Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

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MANAGEMENT SCIENCE
Articles in Advance, pp. 1–23
ISSN 0025-1909 (print), ISSN 1526-5501 (online)
http://pubsonline.informs.org/journal/mnsc/

Understanding the Sources of Risk Underlying the Cross Section of Commodity Returns

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Received: January 7, 2016
Revised: January 22, 2017
Accepted: April 1, 2017
Published Online in Articles in Advance: October 31, 2017

https://doi.org/10.1287/mnsc.2017.2840

Abstract. We show that a model featuring an average commodity factor, a carry factor, and a momentum factor is capable of describing the cross-sectional variation of commodity returns. More parsimonious one- and two-factor models that feature only the average and/or carry factors are rejected. To provide an economic interpretation, we show that innovations in global equity volatility can price portfolios formed on carry, while innovations in a commodity-based measure of speculative activity can price portfolios formed on momentum. Finally, we characterize the relation between the factors and the investment opportunity set.

History: Accepted by Neng Wang, finance.
Supplemental Material: Data and the Internet appendix are available at https://doi.org/10.1287/mnsc.2017.2840.

Keywords: commodity asset pricing models • carry • momentum • innovations in equity volatility • speculative activity

1. Introduction

The interaction of storage and convenience yield, and the hedging motives of producers, consumers, and speculators, has led to the development of theories about the behavior of commodity futures prices and has spearheaded efforts to understand the economic drivers of commodity risk premia. Despite substantial headway, several key questions remain unresolved: Which asset pricing models are capable of reconciling the cross-sectional properties of commodity futures returns at both the portfolio and individual commodity levels? What is a possible explanation for the positive average returns of the commodity carry and momentum factors? How are the commodity pricing factors related to innovations in economic variables? How should one interpret the behavior of the commodity factors over the different stages of the business cycle? Our aim is to fill the aforementioned gaps in a market that has grown tremendously with the advent of financialization.

Using a set of baseline portfolios as well as managed portfolios, we first show that an average commodity factor, a carry factor, and a momentum factor can price the cross section of commodity returns. Our analysis highlights several results: (i) the Hansen and Jagannathan (1997) distance test does not reject correct model pricing, and (ii) the average pricing errors are not statistically different from zero when standard errors are computed using the Newey and West (1987) procedure, with and without the Shanken (1992) correction. We also examine the joint pricing ability of the three-factor model using time-series regressions and find that statistical tests do not reject model adequacy based on the implied alphas.

Additionally, we show that the three-factor model that incorporates the momentum factor appears better aligned with commodity futures returns compared with a one- or two-factor nested counterpart that contains the carry and/or the average factor, as studied in Yang (2013) and Szymanowska et al. (2014). Our specification tests further show that incorporating an additional commodity value factor (along the lines of Asness et al. 2013) or a commodity volatility factor (along the lines of Menkhoff et al. 2012) fails to improve the pricing ability across our set of test assets. Furthermore, our pricing results are robust to a randomization exercise.

Robustness of conclusions is reinforced through three exercises. First, the shrinkage-based estimator proposed by Bryzgalova (2014) reveals that the factor risk premia are close to those of the standard Fama–MacBeth and one-step generalized method of moments (GMM) estimation procedures, and the coefficients remain statistically significant. Second, we find that extending the three-factor model with the downside capital asset pricing model (CAPM) factor, as proposed by Lettau et al. (2014), does not affect the statistical significance of the commodity carry and momentum factors. Finally, we conduct our analysis on individual commodities, following Gagliardini et al. (2016), and show that the three-factor model is not rejected when the universe of 29 individual commodities is used as test assets, allaying possible concerns regarding the results obtained using portfolios as test assets.

What is a possible economic rationale for the positive average returns of the carry and momentum factors? Elaborating on this question, we first show that the commodity carry factor is linked to innovations in global equity return volatility. In periods in which global equity volatility increases (decreases), the carry factor delivers low (high) returns. Additionally, innovations in global equity volatility can price the commodity portfolios sorted on carry. At the same time, we show that innovations in global equity volatility cannot price commodity portfolios sorted on momentum. The economic intuition is that the high average returns to carry are compensation for the low payoff of the strategy when volatility increases.

Second, we consider an explanation of commodity momentum returns based on the trading behavior of market participants, and we show that innovations in a commodity-based measure of speculative activity are positively related to the momentum factor. Our analysis follows Basu and Miffre (2013) and Kang et al. (2014). In particular, the latter study provides evidence that speculators behave as momentum traders: they increase (decrease) their positions in commodities that are increasing (decreasing) in price. The key finding is that innovations in speculative activity are able to price commodity portfolios sorted on momentum but not the ones sorted on carry. We further examine speculative activity at the individual commodity level and show that high (low) momentum commodities are indeed associated with increased (decreased) positions of speculators. These findings appear to be important for two reasons. First, many traditional risk factors fail to explain commodity momentum. Second, our speculation measure is specific to the commodity space. We consider alternative measures of liquidity provision and proxies of available arbitrage capital constructed from equity and bond markets, and we find low—and statistically insignificant—correlations with our commodity-based measure of speculative activity.

Third, we establish that innovations in commodity volatility, log open interest, hedging pressure, scarcity, log of G7 industrial production, U.S. TED spreads, and G7 inflation cannot price portfolios sorted either on carry or momentum. These results reinforce the importance of global equity volatility (speculative activity) in pricing the carry (momentum) portfolios.

The commodity factors perform differently over the various stages of the business cycle. Specifically, we show that both carry and momentum perform well during recessions, whereas the average commodity factor and equities experience negative returns. Because the carry and momentum factors can hedge against equity market declines, standard theory suggests they should be associated with low average returns. On the other hand, our cross-sectional exercises indicate that the carry (momentum) strategy earns a positive risk premium because of its exposure to innovations in global equity volatility (speculative activity). The takeaway is that the high average returns of carry and momentum speak to the multifaceted nature of risk compensation in commodity markets.

Our efforts complement a growing literature that studies the behavior of commodity returns. Specifically, our research can be differentiated from Erb and Harvey (2006), Gorton and Rouwenhorst (2006), and Gorton et al. (2013) in that our focus is on commodity asset pricing models and their ability to price the cross section of commodity returns. Our study also departs from Hong and Yogo (2012), who provide a horse race among alternative predictors of commodity futures returns but do not investigate cross-sectional implications. We also differ from Asness et al. (2013) and Koijen et al. (2017), whose focal point is to construct an empirically viable global asset pricing model, and from Ready et al. (2017), who relate commodity returns to the returns of carry trade strategies in foreign exchange markets. Yang (2013) and Szymanowska et al. (2014) provide evidence on the cross section of commodity returns, but our emphasis is on identifying the economic drivers of carry and momentum risk premia. Furthermore, we evaluate the performance of the asset pricing models using individual commodities as test assets.

The focus on understanding the cross section of commodity returns distinguishes our work from the approaches in Deaton and Laroque (1992), Litzenberger and Rabinowitz (1995), Hirshleifer (1988), Routledge et al. (2000), Casassus and Collin-Dufresne (2005), and Kogan et al. (2009). The compatibility of the three-factor model with the documented commodity return patterns has implications for investment theory and practice.[1]

2. Data Description and Commodity Futures Returns

The commodity futures returns are constructed from end-of-day data provided by the Chicago Mercantile Exchange. For each commodity and maturity available, the database contains, at the daily frequency, a record of the open, low, high, and closing prices, along with information on open interest and trading volume. Our analysis centers on 29 commodity futures contracts covering four major categories—namely, agriculture, energy, livestock, and metal.

We take the start (end) date for our commodity futures sample to be January 1970 (September 2011). Starting the sample in January 1970 allows us to construct carry and momentum portfolios that contain at least three commodities. The number of commodities available ranges from a minimum of 15 in 1970 to a maximum of 28 in July 1994.

An important element to the calculation of monthly futures returns is the treatment of the first notice day, which varies across commodities (as can be seen from Table Internet-I of the Internet appendix). For each commodity, we take a position in the futures contract with the second shortest maturity at the end of month t while guaranteeing that its first notice day is *after* the end of month $t+1$. We follow this treatment because, if the first notice day occurs before a long (short) position is closed, the investor may face a physical delivery (delivery demand) from the counterparty.

Consider our return calculation in the context of crude oil futures between the end of February and March 2011. Let $F_t^{(0)}$ be the price of the front-month futures contract, and let $F_t^{(1)}$ be the price of the next maturity futures contract, both observed at the end of month t. Among the available contracts at the end of February 2011, we take a position in the May 2011 contract (i.e., $F_t^{(1)}$), as its first notice day falls in the middle of April. We do not invest in the April 2011 contract (i.e., $F_t^{(0)}$) because its first notice day falls in the middle of March 2011. The position in the May 2011 contract is closed at the end of March at price $F_{t+1}^{(1)}$. In the same vein, we switch to the June 2011 contract at the end of March 2011.

We calculate the returns of the long and short futures positions as

$$r_{t+1}^{\text{long}} = \frac{1}{F_t^{(1)}}(F_{t+1}^{(1)} - F_t^{(1)}) + r_t^f \quad \text{and} \qquad (1)$$
$$r_{t+1}^{\text{short}} = -\frac{1}{F_t^{(1)}}(F_{t+1}^{(1)} - F_t^{(1)}) + r_t^f,$$

where r_t^f reflects the interest earned on the fully collateralized futures position (e.g., Gorton et al. 2013, equation (14) or Koijen et al. 2017, equation (3)). Define

$$e_{t+1}^{\text{long}} \equiv r_{t+1}^{\text{long}} - r_t^f \quad \text{and} \quad e_{t+1}^{\text{short}} \equiv r_{t+1}^{\text{short}} - r_t^f \qquad (2)$$

as the excess return of a long and short futures position between the ends of months t and $t+1$, respectively.

Our procedure for constructing futures returns, which accounts for the first notice day, deviates from Shwayder and James (2011) but is broadly consistent with Gorton et al. (2013) and Hong and Yogo (2012). We note that $F_t^{(0)}$ never enters our return calculation because of the way that the first notice day calendar interacts with our returns, which are based on end-of-month observations.[2]

The summary statistics tabulated in Table Internet-II of the Internet appendix show that 20 out of 29 commodities have Sharpe ratios below 0.25, indicating that stand-alone investments in commodities are not attractive. Among other salient features, the commodity returns are serially uncorrelated (the absolute first-order autocorrelations are below 0.1 for 22 commodities) and typically positively skewed. Corn is the most liquid futures contract, as measured by its open interest, and propane is the least liquid.

Our data offer flexibility in two additional ways. First, the availability of daily futures returns allows us to construct monthly realized volatilities for each commodity. Second, futures prices at multiple maturities help to identify whether a commodity is in backwardation or contango.

Inspection of Table Internet-II indicates that (i) the fraction of the months in which a commodity is in contango is often greater than when it is in backwardation, and (ii) a predominant portion of the commodities exhibit contango on average. Overall, the magnitudes reported in Table Internet-II appear aligned with the corresponding ones in others—for example, Erb and Harvey (2006, table 4) and Gorton et al. (2013, table I).

3. Asset Pricing Approach and Methodology

To outline our approach and empirical tests, we denote the time $t+1$ excess return of a commodity portfolio i by e_{t+1}^i and collect the returns on all test assets in a vector $\mathbf{e}_{t+1}$. No-arbitrage implies the existence of a stochastic discount factor (SDF) m_{t+1} such that (Cochrane 2005, chap. 12):

$$E[m_{t+1}\mathbf{e}_{t+1}] = \mathbf{0}, \quad \text{with } m_{t+1} = 1 - \mathbf{b}'(\mathbf{f}_{t+1} - \boldsymbol{\mu}), \qquad (3)$$

where $\mathbf{f}_{t+1}$ is a vector of risk factors and $\boldsymbol{\mu}$ are the factor means.

In our setup, the parameter vector $\mathbf{b}$ is estimated in the system

$$E\begin{bmatrix} (1 - \mathbf{b}'(\mathbf{f}_{t+1} - \boldsymbol{\mu})) \otimes \mathbf{e}_{t+1} \\ \mathbf{f}_{t+1} - \boldsymbol{\mu} \\ \text{vec}((\mathbf{f}_{t+1} - \boldsymbol{\mu})(\mathbf{f}_{t+1} - \boldsymbol{\mu})') - \text{vec}(\Sigma_{\mathbf{f}}) \end{bmatrix} = \mathbf{0}, \qquad (4)$$

using the generalized method of moments of Hansen (1982), where $\Sigma_{\mathbf{f}}$ is the variance–covariance matrix of $\mathbf{f}_{t+1}$. Our formulation follows that of Burnside et al. (2011) and Menkhoff et al. (2012, equation (A4)) in that our estimates incorporate the uncertainty associated with estimating the means and covariances of $\mathbf{f}_{t+1}$.

The specification of the SDF in Equation (3) implies a beta representation, in which the expected excess returns of each asset depend on the vector of factor risk premia $\boldsymbol{\lambda}$, which is common to all assets, and the vector of risk loadings $\boldsymbol{\beta}_i$, which is asset specific. More formally,

$$E[e^i] = \boldsymbol{\lambda}'\boldsymbol{\beta}_i, \quad \text{where } \boldsymbol{\lambda} = \Sigma_{\mathbf{f}}\mathbf{b}. \qquad (5)$$

As in Cochrane (1996), we first focus on a one-step GMM that uses the identity matrix as a weighting matrix; we then also report results for a two-step GMM that uses the optimal weighting matrix. The standard errors are based on the Newey and West (1987) procedure with lags selected automatically according to Newey and West (1994).

