The Stock Market Price of Commodity Risk*

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ABSTRACT

We find that commodity risk is priced in the cross section of US stock returns. Following the Commodity Futures Modernization Act (CFMA) in 2000, investors can hedge commodity price risk directly in the futures market, primarily via commodity index investments, whereas before the CFMA they could gain commodity exposure mainly via the stock market. As a result, we find that the stock market price of commodity risk changes from -5.5% per year pre-CFMA to 8.5% per year post-CFMA. Both time-series and cross-sectional regressions show that the commodity risk premium is separate from the traditional market, small-minus-big, high-minus-low, and momentum factors.

JEL Classification Codes: G11, G12, G13

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Commodity prices are a risk factor that affects consumers, producers and investors alike. Before the passage of the Commodity Futures Modernization Act (CFMA) in December, 2000, (institutional) investors seeking commodity exposure mainly had to do so via (expensive) investments in physical commodities or via commodity-related equity investments. Until then, most investors faced position limits set by the Commodity Futures Trading Commission (CFTC) on traded futures contracts as well as swaps and other over-the-counter derivatives related to commodity futures. This is no longer the case after the CFMA, leading to a strong increase in institutional index investment in commodity futures markets from less than \$ 10 billion in 1998, to around \$ 15 billion in 2003, and to over \$ 210 billion at the end of 2009 (CFTC (2009)). The introduction of the CFMA therefore serves like a quasi-natural experiment that changes the behavior of investors.

This papers analyzes the effect of commodity risk on stock returns, as well as the effect of increased commodity index investment following the CFMA on the stock market. We find that commodity risk is priced in the cross section of stock returns, but in opposite ways before and after the CFMA. This reversal is consistent with investors first seeking commodity exposure in the stock market and subsequently in the commodity futures market. Sorting stocks according to their beta with respect to a broad index of 33 commodity futures, we find a cross-section of expected returns that cannot be explained by the traditional portfolio return-based asset pricing models.[1] Pre-CFMA, high commodity beta stocks underperform by about -8% in average returns, which translates into -11.5% to -8.5% in risk-adjusted returns. Post-CFMA, this performance reverses to around 11% in both average and risk-adjusted returns. The magnitude of these returns

[1] These are the CAPM (Sharpe (1964), Lintner (1965) and Mossin (1966)), the Fama-French three-factor model (Fama and French (1993)), and the Fama-French-Carhart model (Carhart (1997)).

is similar to other sorts reported in the literature, such as momentum (Jegadeesh and Titman (1993)).

A single commodity factor is shown to capture this spread, and cross-sectional regressions show that a unit exposure to the commodity factor results in a premium of -5.5% pre-CFMA and 8.5% post-CFMA. We find that the reversal in risk premium is largely driven by commodities with the largest open interest and trading volume (Energy, and Metals and Fibers), exists both between and within industries, and is most profound among big stocks. We also find it not to be related to inflation risk, or the recent reversal in the correlation between inflation and the stock market. Our results suggest that the commodity factor is an additional, separate source of risk, not subsumed by any of the traditional stock market factors.

We develop a model in the spirit of Hirshleifer (1988, 1989) that explains the reversal in the commodity risk premium and establishes an important link between stock and commodity futures markets. We model investors that maximize utility over the consumption of a basket of commodities and producers that maximize utility over income from these commodities, which they hedge in the futures market. When investors cannot hedge their commodity price risk in the futures market, but need to do so in the stock market, the hedge portfolio implies the observed negative hedging premium. When investors are able to hedge directly with a futures contract, the hedging premium in the stock market goes to zero if the contract is used exclusively for hedging. When the futures contract is attractive from an investment (or, speculative) point of view as well, our model indicates the observed reversal. We find plausible conditions for such a positive speculative investment to be optimal: the presence of sufficiently many producers relative to investors (speculators) in the futures market and producers that are sufficiently more risk averse than investors (as in Hirshleifer (1988, 1989)).

As discussed in Lewis (2007), the most common approach for institutional investors to gain commodity exposure has historically been via equity investments. However, with the emergence of commodity index-based products, these products have become the most popular route. Figure 1 illustrates this surge in commodity investments. The figure plots total open interest in 33 commodities over time (200312 = 100) in US$ (top) and the number of contracts outstanding (bottom). For both measures we see that open interest increases to record-high levels in each sector around 2003 without ever returning to historical levels. Indeed, according to Stoll and Whaley (2009), the total trading volume of US exchange-traded commodity futures has grown six fold from 0.6 to 3.5 billion contracts during the period from 1998 to 2008. Even more important for our analysis, the share of total open interest in the futures market that is attributable to institutional index investment has grown from around 6% in 1998 to around 40% in 2009, representing dollar values of \$ 10 billion to \$ 210 billion respectively. In line with the conditions mentioned above we show that these index investments are well-accommodated by traditional hedgers in futures markets (see, among others, Stoll and Whaley (2009), Irwin and Sanders (2010) and Cheng et al. (2011)). Following related studies, such as Domanski and Heath (2007) and Tang and Xiong (2009), we use December 2003 as the effective breakpoint in our empirical work. This breakpoint assumes that the CFMA did not become fully effective immediately after 2000 and is consistent with structural break tests that indicate a break in the returns of commodity beta sorted portfolios after the introduction of the CFMA, between 2002 and 2004.

Our findings contribute to the literature on cross-sectional asset pricing and commodities. First of all, we introduce a new factor that helps to explain the cross-section of expected stock returns. Unlike many anomalies, such as size, book-to-market, net stock issues, accruals, momentum, asset growth, and profitability[2] that can be explained by the Fama and French's (1993) factors as well as Carhart's (1996) momentum factor, we introduce a new commodity risk-based factor that is priced after adjusting for these traditional factors. Similar to Chen et al. (2010), our results suggest that real factors matter in asset pricing. Furthermore, we find the commodity risk premium to be larger among big stocks, which sets our work apart from those on anomalies that are more pronounced among small, illiquid and financially distressed stocks (see Fama and French (2008) or Avramov et al. (2010)).

Also, we show that the commodity premium and its reversal show up using only the between-industry or only the within-industry variation in commodity betas. This finding indicates that within-industry variation, due to, for instance, corporate hedging practices, market power, or the place of a firm in the supply chain, is priced in addition to the pricing of between-industry variation due to differences in fundamental exposures to certain commodities. In fact, our regression-based measure of commodity risk essentially controls for the fact that some firms hedge (or unhedge) their exposures and therefore provides for a more natural measure of commodity risk than looking at SIC codes alone, as in Gorton and Rouwenhorst (2006).

Our second contribution is to establish an important link between stock markets and commodity (futures) markets. These markets were previously thought to be segmented, given that the traditional portfolio return-based stock market factors play a weak role, if any, in explaining the cross-section of commodity futures returns (see, e.g., Dusak (1973), Bessembinder (1992), Bessembinder and Chan (1992) and Erb and Harvey (2006)). We

[2] These cross-sectional patterns are documented in, among many others: Fama and French (1992) (size and book-to-market); Loughran and Ritter (1995) (net stock issues); Sloan (1996) (accruals); Jegadeesh and Titman (1993) (momentum); Fairfield et al. (2003) (asset growth); and Haugen and Baker (1996) (profitability).

show that, conversely, commodity risk does play a role in explaining the cross section of stock returns. Our results imply that the two markets are linked due to investor's need to hedge commodity risk pre-CFMA and, in addition, their speculative demand in commodity futures markets post-CFMA. Thus, our findings are also an important addition to papers that investigate the financialization of commodity futures markets (see, e.g., Tang and Xiong (2009), Irwin and Sanders (2010), Stoll and Whaley (2009), Buyuksahin et al. (2010), Buyuksahin and Robe (2010) and Cheng et al. (2011)).

In the next two sections we introduce our model that links commodity, stock, and futures markets and describe the change in institutional background around the introduction of the CFMA. Section III elaborates on the data and method. Section IV presents returns along the cross-section of commodity exposures. In Section V we analyze industry effects and the relation between inflation and commodity risk premium, while Section VI asks whether a commodity factor is priced next to traditional risk factors. Section VII summarizes and concludes.

I Theoretical framework

We start out by developing a model that links commodity spot and futures markets to the stock market. Here, changing participation in the futures market implies a reversal in the commodity risk premium in the stock market. Our model uses a standard two-date mean-variance framework in the spirit of Hirshleifer (1988, 1989) and Bessembinder and Lemmon (2002). An important difference with these papers is that we do not model the stock market as one security, rather we model it as consisting of multiple stocks, thereby allowing for a price of commodity risk in the cross-section of stock returns.

A Economic setting

There are three markets: a spot commodity market, a stock market and a commodity futures market. There are three types of agents: N_P commodity Producers, N_C pure Consumers and N_I Investors that are also consumers. Initially, the Investors invest only in the stock market. Later, we introduce a futures market. Both Producers and Consumers defer from investing in the stock market, for instance, because of explicit charges or the costs of becoming informed.[3] A similar cost also prevents pure Consumers, but not Producers, from participating in the futures market. Producers maximize a mean-variance utility function over income, Investors over end-of-period consumption. There is no expected utility maximization for the pure Consumers, as they trade only in the spot commodity market at the end of the period.

B The spot commodity market

The N_P Producers each produce n units of the commodity, which are available at $t+1$. The commodity can either be a single commodity or a basket of commodities, that is, an index. Consumers and Investors jointly have a stochastic aggregate demand function for the commodity, $D_{C+I}(S_{t+1})$, that is a function of the spot price of the commodity S_{t+1} at $t+1$.[4] The equilibrium spot price results from equating demand and supply,

$$S_{t+1} = D_{C+I}^{-1}(nN_P). \tag{1}$$

[3] See, e.g., Hirshleifer (1988) for a detailed analysis of trading costs that limit the participation in a financial market. For the sake of simplicity, we keep the number of non-participating Consumers in the stock market exogenous.

[4] The presence of pure Consumers ensures that S_{t+1} is not perfectly correlated with the end-of-period wealth of Investors.

Thus, all randomness is contained in S_{t+1} and in this setting results from demand shocks only.[5] Hirshleifer (1989) studies the case where n is also random and where the demand and supply function of Consumers and Producers jointly determine S_{t+1}. For our purposes, we keep the commodity market as simple as possible and treat S_{t+1} as exogenous. For later use, we define $R_{S,t+1} = S_{t+1}/S_t - 1$ as the commodity return.

C The stock market

At time t, Investors invest their endowed wealth W_t in a riskfree asset (with return $R_{f,t}$) and K risky stocks (with excess returns $r_{i,t+1} = R_{i,t+1} - R_{f,t}$). The K-vector of expected excess returns is denoted as $\mu_r = E[r_{t+1}]$ and the $K \times K$ covariance matrix as $\Sigma_{rr} = Var[r_{t+1}]$. The K-vector of covariances of the stocks with the commodity returns is denoted as Σ_{rS} and the variance of the commodity returns is denoted as σ_{SS}. At time $t+1$, Investors consume their random wealth. Risk aversion is homogenous for the investors and equals γ_I.[6] Thus, Investors maximize mean-variance utility over consumption in units of the commodity (basket) by choosing w_r, the K-vector of the portfolio weights for the stocks, such that,

$$\max_{w_r} \; E[C_{t+1}] - \frac{\gamma_I}{2} Var[C_{t+1}], \text{ where} \tag{2}$$

$$C_{t+1} = \frac{W_{t+1}}{S_{t+1}} \text{ and } W_{t+1} = W_t(1 + R_{f,t} + w_r' r_{t+1}). \tag{3}$$

[5] Postulating a given demand function is standard in partial equilibrium models. For instance, a commonly used function is $D_{C+I} = (N_C + N_I)\,\delta\,(S_{t+1})^{\eta}$ with $\eta < 0$ the price elasticity of demand and δ a stochastic demand shock. Equating this aggregate demand to nN_P, gives $S_{t+1} = \left(\frac{N_P}{N_C+N_I}\frac{n}{\delta}\right)^{1/\eta}$.

[6] Alternatively, one can interpret γ_I as the wealth-weighted risk aversion.

Appendix A.1 shows that this problem can be approximated as

$$\max_{w_r} \; w_r'\mu_r - q_0 w_r'\Sigma_{rS} - 0.5\gamma_I \left(w_r'\Sigma_{rr}w_r - 2q_1 w_r'\Sigma_{rS} + q_1^2\sigma_{SS} \right), \tag{4}$$

where $q_0 = 1/\left(1+\overline{R}_S\right)$ and $q_1 = \left(1+R_{f,t}\right)/\left(1+\overline{R}_S\right)$ are linearization coefficients, with $\overline{R}_S$ equal to the mean of $R_{S,t+1}$. This optimization gives familiar first-order conditions

$$\mu_r = \gamma_I \Sigma_{rr} w_r - \widetilde{\gamma}_I \Sigma_{rS}, \tag{5}$$

with $\widetilde{\gamma}_I = (\gamma_I q_1 - q_0)$, a pseudo risk aversion defined in terms of γ_I and the linearization coefficients. Rearranging, the optimal portfolio is written as

$$w_r = \gamma_I^{-1}\Sigma_{rr}^{-1}\mu_r + \frac{\widetilde{\gamma}_I}{\gamma_I}\Sigma_{rr}^{-1}\Sigma_{rS}, \tag{6}$$

and combines a standard speculative demand (the tangency portfolio) with a minimum-variance hedge demand, as in the Intertemporal-CAPM of Merton (1973) and Anderson and Danthine (1981), for instance. Because all investors are exposed to commodity risk in the same way, the optimal portfolio in equation (6) is also the market portfolio w_m. Then, for each asset i, equation (5) implies

$$E\left[r_{i,t+1}\right] = \gamma_I Cov\left[r_{i,t+1}, r_{m,t+1}\right] - \widetilde{\gamma}_I Cov\left[r_{i,t+1}, R_{S,t+1}\right], \tag{7}$$

so that equilibrium expected returns are determined by an asset's covariance with the market portfolio ($r_{m,t+1}$, as in the CAPM) and the commodity return. Here, agents accept lower expected returns (or, pay higher prices) for stocks that co-move with the commodity, because these stocks are good hedges.

As in Fama (1996) and shown in Appendix A.2, this two-factor asset pricing model can be equivalently written in beta-form,

$$E(r_{i,t+1}) = \beta_{i,m} E(r_{m,t+1}) + \beta_{i,h} E(r_{h,t+1}), \tag{8}$$

where $E(r_{h,t+1}) < 0$ is the expected return on a hedge portfolio that is long (short) high (low) commodity beta stocks.

D The introduction of a futures market

We now introduce a futures contract for the commodity (basket). The return on the futures contract is denoted as $r_{F,t+1} = S_{t+1}/F_t - 1$, which we assume is perfectly correlated with the commodity return.[7]

Also, for simplicity, we assume that the two variances are equal, $\sigma_{FF} = \sigma_{SS} = \sigma_{FS}$. Use μ as the $(K+1)$-vector of the expected excess returns on the expanded set of assets $(r_{F,t+1}, r'_{t+1})'$, Σ as the corresponding covariance matrix, and Σ_S as the $(K+1)$-vector of covariances with the commodity return.

Using the same approximation of the utility problem as before, but solving for the extended vector of optimal weights $w = (w_F, w'_r)'$, Appendix A.3 shows that the optimal portfolio again combines a standard speculative demand with a minimum-variance hedge demand,

$$w = \gamma_I^{-1} \Sigma^{-1} \mu + \frac{\widetilde{\gamma}_I}{\gamma_I} \Sigma^{-1} \Sigma_S. \tag{9}$$

[7] This perfect correlation is true conditionally. Further, we only need a perfect correlation for expositional purposes: the hedge demand will tilt towards the futures contract as long as it is a better hedge, such that similar implications hold.

Using the above assumptions, the partitioned inverse of Σ, and the auxiliary regression

$$\begin{aligned} r_{F,t+1} &= a + br_{t+1} + e_{t+1}, \text{ with} \\ \sigma_{ee} &= Var(e_{t+1}), \end{aligned} \tag{10}$$

we can write the composition of the two demands in equation (9) as

$$w = \begin{pmatrix} w_F \\ w_r \end{pmatrix} = \begin{pmatrix} w_{F,spec} \\ \gamma_I^{-1}\Sigma_{rr}^{-1}\mu_r - \Sigma_{rr}^{-1}\Sigma_{rS}w_{F,spec} \end{pmatrix} + \begin{pmatrix} \frac{\widetilde{\gamma}_I}{\gamma_I} \\ 0_K \end{pmatrix}, \text{ with} \tag{11}$$

$$w_{F,spec} = \gamma_I^{-1}\sigma_{ee}^{-1}a \tag{12}$$

The individual components of this demand have a natural interpretation. First, the hedge demand, $(\widetilde{\gamma}_I/\gamma_I, 0_K')'$, focuses completely on the futures contract, because $r_{F,t+1}$ is perfectly correlated with the commodity return $R_{S,t+1}$. Second, Investors want an additional investment in the futures contract, $w_{F,spec}$, that is a standard speculative demand given that the futures contract is hedged with the stocks using equation (10). Third, the optimal demand for stocks, w_r, adjusts the tangency portfolio with a minimum-variance hedge demand for $w_{F,spec}$. Comparing equation (11) to equation (6), we see that the hedge demand for stocks switches sign if in equation (10) $a > 0$ (or equivalently if $w_{F,spec} > 0$). Indeed, if Investors seek additional commodity exposure (beyond a hedge demand) in the futures market, they will hedge this exposure in the stock market in order to reap the positive excess return a.

Now, we can rewrite the portfolio choices in equation (11) to the asset pricing model

$$E\left[r_{i,t+1}\right] = \gamma_I Cov\left[r_{i,t+1}, r_{m,t+1}\right] + \gamma_I w_{F,spec} Cov\left[r_{i,t+1}, R_{S,t+1}\right], \tag{13}$$

where we see that the commodity risk premium switches sign if $a > 0$ (and thus $w_{F,spec} > 0$). Alternatively, in the two-factor beta asset pricing model given in equation (8), $a > 0$ implies that the expected return of the hedge portfolio is positive. However, the hedge portfolio is defined over $\Sigma_{rr}^{-1}\Sigma_{rS}$ as before.

Futures market clearing and the speculative demand for futures

An important question is whether or not $a > 0$, as this is needed for a reversal of the commodity risk premium in the stock market. Let us assume there is only one commodity or that each Producer produces the complete basket. Also, the Producers maximize a mean-variance utility function over income from output (nS_{t+1}), which is hedged by investing in h futures contracts. The optimal hedge demand h then follows from

$$\max_h \; E\left[Y_{t+1}\right] - \frac{\gamma_P}{2} Var\left[Y_{t+1}\right] \tag{14}$$

$$Y_{t+1} = nS_{t+1} + h\left(S_{t+1} - F_t\right),$$

which (conditional on current spot prices) is equivalent to maximizing the mean-variance function over Y_{t+1}/S_t, or

$$\max_h \; n\mu_S + h\mu_F \frac{F_t}{S_t} - \frac{\gamma_P}{2}(n^2\sigma_{SS} + h^2\sigma_{FF}\frac{F_t^2}{S_t^2} + 2nh\sigma_{FS}\frac{F_t}{S_t}). \tag{15}$$

The FOC's imply that the optimal demand for futures again separate a speculative demand and a hedge demand,

$$h = (\gamma_P^{-1}\frac{\mu_F}{\sigma_{FF}} - n)\frac{S_t}{F_t}. \tag{16}$$

Assuming, for simplicity, that $W_t = 1$, $Y_t = 1$, and $n = 1$ so that the total wealth of Producers and Investors is measured by N_P and N_I, we can write the futures market clearing condition as

$$N_I w_F = -N_P h. \tag{17}$$

Appendix A.4 shows that in equilibrium

$$\frac{a}{\gamma_I \sigma_{ee}} = w_{F,spec} = \left(\frac{N_P}{N_I} \frac{S_t}{F_t} - \frac{\widetilde{\gamma}_I}{\gamma_I} \right) - \frac{N_P}{N_I} \frac{\mu_F}{\gamma_P \sigma_{FF}} \frac{S_t}{F_t}. \tag{18}$$

The first term on the right-hand side of equation (18) reflects the traditional hedging pressure: a short hedging pressure resulting from the hedge demand by Producers and a long hedging pressure resulting from the hedge demand by Investors that want to hedge their consumption. The second term on the right-hand side reflects the speculative demand of Producers. This equation states that $a > 0$ if the hedging pressure of Producers exceeds that of Investors and if this net hedging pressure is not offset by the speculative demand of Producers. Hence, there must be sufficiently many Producers relative to Investors. Producers also must be sufficiently risk averse in order for their speculative demand to be small in equilibrium.

