Are there common factors in individual commodity futures returns?*

Charoula Daskalaki[a], Alexandros Kostakis[b], and George Skiadopoulos[c]

Forthcoming in the *Journal of Banking and Finance*

Abstract

We explore whether there are common factors in the cross-section of individual commodity futures returns. We test various asset pricing models which have been employed for the equities market as well as models motivated by commodity pricing theories. The use of these families of models allows us also to test whether the commodities and equities market are integrated. In addition, we employ Principal Components factor models which do not require à priori specification of factors. We find that none of the models is successful. Our results imply that commodity markets are segmented from the equities market and they are considerably heterogeneous per se.

JEL Classification: G12; G13; G21.

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

---

* We are grateful to two anonymous referees for their thorough, constructive and stimulating comments. We would also like to thank Carol Alexander, Michail Anthropelos, Angelos Antzoulatos, Chris Brooks, Bahattin Buyuksahin, John Cochrane, Frans de Roon, Deepa Dhume, Gordon Gemmill, Amit Goyal, Richard Harris, Cam Harvey, Fumio Hayashi, Dimitris Malliaropoulos, Joelle Miffre, Tyler Muir, Anna Pavlova, Peter Pope, Marcel Prokopczuk, Lucio Sarno, Theodoros Stamatiou, Andreas Stathopoulos, Marta Szymanowska, Dimitris Vayanos, Andrea Vedolin, Chris Veld, Christian Wagner, Motohiro Yogo, Josef Zechner and participants at Bath University, Cass Business School, Exeter Business School, ICMA Centre University of Reading, Imperial College London, Maastricht University, Queen Mary University of London, University of Cyprus, University of Geneva, and WU Vienna University of Economics and Business seminar series and the 2012 Macro and Financial Economics Conference at Brunel University, 2012 Annual Conference on Research in Economic Theory and Econometrics (Milos) and 2013 Queen Mary, University of London Conference on Recent Advances in Commodity Markets for useful comments and discussions. Financial support from the Research Centre of the University of Piraeus and the Fundação Ciência e Tecnologia's grant number PTDC/EGE-ECO/099255/2008 is gratefully acknowledged. Any remaining errors are our responsibility alone.

[a] Department of Banking and Financial Management, University of Piraeus, Greece, e-mail: chdask@webmail.unipi.gr

[b] Manchester Business School, UK, e-mail: alexandros.kostakis@mbs.ac.uk

[c] Corresponding author. Department of Banking and Financial Management, University of Piraeus, Greece, School of Economics and Finance, Queen Mary, University of London, UK, Cass Business School, City University, UK, e-mail: gskiado@unipi.gr

1. Introduction

The primary goal of the asset pricing literature is to develop a model which explains (i.e. prices) the *cross-section* of the assets returns by means of a small set of common factors. There is an extensive research 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) which price the cross-section of equities. However, there is no consensus on whether there is an asset pricing model which may explain the cross-section of individual commodity futures returns. We contribute to this debate by conducting a comprehensive study.

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 model for commodities is also of particular importance to practitioners. Institutional investors have increased their portfolio allocations to commodities over the last years (Daskalaki and Skiadopoulos, 2011, Skiadopoulos, 2013). Therefore, commodity investors need to have reliable asset pricing models to evaluate their risk-adjusted performance.

The literature on the validity of asset pricing models to price the *cross-section* of commodities has been developing only recently. In the earlier literature, the vast majority of papers tests only the *time series* pricing properties of asset pricing models for each commodity individually rather than evaluating their performance within a cross-sectional setting. These studies employ either models that are designed to price *any* asset (stochastic discount factor, SDF, paradigm, Dusak, 1973, Bodie and Rosansky, 1980, Breeden, 1980) or commodity-specific factors (Stoll, 1979, Carter et al. 1983, Hirshleifer, 1988, 1989, Bessembinder, 1992, de Roon et al., 2000, Gorton et al., 2012, Acharya et al., 2013, Gospodinov and Ng, 2013) as determinants of the time series of each commodity futures premium. The latter family of models is motivated by the hedging pressure hypothesis (Keynes, 1930, Cootner, 1960) and the theory of storage (Working, 1949, Brennan, 1958).

The prior literature that examines the existence of common factors in the cross-section of individual commodity futures finds mixed results. Jagannathan (1985) rejects the Consumption Capital Asset Pricing model (CCAPM) over monthly horizons whereas de Roon and Szymanowska (2010) find that CCAPM explains commodity futures returns (only) at quarterly horizons. Roache (2008), Shang (2011) and Etula (2013) find that the real interest rate, a foreign exchange variable and a quantity related to the broker dealers' leverage price commodity futures, respectively. Miffre et al. (2012) find that the idiosyncratic volatility of the commodity futures is not priced once one controls for commodity-specific factors. Basu and Miffre (2013) find that the hedging pressure is priced by constructing 16 different versions of the hedging pressure factor. However, their cross-sectional pricing evidence is based on pooling the 16 risk premium estimates from the different hedging pressure factors. This evidence though does not necessarily imply that any of these 16 different factors can individually explain the cross-section of commodities futures returns. In sum, the existing evidence suggests that further research should be conducted within a unified setting.

Building on the previously discussed literature, we comprehensively investigate whether there are any factors which explain the *cross-sectional* variation in individual commodity futures returns. We use a cross-section of 22 individual commodity futures contracts over the period January 1989-December 2010. The employed contracts represent the five main commodity categories (grains and oilseeds, softs, livestock, energy and metals). This cross-section is similar to the one employed by the previous cross-sectional studies on individual commodity futures. Moreover, this time period incorporates the 2003-2008 commodity boom period and the recent 2007-2009 financial crisis.

We begin our research by testing a number of macro-factor (aggregate variables) models. These models are designed to price *any* asset class including commodity futures if the markets are integrated (market integration is defined to be the case where the same SDF prices all markets, as in Bessembinder, 1992). We choose macro-factor models which use factors that play an important role in commodity futures markets, and hence they are appealing candidates for pricing purposes.

We find that no macro-factor model prices commodity futures. Next, we examine popular equity-motivated tradable factor models which have been shown to price the cross-section of equity returns (Fama-French, 1993, Carhart, 1997, and Pastor and Stambaugh, 2003). The rationale lies in Cochrane's (2005, page 64) theorem: under the law of one price, free portfolio formation, and provided that markets are not segmented, if a certain factor prices a given market, then it should also price the other markets. Hence, if the theorem's conditions hold, then these empirically successful factors for the equity market should price the cross-section of commodity futures too. Notice that our research approach does not assume in advance that the equity markets are integrated with the commodity futures ones.[1] In fact, testing whether macro-models or equity-motivated tradable factors price the cross-section of commodity futures provides a clean test for the markets integration hypothesis given Cochrane's (2005) theorem (for a similar approach, see also Bessembinder, 1992).

We find that the equity-motivated tradable factors models do not price commodity futures either. This finding implies that commodity futures markets are segmented from equity markets corroborating the results of Bessembinder (1992) and Bessembinder and Chan (1992). Consequently, we then focus on commodity-specific factors. We construct theoretically sound commodity-specific factors by relying on the two main theories for the determination of commodity futures returns; hedging

[1] The empirical evidence on the integration of commodity and equity markets is mixed. 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), term spread, default spread, and foreign exchange factors do not drive the time-series variation of 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 (2012) argue that the increase of investments in commodities via commodity indexes (financialization of commodities) tends to integrate the equity with the commodity markets (see also Basak and Pavlova, 2012, Henderson et al., 2012, and Singleton, 2012). Bakshi et al. (2011) and Hong and Yogo (2012) find that there are common variables which predict commodity futures and equity returns. However, this is a necessary but not a sufficient condition for market integration (Bessembinder and Chan, 1992).

pressure and the theory of storage. We also construct a commodity-specific liquidity risk factor and a commodity futures open interest factor motivated by Marshall et al. (2012, 2013) and Hong and Yogo (2012), respectively. We find that commodity-specific factors fail in pricing commodity futures too. This finding implies that there is no common risk factor structure in the cross-section of commodity futures risk premiums. We verify the heterogeneous structure of the commodity futures markets by showing that there is no single factor from our factors' menu which can explain the *time series* of returns of *every* single commodity futures.