Additionally, we provide estimates of λ using the cross-sectional regression methodology of Fama and MacBeth (1973). In the first step, we run a time- series regression of returns on the factors. In the second step, we run a cross-sectional regression of average returns on the betas without including a constant. The standard errors of λ are computed using the Newey and West (1987) procedure with automatic lag selection with and without the correction of Shanken (1992).

4. Motivating a Model with Average, Carry, and Momentum Factors

In this section, we consider an asset pricing model for commodities that incorporates an average factor, a carry factor, and a momentum factor. Our analysis centers on the following specification of the SDF:

$$\begin{aligned} m_{t+1} = 1 &- b_{\mathrm{AVG}}(AVG_{t+1} - \mu_{\mathrm{AVG}}) \\ &- b_{\mathrm{CARRY}}(CARRY_{t+1} - \mu_{\mathrm{CARRY}}) \\ &- b_{\mathrm{CMOM}}(CMOM_{t+1} - \mu_{\mathrm{CMOM}}), \end{aligned} \tag{6}$$

implying that the expected excess returns are a function of exposure to three factors.

The average factor, denoted by AVG_{t+1}, is the excess return of a long position in all available commodity futures (see Equation (2)). Note that AVG_{t+1} is required because models that do not incorporate this average factor fail to explain the time-series variation in commodity returns (see Section 5.2).

The commodity carry factor, denoted by $CARRY_{t+1}$, and the momentum factor, denoted by $CMOM_{t+1}$, deserve further comments since these factors can be constructed in a variety of ways and depend on the implementation of the underlying carry and momentum strategies. As detailed in Internet appendix (Sections A and B) and the caption of Table 1, we construct $CARRY_{t+1}$ as the return on a portfolio that is long in the five commodities that are most backwardated (i.e., the lowest $\ln(y_t) < 0$) and short the ones that are most in contango (i.e., the highest $\ln(y_t) > 0$), where $y_t \equiv F_t^{(1)}/F_t^{(0)}$ is the slope of the futures curve.

As noted in panel A of Table 1, over the past 42 years the carry factor (strategy C5) has been economically profitable, with an average annualized return of 16.34%—several times larger than the returns generated by investing in commodity indexes, as seen in Table 2. The average return of the carry factor is statistically different from zero as indicated by the bootstrap confidence intervals. The 95% confidence intervals, denoted as "PW, lower CI" and "PW, upper CI," are based on a stationary bootstrap with 10,000 iterations, where the block size is based on the algorithm of Politis and White (2004).

In our analysis, $CMOM_{t+1}$ is constructed as the return on a portfolio that is long in the five commodities with the highest returns over the previous six months and short in the ones with the lowest returns over the previous six months. The average return of the momentum factor is 16.11% (see strategy M5 in panel C of Table 1), and it is statistically significant.

Several considerations motivate an SDF driven by three factors. First, we conduct a principal component analysis with our test assets, which reveals that AVG_{t+1} is highly correlated (98.8%) to the first principal component, $CMOM_{t+1}$ is highly correlated with the second and third principal components (63.1% and 44.6%, respectively), and $CARRY_{t+1}$ loads only, but substantially, on the third principal component (71.7%). Importantly, the first three components explain 71% of the variation in the 12 baseline portfolios, which is nontrivial, given that there are 12 potential principal components.

Second, the top panel of Figure 1 plots the cumulative payoff of the carry, momentum, and average factors, and it shows that the first two are considerably more profitable than the average factor. While the top panel may give the visual impression that the carry and momentum factors display similar returns, the two strategies are distinct, as shown by the middle panel of Figure 1, which plots $e_t^{cm} \equiv CARRY_t - CMOM_t$. The standard deviation of e_t^{cm} is 8.5%, the minimum is −40.1%, and the maximum is 39.4%. The factors also perform differently over different economic conditions. For example, in March 1980, the momentum (carry) factor delivered a return of −28.2% (11.2%). The poor performance of momentum over this month was caused by the sharp decline in silver prices, but such a decline had no impact on the returns to carry. Finally, $CARRY_t$ and $CMOM_t$ *do not share* the same sign in 41% of the months.

That the two return strategies are distinct can be further seen by computing their conditional correlations. We estimate the time-varying correlation between the returns generated by the carry and momentum factors using a dynamic conditional correlation model (Engle 2002), in which the dynamics of carry and momentum returns are modeled using a bivariate generalized autoregressive conditional heteroscedasticity (GARCH) (1, 1) model. The results, reported in the bottom panel of Figure 1, indicate that the correlation between the two strategies has not increased or decreased over time. Furthermore, their unconditional correlation is 0.27. In Section 6, we also show that the carry and momentum factors load differently on economic variables.

5. The Key Results on Pricing the Cross Section of Commodity Returns

In this section, we study the ability of the three-factor model to explain the cross-section of commodity returns. We also compare, statistically and

Table 1. Excess Returns of Commodity Carry and Momentum Strategies

	Panel A: Carry strategies					Panel B: Backwardation/contango portfolios				
	Commodities long backwardation and short contango					Commodities sorted based on				
						$\ln(y_t) < 0$		$\ln(y_t) > 0$		
	C1	C2	C3	C4	C5	P1	P2	P3	P4	P1 – P4
Mean	9.31	10.08	12.14	14.27	16.34	16.32	13.50	4.63	−0.53	16.85
PW, lower CI	−2.04	0.60	2.04	6.48	9.36	8.28	7.44	−0.96	−6.00	9.48
PW, upper CI	22.32	21.24	22.56	21.84	23.40	26.16	19.56	10.20	5.40	26.16
SD	48.21	34.87	27.46	24.16	22.26	23.23	19.48	17.02	16.94	23.08
SR	0.19	0.29	0.44	0.59	0.73	0.70	0.69	0.27	−0.03	0.73
Skewness	−0.29	0.02	−0.05	−0.03	0.30	0.47	0.25	0.18	0.82	0.45
$1_{e>0}$	53.13	53.54	53.94	55.76	56.77	55.56	58.59	51.92	48.69	57.17

	Panel C: Momentum strategies					Panel D: Momentum portfolios					
	Commodities long winners and short losers					Commodities sorted based on past six-month performance					
	M1	M2	M3	M4	M5	Q1	Q2	Q3	Q4	Q5	Q5 – Q1
Mean	10.75	17.04	13.88	14.70	16.11	−1.66	1.31	10.07	9.16	14.35	16.00
PW, lower CI	−4.32	5.64	6.00	6.96	9.36	−7.56	−4.08	3.72	3.84	6.60	7.92
PW, upper CI	29.40	30.36	22.92	22.92	22.92	4.44	7.20	17.04	14.76	24.00	24.24
SD	59.75	42.51	34.33	29.19	26.28	20.84	16.76	18.40	18.22	25.58	27.61
SR	0.18	0.40	0.40	0.50	0.61	−0.08	0.08	0.55	0.50	0.56	0.58
Skewness	0.14	0.09	0.11	0.06	0.34	0.53	0.43	1.53	0.45	0.44	0.34
$1_{e>0}$	52.53	54.14	53.54	55.56	57.37	46.67	50.51	55.56	54.55	57.78	55.56

Notes. This table presents the descriptive statistics of the excess returns generated by commodity carry and momentum strategies. Let $y_t \equiv F_t^{(1)}/F_t^{(0)}$, where $F_t^{(0)}$ is the price of the front-month futures contract and $F_t^{(1)}$ is the price of the next maturity futures contract, both observed at the end of month t. A commodity is in backwardation if $\ln(y_t) < 0$ and in contango if $\ln(y_t) > 0$. The carry strategy entails taking a long (short) futures position in a commodity that is in backwardation (contango) at the end of month t, and we compute the returns over the subsequent month. For example, carry strategy C5 (C2) contains an equally weighted portfolio consisting of five (two) commodities with the most negative $\ln(y_t)$ and five (two) commodities with the most positive $\ln(y_t)$. In addition, each month t, we divide the commodity universe into two backwardation portfolios (P1 and P2) and two contango portfolios (P3 and P4) based on their respective rankings of $\ln(y_t)$, and then we compute the next-month returns. For the momentum strategies, the commodities are ranked on the basis of their past six-month performance. Analogously, the momentum strategy M5 (M2) contains an equally weighted portfolio consisting of five (two) commodities with the highest past returns (winners) and five (two) commodities with the lowest past returns (losers). Ranking the commodities by the past six-month performance, the commodities are collected in quintile portfolios Q1 (lowest) through Q5 (highest). For each portfolio, we report the average annualized monthly return and its 95% confidence interval based on a stationary bootstrap (denoted by "PW, lower CI" and "PW, upper CI") with 10,000 bootstrap iterations, in which the block size is based on the algorithm of Politis and White (2004), the annualized monthly standard deviation (SD), the annualized Sharpe ratio (SR), and the monthly skewness. The percentage of months in which the excess return of a strategy is positive is recorded as $1_{e>0}$. There are 501 monthly observations in our sample from January 1970 to September 2011.

economically, the performance of the three-factor model with nested one-factor and two-factor counterparts as well as alternative specifications that include a commodity value, a commodity volatility factor (constructed in various ways), and a downside risk CAPM factor.

We report results for (i) 12 baseline portfolios, (ii) managed portfolios constructed using conditioning information (Cochrane 2005, chap. 8.1), and (iii) individual commodity returns (based on the procedure of Gagliardini et al. 2016). As a robustness check, we present results from the shrinkage-based estimator of Bryzgalova (2014) and the randomization exercise of Lustig et al. (2011).

5.1. AVG_t, $CARRY_t$, and $CMOM_t$ Summarize the Cross Section of Commodity Returns

Can the three-factor model explain the cross section of commodity returns? Are carry and momentum priced risk factors? Could these factors rationalize the documented average returns across our test assets?

5.1.1. The Results from the Baseline Portfolios Are Supportive of the Model. To answer these questions, we first consider the baseline case of 12 portfolios as test assets constructed from 29 individual commodities: (i) four carry portfolios; (ii) five momentum portfolios; and (iii) three category portfolios—that is, agriculture, livestock, and metal. We exclude the energy sector as a category portfolio because of its

Table 2. Excess Returns of the Commodity Factors, the Commodity Indexes, and the Four Commodity Categories

	Mean	PW bootstrap CI Lower	PW bootstrap CI Upper	SD	SR	Skewness	ρ_1	$1_{e>0}$
			Panel A: Commodity factors					
AVG	6.27	1.32	12.60	14.32	0.44	0.22	0.05	57.37
CARRY	16.34	9.36	23.40	22.26	0.73	0.30	0.09	56.77
CMOM	16.11	9.36	22.92	26.28	0.61	0.34	−0.01	57.37
			Panel B: Commodity indexes					
GSCI	5.43	−0.84	11.52	20.04	0.27	0.06	0.16	54.75
CRB	3.53	−0.36	8.04	13.56	0.26	−0.06	0.08	52.53
			Panel C: Commodity categories					
Agriculture	3.79	−2.88	11.28	16.78	0.23	0.79	0.00	50.71
Livestock	4.29	0.12	14.64	19.65	0.22	0.13	−0.01	52.73
Metal	6.98	−0.84	8.76	22.96	0.30	0.39	0.11	52.53
Energy	14.20	3.84	24.48	35.18	0.40	1.70	0.08	53.59
			Panel D: Additional commodity factors					
VALUE	6.15	−2.16	14.28	28.17	0.22	−0.19	−0.01	52.61
$\Delta VOL^{\text{commodity}}$	0.02	−0.12	0.12	0.68	—	0.24	−0.25	—

Notes. Panel A first reports the descriptive statistics for each of the factors. The average factor, denoted by *AVG*, is the excess return of a long position in all available commodity futures. The carry factor, denoted by *CARRY*, is the return on strategy C5, while the momentum factor, denoted by *CMOM*, is the return on strategy M5. Panel B corresponds to the excess returns of the Goldman Sachs Commodity Index (*GSCI*, source: ticker GSCIEXR in Datastream) and the Commodity Research Bureau index (*CRB*), while panel C corresponds to the equally weighted commodity returns across four categories. Panel D reports the summary statistics for two additional factors (details of the construction are in the Internet appendix (Section C)). Our procedure for constructing the value factor, denoted by *VALUE*, is similar to that of Asness et al. (2013), in that in each month, we rank all the commodities by the ratio of the second-nearest maturity futures price five years ago to its current price. We divide the commodities into five groups and compute the next-month portfolio returns. The value factor is the return difference between the top and bottom quintiles. The factor $\Delta VOL^{\text{commodity}}$ corresponds to the innovation in commodity volatility and is computed following Menkhoff et al. (2012, equation (4)). For AVG_t, $CARRY_t$, and $CMOM_t$, we investigate seasonality of the form: $f_t = v_0 + \sum_{j=2}^{12} v_j 1_{j,t} + \epsilon_t$, where the 1_j's are dummy variables for the months of February through December. We do not find evidence of seasonality in the factors.

shorter time series. Therefore, we estimate 12 parameters using 21 moment conditions.

We report in panel A of Table 3 the GMM estimates of the factor risk premia $\boldsymbol{\lambda}$, the loadings on the SDF $\mathbf{b}$, and the Hansen and Jagannathan (1997) distance measure. The Newey and West (Shanken) p-values are reported in parentheses (curly brackets).

The estimated risk premia of both carry and momentum are positive, implying that portfolios that covary more with $CARRY_{t+1}$ and $CMOM_{t+1}$ earn extra compensation. In particular, the estimate of 0.018 (0.012) for λ_{CARRY} (λ_{CMOM}) amounts to an annualized risk premium of 21.6% (14.4%) for $CARRY_{t+1}$ ($CMOM_{t+1}$). The p-values attest to the statistical significance of both factors in pricing the test portfolios.

