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Commodity price exposure and ownership clienteles

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Abstract

This paper examines the association between commodity price exposure and investor interest in stocks of firms in two commodity-based industries: Gold Mining, and Oil and Gas Exploration. Investors, on average, are attracted to commodity price exposure. Using market-based measures of commodity price exposure, there is robust evidence that commodity stocks with high commodity price exposures have higher turnover and a larger number of institutional investors, in particular mutual fund investors, than commodity stocks with low exposures. We conduct cross-sectional analysis that condition on the source of the exposure, the type of investor, and the performance of the underlying commodity. Overall, investors' revealed preferences for high exposure stocks appear to reflect a desire to gain exposure to the underlying commodity through an exposed equity security. They are not consistent with an attraction to exposure because of its transparency.

1. Introduction

This paper examines whether investors reveal preferences for commodity price exposure through their investments in commodity-based stocks. If they do, remaining exposed to commodity price risk may be a value-maximizing activity for a firm. The resulting broader interest means greater liquidity, and hence a lower cost of capital, given the evidence that liquidity is a priced risk factor (e.g., Chordia, Subrahmanyam, and Anshuman, 2001, Chan, 2002, Pastor and Stambaugh, 2003, Acharya and Pedersen, 2005, and Wang, 2003). The idea that remaining exposed to commodity price risk is a value-maximizing decision is in contrast to traditional risk management theories. The established theories focus on explaining why reducing exposure through hedging is a value-maximizing activity, with the explanations relying on capital market imperfections such as taxes, financial distress costs, and information asymmetries.[1] Thus, our analysis may shed light on the somewhat surprising evidence that commodity-based firms that manage their price risk do not have higher valuations than commodity firms that remain exposed to commodity price risk (Tufano, 1996, and Jin and Jorion, 2006). Our hypothesis suggests that we should not expect to see cross-sectional variation in firm value as a function of exposure if remaining exposed also can be a value-maximizing strategy.

We propose two explanations for why investors may be attracted to stocks with commodity price exposure: the *unique asset* hypothesis and the *transparency* hypothesis. The unique asset hypothesis predicts that investors are attracted to stocks with commodity price exposure because these securities are an efficient means to acquire exposure to the underlying commodity. Commodities represent a unique and attractive asset class both in terms of expected returns and covariances, but gaining exposure to commodities directly, rather than through an

[1] See Stulz (2003) for a summary of this research.

exposed stock, is impractical for many investors. The transparency hypothesis predicts that investors are attracted to firms with commodity price exposure because the value-relevant information that is available about firms with high commodity price exposure is more transparent than the information about firms with low commodity price exposure. Investors are attracted to more transparent firms because their stock prices are likely to be more informative and because the information advantage of informed investors is lower.

We analyze the association between commodity price exposure and ownership interest for firms in two commodity-based industries: Gold Mining, and Oil and Gas Exploration. We relate market-based measures of commodity price exposure to share turnover, a proxy for overall investor interest, and also to the number of investors as a more direct measure of ownership intensity. We are able to determine the number of investors for institutions and separately for metals sector funds and energy sector funds. The number of sector fund investors is a proxy for individual investor interest.

We find robust evidence across our proxies for investor interest that investors, on average, are attracted to stocks with high commodity price exposure. Commodity stocks with high commodity price exposures have higher turnover and a larger number of institutional investors and sector fund managers than commodity stocks with low exposures. The positive association comes from both an attraction to high exposure stocks and an aversion to low exposure stocks. In terms of economic magnitude, the turnover in stocks of oil and gas firms with high exposure to energy prices is 18% higher than that of firms with intermediate levels of exposure, ceteris paribus, while the turnover of low exposure firms is 33% lower than the turnover of firms with intermediate exposures. The results for gold firms are similar in terms of magnitude.

To better understand the reasons behind investor preferences for exposure we conduct three cross-sectional analyses to examine whether investor preferences for exposure are consistent with the unique asset hypothesis and/or the transparency hypothesis. The first analysis conditions on whether the firm uses derivatives (financial hedging) or is diversified (operational hedging). Both activities create complexity for investors seeking to evaluate a firm. Exposure is predicted to have transparency benefits only if it is correlated with *not* engaging in these hedging activities. The results are weak. Derivatives use is not associated with a reduction in investor attraction to high exposure gold or oil and gas firms. Diversification is negatively associated with investor attraction to exposure, but only for the gold firms, and only when using turnover as a proxy for investor interest. Further, investor interest, as measured by the number of institutional investors or fund managers, is not associated with either diversification or derivatives use. These results provide only weak evidence that investors prefer high-exposure stocks because they are more transparent.

The second cross-sectional analysis, which conditions on institutional owner type, indicates that investment companies and advisors show a greater preference for commodity exposure than banks, insurance companies, and other institutions (pensions, trusts and endowments). This finding is *not* consistent with the transparency hypothesis, which does not predict different preferences for exposure across owner type. If, however, high commodity price exposure is viewed as imprudent, this cross-sectional pattern is consistent with existing evidence that institutions that face higher fiduciary standards and are more subject to social norms tilt their portfolios towards high quality (high S&P stock ranking) stocks (Del Guercio, 1996) and avoid holding sin stocks (Hong and Kacperczyk, 2007). Such patterns are consistent with the unique asset hypothesis because it is more costly for firms with high fiduciary standards to hold high exposure stocks as a substitute for investing in the underlying commodity directly.

As well as conditioning on institutional owner types based on fiduciary standards, we also condition on institutional owner types based on monitoring incentives (Bushee, 1998). There is no robust evidence that dedicated owners, quasi-indexers, and transient investors have different preferences for commodity price exposure. Differences in the expected benefits of transparency across these investor types would predict differences in ownership under the transparency hypothesis but not under the unique asset hypothesis. Thus, the evidence is again more consistent with the unique asset hypothesis.

Finally, the cross-sectional analysis of investor preferences for exposure as a function of the market performance of the underlying commodity suggests that energy funds, in particular, seek to time the underlying commodities' markets. During periods in which oil and gas prices rise sharply, energy funds tilt their portfolios toward high exposure firms and during periods in which oil and gas prices fall, energy funds tilt their portfolios toward low exposure firms.

Overall, the results of all three cross-sectional analyses support the notion that commodities are a unique asset and that commodity stocks are an efficient means for individuals and institutions to gain commodity price exposure. The results provide only limited evidence that exposure is attractive because it is correlated with greater transparency, although the two explanations for investor attraction to exposure are not mutually exclusive.

The paper is organized as follows. Section 2 develops our hypotheses and predictions. Section 3 describes the sample and methodology. Section 4 presents the results for the analysis of the association between exposure and proxies for investor interest. Section 5 examines cross-sectional differences in preferences for exposure as a function of the source of the exposure, the institutions' fiduciary and monitoring incentives, and the performance of the underlying commodity. Section 6 concludes.