II Institutional setting

For the model to explain the observed reversal in the commodity risk premium, a structural break must have occurred in the investment practices of a large group of agents (Investors). We argue that this break actually occurred following the passage of the Commodity Futures Modernization Act (CFMA) on December 21, 2000. The act allowed institutional investors (insurance companies, pension funds, foundations and hedge funds e.g.) and wealthy individuals to take large positions in commodity futures and other commodity derivatives, whereas before 2000 most of them faced narrow position limits imposed by the Commodity Futures Trading Commission (CFTC) to prevent "excessive speculation".

In terms of our model, this means that Investors could not hedge their commodity risk in the futures market historically, but had to resort to hedging in the stock market or to directly investing in physical commodities, which is expensive (Lewis (2007)). After the CFMA, Investors can get the desired commodity exposure via the futures market and other commodity derivatives markets. As a result, commodity index investment by such investors in over-the-counter swap agreements, exchange-traded funds (ETF), exchange-traded notes (ETN), and managed funds, benchmarked to well-diversified and transparent indices like the SP-GSCI and DJ-UBSCI, jumped from $ 15 billion in 2003 to over $ 210 billion at the end of 2009 (CFTC (2009) and Muo (2010)). These numbers underestimate the true investments in commodities, because the exchange-traded market still represents less than 10% of the total market for commodity derivatives (Etula (2010)).

Following the CFMA, the demand for diversified commodity investments increased sharply, when the equity market collapse and the widely publicized findings of Greer (2000), Gorton and Rouwenhorst (2006), and Erb and Harvey (2006) suggested that commodity futures are an attractive asset class for the prudent investor. First, historical returns on broad commodity indexes are similar to stocks in risk and return. Second, correlations between commodities and traditional asset classes are small and sometimes negative, largely due to different behavior over the business cycle. Third, commodities are useful as a hedge against inflation, unexpected inflation and changes in expected inflation (see, e.g., Bodie (1983), Gorton and Rouwenhorst (2006) and Bekaert and Wang (2010)).

In line with, among others, Domanski and Heath (2007) and Tang and Xiong (2009), we use the observable change in total open interest seen in Figure 1 to motivate splitting our sample at December 31, 2003. We refer to the period before December 31, 2003 as "pre-CFMA" and the period thereafter as "post-CFMA". Below we show that our results are not sensitive to the exact breakpoint, and our tests suggest the existence of a structural break in the returns of commodity beta-sorted portfolios after the introduction of the CFMA, between 2002 and 2004.

In the context of our model, this structural break means that there exists a negative hedging premium pre-CFMA, when institutional investors hedge their commodity risk in the stock market. Post-CFMA, commodity futures represent a considerable fraction of many, large institutional investors' portfolios. If these positions solely reflect a hedge demand, the hedging premium will go to zero. However, to the extent that a significant fraction of these positions reflect a speculative demand, $w_{F,spec} > 0$, the subsequent incentive to hedge this demand in the stock market will induce a reversal in the stock market price of commodity risk.

Although, a positive speculative demand makes historical sense, it is hard to justify a positive speculative investment if the influx of index investor capital drives up prices too much. Results from Irwin and Sanders (2010), Stoll and Whaley (2009), and Buyuksahin and Robe (2010) question this price impact. Moreover, the conditions for $w_{F,spec} > 0$ (i.e., sufficiently more Producers and sufficiently risk-averse Producers) are fairly mild and do not seem to be violated post-CFMA.

To illustrate this, Figure 2 shows that commercial hedger's (net) short positions are sufficient to cover non-commercial speculator's (net) long positions, using data from the CFTC Commitment of Traders Report from January 1986 to December 2010. To be precise, Panel A demonstrates that the OIW average net short position of hedgers has historically been larger than the OIW average net long position of speculators, whereas the difference is decreasing steadily since 1986. Further, Panel B demonstrates that the total short position of hedgers has always been larger than the total long position of speculators, although this difference is decreasing since 2000.

We recognize that these results are perhaps biased, as the CFTC's historical classification rules are outdated. However, using more detailed daily data from the CFTC's Large Trader Reporting System, Cheng et al. (2011) arrive at a similar conclusion. For the average commodity, traditional hedgers' short positions increase in lockstep with index investors' long positions over the last decade.

III Empirical framework

A Commodity futures data

We construct an index of commodity futures to represent the futures contract modeled in Section I. We collect data on prices and open interest of 33 exchange-traded, liquid commodities from the Commodity Research Bureau (CRB), supplemented with data from the Futures Industry Institute (FII). A detailed overview of the sample is given in Table I. The commodities are divided into four broad sectors: Energy, Agriculture, Metals and Fibers, and Livestock and Meats.[8]

Table I about here.

We calculate futures returns by using a roll-over strategy of first and second nearest-to-maturity contracts. First, we focus on contracts that are relatively close to maturity because these are typically the most liquid. Second, this strategy is similar to the construction of commercial indexes, like the SP-GSCI and the DJ-UBSCI. We roll out of the first nearest contract and into the second nearest contract at the end of the month before

[8] For instance, Hong and Yogo (2012) use a similar partitioning.

the month prior to maturity. In this way, we guard against the possible confounding impact of erratic price and volume behavior commonly observed close to maturity.[9] For Energy commodities we have contracts maturing in all months of the year; for most other commodities we have between four and eight delivery months available. For all contracts except Sugar and Pork Bellies, the delivery months are never more than three months apart.

To be precise, we calculate uncollateralized futures returns in month t, as

$$R_t = \frac{F_{t,T}}{F_{t-1,T}} - 1, \tag{19}$$

where $F_{t,T}$ is the futures price at the end of month t of the nearest contract whose expiration date T is after the end of month $t+1$. These uncollateralized futures returns are comparable with excess returns on stocks and are made up of both the spot return and the roll return.

Table I reports average returns, standard deviations (both in annualized percentages) and median total open interest (TOI) in US\$ for each individual contract.[10] Historically, the Energy sector has contained the largest commodities and the Livestock and Meats sector the smallest in open interest and trading volume. Throughout, we focus on an open interest-weighted total index (OIW) that aggregates all 33 commodities, and which, similar to value-weighted stock indices or production-weighted commercial commodity indices, weights month t commodity returns according to TOI at the end of month $t-1$. We show that the main results are robust for an equal weighted total index (EW) and

[9] This erratic behavior might be partly caused by the commonality in index investors' roll-over strategies. By rolling over approximately one to two weeks before most commercial indices do, our index is not affected by their short-term market impact (see, e.g., Muo (2010)).

[10] TOI is defined as the sum of the open interest of all outstanding contracts (i.e., contracts with different maturities) for a specific commodity, multiplied by the first-nearest futures price.

present additional robustness checks for OIW sector indexes and the SP-GSCI Excess Return Index in the Internet Appendix.

B Estimating commodity exposures

To find out whether commodity prices are a relevant risk factor, we apply the Fama and French (1992, 1993, 1996) portfolio approach. We sort both individual stocks (that is, all ordinary common shares traded on NYSE, AMEX and NASDAQ excluding financial firms) and 48 industry portfolios on their beta with respect to the OIW commodity index.[11]

At the end of each month $t-1$, we re-estimate the commodity beta for stock (or industry) i, $\beta_{i,t-1}$, over a 60-month rolling window using

$$R_{i,s} - R_{f,s} = \alpha_{i,t-1} + \beta_{i,t-1} R_{oiw,s} + \varepsilon_{i,s}, \text{ for } s = t-60, ..., t-1, \tag{20}$$

where we require that at least three out of the last five years of returns are available. We apply equation (20) from January 1975 onwards to ensure that the OIW total index consists of at least 20 commodities, such that it can be reasonably expected to mimic the important macroeconomic impact that commodities have.[12] As a result, the sample of post-ranking portfolio returns spans from January 1980 to December 2010. To allow for the hypothesized reversal, we split the sample at December 2003, which adds up to 288 months in the pre-CFMA period and 84 months in the post-CFMA period.

First, we construct 25 market value-weighted stock portfolios based from an independent sort in five commodity beta groups and five size groups. We also consider results

[11] The 48 industry portfolios are sourced from Kenneth French's Web site.

[12] This number corresponds to the number of commodities in well-know commercial indexes.

for a one-dimensional sort on commodity beta in five value-weighted stock portfolios.[13] Second, a one-dimensional between-industry sort constructs five industry portfolios from the 48 industries, equally weighting nine or ten industries in each portfolio.

C Benchmarking

We apply the time-series regression approach of Black et al. (1972) to analyze average and risk-adjusted post-ranking returns of the portfolios introduced above as well as the High minus Low commodity beta (HLCB) spreading portfolios constructed therefrom. To this end, we use the Fama-French-Carhart factors (MKT, SMB, HML and MOM, available from Kenneth French's Web site) to benchmark against the CAPM of Sharpe (1964), Lintner (1965) and Mossin (1966), the three-factor model of Fama and French (1993, denoted as FF3M), and the four-factor model of Carhart (1997, denoted as FFCM).

In a robustness check, we also estimate commodity betas using

$$R_{i,s} - R_{f,s} = \alpha_{i,t-1} + \beta_{i,t-1} R_{oiw,s} + \gamma'_{i,t-1} F_s + \varepsilon_{i,s}, \text{ for } s = t-60, ..., t-1, \qquad (21)$$

where F_s contains either the CAPM, FF3M or FFCM factors. This method ensures that $\beta_{i,t-1}$ captures an asset's comovement with the commodity index that is distinct from its comovement with the benchmark factors,

IV The cross-section of commodity exposures

We start out by documenting the main implications of the model outlined in Section I, that is the pricing of commodity risk in the stock market and a reversal in this price

[13] Throughout, we present this one-dimensional sort also for the EW commodity index.

post-CFMA.

A Basic sorting results

Table II presents summary characteristics for the portfolios of interest over the full sample, i.e., average returns and standard deviations (in annualized %'s) as well as pre- and post-ranking betas, which serve to verify the validity of our sorting procedure. We are particularly interested in the high minus low commodity beta (HLCB) spreading portfolios, presented in each sixth row.

Table *II* about here.

First, stocks and industries with high commodity betas underperform consistently, but the performance differential of -3.55% (-1.82%) for the one-dimensional sort of stocks using the OIW commodity index (EW commodity index) is small and insignificant. Thus, unconditionally, a commodity risk premium is absent over the entire sample period.

Nevertheless, portfolio standard deviations increase almost monotonically in commodity beta in both subperiods, which suggests that commodity beta captures an exposure to risk that is systematic. In accordance with this suggestion, we find that stocks and industries show a wide spectrum of exposures, given pre-ranking betas for the one-dimensional sorts ranging from -0.54 to 0.73 and -0.23 to 0.41 for the OIW commodity index. These betas are useful predictors of post-ranking betas, which line up monotonically. The resulting HLCB portfolio beta for the one-dimensional sort of stocks and industries is economically large and significant at 0.51 and 0.43 ($t > 8.0$), respectively, which translates to an increase in monthly return of about 2.5% whenever the OIW commodity index increases by one standard deviation.

Our main results are presented in Table III. Here, we analyze whether a commodity risk premium is present when conditioning on the pre- and post-CFMA period, in line with the hypothesized reversal. We present average and risk-adjusted returns (α's) for the two sub-periods of interest in Panel A and Panel B, respectively. Each block in these panels corresponds to a specific benchmark (average return or CAPM, FF3M and FFCM α's) and presents estimates (left) and corresponding heteroskedasticity-consistent t-statistics (right). Further, Panel C tests the difference for the HLCB spreading portfolios between the two sub-periods. Panel D tests similar differences, but allows the breakpoint to vary from December 2000, directly after the introduction of the CFMA, to December 2005.

Table III about here.

In average returns, stocks and industries with high commodity betas underperform consistently pre-CFMA. The HLCB spread is economically large and statistically significant at -8.11% for the one-dimensional sort of stocks and at -4.72% for industries.[14] This pattern reverses completely post-CFMA, when high commodity beta stocks outperform consistently. Again, the HLCB spread is economically large and statistically significant at 12.08% for the one-dimensional sort of stocks and at 12.22% for industries. The results in Panel C show that the pre- and post-CFMA difference in the HLCB returns of around 20% for individual stocks and 17% for industries is highly significant, whereas the difference in returns over the two-subperiods increases monotonically with commodity beta.

Next, we see that the previously documented performance-beta relation and its re-

[14] We find Construction, Steel Works (etc.), Petroleum and Natural Gas, Precious Metals, Mining, Coal and Machinery among the industries with consistently high commodity betas and Retail, Insurance and Consumer Goods among the industries with consistently low commodity betas.

versal easily survive when controlling for the usual risk factors. Pre-CFMA, the HLCB spread actually widens to large and significant CAPM, FF3M and FFCM alphas of -10.54%, -8.61% and -11.66%, respectively, for the one-dimensional sort of stocks and -5.85%, -5.73% and -6.87%, respectively, for industries. Post-CFMA, only about 2% of the HLCB spread is captured by the MKT factor, leaving HLCB α's that are over 10% for both stocks and industries. Panel C summarizes this evidence and shows that the difference in the two commodity risk premiums adds up to an economically large and highly significant difference of about 20% (17%) for stocks (industries). Highlighting the importance of controlling for size, we find that the performance-beta relation is strongest, adding up to the largest performance differential, among the bigger stocks in both sub-periods.

These conclusions easily extend for the one-dimensional sort on the EW commodity index, where performance differentials in both means and risk-adjusted returns follow the same patterns and are only slightly smaller, adding up to a similar reversal that is large and significant at 13.58% in average returns and over 12% in risk-adjusted returns. This shows that the documented reversal in risk premium is not driven by changing shares of open interest of the commodities within our index.

A.1 Exploring the structural break

Our analysis sofar sets the structural break for the pre- and post-CFMA period at December 2003. To test the sensitivity of our results for the exact breakpoint, Panel D of Table III reports the HLCB reversal for different breakpoints from December 2000 until December 2005. A breakpoint at December 2000 would imply the effects of the CFMA to be effective immediately after its passage, whereas the subsequent breakpoints allow the effects to materialize more gradually over time. Panel D reports both average returns and FFCM alphas.

For all breakpoints, the one-dimensional sort for stocks and industries results in a reversal between 13% and 23% in average and risk-adjusted returns, which is always statistically significant. Thus, our results are not sensitive to the exact dating of the breakpoint. Moving from 2000 to 2005, we see an inverted U-shape. For individual stocks, the largest difference in average returns is obtained when we split the sample in December 2002 (20.69%), whereas the largest difference in FFCM α is obtained when we split in December 2004 (23.00%). For industries, both spreads are largest when we split in December 2002. These results suggest that the structural break occurs between December 2002 and 2004, giving support to choosing December 2003 as the breakpoint, as in Domanski and Heath (2007) and Tang and Xiong (2009).

A related issue is whether the composition of these portfolios is stable following the CFMA. To this end, Table IV presents the time-series average of the diagonal elements of Markov switching matrices for the five stock portfolios sorted one-dimensionally on commodity beta for each of the five-year subperiods in our sample. For instance, in the first column, we see that on a month-to-month basis, 95% (93%) of the stocks in the High (Low) beta portfolio do not switch. The different columns demonstrate that the average percentage of stocks that do not switch portfolios varies between 82% and 89% in the different subperiods. Further, the unreported full Markov matrices show that stocks hardly ever move more than one portfolio at a time in any given subperiods. Importantly, there is no substantial drop in this percentage in the subperiod 2001-2005, when the effects of the CFMA should be most apparent. On the contrary, we observe a relatively high percentage of 89%, suggesting that the portfolios are stable.

Table IV about here.

In short, the stability post-CFMA indicates that the documented reversal is not driven by changing covariances. Rather, in line with our model, the reversal is driven by changing average returns. To further substantiate this finding, we fix the portfolio composition to what it is in December 2003 and compare the resulting HLCB portfolio to the HLCB portfolio that updates its weights every month in Panel B of Table IV. First, we see that the returns of the two strategies are highly correlated post-CFMA. For the one-dimensional sort of stocks (for the industry sort), the correlation between the two HLCB portfolios equals 90% (92%) from January 2004 until the onset of the crisis in June 2007, and 0.66 (0.57) until December 2010. Second, we also observe a similar reversal in the risk premiums.

B Robustness checks

In the Internet Appendix, we show that our results are robust in a number of dimensions. First, we find similar reversals in average and risk-adjusted returns when we estimate commodity betas while controlling for the benchmark factors in each rolling window, as in equation (21). Thus, commodity exposures capture a risk factor that is separate from the traditional risk factors.

Second, we obtain similar spreads for the (production-weighted) SP-GSCI commodity index and when excluding individual commodities that are important for reasons other than consumption, such as gold. Moreover, we observe economically meaningful reversals for sorts on an Energy and a Metals and Fibers index, consistent with the relatively large proportion of index investment flowing into these sectors post-CFMA. For the Energy index, the HLCB spread is relatively small pre-CFMA at -4%, but our main result is replicated post-CFMA, when high Energy beta stocks outperform by about 13.5%. Sorting on exposures to a Metals and Fibers index gives HLCB spreads of -6% pre-CFMA and 6% post-CFMA. Note, however, these returns are not a mirror image of the returns on the sector indexes themselves, which are -2% for Energy and 16% for Metals and Fibers post-CFMA.

Finally, given that both commodity beta and size are persistent, transaction costs are unlikely to subsume the spreads. Indeed, we find similar results when rebalancing only once a year and when varying the length of the rolling window from two to ten years. Also, our results are not driven by the recent financial crisis, as excluding it actually strengthens our result.

V Industry effects and inflation

We next focus on alternative sorts to further explore the commodity risk within industries and analyze whether our results are driven by inflation.

A Within-industry effects

The robustness of our main results for a one-dimensional sort of industries suggests that the reversal in the commodity risk premium can be captured using only between-industry variation in commodity betas. This subsection demonstrates that the reversal can also be captured using only within-industry variation. To this end we construct five market value-weighted stock portfolios within each industry by splitting at the quintiles of ranked commodity betas within that industry. Here, we exclude four financial industries and in each month $t-1$ industries that contain fewer than ten stocks.

Table V presents average returns and FFCM alphas for the within-industry sort in a similar vein as Table III.[15] In each block, the first five rows and columns present results for portfolios that equally weight the within-industry portfolios (i.e., within-industry group High, 2, 3, 4 or Low, where High consists of stocks whose beta is high relative to other stocks in the industry) of typically seven or eight industries that fall into the relevant group of the between-industry sort (i.e., between-industry group High, 2, 3, 4 or Low). The sixth column presents the average within-industry effect, which is a portfolio that equal-weights five between-industry groups. The sixth row presents the HLCB within-industry portfolios.

Table V about here.

Panel A demonstrates that low commodity beta stocks underperform high commodity beta stocks pre-CFMA across the full spectrum of industry betas. In average returns, the underperformance within industries ranges from -6% to -3% per year, which adds up to a strictly monotonic commodity beta-return relation for the average within-industry portfolio and a significant HLCB spread of -4.35% ($t = -2.13$). These conclusions strengthen substantially in risk-adjusted returns. For instance, the FFCM alphas for the HLCB within-industry portfolios range from -9% to -4%, adding up to a large and significant FFCM alpha of -6.55% ($t = -3.40$) for the average within-industry portfolio.

