Scarcity risk, liquidity provision and risk premia in commodity markets

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Abstract

The contribution of this paper to the literature is threefold. First, I revisit the cost of carry model and propose a decomposition of the futures basis that disentangles the seasonality premium from the scarcity premium. I show that the effect on the convenience yield of expected seasonal shocks are priced in the futures curve while unexpected shocks to inventories beyond those transitory dynamics carry predictive power. The second contribution of this paper is to characterize the liquidity provision premium under scarcity risk. Liquidity providers have been rewarded for ensuring the well-functioning of markets and earn positive returns that are both economically and statistically highly significant. This premium originates from underreaction in the neighborhood of the scarcity risk and more than compensates the risks born. Finally, this paper revisits the main commodity market anomalies in the presence of seasonality and unexpected supply and demand shocks. I find that the level of the scarcity risk premium is most informative for both outright and relative opportunities along the curve. The lack of empirical evidence for many factors comes in stark contrast with earlier literature findings. I propose a four factors portfolio to harvest the risk premia in the cross-section of commodity futures' curves.

Keywords: Commodities, theory of storage, seasonality, scarcity, risk premium, hedging, liquidity provision, under-reaction, market anomalies, factors.

The cost-of-carry relationship is the corner stone of the theory of storage. It assumes the difference between the futures and spot prices, i.e. the futures basis, can be explained by the interest foregone when buying commodities in the physical market, the associated storage costs and a convenience yield. The latter is defined as a benefit that accrues to the commodity holder resulting from the potential productive value of his inventory. This value of physical ownership reflects market expectations about the future availability of a commodity. More importantly, the future basis has been found to be informative about futures risk premia.

As production and demand seasonality can have a large influence on the anticipations about the future state of inventories, this paper aims at shedding light on the origin of this predictability by disentangling various expectations embedded in the basis. A convenience yield decomposition is proposed to dissociate known seasonal supply and demand imbalances from abnormal shocks above and beyond those transitory dynamics. Agents form expectations about the impact of inventories' seasonality on the basis (henceforth the seasonality premium) and adjust their conditional expectations as new information arrives. These marginal changes in expectations about unanticipated shocks to supply and demand capture the risk of scarcity (henceforth the scarcity premium) and the non-linearities in the futures basis.

The first contribution of this paper is to show that the scarcity premium carries all the predictive power embedded in the futures basis. The seasonality premium is priced-in while the other basis components, i.e. the foregone interest and the net cost of storage, have no information content. Those findings are robust to the introduction of commodity sectors and seasons as control variables.

To better understand the origin of this forecasting power, I investigate two competing but not mutually exclusive hypotheses. The first one postulates that the presence of recurring unexpected shocks could be the source of the observed return predictability, but the absence of significant autocorrelation coefficient for the change in the scarcity risk premium leads me to reject this hypothesis. The second hypothesis argues that the slow diffusion of information and market participants underreaction to new information are the key drivers. Consistent with this hypothesis I provide evidence that the scarcity risk premium is associated with highly significant excess return above the market for a holding horizon up to three months, along the whole futures curve, for both positive and negative premia.

As the probability of stock-out increases, the net hedging demand rises. On the one hand, commodity consumers need to hedge out the scarcity risk by buying spot and storing the commodity or by taking long futures positions with delivery at the time of likely scarcity. On the other hand, producers would benefit from unwinding their hedges or taking outright long commodity exposures when inventory levels are low and eroding.[1] At the same time, other informed market participants, e.g. speculators, know about the predictive power embed-

[1]Hirshleifer (1991) refutes the general pre-conception of a short hedging pressure resulting from producers simply willing to hedge their bottom line volatility. He argues that when demand shocks are arising from changes in aggregate wealth, the optimal hedging policy of producers with non-stochastic output might be to remain unhedged or even to take a long hedge position.

ded in the basis. This raises the question of who might be a willing counterparty to the hedging and speculative demand in the presence of scarcity risk.

The second contribution of this paper is to shed light on the motivations that drive liquidity provision under such conditions and the resulting risk exposures. More specifically I characterize the liquidity provision premium and investigate empirically whether market makers have been rewarded for ensuring the well-functioning of markets, i.e. for facilitating the needs of hedgers as well as the objectives of speculators.

Assuming pure liquidity providers hold no speculative positions and hedge out any spot risk, by being structurally short the scarcity risk premium, they carry a negative skewness exposure. They are thus negatively exposed to the non-linearity in spot prices resulting from an increasing likelihood of stockout. Market makers are utility maximizing agents such that a short skewness exposure might deter natural liquidity providers in the absence of a positive expected return.

The liquidity providing trade earns positive returns that are both economically and statistically highly significant, more than compensating the risks born. Those findings are consistent when conditioned on the sign of the scarcity premium, across sectors and seasons. The results are persistent through time and robust to the portfolio construction methodology. An additional important finding is that while the premium earned by liquidity providers is positive, it does not erode the hedging benefits which are still substantial in the presence of a stockout risk.

An empirical analysis of the futures curve dynamics provides strong support for the hypothesis that this risk premium originates from the local underreaction in the neighbourhood of the event risk. I advocate that market participants are subject to a framing bias whereby they are not able to extrapolate the implications of the risk of stockout. This leads hedging and liquidity demand to be primarily concentrated in the seasonal contract where the risk is located and results in the mispricing of both the risk that the inventory depletion happens at a faster rate than anticipated as well as the risk that inventory imbalances might resorb at a lower speed than expected due to the slow adjustment of supply. This hypothesis is consistent with the long value exposure that liquidity providers exhibit and confirms their role as arbitrageurs.

The literature on commodity markets abounds with supportive evidence on various market anomalies. Fundamental and behavioral explanations have been brought forward to explain the existence of those risk premia. The third contribution of this paper is to revisit the main commodity market anomalies in the presence of seasonality and unexpected supply and demand shocks above and beyond those transitory dynamics. More specifically I investigate whether the seasonal and scarcity premia as well as the liquidity provision premium are related to some of the most documented risk factors in the literature, most notably the original futures basis and other correlated measures capturing price pressure resulting from inventory imbalances (e.g. price and basis momentum), as well as risk related factors (e.g. volatility and skewness risk premia). The objective is to contribute to the understanding of risk factors influencing the pricing of commodity futures.

To address the specificities of commodity markets, this paper introduces a novel portfolio formation methodology. First, in order to avoid seasonal distortions that might be associated with the active contracts maturing in different months across commodities, I propose an alternative approach that controls for seasons by sorting on contracts with the same delivery month. By using all available contracts along the futures curve maturing within a year, this approach forms quintile portfolios for each season. This substantial expansion of the sample size offers the additional benefit of an increase in power for testing the statistical significance of factors. Second, to control for the large cross-sectional dispersion and timeseries variation in risk across commodity markets, I propose to equally weight risk-targeted futures contracts at an arbitrary 10% volatility level. To guarantee that the top-minus-bottom portfolio mazimixes its factor exposure given the chosen weighting scheme, characteristics are adjusted by the underlying commodity risk before being ranked and allocated to sorting portfolios. The results are robust to those methodological choices.

Interested in the identification of factor premia in the cross-section of the whole futures curves, this paper investigates both outright and relative opportunities. The results confirm that the scarcity risk premium distilled from the cost-of-carry relationship is the sole risk premium embedded in the basis. More importantly, the key result from this paper is that the level in the scarcity risk premium, as well as their differences for curve positions, span most of the factors considered in the cross-section of both outright and spread trades. They all have a statistically significant alpha with a t-statistic well above the Harvey et al. (2016) cutoff. Only the value factor in the cross-section of outright trades remains unexplained. Those findings are consistent across the various robustness checks performed.

Another important result is that among the non-exhaustive set of factors considered for the cross-section of outright trades, none earns statistically significant returns, to the exception of basis momentum which is spanned by the scarcity risk premium. The empirical evidence put forward in this paper thus comes in stark contrast with earlier literature findings. Those findings raise robustness concerns and while further investigation is warranted, it is outside the scope of this paper. I leave for future research the objective to analyze whether those weak results originate from sensitivities to methodological choices or whether they are the reflection of false positives.

To broadly harvest risk premia in the cross-section of commodity markets, I propose a four factors portfolio combining the scarcity risk premium with the value factor in the cross-section of outright characteristics, as well as the differential in the level of the scarcity risk premium with the liquidity providing premia in the cross-section of relative characteristics along the futures curves. Following the literature, I form an equal volatility-weighted portfolio combining all four factors. The risk-targeting of individual long-short factor portfolios is justified by the heterogeneity in the risk profiles. This combination of outright and relative characteristic premia portfolios adds value thanks to their close to zero correlation. The four factors portfolio earns economically and statistically highly significant gross and net returns.

Limits to arbitrage heavily weights on the ability to harvest relative opportunities along the futures curves. After accounting for transaction costs, none of the selected factors are statistically significant to the exception of the scarcity risk premium and the loss in significance outweights the diversification benefits.

This paper is organized as follows. Section 1 provides a review of the literature on the theory of storage and on the seasonality in commodity markets. It proposes a decomposition of the futures basis that disentangles expected seasonal shocks from unexpected shocks to inventories. The data and methodologies are then presented before discussing the factors driving the futures premia in the presence of a seasonal and scarcity premia. Section 2 analyzes the provision of liquidity under scarcity risk. The last section reviews the performance of commodity market anomalies in the context of the various premia embedded in the futures basis. Finally, I summarize the main results documented in this paper and discuss future avenues of research.

1 Scarcity Risk

The cost-of-carry relationship describes the no-arbitrage condition between the spot and the futures price and defines the futures basis. In commodity markets the traditional defintion is augmented by a term very specific to perishable goods, the convenience yield. This value of physical ownership is the corner stone of the theory of storage and reflects market expectations about the future availability of a commodity. More importantly, the future basis has been found to be informative about futures risk premia. As production and demand seasonality can have a large influence on the anticipations about the future state of inventories, this paper aims at shedding light on the origin of this predictability by disentangling various expectations embedded in the basis.

1.1 Literature review

1.1.1 Theory of storage

The theory of storage which finds its foundation in the work of Kaldor (1939) and Working (1948) has been largely documented in the literature on commodity markets. Its corner stone, the cost-of-carry relationship, assumes the difference between futures prices and spot prices can be explained by the interest foregone when buying commodities in the physical market, the associated storage costs and a convenience yield. The latter is defined as a benefit that accrues to the commodity holder resulting from the potential productive value of this inventory. Various model specification have been proposed in the literature to define this cost-of-carry relationship. Fama and French (1987) consider a model with fixed marginal storage cost and convenience yield. Szymanowska et al. (2014) propose an alternative definition with proportional storage costs that accrues per period.

$$F_t^{(n)}=S_t\left(1+RF_t^{(n)}\right)^n\left(1+U_t^{(n)}\right)^n-C_{t+n}$$

$F_t^{(n)}$ is the futures price at time t expiring in n-periods and S_t is the spot price at time t. $RF_t^{(n)}$ is the per-period risk-free rate at time t with maturity $t+n$ and known at t. $U_t^{(n)}$ is the per-period physical storage costs, for storing commodities over n periods, expressed as a percentage of the spot price and known at t. Finally, the convenience yield C_{t+n} is defined as a cash payment occurring at time $t+n$ and is also known in t.

The convenience yield can be interpreted as the net income, valued at time t, that the physical holder requires to sell his inventory at time $t+n$ at the price $F_t^{(n)}$, once he has been compensated for the interest foregone and for the storage costs he is facing. Likewise, the convenience yield represents the net amount the futures investor is willing pay, beyond the current spot price S_t, i.e. the interest and storage costs compensation required by the commodity seller, in exchange for settling the purchase of the physical commodity at a price $F_t^{(n)}$. As such the convenience yield is foremost an implied quantity that rules out any arbitrage opportunity in the cost-of-carry model and describes the current equilibrium in futures markets.

A related concept is the futures basis which ties the current futures price $F_t^{(n)}$ maturing in n periods to the current spot price S_t and summarizes the cost-of-carry relationship. The futures basis has also been coined the futures carry or roll-yield in the literature on commodities and is similar to other asset classes carry definition.[2] The below equation defines the n-period log or percentage basis $y_t^{(n)}$, i.e. the per-period futures carry for maturity n.

$$F_t^{(n)}=S_t \exp\left\{y_t^{(n)}\times n\right\}$$

Accordingly, the basis is a reflection of the foregone interest, the storage costs and the convenience yield and can be directly estimated from observed futures and spot prices.

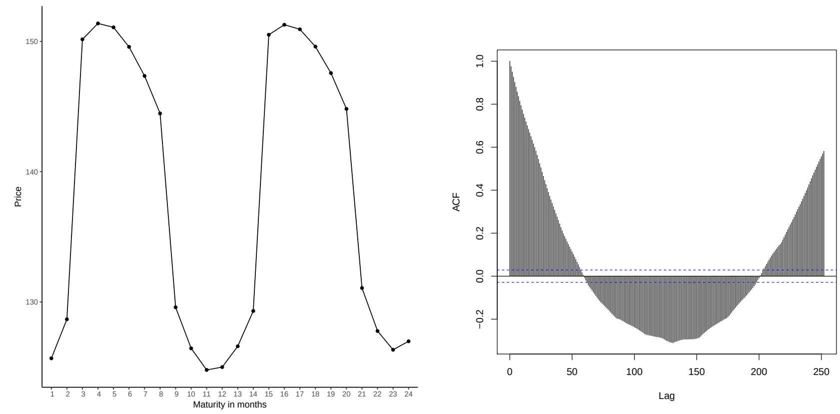
$$y_t^{(n)}=\frac{1}{n}\ln\left\{\left(1+RF_t^{(n)}\right)^n\left(1+U_t^{(n)}\right)^n-\frac{C_{t+n}}{S_t}\right\}=\frac{1}{n}\ln\left\{\frac{F_t^{(n)}}{S_t}\right\}$$

A large part of the literature on the theory of storage has focused on trying to model the dynamics of supply and demand that could explain the empirical distribution of commodity prices. Most commodities display non-normal distributions with high positive skewness and kurtosis, price jumps, non-linearities in prices and in conditional variance, as well as autocorrelation. The main hypothesis put forward to explain the behavior of prices are the inelasticity of demand in the presence of supply shocks with a non-linear functional form, the slow adjustment of supply and the lower boundaries on the level of inventories.

The impossibility to carry negative inventories plays a crucial role in the model of storage dynamics by Deaton and Laroque (1992) as it introduces the non-linearity able to characterize both the observed price jumps and conditional variance. Routledge et al. (2000) propose an equilibrium model for the commodity forward curve in which the non-negativity constraint on inventory levels introduces an immediate consumption timing option in spot prices. The value of this option fluctuates with inventories and transitory shocks to supply and demand.

Gorton et al. (2013) provide the first comprehensive study of the relationship between physical inventories and commodity futures. They show that the

[2] Koijen et al. (2018) provide evidence of the presence of a carry factor across multiple asset classes.



(a) Gasoline RBOB futures prices

(b) Lean Hogs futures basis

Figure 1: Illustration of seasonality in commodity contracts prices and futures basis

shape of the futures curves is associated with the level of inventories and that this relationship becomes highly non-linear as the risk of a stock-out increases. This confirms the model predictions of Routledge et al. (2000) in which the elasticity of the convenience yield to changes in inventory levels is a decreasing function of inventory levels. Hevia et al. (2018) find that the non-linearity between inventories and commodity prices is negatively related to the maturity of the futures contract.

1.1.2 Seasonality

Seasonality plays an important role in the theory of storage as both production and demand can exhibit seasonal patterns that impact inventories. The resulting inventory seasonality should influence directly the convenience yield embedded in the basis and thus both the futures price and its carry. Figure 1 illustrates the presence of seasonality in both commodity futures prices as well as in the futures basis. Panel a of Figure 1plots the futures curve of the Gasoline RBOB contract on 2016-01-05. Panel b of Figure 1 shows the autocorrelation coefficients of the futures basis in excess of the foregone interest for Lean Hogs futures contracts over 252 daily lags.

Finding support in the theory of storage and in the work of Brennan (1958) and Telser (1958) on the relationship between the convenience yield and the level of physical inventories, Fama and French (1987) test for the presence of seasonal variation in the basis using seasonal dummies. They find reliable evidence of seasonality in some agricultural and animal commodities but none in metals. Moreover, they provide evidence that the basis has forecasting power for future spot changes of seasonal commodities. More recently Brooks et al. (2013) have confirmed those findings using a larger sample size and a broader universe of commodities. They provide additional robustness checks on the presence of seasonality in the basis and show that the forecasting power of the basis cannot be related to the magnitude of the seasonal patterns a commodity exhibits.

Fama and French (1987) argue that for commodities that exhibit seasonality in supply or demand, the predictability of future spot variation should be increasing in storage costs. Indeed, high costs should deter the build-up of inventories whose main function is to smooth demand and supply imbalances. The presence of forecasting power for some of the perishable commodities (i.e. with high storage costs) and its absence for metals should support this hypothesis.

French (1986) proposes a two-period model of production, consumption, and storage to describe the relation between the expected seasonal variation in spot prices, the convenience yield as well as the underlying seasonality of demand and supply. Intuitively, in this model, the sensitivity of the convenience yield to the level of inventories will influence how pronounced the seasonal patterns in spot prices are. Moreover, the elasticity of the convenience yield to changes in inventory levels is a decreasing function of inventory levels.

Following the Fama and French studies, a large strand of the literature has focused on incorporating seasonality in the modeling of the futures curve dynamics. A number of publications have proposed multi-factor state-space model representations under no-arbitrage conditions and constant risk premium, which include seasonal terms to model seasonal variations both in spot prices and volatilities. Among those, Sørensen (2002) introduces a deterministic seasonal component in the pricing of futures. He prefers as an alternative to the standard dummy variable estimation of the deterministic component an evaluation through a linear combination of trigonometric functions, following the approach of Hannan et al. (1970).

Next to the deterministic seasonal component present in spot prices, Geman and Nguyen (2005) incorporates in the dynamics of the deseasonalized stochastic component of the spot price a deterministic term to model the seasonal variation observed in the volatility of commodity futures. This follows from Deaton and Laroque (1992) who document that the conditional variance of commodity prices is increasing in the level of prices. If spot price increases are driven by seasonal variations in the level of inventories, then it is likely that the coincident volatility spikes originate from the seasonality observed in physical inventories.

Both papers share a limitation when it comes to the estimation of the seasonal component. More specifically, the later is function of the estimation date rather than of the maturity of the contract. Borovkova and Geman (2006) tackle this issue and consider a cost-of-carry model with a deterministic seasonal premium within a stochastic convenience yield. By relying on an average futures price along the curve, this approach does not disentangle the interest foregone from the seasonal component in the estimation.

More recently Hevia et al. (2018) develop a multi-factor affine model of commodity futures with stochastic seasonal fluctuations. In their nine factor approach, the seasonal shocks are driven by two unobserved factors which only explain marginally the observed risk premia but still are non-negligible. Most of the risk premia originate from the spot factor and the three factors (i.e. level, slope, curvature) describing the cost-of-carry term structure. Interest rate factors' influence increases with the level of interest rate. Finally, the authors reveal the importance of allowing for time variation in the estimation of the seasonal component to match the time-variation of seasonal patterns observed in inventories. More importantly this helps to avoid attributing erroneously those dynamics to other factors. The presence of non-linearities between inventories and the net convenience yield supports the theory of storage.

This paper differs from this strand of the literature in that it focuses solely on the identification of a seasonal risk premium within the futures basis rather than the modeling the futures curve dynamics. In that sense, it does not impose any structure neither on the forward curve nor on the spot or futures price dynamics, beyond the cost-of-carry relationship. Its contribution to the literature on seasonality within commodity markets is twofold. First, this paper addresses some of the concerns noted above on the estimation of the seasonal premium. More specifically, we consider the delivery month of futures contracts to define seasons and exclude the foregone interest from the estimation. This allows one to clearly exclude any term premium that would originate from the interest rate compensation. Moreover, using all contracts along the futures curve provides robust estimates of the seasonal premium per commodity.

Another strand of literature addresses the presence of seasonality within general equilibrium models. Most notably, Hirshleifer (1991) investigates the hedging decision with sequential arrival of information and agents maximizing utility derived from a multi-good consumption. Contrary to most partial equilibrium models, the futures price is here a martingale.[3] He shows that the optimal hedging policy is affected by amongst others, the correlation of the producer's output with the aggregate, the relative sensitivity of his production to the environment versus other producers and the demand price elasticity. In this setup, the sequential arrival of information resolves uncertainty and defines the optimal hedging policy of producers. This in turn drives the seasonal patterns observed in commodity futures markets. Interestingly, Hirshleifer refutes the general pre-conception of a short hedging pressure resulting from producers willing to hedge their bottom line volatility. He argues for example that when demand shocks are arising from changes in aggregate wealth, the optimal hedging policy of producers with non-stochastic output might be to remain unhedged or even to take a long hedge position.

Finally, a more recent strand of literature has focused on providing evidence of seasonality in returns across asset classes and of the profitability of the strategies aiming at exploiting these return dynamics.

Keloharju et al. (2016) document the presence of seasonality in returns across various stock portfolios and factors as well as in commodities using same month past returns as predictor. The authors investigate the source of the seasonality observed at the stock level. They suggest it could either emanate from the underlying risk factors' seasonality, thus having a systematic origin, or resides within each individual security, being therefore essentially of idiosyncratic nature. An alternative explanation to the recurrent variation in securities returns is that seasonality is merely the result of serial-correlation in innovations. Within stock markets, the authors find supportive evidence for the hypothesis that seasonality at the stock level is induced by their exposure to the underlying risk factors

[3] This is based on the assumption of additively separable preferences, complete markets and non-stochastic endowment of the numeraire.

own seasonality. Finally, they show that return-based seasonal strategies are economically significant, cannot be explained by exposure to macroeconomic risks and are resilient to investors sentiment.

This study adds to this literature by investigating the systematic nature of returns seasonality in commodity markets. Moreover, its main contribution is to characterize and quantify the the risk premium attached to seasonality while dissociating it from the documented return-based seasonal strategies.

1.2 Supply and demand expectations

Seasonality plays an important role in the theory of storage as both production and demand can exhibit seasonal patterns that impact inventories. The resulting inventory seasonality influences directly the convenience yield embedded in the basis and thus both the futures price and its carry. It is only fair to assume that agents and market participants have expectations about the seasonal impact on the basis resulting from seasonality in inventories. Without any information on the future state of supply and demand, they can form priors based on the information available to them at any point in time, i.e the current filtration. As new information arrives agents adjust their conditional expectations away from their original prior to account for the anticipated marginal change in supply and demand imbalance. These adjustments in expectations for "unexpected" shocks to inventories characterize the scarcity risk. In order to differentiate the seasonality premium from the scarcity premium, I propose in this section a decomposition of the futures basis in excess of the long-run futures cost-of-carry that allows to disentangle the effect on the convenience yield of expected seasonal shocks versus unexpected shocks to inventories.

1.2.1 Definitions

Let us define the convenience yield C_{t+n} with Z_{t+n} the seasonal impact on the basis resulting from seasonality in inventories and X_{t+n} the residual convenience yield in excess of the seasonal basis contribution. This decomposition allows to disentangle the effect on the convenience yield of expected seasonal shocks versus unexpected shocks to inventories.

$$C_{t+n}=Z_{t+n}+X_{t+n}$$

Here Z_{t+n} can be interpreted as the premium futures investors are willing to pay at time $t+n$ respectively to buy commodities at a forward date in the presence of known transitory supply and demand imbalances. When inventories are expected to be low, commodity holders value the future productive capacity of their current inventory and are requiring a premium to sell their inventory forward (i.e. a negative Z_{t+n}). When inventories are expected to be high, the future productive value of inventories diminishes and commodity holders are willing to offer their current stock at a forward discount (i.e. a positive Z_{t+n}).

The residual convenience yield X_{t+n} arises from unexpected supply and demand imbalances. Unexpected imbalances are here understood as the expectations given the current set of information on future risks beyond "normal" seasonal expectations Z_{t+n}. X_{t+n} defines the scarcity risk premium and captures the non-linearities observed in the basis[4].

I assume that agents learn about seasonal patterns over time. They have the ability to forecast temporary supply and demand imbalances based on their knowledge about the production and demand cycles or simply by evaluating their impact on the futures basis. Assuming a m periods seasonality cycle, the expectation conditional on information up to time t of the seasonal Z_{t+n} is thus equal to last year same period seasonal convenience yield. It is a martingale.

$$E_t[Z_{t+n}]=Z_{t+n-m_n^+}$$

$$m_n^+=m\times\lceil \tfrac{n}{m}\rceil$$

Here m_n^+ defines the number of complete seasonal cycles we need to look backward in order to obtain the last observable seasonal convenience yield with the same seasonal period as time $t+n$. The notation $\lceil i\rceil$ describes the largest integer not less than i. It is assumed that the observations have the same frequency as the seasonal periodicity.

1.2.2 Basis decomposition

The basis can be further decomposed to incorporate this distinction between the expected seasonal convenience yield and the unexpected residual convenience yield. In the rest of the paper log prices will be denoted using lower cases.

$$\begin{aligned}
y_t^{(n)} &= \tfrac{1}{n}\ln\left\{\left(1+RF_t^{(n)}\right)^n\left(1+U_t^{(n)}\right)^n-\tfrac{C_{t+n}}{S_t}\right\}\\
&= \tfrac{1}{n}\ln\left\{\left(1+RF_t^{(n)}\right)^n\left(1+U_t^{(n)}\right)^n\left(1-\frac{Z_{t+n}+X_{t+n}}{S_t\left(1+RF_t^{(n)}\right)^n\left(1+U_t^{(n)}\right)^n}\right)\right\}\\
&= rf_t^{(n)}+u_t^{(n)}+\tfrac{1}{n}\ln\left\{1-\frac{Z_{t+n}+X_{t+n}}{S_t\left(1+RF_t^{(n)}\right)^n\left(1+U_t^{(n)}\right)^n}\right\}
\end{aligned}$$

The last term of the equation can be log-linearized following the approach used by Campbell and Shiller (1988). I thus proceed to a first-order Taylor series expansion around the long-run mean of both components of the convenience yield, respectively $\bar{Z}$ and $\bar{X}$.