2. Hypothesis development

We consider two hypotheses to explain investor preferences for commodity price exposure in commodity-based stocks. The first hypothesis – the *unique asset* hypothesis – is that investors are attracted to commodity stocks with commodity price exposure because they are an efficient means to acquire exposure to the underlying commodity. This hypothesis relies on the implicit assumption that exposure to the underlying commodity is desirable. Over the past decade commodities have outperformed traditional assets such as stocks and bonds. For example, annual returns to the Dow Jones AIG Commodity Index between 2001 and 2006 averaged 10.6% compared to 2.6% for the S&P 500, while in 2005 returns on the Goldman Sachs Commodity index were in excess of 25%. These higher returns have attracted significant investor interest and investment in commodities.[2] Commodities also offer diversification. Commodity returns tend to be negatively correlated with stock market returns. Finally, commodity prices usually rise when inflation is accelerating, suggesting that investing in commodities may be a hedge for inflation (Gorton and Rouenhorst, 2005; Kat and Oomen, 2007).

Although commodities may represent a unique and attractive asset class based on expected returns and covariances, investors may not want to trade the physical commodity or take positions in derivatives markets. For the vast majority of investors, it is not practical to

[2] Survey by Barclays Capital, as reported by Reuters, December 16th, 2005.

invest in the physical commodity.[3] In addition, institutions, because of their fiduciary responsibilities, may be precluded directly or indirectly from trading in commodity spot markets or derivatives markets. The unique asset hypothesis predicts that investors who seek an investment vehicle to gain commodity-price exposure may invest in the stocks of commodity firms, specifically in those stocks with greater exposure to the underlying commodity.

The second hypothesis – the *transparency* hypothesis – is that investors are attracted to firms with commodity price exposure because investors value transparency and exposure is positively correlated with transparency. The first part of this hypothesis – that transparency is associated with greater investor interest – is consistent with adverse selection models of trade with heterogeneously informed investors (Glosten and Milgrom, 1985; Kyle, 1985; Amihud and Mendelson, 1986; Admati and Pfleiderer, 1988; Diamond and Verrecchia, 1991). Assuming greater transparency reduces information asymmetry among investors, it will lead to greater liquidity in the firm's equity.

An extensive empirical literature documents that "liquidity," measured in a variety of ways, is associated with transparency. The studies exploit international differences in transparency (e.g., Leuz and Verrecchia, 2000); firm-specific differences in transparency related to the ability of the financial reporting system to capture value-relevant information (e.g., Bartov and Bodnar, 1996; Boone and Raman, 2001); or time-series changes in transparency due to regulation (e.g., Eleswarapu, Thompson, and Venkataraman, 2004). Graham, Harvey and Rajgopal (2005) provide survey evidence that managers believe that better transparency is associated with improved liquidity. In addition, empirical evidence suggests that investors in general, and institutions in particular, are attracted to transparency. (For evidence on

[3] Recently exchange traded funds (ETFs) have started to be developed for commodities. For example, in 2005 the iShares COMEX Gold Trust was launched which holds gold in storage.

institutional preferences for transparency see Healey, Hutton, and Palepu, 1999; Bushee and Noe, 2000; Aggarawal, Klapper, and Wysocki, 2003; Ferreira and Matos, 2006.)

The second part of the transparency hypothesis – that exposure is positively correlated with transparency – is an assumption. The premise of this assumption is that two activities of the firm that can significantly reduce exposure – operational hedging (i.e., diversification) and financial hedging (i.e., derivatives use) – also reduce transparency and create complexity. The increased complexity in turn reduces an investor's ability to understand and predict a firm's current and future cash flows. If high commodity exposure is correlated with *not* hedging, and if these hedging activities indeed create complexity, then exposure will be positively correlated with transparency.

Diversification is predicted to create complexity because the aggregate exposure of a diversified firm is a function of the exposure in each line of business and the covariances across businesses. *Ceteris paribus*, firms that operate in a single segment are more transparent than firms with multiple segments and multiple sources of exposure that yield additional variance and covariance terms. In addition, a diversified firm may face significant commodity price risk from multiple commodities. With costly information acquisition, there will be greater information asymmetry about firms that face commodity price risk from multiple sources (see, for example, Nieuwerburgh and Veldkamp, 2006). The notion that diversification is associated with lower transparency is espoused by Bushman, Chen, Engel, and Smith (2004), who show a link between diversification and governance mechanisms that mitigate the information asymmetry associated with line of business and geographic diversification, and by Berger and Hann (2003) and Bens and Monahan (2004), who show that cross-sectional variation in reporting quality by multi-segment firms is associated with lower diversification discounts.

Derivatives use also is predicted to create complexity in terms of measuring commodity price exposure. Firms provide thorough disclosures about commodity reserves, but despite disclosures regarding hedging activities, it can be difficult to understand the net exposures a hedged firm faces. Hodder, Koonce, and McAnally (2001) question whether derivatives-related disclosures are useful given how investors process risk-related information. In addition, hedging activities can be altered more quickly than core business activities, so understanding and predicting net cash flows in firms using derivatives is a complex task for investors deciding whether to invest in a firm or not.

The empirical evidence on this point, in broad terms, suggests a significant improvement in the informativeness of derivatives disclosures since the SEC mandated increased disclosure in 1997 both in general settings (Linsmeier, Thornton, Venkatachalam, and Welker, 2002; Roulstone, 1999) and specifically in the oil and gas industry (Thornton and Welker, 2002; Rajgopal, 1999). However, the benchmark in these studies is derivatives disclosures *prior to* the mandated requirements. We are not aware of any cross sectional studies that test whether derivatives use enhances or impairs reporting transparency about *net* exposure.

Recognizing that diversification and derivatives use are negatively associated with both exposure and transparency leads to cross sectional predictions for the transparency hypothesis. The transparency hypothesis predicts that the association between ownership interest and commodity price exposure will be negative for more diverse firms and for firms that use more derivatives because the exposures of these firms are not correlated with transparency.

The predictions from both the unique asset hypothesis and the transparency hypothesis – that certain investors are “attracted to” exposure, or that there is increased “investor interest” in exposure – sound similar to those generated by models that assume behavioral biases on the part of investors. Neither the unique asset hypothesis nor the transparency hypothesis relies on behavioral biases. Rather, both assume a market inefficiency that affects optimal portfolio selection. The unique asset hypothesis assumes that it is costly for investors to transact in the underlying commodity and that high exposure stocks can serve as a less costly substitute, while the transparency hypothesis assumes that information acquisition is costly. In both cases, a revealed preference for exposure is a second-best portfolio decision, but it is not a suboptimal decision.

3. Data and methodology

Our sample consists of firms in two commodity-based industries identified by Gorton and Rouwenhorst (2005) and Jin and Jorion (2006) using 4-digit SIC codes: gold mining (1040; 1041) and crude oil and natural gas exploration (1311).[4] We require each firm to have CRSP and COMPUSTAT data at some time between 1995 and 2005. We delete 53 firm-year oil and gas firm observations that represent Class A shares, limited partnerships, and trusts.

