (PC) asset pricing models is also examined. The empirical evidence indicates that none of the employed factors prices the cross-section of commodity futures. This is also corroborated by the PC model. Moreover, we find that the commodity futures markets are significantly heterogeneous. The results survive all robustness tests.

The findings have the following implications. First, the popular factor models that have been found to price the cross-section of stock returns should not be used by the institutional investors industry to evaluate the risk-adjusted performance of commodity funds. Second, the inability of the employed models to price commodity futures may be attributed to the fact that equity and commodity markets are segmented and/or that there exist arbitrage opportunities in the economy and/or there are market frictions. The absence of any common-factors in the cross-section of commodity futures could also be explained by its heterogeneous structure. Third, the results that the commodity-specific factors are not priced either confirm that the commodity market is segmented itself.

As far as the *third* research question is concerned, the impact of margin changes on the commodity futures markets is comprehensively investigated. The recent commodity boom and the Dodd-Frank reform have revived the debate about whether the commodity futures margin requirements should be regulated or not. To further contribute on this discussion, the effect of margin changes on the prices/returns, the sharing of risk between speculators and hedgers, and the price stability (volatility/liquidity) of the commodity futures markets is assessed. Understanding how the margin changes impact on vital characteristics of the commodity futures markets is prerequisite prior to their regulation.

The reported evidence have a number of implications for academics, market participants and policy makers. The results indicate that the regulation of margins has pros and cons. Margin increases can restrict the rate at which commodity prices increase; this property is of particular importance to regulators especially over periods where the commodity prices rise. In addition, margin increases can constrain excessive speculation, but only for some markets. On the other hand, the margin increases may harm the risk sharing function, primary objective of the commodity futures contracts, and the market liquidity for some markets. Interestingly, changes in the margins of one commodity future may affect other related commodity futures that belong in the same commodity group. The policymakers should also take into account that the effect of margin changes varies across commodity groups and the margin effect on each one of them should be examined separately.

Finally, this thesis indicates potential avenues for future research. First, in the asset allocation context, researchers should look at the benefits of commodity investing within a dynamic optimization framework. The literature on the dynamic asset allocation has focused predominantly on traditional asset classes (stocks and bonds). Therefore, the issue whether commodities are useful to investors for intertemporal hedging remains open to discussion. Such an exercise should take into account all commodity related factors that affect the dynamics of the investment opportunity set (see e.g., Schwartz and Trolle, 2009). To the best of our knowledge, Dai (2009) is the only study that studies the intertemporal hedging benefits of investing in commodities. However, his analysis is quite limited and uses a single factor model for the dynamics of commodity prices.

Second, with regard to the asset pricing task, future research should explore whether it is possible to construct any common factors that take into account the heterogeneity of the commodity futures market; features in the demand and supply of the underlying commodities may be proven useful. Conditional asset pricing models may also serve to this end. These models will include parameters that may vary over time as functions of conditioning information (Cochrane, 2005). The literature on the conditional asset pricing models has also focused on equities. This implies that this question is left unanswered for commodity futures returns and calls for further research in this vein. Third, future research on the margins literature should take into account potential endogeneity issues that may arise. The margin in futures markets are set by the exchanges based on market conditions (e.g., volatility, see Figlewski, 1984, Fenn and Kupiec, 1993). To address this endogeneity constraint, one could employ the instrumental variables technique. However, there is no theory in the margins literature that dictates the choice of these instrumental variables. Therefore, this remains an open issue that needs to be addressed by futures research.

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