In Panel B we demonstrate that the post-CFMA reversal is present across the full spectrum of industry betas, as well. The outperformance of high commodity beta stocks within each industry is monotonic and adds up to 11.69% ($t = 1.98$) for the average within-industry portfolio. This outperformance extends to risk adjusted returns with a FFCM alpha of 9.18% ($t = 2.14$). Further, in Panel C we show that this reversal is economically large and significant in four out of five between-industry groups.

[15] CAPM and FF3M alphas are similar but not presented to conserve space.

In summary, these within-industry effects suggest that variation in commodity beta within industries, perhaps due to differences in corporate hedging practices, market power or the place of a firm in the supply chain, is priced in a manner consistent with our hypothesis. This indicates that our findings are not merely picking up the fundamental commodity exposure of a given industry. Rather, there are important differences in firm exposures to commodity risk within industry, even when the industry at large is not exposed.

B Inflation

One natural question is whether sorting on commodity returns is tantamount to sorting on (unexpected) inflation and therefore whether the results are driven by the reversal in the correlation between inflation and the stock market after the turn of the century (see e.g., Bekaert and Wang (2010) and Campbell et al. (2011)). To verify that the commodity effect we document is separate, we consider sorts wherein we first orthogonalize stock returns from inflation effects. Thus, in each rolling window, we run two regressions to find $\beta_{i,t-1}$

$$\begin{aligned} R_{i,s} - R_{f,s} &= a_{i,t-1} + c_{i,t-1} I_s + e_{i,s} \\ e_{i,s} &= \alpha_{i,t-1} + \beta_{i,t-1} R_{oiw,s} + \varepsilon_{i,s}, \text{ for } s = t-60, ..., t-1, \end{aligned} \tag{22}$$

where I_s is either unexpected inflation (UI) or a mimicking portfolio of unexpected inflation (UIF), which addresses the concern that stock's exposures to non-traded factors typically economically small and hard to estimate. For the non-traded measure of inflation UI, we follow e.g., Erb and Harvey (2006) and Hong and Yogo (2012) and use the month t change in the annual inflation rate, i.e., $UI_t = \frac{CPI_t}{CPI_{t-12}} - \frac{CPI_{t-1}}{CPI_{t-13}}$, which assumes annual inflation is integrated of order one.[16] The inflation factor UIF is constructed using a three-by-two sort on betas with respect to UI and size, similar to Fama and French (1993).

In Table VI we present means and FFCM alphas for the usual one- and two-dimensional sorts on these inflation-controlled commodity betas for both sub-periods of interest in Panels A and B, and test the difference in Panel C. Note, the left block of results orthogonalizes returns from non-traded unexpected inflation UI, the right block from the traded unexpected inflation factor UI1F.

Table VI about here.

When controlling for UI, we see that both mean and risk-adjusted returns remain economically large and significant in both subperiods, adding up to a HLCB spread in average returns of -7.36% (-5.14%) for the one-dimensional sort on stocks (industries) in the first sub-period and 9.74% (10.12%) in the second sub-period. The performance differentials add up to a difference of around 15% for both stocks and industries in case of both the OIW and the EW index, which is very similar to what we found in Table *III*. Again, these performance differentials are typically significant, strengthen in risk-adjusted returns and are strongest among the biggest stocks.

This result may not come as a surprise, given that one may not expect the commodity beta to change much when stocks' exposures to non-traded inflation are small. Indeed, we find that commodity betas are by and large similar with and without UI. However, the right panel documents that the commodity risk premium easily extends when controlling

[16] Our results extend using three alternative measures of (unexpected) inflation used by others in the past: (i) the difference between the monthly inflation rate and the short-term t-bill rate; (ii) an ARIMA(0,1,1)-innovation extracted from the monthly inflation series; and, (iii) monthly inflation itself.

for UIF as well. Although in the first sub-period the HLCB spreads are slightly smaller, we see that they remain economically large and significant in risk-adjusted returns. Post-CFMA the HLCB spreads are very similar, adding up to a difference of over 14%, which is only slightly smaller than what we had before. Again, the commodity beta-return relation is typically quite monotonic and stronger among big stocks.

VI Commodity factor versus traditional factors

In this section, we study what the commodity factor adds to the benchmark factors in explaining the cross-section of expected returns.

A Sorting results when factor models include a commodity factor

Table VII presents results in a similar vein as Table III but using factor models that additionally include the commodity factor COM. Along the lines of the Fama and French portfolio approach, we add to each asset pricing model one factor derived from the cross-section of firms' commodity exposures. The commodity factor COM is constructed as follows. At the end of each month $t-1$, we sort all CRSP stocks independently into three commodity beta groups split at the 30th and 70th percentile of ranked values estimated using equation (20) and two size groups that are split at the NYSE median market value. Then, the factor that captures the common variation in returns related to commodity betas is the average of the portfolios "high beta, small" and "high beta, big" minus the average of the portfolios "low beta, small" and "low beta, big".

COM shares the reversal in returns (from -5.92% to 9.85%) and given that the post-ranking betas with respect to COM line up over the portfolios, the inclusion of COM improves the fit considerably in both subperiods. Even in a single-factor model, only including COM, the alpha for the HLCB spreading portfolio for the one-dimensional sort of stocks is as low as -0.17% ($t = -0.11$) pre-CFMA, and -0.33% ($t = -0.19$) post-CFMA. These economically small risk-adjusted returns extend to the other factor models, within each size quintile, for industries and also largely for the sort on the EW commodity index. In fact, in almost all cases, COM eradicates the monotonic performance-beta relation and captures the difference in HLCB returns over the two subperiods well.

Table VII about here.

On the other hand, in the first subperiod, the commodity factor in itself does not perform well in explaining the level of returns. This shortcoming is easily resolved by adding the market factor, as all but one stock portfolio show an alpha indistinguishable from zero in the two-factor model CAPMCOM. Importantly, CAPMCOM compares favorably even with four- and five-factor models that use the commodity factor alongside the FF3M and FFCM, respectively. In the second subperiod, COM does capture the level of returns on both individual stocks and industries and again we find that CAPMCOM performs relatively well.

In the Internet Appendix we show that this conclusion extends when we control for the benchmark factors in each rolling window. The consistent improvement in fit is important, because COM itself is constructed from commodity betas that do not control for any of the benchmark factors.

B Analyzing the commodity factor: spanning regressions

To ascertain that the commodity factor is an additional risk factor, we run standard spanning regressions and present these in Table VIII. Panel A first shows summary statistics for all factors across the two sub-samples. Pre-CFMA, COM shows a significant average return of -5.92%. Also, MKT, HML, and MOM are significant at 7.49%, 4.76% and 10.45%, respectively. Post-CFMA, the average returns on MOM and COM change dramatically to -1.52% and 9.85%, respectively. In fact, it is only COM that provides investors with a significant average return post-CFMA.

Table VIII about here.

Next, Panel A presents correlations from 1980 to 2003 on the lower-triangular and from 2004 to 2010 on the upper-triangular. First, the correlation between MKT and COM is relatively stable over time at 0.24 and 0.46, respectively. The correlation between COM and both HML and MOM switches sign in the recent period. Importantly, the correlations of both HML and MOM with MKT change significantly as well, which suggests that the changing correlations we observe are likely due to changes in HML and MOM rather than in COM.

Also, Panel A presents summary statistics for the OIW and EW commodity indexes. As expected, the correlation between OIW (EW) and COM is large and significant in both subperiods at 0.42 and 0.66 (0.36 and 0.67). However, we see that the average return on OIW is small in both subperiods at -0.96% and 1.88%, adding up to an insignificant reversal of 2.84%. For EW, the reversal of 6% is relatively small and insignificant as well. These findings rule out that the returns on COM are driven by the post-ranking returns of commodities (and the stocks that are particularly exposed or unexposed to them). Note, also, the positive average return in the post-CFMA period is consistent with a speculative demand by Investors for futures contracts.

In Panels B and C, the first set of spanning regressions serves to analyze whether COM is spanned by the benchmark asset pricing models. The second set tests whether COM might replace any of the benchmark factors by regressing SMB, HML, and MOM on the two-factor model that was found to perform well in previous tests (CAPMCOM), and a four-factor model containing all factors but the regressand.

In the first subperiod, spanning is strongly rejected for COM given significant $\alpha's$ for all the models, varying from -7.48% for the CAPM, to a slightly higher FF3M α of -5.66%, and an even lower FFCM α of -8.70%. From the second set of spanning regressions for SMB, HML and MOM, two results stand out. First, spanning is strongly rejected for HML and MOM, but only marginally for SMB. Second, the benchmark factors load significantly on COM.

In the second subperiod, spanning is again rejected in each model with significant CAPM, FF3M and FFCM α's of about 8.5%. In fact, it is only the MKT factor that captures about 1.5% of COM's outperformance. Furthermore, we see that spanning of SMB, HML and MOM is never rejected in either of the two- or four-factor models.

Overall these results show that the commodity factor COM is not spanned by the traditional factors MKT, SMB, HML, and MOM, nor are any of these factors substituted for by COM, at least in the pre-CFMA period.

C Estimating the commodity risk premium: cross-sectional regressions

We now proceed by running Fama and MacBeth (1973) cross-sectional regressions to estimate risk premiums directly from the set of 30 commodity beta-sorted portfolios (COMS30), being 25 stock portfolios sorted on size and commodity beta as well as 5 industry portfolios sorted on commodity beta alone. The cross-sectional regressions presented in Table IX do not include an intercept in order to increase efficiency.[17] We present risk premiums and Fama-MacBeth-Shanken-corrected t-statistics (Shanken (1992)) for the benchmark factor models as well as models that add COM. We also present two R^2's. R_s^2 is the standard cross-sectional adjusted R^2 from a regression of average returns on betas. R_p^2 is the adjusted R^2 from a regression of average returns on predicted average returns that, in this case, are the product of betas and risk premiums fixed at their time-series average.[18] As before, Panel A and B cover the pre-CFMA and post-CFMA period, respectively, while in Panel C we test the difference.

Table IX about here.

In the first column of Panel A we see that the market risk premium is positive and significant in all models at around 7% to 8%, but the cross-sectional fit of the CAPM is poor given negative R^2's. The FF3M shows an improvement, as HML is priced and R_s^2 equals 36%. The estimated risk premium for HML (10.64%) is far from its sample average

[17]Asset pricing theory dictates that this intercept is zero. Without the intercept, however, the R^2 is negative whenever the model misses the level of average returns. The Internet Appendix documents that our results are robust to including an intercept.

[18]Note, by construction $R_s^2 \geq R_p^2$. Moreover, we find that the slope in the regression we run for R_p^2 is always close to one for models that include COM, which implies that the second-stage pricing errors are similar to the first-stage α's. Note, we estimate multiple regression betas in the first stage, but our main conclusions extend when we estimate simple regression betas.

return (4.76%) though, which forces R_p^2 down to 9%. The FFCM is flawed in a similar way. In sum, the benchmark asset pricing models provide a poor fit for commodity beta sorted portfolios.

On the other hand, the addition of COM provides an unanimous improvement in cross-sectional fit. First, a unit exposure to COM is significant and is priced at -5.84% in the CAPMCOM, -5.76% in the FF3MCOM and -5.32% in the FFCMCOM. In all cases, the estimate is close to COM's average return of -5.92%. Second, in the CAPMCOM, both R^2s equal 68% up from -62% in the CAPM. Similarly, in the FF3MCOM, R_s^2 increases to 74% and R_p^2 to 69%, while the inclusion of COM eradicates the importance of HML. The addition of COM to the FFCM flips the risk premium on MOM to an insignificant, but economically meaningful, 8.95% and improves R_s^2 even further to 79%. However, in terms of R_p^2, FFCMCOM is not a meaningful improvement over either CAPMCOM or FF3MCOM at 70%.

Several similar results stand out in the post-CFMA period. First, none of the estimated risk premiums is significant in either the CAPM, FF3M or FFCM. This insignificance is partly due to the small number of observations (84 months) relative to the number of portfolios (30). If anything, the CAPM is relatively useful in explaining average returns, because the market risk premium is economically large at 7.11% and the R^2's equal 40%, which compares favorably to both the FF3M and the FFCM. As before, COM improves the fit considerably in all models. Both R_s^2 and R_p^2 increase to values of 75% and 59% in the CAPMCOM and to values of 74% and 72% in the FFCMCOM. Also, the estimated risk premium on COM is significant and positive at 8.6% in all models. Again, this estimate is close to the sample average return of 9.85%.

Panel C summarizes. In the CAPMCOM, FF3MCOM and FFCMCOM we find economically and statistically large post-CFMA minus pre-CFMA differences of around 14%

per year. In unreported results, we find that the estimated risk premiums for the benchmark factors do not differ significantly over the two sample periods.

Because these estimates are close to average factor returns, it follows that the premiums are not only qualitatively, but also quantitatively similar to those from time-series regressions. Consider, for instance, the max-min spread in post-ranking COM betas in the two-factor model CAPMCOM pre-CFMA: 1.41. Combined with COM's estimated risk premium of -5.84%, this spread translates to a familiar difference in average returns of about -8.29% ($= -5.84 \times 1.42$), which is close to the HLCB spread of -8.11% in average returns documented in Panel A of III. Post-CFMA, the same calculation yields a difference in average returns of about 12.90% ($= 8.62 \times 1.50$), close to the HLCB spread of 12.08% in Panel B of Table III.

To summarize, the Fama and MacBeth (1973) regressions show that the price of commodity risk reverses around December 2003. Importantly, this commodity risk premium is not sensitive to the other factors included, in contrast to HML and MOM. Furthermore, we find that cross-sectional R^2's improve whenever COM is added and especially the two-factor model CAPMCOM performs well.

Robustness checks

These findings are robust in two important dimensions. First, our results extend to generalized least squares (GLS) cross-sectional regressions, although the GLS R^2's are small in absolute magnitude. Second, we document a similarly large, but only marginally significant reversal in the commodity risk premium when we use either industry portfolios (IND48) or size and book-to-market portfolios (SBM25) as test assets. Here, however, we cannot go as far as claiming that the two-factor model CAPMCOM is sufficient.[19]

[19] Results for these robustness checks are in the Internet Appendix.

Further, Table X demonstrates that similar results obtain when the OIW commodity index is used instead of the commodity factor COM, which verifies an important testable implication of our model. Pre-CFMA, the OIW risk premium is large and significant at -19.21% in CAPMOIW, -13.78% in FF3MOIW and -14.87% in the FFCMOIW. Post-CFMA, the risk premiums reverse to marginally insignificant values of around 20%. Although, these risk premiums per unit of exposure are relatively large in absolute value, the total contribution to expected returns is quite similar to what we find when using COM, due to smaller loadings on OIW than COM. For instance, the max-min spread in OIW betas in CAPMOIW combines to -12.69% (0.66×-19.21) pre-CFMA and 11.07% (0.60×18.60) post-CFMA, which is close to -8.29% and 12.90% in the case of CAPM-COM. In unreported results, we find that these contributions to expected returns are even closer when COM and OIW are added to the FF3M or the FFCM.

Table X about here.

Also, in both periods, we see that adding the OIW commodity index to either the CAPM, FF3M or FFCM yields a strong improvement in R_s^2 to values over 68%, which is almost identical to the improvement we find when adding COM. In contrast, the R_p^2's show that the estimated risk premiums for OIW are far from the time-series average return of -0.96% and 1.88%, respectively. This finding suggests that the stock and commodity markets are segmented, as in our model.

VII Conclusion

Because many investment, production and consumption decisions are conditioned on commodity prices, one would expect innovations in these prices to be among the shocks to which the stock market reacts sensitively. Indeed, we find a strong pattern in expected returns existing along the cross-section of commodity exposures. Specifically, from 1980 to 2003, stocks with high commodity betas underperform those with low commodity betas by -8% per year in average returns, while from 2004 to 2010, stocks with high commodity betas outperform by 12% per year. The traditional risk factors cannot capture these spreads. We find that a novel commodity factor does capture these spreads in time-series regressions. Our cross-sectional regressions estimate a commodity risk premium of around -5.5% pre-CFMA and 8.5% post-CFMA. The effects are driven largely by bigger stocks and commodities in the Energy and Metals and Fibers sectors. In sum, our results suggest that the commodity factor is an additional risk factor, not replacing the Fama-French-Carhart factors.

We attribute the reversal to the surge in commodity index investment by institutions in the early 2000s. In a simple model where investors maximize utility over consumption of a basket of commodities, a switch from hedging the commodity price risk in the stock market to hedging directly in the futures market easily leads to the observed reversal in the risk premium. In this way, we shed a novel light on the integration of stock and commodity markets and contribute to the debate on the impact of institutional index investment in the commodity market.

Our findings are particularly relevant for stocks that are strongly exposed to commodity price risk and suggest that commodity betas can be used in devising strategies that use stocks to hedge or speculate on commodity prices. This finding is particularly interesting for those institutions that might still be prevented or restricted, in any way, from directly investing in commodity markets. Interestingly, the performance differentials we document extend to strategies that use only between-industry variation in commodity betas and to strategies that use only within-industry variation, which implies that commodity risk can be (and is in practice) hedged while holding industry exposures constant.

Appendix A Derivations

This appendix presents detailed derivations for the model outlined in Section I.

A.1 Approximating the First-Order Condition

The goal of this section is to approximate the Investor's first-order condition using a Taylor expansion for consumption at $t+1$. Defining $R_{S,t+1} = S_{t+1}/S_t - 1$ we can write equation (3) as

$$C_{t+1} = \frac{W_t}{S_t} \left(1 + R_{S,t+1}\right)^{-1} \left(1 + R_{f,t} + w_r' r_{r,t+1}\right). \tag{A.1}$$

Note that W_t/S_t is determined at t and does not affect the optimization. In order to simplify the Investor's problem, we approximate $R_{S,t+1}$around its mean $\overline{R}_S$ and write

$$\frac{1}{1 + R_{S,t+1}} \approx \frac{1}{1 + \overline{R}_S} - \frac{1}{\left(1 + \overline{R}_S\right)^2} \left(R_{S,t+1} - \overline{R}_S\right). \tag{A.2}$$

Substituting equation (A.2) in equation (A.1) we get

$$C_{t+1} \approx \frac{W_t}{S_t} \left(\frac{1}{1 + \overline{R}_S} - \frac{1}{\left(1 + \overline{R}_S\right)^2} \left(R_{S,t+1} - \overline{R}_S\right) \right) \left(1 + R_{f,t} + w_r' r_{r,t+1}\right) \tag{A.3}$$

Leaving out the term $W_t/S_t \left(1 + \overline{R}_S\right)^{-1}$, because it does not affect pricing in the aggregate market, defining $q_0 = 1/\left(1+\overline{R}_S\right)$ and $q_1 = (1+R_{f,t})/\left(1+\overline{R}_S\right)$ (with $q_0 \approx q_1 \approx 1$), and, leaving out all moments beyond mean and variance,[20] leads to the optimization problem given in equation (4).

A.2 A beta asset pricing model

This section explains how the first-order conditions in equation (5) can be rewritten as a two-factor asset pricing model in terms of (multiple regression) betas to and expected returns of the market portfolio and a hedge portfolio. By defining a scaled exposure z and a hedge portfolio h as

$$z = \widetilde{\gamma}_I(\iota_K' \Sigma_{rr}^{-1} \Sigma_{rS}) \text{ and} \tag{A.4}$$

$$h = \left(\iota_K' \Sigma_{rr}^{-1} \Sigma_{rS}\right)^{-1} \Sigma_{rr}^{-1} \Sigma_{rS}, \tag{A.5}$$

with $\iota_K' h = 1$,[21] we now have

$$\begin{aligned} \mu_r &= \gamma_I \Sigma_{rr} w_r - \widetilde{\gamma}_I \Sigma_{rS} \\ &= \gamma_I \Sigma_{rr} w + \Sigma_{rr} h z \\ &= \gamma_I \Sigma_{rr} w_r + \Sigma_{rh} z. \end{aligned} \tag{A.6}$$

Because each investor is exposed to commodity risk in the same way, $w_r = w_m$, we

[20] In the Internet Appendix, we report results that show that ignoring these higher moments is easily justified and has a minor effect on the optimization only.