(Insert Table 1 here.)

Table 1 Panel A reports that there are 78 gold mining firms in our sample, of which 60 are foreign. There are 344 firm-year observations for the gold mining industry. The oil and gas sample has 199 firms, of which 45 are foreign. There are 999 firm-year observations for the oil and gas industry.

[4] The primary role of all firms in SIC code 1311 is crude petroleum and natural gas extraction. The advantage of using only firms with SIC code 1311 is that the hedging strategy for these firms should involve selling oil or gas fixed price contracts. Refiners (SIC Code 2911), on the other hand, are likely to have different hedging strategies, such as buying crude oil and shorting natural gas.

To examine whether investors are attracted to exposure, we estimate the following reduced form model of ownership interest on control variables and measures of commodity price exposure:

$$OWNERSHIP_{iy} = \alpha + \sum_k \delta_k CONTROL_{kiy} + \lambda COMEXP_{iy} + \varepsilon_{iy} \quad (1)$$

The first proxy for ownership interest (*OWNERSHIP*) measures aggregate investor interest for each firm *i* for each year *y* across both individuals and institutions using share turnover (Barber and Odean, 2006; Hou, Peng, and Xiong, 2006; Loh, 2008). *TURNOVER* is the natural logarithm of average daily turnover (volume divided by shares outstanding). We also attempt to measure institutional and individual ownership intensity more directly. For institutional investors, *LNUMGR* is the natural log of 1 + the number of institutions that hold stock *i* at the end of year *y*.[5] Data on annual institutional ownership are from the Thomson Financial database.[6]

For individual investors, we examine ownership interest by sector mutual funds. We assume that sector funds reflect the preferences of individual investors as the mere existence of these funds is a response to demand by individuals. The four sector funds we analyze are *Metals Funds*, *Focused Metals Funds, Energy Funds*, and *Focused Oil & Gas Funds*. Focused Metals Funds are Metals Funds with holdings in two-digit SIC 10 > 50%. Focused Oil & Gas Funds are

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[5] We also compute the percentage of firm *i*'s outstanding shares held by institutions at the end of year *y*. Both the unique asset hypothesis and the transparency hypothesis predict that investors will be attracted to high exposure stocks, however, neither hypothesis has direct predictions concerning quantities of holdings. Rather, the quantity an institution allocates to each stock will be a function of expected returns and the variance-covariance matrix for all the stocks in the manager's choice set. While the number of managers (*LNUMGR*) is the appropriate proxy for ownership interest in our setting, we compute both since both are commonly used as alternative proxies in the literature for the generic construct of "ownership interest" (e.g., Bushee and Miller, 2006, and cites therein). As predicted, we observe more pronounced and significant results when we use the number of institutions as a proxy for institutional ownership.

[6] The Thomson database is based on the universe of 13-F filings without any selection or removal of firms. Holdings under $20,000, and holdings by an institution with less than $100 million in equity are not required to be reported on a 13-F. Since all of our firms are publicly traded, we assume that the firm has zero institutional investors if it is not included in the Thomson database.

Energy Funds with holdings in two-digit SIC 13 > 50%. Appendix A provides a detailed discussion of our methodology to identify sector funds. The Metals Fund sample contains 64 unique funds with non-missing assets data in at least one year during the period 1995 to 2005. The Energy Fund sample contains 105 unique funds with non-missing assets data in at least one year during the period 1995 to 2005.

For each gold (oil and gas) sample firm, we compute the log of 1 + the number of fund managers (*LNUMGR*) in Metals Funds and Focused Metals Funds (Energy Funds and Focused Oil & Gas Funds). Data on fund holdings are from the Thomson Financial Mutual Fund database, which covers "almost all" domestic mutual funds and global funds that hold stocks traded on U.S./Canadian exchanges. Using the same database, we also create a measure of *LNUMGR* for all mutual funds ("All Funds"), which serves as a useful benchmark for evaluating the sector fund results.

We draw the control variables (*CONTROL*) from four papers that examine the determinants of institutional ownership: Del Guercio (1996), Falkenstein (1996), Gompers and Metrick (2001), and Hong and Kacperczyk (2007). Broadly speaking, these papers include various specifications of proxies for the following constructs: firm size, share price, systematic risk, dividend yield, past returns, return volatility, and firm age. In the sector fund regressions, we focus on the variables from Falkenstein (1996), who explicitly examines the determinants of mutual fund ownership. Appendix B provides a detailed description of their specific proxies for these constructs.

We use a market-based measure of commodity price risk as a proxy for commodity price exposure (*COMEXP*). Similar to Tufano (1998), we estimate annual commodity exposures for each sample firm i using an extended market model:

$$r_{i,t} = \alpha_i + \sum_{k=-1}^{k=1} \beta_{i,k}^{m} r_{m,t+k} + \sum_{k=-1}^{k=1} \beta_{i,k}^{c} r_{c,t+k} + \sum_{k=-1}^{k=1} \beta_{i,k}^{mc} r_{mc,t+k} + \sum_{k=-1}^{k=1} \beta_{i,k}^{oc} r_{oc,t+k} + \varepsilon_{i,t},$$

where r_m denotes the daily return on the CRSP value weighted market index, and r_c denotes the daily return on the spot market price of commodity *c*. r_{mc} and r_{oc} denote returns on two trade weighted currency indices (major currencies and other currencies versus USD).[7] By including the returns on the two currency indices, we increase the likelihood that $\beta_{i,k}^{c}$ measures commodity exposure and not currency exposure. For a firm-year observation to be included in the sample we require at least 60 daily return observations to estimate the extended market model.

We use the Dimson (1979) adjustment to compute commodity exposure for firm *i* in year *y*:

$$\beta_{i,y}^{c} = \beta_{i,0}^{c} + \frac{1+\rho_1+\rho_2}{1+2\rho_1}\left(\beta_{i,-1}^{c} + \beta_{i,+1}^{c}\right)$$

where ρ_1 and ρ_2 are the autocorrelation coefficients of r_c. The Dimson adjustment mitigates the potential downward bias in the estimated exposures caused by non-synchronicity in daily returns for infrequently traded stocks. Tufano (1998) shows that exposures calculated using the Dimson (1979) approach are similar to estimates obtained using weekly or monthly return data.[8]

For gold firms, r_c is the quoted daily spot price on gold bullion (dollars per troy oz.). For oil and gas firms, we construct a firm-specific "energy" index return series, by year, which is a weighted average of crude oil returns (West Texas Sweet crude oil) and natural gas returns (at

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[7] The major currencies index is composed of the following countries: Euro Zone, Canada, Japan, UK, Switzerland, Australia, and Sweden. The other currencies index consists of: Mexico, China, Taiwan, Korea, Singapore, Hong Kong, Malaysia, Brazil, Thailand, Philippines, Indonesia, India, Israel, Saudi Arabia, Russia, Argentina, Venezuela, Chile, and Columbia. Both indices are freely available at http://research.stlouisfed.org/fred2.

