Financialization of Commodities: an Asset Pricing Perspective

Devraj Basu
Olivier Bauthéac *

Abstract

The last two decades have seen major changes in the nature of the commodity markets with the influx of financial investor inflows followed by the financial crisis. We study the effect of these events on commodity futures pricing dynamics using commodity asset pricing techniques. We find that a non-price based factor is best able to detect the effects of commodity financialization, while the effects of the financial crisis and after are most clearly visible through the performance of the market factor. The effects of financialization seem to go beyond mechanical effects induced by the rise of indexing.

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*Basu: University of Strathclyde, Glasgow, UK, devraj.basu@strath.ac.uk. Bauthéac: University of Strathclyde, Glasgow, UK, olivier.bautheac@strath.ac.uk.

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  Devraj Basu

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1 Introduction

The last twenty years have seen major upheavals in the commodity markets with the onset of financialization[1] as well as the period of the 2008 financial crisis and its aftermath. Financialization appears to have affected a number of economic sectors, including agriculture and energy, and its impact has been hotly debated in the policy, legislative, regulatory, and academic spheres. A vigorous legislative debate has led to regulatory changes accompanied by an equally intense policy and academic debate across a number of disciplines about the perceived effects on commodity prices of the unprecedented inflow of institutional funds brought into commodity futures markets by new index type investors[2]. In response to immediate policy concerns, the academic debate was initially framed rather narrowly. In this paper we take a fundamentally different empirical approach that is broader in scope. We consider the entire cross-section of actively traded commodities on futures markets and use a futures based asset pricing framework that includes factors constructed using both price and non-price attributes.

Commodity futures markets have a history of being the classic physical commodity risks shifting conduit for commodity specialists, and financialization may have altered this long standing paradigm with the entry of long only commodity index traders (CITs) with very different hedging and volume demands from traditional participants. This change could have altered the hedging ontology in these markets and our asset pricing framework is well suited to detect these more subtle effects driven by changes in the nature of traders. Factor model

[1]Starting around 2004, with a view of commodity markets as an emerging asset class and in an effort to hedge against inflation and seek diversification benefits (Büyükşahin and Robe, 2014; Singleton, 2013), institutional investors sent forth an unprecedented flow of capital into commodity futures markets. This phenomenon is commonly referred to as the financialization of commodities (Domanski and Heath, 2007).

[2]See section 2.1 for a detailled discussion.

techniques are well suited to isolating common driving factors and detecting co-movement and building on theory we develop a bespoke commodity-based asset pricing framework that seems well adapted to study these two issues simultaneously.

The first factor model we consider (CHP) is based on the well-known hedging pressure based theory (Anderson and Danthine, 1983; Chang, 1985; Cootner, 1960; Dusak, 1973; Hicks, 1939; Hirshleifer, 1988, 1989, 1990; Kolb, 1992; Keynes, 1930) which postulates that futures prices for a given commodity are inversely related to the extent that commercial hedgers are short or long and we use a factor mimicking portfolio that captures the impact of hedging pressure as a systemic factor (Basu and Miffre, 2013). Our second factor model is based on open interest growth following Hong and Yogo (2012) who find that open interest growth has predictive power for individual commodity returns and again we construct a long-short factor mimicking portfolio. Our third model is based on term structure following Szymanowska et al. (2014) and Fuertes et al. (2015) who demonstrate that the term structure factor has explanatory power for the cross-section of commodity returns. We finally consider an equally weighted portfolio of commodities as a proxy for the market factor. Our two price based and two non-price based factors allow us to compare and contrast different channels that could have led to changes in commodity price dynamics over the last twenty years.

We study the performance of these models on a set of twenty-four US traded commodities and six UK traded (LME exchange) base metals over the 1997/2017 period that we divide into four distinct sub-periods. The first, the pre-financialization phase, spans the 1997/2003 period; the second, the financialization phase, spans the 2004/2007 period[3]; the third, 2008/2013, encompasses both the financial crisis and the loose monetary policy regimes that followed; and the fourth spans the period starting in 2014 to present.

[3]Starting point based on earlier studies (Baker, 2014; Christoffersen et al., 2014).

Consistent with earlier studies, we observe that mean returns for the US traded commodities are sharply higher over the financialization period compared to pre-financialization and this pattern extends to UK traded metals.

The cross-sectional nature of financialization (Basak and Pavlova, 2016; Cheng and Xiong, 2014) leads us to extend the Keynesian individual hedging pressure paradigm by incorporating aggregate CHP (**CHP**), a market wide measure of hedging pressure first considered in Hong and Yogo (2012). This paradigm implies that returns for individual commodities should be high in periods where **CHP** is low (**backwardation**) and low in periods where **CHP** is high (**contango**). Over the first period the cross sectional average returns during **backwardation** for both the US and UK commodities are positive with those for the US statistically significant, and significantly higher than during **contango**, providing broad support for an aggregate version of the Keynesian hedging pressure hypothesis. Over the second period this pattern reverses, with both the US and UK commodities having significant positive returns during **contango** with these returns being significantly higher than during **backwardation**. This change in pattern suggests that the onset of financialization altered the traditional risk shifting nature of hedger's behaviour, which is implied by the Keynesian hypothesis. The arrival of financial investors raises the question of whether they functioned as liquidity providers or liquidity demanders. Arguments have been made for both of these possibilities with Moskowitz et al. (2012) arguing that financial investors provide liquidity while Kang et al. (2017) argue that they demand liquidity. Our analysis of returns in periods of low and high aggregate CHP before and during financialization allows us to analyse this issue from a new perspective and suggests that financial investors may have been liquidity demanders leading hedgers to become liquidity providers.

Goldstein and Yang (2017) as well as Goldstein et al. (2014) argue that the arrival of financial investors has an impact on the extent of normal backwardation in commodity futures markets. Based on their analysis we would expect our average CHP factor, which is based on backwardation measured by hedger's positions, as well our term structure factor, which is based on backwardation measured by roll yield, to be best suited to measure the impact of financialization.

We analyze the pricing dynamics over the different periods by first studying the time series pricing performance of the various factors on all the US traded commodities with the factors constructed using the latter set of commodities. The market based factor outperforms the other three in the first period and it has a similar level of performance in the second period, while the CHP factor shows the greatest improvement in performance in the second period. The performance of the market factor is driven by agricultural commodities and metals in both the first and second period and the dramatic improvement of the CHP factor in the second period is driven by precious and precious-base metals. The best performing commodities for the market factor exhibited approximately the same level of price co-movement both before and during financialization. In contrast, the best performing commodities for the CHP factor exhibited very low pair-wise correlation in the first period, around the average for US traded commodities, while during financialization the average pairwise correlation between the top performing CHP factor commodities is higher than that for the market factor and double of the average for all the US traded commodities. This increase is due to the dramatic rise in average pairwise correlation amongst the US traded metals all of which exhibited high R^2 with respect to the CHP factor during financialization which in turn is due to their common low level of CHP over this period. Thus the CHP factor model is able to establish the strengthening link between a non-price attribute and price dynamics in the US metal sub-sector during financialization.

We explore this issue further by constructing the four factors with the top eight commodities for a given factor (factor picks) in each period[4] and evaluating its performance on these selected commodities as well as on all US traded commodities. The results of this exercise strongly suggest that the hedging pressure co-movement and price co-movement link was concentrated in the metals sub-sector.

The UK traded base metals provide a useful set of assets to test how widespread were the changes in pricing dynamics brought about by the onset of financialization. To that end, we examine the performance of the four factors on the six UK metals, when constructed from each set of factor picks. The resuslts show that here was co-movement in global metals returns in the second period and that this co-movement could be detected by our hedging pressure based model.

The onset of the financial crisis and the monetary policy regimes that followed, on the other hand, also appear to have induced significant changes in pricing dynamics. Returns on both US and UK traded commodities fell dramatically over both the third and fourth periods with the pattern of return for the US traded commodities across **CHP** regimes reverting to Keynesian paradigm. The pricing results indicate the emergence of a systematic factor across the entire cross-section of the US commodities as well as strong evidence of cross-market linkages.

Financialization was an issue of such policy importance that it triggered legislative action. The debate was initially framed around adequacy of speculation, the burning issue of the day, and the consequent analysis focused on the more mechanical effects of financialization. With

[4] See section 2.3 for further details.

the benefit of hindsight, it appears this approach was perhaps too narrow and it now seems necessary to address financialization from a broader perspective. Commodity price dynamics appear to have altered substantially in quite different ways over the financialization and the financial crisis periods and our commodity futures based asset pricing approach seems able to provide new insights into the nature of these changes: financialization was a phenomenon endogenous to the commodity markets transmitted via the commodity futures markets and mainly concentrated in a specific sector (metals) while the crisis and its aftermath seems to have delivered an exogenous shock across the entire cross-section of global commodities. The initial view of financialization was that it consisted of speculative flows which had the effect of driving up and creating bubble like conditions in commodity future prices[5]. However, the fundamental question of the nature of the impact of financialization across the entire cross-section of commodity futures markets has not yet been completely answered. We provide an empirical complement to a new stream of theoretical studies that try to model the impact of financialization on various aspects of commodity futures markets[6] and demonstrate that the effects of financialization extend beyond the mechanical effects induced by indexation as outlined in Basak and Pavlova (2016) as well as Tang and Xiong (2012).

[5] De Schutter (2010); Gilbert (2010a); Gilbert (2010b); Masters (2008); Masters and White (2011); Herman et al. (2011); Schumann (2011); Singleton (2013); UNCTAD and Cooperation (2009).

[6] Etula (2013), Acharya et al. (2013), Cheng et al. (2014), Leclercq and Praz (2014), Sockin and Xiong (2015), **?**, Ekeland et al. (2016), Goldstein and Yang (2017).

2 Data & methods

2.1 Background

The period from 1998 to 2008 saw an influx of investment into commodity index linked products most of which made its way into the commodity futures market. These commodity indexes whose goal was to track the broad movement of commodity prices could be accessed by means of exchange traded funds and exchange traded notes. At least $100 billion of new investment flowed into these products over the 1998-2008 period with this financialization phenomenon leading to substantial legislative changes. Concerns over the consequences of financialization were behind Rule 76 FR 4752 issued by the US Commodity Futures Trading Commission (CFTC) on January 26th, 2011. This provision emanates from the Dodd-Frank Wall Street and Consumer Protection Act of 2010 (Title VII, Section 737) that mandates the CFTC to use position limits to restrict the flow of speculative capital into a number of commodity markets. The Rule was approved in a close 3-2 vote and the ensuing rulemaking process was extremely contentious with several commissioners (Michael Dunn and Scott D. O'Malia in particular) expressing reservations about the lack of supporting evidence and the Rule also triggering thousands of comment letters as well as a lawsuit against the CFTC spearheaded by two Wall Street trade groups, the International Swaps & Derivatives Association (ISDA) and the Securities Industries & Financial Markets Association (SIFMA)[7].