[4] Routledge et al. (2000) propose an equilibrium model of commodity forward curve in which the non-negativity constraint on inventory levels introduces an immediate consumption timing option in spot prices. The value of this option fluctuates with inventories and transitory shocks to supply and demand. Gorton et al. (2013) provide the first comprehensive study of the relationship between physical inventories and commodity futures. They show that the shape of the futures curves is associated with the level of inventories and that this relationship becomes highly non-linear as the risk of a stock-out increases. This confirms the model predictions of Routledge et al. (2000) in which the elasticity of the convenience yield to changes in inventory levels is a decreasing function of inventory levels. Also, the authors document that both the basis and the momentum factors are loading on commodities with current low physical inventories. Both risk premia are thus a compensation for bearing the risk of further deterioration in inventory levels.

$$\ln\left\{1-\frac{Z_{t+n}+X_{t+n}}{S_t\left(1+RF_t^{(n)}\right)^n\left(1+U_t^{(n)}\right)^n}\right\} \simeq \ln\left\{1-\frac{\bar{Z}+\bar{X}}{S_t\left(1+RF_t^{(n)}\right)^n\left(1+U_t^{(n)}\right)^n}\right\} + \frac{(Z_{t+n}-\bar{Z})+(X_{t+n}-\bar{X})}{S_t\left(1+RF_t^{(n)}\right)^n\left(1+U_t^{(n)}\right)^n-(Z_{t+n}+X_{t+n})}$$

Furthermore, I impose a mild distributional restriction on the convenience yield by assuming its unconditional mean is zero. This assumption is easily met by detrending the convenience yield and requiring that any structural benefit the commodity owner might earn from physically holding inventories is reflected in a reduced net storage cost $U_t'^{(n)}$.

$$E[C]=0$$

Given the mean across seasons of an additive seasonal component is zero for a detrended series, the unconditional mean of Z is null.

$$E_m[Z]=\sum_{i=1}^{m} Z_i=0$$

$$E[Z]=0$$

As a result, the unconditional mean of the residual convenience yield is also zero. Thus X_{t+n} captures the convenience yield resulting from transitory inventory imbalances arising from unexpected shocks in supply and demand.

$$E[X]=0$$

Assuming the long-run means $\bar{Z}$ and $\bar{X}$ equal their respective unconditional mean, the log-linearization now simplifies to a sum of two terms, which are simply the proportions of the futures price that can be explained by respectively the seasonal component and the residual convenience yield.

$$\ln\left\{1-\frac{Z_{t+n}+X_{t+n}}{S_t\left(1+RF_t^{(n)}\right)^n\left(1+U_t'^{(n)}\right)^n}\right\}\simeq-\frac{Z_{t+n}}{F_t^{(n)}}-\frac{X_{t+n}}{F_t^{(n)}}$$

The per-period log-basis now simplifies to a linear equation with four terms capturing the foregone interests, the net storage costs, the seasonal premium and the residual convenience yield in excess of this seasonal component, i.e the scarcity premium.

$$\begin{aligned} y_t^{(n)} &\simeq rf_t^{(n)}+u_t'^{(n)}-\frac{1}{n}\left(\frac{Z_{t+n-m_n^+}}{F_t^{(n)}}+\frac{X_{t+n}}{F_t^{(n)}}\right) \\ y_t^{(n)} &= rf_t^{(n)}+u_t'^{(n)}-\zeta_t^{(n)}-\chi_t^{(n)} \end{aligned}$$

Here $\zeta_t^{(n)}$ defines the per-period proportion of the futures prices explained by the seasonal premium. Similarly $\chi_t^{(n)}$ represents the per-period proportion of the futures prices explained by the scarcity premium.

$$\begin{aligned} \zeta_t^{(n)} &= \frac{1}{n}\left(\frac{Z_{t+n-m_n^+}}{F_t^{(n)}}\right) \\ \chi_t^{(n)} &= \frac{1}{n}\left(\frac{X_{t+n}}{F_t^{(n)}}\right) \end{aligned}$$

The foregone interests and the net storage costs can be grouped together to define the long-run cost-of-carry $\Upsilon_t^{(n)}$. The time and futures curve variation observed in $\Upsilon_t^{(n)}$ result solely from the dynamics of interest rates and the shape of the yield curve as the net storage costs are assumed constant across the curve and equal to their full sample conditional mean[5].

$$\Upsilon_t^{(n)} = rf_t^{(n)} + u_t'^{(n)}$$

The basis can thus be expressed as a function long-run cost-of-carry, a seasonal premium and a scarcity premium.

$$y_t^{(n)} = \Upsilon_t^{(n)} - \zeta_t^{(n)} - \chi_t^{(n)}$$

Ultimately, we can incorporate this basis decomposition in the cost-of-carry relationship with the futures price being defined as follows.

$$F_t^{(n)} = S_t \exp\left\{ y_t^{(n)} \times n \right\}$$
$$F_t^{(n)} = S_t \exp\left\{ \left(\Upsilon_t^{(n)} - \zeta_t^{(n)} - \chi_t^{(n)} \right) \times n \right\}$$

1.3 Data and methodology

1.3.1 Futures data

The data set covers 29 commodity futures contracts eligible for inclusion in the Bloomberg Commodity Index over a period going from 1983-05-31 to 2018-08-21. It contains prices, open interest and volumes as well as various static information about the contract (e.g. the maturity date, contract size or minimum tick size). The sector classification follows the Bloomberg sector indices. The data is obtained directly from the CME or ICE database or via Datastream for LME contracts. Data on short interest rates are sourced from the FRED database. I use USD Libor rates for maturities up to 1 year and interpolate with swap rates for longer maturities. Data for Libor rates and swap rates are available starting respectively on 1986-01-09 and 2000-07-03. Table A1 in the appendix provides an overview of the different commodity markets, their sector classification, as well as the year of the first futures contract.

Based on the set of available futures contracts, I create generic futures curves which allows to roll the futures contracts according to the desired rolling scheme. This allows to align the measurement of the signal based on the futures curve (e.g. the basis) with the desired implementation. For the purpose of this paper, futures contracts are rolled one day before the last trade date, defined as the minimum of the first notice date, the last tradeable date and the last delivery date in order to accommodate varying contract specifications across commodity futures.

This implementation differs from the traditional approach followed in the literature which rolls futures contracts on the last day of the previous month.

[5]This assumption can be relaxed to incorporate non-seasonal dynamics in the net costs of storage and any potential structural change. Any seasonal variation in the storage costs is in this model captured by the seasonal premium.

This allows one to capture the dynamics of the scarcity risk up until it materializes. Indeed for contracts expiring close to month-end rolling at the beginning of the month would mean forgoing potentially valuable information about season specific expectations of demand and supply imbalances.

Some commodities exhibit a non-regular contract cycle such that there might not be an outstanding contract for each season (e.g. there is only five monthly contracts for wheat futures with delivery in March, May, July, September and December). To complement the set of available contracts, I create synthetic contracts to increase the breadth of the strategy. Upon data availability, these contracts are constructed by simple linear interpolation between a near and a far contract to obtain the desired maturity.

The futures exchange can issue two types of contract. On the one hand, most listed futures are issued for a subset of regular delivery months and constitute the contract cycle. On the other hand, the exchange can also issue serial contracts, which are "off" cycle. While the liquidity might be limited on serial contracts, it is difficult to identify those contracts through time as the choice by the exchanges of maturities up for issuance changes through time. Instead, to control for illiquidity, we handle the problem at the core and clean the data for stale pricing and impose a minimum number of pricing observations (set arbitrarily to 10).

1.3.2 Basis and components estimation

In the absence of reliable spot data and following the literature, the basis is measured between every consecutive contract along the futures curve starting from the first active contract and is expressed in percent of the front contract price adjusted for the number of days until delivery in order to allow for a fair comparison across contracts with different maturities. Note that the term premium is defined from the second nearest contract and beyond this maturity.

The seasonal convenience yield is estimated by regression of a detrended log-basis in excess of the foregone interest on seasonal dummies. Note that given the non-linearities observed in the basis, I use a robust regression methodology and the median is preferred to the mean for detrending.

$$y_t^{(n)} - rf_t^{(n)} - u_t'^{(n)} = \sum_{i=1}^{m} \beta_{t,i} d_i + \epsilon_t$$

The restriction imposed on the unconditional mean of the convenience yield is enforced by setting the net storage cost $u_t'^{(n)}$ equal to the median of the log-basis in excess of the foregone interests $\tilde{v}^{(n)}$.

$$\begin{aligned} u_t'^{(n)} &= \tilde{v}^{(n)} \\ v_t^{(n)} &= y_t^{(n)} - rf_t^{(n)} \end{aligned}$$

The long-run cost-of-carry $\Upsilon_t^{(n)}$ is thus simplified to incorporate this restriction while the two components of the convenience yield, i.e. the seasonal premium and the residual convenience yield in excess of the seasonal component, are defined as follows.

$$
\begin{aligned}
\Upsilon_t^{(n)} &= rf_t^{(n)} + \tilde{v}^{(n)} \\
\zeta_t^{(n)} &= -\textstyle\sum_{i=1}^{m} \beta_{t,i} d_i \\
\chi_t^{(n)} &= -\epsilon_t
\end{aligned}
$$

I use a panel approach along the futures curve, i.e. considering all available contracts at any point in time, and carry out the estimation on an expanding window to allow for the slow adjustment of expectations about the seasonal premium. The long-run net storage costs are estimated on the same measurement window as the seasonal convenience yield.

1.3.3 Full-sample estimation

Tables A2, A3, A4 and A5 in the Appendix show the full-sample estimates of the seasonal premium over the long-run cost-of-carry per commodity. The estimation has been carried out by means of robust regression using a panel approach along the futures curve, i.e. considering all available contracts at any point in time, using seasonal dummies. The results are reported using Newey-West standard errors, i.e. heteroskedasticity and autocorrelation consistent estimate of the covariance matrix of the coefficient estimates.

Those results provide interesting insights on the heterogeneity of commodities with regards to the seasonal risk premium and the influence of time-variation in supply and demand. First, looking at the adjusted R^2 of the regression allows to characterize the influence of the seasonal factor as a driver of the futures basis. We see that highly seasonal commodities like natural gas (NG) have a R^2 close to 0.6 while for aluminum this number is barely different from zero. The more pronounced the seasonal variations are, i.e. the amplitude of the premium across seasons, the higher the adjusted R^2 of the regression as they are large contributors to the variance of the basis. This is thus a useful indicator to classify commodities as seasonal or non-seasonal commodities.

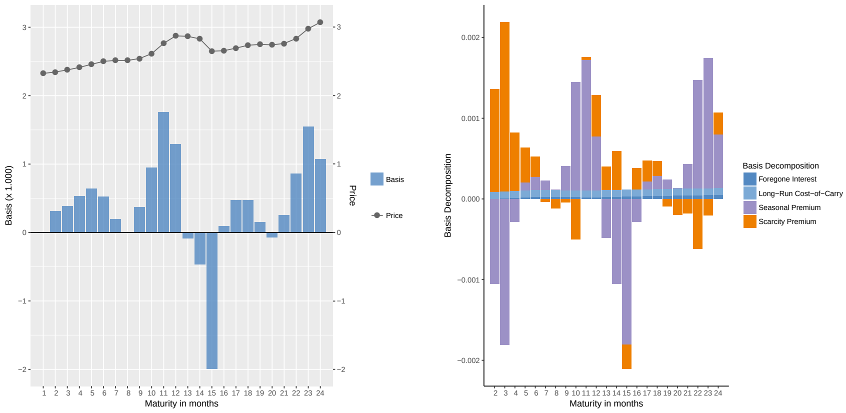
Second, for seasonal commodities the per season estimated premiums are usually highly statistically significant, i.e. at the 1% confidence level. Still, apparently non seasonal commodities like platinum (PL) can have specific seasons with a statistically significant premium. While the alternative and equivalent trigonometric approach[6] to estimating seasonal components is convenient to understand the components of the seasonal cycle, the simple dummy regression approach suffices in easily characterizing the premium attached to futures contract maturing in specific seasons.

1.3.4 Futures curve

The basis measured over various investment horizons n fully describes the shape of the futures curve. Likewise measuring the basis between every subsequent

[6]See, for example, Hannan et al. (1970), Sørensen (2002), Borovkova and Geman (2006) or Hevia et al. (2018) for more details on the trigonometric specification of seasonality. The results indicate the need to tailor the inclusion of the harmonics beyond the fundamental frequency to differentiate between commodities.

futures along the curve delivers an equivalent representation.[7] Given the above basis decomposition, we can assess how the time to maturity influences each component independently along the curve. For illustration purpose, Figure 2 shows the log-basis decomposition of the Natural Gas futures curve on January 5, 2016 when measured from consecutive contracts.



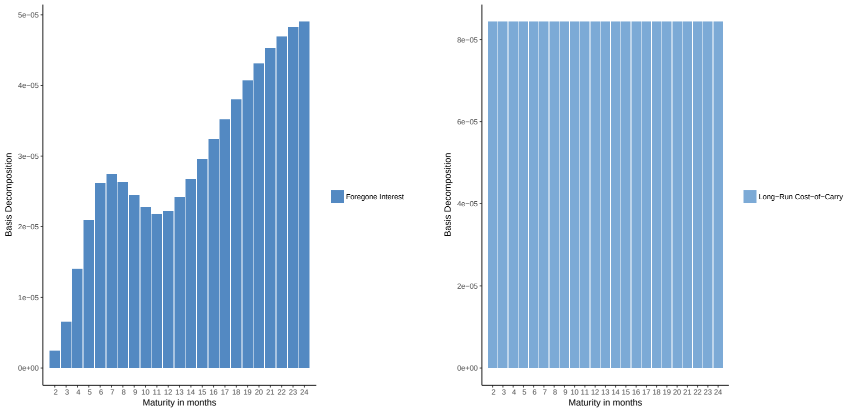
(a) Basis (b) Basis decomposition

Figure 2: Natural Gas futures basis decomposition along the curve

The curve associated with the long-run cost-of-carry $\Upsilon_t^{(n)}$ captures the convexity or concavity of respectively backwardated and contangoed commodities resulting from the variation in the long-run net storage costs and in interest rates across maturities. Thus the contribution to the log-basis of the foregone interests reflects the shape of the interest rate curve. The contribution of the long-run net storage costs is assumed constant along the futures curve and seasonal variation in storage costs resulting transitory supply and demand imbalances are captured by the seasonal component. While the long-run storage costs curve is flat on any given day its level can vary over time. Figure 3 shows the contribution to the log-basis decomposition of the Natural Gas futures curve on January 5, 2016 of both the foregone interest and the long-run net storage costs.

The seasonal premium curve describes how the cyclicality in demand and supply command a premium $\zeta_t^{(n)}$ that varies according to the specific season the maturity n is associated with. This generates the observed oscillation along the futures curve for seasonal commodities.

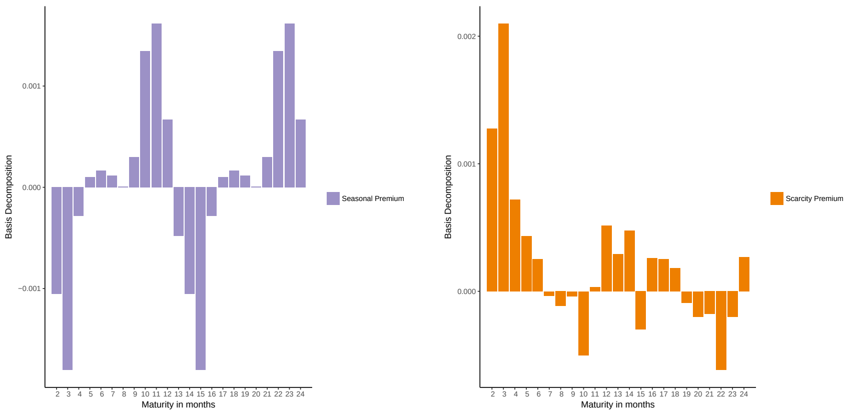
[7]Such a representation is conceptually similar to the notion of forward rates along fixed income yield curves.



(a) Foregone interest (b) Long-run net storage costs

Figure 3: Long-run cost-of-carry along the curve

Next we can define the curve originating from the scarcity premium $\chi_t^{(n)}$. It carries information about how market participants are pricing recent shocks to supply and demand. Indeed the curve describes the priced persistence of those shocks by market participants, i.e. the extent to which they are expecting those shocks to be transitory in nature. Then, the scarcity premium curve also describes the pace at which investors expect those shocks to correct, i.e. the curve captures the expected resolution speed of supply and demand imbalances through time. Figure 4 shows the contribution to the log-basis decomposition of the Natural Gas futures curve on January 5, 2016 of both the seasonal and scarcity premia.[8]



(a) Seasonal premium (b) Scarcity premium

Figure 4: Seasonal and scarcity premia along the curve

[8]As the additive decomposition of the basis is visually more appealing, the contributions to the basis in Figure 4 actually represents the negative of the seasonality and scarcity premia. See Section 1.2.2 for the basis decomposition and a clarification of the premia's signs.

1.4 Futures returns and risk premia

1.4.1 Definitions

Following Szymanowska et al. (2014) and Hevia et al. (2018), some key concepts about futures returns and risk premia are reviewed below in the context of the basis decomposition proposed above.

1.4.1.1 Spot premium

The expected hold-until-maturity return of a n-period futures contract is defined as a series of one-period expected holding returns of the futures plus a settlement return at maturity.

$$
\begin{aligned}
E_t\left[r_{f_t^{(n)}}\right] &= E_t\left[\ln(S_{t+n})-\ln\left(F_t^{(n)}\right)\right] = E_t\left[s_{t+n}-f_t^{(n)}\right] \\
&= E_t\left[\left(s_{t+n}-f_{t+n-1}^{(1)}\right)+\left(f_{t+n-1}^{(1)}-f_{t+n-2}^{(2)}\right)+...+\left(f_{t+1}^{(n-1)}-f_t^{(n)}\right)\right]
\end{aligned}
$$

The special case of the nearest one-period futures contract holding return is then defined as follows.

$$
E_t\left[r_{f_t^{(1)}}\right] = E_t\left[\ln(S_{t+1})-\ln\left(F_t^{(1)}\right)\right] = E_t\left[s_{t+1}-f_t^{(1)}\right]
$$

The spot risk premium $\pi_{s,t}^{(1)}$ is defined as the expected return from holding the nearest one-period futures contract until maturity. An alternative equivalent representation is the expected spot return in excess of the futures basis. Essentially it captures the expected return above and beyond what is priced in the futures curve.

$$
\pi_{s,t}^{(1)} = E_t\left[r_{f_t^{(1)}}\right] = E_t\left[r_{s_{t+1}}\right]-y_t^{(1)}
$$

The spot risk premium corresponds thus to the expected return of an outright long position in the front contract. In the absence of expected spot change or parallel shift in the futures curve, the spot risk premium would correspond to the negative of the futures basis, that is the convergence of the futures price to the spot price.

Incorporating the proposed basis decomposition, the spot premium correspond to the expected spot return in excess of the long-run cost of carry, the next period seasonal and scarcity premia.

$$
\pi_{s,t}^{(1)} = E_t\left[r_{s_{t+1}}\right]-\Upsilon_t^{(1)}-\zeta_t^{(1)}-\chi_t^{(1)}
$$

1.4.1.2 Term premium

As in Hevia et al. (2018), the term risk premium is defined as the one-period expected holding return of a n-period futures contract in excess of the spot risk premium.

$$
\begin{aligned}
E_t\left[\left(\ln\left(F_{t+1}^{(n-1)}\right)-\ln\left(F_t^{(n)}\right)\right)-\left(\ln(S_{t+1})-\ln\left(F_t^{(1)}\right)\right)\right] &= E_t\left[\left(f_{t+1}^{(n-1)}-f_t^{(n)}\right)-\left(s_{t+1}-f_t^{(1)}\right)\right] \\
&= E_t\left[\left(f_{t+1}^{(n-1)}-f_t^{(n)}\right)\right]-\pi_{s,t}^{(1)} \\
&= \pi_{y,t}^{(n)}
\end{aligned}
$$

Expanding the definition provides interesting insights into the factors driving the term premium.

$$
\begin{aligned}
\pi_{y,t}^{(n)} &= E_t\left[\left(f_{t+1}^{(n-1)}-f_t^{(n-1)}+f_t^{(n-1)}-f_t^{(n)}\right)\right]-\pi_{s,t}^{(1)} \\
&= E_t\left[\left(f_{t+1}^{(n-1)}-f_t^{(n-1)}\right)\right]-y_t^{(n)}-\pi_{s,t}^{(1)} \\
&= E_t\left[\left(f_{t+1}^{(n-1)}-f_t^{(n-1)}\right)\right]-E_t\left[r_{s_{t+1}}\right]-\left(y_t^{(n)}-y_t^{(1)}\right)
\end{aligned}
$$

The first term on the right-hand side of the last equation corresponds to the expected one-period change for a futures contract of constant $n-1$ maturity while the second term is the expected spot change. Those two terms describe both the parallel shift and twist in the futures curve. Expectations about a parallel shift in the curve simplifies the term premium to the last term while a steepening of the futures curve would result from the changes in the back-end of the curve dominating the front-end and lead to a rise in the term premium. Those two terms thus correspond to the expected return of a curve trade long a far contract and short the spot, also coined a calendar spread, betting on the steepening of the futures curve.

The last term of the equation describes the basis differential between the n-period futures contract and the front contract maturing one period ahead. This corresponds to the one-period expected return of the calendar spread ceteris paribus. When the basis term structure is flat, this term drops out. For a curve in contango the term is positive and impacts negatively the term premium while for a backwardated curve the term is negative and would contribute positively to the term premium.

Akin to the spot premia, the term premia is defined by the one-period expected return of a curve trade above and beyond what is priced in the futures curve. This interpretation deviates from the one proposed in Szymanowska et al. (2014) where the term premium is defined as the expected deviation from the expectation hypothesis of the basis term structure.

$$
\begin{aligned}
n\left(y_t^{(n)}\right) &= \left(y_t^{(1)}\right)+(n-1)E_t\left[\left(y_{t+1}^{(n-1)}\right)\right]-\pi_{y,t}^{(n)} \\
\pi_{y,t}^{(n)} &= (n-1)E_t\left[\left(y_{t+1}^{(n-1)}\right)-y_t^{(n)}\right]-\left(y_t^{(n)}-y_t^{(1)}\right)
\end{aligned}
$$

The above definition of the term premium also captures in the first term in the right-hand side of the equation the expected slope change of the futures curve as measured by the change in the basis as time passes for the long maturity contract. This definition imposes a slightly more restrictive assumption on the dynamics of the futures curve as it assumes the basis term structure is flat and would thus fail to capture the impact of the current shape of the curve on the estimation of the term premium.

To get a further understanding of what drives the term premium let's now focus on the last term of the equation and incorporate the basis decomposition. We see below that it captures the differential between the front and far contract in terms of the long-run cost of carry, which captures the influence of the interest rate curve. For constant net storage cost and a flat forward rate curve, this term drops out. It also reflects the relative influence of season between contracts. When the term premium is measured from contracts with the same season the difference is null. The last term captures the scarcity risk differential and thus expectations about the relative influence of supply and demand shocks beyond usual seasonal effects. For persistent supply and demand shocks this term disappears.

$$\left(y_t^{(n)}-y_t^{(1)}\right) = \left(\Upsilon_t^{(n)}-\Upsilon_t^{(1)}\right)-\left(\varsigma_t^{(n)}-\varsigma_t^{(1)}\right)-\left(\chi_t^{(n)}-\chi_t^{(1)}\right)$$

In the absence of expected slope change of the futures curve, the term risk premium would correspond to the cumulative differential between the different components of the basis. We can thus rewrite the term premium as follows.

$$\pi_{y,t}^{(n)} = E_t\left[\left(f_{t+1}^{(n-1)}-f_t^{(n-1)}\right)\right]-E_t\left[r_{s_{t+1}}\right]-\left(\Upsilon_t^{(n)}-\Upsilon_t^{(1)}\right)+\left(\varsigma_t^{(n)}-\varsigma_t^{(1)}\right)+\left(\chi_t^{(n)}-\chi_t^{(1)}\right)$$

1.4.1.3 Holding return

Recall the definition of the expected hold-until-maturity return of a n-period futures contract as a series of one-period expected holding returns of the futures plus a settlement return at maturity.

$$E_t\left[r_{f_t^{(n)}}\right] = E_t\left[\left(s_{t+n}-f_{t+n-1}^{(1)}\right)+\left(f_{t+n-1}^{(1)}-f_{t+n-2}^{(2)}\right)+\ldots+\left(f_{t+1}^{(n-1)}-f_t^{(n)}\right)\right]$$

Using the definition of the term premium, we see that the one-period holding return of the futures maturing in n periods is the sum of the one-period spot risk premium and the n-periods term premium.

$$E_t\left[\left(f_{t+1}^{(n-1)}-f_t^{(n)}\right)\right] = \pi_{s,t}^{(1)}+\pi_{y,t}^{(n)}$$

Let's now turn to the settlement return which is defined as the one-period spot risk premium plus the seasonal risk premium attached to the season when the futures expires.

$$E_t\left[\left(s_{t+n}-f_{t+n-1}^{(1)}\right)\right] = E_t\left[\pi_{s,t+n-1}^{(1)}\right]$$

The hold-until-maturity return can then be rewritten as a sum of spot and term premia plus a seasonal risk premium specific to the maturity of the futures.

$$E_t\left[r_{f_t^{(n)}}\right]=\sum_{j=0}^{n-1} E_t\left[\pi_{s,t+j}^{(1)}\right]+\sum_{j=0}^{n-1} E_t\left[\pi_{y,t+j}^{(n-j)}\right]$$

1.4.1.4 Calendar spread return

The curve or calendar spread is a relative return trade along the futures curve that takes a long position in a far contract maturing in n periods and shorts a near contract maturing in $n-j$ periods and thus benefits from a steepening in the futures curve. Note that the term premium definition is the specific case where j is set at $n-1$.

$$\begin{aligned} E_t\left[r_{f_t^{(n)}} - r_{f_t^{(n-j)}}\right] &= E_t\left[\left(f_{t+1}^{(n-1)} - f_t^{(n)}\right) - \left(f_{t+1}^{(n-j-1)} - f_t^{(n-j)}\right)\right] \\ &= \left(\pi_{y,t}^{(n)} - \pi_{y,t}^{(n-j)}\right) + \left(\Upsilon_t^{(n)} - \Upsilon_t^{(n-j)}\right) - \left(\zeta_t^{(n)} - \zeta_t^{(n-j)}\right) - \left(\chi_t^{(n)} - \chi_t^{(n-j)}\right) \end{aligned}$$

The main factors driving the curve trade are thus the relative term premium between the contracts above and beyond what is priced in the futures curve (i.e. their relative long-run cost-of-carry), as well as the difference in seasonal and scarcity premia. The seasonal premium differential between two consecutive seasons corresponds to the expected basis change resulting from the the dynamics of supply and demand imbalances across seasons and is driven by the change in inventory levels. The scarcity premium differential captures the expected normalization of unexpected supply or demand shocks over that period.

1.4.2 Factors driving the futures premia

In this section, I investigate the influence of the various factors driving the basis on the futures spot and term risk premia. To this aim and following Bakshi et al. (2013) I define the market as an equally-weighted portfolio of all commodities, using the front contracts. Acknowledging the relevance of seasons, I investigate the premia conditional on seasons. As the influence of seasonality varies across commodities and sectors, the results are also presented for all sectors. In order to better reflect the nature of the different premia driving the basis, especially the non-linearity of the scarcity premium, I focus here on daily holding returns. This should allow to capture more effectively the influence of the different factors driving the futures spot and term premia.

1.4.2.1 Spot risk premia

The spot risk premia is defined in Section 1.4 as the expected return of holding the nearest one-period futures contract until maturity. Table 1 sheds light on the spot premia across sectors and through seasons. While the spot premium is significantly different from zero for the overall market, it is only significant for the industrial metals sector over the full sample. We can observe large seasonal variations in the spot premium both at the market and at the sector levels.

Next, I investigate the forecasting ability of the futures basis with respect to the spot risk premium. While the literature mainly focuses on the evaluation of the unbiased forward hypothesis, the objective is here to gain understanding in which factors within the basis carry predictive power. Table 2 reports the results of forecasting regressions of the forward excess returns relative to the market on the basis, its constituents and other control variables (e.g. sectors and seasons). Consistent with Bakshi et al. (2013) I find that the market is a major risk

Table 1: Spot Risk Premium

		Season											
Sector	All	1	2	3	4	5	6	7	8	9	10	11	12
Annualized Mean Returns (%)													
Market	4.16	7.74	21.32	7.86	14.17	5.86	3.01	10.34	5.98	4.30	-7.82	-0.74	5.74
Energy	0.62	-19.33	11.19	32.06	42.55	35.11	17.75	-5.57	-25.88	-7.52	-3.75	-1.86	-42.60
Grains	1.32	11.17		8.15		-1.63		5.99	-23.27	1.55	-46.85	-4.23	-2.51
IndustrialMetals	9.18	21.02	35.85	23.43	10.03	11.67	-16.95	-3.45	11.97	-5.13	9.80	-1.42	-7.17
Livestock	1.96	-0.90	5.77	5.05	-8.49	13.47	-1.63	12.49	12.00	6.28	0.71	-17.78	-2.67
PreciousMetals	8.01	0.68	44.24	42.80	-0.75	4.49	-1.42	-32.41	16.03	9.17	6.36	1.62	6.63
Softs	1.43	-0.89		9.67		-5.65		3.33		7.56	-4.41	26.92	3.10
Annualized Standard Deviations (%)													
Market	16.33	20.81	19.09	20.04	17.47	17.22	19.48	17.55	14.95	18.35	18.80	20.88	20.07
Energy	31.31	36.29	35.48	38.07	34.27	30.63	28.23	29.36	28.59	28.92	32.84	34.83	32.72
Grains	20.61	20.69		18.93		20.86		20.73	26.87	26.75	20.11	25.58	22.40
IndustrialMetals	23.36	25.58	25.76	24.24	23.02	23.44	24.45	25.05	23.37	22.84	25.00	29.59	26.37
Livestock	13.87	14.91	17.47	13.12	15.58	16.66	16.08	19.22	13.66	11.25	17.92	12.74	20.55
PreciousMetals	23.50	24.35	21.11	20.43	23.05	25.11	23.92	23.04	21.20	21.43	28.70	24.52	24.50
Softs	19.46	30.95		22.83		19.70		19.20		23.27	23.83	34.23	24.66
t-Statistics													
Market	1.26	0.80	2.03	1.33	1.58	0.76	0.28	1.26	0.88	0.53	-1.08	-0.07	0.77
Energy	0.08	-0.79	0.47	1.24	1.89	1.74	0.96	-0.29	-1.39	-0.40	-0.17	-0.08	-1.90
Grains	0.29	0.90		1.01		-0.13		0.50	-1.05	0.10	-2.69	-0.28	-0.26
IndustrialMetals	1.65	1.20	2.07	1.39	0.64	0.73	-1.03	-0.20	0.76	-0.33	0.56	-0.07	-0.39
Livestock	0.60	-0.11	0.59	0.65	-1.05	1.11	-0.17	0.79	1.94	0.65	0.08	-1.34	-0.23
PreciousMetals	1.40	0.03	2.53	2.41	-0.04	0.22	-0.07	-1.68	0.91	0.51	0.25	0.08	0.32
Softs	0.36	-0.05		1.35		-0.56		0.34		0.64	-0.43	1.32	0.31

Note: Following Harvey et al. (2016), t-statistics in bold satisfy the statistical significance threshold of 3.0. For those we can safely reject the null hypothesis of returns not being significantly different from zero.

factor and can explain a large portion (about 25%) of the timeseries variation in the future spot risk premium. I thus control for the market as a risk factor by focusing on excess returns and keep the market as an independent variable to evaluate the efficacy of the adjustment. Results shown below are robust to this choice of specification. The t-statistics rely on the heteroskedasticity and autocorrelation consistent Newey and West (1987) standard errors estimates, using the Newey and West (1994) automatic lag selection procedure.