[21] Note, this hedge portfolio h is nothing more than a vector of scaled coefficients from the multivariate regression:
$R_{S,t+1} = a + b' r_{r,t+1} + e_{t+1}$.

can write

$$\mu_r = \begin{pmatrix} \Sigma_{rM} & \Sigma_{rh} \end{pmatrix} \begin{pmatrix} \gamma_I \\ z \end{pmatrix}. \tag{A.7}$$

Because the first-order conditions in equation (A.7) must also hold for the market portfolio and the hedge portfolio themselves, we get

$$\begin{pmatrix} \mu_m \\ \mu_h \end{pmatrix} = \begin{pmatrix} \sigma_{mm} & \sigma_{mh} \\ \sigma_{hm} & \sigma_{hh} \end{pmatrix} \begin{pmatrix} \gamma_I \\ z \end{pmatrix}. \tag{A.8}$$

Solving equation (A.8) for γ_I and z, and substituting in equation (A.7) gives

$$\begin{aligned} \mu_r &= \begin{pmatrix} \Sigma_{rm} & \Sigma_{rh} \end{pmatrix} \begin{pmatrix} \sigma_{mm} & \sigma_{mh} \\ \sigma_{hm} & \sigma_{hh} \end{pmatrix}^{-1} \begin{pmatrix} \mu_m \\ \mu_h \end{pmatrix}, \text{ or} && \text{(A.9)} \\ E(r_{i,t+1}) &= \beta_{i,m} E(r_{m,t+1}) + \beta_{i,h} E(r_{h,t+1}). && \text{(A.10)} \end{aligned}$$

A.3 Optimal portfolio with a futures contract

This section details the Investor's optimal portfolio decision when the set of investable assets is expanded with a futures contract (or a basket of futures contracts). For the expanded set of assets $r_{t+1} = (r_{F,t+1}, r'_{r,t+1})'$ denote $\mu = (\mu_F, \mu'_r)'$, a $(K+1)$-vector of expected excess returns; $\Sigma = \begin{pmatrix} \sigma_{FF} & \Sigma_{Fr} \\ \Sigma_{rF} & \Sigma_{rr} \end{pmatrix}$, a $(K+1) \times (K+1)$-matrix of (co-) variances; and, $\Sigma_S = \begin{pmatrix} \sigma_{FS} \\ \Sigma_{rS} \end{pmatrix}$, a $(K+1)$-vector of covariances with the commodity return, where $\sigma_{FF} = \sigma_{SS} = \sigma_{FS}$. By using the same approximation as before, the

Investor now solves the following problem for the optimal weights $w = (w_F, w_r')'$:

$$\max_{w} \; w'\mu - q_0 w'\Sigma_S - \frac{\gamma}{2}\left(w'\Sigma w - 2q_1 w'\Sigma_S + q_1^2\sigma_S^2\right), \tag{A.11}$$

with first-order conditions

$$\begin{pmatrix} \mu_F \\ \mu_r \end{pmatrix} = \gamma_I \begin{pmatrix} \sigma_{FF} & \Sigma_{Fr} \\ \Sigma_{rF} & \Sigma_{rr} \end{pmatrix} \begin{pmatrix} w_F \\ w_r \end{pmatrix} - \widetilde{\gamma}_I \begin{pmatrix} \sigma_{FS} \\ \Sigma_{rS} \end{pmatrix}. \tag{A.12}$$

Rearranging, the optimal portfolio takes on a familiar form

$$\begin{pmatrix} w_F \\ w_r \end{pmatrix} = \gamma_I^{-1} \begin{pmatrix} \sigma_{FF} & \Sigma_{Fr} \\ \Sigma_{rF} & \Sigma_{rr} \end{pmatrix}^{-1} \begin{pmatrix} \mu_F \\ \mu_r \end{pmatrix} + \frac{\widetilde{\gamma}_I}{\gamma_I} \begin{pmatrix} \sigma_{FF} & \Sigma_{Fr} \\ \Sigma_{rF} & \Sigma_{rr} \end{pmatrix}^{-1} \begin{pmatrix} \sigma_{FS} \\ \Sigma_{rS} \end{pmatrix}. \tag{A.13}$$

Consider the auxiliary regression given in equation (10) that 'hedges' the risk in the futures contract, $r_{F,t+1}$, with the stocks, $r_{r,t+1}$. Thus, a is the hedged expected return on the futures contract, b is the vector of minimum-variance hedge weights and σ_{ee} is the idiosyncratic variance of the futures contract. From the definition of a partitioned inverse the hedge demand will equal

$$\begin{aligned}
\frac{\widetilde{\gamma}_I}{\gamma_I} \begin{bmatrix} \sigma_{FF} & \Sigma_{Fr} \\ \Sigma_{rF} & \Sigma_{rr} \end{bmatrix}^{-1} \begin{bmatrix} \sigma_{FS} \\ \Sigma_{rS} \end{bmatrix} &= \frac{\widetilde{\gamma}_I}{\gamma_I} \begin{pmatrix} \sigma_{ee}^{-1}\sigma_{FS} - \sigma_{ee}^{-1} b'\Sigma_{rS} \\ -\sigma_{ee}^{-1} b\sigma_{FS} + \Sigma_{rr}^{-1}\Sigma_{rS} + \sigma_{ee}^{-1} bb'\Sigma_{rS} \end{pmatrix} \\
&= \frac{\widetilde{\gamma}_I}{\gamma_I} \begin{pmatrix} \sigma_{ee}^{-1} b'\Sigma_{rS} + \sigma_{ee}^{-1}\sigma_{eS} - \sigma_{ee}^{-1} b'\Sigma_{rS} \\ -\sigma_{ee}^{-1} bb'\Sigma_{rS} - \sigma_{ee}^{-1} b\sigma_{eS} + \Sigma_{rr}^{-1}\Sigma_{rS} + \sigma_{ee}^{-1} bb'\Sigma_{rS} \end{pmatrix} \\
&= \begin{pmatrix} \gamma_I^{-1}\widetilde{\gamma}_I \\ 0_K \end{pmatrix},
\end{aligned} \tag{A.14}$$

where the second equality follows from defining $\sigma_{FS} = b'\Sigma_{rS} + \sigma_{eS}$ and the third equality from $\sigma_{ee}^{-1}\sigma_{eS} = 1$ and $b = \Sigma_{rr}^{-1}\Sigma_{rF} = \Sigma_{rr}^{-1}\Sigma_{rS}$, when $r_{F,t+1}$ and $R_{S,t+1}$ are perfectly correlated.

Substituting this hedge demand into the total demand we get

$$\begin{aligned}
\begin{pmatrix} w_F \\ w_r \end{pmatrix} &= \gamma_I^{-1} \begin{pmatrix} \sigma_{ee}^{-1} & -\sigma_{ee}^{-1}b' \\ -\sigma_{ee}^{-1}b & \Sigma_{rr}^{-1} + \sigma_{ee}^{-1}bb' \end{pmatrix} \begin{pmatrix} \mu_F \\ \mu_r \end{pmatrix} - \begin{pmatrix} \gamma_I^{-1}\widetilde{\gamma}_I \\ 0_K \end{pmatrix} \\
&= \gamma_I^{-1} \begin{pmatrix} \sigma_{ee}^{-1}(\mu_F - b'\mu_r) \\ \Sigma_{rr}^{-1}\mu_r - \sigma_{ee}^{-1}b(\mu_F - b'\mu_r) \end{pmatrix} - \begin{pmatrix} \gamma_I^{-1}\widetilde{\gamma}_I \\ 0_K \end{pmatrix} \\
&= \begin{pmatrix} w_{F,spec} \\ \gamma_I^{-1}\Sigma_{rr}^{-1}\mu_r - \Sigma_{rr}^{-1}\Sigma_{rS}w_{F,spec} \end{pmatrix} - \begin{pmatrix} \gamma_I^{-1}\widetilde{\gamma}_I \\ 0_K \end{pmatrix}, \qquad \text{(A.15)}
\end{aligned}$$

where the last equality defines $w_{F,spec} = \gamma_I^{-1}\sigma_{ee}^{-1}a$, which is a speculative demand for the futures contract given that it is hedged with the risky assets. Following equations (A.4) to (A.10), we can rewrite this demand again as a two-factor beta asset pricing model.

A.4 Futures market clearing

This section derives what futures market clearing implies for the speculative investment in the futures contract $w_{F,spec}$, or equivalently, a. Note first that the expected return on the futures contract follows from substituting the market portfolio of stocks, $w_{m,}$ into the investor's first-order condition in equation (A.12), that is,

$$\mu_F = \gamma_I\sigma_{FF}w_F + \gamma_I\sigma_{FM} - \widetilde{\gamma}_I\sigma_{FS}. \qquad \text{(A.16)}$$

To see what this model means for the sign of a and thus for the price of commodity risk in the stock market when a futures contract is introduced, we consider the aggregate demand for futures from Producers and Investors given in equation (17)

$$w_F = \gamma_I^{-1} \frac{a}{\sigma_{ee}} + \frac{\widetilde{\gamma}_I}{\gamma_I} \text{ and} \tag{A.17}$$

$$h = (\gamma_P^{-1} \frac{\mu_F}{\sigma_{FF}} - 1) \frac{S_t}{F_t}, \tag{A.18}$$

where (i) the hedge demands are of opposite sign, which reflects the opposite sides of the market, and (ii) the speculative demand for Producers is based on the futures expected return and risk, whereas for Investors it is based on the futures excess expected return, given that the futures contract is hedged in the stock market. Next, defining the relative wealth of Investors $\alpha_I = N_I/(N_I + N_P)$ and of Producers $\alpha_p = 1 - \alpha_I$, leads to the market clearing condition given in equation (17).

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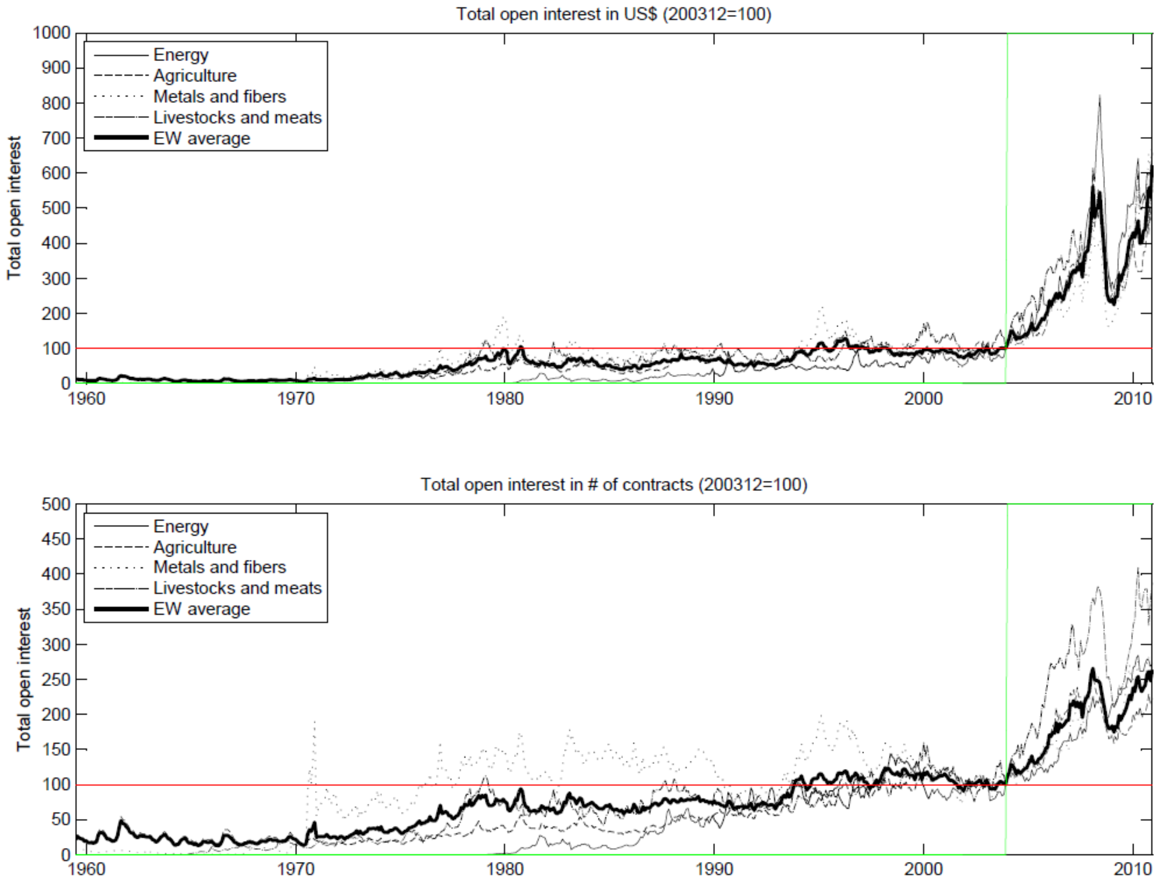

Figure 1: Total Open Interest in 33 commodities (1959 to 2010)
The top figure displays total open interest in 33 commodities in US$, which is calculated as the sum of the US$ open interest in each commodity (number of contracts outstanding times nearest-to-maturity futures price). The bottom figure displays total open interest in terms of the number of contracts outstanding. Both series are normalized to equal 100 in December 2003.

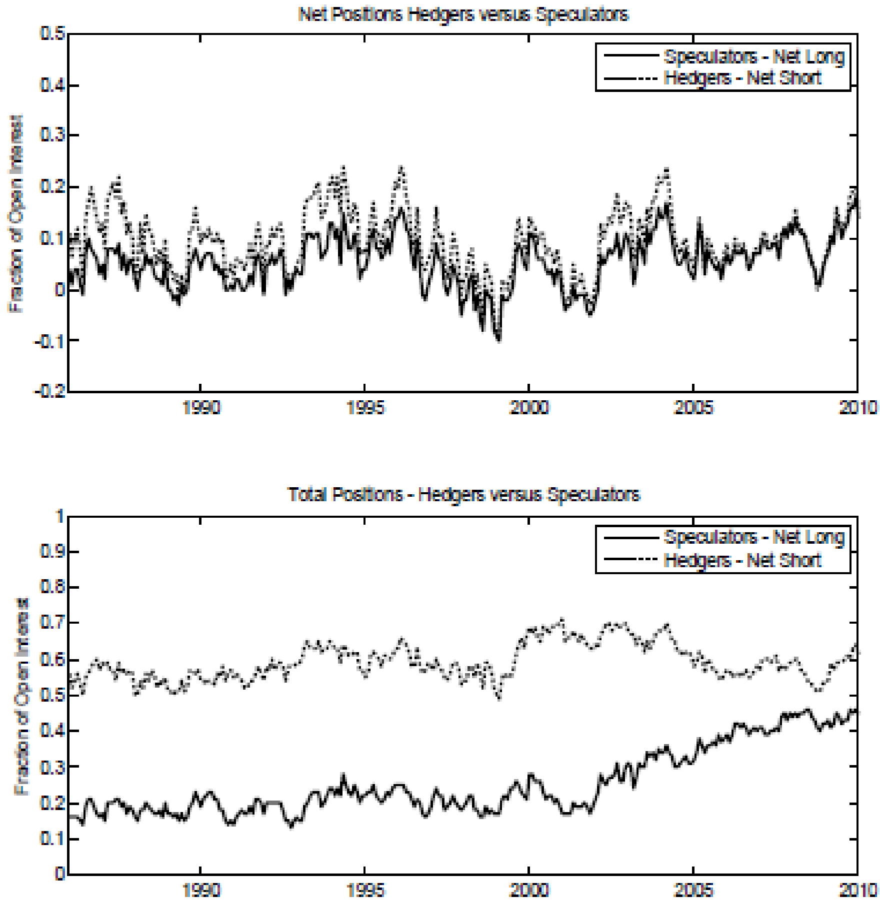

Figure 2: OIW Positions of Hedgers versus Speculators (1986-2010)
The top figure displays the Open Interest Weighted average over all commodities in the CFTC's historical Commitment of Traders (COT) reports of the net short position (short minus long) of commercial hedgers versus the net long position (long minus short) of non-commercial speculators. The bottom figure displays the Open Interest Weighted average of the short position of commercial hedgers versus the long position (long plus spreading) of non-commercial speculators. All series are presented as a fraction of Open Interest. Traders are classified as in the COT reports, which are available from 1986 onward.

Table I: Overview of commodity futures

This table presents detailed characteristics of 33 commodity futures, divided over four sectors: Energy (E), Agriculture (A), Metals and Fibers (M) and Livestock and Meats (L). The table lists: (i) a commodities' sector (sec.) and symbol (sym.; as it appears in the CRB data); (ii) the exchange on which it is traded [(1)]; (iii) the delivery months considered; (iv) the first month in which both a return and total open interest (TOI) are observed (the end date, December 2010, is common to all contracts except propane and flaxseed, for which TOI approaches zero in 2007 and 2003, respectively); (v) annualized average return and standard deviation (in US$, * indicates significance at the 10%-level); and finally, (vi) the median TOI (in US$ MM).

(Sec.) Comm. (Sym.)	Exchange	Delivery Months	First Obs.	Avg. Ret.	St. Dev.	TOI
(E) Crude Oil (CL)	NYMEX	All	198304	12.75*	33.71	7793
(E) Gasoline (HU/RB) [(2)]	NYMEX	All	198501	18.35*	35.80	2353
(E) Heating Oil (HO)	NYMEX	All	197904	9.92*	31.95	2925
(E) Natural Gas (NG)	NYMEX	All	199005	-3.74	51.79	11233
(E) Gas-Oil-Petroleum (LF)	ICE	All	198910	13.59*	32.12	2491
(E) Propane (PN)	NYMEX	All	198709	27.13*	47.05	21
(A) Coffee (KC)	ICE	3,5,7,9,12	197209	8.21	37.84	1234
(A) Rough Rice (RR)	CBOT	1,3,5,7,9,11	198701	-2.82	28.90	76
(A) Orange Juice (JO)	ICE	1,3,5,7,9,11	196703	5.50	32.75	217
(A) Sugar (SB)	ICE	3,5,7,10	196102	7.73	43.73	941
(A) Cocoa (CC)	ICE	3,5,7,9,12	195908	3.60	31.05	463
(A) Milk (DE)	CME	2,4,6,9,12	199602	2.57	24.42	531
(A) Soybean Oil (BO)	CBOT	1,3,5,7,8,9,10,12	195908	7.88*	29.85	822
(A) Soybean Meal (SM)	CBOT	1,3,5,7,8,9,10,12	195908	9.13*	29.06	1005
(A) Soybeans (S-)	CBOT	1,3,5,7,8,9,11	196501	5.69	26.98	3514
(A) Corn (C-)	CBOT	3,5,7,9,12	195908	-1.38	23.43	2083
(A) Oats (O-)	CBOT	3,5,7,9,12	195908	-0.46	29.16	51
(A) Wheat (W-)	CBOT	3,5,7,9,12	195908	0.17	24.48	833
(A) Canola (WC)	WCE	3,5,6,7,9,11	197702	0.38	22.18	196
(A) Barley (WA)	WCE	3,5,7,10,12	198906	-2.59	22.15	18
(A) Flaxseed (WF)	WCE	3,5,7,10,11,12	198501	1.27	20.26	21
(M) Cotton (CT)	ICE	3,5,7,10,12	195908	3.20	23.30	1086
(M) Gold (GC)	NYMEX	2,4,6,8,10,12	197501	1.70	19.47	6224
(M) Silver (SI)	NYMEX	3,5,7,9,12	197202	6.48	32.50	2790
(M) Copper (HG)	NYMEX	1,3,5,7,9,12	197210	10.77*	27.77	1250
(M) Lumber (LB)	CME	1,3,5,7,9,11	196911	-3.15	27.62	121
(M) Palladium (PA)	NYMEX	3,6,9,12	197702	13.26*	36.01	94
(M) Platinum (PL)	NYMEX	1,4,7,10	197208	7.69*	27.79	324
(M) Rubber (YR)	TOCOM	All	199204	9.46	32.58	565
(L) Feeder Cattle (FC)	CME	1,3,4,5,8,9,10,11	197112	3.90	16.40	516
(L) Live Cattle (LC)	CME	2,4,6,8,10,12	196412	5.46*	16.49	1925
(L) Lean Hogs (LH)	CME	2,4,6,7,8,10,12	196603	4.52	25.51	692
(L) Pork Bellies (PB)	CME	2,3,5,7,8	196402	2.03	33.72	191

[(1)] CBOT = Chicago Board of Trade; CME = Chicago Mercantile Ex.; ICE = ICE Futures US; NYMEX = New York Mercantile Ex.; TOCOM = Tokyo Commodity Ex.; WCE = Winnipeg Commodity Ex.

