A tale of two premiums revisited

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February 1, 2022

Abstract

This paper investigates the effect of the "financialization" of commodity markets in terms of pricing. I explore whether the emergence of commodity index traders affects weekly returns and turn-over during the roll periods. I split the sample (1994–2017) into the pre-financialization (1994–2003) and the post-financialization (2004–2017). I directly test whether the CIT market share (CIT/Open Interest) contributes to commodity returns and whether risk adjustments (based on momentum, basis, basis-momentum, open interest, crowding, and average factors) alter liquidity and insurance premiums documented in Kang, Rouwenhorst, and Tang (2020). I also examine how the financialization affects liquidity and insurance premiums. Finally, since previous results are obtained with Fama-MacBeth regressions, I use an alternative method to test how liquidity and insurance premiums determine commodity returns.

JEL classification: G13, G14, G23

Keywords: commodity futures, risk premium, liquidity premium, hedging pressure, financialization

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1. Introduction

In a recent paper, Kang et al. (2020) (hereafter, KRT) uncover two risk premiums in commodity returns, *i.e.*, the long-term horizon insurance premium paid by producers through hedging demand, and the short-term horizon liquidity premium earned by these producers for easing the trading activity of speculators. The goal of this paper is to check the robustness of these results under different scenarios. I conjecture that the presence of a third category of investors, the commodity index traders (CITs), affects these premiums since their objective is to get exposure to the spot price of commodities rather than just grabbing the insurance premium. These investors are net "buyers" of commodity contracts. On one hand, this should decrease the insurance premium and, on the other hand, CITs rolling their position from the nearby to higher maturity contracts should increase the liquidity premium on the nearby contract, at least during the period starting after the roll to the maturity of the contracts. The net effect of CITs on contract demand mirrors that of processors and users. However, the causes of this demand are different. While the former are including commodities in their portfolio for diversification purpose (wealth management), the latter are hedging their position (risk management).

Testing for the existence of (risk) premiums in commodity futures markets is a long-lasting challenge. The reasons include, among others, the small number of contracts available (cross-section), their heterogeneity in terms of demand, their lack of integration with traditional asset classes, and non-available spot prices. From a theoretical perspective, Black (1976) denies the existence of a commodity risk premium resulting from the exposure to a global factor. A large strand of the empirical literature supports this view when additional commodity market peculiarities (*e.g.* hedging pressure) are not controlled appropriately; see, *e.g.*, Dusak (1973), Bodie and Rosansky (1980), or Carter, Rausser, and Schmitz (1983). Moreover, whereas it seems natural to relate commodities returns to changes in aggregate consumption, and despite the existence of theoretical models (consumption-based CAPM) designed for commodity pricing, there is weak empirical evidence concerning the existence of a significant risk premium; see, *e.g.*, Hazuka (1984) and Jagannathan (1985). Empirical tests built on characteristics derived from the theory of "Normal Backwardation" or the theory of "Storage" do not provide more convincing results; see Keynes (1930), Hicks (1946), Kaldor (1939), Working (1949), and Brennan (1958). Similarly, characteristics derived from market frictions common to many asset markets, such as transaction costs, liquidity, or limits to arbitrage, also work well to explain the cross-section of commodity futures returns. This research uses these characteristics, and traded factors built upon these characteristics, to provide risk adjustments.

To identify under which conditions the results of KRT hold after the inclusion of variables related directly or indirectly to the financialization, I determine the set of factors that allows for an optimal risk adjustment. Beyond insurance and risk premiums, I use six additional characteristics, which are known to predict commodity futures returns. Next, from these characteristics, I construct factors (long-short portfolios sorted on characteristics, and rebalanced weekly). As previously documented for monthly or bi-monthly frequencies, I document a superior performance for portfolios sorted on (i) basis (annualized average weekly returns of 15.75%), (ii) momentum (14.46%), and (iii) basis-momentum (14.04%). I also confirm their performance at weekly frequency for portfolios sorted on (i) average hedging pressure (9.99%), (ii) net trading of "commercials" (17.99%), and (iii) crowding (17.85%); see Kang et al. (2020), and Kang, Rouwenhorst, and Tang (2021). In contrast, the portfolios sorted on the β with an average portfolio (Bakshi, Gao, and Rossi, 2019) or on the growth of open interest (Hong and Yogo, 2012) deliver poor annualized average weekly returns (-0.58% and -1.51%, respectively).

Next, I select the optimal subset of factors with the Bayesian asset pricing test derived by Barillas and Shanken (2018). The initial set of factors does not include the characteristics under scrutiny (average hedging pressure and net trading). I find that the highest probability (61%, for a prior on the maximum attainable Sharpe ratio of 1.25) is obtained with the four-factor model that includes the basis, momentum, basis-momentum, and the crowding factor. This result holds when the test-assets are the remaining portfolios or the remaining portfolios plus the 26 individual commodities of the sample.

First-generation indices have a systematic methodology to carry their long position from the nearby onto the first deferred futures contract called the "roll". The amount rolled every day over the window is known.[1] Using panel data and time series regression, I perform preliminary analyses concerning the impact of the roll days on commodities returns and turnover panels, and on the factor returns, respectively. I do not find any statistically significant systematic effect of the roll-days on individual commodity returns, and on the factors, in both pre- and post-financialization periods. This result supports the view that the financialization does not affect prices through the rolling of SP-GSCI contracts. Conversely, I find that the roll is associated with a significant increase in turnover, in particular for the nearby contract. Moreover, this effect is the most visible in the post-financialization period, with an average cumulative abnormal turnover of 17.56%.

Next, I replicate the analysis of KRT (Fama-MacBeth regressions, Fama and MacBeth, 1973). I also estimate a related model where I introduce the optimal set of factors selected previously. I find that the insurance (average hedging pressure) and liquidity (net trading) premiums are robust to this adjustment, despite a drop in the economic magnitude (from 0.43 to 0.34), and the statistical significance (from the 1% to the 10%) of the insurance premium. A one standard deviation change in AHP impacts the returns by 8.2 and 6.5 bps, respectively.

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[1] From the fifth to the ninth workable days for the SP-GSCI.

I pursue these robustness tests, and control for the financialization with three different approaches. First, I directly add a measure of index funds pressure to the regression. I find that KRT results are not affected by this variable and that the coefficient of this variable does not show any statistical significance at the usual levels. Second, I restrict the Fama-MacBeth regressions to the cross-sections of the weeks that have at least a three-day overlap with the roll of the SP-GSCI. This aims to control whether KRT results are not driven by the particular roll weeks. The significance levels of the insurance and liquidity coefficients drops at the 5% and 10% level, respectively. In addition, while the economic magnitude of the insurance coefficient is unchanged, that of Q is halved at 2.32%. Third, I split the sample in a pre- and post-financialization period to capture more generally a change in the risk-sharing structure based on the study period. I find that the liquidity coefficient is not affected by the period, but that of the insurance is not significant at the usual level (significant at the 10% level) in the pre- (post-)financialization period.

Several papers have documented the econometric limits of the Fama-MacBeth approach; see Petersen (2009), and Gow, Ormazabal, and Taylor (2010). Therefore, I use an alternative approach developed by Hoechle, Schmid, and Zimmermann (2020).[2] It permits to include contract fixed-effects, a feature that seems necessary, given the important heterogeneity of commodities. It additionally allows to control for the dependence between the construction of risk-adjustment factors, and the characteristics of interest (or unobservable characteristics). In this setting, I confirm that contract fixed-effects contributes significantly to explain the returns. The Haussman (1978) test rejects the random effect hypothesis at the 1% level in all specifications. However, I find that the liquidity premium is robust to econometric and risk-adjustments, but not the insurance premium. When fixed effects are added, the coefficient is not significant at the usual levels. Moreover, this latter coefficient becomes negative (and not statistically significant) in the post-financialization period. Finally, I conclude the analysis with an economic robustness specification.The disaggregated CFTC dataset, available since 2007, allows the computation of more accurate values of CITs pressure. I do not find any statistically significant effect related to CITs pressure, and confirm that in the post-financialization period, additionally extended until 2020, the price of insurance is not statistically significant either.

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[2] An obvious limitation is the limited cross-sectional dimension, of 26 commodity contracts, in this context.

My contribution is threefold. First, I identify a set of factors that optimally price commodity futures returns. This has implications in research, to *e.g.* improve the counterfactual of event-studies or benchmark the performance of future factors. Contrary to Boons and Porras Prado (2019), who compare the performance of the basis-momentum in turn, against the basis and Bakshi et al. (2019) factors (momentum, basis, and average factor), I find that, at the weekly frequency, basis-momentum does not suffice to generate the optimal asset pricing model. This result is also useful for portfolio management in practice. Second, I show that the roll of index funds neither affects the returns, nor the factors. However, I find that the roll days do increase the turnover, implying that CITs modify the functioning of commodity markets. Finally, using an appropriate methodology for longitudinal panels, I find that the financialization does not affect the liquidity premium earned by producers, whereas the price of the insurance premium decreases, and eventually vanishes. This goes against the argument that index funds activity is detrimental to the commodity economic activity, since it benefits commodity producers.

The remainder of the paper is organized as follows. Section 2 provides a literature review and develops hypotheses on previously identified characteristics, risk premiums, and integration of commodity markets in the broader economy. Section 3 describes the data and presents the summary statistics. Section 4 presents the empirical results, and Section 5 provides the econometric robustness tests. Section 6 concludes.

2. Literature review and hypotheses development

2.1. Theoretical models of commodity prices

2.1.1. Normal backwardation

The theory of Normal Backwardation states that producers depress the futures price below the expected spot price because they sell future output through futures contracts to hedge against price fluctuations; see Keynes (1930) and Hicks (1946). Hence, a long futures investor obtains a positive premium from the producer that insures herself. Cootner (1960) and Gray (1961) extend the theory to buyers of physical commodities who generate net long hedging pressure, and potentially a sign reversal of the insurance premium. Testing this theory is a threefold question: (i) Is the futures price a downward biased estimate of the expected spot price? (ii) Are speculators' profits positive on average? (iii) Do speculators' profits arise from the insurance premium or superior forecasting ability? A subsequent strand of literature builds on the real or latent substitution effects across commodities, leading to cross-hedging. Many physical commodities do not have corresponding futures markets.

Therefore, commodity hedgers may use a resembling or a linear combination of resembling futures contracts to hedge their position; see Anderson and Danthine (1981). If the cross-hedging hypothesis holds, the hedging pressure in one futures contract is also a function of other cash markets; see, *e.g.*, Roon *de*, Nijman, and Veld (2000) and Chng (2009).

2.1.2. Normal backwardation and integration with asset markets

To test whether commodity futures contracts embed a risk premium, Dusak (1973) develops a model, similar to the CAPM, where commodity returns covariations with an aggregated wealth index are positive. She tests her model on three agricultural futures contracts and finds that commodity futures betas are not significantly different from zero. Black (1976) argues that, even if (commodity) futures are included in the market portfolio, their aggregation sums up to zero. Thus, there is no reason to detect a risk premium in commodity futures arising from covariation with the market. In relaxing the assumption that speculators are net long, and adding the conjecture that the market portfolio does include commodity futures, Carter et al. (1983) derive a commodity CAPM that includes the market index and the net position of speculators. They argue that commodity futures premiums depend on commodity futures prices covariation with the market, and on the extent to which speculators are incentivized to trade. The empirical findings confirm that speculators do earn excess returns, and that the level of systematic risk is a function of the speculators' position. Hirshleifer (1988, 1990) derives an equilibrium model where physical commodities may be hardly marketable (Mayers, 1973). In this setting, market frictions materialize through trading setup costs (Merton, 1987); see also Stoll (1979) and Carter et al. (1983). Bessembinder (1992, 1993) find empirical support for this model; see also Roon *de* et al. (2000).

2.1.3. Consumption, industrial production, and inflation

Given the nature of commodities, *i.e.*, goods that are produced and consumed, it is natural to relate their price to consumption growth or production growth as well as unexpected inflation. Breeden (1980) derives a commodity consumption-based CAPM, in which the consumption betas gather individual commodity futures exposure to consumption and specific income elasticity of demand.[3] The income elasticity of demand may theoretically drive the consumption beta below zero, depending on the nature of the commodity. He confirms empirically that grain products have negative consumption betas. Interestingly, the derivation of the model through elasticities also allows to switch the model from a consumption to a production-based CAPM. However, Breeden (1980) does not test the relation between consumption betas and returns. Hazuka (1984) regresses a single cross-section of 14 commodity futures monthly returns, defined as the exposures of price changes over the basis, on consumption betas. The author finds that the price of risk is statistically significant at the 1% level.[4] Jagannathan (1985) derives a multi-period commodity consumption model. Based on three commodities (corn, soybeans, and wheat contracts), he shows that the risk aversion and the stochastic discount factor are similar to those obtained for stocks. Nevertheless, the model is rejected at the 1% level. Grauer and Litzenberger (1979) derive a two-period model where commodity futures prices are biased estimates of expected spot prices due to inflation risk borne by investors. The model collapses with the CAPM when the market risk premium is adjusted appropriately (deflated terminal wealth scaled by initial market portfolio value).[5]

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[3] This approach considers that constant time to maturity provides the same distribution for all periods (debatable for commodities whose supply is seasonal such as agricultural products). It departs from Dusak (1973), who considers that each maturity has its own (stable) distribution.

2.1.4. Theory of Storage

Kaldor (1939), Working (1949), and Brennan (1958) view the futures price as the spot price compounded by interest rate and storage costs, and discounted by a convenience yield, similar to a continuous dividend yield in stock index futures. This convenience yield represents the benefit to physically own the product instead of receiving it later. It depends on the risk aversion of the buyer and the levels of inventory. The theory of Storage is extended by Deaton and Laroque (1992, 1996) who consider the non-negativity constraint of inventories. In particular, their model explains the high skewness of commodity futures returns induced by the non-linear price-inventory relation. They attribute the high level of autocorrelation in commodity futures returns to the presence of speculators who smooth futures prices. They conclude that autocorrelation is likely induced by supply and demand processes that are not identically, and independently distributed (*e.g.* serial dependence in harvests). Other models of storage analyze the physical commodity price as a call option ; see respectively Routledge, Seppi, and Spatt (2000), and Schwartz (1997).

2.2. Market integration and financialization

2.2.1. Common factors

There is weak evidence of commodity markets being integrated with stock and bond markets. Empirical tests confirm that the systematic risk premium is zero; see Dusak (1973) and

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[4] Note that the author provides little details on the methodology.

[5] For empirical evidence of commodities (futures) as a hedge against (unexpected) inflation, also see Greer (2000), and Erb and Harvey (2006, 2016).

Bodie and Rosansky (1980).[6] In an exercise similar to Fama and French (1993), Daskalaki, Kostakis, and Skiadopoulos (2014) use various stock factors (market portfolio, size, value) and macro-economic factors (liquidity, consumption, and foreign exchange) to test whether commodities are integrated.[7] They find that none of the classic factors price the cross-section of commodity futures returns. They also show that commodities are heterogeneous within their asset class since the first five principal components of commodity futures returns explain only 60% of the total variance. Moreover, the principal components do not price the cross-section of commodity returns, as opposed to equities; see Roll and Ross (1980).