As a final step, we implement principal components (PCs) factor models in the spirit of Cochrane (2011). In contrast to the previously employed models, these models do not require à priori specification of factors and they enable detecting the presence of *any* factor that may be used as a candidate for pricing commodity returns. We find that the PC models also perform poorly. Moreover, the results from the PC models confirm that there is a significant degree of segmentation in commodities futures markets. This finding also explains the failure of all previously employed factors.

We conclude this introduction by discussing the choice of our universe of test assets. Szymanowska et al. (2012), Bakshi et al. (2013) and Yang (2013) use commodity futures portfolios as test assets in line with the practice in the equities pricing literature.[2] Instead, we use individual commodity futures as test assets because the latter approach has a number of shortcomings in the case of commodities. First, the cross-section of commodity futures is small. Hence, only a small number of portfolios can be formed and this poses econometric challenges for model testing purposes. Second, the formation of commodity portfolios may mask the heterogeneous characteristics of individual commodities. This may also lead to large efficiency losses, potentially distorting the estimated factor risk premiums (Ang et al., 2010). Finally, the portfolio formation process is subject to data snooping

[2]These portfolios are formed by using as sorting criterion variables that are found to predict commodity futures returns (e.g., basis, momentum, volatility). They find that the futures basis and momentum factors are priced. However, this is not an entirely unexpected result because these factors are identical/ highly related to some of the sorting criteria employed to form the test portfolios (e.g., the basis is correlated with the momentum and volatility criteria, see Gorton et al., 2012). This may lead to a tautology and hence these factors ought to price the basis/momentum-sorted portfolios by construction.

criticism (Lo and MacKinlay, 1990). Nevertheless, we conduct a robustness analysis by using commodity futures portfolios formed by the type of the underlying commodity. The results from the portfolio test assets are in line with these obtained from the individual test assets.

Finally, a word is in order regarding the fact that we employ individual commodity futures asset class in a stand-alone fashion rather than augmenting our test assets universe with other asset classes. Dhume (2011) and Asness et al. (2013) use an augmented test asset universe and they find that certain factors are priced (consumption growth of durable goods and value/ momentum factors, respectively). However, the fact that these factors price multiple asset classes when they are jointly examined does not imply that they also price any given asset class separately. This will only be true in the case where these markets are integrated because in this case the SDF is unique.[3] In fact, we find that neither the consumption growth of durable goods nor the momentum factors are priced when the test assets include only individual commodity futures. The difference in results is explained by our findings which imply that the commodity and equity markets are segmented (for a review see also Skiadopoulos, 2013).

The rest of the paper is structured as follows. Section 2 describes the datasets. Section 3 reviews the employed macro and equity-motivated tradable factors asset pricing models and Section 4 describes the construction of commodity-specific factors. Section 5 discusses the results from asset pricing tests and Section 6 provides further robustness tests. Section 7 describes the Principal Component Analysis (PCA) factor models and it discusses the results. Section 8 concludes and it discusses the implications of our research.

[3] This argument can be also explained in terms of the regression mechanics. These asset pricing tests are essentially tests on the significance of coefficients (i.e. the risk-premiums) estimated from cross-sectional regressions. The significance of these coefficients refers to the entire cross-section, without implying that these results would necessarily carry over to sub-samples of the cross-section. This observation becomes rather important when the cross-section is the union of heterogeneous subsamples, as in the case of segmented markets. In this case, it is possible that the significance of the risk-premium is solely driven by a particular sub-sample.

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.[4] For each underlying commodity, we create a continuous time series of monthly and quarterly futures percentage excess returns. To calculate the monthly excess 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 excess returns using the successive monthly prices of a contract recorded on the first day of the month for a given delivery date, i.e. we do not compute returns by using prices across contracts with different delivery dates. Hence, the returns correspond to 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 (for a similar approach see 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. TABLES

Table 1 reports the descriptive statistics for the constructed series of monthly and quarterly commodity futures excess returns over the period January 1989-December 2010. The average excess return varies across commodities; the greatest average returns are earned by energy, copper and palladium futures, both for the monthly and quarterly frequencies. These contracts, along with the platinum futures, outperform the other contracts also in terms of risk-adjusted performance (annualized 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

[4] We have also conducted the analysis by employing a larger sample that spans the period 1975-2010. Due to data availability constraints, the 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.

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 to proxy 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 6.2. We obtain the time series data on the Pastor-Stambaugh (2003) liquidity, Lustig et al. (2011) foreign exchange and Adrian et al. (2012) 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 frequencies. We obtain data on the U.S. Consumer Price Index (CPI), the U.S. Gross Domestic Product (GDP), the U.S. Industrial Production and the U.S. 3-month T-bill yield from Datastream.

To calculate real consumption growth per capita, 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 quarterly and monthly frequencies, respectively. Money growth is measured by 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 money growth. These data are available only for the period January 1998-December 2010. The observation which is closest to the beginning of the month / 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. Finally, we obtain open interest and volume data on the individual commodity futures contracts from Bloomberg.

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 returns. Let the beta formulation of a *K*-factor asset pricing model

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

where r_i denotes the futures *i* excess return, λ is the $(K \times 1)$ vector of factor risk premiums and β_i is the $(K \times 1)$ vector of betas for asset's *i* returns with respect to the *K*-factor returns. We employ a set of aggregate factor models that consists of CAPM, CCAPM, Money-CAPM (MCAPM), Money-CCAPM (MCCAPM), the leverage factor model, the international CAPM as well as a model that includes a set of macro shocks. All these models are designed to price any asset class. The set of the equity-motivated tradable factors comprises the Fama-French (1993), Carhart (1997), and Pastor and Stambaugh (2003) ones.

3.1. CAPM and CCAPM

First, we consider the popular one-factor CAPM and CCAPM (Breeden, 1979) asset pricing models which amount to using the risk premiums of the excess returns of the market portfolio and the consumption growth $g_{t+1} = \left(\left(c_{t+1} / c_t \right) - 1 \right)$ in equation (1), respectively. CAPM and CCAPM betas are defined as $\beta_{i,MKT} = Cov\left(r_{i,t+1}, r_{M,t+1} \right) / Var\left(r_{M,t+1} \right)$ and $\beta_{i,CON} = Cov\left(r_{i,t+1}, g_{t+1} \right) / Var\left(g_{t+1} \right)$, respectively, where $r_{M,t+1}, r_{i,t+1}$ are the excess returns of the market portfolio and an asset *i,* respectively. 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 they result in increases in their prices.

Following Dhume (2011), we also estimate a consumption-based asset pricing model developed by Yogo (2006). In this model, an intertemporal household optimization problem with choices over durable and nondurable consumption is combined with portfolio choice theory. The resulting asset pricing equation includes the market factor as well as both the durable and non-durable consumption growth variables. We calculate the non-durable and durable consumption growth variables by using data from the NIPA Tables (for a description, see Dhume, 2011).

3.2. MCAPM and MCCAPM

A number of papers find that the monetary policy affects the returns of the individual commodity futures (e.g., Frankel, 2008, and Anzuini et al., 2013). However, 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 money supply growth variable to the traditional CAPM and CCAPM setting. The intuition is that the presence of money facilitates transactions and hence it decreases transaction costs. Therefore, the money supply growth affects the adjusted for transaction costs marginal utility of wealth and therefore it affects the SDF of the representative agent. The beta formulations for the *i*th asset's expected excess return for MCAPM and MCCAPM are given by augmenting the CAPM and CCAPM beta formulations with the money growth market price of risk, respectively.

We proxy money growth by two alternative measures of the money supply in the economy. The first measure 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 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). 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.[5]

3.3. Commodity futures returns and financial intermediaries

Next, we explore whether a factor constructed from data obtained from broker dealers' balance sheets explains the cross section of commodity returns. Etula (2013) shows that 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. (2013) delivers a similar prediction. Both models predict a negative relationship between broker dealers' leverage and the individual commodity futures risk premium. The intuition is that leverage reflects the ease of access to capital. The greater leverage is, the easier is for broker dealers to meet the hedging demand of producers and therefore the lower the required futures risk premium. This state variable is also an appealing candidate pricing factor for

[5] 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.

commodity futures returns given the importance of broker dealers for commodity futures markets (Basak and Pavlova, 2012, Henderson et al., 2012, Singleton, 2012, Tang and Xiong, 2012).[6]

We adopt Adrian et al. (2012) intertemporal broker dealers' leverage CAPM setting and we examine whether shocks to broker-dealers' financial leverage explain the cross sectional variation in commodity futures returns. The leverage factor is obtained from Tyler Muir's website (quarterly frequency). Within this setting, the beta formulation for the *i*th asset's expected excess return includes the risk premium associated with the leverage factor.