A world-wide debate has ensued about the role of index funds in commodity markets. The first responses to the 2007/2008 crisis of escalating food and energy prices took the form of policy reports, many of which reasoned that the growth of commodity index funds came

[7]ISDA & SIFMA v US CFTC; Complaint, 1:11-cv-02146; December 2nd, 2011.

along with an influx of largely speculative capital that was responsible for driving commodity prices beyond their historic highs (De Schutter, 2010; Gilbert, 2010b; Herman et al., 2011; Schumann, 2011; UNCTAD and Cooperation, 2009). The US and various european countries also became involved in this issue. Early US Senate investigations drew on pricing and trading data supplied by the CFTC as well as interviews with numerous experts including hedge fund manager Michael Masters who linked the growing presence of index investors in US wheat markets to the observed surges in both futures and cash prices (Masters, 2008; Masters and White, 2011)). This contention has since come to be known as the Masters' hypothesis and was largely endorsed by the final US Senate report on the issue (Senate, 2009). At this stage, the question thrust on the academic sphere was whether "excessive speculation" (understood as the market activity peculiar to index type investors) was linked to escalating energy and agricultural commodity prices. A number of academic studies, most of which used commodity specific causality and correlation based analysis have disproved this contention, particularly in the case of agricultural and energy commodities. Irwin et al. (2009), Sanders et al. (2010), Sanders and Irwin (2011a), Sanders and Irwin (2011b), Irwin (2013), Brunetti and Reiffen (2014), Hamilton and Wu (2015) and Bruno et al. (2017) study the agricultural markets. Büyükşahin and Harris (2011), Tokic (2012), Fattouh et al. (2013), Kilian and Murphy (2014), Knittel and Pindyck (2016) and Manera et al. (2016) study the energy markets. Bohl and Stephan (2013), Kim (2015) and Boyd et al. (2016) study both energy and agricultural markets while Irwin and Sanders (2011), Irwin and Sanders (2012) and Stoll and Whaley (2011) study the commodity markets in general.

Other studies have underlined various alterations in commodity pricing dynamics over the period. Gilbert and Pfuderer (2014) reject the view that financialization has not had any effects in the grains markets and demonstrate that trades originated by financial actors, and specifically index investors, can move prices but tend typically to be volatility-reducing. Cheng and Xiong (2014) show that in the case of index commodities, financialization has transformed the risk sharing, and information discovery functions of commodity futures markets. Juvenal and Petrella (2015) contend that the oil price increase between 2004 and 2008 was mainly driven by the strength of global demand but that the financialization process of commodity markets also played a role. Henderson et al. (2015) show that non-information-based financial investments have important impacts on commodity prices.

2.2 Data

Commodity index funds (CIFs), commodity based exchange traded funds (ETFs) and notes (ETNs) as well as commodity linked notes (CLNs) were amongst the main investment vehicules that allowed institutional and retail investors to build up commodity exposure in the early 2000s (Boons et al., 2012; Henderson et al., 2015; Irwin and Sanders, 2011; UNCTAD and Cooperation, 2009; Schumann, 2011). Most of these products were primarily designed to track prominent commodity indexes amongst which the S&P-GSCI, the most popular. Most of its constituents at the time of writting form the basis of the broad cross-section of commodities that we consider in this study[8]. Unleaded gasoline, the NYMEX legacy contract for gasoline stopped trading in 2006 when it was replaced by Reformulated Gasoline Blendstock for Oxygen Blending (RBOB) with the two futures series trading alongside for most of the year. For our NYMEX gasoline data series, we consider unleaded gasoline up to September 1st, 2006 and RBOB gasoline thereafter, date at which liquidity for the latter overtook that for the former.

[8]See section 5.1 for details on the commodity pool considered.

The commodity futures trading commission (CFTC) operates a comprehensive system of collecting information on market participants known as the large trader reporting program (LTRP) where it records and reports to the public market position data on market particpants who have position levels in excess of a particular futures market specific threshold[9]. The commission collects market data and position information daily from clearing members, futures commission merchants (FCMs) and foreign brokers and publishes corresponding summaries weekly in a series of market specific reports. In these reports, individual traders are categorised according to the nature of their trading activity on the basis of self-reported information[10] that is subject to review by CFTC staff for reasonableness. Position information is then aggregated by category and asset type with each report providing an aggregation for a set of report specific categories and, for each category, a breakdown between futures only positions and positions in futures and options combined.

In its legacy report, the commitment of trader report (COT) with data dating back to 1962, the CFTC distinguishes "commercial" and "non-commercial" market participants where a "commercial" participant is defined as one "[. . .] engaged in business activities hedged by the use of futures and option markets"[11]. A third category, "non-reportable", aggregates positions for participants not meeting the reporting threshold. In response to concerns related to category accuracy[12] the CFTC now refines its classification in the disaggregated commitment of trader report (DCOT) where participant categories include "Producer/Merchant/Processor/User", "Swap dealer", "Money manager" and "Other reportable" as well as in the supplemental commitment of trader report (SCOT) that details commodity index trader aggregate positions for thirteen agricultural commodity futures markets. Data for DCOT and SCOT dates back

[9]Current reporting level thresholds available at: www.ecfr.gov.
[10]CFTC form 40. Available at: www.cftc.gov.
[11]See CFTC regulation 1.3, 17 CFR 1.3(z) for details.
[12]See for example Ederington and Lee (2002).

to 2006 and 2007 respectively.

We study the 1997/2017 period where we observe futures only position data from the COT report, the only CFTC report with data available for the whole period of interest; as well as futures term structure price and open interest data from Bloomberg.

2.3 Methods

On the one hand, futures markets have a long history of serving commodity producers to alleviate their commodity price and output risks. Keynes (1930) and Hicks (1939) emphasise the "normal" behaviour of naturally short hedgers outsourcing their commodity risk to naturally long commodity specialist speculators. This market configuration is referred to as "backwardation" where futures is expected to trade at a discount to spot, providing speculators with incentives to take the long side. The opposite market paradigm is referred to as "contango". Working (Working, 1948, 1953) and Cootner (Cootner, 1960, 1967) somehow relax this "supply-of-speculative-services" (Till, 2007) approach by introducing processors and merchants, also commodity experts, on the hedgers side and relating the notions of backwardation and contango more directly to the term structure via the theory of storage where the shape of the front end of the term structure (basis) is directly related to the market price of storage.

Financialization, on the other hand, refers to the entry of financial investors into the commodity futures markets who, for the most part, are not commodity experts. Besides, these new market participants tend to exhibit herding like behaviour, often taking massive long-only positions on the whole cross-section of indexed commodities in an attempt to hedge against inflation and/or seek further diversification benefits for portfolios with, in most cases, existing large positions across various asset classes (Brunetti et al., 2016; Boyd et al., 2016; Cheng et al., 2014; Juvenal and Petrella, 2015; Singleton, 2013; Tang and Xiong, 2012). This contrasts with the traditional approaches of Keynes and Working and in this context the issues of co-movement and aggregate market participants behaviour seem particularly relevant.

Asset pricing techniques are well suited to study co-movement. Building on theory we develop an ad-hoc commodity based asset pricing framework that we believe is well adapted to study these two issues simultaneously and implement it over four periods of interest. The first, the pre-financialization period, starts in 1997 and is naturally followed by financialization, spanning the 2004/2007 period, and the financial crisis and its aftermath, spanning the 2008/2013 period. The last period spans the 2014/present period sarting with the beginning of the tapering/end of the US Quantitative Easing program (QE).

Using the weekly price, open interest and market position data described above we construct market portfolios of commodity nearby futures as well as mimicking portfolios for market, commercial hedging pressure, term structure and liquidity risk factors in returns. While our market portfolios are long only, equally weighted portfolios of particular commodity sets, our other mimicking portfolios for risk factors are constructed as combinations of two sub-portfolios (legs), one held long, one held short, which respective constituents are pooled on a weekly basis according to risk factor specific criterias. The weekly return for a particular mimicking portfolio is calculated as the difference between the average return for constituents of the long portfolio and that for the constituents of the short portfolio. i.e, return on the mimicking portfolio for risk factor i (f_i) for week t:

$$r_t^{f_i} = \frac{1}{x} \sum_{j=1}^{x} r_{j,t} - \frac{1}{x} \sum_{j=n-x}^{n} r_{j,t}$$

$n \equiv$ number of commodities in the set considered for mimicking portfolio construction.

$x = \lceil n \cdot s \rceil$

$s \equiv$ selection threshold ($\frac{1}{3}$ here).

$r_{j,t} = \frac{C_{j,t}}{C_{j,t-1}} - 1$

$C_{j,t} \equiv$ week t close price for commodity j.

$j \equiv$ commodity rank in the ordered set $Y_t^{f_i}$.

$Y_t^{f_i} \equiv$ week t ordered set of the commodities considered for mimicking portfolio construction where the ordering rule is specific to f_i.

For our portfolio CHP (commercial hedging pressure), we sort the set of commodities considered on past twenty six-week average CHP from lowest to highest. The bottom third constituents (lowest $\overline{CHP}$s) of the corresponding ordered set form the long leg of the portfolio while the top third form the short leg:

$$Y_t^{CHP} \equiv \left\{ \left\{ \overline{CHP_1}, \overline{CHP_2}, ..., \overline{CHP_n} \right\}, \leq \right\}$$

$\overline{CHP_j} = \frac{1}{26} \sum_{k=0}^{25} \frac{L_{j,t-k}}{L_{j,t-k}+S_{j,t-k}}$

$L_{j,t} \equiv$ number of long positions held by commercial hedgers for week t on the futures series of commodity j.

$S_{j,t} \equiv$ number of short positions held by commercial hedgers for week t on the futures series of commodity j.

For our portfolio TS (term structure), we sort the set of commodities considered on past twenty six-week average roll-yield from highest to lowest. The bottom third constituents (highest $\overline{RY}$s) of the corresponding ordered set form the long leg of the portfolio while the top third form the short leg:

$$Y_t^{TS} \equiv \left\{ \left\{ \overline{RY_1}, \overline{RY_2}, ..., \overline{RY_n} \right\}, \geq \right\}$$

$\overline{RY_j} = \frac{1}{26} \sum_{k=0}^{25} (\frac{F^1_{j,t-k}}{F^2_{j,t-k}} - 1)$
$F^1_{j,t} \equiv$ week t close price for commodity j first nearby futures contract.
$F^2_{j,t} \equiv$ week t close price for commodity j second nearby futures contract.

For our portfolio OI (open interest), we sort the set of commodities considered on past twenty six-week average aggregate open interest growth from highest to lowest. The bottom third constituents (highest $\overline{\mathbf{OI}^{\Delta\%}}$s) of the corresponding ordered set form the long leg of the portfolio while the top third form the short leg.

$$Y_t^{OI} \equiv \left\{ \left\{ \overline{\mathbf{OI}_1^{\Delta\%}}, \overline{\mathbf{OI}_2^{\Delta\%}}, ..., \overline{\mathbf{OI}_n^{\Delta\%}} \right\}, \geq \right\}$$

$\overline{\mathbf{OI}_j^{\Delta\%}} = \frac{1}{26} \sum_{k=0}^{25} (\frac{\mathbf{OI}_{j,t-k}}{\mathbf{OI}_{j,t-k-1}} - 1)$
$\mathbf{OI}_{j,t} = \sum_{k=1}^{l_{j,t}} OI_{j,t,k}$
$OI_{j,t,k} \equiv$ open interest at close of week t for the k^{th} nearby contract on the futures term structure for commodity j.
$l_{j,t} \equiv$ length of commodity j's futures term structure on week t close.

We use a time series regression approach where we start with regressions of the US traded individual commodity weekly front returns on returns to the mimicking portfolio for a particular risk factor where the portfolio is constructed using the whole cross-section of US traded commodities. The corresponding adjusted R^2s are averaged and the process is repeated for each of our four risk factors (market, hedging pressure, term structure and liquidity) and periods (1997/2003, 2004/2007, 2008/2013 and 2014/2017). i.e, average adjusted R^2 for risk factor i (f_i) over period t:

$$\overline{\tilde{R}^2_{f_i,t}} = \frac{1}{24}\sum_{j=1}^{24}\tilde{R}^2_{j,t}$$

$\tilde{R}^2_j = 1 - (1 - R^2_j)\frac{T-1}{T-p-1}$[13]

$T \equiv$ length of period t (number of weeks here).

$p \equiv$ number of regressors (1 here).