Despite the segmentation of commodity futures markets relative to other asset classes, academic studies find strong evidence for an integration of the commodity term structure in the broader economy. In particular, Bailey and Chan (1993) directly relate the basis (the price difference between two contracts on the same commodity but with different maturities), to macro-economic variables such as recession, liquidity, and volatility. Similarly, Yang (2013) relates theoretically and empirically the basis to investment shocks in the economy. A plausible explanation is that the basis filters out the heterogeneous and specific commodity effects, leaving the core free to react to economic innovations; see also Hirshleifer (1988, 1989). Finally, the integration of the basis/term structure is also consistent with the interest rate component of the futures prices that spot prices do not carry; see Schwartz (1997).

2.2.2. Limits to arbitrage

In two mirror studies, Acharya, Lochstoer, and Ramadorai (2013) and Rampini, Sufi, and Viswanathan (2014) analyze the relation between firm distress, approximated by the expected default frequency (EDF), and hedging demand.[8] Acharya et al. (2013) study this relation from the producer side. If arbitragers (speculators) of commodity futures are capital constrained, they will increase the (aggregate) insurance premium, turning producers to hedge less and to sell their output outright, thereby also decreasing spot prices. To test this model empirically, they use the EDF and financial disclosures of natural gas and crude oil-producing firms to estimate the hedging demand. They confirm that the cross-section of hedging demand is positively related to the firm default risk. Additional tests show that (i) the futures risk premium increases with the producer's hedging demand, (ii) spot prices respond negatively to aggregated measures of default risk, and (iii) the two previous relations are exacerbated when speculators have a low-risk capacity; see Etula (2013). Rampini et al. (2014) consider the buyer's standpoint. Their model shows that hedging is positively related to income (net worth) and inversely related to default risk, which is confirmed empirically with data from airline companies. These findings hold both in cross-section and time series. At the first glance, the results of Acharya et al. (2013) and Rampini et al. (2014) are contradictory, and contribute to an existing debate on the firm's propensity to hedge when they are financially constrained. In brief, theoretical models predict a positive relation between default risk and hedging, whereas empirical evidence point to the opposite; see, *e.g.*, Tufano (1996). However, the peculiarities of the two industries they study matter. First, in Rampini et al. (2014), the model incorporates collateralization for the buyer, which in turns imply a trade-off between hedging demand and financing. This feature is absent from Acharya et al. (2013) and, most probably, absent from the true supplier's decision model. Second, the buyer's profit function is convex and decreasing in input prices. Therefore, the buyer's incentive to hedge, which is costly, decreases in the high price scenarios. Instead, from the producer perspective, the profit function is increasing and linear in the output price. Moreover, the producer may optimize her hedging demand in managing inventories.[9]

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[6] The scope of this review concerns commodity futures prices in relation with the broader economy. It does not treat commodities futures as pricing factors of other assets; see, *e.g.*, Hong and Sarkar (2008) and Hong and Yogo (2012).

[7] Note that the bond-stock market segmentation is now revised down, and a number of empirical studies find that corporate bonds are exposed to the same risk factors as stocks; see, *e.g.*, Bai, Bali, and Wen (2019).

[8] See also Cheng, Kirilenko, and Xiong (2015).

2.2.3. Commodity pricing: The consequences of the financialization

Gorton and Rouwenhorst (2006), and Erb and Harvey (2006) document the long-run properties of the investments in commodity futures, either as a diversification asset class or in terms of absolute performance. These papers are concomitant to new and large inflows from investors into commodity markets, a phenomenon coined as the "financialization" of commodities. Subsequently, given the size of the inflows, the novelty of these investments, and the commodity prices increase before the 2008 crisis, both academic research and newspapers suspected these inflows to cause distortions in the functioning of commodity markets. In particular, Masters and White (2008), and Masters (2008) in a public hearing before the US Senate, argue that the sharp increase in the share of index investing in the total open interest of commodities was responsible for market distortions and prices misaligned with their fundamental values. Typically, the financialization generates excess co-movements between commodity futures prices (Tang and Xiong, 2012), increases the correlation between commodities and stock markets (Buyuksahin and Robe, 2014), induces price pressure effects during the roll of the larges commodity indices (Mou, 2011), and changes in the risk-sharing structure of commodity markets; see Brunetti and Reiffen (2014), and Dubois and Maréchal (2021). The date attributed to the materialization of "financialization" varies across studies from 1999 (Mou, 2011) to 2008 (Adams and Gluck, 2015) but the consensus and the statistical evidence point to December 2003; see Dubois and Maréchal (2021). Brunetti and Reiffen (2014) derive a model in which uninformed CITs mitigate hedging costs. Using a non-public data-set of individual traders' positions, they find evidence that CITs supply insurance to producers through their activity. If this risk-sharing in the commodity market changes, it also induces a modification of the liquidity premium.

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[9] The different profit functions of producers and buyers also relate to Keynes (1930) view, that a buyer/processor can report an increase in input prices on output prices (pass-through), whereas the commodity producer's profit only depends on her output price. This also justifies, in the theory of Normal Backwardation, that the futures price should be a downward biased estimate of the expected spot price, even with a negative or nil net hedging pressure.

2.3. Commodity characteristics, risk factors, and returns: Empirical evidence.

2.3.1. Hedging pressure

Chang (1985) disentangles the speculators' forecasting ability and the Normal Backwardation hypothesis for three agricultural commodity contracts split by maturity, over the period 1951-1980. The results vary greatly over time, maturity months, and commodities, but the existence of a risk premium in the Keynes-Hicks sense cannot be discarded. In empirical tests, Bessembinder (1992, 1993) shows that the residual risk explains agricultural futures returns, conditional on hedging pressure. Roon *de* et al. (2000) study the hedging pressure aggregated at the sector level (cross-hedging pressure). Futures premiums depend on the market, own-hedging pressure, and cross-hedging pressure. Additionally, they show that this effect is not conditional on price pressure defined as the period-to-period change of hedging pressure.[10] KRT extend the hedging pressure framework. They uncover a second premium arising from the speculators' liquidity demand. The existence of this premium explains why empirical tests on hedging pressure fail to identify risk premium when liquidity is not controlled appropriately. Speculators have no superior forecasting ability but, on average, they are rewarded the positive insurance premium; see Buyuksahin, Haigh, Harris, Overdahl, and Robe (2009), Ederington and Lee (2002), Buyuksahin and Harris (2011), and Dewally, Ederington, and Fernando (2013). Basu and Miffre (2013) construct portfolios of commodity futures sorted on hedging pressure. The cross-sectional returns of these portfolios is priced with a long-short inter-quartile factor built on the same characteristics. This premium is orthogonal to momentum and carry premiums; see also Szymanowska, Roon *de*, Nijman, and Goorbergh *van den* (2014).

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[10] For cross-characteristics and commodity relations see Casassus, Liu, and Tang (2013).

2.3.2. Test of the theory of Storage and the basis

There are three approaches to test the theory of Storage. The first one uses actual data on inventories and relate them to the level of prices and basis. However, inventory data are scarce, difficult to aggregate across countries, and often do not include governmental strategic reserves; see Pindyck (1994, 2004), Gorton, Hayashi, and Rouwenhorst (2012), and Dincerler, Khokher, and Simin (2020). Combining Deaton and Laroque (1992) with Routledge et al. (2000), Gorton et al. (2012) find support for non-linear relations between bases and inventories, and between inventories and risk premiums. Since they provide evidence for a close, convex, relation between convenience yield (basis) and inventories, the basis is a noisy proxy for inventories. Further evidence is provided by Fama and French (1987, 1988).

The second approach consists of extracting inventory levels through filtering the convenience yield with a state-space representation. However, the process of the convenience yield (Brownian or Ornstein-Uhlenbeck motion) must be specified ahead; see, *e.g.*, Gibson and Schwartz (1990), Schwartz (1997), and Casassus and Collin-Dufresne (2005).

Third, the nearby futures contract is used as a proxy for the spot price; see, *e.g.*, Fama and French (1987, 1988), Bailey and Chan (1993), Yang (2013), Szymanowska et al. (2014), and Koijen, Moskowitz, Pedersen, and Vrugt (2018). Using 21 nearby monthly returns over the period 1966-1984, Fama and French (1987) find strong support for the theory of Storage, whereas the insurance premium (Normal Backwardation) is present in only five contracts. They uncover further support by examining the basis of LME forward contracts for which spot prices are observable; see Fama and French (1988). Given the fact that commodity bases are readily measurable at any frequency, portfolio returns sorted on basis are used in asset pricing tests. For instance, Yang (2013) combines a basis factor with an average commodity factor to price commodity futures returns in cross-section. He finds that the basis is related to investment shocks affecting the broader economy. This is consistent with the basis being correlated with other macroeconomic risks (stock index dividend yield and corporate bond quality spread); see Bailey and Chan (1993). Szymanowska et al. (2014) also document the superior performance of the basis. They find insignificant alphas for a variety of portfolios (commodity portfolios sorted on basis and other characteristics such as momentum, volatility, hedging pressure, inflation, and liquidity). Finally, Koijen et al. (2018) find that the "carry" factor predicts returns in time series, and in cross-section, for various asset classes such as equities, bonds, commodities, and options.

2.3.3. Momentum

Financial research struggles to produce a risk-based explanation of the stock momentum anomaly; see, *e.g.*, Jegadeesh and Titman (1993) and Asness, Moskowitz, and Pedersen (2013). The rationale of momentum in commodity futures prices is more readily available. As Deaton and Laroque (1992, 1996) emphasize, if the underlying process of supply (*e.g.*, the harvest) is not independent, and identically distributed, the commodity returns are serially correlated.[11] Miffre and Rallis (2007) find that short-term momentum (up to 12-month ranking period, 1-month holding period) is associated with long-term reversals (value effect). Asness et al. (2013) test the value and momentum factors in several asset classes including commodities, and find statistically significant risk premiums induced by exposure to these factors. If the identification of the momentum is straightforward for any asset class, that of the value factor is ambiguous for commodities (longer-term sum of returns). Moskowitz, Ooi, and Pedersen (2012) confirm the momentum effect in various asset classes, including commodities. This predictability is unrelated to other risk factors. It is beneficial to speculators, and detrimental to hedgers. Bakshi et al. (2019) include momentum as one of the three factors describing commodity futures premiums along with the basis and the commodity average portfolio. Taken individually, these factors perform poorly.

2.3.4. Basis-momentum

As for bonds, the convexity of the term structure also matters for commodity futures. Boons and Porras Prado (2019) use the difference between two momentum signals in the nearby and deferred commodity futures contracts to obtain a variable that aggregates both the slope and the curvature of the commodity term structure. In the longest monthly time series available (1959-2014), and broadest cross-section (32 commodities), they find that a portfolio sorted on this signal has a superior pricing ability over other known commodity factors. They additionally document that this factor is not subsumed by momentum and basis factors, and that the curvature is the most important component of the signal. Moreover, in pooled regressions, they find that this factor predicts nearby and first deferred contracts, as well as spreading returns. Finally, they observe that the commodity futures exposure to this factor alone prices the cross-section of individual futures returns and proxies for the volatility risk.[12]

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[11] This might explain why the trend-following strategy is so popular in the CTAs industry; see Fung and Hsieh (1997).

[12] See also Groot *de*, Karstanje, and Zhou (2014).

2.3.5. Open interest, commodity liquidity, and crowding

If commodities forecast the economy through their hedging demand, prices may cancel out this demand as it represents the sum of long and short hedging (*e.g.* a commodity producer *vs.* a processor). Following this principle, Hong and Yogo (2012) use the growth in total open interest, averaged over commodity sectors, which represent the average absolute hedging demand. They find that commodity open interest forecasts commodity futures, stock, and bond returns, even after controlling for the usual conditioning variables including short-term interest rate, yield spread, dividend yield, and stock returns. In their commodity returns predictability test, they also include popular commodity forecasting variables (cross-hedging pressure, basis, and lagged returns). In opposition to the traditional view that commodity markets are segmented from the equity market, their results indicate that open interest of commodity futures is a leading indicator of economic activity, including commodity futures returns. Similarly, Marshall, Nguyen, and Visaltanachoti (2012, 2013) and Beckmann, Belke, and Czudaj (2014) notice that commodity market liquidity and global liquidity, respectively, drive commodity prices. Finally, Kang et al. (2021) uncovers a new "crowding" factor, built as the deviation of the net-long position of speculators from their one-year trailing average. This factor alone predicts the cross-section of commodity futures returns, and also helps to predict the returns of popular commodity factors such as momentum, value, and basis. They do not test whether it improves the performance of the basis-momentum factor.[13][14]

2.4. Hypotheses development

An important result that emerges from the literature is that the "factor zoo" that populates the equity market has contaminated the commodity market; see Cochrane (2011). While only 30 commodities are traded, corresponding to less than 10,000 monthly returns over the 1994–2020 period, the literature identifies at least six factors constructed on contract characteristics. Note that only five factors suffice to price reasonably the cross-section of more than 200,000 stock monthly returns from 1962 to 2014, and four factors perform well to price the cross section of 400,000 corporate bond monthly returns from 1999 to 2020; see Fama and French (2015), Kelly, Pruitt, and Su (2019), and Kelly, Palhares, and Pruitt (2020). Given the aforementioned results, I first check whether the factor dimensionality can be reduced :

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[13] Since the earliest version of Boons and Porras Prado (2019) was circulating only in 2016, it is possible that this factor is not yet "crowded".

[14] These findings confirm previous results derived from the equity market. The literature documents that the less crowded the strategy is, the higher its returns are; see, *e.g.*, Baltas (2019).

Hypothesis 1. *There is a (parsimonious) subset of previously identified factors, which optimally adjust commodity futures weekly returns for risk.*

Beyond risk adjustments, commodity markets have experienced the emergence of a new class of investors (CITs) in 2000-2003, whose potential impact on returns, turnover, and factor returns, deserve a special attention, I specify my hypothesis as follows:

Hypothesis 2. *The days of the roll of the SP-GSCI affect:*

a. *Commodity futures returns*

b. *Turnover*

c. *Factor returns*

Among all documented effects of the financialization developed in Section 2.2.3, the price-pressure generated by CITs around the roll could affect KRT findings. In particular, Brunetti and Reiffen (2014) document that CITs act as insurance suppliers. They modify the risk-sharing structure in the post-financialization, and potentially the prices of insurance. By the same token, liquidity needs are increased during the roll because CITs roll positions, which should affect the price of liquidity during this specific week. Therefore, I specify the last hypothesis:

Hypothesis 3. *The liquidity and insurance premiums are not altered after:*

a. *The risk adjustment*

b. *The financialization (roll days, measure of the CITs' activity, and the pre- and post-financialization periods).*

3. Data and methodology

3.1. Data

From Thomson-Reuters, I download the daily closing prices of 26 commodity futures nearby and first deferred contracts, among which, 18 are SP-GSCI components. The sample starts on January, 1994 and ends on January, 2020. I compute the Tuesday to Tuesday, weekly arithmetic excess returns for each maturity m as: $R^m_{c,t} = \frac{F^m_{c,t} - F^m_{c,t-1}}{F^m_{c,t-1}}$ where $F^m_{c,t}$ is the futures price of commodity c, on day t. To mitigate the effect of thinly traded contracts as they approach maturity, I follow KRT. I define the nearby contract as the actual nearby for the weeks ending with a Tuesday prior to the seventh calendar day of the month. I define the nearby contract as the first deferred if it matures in the current month and if the week ends on a Tuesday that is on or after the seventh day of the month. All contracts are under the CFTC supervision. This institution releases the commitment of traders weekly report (COT) from Tuesday to Tuesday. The COT includes the long and short positions of the "commercials" and the long, short, and spreading positions of the "non-commercials" categories for every U.S. futures contract. In 2006, the CFTC revised the compositions of these groups and added the "disaggregated" COT report (DCOT), that splits "commercials" and "non-commercials" trades into "Producer/Merchant/Processor/User", "Money managers", "Swap dealers", and "Other reportables".[15]. From the CFTC, the following three contract characteristics are computed, (i) the net trading of the "commercials" category (intensity with which commercial provide short-term liquidity), (ii) the average hedging pressure (demand for insurance), (iii) the "crowding" (intensity with which speculators are involved). The latter variable is used by Kang et al. (2021).

