Carry Trades and Tail Risk: Evidence from Commodity Markets*

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Abstract

I investigate the relationship between carry trades and tail risk for a panel of commodity futures contracts. Unlike other asset classes, carry in commodities is highly volatile both in the time series and in the cross section. By using a panel quantile regression with commodity fixed effect, I document the tail-specific effect of carry on the conditional distribution of futures returns both in the short-term and in longer-term. The main empirical results show that carry has a significant effect on tail risk mostly in the short term and for the front end of the futures curve. In addition, the empirical evidence shows that such relationship can be explained by the role of non-natural hedgers, such as non-commercial traders, money managers and index traders, which tend to unwind their net-long futures positions when exposed to deteriorating aggregate financial conditions and increasing market uncertainty. This is consistent with existing theoretical models in which speculators and insurance providers are subject to limited risk capacity and financing liquidity constraints.

Keywords: Commodity Markets, Carry, Panel Quantile Regressions, Tail Risk, Empirical Asset Pricing, Risk Management, Bayesian Regressions.

JEL codes: G12, G17, E44, C58

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1 Introduction

Carry can be defined as the returns on a futures position that comes from something other than spot price changes. In the case of currencies, where the concept of carry is more familiar, carry trades arise from the differential of interest rates between foreign and domestic money markets. In commodities, returns from a carry strategy come from the fact that, on average, a commodity which is in backwardation (contango) will tend to fall (increase) in price, but not by as much as the futures curve predicts. In this respect, investors can earn returns as the futures contract they are holding rolls down (or up) the futures price curve, even if spot prices remain constant.

At first glance, this is a violation of the efficient markets hypothesis as it appears that the futures curve systematically misjudges the spot movement, that is, there exists a "forward premium puzzle" which makes the carry trade a profitable strategy. There is an extensive literature on exchange rates on the forward premium puzzle, which focuses implicitly on the mean return of the carry trade (see, e.g., Engel 1996 and the references therein). Brunnermeier and Pedersen (2008) empirically showed that carry in exchange rates, i.e., the interest rates differentials, is linked to the skewness of exchange rate movements.

While most, if not all, of the literature investigates crash risk in the context of currencies to rationalize the forward premium puzzle, the evidence for commodity markets is very thin, at best. However, there are at least four reasons why commodities are of particular interest compared to other standard asset classes when it comes to investigate carry strategies.[1] First, unlike in bond and equity, commodity carry can be either negative or positive depending on the shape of the futures curve.[2] Figure 1 makes this case in point. Left panel shows the carry for both first and second nearest-to-maturity contracts. Clearly, carry switches sign and tends to drop substantially during extreme market downturns. Second, commodity carry can be highly volatile relative to, say, carry in exchange rates. Bottom right panel of Figure 1 shows as an example the carry for three major currencies, i.e. the Euro, the Japanese Yen and the Swiss Franc, where the domestic currency is the US dollar. By looking at the scale of the graphs it is evident that volatility of currency carry is much lower than commodities, in fact a separate calculation for commodities and currency carry shows that the latter standard deviation is about a half of the former.[3] Third, carry in commodities is quite heterogeneous across sectors,

[1] Another obvious reason why carry in commodities is of particular interest is the size of the market. As of May 2017 the average trading volume of commodity futures at the CME Group is second only to interest rates, almost doubling the amount of trading in equity indexes and many times larger than futures trading on currencies (source CME Group).

[2] In equity and fixed income carry can be thought of as a forward-looking measure of dividend yield and the coupon payment, respectively.

[3] Carry for currencies is constructed as the differentials of 3-month interbank rates of US vs EUR (dashed dark line), US vs JPN (blue long-dashed line), and US vs CHF (red solid line). Data are from Bloomberg,

especially on the long side of the trade. Bottom-right panel of Figure 1 shows that indeed carry in exchanges rates is much more stable and tend to co-move, at least for major currencies, and converged towards zero due to the global regime of zero interest rates implemented by major central banks in the aftermath of the great financial crisis. As a whole, carry in commodities is much more extreme, volatile, and heterogeneous than for other asset classes. This is possibly due to the fact that, unlike for instance fixed income and FX, commodity markets do not have a dependable "Bear-whale" like a central bank that is prepared to buy commodity assets at any resort and in the process manipulate forward expectations. In this respect, carry in commodities can hardly be stabilized by regulators and policy makers alike. Fourth, public available data on speculators' futures positions are much larger, deeper, and more granular for commodities than for any other asset class. This allows to exploit a much larger amount of information in investigating the relationship between carry and the net futures positions of non-natural hedgers.

In this paper I exploit the cross-sectional heterogeneity of carry in commodity markets and show that while profitable on average, carry is significantly subject to tail risk, that is, there is a strong and negative effect of carry on the left tail of the conditional distribution of futures returns. In the spirit of Brunnermeier and Pedersen (2008), I conjecture that crash risk in carry trades can be due to the unwinding of carry trades when speculators near funding constraints. This idea is consistent with the empirical findings that the net long futures positions of non-commercial and money managers, as well as index traders, are positively correlated with carry in the cross section. These findings are in line with existing theories of financing constraints and preferences for skewed returns such as in Brunnermeier, Gollier, and Parker (2007) and Acharya, Lochstoer, and Ramadorai (2013). In particular,Acharya et al. (2013) show that a decrease in the risk capacity of capital constrained speculators increases hedging costs and reduces producers' inventory holdings, and thus returns on futures contracts.[4]

The interplay between financing constraints and trade strategies is likely to be particularly important during financial downturns, when speculators and non-natural hedgers face capital losses and increasing margin calls. A battery of panel regressions show that there is a significant and negative effect of global risk aversion, as measured by the VIX, and the net-long futures positions of both non-commercial traders and managed money. For the latter, the same negative relationships turns out to be true by interacting the sign of carry with the changes in the Financial Stress Index maintained by the St. Louis Fed and the National Financial Conditions Index held by the Chicago Fed. The empirical evidence for swap dealers is much

weekly, 1999-2017.

[4]Related to the mutual funds industry, Boguth and Simutin (2017) propose a measure for leverage constraint tightness and show that the average market beta of intermediaries facing leverage restrictions captures their desire for leverage and thus the tightness of constraints. Similarly, Etula (2013) show that the risk-bearing capacity of U.S. securities brokers and dealers is a strong determinant of risk premia in derivatives markets.

weaker, albeit still marginally significant. As a whole, the empirical results provide substantial evidence that carry traders tend to unwind their net long positions when facing increasing global risk and possibly lower risk tolerance.

In addition, I investigate a complementary economic mechanism behind carry trades which is the interaction between supply and demand. Production dynamics is of particular relevance to assess the mechanism behind carry trades. As a matter of fact, the slope of the terms structure provides information about the expected value of the commodity in the future. On the one hand, a commodity that is abundant relatively to its past supply will tend to be in contango. On the other hand, the term structure tend to be in backwardation if a commodity is scarce relatively to its past supply. That is, we should expect a positive relationship between aggregate production of a commodity and the futures positions. The empirical results show that when production increases the tendency by non-commercial traders and money managers is to increase carry trades to speculate for downward sloping curve.

Conventional wisdom associate negative skewness with crash risk. A natural estimate of skewness is obtained by replacing expectations with simple averages in the third normalized moment (see, e.g., Amaya, Christoffersen, Jacobs, and Vasquez 2015). However, it is well-known at least since Pearson (1895) and Bowley (1920) that the skewness is highly sensitive to outliers, as returns are raised to the third power, and therefore represents a biased estimated of crashes and downside risk more generally (see, e.g., Neuberger 2012 for details).

In this paper, I do not look at measures of skewness but at the very left tail of the conditional distribution of futures returns. More precisely, I make use of a panel quantile regression framework with commodity fixed effects. Quantile regression analysis have proven to provide information on the effect of a variable of interest at different points in the conditional distribution of the outcome variable, which cannot be captured by standard mean regression techniques (see, e.g. James, Lahti, and Hoynes 2006). More specifically, quantile regressions generalize traditional least squares regression by fitting a distinct regression function for each quantile of the distribution of the variable of interest, therefore allow to explicitly investigate predictive relationships between carry and the very left tail of the distribution of futures excess returns, conditional on a set of control variables and quantile-specific additive commodity fixed effects. Examples related to modelling the dynamics of downside risk can be found in Engle and Manganelli (2004), Baur (2013), White, Kim, and Manganelli (2015), and Adrian and Brunnermeier (2016).

As far as the model estimation is concerned, I follow Kozumi and Kobayashi (2011) by using a latent location-scale mixture representation of the asymmetric Laplace distribution that makes sampling from the full conditional distribution of the quantile-specific parameters not only computationally efficient but also easy implement as the panel quantile regression can be expressed as a simple Gaussian linear model conditionally on the Laplace distributed error term. By sampling from the posterior distribution I explicitly address uncertainty on the quantile-specific effect of carry on the k-step ahead distribution of futures returns, conditional on commodity fixed effects and a set of control variables. Yet, the relative large amount of information from the panel, coupled with an uninformative prior elicitation, makes posterior inference not sensitive to prior information. Convergence properties of the Gibbs sampler are provided in Appendix B.

I investigate the longer-term effect of carry on the tail of futures returns by using a local projection framework as indicated by Jordà (2005), and recursively estimating panel quantile regressions up to three month ahead. The empirical evidence shows that carry has a relatively short-lived effect which disappears after few weeks. Interestingly, changes in aggregate risk aversion, as proxied by the VIX, turn out to have a more persistent effect on tail risk which lasts up to six weeks ahead. Finally, the empirical evidence shows that a one unit shock to the net-long futures positions of non-commercial traders do not affect tail risk for none of the horizons.

Apart from notable exceptions (see, e.g., Chen, Hong, and Stein 2001 and Koijen, Moskowitz, Pedersen, and Vrugt 2017), the concept of carry has been almost exclusively studied for currencies, where carry is defined as the interest-rate differential between two countries. In this context, various papers have provided alternative explanations of the origins of the "forward premium puzzle", such as time-variation in risk premia (see, e.g., Lustig, Roussanov, and Verdelhan 2011, Menkhoff, Sarno, Schmeling, and Schrimpf (2012), Wagner 2012, Cenedese, Sarno, and Tsiakas 2014, Lustig, Roussanov, and Verdelhan 2014, and Doskov and Swinkels 2015), bounded rationality (see, e.g., Burnside, Han, Hirshleifer, and Wang 2011, Snaith, Coakley, and Kellard 2013, and adverse selection (see, e.g., Burnside, Eichenbaum, and Rebelo 2009). Other studies also point out issues related to econometric methods as a potential explanation for why there appears to be a forward premium puzzle in the first place (see, e.g., Baillie and Bollerslev 1994 and Maynard 2006).

Another common explanation for the significance of excess returns of carry trade is compensation for crash risk. Still in the context of currencies, Brunnermeier and Pedersen (2008) was one of the first to empirically investigate the linkage between carry and large losses, as proxied by negative skewness. Similarly, Dobrynskaya (2014) show that carry trades in currency markets crash systematically in the worst states of the world when the global stock market plunges or when a disaster occurs. This link between carry trade excess return and crash risk is supported by theoretical model built by Farhi and Gabaix (2015) and Verdelhan (2010). Yet, no consensus has been solidly reached. Burnside, Eichenbaum, Kleshchelski, and Rebelo (2010) found that peso problem cannot be a major determinant of the payoff to the carry trade by developing a version of the carry trade that uses currency options to protect the investor from the downside risk of large exchange rate movements. Similarly, Jurek (2014) also suggested that the high returns to carry trades are not due to peso problems.

This paper contributes to this literature by using commodity markets as an “out-of-sample” framework to test for the external validity of crash risk as a possible determinant of carry trades profitability, and as a consequence as a potential explanation of the forward premium puzzle. In this respect, despite the many peculiarities of commodity markets vis-a-vis currencies, virtually no systematic evidence on the relationship between crash risk and carry has bee provided in this context.

The role of skewness in commodity markets has been recently emphasized by Fernandez-Perez, Frijns, Fuertes, and Miffre (2015). They show that a long-short portfolio that buys (sells) low- (high-) skewness commodities can generate excess returns of up to 8% a year. However, to the best of my knowledge, the analysis in this paper is one of the first to empirically the quantile-specific effect of trading signals from the slope of the term structure and the probability of having large losses in commodity futures, i.e., tail risk in commodity carry trades.

The structure of the paper is the following. Section 2 provides a description of the data and the variables of interest. Section 3 outlines the modelling framework and the estimation strategy. Section 4 represents the core of the paper and presents the main empirical results. Section 5 investigates possible mechanisms behind the positive relationship between carry and tail risk. Section 6 concludes.

2 Data and Variables Definition

I collect data on exchange-traded, liquid commodity futures contracts from Bloomberg on eighteen commodity markets from 1992 to 2017. I construct returns using a roll-over strategy. The focus of the empirical analysis is on first- and second-nearby contracts.

[Insert Figure 2 about here]

Figure 2 shows why; first and second nearest-to-maturity contracts represent the most liquid maturities. Left panel shows the average daily open interests over the sample period for several generic futures contracts. It is fairly evident how liquidity substantially drops from the third nearby contract on. Such drop in market activity holds on average across commodities as shown by the right panel of Figure 2. For each contract I calculate weekly returns on a fully collateralized position using;

$$y_{t+1}^{h} = \frac{F_{t+1}^{h}}{F_{t}^{h}} - 1, \qquad h = 1, 2 \tag{1}$$

where F_t^h denote the end-of-the week price of the hth-nearby futures contract with expiration in month $t+h$. To capture the roll yield, the futures position is liquidated the day before the generic curve moves down by one contract. Thus, if the hth-nearby contract expires at $t+h$, the strategy rolls into the $h+1$th-nearby contract in $t+h-1$. I follow Singleton (2014) and assume the roll takes place on the 11th calendar day of each month. This is consistent with the strategy implemented in long-only commodity indexes in which the roll typically takes place within the first ten days of the month. The returns are computed on a weekly basis from Tuesday to Tuesday to match the measurement of the positions by the Commodity Futures Trading Commission (CFTC).[5]

In a cash investment in which an investor buys literally the physical commodity on the spot market, the carry return would coincide with the convenience yield in excess of storage costs (see, e.g. Fama and French 1988). Unfortunately, neither the convenience yield nor the cost of storage are easily observable and might depend on the specific commodity, maturity and type of investors. However, we can infer the level of carry by using information from the slope of the futures curve. Indeed, a decrease in the convenience yield or an increase in storage costs makes holding the physical commodity less attractive relative to holding a futures contract. As a result, the price investors are willing to pay on the spot market decreases relative to the futures price, making the futures curve more upward sloping.[6] In general, the no-arbitrage price of a futures contract can be defined as $F_t^{T_h} = S_t\left(1+\left(r_t^f - cy_t\right)T_h\right)$, where cy_t represents the convenience yield in excess of the storage costs and T_h the maturity of the contract. Hence, a measure of carry which is conceptually linked to both the convenience yield and storage costs for the hth maturity and the ith contract is given by

$$Carry_t^h = \frac{S_t - F_t^{T_h}}{F_t^{T_h}} = T_h\left(cy_t - r_t^f\right)\frac{S_t}{F_t^{T_h}}, \tag{2}$$

The price $F_t^{T_h}$ in the denominator implies that carry is related to a fully collateralized position in the futures market (see Koijen et al. 2017). A carry strategy implies that investors take long positions in those commodities where markets are in backwardation (the roll yield is positive), and short positions where markets are in contango (the roll yield is negative).[7] To compute Eq.(2) we need data on the current spot prices. However, spot valuations, if available, are often illiquid and subject to measurement errors. For this reason, I replace the often unreliable spot

[5]Notice the risk free rate does not enter the calculation. The rationale is that a long position in a futures contract represents a zero cost investment, net of initial and margin calls.