$R^2_{j,t} = 1 - \frac{\sum_{k=1}^{T}(y_{j,k} - \hat{y_{j,k}})^2}{\sum_{k=1}^{T}(y_{j,k} - \overline{y_j})^2}$

$y_{j,t} \equiv$ week t nearby return for commodity j.

$\hat{y_{j,t}} = \beta_0 + \beta_1 f_{i,t} + \epsilon$

$\beta s \equiv$ classic OLS coefficient estimates.

$f_{i,t} \equiv$ week t return on mimicking portfolio for risk factor f_i

The same operation is repeated for the two ($p = 2$) and three ($p = 3$) factor model cases, where regressors include in turn all combinations of any two and three risk factors respectivly, as well as for the four ($p = 4$) factor model case where all the risk factor mimicking portfolios are included. Results are reported for the one-factor model case with the other results available from the authors upon request.

For each period we also implement the analysis described above over periods of low and high aggregate CHP (**CHP**), a notion which we introduce in this study and which we believe is particularly relevant in the context of financialization where issues of co-movement and aggregate market participants' behaviour play a central role. We define **CHP** as the

[13] The Wherry formula-1.

cross-sectional average of CHPs for a particular pool of assets. i.e, Week t **CHP** for asset pool x:

$$\mathbf{CHP}_t^x = \frac{1}{n}\sum_{j=1}^{n} CHP_{j,t}$$

$n \equiv$ number of commodities in set x.

$CHP_{i,t} \equiv$ week t CHP for commodity i as defined above.

We further define aggregate backwardation (**backwardation**) and contango (**contango**) **CHP** regimes as, for a given period, **CHP** levels below and above the period's median respectively and, in contrast with (Hong and Yogo, 2012) who aggregate across sub-sectors, the asset pool we consider for **CHP** construction include the whole cross-section of US traded commodities.

In the next part of the analysis, our mimicking portfolios for risk factors, constructed from the set of all US traded commodities are used as commodity picking devices on the latter commodity set. For each risk factor and period, individual US traded commodity front returns are regressed on returns for the corresponding mimicking portfolio. Individual commodities are sorted by adjusted R^2 ($\tilde{R}^2$) accordingly from highest to lowest and the bottom third (highest $\tilde{R}^2$s) are selected as commodity picks for the risk factor for the period. i.e, set of picks $P_t^{f_i}$ for risk factor i (f_i) over period t:

$$P_t^{f_i} \equiv \{P_1, P_2, ..., P_x\}$$

$x = \lceil n \cdot s \rceil$

$n \equiv$ number of commodities in the set considered for the picking excersise (twenty-four here).

$s \equiv$ selection threshold ($\frac{1}{3}$ here).

$P_j \equiv$ commodity pick j for risk factor f_i over period t

$j \equiv$ rank in the ordered set $Y_t^{f_i}$

$$Y_t^{f_i} \equiv \left\{ \left\{ \tilde{R}_1^2, \tilde{R}_2^2, ..., \tilde{R}_n^2 \right\}, \geq \right\}$$

$n \equiv$ number of commodities in the set considered for picking (twenty-four here).

$\tilde{R}_j^2 \equiv$ risk factor f_i returns' explanatory power on commodity j nearby futures returns over period t as defined above.

For each period and **CHP** regime we record the proportion of time each pick is held in the long and (/or) short leg of the corresponding risk factor mimicking portfolio as well as the average pairwise correlation amongst every sets of picks.

In the last part of the analysis, for each period our mimicking portfolios for risk factors in returns are constructed using each set of commodity picks independently as the asset pool for portfolio construction. A similar time series approach to that described above is then implemented using these newly formed mimicking portfolios. In this case, a first set of dependent variables includes the sets of commodity picks themselves, a second set includes the whole cross-section of US traded commodities while a third set includes the six UK traded metals considered. The latter are also used as dependent variables in the last series of regressions where the long and short legs of the newly formed risk factor mimicking portfolios described above are considered separately as regressors.

3 Results & discussion

The descriptive statistics over the various time periods for our two sets of commodities (US and non-US) as well as the four factors considered are shown in Table 1. The traditional Keynesian hedging pressure paradigm postulates a negative relationship between the return on an individual commodity and its hedging pressure. Financialization has been seen as a cross-sectional commodity market phenomenon; this naturally leads us to extend the individual hedging pressure paradigm by incorporating aggregate CHP (**CHP**), a market wide measure of hedging pressure. The extended Keynesian hedging pressure paradigm should also imply that returns for individual commodities should be high in periods where **CHP** is low and vice et versa.

In table 2 the mean returns are shown over high (**contango**) and low (**backwardation**) **CHP** regimes for each time period. Over the first period eighteen of the twenty-four US commodities have higher mean returns during periods of **backwardation** as compared to **contango**, with the difference being statistically significant at the 5% level for one commodity and for the remaining six commodities the higher mean return during **contango** is not statistically significant for any of them. For the six UK commodities, all metals, four of them had higher mean returns during phases of **backwardation** as compared to **contango** in the first period, with one of these differences being statistically significant at the 5% level while for the remaining two the higher mean return during **contango** is not statistically significant for either. An equally weighted portfolio of the twenty-four US commodities had a mean return of 10.98% during **backwardation** phases, statistically significant at the 1% level, and a mean return of 0.93% during **contango**, both in the first period, with the difference between them statistically significant at the 5% level. The corresponding figures for an equally weighted portfolio of the UK metals were 8.35% and -1.71%, the difference again statistically significant at the 5% level. These results provide broad support for an aggregate version of the Keynesian hedging pressure hypothesis and suggests that hedgers in the aggregate were engaged in risk transfer during this period.

Over the second period the pattern essentially reverses. For the twenty-four US commodities over this period, eighteen have higher mean returns during phases of **backwardation** over **contango**, with the difference statistically significant for four commodities and of the remaining seven the higher mean return during **backwardation** is statistically significant for one commodity. All of the six UK metals achieved higher mean returns over **backwardation** than contango with the difference being statistically significant for one commodity. The equally weighted US portfolio had a mean return of 11.16% over **backwardation** while it was 26.68% during **contango**, the first statistically significant at the 5% level and the second at the 1% level, with the difference statistically significant at the 1% level. The difference was considerably more pronounced for the equally weighted UK metals portfolio with a mean return of 6.43% during **backwardation** rising to 41.22% during **contango**, with the difference also significant at the 1% level.

Thus the onset of financialization seems to have engendered a change in the nature of hedger's behaviour in the aggregate, taking it away from risk shifting, the traditional Keynesian view. This phenomenon has been noted in earlier theoretical and empirical work (Danthine, 1978, Stout (1998)) in different context from which two competing models of behaviour have emerged. The information arbitrage model implies that hedgers may often be seeking out counterparties to trade with rather than being purely passive. This issue is also raised in both Cheng and Xiong (2014) and Stulz (1996) who point out that hedgers may be taking a view on prices just as speculators do. In fact, by hedging away some of their risk, hedgers are able to speculate more heavily based on their disagreement against speculators regarding futures price movement (Simsek, 2013), which fits into a heterogenous expectation theory of speculation. As Stout (1998) points out, this disagreement-based theory of trading is one of the main reason the public and the law disapproves the speculators as this form of trading is regarded as non-productive[14]. In the second model hedgers are seen as liquidity providers as in Kang et al. (2017). This explanation is also consistent with the nature of financialization which led to the arrival of long term, long only investors who require substantial liquidity to roll-over their positions.

The average time series pricing performance of the various one factor models on the US traded assets over the four periods is shown in Table 3. Over the first period the market factor has the best average time series performance with the highest average adjusted R^2 with all three futures market factors performing poorly and the overall pricing performance consistent across periods of high and low **CHP** (below period median). The two factor models average R^2s (results available upon request) are roughly the sum of the one factor R^2s indicating that the factors are almost orthogonal over this period. The onset of financialization leads to a substantial improvement in the performance of the CHP factor with its average R^2 increasing to 5.4% in the second period relative to 1.4% in the first. The performance of the market factor also improves though not by as much in a relative sense (18.6% from 12.2%). Both the term structure factor and the open interest growth factor show a much smaller improvement in pricing performance. Over all periods, all of our factor models show similar pricing performance across regimes of high and low **CHP**.

We next investigate the top eight of the US traded commodities which achieved the highest

[14] Duffie (2014) also discusses some of the challenges faced by a policy treatment of speculative trading motivated by differences in beliefs.

time series R^2 for the CHP, market, open interest and term structure factors, in each of the four time periods with the commodity picks shown in Table 4. For the CHP factor the commodities that achieve high R^2 in a given period are likely to be those with relatively high or low CHP over that period, or those commodities that co-vary with the short or the long side of the factor. The same applies to the open interest and term structure factors with CHP replaced by open interest growth and roll yield respectively; while for the market factor the picks are those that co-vary most strongly with the market factor over that period. For the CHP factor, we observe a change in the picks between the first and the second period; the picks in the first period included five agricultural commodities and three metals while in the second period include all of the five base and precious metals and only three agricultural commodities. This pattern is also visible for the term structure factor for which there are four metals (gold, copper, palladium and platinum) picks in the second period against three in the first (gold, palladium and platinum). The market factor has two metal picks in the second period (palladium and silver) while all of the picks in the first period were agricultural or energy commodities. Over the third period, the average CHP factor has four metal picks while both the term structure factor and market factor have three. Table 4 also shows the proportion of time that these picks were constituents of the corresponding factor. All of the picks of the long-short factors (average CHP, open interest growth and term structure factors) were constituents of the corresponding factor for some proportion of time in all of the time periods. In this respect, there is a contrast between the first and second periods for the average CHP with the picks appearing predominantly on the long side in the second period, as opposed to both legs in the first. This indicates that the picks in the second period consistently exhibited low CHP. This behaviour continued over the third period.

In table 5, we show the average pairwise correlation between each set of picks in each time period. This exercise gives an indication of the extent to which attribute co-movement reveals price co-movement, which is particularly relevant for the long-short factors for which the corresponding attribute is not directly related to price co-movement. In the first period, the average CHP factor picks pairwise correlation is similar to the average across the US traded twenty-four commodities (around 0.1) with the market factor picks showing the highest figure (0.21). In the second period however it is the highest (0.27), comparable with the market (0.26) and double of the US traded commodities average (0.13). This increase is a consequence of the dramatic increase in average pairwise price correlation amongst the US traded metals, all of which are CHP factor picks. Taken together with the fact that four of these metals had consistently low CHP, we see that CHP co-movement in the second period is strongly correlated with price co-movement. It is also interesting to note that US traded metals returns were negatively correlated with the rest of US traded commodities in the first period and positively in the second (Results available upon request).

In order to further understand the link between attribute and price co-movement we build all of the factors from every set of factor picks and assess their pricing performance on these sets of picks. The results are shown in table 6. The long-short factors for a particular attribute select the top and bottom three of the corresponding picks based on that attribute while the market factor takes an equally weighted combination of the eight corresponding picks. In the absence of price co-movement between the picks, this market factor will achieve an average R^2 of around 12.5%[15], while there is no non-zero R^2 lower bound for the corresponding long-short factors. A high average R^2 for the market factor is indicative of strong price co-movement while for the long-short factors it is indicative of simultaneous attribute and

[15]Market factor lemma: $\overline{R^2_{r_{mkt},p}} = \frac{1}{n}\sum_j R^2_{r_j,r_{mkt},p} = \frac{1}{n}$; $n \equiv$ size of market portfolio (eight here). See section 5.2 for a formal proof.

price co-movement. The most dramatic change in pricing performance occurs for the average CHP factor picks where the market factor built from these picks has an average R^2 of 21.3 % in the first period (close to the 0 correlation situation) and jumps to 37.4 % in the second period. The average CHP factor built with average CHP factor picks also shows a sharp increase in pricing performance over the second period. There is also substancial improvement in pricing performance of the CHP factor built with term structure picks (3.4% vs. 21.2%)[16], providing evidence of convergence of Keynesian and Working's theories of the term structure in detecting price co-movement during financialization. In table 7 we assess the performance of the same factors on all the commodities instead of just the picks. While the average R^2s are expectedly lower, the relative performance of the market factors built with different sets of picks is similar to table 6. In contrast, the increase in R^2 for the average CHP factor built with average CHP factor picks is lower indicating that the link between CHP co-movement and price co-movement is strongest amongst the picks which are predominantly metals.