3.4. Commodity futures returns and foreign exchange risk

We consider a risk factor that takes into account the exposure of commodity futures to foreign exchange rate risk. Erb and Harvey (2006) document a relationship between commodity futures and 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 and hence their prices. For instance, a depreciation of the U.S. currency makes commodities more attractive to non-U.S. consumers and hence it increases their prices as global demand rises. On the supply side, 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 dollar-denominated financial assets which may make commodities a more attractive class of "alternative assets" to foreign investors.

We adopt the international-CAPM setting (Dumas and Solnik, 1993, DeSantis and Gerald, 1998). In this setting, any investment for a non-U.S. investor in a commodity is a combination of an

[6] To a large extent, broker dealers are the marginal investor on the speculative side of 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, 2013) further support the importance of the broker-dealers' risk-bearing capacity for the determination of commodity futures premiums.

investment in the performance of the commodity and an investment in the performance of the domestic currency relative to U.S. dollar. The premium for the exposure to exchange rate risk is aggregated over investors from different countries. The beta formulation for the *i*th asset's expected excess return includes the foreign exchange risk premium. We proxy this risk factor by using Lustig et al. (2011) tradable factor (carry trade).

3.5. Commodity futures returns and macro shocks

Finally, we consider a model that includes a set of macro shocks in line with some previous commodities literature. Following de Roon and Szymanowska (2010), we treat shocks to industrial production growth, shocks to GDP growth and shocks to consumption growth as potential sources of priced risk in commodity futures markets. In addition, we enrich the model with shocks to inflation (Erb and Harvey, 2006, Gorton and Rouwenhorst, 2006) and interest rate shocks (Fama and French, 1987). We calculate shocks as the residuals from an an autoregressive of order 1 (AR(1)) model applied to the respective variables.

3.6. Commodity futures returns and equity-motivated tradable factors

We employ Fama-French's (1993) size and value, Carhart's (1997) momentum, and Pastor and Stambaugh's (2003) liquidity factor mimicking portfolios which have been found to explain the cross-section of stock returns. Cochrane (2005) provides the theoretical foundation for applying these equity factors to 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. Therefore, our approach provides a clean test of the equities and the commodities markets integration hypothesis just as the application of macro-models does. Integration of the equity and the commodity futures markets implies that the expected return of equities should equal the expected return of commodity futures provided that the systematic risk is the same in the two markets (Bessembinder, 1992).

The full Fama-French-Carhart-Pastor and Stambaugh model beta formulation for the *i*th asset's expected excess return is given by

$$E\left(r_{i,t+1}\right) = a_i + \beta_{i,MKT}\lambda_{MKT} + \beta_{i,SMB}\lambda_{SMB} + \beta_{i,HML}\lambda_{HML} + \beta_{i,MOM}\lambda_{MOM} + \beta_{i,L}\lambda_L \qquad (2)$$

where $\lambda_{MKT}, \lambda_{SMB}, \lambda_{HML}, \lambda_{MOM}, \lambda_L$ denote the risk premiums on the market, value, size and liquidity factors, respectively, and $\beta_{i,MKT}$, $\beta_{i,SMB}, \beta_{i,HML}, \beta_{i,MOM}, \beta_{i,L}$ denote the *i*th asset's sensitivities derived from the following multi-factor linear model

$$r_{i,t+1} = a_i + \beta_{i,MKT} r_{M,t+1} + \beta_{i,SMB} SMB_{t+1} + \beta_{i,HML} HML_{t+1} + \beta_{i,MOM} MOM_{t+1} + \beta_{i,L} L_{t+1} + e_{i,t+1} \qquad (3)$$

where $r_{M,t+1}, SMB_{t+1}, HML_{t+1}, MOM_{t+1}, L_{t+1}$ denote the market, size, value, momentum and liquidity factors, respectively. Fama-French and Carhart models are nested within the specification of equation (2) for $\beta_{i,MOM} = \beta_{i,L} = 0$ and $\beta_{i,L} = 0$, respectively.

4. Commodity-specific factors: Construction

In this section, we describe the construction of five distinct commodity-specific factors that may serve as potential sources of priced risk in commodity futures markets. First, we construct one hedging pressure and two inventory-related factors which represent returns to a long/short commodity futures portfolio strategy; the commodity futures included in the two portfolios are equally weighted. Next, we construct a commodity-specific liquidity risk factor. Finally, we construct an aggregate open interest factor for commodity futures markets.

4.1. Hedging-pressure risk factor

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

$$HP_{i,t} = \frac{\#\,of\;\,short\;hedge\;positions_{i,t}\;\text{-}\;\#\,of\;\,long\;hedge\;positions_{i,t}}{Total\;\;\#\,of\;hedge\;positions_{i,t}} \tag{4}$$

According to the hedging pressure hypothesis (Keynes, 1930, Cootner, 1960), futures markets provide a risk transfer mechanism whereby risk averse speculators demand compensation to take futures positions and share 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 construct a zero-cost portfolio which mimics this strategy. At each point in time *t* (first day of the month or quarter), we calculate the hedging pressure for each futures contract. Then, 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 going short in a portfolio consisting of commodities with a negative HP. Then, on the first day of the following month or quarter, we calculate the mimicking portfolio return. We rebalance the portfolios every month and quarter throughout the sample and we obtain the time series of the factor returns. We construct the two portfolios by using the following two alternative methods:

a. Portfolio H contains all commodities with positive HP whereas portfolio L contains all commodities 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, Gorton et al. (2012) 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 inventory data. As a result, the data are not recorded on the same dates across the different sources. Second, there is a notorious difficulty in measuring inventories accurately because commodities are produced, consumed and traded internationally. The aggregation of these quantities is not always feasible. Given these constraints, in accordance with Gorton et al. (2012) we construct inventory-related factors by using the basis and the prior futures returns attributes which reflect the level of inventories, they are readily available and they do not suffer from measurement errors.[7]

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

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

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, see Fama and French, 1987, Gorton and Rouwenhorst, 2006, Bakshi et al., 2013, Yang, 2013).

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 (short) in the portfolio of commodities which have a positive (negative) basis. The time series of the factor returns are obtained just as in the case of the HML_{HP} factor. We construct portfolios H and L by using two alternative methods:

a. Portfolio H contains all commodities with positive basis (High Basis Portfolio) whereas portfolio L contains all commodities with negative basis (Low Basis Portfolio).

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

B. Momentum risk factor: Construction

Gorton et al. (2012) document a momentum in the individual commodity futures excess returns and they explain it 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 is because inventories can be restored slowly through the time-consuming process of new production. The limited supply cannot meet the demand for this commodity over this period of time and this creates a price momentum.

At each point in time *t*, we construct a zero-cost HML_M (high minus low momentum) risk factor by going long (short) in the portfolio comprising commodities with a positive (negative) prior 12-

month average return. Gorton et al. (2012) and Bakshi et al. (2013) find that this is a profitable strategy. We construct the two portfolios by using the following two alternative methods:

a. Portfolio H contains all 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 a positive or a negative 12-month average prior average futures return, we use the number of available contracts with these features.

Table 4 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). We can see that the hedging pressure hypothesis is not verified in all cases because both the long and the short portfolios earn positive returns. In addition, the mean return on HML_{HP} is barely positive and it is statistically insignificantly different 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 statistically significant. These findings suggest that the basis and the prior-futures returns constitute meaningful sorting criteria.