Next, from the commodity futures prices, I compute the following four characteristics, (i) the basis *i.e.*, (ii) the momentum, (iii) the β, and (iv) basis-momentum. I summarize the characteristics and their definition in the table below,

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[15] See http://www.cftc.gov/MarketReports/CommitmentsofTraders/index.htm

Name	Formula	Variables	Meaning	Authors
Net trading	$Q_{c,t} = \frac{(CL_{c,t}-CS_{c,t})-(CL_{c,t-1}-CS_{c,t-1})}{OI_{c,t-1}}$	CL (CS) is the long (short) position of "commercials" and OI the total open interest.	The intensity at which the "commercials" category ease the short-term speculative activity of "non-commercials".	Kang et al. (2020, 2021); Dubois and Maréchal (2021)
Average hedging pressure	$AHP_{c,t} = \frac{\frac{1}{52}\sum_{j=0}^{51}(CS_{c,t-j}-CL_{c,t-j})}{OI_{c,t}}$	see Net trading	The net short position of "commercials" *i.e.* the intensity at which producers hedge their cash position, smoothed over the previous 52 weeks.	Cootner (1960); Gray (1961); Roon *de* et al. (2000); Chng (2009); Gorton et al. (2012); Basu and Miffre (2013); Kang et al. (2020)
Basis	$B_{c,t} = \frac{\ln F^2_{c,t}-\ln F^1_{c,t}}{T_2-T_1}$	T_m is the time to maturity of the contract of maturity m.	Proxies for the levels of inventory, as scarcity implies backwardation in the theory of storage.	Bailey and Chan (1993); Gorton et al. (2012); Yang (2013); Szymanowska et al. (2014); Koijen et al. (2018); Bakshi et al. (2019); Kang et al. (2021)
Momentum	$M_{c,t} = \prod_{j=0}^{51}\left(1+R^1_{c,t-j}\right)$		The past-year performance predicts future performance.	Jegadeesh and Titman (1993); Miffre and Rallis (2007); Moskowitz et al. (2012); Asness et al. (2013); Bakshi et al. (2019)
Basis-momentum	$BM_{c,t} = \prod_{j=0}^{51}\left(1+R^1_{c,t-j}\right) - \prod_{j=0}^{51}\left(1+R^2_{c,t-j}\right)$		Difference in two momentum signals of contracts of difference maturities, relates to the term-structure convexity.	Boons and Porras Prado (2019)
Average factor β	$\beta_{c,t} = \frac{Cov\left(R^1_{c,t-51\|t};AVG_{t-51\|t}\right)}{Var\left(AVG_{t-51\|t}\right)}$	AVG is the returns on an equally-weighted portfolio of the 26 commodities.	Relates to the CAPM principles.	Bakshi et al. (2019)
Crowding	$CR_{c,t} = \frac{NCL_{c,t}-NCS_{c,t}}{OI_{c,t}} - \frac{1}{52}\sum_{j=0}^{51}\frac{NCL_{c,t-j}-NCS_{c,t-j}}{OI_{c,t-j}}$	NCL (NCS) is the long (short) position of "non-commercials" and OI the total open interest.	The intensity at which speculators enter systematic strategies, thereby diminishing future returns.	Kang et al. (2021)
Open interest growth rate	$\Delta OI_{c,t} = \prod_{j=0}^{51}\left(\frac{OI^{USD}_{c,t-j}}{OI^{USD}_{c,t-j-1}}\right)^{1/52} - 1$	$OI^{USD}_{c,t} = OI_{c,t} \times F^1_{c,t} \times DQ_c$. $OI_{c,t}$ is the open interest in contracts, $F^1_{c,t}$ the price of the nearby contract and DQ_c, its deliverable quantity; see Appendix III.A1, column "underlying".	Considers commodity futures as predictors of the general economy, through the quantity of open interest (relates to hedging).	Hong and Yogo (2012)

3.2. Methodology

3.2.1. Factors construction and selection

To test hypothesis 1, I use the eight characteristics defined above, and compute the weekly returns of the corresponding portfolios. I use the characteristic observed on week t, and sort five quantile portfolios based on the characteristic. Each quintile contains five contracts, except for the median quintile which includes six. To select the optimal set of factors, I use the Bayesian approach of Barillas and Shanken (2018). This approach builds upon Gibbons, Ross, and Shanken (1989), and the “Bayes factor”. The likelihood ratio of the unrestricted time series regressions (with intercept) with that of the restricted (without intercept) indicates the marginal contribution of the α.

$$ML_z = |X'X|^{N-2}|S_z|^{-\frac{T-K}{2}} \times H_z, \tag{1}$$

where X is the (sub)set of factors considered, N is the number of test assets, T the number of time observations and K the number of factors. S_z is the $N \times N$ cross-product of the time series regressions residuals for the unrestricted $z = 1$ and restricted $z = 0$ cases. In addition,

$$H_z = \begin{cases} 1 & \text{if } z = 0 \\ \left(1 + \frac{a}{a+k}\left(\frac{W}{T}\right)\right)^{-(T-K)/2}\left(1 + \frac{k}{a}\right)^{-N/2} & \text{if } z = 1 \end{cases}$$

where W is the Gibbons et al. (1989) F-statistic, $a = \frac{1+\text{Sharpe}_X^2}{T}$ and k is a prior multiple given the prior chosen for the maximum Sharpe ratio, such that $k = \frac{\text{Sharpe}^2_{max} - \text{Sharpe}^2_X}{N}$, where Sharpe_X is the Sharpe ratio of the set of factors X and Sharpe_{max} the maximum prior Sharpe ratio, that I select in turn as 1.25, 1.5, 1.75, and 2; see Barillas and Shanken (2018, Proposition 1). Finally, Barillas and Shanken (2017) demonstrate that the optimal factor selection does not depend on additional test assets and that using factors out of the subset as dependent variables suffices to test whether the α depart from zero (relative test). In the alternative (absolute test), both remaining factors and test assets are used as dependent variables. Thus, I use relative and absolute tests. Since the cross-section of commodities is limited, the additional assets in the absolute tests are simply the individual commodity returns. Because the purpose of this study is to optimally adjust for the risk, I leave out the two factors built upon the liquidity (Q) and insurance (AHP) characteristics from the selection, and report the optimal factor selection from the full set in the Appendix III.A4.

3.2.2. Day of the roll effect

To test hypothesis 2, I capture the individual effects of each five SP-GSCI roll days on the 18 contracts that are concerned with dummy variables.The following panel data-regression is estimated for the 26 contracts simultaneously,

$$R^{m}_{c,t} = \mu_c + \sum_{i=1}^{5} \delta_i d_{c,t,i} + \epsilon_{c,t}, \tag{2}$$

where μ_c is a contract fixed effect, and $d_{c,t,i}$ is a dummy variable set to "1" when the contract c, in a week t, includes the ith day of contract roll, and to "0" otherwise. I cluster the variance at the contract level.

To capture the effect of the roll-days on the factors individually, I regress each factors time series on five dummy variables set to "1" when the factor f in week t includes the ith day of the SP-GSCI, *i.e.* roll.

$$R_{f,t} = \alpha_f + \sum_{i=1}^{5} \delta_i d_{t,i} + \epsilon_t, \tag{3}$$

where $R_{f,t}$ is the return on f, $f = 1, 2, \ldots, 8$. These regressions allows to control for systematic roll-day effects on the factors, with no assumptions on whether the individual contracts, experience a roll or not.

3.2.3. Fama-MacBeth regressions

To make the results easy to compare with KRT, I use Fama-MacBeth regressions to replicate and extend the tests on the forecasting power of the liquidity and insurance characteristics. The cross-sectional estimation on week t is,

$$R^{1}_{c,t} = \beta_{0,t} + \beta_{1,t} AHP_{c,t-1} + \beta_{2,t} Q_{c,t-1} + \beta_{3,t} CIT_{c,t-1} + {}^{\mathbf{T}}\mathbf{b_t} \mathbf{RISK}_{c,t-1} + \epsilon_{c,t}, \tag{4}$$

where $R^{1}_{c,t}$ is the returns on the nearby contract in week t, AHP and Q are the insurance and liquidity characteristics of the contract, and CIT is the pressure from index investment weighted by the number of roll-days of the contracts during the week,

$$CIT_{c,t} = \frac{OI_{CIT,c,t} \times d_{c,t}}{OI_{c,t}}, \tag{5}$$

where $OI_{c,t}$ is the total open interest, $OI_{CIT,c,t}$ is the SP-GSCI investment computed using the Masters and White (2008) procedure, and $d_{c,t} = {}^{1}\!/_{5}, {}^{2}\!/_{5}, \ldots 1$, when the contract c in week t includes $1, 2, \ldots, 5$ days. **RISK** includes the three controls of Kang et al. (2020), (i) the basis, (ii) the annualized standard deviations of the residuals from 52-weeks trailing-window regressions of the commodity returns on the S&P 500, multiplied by an indicator variable equals to "1" when "non-commercials" are net long and to "-1" otherwise, and (iii) the lagged returns $R^1_{c,t-1}$. Alternatively, **RISK** includes the factors selected as in Section 3.2.3.[16]

4. Empirical results

4.1. Descriptive statistics

4.1.1. Futures returns

Table 1 reports the summary statistics of the 26 nearby futures contracts returns, over the 1994–2017 period (KRT), and the 1994–2003 and 2004–2017 sub-periods (pre- and post-financialization).[17]

[Insert Table 1 here]

Over the pre-financialization, annualized mean weekly returns range between -0.81% (livestock) and 15.98% (energy). In the post-financialization period, the mean returns of the nearby contract range between -9.62% (energy) and 11.41% (metal). Table 1 also reports the skewness, which is positive for 20 out of the 26 contracts, for both nearby and first deferred positions, in line with the results of Gorton and Rouwenhorst (2006). These commodity characteristics underlie the popularity of commodity index investment; see Gorton and Rouwenhorst (2006); Erb and Harvey (2006). However, when the returns are averaged in an equally-weighted sector (or all commodities) portfolio, the skewness vanishes; a result similar to stocks, see, Albuquerque (2012). Commodity futures returns have excess kurtosis, and this at the individual, sector, and average market levels. Finally, the higher moments of commodity returns do not show any sizeable change between the pre- and the post-financialization period, and this at the individual and portfolio levels.

4.1.2. Commodity futures characteristics

Table 2 reports the summary statistics of the eight commodity futures characteristics and the β detailed in Section 3.1 and for the variable CIT of Eq. (5) for the whole KRT period

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[16] Estimations with CIT defined as the non-weighted ratio: $\frac{OI_{CIT,c,t}}{OI_{c,t}}$ yield similar results. They are available upon request.

[17] I report the statistics for the first deferred contracts in the Appendix III.A2.

(1994–2017, “All”), and the pre- (1994–2003, “Pre”) and post-financialization (2004–2017, “Post”) sub-periods.

[Insert Table 2 here]

In Columns (1-3), the first characteristic AHP shows that commercial traders are structurally net short. Only two contracts, natural gas, and feeder cattle display a net long “commercials” position over the full sample. The metal (livestock) group reports the highest (lowest) hedging pressure, during both sub-periods. The equally-weighted hedging pressure increases by almost three percentage points in the post-financialization period, the largest increase being for the palladium contract (from 11.63 to 53.45%). Given that Q is a week-to-week difference, I report the mean absolute value in Columns (4-6). The highest (lowest) absolute net trading is present in the metal (energy) group over the full sample and the group ranking remains steady across sub-periods.

Columns (7-9) report β computed as the mean of 52-weeks trailing window regressions of each contract on an equally-weighted average factor AVG; see Bakshi et al. (2019). The energy (livestock) group displays the highest (lowest) average β, at 1.35 (0.80). No sizeable difference exist between the two sub-periods, except for the energy (decrease from 1.44 to 1.29) and metal groups (increase from 0.84 to 1.05). Overall, the betas of commodities are steady across periods, excepted for natural gas (from 1.67 to 1.16), silver (from 0.78 to 1.41), and lean hogs (0.84 to 0.29). Columns (10-12) report the mean basis, which (B) indicates how backwardated (negative), or contangoed (positive figure), was the nearby term structure over the period. The contract with the highest contango on average (natural gas, 7.05 bps) is also the one with the lowest annualized mean returns (-14.18%), whereas the most backwardated (soybean meal, -3.16 bps) delivers the highest returns (14.80%). This well-documented cross-sectional relation holds as shown further in the paper. Only five contracts are in backwardation on average, and none in the energy group. The basis of the equally-weighted portfolio increases from the pre- (0.85 bps) to the post-financialization period (1.55), a change mostly driven by the energy group (from 0.28 to 4.57 bps), confirming documented results about commodities becoming more backwardated along with the financialization; see *e.g.*, Adams and Gluck (2015). In columns (13-15), only six contracts display an average negative momentum (M) over the 1994–2017 period, with two sizeable changes in the sub-periods for the energy and metal groups, decreasing from 16.24 to -6.92% and increasing from 3.21 to 11.10%, respectively. The basis-momentum characteristic (BM, columns 16-18) is more homogeneous across contracts, groups and period. The largest period-to-period change occurs for the palladium contract (from -10.94 to 5.69%), while its annualized mean rises from 8.32 to 20.29%). Whereas the growth in open interest (ΔOI, columns 19-21) is steady across contracts and sub-periods, the crowding factor (CR, columns 22-24) increases from -0.44 to 0.07% on average across periods, the largest increase in the metal (from -3.30 to -0.08%), followed by the soft group (from -0.69 to 0.42%). This supports the view of an increase usage of factor investing in commodities; see Miffre (2016) and Kang et al. (2021).[18] Columns (25-27) report the statistics for the CIT, for the 18 contracts of the SP-GSCI. Over the full sample, the share of CITs is the highest for the feeder cattle (9.03%), wheat (8.39%), lean hogs (8.35%), and crude oil (8.16%) contracts. It is the lowest for the silver (0.78%) and gold (1.64%) contracts. These figures depart from the SP-GSCI average weights over the periods, *e.g.*, 26% for the crude oil and less than 0.4% for the feeder cattle. The average share of CITs is 2.53% in the pre-financialization period and 6.25% after. This confirms the sharp increase of CIT investment and the identified break date; see Dubois and Maréchal (2021). The energy group experiences the largest increase (*e.g.* the crude oil contract from 3.73% to 10.63%), and the CIT of all contracts increase over the period.[19]

4.2. Factor performance

Table 3 reports the annualized weekly returns of the quantile (equally-weighted) portfolios constructed from the eight characteristics detailed in Section 3.1.