The conclusion from Tables 6 and 7 is that the onset of financialization seems to have had a major impact on the dynamics of US traded precious and precious-base metals and we now seek to analyse whether this phenomenon is true for the non-US metal futures. To that end we examine the pricing performance of the factors used in Table 6 on the six UK metals futures. The results are reported in Table 8. In the first period, the average R^2s across the board are always less than 4.5%. In the second period we see a dramatic increase in R^2 for the market factor built with average CHP factor picks and average term structure factor picks (4.48% to 25.1% and 1.3% to 20.6% respectively) showing dramatically higher co-movement between UK traded metals and the corresponding picks all of which are US traded commodities. The increase in R^2 for the market factor built with market factor picks

[16] In contrast to the market factor, there is no pricing performance lower bound for the CHP factor built with a set of picks.

is much more modest, providing further evidence of concentration of co-movement in the metal sector during financialization.

In order to understand this better, in table 9, we examine the pricing performance of both long and short legs of the corresponding factors separately on the same set of UK traded metals. The most striking result here is the dramatic increase in R^2 for the long leg of the term structure factor built with CHP factor picks which achieves the highest overall R^2 in the second period (1.91% vs. 27.37%). This provides further evidence that global metals co-movement could be detected by US based factor models that combined the Keynesian and Working's notions of backwardation.

We then turn our analysis to the crisis and post-crisis period (2008-2013). In table 1 we see that the returns on both US and non-US commodities fall dramatically over this period, going down to -4.3% for the UK metals and 8% for the US traded commodities although volatility for both sets of assets is similar to that during the second period. Two of the UK metals have negative mean returns over the third period compared to one over the first and none over the second. This trend continues in from 2014 to 2017 with the US traded commodities recording an average mean return of -0.6% and the UK metals an average of 4.9% over this period, with fourteen US traded commodities and one UK metal having negative mean returns. The volatility of both sets of assets is lower than over the 2004-2007 period, particularly for the UK metals, suggesting the impact of the investment outflows from the commodity futures markets has had a much lower impact on volatility than the corresponding inflows witnessed over the financialization period. The market factor dominates pricing performance over this period with an increase of mean average R^2 of over 50% while that for the other factors increases slightly at best (table 3). From table 5 we see that there is an across the board increase in pairwise correlations with a doubling in the average pairwise correlation of all US traded commodities and a levelling in the pairwise correlation of the picks of the three long-short factors. Taken together, these results indicate the presence of a systematic factor across the entire cross-section of the US commodities. This is clearly evident in the performance of the market factor built with any set of picks on the entire set of US traded commodities (table 7) as we see a dramatic rise across the board in pricing performance. Table 8 provides further evidence of systematic linkages, in this case between US and non-US traded commodities as the market factor built with its own picks (US traded commodities) achieves an average R^2 of 33.7% on the UK metals compared to 9.9% in the previous period.

4 Conclusion

In the early 2000s, against a backdrop of a low yield environment and poor stock market performance, a combination of financial innovation[17] and deregulation[18] led to a large inflow

[17]Tradable commodity price indexes (commonly referred to as commodity index funds or CIFs), and commodity-based exchange traded funds (ETFs) were the main financial innovations which allowed the large global banks to offer commodity investment products to institutional and retail investors. In 1991 Goldman Sachs created the S&P-GSCI which provides investors with buy-side exposure to commodities via the OTC swap market and thus without having to participate in the formal futures markets with their position limit restrictions. At this stage these restrictions still applied to the bank though, as it hedged its commodity swap exposure in the futures markets. The first commodity-based ETFs were created through buying physical precious metals with gold and silver ETFs offered as early as 2002/2003. The regulatory hurdle here related to the licensing of commodity trading professionals. Typically, investors had to sign a statement with their broker stating that they understood the risks of commodity investments; a rather inconvenient paperwork for a product designed to trade like a stock, as set forth by a number of industry players at the time.

[18]In 2000, the Commodity Futures Modernization Act (CFMA) granted non-agricultural commodity futures statutory exemption from regulation ("Enron loophole") while it required that agricultural commodity derivatives be traded on a CFTC-regulated exchange. Notwithstanding, the CFTC classified swap dealers as "bona fide" hedgers, granting them position limits exemption ("swap dealer loophole").
In 2005, the CFTC waived the rule that required commodity investors to sign a statement saying they understood the risks, letting the funds replace it with their prospectus and thus unleashed commodity-based ETFs investments.

of institutional and financial capital into the commodity futures markets. This process known as financialization lead to a heated public policy debate about whether the increase in open interest and trading volume in commodities exerted upward pressure on prices. Perhaps in response to this, most of the early studies focused on the more mechanical effects of financialization, relying on commodity specific causality and correlation based analysis. With the benefit of hindsight this focus appears to have been too narrow and it seems important to analyze the effects of financialization from a broader perspective which we do in this study. We consider the entire cross-section of actively traded commodities on futures markets and use a futures based asset pricing framework that includes factors constructed using both price and non-price attributes. Factor model techniques are well suited to isolating common driving factors and detecting co-movement, a central issue in financialization which we believe the existing literature has not fully analyzed. Our analysis suggests that financialization was a phenomenon endogenous to the commodity markets transmitted via the futures markets and appears to have had the deepest impact on global metal futures markets. The onset of the financial crisis and the monetary policy regimes that followed appear to have also induced significant changes in commodity pricing dynamics and our analysis suggest that in contrast with financialization, the crisis and its aftermath have delivered an exogenous shock across the entire cross-section of global commodities.

Table 1: This table shows descriptive statistics for nearby futures returns on various commodity groups as well as for mimicking portfolios for risk factors where the factor portfolios are constructed using the whole cross-section of the US traded commodities considered in the study. Figures labelled *** (**, *) are significant at the 1% (5%, 10%) level. See section 2.3 for more details.

Assets	Variable	1997/2003	2004/2007	2008/2013	2014/2017
US-Agriculturals-Grains	Mean return	3.75%	***18.99%	5.34%	-4.14%
US-Agriculturals-Grains	Volatility	27.14%	29.17%	33.52%	25.18%
US-Agriculturals-Livestock	Mean return	3.81%	5.84%	*9.53%	0.16%
US-Agriculturals-Livestock	Volatility	26.53%	21.59%	23.94%	26.55%
US-Agriculturals-Softs	Mean return	1.57%	**14.26%	9.53%	2.97%
US-Agriculturals-Softs	Volatility	33.47%	30.19%	35.53%	28.08%
US-Metals-Industrial	Mean return	2.42%	**33.08%	6.74%	1.35%
US-Metals-Industrial	Volatility	20.2%	30.44%	31.66%	19.95%
US-Metals-Precious	Mean return	*9.39%	***22.7%	9.99%	2.13%
US-Metals-Precious	Volatility	26.2%	25.61%	31.76%	21.57%
US-Agriculturals	Mean return	2.89%	***14.45%	**7.86%	-0.44%
US-Agriculturals	Volatility	29.72%	28.24%	32.69%	26.64%
US-Energy	Mean return	13.56%	***28.33%	6.94%	-4.13%
US-Energy	Volatility	44.03%	42.77%	39.5%	36.52%
US-Metals	Mean return	*7.99%	***24.77%	9.34%	1.98%
US-Metals	Volatility	25.12%	26.64%	31.73%	21.24%
US-Commodity	Mean return	**5.73%	***18.9%	***8.01%	-0.55%
US-Commodity	Volatility	31.73%	30.84%	33.72%	27.56%
UK-Commodity	Mean return	2.95%	***23.91%	4.25%	4.87%
UK-Commodity	Volatility	20.33%	33.43%	35.99%	22.33%
CHP factor	Mean return	0.34%	1.09%	-0.15%	-1.98%
CHP factor	Volatility	7.78%	8.05%	8.93%	7.45%
Market factor	Mean return	5.99%	***18.81%	8.01%	-0.55%
Market factor	Volatility	10.2%	12.39%	17.26%	10.3%
OI factor	Mean return	-0.2%	2.79%	-4.28%	2.28%
OI factor	Volatility	8.26%	8.16%	8.1%	6.69%
TS factor	Mean return	**-9.49%	*-7.15%	-5.77%	**-9.02%
TS factor	Volatility	10.25%	8.31%	9.91%	8.52%

Table 2: This table shows descriptive statistics for nearby futures returns on various commodity groups as well as for mimicking portfolios for risk factors where the factor portfolios are constructed using the whole cross-section of the US traded commodities considered in the study. For each period the results are shown for **contango** (high) and **backwardation** (low) **CHP** regimes independently. Figures labelled *** (**, *) are significant at the 1% (5%, 10%) level. See section 2.3 for more details.

Assets	CHP regime	Variable	1997/2003	2004/2007	2008/2013	2014/2017
US-Agriculturals-Grains	High	Mean return	4.25%	***29.78%	-2.92%	-0.55%
US-Agriculturals-Grains	High	Volatility	27.61%	30.17%	36.06%	24.93%
US-Agriculturals-Grains	Low	Mean return	3.24%	8.26%	*13.66%	-7.76%
US-Agriculturals-Grains	Low	Volatility	26.67%	28.09%	30.73%	25.43%
US-Agriculturals-Livestock	High	Mean return	-2.15%	-1.68%	4.05%	-15.8%
US-Agriculturals-Livestock	High	Volatility	29.3%	20.65%	23.59%	25.46%
US-Agriculturals-Livestock	Low	Mean return	9.84%	13.43%	*15.04%	16.28%
US-Agriculturals-Livestock	Low	Volatility	23.38%	22.47%	24.29%	27.48%
US-Agriculturals-Softs	High	Mean return	-1.31%	***24.85%	11.43%	-3.34%
US-Agriculturals-Softs	High	Volatility	32.54%	30.48%	36.06%	28.72%
US-Agriculturals-Softs	Low	Mean return	4.47%	3.67%	7.62%	9.33%
US-Agriculturals-Softs	Low	Volatility	34.4%	29.84%	35%	27.42%
US-Metals-Industrial	High	Mean return	-0.45%	**51.48%	1.3%	-13.36%
US-Metals-Industrial	High	Volatility	20.55%	31.58%	36.97%	18.91%
US-Metals-Industrial	Low	Mean return	5.3%	14.86%	12.22%	16.2%
US-Metals-Industrial	Low	Volatility	19.89%	29.2%	25.31%	20.85%
US-Metals-Precious	High	Mean return	-3.38%	***37.17%	-2.16%	-3.58%
US-Metals-Precious	High	Volatility	28.72%	23.7%	32.66%	22.64%
US-Metals-Precious	Low	Mean return	***22.26%	8.36%	**22.23%	7.9%
US-Metals-Precious	Low	Volatility	23.28%	27.26%	30.77%	20.42%
US-Agriculturals	High	Mean return	0.74%	***21.45%	4.21%	-4.72%
US-Agriculturals	High	Volatility	30%	28.67%	33.93%	26.61%
US-Agriculturals	Low	Mean return	5.06%	7.46%	**11.52%	3.88%
US-Agriculturals	Low	Volatility	29.44%	27.79%	31.39%	26.67%
US-Energy	High	Mean return	3.9%	*29.75%	-3.1%	-23.15%
US-Energy	High	Volatility	43.76%	45.83%	45.46%	40.32%
US-Energy	Low	Mean return	*23.3%	*26.93%	*17.04%	15.07%

