Are there common factors in commodity futures returns?*

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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.

Keywords: Common factors; Commodity-specific factors; Hedging pressure; Inventories; Market segmentation; Principal components analysis.

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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, 2007). 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 (Daskalaki and Skiadopoulos, 2011). 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 (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 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

[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.

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 2 describes the datasets. Sections 3 and 4 review the employed macro and equity-motivated tradable factors asset pricing models and describe the construction of the commodity-specific factors, respectively. Sections 5 and 6 outline the econometric estimation of the asset pricing models and discuss the results on their performance, respectively. Section 7 provides further robustness tests. Section 8 describes the Principal Component

[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).

Analysis (PCA) factor models and discusses results. Section 9 concludes and discusses the implications of our research.

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 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 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

[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.

contracts, along with the platinum futures, outperform the other contracts also in terms of the risk-adjusted performance, i.e. the Sharpe ratio figures.

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 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. 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).

3.1. 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

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

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

$$E\left(r_{i,t+1}\right)=\beta_{i,CON}\lambda_{CON} \tag{2}$$

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.

3.2. 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:

$$E\left(r_{i,t+1}\right)=\beta_{i,MKT}\lambda_{MKT}+\beta_{i,MG}\,\lambda_{MG} \tag{3}$$

$$E\left(r_{i,t+1}\right)=\beta_{i,CON}\lambda_{CON}+\beta_{i,MG}\lambda_{MG} \tag{4}$$

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 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.

[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.

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

$$E\left(r_{i,t+1}\right) = \beta_{i,f}\lambda_f + \beta_{i,Lev}\lambda_{Lev} \tag{5}$$

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

$$r_{i,t+1} = a_i + \beta'_{i,f} f_{t+1} + \beta_{i,Lev} Lev_{t+1} + e_{i,t+1} \tag{6}$$

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

3.4 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

$$E\left(r_{i,t+1}\right) = \beta'_{i,f}\lambda_f + \beta_{i,fx}\lambda_{fx} \tag{7}$$

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

$$r_{i,t+1} = a_i + \beta'_{i,f} f_{t+1} + \beta_{i,fx} FX_{t+1} + e_{i,t+1} \tag{8}$$

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).

3.5 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

$$E\left(r_{i,t+1}\right)=\beta_{i,MKT}\lambda_{MKT}+\beta_{i,SMB}\lambda_{SMB}+\beta_{i,HML}\lambda_{HML} \tag{9}$$

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

$$r_{i,t+1}=a_i+\beta_{i,MKT}r_{M,t+1}+\beta_{i,SMB}SMB_{t+1}+\beta_{i,HML}HML_{t+1}+e_{i,t+1} \tag{10}$$

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

$$E\left(r_{i,t+1}\right)=\beta_{i,MKT}\lambda_{MKT}+\beta_{i,SMB}\lambda_{SMB}+\beta_{i,HML}\lambda_{HML}+\beta_{i,MOM}\lambda_{MOM} \tag{11}$$

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

$$r_{i,t+1} = a_i + \beta_{i,MKT} r_{M,t+1} + \beta_{i,SMB} SMB_{t+1} + \beta_{i,HML} HML_{t+1} + \beta_{i,MOM} MOM_{t+1} + e_{i,t+1} \quad (12)$$

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

$$E\left(r_{i,t+1}\right) = \beta'_{i,f} \lambda_f + \beta_{i,L} \lambda_L \quad (13)$$

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

$$r_{i,t+1} = a_i + \beta'_{i,f} f_{t+1} + \beta_{i,L} L_{t+1} + e_{i,t+1} \quad (14)$$

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.

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.

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.:

$$HP_{i,t} = \frac{\#\, of\ short\ hedge\ positions_{\iota,t} - \#\, of\ long\ hedge\ positions_{\iota,t}}{Total\ \ \#\, of\ hedge\ positions_{\iota,t}} \tag{15}$$

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.

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 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).

[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.

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 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 HML_{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.