The average factor helps to describe the cross section of commodity returns, and such a finding contrasts the corresponding one from the equity market (Fama and French 1992) and the currency market (Lustig et al. 2011, table 4, and Menkhoff et al. 2012, table 2). However, the estimated annualized risk premium for the average factor is about 6%, which is below the risk premia for the other two commodity risk factors.

Displayed in the column "HJ-Dist." is the Hansen and Jagannathan (1997) distance measure, which quantifies the normalized maximum pricing errors. For the three-factor model, the distance measure is 0.006 with a p-value of 0.22. Consequently, we do not reject correct pricing.

The estimates of $\boldsymbol{\lambda}$ obtained using the Fama–MacBeth procedure are identical, by construction, to those obtained using the one-step GMM. The p-values based on Newey–West and Shanken are in agreement and establish the statistical significance of the three risk premia, even after accounting for the fact that the $\boldsymbol{\beta}_i$'s are estimated. Overall, our evidence supports the presence of priced risk factors.[3]

With a generalized least squares (GLS) cross-sectional uncentered R^2 of 96.3% (Lewellen et al. 2010, prescription 3) and an ordinary least squares (OLS) uncentered R^2 of 93.9%, the three factors capture a large fraction of the cross-sectional variation of the commodity portfolios. Furthermore, the χ^2 tests for the null hypothesis that the pricing errors are zero have p-values equal to 0.22 and 0.25 for Newey and West (1987) and Shanken (1992), respectively, indicating that the asset pricing model cannot be rejected. The model pricing errors, displayed in panel A of Figure 2, as measured by the deviation from the 45° line, reveal that the unexplained returns are small.

How can one quantify the contribution of each factor in explaining the returns cross section? The issue of a possibly redundant factor is addressed from two different perspectives. First, panels B and C of Table 3 report results for restricted versions of the baseline model that exclude, alternatively, the momentum or the carry factor. In this regard, the χ^2_{SH} tests of the pricing errors show that both restricted models are rejected, with p-values equal to 0.01 for the model that excludes $CMOM_{t+1}$ and 0.00 for the model that excludes $CARRY_{t+1}$. In particular, omitting the carry (momentum) factor worsens the performance, as the GLS R^2 drops to 67.7% (82.9%), and the p-value for the HJ-Dist. drops to 0.00 (0.15). In sum, the three-factor generalization provides a better characterization of commodity returns compared with its nested counterparts.

Building on our analysis, we also perform a two-step GMM estimation based on an optimal weighting matrix (e.g., Cochrane 1996, table 1, and Lustig et al. 2011, row "GMM$_2$" in table 4). We first test three exclusion restrictions on the SDF in Equation (6): (i) $b_{\mathrm{CARRY}} \equiv 0$, (ii) $b_{\mathrm{CMOM}} \equiv 0$, and (iii) $b_{\mathrm{CARRY}} = b_{\mathrm{CMOM}} \equiv 0$, and we report the results below.

$b_{\mathrm{CARRY}} \equiv 0$	$b_{\mathrm{CMOM}} \equiv 0$	$b_{\mathrm{CARRY}} = b_{\mathrm{CMOM}} \equiv 0$
$\chi^2(1) = 14.18$, p-val. $= 0.00$	$\chi^2(1) = 5.30$, p-val. $= 0.02$	$\chi^2(2) = 30.13$, p-val. $= 0.00$.

Figure 1. (Color online) Properties of the Commodity Factors

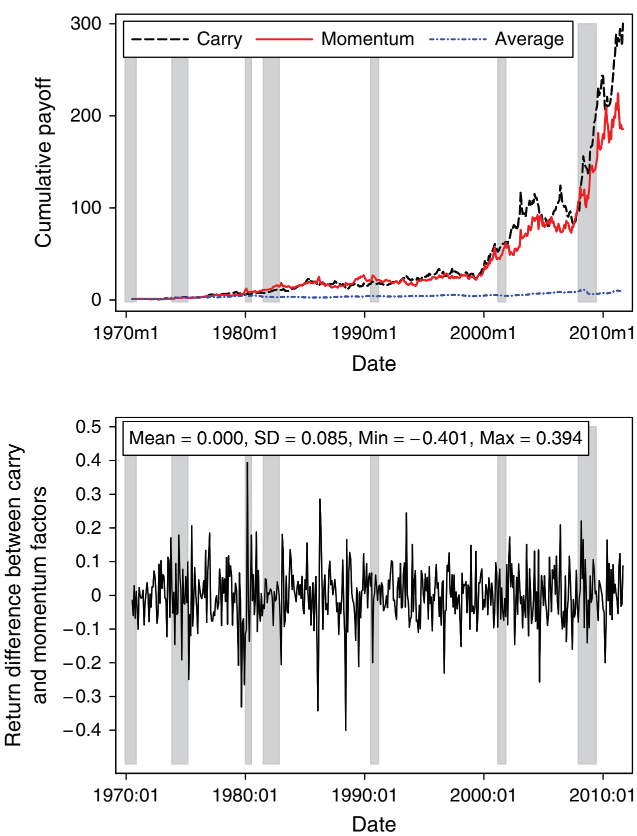
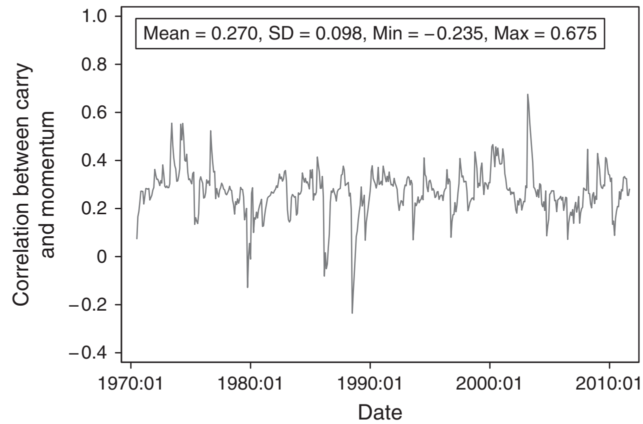


Figure 1. (Continued)



Notes. Plotted in the top panel is the cumulative payoff of the carry, momentum, and average factors, respectively. The middle panel plots the time series of $e_t^{cm} \equiv CARRY_t - CMOM_t$ for $t = 1, \ldots, T$ and reports the mean, standard deviation, minimum, and maximum of the e_t^{cm} series. The shaded areas indicate National Bureau of Economic Research recessions. Plotted in the bottom panel is the correlation between the carry and momentum factors based on the dynamic conditional correlation model of Engle (2002). The estimated correlation relies on a bivariate GARCH (1, 1) model for carry and momentum factors. We report the mean, standard deviation, minimum, and maximum of the correlation series. Let $y_t \equiv F_t^{(1)}/F_t^{(0)}$, whereby, at the end of month t, a commodity is in backwardation if $\ln(y_t) < 0$ and in contango if $\ln(y_t) > 0$. The carry strategy entails taking a long position in the five commodities with the lowest $\ln(y_t)$ and a short position in the five commodities with the highest $\ln(y_t)$. The momentum strategy entails taking a long position in the five commodities with the highest returns over the previous six months and a short position in the five commodities with the lowest returns over the previous six months. The average factor is an equally weighted portfolio of all the commodities available at each point in time. Our sample period is July 1970 to September 2011.

All the restrictions are rejected, illustrating that both the carry and the momentum factors have loadings on the SDF that are statistically different from zero and, hence, provide additional pricing flexibility. Second, we perform the Hansen (1982) J-test of overidentifying restrictions, which is $\chi^2(9)$-distributed, and find that it has a p-value of 0.167, reinforcing the conclusion that the three-factor model cannot be rejected.[4]

Lewellen et al. (2010) note that when portfolios exhibit a relatively strong factor structure, variables that are correlated with the true—but unobserved—risk factors might get identified as significant determinants of the cross section of commodity returns. To address the issue of potentially spurious factors, we implement the shrinkage-based estimator proposed by Bryzgalova (2014).[5] The results, reported in the last rows of panels A–C of Table 3, show that the factors have virtually identical coefficients to their nonpenalized counterparts—they differ only at the fourth decimal place—and maintain their statistical significance. This evidence indicates that the factors are not spurious.

Table 3. Cross-Sectional Asset Pricing Results with the Average, Carry, and Momentum Factors

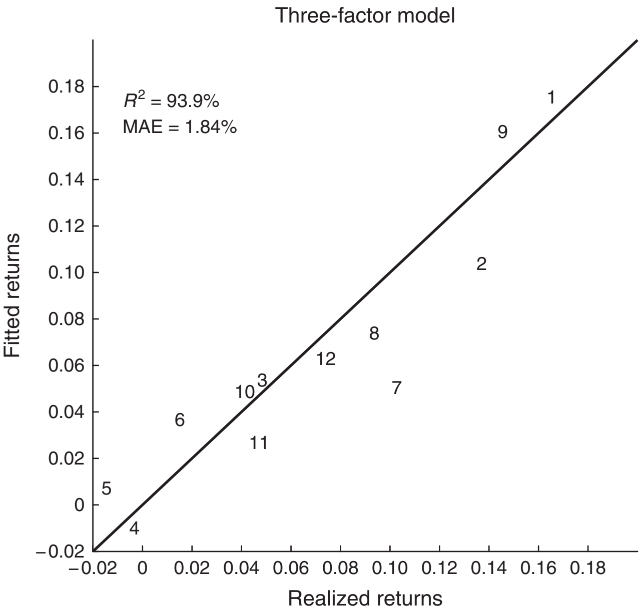
	Factor risk premia			Loadings on the SDF				Pricing errors		
	λ_{AVG}	λ_{CARRY}	λ_{CMOM}	b_{AVG}	b_{CARRY}	b_{CMOM}	R^2_{GLS} $\lfloor R^2 \rfloor$	χ^2_{NW} (p-value)	χ^2_{SH} {p-value}	HJ-Dist. (p-value)
				Panel A: Three-factor model						
GMM	0.005	0.018	0.012	2.276	3.954	1.067				0.006
	(0.01)	(0.00)	(0.00)	(0.07)	(0.00)	(0.11)				(0.22)
Fama–MacBeth	0.005	0.018	0.012				96.3	11.91	11.40	
	(0.02)	(0.00)	(0.00)				⌊93.9⌋	(0.22)	{0.25}	
	{0.02}	{0.00}	{0.00}							
Penalized Fama–MacBeth	0.005	0.018	0.012							
	(0.01)	(0.00)	(0.00)							
				Panel B: Restricted model omitting a role for $CMOM_{t+1}$						
GMM	0.005	0.020		2.394	4.661					0.008
	(0.01)	(0.00)		(0.05)	(0.00)					(0.15)
Fama–MacBeth	0.005	0.020					82.9	23.87	22.70	
	(0.02)	(0.00)					⌊91.3⌋	(0.01)	{0.01}	
	{0.02}	{0.00}								
Penalized Fama–MacBeth	0.005	0.020								
	(0.01)	(0.00)								
				Panel C: Restricted model omitting a role for $CARRY_{t+1}$						
GMM	0.006		0.014	2.891		2.300				0.012
	(0.01)		(0.00)	(0.02)		(0.00)				(0.00)
Fama–MacBeth	0.006		0.014				67.7	29.67	28.65	
	(0.02)		(0.00)				⌊77.3⌋	(0.00)	{0.00}	
	{0.02}		{0.00}							
Penalized Fama–MacBeth	0.006		0.014							
	(0.01)		(0.00)							

Notes. Reported are the factor risk premia ($\boldsymbol{\lambda}$) and the SDF parameters (**b**). The SDF specification in panel A is of the form: $m_{t+1} = 1 - b_{\text{AVG}}(AVG_{t+1} - \mu_{\text{AVG}}) - b_{\text{CARRY}}(CARRY_{t+1} - \mu_{\text{CARRY}}) - b_{\text{CMOM}}(CMOM_{t+1} - \mu_{\text{CMOM}})$, where AVG_{t+1} is the average factor (excess return obtained by holding all commodities available), $CARRY_{t+1}$ is the carry factor (which corresponds to the returns of strategy C5), and $CMOM_{t+1}$ is the momentum factor (which corresponds to the returns of strategy M5). Reported in panels B and C are results for the restricted versions of the SDF that impose $b_{\text{CMOM}} \equiv 0$ and $b_{\text{CARRY}} \equiv 0$, respectively. In the row marked "GMM," the parameters are estimated based on the system (4) following a one-step GMM procedure, while those in the row "Fama–MacBeth" are based on a two-step cross-sectional regression. Finally, those in the row "Penalized Fama–MacBeth" are based on the shrinkage estimator proposed by Bryzgalova (2014). For the GMM procedure, the p-values rely on the Newey and West (1987) procedure, with lags selected automatically according to Newey and West (1994), and are reported in parentheses. For the Fama and MacBeth procedure, the p-values are computed using the Newey and West (1987) procedure without (with) the Shanken (1992) correction in parentheses (curly brackets). For the Penalized Fama–MacBeth procedure, the p-values are computed using the bootstrap—following Bryzgalova (2014)—and are reported in parentheses. We report the GLS cross-sectional uncentered R^2 (Lewellen et al. 2010, prescription 3) and the OLS uncentered R^2 as $\lfloor \cdot \rfloor$, and we report the χ^2-test corresponding to the null hypothesis that the pricing errors are zero, with p-values computed both based on the Newey–West and Shanken standard errors. The Hansen and Jagannathan (1997, equation (29)) distance measure (HJ-Dist.), with the associated p-value, is shown, which tests whether the distance measure is equal to zero.

