Convenience Yield Risk

Marcel Prokopczuk[*,¶] Lazaros Symeonidis [†] Chardin Wese Simen [‡]

Robert Wichmann [§]

January 29, 2023

Energy Economics, forthcoming

Abstract

We develop a framework to quantify the convenience yield risk (CYR) inherent to each commodity futures market. Implementing our approach, we document that our novel CYR measure is informative about future commodity returns. In panel regressions, the CYR predicts future returns with a positive sign. Economically, a strategy that opens long positions in commodity markets with a higher than median CYR signal and sells the remaining commodities yields an average return of 6.93% per year. The performance of the CYR strategy cannot be explained by exposure to existing commodity strategies or other variables that capture changes in the investment opportunity set.

JEL Classification: G12, Q02

Keywords: Commodity Risk Factors, Convenience Yield, Futures Curve, Return Predictability

[*]School of Economics and Management, Leibniz University Hannover, Königsworther Platz 1, 30167 Hannover, Germany.

[†]Essex Business School, University of Essex, Wivenhoe Park, Colchester, CO4 3SQ, United Kingdom.

[‡]Management School, University of Liverpool, L69 7ZH, United Kingdom.

[§]ICMA Centre, Henley Business School, University of Reading, Reading, RG6 6BA, United Kingdom.

1 Introduction

The convenience yield, defined as the benefit that accrues to the holder of the physical commodity, plays a very central role in commodity markets (Kaldor, 1939; Working, 1949; Brennan, 1958; Telser, 1958). Given its prominence, it is therefore not surprising that several studies analyze its information content. Gorton et al. (2013) document a significant cross-sectional relationship between the convenience yield and future commodity returns. Koijen et al. (2018) show that the "carry", which is related to the convenience yield, predicts commodity returns in the time series and cross-section. A common theme across these papers is that they focus on the level of the convenience yield. Naturally, one may wonder: what is the information content of the other moments of the convenience yield?

In this paper, we focus on the second moment of the convenience yield and explore its information content. To achieve this goal, we propose a measure of convenience yield risk (CYR). The computation of our novel measure is simple. For each commodity market, we compute the convenience yield implied by (i) the first and second nearby futures contracts as well as (ii) the second and third nearby futures contracts. For ease of exposition, we denote these quantities the first and second convenience yield estimates, respectively. At the end of each month, we use all daily data pertaining to the month to compute the monthly volatility of each of the two convenience yield series. Finally, we obtain the CYR signal as the trailing 12-month average of the difference between the volatility of the first and second convenience yield series.[1] We use a cross-section of 27 commodities spanning the period from July 1959 to December 2018 to operationalize our new measure. We estimate a panel regression of commodity returns on the lagged CYR signal. We find that the CYR signal positively predicts commodity returns as evidenced by the significant t-statistic of 2.26. This finding mirrors that of Li and Yang (2013) who document that the volatility of the dividend growth

[1] Intuitively, we take the difference between the two volatility estimates in order to remove any asset specific effect. This is akin to the approach used in Gu et al. (2019). Furthermore, we average the difference in the volatility estimates over a 12-month trailing window in order to alleviate concerns about measurement errors.

rate positively forecasts stock market returns. We augment our baseline panel regression with time- and commodity-fixed effects and reach similar conclusions. We also control for the impact of other prominent commodity signals documented in the literature and reach the same conclusion: the CYR is a significant predictor of commodity futures returns.

We examine the economic value of the predictive power of CYR. To this end, we develop and implement a simple trading strategy. At the end of each month, we sort all commodities by their CYR signal. We then open long and short positions in the commodities with CYR signal higher and lower than the median CYR signal, respectively. The strategy generates a positive and significant annualized average return of 6.93% (t-stat.=3.24) and an annualized Sharpe ratio (SR) of 0.46. We estimate spanning regressions of the CYR strategy returns on a set of commodity risk factors recently proposed in the literature. We find that the average risk-adjusted return of the CYR strategy (Average=4.6%, t-stat=2.09) is positive, highly significant, and comparable to the unadjusted average return (Average=6.93% and t-stat=3.24). Collectively, the empirical evidence suggests that the returns of the CYR strategy are unspanned by the existing commodity market strategies. We also analyze the extent to which the CYR returns may be explained by exposure to macroeconomic risk and equity risk factors. We find limited evidence to support this conjecture.

We perform several checks to assess the robustness of our findings. We show that our results are robust to the addition of more nearby futures contracts when computing the CYR signal. Furthermore, we show that the CYR strategy remains profitable when the assets are rank-, rather than equal-, weighted in the portfolios. We also repeat our analysis focusing on the top and bottom tertile portfolios and obtain similar results. We analyze the impact of a decision delay of 1-month between the computation of the signal and the implementation of the trading strategy. Overall, we find that the decision delay does not materially affect our results. Furthermore, we show that the CYR strategy is profitable across various periods, including the high and low volatility regimes. Additionally, we consider alternative formation periods for the computation of the CYR signal and obtain qualitatively similar results. Moreover, we document that the CYR is also informative about the cross-section of spreading returns. However, the CYR spreading returns are spanned by those of the existing commodity factors. Finally, we establish that the CYR strategy returns remain profitable after accounting for transaction costs.

Our research contributes to the broader literature on commodity risk premia. Szymanowska et al. (2014) analyze a broad range of commodity trading strategies, including the momentum strategy (Miffre and Rallis, 2007), the carry strategy (Gorton et al., 2013), and the hedging pressure strategy (Basu and Miffre, 2013). Fernandez-Perez et al. (2016) and Fernandez-Perez et al. (2018) analyze trading strategies based on the idiosyncratic volatility and skewness signals, respectively. Fan et al. (2020) focus on trading strategies based on the speculative pressure. We add to this literature by proposing a novel predictor of commodity futures returns based on the convenience yield risk. We show that this new predictor is weakly correlated with predictors already identified in the literature. Furthermore, the CYR strategy returns are not spanned by existing commodity strategies.

Our work also contributes to the strand of literature that employs information from the term structure of commodity futures to build profitable trading strategies. de Groot et al. (2014) show that momentum strategies that involve use contracts with the highest expected roll yield earn significantly higher risk-adjusted returns compared to the traditional momentum strategy. Boons and Prado (2019) introduce the basis-momentum, which is defined as the difference in the momentum of the two nearest futures contracts and document substantial profits from its implementation. Gu et al. (2019) propose the relative basis which relies on the spread between the two nearest bases. They find the relative basis signal to be more strongly related to the inventory scarcity than the traditional basis. Paschke et al. (2020) implement the curve momentum strategy that works within the futures curve by trading the nearest two futures contracts. We add to this stream of the literature by proposing and analyzing a novel trading strategy based on the CYR signal.

The remainder of the paper is structured as follows. Section 2 describes the data. Section 3 introduces our measure of convenience yield risk, and presents the results. Section 4 discusses the results from various robustness checks. Finally, Section 5 concludes.

2 Data

We obtain daily futures price and trading volume data for 27 commodities. The dataset comes from Bloomberg and covers the period from July 7, 1959 to December 31, 2018. This dataset includes a broad range of liquid commodity futures markets which can be grouped into 6 sectors: energy, grains, livestock, metals, oilseeds, and softs. Table A.1 of the appendix contains a detailed description of the dataset. The table shows the commodities included in our analysis, together with information on the exchange where each commodity futures trades, its expiry schedule, and contract size.

Following the standard practice (e.g., Szymanowska et al., 2014; Boons and Prado, 2019), we construct continuous futures price series by rolling over each contract at the end of the month preceding the month prior to the delivery month. By taking this step, we aim to alleviate concerns about stale prices occurring in the final month before the end of trading of the futures contracts.[2] This means that on the day prior to a rollover, we have to account for the fact that the $(n+1)^{th}$ nearby futures contract will become the n^{th} nearby futures contract on the following day. Using this approach, we ensure that the computed excess return series is based on the same contract and is realizable (Singleton, 2014). We compute the return on the n^{th} nearby futures contact on day t as

$$r_t^{(n)} := \begin{cases} f_t^{(n)} - f_{t-1}^{(n+1)}, & \text{if } t-1 \text{ is a rollover day} \\ f_t^{(n)} - f_{t-1}^{(n)}, & \text{otherwise} \end{cases} \tag{1}$$

where $f_t^{(n)}$, $f_{t-1}^{(n+1)}$, and $f_{t-1}^{(n)}$ denote the logarithmic price of the n^{th}, the $n+1^{th}$ and the n^{th}

[2]Even though this procedure is standard in the literature (Szymanowska et al., 2014; Paschke et al., 2020), as a robustness check we roll over the contracts at the end of the month prior to the delivery month. The results are qualitatively similar.

nearby futures contract at times t, $t-1$, and $t-1$, respectively. The first case in Equation (1) corresponds to the situation where a rollover has occurred on the previous day, $t-1$. Then, the excess futures return is computed as the logarithmic difference in the prices of the n^{th} futures contract on day t and the $(n+1)^{th}$ contract on day $t-1$ (i.e., the rollover day). The second case in Equation (1) is when there is no rollover on day $t-1$ and hence the excess futures return is computed as the logarithmic difference in the price of the n^{th} nearby futures contract from day $t-1$ to day t. We thus end up with a continuous excess return series for each commodity and contract maturity. The summary statistics on the returns of the first nearby futures contract, presented in Table A.2 of the appendix, reveal the typical cross-sectional variation in the average returns and standard deviations across commodity markets and sectors (de Groot et al., 2014).[3]

We also collect data on the open interest (number of futures contracts outstanding), and the positions of commercial and non-commercial traders obtained from the Commitment of Traders (CoT) report of the Commodity Futures Trading Commission (CFTC). Finally, we consider data on economic and financial variables. Further details on this data are discussed in Subsection 3.5.

3 Convenience Yield Risk

We start by computing the daily implied convenience yield using the cost-of-carry relationship. For the i^{th} and j^{th} nearby futures contracts, it holds that:

$$f_t^{(j)} = f_t^{(i)} + \left(rf_t^{(i,j)} - y_t^{(i,j)}\right) \frac{M_t^{(j)} - M_t^{(i)}}{365}, \tag{2}$$

where $f_t^{(j)}$ and $f_t^{(i)}$ are the logarithmic prices of the j^{th} and i^{th} nearby futures contracts on day t (with $j > i$), respectively. $rf_t^{(i,j)}$ is the annualized risk-free rate on day t for the

[3]When we employ the same sample as de Groot et al. (2014) and Paschke et al. (2020), we find that the average returns are very similar to those of the authors.

period starting at i and ending at j. The risk-free dataset comes from the term structure of interest rates obtained from the Federal Reserve Economic Data (FRED) database.[4] $y_t^{(i,j)}$ is the annualized convenience yield on day t referring to the period between the expiration dates of the i^{th} and j^{th} futures contracts.[5] $M_t^{(j)}$ and $M_t^{(i)}$ are the days to expiry of the above contracts (with $M_t^{(j)} > M_t^{(i)}$).

We then compute the convenience yield by rearranging Equation (2). Our methodology is deliberately non-parametric as opposed to approaches which model convenience yield as a continuous-time stochastic process (Schwartz, 1997; Sørensen, 2002; Prokopczuk and Wu, 2013). Apart from avoiding restrictive assumptions, our approach has the benefit of allowing us to back out the convenience yield for any pair of contract maturities, which is our main objective.[6]

Descriptive statistics for the nearest convenience yield, $y^{(1,2)}$, i.e., the one computed from the first and second nearby futures contracts, are presented in Table 1. The first order autocorrelation coefficients (AR(1)) indicate that the convenience yield is persistent. These figures are of similar magnitude to those reported in Gu et al. (2019). Moreover, in line with the existing literature (Gorton et al., 2013; Prokopczuk and Wu, 2013), we document substantial variation in the first two moments of the convenience yields across commodities.

[4]We use the overnight, 1-, 2-, 3-, 6-month as well as 1- and 2-year constant maturity rates.