Table 2: continued

Assets	CHP regime	Variable	1997/2003	2004/2007	2008/2013	2014/2017
US-Energy	Low	Volatility	44.3%	39.55%	32.39%	32.06%
US-Metals	High	Mean return	-2.79%	***40.04%	-1.47%	-5.54%
US-Metals	High	Volatility	27.27%	25.45%	33.54%	21.93%
US-Metals	Low	Mean return	***18.86%	9.66%	***20.22%	9.56%
US-Metals	Low	Volatility	22.65%	27.63%	29.75%	20.49%
US-Commodity	High	Mean return	0.53%	***26.68%	1.81%	*-7.96%
US-Commodity	High	Volatility	32.19%	31.59%	36.02%	28.52%
US-Commodity	Low	Mean return	***10.98%	**11.16%	***14.25%	*6.93%
US-Commodity	Low	Volatility	31.25%	30.04%	31.22%	26.52%
UK-Commodity	High	Mean return	-1.71%	***41.22%	-1.32%	**-13.66%
UK-Commodity	High	Volatility	21.05%	33.54%	38.82%	21.69%
UK-Commodity	Low	Mean return	*8.35%	6.43%	10.04%	***23.4%
UK-Commodity	Low	Volatility	19.45%	33.17%	32.8%	22.69%
CHP factor	High	Mean return	1.45%	7.88%	0.89%	-3.48%
CHP factor	High	Volatility	8.08%	8.28%	9.81%	7.11%
CHP factor	Low	Mean return	-0.98%	-5.63%	-1.2%	-0.47%
CHP factor	Low	Volatility	7.43%	7.75%	7.97%	7.81%
Market factor	High	Mean return	0.67%	***26.46%	1.81%	-7.96%
Market factor	High	Volatility	10.27%	11.96%	18.97%	11.24%
Market factor	Low	Mean return	**11.43%	11.16%	14.25%	6.93%
Market factor	Low	Volatility	10.1%	12.78%	15.37%	9.19%
OI factor	High	Mean return	-0.76%	4.89%	-6.9%	3.84%
OI factor	High	Volatility	7.92%	8.79%	8.64%	6.7%
OI factor	Low	Mean return	0.46%	0.72%	-1.65%	0.7%
OI factor	Low	Volatility	8.66%	7.52%	7.53%	6.7%
TS factor	High	Mean return	**-13.59%	-7.38%	-8.14%	*-11.23%
TS factor	High	Volatility	10.38%	8.71%	10.76%	8.39%
TS factor	Low	Mean return	-4.6%	-6.92%	-3.37%	-6.79%
TS factor	Low	Volatility	10.08%	7.94%	9%	8.69%

Table 3: This table shows the average time series adjusted R^2s for a set of commodity factor models. The dependent variables are individual nearby futures returns on the commodities forming the entire cross-section of US traded commodities considered in the study while the regressors are returns on mimicking portfolios for risk factors where the factor portfolios are constructed using whole set of US traded commodities considered. For each period and model, the corresponding individual commodity adjusted R^2s are averaged. For each period, the models are implemented over the whole period, as well as over **contango** (high) and **backwardation** (low) **CHP** regimes independently. See section 2.3 for more details.

Factor asset pool	Model	CHP regime	1997/2003	2004/2007	2008/2013	2014/2017
US commodities	~ CHP factor	High	1.54%	5.5%	5.89%	3.73%
US commodities	~ CHP factor	Low	1.39%	5.64%	7.33%	5.43%
US commodities	~ CHP factor	None	1.37%	5.43%	5.99%	4.47%
US commodities	~ Market factor	High	13.04%	16.96%	30.45%	17.62%
US commodities	~ Market factor	Low	11.61%	19.83%	28.92%	13.53%
US commodities	~ Market factor	None	12.2%	18.55%	29.45%	15.57%
US commodities	~ OI factor	High	0.82%	1.32%	1.19%	0.31%
US commodities	~ OI factor	Low	1.42%	-0.39%	0.54%	0.56%
US commodities	~ OI factor	None	0.66%	0.36%	0.31%	0.31%
US commodities	~ TS factor	High	2.12%	3.36%	4.68%	2.69%
US commodities	~ TS factor	Low	2.88%	2.72%	5.57%	3.09%
US commodities	~ TS factor	None	2.4%	2.7%	4.69%	2.52%

Table 4: For each risk factor and period, this table displays the list of corresponding commodity factor picks along with the proportion of time they are individually held on the long and short legs of the corresponding risk factor mimicking portfolio. The factor portfolios are constructed from the whole set of the twenty four US traded commodities considered which is also used as asset pool for the commodity picking exercise. See section 2.3 for more details.

Factor	Period	Asset	Long	Short
CHP	1997/2003	XCBT - Oats	97%	0%
CHP	1997/2003	XCBT - Soy-oil	42%	32%
CHP	1997/2003	XCBT - Wheat-SRW	29%	9%
CHP	1997/2003	XCEC - Copper	43%	18%
CHP	1997/2003	XCEC - Silver	100%	0%
CHP	1997/2003	XNYM - Platinum	91%	4%
CHP	1997/2003	IFUS - Coffee	22%	17%
CHP	1997/2003	IFUS - Orange juice	67%	18%
Market	1997/2003	XCBT - Corn	100%	0%
Market	1997/2003	XCBT - Oats	100%	0%
Market	1997/2003	XCBT - Soy-meal	100%	0%
Market	1997/2003	XCBT - Wheat-SRW	100%	0%
Market	1997/2003	XNYM - Crude oil	100%	0%
Market	1997/2003	XNYM - Gasoline	100%	0%
Market	1997/2003	XNYM - Heating oil	100%	0%
Market	1997/2003	XNYM - Natural gas	99%	0%
OI	1997/2003	XCME - Feeder cattle	27%	39%
OI	1997/2003	XCME - Lean hogs	36%	30%
OI	1997/2003	XNYM - Crude oil	24%	28%
OI	1997/2003	XNYM - Natural gas	46%	24%
OI	1997/2003	XCEC - Gold	39%	28%
OI	1997/2003	XNYM - Palladium	46%	33%
OI	1997/2003	IFUS - Coffee	39%	23%
OI	1997/2003	XCME - Lumber	42%	33%
TS	1997/2003	XCBT - Soy-meal	71%	0%
TS	1997/2003	XNYM - Crude oil	53%	9%
TS	1997/2003	XNYM - Gasoline	61%	17%
TS	1997/2003	XNYM - Heating oil	35%	24%
TS	1997/2003	XCEC - Gold	10%	1%
TS	1997/2003	XNYM - Palladium	61%	0%
TS	1997/2003	XNYM - Platinum	96%	0%
TS	1997/2003	IFUS - Sugar	60%	26%
CHP	2004/2007	XCBT - Oats	100%	0%
CHP	2004/2007	XCEC - Copper	44%	37%

Table 4: continued

Factor	Period	Asset	Long	Short
CHP	2004/2007	XCEC - Gold	100%	0%
CHP	2004/2007	XCEC - Silver	100%	0%
CHP	2004/2007	XNYM - Palladium	100%	0%
CHP	2004/2007	XNYM - Platinum	100%	0%
CHP	2004/2007	IFUS - Coffee	15%	5%
CHP	2004/2007	IFUS - Orange juice	66%	15%
Market	2004/2007	XCBT - Corn	100%	0%
Market	2004/2007	XCBT - Soybeans	100%	0%
Market	2004/2007	XNYM - Crude oil	100%	0%
Market	2004/2007	XNYM - Gasoline	100%	0%
Market	2004/2007	XNYM - Heating oil	100%	0%
Market	2004/2007	XNYM - Natural gas	100%	0%
Market	2004/2007	XCEC - Silver	100%	0%
Market	2004/2007	XNYM - Palladium	100%	0%
OI	2004/2007	XCME - Lean hogs	38%	22%
OI	2004/2007	XCME - Live cattle	32%	35%
OI	2004/2007	XNYM - Natural gas	32%	35%
OI	2004/2007	XNYM - Palladium	43%	28%
OI	2004/2007	IFUS - Cocoa	18%	36%
OI	2004/2007	IFUS - Coffee	34%	28%
OI	2004/2007	IFUS - Cotton	33%	17%
OI	2004/2007	IFUS - Sugar	48%	16%
TS	2004/2007	XCEC - Copper	86%	0%
TS	2004/2007	XCME - Feeder cattle	86%	0%
TS	2004/2007	XCME - Lean hogs	44%	46%
TS	2004/2007	XCME - Live cattle	56%	23%
TS	2004/2007	XCEC - Gold	28%	0%
TS	2004/2007	XNYM - Palladium	0%	6%
TS	2004/2007	XNYM - Platinum	95%	0%
TS	2004/2007	IFUS - Cocoa	15%	12%
CHP	2008/2013	XCBT - Soy-meal	79%	4%
CHP	2008/2013	XNYM - Gasoline	46%	0%
CHP	2008/2013	XNYM - Heating oil	1%	18%
CHP	2008/2013	XCEC - Gold	96%	0%
CHP	2008/2013	XCEC - Silver	90%	0%
CHP	2008/2013	XNYM - Palladium	100%	0%
CHP	2008/2013	XNYM - Platinum	100%	0%
CHP	2008/2013	IFUS - Orange juice	96%	0%
Market	2008/2013	XCBT - Corn	100%	0%
Market	2008/2013	XCBT - Oats	100%	0%

Table 4: continued

Factor	Period	Asset	Long	Short
Market	2008/2013	XCEC - Copper	100%	0%
Market	2008/2013	XNYM - Crude oil	100%	0%
Market	2008/2013	XNYM - Gasoline	100%	0%
Market	2008/2013	XNYM - Heating oil	100%	0%
Market	2008/2013	XCEC - Silver	100%	0%
Market	2008/2013	XNYM - Palladium	100%	0%
OI	2008/2013	XCBT - Corn	21%	37%
OI	2008/2013	XCBT - Soy-meal	37%	34%
OI	2008/2013	XNYM - Crude oil	23%	31%
OI	2008/2013	XNYM - Gasoline	33%	27%
OI	2008/2013	XNYM - Heating oil	27%	34%
OI	2008/2013	IFUS - Orange juice	32%	43%
OI	2008/2013	IFUS - Sugar	36%	31%
OI	2008/2013	XCME - Lumber	35%	38%
TS	2008/2013	XCBT - Soy-meal	69%	1%
TS	2008/2013	XCBT - Soybeans	59%	0%
TS	2008/2013	XNYM - Crude oil	25%	30%
TS	2008/2013	XNYM - Gasoline	61%	6%
TS	2008/2013	XNYM - Heating oil	33%	6%
TS	2008/2013	XCEC - Silver	64%	0%
TS	2008/2013	XNYM - Palladium	38%	0%
TS	2008/2013	XNYM - Platinum	47%	1%
CHP	2014/2017	XCEC - Copper	0%	79%
CHP	2014/2017	XNYM - Gasoline	13%	0%
CHP	2014/2017	XCEC - Gold	78%	0%
CHP	2014/2017	XCEC - Silver	69%	0%
CHP	2014/2017	XNYM - Palladium	100%	0%
CHP	2014/2017	XNYM - Platinum	100%	0%
CHP	2014/2017	IFUS - Orange juice	62%	2%
CHP	2014/2017	XCME - Lumber	38%	53%
Market	2014/2017	XCBT - Soy-meal	100%	0%
Market	2014/2017	XNYM - Crude oil	100%	0%
Market	2014/2017	XNYM - Gasoline	100%	0%
Market	2014/2017	XNYM - Heating oil	100%	0%
Market	2014/2017	XNYM - Natural gas	100%	0%
Market	2014/2017	XNYM - Palladium	100%	0%
Market	2014/2017	IFUS - Coffee	100%	0%
Market	2014/2017	IFUS - Sugar	100%	0%
OI	2014/2017	XCBT - Oats	32%	45%
OI	2014/2017	XCBT - Soy-meal	39%	27%

Table 4: continued

Factor	Period	Asset	Long	Short
OI	2014/2017	XCEC - Copper	48%	15%
OI	2014/2017	XCEC - Gold	39%	23%
OI	2014/2017	XCEC - Silver	44%	28%
OI	2014/2017	IFUS - Cocoa	33%	34%
OI	2014/2017	IFUS - Cotton	42%	31%
OI	2014/2017	XCME - Lumber	50%	30%
TS	2014/2017	XCBT - Soy-meal	68%	10%
TS	2014/2017	XCBT - Soybeans	56%	10%
TS	2014/2017	XCME - Feeder cattle	75%	10%
TS	2014/2017	XCME - Live cattle	65%	24%
TS	2014/2017	IFUS - Cocoa	54%	1%
TS	2014/2017	IFUS - Cotton	40%	2%
TS	2014/2017	IFUS - Orange juice	41%	23%
TS	2014/2017	XCME - Lumber	41%	39%

Table 5: This table displays the average pairwise nearby futures returns correlations for various sets of commodities including the multiple sets of risk factor commodity picks, the whole cross-section of US traded commodities considered in the study, the latter with metals omitted, and the cross-section of US traded metals. For each period and commodity set the correlations are calculated independently over the whole period as well as over **contango** (high) and **backwardation** (low) **CHP** regimes. See section 2.3 for more details.