4.3. Commodity liquidity risk factor

Marshall et al. (2013) find evidence of commonality in liquidity across commodity futures markets; liquidity risk is defined as the change of a common liquidity factor over time. Marshall et al. (2012) conduct a horse race among various liquidity proxies for commodity futures markets. They conclude that Amihud's (2002) ratio has the largest correlation with liquidity measures constructed from high-frequency data; the latter measures represent actual commodity transaction costs. Hence, we construct a commodity liquidity risk factor by computing Amihud's illiquidity measure for commodity futures markets in line with Marshall et al. (2012, 2013). For a given commodity *i* on day *t*, the $Amihud_{i,t}$ illiquidity measure is defined as

$$Amihud_{i,t} = \frac{|r_{i,t}|}{Volume_{i,t}} \tag{5}$$

where $r_{i,t}$ is the daily return of the commodity futures *i* on day *t* and $Volume_{i,t}$ is the futures dollar volume on day *t*. We obtain daily data for the individual futures contracts and we form continuous series of daily futures returns as described in Section 2. To compute the denominator of equation (5), we collect the daily volume of each contract and we multiply this by the product of the futures contract size and its settlement price quoted in USD. Then, we compute the monthly illiquidity proxy for each individual futures contract by averaging the daily illiquidity measures. Finally, we calculate the market illiquidity across commodity futures in a given month by averaging the individual futures monthly averages.

4.4. Open interest risk factor

Hong and Yogo (2012) find that the open interest in commodity futures markets predicts commodity futures returns. We construct an aggregate open interest factor by adding the open interest of the individual futures contracts across all traded maturities. Next, within an intertemporal CAPM (ICAPM) setting, we estimate the open interest shock series using an AR(1) with a linear time trend model and we investigate it's cross-sectional asset pricing ability.

5. Testing the asset pricing models: Results and discussion

We employ the standard Fama-MacBeth (1973) two-pass approach to estimate the various asset pricing models described in Sections 3 and 4. We use a cross-section of 22 individual commodity futures excess returns as test assets. In line with Fama-MacBeth (1973), in the first-pass regression we estimate the beta coefficients using a rolling window of 60 monthly observations. To address the errors-in-variables problem, we use Shanken's (1992) adjustment for the standard errors of the risk premium estimators. We have also estimated the models using the generalized method of moments (GMM) and the results (available upon request) did not change.

5.1. Macro-factor models

Regarding the performance of the macro-factor asset pricing models, Table 5 reports the (average) constant coefficients, risk premiums, *t*-statistics, Shanken's (1992) adjusted *t*-statistics, R^2 and adjusted R^2 . We implement CAPM, CCAPM, MCAPM, MCCAPM, International CAPM, Leverage CAPM and a model with a set of macro-shocks 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. CAPM delivers an adjusted R^2 of 6.82% and 4.76% for monthly and quarterly frequencies, respectively, whereas CCAPM delivers an adjusted R^2 of 5.01% and 2.09% for monthly and quarterly frequencies, respectively. Moreover, both models yield insignificant risk premiums. The poor performance of CAPM and CCAPM is in line with the previous evidence on their performance in equities and commodity futures markets (Jagannathan, 1985). Interestingly, the evidence on the performance of CCAPM differs partially from the findings of de Roon and Szymanowka (2010) who find significant risk premium and high explanatory power for 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. De Roon and Szymanowka (2010) study an unbalanced dataset over the period 1968-2004 and they estimate a full sample rather than a rolling beta in the first step Fama-MacBeth time series regression as we do. However, unreported results show that betas have a significant time variation, and hence a rolling beta should be used to capture this pattern. Finally, notice that Dhume (2011) finds that the durable consumption growth is priced in a cross-section of commodity portfolios augmented with other asset classes. If markets were integrated, then Dhume's factor should price any individual asset class as well. In contrast, we find that this factor is not priced when we consider only commodity futures as test assets. These findings imply that the commodity futures markets are segmented from the other asset classes.

Regarding the performance of the MCAPM and MCCAPM models, in the case where we implement them by measuring the money growth by 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 is 10.64% for MCAPM(a) whereas it is 6.82% for CAPM). In addition, the monetary factor's risk premium is statistically insignificant. This is in contrast to the evidence provided by Balvers and Huang (2009) for the case of equity portfolios. Qualitatively similar conclusions are drawn in the case where we measure 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 it is conducted by employing only the monthly frequency data. We do not use 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 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 commodity futures returns.

Next, we augment CAPM with the innovations in 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 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. Interestingly, this finding is not directly comparable with Etula's (2013) who finds that a *function* of the leverage is priced on a *smaller* cross-section of commodity futures (14 commodity futures). Similar conclusions are drawn when we augment CAPM with 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 is 9.76% for FXCAPM whereas it is 6.82% for CAPM). Moreover, the statistical insignificance of the risk premium indicates that the foreign exchange risk factor does not price the cross section of commodity futures returns. This is in contrast to the evidence reported by Shang (2011) who finds that the foreign exchange risk factor prices commodity futures. [8]

Finally, in the case of the macro-shocks model, we find that the industrial production growth shocks, the consumption growth shocks, the inflation shocks, the interest rate shocks as well as the GDP growth shocks (only for the quarterly frequency) do not price the cross section of commodity futures returns either. The explanatory power of the model increases compared to that delivered by the other macro models, yet it is still low (e.g., in the monthly frequency, the adjusted R^2 equals 23.23%, whereas for the quarterly frequency equals 22.40%).[9]

[8] We employed shocks of Shang's (2011) foreign exchange factor (U.S. effective exchange rate on major currencies) and we found that they are not significant either in a stand-alone fashion or in a multivariate setting used along with shocks of the other macro-variables; the intertemporal CAPM setting dictates that shocks of the factors rather than the factors per se should be used.

[9] Interestingly, Roache (2011) finds that the real interest rate prices commodity futures. We employed real interest rate shocks, measured using the U.S. three-month treasury bill yield minus the CPI inflation rate over the previous 12 months. We found that that the factor is not statistically significant neither in a stand-alone fashion nor in a multivariate setting along with the shocks of the other macro-variables. The difference in results can be attributed to the employed different datasets and time periods.

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. Balvers and Huang (2009) apply MCAPM (MCCAPM) to quarterly frequencies for the period 1959-2010 and they report R^2's in the range 11% - 64% (25% - 58%) depending on the type of equity portfolio under consideration. Similarly, Adrian et al. (2012) apply the leverage factor over quarterly frequencies for the period 1968-2009 and they report R^2's in the range 24%- 75%.

5.2. 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 6 reports the results. In the case of the FF model, the explanatory power in adjusted R^2 terms increases compared to 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 Carhart's model, the goodness-of-fit increases further (24.82% and 16.63% for monthly and quarterly frequencies, respectively), yet the risk premiums are statistically insignificant again regardless of the frequency. To determine whether the liquidity risk is priced in the cross-section of commodity futures returns, we augment FF and Carhart models with Pastor and Stambaugh's (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 premiums of all risk factors are insignificant.

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) in a time-series setting. 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 equity and foreign exchange markets.

5.3. 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 returns. Table 7 reports the results. First we examine the asset pricing ability of the hedging pressure factor HML_{HP} (panel A). 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 risk premiums of the HP factors are insignificant. This is in line with the results in Miffre et al. (2012, footnote 11).

Next, we examine whether the constructed inventory-related factor prices the cross-section of commodity futures returns. To this end, we examine the asset pricing ability of the inventory-related factors, HML_B or HML_M (basis and momentum factors, respectively) constructed in Section 4.2. 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 models yield insignificant risk premiums for all factors and frequencies. Note that our results are not comparable to the ones obtained by Szymanowska et al. (2012), Bakshi et al. (2013) and Yang (2013) who report a significant risk premium for the basis and momentum factors; they use commodity portfolios rather than individual commodity futures. We comment further on their findings in section 6.2.

Finally, we examine whether Amihud's illiquidity factor and shocks of the commodity futures open interest price the cross-section of commodity futures returns. Panels D and E report the respective results. We can see that the illiquidity and open interest risk premiums are insignificant for both frequencies just as it was the case with these of the other commodity-related factors.

Overall, commodity-specific factor models cannot price the cross-section of individual commodity futures either. This implies that there is a degree of segmentation in the commodity futures market. Hence, it is not surprising that our results differ from the ones in Asness et al. (2013) just as it was the case with the divergence from Dhume's (2011) results; they find that their momentum factor prices an *augmented* test asset universe that includes commodity futures portfolios as well as other asset classes. In the next section, we explore the heterogeneity of the commodity futures markets further.