Lettau et al. (2014) show that extending the CAPM with a downside risk factor improves the pricing of currencies, commodities, equities, equity index options, and sovereign bonds. We therefore extend our model by including a downside factor and obtain the following estimates for $(\lambda_{\text{AVG}}, \lambda_{\text{CARRY}}, \lambda_{\text{CMOM}}, \lambda_{\text{DR}}) = (0.003, 0.014, 0.009, 0.008)$ with p-values equal to $(0.29, 0.01, 0.09, 0.27)$, where the risk premium for the downside risk factor is denoted by λ_{DR}.[6] The risk premia estimates are affected by the introduction of the downside risk factor—they become smaller—but both carry and momentum stay significant at the 10% level. Finally, the average factor and the downside risk factor are statistically insignificant.

Finally, are our conclusions robust when commodities are double-sorted first by momentum and then by carry, as described in Section B of the Internet appendix? We conduct cross-sectional tests on four double-sorted portfolios. The main finding is that the χ^2_{NW} test for the model that excludes the carry (momentum) factor is rejected with a p-value of 0.07 (0.00). On the other hand, the model that includes both is not rejected. For instance, the χ^2_{NW} has a p-value of 0.38, affirming that the pricing errors are statistically indistinguishable from zero. Furthermore, the magnitudes of the factor risk premia are consistent with those in Table 3. The three-factor model offers considerable flexibility in pricing the various test assets.

Figure 2. Realized vs. Fitted Returns Across the Commodity Portfolios



Notes. Plotted are the realized returns (x axis) and the fitted returns (y axis) corresponding to the commodity portfolios indexed from 1 to 12 (see Table 6). The fitted average returns are based on Equation (5). We also display the uncentered R^2 values and the mean absolute errors (denoted by MAE) as goodness-of-fit yardsticks. The MAE is computed as $(1/12)\sum_{i=1}^{12}|Fitted_i - Realized_i|$, in monthly percentage units.

5.1.2. The Evidence from Managed Portfolios Remains Supportive of the Model. Following Cochrane (2005, chap. 8.1), this section generates additional test assets by interacting the baseline portfolios with one conditioning variable z_t at a time. Specifically, we define the augmented return vector $\mathbf{e}^*_{t+1} \equiv \mathbf{e}_{t+1} \otimes [1\ \ z_t]$ and estimate the parameter vector $\mathbf{b}$ using $E[m_{t+1}\,\mathbf{e}^*_{t+1}] = \mathbf{0}$.

For each conditioning variable z_t, Table 4 presents the results from the Hansen and Jagannathan (1997) distance test as an overall measure of fit as well as exclusion tests that analyze whether the performance of the model is robust to the inclusion of the additional set of managed portfolios. Each set of results is based on 24 portfolios.

We focus on five conditioning variables (defined in Section C of the Internet appendix): (i) open interest growth, (ii) change in commodity volatility $\Delta VOL_t^{\text{commodity}}$, (iii) the average slope of the futures curve for the commodities in backwardation (i.e., $\ln(y_t) < 0$), (iv) the currency returns (U.S. dollar index, FX | USD), and (v) industrial production growth (G7 countries). Our choices of z_t are meant to reflect developments in commodity markets and to capture the state of the economy. For example, the aggregate open interest is a slight variation of the one used in Hong and Yogo (2012), while the relation between the commodity risk premia, currency returns, the slope of the futures curve, and macroeconomic variables has been studied by, among others, Bailey and Chan (1993, table 1), and Chen et al. (2010, table IV).

In four out of five cases, we are unable to reject the null that the HJ-Dist. measure is equal to zero (panel A), as the p-values are greater than 0.05. The same holds for the J-test results (panel B). This implies that when additional test assets are included in the analysis, the performance of our model does not deteriorate substantially. The joint tests of significance for

Table 4. Unconditional Tests Using Conditioning Variables to Construct Additional Managed Portfolios

	Panel A		Panel B	Panel C: Exclusion restrictions					
	HJ-Dist. test		J-test	$b_{\text{CARRY}} = 0$, $b_{\text{CMOM}} = 0$		$b_{\text{CARRY}} = 0$		$b_{\text{CMOM}} = 0$	
Conditioning information, z_t	Dist.	p-value	p-value	$\chi^2(2)$	NW[p]	$\chi^2(1)$	NW[p]	$\chi^2(1)$	NW[p]
Open interest growth	0.007	0.30	0.23	28.19	0.00	10.01	0.00	6.60	0.01
$\Delta VOL^{\text{commodity}}$	0.008	0.09	0.04	37.47	0.00	21.77	0.00	1.65	0.20
$\ln(y_t)1_{\ln(y_t)<0}$	0.007	0.17	0.15	32.87	0.00	12.67	0.00	5.10	0.02
Currency returns (FX | USD)	0.007	0.32	0.51	39.53	0.00	21.40	0.00	8.23	0.00
Industrial production growth	0.010	0.01	0.09	38.01	0.00	13.45	0.00	5.21	0.02

Notes. Here, we expand the exercise reported in Table 3 by including additional test assets constructed using conditioning variables (see Cochrane 2005, chap. 8.1). The SDF specification is of the form $m_{t+1} = 1 - b_{\text{AVG}}(AVG_{t+1} - \mu_{\text{AVG}}) - b_{\text{CARRY}}(CARRY_{t+1} - \mu_{\text{CARRY}}) - b_{\text{CMOM}}(CMOM_{t+1} - \mu_{\text{CMOM}})$, where AVG_{t+1} is the average factor (excess return obtained by holding all commodities available), $CARRY_{t+1}$ is the carry factor (which corresponds to the returns of strategy C5), and $CMOM_{t+1}$ is the momentum factor (which corresponds to the returns of strategy M5). Let the vector $\mathbf{e}_{t+1}$ contain the 12 test assets in Table 3—namely, the 4 carry portfolios, the 5 momentum portfolios, and the 3 sector portfolios. The new set of test assets is defined as $\mathbf{e}_{t+1} \otimes [1\ z_t]$, generating a total of 24 portfolios. We first report, in panel A, the Hansen and Jagannathan (1997, equation (29)) distance measure (HJ-Dist.), and the associated p-value, which assesses whether the distance measure is equal to zero. In panel B, we report the p-values from the Hansen (1982) test of overidentifying restrictions (J-test), testing for overall model adequacy. Finally, in panel C, we test the null hypothesis $b_{\text{CARRY}} = b_{\text{CMOM}} \equiv 0$ against the alternative that at least one is different from zero as well as test the individual parameter restrictions $b_{\text{CARRY}} \equiv 0$ and $b_{\text{CMOM}} \equiv 0$. The p-values rely on the Newey and West (1987) procedure with lags selected automatically according to Newey and West (1994). Each conditioning variable is defined in the Internet appendix (Section C).

carry and momentum (panel C) robustly reject the null hypothesis that the factor loadings are jointly equal to zero. Moreover, the carry factor is significant in all cases, and the momentum factor is significant in four out of five cases. Overall, this exercise illustrates that the results established using the baseline portfolios extend to a variety of managed portfolios.

5.1.3. The Results Are Robust Under a Randomization Procedure. How sensitive are our results to the randomization procedure suggested in Lustig et al. (2011)? Following their approach, in the first step, we construct the average, carry, and momentum factors based on commodities whose ticker symbols start with the letter A and continue through the letter M. In the second step, we construct two carry, two momentum, and three category portfolios based on commodities whose ticker symbols start with the letter N and continue through the letter Z. Finally, we use the factors constructed on the first set of commodities to price portfolios formed on the second set of commodities, and we also conduct the reverse exercise.

Such a procedure poses a higher hurdle for the pricing models, given that the commodities included in the pricing factors are different from the ones included in the priced portfolios.

Together, the evidence from Table Internet-III of the Internet appendix provides justification for the inclusion of both carry and momentum to price the cross section of commodity returns. The three-factor model is not rejected on the first set of commodities and is borderline rejected on the second. On the other hand, the two-factor model that features the average and the carry factor is rejected in both cases. The model that features the average and the momentum factors is not rejected in the first subsample but is rejected in the second.[7]

5.1.4. Additional Tests Reject the Relevance of Commodity Value and Commodity Volatility Factors. Could other economically relevant factors drive out the explanatory ability of our commodity factors? To investigate additional models, we augment the three-factor model in Equation (6) with either (i) a commodity value factor (*VALUE*, in the spirit of Asness et al. 2013) or (ii) a commodity volatility factor ($\Delta VOL^{\text{commodity}}$, in the spirit of Menkhoff et al. 2012).[8]

As reported in panel A of Table 5, the Newey–West p-values for the null hypothesis of $\lambda_{\text{VALUE}} = 0$ and $\lambda_{\Delta\text{VOL}} = 0$ are, respectively, 0.21 and 0.94, indicating that these additional risks are not priced. Next, to examine the relevance of each additional factor in the SDF specification, we also perform a χ^2 exclusion restriction test in the context of a two-step GMM. The p-values for the $\chi^2(1)$ statistics are 0.51 (0.41) for the commodity value (volatility) factor. Thus, our tests seem to favor a more parsimonious three-factor model specification.[9]

Table 5. Exclusion Tests That Evaluate Whether Commodity Value and Volatility Are Additional Priced Factors

	Fama–MacBeth		GMM
	Value factor	Volatility factor	(Two-step)
Panel A: Factor risk premia			
λ_{AVG}			
Estimate	0.003	0.005	
NW[p]	(0.11)	(0.02)	
Shanken[p]	{0.11}	{0.02}	
λ_{CARRY}			
Estimate	0.017	0.018	
NW[p]	(0.00)	(0.00)	
Shanken[p]	{0.00}	{0.00}	
λ_{CMOM}			
Estimate	0.012	0.012	
NW[p]	(0.00)	(0.00)	
Shanken[p]	{0.00}	{0.00}	
λ_{VALUE} (Commodity value)			
Estimate	−0.014		
NW[p]	(0.21)		
Shanken[p]	{0.22}		
$\lambda_{\Delta\text{VOL}}$ (Commodity volatility)			
Estimate		0.000	
NW[p]		(0.94)	
Shanken[p]		{0.94}	
Panel B: Exclusion tests for the loadings on the SDF			
H_0: $b_{\text{VALUE}} \equiv 0$			
(Commodity value)			
$\chi^2(1)$			0.43
(p-value)			(0.51)
H_0: $b_{\Delta\text{VOL}} \equiv 0$			
(Commodity volatility)			
$\chi^2(1)$			0.68
(p-value)			(0.41)

Notes. Reported are the factor risk premia and exclusion tests for the validity of a four-factor asset pricing model when we incrementally add the value factor and the commodity volatility factor to the SDF specification in Equation (6). Specifically, the SDF specification is of the form: $m_{t+1} = 1 - b_{\text{AVG}}(AVG_{t+1} - \mu_{\text{AVG}}) - b_{\text{CARRY}}(CARRY_{t+1} - \mu_{\text{CARRY}}) - b_{\text{CMOM}}(CMOM_{t+1} - \mu_{\text{CMOM}}) - b_{\text{VALUE}}(VALUE_{t+1} - \mu_{\text{VALUE}})$, or, $m_{t+1} = 1 - b_{\text{AVG}}(AVG_{t+1} - \mu_{\text{AVG}}) - b_{\text{CARRY}}(CARRY_{t+1} - \mu_{\text{CARRY}}) - b_{\text{CMOM}}(CMOM_{t+1} - \mu_{\text{CMOM}}) - b_{\Delta\text{VOL}}(\Delta VOL_{t+1}^{\text{commodity}} - \mu_{\text{VOL}})$. Our procedure for constructing the value factor, denoted by $VALUE_{t+1}$, is similar to that in Asness et al. (2013), in that in each month, we rank all the commodities by the ratio of the second-nearest maturity futures price five years ago to its current price. We divide the commodities into five groups and compute the next-month portfolio returns. $VALUE_{t+1}$ is the return spread between the top and bottom quintiles (see Section C in the Internet appendix). The $\Delta VOL_{t+1}^{\text{commodity}}$ corresponds to the innovation in commodity volatility (see Section C in the Internet appendix) and is computed following Menkhoff et al. (2012, equation (4)). The estimates of the factor risk premia λ are based on a cross-sectional regression. The p-values are computed using both the Newey and West (1987) procedure and the Shanken (1992) correction (in curly brackets). The test of individual parameter restriction $b_{\text{VALUE}} \equiv 0$ and $b_{\Delta\text{VOL}} \equiv 0$ is based on the two-step GMM χ^2-test, in which the p-values rely on the Newey and West (1987) procedure with lags selected automatically according to Newey and West (1994).

5.1.5. The Model Is Not Rejected When Using Individual Commodities as Test Assets. While the tradition is to examine the performance of factor models using portfolios of assets sorted on identifiable characteristics, there appears to be some interest in examining models based on individual assets (e.g., Ang et al. 2010, Chordia et al. 2013, and Jegadeesh and Noh 2013). Catering to this line of thinking, we assess the robustness of our model using individual commodities.

We follow the baseline time-invariant specification described in Gagliardini et al. (2016, section 4.2) and use the universe of 29 commodities as test assets.[10] When we compute the statistics $\hat{Q}_e$ and $\hat{Q}_a$ in Gagliardini et al. (2016, proposition 6), we obtain the values 32.74 and 39.02—with associated p-values 0.17 and 0.10—indicating that our three-factor model is not rejected when individual commodities are used as test assets.