[5]Strictly speaking, $y^{(i,j)}$ encodes information about (i) the interest rate expense, (ii) the pure convenience yield, and (iii) the storage costs (Gu et al., 2019). Stancu et al. (2021) emphasize that the storage costs include the cost of renting the storage facilities as well as all ancillary expenses such as pumping fees in the case of oil and spoilage fees for agricultural commodities. If the storage cost estimates are available, one can easily re-arrange the cost-of-carry formula to retrieve the time-series of the pure convenience yield. Such time-series would be very useful for our empirical analysis. Unfortunately, the storage cost estimates are difficult to obtain in practice, as evidenced by the dearth of research on the topic of storage costs. One notable exception relates to the work of Stancu et al. (2021) who use the LOOP storage futures contract to analyze the cost of storing the LOOP Gulf Coast Sour crude oil. To the best of our knowledge, there are no storage futures contracts related to any of the 27 commodity markets that we analyze. Since the storage cost data are not readily available for the broad cross-section of markets that we analyze, we are not currently able to pursue this analysis. We leave this avenue for future research.

[6]Typically, the definition of the convenience yield revolves around the first two nearby contracts, where the first nearby contract is used as a proxy for the spot price and the second nearby contract is informative about the futures price. In this paper, we extract the convenience yield implied by any i and j nearby contracts too (i.e., $i > 1$). Strictly speaking, it is the forward convenience yield implied by the futures curve from the maturity of the i nearby contract to that of the j nearby contract. For ease of exposition, in the paper, we commit a slight abuse of terminology and refer to this quantity as the convenience yield.

For instance, the mean (standard deviation) of the convenience yield of natural gas is equal to 10.45% (173.35%), while the corresponding figure for gold is 0.53% (1.47%). This cross-sectional variation in the convenience yield is strongly influenced by seasonal demand and supply patterns. For example, the seasonal variation in the convenience yield of natural gas and heating oil is mainly driven by the heating demand during cold months. Similarly, the seasonality in the convenience yield of agricultural commodities, such as corn or soybeans, relates to the annual harvest cycle.

To formally investigate the seasonal behavior of the convenience yield, we estimate regressions of the monthly average convenience yield of each commodity on monthly dummy variables. Table A.3 of the appendix presents the slope estimates and R^2 coefficients of these regressions. The p-value of the F-test reported in the last column of the table indicates rejection of the null hypothesis that the coefficients of the twelve monthly dummy variables are jointly equal to zero for most markets.[7] As one would expect, we obtain the strongest evidence of seasonality in the convenience yield of commodities in the energy, agricultural and livestock sectors, and the weakest in metals.

We next compute the monthly volatility of the convenience yield as follows:

$$\sigma_t(y^{(i,j)}) = \sqrt{\frac{1}{N_t - 1}\sum_{\tau=1}^{N_t}(y_\tau^{(i,j)} - \overline{y_t^{(i,j)}})^2}, \tag{3}$$

where $\sigma_t(y^{(i,j)})$ denotes the month t volatility of the convenience yield associated with nearby contracts i and j, respectively. N_t is the number of daily observations in month t, $y_\tau^{(i,j)}$ is the convenience yield on day τ of month t for the pair of nearby contracts i and j, and $\overline{y_t^{(i,j)}}$ is the average of $y^{(i,j)}$ during month t. Table A.4 of the appendix reports that the average convenience yield volatility exhibits strong cross-sectional variation. In particular, energy, livestock, and agricultural commodities have higher average convenience yield volatility compared to metals.

[7]This finding is consistent with the work of Back et al. (2013) who document seasonal variation in the volatility of agricultural and energy commodities.

We then define the *convenience yield risk* (CYR) as follows:

$$\mathrm{CYR}_t = \frac{1}{12}\sum_{i=1}^{12}\left[\sigma_{t-i}(y^{(1,2)}) - \sigma_{t-i}(y^{(2,3)})\right], \tag{4}$$

where CYR_t is the convenience yield risk at time t. $\sigma_{t-i}(y^{(1,2)})$ and $\sigma_{t-i}(y^{(2,3)})$ are the volatilities of the first and second nearest convenience yields of month $t-i$.[8]

Several factors motivate our computation of the convenience yield risk. First, by computing the monthly volatility of the convenience yield (see Equation (3)), we capture the monthly time-variation in the convenience yield. Second, we compute the difference between the monthly volatility of the first two convenience yield series. In so doing, we aim to remove any market-specific effect. This approach is akin to that of Gu et al. (2019). Third, we use a 12-month measurement period to (i) address the issue of seasonality in both the level and volatility of the convenience yield series and (ii) alleviate concerns about measurement errors. The use of a 12-month trailing window is consistent with the standard formation period used in benchmark trading strategies (Moskowitz et al., 2012; Boons and Prado, 2019).[9] Fourth, our CYR measure in Equation (4) relies on data pertaining to the first three nearest futures contracts, which are typically the most liquid ones.[10]

Table 2 summarizes the descriptive statistics of the CYR of each commodity market. We observe substantial variation in the first two moments of the CYR across commodities. Moreover, the first order autocorrelation coefficient (column AR(1)) shows that the CYR signal is persistent. This is to be expected as it is based on a 12-month average which may induce serial dependence in the series.

[8]In Table A.5 of the appendix, we report the volatility of the first four convenience yields, i.e., $\sigma(y^{(1,2)})$ to $\sigma(y^{(4,5)})$. The volatility of the nearest convenience yield is generally higher than the volatility of the second nearest convenience yield.

[9]We examine the sensitivity of our findings to alternative formation periods in Section 4.

[10]Gu et al. (2019) show that the open interest of the third nearby contract is around 40% of that of the second nearby contract, suggesting sufficient liquidity.

3.1 Predicting Commodity Returns

In this section, we explore the predictive ability of the CYR for excess commodity futures returns. Similar to Boons and Prado (2019), we estimate the following predictive panel regressions:

$$r_{i,t+1} = \gamma_0 + \gamma_1 \mathrm{CYR}_{i,t} + \gamma_2' X_{i,t} + \theta_{t+1} + \kappa_i + \eta_{i,t+1}, \tag{5}$$

where $r_{i,t+1}$ is the excess return on commodity i in month $t+1$. γ_0 is the intercept. γ_1 is the loading of the convenience yield risk $CYR_{i,t}$. γ_2 is the vector of loadings on the explanatory variables $X_{i,t} = (\mathrm{BAS}_{i,t},\ \mathrm{MOM}_{i,t},\ \mathrm{BASMOM}_{i,t},\ \mathrm{IVOL}_{i,t},\ \mathrm{TVOL}_{i,t},\ \mathrm{SKEW}_{i,t},\ \mathrm{RELBAS}_{i,t},\ \mathrm{HP}_{i,t},\ \mathrm{SP}_{i,t})'$. Specifically, the vector $X_{i,t}$ contains for each commodity i in month t: the futures basis (BAS) in the spirit of Gorton and Rouwenhorst (2006), the momentum (MOM) signal as in Miffre and Rallis (2007), the basis-momentum (BASMOM) signal of Boons and Prado (2019), the idiosyncratic volatility (IVOL) signal as in Fernandez-Perez et al. (2016), the total volatility (TVOL) signal, the skewness (SKEW) signal of Fernandez-Perez et al. (2018), the relative basis (RELBAS) signal of Gu et al. (2019), the hedging pressure (HP) signal of Basu and Miffre (2013) and the speculative pressure (SP) signal of Fan et al. (2020).[11] Appendix A presents a detailed description of the construction of these variables. θ_{t+1} captures the time fixed effects. κ_i picks up the commodity fixed effects. $\eta_{i,t+1}$ is the error term associated with commodity market i at time t. Following Boons and Prado (2019), we cluster the standard errors by time.[12]

The results from the above predictive regressions are presented in Table 3. Column (1)

[11] It is worth pointing out that the commitment of traders (CoT) dataset underpinning the computation of the HP and SP variables is only available from 1986 onwards. Accordingly, the sample period associated with either SP or HP is much shorter than our main sample.

[12] One–way clustered standard errors are used to account for the correlation of the residuals within a cluster. Since commodity futures returns are not strongly autocorrelated, it is sensible to cluster only by time. In doing so, we account for the possible correlation between observations on different commodities at the same point in time. Essentially, this is the same methodology as that of Boons and Prado (2019). We have also tried a two-way clustering and obtained similar results. Another possibility is to compute the Newey and West (1987) standard errors. In an untabulated analysis, we have tried this approach and found that the results were stronger when using the Newey and West (1987) than when using the one-way clustered standard errors.

contains the results from panel regressions of commodity returns on the lagged CYR. We can see that CYR predicts future commodity returns with a positive sign. This result is robust to the inclusion of commodity fixed effects (column (2)) or time fixed effects (column (3)). When both commodity and time fixed effects are considered (column (4)), the CYR remains significant (t-stat = 2.79). Since all independent variables are standardized, the coefficient γ_1 indicates that a one standard deviation increase in CYR predicts an increase in returns of 5.16%. This effect stems solely from the variation in the CYR as return variations across time and commodity markets have been accounted for, through fixed effects. Lastly, as shown in the last column of Table 3 (column (5)), our evidence remains robust when we control for the other commodity return predictors.

3.2 Single Sorts

The previous analysis reveals that CYR is a significant predictor of commodity futures returns. However, the analysis does not speak to the economic value of the predictability. To shed light on this, we implement the following CYR strategy. At the end of month t, we sort the 27 commodities on their CYR signal. We build a "High" portfolio containing all commodities with a CYR above the median and a "Low" portfolio containing the remaining commodities.[13] All commodities are equal-weighted in the portfolios.[14] We then compute the return of the "High-Low" portfolio for month $t+1$ as the difference between the 1-month returns of the High and Low portfolios. We repeat the aforementioned steps each month, thus obtaining the time series of monthly returns on the CYR strategy.

Table 4 reports the annualized average return, Newey and West (1987) t-statistics (with a bandwidth of 6), and Sharpe ratios for the "High", "Low" and "High-Low" portfolios.[15]

[13] This sorting procedure is similar to that of Gorton et al. (2013). It has the advantage that it leads to more well-diversified portfolios compared to an approach based on quantiles which would result in portfolios containing very few commodities. However, we acknowledge that there are alternatives. To this end, in Section 4, we employ alternative sorting procedures and reach very similar findings.

[14] The equal-weighted approach is quite standard in the commodity literature (Boons and Prado, 2019; Paschke et al., 2020). In a robustness check, we also build rank-weighted portfolios (see Table A.7 of the appendix).

[15] Throughout this paper, we employ the commonly used observations–based criterion for the bandwith of

We obtain a highly significant average nearby futures return of 6.93% per annum (t-stat = 3.40) for the "High-Low" portfolio. We see that it is mainly the "High" portfolio which contributes to the positive and significant "High-Low" return. This result is in line with Boons and Prado (2019) who find that it is mainly the "High" portfolio that drives the returns of the basis–momentum strategy.

3.3 Double Sorts

We next explore whether the relation between CYR and commodity futures returns persists after controlling for established commodity return predictors in independent double sorts. Specifically, we use the intersection of the "High" and "Low" CYR portfolios with the two "High" and "Low" portfolios formed by sorting on a second variable selected from the following: basis, momentum, basis-momentum, idiosyncratic volatility, total volatility, skewness, relative basis, hedging pressure, and speculative pressure. If any of the above variables can explain the relation between CYR and commodity futures returns, then the average return of the "High-Low" CYR portfolio should be insignificant.

Table 5 presents the average return of the portfolios created from independent double sorts on the CYR and the control variable (name in row) as well as the average return of the corresponding high minus low ("High-Low") portfolios.[16] Of particular interest is the average "High-Low" CYR return within each control group, reported in the last column of the table. For example, focusing on the last column of the "Basis" panel, we observe a 7.30% (6.37%) average return of the "High-Low" CYR portfolio within the portfolio of commodities with high (low) basis. Similarly, the returns of the CYR remain significant after controlling for

the Bartlett kernel of the Newey and West (1987) estimator: $4(T/100)^{2/9}$ where T denotes the total number of observations. We round the window size to the nearest integer.