[Insert Table 3 here]

Table 3, Panel A reports the annualized weekly returns for the full sample (1994–2017). Five out of eight portfolio sorts (on Q, B, M, BM, and CR) report a monotonic increase of the returns across quintiles (annualized means weekly returns, and probability that week t delivers positive return). As previously documented by Bakshi et al. (2019), the long-short portfolio sorted on the rolling β alone delivers a performance that is not statistically different from zero. The next three columns report the performance of the long-short strategy (P5-P1), for the full period, the pre- and the post-financialization sub-periods. Factor Q delivers the highest mean weekly returns (17.99%), and is statistically different from 0 (t-statistic = 4.80), followed by CR (17.85%, and t-statistic = 3.68) and B (15.75%, and t-statistics = 3.84). Note that the average annualized weekly returns of the Q, B, M, BM, and CR factors are statistically different from 0 at the 1% level. However, the momentum and crowding factors display noticeable changes across sub-periods. The crowding (momentum) strategy is not significant at the usual levels in the first (second) period, and significant at the 1% level in the second (first) period. This supports the view that factor strategies have been developed along with the financialization (in the form of "third-generation index investing"), the momentum strategy being the most popular; see Miffre and Rallis (2007) and Kang et al. (2021). This increased popularity may have altered the performance due to "crowding", an effect also documented on the stock markets; see, *e.g.*, McLean and Pontiff (2016). Therefore, the parallel surge of the crowding factor performance reinforces Kang et al. (2021) view.

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[18] In commodities factor investing is coined as "third-generation" index investment.

[19] Note that in the post-financialization periods, there is no value for the platinum and orange juice contracts since the SP-GSCI delisted these contracts in 2003–2004.

Panel B reports the correlation of the factors over the full-sample period. The highest correlation is reported for ΔOI and M factors.[20] This correlation, however, does not relate to the factor ability, given the poor performance of ΔOI. In contrast, and as documented by Boons and Porras Prado (2019), the correlation of BM with M and B remains below 30%, despite the fact it encompasses them. Overall, the lowest correlation coefficients are between factors constructed from market-level data (B, M, BM, and β) with those constructed from CFTC or trader-level data (AHP, Q, CR). Finally, the CR factor is negatively correlated with four out of seven strategies, an additional indication of its ability to predict the (poor) performance of other factors; see Kang et al. (2021).

4.3. Optimal subset of factors

Table 4 reports the results of the Bayesian asset-pricing test detailed in Eq. (1); see Barillas and Shanken (2018). I use a set of six factors excluding those constructed on the two characteristics of interest (AHP and Q) out of the eight long-short factors presented in Table 3.[21] There are $2^n - 1$ arrangements, that is 63 (255) in the six (eight) factors scenario. I report the best results for each of the subset size (from one to six) for each prior on the maximum attainable Sharpe ratio $1.25, 1.50, 1.75, 2.00$.

[Insert Table 4 here]

The left columns ("Relative") report the statistics for the relative test in which only factors are included in the set of dependent variables of the time series regressions. The right columns ("Absolute"), reports the statistic for which both remaining factors and the 26 commodity returns are in the dependent variables. The selection is robust to the choice of the test (relative or absolute) and to the prior chosen. In the six potential subsets, the basis factor is selected, and each restricted set of factors of size n is nested in the $n+1$ selection. This approach also allows to compare the probability of obtaining the optimal set of factors, across the subset size. In both relative and absolute specifications, and for all priors, the highest probability is reached with a four factor model (B-M-BM-CR), with 61% and 36%

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[20] Both factors are constructed using some forms of price trends.

[21] I report the full comparison of the eight factors in the Appendix III.A4.

in the relative and absolute test, respectively. Moreover, this four-factor model also yields the lowest (second to lowest) GRS statistic in the absolute (relative) specification, at 1.41 (0.34). Given the fact that the lowest GRS statistic is only obtained with the inclusion of an additional factor in the relative specification, it further supports this choice from the "frequentist" inference perspective; see Gibbons et al. (1989) and Barillas and Shanken (2017). Thus, I select these factors to optimally adjust commodity returns for risk.

4.4. Effects of the day of the roll

Table 5 reports the results of the panel and time series regressions of Eq. (2) and Eq. (3). Panel A reports the results of the panel regression that includes the 26 contracts, and for the 18 contracts, components of the SP-GSCI. I also present the results for the first deferred contracts since they might be affected differently during the roll-days.

[Insert Table 5 here]

Over the full period, no roll-day coefficient is significant at the 10% level. Moreover, no systematic pattern emerges in any set of contracts. For instance, the coefficient for the first roll-day is 16.28 bps, when that of the second is -10.31 bps. Moreover, the period-to-period comparison is inconclusive. Some coefficients reach the traditional significance levels in the post-financialization period, but they are of opposite signs across days. These results confirm the view that no systematic effect on the prices can be attributed to the roll of the major index, thus supporting the "Sunshine trading" view of Admati and Pfleiderer (1991). In addition, the low (negative) adjusted R^2 regressions constitutes further evidence of the little predictability of the roll on returns. Hence I cannot reject the hypothesis 2a.

Table 5, Panel B, presents the results concerning the turnover of the contracts. I define turnover as as $\frac{VOL^{m}_{c,t}}{OI_{c,t}}$ where VOL is the trading volume of the contract of maturity $m = 1; 2$, c and t the contract and week, respectively, and OI the total open interest. These results show a different picture. In the first specification (26 nearby contracts), the pre-financialization period does not show any roll-day coefficient statistically significant at the 10% level or less. During the post-financialization period, however, all coefficients are positive, four of which are significant at the 1% level. Zooming into the 18 SP-GSCI contracts confirms this pattern. In addition, the adjusted R^2 is 5.08%. These results point to an effect on the market functioning and risk-sharing structure, with CITs trading significantly more than traditional traders during the roll. The coefficients for the first deferred contracts of the SP-GSCI also increase across periods, but less. Only one coefficient is significant at the 1% level for the third day (10% for the first) and one is negative (fifth day). This post-period difference may be explained by the concurrent entry of second-generation index funds, which are optimizing the "roll yield", investing in contracts of further-deferred maturities.

Finally, Panel C reports the results of time series regressions of the eight factors (see Table 3) onto SP-GSCI roll-day dummies (one roll each month). The factors computed on the two characteristics of interest (AHP and Q) are not systematically affected by the roll, except for the first day that shows statistical significance at the 1% level. In addition, there is no sizeable change across periods, which reinforces the view that the financialization has not affected these factors. However, except for the β factor, the first day of the roll is the single day which is systematically positive across strategies and periods. It is statistically significant at the 5% level for the factors B, M, BM, and CR. Given its construction, and if speculators use strategies that front-run the index roll, the crowding factor should be affected. Instead, I do not find any coefficient statistically significant at the 5% level, and their sign varies across roll-days. Overall, I reject the hypothesis 2b, when the turnover is considered. There is no evidence for an impact of the roll days on the returns and on the factors, and I do not reject hypotheses 2a and 2c.

4.5. Performance of the liquidity and insurance premiums

Table 6 reports the results of the Fama-MacBeth regression Eq. (4). I first replicate KRT (see Table VI, 2nd and 3rd columns) results in columns (1) and (2).[22]

[Insert Table 6 here]

In column (3), I report the results with the optimal set of factors obtained in Section 4.3 (B-M-BM-CR). In this specification, the size of the coefficients of AHP and Q decreases slightly and the coefficient of AHP is statistically significant at the 10% level, while Q is robust to this risk adjustment and remains statistically significant at the 1% level. Thus, I do not reject hypothesis 3a. The risk adjustment increases the average (adjusted) R^2 by about five (two) percentage points. Column (4) restricts the estimations for weeks with at least three roll-days. In this case, the magnitude of the AHP coefficient is unchanged, and its statistical significance reaches the 5% level. In contrast, in this specification, the size of the Q coefficient is halved and is only significant at the 10% level. This indicates that the roll affects the predictability of Q, but not through the CIT inclusion. Column (5) reports the results for the 18 SP-GSCI contracts, including the variable CIT. The

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[22] I obtain very close results for the coefficients of AHP and Q, using the same Newey-West adjustment with four lags, albeit my t-statistics are slightly smaller. I cannot compare the coefficients for risk-adjustment since they do not report them, however, the (unadjusted) R^2 are also identical.

AHP coefficient decreases economically and is not statistically significant at the usual levels, whereas the Q coefficient is robust to this specification. Column (6) also includes CIT for the 26 commodity contracts (the CIT value is zero for the eight non-SP-GSCI contracts). This aims to disentangle the CIT from the cross-sectional dimension effect. In this specification, the AHP coefficient is statistically significant at the 5% level. Note that the coefficient of CIT is not statistically significant at usual levels. Columns (7) and (8) split the sample pre- and post-financialization. Whereas the average explanatory power of both estimations is unchanged across periods, the size of the coefficients of AHP and Q increases twofold post-financialization, and the coefficient of AHP is significant (at the 10% level) post-financialization only. However, a t-test that compares the series of coefficients before and after does not reject equality neither for AHP, nor for Q, at the 10% level. Finally, Column (9) extends the sample until December 2020, for which the results hold. Altogether, the results of KRT are valid under this extension, although the statistical significance, and the magnitude of the coefficients, decreases under this optimal risk-adjustment.

Altogether, these results point to a modification of the risk-sharing structure in commodity markets, with major changes related to the insurance (AHP), but not to the liquidity component (Q). Hence, hypothesis 3b is rejected. In line with previous results, the financialization has eased the activity of the "commercials" category, and decreased the magnitude of the insurance premium. There is no evidence that the financialization (through the roll days, CIT pressure, or the change in periods) has affected the liquidity premium paid by speculators. However, the Fama-MacBeth approach has limited power in the context of a small cross-section (26 contracts). The next section intends to overcome these limitations.

5. Robustness tests

5.1. Econometric robustness

I use the "Generalized Portfolio Sorts" (GPS) method, which controls for the correlation between contract characteristics and factors built upon other characteristics; see Hoechle et al. (2020). If characteristics are observable, the inclusion of the interaction terms, and their time series average by contract, controls for the dependence. If they are unobservable, contract fixed effects are introduced to avoid the bias. In particular, a Haussman test (Haussman, 1978) is achieved on either type of fixed effects (FE). The panel estimation is,

$$R^1_{c,t} = \mu_c + {}^{\mathbf{T}}\big({}^{\mathbf{T}}\mathbf{z}_{c,t} \odot {}^{\mathbf{T}}\mathbf{x}_t\big)\mathbf{\Theta} + \epsilon_{c,t}, \tag{6}$$

where $\mathbf{z}_{c,t} = [1, z_{2,c,t}, \ldots, z_{M,c,t}]$ is a vector of constant and contract characteristics $m = 2, \ldots, M$, and $\mathbf{x}_{c,t} = [1, x_{2,t}, \ldots, x_{K,t}]$ is a vector of constant and factors, $\odot$ denotes the Khatri-Rao product. When transposed, it yields the column-wise multiplication of the matrices of characteristics and factors, and hence the fully integrated model.[23] Thus, the dependent variables are (i) a constant, (ii), the characteristics, (iii) the factors, and (iv) the factor-characteristic interactions. I introduce characteristics, and their factor-interactions FE in the specifications that adjust for risk with the optimal set of factors, and apply the corresponding Haussman test, using standard errors based on the Driscoll-Kraay (Driscoll and Kraay, 1998) covariance matrix. To introduce characteristics/interactions FE, I compute the time series average of each characteristics and interactions, pooled over the time dimension; see Hoechle et al. (2020, Eq. 18). I report the results of the estimations in Table 7, using the FE specifications when the Haussman test rejects the RE assumptions at the 5% level.

[Insert Table 7 here]

Panel A, reports the results for the full sample without (with) risk adjustment column (1)(column (2)). The coefficient of *AHP* is equal to 0.33% (*vs.* 0.47% in the Fama-MacBeth regressions), and statistically significant at the 5% level. *Q* is equal to 2.78/2.80 and statistically significant at the 1% level. However, the coefficient is smaller than that of the Fama-MacBeth regression (3.80).

In the two specifications, the Haussman test does not reject the RE assumption for the characteristics and factor-interactions. Again, the *CIT* coefficient is not statistically significant at the 10% level. Moreover, none of the factors show statistical significance at the usual levels. Columns (3-4) and (5-6) report the results for the pre- and post-financialization periods. In contradiction with the results of Table 6, the size of the *AHP* coefficient is equal to 0.50%, and significant at the 5% level in the first period, but of 0.25% and not significant at the 10% level in the second period. Instead, the coefficient of *Q* increases from 3.19% to 4.79% across periods, and is significant at 1%. 6. This further supports the view that the financialization has modified the risk-sharing structure from the "commercials" (producer) perspective and decreased, in particular, the price of insurance. For instance when computing the average annualized premiums, I find that of insurance decreases by 43 bps, from 1.11 to 0.68% and that of liquidity increases by 2.92 percentage points. A one standard deviation change in *AHP* during the pre- (post-) financialization translates into a 8.33 bps (5.12) bps change in weekly returns. For Q, a one standard deviation change implies a 15.91 and 13.05 bps change in returns for the pre- and post-financialization, respectively. Finally, the RE assumption for the characteristics and factor-interactions is rejected at the 5% level, only in the post-period and for the risk-adjusted setting.

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[23] The original notation of Hoechle et al. (2020) uses a Kronecker product, which provides the correct dimension only if the characteristics are constant over time (in a vector). This notation generalizes it in the case of time-varying characteristics; For transpose of Kathri-Rao products and "face-splitting" products see also Slyusar (1999).

5.2. Economic robustness

Since mid-2006, the CFTC adds the disaggregated commitment of traders report (DCOT), in which the categories of the "legacy" COT are refined. The commercials category is split in the "producers" and "swap dealers" category. Swap dealers' commercial activity consists in hedging CIT positions on behalf of index traders. Thus, DCOT allows to obtain a more timely and accurate measure of the CIT pressure. It also improves the measurement of the "commercials", and should lead to less noisy variables AHP and Q. Table 7, Panel B, reports the results for the 2007–2017 period in column (1), *i.e.*, the overlap between the KRT sample and the DCOT, and for the 2007–2020 period in column (2). I construct Q^{PROD}, AHP^{PROD}, and CIT^{SWAP} with the "producers" and "swap dealers" DCOT positions, with the same methodology as above.[24] I report the results of the restricted estimations (no risk-adjustment) with characteristics FE as implied by the rejection of the RE assumption at the 1% level. The results are very similar to those of the COT in the post-financialization period. The coefficient of AHP^{PROD} is not significant at the 10% level and turns negative (about -0.35%), thereby confirming the results of the post-financialization period of Panel A. In contrast, the coefficient of Q^{PROD} remains statistically significant at the 1% level, and is of similar size as the COT/post-financialization setting. Again, the coefficient of CIT^{SWAP} does not show any economic and statistical significance at the usual levels. From an investor perspective, the robustness of Q, in the light of these econometric, risk, and economic adjustments also confirms the validity of the net trading or liquidity demand characteristic up to today. On the other hand, a Chow test does not reject the null hypothesis of stable coefficients over the pre- and post-financialization periods (Panel A) (in particular for AHP). When the coefficients of the post-financialization period are replaced by those of the 2007–2020 period in the DCOT setting, the test does reject the null for AHP. Since the covariance matrices are built on different sets of variables, this is not a statistical test. However, it points to a drastic reduction of the insurance premium paid by hedgers.