[6]More precisely, a commodity which tend to be scarce relative to its supply will tend to be in backwardation, so that the commodity is priced at a premium in the spot market rather than in the future. The opposite case applies with steep contango: the commodity is sold at a discount on the spot market, reflecting its relative abundance.

[7]The roll yield is the return which accrues to the speculator due to the difference between spot and futures prices.

price with its synthetic counterpart calculated by interpolating the first two nearby contracts and extrapolate the front end of the futures curve. Based on these synthetic spot prices, I calculate carry as in (2). As a results, following Equation (2), we can simply use the slope of the futures curve to get a measure of carry that captures the convenience yield and provides an interpretation of some of the predictors of commodity returns examined in the literature (see, e.g. Gorton, Hayashi, and Rouwenhorst 2013, and Hong and Yogo 2012). The time horizon of carry is matched with the time horizon of the returns, namely, carry is constructed by using the data on the futures curve on Tuesday each week, consistent with the calendar of the CFTC futures traders positions and the calculation of the returns.

As an observable proxy for carry trade activity, I use the futures position data from the CFTC for each commodity in the sample. The main variable of interest is the net (long minus short) futures position in a given commodity, normalized by the open interest which represents the total of all futures contracts entered into by both commercial (hedgers) and non-commercial (speculators) traders and not yet offset by a transaction, by delivery or exercise. I consider three main classifications of traders which do not use futures contracts in that particular commodity for hedging purposes as defined by the CFTC: first, "non-commercial" traders, which include large institutional investors, hedge funds, and other entities which are presumably trading on the commodity futures markets for speculative purposes. The CFTC includes both swap dealers and money managers under the heading "non-commercial". Swap dealers deal primarily in swaps for a commodity and use the futures markets to manage or hedge the risk associated with those transactions. The dealer's counter-parties may be either speculative traders or traditional commercial clients that are managing risks in the physical commodity. Money managers are registered commodity trading advisor (CTA), registered commodity pool operator (CPO), or an unregistered fund identified by CFTC, and are mostly engaged in conducting organized futures trading on behalf of clients.

In addition to the aggregate non-commercial traders and the disaggregated swap dealers and managed money classification, I also look at the net-long futures positions of commodity Index Traders. The "Index Traders" category includes pension and other investment funds that place their index investment directly into the futures markets rather than going through a swap dealer. In this respect, there is some overlapping with "managed money", depending on the specific details of their business and trading. The commodity index trader supplement has been published only for agricultural commodities since January 2007.

The CFTC releases data on traders positions each Friday but the report is current as of the Tuesday before each Friday's release. A positive futures position is economically equivalent to a carry trade in which speculators take the long side of a contract in backwardated commodities. Two comments are in order; first, the CFTC data are aggregated along the curve and a maturity-specific analysis is not feasible, which limits the information content of the variable.

Second, it must be noted that the classification of the position data is not perfect. As a matter of fact, although a single entity cannot be classified as both hedger and speculator in the same commodity, the same trader may be classified as, for instance, "commercial" for some commodities and "non-commercial" for others. Nevertheless, these data are the best public available source and arguably give up to date first-hand information about the strength of the commitment traders have towards that trend in each commodity market.

2.1 Descriptive Statistics and Portfolio Evidence

Table 1 presents summary statistics for the excess returns and the carry of each commodity in the sample. The sample mean, standard deviation and Sharpe ratios are reported in annualized terms while carry is reported in weekly terms. Panel A and B show the descriptive statistics for the excess returns and carry computed on the first- and second-nearby futures contracts, respectively.

[Insert Table 1 about here]

Not surprisingly, there is evidence of a great deal of cross-sectional variation in mean and standard deviation of both excess returns and carry. This is due to the heterogeneous nature of commodity markets which cover the most diverse assets, from precious metals to agricultural and livestock. Table 1 shows that there is a positive cross-sectional correlation between the average carry and the average excess returns. For example, the three commodities with the most negative carry, i.e. Natural Gas, Corn and Wheat, are also the ones with the weakest performance, with almost -20%, -12% and -15% average annual excess returns. On the other hand, the three commodities with the highest average carry, such as Soybean and SoybeanMeal have the strongest performance with 7% and 13.7% annual average excess returns. Similarly, Figure 3 shows that the higher the carry trades the higher the asymmetry of the distribution of futures returns. Specifically, left panel shows the scatter plot of carry and the asymmetry of the returns distribution. The latter is measured by using the Bowley (1920) robust coefficient of skewness for a cross-section of commodities.

[Insert Figure 3 about here]

Although the magnitude is small, there is a significative and negative relationship between carry and the probability of large losses vs. large gains for futures returns, as indicated by the negative regression line. That is, there appears to be a cross-sectional negative relationship between the probability of having large losses and carry. For instance, an investor taking carry trade investing in the first nearest-to-maturity contract of SoybeanMeal would have obtained a positive profit, but in the same time would have been subject to a negative skewness of -0.3, on average, on the weekly excess returns of the long-only strategy. Similarly, an investor taking a longer-maturity trade on, say, second nearest-to-maturity futures contract of Soybean would have accrued a positive 5.4% a year, but at the same time would have been exposed to a crash risk as proxied by a skewness of -0.34. Although less significant, the same negative relationship appears for the second nearest-to-maturity contracts (right panel).[8]

There is an extensive existing literature which focuses on speculative strategies and expected returns across asset classes. For instance, Moskowitz, Ooi, and Pedersen (2012b) provide evidence that speculators predominantly follow strategies based on futures past performances, which are highly interlinked with expectations on the future curve and therefore carry. The behaviour of traders in commodity markets is also linked to the so-called "financialization" of commodities. On the one hand, Tang and Xiong (2012) argue that the increasing presence of investors in commodity indexes precipitated a process of financialization of commodity futures, through which the volatility of returns and the risk inherited in commodity futures sensibly increased. On the other hand, Brunetti, Büyük*c*sahin, and Harris (2016) study the separate impact of trading by different types of investors in oil, corn and natural gas between 2005 and 2009 and conclude that non-commercial traders react to market conditions in ways to provide liquidity to the market, and stabilize price fluctuations.

[Insert Figure 4 about here]

Despite conflicting evidences, Figure 4 shows there is a positive correlation between the average carry and the average net-long futures positions from the CFTC commitment of traders report. For example, speculators have on average large short positions in Natural Gas, which has the most negative average carry. This somewhat confirms, although with a small magnitude, that the trading behaviour of non-natural hedgers significantly correlates with the expectations implied by the futures curve.

I now take a portfolio perspective and show some of the key properties of carry trades, with a particular emphasis on tail risk. A carry strategy takes a long position in commodities in which the market is expected to relax (backwardation) and a short position in those commodities in which the market is expected to tighten (contango). This is analogous to a carry trade in currencies which means taking a long position in high interest rate currencies (where the future is at discount to spot) and a short position in low interest currencies (where the futures price is at a premium to spot). There are various ways to construct a carry trade portfolio. I follow Moskowitz, Ooi, and Pedersen (2012a), Asness, Moskowitz, and Pedersen (2013), and Koijen

[8] In the main empirical analysis below, I will show that such smaller significance is reflected in the panel quantile regression results.

et al. (2017) and construct a carry portfolio that weights each commodity by

$$w_{it}^{h} = z\left(rank\left(Carry_{it}^{h}\right) - \frac{n+1}{2}\right), \tag{3}$$

where z is a scalar that ensures that the sum of of the long and short positions equals 1 and -1, respectively, and $rank\left(Carry_{it}^{h}\right)$ represents the rank of the carry for the ith commodity at time t for maturity $t+h$. Alternatively, one can construct the carry trade by ranking commodities by their carry and go long the top x% of contracts and short the bottom x%, with equal weights, and ignore (e.g., place zero weight on) the contracts in between these two extremes (see, e.g., Brunnermeier, Nagel, and Pedersen 2008) for an example. Results are robust across such alternative portfolio weighting schemes and are available upon request.

Following Koijen et al. (2017), I consider two measures of carry: (i) The "current carry" which is measured each Tuesday consistent with the schedule of the returns and the CFTC commitment of traders report, and (ii) "carry1-12," which is a moving average of the current carry over the past 12 weeks (including the most recent one). Most of the results in the paper relate to the current carry, but I report basic graphs for portfolios calculated based on carry1-12 as well.

The average excess returns are positive throughout and tend to be higher for longer maturity contracts. The riskiness of the portfolios is similar across maturities which generate a higher annualized Sharpe ratio for second nearest-to-maturity futures contracts. The annualized Sharpe ratio has a range between 0.1 to 0.3 annual, which is in line with existing research (see, e.g. Koijen et al. 2017 and Fuertes, Miffre, and Fernandez-Perez 2015).[9]

Although the nature of carry trades suggest that the excess return on a carry strategy should be negative, the portfolio returns show that the roll yield more than cancels out the negative average return. This possibly comes from the fact that on average, a contract which is in backwardation tends to fall in price, but not as much as it is implied by the futures curve. Similarly, a contract which is in contango will tend to increase price but not as much as the futures curve predict. In other words, a carry trade strategy makes profits out of a systematic misjudgment of the futures curve about what will be the prevailing future spot price. Although this seems a violation of the efficient market hypothesis, likely non-zero expected returns come as a compensation to speculators for bearing the risk of uncertain fluctuations of future spot prices.

Top panels of Figure 5 show the quantile-quantile plot comparing the returns for a carry strategy on the first nearby contracts to a standard normal distribution. The results show that there is a substantial and significant negative skewness on the portfolio returns, that

[9]Koijen et al. (2017) found an annualized Sharpe ratio between 0.48 and 0.6 for a sample which did not include the collapse of energy commodity prices from 2014 onward.

is tail risk does not get diversified away in the portfolio construction. This holds both by constructing a carry portfolio using the current carry (left panel) and the smoother carry1-12 (right panel). Bottom panels show that, although by a lower magnitude, there is a significant negative skewness in the distribution of carry trade returns also for second nearby contracts.

[Insert Figure 5 about here]

As a whole, Figure 5 shows that carry trade is significantly exposed to tail risk, that is, a small probability of having large losses, and that risk cannot be diversified away within a portfolio. This suggests that crash risk might represents a systematic component in the dynamics carry returns. These results are consistent and extend on the equity premium and carry trades in currency markets (see, e.g., Brunnermeier and Pedersen 2008, Dobrynskaya 2014, and Fernandez-Perez et al. 2015).

Figure 4 shows there is a mild positive correlation between carry and the net-long futures positions of non-commercial traders. If there is any economically and positive correlation between carry and trading behaviours by speculators and insurance providers we should expect to see the same features on returns on carry trades based on CFTC positions. I construct portfolios based on the net-long futures positions of non-commercial traders as in Eq. (3). More precisely, instead of ranking contracts by carry, I rank them based on the net-long exposure of non-commercial traders the ith commodity at time t for maturity $t+h$. Left panels of Figure 6 show the quantile-quantile plot for the returns on the portfolio of first (top panel) and second nearest-to-maturity (bottom panel) contracts. In both cases there is substantial evidence of a negative skewness.

[Insert Figure 6 about here]

Similarly to Figure 5, I construct portfolios based on a smoother, three-month average of the net-long futures positions to smooth out short-term volatility effects. Right panels show the results for both first nearby (top panel) and second nearby (bottom panel) contracts. Again, and similar to carry trade portfolios, there is substantial evidence of a significant tail risk in the dynamics of commodity portfolios returns.

As a whole, Figure 6 provides further evidence of a significant and positive economic relationship between carry and the net-long positions of speculators and insurance providers, as proxy by non-commercial traders.

3 Bayesian Panel Quantile Regression

Quantile regressions have been originally introduced by Bassett and Koenker (1978) and Koenker and Bassett (1978). Quantile regressions are particularly useful to investigate the relationship between quantiles of the response distribution and available covariates. Since the set of quantiles provides a far more complete description of the response distribution than the standard mean, quantile regression offers a practically important alternative to classical regression analysis. A comprehensive overview of the literature on quantile regressions can be found in Yu, Lu, and Stander (2003) and Koenker (2005).

Let y_{it+1} be the commodity futures returns, $\mathbf{x}'_{it} = (Carry_{it},\ Controls'_{t})$ the $k \times 1$ vector of explanatory variables at time t, and α_i a commodity fixed effect. I consider the following linear model for futures returns:

$$y_{it+1} = \mathbf{x}'_{it}\boldsymbol{\beta}_p + \alpha_{ip} + \epsilon_{it}, \tag{4}$$

where both $\boldsymbol{\beta}_p$ and α_{ip} depend on the pth quantile of the random error term ϵ_{it}, which is defined as the value q_p for which $Pr\left(\epsilon_{it} < q_p\right) = p$. The distribution of the error terms is often left unspecified and is restricted to have the pth quantile equal to zero, that is, $\int_{-\infty}^{0} f_p\left(\epsilon_i\right) d\epsilon_i = p$. Thus, quantile regression estimation for the parameters is the solution to the minimization problem

$$\min_{\left(\boldsymbol{\beta}_p, \alpha_{1p}, \ldots, \alpha_{np}\right)} \sum_{t=1}^{T} \sum_{i=1}^{n} \rho_p\left(\epsilon_{it}\right), \tag{5}$$

where $\rho_p\left(\cdot\right)$ is the loss function defined by $\rho_p\left(u\right) = u\left[p - I\left(u < 0\right)\right]$, and $I\left(a\right)$ denotes an indicator function that takes value one if the event a is true, and zero otherwise.