The first regression corresponds to the usual projection of forward returns onto the futures basis. Consistent with previous literature results, a high basis (contangoed curve) leads to negative forward returns. This relation is highly significant but does not pass the requirements put forward in Harvey et al. (2016). The second regression focuses on the different basis factors as explanatory variables for forwards excess returns. We see that the first factor, the foregone interest, is not statistically significant and has little influence but the sign of the coefficient is as per expectation, i.e. futures contracts trade at a premium relative to spot prices to compensate for the interests foregone by physical commodity holders. As time passes the futures is expected to converge to the spot price if nothing else changes.

The second factor, the long-run cost-of-carry which captures the storage costs net of any structural convenience yield, shows a large negative beta that is statistically significant at the traditional 5% level. The sign is consistent with the traditional basis sign and the expectation that commodity futures with high storage costs trade at a premium and converge to spot overtime.

The third basis factor, the seasonality premium, although not significant deserves a short comment. Indeed an interesting observation is that the seasonal premium coefficient has an opposite sign to the scarcity premium although both are components of the convenience yield. This suggests both insurance premia have different roles and relates to separate hedging demands. In order to inter-

Table 2: Regression excess spot premium above market on basis factors.

	Basis	Basis Factors	Control Sectors	Control Seasons
Constant	0.0001 $t = 1.088$	0.00003 $t = 0.548$		
MarketEW	0.00003 $t = 0.001$	0.0001 $t = 0.003$	0.0001 $t = 0.010$	-0.0001 $t = -0.009$
Basis	-0.353 $t = -2.720^{***}$			
ForegoneInterest		-0.109 $t = -0.124$	0.035 $t = 0.039$	-0.149 $t = -0.173$
LongRunCostOfCarry		-0.912 $t = -2.058^{**}$	-0.961 $t = -1.649^{*}$	-0.898 $t = -1.849^{*}$
SeasonalPremium		-0.225 $t = -1.311$	-0.280 $t = -1.574$	-0.223 $t = -1.269$
ScarcityPremium		0.572 $t = 3.324^{***}$	0.563 $t = 3.658^{***}$	0.592 $t = 4.136^{***}$
Sector_Energy			-0.00001 $t = -0.045$	
Sector_Grains			0.0001 $t = 0.545$	
Sector_IndustrialMetals			0.0002 $t = 1.808^{*}$	
Sector_Livestock			-0.0002 $t = -1.187$	
Sector_PreciousMetals			0.0002 $t = 1.491$	
Sector_Softs			-0.0001 $t = -1.143$	
Season_1				-0.00004 $t = -0.323$
Season_2				0.00000 $t = 0.016$
Season_3				0.0002 $t = 0.923$
Season_4				0.0001 $t = 1.001$
Season_5				0.0004 $t = 2.017^{**}$
Season_6				-0.0001 $t = -0.770$
Season_7				-0.0001 $t = -0.343$
Season_8				0.00002 $t = 0.160$
Season_9				-0.0001 $t = -0.665$
Season_10				0.0002 $t = 1.180$
Season_11				-0.0001 $t = -0.355$
Season_12				0.00000 $t = 0.007$
Adjusted R^2	0.0002	0.0004	0.0004	0.0003
Residual Std. Error	0.015 (df = 119193)	0.015 (df = 119190)	0.015 (df = 119185)	0.015 (df = 119179)

Note: The t-statistics rely on the heteroskedasticity and autocorrelation consistent Newey-West (1987) standard errors estimates, using the Newey-West (1994) automatic lag selection procedure. *p<0.1; **p<0.05; ***p<0.01

pret the negative coefficient of the seasonal premium let's recall from Section 1.2.2 that here a high value actually indicates that the futures trades at a discount. A high seasonal premium thus relates to a period of expected oversupply and the negative sign of the coefficient suggests that during those periods the futures price actually move beyond what is priced in. Hedging seasonal risk is a fruitful strategy for risk averse investors. This also suggests that this factor does not simply capture the seasonal variation in the costs of storage in which case the coefficient would be of opposite sign to the interest rate and long-run cost-of-carry factors.

Finally, the last factor, the scarcity premium, is highly significant with a t-statistic well above 3.0. One interpretation for the positive coefficient is that when market participants are pricing a high risk of scarcity, the scarcity premium pushes down futures prices which leads to positive forward returns. A probably more accurate explanation is that a high scarcity premium is actually driven by the front end of the curve and that the slow diffusion of information combined to the slow adjustment of supply and demand leads to a curve shift in the direction of the scarcity risk and thus to futures returns predictability. Further insights into the dynamics of the futures curve in presence of scarcity risk is provided in Section 2.

The next two regressions introduce commodity sectors and seasons as control variables but overall those dummy variables are not significant. More importantly their introduction weakens the significance of the long-run cost of carry factor suggesting our initial finding might not be robust and that there is a large cross-sectional dispersion across sectors (the factor is constant through seasons). The result for the scarcity premium on the other hand becomes more significant, suggesting those findings are robust to the model specification.

1.4.2.2 Term risk premia

The term risk premia is defined in Section 1.4 as the one-period expected holding return of a n-period futures contract in excess of the spot risk premium. Here all contracts with a maturity up to one year out from the front month contract are considered. This allows to capture all seasons at any point in time as well as to diversify the exposure to the forward rate along the curve. Table 3 sheds light on the term premia across sectors and through seasons. The results are similar to the one obtained for the spot premum. The term premium is only significant for the industrial metals and energy sectors over the full sample. We can observe large seasonal variations in the term premium both at the market and at the sector levels.

Table 3: Term Risk Premium

		Season											
Sector	All	1	2	3	4	5	6	7	8	9	10	11	12
Annualized Mean Returns (%)													
Market	0.93	0.34	2.28	0.55	2.94	2.23	3.43	2.10	2.93	0.23	2.48	1.18	2.23
Energy	5.23	3.23	4.06	2.99	5.47	6.22	6.19	6.52	6.73	5.68	5.88	4.96	5.58
Grains	1.38	-0.62		1.96		1.57		2.36	0.52	1.17	-0.86	-0.72	3.38
IndustrialMetals	1.39	1.15	1.34	1.72	1.74	1.25	1.68	1.49	1.49	1.29	0.90	1.48	1.16
Livestock	2.95	-3.24	4.92	-2.82	3.48	2.68	6.59	7.92	4.46	-0.14	0.78	-1.83	4.85
PreciousMetals	0.07	0.04	-0.01	0.32	0.11	0.43	-0.03	0.32	-0.12	0.11	-0.05	-0.05	0.18
Softs	0.35	-4.53		0.99		2.71		0.90		-1.59	3.32	-5.42	1.18
Annualized Standard Deviations (%)													
Market	4.29	3.65	4.14	4.63	3.90	4.05	4.21	4.57	3.52	4.40	5.43	4.11	4.63
Energy	9.95	11.37	10.98	10.25	10.58	10.54	10.77	10.81	11.01	10.79	11.11	10.89	11.09
Grains	5.00	7.66		5.42		5.34		5.71	6.44	5.80	7.84	9.84	6.09
IndustrialMetals	2.33	2.58	2.58	2.61	2.62	2.64	2.64	2.59	2.63	2.66	2.74	2.64	2.60
Livestock	8.82	6.93	13.60	7.04	10.22	13.88	13.66	18.13	12.57	6.22	11.41	6.73	14.73
PreciousMetals	0.54	0.98	0.69	1.54	0.69	1.45	0.66	0.98	0.73	1.08	0.67	0.71	0.74
Softs	5.68	11.63		6.21		5.57		6.08		6.00	10.57	12.52	6.40
t-Statistics													
Market	1.30	0.53	**3.10**	0.71	**4.24**	**3.23**	**4.62**	2.69	**4.67**	0.30	2.71	1.62	2.85
Energy	**3.04**	1.52	1.98	1.56	2.76	**3.16**	**3.08**	**3.23**	**3.27**	2.82	2.83	2.44	2.70
Grains	1.64	-0.44		2.06		1.64		2.31	0.43	1.16	-0.58	-0.40	**3.21**
IndustrialMetals	**3.14**	2.20	2.51	**3.22**	**3.26**	2.32	**3.10**	2.83	2.77	2.38	1.61	2.75	2.19
Livestock	1.87	-1.64	1.78	-1.62	1.65	0.86	2.38	2.10	1.75	-0.09	0.34	-1.11	1.62
PreciousMetals	0.80	0.22	-0.11	1.18	0.89	1.71	-0.27	1.84	-0.93	0.58	-0.37	-0.08	1.40
Softs	0.36	-2.08		0.95		2.83		0.86		-1.52	1.85	-2.27	1.09

Note: Following Harvey et al. (2016), t-statistics in bold satisfy the statistical significance threshold of 3.0. For those we can safely reject the null hypothesis of returns not being significantly different from zero.

Following the approach put forward when investigating the unbiased forward hypothesis, I investigate the forecasting ability of the relative futures basis with respect to the term risk premium. Table 4 reports the results of forecasting regressions of the forward relative returns on the basis differential, the difference in the basis factors and other control variables (e.g. sectors and seasons). It is worth noting that the long-run cost-of-carry factor drops off the set of independent variables across the various regressions. This follows from the basis decomposition proposed in Section 1.2.2 and the restriction imposed on this factor to be constant across maturities at any point in time.

Table 4: Regression term premium on basis factors differential.

	Basis	Basis Factors	Control Sectors	Control Seasons
Constant	0.0001 $t = 5.256^{***}$	0.0001 $t = 5.378^{***}$		
MarketEW	−0.003 $t = -1.872^{*}$	−0.004 $t = -2.140^{**}$	−0.004 $t = -1.993^{**}$	−0.004 $t = -2.025^{**}$
BasisDiff	−0.184 $t = -3.659^{***}$			
ForegoneInterestDiff		−4.504 $t = -2.716^{***}$	−4.400 $t = -2.204^{**}$	−4.571 $t = -2.128^{**}$
SeasonPremiumDiff		−0.067 $t = -1.214$	−0.067 $t = -1.138$	−0.072 $t = -1.169$
ScarcityPremiumDiff		0.377 $t = 6.462^{***}$	0.362 $t = 4.862^{***}$	0.379 $t = 4.783^{***}$
Sector_Energy			0.0002 $t = 2.956^{***}$	
Sector_Grains			0.0001 $t = 2.492^{**}$	
Sector_IndustrialMetals			0.0001 $t = 3.682^{***}$	
Sector_Livestock			0.0001 $t = 1.672^{*}$	
Sector_PreciousMetals			0.00003 $t = 2.416^{**}$	
Sector_Softs			0.00004 $t = 1.133$	
Season_1				0.0001 $t = 3.393^{***}$
Season_2				0.0001 $t = 4.072^{***}$
Season_3				0.0001 $t = 4.499^{***}$
Season_4				0.0001 $t = 4.231^{***}$
Season_5				0.0001 $t = 6.287^{***}$
Season_6				0.0001 $t = 3.825^{***}$
Season_7				0.0001 $t = 5.050^{***}$
Season_8				0.0001 $t = 4.872^{***}$
Season_9				0.0001 $t = 3.130^{***}$
Season_10				0.00005 $t = 1.820^{*}$
Season_11				0.00004 $t = 1.649^{*}$
Season_12				0.0001 $t = 3.235^{***}$
Adjusted R^2	0.001	0.001	0.002	0.002
Residual Std. Error	0.005 (df = 942219)	0.005 (df = 942217)	0.005 (df = 942212)	0.005 (df = 942206)

Note: The t-statistics rely on the heteroskedasticity and autocorrelation consistent Newey-West (1987) standard errors estimates, using the Newey-West (1994) automatic lag selection procedure. *p<0.1; **p<0.05; ***p<0.01

The first specification regresses the forward futures return relative to the front contract return against the market and the basis differential. The basis differential is highly significant and in line with expectations a high spread predicts negative relative returns. Although only significant at the 10% threshold it is worth highlighting the influence of the market factor on the term premium whereby a rise in commodity markets leads to a negative term premium. To some extent this result is a reflection of the correlation structure and relative risk along the futures curve, i.e. contracts further along the curve exhibit lower beta to spot changes. This effect is consistent across the various regressions performed. Supportive evidence is provided by Table 5 which shows the panel full-sample correlation estimates of the first twelve futures contract along the curve with the active contract as well as the volatilities of the contracts as we move along the curve (e.g. column 1 is the active front contract while column 3 refers to the third contract along the curve).

Table 5: Risk and correlation along the futures curve

	1	2	3	4	5	6	7	8	9	10	11	12
Correlation	1.00	0.99	0.98	0.97	0.96	0.95	0.94	0.94	0.93	0.93	0.92	0.91
Volatility (%)	29.69	28.69	27.46	25.77	25.00	24.49	24.09	23.81	23.56	23.64	23.72	23.91

The second regression focuses on the various basis factors' differentials as explanatory variables of the forward relative returns. The first factor differential, the foregone interest one, is found to be significant at the 1% level. The sign of the coefficient is in line with expectations and the previous findings on the spot risk premium. The second factor differential, the seasonal premium one, is here as well not significant but the result is consistent with the findings on the spot premium. This provides comfort in the interpretation put forward above. The last factor differential, the scarcity premium one, is highly significant with a t-statistic well above 3. Here as well the results are consistent with earlier findings.

The next two regressions introduce commodity sectors and seasons as control variables. As opposed to the results on the spot risk premia, here the control variables are often significant at the 5% level or lower. This hints at a large cross-sectional dispersion across sectors. With regards to seasons while these results suggest the term premium remains exposed to seasonal fluctuations it is worth mentioning this control variable only captures the season exposure of the far contract. The result for the scarcity premium are left unchanged suggesting those findings are robust to the model specification.

1.4.3 Slow diffusion of information, underreaction and return predictability

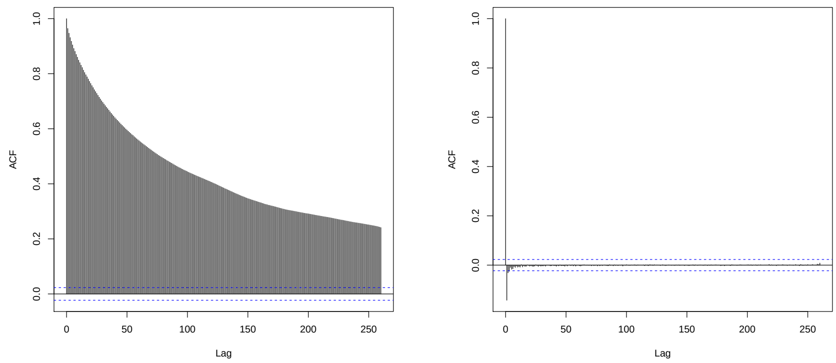
The scarcity risk premium has been identified above as the key driver beyond the futures spot and term premia but little is known on the origin of this return predictability. The efficient market hypothesis[9] suggests that in the presence of shocks to supply and demand market participants adjust their expectations and incorporate instantaneously this new information in prices such that return predictability is precluded. Under such hypothesis the scarcity risk premium should

[9] See amongst others Malkiel and Fama (1970).

reflect the incorporation of new information and the resulting expectations into the futures curve but should not be able to forecast forward returns.

At the same time commodity markets are characterized by the slow adjustment of demand and supply which leads to shock persistence. On the one hand, price inelastic demand originates from the absence of substitutes in the short run. On the other hand, the supply of commodities is subject to the inelasticity of production in the short run driven by seasonal production cycles for perishable commodities and the long run effects of investments and productivity increase on the total supply. Those two effects combined result in a lengthy resolution of supply and demand imbalances.

Two potential competing but not mutually exclusive hypotheses could explain the observed return predictability. The first one would be the presence of autocorrelation in unexpected net supply shocks such that selecting commodities on the basis of previous shocks would provide valuable information about future expected returns. The second hypothesis would be that the slow diffusion of information and/or market participants underreaction to new information lead to return predictability.[10]



(a) Level autocorrelation coefficients (b) Change autocorrelation coefficients

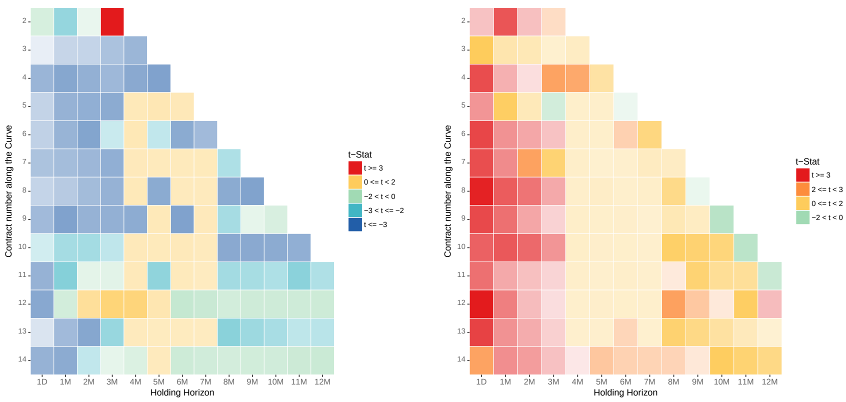
Figure 5: Scarcity risk premium dynamics

In order to asses the first hypothesis of recurring shocks, I consider in Figure 5 the average autocorrelation coefficients up to one year accross all combinations of market and season for the level and the change in the scarcity risk premium as it captures unexpected shocks to the net supply. While the dynamics of the level coefficients corroborates the persistence of shocks and the slow adjusment of fundamentals, the autocorrelation coefficients for the changes in the scarcity risk premium cannot attest of the presence of a systematic recurrence of shocks through time. Indeed, the absence of large and significant autocorrelation coefficient for the change of the scarcity risk premium suggests unexpected shocks

[10]Both behavioral phenomema have been widely documented in equity markets. See amongst others the seminal paper of Jegadeesh and Titman (1993) for the underreaction of market participants. See amongst others Hong and Stein (1999) and Hong et al. (2000)for the slow diffusion of information. Dissociating those two potential sources of return predictability is beyond the scope of this paper.

to supply and demand are not autocorrelated and I thus dismiss this first hypothesis.

The second hypothesis of slow diffusion of information and market participants underreaction leverage on a growing body of literature whereby behavioral and cognitive biases[11] as well as limits to arbitrage[12] impair market efficiency. To investigate this alternative hypothesis, I consider the persistence of excess returns relative to the market over multiple holding horizons and along the curve for various distance to maturity for both the top and bottom quintile scarcity risk portfolios. Figure 6 shows a heatmap of the t-statistics of the excess returns over multiple horizons (from 1 day to 12 months) for the different contracts along the curve, where the contract number indicates its location on the curve and increases with the distance to maturity. The colors allows to classify the t-statistics in various categories depending on its level (e.g. following Harvey et al. (2016) blue and red correspond to t-statistics respectively above 3 and below -3) while the colour shading allows to distinguish for various t-statistic levels within a category.



(a) Scarcity Risk Premium Q1 (b) Scarcity Risk Premium Q5

Figure 6: Excess performance persistence

Beyond allowing to detect the presence of excess return persistence, i.e. the source of the forecasting power, this representation carries lots of valuable information. First, by conditioning on the quintile number it allows to distinguish the direction of the excess return predictability between high and low scarcity risk. Second, by evaluating multiple holding horizons, this analysis allows to assess the decay in the excess return over time and thus to define the return predictability horizon. Third, by considering the whole futures curve, we can identify whether the excess returns are uniformly distributed along the curve or whether they are concentrated in a specific location (e.g. the front end) of the curve.

We see from Figure 5a that an unexpected risk of over-supply, i.e. a negative scarcity risk premium, leads to negative highly significant excess returns over the market for a holding horizon up to 3 months. This pattern is mostly observable

[11]See amongst others Hirshleifer (2001).
[12]See amongst others Shleifer and Vishny (1997).

in the front end of the curve, for contract with a time to maturity up to 9 months. Figure 5b shows that unexpected risks of scarcity, i.e. a positive premium is associated with highly significant positive excess returns over the market accross the whole curve for a holding horizon up to 3 months.

In both figures we observe that the excess returns are most significant right after the unexpected shocks suggesting the information is largely incroporated by market participants without delay. The persistence through time and the diminishing stignificance with the length of the holding horizon indicate that the information is progressively diffused throughout the market up until it is fully incorporated in futures prices. Those results thus support the hypothesis of underreaction and slow diffusion of information as potential sources for the futures returns' predictability and drivers of the spot and term premia.

2 Liquidity provision under scarcity risk

As the probability of stock-out increases commodity consumers need to hedge out the scarcity risk by buying spot and storing the commodity or by taking long positions with delivery at the time of likely scarcity. With regards to producers, Hirshleifer (1991) refutes the general pre-conception of a short hedging pressure resulting from producers simply willing to hedge their bottom line volatility. He argues that when demand shocks are arising from changes in aggregate wealth, the optimal hedging policy of producers with non-stochastic output might be to remain unhedged or even to take a long hedge position. The net hedging demand might benefit from taking an outright long commodity exposure when inventory levels are low and eroding, which would add to any outstanding speculative pressure. In the presence of periodic supply and demand imbalances leading to potential scarcity risk, the question of who might be a willing counterparty to the hedging demand is thus warranted.

2.1 Liquidity providing trade

Assuming pure liquidity providers hold no speculative positions and hedge out any spot risk, they enter calendar spread trades selling the contract exposed to scarcity risk.[13] More specifically, when the scarcity premium is high (low), the convenience yield is high (low), the futures prices trade at a discount (premium) relative to spot and the curve is locally in backwardation (contango). The risk of stock-out is located in the front (back) of the curve and market makers would facilitate hedging demand by selling spot (forward) and buying the commodity forward (spot).

[13]Table A6 in the appendix provides information on the calendar spread premium across sectors and through seasons in the spirit of the previous section. Overall the results remain strong at the market level but the evidence per sector or season weakens. Table A7 reports the result of a set of predictive regressions as in Section 1.4.2. The calendar spread forward returns are regressed against the factors identified in Section 1.4 that are driving this curve trade as well as other control variables. The results are similar to those on the term premium presented in Table 4.

In order to guarantee the hedge efficiency I assume that market makers take positions in two neighboring contracts. As mentioned earlier the correlation structure and relative risk along the futures curve implies that large distances between contracts renders the hedge less effective, as contracts further along the curve exhibit lower beta to spot changes. Adjusting position sizes for the beta exposure of the contracts could to some extent mitigate this concern although they would remain exposed to estimation risk. Moreover, I assume in this section that liquidity providers have access to synthetic contracts and can gain synthetic exposure to unavailable neighboring contracts. Results are robust to this specification.

Table 6: Liquidity Providing Trade Characteristics

Sector/Season	Scarcity	BasisDiff	ForegoneIntDiff	SeasonDiff	ScarcityDiff	MomDiff	ValueDiff	RetSeasonDiff	VolDiff	SkewDiff	OpenIntDiff	VolumeDiff
Average	-3.15	-0.46	-0.45	-0.22	0.68	-0.18	0.56	-0.11	0.03	-0.36	786.24	324.08
Sectors												
Grains	-3.37	-0.40	-0.36	-0.07	0.48	-0.21	0.61	-0.10	0.04	-0.22	756.56	176.25
Softs	-3.51	-0.36	-0.57	-0.02	0.38	-0.18	0.65	-0.06	0.08	-0.76	511.03	108.03
Energy	-5.30	0.84	-0.48	-1.62	0.77	-0.27	0.85	-0.20	0.05	-0.50	1928.39	977.06
Livestock	-4.90	-4.93	-0.35	0.80	4.12	-0.39	1.47	-0.44	0.06	-0.49	305.73	112.49
PreciousMetals	-0.33	-0.21	-0.33	-0.01	0.22	0.00	0.06	-0.02	-0.01	0.09	3096.71	1467.17
IndustrialMetals	-2.38	-0.06	-0.60	-0.06	0.11	-0.12	0.34	-0.07	-0.09	-0.28	454.45	236.88
Seasons												
1	-3.46	-0.32	-0.52	-0.13	0.45	-0.11	0.41	-0.10	0.08	0.01	2574.69	1101.48
2	-3.43	0.82	-0.82	-1.78	0.96	-0.17	0.47	-0.12	0.07	-0.60	1146.72	347.65
3	-3.90	0.38	-0.92	-1.34	0.95	-0.15	0.45	-0.08	0.05	-0.31	-348.01	173.84
4	-2.38	-2.22	-0.86	0.58	1.63	-0.18	0.55	-0.09	0.00	-0.10	2584.94	712.62
5	-3.93	-0.33	-0.62	0.88	-0.56	-0.17	0.54	-0.03	0.02	-0.42	811.24	439.56
6	-2.72	-1.27	-0.54	0.37	0.89	-0.19	0.55	-0.13	0.06	-0.61	722.26	438.64
7	-2.75	-1.14	-0.36	0.49	0.65	-0.18	0.60	-0.11	0.03	0.11	1235.88	512.26
8	-2.32	-1.65	-0.27	-0.08	1.73	-0.14	0.57	-0.12	0.09	-0.54	3117.65	665.18
9	-2.22	-1.77	-0.17	0.28	1.49	-0.20	0.69	-0.12	0.03	-0.43	511.23	316.48
10	-3.03	0.22	-0.18	-0.27	0.05	-0.16	0.64	-0.12	-0.03	-0.48	1072.35	303.54
11	-3.26	1.48	-0.21	-1.61	0.13	-0.18	0.55	-0.13	0.00	-0.42	-1151.19	-212.10
12	-3.11	0.17	-0.22	0.01	-0.18	-0.21	0.53	-0.14	0.02	-0.39	-1552.86	-335.15

Note: To the exception of the skewness ,open interest and volume differentials, characteristics are expressed as annualized percentage numbers. Foregone Interest, momentum, skewness and return seasonality differentials have been scaled by a hundred to ensure the table reflects the correct directionality of the exposure.

As the sign of the scarcity risk premium determines the direction of the calendar spread, market makers are structurally short the scarcity risk premium. They are thus exposed to the negative non-linearity in spot prices resulting from an increasing likelihood of stock-out. Intuitively we would expect such position to also load on other risk factors (e.g. skewness, momentum or value). Table 6 reports the characteristics of this calendar spread position conditioned on the scarcity premium. It confirms the short exposure to the scarcity premium and shows that this relative trade has on average a negative basis, foregone interest, seasonal and term premia differentials while it carries a positive scarcity differential. This table also sheds light on the long value and volatility exposures as well as the negative skewness exposure, the negative momentum and return seasonality exposures.