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[24] I also compute CIT^{SWAP} with no weight on the roll-days overlap and I find no difference in the results. These results are available upon request.

6. Conclusion

This paper studies the robustness of the risk premiums uncovered by Kang et al. (2020), in the light of the financialization. From the extant literature, I first select the characteristics that are identified as good predictors of commodity futures returns. I build factors from these characteristics, and using the Bayesian factor selection approach, I find an optimal asset-pricing model consisting of four factors: (i) the basis, (ii) basis-momentum, (iii) momentum, and (iii) the "crowding". This model stands out all other factor combinations, both in terms of alpha and probability. Beyond its usage in this research, this selection already contributes to the literature, reducing slightly the dimension of a rising "factor zoo". Next, I find that the roll-days of popular indices are significant predictors of the turnover, and that this predictability further increases in the post-financialization period. In contrast, I do not find any evidence that the roll affects returns on commodities or factors, in the pre- and post-financialization periods, and the whole sample period. This contributes to the view that the financialization has not influenced prices, but plays a role in the reorganization of futures markets as an insurance market. To find support for this hypothesis, I use the aforementioned uncovered four-factor model to optimally adjust the specification of Kang et al. (2020) for risk, and provide the results of additional tests aiming to disentangle the financialization effects on this market organization. First, I find that Kang et al. (2020) findings are robust to risk-adjustment. Second, I do not find any influence for a direct measure of index funds pressure. Third, when I select only the weeks overlapping the roll, the results are not affected. Fourth, the insurance premium varies across periods, but not that of liquidity, which supports the view of a market reorganization, in which the index traders supply insurance to producers, thereby decreasing its price; see also Brunetti and Reiffen (2014). Conversely, this market reorganization does not affect the premium captured by producers in providing liquidity to speculators. Given these results, the financialization would benefit the producers both ways. Finally, I implement the panel data approach of Hoechle et al. (2020) and include disaggregated data from the CFTC to obtain robustness inferences from both econometric and economic perspectives. I confirm the aforementioned results. The poor performance of the risk-adjustment with common, optimal factors, also confirm the strong heterogeneity of commodities, and possibly the necessity to identify a more restricted set of more efficient factors. A second line of research would be to consider monthly returns. Finally, a possible research extensions includes the estimation of a latent risk factors and time-varying loading with Instrumented Principal Component Analysis; see Kelly et al. (2019), and Kelly et al. (2020). I leave these methodologies for future research.

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Table 1: **Descriptive statistics: Futures returns**

This table reports the annualized means and standard deviations, and the skewness and kurtosis of the weekly returns on the 26 nearby commodity futures contracts. The period of interest is 1994–2017, and two sub-periods before (1994–2003) and after (2004–2010) the financialization. The table reports the statistics for the equally-weighted portfolios for each group (Energy, Metal, Agriculture, Soft and Livestock) and for the 26 contracts equally-weighted portfolio. The tickers are defined in the Appendix Table A.1.

	1994–2017				1994–2003				2004–2017			
Ticker	Mean (%)	S.d. (%)	Skewness	Kurtosis	Mean (%)	S.d. (%)	Skewness	Kurtosis	Mean (%)	S.d. (%)	Skewness	Kurtosis
CL	8.64	33.67	-0.13	4.60	22.56	32.41	-0.34	4.32	-1.31	34.49	0.02	4.79
HO	8.72	31.69	0.12	4.32	14.89	31.08	-0.13	3.50	4.30	32.13	0.29	4.86
NG	-14.18	45.91	0.24	3.93	10.50	50.57	0.17	3.77	-31.84	42.13	0.25	3.87
PL	6.00	24.81	2.12	6.80	14.64	28.59	3.09	83.77	-1.07	21.20	-0.13	4.54
PA	15.06	36.84	-2.67	4.35	8.32	43.67	-3.55	48.98	20.29	30.52	-0.21	3.88
SI	6.51	28.84	0.00	6.26	-0.14	20.46	0.53	4.96	11.23	33.54	-0.12	5.39
HG	10.34	24.91	0.03	5.53	4.66	21.12	0.06	3.61	14.37	27.28	-0.01	5.65
GC	4.02	16.52	0.48	9.27	-1.98	13.34	2.04	21.27	8.30	18.45	0.00	6.18
W	-8.29	29.16	0.45	4.48	-9.17	23.72	0.46	4.34	-7.66	32.52	0.42	4.09
KW	-0.76	27.47	0.38	4.42	1.18	23.35	0.47	5.52	-2.14	30.08	0.35	3.85
MWE	6.02	26.05	0.31	6.82	2.75	21.28	0.72	6.17	8.36	29.01	0.17	6.35
C	-3.15	26.86	0.32	5.60	-7.27	21.80	0.30	4.68	-0.21	29.96	0.30	5.26
O	7.32	34.15	0.54	7.80	5.46	30.40	0.21	4.37	8.62	36.57	0.67	8.63
S	7.45	23.50	-0.01	4.15	3.54	19.95	0.14	4.02	10.23	25.74	-0.07	3.92
BO	-0.64	23.57	0.18	4.06	-1.86	20.80	0.21	3.77	0.23	25.38	0.16	3.97
SM	14.80	27.35	0.23	4.36	12.17	22.92	0.41	4.14	16.68	30.12	0.16	4.09
RR	-7.36	25.47	-0.10	5.21	-12.98	26.92	-0.22	6.65	-3.35	24.38	0.04	3.55
CT	0.53	28.53	0.06	5.02	-3.44	25.98	0.26	4.21	3.37	30.23	-0.05	5.21
OJ	5.26	32.76	0.36	5.18	-5.96	27.24	0.22	5.37	13.20	36.13	0.35	4.72
LB	-8.58	31.12	0.36	3.59	-9.91	31.45	0.13	2.61	-7.64	30.90	0.52	4.34
CC	3.96	29.50	0.68	6.58	2.51	30.43	0.97	7.65	5.00	28.83	0.43	5.61
SB	4.67	30.93	0.05	4.16	7.66	28.96	0.23	3.88	2.53	32.28	-0.04	4.21
KC	3.81	37.45	0.67	7.12	6.69	44.06	0.83	7.44	1.75	31.91	0.26	3.79
LH	-0.69	28.85	0.18	6.72	-4.59	28.72	0.33	7.78	2.06	28.96	0.07	6.02
LC	2.77	15.81	-0.13	5.81	2.70	15.62	-0.42	8.57	2.82	15.95	0.06	3.98
FC	2.70	15.26	-0.39	6.38	-0.39	13.53	-0.90	11.74	4.91	16.39	-0.20	4.31
Energy	1.06	29.81	0.01	3.80	15.98	30.24	-0.09	3.58	-9.62	29.44	0.08	4.02
Metal	8.86	19.31	-0.17	5.97	5.29	15.37	-0.06	9.43	11.41	21.70	-0.22	4.75
Agriculture	1.67	19.02	0.26	4.59	-0.80	15.82	0.45	4.35	3.43	21.02	0.18	4.29
Soft	1.58	16.03	0.04	3.60	-0.45	14.70	0.31	3.32	3.03	16.92	-0.10	3.64
Livestock	1.63	15.11	-0.05	4.71	-0.81	14.95	-0.04	6.18	3.37	15.24	-0.05	3.74
Average	2.71	12.56	-0.06	5.01	2.33	9.64	0.12	3.04	2.98	14.29	-0.10	4.68

Table 2: **Descriptive statistics: Beta and Futures characteristics**

This table reports the mean and standard deviations of nine commodity characteristics. AHP is the 52 weeks rolling average of the hedging pressure computed as the net-short position of "commercials" traders scaled over total open interest. Q is the liquidity measure of Kang et al. (2020) and is the change in "commercials" net long position in week t from week $t-1$. The beta is obtained from 52 weeks rolling regressions of the nearby returns with the equally-weighted average returns of the 26 commodities. B, the basis is the difference of the first deferred and nearby log prices, scaled by their difference in time to maturity. M is the momentum, geometric sum of the 52 weeks' previous nearby returns. BM, basis-momentum is the difference in the momentum of the first deferred and nearby returns (see Boons and Porras Prado, 2019). CR is the "crowding" factor of Kang et al. (2021), defined as the difference between the net long position of the "non-commercials" with its 52-weeks average. OI is the geometric mean of the growth rate in the open-interest (in USD); see Hong and Yogo (2012). Finally, CIT is the index pressure during the roll, weighted by the number of roll-days overlapping the week; see Eq. (5). The period of interest is 1994–2017. The tickers are defined in the Appendix Table III.A1.

	AHP (%)			$\|Q\|$(%)			β			B (bps)			M (%)			BM (%)			$\|\Delta OI\|$ (%)			CR (%)			CIT (%)		
Ticker	All (1)	Pre (2)	Post (3)	All (4)	Pre (5)	Post (6)	All (7)	Pre (8)	Post (9)	All (10)	Pre (11)	Post (12)	All (13)	Pre (14)	Post (15)	All (16)	Pre (17)	Post (18)	All (19)	Pre (20)	Post (21)	All (22)	Pre (23)	Post (24)	All (25)	Pre (26)	Post (27)
CL	6.25	2.01	9.28	1.72	2.68	1.03	1.37	1.32	1.40	0.73	-2.62	3.13	9.45	22.51	0.10	-2.02	0.65	-3.93	0.64	0.47	0.75	0.48	0.27	0.63	8.16	3.73	10.63
HO	9.15	12.21	6.96	2.49	3.08	2.06	1.31	1.32	1.30	0.60	-0.97	1.73	8.66	13.91	4.90	-0.51	0.82	-1.47	0.51	0.41	0.59	0.20	0.35	0.09	6.57	3.48	8.29
NG	-0.65	7.75	-6.67	1.63	2.50	1.01	1.37	1.67	1.16	7.05	4.42	8.95	-9.88	12.29	-25.75	-8.02	-9.48	-6.99	0.72	0.68	0.74	-0.12	-0.39	0.07	3.05	1.74	3.78
PL	49.49	41.72	55.05	5.93	7.28	4.96	0.96	0.96	0.96	0.05	-0.21	0.27	4.50	10.56	0.16	-1.75	0.82	-3.58	0.81	1.00	0.68	-2.55	-5.34	-0.85	1.67	1.67	
PA	36.01	11.63	53.45	4.43	4.90	4.09	1.24	1.36	1.16	0.64	1.05	0.32	11.20	7.36	13.95	-1.25	-10.94	5.69	0.81	0.62	0.94	0.74	0.04	1.25			
SI	39.71	42.04	38.03	3.67	4.82	2.85	1.14	0.78	1.41	0.45	0.66	0.30	6.69	-1.34	12.43	0.48	0.84	0.23	1.03	1.60	0.69	-1.89	-4.99	-0.24	0.78	0.25	1.07
HG	7.76	17.09	1.08	3.99	5.69	2.78	0.85	0.65	1.00	-0.76	-0.59	-0.89	12.59	2.19	20.03	0.39	-1.03	1.41	1.08	1.74	0.67	-0.32	0.23	-0.61			
GC	23.80	2.49	39.04	4.93	6.77	3.61	0.59	0.43	0.71	0.40	0.61	0.25	4.06	-2.72	8.92	0.32	0.39	0.28	0.80	1.17	0.54	0.70	1.76	0.08	1.64	0.85	2.09
W	1.34	13.01	-7.02	3.03	4.28	2.13	1.46	1.46	1.46	3.25	2.59	3.73	-7.04	-7.20	-6.93	-2.54	-3.55	-1.82	0.62	0.50	0.70	-0.68	-0.29	-0.95	8.39	4.96	10.26
KW	8.51	5.80	10.44	2.82	3.35	2.44	1.35	1.41	1.31	1.53	0.48	2.28	2.02	4.30	0.39	1.40	3.46	-0.06	0.60	0.43	0.72	-0.22	-0.47	-0.04	6.35	3.84	7.19
MWE	8.49	3.86	11.80	2.83	3.44	2.40	1.16	1.22	1.11	0.20	0.39	0.07	9.39	6.01	11.81	3.77	3.63	3.88	0.51	0.11	0.76	0.56	4.18	0.04			
C	2.91	-0.51	5.36	2.37	3.16	1.81	1.39	1.38	1.39	2.49	2.41	2.55	-1.92	-4.89	0.21	0.60	0.42	0.74	0.68	0.62	0.72	-1.15	-2.43	-0.27	3.93	1.82	5.08
O	31.63	38.70	26.58	4.02	4.16	3.91	1.46	1.54	1.40	0.63	0.01	1.05	8.49	8.40	8.55	5.89	6.74	5.27	0.66	0.71	0.63	-0.62	-2.30	0.45			
S	10.75	14.10	8.35	2.78	3.28	2.42	1.31	1.28	1.33	-1.16	-0.74	-1.45	7.85	1.92	12.09	1.17	0.18	1.87	0.63	0.57	0.68	0.97	2.98	-0.35	2.35	0.92	3.15
BO	12.99	14.48	11.92	3.89	4.85	3.20	1.12	0.99	1.21	1.24	1.14	1.31	0.65	-1.60	2.25	0.77	1.66	0.14	0.56	0.47	0.62	-0.85	-1.72	-0.22			
SM	19.00	17.98	19.73	3.46	4.00	3.08	1.30	1.29	1.31	-3.16	-3.10	-3.20	15.26	10.04	19.00	3.58	3.40	3.71	0.54	0.47	0.59	-0.08	0.19	-0.27			
RR	9.73	3.57	14.15	3.75	3.90	3.64	0.73	0.85	0.64	2.88	3.06	2.76	-4.62	-7.77	-2.36	-1.42	-1.98	-1.01	0.93	1.07	0.84	0.41	1.71	-0.43			
CT	8.97	1.75	14.14	4.42	5.62	3.56	0.79	0.68	0.87	1.63	2.21	1.21	1.21	-3.77	4.78	-0.51	-3.60	1.70	0.75	0.70	0.78	0.71	1.65	0.04	4.75	2.06	6.25
OJ	26.48	17.60	32.83	4.85	5.35	4.49	0.77	0.78	0.77	1.51	2.79	0.61	4.45	-4.94	11.17	5.56	6.36	4.99	0.93	0.47	1.26	-0.05	-1.39	0.98	4.67	4.67	
LB	10.15	12.86	8.21	4.59	4.93	4.35	0.53	0.55	0.51	3.47	2.58	4.12	-8.02	-7.00	-8.76	-2.95	-5.35	-1.24	0.67	0.71	0.64	0.01	-0.89	0.66			
CC	13.70	9.55	16.67	2.77	3.21	2.46	0.74	0.83	0.67	1.18	2.03	0.57	3.94	4.50	3.53	1.71	1.46	1.89	0.45	0.50	0.42	-0.53	-1.45	0.12	1.94	0.52	2.71
SB	16.40	16.86	16.07	3.64	5.49	2.31	0.89	0.83	0.93	-0.59	-0.87	-0.39	5.34	9.69	2.23	-1.13	3.81	-4.66	0.65	0.65	0.65	-0.21	-0.72	0.16	4.00	2.25	4.94
KC	13.44	15.78	11.77	3.80	5.29	2.74	1.36	1.45	1.30	1.91	0.82	2.69	6.60	13.27	1.83	1.63	1.46	1.76	0.68	0.69	0.68	-0.50	-1.29	0.07	2.67	1.21	3.46
LH	2.54	1.85	3.04	2.54	3.43	1.89	0.52	0.84	0.29	5.62	4.82	6.19	-2.17	-4.14	-0.75	-0.12	-4.29	2.87	0.69	0.68	0.70	0.28	-0.02	0.49	8.35	5.82	9.77
LC	5.11	4.11	5.83	1.79	2.14	1.55	0.30	0.29	0.30	0.39	-0.34	0.93	2.45	0.75	3.66	1.31	-0.71	2.76	0.43	0.38	0.46	0.64	1.07	0.33	6.80	3.50	8.65
FC	-7.65	-5.77	-8.99	2.13	2.63	1.76	0.09	-0.02	0.17	-0.16	-0.55	0.13	2.66	-0.77	5.11	0.90	0.91	0.90	0.59	0.58	0.60	0.47	0.51	0.44	9.03	6.02	9.47
Energy	4.91	7.32	3.19	1.94	2.75	1.36	1.35	1.44	1.29	2.78	0.28	4.57	2.74	16.24	-6.92	-3.52	-2.67	-4.13	0.62	0.52	0.70	0.19	0.08	0.26	5.93	2.98	7.57
Metal	31.35	22.99	37.33	4.59	5.89	3.66	0.96	0.84	1.05	0.13	0.26	0.04	7.81	3.21	11.10	-0.36	-1.99	0.81	0.92	1.21	0.70	-1.43	-3.30	-0.08	1.58	1.09	1.85
Agriculture	11.70	12.33	11.26	3.22	3.82	2.78	1.25	1.27	1.24	0.88	0.69	1.01	3.34	1.02	5.00	1.47	1.55	1.41	0.63	0.54	0.69	-0.24	-0.26	-0.23	4.16	2.09	5.34
Soft	14.86	12.40	16.62	4.01	4.98	3.32	0.85	0.85	0.84	1.52	1.60	1.47	2.25	1.96	2.46	0.72	0.69	0.74	0.69	0.62	0.74	-0.04	-0.69	0.42	3.70	2.16	4.61
Livestock	0.00	0.06	-0.04	2.15	2.74	1.73	0.30	0.37	0.25	1.95	1.29	2.42	0.98	-1.39	2.67	0.70	-1.36	2.18	0.57	0.55	0.59	0.46	0.52	0.42	8.10	4.87	9.41
Average	14.08	12.40	15.27	3.39	4.24	2.79	1.00	1.01	1.00	1.26	0.85	1.55	3.61	3.14	3.95	0.28	-0.15	0.59	0.69	0.68	0.69	-0.14	-0.44	0.07	4.92	2.53	6.25