Yu and Moyeed (2001) showed that the quantile regression (4) has a convenient mixture representation which allows to solve (5) by maximizing the likelihood function under the asymmetric Laplace error distribution (see also Tsionas 2003). Reed, Yu, Kozumi, and Kobayashi (2011) established both theoretically and empirically that the asymmetric Laplace provides an accurate approximation of the quantiles of many different distributions. Similarly, Kotz, Kozubowski, and Podgorski (2012) showed that the asymmetric Laplace distribution can admit various mixture representations. One that has particular convenient properties for Bayesian analysis is the scale mixture of normals, with a scale parameter following an exponential distribution. This allows to write the likelihood function in a conditionally Gaussian form such that inference based on the conditional distribution is straightforward. In this respect, unlike Yu and Moyeed (2001) which requires a random-walk Metropolis-Hastings algorithm for posterior inference, with a location-scale mixture representation of the asymmetric Laplace distribution one can sample from the conditional posteriors by relying on the Gibbs sampler. Kozumi and Kobayashi (2011) show that when the conditional likelihood admits a mixture of normals form, the conditional posteriors are conjugate, and thus, are easy to draw samples from.

Following Kozumi and Kobayashi (2011), I utilized a mixture representation based on a scaled exponential normal distribution of the error term in (4) (see Kotz et al. 2012)

$$\epsilon_{it} = \theta v_{it} + \tau \sqrt{v_{it}} u_{it} \tag{6}$$

where $v_{it} \sim \mathit{Exponential}(1)$ is a variation from a standard exponential distribution with rate parameter equal to one, and $u_{it} \sim N(0,1)$. In this formulation it holds that $\theta = (1-2p)/p(1-p)$ and $\tau^2 = 2/p(1-p)$, for a given quantile $p \in [0,1]$. Substituting (6) in (4) gives the new quantile regression form

$$y_{it+1} = \mathbf{x}'_{it}\boldsymbol{\beta}_p + \alpha_{ip} + \theta v_{it} + \tau\sqrt{v_{it}}u_{it}, \tag{7}$$

Let $\mathbf{y}'_i = (y_{i2}, \ldots, y_{iT})$ the futures returns for the ith commodity. As the conditional distribution of y_{it+1} given v_{it} is normal with mean $\mathbf{x}'_{it}\boldsymbol{\beta}_p + \alpha_{ip} + \theta v_{it}$ and variance $\tau^2 v_{it}$, the joint density of $\mathbf{y} = (\mathbf{y}'_1, \ldots, \mathbf{y}'_n)$, is given by

$$p\left(\mathbf{y}|\mathbf{v}, \boldsymbol{\beta}'_p, \alpha_{1p}, \ldots, \alpha_{np}\right) \propto \prod_{i=1}^{n}\left(\prod_{t=2}^{T} z_{it-1}^{-\frac{1}{2}}\right) \times \exp\left(-\sum_{t=2}^{T}\frac{\left(y_{it} - \mathbf{x}'_{it-1}\boldsymbol{\beta}_p - \alpha_{ip} - \theta v_{it-1}\right)^2}{2\tau^2 v_{it-1}}\right) \tag{8}$$

where $\mathbf{v} = (\mathbf{v}'_1, \ldots, \mathbf{v}'_n)$, and $\mathbf{v}_1 = (v_{11}, \ldots, v_{1T-1})$.

3.1 Prior Specification

Given the likelihood function (8), I can now formulate the prior distributions. Note that the model in Eq.(7) can be rewritten as

$$\mathbf{y} = Z'\boldsymbol{\gamma}_p + \theta\mathbf{v} + \tau\sqrt{\mathbf{v}}\mathbf{u} \tag{9}$$

where $\mathbf{y}$ and $\mathbf{v}$ are defined above and $\mathbf{u} = (\mathbf{u}'_1, \ldots, \mathbf{u}'_n)$, with $\mathbf{u}_1 = (u_{11}, \ldots, u_{1T-1})$. Here Z' contains both the regressors and the individual effects, that is $Z = [X,\ \mathbb{I}_n \otimes \iota]$ with $X' = (\mathbf{x}'_1, \ldots, \mathbf{x}'_n)$, with $\mathbf{x}_i = (x_{i1}, \ldots, x_{iT-1})$, ι a $T \times 1$ vector of ones and $\mathbb{I}_n$ an $n \times n$ identity matrix. The vector of regression coefficients contains both the slope parameters and the fixed effects and is defined as $\boldsymbol{\gamma}'_p = \left(\boldsymbol{\beta}'_p, \alpha_{1p}, \ldots, \alpha_{np}\right)$. That is, under a non-hierarchical prior the model can be written as the Yu and Moyeed (2001) conditional Gaussian specification with higher dimensions.

One comment is in order. Numerical problems can arise as n increases, because we need to invert big matrices. Theorems on the inverse of partitioned matrix can be of some help. However, the cross-sectional dimension of the empirical exercise is rather limited, i.e. $n = 18$, and much smaller than the time series dimension. In addition, under a non-hierarchical prior we can map the Bayesian estimates to the frequentist fixed effects model, that is, one can test for the consistency of the two estimates under the two frameworks and in principle should obtain similar results.

Yu and Moyeed (2001) proved that all posterior moments of the regression parameters exist under a conditional Normal prior. Thus, for the regression parameters and the fixed effects I consider a conditionally normal prior

$$\boldsymbol{\gamma}_p|\sigma_p^2 \sim N\left(\boldsymbol{\mu}_{\gamma_p}, \sigma_p^2 V_{\gamma_p}\right), \qquad \sigma_p^2 \sim IG\left(a/2, b/2\right)$$

this is a standard conjugate Normal-Inverse-Gamma prior. The prior distributions are set to be highly uninformative, that is a priori there is no information on the magnitude of the effect conditioning information on a specific quantile. That is, the prior mean of the regression parameters and the individual effects is set to zero, i.e., $\boldsymbol{\mu}_\gamma = 0$, with a high uncertainty, i.e., $V_\gamma = \mathbb{I}_{k+p} \times 10,000$. In addition, I introduce a prior hyper-parameters for σ_p^2 such that the uncertainty around the parameters estimates is not set subjectively but is estimated from the likelihood. The prior for σ_p^2 is set to be highly uninformative, i.e., $a = 0.001, b = 0.001$. Such uninformative prior structure allows to avoid concerns on the dependence of posterior estimates from the prior elicitation.

Posterior computation is constructed by sampling $\boldsymbol{\gamma}_p$ and $\mathbf{v}$ from the full conditional distributions using data augmentation. Prior distributions are conjugate such that posterior distributions can be sampled using a relatively standard Gibbs sampler algorithm. More details are provided in Appendix A. For the main empirical results, I used 60,000 simulations discarding the initial 10,000 draws as a burn-in sample and retaining one in ten draws from the remaining 50,000 iterations. A justification of this approach and the selection of draws based on convergence diagnostics is provided in Appendix B. The convergence of the Gibbs sampler is remarkable, and the amount of simulations can be considered sufficient for the nature of empirical application and the length of the sample available.

4 Empirical Analysis

This Section formally tests for the effect of carry on tail risk, which is the relationship between carry at time t and the quantiles of the conditional distribution of futures returns one or several steps ahead. I propose a panel quantile regressions which allows to directly link observable predictors to the left tail of the returns distribution. The inclusion of fixed effects allows to account for unobserved heterogeneity across commodities. In fact, it is hard to believe that the overall effect of carry trades on tail risk is perfectly identified cross-sectionally, unless individual effects are introduced to relax restrictive exogeneity assumptions which open the possibility that tail risk is endogenously created by carry trade activity. For example, gains in past carry trades may lead to a further build up of carry trade activity, which increase the overall exposure to tail risk due to the subsequent unwinding of those carry trades. The implicit assumption of "additive" fixed effects in the location-scale mixture representation (7) implies that α_{ip} enter linearly conditional on the quantile p and the exponentially distributed error terms $\mathbf{v}$. The functions $\boldsymbol{\beta}_p$ are strictly increasing in the set of quantiles $p \in (0, 1)$ for any given realization of $\mathbf{x}'_{it}$. As discussed by Koenker (2005), the quantile regression coefficients do not represent the impact of covariates on the quantiles of the unconditional distribution of the outcome variable. In fact, quantile estimation is influenced only by the local behaviour of the response variable to the regressors near a given quantile. Therefore, $\boldsymbol{\beta}_p$ represents the local effect of of the set of regressors near the pth quantile of the *conditional* distribution of futures returns.

4.1 Carry Trades and Tail Risk

The descriptive statistics in Table 1 have shown there is a positive and significant relationship between carry and tail risk, meaning the higher the carry the higher the probability of having large losses in the near future. The portfolio results in Figure 5 have shown that such tail risk is not diversified away at the portfolio level but represents a source of systematic risk which arguably asks for compensation. Figure 7 reports the posterior distribution of the beta on carry for each quantile from the median (top of the y-axis) to the 1st quantile (bottom of the y-axis). The x-axis represents the magnitude of the coefficient. Posterior distributions are generated from the Gibbs sampler outlined in Section 3 and detailed in Appendix A.

[Insert Figure 7 about here]

Left panel of Figure 7 shows the results for the first nearest-to-maturity contracts. The effect of carry is negative and significant only on the very left tail of the distribution while disappearing as we approach the median of the conditional distribution of futures returns, that is carry trades are a strong negative predictor of tail risk although does not appear to have any predictive content for the median returns.

Right panel of Figure 7 shows the results for the second nearest-to-maturity contracts. The evidence on the relationship between carry and tail risk is much weaker, albeit still significant for the very left tail of the conditional distribution of futures returns. As a matter of fact, the negative linkage between carry and futures returns still holds only for the first three quantiles of the returns distribution and becomes not statistically significant afterwards.

Interestingly, Figure 7 shows that $Carry_t$ does not have any effect on the median of the distribution of the one-step ahead futures returns. This is true both for the first- and second-nearby contracts. This result on the median is somewhat consistent with some of the existing evidence on commodity markets. For instance, Koijen et al. (2017) have shown that the coefficient on the carry of a standard least squares predictive regression is not different from zero for the majority of commodity futures contracts. Any eventual discrepancy in the results can be explained by the fact that a quantile regression on the median can be interpreted as a robust least absolute error regression that excludes outliers (see Bassett and Koenker 1978, Koenker and Bassett 1978, and Koenker 2005).

As a whole Figure 7 provides evidence that there is a quite heterogeneous effect of carry on the conditional distribution of futures returns, especially on the front-end of the curve. As a matter of fact, there is a significant difference in the effect of carry between the very left tail of the distribution and the median, especially for the nearest-to-maturity contracts. In addition, a closer look at the left tail shows that the effect of carry is pronounced and much more significant for extreme tail events, i.e. $p < 0.05$. If we couple these results with the findings in Table 1 and Figure 5 there is considerable evidence that carry trades affect almost uniquely the tail of returns distribution, that is tail risk appears to enter non-linearly in the returns dynamics of commodity futures returns. Such quantile-specific effect of carry hardly could have been captured by using standard least squares regressions.

Together with carry, I include a set of control variables in the regression specification (7). The first control variable included is the net long futures positions for non-commercial traders. For the latter the time series goes back to the 1992 which makes it suitable for the estimation of quantile regressions. As a matter of fact, to detect the conditional effect of exogenous regressors on the smallest quantiles, quantile regressions need a fair amount of data (see Koenker 2005 for details). Also, the inclusion of the net-long futures positions allows to challenge the significance of carry to a greater extent as the two are economically correlated. More precisely, by including futures positions one can explicitly control for the information content of actual, observable, trading positions which have been shown above to be economically linked to carry trade positions.

Figure 8 reports the posterior distribution of the beta on the net-long futures positions of non-natural hedgers for each quantile. As before, the x-axis represents the magnitude of the coefficient, while the y-axis represents the quantiles from the median from the median (top of the y-axis) to the 1st quantile (bottom of the y-axis).

[Insert Figure 8 about here]

The Figure shows that once conditioning for carry there is no significant predictive content of net-long futures positions by non-commercial traders on tail risk. This result holds both for the front-end of the curve (left panel) and the second nearest-to-maturity contracts. Neither of the two cases show any significant beta on the left hand of the conditional distribution of futures returns. As a whole, the net futures positions are driven out by carry and the other control variables. One possible explanation rests on the limitation of the CFTC data as a measure of speculators' positions. Indeed, the futures positions data do not include over-the-counter forward transactions, where a non-negligible fraction of the liquidity of commodity markets lies.

A second control variable included is the change in the implied volatility of S&P500 options, i.e. the VIX. This is to control for the effect of aggregate changes in risk aversion and investors' uncertainty more generally. Figure 9 shows the posterior estimates of the quantile-specific betas on $\Delta VIX_t = VIX_t - VIX_{t-1}$.

[Insert Figure 9 about here]

Two facts emerge; first, there is a consistent negative relationship between changes in aggregate investors' uncertainty and the left tail of the returns distribution, that is, an increase in the VIX is correlated with an increasing probability of having large losses one week ahead. Such negative effect across the whole distribution is consistent with the conventional wisdom that increasing aggregate risk is associated with higher potential losses (see, e.g., Engle and Manganelli 2004). Second, the effect of changes in aggregate risk aversion is not homogeneous across the conditional distribution of returns but is much more pronounced on the very left tail. That is, although the VIX significantly predicts a drop in futures returns, such predictive content is non-linear across quantiles and much more correlated with large infrequent losses than with average drop in returns.

As additional control variables I also include lagged futures returns and commodity-specific risk computed under the physical measure, proxied by the one-week ahead forecast of conditional volatility from a GARCH(1,1) model with leverage effects. The lagged values of the excess returns are included to account for a simple form of dynamic in the tails as lagged shocks to the dependent variable are explicitly taken into account. The results show that the effect of commodity-specific risk is driven out by aggregate market uncertainty as proxied by changes in the VIX, while past futures returns negatively predict tail risk. In the context of this paper, such evidence can be interpreted as gains in futures positions leading to larger carry trades and speculator positions, and as a consequence to larger than expected drops in returns. Times when past returns are high, also tend to be times when futures returns positions are high.