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:

$$E(r_i) = \beta_i' \lambda, \ \ i = 1, 2, ..., N. \quad (16)$$

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.:

$$r_{i,t} = a_i + \beta_i' f_t + e_{i,t}\,, \ \ t = 1, 2, ..., T \ for \ each \ i \quad (17)$$

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*,

$$r_i = \lambda_{0i} + \beta_i' \lambda + e_i\,, \ \ i = 1, 2, ..., N \ for \ each \ t \quad (18)$$

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, 2007). To address the EIV problem, we use Shanken's (1992) adjustment for the standard errors of the risk premium estimators.

6. Testing the asset pricing models: Results and discussion

6.1. Macro-factor models

Regarding the performance of the macro-factor asset pricing models, Table 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 (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%.

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 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.

6.3. Commodity-specific risk factors models

In this section, we investigate whether the constructed commodity-specific factors described in Section 4 price the cross-section of commodity futures expected returns. Table 8 summarizes the results. First we augment the CAPM with the hedging pressure factor HML_{HP} (HP-CAPM). Panel A reports the results for monthly and quarterly frequencies. Notice that we have constructed two distinct HML_{HP} factors (HP factor (a) and (b) under the assumptions (a) and (b) in Section 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 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 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 futures market is segmented itself. In the next section, we explore further the heterogeneity of the commodity futures markets.

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 9 shows the estimated factor coefficients for every model and every commodity futures for the monthly (panel A) and quarterly

[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.

(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, 2007). 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.

7. Further robustness tests

In this section we perform further tests to assess the robustness of the results reported in Section 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.

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

$$R_t = a + Bf_t + e_t \tag{19}$$

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:

$$E(R_t) = B\lambda_f \tag{20}$$

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 tth period. Using a sample of size T, the GMM estimate of θ is obtained by minimizing the quadratic function:

$$J_T(\theta) = g_T(\theta)'Wg_T(\theta) \tag{21}$$

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

$$g_T(\theta) = E\left(g\left(x_t,\theta\right)\right) = \begin{bmatrix} E\left(R_t - a - Bf_t\right) \\ E\left(R_t - B\lambda_f\right) \\ E\left[\left(R_t - a - Bf_t\right)\otimes f_t\right] \end{bmatrix} = \begin{bmatrix} 0_N \\ 0_N \\ 0_{NxK} \end{bmatrix} \tag{22}$$

The two stage GMM yields asymptotically efficient estimates of θ because it uses an optimal weighting matrix W in equation (21) calculated as

$$W = S^{-1},\ S = \sum_{j=-\infty}^{\infty} E\left[g\left(x_t,\theta\right) g\left(x_t,\theta\right)' \right] \tag{23}$$

(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 10 and 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.

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 (Daskalaki and Skiadopoulos, 2011, find 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 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 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.

7.3. Extended commodity futures dataset

We estimate all asset pricing models described in Sections 3 and 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

[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.

described in Section 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.

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 ith 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.

$$f_{i,t} = q_i' r_{t,t} \tag{24}$$

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

$$r_{i,t} = q_{1i} f_{1,t} + q_{2i} f_{2,t} + q_{3i} f_{3,t} + ... + q_{22i} f_{22,t} \tag{25}$$

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

Equation (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 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 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.

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.

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TABLES

Table 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 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 Horizon			Quarterly Horizon		
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: List of the various employed asset pricing models

The table presents 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 4: Description of the risk factors

The table explains the set of risk factors employed in this study; panel A includes the macro and equity-motivated tradable factors, and panel B includes 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 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 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 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 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 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 and 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 9 (cont'd): GMM results for one factor asset pricing models