[(2)] Until June 2006 returns are based on the Unleaded Gasoline (HU) contract, from July 2006 on the Reformulated Gasoline Blendstock (RB) contract

Table II: Characteristics of commodity-beta sorted portfolios
This table presents characteristics for portfolios sorted on commodity beta, where we use either the Open Interest Weighted commodity index (OIW) or the Equal Weighted commodity index (EW). The portfolios analyzed are: (i) 25 stock portfolios at the intersections of five equal-sized commodity beta (CB) groups and five size groups (split at NYSE market value quintiles); (ii) five stock and industry portfolios sorted one-dimensionally on OIW commodity betas; (iii) five stock portfolios sorted one-dimensionally on EW commodity betas; and finally, (iv) the resulting high minus low commodity beta (HLCB) spreading portfolios. We present (i) average portfolio return (μ) and its corresponding t-statistic, (ii) standard deviation (σ), (iii) pre-ranking commodity beta (averaged within each portfolio and over time; β_{pre}) and (iv) post-ranking commodity beta from a time-series regression of each portfolio's returns on the relevant commodity index (β_{post}) as well as its corresponding t-statistic (using White's heteroskedasticity-consistent standard errors). The sample period is 198001 to 201012, or 372 months. To conserve space, we do not report results for the second and fourth size group.

Portfolio characteristics for 198001 to 201012

	OIW	OIW	OIW	OIW	OIW	EW	OIW	OIW	OIW	OIW	OIW	EW
CB	Size quintile			One-way			Size quintile			One-way		
group	S	3	B	Stocks	48 Ind.	Stocks	S	3	B	Stocks	48 Ind.	Stocks
	Average return (μ)						t-statistic for μ					
H	7.29	6.20	5.21	4.83	7.16	6.14	1.45	1.27	1.21	1.12	1.94	1.34
4	9.59	7.60	6.53	6.36	7.72	6.12	2.31	2.13	1.98	1.97	2.28	1.65
3	10.67	9.24	5.36	6.26	7.57	7.55	2.86	2.83	1.76	2.09	2.32	2.63
2	10.26	10.55	7.85	8.25	9.26	7.96	2.82	3.24	2.73	2.90	3.11	2.99
L	7.34	10.53	8.48	8.38	8.06	7.96	1.73	2.76	2.77	2.71	2.87	2.90
HLCB	-0.04	-4.33	-3.27	-3.55	-0.90	-1.82	-0.02	-1.24	-0.89	-1.03	-0.34	-0.51
	Standard deviation (σ)						Pre-ranking commodity beta (β_{pre})					
H	28.02	27.15	23.89	24.00	20.50	25.56	0.87	0.82	0.66	0.73	0.41	1.28
4	23.11	19.90	18.41	17.99	18.82	20.71	0.27	0.26	0.25	0.25	0.09	0.59
3	20.81	18.16	16.92	16.66	18.13	16.01	0.02	0.02	0.01	0.02	-0.01	0.24
2	20.26	18.15	16.01	15.84	16.56	14.83	-0.21	-0.21	-0.21	-0.21	-0.09	-0.08
L	23.63	21.24	17.07	17.24	15.65	15.26	-0.72	-0.60	-0.50	-0.54	-0.23	-0.49
HLCB	13.05	19.38	20.45	19.12	14.55	19.90	1.59	1.42	1.16	1.27	0.64	1.77
	Post-ranking commodity beta (β_{post})						t-statistic for β_{post}					
H	0.39	0.56	0.49	0.53	0.48	0.87	3.58	6.31	6.39	6.87	6.98	9.05
4	0.20	0.25	0.21	0.21	0.20	0.49	2.17	3.25	3.03	3.10	2.90	5.46
3	0.14	0.16	0.14	0.14	0.16	0.35	1.58	2.17	2.22	2.22	2.00	4.18
2	0.13	0.10	0.06	0.06	0.10	0.22	1.39	1.41	1.07	1.15	1.70	2.92
L	0.10	0.08	0.00	0.02	0.05	0.19	0.97	0.94	-0.07	0.29	0.88	2.23
HLCB	0.29	0.48	0.50	0.51	0.43	0.68	8.00	9.10	7.39	8.41	10.71	10.59

Table III: Average and risk-adjusted returns over subsamples

This table presents average and risk-adjusted returns (α's, in annualized %'s) for the commodity-beta sorted portfolios of interest. We use the CAPM, FF3M and FFCM as benchmark asset pricing models. Panel A covers 198001 to 200312 (Pre-CFMA) and Panel B covers 200401 to 201012 (Post-CFMA). Panel C tests the difference over the two sample periods. Here, we present average returns for all portfolios, but only risk-adjusted returns for the HLCB spreading portfolios. Panel D tests the difference over two sample periods for alternative breakpoints after the introduction of the Commodity Futures Modernization Act, i.e., December 2000, 2001, 2002 , 2003, 2004 and 2005. Here, we focus on average returns and FFCM α's for the HLCB portfolios. All t-statistics are based on White's heteroskedasticity-consistent standard errors.

Panel A: (Risk-adjusted) Returns for 1980-2003 (Pre-CFMA)													
		OIW	OIW	OIW	OIW	OIW	EW	OIW	OIW	OIW	OIW	OIW	EW
	CB	Size quintile				One-way		Size quintile				One-way	
	group	S	3	B	Stocks	48 Ind.	Stocks	S	3	B	Stocks	48 Ind.	Stocks
		α's, in ann. %'s						t-statistics					
Means	H	5.88	3.55	2.33	1.91	5.00	4.45	1.06	0.65	0.47	0.38	1.28	0.84
	4	8.88	6.90	7.04	6.58	8.23	5.77	2.00	1.76	1.80	1.76	2.28	1.34
	3	10.56	9.44	6.32	7.04	7.84	8.25	2.69	2.65	1.80	2.06	2.17	2.50
	2	10.55	11.32	9.24	9.53	10.07	8.81	2.66	3.10	2.74	2.89	3.04	2.87
	L	8.93	13.03	10.01	10.02	9.72	9.33	1.85	2.95	2.76	2.75	3.03	2.92
	HLCB	-3.04	-9.47	-7.68	-8.11	-4.72	-4.88	-1.17	-2.36	-1.77	-2.02	-1.70	-1.16
CAPM	H	-3.59	-6.71	-6.95	-7.73	-2.67	-5.86	-0.98	-2.14	-2.35	-2.95	-1.29	-2.14
	4	0.92	-1.19	-0.72	-1.30	0.72	-3.29	0.33	-0.67	-0.36	-0.84	0.45	-1.84
	3	3.49	2.13	-1.25	-0.52	0.38	0.98	1.42	1.25	-1.00	-0.56	0.23	0.98
	2	3.55	3.99	2.16	2.44	3.22	2.36	1.39	2.18	1.56	2.05	2.13	1.90
	L	0.60	4.59	3.21	2.82	3.18	2.91	0.19	1.80	1.49	1.46	2.02	1.80
	HLCB	-4.18	-11.30	-10.16	-10.54	-5.85	-8.77	-1.63	-2.82	-2.41	-2.72	-2.11	-2.30
FF3M	H	-3.99	-6.34	-4.36	-6.19	-4.68	-3.78	-1.74	-2.51	-1.50	-2.54	-2.46	-1.56
	4	-1.36	-3.02	1.22	-0.11	-1.40	-0.87	-0.83	-2.38	0.60	-0.07	-0.98	-0.55
	3	0.27	-0.36	0.15	0.27	-2.57	1.15	0.19	-0.28	0.12	0.27	-1.79	1.15
	2	-0.21	1.25	2.42	2.18	1.45	1.54	-0.12	0.81	1.97	1.96	0.97	1.36
	L	-1.86	2.18	3.70	2.42	1.05	2.08	-0.82	0.90	1.73	1.21	0.67	1.32
	HLCB	-2.13	-8.53	-8.06	-8.61	-5.73	-5.86	-0.83	-2.09	-1.92	-2.25	-2.06	-1.69
FFCM	H	-1.73	-6.12	-5.52	-6.67	-4.75	-3.52	-0.70	-2.29	-1.92	-2.75	-2.42	-1.47
	4	0.69	-3.23	-0.97	-1.73	-0.92	0.40	0.43	-2.49	-0.52	-1.23	-0.63	0.25
	3	2.41	0.43	-0.61	-0.13	-1.99	0.76	1.57	0.34	-0.50	-0.13	-1.31	0.78
	2	2.82	3.48	3.22	3.33	2.13	1.08	1.58	2.59	2.66	3.14	1.45	0.95
	L	2.75	5.59	5.88	4.99	2.12	2.77	1.09	2.54	2.82	2.65	1.33	1.70
	HLCB	-4.48	-11.71	-11.39	-11.66	-6.87	-6.30	-1.91	-2.85	-2.75	-3.10	-2.44	-1.80

Table III continued

Panel B: (Risk-adjusted) Returns for 2004-2010 (Post-CFMA)													
		OIW	OIW	OIW	OIW	OIW	EW	OIW	OIW	OIW	OIW	OIW	EW
	CB	Size quintile				One-way		Size quintile				One-way	
	group	S	3	B	Stocks	48 Ind.	Stocks	S	3	B	Stocks	48 Ind.	Stocks
		α's, in ann. %'s						t-statistics					
Means	H	12.13	15.29	15.10	14.85	14.57	11.93	1.03	1.42	1.86	1.73	1.56	1.29
	4	12.02	9.97	4.78	5.64	5.97	7.33	1.16	1.18	0.81	0.89	0.70	0.99
	3	11.07	8.58	2.08	3.58	6.62	5.16	1.14	1.11	0.35	0.57	0.89	0.88
	2	9.25	7.91	3.08	3.87	6.47	5.07	1.06	1.10	0.57	0.70	0.97	0.94
	L	1.88	1.98	3.25	2.77	2.35	3.24	0.21	0.27	0.60	0.49	0.40	0.62
	HLCB	10.25	13.31	11.85	12.08	12.22	8.69	1.98	2.00	1.88	1.95	1.92	1.34
CAPM	H	4.40	8.32	10.30	9.45	8.61	6.07	0.92	1.72	2.13	2.12	1.86	1.31
	4	5.18	4.32	0.93	1.24	0.17	2.23	1.24	1.34	0.34	0.61	0.06	0.90
	3	4.76	3.30	-2.01	-0.77	1.46	1.07	1.13	1.26	-0.98	-0.43	0.61	0.65
	2	3.49	3.13	-0.54	0.06	1.88	1.37	0.96	1.04	-0.27	0.03	0.88	0.77
	L	-3.99	-2.93	-0.08	-0.92	-1.65	-0.25	-0.98	-0.96	-0.03	-0.38	-0.84	-0.12
	HLCB	8.38	11.25	10.38	10.37	10.26	6.31	1.91	1.89	1.71	1.77	1.70	1.10
FF3M	H	1.47	6.71	11.42	9.91	8.65	6.33	0.39	1.55	2.48	2.31	1.97	1.45
	4	2.20	2.41	1.74	1.37	-0.92	1.72	0.74	1.02	0.73	0.73	-0.37	0.77
	3	1.43	1.57	-1.88	-0.99	1.01	1.16	0.60	0.85	-0.93	-0.57	0.42	0.75
	2	0.68	1.51	-0.48	-0.20	1.16	1.14	0.32	0.64	-0.24	-0.11	0.61	0.63
	L	-6.71	-4.65	0.42	-1.02	-2.03	-0.04	-2.84	-2.06	0.14	-0.44	-1.09	-0.02
	HLCB	8.17	11.36	11.00	10.93	10.68	6.37	1.96	1.97	1.84	1.91	1.89	1.13
FFCM	H	1.65	6.81	11.30	9.82	8.60	6.23	0.47	1.57	2.53	2.32	1.98	1.46
	4	2.40	2.46	1.67	1.33	-0.82	1.76	1.03	1.05	0.72	0.72	-0.32	0.78
	3	1.60	1.66	-1.83	-0.93	1.08	1.16	0.80	0.95	-0.91	-0.55	0.47	0.74
	2	0.77	1.53	-0.47	-0.19	1.23	1.18	0.40	0.65	-0.23	-0.11	0.65	0.65
	L	-6.66	-4.67	0.36	-1.08	-2.01	-0.09	-2.90	-2.06	0.12	-0.47	-1.09	-0.05
	HLCB	8.31	11.48	10.94	10.90	10.60	6.32	2.02	1.98	1.82	1.90	1.90	1.12

Table III continued

		Panel C: Difference (Post-CFMA)-(Pre-CFMA)											
		OIW	OIW	OIW	OIW	OIW	EW	OIW	OIW	OIW	OIW	OIW	EW
	CB	Size quintile				One-way		Size quintile				One-way	
	group	S	3	B	Stocks	48 Ind.	Stocks	S	3	B	Stocks	48 Ind.	Stocks
		α's, in ann. %'s						t-statistics					
Means	H	6.25	11.74	12.78	12.94	9.57	7.48	0.48	0.97	1.34	1.30	0.95	0.70
	4	3.14	3.06	-2.26	-0.93	-2.26	1.56	0.28	0.33	-0.32	-0.13	-0.24	0.18
	3	0.51	-0.85	-4.24	-3.46	-1.22	-3.09	0.05	-0.10	-0.61	-0.49	-0.15	-0.46
	2	-1.30	-3.41	-6.16	-5.66	-3.60	-3.74	-0.14	-0.42	-0.97	-0.88	-0.48	-0.60
	L	-7.04	-11.04	-6.75	-7.25	-7.37	-6.09	-0.69	-1.28	-1.03	-1.08	-1.11	-1.00
Means	HLCB	13.29	22.78	19.53	20.19	16.95	13.58	2.29	2.93	2.55	2.73	2.44	1.75
CAPM	HLCB	12.57	22.55	20.54	20.92	16.11	15.09	2.47	3.14	2.78	2.98	2.43	2.18
FF3M	HLCB	10.31	19.89	19.05	19.54	16.41	12.23	2.10	2.82	2.60	2.84	2.60	1.85
FFCM	HLCB	12.79	23.19	22.33	22.56	17.47	12.61	2.70	3.27	3.06	3.28	2.79	1.90
		Panel D: Difference: alternative breakpoints after CFMA											
		α's, in ann. %'s						t-statistics					
		Dec. 2000											
Means	HLCB	9.18	12.63	14.49	15.72	15.38	9.44	1.84	1.73	2.01	2.33	2.63	1.27
FFCM	HLCB	8.93	15.18	17.92	18.31	15.59	9.79	2.06	2.17	2.47	2.76	2.80	1.58
		Dec. 2001											
Means	HLCB	8.65	14.81	19.77	19.00	15.29	10.30	1.68	2.02	2.76	2.81	2.50	1.42
FFCM	HLCB	8.92	17.79	21.60	20.75	15.18	8.22	2.04	2.49	3.03	3.15	2.69	1.32
		Dec. 2002											
Means	HLCB	13.38	18.60	21.31	20.69	18.89	15.76	2.51	2.53	2.89	2.95	2.92	2.17
FFCM	HLCB	11.90	18.65	23.40	22.21	18.03	12.32	2.70	2.75	3.31	3.38	3.06	1.97
		Dec. 2003											
Means	HLCB	13.29	22.78	19.53	20.19	16.95	13.58	2.29	2.93	2.55	2.73	2.44	1.75
FFCM	HLCB	12.79	23.19	22.33	22.56	17.47	12.61	2.70	3.27	3.06	3.28	2.79	1.90
		Dec. 2004											
Means	HLCB	12.56	22.19	20.13	20.48	17.15	15.85	1.94	2.59	2.42	2.52	2.20	1.90
FFCM	HLCB	12.24	22.63	23.17	23.00	18.14	15.83	2.36	2.95	2.93	3.06	2.61	2.20
		Dec. 2005											
Means	HLCB	10.91	22.19	15.11	16.97	13.60	13.40	1.47	2.29	1.68	1.89	1.55	1.43
FFCM	HLCB	9.51	21.29	18.32	19.37	14.15	13.34	1.65	2.52	2.17	2.36	1.84	1.64

Table IV: Stability of sort post-CFMA

This table presents two results that demonstrate that our portfolios are stable after the introduction of the CFMA. Panel A presents a summary of Markov switching matrices for the five one-dimensional stock portfolios (from H to L) for five-year subperiods. Each column represents the diagonal of the switching matrix (averaged over all months in the subperiod), which represents the fraction of stocks that does not switch out of that respective portfolio. Panel B presents means and FFCM alphas for stock and industry portfolios sorted one-dimensionally in five commodity beta groups, where we fix the ranking on its December 2003 value. Note, the stock portfolios contain only those stocks that are in the December 2003 sample. We present average returns and FFCM α's for the long-only portfolios and for the high minus low commodity beta (HLCB) portfolios we also present the corresponding t-statistics based on White's heteroskedasticity-consistent standard errors. Also, we present two correlations of these portfolios with the original portfolios (that allow the composition to change freely post-CFMA): $Corr(r_{free}, r_{fixed})$. This correlation is presented for the period until June 2007, just before the financial crisis, and until December 2010.

Panel A: Diagonal of Markov switching matrices

	1980-1985	1986-1990	1991-1995	1996-2000	2001-2005	2006-2010
H	0.95	0.93	0.95	0.92	0.94	0.94
4	0.87	0.83	0.87	0.79	0.86	0.83
3	0.84	0.79	0.84	0.75	0.84	0.79
2	0.85	0.82	0.87	0.77	0.87	0.81
L	0.93	0.92	0.94	0.89	0.95	0.92
Average	0.89	0.86	0.89	0.82	0.89	0.86

Panel B: Returns when portfolio composition is fixed at December 2003

	Stocks		48 Ind.	
	Means	FFCM	Means	FFCM
H	9.98	5.71	12.20	7.61
4	4.74	1.43	8.78	3.34
3	3.13	-0.74	1.76	-3.79
2	5.93	0.87	7.67	1.79
L	2.88	-2.20	4.87	-1.45
HLCB	7.10	7.91	7.33	9.06
t-stat	1.55	1.67	1.41	1.97
	June 2007	December 2010	June 2007	December 2010
$Corr(r_{free}, r_{fixed})$	0.90	0.66	0.92	0.57

Table V: Within-industry sorted commodity beta portfolios

This table demonstrates the results from the within-industry sort as explained in Section III.B. First, we sort all stocks within each industry into five commodity beta bins (presented row-wise). Then, using the aggregate industry portfolios, we sort the industries into five bins (presented column-wise). Combining, in each 5-by-5 block, a cell presents the equal weighted average of the respective (H,2,3,4 and L) within-industry portfolios among the respective (H,2,3,4 and L) beta industries. The sixth column presents the equal weighted average over rows, that is, an average within-industry portfolio. The sixth row presents the HLCB within-industry portfolio. Panel A presents the results for the first subperiod, Panel B for the second subperiod. In each panel we present average returns and FFCM α's (in annualized %'s, left). To conserve space, we present corresponding t-statistics (based on White's heteroskedasticity-consistent standard errors, right) only for the average within-industry portfolio and the HLCB within-industry portfolios.