[16] Table A.6 of the appendix summarizes the average monthly returns for single portfolio sorts on the control variables (names in rows). To compute the strategy returns associated with a given signal, we proceed as follows. At the end of each month, we sort all commodities based on the signal. We then buy (sell), in equal weight, the commodities with a higher (lower) than median signal. We hold the positions for 1 month and compute the High-Low portfolio return. Newey-West t-statistics (computed using 6 lags) are reported in parentheses. The results confirm the cross-sectional predictive ability of these variables documented in the literature.

predictors such as basis–momentum, skewness, hedging pressure, and speculative pressure. However, when we focus on the "Low" idiosyncratic volatility, total volatility, and relative basis portfolios, the "High-Low" CYR return is no longer significant. Overall, the results suggest that the predictive power of the CYR is most discernible in the "High" portfolios.

3.4 Spanning Tests

We next examine whether the CYR factor (i.e., the return on the long-short CYR portfolio) provides independent information for commodity futures returns beyond that of known commodity risk factors. We consider a broad range of strategies, namely the High-Low portfolio returns based on the following signals: BAS, MOM, BASMOM, IVOL, TVOL, SKEW, RELBAS, HP, and SP. Table 6 contains the full sample correlations between the factor returns. As the table shows, the return on the CYR is weakly correlated with that of the other risk factors. One implication of this finding is that, alone, none of the existing strategies is able to explain the performance of the CYR strategy.

It is, however, possible that the strategies can collectively explain the performance of the CYR strategy. To shed light on this, we turn to the spanning regression:

$$r_{CYR,t} = \alpha + \sum_{j=1}^{K} \beta_j F_{j,t} + \epsilon_t, \tag{6}$$

where $r_{CYR,t}$ is the return on the High-Low CYR portfolio at time t. α is the intercept. Economically, this intercept is informative about the average risk-adjusted return of the High-Low CYR portfolio. β_j is the slope parameter associated with $F_{j,t}$, which denotes the return at time t of the strategy j.

Table 7 documents that the intercepts are highly significant at the 5% level. This is true, irrespective of whether we look at univariate or multivariate regressions. Moreover, the risk-adjusted return of the CYR strategy (regression α) is of similar magnitude to the average return of the long-short CYR strategy in Table 4. Collectively, the results confirm that the performance of the CYR strategy cannot be explained by exposure to well-known commodity factors.

3.5 Relationship to Economic and Financial Variables

Szymanowska et al. (2014) show that commodity factors are useful to price the cross-section of commodity returns. Bakshi et al. (2019) confirm this finding and go a step further by documenting that changes in the investment opportunity set can help understand the performance of commodity risk factors. This finding motivates us to directly examine the potential link between the CYR and a broad range of macroeconomic variables that capture changes in the investment opportunity set. The first set of variables reflects the state of the economy and financial market conditions. These variables include the growth rate of the U.S. industrial production (ΔIP), the term spread (TERM) computed as the difference between the yield on the 10-year U.S. Treasury bond and the 3-month U.S. Treasury bill rate, the default return spread (DEF) defined as the difference between corporate and government bond returns as a measure of credit risk, and the TED spread (TED) as the difference between the 3-month LIBOR and the 3-month U.S. Treasury bill rate, used as a proxy for funding illiquidity (Brunnermeier et al., 2008).[17] The data on corporate and government bond returns used for the default return spread are collected from Amit Goyal's webpage.[18] We collect the remaining data from the FRED database of the Federal Reserve Bank of St Louis.[19]

One may argue that (i) these macroeconomic variables are measured with noise and (ii) it would be interesting to cast our net wide and bring in equity risk factor data, which are known to relate to changes in the investment opportunity set.[20] The advantage of this

[17] In an untabulated analysis, we have also included the VIX index and the trade-weighted USD index against major currencies and found that they did not alter our findings.

[18] http://www.hec.unil.ch/agoyal/.

[19] We use the first release of the industrial production (vintage series) and lag the series by one month to address issues related to data revision and publication lags.

[20] For instance, Fama and French (1992) report a relationship between the value premium and market-wide financial distress. Similarly, Liu and Zhang (2008) document a strong link between equity momentum

approach is that the equity factor returns are better measured and aggregate information about the state of the economy from various sources. Accordingly, we use a benchmark factor model that consists of factors related to the equity market. These include the market factor (MKT), namely the return on the value-weighted portfolio of all US-based common stocks in the CRSP database minus the one-month treasury bill rate, the size (small-minus-big, SMB) factor, the value (high-minus-low, HML) factor, and the momentum factor (UMD).[21] We obtain the monthly data on these factors from the website of Kenneth French.[22] Finally, we consider the liquidity factor of Pástor and Stambaugh (2003). The data on the liquidity factor are collected from the website of Robert Stambaugh.[23]

The results from contemporaneous regressions of the returns on the CYR strategy on the above variables are presented in Table 8. We employ Newey-West (1987) standard errors (computed using a bandwidth of 6) for the estimations. As the table shows, most of the slope parameter estimates of the explanatory variables in the univariate regressions are insignificant at the 5% level. Moreover, the variables explain very little of the variation in the excess returns of the CYR strategy as indicated by the very low R^2 coefficients shown in the penultimate row of the table. The results from a multiple regression that includes all the explanatory variables (last column), supports the findings from univariate regressions.[24] Overall, we conclude that these variables cannot explain the performance of the CYR strategy.

returns and the change in industrial production.

[21]For further details on the construction of these factors, we refer the interested reader to Fama and French (1996).

[22]https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[23]http://finance.wharton.upenn.edu/~stambaug/

[24]We omit the TED spread from this regression as the sample history for the LIBOR rate begins in January 1986. Thus, including the TED spread would lead to a considerably shorter sample.

4 What About ...

4.1 Alternative Measures of CYR?

One may wonder to what extent the CYR signal is robust to the inclusion of the convenience yield signals stemming from other nearby contracts. This concern motivates us to compute an alternative measure of CYR based on the spread between the nearest convenience yield volatility ($\sigma_{t-i}(y^{(1,2)})$ and the average of the next 5 convenience yield volatilities (Next5Avg):[25]

$$\textbf{Next5Avg:} \qquad \tfrac{1}{12}\textstyle\sum_{i=1}^{12}\left[\sigma_{t-i}(y^{(1,2)}) - \tfrac{1}{5}\sum_{j=2}^{6}\sigma_{t-i}(y^{(j,j+1)})\right], \tag{7}$$

where $\sigma_t(y^{(j,j+1)})$ is the monthly volatility of the j^{th} convenience yield (i.e., the one computed using the j^{th} and $(j+1)^{th}$ contracts).

Our untabulated analysis reveals that this alternative signal shares a correlation of 0.68 with our baseline CYR signal. Moreover, the trading strategy associated with this alternative signal yields an average return of 4.78% (t-stat=2.51) and a Sharpe ratio of 0.32. These estimates are comparable though sligthly lower than those associated with the baseline CYR strategy (Mean=6.93%, Sharpe Ratio=0.46).

4.2 The Weighting Scheme?

One may wonder whether our results are sensitive to the specific sorting procedure followed to create the long-short cost CYR portfolios or by the equal-weighting of the commodities in these portfolios. To this end, we analyze the performance of the CYR strategy under the following alternative scenarios: (i) instead of using the median rank to form the long-short CYR portfolio, we sort all commodities based on CYR and then take the spread in the returns of the top and bottom tertiles, and (ii) we employ a scaled rank-based weighting

[25] The choice of five convenience yields is motivated by the maximum number of convenience yields available across all commodity markets.

instead of an equal-weighting scheme.[26]

Table A.7 of the appendix reports the excess returns of the "High-Low" CYR portfolios based on the above two scenarios. We see that the returns of the strategy remain significant and notably higher in some cases compared to the baseline CYR strategy. For example, using tertiles for the sorting, leads to an increase in the annualized average excess return of the strategy to 8.47% (t-stat.=2.91) and to a very similar Sharpe ratio (=0.44). Using rank-based weights leads to an annualized average excess return of 8.10% (t-stat. = 3.02). In sum, our results remain robust to the above considerations.

4.3 Decision Delay?

Our baseline analysis is based on the assumption that the portfolios are formed immediately after the computation of the trading signal. One may argue that this assumption is not always true in real-life, as investors may face decision delays. This means that there might exist a time gap between the measurement of the trading signal and the practical implementation of the strategy (see, Paschke et al., 2020).

To account for the possibility of decision delays, we allow for a one month gap between the measurement of the signal and the implementation of the trade. At the end of month t, we compute CYR based on data observed over the past 12-month period. We then implement the trading strategy at the end of month $t+1$. The last column of Table A.7 shows the results from this modified strategy. The table clearly indicates that the modified strategy has very similar performance to the baseline CYR strategy (average excess return of 7.30% compared to 6.93% for the original strategy) and a similar Sharpe ratio (0.50 vs. 0.46 for the baseline strategy). These findings lead us to conclude that the performance of the CYR strategy remains robust once we account for decision delays.

[26] We scale the rank-weights to ensure that the weights in each portfolio add up to 1. See also Asness et al. (2013) and Koijen et al. (2018) for a similar approach.

4.4 The Sample Choice?

We conduct a series of robustness checks to examine the extent to which our results may be driven by the choice of sample period. First, rather than starting our sample period from the first available data point (i.e., July 7, 1959), we focus on the period from January 1, 1990 to December 31, 2018.[27] The untabulated results indicate that the performance of the strategy is robust.

Second, we study the performance of the CYR strategy across different volatility regimes. For each trading day, we create an equal-weighted average of all commodity returns. We refer to this quantity as the daily commodity index return. Each month, we compute the volatility of the daily commodity index returns observed during the month (Prokopczuk et al., 2019). By following these steps, we obtain a monthly time-series of commodity index return volatility. We then use the median of the time-series of monthly volatility to identify the high and low volatility states. To be specific, the high (low) volatility regime consists of all observations with volatility higher (lower) than the median volatility. For each of these two states, we calculate the average return, variance, and Sharpe ratio of the CYR strategy. Table A.8 of the appendix establishes that the strategy is profitable in both regimes, and more so, in the high volatility regime.

Third, we re-compute the return of the CYR strategy when we drop one of the 6 commodity sectors. We do this in order to check whether our results are driven by a specific sector. Table A.9 demonstrates that the average return of the CYR strategy remains statistically and economically significant in all cases as evidenced by the annualized average returns ranging from 6.13%, when we exclude the grains sector, to 8.92%, when we exclude the softs sector.

[27] We choose January 1, 1990 as the start of our sample because it corresponds to the earliest date when data on all 27 commodity markets are available.

4.5 The Formation Period?

In our main analysis, the CYR signal is based on a formation period of 12 months. One may naturally wonder if the performance of the strategy is robust to alternative formation periods. In Table A.10 of the appendix, we report the summary statistics of the CYR strategy based on formation periods of 1, 6, 12, and 18 months, respectively. The results clearly indicate that the CYR strategy yields positive and significant average returns when using alternative formation periods, including the 18-month horizon. Comparing all formation periods, we can see that the performance of the CYR strategy peaks at the 12-month horizon.

4.6 Spreading Returns?

Szymanowska et al. (2014) and Boons and Prado (2019) highlight that it is interesting to analyze the spreading return. At each point in time, we compute the spreading return of each commodity market as the difference between the return on the first nearby contract and that of the second nearby contract. By repeating these steps over time and for all commodity markets, we obtain the time-series of spreading returns for each commodity.

At the end of month t, we sort all commodity markets by their CYR risk measure. We then create the high (low) equal-weighted portfolio by opening long (short) spreading positions in all markets associated with a CYR measure that is higher (lower) than the median CYR. The High-Low CYR spreading return is simply the difference between the performance of the aforementioned high and low CYR spreading portfolios. Table A.11 of the appendix shows that this strategy yields a positive and significant average return (0.81%, t-stat = 1.99). Pursuing our analysis, we compute the spreading returns associated with our main control variables and use the resulting time-series as explanatory variables in the spanning regression. We find that the CYR spreading returns are spanned by the spreading returns of some of the popular commodity trading signals (see Table A.12 of the online appendix).