4.2 Longer-Horizon Effects

The analysis so far has revealed a significant degree of co-movement between tail risk in one-step ahead futures excess returns and carry. As it stands, this picture does not tell us much as to how persistent the effect of carry, or any of the control variables, on tail risk is. The next step in the analysis explicitly addresses these issues by exploring the transmission of current changes in carry and other control variables onto tail risk several steps ahead. Ideally, this would requires the identification of structural shocks to generate quantile-specific impulse response functions (IRF). Recently, Chavleishvili and Manganelli (2016) provided a statistical framework to define structural quantile shocks and the associated quantile impulse response functions. However, such framework is designed for a bivariate system of dynamic conditional quantiles of random variables and therefore cannot accommodates the cross-sectional heterogeneity of the commodity contracts when calculating an aggregate IRF.

Therefore, I follow a local projection method as indicated by Jordà (2005) and produce a set of impulse responses estimated directly as the change in the forecast of an outcome variable that is brought about by a change in the impulse variable. Local projections have recently also been used in the empirical fiscal policy literature, see e.g. Auerbach and Gorodnichenko (2012), to investigate heterogeneous effects of aggregate technology shocks on firms' growth, e.g. Distante, Petrella, and Santoro (2014), and applied macroeconomics literature, see e.g. Owyang, Ramey, and Zubairy (2013) and Tenreyro and Thwaites (2016).

In the context of panel quantile regressions, local projections represent a very convenient approximation, as it does not require to extrapolate exogenous shocks from structural representations of the model. The response to a generic shock can be directly computed from predictive regressions. More specifically, I estimate a set of predictive regressions at each horizon $h = 1, ..., H$ of the form

$$y_{it+h} = \mathbf{x}_{it}'\boldsymbol{\beta}_p^h + \alpha_{ip}^h + \theta v_{it+h} + \tau\sqrt{v_{it+h}}u_{it+h}, \tag{10}$$

where y_{it+h} represents the h-step ahead futures returns, $\boldsymbol{\beta}_p^h$ the horizon-specific regression betas for the quantile $p \in (0,1)$ and α_{ip}^h the commodity fixed effect for horizon h and quantile p. A structural shock in such predictive regression can be thought of a random variable η_{it}^h that approximate the shock of interest. As a result, the IRF for the pth quantile can be computed as the difference in the conditional forecasts with and without the shock:

$$IRF\,(p,h) = E\left[y_{it+h}|\mathbf{x}_{it}', \boldsymbol{\beta}_p^h, \alpha_{ip}^h, \eta_{it} = 1\right] - E\left[y_{it+h}|\mathbf{x}_{it}', \boldsymbol{\beta}_p^h, \alpha_{ip}^h, \eta_{it} = 0\right],$$

where we have the implicit assumption of a one unit shock. In this setting, since the forecasts are directly computed from a predictive regression in Eq.(10) at each horizon $h = 1, ..., H$, the response to a one unit shock in carry can be approximate as $IRF(p,h) = \beta^h_{Carry,p}$, where $\beta^h_{Carry,p}$ represents the predictive beta on carry for horizon h. The same methodology allows to approximate the average quantile-specific response to a one unit change in the VIX or the net-long futures positions of non-commercial traders.

Figure 10 shows the response of the first quantile of the conditional distribution of futures returns up to 12 weeks ahead to a shock in carry (top-left panel), in the VIX (top-right panel), and in the net-long futures positions of non-commercial traders (bottom panel). More precisely, the figure reports the posterior distribution of the $\beta^h_{j,p}$ for $j = Carry, VIX, NetPos$ and $h = 1, ..., 12$. Posterior densities are from 60,000 draws from the Gibbs sampler outlined in Section 3 and detailed in Appendix A. The initial 10,000 draws are discarded as a burn-in sample and only one in ten draws are retained from the remaining 50,000 iterations to increase the effective sample size (see Appendix B for details on the convergence properties of the estimation algorithm).

The figure focuses on first nearest-to-maturity contracts, results for second nearest-to-maturity contracts are qualitatively equivalent and available upon request. Figure 7 showed that indeed the correlation between current carry and future crash risk is mostly concentrated in the front-end of the curve. Also, I report the results for the first quantile consistent with standard thresholds in popular financial risk management models such as the Value-at-Risk and the Expected Shortfall (see, e.g., Engle and Manganelli 2004, Adrian and Brunnermeier 2016, and White et al. 2015).

[Insert Figure 10 about here]

Top-left panel shows the IRF for a one-unit shock in carry. As expected the effect of carry is highly negative and significant in the short term, consistent with the above results. Such an effect remains significant in the short term, up to about a month ahead. However, the posterior distribution of the shock sensitivity is concentrated around the zero line in the medium-to-longer term, where effectively becomes statistically not different from zero. The clarity of the effect in the short term is quite remarkable. In other words, the negative effect of carry shocks on tail risk is relatively short-lived. This is consistent with Abreu and Brunnermeier (2003) which argue that each individual trader may find optimal to hold carry trades since there is incomplete information on when other traders unwind their positions. Consequently, a price crash can occur with some delay when carry trades suddenly unwind.

Top-right panel shows the IRF for a one-unit shock in the VIX. Interestingly, the persistence of a shock in aggregate risk aversion and market uncertainty is double than carry. As a matter of fact, a one unit shock in the VIX has a significant effect almost up to two months ahead, when reverse back to zero. This is consistent with the conventional wisdom and some of the existing evidence that posits aggregate risk exacerbates portfolios and single trades losses (see, e.g., Adrian and Brunnermeier 2016).

Finally, the bottom panel shows of Figure 10 shows the IRF of a one-unit shock in net-long futures positions of non-natural hedgers on tail risk. The response of the first quantile is neither sizeable nor significant for each of the horizons and there is no significant path for each of the response horizons. However, results for the futures positions should be taken with a grain of salt as the absence of significance could be due to the inevitable limitations of the CFTC futures positions as a proxy of speculators' behaviour.

4.3 A Discussion on the Quantile-Specific Fixed Effects

I now the discuss the effect of the quantile-specific fixed effects in capturing the relationship between carry and tail risk as documented above. Contracts fixed-effects are assumed to capture unobserved cross-sectional heterogeneity which dilutes the average effect of the sensitivity between carry and the conditional distribution of futures returns. An interesting question is to see if such fixed effects are actually time-varying in the cross section and statistically different from zero. Figure 11 show the posterior distribution of the quantile-specific fixed effects across commodities. For the ease of exposition I report the results for the first nearby contracts. Results on the second nearest-to-maturity futures are qualitatively similar and available upon request. Left panel shows the fixed effects on the first quantile of the conditional distribution of futures returns.

[Insert Figure 11 about here]

It is quite evident that there is a substantial heterogeneity in the intercept parameters across commodities. As a matter of fact, although are all negative and significant, the fixed effects on the first quantile are quite different in value across commodities, with posterior distributions that only marginally overlaps, and in most cases are quite significantly separate from each other, as an indication that the null hypothesis of equivalent fixed effects across contracts can be confidently rejected. In this respect, although a formal test of such null hypothesis is beyond the scope of this section, the posterior distributions make clear that there is a substantial difference in the commodity specific intercepts in the cross section. Right panel shows the fixed effects on the fifth quantile and confirms such significance heterogeneity, although two out of eighteen fixed effects are only borderline significantly different from zero.

The evidence from the posterior densities implicitly suggest that overlooking the heterogeneity across futures contracts may end up to affect the estimates of the betas on carry on tail risk. Figure 11 shows the posterior distribution of the beta on carry for each quantile from the median (top of the y-axis) to the 1st quantile (bottom of the y-axis). The x-axis represents the magnitude of the coefficient. Posterior distributions are generated from the Gibbs sampler outlined in Section 3 and detailed in Appendix A. Unlike before, I now exclude commodity fixed effects and consider only a global intercept which somewhat "averages out" commodity specific intercepts.

[Insert Figure 12 about here]

As somewhat expected, by collapsing the unobservable cross-sectional heterogeneity and treat all commodities alike the significance of the relationship between carry and tail risk substantially diminishes. In fact, it is only marginally significance on the very left tail of the distribution of futures returns on first nearby contracts (left panel) while is virtually not different from both from higher quantiles and from the whole distribution of the futures returns on second nearest-to-maturity contracts. Around the median the relationship between carry and returns is marginally positive although not significant, consistent with the conditional expectations results in Koijen et al. (2017).

As a whole, Figures 11 and 12 show that there is a substantial and significant heterogeneity in the dynamics of the conditional distribution of futures returns across commodity contracts, and that neglecting such heterogeneity does not allow to disentangle the quantile-specific effects of carry trades on futures returns.

5 Understanding the Mechanism

The results so far suggest that there is a significant relationship between trading signals that come from the futures curve and tail risk in commodity markets. Theoretical models such as Abreu and Brunnermeier (2003), Brunnermeier et al. (2007) and Acharya et al. (2013) argue that this kind of dynamics could be driven by a decrease in the risk capacity of capital constrained speculators which tend to unwind their long futures positions when facing reducing liquidity and increasing hedging costs and margin calls. Specifically, when facing aggregate deteriorating conditions speculators and insurance providers reduce their futures exposures causing drops in the values of futures contracts and thus the returns on collateralized positions. To test this mechanism I follow and extend Brunnermeier and Pedersen (2008) by estimating the following panel regression for different categories of non-natural hedgers,

$$\Delta NetPos_{it} = \alpha + \boldsymbol{\beta}' \Delta \tilde{\boldsymbol{z}}_{it-1} + \boldsymbol{\gamma}' \boldsymbol{x}_{t-1} + a_i + \epsilon_{it}$$

where $\Delta NetPos_{it}$ represent the one-period changes in the net-long futures positions on the ith commodity, $\boldsymbol{x}_{t-1}$ a set of control variables, a_i the commodity fixed effect, and $\Delta \tilde{\boldsymbol{z}}_{it-1} = \Delta \boldsymbol{z}_{t-1} \cdot sign\left(Carry_{it-1}\right)$ with $sign\left(Carry_{it-1}\right)$ the sign of carry for commodity i at time t and $\Delta \boldsymbol{z}_{t-1}$ the one-period change in variables that capture states of the world in which speculators are likely to be forced to unwind their long positions.

Identifying these states of the world is not an easy task. Ideally, one should use a precise measure of speculators' willingness and ability to risk capital and bear losses. Unfortunately, this depends on a variety of unobservable, perhaps unmeasurable, factors. To proxy for such states I use several measures directly related to aggregate market uncertainty, financial conditions, and commodity world production.

Aggregate market uncertainty and changes in risk aversion are proxied by the one-period change in the VIX. Prior research has shown that the VIX index is a useful measure of market uncertainty and aggregate risk appetite which spans several markets (see, e.g., Whaley 2000). As additional measure of aggregate market uncertainty I use the equity-related economic policy uncertainty index provided by Baker, Bloom, and Davis (2016). Such index reflects the frequency of articles in 10 leading US newspapers that contain the following trio of terms: "economic" or "economy"; "uncertain" or "uncertainty"; and "stock price", "equity price" or "stock market".

Production dynamics is of particular relevance to assess the mechanism behind carry trades. As a matter of fact, the slope of the terms structure provides information about the expected value of the commodity in the future. On the one hand, a commodity that is abundant relatively to its past supply will tend to be in contango. On the other hand, the term structure tend to be in backwardation if a commodity is scarce relatively to its past supply. That is, we should expect a positive relationship between aggregate production of a commodity and the futures positions. As a direct measure of supply I use the monthly compounded year-on-year growth on the world total production for a subset of nine commodities for which I have reliable data available.[10]

Panel A of Table 2 shows the results by using the changes in the net-long futures position for the non-commercial traders (column 2 to 5) and for more disaggregated "managed money" (column 6 to 9). The independent variables are the interaction between the lagged change in the state variables that capture aggregate market uncertainty, or world commodity production, and the sign of the corresponding lagged carry. The one-period change in market uncertainty and the monthly year-on-year growth in commodity production are interacted with the sign of carry as now the direction of the trading signal from the futures curve directly related to market

[10]Data for the total world production of Crude oil and (in barrels) and natural gas (in cubic feet) are retrieved from the International Energy Agency. Data on the production of metals, both precious and industrial are obtained from the World Bureau of Metal Statistics; world mine production of gold, silver and aluminium are expressed in kilograms, while for copper production is expressed in metric tons. Data for agricultural commodities production are from the U.S. Department of Agriculture, all commodities, i.e. corn, wheat, and cotton, are expressed in million tons. Since natural gas and agricultural commodities data is only available in annual frequency, a cubic spline interpolation is used to fill the gaps between each year and transform the data into monthly. Changes in production are computed as log difference.

conditions.[11] In addition to the interacted state variables, a set of controls is included, such as the lagged realized futures returns and the lagged volatility proxied by the forecast from a GARCH(1,1). These control variables are assumed to capture commodity market-related conditions which might affect the corresponding trading positions.

[Insert Table 2 about here]

Panel A shows that changes in futures positions are significantly and negatively related to past changes in the VIX, that is carry trades tend to be unwound when aggregate risk aversion and/or market uncertainty increases, consistent with the results in Brunnermeier and Pedersen (2008). The negative correlation between the VIX and futures positions is not crowded out by the inclusion of a text-based measure of market uncertainty. Columns 6 to 9 show that the results are robust by looking at a more granular classification of non-natural hedgers, namely money managers. A direct comparison with non-commercial traders though is far from trivial as the sample size is different (managed money is reported only from 2006) and the as a results the number of observations is about a half for the disaggregated measure.

In this respect, Panel B suggests that the effect on managed money dominates the non-natural hedgers classification. Specifically, column 2 to 5 show that for the complementary classification "swap dealers" there is no significant effect of aggregate market uncertainty and risk aversion on futures positions. To a broader extent this is also true for index traders (column 6 to 9) where the effect of changes in the VIX in isolation is only borderline significant and becomes non-significant when the text-based measure of market uncertainty is included as additional regressor. However, the loading on the changes in the uncertainty index are negative and significant, consistent with the logic of Panel A. However, notice that the index traders classification uniquely involves those contracts which are included in the commodity indexes, the majority of which is agricultural commodities. This further reduces the sample size, which possibly explain the lower power in the panel regression estimates.