Interestingly the long value exposure confirms the role of liquidity providers as arbitrageurs. One key question is whether these market participants have incentives to provide liquidity structurally under all conditions given the risk they are facing.

2.2 Agents' motivation

Market makers are utility maximizing agents such that a short skewness exposure might deter natural liquidity providers in the absence of a positive expected return. Table 7 focuses on the performance of the liquidity providing trade which is short the scarcity premium, contemporaneous on the measurement of the scarcity premium. This provides valuable insights on the risk liquidity providers are facing. The t-statistics are unequivocal, being on the wrong side of this trade is costly. Essentially, providing liquidity under scarcity risk is a risky business. Still the high contemporaneous correlation between the measurement and the outcome, i.e. the high scarcity risk results from the price changes, inflates the results such that it is best interpreted as an upper boundary on the potential loss facing liquidity providers.

Table 7: Liquidity Providing Trade (Contemporaneous)

		Season											
Sector	All	1	2	3	4	5	6	7	8	9	10	11	12
Annualized Mean Returns (%)													
Market	-2.66	-2.65	-2.41	-2.47	-3.00	-3.05	-3.85	-2.66	-3.11	-3.16	-2.50	-2.27	-2.07
Energy	-2.92	-3.27	-2.36	-2.24	-2.98	-2.58	-3.36	-3.16	-1.88	-1.97	-1.88	-2.30	-2.25
Grains	-2.85	-3.13	-2.23	-2.00	-3.02	-2.47	-2.46	-2.07	-4.43	-4.38	-2.77	-1.84	-1.86
IndustrialMetals	-1.25	-0.82	-1.63	-2.01	-1.10	-1.05	-0.88	-0.97	-0.80	-0.81	-0.83	-1.09	-0.99
Livestock	-5.43	-4.64	-4.45	-4.08	-4.58	-8.03	-5.94	-7.95	-7.61	-4.24	-4.92	-4.79	-4.31
PreciousMetals	-1.28	-1.95	-1.34	-1.40	-1.27	-1.37	-2.80	-0.98	-1.26	-1.28	-0.80	-0.66	-0.57
Softs	-2.72	-1.87	-2.19	-2.31	-3.32	-3.46	-3.02	-2.83	-2.91	-3.12	-2.82	-2.41	-2.20
Annualized Standard Deviations (%)													
Market	0.37	0.97	0.77	0.79	0.94	1.06	2.04	0.95	1.05	1.05	1.25	1.13	1.01
Energy	1.31	3.24	1.93	1.72	2.80	1.85	1.99	1.59	1.35	1.36	1.82	1.94	1.89
Grains	0.59	0.99	0.79	0.77	1.23	1.16	1.33	1.20	1.86	2.22	1.62	0.89	0.88
IndustrialMetals	0.65	0.98	1.90	1.87	1.18	1.01	0.86	0.90	0.89	0.93	0.84	1.10	1.00
Livestock	1.52	3.22	2.75	2.64	3.41	4.93	3.92	4.46	4.89	2.79	2.96	2.79	2.80
PreciousMetals	0.72	2.17	1.27	1.24	1.03	1.13	3.04	1.20	1.19	1.48	0.97	0.92	0.67
Softs	0.61	0.95	1.14	1.13	1.51	1.69	1.51	1.49	1.64	1.74	1.96	1.75	1.65
t-Statistics													
Market	**-42.95**	**-16.05**	**-18.36**	**-18.65**	**-18.83**	**-17.01**	**-11.16**	**-16.38**	**-17.54**	**-17.69**	**-11.94**	**-11.87**	**-12.09**
Energy	**-12.89**	**-5.50**	**-6.65**	**-7.09**	**-5.78**	**-7.57**	**-9.18**	**-10.81**	**-7.56**	**-7.91**	**-5.65**	**-6.47**	**-6.46**
Grains	**-28.59**	**-17.53**	**-15.91**	**-14.83**	**-13.73**	**-11.97**	**-10.29**	**-9.65**	**-13.27**	**-11.25**	**-9.47**	**-11.70**	**-12.26**
IndustrialMetals	**-10.13**	**-4.17**	**-4.25**	**-5.33**	**-4.61**	**-5.16**	**-5.05**	**-5.37**	**-4.46**	**-4.36**	**-4.93**	**-4.92**	**-4.91**
Livestock	**-20.01**	**-6.93**	**-8.04**	**-7.54**	**-6.52**	**-7.90**	**-7.54**	**-8.60**	**-7.70**	**-7.34**	**-8.26**	**-8.36**	**-7.59**
PreciousMetals	**-10.65**	**-5.26**	**-6.12**	**-6.57**	**-7.19**	**-7.13**	**-5.37**	**-4.77**	**-6.17**	**-5.05**	**-4.80**	**-4.22**	**-4.95**
Softs	**-26.46**	**-11.43**	**-11.26**	**-12.18**	**-12.68**	**-11.95**	**-11.53**	**-11.10**	**-10.27**	**-10.48**	**-8.51**	**-8.03**	**-7.88**

Note: Following Harvey et al. (2016), t-statistics in bold satisfy the statistical significance threshold of 3.0. For those we can safely reject the null hypothesis of returns not being significantly different from zero.

A more realistic perspective though is for liquidity providers to use the last available information, evaluate the risk of scarcity and take position accordingly. Table 8 thus looks at the performance of the liquidity providing trades when the direction of the trade is conditioned on information up until that point in time. One of the most striking observation is the consistent positive forward return of this trade, a result that stands out given the findings just presented in table 7. The returns earned for ensuring the well functioning of markets are economically significant.

These results shed light on the motivations that drive liquidity provision under scarcity risk. Despite the risks born, market makers have been rewarded for ensuring the well-functioning of markets, i.e. for facilitating the needs of hedgers as well as the objectives of speculators.

2.3 Curve dynamics

While Table 8 provides strong evidence that the liquidity trade is economically significant, its performance prior to establishing the position as documented in table 7 raises questions on the underlying drivers behind the premium earned. On the back of those results, a first hypothesis is that market makers benefit from the overreaction of hedgers. Indeed, the fast paced return reversal suggests that protection buyers rush to hedge as the likelihood the risk increases. This leads to price distortion as risk-averse agents misprice the probability of a stock-

Table 8: Liquidity Providing Trade

		Season											
Sector	All	1	2	3	4	5	6	7	8	9	10	11	12
Annualized Mean Returns (%)													
Market	1.53	1.72	1.24	1.34	1.94	1.94	2.48	1.60	2.18	1.93	1.51	1.52	1.33
Energy	0.96	1.83	0.33	-0.12	0.20	-0.46	1.27	1.49	0.81	0.89	0.35	0.41	0.71
Grains	1.84	2.29	1.55	1.32	2.26	1.79	1.46	1.08	3.00	2.54	1.96	1.14	1.18
IndustrialMetals	0.63	0.49	1.02	1.43	0.50	0.58	0.22	0.51	0.31	0.38	0.43	0.71	0.83
Livestock	2.66	1.51	1.12	1.37	1.91	4.29	3.66	5.63	4.83	1.40	1.64	2.02	1.65
PreciousMetals	1.28	1.81	1.20	1.37	1.32	1.45	2.13	0.90	1.45	1.51	1.02	0.78	0.56
Softs	1.46	1.14	0.86	1.00	2.46	2.48	2.02	1.47	1.55	1.49	0.94	1.55	1.35
Annualized Standard Deviations (%)													
Market	0.37	0.97	0.75	0.79	0.89	0.92	2.05	0.94	1.04	1.05	1.31	1.12	1.02
Energy	1.31	3.24	1.77	1.69	2.89	1.88	1.99	1.61	1.36	1.36	1.88	1.91	1.88
Grains	0.61	0.99	0.79	0.79	1.22	1.14	1.20	1.21	1.87	2.25	1.67	0.90	0.83
IndustrialMetals	0.65	1.01	1.72	1.92	1.15	1.01	0.88	0.91	0.90	0.93	0.85	1.11	1.00
Livestock	1.52	3.18	2.76	2.69	2.93	5.00	3.94	4.51	4.92	2.81	2.99	2.78	2.82
PreciousMetals	0.69	2.16	1.27	1.24	1.06	1.12	3.06	1.15	1.22	1.47	0.96	0.90	0.73
Softs	0.63	0.95	1.36	1.20	1.42	1.62	1.54	1.52	1.63	1.70	1.97	1.69	1.66
t-Statistics													
Market	**24.75**	**10.42**	**9.75**	**10.08**	**12.85**	**12.34**	**7.14**	**10.00**	**12.31**	**10.84**	**6.87**	**7.99**	**7.73**
Energy	**4.24**	**3.08**	1.02	-0.39	0.38	-1.32	**3.46**	**5.04**	**3.26**	**3.54**	1.03	1.17	2.07
Grains	**17.93**	**12.85**	**11.14**	**9.57**	**10.38**	**8.78**	**6.79**	**5.00**	**8.99**	**6.44**	**6.50**	**7.18**	**8.29**
IndustrialMetals	**5.10**	2.41	2.93	**3.70**	2.14	2.84	1.27	2.78	1.71	2.03	2.54	**3.19**	**4.13**
Livestock	**9.79**	2.28	2.01	2.49	**3.17**	**4.16**	**4.63**	**6.03**	**4.86**	2.40	2.74	**3.54**	2.89
PreciousMetals	**11.04**	**4.88**	**5.50**	**6.43**	**7.23**	**7.60**	**4.06**	**4.59**	**6.90**	**5.98**	**6.21**	**5.01**	**4.45**
Softs	**13.71**	**6.92**	**3.74**	**4.93**	**10.01**	**8.89**	**7.56**	**5.63**	**5.52**	**5.09**	2.84	**5.34**	**4.80**

Note: Following Harvey et al. (2016), t-statistics in bold satisfy the statistical significance threshold of 3.0. For those we can safely reject the null hypothesis of returns not being significantly different from zero.

out. Ultimately those temporary liquidity driven price distortions are arbitraged away by amongst others liquidity providers.

A second hypothesis is that market participants underreact to the risk of scarcity and that the underestimation of the probability of stock-out is larger in the seasons neighboring the potential materialization of the event. In equity markets the slow diffusion of information has been put forward to explain underreaction and the momentum factor.[14] Assuming market participants can trade the whole futures curve, this theory could explain a parallel shift in the futures curve but not the dynamics of local underreaction around the event risk. An alternative interpretation is that market participants are subject to a framing bias whereby they are not able to extrapolate the implications of the risk of stock-out. This leads hedging and liquidity demand to be primarily concentrated in the seasonal contract where the event is located and to the mispricing of both the risk that the inventory depletion happens at faster rate than anticipated as well as the risk that inventory imbalances might resorb at a lower speed than expected due to the slow adjustment of supply. As the risk of scarcity rises further, investors would recalibrate their probabilities, or be arbitraged away, and reassess the risks surrounding the event.

According to the first hypothesis, the futures where the scarcity risk is located should experience negative returns following a sharp overreaction, such that most of the liquidity trade return would be attributed to the short leg. In the second hypothesis, the expectation adjustment would be located in the long leg of the trade, in the direction of the short leg. For both hypothesis, the mispricing error would be larger as the risk of scarcity rises, leading to sharper adjustments. Investigating the futures curve dynamics can thus provide insights into the drivers of the liquidity provision premium.

[14]See amongst others Hong and Stein (1999) and Hong et al. (2000)

Table 9: Curve Dynamics

	Contemporaneous		*Forward information*								
	Near	Far	Near contract			Far contract			Liquidity Trade		
Sector/Season	Return	Return	Return	Volatility	t-statistic	Return	Volatility	t-statistic	Return	Volatility	t-statistic
Positive scarcity premium											
Average	17.50	14.29	5.92	12.22	2.89	7.98	12.05	**3.95**	2.05	0.63	**19.41**
Energy	17.96	14.71	7.33	22.24	1.85	9.45	21.47	2.47	2.12	2.37	**5.03**
Grains	12.02	8.20	4.05	18.59	1.29	7.13	18.29	2.30	3.08	1.23	**14.79**
IndustrialMetals	23.25	19.60	10.74	22.44	2.22	12.62	22.08	2.65	1.88	2.67	**3.27**
Livestock	10.99	4.95	3.10	12.47	1.37	6.49	12.05	2.96	3.39	2.23	**8.34**
PreciousMetals	3.20	1.68	0.23	23.73	0.05	1.71	23.69	0.39	1.48	0.85	**9.50**
Softs	15.34	10.76	-0.05	18.06	-0.01	2.58	17.76	0.86	2.63	1.69	**9.24**
1	18.05	15.14	5.88	14.41	2.38	8.02	14.24	**3.28**	2.14	1.60	**7.82**
2	19.42	16.65	7.08	14.27	2.88	8.72	14.05	**3.60**	1.64	1.34	**7.12**
3	18.43	15.67	8.61	13.93	**3.63**	10.42	13.79	**4.44**	1.81	1.32	**8.04**
4	21.88	18.55	6.16	13.82	2.58	8.72	13.52	**3.73**	2.55	1.43	**10.34**
5	19.47	16.22	7.19	13.91	**3.01**	9.68	13.70	**4.12**	2.49	1.42	**10.24**
6	18.19	14.07	4.86	13.74	2.05	7.65	13.58	**3.27**	2.80	2.09	**7.74**
7	16.82	13.96	7.15	14.31	2.92	9.11	14.16	**3.76**	1.96	1.38	**8.26**
8	20.29	16.54	6.17	13.76	2.60	8.69	13.46	**3.74**	2.52	1.55	**9.37**
9	16.62	12.95	6.22	13.39	2.71	8.41	13.20	**3.71**	2.18	1.69	**7.55**
10	16.28	13.19	3.77	13.35	1.65	5.21	13.13	2.32	1.44	1.62	**5.18**
11	14.67	12.44	3.53	13.13	1.57	5.27	12.96	2.37	1.74	1.33	**7.64**
12	12.59	10.60	3.60	13.10	1.61	5.22	13.01	2.36	1.62	1.34	**7.12**
Negative scarcity premium											
Average	-10.18	-7.54	-0.72	12.53	-0.34	-2.13	12.35	-1.03	1.42	0.46	**18.23**
Energy	-1.53	1.73	8.07	25.19	1.79	6.18	24.31	1.42	1.89	2.30	**4.60**
Grains	-6.36	-3.03	-0.93	18.25	-0.30	-2.88	17.94	-0.95	1.94	0.87	**13.25**
IndustrialMetals	-3.34	-1.62	1.81	21.82	0.42	0.92	21.64	0.21	0.89	0.70	**6.40**
Livestock	-2.73	3.54	4.28	13.06	1.79	0.67	12.33	0.30	3.61	2.25	**8.76**
PreciousMetals	-4.61	-2.94	-0.09	21.28	-0.02	-1.78	21.22	-0.50	1.69	1.02	**9.83**
Softs	-13.88	-11.15	-1.31	15.58	-0.50	-2.78	15.23	-1.09	1.47	0.84	**10.38**
1	-13.35	-10.75	-2.63	13.09	-1.16	-4.10	12.88	-1.84	1.47	1.03	**8.26**
2	-11.78	-9.54	-2.64	13.41	-1.15	-3.57	13.23	-1.58	0.93	0.93	**5.90**
3	-8.98	-6.74	-2.29	13.46	-1.00	-3.29	13.30	-1.46	1.00	0.92	**6.39**
4	-11.24	-8.27	0.74	13.14	0.33	-0.83	12.93	-0.37	1.57	1.07	**8.53**
5	-9.25	-6.24	0.81	13.55	0.35	-0.73	13.39	-0.32	1.55	1.14	**7.86**
6	-9.91	-6.68	-0.07	14.23	-0.03	-2.07	14.13	-0.86	2.00	2.27	**5.14**
7	-10.36	-7.85	-2.15	14.10	-0.88	-3.52	13.97	-1.46	1.37	1.17	**6.81**
8	-11.81	-8.89	0.49	13.95	0.21	-1.48	13.67	-0.63	1.97	1.23	**9.35**
9	-9.69	-6.78	-0.64	13.89	-0.27	-2.48	13.68	-1.06	1.84	1.29	**8.34**
10	-10.82	-8.60	1.18	14.52	0.48	-0.25	14.37	-0.10	1.44	1.52	**5.52**
11	-9.01	-6.83	0.96	14.10	0.40	-0.27	13.88	-0.12	1.23	1.21	**5.93**
12	-10.01	-7.89	-1.72	13.98	-0.72	-2.80	13.84	-1.19	1.09	1.09	**5.82**

Note: Following Harvey et al. (2016), t-statistics in bold satisfy the statistical significance threshold of 3.0. For those we can safely reject the null hypothesis of returns not being significantly different from zero. Returns and volatility are reported as annualized figures.

Table 9 sheds light on the dynamics at play. The first two columns display the contemporaneous performance of the near and far contracts, i.e. before initiation of the liquidity trade, conditional on the scarcity premium being positive or negative. We see that a positive (negative) scarcity premium is accompanied with a more positive (negative) return of the front contract relative to the far contract. The next columns report forward information (return, volatility and t-statistic) for the near and far contracts, as well as for the liquidity trade. Following the emergence of a positive scarcity premium, i.e. a risk of stock-out, we see that the futures curve shifts upward and flattens. Likewise the formation of a negative scarcity premium, i.e. a risk of oversupply, leads to a downward shift and a flattening of the futures curve.

Those results thus support the hypothesis of local underreaction in the neighborhood of the season related to the event risk. This underreaction is arbitraged away by amongst others market makers. We see in the last columns of the table that the liquidity providing trade earns positive returns that are both economically and statistically highly significant. Those findings are consistent when conditioned on the sign of the scarcity premium, across sectors and seasons.

It worth noticing that the forward returns of the near and far contracts are only statistically significant when the scarcity premium is positive. Also, those findings are only consistent across seasons for the far contract. This suggests the liquidity providing premium is not simply a by-product of a long-only premium but rather a singular premium. A second relevant observation is that while the premium earned by liquidity providers might erode the hedging benefits, those are still substantial in the presence of a stock-out risk.

2.4 Reward and alpha decay

One key question for market participants is whether the premium attached to the provision of liquidity under scarcity risk can effectively be harvested. Recall from Section 2.1 that the liquidity providing trade is defined as a calendar spread trade selling the contract exposed to the scarcity risk. The liquidity providing portfolio (LiqProv) is thus defined as an equally-weighted allocation to all calendar spreads along all curves, where the sign of the scarcity premium defines the direction of the calendar spread. Essentially in the analysis conducted so far it was assumed positions were rebalanced on a daily basis and that liquidity providers were investing in all contracts in the cross-section of the futures curves.

Acknowledging the limitations of such an assumed implementation and to address concerns on whether one could realisticly implement such a portfolio, I consider two alternative implementations. The first one consists in lowering the rebalancing frequency of the portfolio from daily to monthly. The end-of-month rebalanced portfolio (LiqProvEOM) thus carries old information throughout the month and is sensitive to the speed at which the arbitrage opportunities harvested by the liquidity providers are correcting, i.e. the alpha decay.

The second alternative implementation of the liquidity providing trade aligns with the methodology put forward in this paper and discussed in Section 3.3. Effectively the liquidity providing trade is investing in the whole cross-section of calendar spread trades, along and across commodity futures curves, where the sign of the scarcity premium embedded in the far contract defines the direction of the far-minus-near trade. We can thus consider the top-minus-bottom portfolio (LiqProvSP) of curve trades sorted on the far contract scarcity premium an equivalent representation of the liquidity providing trade. As the sorting portfolios are rebalanced at month-end, this implementation is also sensitive to the alpha decay. one difference with the previous alternative relates to the investment universe which is narrower in this implementation as we consider only calendar spreads eligible for the seasonal portfolios. Moreover, a second difference is that the direction of the liquidity trade might deviate here from the intended one as in the top-minus-bottom implementation considerations about the sign of the scarcity premium are dropped to the benefit of relative perspectives. This alternative approach provides an additional robustness check on the above findings and will allow to assess the sensitivty of the liquidity providing premium to the portfolio construction methodology.

Table 10 displays the risk and return characteristics of those various implementation as well as their correlation structure. The results carry a number of interesting observations. First we observe a large reduction in return once the portfolio rebalancing frequency is lowered. While the return is still econom-

Table 10: Liquidity providing trade alternative implementations.

	LiqProv	LiqProvEOM	LiqProvSP
Risk and Returns			
Return (%)	1.58	0.18	0.81
Volatility (%)	0.36	0.16	1.02
t-statistic	26.35	6.93	4.80
Skewness	3.29	0.06	-0.79
Kurtosis	26.62	43.20	56.65
Correlations			
LiqProv		***	***
LiqProvEOM	0.44		***
LiqProvSP	0.28	0.54	

Note: Returns and volatilities are expressed as annualized percentage numbers. Kurtosis correponds to the excess kurtosis. LiqProv is the liquidity providing trade under scarcity in its unconstrained daily rebalanced implementation, while LiqProvEOM corresponds to its implementation with end-of-month rebalancing. LiqProvSP corresponds to the liquidity providing portfolio constructed according to the sorting portfolio methodology. *p<0.1; **p<0.05; ***p<0.01 indicate the level of statistical significance of the correlation estimates.

ically and statistically significant, it is more than three times lower than the unconstrained daily rebalanced portfolio, suggesting this risk premium decays at a high speed. Second, looking at the sorting portfolio implementation which suffers from the same alpha decay, we can see that the risk and returns are about four times higher as the end-of-month implementation. This suggest the alpha is stronger in the tails but that this is compensated by a equally important rise in risk originating from owning a more concentrated portfolio. Note that the risk remains unchanged between the daily and monthly rebalancing frequency implementations, corroborating the source of the risk increase. More importantly, we see that all three portfolios are highly correlated, on average around 0.80, suggesting they do indeed all relate to the same trade. As expected the sorting portfolio construction methodology introduces additional distortions such that overall this implementation displays the lowest, although still high, correlation with the unconstrained liquidity providing trade.

I thus conclude that the liquidity providing premium originates from fast decaying arbitrage opportunities. Although those opportunities are substantially more sizeable when the scarcity risk is more pronounced, the rise in the associated risk leaves the risk-return trade-off unchanged. The high time sensitivity adds to the risk associated with providing liquidity as the rapid erosion of returns impairs the ability to harvest the premium, requiring both speed and efficiency of execution. If anything, I would expect market makers earning the bid-ask spread to be more proficient in collecting this premium than other liquidity providers facing transaction costs, e.g. speculators. I leave for future research the question of whether or not this premium can be harvested in practice, acknowledging that limits to arbitrage have not been taken into account in this research.

3 Futures risk premia and market anomalies

The asset pricing literature on commodity markets abounds with factors that explain the cross-sectional and timeseries variations of commodity futures' returns. Risk, behavioral, as well as limits to arbitrage arguments have been brought forward to explain the existence of those premia. The third contribution of this paper is to revisit the major commodity market anomalies in the presence of seasonality and unexpected supply and demand shocks. More specifically, I investigate if the seasonal and scarcity risk premia are related to other documented factors in the literature, most notably the original futures basis and other correlated measures capturing price pressure resulting from inventory imbalances (e.g. price momentum), as well as risk related factors (e.g. volatility and skewness risk premia).

This paper contributes to the literature on the factors and risk premia influencing the pricing of commodity futures by proposing a consistent evaluation framework applied systematically to all the selected variables documented in the literature while accounting for the multiple testing bias.[15] The focus is on a robust identification of the factors driving both outright and relative-value trades along a broad cross-section of futures curves. To this aim, I exploit a very large sample of daily historical information over more than 30 years covering the whole futures curves of 29 commodity markets. Compared to previous studies, this represents a substantial expansion of the sample size which offers the benefit of an increase in power for testing the statistical significance of factors.

3.1 Literature review

A large strand of the literature on commodity markets has focused on the investigation of market anomalies.[16] Amongst those factors, the cost of carry, momentum and value as well as risk measures like skewness or volatility related metrics, open interest, hedging pressure, inventories, a broad market return or simple return seasonality have been brought forward. This section provides a non-exhaustive review of the literature on market anomalies and risk factors driving commodity returns.

3.1.1 Carry, Momentum and Value

Koijen et al. (2018) define carry as the expected return of a futures contract if the futures curve is unchanged over the holding horizon. They show the presence of a carry factor across asset classes, including in commodity markets where this concept is tightly related to the convenience yield. While carry in commodity space is positively related to momentum, it has forecasting power beyond this factor.

[15] See, among others, Harvey and Liu (2015), Harvey et al. (2016), Harvey (2017), Hou et al. (2015), Hou et al. (2017), Chordia et al. (2017) and Linnainmaa and Roberts (2018). See also the discussion in section 3.3.4.

[16] See for example Miffre (2016) and the references therein.

The carry factor has been largely documented in commodity markets by amongst others Erb and Harvey (2006) and Gorton and Rouwenhorst (2006). Szymanowska et al. (2014) decompose the commodity futures expected returns into a spot and term risk premia, which are respectively related to the actual price risk of the underlying commodity and to the change in the convenience yield. They find that a single carry factor can describe the cross-section of commodity returns for the spot risk premium while a two basis factors model explains the term premium.

Fama and French (1988) proxy the inventory levels by the sign of the basis adjusted for the foregone interests. They document a higher variability of the basis and of spot prices relative to futures prices when inventories are low, in line with the theory of storage[17]. Gorton et al. (2013) document an inverse and non-linear basis-inventory relationship using actual inventory data. This non-linearity originates from the risk of stock-out in inventories whereby the fear of scarcity lead to larger price increases as the inventory level drops lower.

Momentum in commodity markets has been widely documented. Following the seminal paper of Jegadeesh and Titman (1993), momentum has been investigated in the cross-section of commodities by amongst others Pirrong (2005), Erb and Harvey (2006), Miffre and Rallis (2007) and Shen et al. (2007). Timeseries momentum in commodities has been documented by amongst others Szakmary et al. (2010) and Moskowitz et al. (2012). Asness et al. (2013) document the presence of cross-sectional momentum across asset classes, including in commodities where it earns a highly significant premium. For the sake of consistency they uses a 12 minus 1 months typical from the equity literature but argue that for asset classes less subject to liquidity issues excluding the most recent month information is not relevant. Gorton et al. (2013) show that the slow adjustment of supply and replenishment of inventories lead to momentum in prices. Indeed the continuous depletion of inventories triggers persistence in price increases such that past momentum is informative about the current state of inventories. Boons and Prado (2019) introduce the basis-momentum, a relative momentum measure along the futures curve, as a return predictor associated with the futures curve dynamics and argue it is mainly a compensation for providing liquidity when the market-clearing ability is impaired.

Asness et al. (2013) document the presence of a cross-sectional value factor across asset classes that is negatively correlated with momentum. Motivated by the work of Bondt and Thaler (1985) in equities who characterize expensiveness relative to an asset's own price history, they propose to use a uniform long-term past return measure for asset classes like commodities without a book value. Despite the light statistical significance of the stand-alone value factor, the authors show that value adds to momentum.

Gorton et al. (2013) provide the first comprehensive study of the relationship between physical inventories and commodity futures. They show that the shape of the futures curves is associated with the level of inventories and that

[17] The declining term structure of futures volatility is also known as the "Samuelson (1965) effect". Fama and French (1988) document a violation of this effect when inventories are high. Hong (2000) propose a model in which information asymmetry dampens the volatility towards the expiration of futures contracts, leading to non-monotonic term structure of volatilities.

this relationship becomes highly non-linear as the risk of a stock-out increases. This confirms the model predictions of Routledge et al. (2000) in which the elasticity of the convenience yield to changes in inventory levels is a decreasing function of inventory levels. Also, the authors document that both the basis and the momentum factors are loading on commodities with current low physical inventories. Both risk premia are thus a compensation for bearing the risk of further deterioration in inventory levels.