Table 3: **Factor returns**

This table reports the annualized weekly portfolio and factor returns built upon the eight commodity characteristics of Table 2. Panel A reports the returns on portfolios sorted as follows: 5–5–6–5–5, and the performance of the strategy that is long (short) in the top (bottom) quantile. The table reports the annualized means, standard deviations, and Sharpe ratios, the percentage of weeks during which the portfolio returns were positive and the t-statistic of the mean of the long-short strategy. Panel B reports the correlation between the long-short strategies. The period of interest is 1994–2017 and the pre- (1994–2003) and post-financialization (2004–2017) sub-periods.

Panel A: Factor performance

	1994–2017						Pre	Post	1994–2017						Pre	Post
	AHP								Q							
	P1 (low)	P2	P3	P4	P5 (high)	P5-P1	P5-P1	P5-P1	P1 (low)	P2	P3	P4	P5 (high)	P5-P1	P5-P1	P5-P1
Ann. mean (%)	-0.33	-4.67	3.57	6.44	9.66	9.99	6.78	10.45	-7.05	-0.70	2.19	8.23	10.94	17.99	21.37	17.36
Ann. σ (%)	14.92	17.19	17.29	16.89	18.20	19.27	17.02	20.86	17.23	16.39	16.53	16.86	16.03	18.31	18.42	18.35
Ann. Sharpe ratio	-0.02	-0.27	0.21	0.38	0.53	0.52	0.40	0.50	-0.41	-0.04	0.13	0.49	0.68	0.98	1.16	0.95
$P(>0)$	48.03	46.41	50.52	51.41	52.05	53.18	50.68	54.21	46.98	50.52	49.48	52.30	55.12	56.16	56.09	56.15
t-statistic						2.53	1.26	2.06						4.80	3.66	3.89

	β								B							
	P1 (low)	P2	P3	P4	P5 (high)	P5-P1	P5-P1	P5-P1	P1 (high)	P2	P3	P4	P5 (low)	P5-P1	P5-P1	P5-P1
Ann. mean (%)	-1.30	5.13	7.69	3.86	-1.88	-0.58	1.88	-2.57	-4.21	-2.75	2.39	7.72	11.54	15.75	17.77	15.13
Ann. σ (%)	11.97	14.97	17.03	19.43	22.32	23.02	22.53	23.75	17.26	17.58	16.17	16.78	17.75	20.05	20.02	21.17
Ann. Sharpe ratio	-0.11	0.34	0.45	0.20	-0.08	-0.02	0.08	-0.11	-0.24	-0.16	0.15	0.46	0.65	0.79	0.89	0.71
$P(>0)$	49.96	52.62	54.71	51.41	49.40	49.15	49.90	48.86	47.06	49.72	49.88	53.10	53.02	55.28	56.29	55.01
t-statistic						-0.12	0.26	-0.44						3.84	2.80	2.94

	M								BM							
	P1 (low)	P2	P3	P4	P5 (high)	P5-P1	P5-P1	P5-P1	P1 (low)	P2	P3	P4	P5 (high)	P5-P1	P5-P1	P5-P1
Ann. mean (%)	-3.92	-0.39	2.98	4.70	10.54	14.46	22.79	5.71	-4.79	-3.37	6.21	5.78	9.25	14.04	13.85	10.31
Ann. σ (%)	18.71	16.13	14.84	16.32	20.19	23.37	23.78	23.53	17.42	16.85	15.65	16.18	17.20	19.39	19.72	19.68
Ann. Sharpe ratio	-0.21	-0.02	0.20	0.29	0.52	0.62	0.96	0.24	-0.27	-0.20	0.40	0.36	0.54	0.72	0.70	0.52
$P(>0)$	47.38	49.48	51.73	52.54	53.99	54.07	56.67	51.82	47.86	47.86	51.89	52.22	53.34	54.79	53.58	54.44
t-statistic						3.02	3.02	1.00						3.54	2.21	2.15

	ΔOI								CR							
	P1 (low)	P2	P3	P4	P5 (high)	P5-P1	P5-P1	P5-P1	P1 (high)	P2	P3	P4	P5 (low)	P5-P1	P5-P1	P5-P1
Ann. mean (%)	0.37	4.07	1.91	9.33	-1.14	-1.51	12.77	-10.80	-4.82	-1.41	6.52	8.90	13.03	17.85	16.55	18.43
Ann. σ (%)	17.74	16.50	15.82	17.47	17.90	20.32	19.15	21.27	17.81	18.58	17.79	17.17	18.00	19.36	17.93	19.46
Ann. Sharpe ratio	0.02	0.25	0.12	0.53	-0.06	-0.07	0.67	-0.51	-0.27	-0.08	0.37	0.52	0.72	0.92	0.92	0.95
$P(>0)$	49.14	50.43	50.69	53.01	48.97	51.03	56.85	46.92	46.31	51.87	52.48	52.36	54.53	57.07	53.40	57.29
t-statistic						-0.35	1.94	-2.09						3.68	1.30	3.89

Panel B: Factor correlation

	β	B	M	BM	AHP	Q	OI
B	-0.01						
M	0.08	0.44					
BM	-0.07	0.29	0.23				
AHP	0.13	0.25	0.34	0.08			
Q	-0.02	-0.01	-0.02	0.01	0.00		
ΔOI	-0.01	0.11	0.52	-0.02	0.13	-0.02	
CR	-0.01	0.00	-0.17	0.02	-0.02	0.19	-0.23

Table 4: **Optimal subset of factors**

This table reports the optimal factor selection based on the Bayesian procedure of Barillas and Shanken (2018). The left columns ("Relative") reports the statistics for the relative test of Barillas and Shanken (2017), in which only factors are included in the set of dependent variables of the time series regressions. The right columns ("Absolute"), reports the statistic for which both remaining factors and the 26 commodity returns are in the dependent variables. I report the optimal set of factors for each subset size $n = 1, \dots, 5$, (relative) and $n = 1, \dots, 6$ (absolute). The optimal selection is based on the probability "Prob." derived from the Bayes factor BF, for each of the priors chosen for the maximum Sharpe ratio 1.25; 1.5; 1.75; 2. The table also reports the average absolute α (Avg. $|\alpha|$), the Wald (W), and the Gibbons et al. (1989) (GRS) statistic and its p-value. The period of interest is 1994–2017 and the set of factors includes the basis B, momentum M, basis-momentum BM, open-interest growth ΔOI, β, and crowding CR.

Prior ($Sharpe_{max}$)	Nb. Factors	Selected factors	Relative						Absolute					
			Avg. $\lvert\alpha\rvert$ %	W	GRS	P-value GRS	BF	Prob.	Avg. $\lvert\alpha\rvert$ %	W	GRS	P-value GRS	BF	Prob.
1.25	1	B	0.12	23.24	4.63	0.00	0.13	0.11	0.10	63.96	2.01	0.00	0.05	0.04
	2	B-CR	0.09	9.76	2.43	0.05	0.42	0.29	0.10	50.05	1.63	0.02	0.13	0.12
	3	B-BM-CR	0.06	3.70	1.23	0.30	1.05	0.51	0.09	43.79	1.47	0.05	0.36	0.26
	4	**B-M-BM-CR**	**0.03**	**0.68**	**0.34**	**0.71**	**1.54**	**0.61**	**0.09**	**40.67**	**1.41**	**0.07**	**0.56**	**0.36**
	5	B-M-BM-ΔOI-CR	0.01	0.02	0.02	0.90	1.34	0.57	0.09	39.98	1.44	0.07	0.50	0.33
	6	β-B-M-BM-ΔOI-CR	-	-	-	-	-	-	0.09	39.97	1.50	0.05	0.38	0.27
1.5	1	B					0.03	0.03					0.01	0.01
	2	B-CR					0.34	0.25					0.31	0.24
	3	B-BM-CR					1.35	0.58					2.15	0.68
	4	**B-M-BM-CR**					**2.22**	**0.69**					**4.73**	**0.83**
	5	B-M-BM-ΔOI-CR					1.66	0.62					3.80	0.79
	6	β-B-M-BM-ΔOI-CR											2.32	0.70
1.75	1	B					0.01	0.01					0.01	0.01
	2	B-CR					0.36	0.27					2.01	0.67
	3	B-BM-CR					1.84	0.65					26.79	0.96
	4	**B-M-BM-CR**					**3.03**	**0.75**					**71.52**	**0.99**
	5	B-M-BM-ΔOI-CR					1.97	0.66					52.15	0.98
	6	β-B-M-BM-ΔOI-CR											26.79	0.96
2	1	B					0.01	0.01					0.02	0.02
	2	B-CR					0.44	0.30					18.79	0.95
	3	B-BM-CR					2.49	0.71					386.69	1.00
	4	**B-M-BM-CR**					**3.97**	**0.80**					**1140.45**	**1.00**
	5	B-M-BM-ΔOI-CR					2.28	0.70					755.92	1.00
	6	β-B-M-BM-ΔOI-CR											336.32	1.00

Table 5: **Roll-day effect**

This table reports the results of a panel regression with contract fixed effects, and variance clustering at the contract level. Panel A (B) presents the results for commodity returns (turn-over) for the nearby and first deferred contract. The dependent variables are regressed onto five dummies that takes the value "1" ("0") when the current date t is a rolling day for contract c. The variable $di_{c,t}$ takes a value "1" when the week includes the ith day of the five-day roll of the SP-GSCI, $i = 1, \ldots, 5$. Panel C reports the results for the time series regressions on the eight factors, for which I assume a monthly roll such as the one of the WTI crude oil contract. "Pre" and "Post" indicate the pre- (1994–2003) and post-financialization (2004–2017) sub-periods. All coefficients are expressed in basis points with the corresponding t-statistics in parenthesis. The period of interest is 1994–2017.

Panel A: Returns

	Nearby contract						First deferred contract					
	All contracts			SP-GSCI contracts			All contracts			SP-GSCI contracts		
	Pre	Post	All	Pre	Post	All	Pre	Post	All	Pre	Post	All
$d1_{c,t}$	-2.05	25.53	16.28	4.92	28.28	20.89	-14.99	23.31	9.97	-9.42	20.94	10.99
	(-0.14)	(1.69)	(1.49)	(0.30)	(1.54)	(1.57)	(-1.03)	(1.65)	(1.03)	(-0.59)	(1.19)	(0.91)
$d2_{c,t}$	19.68	-27.95	-10.31	28.06	-28.34	-7.02	29.87	-32.67	-9.09	31.68	-30.44	-7.05
	(1.27)	(-1.86)	(-0.94)	(1.43)	(-1.62)	(-0.52)	(1.88)	(-2.26)	(-0.87)	(1.59)	(-1.82)	(-0.55)
$d3_{c,t}$	25.16	-13.37	3.35	6.32	-22.78	-10.23	10.03	-8.28	-0.35	7.12	-19.37	-7.98
	(1.53)	(-1.18)	(0.36)	(0.37)	(-2.19)	(-1.12)	(0.81)	(-0.75)	(-0.05)	(0.44)	(-1.87)	(-1.02)
$d4_{c,t}$	20.12	-40.83	-18.58	20.84	-38.59	-16.32	30.69	-46.29	-17.01	24.14	-46.60	-19.42
	(0.76)	(-2.38)	(-1.07)	(0.62)	(-2.05)	(-0.72)	(1.38)	(-2.81)	(-1.13)	(0.86)	(-2.70)	(-0.98)
$d5_{c,t}$	-18.00	39.28	18.23	-0.90	34.27	22.09	-15.47	38.42	18.81	2.45	39.28	26.36
	(-0.95)	(2.70)	(1.49)	(-0.04)	(1.84)	(1.36)	(-0.82)	(2.84)	(1.62)	(0.12)	(2.27)	(1.79)
Adj R^2 (%)	-0.07	-0.05	-0.08	-0.06	-0.03	-0.08	-0.06	-0.02	-0.08	-0.03	0.02	-0.08
Nb. obs.	13468	18824	32292	9324	13032	22356	13468	18824	32292	9324	13032	22356