Both panel A and panel B show that the relationship between lagged changes in production and changes in futures positions is positive, that is, when production increases the tendency is to increase carry trades to speculate for downward sloping curve. That is, carry is a trading signal coming from the futures curve that partly reflects investors expectations on the supply-demand curve, consistent with the Theory of Storage (see, e.g. Working 1949 and Brennan 1958). However, such positive relationship is not significant for any of the traders classifications. Few comments are in order. First, data on world commodity production relates only a half of the commodities involved in the main empirical analysis. This substantially reduces the cross-sectional dimension and the amount of heterogeneity that can be exploited for identi-

[11] In the panel regression framework above one can avoid to take explicitly into account the direction of trades since carry, payoffs and futures positions they all jointly switch sign when the direction of the trades is reversed.

fication purposes. Second, world production for this subset of commodities is calculated at the monthly year-on-year growth rate, which means that also the time-series dimension decreases significantly, especially for the disaggregated trader classification. The monthly compounding comes from the fact that, to the best of my knowledge, there are no reliable higher-frequency data on commodity production which perhaps crude oil being the only exception. For these reasons, the results stating a positive but non-significant relationship between changes in futures positions and production growth should be taken with a grain of salt and possibly be further investigated in future research. Third, the effect of production is not tested for index traders as the intersection between the commodities for which reliable data on world production were available and those commodities for which the CFTC provides data on index traders was to small to draw any meaningful statistical analysis.

I now replicate the same exercise with a set of alternative measures of funding constraints and aggregate financing conditions. Specifically, to capture tightening funding liquidity risk I use the TED spread, the difference between the LIBOR interbank market interest rate and the risk-free T-Bill rate, the Financial Stress Index (FSI) maintained by the St. Louis Fed, and the Financial Condition Index (FCI) held by the Chicago Fed.[12] The FSI measures the degree of financial stress in the U.S. market and is constructed as a weighted average of 18 weekly data series: seven interest rates, six yield spreads, plus five other indicators related to the financial sector. Similarly, the FCI measures risk, liquidity and leverage in money, debt and equity markets as well as in the traditional and "shadow" banking systems. Crucially for my analysis, both indexes are available at the weekly frequency. The interpretation of these indexes is similar; in both cases a level of zero indicates normal financial markets conditions. Values below zero suggest below-average financial market stress for FSI and financial conditions looser than average for FCI, while on the opposite values above zero indicate above-average financial market stress for FSI and financial conditions tighter than average. A deterioration of financing conditions is expected to have similar effects of a change in the VIX, at least directionally. Table 3 shows the results.

[Insert Table 3 about here]

As far as funding liquidity constraints are concerned, it is reassuring that the sign of the coefficients on the TED spread, FSI and FCI coincide with the coefficient on the signed VIX and other measures of market uncertainty in Table 2. However, not all of those coefficients are statistically significantly.

Panel A shows the results for both the aggregate non-commercial traders classification and

[12] More information on the National Financial Conditions index of the Chicago Fed and the St.Louis Financial Stress Index can be found here http://www.chicagofed.org/webpages/publications/nfci/index.cfm and here https://files.stlouisfed.org/research/publications/es/10/ES1002.pdf, respectively.

the disaggregated “Managed Money” category. Interestingly, the signed one-period change in the FCI index turns out to be significant across specifications, especially when considered in conjunction with the other financial conditions measures. While the TED spread turns out to be significant for non-commercial traders but not for money managers, the significance of the FSI index is somewhat negligible. Panel B shows that the significance of the FCI vis-a-vis the FSI is confirmed both for swap dealers and for index traders. Beyond the obvious correlation that exists between the two indexes, one possible explanation of such discrepancy in significance lies in the different composition and purpose of the two indexes. As a metter of fact, while the FSI can be considered a snapshot of the level of fragility in the financial markets, an FCI represents a mapping of financial conditions onto macroeconomic conditions (see Carlson, Lewis, and Nelson 2012). In this respect, FDI lacks of observable counterparts in the real world and can only be measured relative to itself, while FCI assumes a relationship between the financial sector and the real economy.[13]

Taken together, the results of Table 2 and 3 show that unwinding of carry trades in response to deteriorating financial conditions and increasing market uncertainty can possibly explain the results in Section 4: increasing risk aversion and reducing risk bearing capacity faced by speculators force a reduction in carry trade positions, thus making drops in market prices more likely and returns higher going forward. More generally, the empirical findings are coherently with the frameworks outlined in Brunnermeier et al. (2007) and Acharya et al. (2013), whereby tail risk and crashes can be endogenously generated as part of the movement in investment and funding across commodity markets driven by changes in risk tolerance and financing conditions.

6 Conclusion

I am interested in the relationship between carry trades and tail risk. I propose a comprehensive panel quantile regression framework and show that higher carry leads to a higher probability of having large losses conditional on past returns, past volatility, aggregate market uncertainty, and the amount of net-long futures positions by non-commercial traders.

Commodity markets offer an ideal setting to investigate carry trades for funding constrained speculators at least for two reasons: first, commodity carry can be highly volatile and heterogeneous in the cross section relative to, say, exchange rates. Higher time series volatility and cross-sectional variation allows for a better identification of the leading correlation effects between carry and the conditional distribution of futures returns. This is due to the fact that, unlike for instance fixed income and currencies, commodity markets do not have a dependable

[13] In an unrelated forecasting exercise, Kliesen, Owyang, Vermann et al. (2012) show that given FCIs tend to use more economic indicators, such as loan or debt measures, they produce better forecasts of macroeconomic conditions, on net.

"Bear-whale" like a central bank that is prepared to buy commodity assets at any resort and in the process manipulate forward expectations. In this respect, carry in commodities can hardly be stabilized by regulators and policy makers alike. Second, public available data on speculators' futures positions are much larger, deeper, and granular for commodities than for any other asset class. This allows to exploit a much larger amount of information in investigating the relationship between carry and the behavior of non-natural hedgers, speculators, and insurance providers.

Methodologically, I propose a panel quantile regression framework with additive commodity fixed effects which allows to explicitly investigate predictive relationships between carry and the very left tail of the distribution of futures excess returns one or several steps ahead. The inclusion of fixed effects allows to account for the substantial heterogeneity that exists across commodities. I propose an efficient Gibbs sampler algorithm for the estimation which allows to sample draws from the posterior distribution of quantile-specific slope parameters and fixed-effects while explicitly acknowledging parameter uncertainty.

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Appendix

A Gibbs Sampler

The panel quantile regression model is given in Eq. (9), which I rewrite here for convenience:

$$\mathbf{y} = Z'\boldsymbol{\gamma}_p + \theta\mathbf{v} + \tau\sqrt{\mathbf{v}}\mathbf{u} \tag{A.1}$$

where Z is the set of exogenous regressors and fixed effects, $v_{it} \sim \mathit{Exponential}(1)$, and $u_{it} \sim N(0,1)$ for $i = 1, ..., N$, $t = 1, ..., T$ are the new variables that are introduced to transform the likelihood such that the model becomes conditionally Normal. The prior are conjugate and specified as a joint Normal-Inverse-Gaussian for the regression slopes and commodity fixed effects, i.e.,$\boldsymbol{\gamma}_p|\sigma_p^2 \sim N\left(\boldsymbol{\mu}_{\gamma_p}, \sigma_p^2 V_{\gamma_p}\right)$, and $\sigma_p^2 \sim IG\left(a, b\right)$. Draws from the posterior distributions of all the unknown parameters are obtained by sequentially sample from the conditional distributions through the following steps:

Step 1. Sampling the betas and fixed effects

Since conditional on $\mathbf{v}$ and θ, τ equation (A.1) is a linear regression model, the full conditional density is standard, that is sampling $\boldsymbol{\gamma}_p$ conditional on a given quantile p, knowledge of all other parameters and $\mathbf{v}$, and the data $\mathbf{y}, Z$, is given by

$$\boldsymbol{\gamma}_p|\sigma_p^2, \mathbf{y}, Z, \mathbf{v} \sim N\left(\hat{\boldsymbol{\mu}}_{\gamma_p}, \hat{V}_{\gamma_p}\right)$$

where

$$\hat{V}_{\gamma_p}^{-1} = \tilde{Z}'\tilde{Z} + V_{\gamma_p}, \qquad \text{and} \qquad \hat{\boldsymbol{\mu}}_{\gamma_p} = \hat{V}_{\gamma_p}\left(\tilde{Z}'\tilde{\mathbf{y}} + V_{\gamma_p}^{-1}\boldsymbol{\mu}_{\gamma_p}\right), \tag{A.2}$$

with $\tilde{Z}$ and $\tilde{\mathbf{y}}$ rescaled versions of the response and covariates such that $\tilde{Z}_{it} = Z_{it}/\sqrt{\tau^2\sigma v_{it}}$ and $\tilde{y}_{it} = \left(y_{it} - \theta v_{it}\right)/\sqrt{\tau^2\sigma v_{it}}$. It is easy to see that (A.2) represents the posterior distribution from a usual linear regression model conditional on the exponential distribution terms $\mathbf{v}$.

Step 2. Sampling the conditional variances

The scale parameter for the regression parameters and the fixed-effects can be easily obtained as

$$\sigma_p^2|\mathbf{y}, Z, \boldsymbol{\gamma}_p, \mathbf{v} \sim IG\left(\hat{a}/2, \hat{b}/2\right), \tag{A.3}$$

where

$$\hat{a} = a + Tn, \qquad \text{and} \qquad \hat{b} = b + 2\sum_{i=1}^{n}\sum_{t=1}^{T} v_{it} + \overline{\mathbf{y}}'\overline{\mathbf{y}}$$

where $\overline{y}_{it} = \left(y_{it} - Z'_{it}\boldsymbol{\gamma}_p - \theta v_{it}\right)/\tau v_{it}$, represents a demeaned and re-scaled version of the dependent variable.

Step 3. Sampling the exponential distributed terms

From Eq.(8) and the exponential density assumption for v_{it} for $i = 1, ..., n$ $t = 1, ..., T$, the full conditional distribution of v_{it} is proportional to

$$z_{it}^{-1/2} \exp\left\{ -\frac{1}{2}\left(\delta_{it}^2 z_{it}^{-1} + \xi v_{it}\right)\right\} \tag{A.4}$$

where $\delta_{it}^2 = \left(y_{it} - Z'_{it}\gamma_p\right)^2/\tau^2\sigma$ and $\xi^2 = 2/\sigma + \theta^2/\tau^2\sigma$. Since (A.4) is the kernel of a Generalized Inverse Gaussian distribution, we have

$$z_{it}|\mathbf{y}, Z, \boldsymbol{\gamma}_p \sim GIG\left(\frac{1}{2}, \delta_{it}, \xi\right)$$

the p.d.f. of the generalized inverse Gaussian density is of the form

$$f\left(x|\nu, a, b\right) = \frac{(b/a)^{\nu}}{2K_{\nu}\left(ab\right)} x^{\nu-1} \exp\left\{ -\frac{1}{2}\left(a^2x^{-1} + b^2x\right)\right\}, \qquad x > 0, -\infty < \nu < \infty, a, b \geq 0$$

and $K_{\nu}\left(.\right)$ is a modified Bessel function of the third kind (see Barndorff-Nielsen and Shephard 2001).

B Convergence Diagnostics

Further to understand the properties of the estimation framework, I investigate the convergence properties of the Gibbs Sampling algorithm outlined in Appendi A above. The results below are based on 60000 posterior draws with a burn-in of 10000 and thinning value of 10. If the algorithm is designed properly, we should expect the Markov chain of the posterior draws of the parameters will convergence to some stable distribution (see, e.g., Gelman and Rubin 1992, Geweke 1992, Raftery and Lewis 1992, and Brooks and Gelman 1998, for details).

One way to see if our Markov chain is mixing is to see how fast it convergences to same stable mean. Left panel of Figure B.1 shows the running mean plot. A running mean plot is a plot of the iterations against the mean of the draws up to each iteration. More precisely, Figure B.1 reports the running mean for some of the quantile-specific betas obtained from the panel quantile regression specification where the dependent variable is the returns on first nearby contracts. Results for the second nearest-to-maturity contracts are qualitatively the same. The benchmark specification involves uninformative priors.

[Insert Figure B.1 about here]

A good mixing chain is assumed to converge quickly to some long-run mean value. Left panel of Figure B.1 shows that this is indeed the case for several representative quantiles of the conditional distribution. The running mean quickly converges and remains highly stable after the burnin-in sample.

Another graphical way to assess convergence is to check for the autocorrelations between the draws of the Markov chain. If autocorrelation is still relatively high for higher lags, this indicated a high correlation between draws and slow mixing. That is, the higher the autocorrelation the lower the effective sample size used to approximate the posterior quantities of interest (see, e.g., Gelman and Rubin 1992). Right panel of Figure B.1 shows the autocorrelation function (ACF) for the beta on carry for the 1st quantile on the conditional distribution of first nearby contracts. The ACF is virtually zero from the very initial lags. This is due to the fact that only one in ten draws are kept while the others are discarded, which significantly reduces the persistence of the draws and increases the efficiency of the posterior estimates.

Although informative, the evidence provided in Figure B.1 is not conclusive. I now test the Markov chain convergence by implementing a difference of means test to investigate if draws are from the same distribution (see Geweke 1992). The test statistics is a standard Z-score with standard errors computed using the Newey and West (1987) heteroschedasticity and autocorrelation robust variance estimator with a bandwidth set to 4%,8%, and 15% of the utilised sample size. Table C.1 shows the results for the betas on carry for different representative quantiles of the conditional distribution of first nearby futures contracts.

[Insert Table C.1 about here]

Column one of the summary of convergence diagnostics shows that even without correcting for autocorrelation the t-statistic does not reject the null hypothesis of equal means in the sub-samples for all the four quantiles. As expected, the evidence of convergence significantly increases by adjusting the standard errors for autocorrelation and heteroschedasticity. By using a kernel estimation of standard errors with a bandwidth of 4%, 8% and 15% of the data the Z-score shows strong evidence of convergence with none of the quantile-specific betas rejecting the null hypothesis.

To summarise, Figure B.1 and Table C.1 provide evidence that our model appears to be reasonably accurate when we base posterior inference on 60000 draws with a burn-in of 10000 and thinning value of 10, which keeps the computational burden relatively low.

Table 1. Summary Statistics

This table shows the descriptive statistics for the futures returns on each commodity used in the empirical analysis. Excess returns are computed from a roll-over strategy and represent the net returns from holding a long position in a generic contract, liquidating the long position the day before the curve moves down by one contract, and going long in the latter. This strategy is followed from Tuesday to Tuesday every week to match the measurement of the positions by the Commodity Futures Trading Commission (CFTC). I assume the roll takes place on the 11th calendar day of each month (see, e.g., Singleton 2014). The sample mean, standard deviation, and Sharpe ratios are expressed in annualized terms. The table also reports the unconditional mean and standard deviation of a measure of carry as in Koijen et al. (2017) calculated on a weekly basis matching the schedule of the CFTC futures position releases and the weekly returns. **Panel A:** reports summary statistics for the excess returns and carry on first-nearby contracts. Carry is computed as the negative of the slope between the nearest-to-maturity contract and the first next-to-nearest available futures contract on the same commodity, normalized by the latter. **Panel B:** shows the summary statistics for the excess returns and carry of second-nearby futures contracts. Carry is constructed as the negative of the slope between the nearest-to-maturity contract and the second next-to-nearest available futures contract on the same commodity, normalized by the latter. Data on exchange-traded, liquid commodity futures contracts are from Bloomberg. The sample period is weekly and is from 1992 to 2017.