3.1.2 Hedging pressure and open interest

The theory of normal backwardation by Keynes (1930) and Hicks (1939) assumes that hedgers are net short. This assumption is relaxed in the work of Cootner (1960) which lays the foundation for the hedging pressure hypothesis. Hirshleifer (1988) propose a market model in which the commodity futures risk premium is function of its systematic risk relative to equity markets and its idiosyncratic dispersion. The hedging component of the risk premium is a function of the residual risk. Limits to arbitrage increase the impact of the hedging demand on the risk premium.[18] This is consistent with the model of Hirshleifer (1990) where transaction costs deter consumers hedging activity.

These models' predictions have been corroborated by the empirical evidence provided in Bessembinder (1992) which supports the hedging pressure hypothesis as a determinant of risk premia. More specifically he shows that for some futures markets including agricultural commodities the residual returns vary with the net holdings of hedgers. Roon et al. (2000) extend the work of Bessembinder (1992) to consider cross-market hedging pressure and confirm the hedging demand influence on commodity futures risk premium. Basu and Miffre (2013) construct a long-short portfolio using open interests of both hedgers and speculators in order to capture the hedging pressure risk premium embedded in commodity futures. They find that the risk premium is significant and positively correlated with lagged volatility.

Hong and Yogo (2012) find that the futures open interest has predictability in the timeseries of future commodity returns. They propose a model in which the forecasting power of futures returns originates from the slow diffusion of information and depends on the level of hedging demand. The low risk-bearing capacity of hedgers acts as a limit to arbitrage that offsets the positive autocorrelation in returns originating from uninformed traders when hedging demand is high. In this model the futures open interest carries positive news about the economy and thus future expected returns. Hong (2001) put forward a model in which the nature of the convenience yield shocks has implication for the distribution of open interest along the futures curve. Persistent shocks concentrate the open interest in the nearest contract maturity while transitory shocks lead to wider distribution of open interest along the futures curve.

[18] Hirshleifer (1989) proposes a market model in which the futures risk premia are influenced by a wide number of factors including amongst others the harvest costs, the price and income elasticities of supply and demand, the stock market variability and the supply response.

3.1.3 Risk

Deaton and Laroque (1992) proposed a model relating the level of inventories to future variance in spot prices. In this setup, inventories act as a buffer against transitory supply and demand shocks and thus smooth the price adjustment. Inventory depletion results in a rise of future expected spot price volatility. Gorton et al. (2013) extend this model by introducing risk-averse agents and by providing a hedging motive for producers. This allows them to link inventory levels to both the shape of the futures curve and the expected futures risk premium as the futures provide a hedge against price volatility. The risk premium is negatively related to the level of inventories.

Leveraging the work of Ang et al. (2006) and Ang et al. (2009) in equity markets, Miffre et al. (2012) investigate the presence an idiosyncratic risk premium in commodity markets. While they find support in the stand-alone evaluation, after accounting for the shape of the futures curve they obtain insignificant results.

Frazzini and Pedersen (2014) put forward the betting-against-beta factor which originates from investors leverage constraints. They find evidence of strong risk-adjusted returns for portfolios long low beta assets and short high beta ones, across a broad range of asset classes. Despite economically large returns they could not reject the null hypothesis of zero average return for commodities.

Fernandez-Perez et al. (2018) document a negative and statistically significant price of skewness in commodity markets[19], which is robust to the inclusion in the model of risk factors (i.e. the market, term structure, momentum and hedging pressure). The performance of the low minus high portfolio is also robust to the choice of measure for skewness (i.e. total, systematic, idiosyncratic or expected idiosyncratic skewness), to the ranking or holding period and across various sub-sample time periods. They find that the performance of the low minus high skewness portfolio is mainly originating from the highly skewed assets. As such, their results are consistent with the literature on the investors preference for lottery-like payoff and the resulting under-performance of positively skewed assets.

3.1.4 Returns

A market factor has been document in commodity markets by Bakshi et al. (2013) who propose to use the average commodity return to better describe the cross-section and time-series of commodity returns. They find that adding this average factor helps in reducing pricing errors of parsimonious models consisting solely of carry and momentum for the times-series variations of returns. This average commodity factor is related to future economic growth. Asness et al. (2013) assess the value and momentum premia relative to a market index defined similarly.

[19]For an overview of the literature on the reward for skewness across asset classes, see Ilmanen (2012) and the reference therein.

Keloharju et al. (2016) find strong evidence of the presence of returns seasonality in U.S. as well as in International equities and in commodities, where the difference between the high and low seasonal portfolios is economically important but only marginally significant.

3.2 Factor definitions

The first set of factors selected for this analysis are the futures basis and its components, i.e. the foregone interest, the long-run cost-of-carry, the seasonal premium and the scarcity premium. I also consider their differential, i.e. the far-minus-near information, as they might be more informative for calendar spreads than information about solely one leg of the trade. For example in the case of the basis factors, although measured from both the near and far contracts I would expect the basis to be more informative about the far contract as the basis is defined as the expected return of holding the far contract if nothing else changes. Likewise I would expect the basis differential to be more informative of a calendar spread as it reflects the expected return of a long-short far-minus-near curve trade.

Moreover I investigate the dynamics through time of those components as they capture the evolution of expectations. More specifically, the dynamics in the scarcity premium captures the deterioration in the supply and demand imbalance and the resulting increased likelihood of a stock-out. Given the slow adjustment of fundamentals and slow diffusion of information, it is likely to carry information about forward returns. To increased comparability, I focus on the one year change to align with the measurement window of other factors discussed below. This will allow to better assess potential links or overlaps between factors.

Beyond the basis and its components, I consider some of the most important factors in the literature. Momentum is defined as a 1 year log price change without a skip month. Keeping the last month information in the momentum measure might allow to better detect the correlation with the scarcity premium. Such finding would be in line with the observation by Gorton et al. (2013) that the slow adjustment of supply and replenishment of inventories lead to momentum in prices. Moreover Asness et al. (2013) argue that excluding the most recent month information is not relevant for asset classes less subject to liquidity issues. The value measure simply follows Asness et al. (2013) and is defined as the log of the 1 year price average 4.5 year ago minus the current log price. In the spirit of Keloharju et al. (2016), the return seasonality factor is defined as the expanding window average return per season. The volatility is defined as the exponentially-weighted moving average with a half-life of six months. As in Fernandez-Perez et al. (2018) the skewness is estimated over a 1 year horizon. Both the open interest and volume are contract specific information. To be consistent with the sorting methodology chosen, those characteristics are estimated per season. This means for example that the momentum indicator captures the trend of a contract maturing in a specific season. I also consider the differential of the mose metrics, i.e. the far-minus-near information. Note that the momentum differential corresponds to the negative of the basis momentum variable of

Boons and Prado (2019).

Intentionally, I do not consider the various hedging pressures definitions proposed in the literature as the granularity of the underlying data is insufficient. Indeed, one requirement of this analysis is that factors can be specified for each individual contract along the curve as to be able to explain the cross-sectional variations along and across futures curves. The Commitments Of Traders (COT) data from the U.S. Commodity Futures Trading Commission (CFTC) aggregates reported positions along the curve. This prevents matching the trading activity of hedgers and speculators to the local futures curves dynamics.

3.3 Data and methodology

3.3.1 Investment universe

Interested in the broad harvesting of commodity factor premia in the cross-section of the whole futures curve, I use a large data set covering 29 commodity futures contracts eligible for inclusion in the Bloomberg Commodity Index over a period going from 1983-05-31 to 2018-08-21.[20] I consider the cross-section of far contracts separately from the one of calendar spreads (far-minus-near contracts). Indeed, both subsets carry very different information such that it is justified to analyze them independently. I thus construct sorting portfolios in the cross-section of far contracts to exploit the factors driving the spot premium in excess of the market return, i.e. long-short outright opportunities across commodity markets. In the cross-section of curve trades, I also construct quintile portfolios focusing on the key determinants of the local shape of the futures curves, i.e. long-short relative opportunities per curve across commodity markets.

For each investment opportunity set, I consider both outright factors, i.e. when measured from the far contract, and relative characteristic differentials between the far and near contracts. This allows to consistently evaluate the influence of those two representations of the information on both outright and relative trades across commodity curves. In expectation, far contract based characteristics should be more informative for outright trades while far-minus-near characteristic differentials should be more informative for relative trades along the curve.

3.3.2 Portfolio formation

In order to analyze the impact of the futures risk premia on market anomalies, I create quintile sorting portfolios and a long-short portfolio based on the top-minus-bottom quintiles for each basis factor as well as for other commodity or contract characteristics. This papers adds to the literature by proposing novel portfolio formation approaches.

First, the traditional sorting portfolio approach creates quintile portfolios for each generic futures series, i.e. one for the cross-section of front contracts, one for all the nearest contracts maturing after the active contract and so forth. While

[20] The data set is presented in more details in Section 1.3.1.

widely favored in the literature, this approach might be inappropriate to assess the presence of a seasonal risk premium as it does not differentiate between seasons. Indeed, sorting portfolios defined in such a way might be loading on different seasons depending on the contract cycle of each commodity. In order to avoid distortions that might be associated with the active contracts maturing in different months (i.e. seasons) across commodities, an alternative sorting mechanism is proposed whereby commodities are sorted based on contracts with same delivery month.

This approach results in 12 sets of quintile seasonal portfolios and thus extend the research universe beyond the traditional front contract. The use of all available contracts along the futures curve to include all seasons increases substantially the sample size while controlling at the same time for season differences within quintiles. This leads to an increase in power for testing the statistical significance of factors. This key benefit comes at the potential cost of loading on more illiquid futures contracts as the distance to the front contract increases. To adress this concern I conduct multiple robustness checks discussed in Section 3.3.3.

Second, the traditional portfolio formation methodology relies on an equally-weighted scheme which leaves sorting portfolios potentially exposed to large risk imbalances within and across portfolios. To control for the large cross-sectional dispersion and timeseries variation in risk across commodity markets, I propose to equally weight risk-targeted futures contracts at an arbitrary 10% volatility level. While this approach does not account for correlations, it is favoured for its simplicity and robustness by avoiding the correlation estimation risk. More importantly, this approach should already adress most of the risk imbalances within sorting portfolios, leaving if anything sorting portfolios principally exposed to cross-sectional risk imbalances.

In the presence of risk-adjusted position, each characteristic is also adjusted by the underlying commodity risk before being ranked and allocated to sorting portfolios. This approach preserves the ordering and aligns the commodity selection with its expected contribution in the portfolio.This ultimately guarantees that the top-minus-bottom portfolio mazimixes its factor exposure given the chosen weighting scheme.

The portfolios are rebalanced at month end, i.e. the season frequency. Risk estimates for position sizing are adjusted with the same frequency. Portfolios do not contain synthetic contracts. I require a minimum breadth of 5 futures contract per season in order to create quintile portfolios for a season. To account for the diversity of rolling schemes among commodities and given that for some commodities the curve contains multiple times the same season, the majority of contracts available for a season defines whether the seasonal portfolios relate to the upcoming season or the following one (i.e. the year thereafter). I adjust for the number of seasonal portfolios to account for time-varying breadth in the universe when forming portfolios through time.

3.3.3 Robustness checks

I conduct various robustness checks to confirm the validity of the results put forward in this paper. For the sake of brevity, the results have been omitted from this paper but are available upon request.

Amongst those I conduct a sensitivity analysis on the rebalancing frequency choice for sorting portfolios (i.e. using daily versus monthly frequency), on the inclusion of synthetic contracts (i.e. no synthetic contracts), as well as on the portfolio formation approach (i.e. using seasonal or generic based portfolios, using the full futures curve or solely the front season or active contract, and on the risk-adjusment of positions relative to an equally-weighted scheme). Results are robust to those specifications.

To adress concerns related to the top-minus-bottom portfolio loading on illiquid contracts and a potential illiquidity risk premium, I construct various liquidity measures. More specifically I consider the open interest and volume per contract, their fraction of respectively the total outstanding open interest or traded volume along the curve, the 1 year change in those four metrics as well as the Amihud measure defined in Amihud (2002). Like for other factors, both the far contract outright value and the far-minus-near differential in those measures are evaluated in the cross-section of outright and relative trades. None of the results are statistically significant.

As additional robustness check, I use double sorts for the basis factors on the illiquidity metrics. To ensure we have enough observations per seasonal portfolio, I dissociate high from low liquidity states and then define tertile portfolios within each group. This procedure results in a total of six portfolios, which is quite close to the original quintile sorting portfolios approach such that it should provide approximately the same coverage.The first key finding is that in line with expectations premia are relatively higher in less liquid contracts. The results are consistent accross illiquidity metrics in the cross-section of both outright and relative trades. The second key finding is that the cross-sections of outright positions and curve trades react differently to changes in liquidity conditions. Indeed, while premia in the cross-section of far contracts are relatively higher in contracts that experienced relatively lower changes in liquidity, the opposite is true for spread trades, suggesting the harvesting of premia in the cross-section of curve trades is fostered by improving liquidity conditions. More importantly, the overall statistical significance and monotonicity of factors is not affected by their illiquidity exposure, such that the results presented below are robust.

3.3.4 Multiple testing bias

The risk of p-hacking has received lately increasing attention in the academic literature given the bias to publish positive results and the risk of multiple hypothesis testing.[21] To address data mining considerations I follow the recommendation of Harvey et al. (2016) to raise the statistical significance threshold

[21] See amongst others Harvey and Liu (2015), Harvey et al. (2016), Harvey (2017), Hou et al. (2015), Hou et al. (2017), Chordia et al. (2017), and Linnainmaa and Roberts (2018).

and reject the null hypothesis for t-statistics above 3.0.

3.4 Quintile portfolios

The below tables shed light on the risk, return and t-statistic of quintiles portfolios for the near and far contracts as well as for the relative trade going long the far contract and shorting the near contract. Also the result for the top-minus-bottom portfolios are reported. Table 11 shows the results for the futures basis factors. This table carries a few insightful results. First and foremost, the results confirm earlier literature findings that the futures basis carries information about future returns. The t-statistics for the bottom quintile (the most negative basis) portfolios are highly significant for all contracts (4.27 for the near contract and 4.53 for the far contract). This drives the results for the top-minus-bottom portfolios which exhibit an even higher level of significance (-4.06 and -4.50 for respectively the near and far contracts).

The second key finding is that the sole risk premium embedded in the basis, i.e. the scarcity risk premium, is more informative than the basis itself once distilled from cost-of-carry relationship. The top quintile portfolios have a t-statistic of 4.32, 4.72 and 3.65 for respectively the near, far and far-minus-near contracts. None of the other basis components are informative. A similar conclusion holds for the top-minus-bottom portfolios (3.93, 4.55 and 4.63 for respectively the near, far and far-minus-near contracts). Note that both the seasonal and scarcity premium are of opposite sign relative to the basis as a high scarcity premium leads to a highly negative basis. As a result, the top quintiles for those two premiums relate to the bottom quintiles for the basis and its other components.

It is worth noting that the scarcity premium carries more information for relative trades than outright ones. Recall from Section 2 that the liquidity providing trade is defined as a calendar spread trade selling the contract exposed to the scarcity risk. Effectively the liquidity providing trade correponds to investing in the whole cross-section of calendar spread trades, along and across commodity futures curves, where the sign of the scarcity premium embedded in the far contract defines the direction of the far-minus-near trade. We can thus consider the top-minus-bottom portfolio of curve trades sorted on the far contract scarcity premium an equivalent representation of the liquidity providing trade.

The third key result is that the dynamics through time of the basis carries information, which is not fully captured by the change in the scarcity premium. This might suggest that other basis components' dynamics carry information but here as well the change in the other basis components has no value.

Table 11: Basis Factors Quintile Portfolios (Based on far contract information)

	Near contract			Far contract			Far Minus Near		
Quantile	Return	Volatility	t-statistic	Return	Volatility	t-statistic	Return	Volatility	t-statistic
Basis									
1	4.30	6.34	**4.02**	4.60	6.34	**4.31**	0.30	0.84	2.14
2	2.88	6.27	2.73	3.02	6.25	2.87	0.14	0.58	1.49
3	1.47	6.02	1.45	1.55	6.02	1.53	0.08	0.31	1.45
4	-0.86	6.43	-0.80	-0.89	6.44	-0.82	-0.02	0.38	-0.34
5	0.43	6.23	0.41	0.18	6.20	0.17	-0.25	0.71	-2.10
Top Minus Bottom	-3.87	6.28	**-3.66**	-4.43	6.26	**-4.20**	-0.55	1.13	-2.92
Foregone Interest									
1	1.57	8.40	1.11	1.61	8.36	1.14	0.04	0.69	0.30
2	1.90	6.30	1.79	1.88	6.28	1.78	-0.02	0.55	-0.25
3	1.63	5.92	1.63	1.78	5.94	1.78	0.15	0.45	2.00
4	1.86	6.98	1.58	1.87	6.96	1.60	0.01	0.51	0.09
5	1.02	7.48	0.81	1.03	7.44	0.83	0.01	0.46	0.19
Top Minus Bottom	-0.55	9.47	-0.35	-0.57	9.42	-0.36	-0.02	0.84	-0.15
Long Run Cost Of Carry									
1	2.36	7.80	1.80	2.50	7.76	1.91	0.14	0.76	1.10
2	2.21	6.39	2.05	2.19	6.37	2.04	-0.02	0.46	-0.23
3	1.28	6.19	1.23	1.24	6.19	1.19	-0.04	0.44	-0.49
4	2.63	6.49	2.40	2.77	6.53	2.52	0.14	0.51	1.62
5	-0.40	6.75	-0.35	-0.45	6.71	-0.40	-0.05	0.50	-0.56
Top Minus Bottom	-2.76	8.73	-1.88	-2.95	8.67	-2.02	-0.19	0.92	-1.21
Season Premium									
1	1.83	6.26	1.74	2.05	6.25	1.95	0.21	0.54	2.36
2	1.55	6.17	1.49	1.63	6.15	1.57	0.08	0.37	1.30
3	1.27	5.98	1.26	1.32	5.97	1.31	0.05	0.44	0.71
4	1.52	6.12	1.47	1.51	6.11	1.47	-0.01	0.66	-0.09
5	2.62	5.99	2.60	2.60	5.98	2.58	-0.02	0.73	-0.19
Top Minus Bottom	0.79	5.20	0.90	0.55	5.20	0.63	-0.24	0.91	-1.55
Scarcity Premium									
1	0.14	6.44	0.13	-0.20	6.41	-0.18	-0.34	0.67	-2.99
2	-0.19	6.35	-0.18	-0.25	6.37	-0.24	-0.06	0.44	-0.80
3	0.90	5.94	0.90	0.92	5.93	0.92	0.01	0.41	0.17
4	3.07	6.37	2.86	3.35	6.38	**3.12**	0.28	0.57	2.96
5	4.76	6.55	**4.32**	5.27	6.54	**4.78**	0.50	0.77	**3.86**
Top Minus Bottom	4.63	7.12	**3.86**	5.46	7.09	**4.57**	0.84	1.03	**4.80**
Basis Change									
1	2.87	6.47	2.62	3.36	6.43	**3.09**	0.49	0.81	**3.60**
2	3.31	6.01	**3.26**	3.44	6.01	**3.39**	0.13	0.57	1.41
3	0.71	5.92	0.72	0.76	5.91	0.76	0.05	0.39	0.70
4	0.49	6.22	0.47	0.38	6.21	0.36	-0.11	0.41	-1.60
5	0.37	6.61	0.33	0.00	6.57	0.00	-0.37	0.82	-2.71
Top Minus Bottom	-2.50	6.99	-2.12	-3.36	6.93	-2.87	-0.87	1.15	**-4.45**
Foregone Interest Change									
1	0.14	6.88	0.12	0.13	6.79	0.11	-0.01	0.92	-0.05
2	1.60	6.27	1.51	1.64	6.26	1.55	0.04	0.61	0.39
3	1.61	5.69	1.67	1.71	5.68	1.78	0.10	0.42	1.39
4	1.44	6.37	1.34	1.44	6.35	1.35	0.01	0.49	0.07
5	1.96	6.92	1.67	2.00	6.91	1.71	0.04	0.54	0.44
Top Minus Bottom	1.82	7.75	1.39	1.87	7.66	1.44	0.05	1.07	0.27
Season Premium Change									
1	0.99	6.08	0.96	1.00	6.05	0.98	0.01	0.67	0.13
2	1.71	6.58	1.54	1.68	6.54	1.52	-0.03	0.58	-0.35
3	0.70	5.69	0.73	0.77	5.68	0.80	0.07	0.33	1.31
4	1.84	6.33	1.72	1.77	6.29	1.66	-0.07	0.76	-0.55
5	2.45	6.23	2.33	2.68	6.20	2.56	0.24	0.61	2.30
Top Minus Bottom	1.46	5.80	1.49	1.68	5.75	1.73	0.22	0.88	1.49
Scarcity Premium Change									
1	1.03	6.37	0.96	0.82	6.35	0.76	-0.22	0.81	-1.58
2	-0.36	6.19	-0.35	-0.42	6.18	-0.40	-0.05	0.45	-0.71
3	1.04	5.92	1.04	1.04	5.89	1.05	0.00	0.38	-0.03
4	2.79	6.24	2.65	2.92	6.23	2.78	0.13	0.62	1.21
5	3.09	6.45	2.84	3.50	6.42	**3.23**	0.41	0.82	2.97
Top Minus Bottom	2.06	6.76	1.80	2.68	6.71	2.37	0.63	1.16	**3.20**

Note: Following Harvey et al. (2016), t-statistics in bold satisfy the statistical significance threshold of 3.0. For those we can safely reject the null hypothesis of returns not being significantly different from zero. Returns and volatility are reported as annualized figures.

Table 12: Other Factors Quintile Portfolios (Based on far contract information)

	Near contract			Far contract			Far Minus Near		
Quantile	Return	Volatility	t-statistic	Return	Volatility	t-statistic	Return	Volatility	t-statistic
Momentum									
1	0.99	7.14	0.82	0.92	7.15	0.76	-0.07	0.55	-0.74
2	0.75	6.16	0.72	0.77	6.15	0.74	0.02	0.44	0.24
3	0.88	5.74	0.91	0.90	5.74	0.93	0.02	0.48	0.26
4	3.54	6.46	**3.25**	3.66	6.45	**3.37**	0.12	0.50	1.45
5	2.94	7.56	2.31	3.13	7.53	2.46	0.19	0.59	1.89
Top Minus Bottom	1.95	8.80	1.32	2.21	8.79	1.49	0.26	0.81	1.87
Value									
1	1.14	7.72	0.80	1.47	7.69	1.03	0.33	0.54	**3.30**
2	1.65	6.81	1.31	1.86	6.79	1.48	0.20	0.47	2.35
3	1.68	6.24	1.46	1.78	6.24	1.54	0.09	0.35	1.40
4	0.63	6.93	0.49	0.71	6.91	0.56	0.08	0.47	0.97
5	3.09	7.53	2.22	3.14	7.52	2.26	0.04	0.33	0.70
Top Minus Bottom	1.95	9.36	1.13	1.67	9.33	0.97	-0.29	0.63	-2.44
Return Seasonality									
1	0.06	6.94	0.05	0.06	6.90	0.06	0.00	0.50	0.03
2	1.87	6.33	1.76	1.86	6.35	1.74	-0.01	0.65	-0.12
3	1.56	5.62	1.65	1.60	5.62	1.69	0.04	0.41	0.60
4	2.32	6.53	2.11	2.44	6.52	2.22	0.12	0.50	1.39
5	2.12	7.36	1.71	2.26	7.32	1.83	0.14	0.70	1.16
Top Minus Bottom	2.06	8.37	1.46	2.20	8.32	1.57	0.13	0.89	0.89
Volatility									
1	1.07	6.67	0.95	1.07	6.68	0.95	0.00	0.77	0.00
2	0.81	6.66	0.72	0.88	6.68	0.78	0.07	0.59	0.71
3	2.26	6.10	2.20	2.38	6.09	2.32	0.12	0.39	1.76
4	1.90	6.46	1.74	1.91	6.43	1.77	0.02	0.47	0.21
5	0.67	6.79	0.59	0.65	6.74	0.57	-0.02	0.41	-0.33
Top Minus Bottom	-0.39	7.94	-0.30	-0.42	7.91	-0.31	-0.02	0.90	-0.15
Skewness									
1	1.61	6.93	1.38	1.55	6.93	1.33	-0.06	0.62	-0.60
2	2.56	6.26	2.43	2.54	6.25	2.42	-0.02	0.48	-0.24
3	1.69	5.85	1.72	1.73	5.84	1.76	0.03	0.36	0.56
4	0.77	6.30	0.73	0.93	6.30	0.88	0.16	0.53	1.78
5	1.28	6.76	1.12	1.47	6.76	1.29	0.19	0.50	2.18
Top Minus Bottom	-0.33	7.68	-0.26	-0.08	7.70	-0.06	0.25	0.79	1.86
Open Interest									
1	1.68	6.57	1.40	1.20	6.54	1.01	-0.48	0.84	**-3.11**
2	2.13	6.49	1.80	2.11	6.48	1.79	-0.01	0.61	-0.12
3	1.10	6.33	0.95	1.21	6.32	1.05	0.11	0.54	1.09
4	0.95	6.83	0.76	1.09	6.79	0.88	0.14	0.61	1.24
5	1.15	7.38	0.86	1.41	7.34	1.05	0.26	0.58	2.46
Top Minus Bottom	-0.52	7.60	-0.38	0.21	7.55	0.15	0.73	0.98	**4.11**
Volume									
1	0.00	6.92	0.00	-0.23	6.88	-0.19	-0.24	0.79	-1.70
2	1.07	6.37	0.95	1.15	6.36	1.02	0.08	0.75	0.61
3	2.67	6.16	2.45	2.64	6.12	2.43	-0.03	0.63	-0.31
4	0.27	7.05	0.21	0.50	7.02	0.40	0.23	0.66	1.98
5	0.43	7.67	0.32	0.60	7.62	0.44	0.17	0.59	1.64
Top Minus Bottom	0.42	7.70	0.31	0.83	7.62	0.62	0.41	0.92	2.49

Note: Following Harvey et al. (2016), t-statistics in bold satisfy the statistical significance threshold of 3.0. For those we can safely reject the null hypothesis of returns not being significantly different from zero. Returns and volatility are reported as annualized figures.

Table 12 shows the results for others characteristics of the far contract. The key insight from this table is that none of those factors are statistically significant on a stand-alone basis. This is in stark contrast with earlier findings in the literature and thus deserves some comments. Multiple potential source of divergence could lead to such results. First, the difference in futures rolling scheme where futures are rolled on the day before the minimun of the last tradeable date, the first notice or the expiry date instead of rolling all futures at month-end. Second, as discussed in Section 3.3.2, the portfolio formation methodology differs in multiple ways. Indeed it onboards information from the whole futures curve rather than solely focusing on the front contracts, while controlling for seasonal differences and risk dispersion in the cross-section. Third, the measurement of the characteristics are also controlling for seasonal effects. Ultimately those results raise concerns on the robustness of earlier literature findings. I leave for future research the objective to analyze whether those weak results for previously established factors originate from methodological differences or whether they are the reflection of false positives.

All in all, to a few exceptions, those results confirm the expectation that far-based measures are more informative for far contracts than for near contracts or relative trades.

Next, the sorting portfolios are formed on the basis of the relative characteristic difference between the far and near contracts, such that it should be more informative about the curve trade than sorting solely on the basis of information on the far contract. Comparing Table 13 and Table 11 we find strong support for this hypothesis. Looking at the results for the calendar spread trade (i.e. far-minus-near), the t-statistic for the bottom quintile basis portfolio increases from 2.20 when using solely information from the far contract basis to 3.76 when using the relative basis differential between the far and near contract. Same conclusion holds for the top portfolio (t-statistic drops from -2.08 to -2.22) and the top-minus-bottom portfolio (t-statistic drops from -2.91 to -4.43). Here as well I reach the conclusion that the scarcity premium is the only informative component in the cost-of-carry relationship.

Table 14 sheds light on the influence of other characteristics' differential between the far and near contracts. Consistent with earlier results, none of the characteristics are informative about the near or far contracts. More importantly, the results for the far-minus-near portfolios show that the relative valuation metric is a key drivers of the calendar spread trade. Relatively more under-valued far-minus-near contracts significantly outperform going forward. Likewise the results for the momentum differential suggest that the relative under-reaction is followed by future outperformance. These results are consistent with the futures curve dynamics identified in Section 2.3 and supporting the provision of liquidity under scarcity risk. None of the other factors display statistically significant t-statistics.