[8] As in Tufano (1998), we also calculate exposures using the Scholes and Williams (1977) adjustment; our findings are unchanged.

the Henry Hub). To accommodate cross sectional and time series heterogeneity in oil and gas exposures at the firm level, the composite "energy" returns series for firm *i* in year *y* is constructed as follows. We first calculate energy returns using the formula:

$$r_{energy} = p \times r_{natgas} + (1 - p) \times r_{crudeoil} \text{ for p = 0, 0.01, 0.02,\ldots,0.99, 1,}$$

which results in 101 sets of possible energy returns, ranging from a return series that consists only of natural gas returns to a return series that consists only of crude oil returns. For each firm in each year, we set r_c equal to the composite energy return that results in the lowest residual mean squared error for the adjusted market model.

Table 1 Panel B reports descriptive statistics on returns for the underlying commodities. Returns on gold, natural gas, and crude oil are considerably riskier for each unit of return than stock returns. For example, average returns on natural gas were 0.2617% per day with a standard deviation of 6.7444%. By comparison, average daily returns on the CRSP value weighted stock market index over the period 1995 to 2005 were 0.0493% with a standard deviation of 1.0850%. Consistent with the findings in Kat and Oomen (2007) and Gorton and Rouwenhorst (2005), the correlations between stock market returns and returns on gold, natural gas, and crude oil are close to zero during this time period.

Table 1 Panel C reports descriptive statistics for the risk exposure measures (*COMEXP*). The distribution of the gold exposures is similar to that reported in Tufano (1998). Average gold exposures are approximately ten times larger than the exposures to oil and gas returns. This difference is expected. Crude oil (natural gas) returns are three (seven) times as volatile as gold returns. Therefore, to explain returns at the firm level, the average exposure to gold returns should be larger than the average exposures to crude oil and natural gas.

To assess the effectiveness of the exposure measures to capture commodity price risk, we analyze the relation between the commodity exposures and firm returns in response to extreme price shocks in the underlying commodity markets. We calculate cumulative returns for each firm over the day of a shock in the underlying market and the subsequent two days. We classify a date as extreme if the daily return is greater than (less than) the 99^{th} (1^{st}) percentile of the return series for each commodity over the period 1995 to 2005. If *COMEXP* captures exposure, we expect a positive (negative) relation between *COMEXP* and the cumulative returns on days in which there are large positive (negative) returns in the underlying commodity market. Table 1 Panel D reports the results. We find robust evidence supporting our predictions, which suggests that our market-based measure of exposure, *COMEXP*, contains material information about a firm's exposure to the underlying commodity.

4. The association between investor interest and commodity price exposure

We estimate equation (1) separately for the gold sample and the natural gas and crude oil sample. Section 4.1 discusses the relation between commodity price exposure and turnover as a proxy for ownership interest. Sections 4.2 and 4.3 discuss the relations between commodity price exposure and the number of institutional investors and sector fund managers, respectively, as more direct measures of ownership interest.

In all model specifications, the model includes either the continuous measure of commodity price exposure (*COMEXP*) or two indicator variables that identify firms as high (low) exposure firms if their exposures in any given year are above (below) the 70^{th} (30^{th})

percentile exposure for that year. The indicator variables are denoted *xBETALOW* and *xBETAHIGH*, where *x* represents the commodity.[9] Standard errors are calculated using the Huber-White estimator of variance.

4.1 Analysis of turnover

The first column of Table 2 reports results for the model that includes the continuous measure of exposure (*COMEXP*) for the gold mining firms (Panel A) and the oil and gas firms (Panel B). In both samples, the coefficient on the continuous exposure proxy is positive and significant, which is consistent with the prediction that higher commodity exposure attracts investor interest.

Using indicator variables to measure high and low exposure (Column 2) indicates that the positive association comes from both an attraction to high exposure stocks and an aversion to low exposure stocks. The turnover in stocks of oil and gas firms with high exposure to energy prices is 18% higher than that of firms with intermediate levels of exposure, *ceteris paribus*, while the turnover of low exposure firms is 33% lower than the turnover of firms with intermediate exposures. The results for gold firms are similar in terms of magnitude, although only the coefficient estimate on the high exposure group is significantly different from zero. The difference between the high and low exposure groups (0.5394) is, however, significant.[10]

(Insert Table 2 here.)

[9] We also estimate a model that includes the continuous specification of *COMEXP* and an interaction term of *COMEXP* with an indicator variable that equals 1 if *COMEXP* is negative and equals zero otherwise (12 gold sample observations and 146 oil and gas sample observations). The results of this model estimation do not change the reported results and the coefficient estimate on the interaction term is not significant.

[10] To examine the impact of foreign firms, we estimate all regressions including an indicator variable equal to 1 if Compustat identifies the firm as a foreign firm (i.e., Compustat variable finc > 0) and equal to zero otherwise. The coefficient on the foreign-firm indicator variable is negative and significant in all models. The results for the exposure variables are unchanged.

The results for the control variables are consistent with prior research and show that investor interest is positively associated with firm size, firm age, and inclusion in the S&P 500 index, and negatively associated with listing on the NASDAQ exchange. We also include year indicator variables for 1996 through 2005 (coefficients not tabulated).[11] Figure 1 plots the coefficient estimates on the year indicator variables for the gold sample (Panel A) and the oil and gas sample (Panel B) when investor interest is measured by turnover. The figure also shows the average daily returns on the underlying commodities.

(Insert Figure 1 here.)

Both panels of Figure 1 highlight that investors are attracted to commodity stocks during years in which the underlying commodities perform well, especially in the gold industry. Barber and Odean (2006) document that investors are attracted to a stock following an attention grabbing event. The results in Figure 1 are consistent with Barber and Odean (2006) – high returns in the underlying commodity markets are attention grabbing events that attract investors to stocks in those industries.

A potential concern with the results presented in columns 1 and 2 is that our findings could be driven by measurement error in the exposure proxy related to non-synchronicities in daily stock returns. Exposure estimates for infrequently traded (i.e., low turnover) stocks may be underestimated, even after using Dimson's (1979) adjustment. A downward bias would induce a positive relation between exposures and turnover. Including the stock market β (with Dimson's

[11] As an alternative to including the year indicators, we also estimate the regression including the average return on the underlying commodity for the year. The results are similar.

adjustment) as a control variable in the regression should mitigate this concern since any downward bias due to non-synchronicity also should be reflected in stock market betas. Moreover, if measurement error drives our results, we would expect to observe a negative relation between low exposure firms and turnover, but we would not necessarily expect to observe a positive relation between high exposure firms and turnover. These factors suggest that the results for the full sample in Table 2 are unlikely to result from downward bias in *COMEXP* due to non-synchronous trading.