Panel A: First Nearest-to-Maturity

		WTI	NatGas	HeatOil	Gold	Silver	Copper	Corn	Wheat	Cotton	LiveCattle	Sugar	Soybean	SoybOil	SoybMeal	OrJuice	Platinum	KanWheat	FeedCattle
Returns	Mean (Annualized)	-0.024	-0.197	0.011	0.015	0.027	0.048	-0.122	-0.150	-0.096	-0.003	-0.009	0.071	-0.020	0.137	-0.094	0.054	-0.030	0.017
	St.Dev (Annualized)	0.379	0.551	0.357	0.168	0.291	0.270	0.320	0.327	0.314	0.213	0.356	0.272	0.237	0.326	0.357	0.223	0.304	0.165
	Skewness	-0.650	-0.225	-0.196	-0.106	-0.467	-0.586	-0.218	0.206	-0.307	-0.091	-0.073	-0.669	-0.100	-0.299	0.244	-0.338	0.232	-0.120
	Kurtosis	6.920	4.950	4.904	5.724	5.479	7.036	10.031	5.374	8.506	4.915	4.196	9.193	4.437	7.843	5.076	5.571	5.009	5.194
	SR (Annualized)	-0.062	-0.359	0.030	0.090	0.093	0.178	-0.381	-0.461	-0.306	-0.016	-0.026	0.261	-0.085	0.421	-0.263	0.243	-0.100	0.101
Carry	Mean	-0.002	-0.018	-0.001	-0.004	-0.006	0.002	-0.018	-0.020	-0.010	0.001	0.000	0.002	-0.006	0.011	-0.009	0.002	-0.008	0.001
	St.Dev	0.022	0.049	0.025	0.003	0.004	0.016	0.039	0.031	0.043	0.036	0.046	0.025	0.010	0.032	0.027	0.010	0.031	0.019

Panel B: Second Nearest-to-Maturity

		WTI	NatGas	HeatOil	Gold	Silver	Copper	Corn	Wheat	Cotton	LiveCattle	Sugar	Soybean	SoybOil	SoybMeal	OrJuice	Platinum	KanWheat	FeedCattle
[1em] Returns	Mean (Annualized)	0.007	-0.109	0.020	0.012	0.032	0.064	-0.112	-0.090	-0.067	0.022	0.069	0.058	-0.024	0.091	-0.109	0.057	-0.024	0.006
	St.Dev (Annualized)	0.341	0.492	0.324	0.169	0.290	0.263	0.293	0.310	0.272	0.195	0.315	0.250	0.233	0.279	0.323	0.223	0.287	0.168
	Skewness	-0.484	-0.221	-0.266	-0.111	-0.486	-0.625	-0.073	0.218	0.361	-0.201	0.042	-0.342	-0.087	-0.245	0.048	-0.188	0.127	-0.138
	Kurtosis	5.431	5.315	4.666	5.639	5.530	7.421	5.883	5.076	5.809	6.067	4.438	7.562	4.170	6.427	4.463	6.943	4.505	4.539
	SR (Annualized)	0.022	-0.222	0.062	0.069	0.111	0.245	-0.382	-0.291	-0.245	0.113	0.218	0.233	-0.103	0.326	-0.336	0.254	-0.084	0.037
Carry	Mean	-0.003	-0.029	-0.003	-0.008	-0.011	0.006	-0.032	-0.032	-0.017	0.001	0.008	0.011	-0.011	0.019	-0.021	0.003	-0.014	0.000
	St.Dev	0.038	0.088	0.042	0.006	0.008	0.029	0.068	0.058	0.072	0.057	0.075	0.063	0.019	0.053	0.041	0.022	0.056	0.029

Table 2. Futures Positions, Market Uncertainty and Production

This table shows the results of a panel regression with commodity fixed effects in which the dependent variable is the change in the net-long futures positions for different classification of non-natural hedgers and the dependent variable is an interaction between the sign of carry and the one-period change of a variable indicating aggregate market uncertainty, as proxied by the VIX and a text-based market uncertainty, and the monthly year-on-year change in world commodity production. Text-based market uncertainty is based on the equity-related economic policy uncertainty index provided by Baker et al. (2016). As a direct measure of supply I use data on the world total production for a subset of nine commodities for which reliable data are available. In addition to the interaction terms, a set of control variables is considered in the panel regression; the lagged value of the dependent variables, past returns and past expected volatility proxied by the forecast from a GARCH(1,1). Data on exchange-traded, liquid commodity futures contracts are from Bloomberg. The sample period is weekly and is from 1992 to 2017. Robust tandard errors are reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Non-Commercial Traders and Managed Money

	Non-Commercial Traders				Managed Money			
	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$
$\Delta VIX_{t-1} \cdot sign(Carry_{t-1})$	-0.00057***		-0.00055**		-0.00045**		-0.00069*	
	(0.00019)		(0.00019)		0.00023		(0.00036)	
$\Delta MktUnc_{t-1} \cdot sign(Carry_{t-1})$		-0.00761	-0.00584			-0.01385	-0.01414	
		(0.00585)	(0.00574)			(0.00997)	(0.00991)	
$\Delta Prod_{t-1} \cdot sign(Carry_{t-1})$				0.01908				0.00087
				(0.01382)				(0.00364)
overall R^2	0.0039	0.0002	0.0068	0.0092	0.0005	0.0002	0.0004	0.00005
Obs.	22050	22050	22050	2241	10404	10404	10404	1017
Fixed-effect	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes

Panel B: Swap Dealers and Index Traders

	Swap Dealers				Index Traders		
	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$
$\Delta VIX_{t-1} \cdot sign(Carry_{t-1})$	-0.00028		-0.00013		-0.00030*		-0.00020
	(0.00020)		(0.00012)		(0.00016)		(0.00015)
$\Delta MktUnc_{t-1} \cdot sign(Carry_{t-1})$		-0.00087	-0.00255			-0.02906***	-0.02951***
		(0.00478)	(0.00764)			(0.00855)	(0.00791)
$\Delta Prod_{t-1} \cdot sign(Carry_{t-1})$				0.00081			
				(0.00213)			
overall R^2	0.00024	0.00001	0.00118	0.00007	0.00011	0.00106	0.00119
Obs.	10404	10404	10404	10404	5202	5202	5202
Fixed-effect	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes

Table 3. Futures Positions and Aggregate Financial Conditions

This table shows the results of a panel regression with commodity fixed effects in which the dependent variable is the change in the net-long futures positions for difference classification of non-natural hedgers and the dependent variable is an interaction between the sign of carry and the change of a variable indicating aggregate financial conditions. The latter are captured by the TED spread, the difference between the LIBOR interbank market interest rate and the risk-free T-Bill rate, the Financial Stress Index (FSI) maintained by the St. Louis Fed, and the Financial Condition Index (FCI) held by the Chicago Fed. In addition to the interaction terms, a set of control variables is considered in the panel regression; the lagged value of the dependent variables, past returns and past expected volatility proxied by the forecast from a GARCH(1,1). Data on exchange-traded, liquid commodity futures contracts are from Bloomberg. The sample period is weekly and is from 1992 to 2017. Robust standard errors are reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Non-Commercial Traders and Managed Money

	Non-Commercial Traders				Managed Money			
	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$
$\Delta FSI_{t-1} \cdot sign(Carry_{t-1})$	-0.00179			-0.00319	-0.00999**			-0.03955
	(0.00773)			(0.00970)	(0.00463)			(0.02430)
$\Delta TED_{t-1} \cdot sign(Carry_{t-1})$		-0.00011**		-0.00001		-0.00001		-0.00001
		(0.00004)		(0.00007)		(0.00001)		(0.00001)
$\Delta FCI_{t-1} \cdot sign(Carry_{t-1})$			-0.00826***	-0.00573**			-0.01427**	-0.04928**
			(0.00158)	(0.00161)			(0.00726)	(0.02152)
overall R^2	0.00352	0.00125	0.00126	0.00473	0.01096	0.00003	0.00731	0.01612
Obs.	22050	22050	22050	22050	10404	10404	10404	10404
Fixed-effect	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes

Panel B: Swap Dealers and Index Traders

	Swap Dealers				Index Traders			
	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$	$\Delta NetPos_t$
$\Delta FSI_{t-1} \cdot sign(Carry_{t-1})$	-0.00696**			-0.00899	-0.00128			-0.00771
	(0.00280)			(0.01474)	(0.00147)			(0.00436)
$\Delta TED_{t-1} \cdot sign(Carry_{t-1})$		-0.00001		-0.00001		-0.00004*		-0.00001
		(0.00009)		(0.00001)		(0.00002)		0.00001
$\Delta FCI_{t-1} \cdot sign(Carry_{t-1})$			-0.01084**	-0.00939**			-0.00654	-0.16759***
			(0.00457)	(0.00404)			(0.01017)	(0.04659)
overall R^2	0.01465	0.0002	0.01347	0.01474	0.00024	0.0002	0.00239	0.08056
Obs.	10404	10404	10404	10404	5202	5202	5202	5202
Fixed-effect	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes

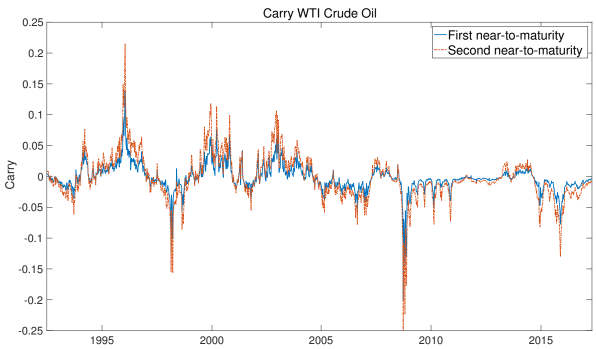
Table C.1. Convergence Diagnostics

This table summarizes the convergence results for the posterior values of the model parameters, estimated over the sample period 1992 to 2017, weekly. In order to assess inefficiencies I used as a benchmark the Bayesian panel quantile regression with additive fixed effects where the dependent variable is the conditional distribution of the futures returns on first nearest-to-maturity contracts. For a series of representative quantile-specific betas, I compute the p-value of the Geweke (1992) t-test for the null hypothesis of equality of the means computed for the first 20% and the last 50% of the retained MCMC draws after burnin. The variances of the means are estimated with the Newey and West (1987) estimator using a bandwidth of 4%, 8%, and 15% of the sample sizes, respectively.

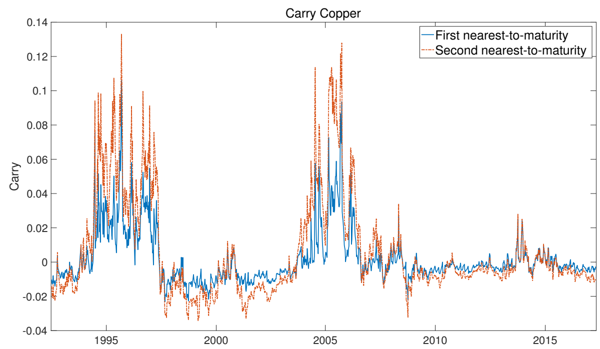
	Summary of Convergence Diagnostics			
Industry	iid	bandwidth of 4%	bandwidth of 8%	bandwidth of 15%
1st quantile	0.1176	0.1351	0.1459	0.1414
5th quantile	0.7084	0.6757	0.6290	0.5993
10th quantile	0.6724	0.6965	0.6585	0.6437
50th quantile	0.8909	0.8826	0.8791	0.8700

Figure 1. Some Examples of Carry

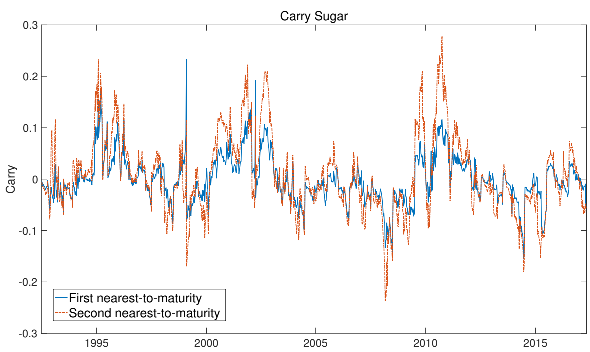
This figure shows as an example Carry for WTI Crude Oil (top-left panel) and Copper (top-right panel), Sugar (bottom-left panel) and Currency Markets (bottom-right panel). Carry for commodities is constructed as the negative of the slope between the nearest-to-maturity contract and the second next-to-nearest available futures contract on the same commodity, normalized by the latter (see Koijen et al. 2017). Carry for currencies is constructed as the differentials of 3-month interbank rates of US vs EUR (blue line), US vs JPN (dark yellow line), and US vs CHF (red line). Data on exchange-traded, liquid commodity futures contracts are from Bloomberg. The sample period for commodities (currencies) is weekly, 1992-2017 (1999-2017).



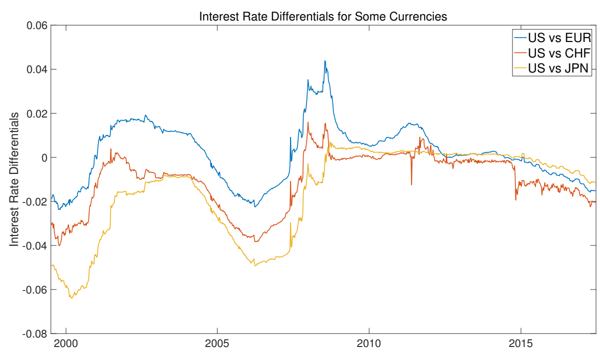
(a) WTI Crude Oil



(b) Copper



(c) Sugar



(d) Currencies

Figure 2. Open Interests by Maturity

This figure shows the open interests for a selection of commodities (left panel) and aggregate across commodities (right panel) for the first four available maturities. Data are from the Chicago Mercantile Exchange. The sample period is weekly and is from 1992 to 2017.