5.4. More on the heterogeneity of the commodity futures markets

Apart from the equity and the commodity futures markets segmentation explanation, 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 betas obtained from the first step of the Fama-MacBeth approach. We undertake this exercise for every asset pricing model and for every commodity. Unreported results show that in most cases, the rolling betas are significantly different from zero. Therefore, the insignificant risk premiums 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 investigate the heterogeneity hypothesis by estimating single factor time series models for each commodity futures returns on a monthly and on a quarterly frequency; we use in turn each one of the 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 time series models by GMM. Table 8 reports the estimated factor coefficients for 16 indicative factors for every commodity futures; results for the other factors used in this paper are available upon request. We can see that there is no factor for which *all* commodities futures returns are significantly exposed (sensitive) to over the full sample period, highlighting the heterogeneity of their returns' nature (see also Erb and Harvey, 2006, Kat and Oomen, 2007). This heterogeneity is due to the fact that the price behaviour of softs is generally "supply-driven", of metals is demand-driven, of precious metals is speculative, and of oil is a mix of fluctuations in demand and supply.

The reported evidence on the heterogeneity of commodity futures explains the lack of common factors in the cross-section of commodity futures returns and it 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 the individual commodity futures returns only in a time series setting and not in a cross-sectional one. Interestingly, the dispersion of the estimated betas confirms our choice to use individual commodity futures rather than portfolios as test assets. Ang et al. (2010) show that in the case of a large cross-sectional dispersion in the estimated betas, the use of portfolios as test assets can distort the Fama-French (1973) factors' risk premiums estimates in the second pass regressions even if it improves the accuracy of the estimated betas in the first-pass regressions. This is because the more disperse the cross-section of betas is, the more information the cross-section contains to estimate the factors risk premiums.

6. Further robustness tests

In this section we perform further tests to assess the robustness of the results reported in Section 5. First, we use alternative proxies for the market portfolio. Second, we use a larger cross-section of commodity futures and commodity futures portfolios as test assets. Third, we conduct a subsample as well as a subsector analysis.[10]

[10] We have also performed an additional robustness check by considering the effect that the seasonality of commodities may have on the results of the asset pricing tests. For each commodity futures, we regress its returns on seasonal dummy variables. Then, we extract the residuals of these 22 time series regressions and we apply the asset pricing tests to the

6.1. Alternative proxies for the market portfolio

In the previous sections, we used a broad stock index to proxy the market portfolio. The results on the estimated risk premiums may 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. This is because 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 they improve investment opportunities (Daskalaki and Skiadopoulos, 2011, find though that this improvement does not hold in an out-of-sample setting).

Consequently, 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) and we estimate the asset pricing models which require the market portfolio as an input (CAPM, MCAPM and LevCAPM). Unreported results show that the risk premiums of all factors are insignificant regardless of the alternative proxy of the market portfolio.

6.2. Alternative test assets

Next, 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 (for a similar choice see 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 futures

residuals rather than to the original commodity futures series. Again, we find that no factor/model prices the cross-section of commodity futures.

returns for the second-nearest-to-maturity futures contracts by following a similar approach as the one described in Section 2. We repeat the described process throughout the dataset for each one of the 22 assumed futures contracts. This delivers a larger cross-section of 44 observations at each point of time. The 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.

In addition, we estimate the asset pricing models described in Sections 3 and 4 by using portfolios of commodity futures as test assets. There are a number of potential sorting criteria for commodities, just as there are for equities. However, we choose to sort the 22 individual commodity futures contracts in portfolios by the *type* of the underlying commodity (commodity type portfolios). This is the simplest and most obvious sorting criterion so as to avoid a data snooping criticism (Lo and MacKinlay, 1990). To this end, we form 5 equally weighted distinct portfolios (grains, softs, livestock, energy, metals; see Table 1 for the description of the type portfolios). We repeat our asset pricing tests for these 5 distinct commodity groups. The results are qualitatively similar to the ones obtained when the analysis was conducted for the individual commodity contracts, i.e. none of the employed factors explains the cross-sectional variation in commodity futures premiums. Interestingly, our results differ from the ones reported by Szymanowska et al. (2012), Bakshi et al. (2013) and Yang (2013) who find a significant risk premium for the basis and momentum factors. This difference may be attributed to the sorting criterion they employ to form portfolios. They sort portfolios by using the same criterion used to construct their factors. Hence, a tautology is incurred and as a result their factors are priced.

6.3. Subsample and Subsector analysis

We conduct a subsample as well as a subsector analysis. First, we repeat the previous analysis described in Sections 3 and 4 over the last decade (2000-2010) so as to investigate whether our results are still robust in the presence of the financialization of commodity futures markets. Second, we perform the asset pricing tests on commodity futures belonging to a specific commodity subsector. We choose the agricultural sector that yields the greatest number of commodity futures consists (11 commodity futures, grains and softs) enabling the performance of asset pricing tests. While other categories would also be interesting to examine (e.g., precious metals), asset pricing tests with less than 5 commodities are infeasible due to extremely low degrees of freedom.

The subsample analysis reveals that our results are robust to the choice of time period. Only the hedging pressure factor is found to be significantly priced in a stand-alone fashion at the monthly frequency only. In the previous sections, we provide robust evidence that there is no common factor in the cross-section of all commodities during the examined full sample period. We do not exclude the possibility that there may be sub-periods during which one might find significant risk premia for certain factors, as for hedging pressure during the sub-period 2000-2010. Nevertheless, this is a rather short time period to extract meaningful pricing conclusions and the risk premium coefficient of this factor is only marginally statistically significant. Moreover, a scatterplot of the 22 actual average commodity returns over this period versus their expected returns implied by the hedging pressure factor model shows that this model fits poorly the cross-section of commodity futures returns even during this short time period.

Regarding the subsector analysis, we find that only inflation shocks are significantly priced on the monthly frequency. Even though one would expect commodities in the agricultural subsector to be more homogeneous, using a battery of pricing models we find almost no evidence that a common factor exists even among agricultural commodities. We do not exclude the possibility that there may be subgroups of our commodities cross-section for which certain factors contain significant pricing ability. Nevertheless, the challenge we face is to find a priced factor for the *entire* cross-section of commodities, not just a subgroup. Supporting the main findings of our study, inflation shocks are not found to be significantly priced in the entire cross-section of commodities returns.

7. 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 commodity futures returns. In this section, we take an alternative approach to identify any factors which may explain the cross-section. In line with Cochrane (2011), instead of positing *in advance* any candidate factors as we did in the previous sections, we let the data determine the candidate factors. Then, we employ them in Fama-MacBeth two step regressions. To this end, we apply Principal Components Analysis (PCA) to the correlation matrix of the 22 commodity futures returns to identify the principal components (PCs) f_i's that account for most of their common variation. The commodity futures excess returns can be represented as a linear combinations of the PCs i.e.

$$r_{i,t} = q_{1i} f_{1,t} + q_{2i} f_{2,t} + q_{3i} f_{3,t} + \ldots + q_{22i} f_{22,t}, \quad i = 1, 2, \ldots, 22 \tag{6}$$

where $q_{1i}, q_{2i}, \ldots, q_{22i}$ denote the correlation loadings corresponding to the ith commodity futures.

Equation (6) shows that the PCA yields PCs which 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 step 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 monthly and quarterly frequencies, 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 5.4.

We implement five different versions of the PCA factor model by including one, two, three, four, and five PCs, respectively. Figure 1 shows the correlation loadings for each 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 9 reports the results on the significance of the risk premiums of the five PC factors. 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. 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 almost zero.

Finally, we conduct two further robustness tests of the PCA models. First, we explore the performance of the PCA models 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 (2012) 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 commodity markets (see also Henderson et al., 2012, and Singleton, 2012, for empirical studies, and Basak and Pavlova, 2012, for a theoretical model). 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 asset pricing performance of the PCA models 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 by applying PCA to the remaining ones. This extends the subsector analysis described in Section 6.3. We find that the percentage of explained variance remains quite small; the greatest explained amount of the total variance is 70% for the case where the softs are removed from the original sample. Therefore, the documented heterogeneity of commodity returns cannot 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 commodity futures markets. In addition, it supports the conclusions drawn from the previous analysis in that none of the employed factors can explain the cross-section of commodity futures returns.[11]

8. Conclusions

We investigate whether there is one or more asset pricing models which may explain (price) the *cross-section* of commodity futures returns. First, we implement a number of macro-models that are appealing for commodities as well as equity-motivated tradable factor models. Then, 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 find that none of the employed factors prices the cross-section of commodity futures. Moreover, we find that the commodity futures market is considerably heterogeneous per se.