Nonetheless, Columns 3 through 6 of Table 2 report results for two subsets of firms that are less likely to have non-synchronous returns. Columns 3 and 4 report that the positive association between exposure (*COMEXP*) and turnover is robust to excluding the smallest quartile of firms in each commodity sector in each year. Columns 5 and 6 report results for a subsample of stocks with a share price above $5. In this restricted sample, there is no evidence that exposure levels are associated with turnover in the gold sample. The results for oil and gas firms, however, are consistent with the results across the full sample. The poor results in the restricted gold sample may be due to a lack of statistical power. The $5 restriction reduces the sample size for gold firms by 60%, resulting in only 20 observations with high exposure and 20 observations with low exposure, which may be insufficient to estimate the coefficients precisely. In contrast, the impact of the $5 restriction is much less severe for oil and gas firms, reducing the sample by 30% to 634 firm-year observations, still more than double the number of observations in the full sample for gold firms.

4.2 Analysis of institutional ownership

This section discusses results for the estimation of equation (1) using the number of institutional owners (*LNUMGR)* as a proxy for institutional ownership interest.[12] Table 3 presents the results. As in Table 2 the results for the control variables are consistent with prior research. Institutional ownership is positively associated with firm size, firm age, and inclusion in the S&P 500 index, and negatively associated with listing on the NASDAQ exchange.

(Insert Table 3 here.)

Overall, the results suggest a positive association between exposure and the number of investors. Column 1 of Table 3 reports that the number of institutions (*LNUMGR*) holding a gold firm's stock is significantly and positively related to the continuous measure of commodity exposure (*COMEXP-GOLD*). In terms of economic magnitude, a change in a firm's exposure from the 25th percentile to the 75th percentile exposure is associated with a 20% increase in the number of institutions holding the stock.

Column 2, which reports results using indicator variables, shows that the association between *LNUMGR* and gold price exposure is greater (lower) for the firms with high (low) commodity exposure relative to the intermediate group. The difference between the high exposure and low exposure coefficient estimates is significant at the 1% level. Firms with high exposure have approximately 22% more institutional investors relative to firms with low exposure, *ceteris paribus*. The results are similar for oil and gas firms, although the economic magnitude is reduced. Oil and gas firms with high exposure have 10% more institutional investors relative to firms with low exposure.

[12] The natural logarithm of turnover is added to the set of control variables. Standard multicollinearity diagnostic tests do not indicate that the inclusion of this variable, or any other, influences the coefficient estimates.

4.3 Analysis of sector fund ownership

This section discusses results for the estimation of equation (1) using the number of sector fund owners (*LNUMGR)* as a proxy for individual ownership interest. Columns 3 to 5 of Table 3 present the results. The results for the control variables show that the number of fund managers is positively associated with firm size, and negatively associated with return volatility, although for oil and gas sector funds there is evidence of a positive relation between fund ownership and return volatility.

In Panel A, within the benchmark sample of mutual funds ("All"), we find no evidence that mutual funds in general prefer high exposure gold firms to low exposure gold firms. However, the sector funds – Metals Funds and Focused Metals Funds – exhibit a preference for high exposure gold firms relative to low exposure firms at a 10% confidence level. Similar to the results in Column 2 for institutional investors, firms with high exposure have approximately 20% more sector fund investors relative to firms with low exposure, *ceteris paribus*.

The results for oil and gas firms in Panel B provide contrasting inferences. Mutual funds in general display strong preferences for high exposure oil and gas firms relative to low exposure oil and gas firms. Firms with a high exposure to oil and gas prices have over 40% more mutual fund investors relative to firms with low exposure. The sector funds, however, show no preference for high exposure oil and gas stocks. In fact, the coefficient estimates for both *ENERGYBETALOW* and *ENERGYBETAHIGH* are negative and significant, and not significantly different from each other, which suggests that these funds display a lower preference for both low and high exposure firms relative to intermediate exposure firms.

One explanation for the lack of results for the oil and gas firms is that the energy sector funds are not as specialized as those in the metals sector. We have defined the sector as "Energy", which could include funds that invest in both oil and gas as well as funds that specialize in oil *or* gas, and this specialization may be consistent through time or may vary with market conditions. In ongoing work, we attempt to understand the results for the energy sector funds by examining the dynamic patterns in the attraction of sector funds to oil exposure separate from gas exposure conditional on market performance in these commodities.

5. Cross-sectional analysis

5.1 Cross-sectional analysis by source of exposure

The transparency hypothesis predicts that exposure is attractive only if it is correlated with transparency. In this section we examine two significant firm activities that are related to both exposure and transparency: diversification (operational hedging) and derivatives use (financial hedging). As discussed in Section 2, the transparency hypotheses predicts that the association between ownership interest and commodity price exposure will be decreasing for more diverse firms and for firms that use more derivatives, because these firms are less transparent and thus more difficult to understand.

We estimate equation (2) which is an extension of equation (1):

$$\begin{aligned} OWNERSHIP_{iy} = {} & \alpha + \sum_k \delta_k CONTROL_{kiy} + \lambda_{LO} xBETALOW_{iy} + \lambda_{HI} xBETAHIGH_{iy} + \\ & \theta_{MAIN} COMPLEX_{iy} + \\ & \theta_{LO} COMPLEX * xBETALOW_{iy} + \theta_{HI} COMPLEX * xBETAHIGH_{iy} + \varepsilon_{iy} \end{aligned} \tag{2}$$

where *COMPLEX* denotes proxies associated with derivatives use or diversification that make understanding the firm more complex (i.e., less transparent). If greater transparency attracts ownership interest, we would expect to observe greater ownership interest for high exposure stocks ($\lambda_{HI} > 0$), as this coefficient reflects the degree of investor attraction to commodity price exposure in the absence of derivatives use or diversification. We expect a negative coefficient on the interaction term between complexity (either derivatives use or diversification) and *xBETAHIGH* ($\theta_{HI} < 0$) because derivatives use and diversification are inversely related to transparency. This test helps to distinguish the transparency hypothesis from the unique asset hypothesis because under the unique asset hypothesis we do not expect to observe cross-sectional variation in the attraction to exposure that is associated with the complexity of the firm.

We measure derivatives use with indicator variables. *DERIVS* equals one if the firm uses any derivatives and equals zero otherwise. *COMMDER* equals one if the firm uses commodity derivatives and equals zero otherwise. *CORECOMM* equals one if a firm uses gold (in the gold sample) or oil or gas (in the oil gas sample) derivatives and equals zero otherwise. The correlation between *COMMDER* and *CORECOMM* is 91.3% in the gold sample and 99.5% in the oil and gas sample. All derivatives activity data are hand-collected from annual reports.