			Between-industry group						
			H	4	3	2	L	Avg	t-stat
Panel A: Returns from 1980-2003 (Pre-CFMA)									
Mean	Within-	H	3.39	4.06	4.53	7.87	7.72	5.52	(1.30)
	industry	4	5.51	4.84	6.84	12.93	9.81	7.99	(2.22)
	group	3	4.25	7.58	7.66	10.59	11.02	8.22	(2.47)
		2	5.98	8.60	10.97	13.42	8.53	9.50	(2.84)
		L	6.78	10.19	8.71	11.21	12.44	9.86	(2.71)
		HLCB	-3.39	-6.13	-4.17	-3.34	-4.72	-4.35	(-2.13)
		t-stat	(-1.02)	(-1.96)	(-1.54)	(-1.14)	(-1.62)	(-2.13)	
FFCM α	Within-	H	-8.27	-6.09	-5.75	-2.46	-2.23	-4.96	(-3.62)
	industry	4	-3.97	-4.64	-3.35	4.22	0.80	-1.39	(-1.24)
	group	3	-5.71	-1.76	-2.09	2.64	3.57	-0.67	(-0.55)
		2	-2.81	0.54	2.05	5.12	1.58	1.30	(1.09)
		L	-1.36	1.49	-1.38	2.40	6.78	1.58	(1.09)
		HLCB	-6.92	-7.58	-4.37	-4.86	-9.01	-6.55	(-3.40)
		t-stat	(-1.84)	(-2.62)	(-1.56)	(-1.68)	(-3.19)	(-3.40)	
Panel B: Returns from 2004-2010 (Post-CFMA)									
			H	4	3	2	L	Avg	t-stat
Mean	Within-	H	18.91	15.32	13.10	18.52	9.95	15.16	(1.41)
	industry	4	17.54	6.05	8.95	7.12	11.31	10.20	(1.20)
	group	3	15.16	9.80	7.57	4.50	6.92	8.79	(1.26)
		2	10.40	7.47	4.14	4.36	4.90	6.25	(0.94)
		L	5.27	4.31	7.72	-0.53	0.58	3.47	(0.50)
		HLCB	13.64	11.01	5.38	19.05	9.37	11.69	(1.98)
		t-stat	(1.67)	(1.68)	(0.70)	(2.24)	(1.29)	(1.98)	
FFCM α	Within-	H	12.60	6.54	3.90	7.64	1.59	6.45	(1.99)
	industry	4	10.22	-1.71	2.52	-0.95	3.98	2.81	(1.70)
	group	3	8.31	3.68	2.27	-1.25	2.21	3.04	(2.12)
		2	4.39	1.29	-1.27	-1.01	0.20	0.72	(0.54)
		L	-1.33	-3.22	1.73	-6.95	-3.90	-2.73	(-1.48)
		HLCB	13.92	9.76	2.17	14.58	5.48	9.18	(2.14)
		t-stat	(1.83)	(1.60)	(0.40)	(2.54)	(1.08)	(2.14)	
Panel C: Difference for HLCB within-industry portfolios									
Mean		HLCB	17.03	17.14	9.55	22.39	14.08	16.04	
		t-stat	(1.94)	(2.36)	(1.18)	(2.49)	(1.80)	(2.57)	
FFCM α		HLCB	20.84	17.34	6.53	19.44	14.49	15.73	
		t-stat	(2.45)	(2.57)	(1.06)	(3.02)	(2.50)	(3.35)	

Table VI: Commodity beta sorts orthogonal to (unexpected) inflation

This table presents average and risk-adjusted returns (FFCM α's) for sorts where inflation effects are netted out. In each 60-month rolling window, we first orthogonalize returns from a measure of unexpected inflation (UI, the monthly change in annual inflation; presented in the left panel) or an unexpected inflation factor (UIF, constructed in the same way as the commodity factor COM; presented in the right panel). Then, we regress the residuals from this regression on the commodity index to estimate betas. Panel A covers 198001 to 200312, Panel B covers 200401 to 201012 and Panel C tests the differences for the HLCB portfolios. * indicates significance at the 10%-level, using White standard errors.

		Returns orthogonalized from unexpected inflation						Returns orthogonalized from unexpected inflation factor					
		OIW	OIW	OIW	OIW	OIW	EW	OIW	OIW	OIW	OIW	OIW	EW
		Size quintile				One-way		Size quintile				One-way	
		S	3	B	Stocks	48 Ind.	Stocks	S	3	B	Stocks	48 Ind.	Stocks
Panel A: Risk-adjusted returns 1980-2003 (Pre-CFMA)													
Means	H	6.20	3.90	1.99	2.31	4.67	4.28	6.79	4.73	3.87	3.38	6.05	5.88
	4	9.30*	7.12*	7.82*	7.09*	8.40*	6.42	8.76*	7.27*	6.78*	6.75*	8.17*	7.12
	3	10.17*	8.79*	6.07*	6.81*	8.65*	7.59*	10.43*	9.91*	6.26*	7.05*	7.97*	6.75*
	2	10.28*	11.95*	8.61*	8.98*	9.38*	8.82*	11.01*	10.94*	8.66*	8.91*	9.44*	8.34*
	L	9.02*	12.72*	9.77*	9.67*	9.81*	9.19*	7.88*	12.17*	8.18*	8.72*	9.35*	9.07*
	HLCB	-2.83	-8.82*	-7.78*	-7.36*	-5.14*	-4.92	-1.09	-7.44*	-4.31	-5.34	-3.30	-3.18
FFCM	H	-1.91	-5.89*	-5.88*	-6.36*	-5.19*	-3.65	-1.23	-4.46*	-4.49	-5.39*	-3.81*	-2.18
	4	1.00	-3.18*	-0.50	-1.64	-1.27	0.63	0.44	-3.26*	-1.43	-2.05*	-1.30	1.34
	3	2.23	-0.02	-0.64	-0.18	-1.00	-0.15	2.50	0.48	-0.41	0.02	-0.55	-0.58
	2	2.44	4.27*	2.90*	3.08*	1.69	1.19	3.35*	2.63*	2.31*	2.36*	0.38	0.44
	L	3.36	5.52*	5.64*	4.77*	2.41	2.93*	2.15	6.07*	3.81*	3.89*	2.11	2.55*
	HLCB	-5.27*	-11.41*	-11.53*	-11.13*	-7.61*	-6.59*	-3.38*	-10.54*	-8.30*	-9.28*	-5.92*	-4.73
Panel B: Risk-adjusted returns 2004-2010 (Post-CFMA)													
Means	H	12.49	12.46	13.11	12.68	12.77	11.20	13.36	14.69	13.65*	13.87	14.31	13.68
	4	10.15	9.65	3.12	4.97	6.73	7.80	11.89	9.93	5.41	6.55	3.09	6.43
	3	9.22	10.16	3.25	4.62	6.62	5.51	7.48	8.61	2.17	3.33	10.62	4.60
	2	8.66	6.16	2.07	2.78	7.03	4.99	9.25	6.26	2.06	2.86	5.06	5.06
	L	5.03	4.12	2.45	2.94	2.65	2.68	3.44	4.00	3.61	3.22	3.28	1.13
	HLCB	7.47	8.34	10.65*	9.74	10.12	8.52	9.92*	10.69	10.04*	10.65*	11.03*	12.54*
FFCM	H	2.02	4.21	9.46*	7.85*	6.46	5.32	2.81	6.53	9.89*	8.82*	7.91*	7.95*
	4	0.56	2.19	-0.15	0.59	0.05	2.62	2.20	2.48	1.99	2.02	-2.99	1.00
	3	0.03	3.22*	-0.74	0.04	1.11	1.31	-1.20	1.91	-1.32	-0.78	5.06*	0.48
	2	-0.05	-0.32	-1.35	-1.17	1.94	1.36	0.61	-0.57	-1.33	-1.06	-0.52	1.44
	L	-3.54	-2.60	-0.33	-0.81	-1.70	-0.65	-5.35*	-2.80	-0.05	-1.57	-1.05	-3.02
	HLCB	5.56	6.81	9.79*	8.66	8.16	5.97	8.16*	9.33	9.94*	10.39*	8.96	10.98*
Panel C: Difference (Post-CFMA)-(Pre-CFMA)													
Means	HLCB	10.29*	17.16*	18.44*	17.10*	15.26*	13.44*	11.01*	18.13*	14.34*	15.99*	14.33*	15.73*
FFCM	HLCB	10.83*	18.22*	21.32*	19.79*	15.77*	12.55*	11.54*	19.87*	18.24*	19.67*	14.88*	15.70*

Table VII: Risk-adjusted returns in factor models that additionally include COM

This table analyzes the same set of portfolios as in Tables II and III, but presents risk-adjusted returns (α's) for the factor models that include the commodity factor COM (constructed as in Section III.C). Specifically, we consider the single-factor model COM as well as CAPMCOM, FF3MCOM and FFCMCOM. Panel A analyzes returns from 198001 to 200312 and Panel B from 200401 to 201012, Panel C tests the differences for the HLCB spreading portfolios. To conserve space, we do not report results for the second and fourth size group. The t-statistics are based on White's heteroskedasticity-consistent standard errors.

Panel A: (Risk-adjusted) Returns for 1980-2003 (Pre-CFMA)													
		OIW	OIW	OIW	OIW	OIW	EW	OIW	OIW	OIW	OIW	OIW	EW
	CB	Size quintile				One-way		Size quintile				One-way	
	group	S	3	B	Stocks	48 Ind.	Stocks	S	3	B	Stocks	48 Ind.	Stocks
		α's, in ann. %'s						t-statistics					
COM	H	11.36	10.34	8.94	8.66	8.89	10.89	2.32	2.36	2.23	2.26	2.55	2.49
	4	11.94	10.10	11.31	10.56	9.84	9.62	2.90	2.83	3.34	3.28	2.80	2.49
	3	12.29	10.72	8.49	9.01	8.16	10.14	3.29	3.12	2.54	2.79	2.27	3.18
	2	11.54	11.50	9.02	9.38	9.91	8.91	3.02	3.17	2.67	2.84	2.98	2.89
	L	9.90	12.50	8.72	8.83	9.12	8.39	2.13	2.84	2.44	2.46	2.88	2.65
	HLCB	1.46	-2.15	0.23	-0.17	-0.23	2.50	0.89	-1.02	0.10	-0.11	-0.12	1.02
CAPM COM	H	0.94	-0.66	-0.85	-1.55	0.27	-0.30	0.26	-0.28	-0.39	-1.01	0.14	-0.14
	4	2.66	0.70	2.70	1.70	0.64	-0.82	0.95	0.41	1.67	1.52	0.40	-0.52
	3	3.72	1.68	-0.58	-0.13	-1.40	1.35	1.48	0.97	-0.47	-0.14	-0.90	1.27
	2	2.80	2.05	-0.22	0.13	0.98	0.59	1.10	1.19	-0.20	0.16	0.75	0.53
	L	-0.57	1.39	-0.53	-0.91	0.43	-0.26	-0.18	0.60	-0.31	-0.68	0.36	-0.23
	HLCB	1.50	-2.04	-0.32	-0.64	-0.16	-0.04	0.87	-0.95	-0.13	-0.42	-0.08	-0.02
FF3M COM	H	-2.19	-2.55	0.23	-1.90	-2.35	-0.30	-1.09	-1.33	0.10	-1.25	-1.37	-0.15
	4	-1.28	-2.05	4.06	2.25	-1.45	0.75	-0.79	-1.72	2.59	2.09	-1.00	0.54
	3	-0.57	-1.09	0.87	0.63	-3.80	1.68	-0.41	-0.86	0.70	0.65	-2.89	1.67
	2	-1.76	-0.74	0.86	0.55	-0.18	0.47	-1.19	-0.61	0.83	0.65	-0.14	0.46
	L	-4.28	-1.11	0.80	-0.68	-1.01	-0.32	-2.37	-0.64	0.49	-0.54	-0.87	-0.28
	HLCB	2.09	-1.43	-0.57	-1.22	-1.34	0.02	1.22	-0.65	-0.23	-0.79	-0.69	0.01
FFCM COM	H	1.94	0.35	1.90	0.44	-0.83	2.42	0.82	0.19	0.92	0.35	-0.47	1.42
	4	1.39	-1.65	3.21	1.80	-0.88	3.48	0.85	-1.35	2.01	1.68	-0.59	2.57
	3	1.59	-0.59	0.39	0.37	-3.92	1.53	1.05	-0.47	0.33	0.39	-2.66	1.54
	2	1.03	0.74	0.79	0.89	-0.44	-0.84	0.63	0.64	0.77	1.04	-0.33	-0.78
	L	-0.05	0.97	1.58	0.47	-1.05	-1.09	-0.02	0.57	0.98	0.36	-0.85	-0.90
	HLCB	1.99	-0.62	0.32	-0.03	0.22	3.51	1.26	-0.26	0.14	-0.02	0.11	1.71

Table VII continued

Panel B: (Risk-adjusted) Returns for 2004-2010 (Post-CFMA)													
		OIW	OIW	OIW	OIW	OIW	EW	OIW	OIW	OIW	OIW	OIW	EW
	CB group	Size quintile S	3	B	Stocks	One-way 48 Ind.	Stocks	Size quintile S	3	B	Stocks	One-way 48 Ind.	Stocks
		α's, in ann. %'s						*t*-statistics					
COM	H	-2.46	-1.04	1.58	0.57	0.03	-2.39	-0.24	-0.13	0.32	0.10	0.00	-0.36
	4	2.10	1.96	-0.55	-0.70	-1.99	-0.90	0.21	0.24	-0.09	-0.11	-0.25	-0.13
	3	2.79	2.22	-2.30	-1.29	0.55	0.63	0.30	0.29	-0.37	-0.20	0.07	0.11
	2	2.85	3.68	0.58	1.07	1.31	1.68	0.32	0.51	0.10	0.19	0.21	0.30
	L	-3.54	-1.61	1.61	0.90	-0.43	0.94	-0.38	-0.21	0.28	0.15	-0.07	0.17
	HLCB	1.07	0.56	-0.03	-0.33	0.46	-3.33	0.40	0.23	-0.01	-0.19	0.15	-1.12
CAPM	H	-0.25	0.74	2.67	1.85	1.51	-0.92	-0.06	0.26	1.05	0.98	0.54	-0.35
COM	4	4.26	3.75	0.68	0.69	-0.13	0.65	1.02	1.18	0.26	0.35	-0.05	0.27
	3	4.84	3.96	-0.91	0.17	2.27	2.01	1.18	1.50	-0.50	0.11	0.98	1.40
	2	4.79	5.36	1.90	2.46	2.85	2.97	1.27	2.04	1.23	1.88	1.50	1.91
	L	-1.49	0.18	2.88	2.30	1.03	2.22	-0.37	0.07	1.09	1.25	0.77	1.38
	HLCB	1.24	0.57	-0.21	-0.45	0.49	-3.14	0.48	0.23	-0.08	-0.26	0.16	-1.10
FF3M	H	-4.05	-1.65	3.58	1.95	1.14	-1.05	-1.57	-0.82	1.47	1.08	0.43	-0.43
COM	4	0.63	1.37	1.61	0.77	-1.45	-0.08	0.24	0.58	0.69	0.43	-0.65	-0.04
	3	0.82	1.91	-0.71	-0.06	1.76	2.14	0.35	1.03	-0.38	-0.03	0.77	1.50
	2	1.46	3.49	2.09	2.26	2.07	2.79	0.72	1.79	1.37	1.77	1.21	1.76
	L	-4.68	-1.76	3.63	2.33	0.72	2.59	-2.10	-0.93	1.43	1.33	0.56	1.78
	HLCB	0.62	0.11	-0.05	-0.38	0.42	-3.64	0.26	0.04	-0.02	-0.22	0.15	-1.30
FFCM	H	-3.69	-1.49	3.27	1.73	0.98	-1.31	-1.53	-0.74	1.46	1.05	0.37	-0.58
COM	4	1.05	1.49	1.45	0.69	-1.23	-0.01	0.44	0.63	0.64	0.39	-0.52	0.00
	3	1.19	2.10	-0.60	0.07	1.93	2.14	0.50	1.14	-0.32	0.05	0.89	1.48
	2	1.66	3.54	2.13	2.30	2.23	2.88	0.85	1.81	1.39	1.77	1.26	1.81
	L	-4.57	-1.79	3.51	2.23	0.79	2.49	-2.05	-0.95	1.40	1.30	0.62	1.75
	HLCB	0.88	0.30	-0.24	-0.51	0.19	-3.80	0.39	0.12	-0.09	-0.30	0.07	-1.38
Panel C: Difference (Pre-CFMA)-(Post-CFMA)													
		α's, in ann. %'s						*t*-statistics					
COM	HLCB	-0.38	2.71	-0.26	-0.16	0.68	-5.83	-0.12	0.83	-0.07	-0.07	0.19	-1.52
CAPMCOM	HLCB	-0.27	2.61	0.11	0.19	0.65	-3.10	-0.09	0.79	0.03	0.08	0.18	-0.83
FF3MCOM	HLCB	-1.46	1.54	0.52	0.84	1.76	-3.66	-0.50	0.45	0.14	0.36	0.51	-1.01
FFCMCOM	HLCB	-1.11	0.92	-0.56	-0.48	-0.03	-7.31	-0.40	0.26	-0.16	-0.22	-0.01	-2.12

Table VIII: Overview spanning regressions

This table presents summary statistics (Panel A) and spanning regressions (Panel B for 1980 to 2003 and Panel C for 2004 to 2010. All returns are annualized. Panel A reports average returns and correlations (lower-triangular: 1980-2003; upper-triangular: 2004-2010) for the factors of interest: MKT, SMB, HML, MOM, COM, OIW and EW where * indicates significance at the 5% level. Panels B and C present two sets of spanning regressions. In the first set, we regress the commodity factor COM on the benchmark factor models: CAPM, FF3M and FFCM. In the second set, we test whether the benchmark factors (SMB, HML, MOM) are spanned by (i) the two-factor model CAPMCOM or (ii) a four-factor model containing all remaining factors. The t-statistics presented underneath each estimate are based on White's heteroskedasticity-consistent standard errors.