4.7 Transaction Costs?

An important question is whether the CYR strategy remains profitable once transaction costs are accounted for. To provide an answer to this question, we analyze the impact of transaction costs on the returns of the CYR strategy. In the absence of bid-ask data for the commodities under consideration, we need to model the transaction costs.

We follow a two-step strategy. First, similar to prior studies (e.g. Miffre and Rallis, 2007; Paschke et al., 2020), we assume a fixed transaction cost of 0.033% per futures contract:

$$TC_t^{(i)} = 0.033\% \tag{8}$$

where $TC_t^{(i)}$ denotes the transaction cost from trading a futures contract on commodity i at time t. The above value is motivated by the work of Locke and Venkatesh (1997) who analyze the transaction costs in the Chicago Mercantile Exchange (CME) in 1992. The authors document that the transaction cost associated with futures trading is low and ranges between 0.0004% and 0.033%. Therefore, the assumed value in Equation (8) corresponds to the most conservative estimate. Furthermore, it is consistent with the range of transaction costs computed by Ferguson and Mann (2001).

Second, we follow the approach of Szakmary et al. (2010) to estimate transaction costs. The authors assume a fixed brokerage fee of \$10 per contract and a bid-ask spread equal to one tick.[28] The transaction cost is then estimated as follows:

$$TC_t^{(i)} = \frac{10 + Tick\_size^{(i)} \times \mathrm{CM}^{(i)}}{F_t^{(i)} \times \mathrm{CM}^{(i)}} \tag{9}$$

where $TC_t^{(i)}$ is the transaction cost estimate of market i at time t. $Tick\_size^{(i)}$ is the minimum tick size for commodity i. $CM^{(i)}$ is the contract multiplier for commodity i (units of the underlying commodity deliverable per contract). The data on the minimum tick size and

[28] This approach is also employed by Paschke et al. (2020) to account for the effect of transaction costs on their curve momentum strategy.

the contract multiplier are obtained from the product specification on the webpage of the exchange where each commodity trades. $F_t^{(i)}$ is the price of the first nearby futures contract of commodity i at time t.

We compute the monthly return of the CYR strategy net of transaction costs as:

$$\widetilde{R}_t = R_t - \frac{1}{2}\sum_{i=1}^{N} TO_t^{(i)} \cdot TC_t^{(i)} \tag{10}$$

where $\widetilde{R}_t$ denotes the net return on the CYR strategy at time t. R_t is the return of the CYR strategy at time t. $TO_t^{(i)}$ denotes the turnover of commodity i at time t. The turnover for commodity i at time t is computed as follows:

$$TO_t^{(i)} = |w_t^{(i)} - \bar{w}_t^{(i)}| \tag{11}$$

where $\bar{w}_t^{(i)}$ denotes the weight on asset i shortly before the position is rebalanced at time t:

$$\bar{w}_t^{(i)} = \frac{w_{t-1}^{(i)}(1 + R_t^{(i)})}{\sum\limits_{i=1}^{N_t} w_{t-1}^{(i)}(1 + R_t^{(i)})} \tag{12}$$

As pointed out by Paschke et al. (2020) the turnover arises not only from the end-of-month rebalancing of the strategy but also from the rollover of futures contracts. In the latter case, the turnover is based on the difference between the weight on the i^{th} nearby contract after the rollover and the weight on the $(i-1)^{th}$ contract before the rollover.

Table A.13 of the appendix presents the summary statistics of the transaction cost estimate associated with each market. We can see that the average transaction cost, reported in percentage point, displays some variations across commodity markets. These differences likely reflect true cross-sectional differences in the liquidity of commodity markets. They might also be affected by the heterogeneity of the beginning of the sample period at the individual commodity level.[29] At the end of each period, we compute the average transaction

[29] Digging deeper, we notice a declining trend in the transaction cost estimates over time. This is consistent

cost estimate across all markets. We then calculate the time-series average of this estimate and report it in the last row of Table A.13. As we can see, the average transaction cost estimate is 0.10%, which is quite comparable to the average estimate (0.08%) of Marshall et al. (2012).

Table A.14 of the appendix shows the excess return of the CYR strategy after accounting for transaction costs. The figures associated with the net returns are fairly similar to those of the raw returns. This observation leads us to the conclusion that transaction costs have a limited impact on the performance of the strategy.

5 Conclusion

In this paper, we quantify the convenience yield risk associated with individual commodity markets. We analyze the information content of the convenience yield risk for future returns. In a panel setting, the convenience yield risk predicts future commodity returns with a positive and statistically significant coefficient. We present a simple trading strategy to shed light on the economic value of the predictability. This strategy delivers a significant annualized average return of 6.93% and an annualized Sharpe ratio close of 0.46.

Pursuing our analysis, we find that existing commodity factors, e.g. carry, momentum, and basis-momentum, and prominent macroeconomic variables do not fully explain the performance of the convenience yield risk strategy. Moreover, the profitability of the strategy is not eroded by transaction costs and survives a battery of robustness checks.

with the literature, e.g. Szakmary et al. (2010), Paschke et al. (2020), and Lauter and Prokopczuk (2022).

References

Asness, C. S., Moskowitz, T. J., and Pedersen, L. H. (2013). Value and momentum everywhere. *Journal of Finance*, 68(3):929–985.

Back, J., Prokopczuk, M., and Rudolf, M. (2013). Seasonality and the valuation of commodity options. *Journal of Banking & Finance*, 37(2):273–290.

Bakshi, G., Gao, X., and Rossi, A. (2019). Understanding the sources of risk underlying the cross section of commodity returns. *Management Science*, 65(2):619–641.

Basu, D. and Miffre, J. (2013). Capturing the risk premium of commodity futures: The role of hedging pressure. *Journal of Banking & Finance*, 37(7):2652–2664.

Boons, M. and Prado, M. P. (2019). Basis-momentum. *Journal of Finance*, 74(1):239–279.

Brennan, M. J. (1958). The supply of storage. *American Economic Review*, 48(1):50–72.

Brunnermeier, M. K., Nagel, S., and Pedersen, L. H. (2008). Carry trades and currency crashes. *NBER macroeconomics annual*, 23(1):313–348.

de Groot, W., Karstanje, D., and Zhou, W. (2014). Exploiting commodity momentum along the futures curves. *Journal of Banking & Finance*, 48:79–93.

Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *the Journal of Finance*, 47(2):427–465.

Fama, E. F. and French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance*, 51(1):55–84.

Fan, J. H., Fernandez-Perez, A., Fuertes, A.-M., and Miffre, J. (2020). Speculative pressure. *Journal of Futures Markets*, 40(4):575–597.

Ferguson, M. F. and Mann, S. C. (2001). Execution costs and their intraday variation in futures markets. *The Journal of Business*, 74(1):125–160.

Fernandez-Perez, A., Frijns, B., Fuertes, A.-M., and Miffre, J. (2018). The skewness of commodity futures returns. *Journal of Banking & Finance*, 86:143–158.

Fernandez-Perez, A., Fuertes, A.-M., and Miffre, J. (2016). Is idiosyncratic volatility priced in commodity futures markets? *International Review of Financial Analysis*, 46:219–226.

Gorton, G. and Rouwenhorst, K. G. (2006). Facts and fantasies about commodity futures. *Financial Analysts Journal*, 62(2):47–68.

Gorton, G. B., Hayashi, F., and Rouwenhorst, K. G. (2013). The fundamentals of commodity futures returns. *Review of Finance*, 17(1):35–105.

Gu, M., Kang, W., Lou, D., and Tang, K. (2019). Relative basis. *Working Paper*.

Kaldor, N. (1939). Speculation and economic stability. *Review of Economic Studies*, 7(1):1–27.

Koijen, R. S., Moskowitz, T. J., Pedersen, L. H., and Vrugt, E. B. (2018). Carry. *Journal of Financial Economics*, 127(2):197–225.

Lauter, T. and Prokopczuk, M. (2022). Measuring commodity market quality. *Journal of Banking & Finance*, pages 1–80.

Li, Y. and Yang, L. (2013). Asset-pricing implications of dividend volatility. *Management Science*, 59(9):2036–2055.

Liu, L. X. and Zhang, L. (2008). Momentum profits, factor pricing, and macroeconomic risk. *Review of Financial Studies*, 21(6):2417–2448.

Locke, P. R. and Venkatesh, P. (1997). Futures market transaction costs. *Journal of Futures Markets*, 17(2):229.

Marshall, B. R., Nguyen, N. H., and Visaltanachoti, N. (2012). Commodity liquidity measurement and transaction costs. *Review of Financial Studies*, 25(2):599–638.

Miffre, J. and Rallis, G. (2007). Momentum strategies in commodity futures markets. *Journal of Banking & Finance*, 31(6):1863–1886.

Moskowitz, T. J., Ooi, Y. H., and Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics*, 104(2):228–250.

Newey, W. K. and West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3):703.

Paschke, R., Prokopczuk, M., and Wese Simen, C. (2020). Curve momentum. *Journal of Banking & Finance*, 113:1–17.

Pástor, L. and Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political economy*, 111(3):642–685.

Prokopczuk, M., Stancu, A., and Symeonidis, L. (2019). The economic drivers of commodity market volatility. *Journal of International Money and Finance*, 98:1–13.

Prokopczuk, M. and Wu, Y. (2013). The determinants of convenience yields. *Working Paper*.

Schwartz, E. S. (1997). The stochastic behavior of commodity prices: Implications for valuation and hedging. *Journal of Finance*, 52(3):923–973.

Singleton, K. J. (2014). Investor flows and the 2008 boom/bust in oil prices. *Management Science*, 60(2):300–318.

Sørensen, C. (2002). Modeling seasonality in agricultural commodity futures. *Journal of Futures Markets*, 22(5):393–426.

Stancu, A., Symeonidis, L., Wese Simen, C., and Zhao, L. (2021). The dynamics of storage costs.

Szakmary, A. C., Shen, Q., and Sharma, S. C. (2010). Trend-following trading strategies in commodity futures: A re-examination. *Journal of Banking & Finance*, 34(2):409–426.

Szymanowska, M., Roon, F., Nijman, T., and Goorbergh, R. (2014). An anatomy of commodity futures risk premia. *Journal of Finance*, 69(1):453–482.

Telser, L. G. (1958). Futures trading and the storage of cotton and wheat. *Journal of Political Economy*, 66(3):233–255.

Working, H. (1949). The theory of price of storage. *American Economic Review*, 39(6):1254–1262.

Table 1: Summary Statistics for the Convenience Yield

This table presents the summary statistics of the nearest convenience yield, $y^{(1,2)}$, for the 27 commodities under consideration, at the monthly frequency. We classify the commodities into 6 sectors: Energy, Grains, Livestock, Metals, Oilseeds, and Softs. For each market, we report the mean (Mean), standard deviation (Std. Dev.), first order autocorrelation coefficient (AR(1)), skewness (Skew), kurtosis (Kurt), and number of observations (Obs.). The mean and standard deviation are reported in percentage points. The sample period is from July 1959 to December 2018.