5.2. Time-Series Regressions: The Hypothesis of Zero Alphas Is Not Rejected

To assess how the three-factor model fares in capturing commodity returns, we perform the following regressions for the baseline test assets indexed by $i = 1, \ldots, 12$:

$$e_t^i = \alpha^i + \beta_{\mathrm{AVG}}^i AVG_t + \beta_{\mathrm{CARRY}}^i CARRY_t + \beta_{\mathrm{CMOM}}^i CMOM_t + \epsilon_t^i \quad \text{for } t = 1, \ldots, T. \tag{7}$$

We gauge model adequacy by testing the joint hypothesis that $\boldsymbol{\alpha} = \mathbf{0}$, where $\boldsymbol{\alpha} = [\alpha^1, \ldots, \alpha^{12}]'$. This hypothesis of zero pricing errors is tested by constructing the statistic $\hat{\boldsymbol{\alpha}}'\mathbf{var}(\hat{\boldsymbol{\alpha}})^{-1}\hat{\boldsymbol{\alpha}}$ in a GMM setting, which is asymptotically distributed as $\chi^2(df)$, where df is the dimensionality of $\boldsymbol{\alpha}$ (see Cochrane 2005, p. 234). We also test the individual significance of α^i for $i = 1, \ldots, 12$.

The results, reported in Table 6, show that the three-factor model can describe the returns variation in the test portfolios. The p-value of 0.11 indicates that we are unable to reject the null hypothesis that $\boldsymbol{\alpha} = \mathbf{0}$. Furthermore, 10 out of the 12 α estimates have p-values that exceed 0.05, and the largest (absolute) α has an annualized value of 4.8% while the majority of α's

Table 6. Time-Series Regressions Based on the Three-Factor Model

							Joint test on α	
Commodity portfolio		α	β_{AVG}	β_{CARRY}	β_{CMOM}	$\bar{R}^2$ (%)	$\chi^2(12)$	p-val.
P1	Estimate	0.002	0.933	0.566	−0.041	66.4		
(backwardation, lowest y)	NW[p]	(0.36)	(0.00)	(0.00)	(0.22)			
P2	Estimate	0.004	0.882	0.284	−0.086	53.9		
	NW[p]	(0.01)	(0.00)	(0.00)	(0.00)			
P3	Estimate	−0.001	1.000	−0.063	0.041	70.9		
	NW[p]	(0.43)	(0.00)	(0.01)	(0.05)			
P4	Estimate	−0.001	1.016	−0.303	−0.038	82.9		
(contango, highest y)	NW[p]	(0.20)	(0.00)	(0.00)	(0.03)			
Q1	Estimate	−0.002	1.160	0.002	−0.443	84.5		
(momentum, lowest)	NW[p]	(0.15)	(0.00)	(0.96)	(0.00)			
Q2	Estimate	−0.002	0.874	−0.015	−0.091	54.5		
	NW[p]	(0.18)	(0.00)	(0.68)	(0.00)			
Q3	Estimate	0.004	0.950	0.000	−0.054	53.1		
	NW[p]	(0.01)	(0.00)	(0.99)	(0.05)			
Q4	Estimate	0.001	0.892	−0.009	0.146	55.9		
	NW[p]	(0.39)	(0.00)	(0.81)	(0.00)			
Q5	Estimate	−0.002	1.165	0.039	0.552	83.5		
(momentum, highest)	NW[p]	(0.15)	(0.00)	(0.15)	(0.00)			
Agriculture	Estimate	−0.001	0.983	−0.042	−0.022	69.1		
	NW[p]	(0.38)	(0.00)	(0.31)	(0.54)			
Livestock	Estimate	0.001	0.659	0.004	−0.094	22.3		
	NW[p]	(0.64)	(0.00)	(0.93)	(0.04)			
Metal	Estimate	0.000	0.985	−0.078	0.132	40.3		
	NW[p]	(0.93)	(0.00)	(0.18)	(0.08)			
All portfolios							18.20	0.11

Notes. Results are based on the time-series regression $e_t^i = \alpha^i + \beta_{\mathrm{AVG}}^i \mathrm{AVG}_t + \beta_{\mathrm{CARRY}}^i \mathrm{CARRY}_t + \beta_{\mathrm{CMOM}}^i \mathrm{CMOM}_t + \epsilon_t^i$ for $i = 1, \ldots, 12$. We report the coefficient estimates and the p-values in parentheses. The p-values are based on the Newey and West (1987) procedure with lags selected automatically according to Newey and West (1994). To test the null hypothesis that all intercepts are jointly equal to zero, we compute the statistic $\hat{\boldsymbol{\alpha}}'\mathbf{var}(\hat{\boldsymbol{\alpha}})^{-1}\hat{\boldsymbol{\alpha}}$ in a GMM setting (Cochrane 2005, p. 234), which is asymptotically distributed $\chi^2(12)$. The underlying test assets are the four carry portfolios, the five momentum portfolios, and the three category portfolios. We have excluded the energy category as a test asset in the time series regressions because of its shorter time series (heating oil started in 1979:04 while crude oil started in 1983:04; see Table Internet-I of the Internet appendix).

are below 2.4%, implying that the departures from the model are economically small.

All the β_{AVG} coefficients are uniformly positive and statistically significant and range from 0.659 to 1.165. The implication of this finding is that the returns of commodity portfolios manifest a strong commodity market component.

The carry coefficients are monotonic for portfolios P1–P4, while the momentum coefficients are monotonic for portfolios Q1–Q5. On the other hand, the momentum coefficients are not monotonic for portfolios P1–P4, while the carry coefficients are not significant—nor monotonic—for portfolios Q1–Q5. This is a strong indication that carry and momentum are distinct factors because, in the time series, the carry factor explains only the returns of the carry-sorted portfolios, while the momentum factor explains only the returns of the momentum-sorted portfolios.

Table 7 reports the performance of the one- and two-factor models. From a statistical standpoint, the R^2 values associated with the one-factor model, driven by the carry factor alone, are negative for 5 out of the 12 portfolios and are significantly lower than the ones associated with the three-factor model. This model is fundamentally misspecified with 5 out of 12 α's significantly different from zero and a $\chi^2(12)$ statistic that points to model inadequacy. The two-factor model, featuring the average and the carry factor, is also rejected according to the $\chi^2(12)$ statistic, indicating that momentum has explanatory power beyond the average and carry factor and is needed to characterize the variation in commodity returns.

Table Internet-V, which presents the performance of the three-factor model under the randomization approach, further reinforces the relevance of the momentum factor. The main message from combining

Table 7. Time-Series Regressions with a Two-Factor Model That Excludes the Momentum Factor

		Panel A: Two-factor model that excludes the momentum factor				Panel B: One-factor model with the carry factor		
Commodity portfolio		α	β_{AVG}	β_{CARRY}	$\bar{R}^2$ (%)	α	β_{CARRY}	$\bar{R}^2$ (%)
P1	Estimate	0.00	0.927	0.553	66.3	0.005	0.609	33.9
(backwardation, lowest y)	NW[p]	(0.47)	(0.00)	(0.00)		(0.04)	(0.00)	
P2	Estimate	0.003	0.875	0.255	53.3	0.007	0.309	12.3
	NW[p]	(0.07)	(0.00)	(0.00)		(0.00)	(0.00)	
P3	Estimate	−0.001	1.008	−0.050	71.2	0.004	0.011	−0.2
	NW[p]	(0.56)	(0.00)	(0.03)		(0.14)	(0.79)	
P4	Estimate	−0.001	1.007	−0.315	82.8	0.003	−0.25	10.9
(contango, highest y)	NW[p]	(0.16)	(0.00)	(0.00)		(0.18)	(0.00)	
Q1	Estimate	−0.005	1.089	−0.135	55.8	0.000	−0.06	0.3
(momentum, lowest)	NW[p]	(0.00)	(0.00)	(0.00)		(0.87)	(0.24)	
Q2	Estimate	−0.003	0.859	−0.044	53.2	0.001	0.008	−0.2
	NW[p]	(0.09)	(0.00)	(0.22)		(0.68)	(0.87)	
Q3	Estimate	0.004	0.943	−0.017	53.4	0.008	0.040	0.0
	NW[p]	(0.02)	(0.00)	(0.64)		(0.01)	(0.49)	
Q4	Estimate	0.002	0.919	0.036	52.8	0.006	0.092	1.1
	NW[p]	(0.13)	(0.00)	(0.31)		(0.01)	(0.08)	
Q5	Estimate	0.003	1.245	0.212	54.2	0.008	0.287	6.1
(momentum, highest)	NW[p]	(0.24)	(0.00)	(0.00)		(0.01)	(0.00)	
Agriculture	Estimate	−0.001	0.983	−0.050	69.6	0.003	0.010	−0.2
	NW[p]	(0.30)	(0.00)	(0.16)		(0.22)	(0.87)	
Livestock	Estimate	0.001	0.612	−0.017	19.5	0.003	0.021	−0.1
	NW[p]	(0.79)	(0.00)	(0.76)		(0.18)	(0.71)	
Metal	Estimate	0.001	1.015	−0.038	39.5	0.005	0.024	−0.1
	NW[p]	(0.65)	(0.00)	(0.45)		(0.11)	(0.68)	
$\chi^2(12)$			28.94				31.28	
(p-value)			(0.00)				(0.00)	

Notes. In panel A, the results are based on the time-series regression $e_t^i = \alpha^i + \beta_{\text{AVG}}^i AVG_t + \beta_{\text{CARRY}}^i CARRY_t + \epsilon_t^i$ for $i = 1, \ldots, 12$. In panel B, the results are based on the time-series regression $e_t^i = \alpha^i + \beta_{\text{CARRY}}^i CARRY_t + \epsilon_t^i$ for $i = 1, \ldots, 12$. We report the coefficient estimates and the p-values in parentheses. The p-values are based on the Newey and West (1987) procedure with lags selected automatically according to Newey and West (1994). To test the null hypothesis that all intercepts are jointly equal to zero, we compute the statistic $\hat{\boldsymbol{\alpha}}'\mathbf{var}(\hat{\boldsymbol{\alpha}})^{-1}\hat{\boldsymbol{\alpha}}$ in a GMM setting (Cochrane 2005, p. 234), which is asymptotically distributed $\chi^2(12)$. The underlying test assets are the four carry portfolios, the five momentum portfolios, and the three category portfolios. We have excluded the energy category as a test asset in the time-series regressions because of its shorter time series (the heating oil started in 1979:04, while crude oil started in 1983:04).

the results from Tables 6, 7, and Internet-V of the Internet appendix is that the three-factor model can explain the cross-sectional dispersion of commodity returns.

6. Economic Interpretations of the Commodity Factors

We have established that, taken together, the average, carry, and momentum factors can summarize the cross-sectional variations in commodity returns. Furthermore, our results show that commodities' exposure to the carry and momentum factors warrants a positive and sizable risk premium.

What are the economic interpretations for these findings? Could one identify the sources of risk that underlie the premia of carry and momentum? How do the commodity factors behave over different stages of the business cycle? Do the long legs of carry and momentum load dynamically on certain economically sensitive commodities and hence explain their high average returns? The rest of this section provides answers to these questions.

6.1. The Carry Factor Is Linked to Innovations in Global Equity Return Volatility

Here, we show that the carry factor loads negatively on innovations in global equity return volatility. In addition, we show that, while global equity volatility is able to price the cross section of carry portfolios, an equivalent measure constructed using commodity returns is not statistically significant.

Our motivation for considering changes in equity return volatility across the G20 countries is that global investors require compensation for holding assets that pay poorly in periods with positive innovations in equity volatility because in these periods investors' marginal utility is high (e.g., Ang et al. 2006; Lustig et al. 2011, section 4.5.3; Menkhoff et al. 2012). We use a two-pronged approach to establish the relation between carry and innovations in global equity volatility, denoted $\Delta VOL_t^{\text{equity}}$. First, we establish the statistical relation between the carry factor and $\Delta VOL_t^{\text{equity}}$ through time-series regressions. Second, and more fundamentally, we use $\Delta VOL_t^{\text{equity}}$ to directly price the four carry test portfolios.

In the first exercise, we regress the carry factor on innovations in global equity volatility:

$$CARRY_t = \phi_0 + \phi_1 \Delta VOL_t^{\text{equity}} + \epsilon_t, \tag{8}$$

where, as described in Section C of the Internet appendix, global equity volatility is obtained—following Menkhoff et al. (2012, equation (4))—by computing the equally weighted average absolute daily return across the G20 equity markets in the first step and computing the average of this quantity over the month in the second step. The volatility factor $\Delta VOL_t^{\text{equity}}$ is the difference between volatility at time t and volatility at time $t-1$.

The results, reported in panel A of Table 8, show that the carry factor is significantly negatively related to $\Delta VOL_t^{\text{equity}}$, with a p-value of 0.06. The inverse

Table 8. The Commodity Carry Factor and Its Relation to Innovations in Global Equity Volatility

Panel A: Univariate time-series regressions of carry on innovations in global equity volatility

	Constant		Slope		
	ϕ_0	p-Value	ϕ_1	p-Value	R^2
Carry factor	0.015	(0.00)	−1.938	(0.06)	0.7
Long, backwardated commodities	0.012	(0.00)	−2.585	(0.01)	1.5
Short, contangoed commodities	0.003	(0.29)	0.647	(0.44)	0.1

Panel B: Pricing the carry portfolios with innovations in global equity volatility

	λ_{AVG}	$\lambda_{\Delta\text{VOL}}$	R^2	χ^2_{NW}	χ^2_{SH}
Fama–MacBeth	0.005	−0.007	⌊94.9⌋	4.099	0.510
	(0.01)	(0.00)		(0.13)	{0.77}
	{0.03}	{0.08}			

Notes. The regression results reported in panel A are based on the univariate regression $CARRY_t = \phi_0 + \phi_1 \Delta VOL_t^{\text{equity}} + \epsilon_t$. We report the Newey and West (1987) p-values (with lags automatically selected, as in Newey and West 1994) and denote them by NW[p]. The returns to the long and short legs of carry are constructed as in the Internet appendix (Section A). For the Fama and MacBeth procedure results reported in panel B, the p-values are computed using both the Newey and West (1987) procedure without (with) the Shanken (1992) correction in parentheses (curly brackets). We report the OLS uncentered R^2 as $\lfloor \cdot \rfloor$. The SDF specification is of the form $m_{t+1} = 1 - b_{\text{AVG}}(AVG_{t+1} - \mu_{\text{AVG}}) - b_{\Delta\text{VOL}} \Delta VOL_{t+1}^{\text{equity}}$, and the factor risk premia are reported as λ. The χ^2_{NW} and χ^2_{SH} tests correspond to the null hypotheses that the pricing errors are zero and their p-values are computed using Newey–West and Shanken standard errors. With four carry test portfolios, the test statistics follow a χ^2 distribution with two degrees of freedom.

relation between the carry factor and $\Delta VOL_t^{\text{equity}}$ is also reflected in the regressions involving the long leg of carry. Specifically, the returns from taking a long position in the backwardated commodities are negatively and significantly related to $\Delta VOL_t^{\text{equity}}$, with a p-value on the slope coefficient of 0.01. By contrast, the returns from shorting contangoed commodities are not related to $\Delta VOL_t^{\text{equity}}$, with a p-value on the slope coefficient of 0.44. This result is important since the bulk of the average carry returns stem from the long leg, as shown in Table 9.