Panel B: Turnover

	Nearby contract						First deferred contract					
	All contracts			SP-GSCI contracts			All contracts			SP-GSCI contracts		
	Pre	Post	All	Pre	Post	All	Pre	Post	All	Pre	Post	All
$d1_{c,t}$	-42.07	6.71	-12.42	-10.52	8.62	0.49	174.16	3.44	74.76	229.87	4.79	100.10
	(-1.22)	(3.94)	(-0.92)	(-0.73)	(4.11)	(0.08)	(1.10)	(1.73)	(1.12)	(1.02)	(1.67)	(1.04)
$d2_{c,t}$	26.54	1.53	10.79	-4.79	2.74	-0.30	-12.01	-0.01	-5.16	-23.58	0.28	-9.85
	(0.91)	(2.13)	(0.98)	(-0.96)	(3.04)	(-0.13)	(-0.76)	(-0.02)	(-0.76)	(-1.07)	(0.38)	(-1.04)
$d3_{c,t}$	1.87	1.33	1.51	4.80	2.13	3.20	-12.16	1.90	-3.99	22.08	1.79	10.67
	(0.51)	(3.30)	(0.99)	(0.94)	(5.14)	(1.51)	(-0.41)	(4.40)	(-0.31)	(1.01)	(3.44)	(1.11)
$d4_{c,t}$	-2.42	0.33	-0.51	0.66	1.23	1.11	4.91	0.24	3.18	4.86	0.58	2.11
	(-0.63)	(0.73)	(-0.36)	(0.97)	(2.85)	(2.78)	(3.17)	(0.51)	(2.78)	(2.50)	(0.90)	(3.66)
$d5_{c,t}$	-5.36	7.66	2.03	-9.39	11.09	2.46	191.18	-2.99	77.16	218.62	-2.87	91.05
	(-0.53)	(3.38)	(0.44)	(-0.65)	(4.40)	(0.38)	(1.19)	(-1.84)	(1.15)	(0.97)	(-1.30)	(0.95)
Adj R^2 (%)	-0.23	2.67	-0.09	-0.24	5.08	-0.10	-0.22	-0.02	-0.09	-0.23	0.02	-0.09
Nb. obs.	13468	18824	32292	9324	13032	22356	13468	18824	32292	9324	13032	22356

Panel C: Factors

	AHP			*Q*			β			*B*		
	Pre	Post	All	Pre	Post	All	Pre	Post	All	Pre	Post	All
$d1_{c,t}$	0.24	0.31	0.28	0.37	0.22	0.28	-0.19	0.00	-0.08	0.29	0.32	0.31
	(1.77)	(2.25)	(2.85)	(2.52)	(1.81)	(3.00)	(-1.09)	(-0.03)	(-0.72)	(1.86)	(2.40)	(3.03)
$d2_{c,t}$	-1.12	0.22	-0.29	0.97	0.13	0.45	0.55	0.00	0.23	1.40	-0.11	0.47
	(-2.47)	(0.50)	(-0.91)	(1.97)	(0.34)	(1.47)	(0.91)	(0.01)	(0.60)	(2.61)	(-0.26)	(1.40)
$d3_{c,t}$	1.06	-0.57	0.06	-0.70	-0.18	-0.36	-0.41	-0.31	-0.36	-1.34	-0.14	-0.59
	(2.19)	(-1.20)	(0.19)	(-1.33)	(-0.43)	(-1.10)	(-0.64)	(-0.58)	(-0.86)	(-2.34)	(-0.30)	(-1.65)
$d4_{c,t}$	0.38	-0.24	0.04	-0.83	0.85	0.12	0.33	-0.30	-0.03	-0.42	-0.21	-0.30
	(0.94)	(-0.55)	(0.12)	(-1.90)	(2.25)	(0.43)	(0.61)	(-0.61)	(-0.08)	(-0.88)	(-0.51)	(-0.96)
$d5_{c,t}$	0.14	-0.08	-0.02	0.46	-0.84	-0.27	0.68	-0.17	0.16	0.28	0.81	0.60
	(0.27)	(-0.15)	(-0.06)	(0.83)	(-1.79)	(-0.76)	(1.00)	(-0.28)	(0.35)	(0.46)	(1.58)	(1.53)
Adj R^2 (%)	1.44	0.03	-0.23	0.62	0.23	-0.15	0.32	-0.03	-0.09	0.75	-0.26	0.08
Nb. obs.	518	724	1242	518	724	1242	518	724	1242	518	724	1242

	M			*BM*			*OI*			*CR*		
	Pre	Post	All	Pre	Post	All	Pre	Post	All	Pre	Post	All
$d1_{c,t}$	0.38	0.33	0.35	0.17	0.31	0.25	0.44	-0.08	0.14	0.00	0.23	0.13
	(2.02)	(2.11)	(2.92)	(1.08)	(2.38)	(2.50)	(2.94)	(-0.56)	(1.35)	(-0.07)	(1.77)	(1.65)
$d2_{c,t}$	0.29	0.25	0.28	0.68	-0.44	0.00	-0.72	0.16	-0.18	0.27	0.39	0.34
	(0.46)	(0.50)	(0.72)	(1.29)	(-1.07)	(0.00)	(-1.40)	(0.36)	(-0.54)	(1.28)	(0.92)	(1.28)
$d3_{c,t}$	-0.38	-0.48	-0.45	-0.82	0.34	-0.12	0.10	-0.65	-0.36	-0.30	0.20	-0.01
	(-0.55)	(-0.91)	(-1.08)	(-1.46)	(0.77)	(-0.33)	(0.19)	(-1.36)	(-1.00)	(-1.32)	(0.44)	(-0.04)
$d4_{c,t}$	-0.09	-0.89	-0.55	-0.31	-0.24	-0.27	0.03	-0.05	-0.01	0.13	0.06	0.08
	(-0.16)	(-1.86)	(-1.49)	(-0.65)	(-0.60)	(-0.89)	(0.07)	(-0.12)	(-0.05)	(0.66)	(0.15)	(0.33)
$d5_{c,t}$	0.58	1.16	0.91	0.12	0.96	0.63	0.16	0.39	0.29	-0.29	-0.32	-0.30
	(0.80)	(1.97)	(2.00)	(0.20)	(1.95)	(1.66)	(0.27)	(0.73)	(0.74)	(-1.19)	(-0.65)	(-0.96)
Adj R^2 (%)	-0.73	0.63	0.17	0.50	0.04	-0.04	0.12	-0.10	0.23	0.69	0.05	0.04
Nb. obs.	518	724	1242	518	724	1242	518	724	1242	518	724	1242

Table 6: **Performance of the liquidity and insurance premiums**

This table reports the time series statistics of second-stage, cross-sectional, Fama-MacBeth regressions of $R_{c,t}$ onto lagged characteristics, (i) AHP and (ii) Q are the KRT characteristics for insurance and liquidity, (iii) CIT is the share of SP-GSCI interest in total OI, (iv) B is the basis, S is the 52-week trailing regression residuals of commodity returns on the S&P 500 returns, multiplied by "-1" when the speculators are net short, (v) $R_{c,t-1}$ is the lagged weekly return, and (vi) M, (vii) BM, and (viii) CR, are the momentum, basis-momentum, and crowding characteristics. Columns "KRT" are the specifications of Kang et al. (2020, Table VI, 2nd and 3rd columns). The column "18-CIT" restrict the estimations to the 18 contracts of the sample that belongs to the SP-GSCI. The column "3+" restrict the sample to the weeks that have at least three days under which the SP-GSCI rolls. The columns "Pre" and "Post" restrict the sample before (1994–2017) and after (2005–2017) the financialization. Finally, 1994–2020 extends the sample until December 2020. The t-statistics computed with Newey-West standard errors with four lags are reported in parenthesis. The period of interest is 1994–2017.

	KRT		Opt. risk	3+	18-CIT	26-CIT	Pre	Post	1994–2020
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$AHP_{c,t-1}$	0.51	0.43	0.34	0.55	0.31	0.38	0.25	0.43	0.41
	(3.35)	(2.67)	(1.93)	(1.98)	(1.18)	(2.04)	(0.92)	(1.84)	(2.33)
$Q_{c,t-1}$		4.66	3.80	2.32	3.78	3.70	2.63	4.82	3.20
		(5.97)	(4.91)	(1.88)	(3.38)	(4.63)	(3.10)	(3.91)	(2.49)
$CIT_{c,t-1}$					-0.14	-0.25			
					(-0.11)	(-0.29)			
$B_{c,t-1} \times 10^2$	-1.38	-1.39	-0.53	-2.70	-0.21	-0.49	0.42	-1.38	1.35
	(-2.52)	(-2.52)	(-0.85)	(-2.09)	(-0.25)	(-0.76)	(0.50)	(-1.55)	(0.65)
$S_{c,t-1} \times 10^{-2}$	-0.21	-0.16							
	(-1.72)	(-1.30)							
R_{t-1}	0.01	0.03							
	(1.19)	(3.14)							
$M_{c,t-1}$			0.11	0.12	0.09	0.09	0.21	0.01	0.03
			(0.67)	(0.42)	(0.39)	(0.54)	(0.88)	(0.06)	(0.16)
$BM_{c,t-1}$			1.52	0.86	1.38	1.51	0.62	2.27	2.32
			(3.06)	(0.88)	(1.95)	(2.98)	(0.97)	(3.09)	(2.32)
$CR_{c,t-1}$			-0.96	-1.05	-0.74	-0.96	-0.15	-1.65	-0.63
			(-3.45)	(-2.03)	(-2.09)	(-3.33)	(-0.59)	(-3.59)	(-1.78)
Intercept	0.05	0.06	0.05	-0.01	-0.01	0.03	0.05	0.05	0.01
	(0.89)	(1.11)	(0.90)	(-0.10)	(-0.10)	(0.42)	(0.79)	(0.60)	(0.15)
Avg. R^2 (%)	25.66	30.02	35.78	35.17	52.92	39.18	36.65	35.02	36.52
Avg. Adj. R^2 (%)	11.06	11.95	13.73	12.81	18.52	13.88	13.65	13.78	14.44

Table 7: **Panel regressions**

This table reports panel data regression predictability results for the AHP, Q, and CIT characteristics. In Panel A, I report the results for the full sample period (columns 1 and 2), and the pre- and post-financialization periods ("Pre" and "Post"). For each sample, I report the results with and without the factor risk adjustment (B-M-BM-CR), common to all contracts, and add characteristics/characteristics interactions time series average FE, when the Haussman (1978) test rejects the null of no FE; see Hoechle et al. (2020). Panel B replicates the study above using the DCOT data available from 2007, for AHP^{PROD}, Q^{PROD}, and adds the variable CIT^{SWAP}, which is the index pressure computed from the swap dealers positions of the DCOT. I do not report the factor coefficients. Panel B also extends the study to 2020. The t-statistics computed with Driscoll and Kraay (1998) standard errors (controlling for heteroscedasticity and autocorrelation at the contract level) are in parenthesis. For the Haussman test, ** and *** indicate the significance levels of 5% and 1%, respectively.

Panel A: COT

	1994–2017		Pre		Post	
	(1)	(2)	(3)	(4)	(5)	(6)
$AHP_{c,t-1}$	0.33	0.33	0.48	0.50	0.25	-0.37
	(2.28)	(2.24)	(2.26)	(2.36)	(1.34)	(-0.76)
$Q_{c,t-1}$	2.78	2.80	2.52	2.69	3.19	4.79
	(5.73)	(5.75)	(4.83)	(4.98)	(3.26)	(3.31)
$CIT_{c,t-1}$	-0.26	-0.18	2.93	1.55	-0.69	-0.86
	(-0.19)	(-0.14)	(0.71)	(0.41)	(-0.48)	(-0.50)
B_t		0.56		2.69		-2.31
		(0.30)		(1.35)		(-0.69)
M_t		2.30		0.39		-1.52
		(1.28)		(0.18)		(-0.51)
BM_t		-1.95		-0.51		-3.97
		(-0.96)		(-0.28)		(-1.23)
CR_t		-1.37		-0.79		0.65
		(-0.80)		(-0.29)		(0.21)
Constant	0.01	0.01	-0.02	-0.03	0.02	-0.55
	(0.18)	(0.19)	(-0.37)	(-0.38)	(0.31)	(-2.01)
FE						✓
Haussman	1.28	15.70	2.87	13.93	6.00	25.16^{**}
Adj. R^2 (%)	0.15	0.17	0.21	0.36	0.11	0.33

Panel B: DCOT

	2007–2017	2007–2020
	(1)	(2)
$AHP^{PROD}_{c,t-1}$	-0.39	-0.34
	(-0.84)	(-0.84)
$Q^{PROD}_{c,t-1}$	4.65	4.78
	(3.20)	(3.81)
$CIT^{SWAP}_{c,t-1}$	0.10	-0.13
	(0.12)	(-0.18)
Constant	-0.14	-0.11
	(-1.07)	(-1.02)
FE	✓	✓
Haussman	9.97^{***}	14.02^{***}
Adj. R^2 (%)	0.21	0.22

Appendix

Table III.A1: **Contract description**

This table reports the specifications of the 26 contracts. The reported characteristics are the trading venues, tickers, underlying commodities, units, maturity months, and the inception date of the corresponding electronically traded contract.

Commodity	Trading venue	Ticker	SP-GSCI	Underlying	Trading months	Electronification date
WTI crude oil	NYMEX/ICE	CL	✓	bbl (1,000)	FGHJKMNQUVXZ	5/9/2006
Heating oil	NYMEX	HO	✓	gal (42,000)	FGHJKMNQUVXZ	5/9/2006
Natural gas	NYMEX/ICE	NG	✓	MMBtu (10,000)	FGHJKMNQUVXZ	5/9/2006
Platinum	NYMEX	PL	✓	ozt (50)	FGHJKMNQUVXZ	4/12/2006
Palladium	NYMEX	PA		ozt (100)	HMUZ	4/12/2006
Silver	CMX	SI	✓	ozt (5,000)	FHKNUZ	4/12/2006
Copper	CMX	HG		lbs (25,000)	FGHJKMNQUVXZ	4/12/2006
Gold	CMX	GC	✓	ozt (100)	GJMQVZ	4/12/2006
Wheat	CBT	W	✓	bu (5,000)	HKNUZ	1/8/2006
Kansas wheat	KBT	KW	✓	bu (5,000)	HKNUZ	13/01/2008
Minn. Wheat	CME	MWE		bu (50,000)	HKNUZ	15/12/2004
Corn	CBT	C	✓	bu (5,000)	HKNUZ	1/8/2006
Oats	CBOT	O		bu (5,000)	HKNUZ	1/8/2006
Soybeans	CBT	S	✓	bu (5,000)	FHKNQUX	1/8/2006
Soybean oil	CBOT	BO		lbs (60,000)	FHKNQUVZ	1/8/2006
Soybean meal	CBOT	SM		sh tn (100)	FHKNQUVZ	1/8/2006
Rough rice	CBOT	RR		CWT (2,000)	FHKNUX	1/8/2006
Cotton	ICE-US	CT	✓	lbs (50,000)	HKNVZ	2/2/2007
Orange juice	ICE	OJ	✓	lbs (15,000)	FHKNUX	2/2/2007
Lumber	CME	LB		m3 (110,000)	FHKNUX	20/10/2008
Cocoa	ICE-US	CC	✓	MT (10)	HKNUZ	2/2/2007
Raw sugar	ICE-US	SB	✓	lbs (112,000)	HKNVZ	2/2/2007
Coffee	ICE-US	KC	✓	lbs (37,500)	HKNUZ	2/2/2007
Lean hogs	CME	LH	✓	lbs (40,000)	GJMNQVZ	4/12/2006
Live cattle	CME	LC	✓	lbs (40,000)	GJMQVZ	4/12/2006
Feeder cattle	CME	FC	✓	lbs (50,000)	FHJKQUVX	24/11/2008

Maturity month code: F = January, G = February, H = Mars, J = April, K = May, M = June,
N = July, Q = August, U = September, V = October, X = November, Z = December.