Following the literature,[13] we use several metrics to proxy for diversification, all of which are specified such that a higher value implies greater diversification and hence greater complexity. The first proxy is the number of business segments in which a firm operates (*NUMSEG*). The second proxy is an indicator variable equal to 1 if the firm is a multi-segment firm (regardless of the number of segments) and equal to zero if the firm is a single-segment firm (*MULTI*). The third proxy captures the degree of diversity across business segments

[13] Bushman, Chen, Engel, and Smith, 2004; Denis, Denis, and Sarin, 1997; Comment and Jarrell, 1995.

(*DIVERSE*). Following Comment and Jarrell (1995), we measure a firm's concentration as a revenue-based Herfindahl index for each firm in each year, and the measure of diversity is 1 – the concentration ratio:

$$DIVERSE_{iy} = 1 - \sum_{j=1}^{N_{it}} \left(REVS_{jiy} / \sum_{j=1}^{N_{it}} REVS_{jiy} \right)^2$$

where $REVS_{jiy}$ is the revenue from segment *j* for firm *i* in year *y* and N is the number of segments reported by firm *i* in year *y*. The minimum measure of diversity is zero, which is 1 less a maximum concentration ratio of one for a firm with a single segment. We focus only on operating segment diversification because geographic diversification *per se* is unlikely to lead to a large reduction in transparency for commodity firms focusing on the extraction and production of a single commodity. *Ceteris paribus*, firms with more segments and higher measures of diversity (lower concentration ratios) should be more complex with respect to understanding their commodity price exposure.[14]

Table 4 reports summary statistics for derivatives use and diversification for firms with either high or low exposures to the underlying commodities. In Panel A, contrary to the implicit assumption of the transparency hypothesis, there is little evidence that derivatives use is more prevalent among firms with low exposure. Indeed for oil and gas firms, the reverse appears to be true – firms with high exposure are more likely to use derivatives. In analyses throughout the remainder of the paper, we use *COMMDER*, a dummy variable equal to 1 if a firm uses commodity derivatives, to proxy for complexity associated with derivatives use. Results using the other proxies are qualitatively similar.

[14] We also compute an asset-based Herfindahl index using the same formula. The correlation coefficient for the asset-based and revenue-based indices is 96.3% (93.8%) in the gold sample (oil and gas sample).

(Insert Table 4 here.)

The diversification proxies for complexity, however, yield different inferences. Panel B shows that firms with high commodity exposure are less diversified than firms with low commodity exposure using any of the three proxies for diversification. These differences are consistent with the assumptions that commodity price exposure of less diversified firms is more transparent. This pattern is true for both gold firms and oil and gas firms, although the differences are only statistically significant for oil and gas firms. In analyses throughout the remainder of the paper, we use *MULTI*, a dummy variable equal to 1 if a firm operates in multiple business segments, to proxy for complexity associated with diversification due to the ease with which the variable can be interpreted as an interaction term. Results using the other proxies are qualitatively similar.

Table 5 presents the results of the cross-sectional analysis. In Column 1, the proxy for investor ownership interest is average daily share turnover (*TURNOVER*). Consistent with Table 2, turnover is significantly positively associated with exposure, both in terms of statistical and economic significance, for both the gold sample (Panel A) and the oil and gas sample (Panel B). For the gold sample, there is no evidence that turnover is lower for gold firms that use commodity derivatives. There is, however, evidence that the attraction to high exposure gold firms is lower when the exposure is associated with greater diversification. The coefficient estimate on the interaction term between *MULTI* and *BETAHIGH* is negative and statistically significant for gold firms.

For the oil and gas firms (Panel B), the coefficient estimate on the interaction term between exposure and complexity is not significantly different from zero for either derivatives use or diversification as measures of complexity. In fact, the unconditional relation between derivatives use (*COMMDER*) and turnover is positive and significant, suggesting that oil and gas firms that use derivatives have greater turnover, contrary to the predictions of the transparency hypothesis.

(Insert Table 5 here.)

Column 2 presents results for the cross-sectional analysis using the number of institutional owners (*LNUMGR*) as the proxy for investor interest. While institutions are attracted to high exposure firms relative to low exposure firms, there is no evidence to suggest that institutions invest in high exposure firms because they are more transparent. Using either commodity derivatives use or operational diversification as proxies for complexity, we find that institutions do not seek to avoid high exposure firms that are more complex (or less transparent).

In Columns 3 to 5 we present results for ownership interest measured by the number of mutual fund and sector fund managers. Consistent with Column 2, there is no evidence that investors seek to avoid more complex high exposure firms regardless of how we measure complexity. Overall the evidence in Table 5 provides little support for the transparency hypothesis. Investors are attracted to high exposure firms regardless of the complexity of the information available about the firm's exposures.

5.2 Cross-sectional analysis by institutional owner type

In this section, we exploit heterogeneity across institutions with respect to fiduciary standards and with respect to information acquisition to investigate further the two hypotheses that predict investor attraction to exposure.

We partition the institutions from the Thomson Financial database that file 13-Fs in two ways. The first partitioning variable is fiduciary standards. Consistent with the classification system in the Thomson Financial database and numerous studies of institutional ownership, we classify institutions into five types: (1) bank trust, (2) insurance company, (3) investment company, (4) investment advisor, and (5) other. The "other" category includes pension and endowment funds.[15] Throughout the remainder of the analysis, we aggregate the investment companies and investment advisors into one institution type because the predictions are the same for both classes of institutions. Moreover, in the Thomson Financial 13-F database, the distinction between the two types is (necessarily) somewhat *ad hoc*. The Investment Company category (type = 3) includes investment advisors for which a "significant" portion of their advisory services are to the mutual fund business (as determined by Thomson).[16]

These institution types are commonly distinguished with respect to their fiduciary responsibilities, which leads to differences in portfolio choices. For example, Del Guercio (1996) finds that banks, which are the only institution governed by the common-law "prudent-man" rule, tilt their portfolios more towards high quality (i.e., high S&P stock ranking) stocks

[15] Brian Bushee provided us with his institution classifications during the sample period. There is a coding error in the Thomson database. Thomson reports that partway through 1998, and in subsequent years, many banks (Type 1) and independent investment advisors (Type 4) are misclassified as other institutions (Type 5). Bushee's database provides a consistent classification of the institutions on the Thomson Financial database.

[16] The Investment Companies in the 13-F database, which includes mutual funds, differ from the funds used in the previous analysis on several dimensions. First, the Thomson Investment Company category includes institutions that are not regulated investment companies (i.e., not mutual funds) but that derive a significant portion of their business from the mutual fund business (determined by Thomson). Second, holdings data on the Thomson Mutual Fund database is compiled primarily from the funds' required semi-annual reports to shareholders (N-30D filings) rather than 13-F filings. Third, we are able to eliminate from the mutual fund database funds with an investment objective code (IOC) = 5 or 6, which represent "Municipal bond" funds and "Bond and Preferred" funds. These funds are included in the Investment Company sample, which adds noise to our analysis of investor attraction to commodity exposure in equities.

than do mutual fund managers. When the courts consider whether an investment is prudent or not, they tend to focus on the characteristics of assets in isolation, rather than considering the role of the asset in the bank's overall portfolio.