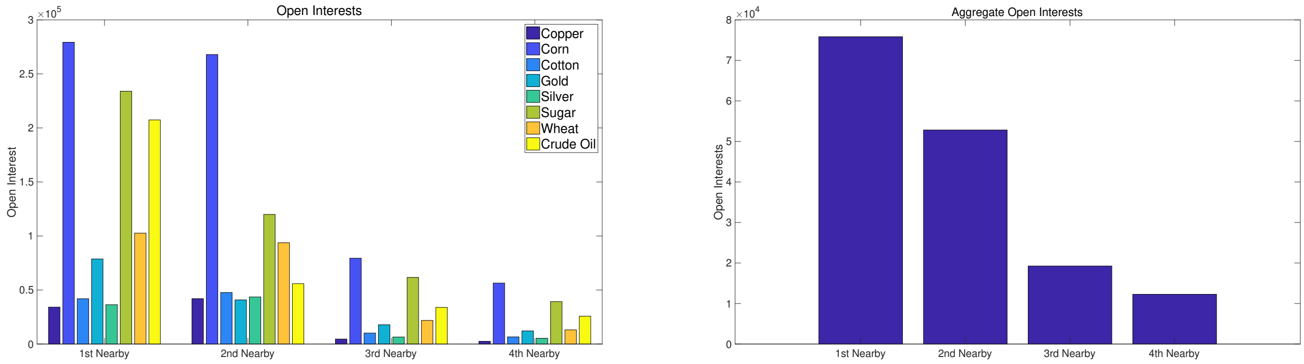
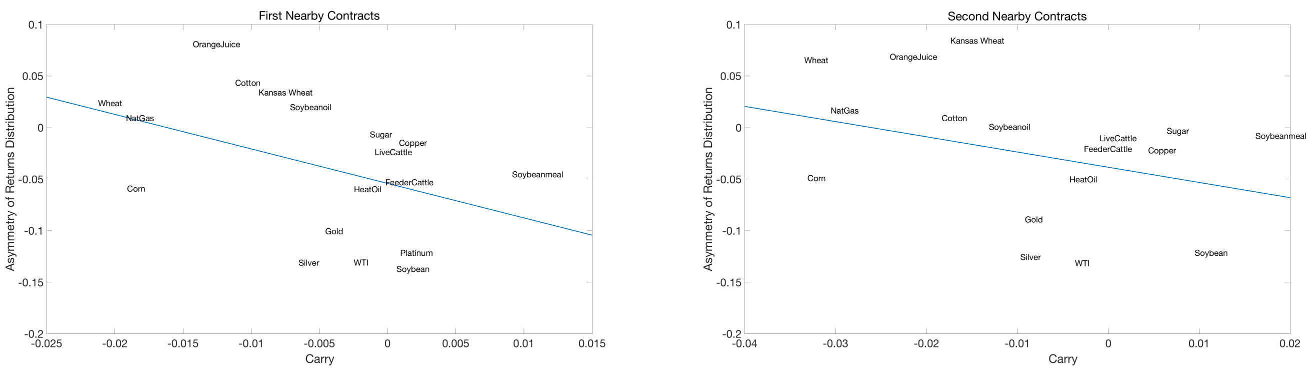


Figure 3. Carry Trades and Asymmetry of Returns Distribution

This figure shows the scatter plot of carry and the asymmetry of the returns distribution. The latter is measured by using the Bowley (1920) robust coefficient of skewness for a cross-section of commodities. Data on exchange-traded, liquid commodity futures contracts are from Bloomberg. The sample period is weekly and is from 1992 to 2017. The left panel shows the scatter plot for first-nearby contracts, and the right panel focuses on the scatter plot of second-nearby contracts.

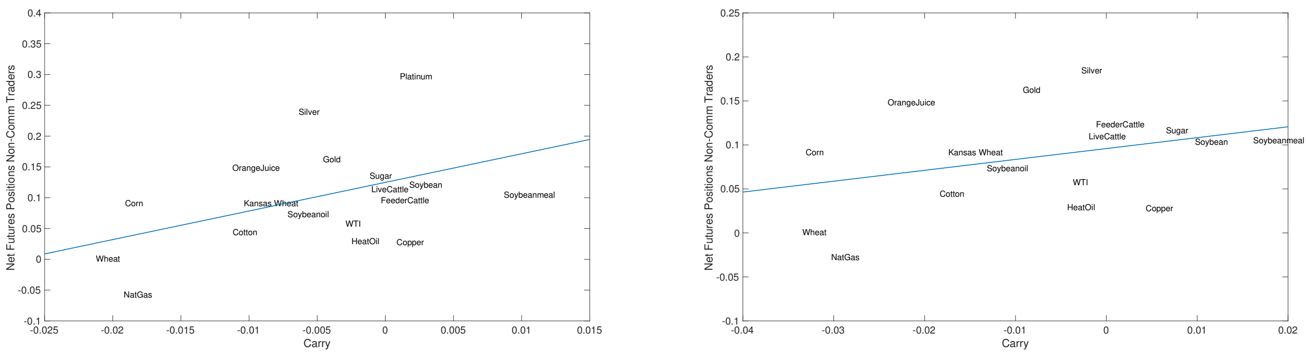


(a) First Nearby

(b) Second Nearby

Figure 4. Carry Trades and Net Long Futures Positions

This figure shows the scatter plot of carry and the net long futures positions by non-commercial traders for a cross-section of commodities. Data for the futures positions of non-commercial traders are obtained from the Commodity Futures Trading Commission (CFTC). CFTC releases data on commitment of traders each Friday but the report is current as of the Tuesday before each Friday's release. Data on exchange-traded, liquid commodity futures contracts are from Bloomberg. The sample period is weekly and is from 1992 to 2017. The left panel shows the cross-sectional correlation for first-nearby contracts, and the right panel focuses on the cross-sectional correlation of second-nearby contracts.

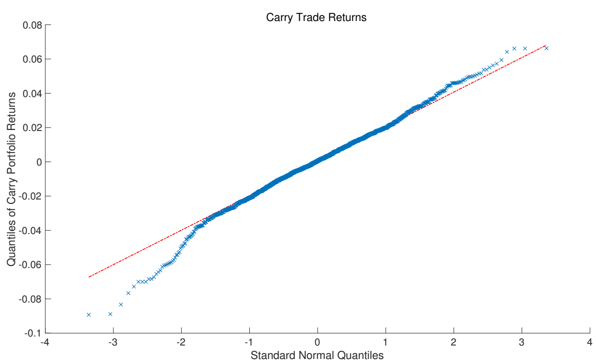


(a) First Nearby

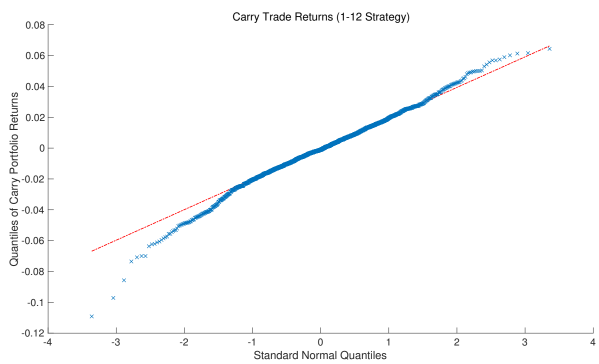
(b) Second Nearby

Figure 5. Returns on Carry Trades

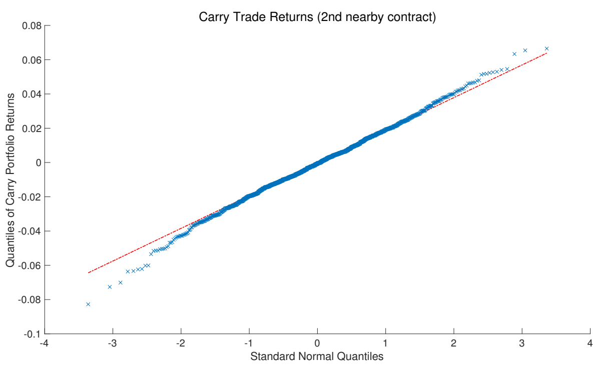
This figure represents a quantile-quantile plot, i.e., qq-plot, for the returns on a carry strategy. A carry strategy takes a long (short) position in commodities in which the market is in backwardation (contango). Portfolio weights are constructed following Moskowitz et al. (2012a), Asness et al. (2013), and Koijen et al. (2017), where weights are assigned based on the ranked carry for each contract. Top panels show the results on first nearby contracts while bottom panels show the results on the second nearby contracts. For the portfolio construction on the left panels carry is measured each Tuesday consistent with the schedule of the returns and the CFTC commitment of traders report. For the portfolio returns on the right panels carry is constructed as a moving average of the current carry over the past 12 weeks (including the most recent one). Data on exchange-traded, liquid commodity futures contracts are from Bloomberg. The sample period is weekly and is from 1992 to 2017.



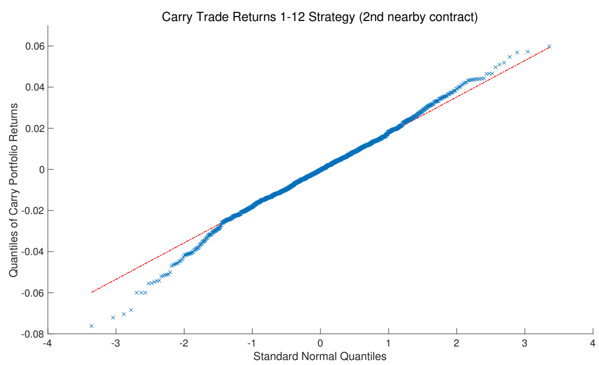
(a) Carry Strategy 1st Nearby



(b) Carry 1-12 Strategy 1st Nearby



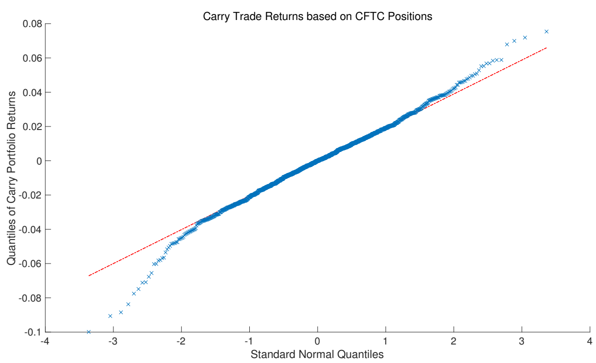
(c) Carry Strategy 2nd Nearby



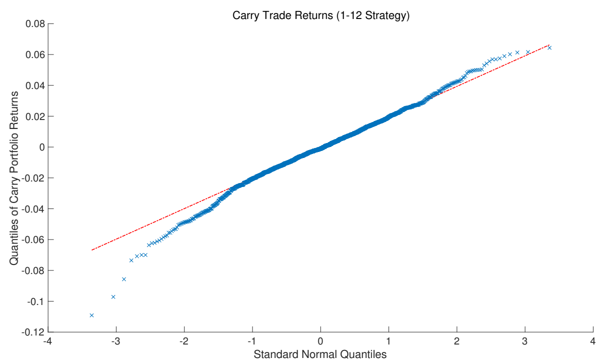
(d) Carry 1-12 Strategy 2nd Nearby

Figure 6. Returns on Carry Trades based on CFTC positions

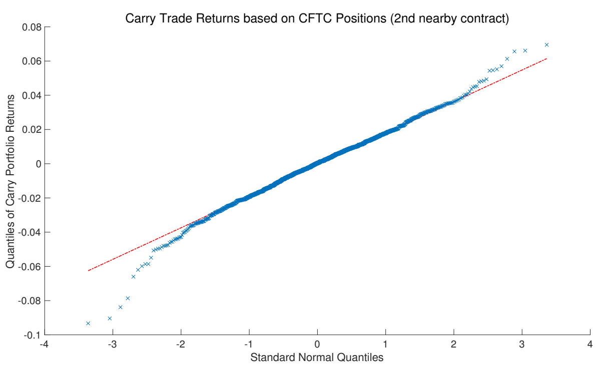
This figure represents a quantile-quantile plot, i.e., qq-plot, for the returns on a carry strategy. Now, a carry strategy is constructed taking a long (short) position in commodities in which the net-long futures positions available from the CFTC are higher (lower). Portfolio weights are constructed following Moskowitz et al. (2012a), Asness et al. (2013), and Koijen et al. (2017), where weights are now assigned based on the net-long futures positions of non-commercial traders. Top panels show the results on first nearby contracts while bottom panels show the results on the second nearby contracts. For the portfolio construction on the left panels carry is measured each Tuesday consistent with the schedule of the returns and the CFTC commitment of traders report. For the portfolio returns on the right panels carry is constructed as a moving average of the current carry over the past 12 weeks (including the most recent one). Data on exchange-traded, liquid commodity futures contracts are from Bloomberg. The sample period is weekly and is from 1992 to 2017.



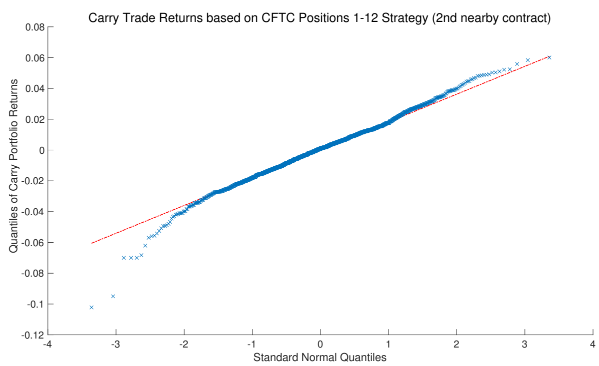
(a) Carry Strategy



(b) Carry 1-12 Strategy



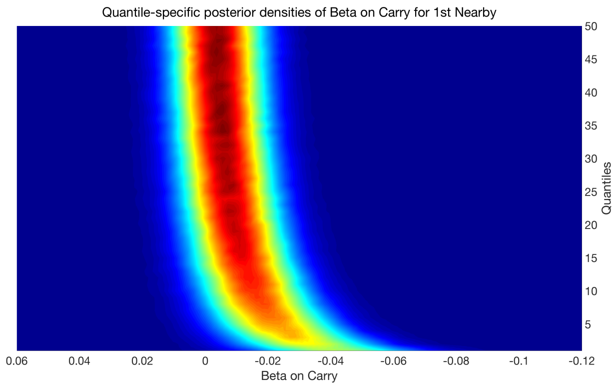
(c) Carry Strategy based on CFTC 2nd Nearby



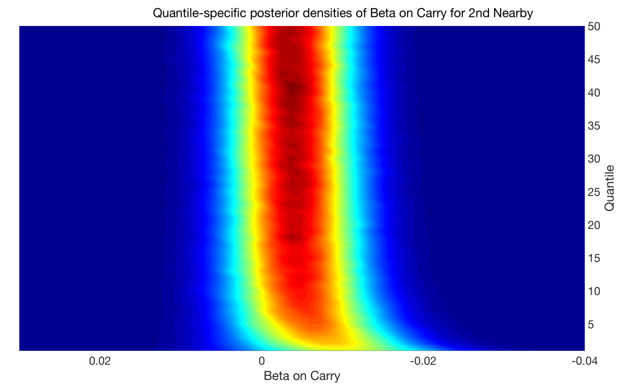
(d) Carry 1-12 Strategy based on CFTC 2nd Nearby

Figure 7. Quantile-Specific Betas on Carry

This figure shows the posterior distribution of the beta on the lagged carry for each quantile from the median (top of the y-axis) to the 1st quantile (bottom of the y-axis). The x-axis represents the magnitude of the coefficient. Posterior distributions are generated from the Gibbs sampler outlined in Section 3 and detailed in Appendix A. Data on exchange-traded, liquid commodity futures contracts are from Bloomberg. The sample period is weekly and is from 1992 to 2017.