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 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 comprises 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 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 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	CAPM	MCAPM(a)	MCAPM(b)	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
t-stat	*(1.170)*	*(1.234)*	*(0.962)*	*(1.170)*	*(1.141)*	*(1.548)*	*(1.269)*	*(1.041)*	*(1.565)*	*(1.422)*
Shanken's t-stat	*(1.166)*	*(1.214)*	*(0.949)*	*(1.166)*	*(1.135)*	*(1.545)*	*(1.247)*	*(1.032)*	*(1.552)*	*(1.418)*
Market factor	0.005	0.005	0.008		0.004	0.003	0.005	0.006	0.004	0.004
t-stat	*(1.052)*	*(1.036)*	*(0.960)*		*(0.900)*	*(0.720)*	*(1.048)*	*(1.243)*	*(0.738)*	*(0.859)*
Shanken's t-stat	*(1.052)*	*(1.033)*	*(0.958)*		*(0.899)*	*(0.720)*	*(1.046)*	*(1.241)*	*(0.737)*	*(0.858)*
Money growth		-0.001	0.009							
t-stat		*(-1.064)*	*(0.647)*							
Shanken's t-stat		*(-1.050)*	*(0.641)*							
Leverage factor										
t-stat										
Shanken's t-stat										
FX factor				0.005						
t-stat				*(1.052)*						
Shanken's t-stat				*(1.051)*						
HP Factor					-0.003	-0.002				
t-stat					*(-0.508)*	*(-0.345)*				
Shanken's t-stat					*(-0.507)*	*(-0.345)*				
Basis Factor							-0.007	0.006		
t-stat							*(-1.192)*	*(0.647)*		
Shanken's t-stat							*(-1.177)*	*(0.642)*		
Momentum Factor									0.006	-0.003
t-stat									*(0.833)*	*(-0.274)*
Shanken's t-stat									*(0.828)*	*(-0.273)*
R-squared	13.93%	22.96%	21.45%	13.93%	24.26%	23.63%	23.75%	23.75%	24.74%	24.74%
Adj-R-squared	9.63%	14.85%	13.18%	9.63%	16.29%	15.59%	15.72%	15.72%	16.81%	16.81%

Quarterly Frequency	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	0.016	0.007	0.017	0.016	0.006	0.003	0.011	0.017	0.016	0.012
t-stat	*(1.111)*	*(0.462)*	*(1.262)*	*(1.111)*	*(0.533)*	*(0.295)*	*(0.835)*	*(1.239)*	*(1.221)*	*(0.952)*
Shanken's t-stat	*(1.106)*	*(0.426)*	*(1.150)*	*(1.105)*	*(0.450)*	*(0.246)*	*(0.714)*	*(1.145)*	*(1.061)*	*(0.810)*
Market factor	0.012	0.016	0.008		0.025	0.026	0.016	0.013	0.011	0.019
t-stat	*(0.425)*	*(0.528)*	*(0.274)*		*(0.846)*	*(0.893)*	*(0.566)*	*(0.462)*	*(0.362)*	*(0.646)*
Shanken's t-stat	*(0.424)*	*(0.509)*	*(0.264)*		*(0.793)*	*(0.828)*	*(0.533)*	*(0.449)*	*(0.342)*	*(0.605)*
Money growth		-0.003								
t-stat		*(-1.255)*								
Shanken's t-stat		*(-1.183)*								
Leverage factor			-0.037							
t-stat			*(-1.173)*							
Shanken's t-stat			*(-1.092)*							
FX factor				0.012						
t-stat				*(0.425)*						
Shanken's t-stat				*(0.420)*						
HP Factor					0.044	0.058				
t-stat					*(1.675)*	*(1.958)*				
Shanken's t-stat					*(1.482)*	*(1.743)*				
Basis Factor							-0.041	0.040		
t-stat							*(-2.035)*	*(0.991)*		
Shanken's t-stat							*(-1.867)*	*(0.931)*		
Momentum Factor									0.045	0.073
t-stat									*(1.150)*	*(1.551)*
Shanken's t-stat									*(1.018)*	*(1.362)*
R-squared	17.68%	24.33%	25.24%	17.68%	29.30%	29.88%	22.84%	23.05%	28.98%	30.49%
Adj-R-squared	13.56%	16.37%	17.37%	13.56%	21.86%	22.50%	14.72%	14.95%	21.50%	23.17%

Table 12 (cont'd): Alternative proxies for the market portfolio

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 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 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.