Hong and Kacperczyk (2007) find that banks, insurance companies, pension funds, and endowments, which they assert are subject to social norms, avoid holding sin stocks – publicly traded companies involved in producing alcohol, tobacco, and gaming. However, mutual funds and investment advisors do not show a negative preference for sin stocks, as they are not subject to the same social norms. As a result, Hong and Kacperczyk (2007) suggest that mutual funds are the group of investors most likely to take advantage of the underinvestment by banks and other institutional investors. Falkenstein (1996) similarly shows that mutual funds prefer stocks with high visibility and low transaction costs. He also finds that mutual funds avoid stocks with low idiosyncratic volatility and stocks about which there is little information available.

The differences across institutions in fiduciary standards suggest different preferences for commodity price exposure under the unique asset hypothesis. If institutions expect that courts will view high commodity price exposure as an imprudent investment, then under the unique asset hypothesis we expect banks, insurance companies, pension funds, and endowments to exhibit a lower preference for exposure than investment companies and advisors. We expect to see investment companies and advisors showing a preference for high commodity exposure firms if these institutions take advantage of the underinvestment by banks and other institutional investors (Hong and Kacperczk, 2007). The different fiduciary standards, however, do not suggest different preferences for transparency. Under the transparency hypothesis, we do not expect to see differences in preferences for high and low exposure firms across institutional types.

The second partitioning variable sorts the 13-F filers into three categories based on monitoring incentives following Bushee (1998) who calls the three types dedicated owners, quasi-indexers, and transient investors. The Bushee (1998) annual institution classifications are based on k-means clustering of standardized factor scores, which are created on an institution-year basis using the weighted average of firm-specific characteristics of an institution's portfolio holdings. In our analysis, 4.3% of institution-year observations are classified as dedicated owners, 59.7% are quasi-indexers, and 36% are transient investors.

The differences in monitoring incentives suggest different preferences for transparency. Dedicated owners have large, long-term holdings, concentrated in a small number of firms, and are more likely to gather private information about the firm and directly monitor its managers. As such, transparency is not an important concern for dedicated owners. Therefore, under the transparency hypothesis we do not expect dedicated owners to display a preference for high exposure stocks. Quasi-indexers tend not to rely heavily on private or public information and adopt a passive monitoring style. Transient investors hold small stakes in many firms and trade frequently on publicly available information but do not acquire private information like dedicated owners. We expect both quasi-indexers and transient investors to have a preference for exposure under the transparency hypothesis. The prediction that the dedicated owners will show a lower preference for exposure than the quasi-indexers and transient investors is unique to the transparency hypothesis. Under the unique asset hypothesis, we expect to see a positive association between commodity exposure and institutional interest across these institution types.

We estimate equation (1) using a multivariate regression within the two partitions of the institutional investors. We estimate the multivariate regression separately for the gold and oil and gas samples. We present results only for the model specification that includes *xBETALOW* and *xBETAHIGH* as proxies for low and high commodity price exposure. Results using the continuous variable (*COMEXP*) yield similar inferences. The models include year indicator variables for 1996 through 2005. Standard errors are calculated using the Huber-White estimator of variance.

(Insert Table 6 here.)

Columns 1 to 4 of Table 6 present the coefficient estimates on *xBETALOW* and *xBETAHIGH* from the multivariate regression estimated across the four types of institutions classified by their fiduciary standards. Coefficients for the year indicator variables and the control variables are untabulated. At a 99% confidence level we find evidence across both gold and oil and gas firms that investment companies and advisors prefer high exposure firms to low exposure firms. Further, there is no robust evidence across gold and oil and gas firms that banks, insurance companies and other funds exhibit significant preferences for high versus low exposure gold and oil and gas firms. These results are consistent with the unique asset hypothesis but not with the transparency hypothesis.

In columns 5 to 8 we examine the results of the multivariate regression model estimated across the three types of institution based on monitoring incentives. The transparency hypothesis predicts that quasi-indexers and transient investors will display significant preferences for high exposure stocks while dedicated owners will not. There is, however, no statistically significant evidence that preferences for high exposure firms differ across dedicated owners, quasi-indexers, and transient investors. In summary, the evidence in Table 6 is consistent with the unique asset hypothesis but not with the transparency hypothesis.

5.3 Conditioning on performance

In Section 3, we argued that the holdings of sector funds should reflect the preferences of individual investors because the existence of sector funds is a response to demand by individuals. The unique asset hypothesis predicts that individuals are likely to have strong preferences for high (low) exposure during periods in which the underlying commodities are expected to perform well (poorly). Investment managers of sector funds also are likely to exhibit similar preferences for exposure even if they are not responding to individual investor demands as they are likely to be evaluated relative to either average returns on the relevant underlying commodity or the relevant commodity firms. The transparency hypothesis, however, does not predict that attraction to exposure is conditional on sector performance. Thus, we view a positive relation between sector performance and the attraction of funds to exposure as evidence in favor of the unique asset hypothesis.

The final cross sectional analysis conditions funds' attraction to exposure on the performance of the underlying commodity. Ideally, we would like to condition on expected returns for the underlying commodities. Because we are unable to observe expected returns, we condition on average realized returns in each calendar year, and estimate a modified version of equation (1):

$$\begin{aligned} OWNERSHIP_{iy} = \alpha + \sum_k \delta_k CONTROL_{kiy} + \lambda_{LO} xBETALOW_{iy} + \lambda_{HI} xBETAHIGH_{iy} + \\ \theta_{LO+} GOODYR * xBETALOW_{iy} + \theta_{LO-} BADYR * xBETALOW_{iy} + \\ \theta_{HI+} GOODYR * xBETAHIGH_{iy} + \theta_{HI-} BADYR * xBETAHIGH_{iy} + \varepsilon_{iy} \end{aligned} \qquad (3)$$

where *GOODYR* (*BADYR*) is an indicator variable equal to one for years in which the average annual return on the relevant underlying commodity is high (low) and zero otherwise.

We identify years in which the underlying commodity performed poorly (*BADY*R =1) and well (*GOODYR* =1) by ranking calendar years in terms of their average daily commodity returns. As highlighted in Figure 1, gold returns are negative in three years (1996, 1997, and 2000), close to zero in four years (1995, 1999, 1998, and 2001), and strongly positive in four years (2002, 2003, 2004, and 2005). Thus, for the gold industry we set *BADYR* = 1 in 1996, 1997, and 2000, and *GOODYR* = 1 in 2002 to 2005.