Sector	Commodity	Mean	Std. Dev.	AR(1)	Skew	Kurt	Obs.
Energy	WTI Crude	7.26	25.03	0.76	1.16	6.32	428
	Heating Oil	8.26	51.82	0.35	9.51	129.77	390
	Natural Gas	10.45	173.35	0.18	10.79	147.84	345
	Gasoil	6.68	28.69	0.59	4.98	40.40	351
	Gasoline	18.65	50.14	0.41	2.23	12.25	385
Grains	Corn	-0.88	21.98	0.62	7.40	88.85	714
	Oats	1.97	24.51	0.73	3.36	22.93	713
	Rough Rice	-4.25	23.16	0.52	4.30	27.98	359
	Chicago Wheat	2.44	26.88	0.64	5.94	60.92	714
Livestock	Feeder Cattle	6.85	14.66	0.62	0.34	4.92	562
	Live Cattle	7.94	21.44	0.61	1.00	4.56	649
	Lean Hogs	13.39	62.81	0.60	1.26	5.72	392
Metals	Copper	6.95	12.00	0.84	2.24	10.14	361
	Gold	0.53	1.47	0.58	2.18	22.87	527
	Palladium	3.99	6.48	0.67	4.78	49.25	381
	Platinum	3.75	4.24	0.89	2.06	9.97	392
	Silver	0.06	1.93	0.41	-5.03	94.48	527
Oilseeds	Soybean Oil	6.32	22.38	0.74	3.77	24.82	714
	Canola	-1.52	8.64	0.60	2.61	12.21	442
	Soybeans	8.37	39.60	0.34	9.31	125.64	714
	Soybean Meal	10.65	30.63	0.56	4.20	26.77	714
Softs	Cotton	6.43	61.04	0.46	17.81	363.24	710
	Lumber	-1.44	23.95	0.73	0.90	5.04	390
	Cocoa	2.72	16.72	0.86	2.79	12.34	713
	Orange Juice	4.82	31.11	0.60	10.07	158.96	621
	Coffee	3.49	22.74	0.84	2.57	12.34	556
	Sugar	4.01	23.03	0.79	1.81	9.09	694

Table 2: Summary Statistics for Convenience Yield Risk

This table reports the summary statistics of the convenience yield risk signal. The convenience yield risk is computed as in Equation (4). We report for each commodity the mean, standard deviation (Std. Dev.), first order autocorrelation coefficient (AR(1)), skewness (Skew), kurtosis (Kurt), and number of observations (Obs.). The dataset contains 27 commodities divided into 6 sectors: Energy, Grains, Livestock, Metals, Oilseeds, and Softs. The sample period runs from July 1959 to December 2018.

Sector	Commodity	Mean	Std. Dev.	AR(1)	Skew	Kurt	Obs.
Energy	WTI Crude	1.41	1.29	0.97	1.72	6.40	430
	Heating Oil	0.97	0.97	0.94	1.65	6.16	390
	Natural Gas	2.31	2.43	0.88	0.47	3.42	345
	Gasoil	0.65	0.61	0.81	-1.08	17.24	354
	Gasoline	1.83	1.16	0.91	0.80	4.52	385
Grains	Corn	0.23	0.58	0.95	1.84	7.41	703
	Oats	0.35	0.80	0.93	0.37	4.22	703
	Rough Rice	0.06	0.84	0.90	0.54	5.58	361
	Chicago Wheat	-0.09	0.75	0.96	-2.61	17.23	703
Livestock	Feeder Cattle	0.38	0.54	0.85	-0.23	4.09	565
	Live Cattle	0.83	0.68	0.95	0.25	3.17	649
	Lean Hogs	1.17	0.95	0.90	0.86	3.94	391
Metals	Copper	0.32	0.56	0.95	2.62	10.19	361
	Gold	-0.01	0.19	0.85	-0.80	15.44	528
	Palladium	0.21	0.55	0.97	3.13	15.51	375
	Platinum	0.07	0.29	0.93	0.84	6.04	392
	Silver	-0.01	0.14	0.89	-2.55	19.27	528
Oilseeds	Soybean Oil	0.09	0.73	0.94	1.90	13.29	703
	Canola	-0.22	0.54	0.94	-1.74	8.12	441
	Soybeans	-0.05	0.61	0.84	0.18	9.04	703
	Soybean Meal	0.53	1.32	0.94	1.49	10.20	703
Softs	Cotton	0.34	0.76	0.94	-0.99	9.19	703
	Lumber	0.69	0.96	0.95	0.26	3.74	389
	Cocoa	0.38	0.51	0.95	1.63	6.83	703
	Orange Juice	0.46	0.52	0.89	0.70	3.97	623
	Coffee	0.65	1.07	0.96	1.97	6.87	557
	Sugar	0.81	0.85	0.93	1.52	7.72	694

Table 3: Predictive Panel Regressions

This table presents the estimation results of the following panel regression model:

$$r_{i,t+1} = \gamma_0 + \gamma_1 CYR_{i,t} + \gamma_2' X_{i,t} + \theta_{t+1} + \kappa_i + \eta_{i,t+1}$$

where $r_{i,t+1}$ denotes the return on commodity i in month $t+1$. $CYR_{i,t}$ is the convenience yield risk of commodity i in month t. $X_{i,t}$ denotes the vector of control variables which includes the basis, momentum, basis-momentum, idiosyncratic volatility, total volatility, skewness, relative basis, hedging pressure, and speculative pressure. θ_{t+1} is the indicator variable for each month (time fixed effect). κ_i is the indicator variable for commodity i (commodity fixed effects). $\eta_{i,t+1}$ is the error term of commodity i observed at $t+1$. We only report the coefficient γ_1 along with the associated t-statistic using standard errors clustered by time. The "Time FE" and "Commodity FE" rows indicate whether time or commodity fixed effects are employed in the panel estimation.

	(1)	(2)	(3)	(4)	(5)
CYR	3.94	5.64	3.53	5.16	4.13
(t-stat)	(2.26)	(2.74)	(2.18)	(2.79)	(2.28)
X	No	No	No	No	Yes
Time FE	No	No	Yes	Yes	Yes
Commodity FE	No	Yes	No	Yes	Yes
R^2	0.01	0.01	0.18	0.19	0.20

Table 4: Performance of the Convenience Yield Risk Strategy

This table reports the average return with the associated t-statistic (in parentheses) using Newey and West (1987) standard errors (computed using 6 lags), and the annualized Sharpe ratio for portfolios sorted on convenience yield risk. We sort the 27 commodities by their CYR at the end of each month and form a "High" portfolio containing the commodities associated with a CYR greater than the median CYR and a "Low" portfolio containing the remaining commodities. We also report the average return on the "High-Low" spread portfolio. The commodities in each portfolio are equally-weighted. The sample period is from July 1959 to December 2018.

	High	Low	High–Low
Av. Return	7.11	0.19	6.93
(t-stat)	(3.31)	(0.23)	(3.40)
Sharpe Ratio	0.46	0.01	0.46

Table 5: Independent Double Portfolio Sorts

This table presents the average monthly excess returns for portfolios formed by independently sorting on the convenience yield risk (CYR) and each of the following signals: basis, momentum, basis-momentum, idiosyncratic volatility, total volatility, skewness, relative basis, hedging pressure, and speculative pressure. Using the median of the two series as breakpoints, we form four portfolios from the intersection of the two CYR portfolios and the two portfolios based on the variable [name in row]. The last column of the table ("High–Low") shows the average returns of the long-short portfolio which buys the commodities in the "High" CYR group and sells the commodities in the "Low" CYR group. The sample covers 27 commodities for the period from July 1959 to December 2018. Returns are annualized and in percentage points. t-statistics based on Newey and West (1987) standard errors (using a bandwidth of 6) are reported in parentheses.

		High	Low	High–Low
Basis	High	11.32 (5.12)	3.95 (1.76)	7.30 (3.26)
	Low	4.14 (2.04)	-2.05 (-1.01)	6.37 (3.12)
	High–Low	7.11 (3.69)	6.04 (3.07)	
Momentum	High	13.17 (5.46)	3.86 (1.59)	9.63 (3.95)
	Low	0.66 (0.34)	-2.63 (-1.38)	3.26 (1.69)
	High–Low	12.09 (5.69)	6.14 (2.89)	
Basis-Momentum	High	14.41 (6.24)	7.32 (3.10)	6.30 (2.66)
	Low	-0.76 (-0.38)	-4.76 (-2.39)	4.30 (2.11)
	High–Low	14.57 (6.89)	12.60 (5.88)	
Idiosyncr. Volatility	High	13.66 (4.73)	2.70 (1.65)	10.78 (3.67)
	Low	1.17 (1.26)	-1.52 (-0.63)	2.72 (1.60)
	High–Low	12.27 (3.97)	4.53 (1.73)	
Total Volatility	High	9.34 (3.70)	-1.89 (-0.74)	11.15 (4.38)
	Low	2.92 (1.75)	0.81 (0.49)	2.02 (1.21)
	High–Low	6.43 (3.07)	-2.72 (-1.30)	
Skewness	High	10.55 (4.33)	-0.22 (-0.09)	10.77 (4.42)
	Low	4.44 (2.25)	0.13 (0.06)	4.32 (2.19)
	High–Low	6.11 (3.23)	-0.34 (-0.18)	
Relative Basis	High	9.21 (4.12)	2.67 (1.19)	6.54 (2.92)
	Low	3.57 (1.66)	-0.56 (-0.26)	4.12 (1.91)
	High–Low	5.65 (3.22)	3.23 (1.84)	
Hedging Pressure	High	7.87 (3.00)	1.18 (0.45)	6.69 (2.55)
	Low	2.85 (1.22)	-5.56 (-2.37)	8.41 (3.59)
	High–Low	5.02 (2.12)	6.73 (2.85)	
Speculative Pressure	High	2.26 (0.98)	-4.38 (-1.91)	6.64 (2.89)
	Low	6.98 (2.60)	0.70 (0.26)	6.28 (2.34)
	High–Low	-4.72 (-1.95)	-5.08 (-2.11)	

Table 6: Correlations between Commodity Factors

This table reports the full sample correlations between the returns on the following commodity factors: convenience yield risk (CYR), market (MRKT), basis (BAS), momentum (MOM), basis-momentum (BASMOM), idiosyncratic volatility (IVOL), total volatility (TVOL), skewness (SKEW), relative basis (RELBAS), speculative pressure (SP), and hedging pressure (HP). The sample includes 27 commodities and spans the period from July 1959 to December 2018.

	MRKT	BAS	MOM	BASMOM	IVOL	TVOL	SKEW	RELBAS	SP	HP
CYR	0.06	0.09	0.06	0.12	0.01	0.01	0.03	0.00	-0.02	-0.02
MRKT		0.03	0.19	0.11	-0.01	-0.01	-0.01	-0.07	-0.04	-0.04
BAS			0.37	0.44	0.03	0.03	-0.08	0.34	-0.02	0.05
MOM				0.27	0.03	0.03	-0.05	-0.07	-0.01	-0.02
BASMOM					-0.05	-0.05	0.03	0.26	0.00	0.06
IVOL						1.00	0.14	-0.05	-0.05	-0.17
TVOL							0.15	-0.05	-0.05	-0.17
SKEW								-0.03	-0.15	-0.08
RELBAS									-0.01	0.08
SP										0.72

Table 7: Spanning Regressions

This table reports the results from spanning regressions of the CYR strategy returns on the returns of an equally-weighted commodity market portfolio (MRKT), and the returns of the strategies based on the basis (BAS), momentum (MOM), basis-momentum (BASMOM), idiosyncratic volatility (IVOL), total volatility (TVOL), skewness (SKEW), relative basis (RELBAS), speculative pressure (SP), and hedging pressure (HP), respectively. The sample covers the period from July 1959 to December 2018. Returns are annualized and expressed in percentage points. t-statistics using Newey and West (1987) standard errors (using 6 lags) are reported in parentheses below the estimated coefficients.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
α	6.68	6.27	6.37	5.04	6.92	6.91	6.69	6.93	7.71	7.76	4.60	6.46
	(3.40)	(2.86)	(3.24)	(2.21)	(3.26)	(3.26)	(3.02)	(3.09)	(3.20)	(3.18)	(2.09)	(2.87)
MRKT	0.07										0.05	0.01
	(0.74)										(0.53)	(0.16)
BAS		0.09									0.06	0.16
		(1.58)									(0.92)	(2.01)
MOM			0.06								0.00	-0.01
			(0.87)								(0.00)	(-0.11)
BASMOM				0.13							0.11	-0.03
				(2.12)							(1.51)	(-0.31)
IVOL					0.01						-0.17	-2.05
					(0.36)						(-0.32)	(-2.11)
TVOL						0.01					0.18	2.13
						(0.39)					(0.34)	(2.26)
SKEW							0.03				0.03	0.16
							(0.75)				(0.72)	(2.71)
RELBAS								0.00			-0.04	-0.08
								(0.03)			(-0.57)	(-0.88)
SP									-0.02			0.02
									(-0.35)			(0.20)
HP										-0.02		-0.01
										(-0.47)		(-0.09)
R^2	0.00	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.04
Obs	713	713	713	713	713	713	713	713	395	395	713	395