Table 13: Basis Factors Quintile Portfolios (Based on far minus near contract information)

	Near contract			Far contract			Far Minus Near		
Quantile	Return	Volatility	t-statistic	Return	Volatility	t-statistic	Return	Volatility	t-statistic
Basis Differential									
1	2.71	6.19	2.60	3.22	6.18	**3.09**	0.51	0.78	**3.90**
2	0.94	6.18	0.90	1.00	6.20	0.96	0.06	0.61	0.58
3	0.43	5.28	0.48	0.48	5.27	0.54	0.05	0.36	0.87
4	1.05	5.95	1.05	1.02	5.94	1.02	-0.03	0.39	-0.42
5	2.45	6.68	2.17	2.11	6.56	1.91	-0.33	1.02	-1.94
Top Minus Bottom	-0.27	4.95	-0.32	-1.11	4.80	-1.37	-0.85	1.27	**-3.94**
Foregone Interest Differential									
1	0.04	6.69	0.04	0.08	6.65	0.08	0.04	0.56	0.42
2	0.35	6.21	0.33	0.36	6.21	0.35	0.02	0.56	0.18
3	1.72	5.62	1.82	1.86	5.62	1.97	0.14	0.41	2.00
4	1.77	6.06	1.73	1.77	6.06	1.74	0.01	0.53	0.06
5	2.68	6.92	2.29	2.63	6.84	2.28	-0.04	0.98	-0.26
Top Minus Bottom	2.63	7.10	2.20	2.55	7.01	2.16	-0.08	1.21	-0.41
Season Premium Differential									
1	1.23	6.49	1.12	1.30	6.48	1.19	0.07	0.64	0.67
2	0.73	6.03	0.72	0.73	6.04	0.72	0.00	0.51	0.04
3	1.29	5.77	1.33	1.30	5.74	1.35	0.01	0.40	0.21
4	1.05	5.68	1.10	1.24	5.68	1.29	0.19	0.51	2.22
5	2.92	5.84	2.96	2.97	5.75	**3.06**	0.05	1.07	0.27
Top Minus Bottom	1.69	5.08	1.98	1.67	4.97	1.99	-0.02	1.22	-0.12
Scarcity Premium Differential									
1	2.82	6.24	2.68	2.53	6.15	2.44	-0.29	1.05	-1.63
2	2.37	5.70	2.47	2.29	5.68	2.39	-0.08	0.52	-0.93
3	0.21	5.54	0.22	0.23	5.52	0.25	0.02	0.34	0.38
4	1.43	6.08	1.40	1.54	6.06	1.51	0.11	0.50	1.33
5	1.14	6.30	1.08	1.69	6.33	1.59	0.55	0.76	**4.31**
Top Minus Bottom	-1.68	4.93	-2.02	-0.84	4.86	-1.02	0.84	1.29	**3.85**
Basis Change Differential									
1	1.87	6.13	1.81	2.21	6.13	2.13	0.34	0.72	2.79
2	0.33	5.93	0.33	0.51	5.89	0.51	0.19	0.55	2.00
3	1.32	5.40	1.45	1.42	5.39	1.56	0.10	0.40	1.46
4	0.82	6.07	0.80	0.69	6.09	0.67	-0.13	0.52	-1.46
5	2.64	6.43	2.43	2.40	6.33	2.25	-0.24	1.03	-1.36
Top Minus Bottom	0.77	4.67	0.97	0.19	4.53	0.25	-0.58	1.25	-2.73
Foregone Interest Change Differential									
1	0.78	6.18	0.74	0.87	6.18	0.84	0.10	0.53	1.09
2	0.96	6.10	0.93	1.09	6.09	1.06	0.13	0.53	1.39
3	1.57	5.64	1.65	1.69	5.61	1.78	0.12	0.49	1.48
4	0.84	6.07	0.82	0.82	6.09	0.80	-0.02	0.65	-0.22
5	2.29	6.19	2.19	2.18	6.11	2.11	-0.11	0.99	-0.68
Top Minus Bottom	1.51	5.55	1.61	1.30	5.47	1.41	-0.21	1.11	-1.13
Season Premium Change Differential									
1	1.11	6.09	1.08	1.18	6.08	1.15	0.07	0.67	0.65
2	0.67	6.00	0.66	0.64	5.97	0.63	-0.03	0.60	-0.26
3	0.88	5.60	0.93	0.78	5.59	0.83	-0.10	0.39	-1.50
4	2.09	5.98	2.07	2.29	5.97	2.28	0.20	0.45	2.66
5	2.29	5.97	2.28	2.49	5.92	2.49	0.20	1.07	1.11
Top Minus Bottom	1.18	4.44	1.58	1.31	4.33	1.79	0.13	1.23	0.61
Scarcity Premium Change Differential									
1	3.08	6.30	2.90	2.91	6.20	2.78	-0.17	1.03	-1.00
2	1.39	5.95	1.39	1.28	5.96	1.27	-0.12	0.51	-1.38
3	0.92	5.46	0.99	1.00	5.44	1.08	0.08	0.42	1.13
4	0.90	6.08	0.88	0.96	6.06	0.94	0.06	0.55	0.64
5	1.11	6.06	1.08	1.52	6.06	1.49	0.41	0.68	**3.57**
Top Minus Bottom	-1.98	4.73	-2.48	-1.39	4.60	-1.79	0.59	1.23	2.83

Note: Following Harvey et al. (2016), t-statistics in bold satisfy the statistical significance threshold of 3.0. For those we can safely reject the null hypothesis of returns not being significantly different from zero. Returns and volatility are reported as annualized figures.

Table 14: Other Factors Quintile Portfolios (Based on far minus near contract information)

	Near contract			Far contract			Far Minus Near		
Quantile	Return	Volatility	t-statistic	Return	Volatility	t-statistic	Return	Volatility	t-statistic
Momentum Differential									
1	4.37	6.03	**4.30**	4.62	6.06	**4.53**	0.25	0.68	2.16
2	2.41	5.90	2.42	2.52	5.90	2.53	0.11	0.50	1.28
3	1.10	5.66	1.15	1.12	5.65	1.18	0.03	0.42	0.36
4	0.51	6.04	0.50	0.47	6.02	0.46	-0.04	0.52	-0.41
5	0.51	6.02	0.51	0.48	6.01	0.47	-0.03	0.55	-0.34
Top Minus Bottom	-3.86	5.34	**-4.30**	-4.14	5.36	**-4.59**	-0.28	0.87	-1.91
Value Differential									
1	1.53	6.65	1.25	1.46	6.62	1.20	-0.07	0.50	-0.71
2	0.88	6.66	0.71	0.92	6.66	0.75	0.04	0.33	0.67
3	0.66	6.24	0.57	0.74	6.23	0.64	0.08	0.24	1.80
4	2.40	6.81	1.91	2.58	6.78	2.06	0.18	0.40	2.42
5	4.69	6.74	**3.77**	5.13	6.71	**4.13**	0.43	0.63	**3.70**
Top Minus Bottom	3.16	7.43	2.30	3.66	7.40	2.67	0.50	0.80	**3.36**
Return Seasonality Differential									
1	2.37	6.18	2.27	2.70	6.18	2.59	0.33	0.70	2.79
2	2.18	5.90	2.20	2.35	5.91	2.36	0.16	0.51	1.91
3	0.86	5.72	0.89	0.88	5.71	0.92	0.03	0.36	0.43
4	1.82	6.08	1.77	1.80	6.09	1.75	-0.02	0.56	-0.20
5	1.75	6.23	1.67	1.52	6.18	1.46	-0.23	0.76	-1.78
Top Minus Bottom	-0.62	6.04	-0.61	-1.17	5.99	-1.16	-0.56	1.01	**-3.27**
Volatility Differential									
1	2.21	6.29	2.09	2.56	6.42	2.37	0.35	0.76	2.75
2	1.98	6.41	1.83	2.18	6.43	2.01	0.20	0.53	2.22
3	1.15	5.78	1.18	1.21	5.77	1.24	0.05	0.34	0.91
4	1.15	6.44	1.06	1.08	6.40	1.00	-0.07	0.45	-0.98
5	2.31	6.39	2.15	2.05	6.28	1.94	-0.26	0.76	-2.02
Top Minus Bottom	0.10	6.81	0.08	-0.51	6.82	-0.45	-0.61	1.09	**-3.32**
Skewness Differential									
1	1.77	5.65	1.86	1.86	5.66	1.95	0.09	0.71	0.76
2	1.31	6.06	1.28	1.32	6.06	1.29	0.01	0.49	0.15
3	1.19	5.80	1.22	1.26	5.79	1.29	0.06	0.29	1.28
4	2.28	5.99	2.26	2.30	6.01	2.28	0.02	0.51	0.21
5	2.11	5.84	2.15	2.19	5.84	2.22	0.07	0.70	0.62
Top Minus Bottom	0.34	4.66	0.44	0.33	4.67	0.41	-0.02	0.97	-0.11
Open Interest Differential									
1	2.52	7.96	1.71	2.56	7.85	1.77	0.04	0.96	0.23
2	1.84	6.94	1.43	1.90	6.92	1.49	0.07	0.64	0.57
3	2.46	5.93	2.24	2.51	5.92	2.30	0.05	0.58	0.48
4	0.63	5.99	0.57	0.69	5.96	0.63	0.06	0.63	0.55
5	0.36	6.39	0.31	0.60	6.33	0.51	0.24	0.79	1.62
Top Minus Bottom	-2.16	5.93	-1.97	-1.96	5.73	-1.86	0.20	1.20	0.88
Volume Differential									
1	3.52	8.25	2.36	3.67	8.10	2.50	0.15	0.94	0.85
2	1.68	6.92	1.34	1.81	6.92	1.45	0.14	0.65	1.16
3	0.95	5.81	0.90	1.10	5.78	1.05	0.15	0.58	1.41
4	2.02	6.02	1.86	1.98	6.01	1.82	-0.04	0.71	-0.33
5	0.37	6.40	0.32	0.47	6.37	0.41	0.10	0.76	0.70
Top Minus Bottom	-3.14	6.37	-2.73	-3.19	6.19	-2.86	-0.05	1.18	-0.23

Note: Following Harvey et al. (2016), t-statistics in bold satisfy the statistical significance threshold of 3.0. For those we can safely reject the null hypothesis of returns not being significantly different from zero. Returns and volatility are reported as annualized figures.

3.5 Spanning tests

In this Section I confront the various factors identified so far in order assess the significance of their added value. For every factor or characteristic of the far contract as well as of the calendar spread trade (i.e. far-minus-near contracts), the performance of the top-minus-bottom sorting portfolios is computed. The performance of each characteristic portfolio is regressed against the performance of the other ones in order to uncover the presence of a statistically significant alpha and to assess their loading on other factors.

The results in table 15 shows both that the top-minus-bottom basis portfolio based on the far contract can be mostly explained by its underlying components and that it is not informative beyond its components. Another important result is that only the scarcity factor adds value above the other basis components, which corroborates earlier findings.

Table 15: Spanning test of the basis on its components.

	Basis	ForegInt	Median	Season	Scarcity
Constant	0.00001	−0.0001	−0.0001	0.00001	0.0003
	$t = 0.534$	$t = -1.060$	$t = -1.519$	$t = 0.607$	$t = 6.023^{***}$
ForegInt	0.025		0.230	0.011	0.040
	$t = 2.096^{**}$		$t = 7.935^{***}$	$t = 0.846$	$t = 1.111$
Median	0.280	0.317		0.109	0.071
	$t = 23.262^{***}$	$t = 7.942^{***}$		$t = 7.453^{***}$	$t = 2.295^{**}$
Season	−0.475	0.069	0.476		−0.071
	$t = -21.851^{***}$	$t = 0.787$	$t = 6.985^{***}$		$t = -1.207$
Scarcity	−0.653	0.072	0.094	−0.022	
	$t = -49.582^{***}$	$t = 1.111$	$t = 2.411^{**}$	$t = -1.274$	
Adjusted R^2	0.729	0.086	0.136	0.060	0.013
Residual Std. Error	0.002 (df = 6707)	0.005 (df = 6708)	0.005 (df = 6708)	0.002 (df = 6708)	0.004 (df = 6708)

Note: The t-statistics rely on the heteroskedasticity and autocorrelation consistent Newey-West (1987) standard errors estimates, using the Newey-West (1994) automatic lag selection procedure. ForegInt is the Foregone Interest component of the basis. *p<0.1; **p<0.05; ***p<0.01

Tables 16 and Table 17 also brings some key insights on the relationship between various factors and characteristics for the cross-section of far contracts. For this analysis, only the characteristics which displayed highly significant top-minus-bottom portfolio performances or significant results for the monotonicity test[22] were selected, as well as the main literature factors as control variables. I'll focus the discussion on the factors with the most significant alpha, which are the scarcity risk premium and the value factor too a lesser extent, as well as the main literature factors.

Looking at the exposures of the scarcity portfolio, we see that its two most significant exposures are the scarcity premium change and the value differential. In the presence of persitent shocks to supply and demand, the level and the change of scarcity are expected to be correlated. The value differential exposure comes as no surprise as this is equivalent to buying the long leg of the liquidity providing trade which benefits from under-valuation relative to the near contract. The scarcity premium also loads positively and significantly on the basis momentum variable (i.e. the negative of the momentum differential). While this suggests both metrics capture the same information, i.e. unexpected fundamental shocks are the key drivers, only the scarcity risk premium exhibit a significant alpha. Next comes momentum as the fourth most significant ex-

[22]Results of the monotonicity tests are reported in the Appendix.

posure. The positive loading on momentum is in line with earlier results in the literature.[23]

Turning now towards the other characteristics, the momentum factor as expected exhibits a highly significant negative exposure to the value factor. More importantly and consistent with the literature, it loads strongly on the scarcity premium, suggesting unexpected supply and demand shocks are a major driver of momentum. The value factor, beyond its large negative loading on momentum, carries a large negative exposure to the value differential which is better explained once we account for the high positive exposure to the change in the scarcity premium. Indeed a large increase in scarcity is accompanied by a more pronounced curvature likely to be driven by the short end of the curve such that the far contract looks relatively more expensive. The other long-short portfolios do not warrant much comments given the lack of supportive evidence that an exposure to those characteristics deserves a premium.

[23]See Section 3.1.1 for a review of the literature on carry, value and momentum in commodity markets.

Table 16: Spanning tests for far contract factors. (1)

	Season	Scarcity	ForegoneIntChg	ScarcityChg	Momentum	Value	RetSeason
Constant	0.00002	0.0001	0.0001	−0.00003	−0.00004	0.0001	0.00002
	$t = 1.038$	$t = 4.408^{***}$	$t = 1.411$	$t = -0.962$	$t = -0.896$	$t = 2.057^{**}$	$t = 0.434$
Scarcity Premium	−0.127		−0.225	0.590	0.429	−0.071	0.147
	$t = -3.618^{***}$		$t = -3.965^{***}$	$t = 19.392^{***}$	$t = 8.048^{***}$	$t = -1.132$	$t = 2.305^{**}$
Season Premium		−0.105	−0.223	0.092	0.016	−0.212	0.082
		$t = -3.669^{***}$	$t = -4.108^{***}$	$t = 2.755^{***}$	$t = 0.280$	$t = -3.653^{***}$	$t = 1.623$
Foregone Interest Change (ForegoneIntChg)	−0.064	−0.053		0.155	0.016	−0.057	0.050
	$t = -3.989^{***}$	$t = -3.907^{***}$		$t = 9.032^{***}$	$t = 0.489$	$t = -1.391$	$t = 1.498$
Scarcity Premium Change (ScarcityChg)	0.068	0.363	0.403		0.009	0.145	−0.091
	$t = 2.708^{***}$	$t = 16.167^{***}$	$t = 8.976^{***}$		$t = 0.193$	$t = 3.069^{***}$	$t = -1.647^{*}$
Momentum	0.005	0.115	0.018	0.004		−0.404	0.142
	$t = 0.280$	$t = 7.780^{***}$	$t = 0.488$	$t = 0.195$		$t = -10.559^{***}$	$t = 3.620^{***}$
Value	−0.054	−0.015	−0.051	0.050	−0.317		−0.092
	$t = -3.805^{***}$	$t = -1.150$	$t = -1.435$	$t = 3.051^{***}$	$t = -10.710^{***}$		$t = -3.204^{***}$
Return Seasonality (RetSeas)	0.020	0.029	0.042	−0.029	0.105	−0.087	
	$t = 1.610$	$t = 2.286^{**}$	$t = 1.499$	$t = -1.650^{*}$	$t = 3.549^{***}$	$t = -3.109^{***}$	
Volatility	−0.024	−0.039	−0.147	0.018	0.058	−0.107	0.125
	$t = -1.511$	$t = -2.873^{***}$	$t = -5.167^{***}$	$t = 1.049$	$t = 1.832^{*}$	$t = -2.837^{***}$	$t = 4.271^{***}$
Skewness	0.044	−0.028	−0.024	0.017	0.086	0.062	0.131
	$t = 2.796^{***}$	$t = -1.852^{*}$	$t = -0.703$	$t = 0.992$	$t = 2.725^{***}$	$t = 1.984^{**}$	$t = 4.115^{***}$
Open Interest (OpenInt)	0.007	−0.054	0.022	0.014	0.012	0.031	0.063
	$t = 0.332$	$t = -2.557^{**}$	$t = 0.429$	$t = 0.557$	$t = 0.237$	$t = 0.474$	$t = 1.355$
Volume	−0.033	−0.035	−0.054	0.010	0.039	−0.070	−0.023
	$t = -1.406$	$t = -1.628$	$t = -1.146$	$t = 0.355$	$t = 0.724$	$t = -1.108$	$t = -0.508$
Scarcity Premium Differential (ScarcityDiff)	0.012	−0.010	−0.085	0.116	−0.081	−0.296	−0.214
	$t = 0.323$	$t = -0.336$	$t = -1.096$	$t = 2.684^{***}$	$t = -1.276$	$t = -4.262^{***}$	$t = -2.690^{***}$
Scarcity Premium Change Differential (ScarcityChgDiff)	0.028	0.050	−0.128	−0.012	−0.047	0.162	−0.012
	$t = 0.792$	$t = 1.689^{*}$	$t = -1.824^{*}$	$t = -0.324$	$t = -0.771$	$t = 2.093^{**}$	$t = -0.164$
Momentum Differential (MomDiff)	0.017	−0.237	−0.044	−0.060	−0.319	−0.280	−0.088
	$t = 0.549$	$t = -9.768^{***}$	$t = -0.718$	$t = -1.901^{*}$	$t = -5.431^{***}$	$t = -4.620^{***}$	$t = -1.519$
Value Differential (ValueDiff)	0.063	0.381	−0.105	0.079	−0.049	−0.434	−0.087
	$t = 2.423^{**}$	$t = 20.006^{***}$	$t = -2.278^{**}$	$t = 2.753^{***}$	$t = -1.138$	$t = -9.132^{***}$	$t = -1.776^{*}$
Adjusted R^2	0.054	0.750	0.104	0.530	0.435	0.361	0.114
Residual Std. Error (df = 6697)	0.002	0.002	0.004	0.003	0.004	0.004	0.004

Note: The t-statistics rely on the heteroskedasticity and autocorrelation consistent Newey-West (1987) standard errors estimates, using the Newey-West (1994) automatic lag selection procedure. *p<0.1; **p<0.05; ***p<0.01

Table 17: Spanning tests for far contract factors. (2)

	Skewness	Volatility	OpenInt	Volume	ScarcityDiff	ScarcityChgDiff	MomDiff	ValueDiff
Constant	−0.0001 $t = -1.731^{*}$	0.0001 $t = 1.466$	0.00002 $t = 0.641$	0.00001 $t = 0.352$	−0.00002 $t = -0.876$	0.00001 $t = 0.349$	−0.00002 $t = -0.758$	−0.00002 $t = -0.578$
Scarcity Premium	−0.131 $t = -1.759^{*}$	−0.187 $t = -2.921^{***}$	−0.079 $t = -2.565^{**}$	−0.048 $t = -1.616$	−0.007 $t = -0.336$	0.034 $t = 1.696^{*}$	−0.289 $t = -9.262^{***}$	0.667 $t = 19.426^{***}$
Season Premium	0.172 $t = 2.605^{***}$	−0.097 $t = -1.578$	0.009 $t = 0.338$	−0.037 $t = -1.406$	0.008 $t = 0.326$	0.016 $t = 0.804$	0.017 $t = 0.560$	0.091 $t = 2.508^{**}$
Foregone Interest Change (ForegoneIntChg)	−0.028 $t = -0.680$	−0.169 $t = -5.360^{***}$	0.008 $t = 0.437$	−0.018 $t = -1.120$	−0.016 $t = -1.092$	−0.021 $t = -1.807^{*}$	−0.013 $t = -0.742$	−0.044 $t = -2.363^{**}$
Scarcity Premium Change (ScarcityChg)	0.049 $t = 0.942$	0.054 $t = 1.060$	0.012 $t = 0.556$	0.008 $t = 0.353$	0.055 $t = 2.740^{***}$	−0.005 $t = -0.327$	−0.045 $t = -1.943^{*}$	0.085 $t = 2.892^{***}$
Momentum	0.110 $t = 2.629^{***}$	0.076 $t = 1.874^{*}$	0.005 $t = 0.246$	0.015 $t = 0.718$	−0.017 $t = -1.285$	−0.009 $t = -0.780$	−0.104 $t = -5.567^{***}$	−0.023 $t = -1.173$
Value	0.062 $t = 1.929^{*}$	−0.109 $t = -2.988^{***}$	0.010 $t = 0.487$	−0.020 $t = -1.090$	−0.048 $t = -4.339^{***}$	0.023 $t = 2.148^{**}$	−0.072 $t = -4.634^{***}$	−0.160 $t = -8.553^{***}$
Return Seasonality (RetSeas)	0.123 $t = 3.885^{***}$	0.121 $t = 4.348^{***}$	0.019 $t = 1.355$	−0.006 $t = -0.508$	−0.033 $t = -2.551^{**}$	−0.002 $t = -0.164$	−0.021 $t = -1.514$	−0.030 $t = -1.773^{*}$
Volatility	−0.044 $t = -1.250$		0.007 $t = 0.523$	−0.024 $t = -1.814^{*}$	0.006 $t = 0.657$	0.011 $t = 1.252$	−0.033 $t = -2.434^{**}$	−0.060 $t = -3.673^{***}$
Skewness		−0.045 $t = -1.325$	0.038 $t = 2.285^{**}$	−0.025 $t = -1.462$	0.045 $t = 3.454^{***}$	−0.008 $t = -0.715$	−0.021 $t = -1.388$	−0.047 $t = -2.373^{**}$
Open Interest (OpenInt)	0.121 $t = 2.233^{**}$	0.022 $t = 0.517$		0.804 $t = 52.815^{***}$	0.018 $t = 0.878$	−0.029 $t = -1.462$	0.015 $t = 0.517$	0.059 $t = 2.137^{**}$
Volume	−0.085 $t = -1.436$	−0.085 $t = -1.819^{*}$	0.863 $t = 52.260^{***}$		0.053 $t = 2.674^{***}$	0.030 $t = 1.519$	−0.030 $t = -1.061$	0.002 $t = 0.085$
Scarcity Premium Differential (ScarcityDiff)	0.281 $t = 3.423^{***}$	0.041 $t = 0.666$	0.034 $t = 0.869$	0.095 $t = 2.823^{***}$		0.356 $t = 13.932^{***}$	0.113 $t = 3.285^{***}$	0.012 $t = 0.310$
Scarcity Premium Change Differential (ScarcityChgDiff)	−0.054 $t = -0.695$	0.081 $t = 1.240$	−0.064 $t = -1.454$	0.060 $t = 1.501$	0.399 $t = 13.605^{***}$		0.107 $t = 3.024^{***}$	−0.083 $t = -2.195^{**}$
Momentum Differential (MomDiff)	−0.082 $t = -1.274$	−0.130 $t = -2.425^{**}$	0.019 $t = 0.520$	−0.034 $t = -1.038$	0.071 $t = 3.244^{***}$	0.060 $t = 2.957^{***}$		−0.081 $t = -2.266^{**}$
Value Differential (ValueDiff)	−0.128 $t = -2.288^{**}$	−0.165 $t = -3.784^{***}$	0.050 $t = 2.115^{**}$	0.002 $t = 0.084$	0.005 $t = 0.306$	−0.033 $t = -2.208^{**}$	−0.056 $t = -2.287^{**}$	
Adjusted R^2	0.073	0.086	0.716	0.717	0.223	0.184	0.386	0.624
Residual Std. Error (df = 6697)	0.004	0.004	0.002	0.002	0.002	0.002	0.002	0.003

Note: The t-statistics rely on the heteroskedasticity and autocorrelation consistent Newey-West (1987) standard errors estimates, using the Newey-West (1994) automatic lag selection procedure. *p<0.1; **p<0.05; ***p<0.01

Table 18: Spanning test of the basis differential on its components.

	Basis	ForegInt	Season	Scarcity	Scarcity
Constant	−0.00001	0.00000	−0.00000	0.00003	0.00002
	$t = -3.497^{***}$	$t = 0.550$	$t = -1.096$	$t = 6.742^{***}$	$t = 5.037^{***}$
ForegInt	0.061		−0.042	0.113	
	$t = 1.490$		$t = -0.798$	$t = 1.764^{*}$	
Season	−0.586	−0.029		0.019	
	$t = -18.047^{***}$	$t = -0.765$		$t = 0.241$	
Scarcity	−0.601	0.057	0.014		
	$t = -16.691^{***}$	$t = 1.667^{*}$	$t = 0.243$		
Basis					−0.596
					$t = -11.681^{***}$
Adjusted R^2	0.612	0.007	0.001	0.006	0.360
Residual Std. Error	0.0003 (df = 6708)	0.0003 (df = 6709)	0.0004 (df = 6709)	0.0004 (df = 6709)	0.0003 (df = 6710)

Note: The t-statistics rely on the heteroskedasticity and autocorrelation consistent Newey-West (1987) standard errors estimates, using the Newey-West (1994) automatic lag selection procedure. All top minus bottom curve trade portfolios are formed on the far minus near characteristic differentials. ForegInt is the Foregone Interest component of the basis. *p<0.1; **p<0.05; ***p<0.01

Table 18 presents the result for the top-minus-bottom calendar spread trade sorting portfolios when they are formed on the basis differential. Here as well we see that most of the variation in the basis differential long-short portfolio can be explained by the basis underlying components differentials. The basis differential actually carries a significant negative alpha well above the Harvey et al. (2016) cutoff. It load negatively and significantly on both the seasonal and scarcity premia differentials. Further investigations confirm earlier findings that the scarcity premium differential contains most of the information in the basis differential. It delivers a highly significant positive alpha above and beyond both the other basis components as well as over the basis differential.

Tables 19 and 20 sheds light on the relationship between various factors and characteristics for the cross-section of calendar spreads. Only the characteristics which displayed highly significant top-minus-bottom portfolio performances or significant results for the monotonicity test[24] were selected, as well as the main literature factors as control variables. I'll focus the discussion on the factors with the most significant alpha, which are the differentials in the scarcity risk premium, momentum, return seasonality and volatility, as well as the main literature factors.

The scarcity premium differential portfolio loads highly on the differential in the change of the scarcity premium, and vice-versa. This essentially indicates that the current local shape of the curve is a reflection of its past changes, i.e. the larger the increase in the scarcity premium of the far contract relative to near contract, the more likely the scarcity premium is larger in the far contract relative to the near one. The scarcity differential loads significanty on the scarcity premium while the scarcity change has a large exposure to the change in the scarcity premium.

The scarcity premium, i.e the liquidity providing trade, is mainly explained by the change in the scarcity premium as well as the momentum and value differentials. These statistically significant exposures corroborates the results of Section 2.3 according to which the local under-reaction in the neighborhood of a scarcity risk creates value opportunities which sufficiently compensate liquidity providers willing to bear this risk and are arbitraged away by amongst others liquidity providers.

[24]Results of the monotonicity tests are reported in the Appendix.