Asset pool	CHP regime	1997/2003	2004/2007	2008/2013	2014/2017
CHP factor picks	High	0.09	0.24	0.32	0.22
CHP factor picks	Low	0.10	0.28	0.37	0.19
CHP factor picks	None	0.10	0.27	0.34	0.21
Market factor picks	High	0.23	0.24	0.40	0.22
Market factor picks	Low	0.20	0.28	0.42	0.19
Market factor picks	None	0.21	0.26	0.41	0.21
OI factor picks	High	0.03	0.04	0.28	0.15
OI factor picks	Low	0.03	0.09	0.22	0.07
OI factor picks	None	0.03	0.07	0.25	0.11
TS factor picks	High	0.16	0.15	0.41	0.11
TS factor picks	Low	0.11	0.17	0.48	0.09
TS factor picks	None	0.13	0.16	0.44	0.10
US - Commodity	High	0.08	0.11	0.25	0.13
US - Commodity	Low	0.07	0.15	0.22	0.09
US - Commodity	None	0.08	0.13	0.24	0.11
US - Commodity - No metals	High	0.09	0.10	0.26	0.12
US - Commodity - No metals	Low	0.08	0.13	0.17	0.10
US - Commodity - No metals	None	0.09	0.12	0.22	0.11
US - Metals	High	0.23	0.55	0.52	0.44
US - Metals	Low	0.19	0.52	0.61	0.42
US - Metals	None	0.21	0.53	0.55	0.43

Table 6: This table shows the average time series adjusted R^2s for a set of commodity factor models. The dependent variables are individual nearby futures returns on risk factors commodity picks while the regressors are returns on mimicking portfolios for risk factors where the factor portfolios are constructed using the corresponding set of risk factor commodity picks shown in table 4. For each period and model, the corresponding individual commodity adjusted R^2s are averaged. For each period, the models are implemented over the whole period, as well as over **contango** (high) and **backwardation** (low) **CHP** regimes independently. See section 2.3 for more details.

Factor asset pool	Model	CHP regime	1997/2003	2004/2007	2008/2013	2014/2017
TS factor picks	~ CHP factor	High	1.45%	20.37%	16.95%	8.81%
TS factor picks	~ CHP factor	Low	7.6%	21.82%	10.29%	4.84%
TS factor picks	~ CHP factor	None	3.42%	21.2%	14.09%	5.06%
TS factor picks	~ Market factor	High	28.64%	27.15%	48.8%	21.54%
TS factor picks	~ Market factor	Low	25.53%	28.87%	54.4%	21.22%
TS factor picks	~ Market factor	None	27.23%	28.26%	50.95%	21.63%
TS factor picks	~ OI factor	High	0.07%	6.42%	4.08%	2.13%
TS factor picks	~ OI factor	Low	2.48%	0.81%	2.68%	0.61%
TS factor picks	~ OI factor	None	0.68%	2.26%	1.81%	0.56%
TS factor picks	~ TS factor	High	2.04%	7.65%	5.2%	2.98%
TS factor picks	~ TS factor	Low	2.22%	6.03%	2%	1.85%
TS factor picks	~ TS factor	None	0.53%	6.91%	4.16%	2.02%
OI factor picks	~ CHP factor	High	3.02%	5.9%	4.56%	10.95%
OI factor picks	~ CHP factor	Low	1.32%	9.37%	7.5%	5.5%
OI factor picks	~ CHP factor	None	1.96%	6.96%	3.95%	6.36%
OI factor picks	~ Market factor	High	14.4%	15.55%	39.51%	24.98%
OI factor picks	~ Market factor	Low	14.99%	20.4%	32.69%	17.31%
OI factor picks	~ Market factor	None	14.86%	18%	36.91%	21.08%
OI factor picks	~ OI factor	High	1.67%	1.82%	0.87%	0.64%
OI factor picks	~ OI factor	Low	0.67%	-0.38%	0.95%	3.52%
OI factor picks	~ OI factor	None	0.29%	0.77%	0.09%	0.74%
OI factor picks	~ TS factor	High	3.24%	7.15%	13.59%	3.69%
OI factor picks	~ TS factor	Low	2.92%	2.7%	4.11%	3%
OI factor picks	~ TS factor	None	3.07%	5.36%	9.97%	3.08%
CHP factor picks	~ CHP factor	High	5.74%	15.05%	12.05%	12.46%
CHP factor picks	~ CHP factor	Low	7.05%	10.85%	8.7%	14.6%
CHP factor picks	~ CHP factor	None	5.83%	13.23%	10.46%	12.91%
CHP factor picks	~ Market factor	High	21.09%	35.23%	41.13%	32.66%
CHP factor picks	~ Market factor	Low	21.6%	38.7%	46.97%	29.72%
CHP factor picks	~ Market factor	None	21.27%	37.36%	43.49%	31.36%
CHP factor picks	~ OI factor	High	1.69%	3.9%	4.04%	0.74%
CHP factor picks	~ OI factor	Low	3.51%	1.61%	1.03%	2.96%

Table 6: continued

Factor asset pool	Model	CHP regime	1997/2003	2004/2007	2008/2013	2014/2017
CHP factor picks	~ OI factor	None	1.57%	1.64%	2.07%	0.23%
CHP factor picks	~ TS factor	High	4.77%	7.1%	1.98%	4.78%
CHP factor picks	~ TS factor	Low	5.36%	5.57%	0.95%	-0.21%
CHP factor picks	~ TS factor	None	4.54%	5.1%	1.84%	1.66%
Market factor picks	~ CHP factor	High	7.79%	8.62%	7.1%	7.84%
Market factor picks	~ CHP factor	Low	4.6%	7.78%	7.63%	7.73%
Market factor picks	~ CHP factor	None	6.06%	8.31%	6.22%	7.07%
Market factor picks	~ Market factor	High	32.85%	34.83%	48.14%	33.71%
Market factor picks	~ Market factor	Low	30.4%	37.35%	49.31%	29.36%
Market factor picks	~ Market factor	None	31.43%	36.1%	48.63%	32.31%
Market factor picks	~ OI factor	High	3.74%	0.77%	2.62%	0.52%
Market factor picks	~ OI factor	Low	0.41%	-0.45%	1.22%	-0.05%
Market factor picks	~ OI factor	None	1.33%	0.29%	0.78%	0.53%
Market factor picks	~ TS factor	High	6.64%	5.3%	2.45%	7.59%
Market factor picks	~ TS factor	Low	8.53%	4.21%	11.16%	4.7%
Market factor picks	~ TS factor	None	7.65%	5.2%	3.25%	6.24%

Table 7: This table shows the average time series adjusted R^2s for a set of commodity factor models. The dependent variables are individual nearby futures returns on the commodities forming the entire cross-section of US traded commodities considered in the study while the regressors are returns on mimicking portfolios for risk factors where the factor portfolios are constructed using the corresponding set of risk factor commodity picks shown in table 4. For each period and model, the corresponding individual commodity adjusted R^2s are averaged. For each period, the models are implemented over the whole period, as well as over **contango** (high) and **backwardation** (low) **CHP** regimes independently. See section 2.3 for more details.

Factor asset pool	Model	CHP regime	1997/2003	2004/2007	2008/2013	2014/2017
TS factor picks	~ CHP factor	High	1.45%	20.37%	16.95%	8.81%
TS factor picks	~ CHP factor	Low	7.6%	21.82%	10.29%	4.84%
TS factor picks	~ CHP factor	None	3.42%	21.2%	14.09%	5.06%
TS factor picks	~ Market factor	High	28.64%	27.15%	48.8%	21.54%
TS factor picks	~ Market factor	Low	25.53%	28.87%	54.4%	21.22%
TS factor picks	~ Market factor	None	27.23%	28.26%	50.95%	21.63%
TS factor picks	~ OI factor	High	0.07%	6.42%	4.08%	2.13%
TS factor picks	~ OI factor	Low	2.48%	0.81%	2.68%	0.61%
TS factor picks	~ OI factor	None	0.68%	2.26%	1.81%	0.56%
TS factor picks	~ TS factor	High	2.04%	7.65%	5.2%	2.98%
TS factor picks	~ TS factor	Low	2.22%	6.03%	2%	1.85%
TS factor picks	~ TS factor	None	0.53%	6.91%	4.16%	2.02%
OI factor picks	~ CHP factor	High	3.02%	5.9%	4.56%	10.95%
OI factor picks	~ CHP factor	Low	1.32%	9.37%	7.5%	5.5%
OI factor picks	~ CHP factor	None	1.96%	6.96%	3.95%	6.36%
OI factor picks	~ Market factor	High	14.4%	15.55%	39.51%	24.98%
OI factor picks	~ Market factor	Low	14.99%	20.4%	32.69%	17.31%
OI factor picks	~ Market factor	None	14.86%	18%	36.91%	21.08%
OI factor picks	~ OI factor	High	1.67%	1.82%	0.87%	0.64%
OI factor picks	~ OI factor	Low	0.67%	-0.38%	0.95%	3.52%
OI factor picks	~ OI factor	None	0.29%	0.77%	0.09%	0.74%
OI factor picks	~ TS factor	High	3.24%	7.15%	13.59%	3.69%
OI factor picks	~ TS factor	Low	2.92%	2.7%	4.11%	3%
OI factor picks	~ TS factor	None	3.07%	5.36%	9.97%	3.08%
CHP factor picks	~ CHP factor	High	5.74%	15.05%	12.05%	12.46%
CHP factor picks	~ CHP factor	Low	7.05%	10.85%	8.7%	14.6%
CHP factor picks	~ CHP factor	None	5.83%	13.23%	10.46%	12.91%
CHP factor picks	~ Market factor	High	21.09%	35.23%	41.13%	32.66%
CHP factor picks	~ Market factor	Low	21.6%	38.7%	46.97%	29.72%
CHP factor picks	~ Market factor	None	21.27%	37.36%	43.49%	31.36%
CHP factor picks	~ OI factor	High	1.69%	3.9%	4.04%	0.74%