Table 8: Relationship to Economic and Financial Variables

This table reports the results from time series regressions of the CYR strategy returns on economic and financial variables. ΔIP is the growth rate in the industrial production (based on first release data), TERM is the term spread (10-year government bond yield minus the 3-month treasury bill yield), DEF is the default return spread (difference between the corporate and government bond returns), TED is the TED spread (difference between the 3-month LIBOR rate and the 3-month treasury bill rate). MKT is the market factor. SMB (small minus big) denotes the size factor. HML (high-minus low) is the value factor. UMD represents the momentum factor as defined in Fama and French (1996). LIQ is the Pástor and Stambaugh (2003) market liquidity factor. The sample period is from July 1959 to December 2018.[a] *Returns are annualized and in percentage terms. We report the t-statistics based on Newey and West (1987) standard errors (computed using a bandwidth of 6) in parentheses below the estimated coefficients.*

Intercept	6.58	11.05	6.95	5.67	7.49	6.99	6.39	6.95	6.37	10.51
	(2.92)	(2.97)	(3.29)	(1.39)	(3.45)	(3.29)	(3.07)	(3.24)	(3.13)	(2.92)
ΔIP	1.71									0.30
	(0.70)									(0.10)
TERM		-2.29								-2.07
		(-1.54)								(-1.44)
DEF			-1.10							-0.73
			(-0.74)							(-0.44)
TED				3.19						
				(0.45)						
MKT					-1.09					-0.74
					(-1.83)					(-1.17)
SMB						-0.33				0.51
						(-0.48)				(0.73)
HML							1.70			1.48
							(1.81)			(1.43)
UMD								-0.03		0.09
								(-0.05)		(0.13)
LIQ									-0.50	-0.26
									(-1.04)	(-0.57)
R sq.	0.07%	0.39%	0.09%	0.09%	0.81%	0.03%	0.78%	0.00%	0.34%	1.85%
Obs.	713	714	714	396	714	714	714	714	677	677

[a]The data for the TED spread start from January 1986 and for the LIQ factor start in August 1968. We omit the TED spread from the multiple regression of the last column to avoid substantially reducing the sample length.

Appendix

To

“Convenience Yield Risk”

Appendix A

This appendix describes the construction of the control variables. The signals used to construct the commodity risk factors are computed as follows:

$$\mathrm{BAS}_t = \left(f_t^{(i)} - f_t^{(j)}\right) \frac{365}{M_t^{(j)} - M_t^{(i)}}, \tag{13}$$

$$\mathrm{MOM}_t = \sum_{j=1}^{12} r_{t-j}^{(1)}, \tag{14}$$

$$\mathrm{BASMOM}_t = \sum_{j=1}^{12} r_{t-j}^{(1)} - \sum_{j=1}^{12} r_{t-j}^{(2)}, \tag{15}$$

$$\mathrm{IVOL}_t = \sigma_t(\epsilon), \tag{16}$$

$$\mathrm{TVOL}_t = \frac{1}{N} \sum_{n=1}^{N} (r_{n,t} - \hat{\mu}_{n,t})^2, \tag{17}$$

$$\mathrm{RELBAS}_t = 365 \left(\frac{f_t^{(1)} - f_t^{(2)}}{M_t^{(2)} - M_t^{(1)}} - \frac{f_t^{(2)} - f_t^{(3)}}{M_t^{(3)} - M_t^{(2)}} \right), \tag{18}$$

$$\mathrm{SKEW}_t = \left[\frac{1}{D} \sum_{d=1}^{D} (r_{d,t} - \hat{\mu}_t)^3 \right] / \hat{v}_t^3, \tag{19}$$

where $f_t^{(i)}$ is the logarithm of the price of the i^{th} nearby futures contract at time t and $M_t^{(i)}$ denotes its time to maturity in days. The return on the nearest and second nearest futures contracts are denoted $r_t^{(1)}$ and $r_t^{(2)}$, respectively, and are computed as in Equation (1). $\sigma_t(\epsilon)$ corresponds to the monthly standard deviation on the residuals of a regression of daily nearest futures returns on a constant and the daily value of the basis (BAS), momentum (MOM), and basis-momentum (BASMOM), estimated in each month t. In Equation (17), $r_{n,t}$ is the return of the nearest futures contract on day n of month t, and $\hat{\mu}_{n,t}$ is the mean of the daily returns in month t. In Equation (19), D is the number of daily returns for the specific commodity in the 12–month window from months t-11 to t, and $\hat{\mu}_t$ ($\hat{v}_t^2$) is the sample mean (variance) of the daily returns over the above 12–month window.

Hedging pressure (HP) is computed as the fraction of long minus short positions over the total number of positions. Speculative pressure (SP) is computed in a similar way by using the positions of the non-commercial traders instead. Positions data are obtained from the Commitment of Traders (CoT) report used in several other studies (e.g., Basu and Miffre, 2013; Fan et al., 2020). It is worth pointing out that the CoT dataset underpinning the computation of the HP and SP variables is only available from 1986 onwards. Accordingly, the sample period associated with these two variables is much shorter than our main sample.

To compute the strategy returns associated with a given signal, we proceed as follows. At the end of each month, we sort all commodities based on the signal. We then buy (sell), in equal weight, the commodities with a higher (lower) than median signal. We hold the positions for 1 month and compute the High-Low portfolio return.

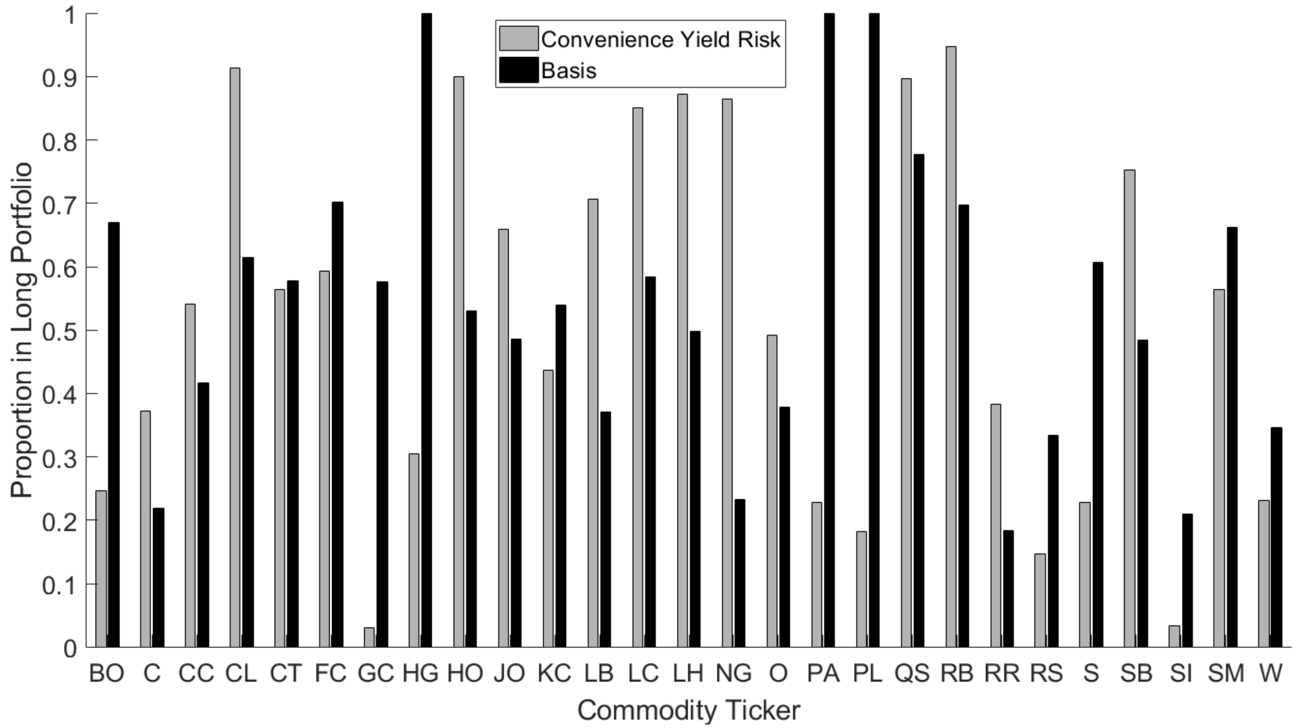

Figure A.1: Relative Frequency of Commodities in the "High" Convenience Yield Risk Portfolio

This figure shows the percentage of months a particular commodity is included in the "High" convenience yield risk portfolio (grey bars) and "High" basis portfolio (black bars). The commodities are sorted on the convenience yield risk (basis) to form two portfolios, a "High" portfolio which includes the commodities with the highest convenience yield risk (basis) and a "Low" portfolios which includes the commodities with the lowest convenience yield risk (basis). The different commodity markets are labeled with their Bloomberg ticker (see Table A.1 of the appendix for details).

Table A.1: Description of the Commodity Futures Data

This table provides details on the commodity futures data. The 27 commodities are divided into 6 sectors [names in first column]. The second and third columns show the name of the commodity and the corresponding Bloomberg ticker. The fourth column reports the exchange on which the contract trades using the following abbreviations: ICE (Intercontinental Exchange), NYMEX (New York Mercantile Exchange), COMEX (Commodity Exchange), CBOT (Chicago Board of Trade), and the CME (Chicago Mercantile Exchange). The penultimate column contains the expiry schedule for each commodity market. The last column reports the contract size.

Sector	Commodity	Ticker	Exchange	Expiry Month	Contract Size
Energy	WTI Crude Oil	CL	NYMEX	Jan-Dec	1,000 Barrels
	Heating Oil	HO	NYMEX	Jan-Dec	42,000 Gallons
	Natural Gas	NG	NYMEX	Jan-Dec	10,000 Million Btu
	Gasoil	QS	NYMEX	Jan-Dec	100 Tonnes
	Gasoline	HU/XB	NYMEX	Jan-Dec	42,000 Gallons
Grains	Corn	C	CBOT	Mar,May,Jul,Sep,Dec	5,000 Bushels
	Oats	O	CBOT	Mar,May,Jul,Sep,Dec	5,000 Bushels
	Rough Rice	RR	CBOT	Jan,Mar,May,Jul,Sep,Nov	2,000 Hundredweights
	Wheat (Chicago)	W	CBOT	Mar,May,Jul,Sep,Dec	5,000 Bushels
Metals	Copper	HG	COMEX	Mar,May,Jul,Sep,Dec	25,000 Pounds
	Gold	GC	COMEX	Feb,Apr,Jun,Aug,Oct,Dec	100 Troy Ounces
	Palladium	PA	NYMEX	Mar,Jun,Sep,Dec	100 Troy Ounces
	Platinum	PL	NYMEX	Jan, Apr, Jul, Oct	50 Troy Ounces
	Silver	SI	COMEX	Mar,May,Jul,Sep,Dec	5,000 Troy Ounces
Livestock	Feeder Cattle	FC	CME	Jan,Mar,Apr,May,Aug,Sep,Oct,Nov	50,000 Pounds
	Lean Hogs	LH	CME	Feb,Apr,May,Jun,Jul,Aug,Oct,Dec	40,000 Pounds
	Live Cattle	LC	CME	Feb,Apr,Jun,Aug,Oct,Dec	40,000 Pounds
Oilseeds	Canola	RS	ICE	Jan,Mar,May,Jul,Nov	20 Metric Tonnes
	Soybeans	S	CBOT	Jan,Mar,May,Jul,Aug,Sep,Nov	5,000 Bushels
	Soybean Meal	SM	CBOT	Jan,Mar,May,Jul,Aug,Sep,Oct,Dec	100 Short Tons
	Soybean Oil	BO	CBOT	Jan,Mar,May,Jul,Aug,Sep,Oct,Dec	60,000 Pounds
Softs	Cotton	CT	ICE	Mar,May,Jul,Oct,Dec	50,000 Pounds
	Lumber	LB	CME	Jan,Mar,May,Jul,Sep,Nov	110,000 Feet
	Cocoa	CC	ICE	Mar,May,Jul,Sep,Dec	10 Metric Tonnes
	Coffee	KC	ICE	Mar,May,Jul,Sep,Dec	37,500 Pounds
	Orange Juice	JO	ICE	Jan,Mar,May,Jul,Sep,Nov	15,000 Pounds
	Sugar	SB	ICE	Mar,May,Jul,Oct	112,000 Pounds

Table A.2: Summary Statistics for First Nearby Returns

This table reports summary statistics for the monthly returns of the first nearby futures of the 27 commodities in our sample. The commodities are grouped in 6 sectors: Energy, Grains, Livestock, Metals, Oilseeds, and Softs. We report the mean (Mean), standard deviation (Std. Dev.), first order autocorrelation coefficient (AR(1)), skewness (Skew), kurtosis (Kurt), and the number of observations (Obs). The mean and standard deviation are annualized and in percentage points. The sample period is from July 1959 to December 2018.