Table 19: Spanning tests for calendar spread factors. (1)

	SeasonDiff	ScarcityDiff	ScarcityChgDiff	MomDiff	ValueDiff	RetSeasonDiff	VolDiff	SkewDiff
Constant	-0.00000 $t = -1.155$	0.00001 $t = 3.631^{***}$	0.00000 $t = 0.299$	0.00001 $t = 3.046^{***}$	0.00001 $t = 1.837^{*}$	-0.00002 $t = -3.582^{***}$	-0.00001 $t = -2.611^{***}$	-0.00000 $t = -0.113$
Scarcity Differential (ScarcityDiff)	-0.043 $t = -0.889$		0.455 $t = 12.443^{***}$	0.016 $t = 0.605$	-0.009 $t = -0.344$	-0.002 $t = -0.062$	-0.069 $t = -2.043^{**}$	0.007 $t = 0.180$
Season Differential (SeasonDiff)		-0.034 $t = -0.871$	0.027 $t = 0.713$	0.009 $t = 0.279$	-0.046 $t = -1.404$	-0.038 $t = -1.047$	0.070 $t = 2.111^{**}$	-0.052 $t = -1.370$
Scarcity Change Differential (ScarcityChgDiff)	0.036 $t = 0.736$	0.485 $t = 13.335^{***}$		-0.043 $t = -1.569$	-0.094 $t = -3.083^{***}$	0.067 $t = 1.787^{*}$	-0.127 $t = -2.889^{***}$	-0.012 $t = -0.301$
Momentum Differential (MomDiff)	0.012 $t = 0.269$	0.017 $t = 0.539$	-0.041 $t = -1.436$		-0.024 $t = -0.783$	0.057 $t = 1.369$	0.134 $t = 3.414^{***}$	0.135 $t = 2.459^{**}$
Value Differential (ValueDiff)	-0.052 $t = -1.347$	-0.008 $t = -0.326$	-0.080 $t = -2.692^{***}$	-0.021 $t = -0.789$		-0.019 $t = -0.534$	0.083 $t = 2.172^{**}$	-0.009 $t = -0.249$
Return Seasonality Differential (RetSeasDiff)	-0.032 $t = -1.082$	-0.001 $t = -0.061$	0.043 $t = 1.597$	0.038 $t = 1.496$	-0.014 $t = -0.528$		0.009 $t = 0.213$	0.016 $t = 0.490$
Volatility Differential (VolDiff)	0.064 $t = 2.005^{**}$	-0.051 $t = -1.877^{*}$	-0.088 $t = -2.818^{***}$	0.097 $t = 3.261^{***}$	0.068 $t = 2.398^{**}$	0.010 $t = 0.199$		0.009 $t = 0.275$
Skewness Differential (SkewDiff)	-0.046 $t = -1.360$	0.005 $t = 0.171$	-0.008 $t = -0.276$	0.093 $t = 2.778^{***}$	-0.007 $t = -0.258$	0.017 $t = 0.470$	0.008 $t = 0.285$	
Open Interest Differential (OpenIntDiff)	0.080 $t = 2.434^{**}$	0.028 $t = 0.892$	-0.034 $t = -1.130$	-0.038 $t = -1.443$	-0.050 $t = -1.734^{*}$	-0.004 $t = -0.099$	0.070 $t = 2.179^{**}$	-0.083 $t = -2.099^{**}$
Volume Differential (VolumeDiff)	0.086 $t = 2.526^{**}$	0.047 $t = 1.506$	0.009 $t = 0.312$	0.032 $t = 1.127$	0.011 $t = 0.361$	-0.030 $t = -0.762$	0.103 $t = 3.275^{***}$	0.086 $t = 2.284^{**}$
Scarcity Premium	0.113 $t = 2.524^{**}$	0.253 $t = 6.559^{***}$	0.034 $t = 0.948$	-0.324 $t = -7.676^{***}$	0.456 $t = 11.123^{***}$	-0.108 $t = -1.929^{*}$	0.039 $t = 0.929$	-0.017 $t = -0.307$
Scarcity Premium Change (ScarcityChg)	-0.009 $t = -0.253$	0.078 $t = 2.349^{**}$	0.220 $t = 6.766^{***}$	-0.167 $t = -4.860^{***}$	0.035 $t = 0.884$	-0.048 $t = -0.831$	0.010 $t = 0.269$	-0.028 $t = -0.770$
Momentum	-0.025 $t = -0.517$	-0.066 $t = -2.152^{**}$	-0.092 $t = -2.649^{***}$	-0.106 $t = -2.706^{***}$	0.021 $t = 0.522$	0.033 $t = 0.605$	-0.058 $t = -1.377$	-0.093 $t = -1.510$
Value	0.082 $t = 2.486^{**}$	-0.009 $t = -0.332$	0.022 $t = 0.846$	-0.057 $t = -1.880^{*}$	-0.214 $t = -6.105^{***}$	-0.045 $t = -1.155$	0.118 $t = 3.425^{***}$	-0.082 $t = -2.380^{**}$
Skewness	-0.027 $t = -0.656$	-0.008 $t = -0.237$	-0.016 $t = -0.528$	0.020 $t = 0.646$	0.029 $t = 0.824$	-0.044 $t = -1.274$	-0.040 $t = -0.757$	0.128 $t = 2.731^{***}$
Adjusted R^2	0.048	0.435	0.424	0.341	0.298	0.035	0.092	0.056
Residual Std. Error (df = 6697)	0.0004	0.0003	0.0003	0.0003	0.0003	0.0004	0.0004	0.0004

Note: The t-statistics rely on the heteroskedasticity and autocorrelation consistent Newey-West (1987) standard errors estimates, using the Newey-West (1994) automatic lag selection procedure. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 20: Spanning tests for calendar spread factors. (2)

	VolumeDiff	OpenIntDiff	Scarcity	ScarcityChg	Momentum	Value	Skewness
Constant	0.00000	0.00000	0.00001	0.00001	0.00001	−0.00000	0.00001
	$t = 0.569$	$t = 0.921$	$t = 1.803^{*}$	$t = 1.724^{*}$	$t = 1.772^{*}$	$t = -0.914$	$t = 1.938^{*}$
Scarcity Differential (ScarcityDiff)	0.038	0.019	0.174	0.066	−0.052	−0.007	−0.006
	$t = 1.548$	$t = 0.892$	$t = 6.529^{***}$	$t = 2.332^{**}$	$t = -2.139^{**}$	$t = -0.328$	$t = -0.255$
Season Differential (SeasonDiff)	0.056	0.043	0.063	−0.006	−0.016	0.053	−0.018
	$t = 2.477^{**}$	$t = 2.407^{**}$	$t = 2.503^{**}$	$t = -0.247$	$t = -0.544$	$t = 2.232^{**}$	$t = -0.686$
Scarcity Change Differential (ScarcityChgDiff)	0.007	−0.024	0.025	0.197	−0.077	0.018	−0.014
	$t = 0.313$	$t = -1.153$	$t = 0.989$	$t = 7.400^{***}$	$t = -2.692^{***}$	$t = 0.842$	$t = -0.542$
Momentum Differential (MomDiff)	0.026	−0.026	−0.227	−0.143	−0.086	−0.046	0.017
	$t = 1.078$	$t = -1.357$	$t = -8.628^{***}$	$t = -4.324^{***}$	$t = -2.758^{***}$	$t = -1.729^{*}$	$t = 0.651$
Value Differential (ValueDiff)	0.008	−0.030	0.284	0.027	0.015	−0.154	0.022
	$t = 0.340$	$t = -1.608$	$t = 7.307^{***}$	$t = 0.833$	$t = 0.516$	$t = -5.474^{***}$	$t = 0.832$
Return Seasonality Differential (RetSeasDiff)	−0.016	−0.002	−0.051	−0.028	0.018	−0.024	−0.025
	$t = -0.757$	$t = -0.098$	$t = -2.226^{**}$	$t = -0.781$	$t = 0.612$	$t = -1.097$	$t = -1.298$
Volatility Differential (VolDiff)	0.061	0.035	0.020	0.006	−0.034	0.069	−0.025
	$t = 2.985^{***}$	$t = 2.155^{**}$	$t = 0.918$	$t = 0.258$	$t = -1.368$	$t = 3.096^{***}$	$t = -0.766$
Skewness Differential (SkewDiff)	0.049	−0.039	−0.008	−0.016	−0.052	−0.046	0.075
	$t = 2.333^{**}$	$t = -2.126^{**}$	$t = -0.305$	$t = -0.801$	$t = -1.541$	$t = -2.338^{**}$	$t = 2.543^{**}$
Open Interest Differential (OpenIntDiff)	0.625		0.012	−0.020	−0.058	−0.057	−0.046
	$t = 23.234^{***}$		$t = 0.495$	$t = -0.613$	$t = -2.130^{**}$	$t = -2.263^{**}$	$t = -1.753^{*}$
Volume Differential (VolumeDiff)		0.517	−0.065	0.025	0.034	0.035	−0.005
		$t = 20.183^{***}$	$t = -2.686^{***}$	$t = 0.921$	$t = 1.191$	$t = 1.560$	$t = -0.146$
Scarcity Premium	−0.076	0.012		0.474	0.085	0.012	−0.069
	$t = -2.596^{***}$	$t = 0.494$		$t = 13.707^{***}$	$t = 2.541^{**}$	$t = 0.406$	$t = -1.744^{*}$
Scarcity Premium Change (ScarcityChg)	0.024	−0.016	0.387		0.030	−0.041	0.027
	$t = 0.923$	$t = -0.617$	$t = 11.013^{***}$		$t = 1.135$	$t = -1.468$	$t = 0.778$
Momentum	0.035	−0.049	0.074	0.032		−0.271	0.123
	$t = 1.155$	$t = -2.068^{**}$	$t = 2.435^{**}$	$t = 1.094$		$t = -7.238^{***}$	$t = 3.258^{***}$
Value	0.035	−0.049	0.011	−0.044	−0.271		0.069
	$t = 1.565$	$t = -2.318^{**}$	$t = 0.430$	$t = -1.448$	$t = -8.153^{***}$		$t = 2.930^{***}$
Skewness	−0.005	−0.037	−0.057	0.027	0.117	0.065	
	$t = -0.144$	$t = -1.608$	$t = -1.689^{*}$	$t = 0.708$	$t = 3.312^{***}$	$t = 2.500^{**}$	
Adjusted R^2	0.357	0.351	0.618	0.521	0.154	0.147	0.037
Residual Std. Error (df = 6697)	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003

Note: The t-statistics rely on the heteroskedasticity and autocorrelation consistent Newey-West (1987) standard errors estimates, using the Newey-West (1994) automatic lag selection procedure. *p<0.1; **p<0.05; ***p<0.01

The momentum differential is mainly related to the scarcity premium and its dynamics. This corroborates the conclusion of Boons and Prado (2019) that basis-momentum is related to the reward for providing liquidity. As discussed above, the value differential is mainly related to the scarcity premium and loads negatively on the value factor.

3.6 Factor portfolios

The analysis of cross-sectional commodity futures characteristics has so far been conducted in parallel to the one of the cross-section of calendar spreads. Ultimately we are interested in the identification of factor premia in the cross-section of the whole futures curves, which encompass both outright and relative opportunities along the curve. This Section thus focuses on the broad harvesting of premia in commodity markets and the combination of the factors uncovered. I will propose parsimonious models to describe first the cross-section of futures contracts, and then the cross-section of calendar spreads. Subsequently, I will propose a factor portfolio that broadly harvest premia across commodity futures curves.

Following the literature, I form factor portfolios combining a selection of factors targeting a 10% risk budget. The risk-targeting of individual long-short factor portfolios is justified by the large heterogenity in the risk profiles and is especially relevant for the factor portfolio harvesting premia in both outrigh and relative opportunities across futures curves.

3.6.1 Cross-section of outright futures contracts

Focusing first on the cross-section of outright futures contracts, I propose a parsimonious equally-weighted two factors model combining the factor with the most significant top-minus-bottom portfolio returns in Section 3.4, i.e. the scarcity premium, with the value factor. Indeed the later factor is found in Section 3.5 to significantly add value above the scarcity risk premium.

Table 21 displays the risk and return characteristics of the three factors portfolio and its underlying premia. Note that for the later the figures reported here vary from the one disclosed in Section 3.4 as a result of the alignment to a common sample size. The results confirm that the combination of selected factors outperforms any subset on a risk-adjusted basis. The EVW_Far portfolio earns economically and statistically highly significant returns, i.e. above 5% on an annual basis for about the same level of risk. The table also sheds light on the correlation structure across factors.

Table 21: Risk and Return of the far contracts factor portfolio.

	EVW_Far	Scarcity	Value
Risk and Returns			
Return (%)	5.38	8.98	1.79
Volatility (%)	5.86	10.00	10.00
t-statistic	4.97	4.86	0.97
Skewness	-0.04	-0.15	0.27
Kurtosis	3.65	2.17	3.26
Correlations			
EVW_Far		***	***
Scarcity	0.59		***
Value	0.59	-0.31	

Note:
Returns and volatilities are expressed as annualized percentage numbers. Kurtosis correponds to the excess kurtosis. EVW_Far corresponds to the equally-weighted two-factors portfolio investing in the Scarcity risk premium and the Value factor. Both underlying factor portfolios target a risk budget of 10%. *p<0.1; **p<0.05; ***p<0.01 indicate the level of statistical significance of the correlation estimates.

3.6.2 Cross-section of calendar spread trades

Focusing now on the cross-section of calendar spread trades, I propose a parsimonious two factors model consisting of the scarcity risk premium differential and the scarcity risk premium, i.e. the liquidity providing trade which was presented in Section 2. Those were the two strongest factors for far-minus-near positions in Section 3.4, after controlling for exposures (e.g. the differential in the change in the scarcity premium loads substantially on the level differential) and robustness issues (e.g. the results for the open interest based on the far contract information are not robust to the choice of portfolio formation methodology).

Table 22 displays the risk and return characteristics of the two factors portfolio of calendar spreads and its underlying premia. The results confirm that the combination of selected factors outperforms any subset on a risk-adjusted basis. The EVW_FMN portfolio earns economically and statistically highly significant returns, i.e. close to 8% on an annual basis for a similar level of risk.

Table 22: Risk and Return of the calendar spread factor portfolio.

	EVW_FMN	ScarcityDiff	Scarcity
Risk and Returns			
Return (%)	7.93	8.73	7.13
Volatility (%)	7.76	10.00	10.00
t-statistic	5.46	4.66	3.81
Skewness	0.82	0.59	0.57
Kurtosis	24.72	16.20	59.47
Correlations			
EVW_FMN		***	***
ScarcityDiff	0.78		***
Scarcity	0.78	0.21	

Note: Returns and volatilities are expressed as annualized percentage numbers. Kurtosis correponds to the excess kurtosis. EVW_FMN corresponds to the equally-weighted two-factors portfolio investing Scarcity risk premium differential and the Liquidity Providing Trade. Both underlying factor portfolios target a risk budget of 10%. *p<0.1; **p<0.05; ***p<0.01 indicate the level of statistical significance of the correlation estimates.

3.6.3 Cross-section of futures curves

Finally, the combination of outright with relative characteristic premia is achieved by following the same portfolio construction approach. The multi-factor portfolio (EVW_All) harvesting the key factors in the cross-section of outright commodity futures and calendar spreads combines the EVW_Far and EVW_FMN portfolios with an equal volatility weighting scheme.

Table 23 displays the risk and return characteristics of the various factor portfolios and their underlying components. The results confirm that the combination of selected factors outperforms any subset on a risk-adjusted basis. The EVW_All portfolio earns economically and statistically highly significant returns, i.e. close to 8.5% on an annual basis for a volatility level of 6%. The table also sheds light on the correlation structure across factors and uncovers the close to zero correlation between the premia portfolios of outright commodity futures and of calendar spreads. It is also important to note that the average pairwise correlation between factors is null. Overall, the diversification benefits originating from the various opportunity sets along the futures curves leads to a substantial risk reduction. This drives the large improvement in the t-statistic which was already well beyond the Harvey et al. (2016) cutoff.

Table 23: Risk and Return of the final multi-factor portfolio.

	EVW_All	EVW_Far	EVW_FMN	Scarcity	Value	ScarcityDiff	LiqProv
Risk and Returns							
Return (%)	8.42	5.56	6.74	6.08	1.66	1.19	0.95
Volatility (%)	6.04	5.76	6.57	6.43	9.27	1.36	1.34
t-statistic	7.44	5.16	5.48	5.05	0.96	4.66	3.81
Skewness	0.34	-0.05	0.84	-0.15	0.28	0.59	0.57
Kurtosis	6.44	3.68	23.58	1.85	3.38	16.20	59.47
Correlations							
EVW_All		***	***	***	***	***	***
EVW_Far	0.78			***	***		
EVW_FMN	0.62	0.00				***	***
Scarcity	0.45	0.58	0.00		***	*	**
Value	0.46	0.59	0.00	-0.33			
ScarcityDiff	0.50	0.01	0.80	0.02	-0.01		***
LiqProv	0.46	-0.01	0.76	-0.03	0.02	0.21	

Note: Returns and volatilities are expressed as annualized percentage numbers. Kurtosis correponds to the excess kurtosis. EVW_All corresponds to the multi-factor portfolio exploiting factors in the cross-section of both outright commodity futures and calendar spreads. It is the equal volatility-weighted portfolio allocating to EVW_Far and EVW_FMN portfolios. EVW_Far corresponds to the equally-weighted two-factors portfolio for the cross-section of far contracts investing in the scarcity risk premium and the value factor. EVW_FMN corresponds to the equally-weighted two-factors portfolio for the cross-section of calendar spreads investing scarcity risk premium differential and the liquidity providing trade. All underlying factor portfolios target a risk budget of 10%. LiqProv is the liquidity providing trade which corresponds to the top-minus-bottom portfolio of calendar spreads sorted on the scarcity premium. *$p<0.1$; **$p<0.05$; ***$p<0.01$ indicate the level of statistical significance of the correlation estimates.

3.6.4 Limits to arbitrage

Transaction costs are a source of trading friction that impairs arbitrage mechanisms. Such limits to arbitrage could thus explain the presence of documented market anomalies.[25] In this Section, I investigate the influence of this impediment on the harvesting of commodity risk premia along the futures curves as so far transaction costs have been ignored from this analysis. To this extent, I follow the literature and assume a tick size as transaction cost for each contract.[26]

Table 24 displays the risk and return characteristics of the various factor portfolios and their underlying components, once transaction costs have been accounted for. The results are unequivocal, transaction costs act as a limit to arbitrage. To the exception of the scarcity risk premium no other factors is statistically significant. As a result, the two-factor portfolio of calendar spreads (EVW_FMN) is also not significant. The two-factor portfolio of far contracts (EVW_Far) remains highly significant with a t-statistic of 4.67 but is now hardly distinguishable from the scarcity risk premium portfolio wouldn't it be for the higher order moments. Finally, the multi-factor portfolio harvesting commodity risk premia along the futures curves (EVW_All) remains highly significant but has become unattractive compared to the harvesting solely in the cross-section of outright trades. Ultimately, the loss in significance for the EVW_FMN portfolio outweights the diversification benefits.

[25]See Shleifer and Vishny (1997)

[26]I acknowledge this assumption is not conservative. Still for the purpose of this analysis it provides sufficient insights to determine whether in optimal conditions the harvesting of commodity risk premia is impaired by transaction costs. I refer the reader to Bollerslev et al. (2018) for an alternative approach to estimating more accurately transaction costs.

Table 24: Net Risk and Return of the final multi-factor portfolio.

	EVW_All	EVW_Far	EVW_FMN	Scarcity	Value	ScarcityDiff	LiqProv
Risk and Returns							
Return (%)	4.87	5.03	2.13	5.59	1.35	0.18	0.25
Volatility (%)	7.02	5.85	7.58	6.56	9.32	1.34	1.42
t-statistic	3.77	4.67	1.53	4.63	0.78	0.74	0.94
Skewness	0.13	-0.04	0.55	-0.15	0.27	0.36	0.83
Kurtosis	8.69	3.62	27.86	2.17	3.23	15.14	101.61
Correlations							
EVW_All		***	***	***	***	***	***
EVW_Far	0.71			***	***		
EVW_FMN	0.70	-0.01				***	***
Scarcity	0.41	0.59	-0.01		***	*	***
Value	0.42	0.59	0.00	-0.32			
ScarcityDiff	0.55	0.01	0.77	0.02	-0.01		***
LiqProv	0.53	-0.02	0.77	-0.04	0.02	0.18	

Note: Returns and volatilities are expressed as annualized percentage numbers. Kurtosis correponds to the excess kurtosis. EVW_All corresponds to the multi-factor portfolio exploiting factors in the cross-section of both outright commodity futures and calendar spreads. It is the equal volatility-weighted portfolio allocating to EVW_Far and EVW_FMN portfolios. EVW_Far corresponds to the equally-weighted two-factors portfolio for the cross-section of far contracts investing in the scarcity risk premium and the value factor. EVW_FMN corresponds to the equally-weighted two-factors portfolio for the cross-section of calendar spreads investing scarcity risk premium differential and the liquidity providing trade. All underlying factor portfolios target a risk budget of 10%. LiqProv is the liquidity providing trade which corresponds to the top-minus-bottom portfolio of calendar spreads sorted on the scarcity premium. *$p<0.1$; **$p<0.05$; ***$p<0.01$ indicate the level of statistical significance of the correlation estimates.

Those results are to some extent expected as the ratio of transaction costs to risk heavily weights on the ability to harvest relative arbitrage opportunities along the futures curves. In comparison, cross-sectional outright trades face half of the cost for about ten times higher risk levels. I leave for future research the question of whether factors in the cross-section of calendar spreads can be harvested more efficiently. Acknowledging the use of non-conservative transaction cost estimates, the threshold is high in light of those results.

4 Conclusion

The first contribution of this paper is to revisit the cost of carry model and to propose a decomposition of the futures basis in excess of the long-run futures cost-of-carry that disentangles the seasonality premium from the scarcity premium. This allows one to differentiate those periodic insurance premia in terms of expectations. The decomposition dissociates the effect on the convenience yield of expected seasonal shocks and the resulting anticipated hedging demand versus unexpected shocks to inventories triggering an adjustment in expectations and the net hedging demand.

In order to gain an understanding of which factors within the cost-of-carry model have predictive power, I analyze the influence of those factors on the futures spot and term premia. I find that, after controlling for the market, the scarcity premium is highly significant with a t-statistic well above the Harvey et al. (2016) cutoff and is the sole variable to explain the timeseries and cross-sectional variations in the future spot risk premia. Additionally, I find that the scarcity premium differential is the only highly significant explanatory variable of the term risk premia. Those findings are robust to the introduction of commodity sectors and seasons as control variables. Ultimately, these results suggest that expected seasonal shocks are priced in the futures curve while the unexpected shocks to inventories are not.

To better understand the origin of this forecasting power, I investigate two competing but not mutually exclusive hypotheses. The first one postulates that the presence of recurring unexpected shocks could be the source of the observed return predictability, but the absence of significant autocorrelation coefficient for the change in the scarcity risk premium leads me to reject this hypothesis. The second hypothesis argues that the slow diffusion of information and market participants underreaction to new information are the key drivers. Consistent with this hypothesis I provide evidence that the scarcity risk premium is associated with highly significant excess return above the market for a holding horizon up to three months, along the whole futures curve, for both positive and negative premia.

In the presence of periodic supply and demand imbalances leading to potential scarcity risk, the question of who might be a willing counterparty to the hedging demand is thus warranted. Assuming pure liquidity providers hold no speculative positions and hedge out any spot risk, they would still remain exposed to the negative non-linearity in spot prices resulting from an increasing likelihood of stock-outs. Such short skewness exposure might deter natural liquidity providers in the absence of a positive expected return.

The second contribution of this paper is to characterize the liquidity provision premium and to investigate whether empirically market makers have been rewarded for ensuring the well-functioning of markets, i.e. for facilitating the needs of hedgers as well as the objectives of speculators. I find that liquidity providers, being structurally short the scarcity risk premium, do carry negative skewness and long value exposures. They are thus negatively exposed to the non-linearity in spot prices resulting from an increasing likelihood of stock-out. Interestingly the long value exposure confirms the role of liquidity providers as arbitrageurs. I find that the liquidity providing trade earns positive returns that are both economically and statistically highly significant, more than compensating the risks born.

I provide strong empirical evidence that market participants underreact to the risk of scarcity in the seasons neighboring the potential materialization of the event. An interpretation is that market participants are subject to a framing bias whereby they are not able to extrapolate the implications of the risk of stockout. This leads hedging and liquidity demand to be primarily concentrated in the seasonal contract where the event is located and to the mispricing of both the risk that the inventory depletion happens at faster rate than anticipated as well as the risk that inventory imbalances might resorb at a lower speed than expected due to the slow adjustment of supply. As the risk of scarcity rises further, investors would recalibrate their probabilities, or be arbitraged away, and reassess the risks surrounding the event.

The third contribution of this paper is to revisit the main commodity market anomalies in the presence of seasonality and unexpected supply and demand shocks. While I confirm earlier literature findings that the futures basis carries information about future returns, I find that the scarcity risk premium distilled from cost-of-carry relationship is the sole risk premium embedded in the basis and is more informative than the basis itself. On the other hand, the empirical evidence put forward in this paper comes in stark contrast with earlier literature findings. Indeed, amongst the factors put forward in the literature, none of the one tested are statistically significant on a stand-alone basis, raising robustness concerns.

Interested in the identification of factor premia in the cross-section of the whole futures curves, which encompass both outright and relative opportunities along the curve, as well as the broad harvesting of premia in commodity markets, I propose a four factor portfolio combining the scarcity risk premium and the value premia in the cross-section of outright characteristics, as well as the scarcity differential and the liquidity providing premia in the cross-section of relative characteristics along the futures curves. Three out of those four factors relate to the scarcity risk premium and the unexpected shock to the net demand beyond expected transitory seasonal shocks. This confirms that seasonal expectations are priced-in and carry no informational content about the forward returns or the risk premia embedded in commodity markets. Only unexpected supply and demand imbalances command a premium as a compensation for the uncertainty associated with the risk of scarcity.

This combination adds value thanks to the close to zero correlation between the outright and relative characteristic premia portfolios. The factor portfolio earns economically and statistically highly significant returns but limits to arbitrage heavily weights on the ability to harvest relative opportunities along the futures curves. After accounting for transaction costs, none of the selected factors are statistically significant to the exception of the scarcity risk premium and the loss in significance outweights the diversification benefits

In this paper, I proposed some avenues of research. First and foremost, I have raised concerns on the robustness of some earlier literature findings. It is thus of penultimate importance for both market participants and academia to re-evaluate critically whether the weak results reported for previously established factors could be a reflection of false positives. Second, in light of the strong liquidity provision premium uncovered in this paper and its fast alpha decay which comes as an additional risk for liquidity providers, future research on the information decay and the impacts of limits to arbitrage will provide valuable insights on the cost of harvesting this premium and the risk born by those market participants to ensure ensuring the well-functioning of commodity futures markets.

Appendix

Data description

The below table presents the universe of commodity futures contract considered in this paper and provides information concerning the starting year of the sample data, the source, the contract code letter for the available contract delivery months and the classification in commodity sectors.