Table 7: continued

Factor asset pool	Model	CHP regime	1997/2003	2004/2007	2008/2013	2014/2017
CHP factor picks	~ OI factor	Low	3.51%	1.61%	1.03%	2.96%
CHP factor picks	~ OI factor	None	1.57%	1.64%	2.07%	0.23%
CHP factor picks	~ TS factor	High	4.77%	7.1%	1.98%	4.78%
CHP factor picks	~ TS factor	Low	5.36%	5.57%	0.95%	-0.21%
CHP factor picks	~ TS factor	None	4.54%	5.1%	1.84%	1.66%
Market factor picks	~ CHP factor	High	7.79%	8.62%	7.1%	7.84%
Market factor picks	~ CHP factor	Low	4.6%	7.78%	7.63%	7.73%
Market factor picks	~ CHP factor	None	6.06%	8.31%	6.22%	7.07%
Market factor picks	~ Market factor	High	32.85%	34.83%	48.14%	33.71%
Market factor picks	~ Market factor	Low	30.4%	37.35%	49.31%	29.36%
Market factor picks	~ Market factor	None	31.43%	36.1%	48.63%	32.31%
Market factor picks	~ OI factor	High	3.74%	0.77%	2.62%	0.52%
Market factor picks	~ OI factor	Low	0.41%	-0.45%	1.22%	-0.05%
Market factor picks	~ OI factor	None	1.33%	0.29%	0.78%	0.53%
Market factor picks	~ TS factor	High	6.64%	5.3%	2.45%	7.59%
Market factor picks	~ TS factor	Low	8.53%	4.21%	11.16%	4.7%
Market factor picks	~ TS factor	None	7.65%	5.2%	3.25%	6.24%

Table 8: This table shows the average time series adjusted R^2s for a set of commodity factor models. The dependent variables are individual nearby futures returns on the six LME traded metals considered in the study while the regressors are returns on mimicking portfolios for risk factors where the factor portfolios are constructed using the corresponding set of risk factor commodity picks shown in Table 4. For each period and model, the corresponding individual commodity adjusted R^2s are averaged. For each period, the models are implemented over the whole period, as well as **contango** (high) and **backwardation** (low) **CHP** regimes independently. See section 2.3 for more details.

Factor asset pool	Model	CHP regime	1997/2003	2004/2007	2008/2013	2014/2017
TS factor picks	~ CHP factor	High	-0.01%	2.1%	3.87%	1.05%
TS factor picks	~ CHP factor	Low	-0.37%	17.79%	3.32%	0.8%
TS factor picks	~ CHP factor	None	-0.05%	7.89%	0.65%	-0.26%
TS factor picks	~ Market factor	High	0.65%	17.55%	30.72%	5.69%
TS factor picks	~ Market factor	Low	1.62%	22.57%	27.92%	0.68%
TS factor picks	~ Market factor	None	1.3%	20.58%	29.6%	3.01%
TS factor picks	~ OI factor	High	-0.36%	4.97%	0.31%	-0.65%
TS factor picks	~ OI factor	Low	0.06%	1.29%	-0.33%	-0.11%
TS factor picks	~ OI factor	None	0.04%	3.02%	-0.02%	-0.18%
TS factor picks	~ TS factor	High	0.45%	4.72%	0.22%	-0.22%
TS factor picks	~ TS factor	Low	0.01%	-0.67%	0.22%	1.72%
TS factor picks	~ TS factor	None	-0.12%	2.11%	0.44%	1.33%
OI factor picks	~ CHP factor	High	1.63%	0.34%	-0.37%	5.03%
OI factor picks	~ CHP factor	Low	-0.04%	8.57%	3.01%	0.43%
OI factor picks	~ CHP factor	None	0.01%	3.54%	0.55%	0.72%
OI factor picks	~ Market factor	High	-0.24%	4.93%	28.78%	12.91%
OI factor picks	~ Market factor	Low	3.59%	10.46%	16.76%	7.99%
OI factor picks	~ Market factor	None	1.17%	7.97%	24.03%	10.37%
OI factor picks	~ OI factor	High	-0.18%	-0.68%	0.43%	0.76%
OI factor picks	~ OI factor	Low	1.79%	0.78%	-0.32%	3.01%
OI factor picks	~ OI factor	None	0.54%	-0.33%	0.07%	-0.12%
OI factor picks	~ TS factor	High	-0.26%	-0.34%	7.07%	-0.26%
OI factor picks	~ TS factor	Low	0.3%	1.01%	0.58%	-0.31%
OI factor picks	~ TS factor	None	0.17%	0.11%	4.57%	-0.17%
CHP factor picks	~ CHP factor	High	0.48%	-0.1%	2.96%	0.46%
CHP factor picks	~ CHP factor	Low	0.15%	-0.55%	2.7%	0.77%
CHP factor picks	~ CHP factor	None	0.05%	-0.43%	0.48%	0.05%
CHP factor picks	~ Market factor	High	4.22%	18.7%	26.41%	15.02%
CHP factor picks	~ Market factor	Low	4.4%	30.16%	27.34%	14.77%
CHP factor picks	~ Market factor	None	4.48%	25.09%	26.83%	14.99%
CHP factor picks	~ OI factor	High	0.28%	6.51%	0%	-0.57%
CHP factor picks	~ OI factor	Low	0.41%	0.18%	0.39%	0.65%

Table 8: continued

Factor asset pool	Model	CHP regime	1997/2003	2004/2007	2008/2013	2014/2017
CHP factor picks	~ OI factor	None	0.49%	3.89%	0.29%	-0.1%
CHP factor picks	~ TS factor	High	-0.36%	4.19%	-0.19%	2.09%
CHP factor picks	~ TS factor	Low	-0.26%	-0.52%	-0.17%	0.28%
CHP factor picks	~ TS factor	None	-0.24%	2.07%	0.13%	1.33%
Market factor picks	~ CHP factor	High	-0.22%	3.62%	0.64%	1.88%
Market factor picks	~ CHP factor	Low	-0.33%	9.62%	1.72%	1.12%
Market factor picks	~ CHP factor	None	-0.1%	6.32%	-0.08%	1.61%
Market factor picks	~ Market factor	High	-0.11%	8.95%	36.58%	11.77%
Market factor picks	~ Market factor	Low	2.08%	9.85%	29.63%	2.79%
Market factor picks	~ Market factor	None	0.88%	9.93%	33.73%	7.69%
Market factor picks	~ OI factor	High	0.24%	-0.58%	0.84%	-0.04%
Market factor picks	~ OI factor	Low	0.66%	0.56%	-0.17%	-0.42%
Market factor picks	~ OI factor	None	-0.04%	0.12%	0.62%	-0.24%
Market factor picks	~ TS factor	High	-0.38%	1.37%	2.9%	-0.37%
Market factor picks	~ TS factor	Low	-0.43%	1.41%	0.32%	0.39%
Market factor picks	~ TS factor	None	-0.23%	1.65%	2.15%	0.12%

Table 9: This table shows the average time series adjusted R^2s for a set of commodity factor models. The dependent variables are individual nearby futures returns on the six LME traded metals considered in the study while the regressors are returns on the long and short legs of mimicking portfolios for risk factors considered independently, where the factor portfolios are constructed using the corresponding set of risk factor commodity picks. For each period and model, the corresponding individual commodity adjusted R^2s are averaged. For each period, the models are implemented over the whole period, as well as over **contango** (high) and **backwardation** (low) **CHP** regimes independently. See section 2.3 for more details.

Factor asset pool	Model	Leg	CHP regime	1997/2003	2004/2007	2008/2013	2014/2017
TS factor picks	~ CHP factor	Long	High	0.91%	11.5%	13.22%	-0.15%
TS factor picks	~ CHP factor	Long	Low	1.51%	29.68%	34.77%	1.21%
TS factor picks	~ CHP factor	Long	None	1.39%	19.71%	20.35%	1.09%
TS factor picks	~ CHP factor	Short	High	0.01%	1.47%	28.59%	4.63%
TS factor picks	~ CHP factor	Short	Low	-0.15%	-0.48%	26.72%	-0.11%
TS factor picks	~ CHP factor	Short	None	0.16%	0.9%	27.93%	1.23%
TS factor picks	~ Market factor	Long	High	0.65%	17.55%	30.72%	5.69%
TS factor picks	~ Market factor	Long	Low	1.62%	22.57%	27.92%	0.68%
TS factor picks	~ Market factor	Long	None	1.3%	20.58%	29.6%	3.01%
TS factor picks	~ OI factor	Long	High	0.36%	4.73%	23.81%	1.72%
TS factor picks	~ OI factor	Long	Low	1.54%	11.1%	30.88%	-0.57%
TS factor picks	~ OI factor	Long	None	0.99%	8.22%	25.87%	0.26%
TS factor picks	~ OI factor	Short	High	0.56%	22.57%	20.33%	2.35%
TS factor picks	~ OI factor	Short	Low	2.01%	20.14%	28.09%	0.2%
TS factor picks	~ OI factor	Short	None	1.42%	21.62%	22.99%	1.8%
TS factor picks	~ TS factor	Long	High	-0.14%	24.07%	19.08%	0.51%
TS factor picks	~ TS factor	Long	Low	1.18%	22.59%	23.52%	-0.54%
TS factor picks	~ TS factor	Long	None	0.37%	23.8%	20.46%	-0.36%
TS factor picks	~ TS factor	Short	High	1.14%	4.16%	25.71%	3.89%
TS factor picks	~ TS factor	Short	Low	0.6%	9.27%	34.98%	2.59%
TS factor picks	~ TS factor	Short	None	1.06%	7.24%	28.35%	4.01%
OI factor picks	~ CHP factor	Long	High	0.19%	8.36%	15.6%	1.65%
OI factor picks	~ CHP factor	Long	Low	3.42%	16.64%	8.36%	6.14%
OI factor picks	~ CHP factor	Long	None	0.03%	12.55%	13.29%	3.64%
OI factor picks	~ CHP factor	Short	High	0.9%	0.79%	23.17%	13.29%

Table 9: continued

Factor asset pool	Model	Leg	CHP regime	1997/2003	2004/2007	2008/2013	2014/2017
OI factor picks	~ CHP factor	Short	Low	0.45%	0.65%	20.93%	3.06%
OI factor picks	~ CHP factor	Short	None	1.01%	1.03%	22.48%	8.42%
OI factor picks	~ Market factor	Long	High	-0.24%	4.93%	28.78%	12.91%
OI factor picks	~ Market factor	Long	Low	3.59%	10.46%	16.76%	7.99%
OI factor picks	~ Market factor	Long	None	1.17%	7.97%	24.03%	10.37%
OI factor picks	~ OI factor	Long	High	-0.39%	1.54%	17.05%	3.59%
OI factor picks	~ OI factor	Long	Low	-0.18%	7.12%	16.74%	6.64%
OI factor picks	~ OI factor	Long	None	-0.22%	3.7%	17.08%	5.56%
OI factor picks	~ OI factor	Short	High	0.01%	3.92%	24.04%	9.07%
OI factor picks	~ OI factor	Short	Low	3.83%	2.41%	15.01%	-1.06%
OI factor picks	~ OI factor	Short	None	1.55%	3.14%	20.57%	2.71%
OI factor picks	~ TS factor	Long	High	-0.24%	5.47%	22.98%	3.39%
OI factor picks	~ TS factor	Long	Low	2.1%	15.43%	16.87%	0.23%
OI factor picks	~ TS factor	Long	None	0.74%	10.28%	20.88%	1.57%
OI factor picks	~ TS factor	Short	High	-0.35%	1.99%	10.81%	8.45%
OI factor picks	~ TS factor	Short	Low	0.56%	1.8%	8.96%	0.35%
OI factor picks	~ TS factor	Short	None	0.16%	2.25%	10.32%	4.29%
CHP factor picks	~ CHP factor	Long	High	0.9%	10.35%	12.52%	5.81%
CHP factor picks	~ CHP factor	Long	Low	3.58%	28.68%	29.36%	11.92%
CHP factor picks	~ CHP factor	Long	None	1.87%	18.04%	18.32%	8.25%
CHP factor picks	~ CHP factor	Short	High	4.73%	21.64%	25.57%	13.39%
CHP factor picks	~ CHP factor	Short	Low	0.15%	22.77%	21.53%	7.38%
CHP factor picks	~ CHP factor	Short	None	2.08%	22.85%	24.23%	10.59%
CHP factor picks	~ Market factor	Long	High	4.22%	18.7%	26.41%	15.02%
CHP factor picks	~ Market factor	Long	Low	4.4%	30.16%	27.34%	14.77%
CHP factor picks	~ Market factor	Long	None	4.48%	25.09%	26.83%	14.99%
CHP factor picks	~ OI factor	Long	High	0.6%	1.73%	19.04%	8.75%
CHP factor picks	~ OI factor	Long	Low	1.32%	21.86%	29.51%	16.19%
CHP factor picks	~ OI factor	Long	None	1.03%	9.08%	22.58%	11.61%
CHP factor picks	~ OI factor	Short	High	2.03%	21.75%	17.79%	8.86%
CHP factor picks	~ OI factor	Short	Low	3.48%	23.02%	30.31%	3.59%
CHP factor picks	~ OI factor	Short	None	2.83%	22.98%	21.6%	6.75%