Sector	Commodity	Mean	Std. Dev.	AR(1)	Skew	Kurt	Obs.
Energy	WTI Crude	6.87	32.62	0.19	0.34	5.61	430
	Heating Oil	8.93	30.81	0.11	0.42	4.45	390
	Natural Gas	-7.78	47.83	0.08	0.59	4.45	345
	Gasoil	9.43	30.60	0.19	0.29	4.89	354
	Gasoline	14.26	32.10	0.16	0.40	5.52	385
Grains	Corn	-2.13	23.68	0.00	1.20	9.71	714
	Oats	-0.43	29.01	-0.03	2.22	23.22	712
	Rough Rice	-7.25	25.33	0.01	0.94	7.93	360
	Chicago Wheat	-1.61	25.13	0.05	0.78	6.84	714
Livestock	Feeder Cattle	3.35	16.49	-0.02	-0.37	5.32	565
	Live Cattle	4.71	16.17	-0.01	-0.19	5.17	649
	Lean Hogs	-2.97	23.64	-0.04	-0.18	3.42	393
Metals	Copper	7.42	24.96	0.07	-0.00	5.66	361
	Gold	1.25	18.97	-0.00	0.49	6.35	528
	Palladium	12.12	31.24	-0.01	0.37	6.41	393
	Platinum	4.12	21.68	0.01	-0.02	6.77	393
	Silver	2.34	31.59	0.05	0.58	8.65	528
Oilseeds	Soybean Oil	5.40	28.38	-0.03	1.25	9.20	714
	Canola	-0.78	19.52	-0.00	0.02	5.47	444
	Soybeans	5.18	25.47	0.03	1.45	13.21	712
	Soybean Meal	9.34	28.97	0.05	1.96	18.37	714
Softs	Cotton	2.12	23.46	0.06	0.62	6.17	712
	Lumber	-5.35	27.22	0.06	0.11	3.49	393
	Cocoa	3.03	30.44	0.00	0.65	4.30	712
	Orange Juice	4.92	32.45	-0.04	1.59	11.18	623
	Coffee	4.29	36.41	-0.01	1.21	6.71	557
	Sugar	4.76	41.66	0.17	1.17	6.65	696

Table A.3: Seasonality in the Convenience Yield

This table reports the average convenience yield for each calendar month (columns "Jan" to "Dec"). The last two columns show the R^2 and the p-value from an F-test of the hypothesis that the slope estimates in a regression of monthly convenience yield on twelve monthly dummies are jointly equal to zero. The sample period spans from July 1959 to December 2018. The commodities are grouped in 6 sectors: Energy, Grains, Livestock, Metals, Oilseeds, and Softs.

Sector	Commodity	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	$\mathbf{R^2}$	**F-stat**
Energy	WTI Crude	-1.96	1.34	0.16	0.81	1.07	-0.20	1.17	3.12	-0.84	0.65	6.89	0.32	0.01	0.990
	Heating Oil	-29.64	-27.28	-7.54	3.99	13.39	16.43	17.96	14.66	13.69	12.00	1.49	-39.44	0.15	0.000
	Natural Gas	-67.90	-81.34	14.92	19.06	16.89	10.52	21.40	53.12	58.52	34.58	-48.82	-84.49	0.08	0.004
	Gasoil	-11.82	-7.24	0.46	3.18	11.05	10.26	11.50	3.54	0.08	1.46	-4.02	-17.66	0.10	0.000
	Gasoline	51.28	4.39	-6.82	-15.39	-24.30	-17.07	-86.23	-39.18	-16.79	-9.26	9.02	14.73	0.41	0.000
Grains	Corn	17.02	14.25	13.78	-5.77	-6.86	4.73	6.15	18.49	18.97	18.36	17.37	17.90	0.17	0.000
	Oats	4.47	-4.86	-1.88	4.66	2.56	16.46	17.53	17.03	15.30	14.96	8.15	5.88	0.09	0.000
	Rough Rice	16.83	15.32	16.53	-16.60	-6.68	11.04	13.26	16.95	18.27	17.27	17.64	15.68	0.21	0.000
	Chicago Wheat	1.38	-11.71	-11.78	15.74	16.88	18.43	18.66	15.02	15.07	13.96	1.39	1.69	0.16	0.000
Livestock	Feeder Cattle	7.11	3.01	8.60	1.45	-0.79	-1.00	3.12	10.36	6.36	-0.04	0.89	5.51	0.07	0.000
	Live Cattle	-9.89	-11.74	-4.48	-3.83	5.26	5.95	10.06	9.83	6.40	6.65	8.21	10.39	0.13	0.000
	Lean Hogs	56.22	60.11	-0.86	-13.04	-102.15	-102.05	-19.32	-10.49	19.02	28.57	7.17	12.99	0.63	0.000
Metals	Copper	0.29	-0.20	0.14	0.23	0.44	0.25	0.98	-0.44	1.14	1.95	0.47	-1.21	0.01	0.998
	Gold	9.97	10.11	9.83	9.66	10.19	10.06	10.24	9.99	10.17	9.59	9.94	9.78	0.00	1.000
	Palladium	3.18	3.99	4.50	2.78	4.80	3.80	3.79	4.41	4.27	4.55	4.67	3.65	0.01	0.989
	Platinum	3.62	3.88	4.23	3.86	4.02	4.48	4.11	4.17	4.90	4.23	4.10	4.95	0.01	0.999
	Silver	10.19	10.33	10.53	10.34	10.51	10.59	10.52	10.68	11.24	10.35	10.39	10.16	0.00	1.000
Oilseeds	Soybean Oil	7.99	7.05	6.11	-1.00	0.39	0.72	-8.34	4.34	8.97	4.72	7.25	8.47	0.05	0.000
	Canola	8.04	11.03	11.26	4.32	5.87	13.64	13.64	13.92	14.09	13.17	12.85	7.95	0.10	0.000
	Soybeans	10.63	9.20	9.15	-8.56	-9.00	-50.92	-0.41	12.64	13.72	12.33	11.76	11.10	0.19	0.000
	Soybean Meal	6.62	9.36	9.77	-1.51	-5.44	-29.32	-23.99	4.24	9.24	3.48	5.79	6.40	0.15	0.000
Softs	Cotton	12.30	7.23	8.29	-17.97	-26.86	2.35	6.23	8.17	12.14	11.23	11.23	11.37	0.04	0.004
	Lumber	9.84	6.86	10.83	4.34	5.11	-10.66	-3.51	15.41	24.95	18.56	18.63	8.92	0.17	0.000
	Cocoa	6.59	8.39	6.17	8.70	8.24	7.18	8.08	8.92	7.57	7.24	7.65	7.02	0.00	1.000
	Orange Juice	12.66	9.36	7.72	8.45	7.75	0.74	-0.49	-3.92	-8.67	10.82	12.34	13.97	0.05	0.001
	Coffee	9.76	8.52	7.85	7.70	7.93	5.30	5.52	6.82	7.00	4.60	8.32	7.93	0.00	0.997
	Sugar	2.72	0.81	0.15	7.63	6.82	11.87	11.94	14.47	6.29	4.75	4.04	5.50	0.03	0.033

Table A.4: Summary Statistics for the Volatility of the Convenience Yield

This table reports the summary statistics of the monthly time series of the volatility of the nearest convenience yield, $\sigma_t(y^{(1,2)})$, i.e., the one computed from the prices of the first and second nearby futures contracts (see Equation (3)). The dataset contains 27 commodities divided into 6 sectors: Energy, Grains, Livestock, Metals, Oilseeds, and Softs. We report for each commodity the mean (Mean), standard deviation (Std. Dev.), first order autocorrelation coefficient (AR(1)), skewness (Skew), kurtosis (Kurt), and number of observations (Obs.). The sample period is from July 1959 to December 2018.

Sector	Commodity	Mean	Std. Dev.	AR(1)	Skew	Kurt	Obs.
Energy	WTI Crude	4.73	4.22	0.55	2.51	11.63	430
	Heating Oil	4.08	4.49	0.51	3.93	27.08	390
	Natural Gas	10.65	12.01	0.46	3.04	16.59	345
	Gasoil	3.60	3.26	0.65	2.83	14.46	354
	Gasoline	6.12	4.89	0.32	2.36	10.86	385
Grains	Corn	1.76	1.99	0.48	5.64	51.51	714
	Oats	3.56	2.83	0.41	2.61	13.34	714
	Rough Rice	2.50	3.16	0.48	3.75	20.58	360
	Chicago Wheat	2.10	1.95	0.43	2.90	14.52	714
Livestock	Feeder Cattle	3.61	2.56	0.45	2.07	8.81	563
	Live Cattle	3.47	1.95	0.37	1.61	6.42	649
	Lean Hogs	6.72	4.32	0.32	2.66	13.77	392
Metals	Copper	1.23	1.43	0.70	2.52	10.75	361
	Gold	0.39	1.37	0.16	10.25	128.25	528
	Palladium	0.70	1.23	0.42	7.35	84.17	381
	Platinum	0.62	0.75	0.70	2.50	10.06	393
	Silver	0.35	0.63	0.31	7.30	73.69	528
Oilseeds	Soybean Oil	2.50	3.11	0.63	3.65	21.62	714
	Canola	1.40	0.93	0.32	2.82	15.45	442
	Soybeans	2.09	3.38	0.48	6.26	58.98	714
	Soybean Meal	3.90	5.71	0.49	7.70	91.12	714
Softs	Cotton	2.61	2.29	0.43	2.65	12.87	712
	Lumber	5.11	3.18	0.40	1.98	9.52	390
	Cocoa	1.92	1.74	0.46	3.18	18.63	714
	Orange Juice	2.98	2.22	0.35	2.95	16.41	623
	Coffee	2.52	3.12	0.64	3.88	25.68	557
	Sugar	3.87	2.99	0.37	3.17	21.82	696

Table A.5: Volatility of Convenience Yield across the Term Structure

This table reports the average values of the monthly volatility estimates of the nearest four convenience yields, i.e., $y^{(1,2)}$, $y^{(2,3)}$, $y^{(3,4)}$, *and* $y^{(4,5)}$, *respectively (see also Equation (3)). Our sample includes 27 commodities spanning 6 sectors: Energy, Grains, Livestock, Metals, Oilseeds, and Softs. The sample period is from July 1959 to December 2018. Nearby series with more than 50% missing values are left blank.*