[11] As a further test for the segmentation between the commodity and equity markets, we pool together the returns of the 25 Fama-French portfolios (formed on size and book to market, see Kenneth French's website) and the commodity futures/ portfolios and we extract their PCs. We find that the loadings of the commodity futures' returns to the PC that the 25 Fama-French portfolios' returns are primarily exposed to are negligible and vice versa, confirming the argument that these two markets are segmented.

Our results have five main implications. First, some of the popular macro and equity-motivated factor models which have been found to price the cross-section of stock returns should not be used to evaluate the performance of investments in commodity futures. Second, the inability of these models to price commodity futures implies that the equity and commodity futures markets are segmented. An explanation for this may lie in investors' heterogeneity since anecdotal evidence suggests that the profile of investors in commodities differs from that of investors in the stock market. Investors in commodities tend to trade on product-specific information and they consider each commodity in isolation. Interestingly, our findings should not be interpreted as a rejection of the "financialization of commodities" hypothesis because our study spans a much longer time period than the one that this hypothesis refers to. Third, the fact that the commodity-specific factors are not priced either confirms that there is a degree of segmentation in commodity futures market.

Fourth, our findings have implications for the choice of the test assets' universe for asset pricing tests in the case of commodities. The asset universe should include only commodities and not other asset classes too; given the markets' segmentation, factors that may price an augmented asset universe will not necessarily price the commodities asset class in a stand-alone fashion. This explains the difference between our results and the ones reported by Dhume (2011) and Asness et al. (2013). In addition, given the heterogeneity of the commodities futures market, the test assets should be individual commodities instead of commodity portfolios. The formation of portfolios in the case of heterogeneous assets may harm the efficiency of the risk premiums' estimates (Ang et al., 2010) and results will be prone to the portfolio formation criterion. These are obvious reasons for the divergence of our results from the ones obtained by Szymanowska et al. (2012), Bakshi et al. (2013) and Yang (2013).

Finally, our findings confirm the testable predictions of the theoretical models of Stoll (1979), Hirshleifer (1988, 1989), de Roon et al. (2000), and Acharya et al. (2013). 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.

References

Acharya, V.V., Lochstoer, L.A., Ramadorai, T., 2013. Limits to arbitrage and hedging: Evidence from commodity markets. Journal of Financial Economics 109, 441-463.

Adrian, T., Shin, H., 2009. Money, liquidity, and monetary policy. American Economic Review 99, 600–605.

Adrian, T., Etula, E., Muir, T., 2012. Financial intermediaries and the cross-section of asset returns. Journal of Finance, forthcoming.

Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Ang, A., Liu, J., Schwarz, K., 2010. Using stocks or portfolios in tests of factor models. Working paper, Columbia Business School.

Anzuini, A., Lombardi, M.J., Pagano P., 2013. The impact of monetary policy shocks on commodity prices. International Journal of Central Banking 9, 125-150.

Asness, C.A., Moskowitz, T.J., Pedersen, L.H., 2013. Value and momentum "everywhere". Journal of Finance 68, 929–985.

Bakshi, G., Panayotov, G., Skoulakis, G., 2011. The Baltic dry index as a predictor of global stock returns, commodity returns and global economic activity. Working paper, University of Maryland.

Bakshi, G., Gao, X., Rossi, A., 2013. Asset pricing models that explain the cross-section and time-series of commodity returns. Working paper, University of Maryland.

Balvers, R.J., Huang, D., 2009. Money and the C-CAPM. Journal of Financial and Quantitative Analysis 44, 337-368.

Basak, S., Pavlova, A., 2012. A model of financialization of commodities. Working paper, London Business School.

Basu, D., Miffre, J., 2013. Capturing the risk premium of commodity futures: The role of hedging pressure. Journal of Banking and Finance 37, 2652-2664.

Bessembinder, H., 1992. Systematic risk, hedging pressure, and risk premiums in futures markets. Review of Financial Studies 5, 637-667.

Bessembinder, H., Chan, K., 1992. Time varying risk premia and forecastable returns in futures markets. Journal of Financial Economics 32, 169-193.

Black, F., 1976. The price of commodity contracts. Journal of Financial Economics 3, 161-179.

Bodie Z., Rosansky, V. I., 1980. Risk and return in futures markets. Financial Analysts Journal 36, 27-39.

Breeden, D.T., 1979. An intertemporal asset pricing model with stochastic consumption and investment opportunities. Journal of Financial Economics 7, 265-296.

Breeden, D.T., 1980. Consumption risk in futures markets. Journal of Finance 35, 503-520.

Brennan, M.J., 1958. The supply of storage. American Economic Review 48, 50-72.

Carhart, M.M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57-82.

Carter, C.A., Rausser, G.C., Schmitz, A., 1983. Efficient asset portfolios and the theory of normal backwardation. Journal of Political Economy 91, 319-331.

Cochrane, J.H., 2005. Asset Pricing, Princeton University Press: New Jersey, 2nd edition.

Cochrane, J.H., 2011. Discount rates. Journal of Finance 66, 1047-1108.

Cootner, P.H., 1960. Returns to speculators: Telser versus Keynes. Journal of Political Economy 68, 396-404.

Daskalaki, C., Skiadopoulos, G., 2011. Should investors include commodities in their portfolios after all? New evidence. Journal of Banking and Finance 35, 2606-2626.

de Roon, F.A., Nijman, T.E., Veld, C., 2000. Hedging pressure effects in futures markets. Journal of Finance 55, 1437-1456.

de Roon, F.A., Szymanowska, M., 2010. The cross-section of commodity futures returns. Working paper, Erasmus University.

De Santis, G., Gerard, B., 1998. How big is the premium for currency risk? Journal of Financial Economics 49, 375-412.

Dhume, D., 2011. Using durable consumption risk to explain commodities returns. Working paper, Federal Reserve Board.

Dumas, B., Solnik, B., 1995. The world price of foreign exchange risk. Journal of Finance 50, 445-479.

Dusak, K., 1973. Futures trading and investor returns: An investigation of commodity market risk premiums. Journal of Political Economy 81, 1387-1406.

Erb, C.B., Harvey, C.R., 2006. The strategic and tactical value of commodity futures. Unabridged working paper version, Duke University.

Etula, E., 2013. Broker-dealer risk appetite and commodity returns. Journal of Financial Econometrics 11, 486-521.

Fama, E.F., French, KR., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3-56.

Fama, E.F.,. French, K.R., 1987. Commodity futures prices: Some evidence on forecast power, premiums, and the theory of storage. Journal of Business 60, 55-73.

Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81, 607-636.

Frankel, J.A., 2008. The effect of monetary policy on real commodity prices. In: Campbell, J. (Eds), Asset Prices and Monetary Policy, University of Chicago Press, 291-327.

Fuertes, A.-M., Miffre, J., Rallis, G., 2010. Tactical allocation in commodity futures markets: Combining momentum and term structure signals. Journal of Banking and Finance 34, 2530–2548.

Gorton, G.B., Rouwenhorst, G.K., 2006. Facts and fantasies about commodity futures. Financial Analysts Journal 62, 47-68.

Gorton, G.B., Hayashi, F., Rouwenhorst, K.G., 2012. The fundamentals of commodity futures returns. Review of Finance 17, 35-105.

Gospodinov, N., Ng, S., 2013. Commodity prices, convenience yields, and inflation. Review of Economics and Statistics 95, 206-219.

Henderson, B.J., Pearson, N.D., Wang, L., 2012. New evidence on the financialization of commodity markets. Working paper, University of Illinois at Urbana-Champaign.

Hirshleifer, D., 1988. Residual risk, trading costs, and commodity futures risk premia. Review of Financial Studies 1, 173-193.

Hirshleifer, D., 1989. Determinants of hedging and risk premia in commodity futures markets. Journal of Financial and Quantitative Analysis 24, 313-331.