Panel A: Summary statistics

	Average return			Correlations						
	1980-2003	2004-2010	Difference	MKT	SMB	HML	MOM	COM	OIW	EW
MKT	7.49*	4.54	-2.96		0.43*	0.38*	-0.36*	0.46*	0.41*	0.52*
SMB	1.54	3.50	1.97	0.19*		0.21	-0.09	0.12	0.01	0.00
HML	4.76*	2.37	-2.39	-0.52*	-0.41*		-0.36*	0.16	0.13	0.10
MOM	10.45*	-1.52	-11.96	-0.03	0.10	-0.14*		-0.21	0.08	-0.01
COM	-5.92*	9.85*	15.78*	0.24*	0.33*	-0.35*	0.32*		0.66*	0.67*
OIW	-0.96	1.88	2.84	0.10	0.10	0.00	0.14*	0.42*		0.86*
EW	0.97	7.03	6.06	0.19*	0.11	-0.07	0.02	0.36*	0.85*	

Panel B: Spanning regressions for 1980-2003 (Pre-CFMA)

	COM vs Benchmark factor models			Benchmark factors - SMB, HML and MOM					
	COM	COM	COM	SMB	SMB	HML	HML	MOM	MOM
Intercept	-7.47	-5.65	-8.69	2.41	4.83	6.05	7.51	13.65	14.68
	(-2.74)	(-2.07)	(-3.46)	(0.95)	(1.81)	(2.85)	(3.52)	(4.43)	(4.45)
MKT	0.21	0.07	0.11	0.09	-0.04	-0.33	-0.32	-0.12	-0.17
	(3.49)	(1.20)	(1.79)	(1.76)	(-0.52)	(-7.21)	(-6.26)	(-1.43)	(-1.83)
SMB		0.27	0.25				-0.27		-0.03
		(2.26)	(2.58)				(-4.60)		(-0.21)
HML		-0.26	-0.20		-0.37				-0.16
		(-2.36)	(-2.20)		(-3.78)				(-1.14)
MOM			0.24		-0.01		-0.06		
			(3.98)		(-0.21)		(-1.14)		
COM				0.26	0.19	-0.20	-0.11	0.39	0.37
				(2.31)	(2.36)	(-2.99)	(-2.25)	(3.88)	(3.30)
Adj. R^2	0.05	0.16	0.23	0.12	0.20	0.32	0.39	0.11	0.11

Panel C: Spanning regressions for 2004-2010 (Post-CFMA)

	COM	COM	COM	SMB	SMB	HML	HML	MOM	MOM
Intercept	8.28	8.66	8.68	3.05	2.89	1.55	1.44	1.13	1.38
	(1.95)	(2.13)	(2.11)	(1.08)	(1.03)	(0.45)	(0.44)	(0.21)	(0.28)
MKT	0.35	0.38	0.37	0.24	0.24	0.22	0.15	-0.39	-0.31
	(3.90)	(3.40)	(3.45)	(4.45)	(3.96)	(2.54)	(1.43)	(-2.74)	(-2.01)
SMB		-0.14	-0.13				0.09		0.21
		(-0.71)	(-0.65)				(0.78)		(0.68)
HML		-0.02	-0.04		0.07				-0.57
		(-0.13)	(-0.23)		(0.72)				(-1.95)
MOM			-0.04		0.04		-0.13		
			(-0.25)		(0.57)		(-2.75)		
COM				-0.06	-0.06	-0.02	-0.02	-0.09	-0.09
				(-0.72)	(-0.66)	(-0.16)	(-0.23)	(-0.24)	(-0.23)
Adj. R^2	0.20	0.19	0.18	0.17	0.16	0.12	0.17	0.11	0.16

Table IX: Cross-sectional regressions - commodity factor COM

This table presents Fama and MacBeth (1973) regressions that use the set of 30 commodity beta-sorted portfolios as test assets. We consider the benchmark factor models (CAPM, FF3M, and FFCM) as well as models that add the commodity factor (CAPM-COM, FF3MCOM and FFCMCOM). We restrict the intercepts to zero. Panel A presents results for returns from January 1980 to December 2003 and Panel B for January 2004 to December 2010. Both panels present estimated risk premiums ($\widehat{\lambda_A}$ and $\widehat{\lambda_B}$) and underneath are Fama-MacBeth Shanken-corrected t-statistics (Shanken (1992)), in parenthesis. The last column contains two R^2's. The top one, R_s^2, is the standard cross-sectional adjusted R^2; the bottom one, R_p^2, is the R^2 from a regression of average returns on the product of betas and risk premiums fixed at their sample average. Panel C tests the difference in the risk premiums over the two subsamples using the standard t-test for the equality of two means with unequal variance and sample sizes using the Shanken-corrected standard errors.

		Panel A: Returns from 1980-2003 (Pre-CFMA)					
		MKT	SMB	HML	MOM	COM	R^2's
CAPM	$\widehat{\lambda_A}$	7.66					-0.62
	FMB-S t	(2.22)					-0.62
CAPMCOM	$\widehat{\lambda_A}$	8.36				-5.84	0.68
	FMB-S t	(2.43)				(-2.02)	0.68
FF3M	$\widehat{\lambda_A}$	6.96	-1.32	10.64			0.36
	FMB-S t	(2.10)	(-0.48)	(2.01)			0.09
FF3MCOM	$\widehat{\lambda_A}$	7.50	0.33	1.15		-5.76	0.74
	FMB-S t	(2.28)	(0.12)	(0.28)		(-2.01)	0.69
FFCM	$\widehat{\lambda_A}$	6.82	-2.34	6.73	-14.78		0.51
	FMB-S t	(2.05)	(-0.81)	(1.55)	(-1.77)		-0.66
FFCMCOM	$\widehat{\lambda_A}$	7.99	2.50	-0.39	8.95	-5.32	0.79
	FMB-S t	(2.42)	(0.89)	(-0.10)	(1.21)	(-1.86)	0.70
		Panel B: Returns from 2004-2010 (Post-CFMA)					
CAPM	$\widehat{\lambda_B}$	7.11					0.40
	FMB-S t	(1.10)					0.40
CAPMCOM	$\widehat{\lambda_B}$	6.58				8.62	0.75
	FMB-S t	(1.02)				(1.77)	0.59
FF3M	$\widehat{\lambda_B}$	8.33	-0.69	5.81			0.40
	FMB-S t	(1.29)	(-0.18)	(0.93)			0.25
FF3MCOM	$\widehat{\lambda_B}$	6.16	1.70	3.43		8.70	0.75
	FMB-S t	(0.98)	(0.50)	(0.57)		(1.79)	0.72
FFCM	$\widehat{\lambda_B}$	8.42	-0.43	7.12	-4.31		0.38
	FMB-S t	(1.31)	(-0.11)	(1.10)	(-0.42)		0.26
FFCMCOM	$\widehat{\lambda_B}$	6.24	1.92	4.55	-2.56	8.59	0.74
	FMB-S t	(0.99)	(0.56)	(0.75)	(-0.25)	(1.77)	0.72

Panel C: Difference risk premium COM		
	$\widehat{\lambda_B} - \widehat{\lambda_A}$	FMB-S t
CAPMCOM	14.46	(2.55)
FF3MCOM	14.46	(2.56)
FFCMCOM	13.91	(2.47)

Table X: Cross-sectional regressions - OIW commodity index
This table is the equivalent of Table IX for the benchmark factor models that additionally include the OIW index, instead of the commodity factor COM. In all models, we restrict the intercept to zero. Panel A presents the results for returns from January 1980 to December 2003 and Panel B for January 2004 to December 2010. Both panels present estimated risk premiums ($\widehat{\lambda_A}$ and $\widehat{\lambda_B}$) and underneath Fama-MacBeth Shanken-corrected t-statistics (Shanken (1992)), in parenthesis. The last column contains two (adjusted) R^2's. The top one, R^2_s, is the standard cross-sectional R^2; the bottom one, R^2_f, is the R^2 from a regression of average returns on the product of betas and risk premiums fixed at their sample average. Panel C tests the difference in the risk premiums over the two subsamples.

		MKT	SMB	HML	MOM	OIW	R^2's
Panel A: Returns from 1980-2003 (Pre-CFMA)							
CAPMOIW	$\widehat{\lambda_A}$	8.73				-19.21	0.72
	FMB-S t	(2.51)				(-2.60)	-0.39
FF3MOIW	$\widehat{\lambda_A}$	7.90	-0.13	1.94		-13.78	0.82
	FMB-S t	(2.40)	(-0.05)	(0.48)		(-2.07)	0.34
FFCMOIW	$\widehat{\lambda_A}$	8.05	0.29	2.05	-0.72	-14.87	0.83
	FMB-S t	(2.45)	(0.10)	(0.50)	(-0.10)	(-2.37)	-0.04
Panel B: Returns from 2004-2010 (Post-CFMA)							
CAPMOIW	$\widehat{\lambda_B}$	7.39				18.60	0.68
	FMB-S t	(1.14)				(1.56)	0.35
FF3MOIW	$\widehat{\lambda_B}$	6.66	1.78	6.47		20.77	0.72
	FMB-S t	(1.05)	(0.52)	(1.01)		(1.66)	0.29
FFCMOIW	$\widehat{\lambda_B}$	6.44	1.32	3.92	-5.19	19.35	0.72
	FMB-S t	(1.02)	(0.38)	(0.64)	(-0.50)	(1.63)	0.29

Panel C: Difference risk premium OIW		
	$\widehat{\lambda_B} - \widehat{\lambda_A}$	FMB-S t
CAPMOIW	37.81	(2.69)
FF3MOIW	34.54	(2.44)
FFCMOIW	34.22	(2.55)

Internet Appendix to "The Stock Market Price of Commodity Risk"

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ABSTRACT

This Internet appendix contains additional material to the paper "The Stock Market Price of Commodity Risk". Section I presents results for the Taylor approximation of the agent's utility problem. Section II presents robustness checks for the empirical analysis.

I Higher order terms

This section evaluates the effect of leaving out higher order moments from the maximand defined in equation (4) in the paper.

Starting from equation (A3) in Appendix A of the paper and after leaving out the term $\frac{W_t}{S_t}\frac{1}{1+\overline{R_S}}$ and defining $q_0 = 1/\left(1+\overline{R_S}\right)$, and $q_1 = \left(1+R_{f,t}\right)/\left(1+\overline{R_S}\right)$ we can compute the variance of C_{t+1} as

$$\begin{aligned} Var\left[C_{t+1}\right] &= Var\left[w_r' r_{t+1} - q_1\left(R_{S,t+1}-\overline{R_S}\right) - q_0\left(R_{S,t+1}-\overline{R_S}\right) w_r' r_{t+1}\right] \\ &= w_r'\Sigma_{rr}w_r + q_1^2\sigma_S^2 - 2q_1 w_r'\Sigma_{rS} + \\ &\quad +q_0^2 w_r' Var\left[\left(R_{S,t+1}-\overline{R_S}\right) r_{t+1}\right] w_r + \\ &\quad +2q_1 q_0 w_r' Cov\left[\left(R_{S,t+1}-\overline{R_S}\right) r_{t+1}, \left(R_{S,t+1}-\overline{R_S}\right)\right] + \\ &\quad -2q_0 w_r' Cov\left[r_{t+1}, \left(R_{S,t+1}-\overline{R_S}\right) r_{t+1}\right] w_r. \end{aligned} \tag{1}$$

When $R_{S,t+1}$ and r_{t+1} are multivariate normally distributed, we can follow Bohrnstedt and Goldberger (1969) and express the last three terms in means and variances only

$$\begin{aligned} Var\left[\left(R_{S,t+1}-\overline{R_S}\right) r_{t+1}\right] &= \mu_r^2\sigma_S^2 + \Sigma_{rr}\sigma_S^2 + \Sigma_{rS}\Sigma_{rS}', \\ Cov\left[\left(R_{S,t+1}-\overline{R_S}\right) r_{t+1}, \left(R_{S,t+1}-\overline{R_S}\right)\right] &= \mu_r\sigma_S^2, \\ Cov\left[r_{t+1}^P, \left(R_{S,t+1}-\overline{R_S}\right) r_{t+1}^P\right] &= \mu_r\Sigma_{rS}. \end{aligned} \tag{2}$$

Hence the difference between the total value of $Var\left[C_{t+1}\right]$ and the value without higher moments is equal to:

$$\begin{aligned} d &= Var\left[C_{t+1}\right] - w_r' \Sigma_{rr} w_r + q_1^2 \sigma_S^2 - 2q_1 w_r' \Sigma_{rS} \\ &= q_0^2 w_r' \left(\mu_r^2 \sigma_S^2 + \Sigma_{rr} \sigma_S^2 + \Sigma_{rS} \Sigma_{rS}'\right) w_r + \\ &\quad +2q_1 q_0 w_r' \mu_r \sigma_S^2 - 2q_0 w_r' \mu_r \Sigma_{rS} w_r. \end{aligned} \tag{3}$$

Note that this difference is a non-linear function of both μ_r and ρ_{rS}.

To asses the magnitude of omitting the higher order moments we analyze the difference relative to the total variance of C_{t+1}, namely $d/Var\left[C_{t+1}\right]$. We consider a numerical example with two assets, r_{t+1} the CRSP value-weighted index and $R_{S,t+1}$ the OIW index of commodities. We allow the expected return on the CRSP index μ_r to vary between between -1.5% to 1.5% per month and the correlation between the two indexes ρ_{rS} to vary between -0.9 to 0.9. Standard deviations are fixed at their sample estimate, i.e., $\sigma_r = \sigma_S = 0.05$, and $q_0 = q_1 = 1$. For each value of parameters on a grid we compute the optimal weights w_r as given in equation (6), assuming a risk aversion of 5.

Table A shows that the differences between the total variance of C_{t+1} and the variance without higher moments is at most 2.5% of the total variance of C_{t+1}. Thus, leaving out the higher moments from the optimization problem means that the agent is ignoring only a small fraction of the total variance of his consumption.

Table A: Percentage differences, $d/Var[C_{t+1}]$

ρ_{rS}/μ_r	-1.50%	-1.25%	-1.00%	-0.75%	-0.50%	-0.25%	0.00%	0.25%	0.50%	0.75%	1.00%	1.25%	1.50%
-0.9	-2.03%	-1.14%	-0.09%	1.15%	2.30%	2.37%	1.04%	-0.05%	-0.35%	-0.19%	0.15%	0.57%	1.03%
-0.8	-0.80%	-0.13%	0.56%	1.17%	1.47%	1.17%	0.43%	-0.13%	-0.25%	-0.06%	0.29%	0.71%	1.15%
-0.7	0.00%	0.47%	0.88%	1.15%	1.13%	0.76%	0.22%	-0.14%	-0.17%	0.06%	0.42%	0.83%	1.26%
-0.6	0.54%	0.84%	1.05%	1.11%	0.94%	0.55%	0.12%	-0.12%	-0.08%	0.17%	0.53%	0.94%	1.36%
-0.5	0.92%	1.07%	1.14%	1.06%	0.80%	0.42%	0.07%	-0.09%	0.00%	0.28%	0.64%	1.04%	1.44%
-0.4	1.18%	1.22%	1.17%	1.00%	0.70%	0.33%	0.04%	-0.06%	0.08%	0.37%	0.75%	1.14%	1.51%
-0.3	1.37%	1.31%	1.18%	0.94%	0.61%	0.26%	0.02%	-0.02%	0.16%	0.47%	0.84%	1.21%	1.57%
-0.2	1.49%	1.36%	1.16%	0.87%	0.53%	0.20%	0.01%	0.02%	0.23%	0.56%	0.92%	1.28%	1.61%
-0.1	1.57%	1.38%	1.12%	0.80%	0.45%	0.15%	0.00%	0.06%	0.30%	0.64%	1.00%	1.33%	1.62%
0	1.61%	1.36%	1.07%	0.72%	0.38%	0.11%	0.00%	0.11%	0.38%	0.72%	1.07%	1.36%	1.61%
0.1	1.62%	1.33%	1.00%	0.64%	0.30%	0.06%	0.00%	0.15%	0.45%	0.80%	1.12%	1.38%	1.57%
0.2	1.61%	1.28%	0.92%	0.56%	0.23%	0.02%	0.01%	0.20%	0.53%	0.87%	1.16%	1.36%	1.49%
0.3	1.57%	1.21%	0.84%	0.47%	0.16%	-0.02%	0.02%	0.26%	0.61%	0.94%	1.18%	1.31%	1.37%
0.4	1.51%	1.14%	0.75%	0.37%	0.08%	-0.06%	0.04%	0.33%	0.70%	1.00%	1.17%	1.22%	1.18%
0.5	1.44%	1.04%	0.64%	0.28%	0.00%	-0.09%	0.07%	0.42%	0.80%	1.06%	1.14%	1.07%	0.92%
0.6	1.36%	0.94%	0.53%	0.17%	-0.08%	-0.12%	0.12%	0.55%	0.94%	1.11%	1.05%	0.84%	0.54%
0.7	1.26%	0.83%	0.42%	0.06%	-0.17%	-0.14%	0.22%	0.76%	1.13%	1.15%	0.88%	0.47%	0.00%
0.8	1.15%	0.71%	0.29%	-0.06%	-0.25%	-0.13%	0.43%	1.17%	1.47%	1.17%	0.56%	-0.13%	-0.80%
0.9	1.03%	0.57%	0.15%	-0.19%	-0.35%	-0.05%	1.04%	2.37%	2.30%	1.15%	-0.09%	-1.14%	-2.03%

II Robustness checks

Table B: Sorts that control for the benchmark factors

This table presents results for sorts on commodity beta, where we control for the CAPM, FF3M or FFCM factors in each rolling window, as in equation (21). In short, our results are robust, in that high commodity beta portfolios underperform pre-CFMA and outperform post-CFMA in average and benchmark-adjusted returns, whereas these large performance differentials are captured well when additionally including the commodity factor COM.

Table C: Sorts on alternative commodity indexes

This table presents means and FFCM alphas for stock portfolios sorted one-dimensionally on commodity indexes other than our open interest weighted index (OIW), that is, an equal-weighted index (EW), the S&P-GSCI index (GSCI), an index of six energy commodities (Energy), an index of 15 agriculture commodities (Agri), an index of eight metals and fiber commodities (Metals) and an index of four livestock and meat commodities (Meats). In short, our main results extend for the aggregate indexes EW and GSCI, and seem to be driven by commodities in the largest sectors in terms of open interest and trading volume: Energy and Metals.

Table D: Cross-sectional regressions including an intercept

This table is the equivalent of Table VIII in the paper, but in this case an intercept is included in the Fama-MacBeth regressions. In short, the results for the commodity factor COM easily extend when an intercept is included in the cross-sectional regressions. This result does not obtain for the other factors and for the market risk premium, in particular.

Table E: GLS cross-sectional regressions (including an intercept)

This table is the equivalent of Table VIII in the paper, but in this case we use generalized least squares (GLS) cross-sectional regressions. The regressions include an intercept to facilitate the interpretation of the GLS R^2 as a measure of closeness to the in-sample mean-variance boundary. In short, the results for the commodity factor COM easily extend in GLS regressions, in terms of significance and improvements in R^2, although GLS R^2's are lower than OLS R^2. Again, this result does not obtain for the other factors.

Table F: OLS cross-sectional regressions for IND48

This table is the equivalent of Table VIII in the paper, but in this case we use 48 industry portfolios (IND48, available from Kenneth French's Web Site) as test assets. In short, in both sub-periods and in all models the estimated risk premiums for COM are of the hypothesized sign, but mostly insignificant. These risk premiums add up to a marginally significant reversal of over 10% in the CAPMCOM and FF3MCOM, as seen in Panel C.

Table G: OLS cross-sectional regressions for SBM25

This table is the equivalent of Table VIII in the paper, but in this case we use 25 size and book-to-market sorted portfolios (SBM25, available from Kenneth French's Web Site) as test assets. In short, in both sub-periods and in all models the estimated risk premiums for COM are of the hypothesized sign, but mostly insignificant. These risk premiums add up to a reversal that is economically large in all models ($> 15\%$) and marginally significant in the FF3MCOM and FFCMCOM, as seen in Panel C.

Table B: Sorts that control for the benchmark factors

This table analyzes (risk-adjusted) returns of the HLCB portfolios that result from a one-dimensional sort of all CRSP stocks. Here we estimate commodity betas using the alternative specification in equation (21). The row headings indicate which factors are controlled for when estimating commodity beta, that is, "No" repeats the results from Tables III and VII, while "MKT", "MKT, SMB, HML" and "MKT, SMB, HML, MOM" control for the respective factors in each rolling window. Column-wise we report average returns (μ) as well as risk-adjusted returns (α) from time-series factor regressions for the benchmark factor models (CAPM, FF3M, FFCM) as well as factor models that add our commodity factor (COM, CAPMCOM, FF3MCOM, FFCCOM). Panel A covers January 1980 to December 2003, and Panel B covers January 2004 to December 2010. Panel C tests the differences. The t-statistics presented underneath each estimate (in parenthesis) are based on White's heteroskedasticity-consistent standard errors.