In the second exercise, we show that $\Delta VOL_t^{\text{equity}}$ is capable of pricing the carry portfolios. Accordingly, we modify our specification in Equation (6) to the following:

$$m_{t+1} = 1 - b_{\text{AVG}}(AVG_{t+1} - \mu_{\text{AVG}}) - b_{\Delta\text{VOL}} \Delta VOL_{t+1}^{\text{equity}}. \quad (9)$$

The results, reported in panel B of Table 8, indicate that $\Delta VOL_{t+1}^{\text{equity}}$ is capable of explaining the cross section of commodity portfolios formed on carry. First, the risk premium on the $\Delta VOL_{t+1}^{\text{equity}}$ factor is negative and statistically significant, consistent with the interpretation that positive changes in equity volatility are associated with a deterioration in the investment opportunity set. Second, the χ^2 tests do not reject the null hypothesis of correct model pricing with a χ^2_{NW} (χ^2_{SH}) p-value of 0.13 (0.77). Our findings therefore identify global equity volatility as one source of risk underlying carry returns.[11]

To show that positive innovations in global equity volatility are unique in capturing deteriorations in the global investment opportunity set, we present evidence from two different perspectives. First, we present evidence that the carry factor is not linked to innovations in commodity volatility. We adopt the same SDF specification as in Equation (9) but replace $\Delta VOL_{t+1}^{\text{equity}}$ with $\Delta VOL_{t+1}^{\text{commodity}}$. Following Menkhoff et al. (2012, equation (4)), the estimate of commodity volatility is obtained by computing the average absolute daily

Table 9. Excess Returns of Long and Short Legs of the Commodity Carry and Momentum Strategies

	Panel A: Long leg of carry strategy					Panel B: Short leg of carry strategy				
	Commodities long backwardation					Commodities short contango				
	C1	C2	C3	C4	C5	C1	C2	C3	C4	C5
Mean	15.34	10.47	11.38	12.93	14.14	−6.03	−0.40	0.76	1.34	2.20
PW, lower CI	2.76	−0.12	2.88	4.92	6.84	−14.16	−6.36	−6.72	−5.64	−4.20
PW, upper CI	30.72	22.44	22.68	21.84	23.16	1.68	6.24	8.04	7.44	8.28
SD	37.02	28.68	24.01	21.57	20.89	35.16	25.33	21.88	19.55	18.08
SR	0.41	0.37	0.47	0.60	0.68	−0.17	−0.02	0.03	0.07	0.12
Skewness	0.98	0.83	0.67	0.48	0.59	−1.56	−1.23	−1.44	−0.80	−0.48
$1_{e>0}$	50.91	52.12	54.95	57.58	55.35	49.29	51.31	50.10	51.31	52.93
	Panel C: Long leg of momentum strategy					Panel D: Short leg of momentum strategy				
	Commodities long winners based on past six-month performance					Commodities short losers based on past six-month performance				
	M1	M2	M3	M4	M5	M1	M2	M3	M4	M5
Mean	13.00	15.62	11.99	12.39	13.63	−2.25	1.42	1.89	2.31	2.48
PW, lower CI	−0.12	4.80	3.00	3.84	6.00	−11.04	−6.48	−6.00	−4.20	−3.48
PW, upper CI	27.60	28.80	22.44	23.04	22.08	6.48	9.00	9.12	8.64	8.64
SD	44.37	34.13	28.40	25.86	24.12	40.50	30.11	25.97	22.98	20.63
SR	0.29	0.46	0.42	0.48	0.56	−0.06	0.05	0.07	0.10	0.12
Skewness	0.84	0.82	0.45	0.16	0.19	−1.36	−1.39	−0.86	−0.53	−0.34
$1_{e>0}$	54.75	54.55	53.94	56.77	56.97	52.73	51.72	53.94	53.94	53.94

Notes. This table presents the descriptive statistics of the excess returns generated by the long and short legs of the commodity carry and momentum strategies. Let $y_t \equiv F_t^{(1)}/F_t^{(0)}$, where $F_t^{(0)}$ is the price of the front-month futures contract and $F_t^{(1)}$ is the price of the next maturity futures contract, both observed at the end of month t. A commodity is in backwardation if $\ln(y_t) < 0$ and in contango if $\ln(y_t) > 0$. The carry strategy entails taking a long (short) futures position in a commodity that is in backwardation (contango) at the end of month t, and we compute the returns over the subsequent month. For example, the long (short) leg of the carry strategy C5 contains an equally weighted portfolio consisting of five commodities with the most negative (positive) $\ln(y_t)$. For the momentum strategies, the commodities are ranked on the basis of their past six-month performance. Analogously, the long (short) leg of the momentum strategy M5 contains an equally weighted portfolio consisting of five commodities with the highest (lowest) past returns. For each of the long and short legs of the strategies, we report the average annualized monthly return and its 95% confidence interval based on a stationary bootstrap (denoted by PW, lower CI and PW, upper CI) with 10,000 bootstrap iterations, in which the block size is based on the algorithm of Politis and White (2004), the annualized monthly standard deviation (SD), the annualized Sharpe ratio (SR), and the monthly skewness. The percentage of months in which the excess return of a strategy is positive is recorded as $1_{e>0}$. There are 501 monthly observations in our sample from January 1970 to September 2011.

return across all commodities in the first step and computing the equally weighted average of this quantity over the month in the second step. The volatility factor $\Delta VOL_{t+1}^{\text{commodity}}$ is the difference between volatility at time t and volatility at time $t-1$. As reported in the first row of Table 11, the χ^2_{NW} test rejects the null of correct model pricing with a p-value of 0.00.[12]

Next, we consider changes in alternative measures of equity return volatility, corresponding to the G7 countries or the United States, and find that the results are similar but weaker.[13] In the time-series regressions, we find that the carry factor is negatively related to innovations in G7 (U.S.) equity volatility, but the coefficient is insignificant, with a p-value of 0.14 (0.11). Furthermore, the Fama–MacBeth regressions reject correct model pricing for the G7 (U.S.) volatility factor with a χ^2_{NW} of 0.08 (0.03).

Finally, to further establish that the effect of global equity volatility is specific to the commodity carry portfolios, we also price the five commodity portfolios formed on momentum using the model in Equation (9). The key finding is that $\Delta VOL_{t+1}^{\text{equity}}$ cannot price the five commodity test portfolios as the χ^2_{NW} equals 10.75, with a Newey–West p-value of 0.01.

Overall, we interpret our findings as an indication that commodity investors require compensation for strategies that perform poorly when global market conditions deteriorate and that positive innovations in global equity volatility are good proxies for such periods. Innovations in aggregate commodity volatility, on the other hand, are likely driven by idiosyncratic developments in individual commodities (such as supply, demand, and inventory) and may be an inadequate proxy for changes in the investment opportunity set.

6.2. The Momentum Factor Is Linked to Innovations in Aggregate Speculative Activity

Next, we provide an economic explanation for the momentum factor. As we show in Section 6.3, commodity momentum is rather elusive, as no traditional risk factor can satisfactorily explain its returns. We therefore turn to an explanation based on the trading behavior of market participants in commodity markets.

Recent evidence by Kang et al. (2014, tables 3 and 4) shows that speculators behave as momentum traders. Working at the individual commodity level, they show that speculators increase their positions in the commodities that increase in price and reduce their positions in the commodities that decrease in price. Following this line of thinking, we hypothesize that if more agents in the market behave as momentum traders, momentum strategies are likely to self-perpetuate: the commodities whose prices have been increasing will continue to increase in price, while the commodities whose prices have been decreasing will continue to decrease in price. To test this mechanism, we propose a proxy for aggregate speculative activity in commodity markets and investigate whether this measure is able to price the cross section of momentum-sorted portfolios.

Our measure of aggregate speculation is constructed in two steps. In the first step, we compute a measure of speculation at the individual commodity level using large trader positions from the U.S. Commodity Futures Trading Commission (CFTC) (i.e., the Commitments of Traders reports):

$$\begin{aligned} &Speculation_{t,i} \\ &= \frac{Noncommercial\_long_{t,i} + Noncommercial\_short_{t,i}}{Total\_long\_positions_{t,i} + Total\_short\_positions_{t,i}}, \\ &\qquad i = 1, \ldots, 29, \end{aligned} \tag{10}$$

where, for example, $Noncommercial\ long_{t,i}$ represents the total long positions of noncommercial traders for commodity futures i in month t (see Gorton et al. 2013, appendix C, or Haase et al. 2014, appendix A, for a description of the CFTC data). Our focus on noncommercial trader positions follows the empirical literature that has traditionally associated commercial traders with hedgers and noncommercial traders with speculators. In the second step, we equally weight the commodity-specific speculation variable in Equation (10) and construct a measure of aggregate speculation activity, denoted by $Speculation_t$, and its innovation, denoted by $\Delta Speculation_t$. Intuitively, the aggregate speculative activity variable proxies for the proportion of commodity investors that follow momentum strategies.

We first investigate whether innovations in aggregate speculative activity can price the five commodity momentum portfolios when the momentum factor is replaced with $\Delta Speculation_{t+1}$. To this end, we consider an altered SDF of the type

$$\begin{aligned} m_{t+1} = 1 &- b_{\text{AVG}}(AVG_{t+1} - \mu_{\text{AVG}}) \\ &- b_{\Delta\text{Speculation}} \Delta Speculation_{t+1}. \end{aligned} \tag{11}$$

The results, reported in panel B of Table 10, show that the risk premium on $\Delta Speculation_{t+1}$ is positive and significant. In addition, the χ^2 tests do not reject the null hypothesis of correct model pricing according to both Newey–West standard errors (p-value of 0.28) and Shanken standard errors (p-value of 0.62).[14]

We also use $\Delta Speculation_{t+1}$ to price the four commodity carry portfolios and obtain a χ^2_{NW} statistic of 21.45 with a Newey–West p-value of 0.00, indicating that the role of $\Delta Speculation_{t+1}$ in pricing momentum portfolios is unique.

In our second empirical exercise, we consider the univariate regression:

$$CMOM_t = \psi_0 + \psi_1 \Delta Speculation_t + \epsilon_t. \tag{12}$$

The results, reported in panel A of Table 10, reveal that the relation between the momentum factor and

Table 10. The Commodity Momentum Factor and Its Relation to Innovations in Aggregate Speculative Activity

Panel A: Univariate time-series regressions of momentum on innovations in aggregate speculative activity

	Constant		Slope		
	ψ_0	NW[p]	ψ_1	NW[p]	R^2
Momentum factor	0.010	(0.01)	0.996	(0.02)	2.2
Long, high momentum (winners)	0.008	(0.02)	0.941	(0.01)	2.5
Short, low momentum (losers)	0.002	(0.55)	0.055	(0.86)	−0.3

Panel B: Pricing the momentum portfolios with innovations in aggregate speculative activity

	λ_{AVG}	$\lambda_{\Delta\text{Speculation}}$	R^2	χ^2_{NW}	χ^2_{SH}
Fama–MacBeth	0.005	0.008	⌊89.8⌋	3.80	1.78
	(0.05)	(0.02)		(0.28)	{0.62}
	{0.05}	{0.10}			

Notes. The regression results reported in panel A are based on the univariate regression $CMOM_t = \psi_0 + \psi_1 \Delta Speculation_t + \epsilon_t$. We report the Newey and West (1987) p-values (with lags automatically selected, as in Newey and West 1994) and denote them by NW[p]. The returns to the long and short legs of momentum are constructed as in Section A of the Internet appendix. For the Fama and MacBeth procedure results reported in panel B, the p-values are computed using both the Newey and West (1987) procedure without (with) the Shanken (1992) correction in parentheses (curly brackets). We report the OLS uncentered R^2 as $\lfloor \cdot \rfloor$. The SDF specification is of the form $m_{t+1} = 1 - b_{\text{AVG}}(AVG_{t+1} - \mu_{\text{AVG}}) - b_{\Delta\text{Speculation}} \Delta Speculation_{t+1}$, and the factor risk premia are reported as λ. The χ^2_{NW} and χ^2_{SH} tests correspond to the null hypotheses that the pricing errors are zero, and their p-values are computed using Newey–West and Shanken standard errors. With five momentum test portfolios, the test statistics follow a χ^2 distribution with three degrees of freedom. The sample period ranges from January 1986 through September 2011.

innovations in aggregate speculative activity is positive and statistically significant (the p-value is 0.02). Our analysis further shows that the long leg of the momentum strategy is positively related to $\Delta Speculation_t$, with a slope coefficient p-value equal to 0.01. On the other hand, we cannot reject that the slope coefficient on the short leg of momentum is equal to zero, as evidenced by a p-value of 0.86.