Sector	Commodity	$\sigma(y^{(1,2)})$	$\sigma(y^{(2,3)})$	$\sigma(y^{(3,4)})$	$\sigma(y^{(4,5)})$
Energy	WTI Crude	4.17	2.47	1.80	1.55
	Heating Oil	3.98	2.70	2.05	1.64
	Natural Gas	12.01	10.29	9.94	4.99
	Gasoil	3.04	2.43	2.05	2.44
	Gasoline	4.80	3.12	2.27	2.18
Grains	Corn	2.16	1.21	1.20	1.70
	Oats	3.23	3.09	5.60	6.44
	Rough Rice	3.21	3.08	3.13	4.94
	Chicago Wheat	1.80	2.39	2.38	2.16
Livestock	Feeder Cattle	1.84	1.51	1.49	1.14
	Live Cattle	1.60	1.08	0.89	0.85
	Lean Hogs	4.46	3.38	3.29	2.93
Metals	Copper	1.14	0.79	0.69	0.67
	Gold	0.11	0.09	0.10	0.10
	Palladium	1.14	0.61	0.56	
	Platinum	0.69	0.67	0.62	
	Silver	0.29	0.31	0.20	0.17
Oilseeds	Soybean Oil	1.87	1.74	1.21	1.45
	Canola	1.00	0.83	0.99	1.30
	Soybeans	2.53	2.27	2.21	1.75
	Soybean Meal	4.24	2.75	3.13	2.61
Softs	Cotton	2.31	1.87	1.68	2.14
	Lumber	3.20	2.44	5.99	4.10
	Cocoa	0.91	0.66	0.54	0.52
	Orange Juice	1.97	1.48	1.14	1.36
	Coffee	2.65	1.39	1.00	1.15
	Sugar	2.22	1.76	1.27	1.06

Table A.6: Summary Statistics for Commodity Strategies

This table reports summary statistics for the monthly returns of commodity strategies that are formed based on the following signals: equally-weighted commodity market return, futures basis, momentum, basis-momentum, idiosyncratic volatility, total volatility, skewness, relative basis, speculative pressure, and hedging pressure. At the end of each month, we sort all commodities based on the value of each signal. We then buy (sell), in equal weight, the commodities with a higher (lower) than median signal. We hold the positions for 1 month and compute the High-Low portfolio return. The sample period is from July 1959 to December 2018. We report the mean (Mean) and the corresponding Newey and West (1987) t-stat. in parenthesis (using 6 lags), standard deviation (Std. Dev.), Sharpe ratio (SR), skewness (Skew), and kurtosis (Kurt) for each strategy. The mean and standard deviation are annualized and reported in percentage points.

Commodity	Mean	Std. Dev.	SR	Skew	Kurt
Market	3.93 (1.97)	13.28	0.30	0.61	8.25
Basis	7.20 (3.66)	14.20	0.51	-0.04	4.27
Momentum	9.89 (4.46)	15.57	0.64	0.14	4.70
Basis-Momentum	14.74 (6.65)	14.61	1.01	0.25	6.29
Idiosyncratic Volatility	7.65 (3.69)	15.29	0.50	-0.03	4.53
Total Volatility	2.42 (1.09)	17.65	0.14	1.14	17.11
Skewness	8.05 (4.03)	14.29	0.56	0.48	5.59
Relative Basis	4.37 (2.49)	13.66	0.32	-0.25	5.45
Speculative Pressure	2.99 (1.32)	11.86	0.25	0.44	4.97
Hedging Pressure	4.47 (1.88)	12.43	0.36	0.12	3.51

Table A.7: Alternative Portfolio Construction Approaches

This table reports the returns on long-short portfolios sorted by the CYR signal. The second column focuses on the top and bottom tertiles to construct the long-short CYR portfolio. The third column employs rank-based weights for the commodities in each portfolio. The last column focuses on a 1-month lag between the formation of the portfolio and the investment. The sample consists of 27 commodities covering the period from July 1959 to December 2018. We report annualized monthly returns (in percentage points), t-statistics based on Newey and West (1987) standard errors (computed using a bandwidth of 6) in parentheses, and annualized Sharpe ratios.

	Tertiles	Rank-Weighting	Decision Delay
Av. Return	8.47	8.10	7.30
(t-stat)	(2.91)	(3.02)	(2.68)
Sharpe Ratio	0.44	0.44	0.50

Table A.8: Volatility Regimes

This table analyzes the performance of the CYR strategy over different volatility regimes. For each trading day, we compute the commodity index return as the equal-weighted average of all commodity returns. We then compute the monthly volatility using the daily commodity index returns observed during the month. By following these steps, we obtain a monthly time-series of commodity index return volatility. We then use the median of the time-series of monthly volatility to identify the high and low volatility regimes. For each of these two regimes, we calculate the average return (Mean) and associated t-statistics using Newey and West (1987) standard errors (with 6 lags), standard deviation (Std. Dev.), and Sharpe ratio (SR) of the CYR strategy. The mean and standard deviation are annualized and expressed in percentage points. The sample period is from July 1959 to December 2018.

Regime	Mean	Std. Dev.	SR
High Volatility	9.46 (2.93)	16.50	0.57
Low Volatility	4.41 (1.65)	13.85	0.32

Table A.9: Robustness to Different Samples

This table reports the returns on long-short portfolios formed by sorting on the main convenience yield risk (CYR) measure and excluding all commodities in a specific sector [name in row]. We report annualized monthly returns (in percentage points), and t-statistics based on Newey and West (1987) standard errors (computed using a bandwidth of 6).

	CYR
Energy	7.61 (3.17)
Grains	6.13 (2.03)
Live Stock	8.77 (3.03)
Metals	8.06 (2.90)
Oilseeds	7.42 (2.67)
Softs	8.92 (3.51)

Table A.10: Alternative Formation Periods

This table summarizes the performance of the CYR strategy where the CYR signal is computed using different formation windows. We separately consider the formation periods: 1-Month, 6-Month, 12-Month, and 18-Month. The sample consists of 27 commodities covering the period from July 1959 to December 2018. We report annualized average returns and t-statistics for Newey and West (1987) (computed using a bandwidth of 6) in parentheses. The average return is expressed in percentage point. The last row shows the annualized Sharpe ratio.

Formation Period	1-Month	6-Month	12-Month	18-Month
Av. Return	4.29	5.38	6.93	6.28
(t-stat)	(2.45)	(2.63)	(3.40)	(2.93)
Sharpe Ratio	0.31	0.37	0.46	0.40

Table A.11:
Performance of the Convenience Yield Risk Strategy: Spreading Returns

This table reports the average CYR spreading return with the associated t-statistic (in parentheses) using Newey and West (1987) standard errors (computed using a bandwidth of 6), and the annualized Sharpe ratio for portfolios sorted on convenience yield risk. We sort the 27 commodities by their CYR at the end of each month and form a "High" portfolio containing the commodities associated with a CYR greater than the median CYR and a "Low" portfolio containing the remaining commodities. We also report the average spreading return on the "High-Low" spread portfolio. The commodities in each portfolio are equally-weighted. The sample period is from July 1959 to December 2018.

	High	Low	High–Low
Av. Return	-0.31	-1.12	0.81
(t-stat)	(-0.80)	(-3.94)	(1.99)
Sharpe Ratio	-0.13	-0.61	0.30

Table A.12: Spanning Regressions: Spreading Returns

This table reports the results from spanning regressions of the CYR spreading returns on the spreading returns of an equally-weighted commodity market portfolio (MRKT), and the spreading returns of the strategies based on the basis (BAS), momentum (MOM), basis-momentum (BASMOM), idiosyncratic volatility (IVOL), total volatility (TVOL), skewness (SKEW), relative basis (RELBAS), speculative pressure (SP), and hedging pressure (HP), respectively. The commodity sample period starts in July 1959 and ends in December 2018. The spreading returns are annualized and expressed in percentage points. t-statistics using Newey and West (1987) standard errors (based on a bandwidth of 6) are reported in parentheses below the estimated coefficients.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
α	1.03	0.79	0.82	0.68	0.81	0.69	0.95	0.54	0.07	0.07	0.84
	(2.73)	(1.97)	(2.00)	(1.67)	(2.00)	(1.76)	(2.38)	(1.41)	(0.17)	(0.16)	(2.20)
MRKT	0.03										0.04
	(2.72)										(2.61)
BAS		0.01									-0.00
		(0.37)									(-0.61)
MOM			-0.01								-0.01
			(-0.29)								(-1.61)
BASMOM				0.01							0.01
				(0.71)							(0.70)
IVOL					0.01						0.01
					(1.39)						(0.97)
TVOL						0.01					0.01
						(1.20)					(1.58)
SKEW							0.01				-0.00
							(2.48)				(-0.29)
RELBAS								0.01			0.01
								(3.31)			(0.53)
SP									0.02		
									(1.46)		
HP										0.01	
										(1.18)	
R^2	0.01	0.01	0.00	0.00	0.01	0.01	0.02	0.03	0.01	0.01	0.07
Obs	713	713	713	713	713	713	713	713	395	395	713

Table A.13: Summary Statistics for Transaction Costs

This table reports the summary statistics of the daily transaction cost estimates based on the modeling approach of Szakmary et al. (2010).

$$TC_t^{(i)} = \frac{10 + Tick\_size^{(i)} \times CM^{(i)}}{F_t^{(i)} \times CM^{(i)}} \quad (20)$$

where $TC_t^{(i)}$ is the transaction cost estimate of market i at time t. The transaction cost estimates are expressed in percentage points. $Tick\_size^{(i)}$ is the minimum tick size for commodity i. $CM^{(i)}$ is the contract multiplier for commodity i. $F_t^{(i)}$ is the price of the first nearby futures contract of commodity i at time t. We report for each commodity the mean (Mean), standard deviation (Std. Dev.), skewness (Skew), kurtosis (Kurt), and number of observations (Obs.). The sample period is from July 1959 to December 2018.

Sector	Commodity	Mean	St. Dev	Skew	Kurt	Obs.
Energy	WTI Crude	0.07	0.04	0.40	2.30	430
	Heating Oil	0.03	0.02	0.30	1.85	390
	Natural Gas	0.07	0.03	0.67	3.01	345
	Gasoil	0.24	0.15	0.48	2.16	354
	Gasoline	0.03	0.02	0.30	1.81	385
Grains	Corn	0.09	0.04	0.78	2.49	714
	Oats	0.16	0.08	0.78	2.38	712
	Rough Rice	0.12	0.05	1.21	4.44	360
	Chicago Wheat	0.07	0.03	1.03	3.29	714
Livestock	Feeder Cattle	0.03	0.01	1.35	5.27	565
	Live Cattle	0.04	0.02	1.29	3.74	649
	Lean Hogs	0.04	0.01	0.34	2.58	393
Metals	Copper	0.03	0.02	0.31	1.76	361
	Gold	0.05	0.03	1.46	5.91	528
	Palladium	0.09	0.06	0.68	2.40	393
	Platinum	0.05	0.02	0.14	1.55	393
	Silver	0.10	0.05	-0.10	1.64	528
Oilseeds	Soybean Oil	0.09	0.05	1.07	3.11	714
	Canola	0.16	0.04	0.26	2.30	444
	Soybeans	0.04	0.02	1.07	3.02	712
	Soybean Meal	0.14	0.09	1.23	3.40	714
Softs	Cotton	0.04	0.02	1.12	3.31	712
	Lumber	0.07	0.02	0.60	2.54	393
	Cocoa	0.18	0.12	1.50	5.18	712
	Orange Juice	0.07	0.04	1.39	4.42	623
	Coffee	0.03	0.01	1.09	3.59	557
	Sugar	0.13	0.11	2.11	7.45	696
	Eq. Weighted	0.10	0.06	1.07	2.90	714

Table A.14: Accounting for Transaction Costs

This table analyzes the impact of transaction costs on the performance of the CYR strategy. The column "Raw" focuses on the gross strategy returns. The Columns "TC_1" and "TC_2" focus on the performance of the CYR strategy net of fees modeled as in Equation (8) and (9), respectively. We report the annualized average returns in percentage points. The figures in parentheses indicate the Newey and West (1987) t-statistic computed using a window of 6. The last row shows the annualized Sharpe ratio after accounting for transaction costs. The sample period is from July 1959 to December 2018.

	Raw	TC_1	TC_2
Av. Return	6.94	6.88	6.71
(t-stat)	(3.36)	(3.34)	(3.25)
Sharpe Ratio	0.46	0.46	0.45