Hong, H., Yogo, M., 2012. What does future market tell us about the macroeconomy and asset prices? Journal of Financial Economics, 105, 473–490.

Jagannathan, R., 1985. An investigation of commodity futures prices using the consumption-based intertemporal capital asset pricing model. Journal of Finance 40, 175-191.

Kat, H.M., Oomen, R.C., 2007. What every investor should know about commodities Part II: multivariate return analysis. Journal of Investment Management 5, 40–64.

Keynes, J. M., 1930. A Treatise on Money, Vol. II. London: Macmillan.

Lo, A.W., MacKinlay, A.C., 1990. Data-snooping biases in tests of financial asset pricing models. Review of Financial Studies 3, 431-468.

Lustig, H., Roussanov, N., Verdelhan, A., 2011. Common risk factors in currency markets. Review of Financial Studies 24, 3731-3777.

Marshall, B.R., Nguyen, N. H., Visaltanachoti, N., 2013. Liquidity commonality in commodities. Journal of Banking and Finance 37, 11-20.

Marshall, B.R., Nguyen, N. H., Visaltanachoti, N., 2012. Commodity liquidity measurement and transaction costs. Review of Financial Studies 25, 599–638.

Miffre, J., Fuertes, A-M., Perez, A., 2012. Commodity futures returns and idiosyncratic volatility. Working paper, EDHEC Business School.

Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Pastor, L., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642-685.

Roache, S., 2008. Commodities and the market price of risk, Working paper, International Monetary Fund.

Shang, H., 2011. Macroeconomic factors and the cross-section of commodity returns, Working paper, Concordia University.

Shanken, J., 1992. On the estimation of beta-pricing models. Review of Financial Studies 5, 1-33.

Singleton, K.J., 2012. Investor flows and the 2008 boom/bust in oil prices. Management Science, forthcoming.

Skiadopoulos, G., 2013. Advances in the commodity futures literature: A review. Journal of Derivatives 20, 85-96.

Stoll, H.R., 1979. Commodity futures and spot price determination and hedging in capital market equilibrium. Journal of Financial and Quantitative Analysis 14, 873-894.

Szymanowska, M., de Roon, F.A., Nijman, T.E., Van den Goorbegh, R., 2012. An anatomy of commodity futures risk premia. Journal of Finance, forthcoming.

Tang, K., Xiong, W., 2012. Index investing and the financialization of commodities. Financial Analysts Journal 68, 54–74.

Working, H., 1949. The theory of price of storage. American Economic Review 39, 1254-1262.

Yang, F., 2013. Investment shocks and the commodity basis spread. Journal of Financial Economics, forthcoming.

Yogo, M., 2006. A consumption-based explanation of expected stock returns. Journal of Finance 61, 539-580.

TABLES

Table 1: Descriptive Statistics

Futures Contract	Monthly Frequency			Quarterly Frequency		
	Av. Return	St. Deviation	Sharpe Ratio	Av. Return	St. Deviation	Sharpe Ratio
Energy						
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
Grains & Oilseeds						
Corn	-4.73**	25.48	-0.19	-5.14**	27.08	-0.19
Kansas Wheat	-3.30*	31.69	-0.10	-4.60	33.46	-0.14
Oats	-5.10**	30.90	-0.17	-5.00	32.02	-0.16
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
Soybeans	3.89**	24.89	0.16	3.04	24.86	0.12
Wheat	-3.93**	26.50	-0.15	-4.55*	26.14	-0.17
Livestock						
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
Lean Hogs	-4.23**	23.31	-0.18	-4.08*	22.74	-0.18
Live Cattle	0.88	12.56	0.07	0.71	13.07	0.05
Metals						
Copper	11.51**	27.30	0.42	12.21**	30.03	0.41
Gold	2.89**	15.12	0.19	2.28**	12.37	0.18
Palladium	13.55**	34.22	0.40	13.88**	36.82	0.38
Platinum	7.92**	20.86	0.38	8.30**	21.08	0.39
Silver	6.17**	26.40	0.23	4.01*	22.41	0.18
Softs						
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

* Significant at 10%.

** Significant at 5%.

Entries report the descriptive statistics for the 22 individual commodity futures used in this study. The dataset spans the period January 1989-December 2010. The left hand side columns report the summary statistics for the annualized mean returns (in % terms), standard deviations (in % terms) and annualized Sharpe ratios for monthly frequencies. The right hand side columns report the respective figures for quarterly frequencies.

Table 2: List of the various employed asset pricing models

.

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)
Macro shocks model

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

Commodity-specific factor models
HP risk factor
Basis risk factor
Momentum risk factor
Amihud commodity illiquidity factor
Open interest factor

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

Table 3: Description of the risk factors

Risk Factor	Definition
Panel A: Macro and tradable factors	
Stock Market index	Value-weighted return on all NYSE, AMEX, and NASDAQ stocks.
Commodity market index	S&P GSCI excess return index.
Hybrid Index	An equally weighted index of the Stock Market index and the S&P GSCI.
Consumption growth	Percentage change in the seasonally-adjusted aggregate real per capita consumption expenditures on non-durable goods and services.
Value factor	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	Difference in the return of a portfolio of small capitalization stocks and the return of a portfolio of large capitalization stocks.
Momentum factor	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)	Percentage change in the seasonally-adjusted M2 money stock.
Money growth (b)	Primary dealers' repo growth.
Pastor and Stambaugh Liquidity factor	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	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	Difference between the return of a portfolio of high interest rate currencies and the return of portfolio of low interest rate currencies.
Industrial production growth shocks	Shocks in the U.S. Industrial production growth.
Inflation shocks	Shocks in the Consumer Price Index (CPI).
Consumption growth shocks	Shocks in the consumption growth.
Interest rate shocks	Shocks in the U.S. 3-month T-bill.
GDP growth shocks	Shocks in the U.S. Gross Domestic Product (GDP).
Panel B: Commodity-related factors	
HP factor (a)	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.
HP factor (b)	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)	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)	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)	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)	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.
Amihud Illiiquity factor	Amihud's illiquidity measure is defined as the average monthly ratio of daily absolute returns to daily trading volume in monetary terms. The illiquidity factor is the average of the illiquidity measures across the individual commodity futures contracts.
Open Interest factor	Shocks in the aggregate open interest across the individual commodity futures contracts.

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

Table 4: Characteristics of the commodity-specific factor mimicking portfolios

	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)*	

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 for 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 frequencies (panels A and B, respectively).

Table 5: Macro-factor models

Panel A: Monthly Frequency

	CAPM	CCAPM	MCAPM(a)	MCAPM(b)	MCCAPM(a)	MCCAPM(b)	FXCAPM	Macro shocks
Constant	0.004	0.003	0.004	0.003	0.001	0.004	0.003	0.004
t-stat	*(1.451)*	*(1.278)*	*(1.764)*	*(0.718)*	*(0.532)*	*(0.876)*	*(1.251)*	*(1.528)*
Shanken's t-stat	*(1.451)*	*(1.277)*	*(1.726)*	*(0.664)*	*(0.524)*	*(0.838)*	*(1.248)*	*(1.375)*
Market Return	0.000		-0.004	0.015			-0.002	
t-stat	*(0.022)*		*(-0.548)*	*(1.669)*			*(-0.238)*	
Shanken's t-stat	*(0.022)*		*(-0.538)*	*(1.583)*			*(-0.238)*	
Consumption growth		0.000			0.000	-0.001		
t-stat		*(0.211)*			*(-0.539)*	*(-0.796)*		
Shanken's t-stat		*(0.211)*			*(-0.532)*	*(-0.767)*		
Money growth			-0.001	0.019	-0.001	0.016		
t-stat			*(-1.093)*	*(1.358)*	*(-0.981)*	*(1.146)*		
Shanken's t-stat			*(-1.074)*	*(1.280)*	*(-0.969)*	*(1.110)*		
FX factor							-0.002	
t-stat							*(-0.386)*	
Shanken's t-stat							*(-0.385)*	
Leverage factor								
t-stat								
Shanken's t-stat								
Production shocks								-0.001
t-stat								*(-1.103)*
Shanken's t-stat								*(-1.009)*
Consumption shocks								-0.001
t-stat								*(-0.985)*
Shanken's t-stat								*(-0.896)*
Inflation shocks								-0.001
t-stat								*(-0.853)*
Shanken's t-stat								*(-0.779)*
Interest rate shocks								0.068
t-stat								*(1.595)*
Shanken's t-stat								*(1.455)*
GDP shocks								
t-stat								
Shanken's t-stat								
R-squared	11.25%	9.54%	19.15%	17.18%	18.79%	16.57%	18.36%	37.85%
Adj-R-squared	6.82%	5.01%	10.64%	8.47%	10.24%	7.79%	9.76%	23.23%