In an effort to understand why aggregate speculative activity is related to the long leg of the momentum portfolio but not the short leg, we work with our measure of speculative activity at the individual commodity level, $Speculation_{t,i}$, and test whether speculators increase their presence in those commodities that have been performing well over the previous six months and decrease their presence in the commodities that have been performing poorly over the previous six months. We find that the average annualized change for high-return commodities is $AVG\_\Delta Speculation_i^{\text{HIGH}} = 1.96\%$, while the average change for low-return commodities is $AVG\_\Delta Speculation_i^{\text{LOW}} = -0.96\%$. The first is statistically different from zero, with a p-value of 0.026, while the second is insignificant, with a p-value of 0.301. These results confirm the hypothesis that changes in speculative activity are positively related to the performance of the commodities selected in the long leg of the momentum portfolio because speculators—who behave as momentum traders—purchase the commodities that have increased in price, pushing their prices even higher.

Finally, given that the speculation variable we have constructed comprises both long and short positions, we create two additional measures to isolate the effects associated with each one of them:

$$Speculation\_Long_{t,i} = \frac{Noncommercial\_long_{t,i}}{Total\_long\_positions_{t,i} + Total\_short\_positions_{t,i}}, \quad i = 1, \ldots, 29, \tag{13}$$

$$Speculation\_Short_{t,i} = \frac{Noncommercial\_short_{t,i}}{Total\_long\_positions_{t,i} + Total\_short\_positions_{t,i}}, \quad i = 1, \ldots, 29. \tag{14}$$

When we repeat the same analysis reported above but decompose the results into long and short speculation variables, we find that—for the high returns commodities—$AVG\_\Delta Speculation\_Long_i^{\text{HIGH}} = 6.77\%$ and $AVG\_\Delta Speculation\_Short_i^{\text{HIGH}} = -4.81\%$. This suggests that $AVG\_\Delta Speculation_i^{\text{HIGH}}$ is positive because speculators increase their long positions more than they reduce their short positions on high returns commodities.

Finally, to explore whether it is related to proxies for availability of arbitrage capital or liquidity, we relate our speculation variable to four measures constructed from equity and bond markets: (i) the liquidity provision variable of Nagel (2012); (ii) the volatility of daily TED spreads as in Frazzini and Pedersen (2014, section 6); (iii) the marketwide liquidity measure, as in Hu et al. (2013, equation (3)); and (iv) the funding liquidity factor of Fontaine and Garcia (2012, section 4.1). We find that the largest absolute correlation between $\Delta Speculation_t$ and any of these variables is 0.06,[15] suggesting that changes in aggregate speculation are largely uncorrelated with the availability of arbitrage capital and liquidity. We conclude that our speculation measure is unique to commodity markets.

6.3. Innovations in Alternative Economic Variables Appear Irrelevant for Pricing

The analyses reported below show that, while innovations in global equity volatility and aggregate speculative activity are able to price carry and momentum portfolios, innovations in many other economic variables do not impact the cross section of commodity returns.

To convey this finding in a parsimonious manner, we focus on the cross-sectional Fama–MacBeth regressions and use as a criterion the significance of the χ^2_{NW} statistic. Throughout, we use alternatively the four commodity carry portfolios or the five commodity momentum portfolios as test assets. The χ^2_{NW} statistics, along with the associated p-values, are reported in Table 11. The construction of the economic variables is in Section C of the Internet appendix.

Table 11. Cross-Sectional Tests with Alternative Economic Variables

	χ^2_{NW} (p-val.)	
ΔX_{t+1}	Carry portfolios	Momentum portfolios
Innovations in commodity volatility	21.88 (0.00)	28.37 (0.00)
Innovations in log open interest	15.24 (0.00)	7.30 (0.06)
Innovations in hedging pressure	21.08 (0.00)	12.36 (0.01)
Innovations in scarcity	21.14 (0.00)	10.33 (0.02)
Innovations in log industrial production	13.86 (0.00)	29.14 (0.00)
Innovations in U.S. TED spread	19.98 (0.00)	12.73 (0.01)
Innovations in G7 inflation	21.31 (0.00)	5.80 (0.12)

Notes. All the results in this table use the SDF specification of the form $m_{t+1} = 1 - b_{\mathrm{AVG}}(AVG_{t+1} - \mu_{\mathrm{AVG}}) - b_{\Delta X}\Delta X_{t+1}$, where ΔX_{t+1} is the innovation in an economic variable. We use each model specification to alternatively price the four carry portfolios or the five momentum portfolios using Fama and MacBeth (1973) regressions. The reported χ^2_{NW} tests correspond to the null hypotheses that the pricing errors are zero, and their p-values are computed using Newey–West standard errors. With four (five) carry (momentum) portfolios, the test statistics follow a χ^2 distribution with two (three) degrees of freedom.

1. *Innovations in commodity volatility*: The first economic variable we consider is innovations in cross-sectional commodity volatility. As shown in Section 6.1, innovations in the cross-sectional commodity volatility do not impact returns of commodity carry portfolios. In addition, innovations in commodity volatility are unable to reconcile the return pattern of momentum portfolios, with a p-value of 0.00.
2. *Innovations in log open interest*: Following Hong and Yogo (2012), we construct the innovations in log open interest and use it as a candidate factor. Our results indicate that this variable is unable to price either the carry or the momentum portfolios, as both p-values are smaller than 0.10.
3. *Innovations in hedging pressure*: Following de Roon et al. (2000, table II), we construct innovations in hedging pressure and find that this variable fails to price both the carry and the momentum portfolios, as the largest p-value is 0.01.
4. *Innovations in scarcity*: Following Gorton et al. (2013), we examine the role of scarcity. Our results indicate that scarcity does not price the carry nor the momentum portfolios, as the largest p-value is 0.02.
5. *Innovations in log of G7 industrial production*. Following Fama (1990), among others, the next variable we consider is innovations in log of industrial production for the G7 countries. With χ^2_{NW} p-values of 0.00 and 0.00 for the carry and momentum portfolios, respectively, the industrial production growth appears to have limited ability to explain the return cross section of either set of commodity portfolios.
6. *Innovations in U.S. TED spread*: Innovations in U.S. TED spread could help capture changes in liquidity as argued by Brunnermeier et al. (2009). With a χ^2_{NW} p-value equal to 0.00 for both carry and momentum portfolios, changes in funding liquidity do not appear to be a source of risk that explains the variation in commodity returns.
7. *Innovations in G7 inflation rate*: Guided by the connection between inflation and commodity prices, we last consider innovations in G7 inflation (e.g., Ferson and Harvey 1993, Ang et al. 2008). Our results indicate that a model featuring the average factor and innovations in inflation is not rejected when pricing the momentum portfolios (the p-value is 0.12) and is rejected in pricing the carry portfolios (the p-value is 0.00).

Because the inflation factor is not rejected on the momentum portfolios, we perform additional exercises to distinguish between innovations in inflation and innovations in aggregate speculative activity as pricing factors. First, we run a univariate time-series regression using innovations in inflation to explain variations in the momentum factor and obtain a marginally significant p-value of 0.09. The associated R^2 is 0.6%, as opposed to 2.2% with innovations in speculative activity. Second, when we run a horse race between innovations in inflation and speculative activity in a bivariate regression, we find that inflation loses its significance while speculative activity remains statistically significant.[16]

The big picture is that innovations in global equity volatility (aggregate speculative activity) occupy special roles in pricing the commodity carry (momentum) portfolios.

6.4. Characterizing the Behavior of Commodity Factors Over the Business Cycle

In search of a unified economic explanation for our findings, we now turn to analyzing the behavior of the commodity factors in conjunction with equity market returns over the U.S. business cycle. In particular, Table 12 highlights that the commodity carry and momentum factors perform well in recessions, whereas the average commodity factor and equity market returns are negative.

Focusing first on the momentum factor, it is evident that the past losers perform poorly during recessions (−2.06%). Displaying an opposite pattern, the past winners deliver relatively small but positive returns (0.40%). Our exercise suggests that the performance of commodity momentum during recessions is mainly driven by shorting the past losers.

Another insight is that the carry strategy also does well during recessions, as it delivers a positive monthly return of 3.18%. Unlike the momentum strategy, however, going long in backwardated commodities is as profitable as shorting contangoed commodities (1.54% versus 1.64%).

In recessions, the average monthly return in equity markets is −0.36%. The return associated with the average commodity factor is also negative and equal to −0.58%. Our results, therefore, suggest that both the momentum and the carry factors can shield investors against equity market declines during recessions.

In periods of economic expansion, the average commodity factor generates a monthly return of 0.73%, while the momentum (carry) factor generates a return of 1.14% (1.03%). Overall, then, our results indicate that the carry and momentum strategies are more profitable in recessions than expansions.

To draw additional insights, we partition expansions (recessions) in early and late expansions (recessions) as in Dangl and Halling (2012, section 4.2): (i) *late expansions*: three months before business cycle peaks, (ii) *early recessions*: three months after business cycle peaks, (iii) *late recessions*: three months before business cycle troughs, and (iv) early expansions: three months after business cycle troughs. Dangl and Halling (2012) show that the equity risk premium and its predictability vary not only *across* recession and expansion states but also *within* recession and expansion states. This finer partition allows us to compare the attributes of commodity and equity returns as the economy transitions from one stage to the next. Interestingly, the carry and momentum factors provide large monthly returns equal to 5.65% and 4.22% at the beginning of recessions, whereas they only provide −0.03% and 0.29% in late recessions. Equities display the opposite behavior; their returns average −2.27% in early recessions and 4.06% in late recessions.

Our analysis also reveals that, while carry and momentum deliver comparable returns during various stages of the business cycle, they generate profits from different legs of the strategy. For instance, it is the long position in backwardated commodities that delivers large returns as opposed to the short position in contangoed commodities: in early recession, the former delivers a return of 4.40% while the latter a return of 1.26%. On the contrary, the high returns to momentum can be traced to shorting the losers, compared with

Table 12. Performance of Commodity Factors and Equity Market Returns Over Different Stages of the Business Cycle

	Carry			Momentum				Equity market
	$CARRY_t$	Long	Short	$CMOM_t$	Long	Short	AVG_t	Returns
Expansion	1.03	1.11	−0.08	1.14	1.27	−0.13	0.73	0.64
Recession	3.18	1.54	1.64	2.46	0.40	2.06	−0.58	−0.36
Late expansion	0.55	−1.53	2.08	1.33	−0.30	1.63	−0.66	−0.33
Early recession	5.65	4.40	1.26	4.22	1.05	3.17	0.21	−2.27
Late recession	−0.03	−1.03	1.00	0.29	−0.66	0.95	−0.53	4.06
Early expansion	−0.23	−1.20	0.97	2.44	1.66	0.78	−0.15	2.36

Notes. Reported are the average *monthly* returns (in percent) of the carry and momentum factors, as well as their long and short positions, over different stages of the business cycle. The returns to the long and short legs of carry and momentum are as constructed in Equations (A1)–(A4) of Section A of the Internet appendix. The long leg consists of taking long positions in five commodities that are most backwardated, or five commodities with the high momentum (winners). The short leg consists of taking short positions in five commodities that are most contangoed, or five commodities with the lowest momentum (losers). We classify the economy in expansions and recessions using the National Bureau of Economic Research classification. We also characterize early and late expansions as well as early and late recessions following Dangl and Halling (2012, section 4.2).

going long in the winners: in early recessions, the former delivers a return of 3.17% while the latter a return of 1.05%.

Completing the picture, the average commodity factor comoves positively with equity returns in late expansions but negatively in early and late recessions and in early expansions. Yet at a broader level, average commodity returns rise (fall) together with equity returns during expansions (recessions), which imparts a risk interpretation to the long-only average commodity factor.

The properties of carry and momentum returns are puzzling at first glance since these factors could hedge equity declines and yet are characterized by large average returns. However, the returns of carry and momentum may not be puzzling if the sources of risk are multifaceted. This is evidenced from the pricing of momentum portfolios with innovations in speculative activity and the pricing of carry portfolios with innovations in global equity volatility. For example, our results show that commodities in backwardation (contango) tend to lose (gain) in value when global equity volatility rises, and therefore, backwardated (contangoed) commodities are poor (good) hedges. These facts are compatible with a positive risk premium for the carry factor.

6.5. Membership in the Long Legs Is Not Skewed Toward Economically Sensitive Commodities

In this final section, we study the nature of the carry and momentum factors by analyzing the composition of the long and short legs of each strategy. Specifically, we compute the number of months in which each commodity enters the long and short legs of carry and momentum (i.e., C5 and M5, respectively) and report the findings in Table 13.

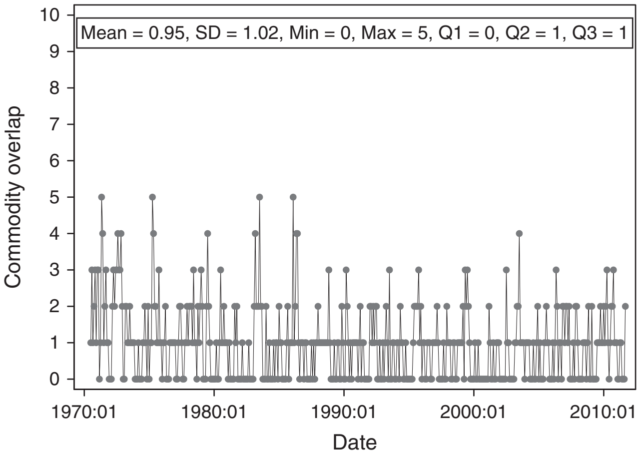
The table shows that the long legs of carry and momentum do not lean on commodities whose prices fluctuate in response to changes in macroeconomic conditions, such as crude oil or industrial metals.