Table III.A2: **Futures returns on the first deferred contract**

This table reports the annualized means and standard deviations, and the skewness and kurtosis of the weekly returns on the 26 first deferred commodity futures contracts. The period of interest is 1994–2017, and two sub-periods before (1994–2003) and after (2004–2010) the financialization. The table reports the statistics for the equally-weighted portfolios for each group (Energy, Metal, Agriculture, Soft and Livestock) and for the 26 contracts equally-weighted portfolio. The tickers are defined in the Appendix Table A.1.

	1994–2017				1994–2003				2004–2017			
Ticker	Mean (%)	S.d. (%)	Skewness	Kurtosis	Mean (%)	S.d. (%)	Skewness	Kurtosis	Mean (%)	S.d. (%)	Skewness	Kurtosis
CL	10.19	32.04	-0.10	4.72	21.37	29.76	-0.33	4.58	2.18	33.56	0.04	4.74
HO	8.78	30.05	0.10	4.30	13.57	28.41	-0.15	3.66	5.34	31.17	0.25	4.59
NG	-7.02	41.01	0.21	3.94	18.73	43.44	0.15	3.96	-25.45	39.01	0.23	3.85
PL	7.31	20.87	-0.03	5.70	11.09	19.43	0.30	5.63	4.19	21.99	-0.20	5.58
PA	16.06	32.51	0.40	5.82	18.93	34.57	0.87	7.07	13.77	30.79	-0.14	4.02
SI	6.00	28.76	-0.01	6.28	-0.73	20.31	0.53	4.99	10.81	33.52	-0.13	5.38
HG	9.91	24.71	0.01	5.64	5.60	20.71	0.00	3.80	12.97	27.21	-0.01	5.67
GC	3.71	16.54	0.50	9.34	-2.21	13.40	2.08	21.45	7.93	18.45	0.00	6.20
W	-5.73	27.85	0.50	4.74	-4.81	22.41	0.46	4.73	-6.39	31.18	0.49	4.29
KW	-1.78	26.56	0.45	4.59	-1.43	22.26	0.57	6.04	-2.03	29.26	0.40	3.90
MWE	2.83	24.19	0.39	6.28	0.29	19.97	0.88	7.42	4.64	26.81	0.22	5.52
C	-3.75	26.11	0.34	5.62	-7.82	20.91	0.37	4.88	-0.83	29.28	0.30	5.19
O	1.19	30.23	0.50	7.54	-2.53	26.21	0.23	4.54	3.77	32.75	0.57	7.98
S	6.21	22.84	0.06	4.13	3.64	19.78	0.16	4.04	8.04	24.81	0.01	3.93
BO	-1.44	23.15	0.21	4.06	-3.52	20.17	0.21	3.84	0.04	25.07	0.20	3.91
SM	11.27	25.80	0.19	3.97	9.14	22.49	0.49	4.50	12.79	27.94	0.07	3.62
RR	-6.22	23.49	0.08	4.24	-10.82	23.90	0.15	5.14	-2.92	23.20	0.04	3.52
CT	0.19	25.48	0.10	4.89	-0.38	22.76	0.17	4.34	0.60	27.27	0.07	4.89
OJ	-0.57	30.28	0.23	5.11	-12.09	25.16	0.01	4.82	7.68	33.43	0.24	4.75
LB	-6.39	26.87	0.27	3.46	-4.06	25.55	0.08	2.86	-8.05	27.79	0.37	3.75
CC	1.70	27.86	0.68	6.44	0.63	29.08	1.03	7.94	2.46	26.98	0.36	4.94
SB	4.99	27.66	-0.06	4.77	2.98	25.12	0.22	4.16	6.43	29.36	-0.18	4.87
KC	1.45	34.98	0.50	6.21	4.07	40.07	0.62	6.78	-0.42	30.86	0.27	3.80
LH	-0.43	27.92	0.15	10.06	0.52	27.92	0.21	16.16	-1.12	27.94	0.11	5.71
LC	1.52	13.77	-0.47	7.90	2.59	12.84	-1.40	15.50	0.73	14.42	0.01	4.31
FC	1.98	15.07	-0.33	5.75	-1.23	12.92	-0.79	9.76	4.28	16.43	-0.19	4.30
Energy	3.98	27.80	0.00	3.84	17.89	27.02	-0.09	3.63	-5.97	28.28	0.07	3.99
Metal	8.71	18.95	-0.14	5.39	5.95	13.63	0.23	3.43	10.69	21.99	-0.21	4.76
Agriculture	0.24	18.59	0.29	4.66	-1.89	15.37	0.44	4.49	1.77	20.60	0.22	4.32
Soft	0.23	15.04	-0.01	3.90	-1.48	13.42	0.32	3.56	1.45	16.10	-0.16	3.88
Livestock	1.17	14.76	-0.23	6.23	0.63	14.27	-0.36	9.53	1.55	15.11	-0.15	4.32
Average	2.27	12.37	-0.10	5.33	2.31	9.17	0.17	3.19	2.24	14.24	-0.14	4.83

Table III.A3: **Relative importance of the financialization in the term structure**

This Table reports the relative importance of the open interest of index investment in the term structure of the 26 commodities. Panel A reports the importance of the SP-GSCI open interest in the total open interest and total commercial long positions from the “legacy” report of the CFTC, in which commercial longs include the swap dealers positions, proxy for index investment. Panel B reports the relative weights of nearby and first deferred open interest and trading volume, in the total open interest and trading volume of the term structure.

	Nearby OI ratio			First deferred OI ratio			Nearby volume ratio			First deferred volume ratio			SP-GSCI in total OI			SP-GSCI in “commercials” long		
	1994–2017	1994–2003	2004–2017	1994–2017	1994–2003	2004–2017	1994–2017	1994–2003	2004–2017	1994–2017	1994–2003	2004–2017	1994–2017	1994–2003	2004–2017	1994–2017	1994–2003	2004–2017
CL	17.05	19.88	16.40	17.02	18.57	16.67	45.44	43.19	45.79	24.61	30.59	23.69	13.21	4.89	15.11	27.29	7.19	34.39
HO	18.95	21.59	17.99	23.48	22.36	23.89	36.30	44.23	34.37	30.27	30.56	30.20	9.39	4.19	11.29	16.83	7.29	20.47
NG	11.82	13.75	11.40	16.02	12.22	16.84	40.60	49.82	39.03	22.50	19.75	22.97	4.78	2.33	5.31	10.63	3.31	13.46
PL	8.53	39.46	2.14	26.72	48.03	22.32	9.14	45.03	2.34	36.05	46.93	33.99	0.23	1.34	0.00	1.01	2.95	0.00
PA	8.59	38.74	4.48	26.91	47.70	24.08	7.72	44.77	4.27	35.11	45.50	34.14						
SI	0.38	0.68	0.29	18.37	19.29	18.11	1.45	2.58	1.17	37.43	35.12	38.01	1.27	0.37	1.53	4.12	0.95	5.38
HG	1.57	2.74	1.25	17.37	20.53	16.51	2.19	6.31	1.50	33.82	30.27	34.41						
GC	0.25	0.30	0.23	19.78	17.92	20.21	1.12	2.03	0.97	38.68	36.33	39.05	2.76	1.14	3.14	7.75	1.78	10.82
W	31.25	33.79	30.77	36.14	38.74	35.64	41.49	40.33	41.71	38.45	41.43	37.89	14.05	6.61	15.48	25.98	8.58	31.18
KW	30.81	31.63	30.59	37.27	41.36	36.20	39.70	38.32	40.06	39.15	42.64	38.23	8.59	3.52	9.90	14.82	3.12	22.67
MWE	27.69	34.12	27.01	36.72	42.35	36.12	38.28	39.88	38.07	39.22	45.06	38.44						
C	26.68	25.45	26.96	32.58	33.32	32.41	38.63	36.63	39.00	34.14	34.43	34.08	6.73	2.40	7.72	11.25	2.09	16.40
O	35.33	33.91	36.47	40.23	38.87	41.33	44.65	43.40	45.90	39.54	39.61	39.48						
S	22.73	22.97	22.67	29.67	30.89	29.39	35.03	34.30	35.20	33.14	35.62	32.56	3.94	1.17	4.58	7.22	1.33	9.76
BO	18.63	17.89	18.85	30.15	30.07	30.17	30.17	29.71	30.27	34.64	36.18	34.33						
SM	18.33	18.40	18.30	28.01	28.17	27.95	30.54	31.22	30.35	33.32	34.03	33.13						
RR	35.08	27.43	37.72	42.45	38.78	43.72	41.31	36.22	43.05	44.47	43.83	44.69						
CT	25.88	24.13	26.37	38.55	34.41	39.70	36.15	34.60	36.69	38.65	37.27	39.13	7.65	2.58	9.07	14.88	4.53	18.18
OJ	40.09	37.62	42.10	39.03	36.33	41.23	48.21	46.58	49.56	40.18	39.28	40.93	1.52	3.33	0.05	3.43	7.09	0.11
LB	43.29	52.12	40.31	42.80	34.69	45.53	50.65	55.18	47.92	39.42	36.51	41.18						
CC	19.68	17.51	20.50	35.79	30.97	37.63	34.78	36.23	34.35	44.59	44.11	44.73	2.82	0.64	3.66	5.11	0.97	7.13
SB	38.63	41.00	38.22	26.19	27.43	25.97	47.54	54.37	46.42	30.06	28.19	30.37	6.47	3.00	7.06	12.26	5.61	13.41
KC	25.17	28.54	24.45	46.08	42.08	46.94	37.19	39.15	36.62	45.04	46.79	44.52	4.31	1.65	4.87	8.84	3.48	9.95
LH	21.28	30.19	20.02	30.93	34.34	30.45	31.32	38.55	30.08	33.54	38.53	32.68	13.58	7.45	14.45	33.74	21.55	35.20
LC	16.29	22.44	14.66	40.19	35.34	41.47	26.97	34.79	24.97	39.86	36.79	40.64	11.34	4.64	13.11	27.38	11.85	31.20
FC	25.16	27.26	24.45	31.08	28.42	31.99	27.84	31.21	26.92	35.10	33.30	35.59	10.57	1.56	13.64	35.69	5.56	45.27

Table III.A4: **Optimal subset of eight factors**

This table reports the optimal factor selection based on the Bayesian procedure of Barillas and Shanken (2018). The left columns ("Relative") reports the statistics for the relative test of Barillas and Shanken (2017), in which only factors are included in the set of dependent variables of the time series regressions. The right columns ("Absolute"), reports the statistic for which both remaining factors and the 26 commodity returns are in the dependent variables. I report the optimal set of factors for each subset size $n = 1, \dots, 7$, (relative) and $n = 1, \dots, 8$ (absolute). The optimal selection is based on the probability "Prob." derived from the Bayes factor BF, for each of the $k = 1, 1.25, 1.75, 2$ priors chosen for the maximum Sharpe ratio. The table also reports the average absolute α (Avg. $|\alpha|$), the Wald (W) and the Gibbons et al. (1989) (GRS) statistic and its p-value. The period of interest is 1994–2017 and the set of factors includes the basis B, momentum M, basis-momentum BM, open-interest growth ΔOI, β, crowding CR, average hedging pressure AHP, and net trading Q.

Prior ($Sharpe_{max}$)	Nb. Factors	Selected factors	Relative						Absolute					
			Avg. $\lvert\alpha\rvert$ %	W	GRS	P-value GRS	BF	Prob.	Avg. $\lvert\alpha\rvert$ %	W	GRS	P-value GRS	BF	Prob.
1.25	1	*Q*	0.18	34.61	4.91	0.00	0.02	0.02	0.13	76.48	2.25	0.00	0.00	0.00
	2	*B-Q*	0.11	19.55	3.24	0.00	0.08	0.07	0.11	60.92	1.85	0.00	0.03	0.03
	3	*B-Q-CR*	0.10	10.83	2.15	0.06	0.39	0.28	0.10	51.91	1.63	0.02	0.16	0.14
	4	*B-BM-Q-CR*	0.07	5.13	1.27	0.28	1.16	0.54	0.10	46.02	1.49	0.04	0.57	0.36
	5	*B-M-BM-Q-CR*	0.05	2.13	0.71	0.55	1.80	0.64	0.09	42.93	1.44	0.06	0.97	0.49
	6	**B-M-BM-AHP-Q-CR**	**0.03**	**0.66**	**0.33**	**0.72**	**1.83**	**0.65**	**0.09**	**41.41**	**1.44**	**0.07**	**1.05**	**0.51**
	7	*B-M-BM-AHP-Q-ΔOI-CR*	0.02	0.04	0.04	0.84	1.47	0.59	0.09	40.77	1.47	0.06	0.86	0.46
	8	*β-B-M-BM-AHP-Q-ΔOI-CR*							0.09	40.73	1.52	0.04	0.59	0.37
1.5	1	*Q*					0.00	0.00					0.00	0.00
	2	*B-Q*					0.04	0.04					0.08	0.08
	3	*B-Q-CR*					0.45	0.31					1.93	0.66
	4	*B-BM-Q-CR*					1.94	0.66					14.13	0.93
	5	*B-M-BM-Q-CR*					3.15	0.76					30.53	0.97
	6	**B-M-BM-AHP-Q-CR**					**2.88**	**0.74**					**32.23**	**0.97**
	7	*B-M-BM-AHP-Q-ΔOI-CR*					1.89	0.65					22.67	0.96
	8	*β-B-M-BM-AHP-Q-ΔOI-CR*											12.18	0.92
1.75	1	*Q*					0.00	0.00					0.00	0.00
	2	*B-Q*					0.05	0.04					0.92	0.48
	3	*B-Q-CR*					0.68	0.40					48.80	0.98
	4	*B-BM-Q-CR*					3.28	0.77					519.70	1.00
	5	*B-M-BM-Q-CR*					5.10	0.84					1212.05	1.00
	6	**B-M-BM-AHP-Q-CR**					**4.11**	**0.80**					**1196.31**	**1.00**
	7	*B-M-BM-AHP-Q-ΔOI-CR*					2.29	0.70					730.62	1.00
	8	*β-B-M-BM-AHP-Q-ΔOI-CR*											324.84	1.00
2	1	*Q*					0.00	0.00					0.00	0.00
	2	*B-Q*					0.06	0.05					14.26	0.93
	3	*B-Q-CR*					1.06	0.52					1259.97	1.00
	4	*B-BM-Q-CR*					5.34	0.84					16352.66	1.00
	5	*B-M-BM-Q-CR*					7.74	0.89					38433.34	1.00
	6	**B-M-BM-AHP-Q-CR**					**5.54**	**0.85**					**34981.22**	**1.00**
	7	*B-M-BM-AHP-Q-ΔOI-CR*					2.68	0.73					18831.22	1.00
	8	*β-B-M-BM-AHP-Q-ΔOI-CR*											7171.01	1.00