Panel B: Quarterly Frequency

	CAPM	CCAPM	MCAPMa	MCCAPMa	LevCAPM	FXCAPM	Macro shocks
Constant	0.009	0.015	0.005	0.003	0.011	0.012	0.009
t-stat	*(0.586)*	*(0.978)*	*(0.307)*	*(0.181)*	*(0.716)*	*(0.748)*	*(0.744)*
Shanken's t-stat	*(0.585)*	*(0.977)*	*(0.290)*	*(0.172)*	*(0.665)*	*(0.726)*	*(0.618)*
Market Return	0.006		0.004		-0.002	0.016	
t-stat	*(0.172)*		*(0.131)*		*(-0.059)*	*(0.510)*	
Shanken's t-stat	*(0.172)*		*(0.125)*		*(-0.055)*	*(0.499)*	
Consumption growth		0.000		0.000			
t-stat		*(0.156)*		*(0.006)*			
Shanken's t-stat		*(0.155)*		*(0.006)*			
Money growth			-0.003	-0.002			
t-stat			*(-0.959)*	*(-0.909)*			
Shanken's t-stat			*(-0.920)*	*(-0.876)*			
FX factor						-0.004	
t-stat						*(-0.140)*	
Shanken's t-stat						*(-0.136)*	
Leverage factor					-0.033		
t-stat					*(-1.063)*		
Shanken's t-stat					*(-1.006)*		
Production shocks							0.003
t-stat							*(0.837)*
Shanken's t-stat							*(0.715)*
Consumption shocks							-0.001
t-stat							*(-0.494)*
Shanken's t-stat							*(-0.422)*
Inflation shocks							-0.001
t-stat							*(-0.255)*
Shanken's t-stat							*(-0.220)*
Interest rate shocks							0.179
t-stat							*(1.239)*
Shanken's t-stat							*(1.104)*
GDP shocks							0.002
t-stat							*(0.796)*
Shanken's t-stat							*(0.687)*
R-squared	9.30%	6.75%	17.46%	15.65%	17.38%	17.82%	40.88%
Adj-R-squared	4.76%	2.09%	8.77%	6.77%	8.69%	9.17%	22.40%

Entries report the results for the set of macro-factor models employed in this study. We examine the CAPM, CCAPM, MCAPM, MCCAPM, LevCAPM, FXCAPM and a set of macro shocks. 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 frequencies (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. In the case where the primary dealers' data are considered, the dataset spans the period January 1998-December 2010, and the reported results refer only to monthly frequency due to data availability constraints,. In addition, in the case where the leverage factor and the GDP growth shocks are considered, the reported results refer only to quarterly frequency. Shocks are calculated as the residuals from an AR(1) model applied to the respective variables.

Table 6: Equity-motivated tradable factor models

	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%

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 frequencies (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.

Table 7: Commodity-specific factor models

	Monthly Frequency		Quarterly Frequency	
Panel A: HP factor				
	HP factor (a)	**HP factor (b)**	**HP factor (a)**	**HP factor (b)**
Constant	0.003	0.004	0.013	0.011
t-stat	*(1.296)*	*(1.516)*	*(0.885)*	*(0.757)*
Shanken's t-stat	*(1.295)*	*(1.515)*	*(0.862)*	*(0.719)*
HP Factor	0.000	0.000	0.018	0.033
t-stat	*(0.068)*	*(0.068)*	*(0.655)*	*(1.106)*
Shanken's t-stat	*(0.068)*	*(0.068)*	*(0.643)*	*(1.072)*
R-squared	11.12%	10.36%	15.51%	15.26%
Adj-R-squared	6.68%	5.88%	11.29%	11.02%
Panel B: Basis factor				
	Basis factor (a)	**Basis factor (b)**	**Basis factor (a)**	**Basis factor (b)**
Constant	0.005	0.004	0.017	0.013
t-stat	*(1.794)*	*(1.262)*	*(1.031)*	*(0.792)*
Shanken's t-stat	*(1.771)*	*(1.256)*	*(0.971)*	*(0.767)*
Basis Factor	-0.007	0.005	-0.027	0.026
t-stat	*(-1.123)*	*(0.641)*	*(-1.263)*	*(0.629)*
Shanken's t-stat	*(-1.113)*	*(0.639)*	*(-1.221)*	*(0.613)*
R-squared	10.71%	10.98%	6.55%	8.04%
Adj-R-squared	6.25%	6.53%	1.88%	3.44%
Panel C: Momentum factor				
	Momentum factor (a)	**Momentum factor (b)**	**Momentum factor (a)**	**Momentum factor (b)**
Constant	0.004	0.004	0.016	0.011
t-stat	*(1.635)*	*(1.676)*	*(1.175)*	*(0.888)*
Shanken's t-stat	*(1.624)*	*(1.675)*	*(1.137)*	*(0.743)*
Momentum Factor	0.006	-0.002	0.021	0.077
t-stat	*(0.789)*	*(-0.174)*	*(0.500)*	*(1.630)*
Shanken's t-stat	*(0.785)*	*(-0.174)*	*(0.486)*	*(1.410)*
R-squared	11.80%	11.62%	13.63%	14.42%
Adj-R-squared	7.39%	7.20%	9.32%	10.14%
Panel D: Amihud Liquidity Measure				
	Liquidity factor		**Liquidity factor**	
Constant	0.005		0.013	
t-stat	*(1.728)*		*(0.756)*	
Shanken's t-stat	*(1.727)*		*(0.662)*	
Amihud Measure	-0.024		0.354	
t-stat	*(-0.151)*		*(1.227)*	
Shanken's t-stat	*(-0.151)*		*(1.097)*	
R-squared	10.28%		6.46%	
Adj-R-squared	5.79%		1.78%	
Panel E: Open Interest				
	Open interest shocks		**Open interest shocks**	
Constant	0.002		-0.013	
t-stat	*(0.565)*		*(-0.623)*	
Shanken's t-stat	*(0.564)*		*(-0.551)*	
Open interest shock	0.044		0.801	
t-stat	*(0.324)*		*(0.742)*	
Shanken's t-stat	*(0.324)*		*(0.669)*	
R-squared	11.72%		21.31%	
Adj-R-squared	7.31%		17.38%	

Entries report the results in the cases where commodity-specific factors are examined within an asset pricing model. We consider hedging-pressure (panel A), inventory-related risk factors proxied by the basis and 12-month prior return (panels B and C, respectively), a liquidity factor (panel D) and an open interest factor (panel E). 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. The dataset spans the period January 1993 to December 2010 for the open interest factor and January 1989 to December 2010 for the other factors.

Table 8: Single factor time series models
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)
Energy															
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
Grains & Oilseeds															
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
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
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
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
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
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
Livestock															
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**
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*
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***
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
Metals															
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
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**
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
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
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**
Softs															
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

Entries report the factors betas obtained by estimating single factor time series models for each commodity futures time series returns, using 16 of the 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 frequencies (panels A and B, respectively). The Newey-West (1987) 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.

Table 8 (cont'd): Single factor time series models
Panel B: Quarterly frequency

	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)
Energy																
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*
Grains & Oilseeds																
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*
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
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
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
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
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
Livestock																
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*
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
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
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
Metals																
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**
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***
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**
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***
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**
Softs																
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*

Entries report the factors betas obtained by estimating single factor time series models for each commodity futures time series returns, using 16 of the 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 frequencies (panels A and B, respectively). The Newey-West (1987) 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.

Table 9: Principal Components Analysis (PCA) factor models

	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%

Entries report the results in the case where we estimate one, two, three, four and five PCA factor models. 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 frequencies (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.

Figure 1: PCA analysis

The figure plots the correlation loadings 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.