Table 13. Membership in the Long and Short Components of the Carry and Momentum Strategies

Panel A: Carry strategy, C5				Panel B: Momentum strategy, M5			
Long		Short		Long		Short	
Live cattle	191	Oats	258	Sugar	143	Sugar	157
Lean hogs	185	Wheat	210	Heating oil	133	Pork belly	142
Pork belly	144	Lumber	206	Palladium	124	Orange juice	137
Sugar	129	Corn	203	Orange juice	119	Lumber	137
Coffee	122	Lean hogs	190	Cocoa	116	Cocoa	137
Orange juice	115	Sugar	171	Coffee	112	Oats	131
Feeder cattle	114	Orange juice	130	Lean hogs	111	Coffee	112
Oats	113	Cotton	126	Pork belly	109	Natural gas	111
Lumber	108	Cocoa	125	Soybean oil	108	Corn	110
Cocoa	103	Coffee	122	Cotton	105	Wheat	99
Soybean meal	102	Rough rice	121	Unleaded gasoline	99	Soybean oil	98
Unleaded gasoline	100	Live cattle	109	Copper	99	Platinum	92
Cotton	94	Natural gas	68	Soybean meal	99	Silver	92
Heating oil	84	Platinum	61	Crude oil	94	Lean hogs	88
Wheat	83	Soybean meal	49	Oats	93	Palladium	88
Soybean oil	78	Pork belly	44	Platinum	85	Copper	87
Crude oil	69	Feeder cattle	38	Silver	85	Rough rice	86
Copper	67	Silver	35	Live cattle	70	Cotton	82
Soybeans	47	Copper	31	Lumber	70	Soybean meal	71
Corn	45	Soybean oil	27	Soybeans	69	Heating oil	68
Platinum	43	Palladium	25	Wheat	68	Soybeans	63
Propane	42	Unleaded gasoline	25	Propane	68	Crude oil	61
Natural gas	40	Soybeans	25	Corn	66	Gold	49
Palladium	38	Barley	25	Feeder cattle	61	Feeder cattle	41
RBOB gasoline	34	Heating oil	19	Natural gas	58	Live cattle	41
Rough rice	23	Crude oil	14	Gold	41	Unleaded gasoline	36
Barley	8	RBOB gasoline	8	Rough rice	40	Propane	33
Silver	2	Propane	7	RBOB gasoline	25	Barley	17
Gold	0	Gold	0	Barley	5	RBOB gasoline	9

Notes. Entries under the column labeled "Long (Short)" depict how many months the respective commodity has entered the backwardation (contango) components of the carry strategy C5 (panel A). The next four columns show how many months the commodity has entered the long and short components of the momentum strategy M5 (panel B). The long leg consists of taking long positions in five commodities that are most backwardated, or five commodities with the high momentum (winners). The short leg consists of taking short positions in five commodities that are most contangoed, or five commodities with the lowest momentum (losers). For example, and more concretely, in 191 (143) months, live cattle (sugar) has been among the five highest backwardated (momentum) commodities. RBOB, reformulated blendstock for oxygenate blending.

Figure 3. Overlap in the Commodities Selected by the Carry and Momentum Factors



Notes. Plotted is the time series of the number of commodities selected by both the carry and the momentum factors. We compute this overlap in two steps. First, we identify the commodities in the long legs of the carry and momentum strategies each month and compute the overlap (the maximum overlap is 5). Second, we compute the same quantity for the short legs of the strategies (the maximum overlap is 5). The plotted overlap is the sum of the overlaps of the long and short legs of the strategies. We report the mean, standard deviation, minimum, maximum, and the three quartiles (Q1, Q2, and Q3) of the overlap distribution. The carry factor entails taking a long position in the five commodities with the lowest $\ln(y_t)$ and a short position in the five commodities with the highest $\ln(y_t)$. The momentum factor entails taking a long position in the five commodities with the highest returns over the previous six months and a short position in the five commodities with the lowest returns over the previous six months. Our sample period is January 1970 to September 2011.

For example, live cattle and oats are the two commodities that appear the most in the long and short legs of the carry strategy. The table also shows that the carry and momentum strategies load on different commodities. For example, the live cattle commodity appears 191 times in the long leg of the carry factor and 70 times in the long leg of the momentum factor.

To additionally assess whether the two strategies are *conditionally* loading on the same set of commodities, we first compute the commodity overlap in the long and short legs of the carry and momentum strategies separately and then sum the two overlaps. The results, reported in Figure 3, indicate that the two strategies are largely decoupled, with the third quartile (Q3) of the overlap distribution equal to 1. Hence, our analysis suggests that the returns of the carry and momentum strategies arise from distinct sources.

7. Concluding Remarks

This paper studies commodity futures returns over the 42-year period ranging from 1970 to 2011. Using a set of baseline portfolios, managed portfolios, and individual commodities, our empirical estimates indicate that a three-factor model—driven by an average factor, a carry factor, and a momentum factor—outperforms the nested one- and two-factor counterparts in capturing the cross section of commodity returns.

Our analysis centers on providing an economic explanation of the commodity factors. The carry strategy performs poorly when global equity return volatility increases, and innovations in global equity volatility can price portfolios sorted on carry. The economic intuition is that investors dislike these adverse changes in the investment opportunity set and require positive average returns to carry as compensation.

Explaining commodity momentum is more challenging, as no traditional macroeconomic variable can satisfactorily explain the returns on such a strategy. We find, however, that the momentum strategy performs well when aggregate speculative activity increases, and innovations in aggregate speculative activity can price portfolios sorted on momentum. Because commodity speculators are known to follow momentum strategies, we interpret this finding as evidence that whenever more agents in the market behave as momentum traders, momentum strategies self-perpetuate: the commodities whose prices have been increasing continue to increase in price, while the commodities whose prices have been decreasing continue to decrease in price.

Three additional findings are worth emphasizing. First, innovations in global equity volatility cannot price momentum portfolios, and innovations in speculative activity cannot price carry portfolios. Second, our measure of speculative activity is specific to commodity markets and is unrelated to many proxies that capture the availability of arbitrage capital and liquidity constructed from the equity and bond markets. Finally, neither carry nor momentum portfolios can be priced by innovations in many other economic variables. This paper provides new insights regarding the sources of risk underlying the cross section of commodity returns.

Acknowledgments

An earlier version of this paper was circulated under the title "A Better Specified Asset Pricing Model to Explain the Time Series and Cross Section of Commodity Returns." Precursors of this paper were presented at the Federal Reserve Bank of New York, the University of Maryland, the National Bureau of Economic Research (NBER) 2013 conference on the economics of commodity markets, the Queen Mary University of London conference on advances in commodity markets, and the 2015 American Finance Association (AFA) meetings in Boston. The authors are particularly grateful for the feedback of Neng Wang (the department editor), the anonymous associate editor, and two referees for their help in improving the paper. The authors acknowledge helpful discussions with Tobias Adrian, Geert Bekaert, Hank Bessembinder (NBER discussant), Nina Boyarchenko, Fousseni Chabi-Yo, Peter Christoffersen, Richard Crump, Alex David, Rob Engle, Andreas Fuster, Steve Heston, Ravi Jagannathan, Mark Loewenstein, George Kapetanios, Leonid Kogan, Alex Kostakis, Pete Kyle, Anthony Lynch, Lars Lochstoer, Dilip Madan, George Panayotov, Anna Pavlova, Geert Roewenhorst, Nick Roussanov, Bryan Routledge, Lemma Senbet, Or Shachar, Ken Singleton, George Skiadopulos, George Skoulakis, Marta Szymanowska, and Anders Trolle (AFA discussant). The authors welcome comments, including references to related papers inadvertently overlooked. Any remaining errors are the authors' responsibility alone.

Endnotes

[1] The commodity literature has evolved considerably since Keynes (1930), Hicks (1939), Kaldor (1939), and Samuelson (1965). For a partial list of empirical treatments, we mention Chang (1985), Fama and French (1988), Bessembinder (1992, 1993), Bessembinder and Chan (1992), Deaton and Laroque (1992), de Roon et al. (2000), Erb and Harvey (2006), Gorton and Rouwenhorst (2006), Gorton et al. (2013), Miffre and Rallis (2007), Yang (2013), Szymanowska et al. (2014), and Chiang et al. (2015). These studies mainly focus on the economic nature of commodity risk premia and their statistical attributes. Complementing the empirical work, a strand of theoretical research has centered around characterizing the shape of the futures curve. Such studies include Hirshleifer (1988, 1990), Litzenberger and Rabinowitz (1995), Routledge et al. (2000), Carlson et al. (2007), Kogan et al. (2009), and Acharya et al. (2013). However, these contributions do not cater to the cross-sectional relations and are silent about the connections between the slope of the futures curves, average commodity returns, and returns of carry and momentum portfolios. The review articles by Till (2006) and Basu and Miffre (2013) provide a historical perspective.

[2] Some data limitations are addressed in the following manner. First, when there is a missing observation (e.g., palladium on a few occasions), we fill in the corresponding return from Bloomberg to maintain a complete time series. Second, if there is no recorded futures price for a commodity on the last business day of a given month, we use prices from the second-to-last business day. For example, because there is no trading record for crude oil, natural gas, gasoline, and heating oil on Monday, May 31, 2010, we employ prices from Friday, May 28, 2010.

[3] While our main results are computed using the full sample, for robustness we also rely on the Fama–MacBeth procedure estimated using a five-year rolling window. The results indicate that the risk premia of both the carry and momentum factors are stable over time. In particular, the 10th, 25th, 50th, 75th, and 90th percentiles of the carry (momentum) risk premia distribution are 0.0058, 0.0084, 0.0133, 0.0188, and 0.0250 (0.0013, 0.0067, 0.0135, 0.0190, and 0.0234), respectively.

[4] Motivated by Tang and Xiong (2013) and Henderson et al. (2015), we also study whether the financialization of commodities had an impact on the performance of the model. To address this issue, we compare model ability from 1970:07 to 2003:12 and 2004:01 to 2011:09 and obtain p-values of 0.15 and 0.24, respectively, for the χ^2_{NW} test of zero pricing errors. Our evidence of correct model pricing on both subsamples shows that the financialization of commodities does not affect model performance.

[5] We follow the standard implementation and set the tuning parameter η to the average standard deviation of the residuals from the first stage; we set d to 4 and use 10,000 bootstrap iterations to compute the p-values. We are grateful to Svetlana Bryzgalova for helping us with the implementation of her shrinkage estimator.

[6] We would like to thank Michael Weber for helping us with the implementation of the DR-CAPM model.

[7] In addition to the randomization based on the ticker symbol name, we conducted a Monte Carlo sample-splitting experiment. For each iteration, we randomly draw two subsamples of the commodities. We build factors on the first subsample and portfolios on the second subsample. We repeat the estimation 1,000 times. Pointing to the robustness of our results, the 10th, 25th, 50th, 75th, and 90th percentiles of the R^2 distribution across Monte Carlo simulations are equal to, respectively, 74%, 82%, 90%, 95%, and 97%.

[8] Refer to Section C of the Internet appendix for the construction of the factors.

[9] Additionally, we augment the composition of the test portfolios to include five portfolios that are sorted based on the volatility of commodity returns computed using daily returns over the past month, as in Menkhoff et al. (2012). The results, reported in Table Internet-IV of the Internet appendix, show that the three-factor model continues to perform well, while the two-factor models are rejected, according to both the χ^2_{NW} and χ^2_{SH} tests.

[10] The codes used for the implementation of Gagliardini et al. (2016) can be found at http://www.econometricsociety.org/publications/econometrica/issue-supplemental-materials/2016/05/ (accessed April 1, 2017).

[11] Yang (2013) finds that the carry factor is negatively and significantly related to investment shocks, which represent the technological progress in producing new capital. While the empirical implementation of the tests may seem similar, it is actually rather different. Our global equity volatility factor is able to explain the performance of the carry portfolios at the monthly frequency. By contrast, the investment shock factor explains portfolios sorted on carry at the annual frequency but not the monthly frequency. Yang (2013, p. 171) writes, "The excess returns of commodity futures portfolios are annualized first before regressions in order to smooth the seasonality of commodity prices."

[12] The results are similar when we price the carry portfolios with alternative commodity volatility specifications that exclude energy contracts—which tend to have a higher volatility—or that compute volatility using squared returns rather than absolute returns. Finally, we are unable to price the carry portfolios when we use the returns of the primitive trend-following strategy as a factor—that is, the commodity options-based lookback straddle of Fung and Hsieh (2001).

[13] The correlation between changes in G20 and G7 (U.S.) volatility equals 0.88 (0.74).

[14] We also considered an aggregated version of Working's T index, adapting the work of Büyükşahin and Robe (2014, p. 50) by equally weighting Working's T indices across all commodities in each month (see also Haase et al. 2014, section 4.1; Manera et al. 2013, equation (1)). When we use innovations in this measure of speculation to price the cross section of momentum portfolios, the risk premium is positive and significant, but the model is rejected with a p-value of 0.048.

[15] None of the correlations is statistically significant.

[16] We also assess whether a common set of factors prices both commodity and equity portfolios by replacing the three commodity factors with the four Fama–French equity factors. Our statistical tests reject correct model pricing, implying that the commodity and equity markets may be segmented (Daskalaki et al. 2014).

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