	Benchmark factor models				Models including COM			
Controls	Avg	CAPM	FF3M	FFCM	COM	CAPM +COM	FF3M +COM	FFCM +COM
Panel A: HLCB returns for 1980-2003 (Pre-CFMA)								
No	-8.11	-10.54	-8.61	-11.66	-0.17	-0.64	-1.22	-0.03
	(-2.02)	(-2.72)	(-2.25)	(-3.10)	(-0.11)	(-0.42)	(-0.79)	(-0.02)
MKT	-5.70	-7.20	-7.36	-10.37	1.35	1.79	-0.48	0.42
	(-1.52)	(-1.96)	(-1.96)	(-2.85)	(0.75)	(1.00)	(-0.28)	(0.24)
MKT, SMB, HML	-8.34	-8.43	-9.59	-12.47	-3.43	-1.89	-3.93	-3.72
	(-2.59)	(-2.63)	(-2.71)	(-3.53)	(-1.50)	(-0.84)	(-1.86)	(-1.60)
MKT, SMB, HML, MOM	-7.28	-7.51	-8.75	-10.84	-2.83	-1.62	-3.71	-2.90
	(-2.40)	(-2.52)	(-2.68)	(-3.12)	(-1.28)	(-0.75)	(-1.79)	(-1.25)
Panel B: HLCB returns for 2004-2010 (Post-CFMA)								
No	12.08	10.37	10.93	10.90	-0.33	-0.45	-0.38	-0.51
	(1.95)	(1.77)	(1.91)	(1.90)	(-0.19)	(-0.26)	(-0.22)	(-0.30)
MKT	3.79	4.05	6.14	5.99	-4.18	-4.81	-2.81	-3.19
	(0.63)	(0.66)	(1.08)	(1.09)	(-0.95)	(-1.28)	(-0.83)	(-0.98)
MKT, SMB, HML	6.25	5.86	7.43	7.32	-2.71	-3.14	-1.78	-2.08
	(1.12)	(1.03)	(1.39)	(1.39)	(-0.82)	(-1.07)	(-0.65)	(-0.76)
MKT, SMB, HML, MOM	7.67	6.50	7.42	7.34	-2.88	-3.09	-2.53	-2.76
	(1.31)	(1.13)	(1.34)	(1.33)	(-0.99)	(-1.08)	(-0.90)	(-0.97)
Panel C: Difference (Post-CFMA)-(Pre-CFMA)								
No	20.19	20.92	19.54	22.56	-0.16	0.19	0.84	-0.48
	(2.73)	(2.98)	(2.84)	(3.28)	(-0.07)	(0.08)	(0.36)	(-0.22)
MKT	9.49	11.25	13.50	16.35	-5.53	-6.60	-2.33	-3.61
	(1.33)	(1.57)	(1.98)	(2.49)	(-1.17)	(-1.59)	(-0.62)	(-0.98)
MKT, SMB, HML	14.58	14.29	17.02	19.79	0.72	-1.26	2.16	1.64
	(2.26)	(2.19)	(2.65)	(3.12)	(0.18)	(-0.34)	(0.62)	(0.46)
MKT, SMB, HML, MOM	14.95	14.01	16.17	18.18	-0.05	-1.48	1.18	0.14
	(2.27)	(2.16)	(2.51)	(2.78)	(-0.01)	(-0.41)	(0.34)	(0.04)

Table C: Sorts on alternative commodity indexes

This table presents means and FFCM alphas for stock portfolios sorted one-dimensionally in five groups on betas with respect to commodity indexes other than our open interest weighted index (OIW), that is, an equal-weighted index (EW), the S&P-GSCI index (GSCI), an index of six energy commodities (Energy), an index of 15 agriculture commodities (Agri), an index of eight metals and fiber commodities (Metals) and an index of four livestock and meat commodities (Meats). We present only (risk-adjusted) returns for the portfolios H, 4, 3, 2, and L and for the high minus low commodity beta (HLCB) portfolios both (risk-adjusted) returns and the corresponding t-statistics based on White's heteroskedasticity-consistent standard errors.

		OIW	EW	GSCI	Energy	Agri	Metals	Meats
		Panel A: Returns from 198001 to 200312						
Mean	H	1.91	4.45	3.35	4.71	8.34	4.59	6.79
	4	6.58	5.77	7.50	7.96	6.53	6.01	9.48
	3	7.04	8.25	6.41	9.09	9.13	7.64	7.65
	2	9.53	8.81	9.19	8.25	7.44	8.62	7.23
	L	10.02	9.33	9.07	8.54	7.43	10.72	5.93
	HLCB	-8.11	-4.88	-5.72	-3.82	0.92	-6.13	0.86
	t-stat	(-2.02)	(-1.16)	(-1.32)	(-0.86)	(0.29)	(-1.46)	(0.28)
FFCM α	H	-6.67	-3.52	-3.69	-3.65	0.77	-0.92	-1.75
	4	-1.73	0.40	1.35	-0.01	-0.04	-0.90	1.14
	3	-0.13	0.76	-0.14	1.50	1.75	1.26	-0.35
	2	3.33	1.08	1.13	1.32	0.73	1.88	1.14
	L	4.99	2.77	1.49	1.05	3.24	3.46	0.19
	HLCB	-11.66	-6.30	-5.18	-4.69	-2.46	-4.38	-1.94
	t-stat	(-3.10)	(-1.80)	(-1.14)	(-1.02)	(-0.80)	(-1.20)	(-0.58)
		Panel B: Returns from 200401 to 201012						
Mean	H	14.85	11.93	14.40	14.84	4.91	8.67	11.63
	4	5.64	7.33	8.35	6.40	6.59	5.76	5.21
	3	3.58	5.16	3.90	3.54	5.41	6.61	4.46
	2	3.87	5.07	3.13	3.81	8.17	4.95	4.19
	L	2.77	3.24	3.81	1.26	3.80	2.83	5.51
	HLCB	12.08	8.69	10.59	13.57	1.11	5.84	6.13
	t-stat	(1.95)	(1.34)	(1.68)	(2.22)	(0.19)	(0.89)	(1.17)
FFCM α	H	9.82	6.23	9.07	9.82	-1.03	2.66	4.96
	4	1.33	1.76	3.35	2.32	1.75	1.10	-0.05
	3	-0.93	1.16	-0.51	-1.13	1.72	2.69	0.35
	2	-0.19	1.18	-0.72	-0.01	4.00	1.03	1.08
	L	-1.08	-0.09	0.16	-2.99	-0.62	-1.15	1.38
	HLCB	10.90	6.32	8.91	12.81	-0.41	3.81	3.58
	t-stat	(1.90)	(1.12)	(1.54)	(2.19)	(-0.08)	(0.68)	(0.96)
		Panel C: Difference						
Mean	HLCB	20.19	13.58	16.31	17.40	0.20	11.97	5.26
	t-stat	(2.73)	(1.75)	(2.13)	(2.30)	(0.03)	(1.54)	(0.87)
FFCM α	HLCB	22.56	12.61	14.09	17.50	2.05	8.18	5.52
	t-stat	(3.28)	(1.90)	(1.91)	(2.35)	(0.35)	(1.23)	(1.11)

Table D: Cross-sectional regressions including an intercept

This table is the equivalent of Table VIII in the paper, but in this case an intercept is included in the cross-sectional regressions that use the set of 30 commodity beta-sorted portfolios as test assets. We consider the benchmark factor models (CAPM, FF3M, and FFCM) as well as models that add the commodity factor (CAPMCOM, FF3MCOM and FFCMCOM). We present estimated risk premiums ($\widehat{\lambda_A}$ and $\widehat{\lambda_B}$) and underneath are Fama-MacBeth Shanken-corrected t-statistics (Shanken (1992)), in parenthesis. The last column contains two R^2's. The top one, R_s^2, is the standard cross-sectional adjusted R^2; the bottom one, R_p^2, is the R^2 from a regression of average returns on the product of betas and risk premiums fixed at their sample average. Panel C tests the difference in the risk premiums over the two subsamples.

		Intercept	MKT	SMB	HML	MOM	COM	R^2's
Panel A: Returns from 198001 to 200312								
CAPM	$\widehat{\lambda_A}$	21.19	-11.91					0.33
	FMB-S t	(2.76)	(-1.43)					0.33
CAPMCOM	$\widehat{\lambda_A}$	6.82	1.92				-5.63	0.72
	FMB-S t	(1.08)	(0.26)				(-1.96)	0.70
FF3M	$\widehat{\lambda_A}$	16.39	-8.63	-0.38	9.27			0.54
	FMB-S t	(2.42)	(-1.14)	(-0.14)	(1.87)			0.08
FF3MCOM	$\widehat{\lambda_A}$	12.06	-4.03	0.85	1.18		-5.81	0.84
	FMB-S t	(1.92)	(-0.57)	(0.31)	(0.29)		(-2.02)	0.71
FFCM	$\widehat{\lambda_A}$	16.07	-8.46	-1.39	5.49	-11.98		0.69
	FMB-S t	(2.38)	(-1.12)	(-0.48)	(1.30)	(-1.51)		0.13
FFCMCOM	$\widehat{\lambda_A}$	10.24	-1.96	2.19	0.17	6.22	-5.51	0.86
	FMB-S t	(1.60)	(-0.27)	(0.80)	(0.04)	(0.89)	(-1.92)	0.78
Panel B: Returns from 200401 to 201012								
CAPM	$\widehat{\lambda_B}$	-7.53	13.20					0.50
	FMB-S t	(-1.11)	(1.45)					0.50
CAPMCOM	$\widehat{\lambda_B}$	0.02	6.56				8.62	0.74
	FMB-S t	(0.00)	(0.66)				(1.77)	0.74
FF3M	$\widehat{\lambda_B}$	-11.54	18.46	-0.17	2.84			0.58
	FMB-S t	(-1.14)	(1.53)	(-0.05)	(0.45)			0.23
FF3MCOM	$\widehat{\lambda_B}$	25.91	-20.02	4.32	6.29		8.83	0.86
	FMB-S t	(3.04)	(-1.88)	(1.22)	(0.91)		(1.79)	0.77
FFCM	$\widehat{\lambda_B}$	-11.59	18.66	0.24	4.88	-4.91		0.57
	FMB-S t	(-1.14)	(1.53)	(0.07)	(0.78)	(-0.47)		0.23
FFCMCOM	$\widehat{\lambda_B}$	26.16	-20.33	4.18	5.49	1.64	8.91	0.86
	FMB-S t	(3.22)	(-1.99)	(1.14)	(0.78)	(0.14)	(1.82)	0.78

Panel C: Difference risk premium COM		
	$\widehat{\lambda_B}$-$\widehat{\lambda_A}$	FMB-S t
CAPMCOM	14.24	(2.52)
FF3MCOM	14.64	(2.57)
FFCMCOM	14.42	(2.54)

Table E: GLS cross-sectional regressions (including an intercept)
This table is the equivalent of Table VIII in the paper, but in this case we use generalized least squares (GLS) cross-sectional regressions. The regressions include an intercept to facilitate the interpretation of the GLS R^2 as a measure of closeness to the in-sample mean-variance boundary. We use the set of 30 commodity beta-sorted portfolios as test assets. We consider the benchmark factor models (CAPM, FF3M, and FFCM) as well as models that add the commodity factor (CAPMCOM, FF3MCOM and FFCMCOM). We present estimated risk premiums ($\widehat{\lambda_A}$ and $\widehat{\lambda_B}$) and underneath are Fama-MacBeth Shanken-corrected t-statistics (Shanken (1992)), in parenthesis. The last column contains the GLS R^2.

		Intercept	MKT	SMB	HML	MOM	COM	R^2
Panel A: Returns from 198001 to 200312								
CAPM	$\widehat{\lambda_A}$	13.39	-5.70					0.05
	FMB-S t	(3.82)	(-1.19)					
CAPMCOM	$\widehat{\lambda_A}$	12.10	-4.41				-5.27	0.12
	FMB-S t	(3.34)	(-0.91)				(-1.86)	
FF3M	$\widehat{\lambda_A}$	15.20	-7.51	1.66	0.39			0.08
	FMB-S t	(3.63)	(-1.42)	(0.66)	(0.12)			
FF3MCOM	$\widehat{\lambda_A}$	15.10	-7.41	2.03	-0.97		-5.43	0.22
	FMB-S t	(3.56)	(-1.39)	(0.80)	(-0.29)		(-1.91)	
FFCM	$\widehat{\lambda_A}$	15.19	-7.55	1.40	0.34	-2.42		0.09
	FMB-S t	(3.62)	(-1.42)	(0.54)	(0.10)	(-0.45)		
FFCMCOM	$\widehat{\lambda_A}$	15.09	-7.35	2.35	-1.15	2.42	-5.43	0.23
	FMB-S t	(3.55)	(-1.38)	(0.90)	(-0.34)	(0.41)	(-1.91)	
Panel B: Returns from 200401 to 201012								
CAPM	$\widehat{\lambda_B}$	8.52	-2.96					0.00
	FMB-S t	(2.07)	(-0.40)					
CAPMCOM	$\widehat{\lambda_B}$	12.29	-6.80				9.92	0.14
	FMB-S t	(2.69)	(-0.88)				(2.09)	
FF3M	$\widehat{\lambda_B}$	13.98	-8.36	3.45	5.29			0.07
	FMB-S t	(2.68)	(-1.03)	(1.06)	(1.14)			
FF3MCOM	$\widehat{\lambda_B}$	22.45	-16.92	4.25	6.67		9.53	0.30
	FMB-S t	(3.37)	(-1.85)	(1.28)	(1.34)		(2.00)	
FFCM	$\widehat{\lambda_B}$	13.74	-8.15	3.29	4.39	-3.43		0.08
	FMB-S t	(2.64)	(-1.00)	(1.00)	(0.88)	(-0.39)		
FFCMCOM	$\widehat{\lambda_B}$	22.36	-16.84	4.21	6.46	0.61	9.54	0.30
	FMB-S t	(3.33)	(-1.84)	(1.25)	(1.19)	(0.06)	(2.00)	
Panel C: Difference risk premium COM								
	$\widehat{\lambda_B}$-$\widehat{\lambda_A}$	FMB-S t						
CAPMCOM	15.19	(2.75)						
FF3MCOM	14.96	(2.70)						
FFCMCOM	14.97	(2.70)						

Table F: OLS cross-sectional regressions for IND48

This table is the equivalent of Table VIII in the paper, but in this case we use 48 industry portfolios (IND48, available from Kenneth French's Web Site) as test assets. We consider the benchmark factor models (CAPM, FF3M, and FFCM) as well as models that add the commodity factor (CAPMCOM, FF3MCOM and FFCMCOM). We present estimated risk premiums ($\widehat{\lambda_A}$ and $\widehat{\lambda_B}$) and underneath are Fama-MacBeth Shanken-corrected t-statistics (Shanken (1992)), in parenthesis. The last column contains two R^2's. The top one, R_s^2, is the standard cross-sectional adjusted R^2; the bottom one, R_p^2, is the R^2 from a regression of average returns on the product of betas and risk premiums fixed at their sample average. Panel C tests the difference in the risk premiums over the two subsamples.

		MKT	SMB	HML	MOM	COM	R^2
Panel A: Returns from 198001 to 200312							
CAPM	$\widehat{\lambda_A}$	8.13					-0.41
	FMB-S t	(2.39)					-0.41
CAPMCOM	$\widehat{\lambda_A}$	7.54				-4.63	-0.06
	FMB-S t	(2.21)				(-1.13)	-0.05
FF3M	$\widehat{\lambda_A}$	9.13	-8.57	-1.22			0.28
	FMB-S t	(2.72)	(-2.4)	(-0.40)			-0.82
FF3MCOM	$\widehat{\lambda_A}$	8.87	-7.92	-1.16		-2.83	0.29
	FMB-S t	(2.66)	(-2.53)	(-0.38)		(-0.69)	-0.56
FFCM	$\widehat{\lambda_A}$	9.68	-7.78	-2.13	6.81		0.37
	FMB-S t	(2.87)	(-2.12)	(-0.74)	(0.98)		-0.85
FFCMCOM	$\widehat{\lambda_A}$	9.37	-6.46	-2.26	7.99	-0.85	0.42
	FMB-S t	(2.79)	(-2.11)	(-0.79)	(1.2)	(-0.20)	-0.51
Panel B: Returns from 200401 to 201012							
CAPM	$\widehat{\lambda_B}$	6.09					0.05
	FMB-S t	(0.95)					0.05
CAPMCOM	$\widehat{\lambda_B}$	5.32				10.20	0.40
	FMB-S t	(0.83)				(1.74)	0.41
FF3M	$\widehat{\lambda_B}$	7.69	-3.52	-5.47			0.35
	FMB-S t	(1.21)	(-0.79)	(-1.01)			-0.21
FF3MCOM	$\widehat{\lambda_B}$	6.60	-2.34	-3.37		8.78	0.49
	FMB-S t	(1.05)	(-0.55)	(-0.69)		(1.58)	0.26
FFCM	$\widehat{\lambda_B}$	7.83	-1.83	-1.86	7.43		0.38
	FMB-S t	(1.23)	(-0.44)	(-0.41)	(0.67)		-0.18
FFCMCOM	$\widehat{\lambda_B}$	6.73	-1.81	-2.19	1.53	8.17	0.49
	FMB-S t	(1.07)	(-0.44)	(-0.49)	(0.15)	(1.48)	0.29
Panel C: Difference risk premium COM							
	$\widehat{\lambda_B}$-$\widehat{\lambda_A}$	FMB-S t					
CAPMCOM	14.84	(2.08)					
FF3MCOM	11.60	(1.68)					
FFCMCOM	9.01	(1.30)					

Table G: OLS cross-sectional regressions for SBM25
This table is the equivalent of Table VIII in the paper, but in this case we use 25 size and book-to-market sorted portfolios (SBM25, available from Kenneth French's Web Site) as test assets. We present estimated risk premiums ($\widehat{\lambda_A}$ and $\widehat{\lambda_B}$) and underneath are Fama-MacBeth Shanken-corrected t-statistics (Shanken (1992)), in parenthesis. The last column contains two R^2's. The top one, R_s^2, is the standard cross-sectional adjusted R^2; the bottom one, R_p^2, is the R^2 from a regression of average returns on the product of betas and risk premiums fixed at their sample average. Panel C tests the difference in the risk premiums over the two subsamples.

		MKT	SMB	HML	MOM	COM	R^2
Panel A: Returns from 198001 to 200312							
CAPM	$\widehat{\lambda_A}$	9.13					-1.15
	FMB-S t	(2.63)					-1.15
CAPMCOM	$\widehat{\lambda_A}$	9.75				-11.33	-0.54
	FMB-S t	(2.82)				(-1.64)	-0.53
FF3M	$\widehat{\lambda_A}$	6.89	1.75	5.17			0.24
	FMB-S t	(2.08)	(0.72)	(2.15)			0.30
FF3MCOM	$\widehat{\lambda_A}$	6.46	1.96	4.62		-11.09	0.25
	FMB-S t	(1.95)	(0.8)	(1.94)		(-1.86)	0.33
FFCM	$\widehat{\lambda_A}$	8.28	1.63	5.85	44.27		0.49
	FMB-S t	(2.47)	(0.66)	(2.38)	(3.96)		0.42
FFCMCOM	$\widehat{\lambda_A}$	7.80	2.09	4.79	54.94	-11.12	0.72
	FMB-S t	(2.31)	(0.83)	(1.96)	(4.14)	(-1.32)	0.50
Panel B: Returns from 200401 to 201012							
CAPM	$\widehat{\lambda_B}$	5.78					0.07
	FMB-S t	(0.90)					0.07
CAPMCOM	$\widehat{\lambda_B}$	5.90				4.29	0.04
	FMB-S t	(0.92)				(0.5)	-0.02
FF3M	$\widehat{\lambda_B}$	4.63	2.89	2.02			0.07
	FMB-S t	(0.74)	(0.90)	(0.56)			0.14
FF3MCOM	$\widehat{\lambda_B}$	4.48	3.33	2.53		9.86	0.09
	FMB-S t	(0.71)	(1.05)	(0.7)		(1.35)	0.21
FFCM	$\widehat{\lambda_B}$	5.05	2.85	0.95	37.44		0.32
	FMB-S t	(0.80)	(0.88)	(0.26)	(2.55)		0.15
FFCMCOM	$\widehat{\lambda_B}$	4.89	3.36	1.49	38.13	10.00	0.39
	FMB-S t	(0.78)	(1.05)	(0.41)	(2.52)	(1.22)	0.22
Panel C: Difference risk premium COM							
	$\widehat{\lambda_B}$-$\widehat{\lambda_A}$	FMB-S t					
CAPMCOM	15.62	(1.42)					
FF3MCOM	20.95	(2.22)					
FFCMCOM	21.11	(1.80)					

References

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