Table 9: continued

Factor asset pool	Model	Leg	CHP regime	1997/2003	2004/2007	2008/2013	2014/2017
CHP factor picks	~ TS factor	Long	High	1.55%	24.47%	16.98%	4.23%
CHP factor picks	~ TS factor	Long	Low	2.4%	29.72%	21.59%	4.46%
CHP factor picks	~ TS factor	Long	None	1.91%	27.37%	18.54%	5.2%
CHP factor picks	~ TS factor	Short	High	2.04%	2.25%	21.16%	11.49%
CHP factor picks	~ TS factor	Short	Low	0.13%	15.94%	28.57%	15.29%
CHP factor picks	~ TS factor	Short	None	1.15%	8.14%	23.54%	12.87%
Market factor picks	~ CHP factor	Long	High	0.14%	14.47%	24.85%	13.11%
Market factor picks	~ CHP factor	Long	Low	1.14%	19%	33.01%	7.1%
Market factor picks	~ CHP factor	Long	None	0.66%	17%	27.85%	10.89%
Market factor picks	~ CHP factor	Short	High	-0.19%	1.81%	31.9%	5.71%
Market factor picks	~ CHP factor	Short	Low	1.53%	3.86%	35.32%	-0.39%
Market factor picks	~ CHP factor	Short	None	0.66%	2.85%	32.76%	2.67%
Market factor picks	~ Market factor	Long	High	-0.11%	8.95%	36.58%	11.77%
Market factor picks	~ Market factor	Long	Low	2.08%	9.85%	29.63%	2.79%
Market factor picks	~ Market factor	Long	None	0.88%	9.93%	33.73%	7.69%
Market factor picks	~ OI factor	Long	High	-0.32%	2.73%	34.04%	7.23%
Market factor picks	~ OI factor	Long	Low	0.07%	5.36%	35.07%	1.56%
Market factor picks	~ OI factor	Long	None	0.07%	4.4%	34.38%	4.78%
Market factor picks	~ OI factor	Short	High	-0.03%	6.86%	24.78%	9.62%
Market factor picks	~ OI factor	Short	Low	2.28%	9.51%	27.82%	1.38%
Market factor picks	~ OI factor	Short	None	0.43%	8.38%	25.68%	6.05%
Market factor picks	~ TS factor	Long	High	-0.03%	11.75%	30.86%	8.57%
Market factor picks	~ TS factor	Long	Low	0.84%	8.74%	30.58%	4.49%
Market factor picks	~ TS factor	Long	None	0.48%	10.83%	30.76%	7.34%
Market factor picks	~ TS factor	Short	High	-0.43%	2.19%	25.29%	6.6%
Market factor picks	~ TS factor	Short	Low	2.06%	2.77%	24.04%	0.2%
Market factor picks	~ TS factor	Short	None	0.53%	2.81%	24.88%	3.76%

5 Appendix

5.1 Assets

Table 10: This table shows details on the individual commodities considered in this study including trading country, sector, subsector as well as trading exchange Market Identifier Codes (MIC, ISO 10383).

Country	Sector	Subsector	Exchange	Name
US	Agriculturals	Grains	XCBT	Corn
US	Agriculturals	Grains	XCBT	Oats
US	Agriculturals	Grains	XCBT	Soy-meal
US	Agriculturals	Grains	XCBT	Soy-oil
US	Agriculturals	Grains	XCBT	Soybeans
US	Agriculturals	Grains	XCBT	Wheat-SRW
US	Agriculturals	Livestock	XCME	Feeder cattle
US	Agriculturals	Livestock	XCME	Lean hogs
US	Agriculturals	Livestock	XCME	Live cattle
US	Agriculturals	Softs	IFUS	Cocoa
US	Agriculturals	Softs	IFUS	Coffee
US	Agriculturals	Softs	IFUS	Cotton
US	Agriculturals	Softs	IFUS	Orange juice
US	Agriculturals	Softs	IFUS	Sugar
US	Agriculturals	Softs	XCME	Lumber
US	Energy	Petroleum	XNYM	Crude oil
US	Energy	Petroleum	XNYM	Gasoline
US	Energy	Petroleum	XNYM	Heating oil
US	Energy	Petroleum	XNYM	Natural gas
US	Metals	Industrial	XCEC	Copper
US	Metals	Precious	XCEC	Gold
US	Metals	Precious	XCEC	Silver
US	Metals	Precious	XNYM	Palladium
US	Metals	Precious	XNYM	Platinum
UK	Metals	Industrial	XLME	Aluminium
UK	Metals	Industrial	XLME	Copper
UK	Metals	Industrial	XLME	Lead
UK	Metals	Industrial	XLME	Nickel
UK	Metals	Industrial	XLME	Tin
UK	Metals	Industrial	XLME	Zinc

5.2 Market factor lemma

$$\overline{R^2_{r_{mkt},p}} = \frac{1}{n}\sum_j R^2_{r_j,r_{mkt},p} = \frac{1}{n}$$

$\overline{R^2_{mkt,p}} \equiv$ period p average R^2 for market risk factor returns.

$R^2_{j,mkt,p} \equiv$ period p R^2 for the regression where the dependent variable is the vector of returns on commodity j nearby contract and the regressor is the vector of returns on the market portfolio; $j \in Y_p^{mkt}$.

$Y_p^{mkt} \equiv$ commodity set considered for the formation of the mimicking portfolio for market risk over period p.

$n \equiv$ number of commodities in Y_p^{mkt}.

Proof

Week t market factor return:

$$r_{mkt,t} = \sum_j w_{j,p} \cdot r_{j,t}$$

$w_{j,p} \equiv$ period p weight for commodity j in the mimicking portfolio for market risk in returns.

$r_{j,t} \equiv$ week t return for commodity j.

Assumptions:

$$w_{j,p} = w_{k,p} = \frac{1}{n}\,\forall\ \{j,\ k\}\,;\ j,\ k\ \in Y_p^{mkt}$$

$$\sigma_{r_j,p} = \sigma_{r_k,p}\,\forall\ \{j,\ k\}\,;\ j,\ k\ \in Y_p^{mkt}$$

$$cov\left(r_j, r_k\right)_p = 0\,\forall\,\{j,\ k\}\,;\ j,\ k\ \in Y_p^{mkt}$$

$$
\begin{aligned}
\sigma^2_{r_{j,p}} &= \beta^2_{r_j,r_{mkt},p} \cdot \sigma^2_{r_{mkt,p}} + \sigma^2_\epsilon \\
\beta^2_{r_j,r_{mkt},p} \cdot \sigma^2_{r_{mkt,p}} &= \sigma^2_{r_{j,p}} - \sigma^2_\epsilon \\
\frac{\beta^2_{r_j,r_{mkt},p} \cdot \sigma^2_{r_{mkt,p}}}{\sigma^2_{r_{j,p}}} &= \frac{\sigma^2_{r_{j,p}} - \sigma^2_\epsilon}{\sigma^2_{r_{j,p}}} \\
\frac{\beta^2_{r_j,r_{mkt},p} \cdot \sigma^2_{r_{mkt,p}}}{\sigma^2_{r_{j,p}}} &= R^2_{r_j,r_{mkt},p}
\end{aligned}
$$

$$
\begin{aligned}
\sigma^2_{r_{mkt,p}} &= \sum_j w^2_{j,p} \cdot \sigma^2_{j,p} + 2 \cdot \sum_j \sum_{k \neq j} w_{j,p} \cdot w_{k,p} \cdot cov\left(r_{j,p}, r_{k,p}\right) \\
&= \sum_j \left(\frac{1}{n}\right)^2 \cdot \sigma^2_{j,p} \\
&= \frac{\sum_j \sigma^2_{j,p}}{n^2}
\end{aligned}
$$

$$
\begin{aligned}
cov\left(r_j, r_{mkt}\right)_p &= cov\left(r_j, \frac{1}{n} \sum_k r_k\right)_p \\
&= \frac{1}{n} \sum_k cov\left(r_j, r_k\right)_p \\
&= \frac{1}{n} cov\left(r_j, r_j\right)_p \\
&= \frac{\sigma^2_{r_{j,p}}}{n}
\end{aligned}
$$

$$
\begin{aligned}
\beta^2_{j,mkt,p} &= \left[\frac{cov(r_j, r_{mkt})_p}{\sigma^2_{r_{mkt,p}}}\right]^2 \\
&= \frac{cov(r_j, r_{mkt})^2_p}{\sigma^4_{r_{mkt,p}}}
\end{aligned}
$$

$$
\begin{aligned}
\beta^2_{j,mkt,p} \cdot \sigma^2_{r_{mkt,p}} &= \frac{cov(r_j, r_{mkt})^2_p}{\sigma^2_{r_{mkt,p}}} \\
&= \left(\frac{\sigma^2_{r_{j,p}}}{n}\right)^2 \cdot \frac{1}{\sigma^2_{r_{mkt,p}}} \\
&= \frac{\sigma^4_{r_{j,p}}}{n^2 \cdot \sigma^2_{r_{mkt,p}}}
\end{aligned}
$$

$$
\begin{aligned}
R^2_{r_j,r_{mkt},p} &= \frac{\sigma^4_{r_j,p}}{n^2 \cdot \sigma^2_{r_{mkt,p}}} \cdot \frac{1}{\sigma^2_{r_{j,p}}} \\
&= \frac{\sigma^2_{r_j,p}}{n^2 \cdot \sigma^2_{r_{mkt,p}}}
\end{aligned}
$$

$$\therefore$$

$$
\begin{aligned}
\overline{R^2_{r_{mkt},p}} &= \frac{1}{n}\sum_j \frac{\sigma^2_{r_j,p}}{n^2 \cdot \sigma^2_{r_{mkt,p}}} \\
&= \frac{1}{n} \cdot \frac{1}{n^2 \cdot \sigma^2_{r_{mkt,p}}} \cdot \sum_j \sigma^2_{r_j,p} \\
&= \frac{1}{n} \cdot \frac{\sum_j \sigma^2_{r_j,p}}{n^2 \cdot \frac{1}{n^2} \cdot \sum_j \sigma^2_{r_j,p}} \\
&= \frac{1}{n}
\end{aligned}
$$

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