Table A1: Data description

Mnemonic	Description	Sector	Exchange	Start Year	Months	Source
BO	Soybean Oil	Grains	CBOT	1961	FHKNQUVZ	CME
C	Corn	Grains	CBOT	1960	HKNUZ	CME
CC	Cocoa	Softs	ICE	1970	HKNUZ	ICE
CL	WTI Crude Oil	Energy	NYMEX	1983	FGHJKMNQUVXZ	CME
CO	Brent Crude Oil	Energy	ICE	1993	FGHJKMNQUVXZ	ICE
CT	Cotton	Softs	ICE	1972	HKNVZ	ICE
FC	Feeder Cattle	Livestock	CME	1974	FHJKQUVX	CME
GC	Gold	PreciousMetals	COMEX	1975	GJMQVZ	CME
HG	Copper	IndustrialMetals	COMEX	1989	FGHJKMNQUVXZ	CME
HO	Heating Oil	Energy	NYMEX	1986	FGHJKMNQUVXZ	CME
HU	Unleaded Gazoline	Energy	NYMEX	1987	FGHJKMNQUVXZ	CME
JO	Orange Juice	Softs	ICE	1967	FHKNUX	ICE
KC	Coffee C	Softs	ICE	1973	HKNUZ	ICE
KW	KC HRW Wheat	Grains	CBOT	1976	HKNUZ	CME
LA	Aluminium	IndustrialMetals	LME	1997	FGHJKMNQUVXZ	Datastream
LC	Live Cattle	Livestock	CME	1965	GJMQVZ	CME
LH	Lean Hogs	Livestock	CME	1987	GJMNQVZ	CME
LL	Lead	IndustrialMetals	LME	1998	FGHJKMNQUVXZ	Datastream
LN	Nickel	IndustrialMetals	LME	1997	FGHJKMNQUVXZ	Datastream
LT	Tin	IndustrialMetals	LME	1998	FGHJKMNQUVXZ	Datastream
LX	Zinc	IndustrialMetals	LME	1997	FGHJKMNQUVXZ	Datastream
NG	Natural Gaz	Energy	NYMEX	1990	FGHJKMNQUVXZ	CME
PL	Platinum	IndustrialMetals	NYMEX	1987	FJNV	CME
S	Soybean	Grains	CBOT	1970	FHKNQUX	CME
SB	Sugar No. 11	Softs	ICE	1964	HKNV	ICE
SI	Silver	PreciousMetals	COMEX	1975	FHKNUZ	CME
SM	Soybean Meal	Grains	CBOT	1964	FHKNQUVZ	CME
W	Wheat	Grains	CBOT	1959	HKNUZ	CME
XB	Gasoline RBOB	Energy	NYMEX	2006	FGHJKMNQUVXZ	CME

Estimation of the seasonal premium

Tables A2, A3, A4 and A5 show the full-sample estimates of the seasonal premium over the long-run cost-of-carry per commodity. The estimation has been carried out by means of robust regression using a panel approach along the futures curve, i.e. considering all available contracts at any point in time, using seasonal dummies. The results are reported using Newey-West standard errors, i.e. heteroskedasticity and autocorrelation consistent estimate of the covariance matrix of the coefficient estimates.

Table A2: Regression of the convenience yield on seasonal dummies.

	BO	C	CC	CL	CT	CO	FC
Season 1	0.021	0.107	−0.001	0.025	0.047	0.051	−0.037
	$t = 3.579^{***}$	$t = 7.964^{***}$	$t = -0.327$	$t = 6.306^{***}$	$t = 7.183^{***}$	$t = 6.659^{***}$	$t = -3.002^{***}$
Season 2				0.001		0.004	
				$t = 0.186$		$t = 0.368$	
Season 3	−0.010	−0.055		−0.001		−0.0001	−0.005
	$t = -1.423$	$t = -3.842^{***}$		$t = -0.197$		$t = -0.005$	$t = -0.279$
Season 4				−0.001		0.003	0.074
				$t = -0.117$		$t = 0.232$	$t = 4.770^{***}$
Season 5	−0.014	−0.058	0.007	0.001	−0.006	0.003	0.087
	$t = -1.900^{*}$	$t = -4.124^{***}$	$t = 1.260$	$t = 0.058$	$t = -0.662$	$t = 0.247$	$t = 4.953^{***}$
Season 6				−0.002		0.001	
				$t = -0.179$		$t = 0.122$	
Season 7	−0.011	−0.084	0.005	−0.001	−0.022	0.002	
	$t = -1.541$	$t = -5.869^{***}$	$t = 0.842$	$t = -0.091$	$t = -2.562^{**}$	$t = 0.203$	
Season 8	−0.048			0.007		0.003	0.129
	$t = -4.863^{***}$			$t = 0.876$		$t = 0.239$	$t = 9.029^{***}$
Season 9	−0.051	−0.267	0.005	−0.0005		0.002	0.045
	$t = -5.054^{***}$	$t = -7.202^{***}$	$t = 0.967$	$t = -0.069$		$t = 0.144$	$t = 3.039^{***}$
Season 10	−0.079			0.005	−0.135	0.0002	0.046
	$t = -5.051^{***}$			$t = 0.692$	$t = -4.338^{***}$	$t = 0.020$	$t = 3.119^{***}$
Season 11		−0.008		0.003		0.004	0.064
		$t = -0.379$		$t = 0.446$		$t = 0.350$	$t = 2.769^{***}$
Season 12	−0.024	−0.153	−0.003	0.003	−0.079	−0.0001	
	$t = -2.567^{**}$	$t = -7.295^{***}$	$t = -0.428$	$t = 0.453$	$t = -4.913^{***}$	$t = -0.006$	
Adjusted R^2	0.075	0.270	0.004	0.001	0.099	0.0003	0.098
Residual Std. Error	0.089 (df = 81587)	0.133 (df = 57322)	0.055 (df = 51736)	0.096 (df = 161832)	0.155 (df = 63712)	0.077 (df = 99610)	0.120 (df = 32764)
Note	The t-statistics rely on the heteroskedasticity and autocorrelation consistent Newey-West (1987) standard errors estimates, using the Newey-West (1994) automatic lag selection procedure. *p<0.1; **p<0.05; ***p<0.01						

Table A3: Regression of the convenience yield on seasonal dummies (cont.).

	GC	HG	HO	JO	KC	KW	LA	LC
Season 1	0.010 $t = 5.004^{***}$	0.014 $t = 2.732^{***}$	0.048 $t = 5.155^{***}$	0.014 $t = 1.781^{*}$	0.030 $t = 3.074^{***}$	0.025 $t = 4.887^{***}$	0.011 $t = 2.164^{**}$	−0.079 $t = -3.429^{***}$
Season 2	−0.007 $t = -3.271^{***}$	−0.002 $t = -0.254$	−0.080 $t = -6.397^{***}$				0.0002 $t = 0.025$	0.138 $t = 5.338^{***}$
Season 3	−0.0002 $t = -0.084$	−0.002 $t = -0.319$	−0.226 $t = -10.332^{***}$	0.020 $t = 2.040^{**}$			−0.002 $t = -0.220$	−0.058 $t = -0.206$
Season 4	−0.008 $t = -3.687^{***}$	0.001 $t = 0.119$	−0.254 $t = -11.934^{***}$				0.002 $t = 0.210$	0.142 $t = 5.191^{***}$
Season 5	−0.001 $t = -0.219$	0.001 $t = 0.082$	−0.214 $t = -7.325^{***}$	0.023 $t = 2.205^{**}$	0.006 $t = 0.485$	−0.084 $t = -5.342^{***}$	0.004 $t = 0.533$	−0.420 $t = -7.741^{***}$
Season 6	−0.008 $t = -3.674^{***}$	0.005 $t = 0.562$	−0.138 $t = -6.773^{***}$				0.004 $t = 0.516$	−0.135 $t = -3.796^{***}$
Season 7	−0.001 $t = -0.229$	0.001 $t = 0.135$	−0.051 $t = -3.419^{***}$	0.015 $t = 1.434$	0.002 $t = 0.182$	−0.139 $t = -4.766^{***}$	0.004 $t = 0.495$	−0.036 $t = -0.114$
Season 8	−0.009 $t = -4.043^{***}$	0.005 $t = 0.577$	0.003 $t = 0.276$				0.002 $t = 0.282$	0.021 $t = 0.819$
Season 9	0.001 $t = 0.390$	−0.001 $t = -0.069$	0.039 $t = 3.383^{***}$	0.003 $t = 0.271$	0.001 $t = 0.075$	0.019 $t = 3.026^{***}$	0.005 $t = 0.699$	0.087 $t = 1.800^{*}$
Season 10	−0.008 $t = -3.610^{***}$	0.002 $t = 0.249$	0.042 $t = 3.499^{***}$				0.003 $t = 0.351$	0.194 $t = 7.004^{***}$
Season 11	−0.001 $t = -0.353$	0.0003 $t = 0.031$	0.037 $t = 3.022^{***}$	−0.031 $t = -2.378^{**}$			0.002 $t = 0.296$	0.029 $t = 0.338$
Season 12	−0.008 $t = -3.389^{***}$	−0.001 $t = -0.064$	0.035 $t = 2.876^{***}$		−0.002 $t = -0.153$	0.040 $t = 6.486^{***}$	0.003 $t = 0.459$	0.175 $t = 7.211^{***}$
Adjusted R^2	0.027	0.001	0.404	0.035	0.001	0.213	0.001	0.459
Residual Std. Error	0.009 (df = 75912)	0.062 (df = 133629)	0.132 (df = 98791)	0.095 (df = 59076)	0.098 (df = 54091)	0.131 (df = 39788)	0.052 (df = 118991)	0.124 (df = 40122)
Note	The t-statistics rely on the heteroskedasticity and autocorrelation consistent Newey-West (1987) standard errors estimates, using the Newey-West (1994) automatic lag selection procedure. *p<0.1; **p<0.05; ***p<0.01							

Table A4: Regression of the convenience yield on seasonal dummies (cont.).

	LH	LL	LN	LT	LX	NG	PL	S
Season 1	0.318	−0.008	−0.005	0.001	−0.009	0.260	0.002	0.024
	$t = 6.019^{***}$	$t = -1.491$	$t = -0.646$	$t = 0.452$	$t = -1.228$	$t = 15.613^{***}$	$t = 0.571$	$t = 12.156^{***}$
Season 2		−0.003	0.001	0.003	0.001	−0.526	0.011	
		$t = -0.337$	$t = 0.102$	$t = 0.660$	$t = 0.073$	$t = -6.548^{***}$	$t = 2.382^{**}$	
Season 3		−0.0004	−0.001	0.005	0.001	−0.728	0.010	−0.012
		$t = -0.051$	$t = -0.058$	$t = 1.033$	$t = 0.119$	$t = -7.855^{***}$	$t = 2.378^{**}$	$t = -2.791^{***}$
Season 4	−0.135	0.001	−0.001	0.005	0.001	−1.105	0.001	
	$t = -2.070^{**}$	$t = 0.130$	$t = -0.134$	$t = 1.159$	$t = 0.107$	$t = -13.161^{***}$	$t = 0.229$	
Season 5	0.598	0.002	−0.0001	0.004	0.004	−0.375	0.008	−0.026
	$t = 7.607^{***}$	$t = 0.301$	$t = -0.014$	$t = 0.912$	$t = 0.440$	$t = -16.475^{***}$	$t = 1.626$	$t = -5.343^{***}$
Season 6	0.222	0.004	0.002	0.004	0.006	−0.218	0.008	
	$t = 3.818^{***}$	$t = 0.482$	$t = 0.242$	$t = 0.667$	$t = 0.577$	$t = -12.081^{***}$	$t = 1.984^{**}$	
Season 7	−0.353	0.006	0.0004	0.005	0.003	−0.192	0.001	−0.016
	$t = -6.170^{***}$	$t = 0.831$	$t = 0.042$	$t = 1.065$	$t = 0.250$	$t = -10.802^{***}$	$t = 0.137$	$t = -4.492^{***}$
Season 8	−0.497	0.003	−0.001	0.004	0.003	−0.220	0.006	−0.112
	$t = -8.918^{***}$	$t = 0.396$	$t = -0.127$	$t = 0.980$	$t = 0.339$	$t = -12.654^{***}$	$t = 1.352$	$t = -10.798^{***}$
Season 9		0.006	0.003	0.006	0.007	−0.264	0.011	−0.259
		$t = 0.698$	$t = 0.315$	$t = 1.391$	$t = 0.644$	$t = -15.064^{***}$	$t = 2.310^{**}$	$t = -11.052^{***}$
Season 10	−0.936	0.003	0.001	0.003	0.001	−0.130	−0.001	
	$t = -15.317^{***}$	$t = 0.369$	$t = 0.131$	$t = 0.688$	$t = 0.074$	$t = -5.571^{***}$	$t = -0.103$	
Season 11		−0.001	−0.001	0.002	0.004	0.271	0.008	−0.106
		$t = -0.104$	$t = -0.106$	$t = 0.485$	$t = 0.395$	$t = 5.062^{***}$	$t = 2.064^{**}$	$t = -8.403^{***}$
Season 12	−0.413	−0.001	0.001	0.003	0.004	0.389	0.011	
	$t = -6.712^{***}$	$t = -0.114$	$t = 0.083$	$t = 0.703$	$t = 0.336$	$t = 8.914^{***}$	$t = 2.151^{**}$	
Adjusted R^2	0.676	0.002	0.0002	0.002	0.001	0.594	0.002	0.310
Residual Std. Error	0.293 (df = 53927)	0.059 (df = 95539)	0.081 (df = 118636)	0.035 (df = 72037)	0.065 (df = 118850)	0.321 (df = 149053)	0.033 (df = 12506)	0.130 (df = 71299)
Note	The t-statistics rely on the heteroskedasticity and autocorrelation consistent Newey-West (1987) standard errors estimates, using the Newey-West (1994) automatic lag selection procedure. *p<0.1; **p<0.05; ***p<0.01							

Table A5: Regression of the convenience yield on seasonal dummies (cont.).

	SB	SI	SM	W	XBW
Season 1	0.032	−0.007	0.010	0.028	0.072
	$t = 0.816$	$t = -4.276^{***}$	$t = 2.346^{**}$	$t = 4.380^{***}$	$t = 8.323^{***}$
Season 2		0.016			0.062
		$t = 7.644^{***}$			$t = 5.733^{***}$
Season 3	0.038	0.005	−0.002		0.112
	$t = 0.929$	$t = 1.982^{**}$	$t = -0.276$		$t = 9.740^{***}$
Season 4		0.014			0.854
		$t = 4.987^{***}$			$t = 10.284^{***}$
Season 5	−0.075	0.003	−0.021	−0.086	0.019
	$t = -1.799^{*}$	$t = 1.171$	$t = -2.777^{***}$	$t = -3.889^{***}$	$t = 1.762^{*}$
Season 6		0.060			−0.054
		$t = 5.789^{***}$			$t = -4.548^{***}$
Season 7	−0.100	−0.003	0.006	−0.161	−0.105
	$t = -2.341^{**}$	$t = -0.956$	$t = 0.898$	$t = -4.683^{***}$	$t = -8.125^{***}$
Season 8		0.015	−0.083		−0.131
		$t = 5.951^{***}$	$t = -6.851^{***}$		$t = -10.167^{***}$
Season 9	−0.048	0.003	−0.147	0.011	−0.180
	$t = -1.118$	$t = 1.385$	$t = -6.334^{***}$	$t = 1.391$	$t = -13.003^{***}$
Season 10	−0.013	0.014	−0.216		−0.702
	$t = -0.324$	$t = 6.529^{***}$	$t = -7.522^{***}$		$t = -22.468^{***}$
Season 11		0.015			−0.191
		$t = 6.547^{***}$			$t = -14.866^{***}$
Season 12		0.002	−0.005	0.031	−0.111
		$t = 0.982$	$t = -0.811$	$t = 4.357^{***}$	$t = -8.429^{***}$
Adjusted R^2	0.107	0.113	0.181	0.210	0.795
Residual Std. Error	0.148 (df = 41501)	0.021 (df = 91352)	0.166 (df = 78655)	0.140 (df = 49092)	0.169 (df = 89852)
Note	The t-statistics rely on the heteroskedasticity and autocorrelation consistent Newey-West (1987) standard errors estimates, using the Newey-West (1994) automatic lag selection procedure. *p<0.1; **p<0.05; ***p<0.01				

Calendar spread trade

Table A6: Calendar Spread Trade

		Season											
Sector	All	1	2	3	4	5	6	7	8	9	10	11	12
Annualized Mean Returns (%)													
Market	0.08	0.14	0.14	0.14	0.34	0.26	0.09	0.05	0.04	-0.08	-0.13	0.07	0.19
Energy	-0.03	0.14	0.11	0.01	1.09	-0.07	0.00	0.11	0.03	-0.14	-0.15	-0.03	0.14
Grains	0.19	0.19	0.11	0.03	0.10	0.26	0.17	0.27	0.37	0.28	0.13	0.32	0.41
IndustrialMetals	0.02	0.03	-0.20	-0.13	0.17	0.19	0.08	0.21	0.10	0.07	0.02	0.09	0.11
Livestock	0.01	0.52	0.58	0.21	0.35	1.38	0.49	0.13	-1.28	-1.35	-1.12	-0.63	-0.56
PreciousMetals	-0.01	-0.03	-0.01	0.02	-0.02	-0.08	0.04	-0.03	0.02	0.05	-0.04	0.02	0.02
Softs	0.01	0.13	0.40	0.43	0.14	0.15	-0.07	-0.13	-0.22	-0.25	-0.20	-0.03	0.23
Annualized Standard Deviations (%)													
Market	0.37	0.86	0.83	0.84	1.04	1.09	1.53	1.05	0.98	1.20	1.48	1.08	1.27
Energy	1.46	3.33	2.05	1.93	3.21	2.16	2.10	1.67	1.44	1.41	1.89	2.18	2.18
Grains	0.68	1.05	0.85	0.83	1.29	1.21	1.37	1.24	1.93	2.33	1.76	0.94	0.91
IndustrialMetals	0.73	1.02	2.25	1.88	1.20	0.96	0.89	0.93	0.90	0.95	0.86	1.14	1.05
Livestock	1.44	3.34	2.79	2.80	3.45	5.03	4.02	4.66	5.22	2.88	3.01	2.86	2.85
PreciousMetals	0.32	2.20	1.19	1.27	1.04	1.14	2.78	0.85	1.17	1.46	0.95	0.58	0.66
Softs	0.62	0.99	1.20	1.15	1.55	1.69	1.56	1.52	1.64	1.73	2.00	1.74	1.66
t-Statistics													
Market	1.30	0.95	1.02	1.00	1.90	1.43	0.35	0.27	0.24	-0.40	-0.51	0.37	0.88
Energy	-0.13	0.23	0.29	0.03	1.81	-0.17	0.01	0.34	0.09	-0.55	-0.43	-0.08	0.34
Grains	1.70	1.00	0.76	0.18	0.43	1.18	0.69	1.22	1.07	0.69	0.40	1.91	2.64
IndustrialMetals	0.18	0.16	-0.43	-0.34	0.70	0.99	0.43	1.11	0.55	0.36	0.12	0.41	0.53
Livestock	0.06	0.75	1.03	0.36	0.49	1.33	0.60	0.14	-1.21	-2.27	-1.86	-1.07	-0.96
PreciousMetals	-0.14	-0.07	-0.05	0.10	-0.09	-0.42	0.08	-0.19	0.08	0.19	-0.25	0.17	0.21
Softs	0.08	0.76	1.94	2.21	0.50	0.50	-0.25	-0.50	-0.76	-0.83	-0.60	-0.11	0.81

Note: Following Harvey et al. (2016), t-statistics in bold satisfy the statistical significance threshold of 3.0. For those we can safely reject the null hypothesis of returns not being significantly different from zero.

Table A7: Regression calendar spread on basis factors differential.

	Basis	Basis Factors	Control Sectors	Control Seasons
Constant	0.00001 $t = 9.604^{***}$	0.00001 $t = 9.381^{***}$		
MarketEW	-0.011 $t = -40.310^{***}$	-0.015 $t = -43.514^{***}$	-0.015 $t = -57.402^{***}$	-0.015 $t = -57.508^{***}$
BasisDiff	-0.154 $t = -12.808^{***}$			
TermPremiumDiff		-0.090 $t = -12.134^{***}$	-0.090 $t = -13.157^{***}$	-0.090 $t = -13.161^{***}$
ForegoneInterestDiff		-3.334 $t = -3.828^{***}$	-3.245 $t = -3.760^{***}$	-3.505 $t = -4.034^{***}$
SeasonPremiumDiff		-0.010 $t = -0.971$	-0.010 $t = -0.987$	-0.009 $t = -0.910$
ScarcityPremiumDiff		0.265 $t = 11.104^{***}$	0.264 $t = 11.352^{***}$	0.267 $t = 11.437^{***}$
Sector_Energy			0.00003 $t = 7.325^{***}$	
Sector_Grains			0.00001 $t = 4.309^{***}$	
Sector_IndustrialMetals			0.00001 $t = 8.502^{***}$	
Sector_Livestock			0.00002 $t = 3.154^{***}$	
Sector_PreciousMetals			0.00000 $t = 4.117^{***}$	
Sector_Softs			0.00001 $t = 4.235^{***}$	
Season_1				0.00002 $t = 7.412^{***}$
Season_2				0.00002 $t = 5.832^{***}$
Season_3				0.00002 $t = 6.022^{***}$
Season_4				0.00002 $t = 3.121^{***}$
Season_5				0.00002 $t = 5.411^{***}$
Season_6				-0.00000 $t = -0.355$
Season_7				0.00002 $t = 5.124^{***}$
Season_8				0.00001 $t = 1.635$
Season_9				-0.00000 $t = -0.918$
Season_10				0.00000 $t = 0.817$
Season_11				0.00002 $t = 5.098^{***}$
Season_12				0.00002 $t = 4.895^{***}$
Adjusted R^2	0.007	0.020	0.020	0.020
Residual Std. Error	0.001 (df = 1486596)	0.001 (df = 1265355)	0.001 (df = 1265350)	0.001 (df = 1265344)
Note:	*p<0.1; **p<0.05; ***p<0.01			

Monotonicity

Table A8 provides additional robustness checks on the results presented in Section 3.4 for the far contracts sorting portfolios and follows Patton and Timmermann (2010) to test for the presence of monotonicity across quintiles. The monotonic relationship (MR) measure tests for the presence of a strictly increasing pattern by specifying the null hypothesis as a flat or weakly decreasing pattern. The MRall is an alternative test evaluating the relationship across all adjacent portfolios. The table also reports the UP and DOWN statistics which account for the frequency, magnitude and direction of deviation from a flat pattern to address the slower growth in power as the sample size increases.

Table A8: Monotonic relationship tests for the far contract

Factor	Reordered	MR p-values	MRall p-values	UP p-values	DOWN p-values
Basis Factors					
Basis	TRUE	0.22	0.20	0.10	0.86
Foregone Interest	TRUE	0.92	0.87	0.04	0.34
Long Run Cost Of Carry	TRUE	0.69	0.78	0.37	0.23
Season	FALSE	0.14	0.12	0.36	0.91
Scarcity	FALSE	**0.00**	**0.00**	**0.06**	0.97
Basis Change	FALSE	0.27	0.81	0.99	0.26
Foregone Interest Change	FALSE	0.80	0.75	0.07	0.44
Season Change	TRUE	0.18	0.17	0.98	0.85
Scarcity Change	TRUE	0.26	0.76	0.97	0.28
Basis Differential	TRUE	0.26	0.22	0.19	0.78
Foregone Interest Differential	FALSE	0.48	0.43	0.27	0.59
Season Differential	FALSE	0.01	0.01	0.10	0.97
Scarcity Differential	FALSE	0.97	0.95	0.07	0.25
Basis Change Differential	TRUE	0.01	0.00	0.49	0.99
Foregone Interest Change Differential	FALSE	0.25	0.44	0.72	0.62
Season Change Differential	FALSE	0.55	0.44	0.81	0.62
Scarcity Change Differential	FALSE	0.14	0.13	0.20	0.90
Other Factors					
Momentum	FALSE	0.13	0.12	0.38	0.89
Value	FALSE	0.59	0.70	0.23	0.25
Return Seasonality	TRUE	0.86	0.84	0.27	0.36
Volatility	TRUE	0.18	0.22	0.27	0.78
Skewness	TRUE	0.47	0.39	0.80	0.71
Open Interest	TRUE	0.38	0.40	0.30	0.60
Volume	FALSE	0.42	0.32	0.42	0.58
Momentum Differential	TRUE	0.01	0.01	0.65	0.98
Value Differential	FALSE	0.75	0.69	0.48	0.48
Return Seasonality Differential	FALSE	0.85	0.91	0.13	0.15
Volatility Differential	FALSE	0.60	0.52	0.27	0.40
Skewness Differential	FALSE	0.85	0.76	0.81	0.35
Open Interest Differential	FALSE	0.87	0.80	0.20	0.35
Volume Differential	FALSE	0.53	0.40	0.27	0.36

Note: This table follows Patton and Timmermann (2010) to test for the presence of monotonicity accross quintiles. The monotonic relationship (MR) tests for the presence of a strictly increasing pattern by specifying the null hypothesis as a flat or weakly decreasing pattern. The MRall is an alternative test evaluating the relationship accross all adjacent portfolios. The table also reports the UP and DOWN statistics which account for the frequency, magnitude and direction of deviation from a flat pattern to address the slower growth in power as the sample size increases. For the various tests, all factors have been reordered in an increasing order. In bold, the factors who have a p-value below 0.10 across all three tests of increasing monoticity.

At a 10% confidence level, a few factors show consistent and statistically significant results across the three tests of upward monoticity considered. Amongst those, only the scarcity risk premium delivers statistically significant performance for the top-minus-bottom portfolio.

Table A9 provides additional robustness checks on the results for the curve trades, i.e. far-minus-near contracts. Here we see that all the basis and the scarcity factors display consistent and significant results at the 10% confidence level. Likewise the value, return seasonality and the volatility differentials exhibit monotonic relationships across quintiles.

Table A9: Monotonic relationship tests for the calendar spread trade

Factor	Reordered	MR p-values	MRall p-values	UP p-values	DOWN p-values
Basis Factors					
Basis	TRUE	**0.00**	**0.00**	**0.00**	0.93
Foregone Interest	FALSE	0.77	0.68	0.12	0.46
Long Run Cost Of Carry	FALSE	0.73	0.59	0.22	0.06
Season	TRUE	0.04	0.04	0.38	0.97
Scarcity	FALSE	**0.00**	**0.00**	**0.00**	0.96
Basis Change	TRUE	**0.00**	**0.00**	**0.00**	0.91
Foregone Interest Change	TRUE	0.38	0.43	0.16	0.61
Season Change	TRUE	0.43	0.38	0.75	0.72
Scarcity Change	FALSE	**0.00**	**0.00**	**0.00**	0.89
Basis Differential	TRUE	**0.00**	**0.00**	**0.00**	0.93
Foregone Interest Differential	FALSE	0.74	0.63	0.36	0.49
Season Differential	FALSE	0.53	0.39	0.84	0.68
Scarcity Differential	FALSE	**0.00**	**0.00**	**0.00**	0.95
Basis Change Differential	TRUE	**0.00**	**0.00**	**0.00**	0.92
Foregone Interest Change Differential	TRUE	0.55	0.44	0.22	0.67
Season Change Differential	TRUE	0.01	0.02	0.48	0.98
Scarcity Change Differential	FALSE	**0.02**	**0.02**	**0.00**	0.91
Other Factors					
Momentum	FALSE	0.42	0.34	0.18	0.74
Value	FALSE	0.51	0.59	0.08	0.34
Return Seasonality	FALSE	0.60	0.98	0.86	0.22
Volatility	TRUE	0.98	0.95	0.10	0.10
Skewness	FALSE	0.58	0.48	0.39	0.48
Open Interest	FALSE	0.13	0.16	0.48	0.80
Volume	FALSE	0.41	0.36	0.36	0.74
Momentum Differential	TRUE	0.23	0.21	0.00	0.84
Value Differential	FALSE	**0.01**	**0.01**	**0.04**	0.99
Return Seasonality Differential	TRUE	**0.00**	**0.00**	**0.01**	0.97
Volatility Differential	TRUE	**0.00**	**0.00**	**0.02**	0.97
Skewness Differential	TRUE	0.25	0.23	0.16	0.82
Open Interest Differential	TRUE	0.42	0.34	0.09	0.45
Volume Differential	TRUE	0.90	0.80	0.06	0.25

Note: This table follows Patton and Timmermann (2010) to test for the presence of monotonicity accross quintiles. The monotonic relationship (MR) tests for the presence of a strictly increasing pattern by specifying the null hypothesis as a flat or weakly decreasing pattern. The MRall is an alternative test evaluating the relationship accross all adjacent portfolios. The table also reports the UP and DOWN statistics which account for the frequency, magnitude and direction of deviation from a flat pattern to address the slower growth in power as the sample size increases. For the various tests, all factors have been reordered in an increasing order. In bold, the factors who have a p-value below 0.10 across all three tests of increasing monoticity.

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