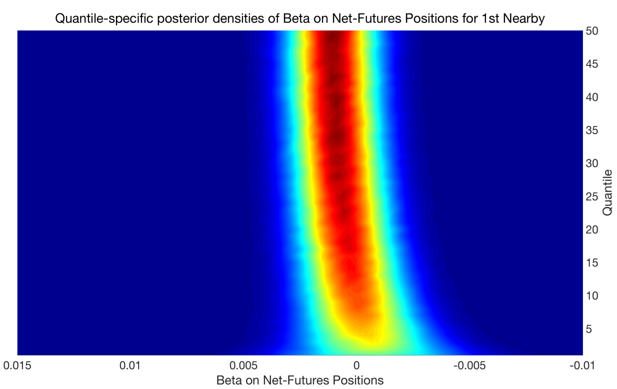
(a) 1st Nearby Contract



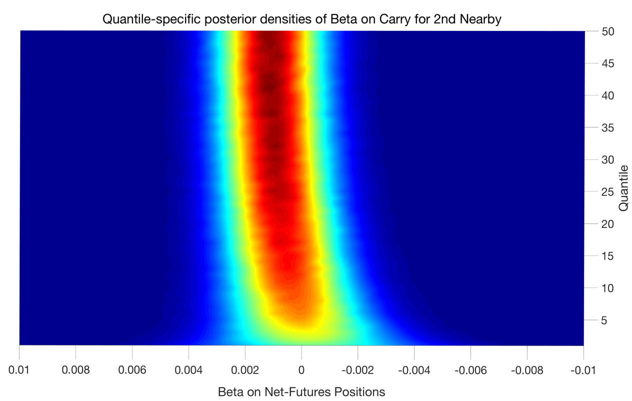
(b) 2nd Nearby Contracts

Figure 8. Quantile-Specific Betas on Net-Futures Positions

This figure shows the posterior distribution of the beta on the lagged net-long futures positions of non-commercial traders, as obtained from the CFTC weekly commitment of traders report, for each quantile from the median (top of the y-axis) to the 1st quantile (bottom of the y-axis). The x-axis represents the magnitude of the coefficient. Posterior distributions are generated from the Gibbs sampler outlined in Section 3 and detailed in Appendix A. Data on exchange-traded, liquid commodity futures contracts are from Bloomberg. The sample period is weekly and is from 1992 to 2017.



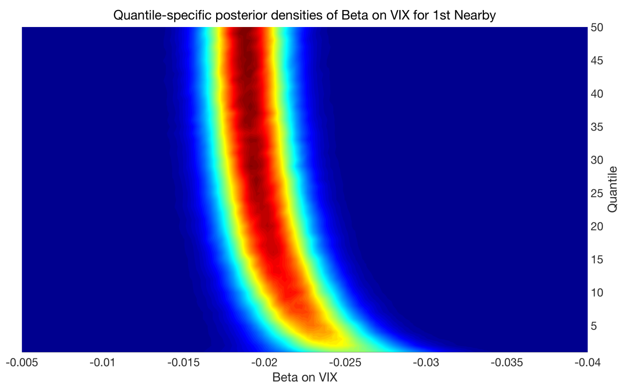
(a) 1st Nearby Contract



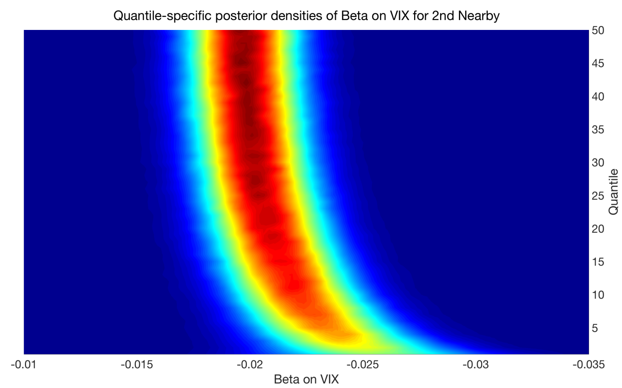
(b) 2nd Nearby Contract

Figure 9. Quantile-Specific Betas on VIX

This figure shows the posterior distribution of the beta on the lagged changes on the implied volatility on the S&P500 options, i.e., the VIX, for each quantile from the median (top of the y-axis) to the 1st quantile (bottom of the y-axis). The x-axis represents the magnitude of the coefficient. Posterior distributions are generated from the Gibbs sampler outlined in Section 3 and detailed in Appendix A. Data on exchange-traded, liquid commodity futures contracts are from Bloomberg. The sample period is weekly and is from 1992 to 2017.



(a) 1st Nearby Contract

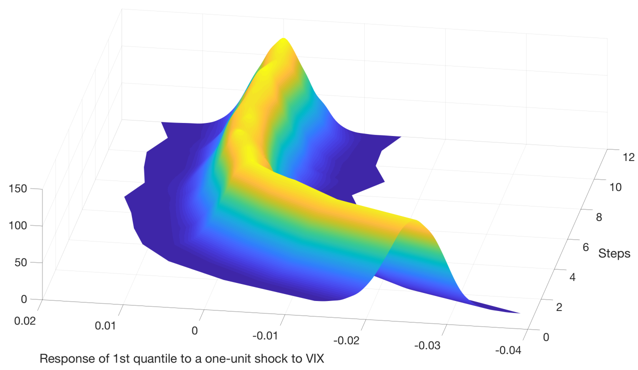


(b) 2nd Nearby Contract

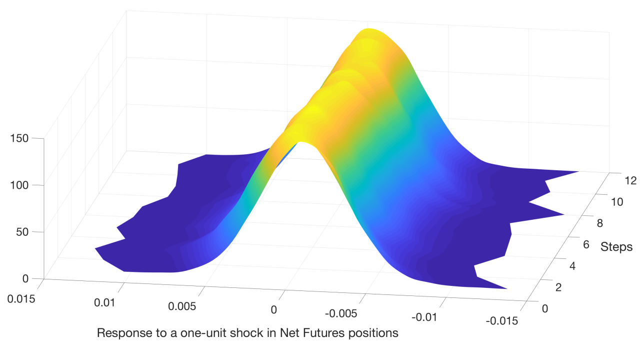
Figure 10. Longer Run Effects

This figure shows the response of the first quantile of the conditional distribution of futures returns up to 12 weeks ahead to a one-unit shock in carry (top-left panel), in the VIX (top-right panel), and in the net-long futures positions of non-commercial traders (bottom panel). Following Jordà (2005) the response to a generic shock can be directly computed from predictive regressions. Posterior distributions are generated from the Gibbs sampler outlined in Section 3 and detailed in Appendix A. Data on exchange-traded, liquid commodity futures contracts are from Bloomberg. The sample period is weekly and is from 1992 to 2017.

(a) Carry



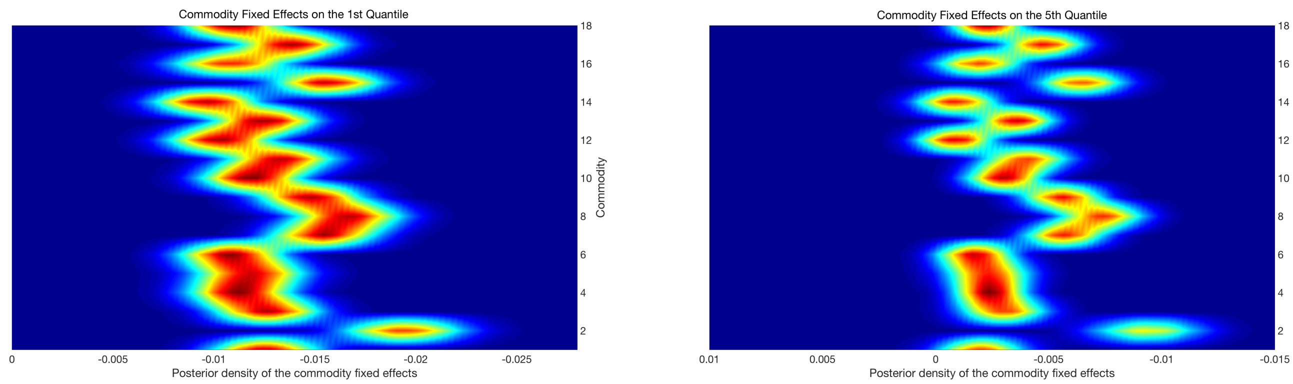
(b) VIX



(c) Net-Futures Positions

Figure 11. Commodity Fixed Effects

This figure shows the posterior distribution of the commodity fixed effects across futures contracts (y axis) for both the first quantile (left panel) and the fifth quantile (right panel). The x-axis represents the magnitude of the coefficient. Posterior distributions are generated from the Gibbs sampler outlined in Section 3 and detailed in Appendix A. The figures report the results for the first nearby futures contract. Data on exchange-traded, liquid commodity futures contracts are from Bloomberg. The sample period is weekly and is from 1992 to 2017.

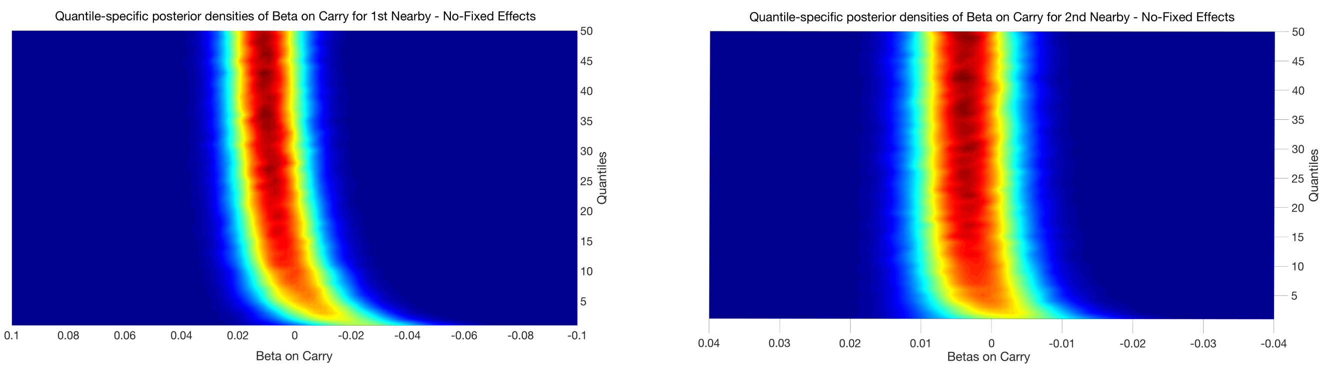


(a) Commodity Fixed Effects on the 1st Quantile

(b) Commodity Fixed Effects on the 5th Quantile

Figure 12. Betas on Carry: Pooled Quantile Regression without Fixed Effects

This figure shows the posterior distribution of the beta on the lagged carry for each quantile from the median (top of the y-axis) to the 1st quantile (bottom of the y-axis). The x-axis represents the magnitude of the coefficient. Posterior distributions are generated from the Gibbs sampler outlined in Section 3 and detailed in Appendix A. The model is a standard pooled quantile regression without additive commodity fixed effects. Data on exchange-traded, liquid commodity futures contracts are from Bloomberg. The sample period is weekly and is from 1992 to 2017.

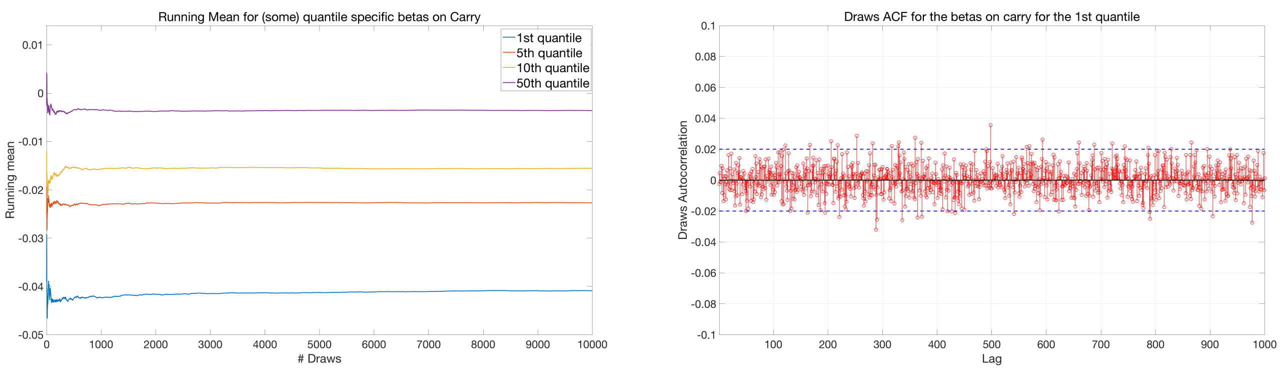


(a) 1st Nearby Contract

(b) 2nd Nearby Contract

Figure B.1. Convergence Diagnostics

This figure shows some convergence diagnostics for the Gibbs sampler outlined in Section 3 and detailed in Appendix A. Left panel shows the running mean for the quantile-specific beta on carry for the 1st, 5th, 10th, and 50th quantile. The running mean is computed by computing the mean for an enlarging window of the MCMC draws. The right panel shows the Autocorrelation Function (ACF) of the betas draws on carry for the 1st quantile. The sample period is weekly and is from 1992 to 2017.



(a) Running Mean

(b) Draws ACF