A similar approach is adopted for the oil and gas industry. We rank calendar years based on average oil returns and average gas returns. We set *BADYR* = 1 for 1997, 1998, and 2001. These three years exhibit the lowest average returns during the sample period for both oil and gas – returns on oil are negative in all three years, while returns on gas are negative in two years and close to zero in the third. Determining the good years for oil and gas is more subjective as the rankings for oil and gas returns are not perfectly correlated. Based on oil returns there is a natural breakpoint; average returns in 1995, 2000, and 2003 are all close to zero, while returns in 1996, 1999, 2002, 2004, and 2005 are strongly positive. Using natural gas returns 1996, 2000, 2002, 2003, and 2005 are years in which natural gas returns are highest, however, in 2000 and 2003 oil returns are close to zero. We use the natural breakpoint based on oil returns and set *GOODYR* = 1 in 1996, 1999, 2002, 2004, and 2005, but using breakpoints based on gas returns yields similar results.

(Insert Table 7 here.)

The results are presented in Table 7. There is no evidence that Metals or Focused Metals funds display market timing behavior consistent with the unique asset hypothesis. Indeed, there is significant evidence that metals and focused metals funds actually prefer high exposure firms to low exposure firms during periods in which gold performed poorly. This behavior is not consistent with either the unique asset hypothesis, or the transparency hypothesis, which did not predict any time variation in investor preferences for high and low exposure firms.

When we examine the preferences of Energy funds and Focused Oil and Gas funds, we find that the funds prefer high exposure stocks to low exposure stocks during calendar years in which oil and gas prices rise sharply. Further, during periods in which oil and gas prices fall, we find that Energy funds are attracted to low exposure stocks rather than high exposure stocks, although the results are only statistically significant for Focused Oil and Gas funds.

Although Energy funds do exhibit preferences for high (low) exposure stocks relative to low (high) exposure stocks during years in which the underlying commodities perform well (poorly), the results appear to be primarily driven by changes in investor preferences for low exposure stocks. During years in which oil and gas returns are low, sector funds are attracted to low exposure stocks, while during years in which oil and gas returns are high sector funds try to avoid low exposure stocks. The final test in Table 7 confirms this conjecture. There is robust evidence that investor preferences for low exposure stocks differ significantly across years in which the underlying commodities perform poorly or well, but the same is not true with regards to investor preferences for high exposure stocks.

Overall the results in Table 7 suggest that investors are attracted to exposure in oil and gas firms because it is a way to gain exposure to the underlying commodities. In contrast, the results for gold firms are not consistent with either the unique asset hypothesis or the transparency hypothesis.

6. Conclusion

In summary, our results indicate that investors are attracted to commodity stocks with high exposure to the underlying commodity prices. This primary result is robust across different proxies for ownership interest including share turnover, which reflects interest by all investors, and the number of institutional investors and sector fund managers. We propose two explanations for investor attraction to commodity price exposure: the unique asset hypothesis and the transparency hypothesis. All test results are consistent with the unique asset hypothesis, which is that investors are attracted to high exposure stocks predominantly because the stock represents an efficient investment vehicle for investors to get exposure to the underlying commodity price. There is some evidence consistent with the notion that investors are attracted to stocks of high exposure firms because information about the firm is more transparent, but the evidence is mixed and holds only for gold firms. The two explanations for investor attraction to exposure are not mutually exclusive, but overall the results indicate that investors seek high exposure stocks as a means to gain exposure to commodity prices.

Related to both hypotheses is the idea that firms with high net exposures may be more visible to investors. According to Merton (1987), greater visibility will increase ownership interest in a firm’s equity, resulting in a lower cost of capital. Merton (1987) assumes that each investor forms his or her portfolio from an exogenously determined set of available stocks, and stocks not in this set receive zero weight in investors’ portfolios. Our results suggest that exposure can increase a firm's visibility among investors, thus, firms might be able to use exposure to attract investment.

The notion that particular firm activities or characteristics are associated with increased visibility and investor attention has been documented for activities such as exchange listing (e.g., Foerster and Karolyi, 1999; Mehran and Peristiani, 2006); investor relations (Bushee and Miller, 2007), and even advertising (Brennan and Tamarowski, 2000). The findings in these papers indicate that the firms attracting new investors obtain tangible benefits from the visibility. For example, Foerster and Karolyi (1999) find evidence consistent with Merton (1987) that listing in the US provides foreign firms with access to a wider shareholder base, and lowers the required rate of return on the stock.

Evidence that exposure choice might be an activity that attracts investor attention, however, is anecdotal. For example, in 1999 the CEO of Newmont Mining Corporation, Ronald Cambre, stated,

"Newmont wears its unwillingness to hedge its production like a badge of honour. When people buy a gold stock, they want the exposure to the commodity … If you're selling forward, you run the risk of capping your upside. And the shareholder is likely to say, 'Why did I pay a premium for a company that's limited its upside?' At Newmont, our hedge, if you will, is our low cost".

Newmont clearly views exposure as an attractive feature of its stock. Newmont uses its exposure to promote its stock and make it more visible to investors. Petersen and Thiagarajan (2000) cites a similar quote by Homestake Mining in their study of the hedging practices of Homestake, a firm that proactively avoids hedging, and American Barrick, a firm that aggressively hedges its gold price risk. They provide evidence consistent with the visibility explanation for remaining exposed. American Barrick, the firm with the larger market capitalization, emphasizes in reports to its investors that it manages its risk, while Homestake, like Newmont, emphasizes to capital markets its attraction as a play on gold.

Given the capital market benefits of wider ownership, the attraction of investors to exposure provides an explanation for the results in Tufano (1996) and Jin and Jorion (2006) that hedging does not appear to add value in commodities industries. There are two competing valuation effects that firms must trade off – the traditionally recognized benefits of risk management and the benefits of wider share ownership. Our evidence suggests investors are attracted to commodity firms with high commodity price exposure. Thus, it appears that the benefits forgone by firms not hedging may be offset by a wider shareholder base and a lower cost of capital.

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Appendix A: Identification of sector funds and a descriptive summary

We identify sector funds by first constructing a preliminary sample of candidate funds. For metals funds, we construct a preliminary sample that contains funds that have an investment objective code (IOC) = 8 (“Metals”) in the Thomson Mutual Fund database; funds identified as “Gold” or “Metals” by Morningstar; funds identified in business press articles about metals sector funds; and funds on the Thomson database with a fund name that includes “metal” or “gold” or “guld”. For each fund in the preliminary sample, we examine the holdings and verify its designation as a metals fund.

The final “Metals Fund” sample contains 64 unique funds with non-missing assets data in at least one year during the period 1995-2005. The Metals Funds on average invest 52.81%, 58.17%, and 65.51%, respectively, of total holdings in gold stocks (SIC = 1041), precious metals stocks (SIC = 104), and metals stocks (SIC = 10). The Metals Funds’ other equity holdings are primarily in SIC 1382 (“Oil and Gas Field Exploration Services”), SIC 1222 (“Bituminous Coal Underground Mining”), and SIC 1499 (“Miscellaneous Nonmetallic Minerals, Except Fuel”).

We use a similar procedure to construct a sample of energy funds. The preliminary sample includes funds identified as “Energy” or “Gas” by Morningstar; funds identified in business press articles about energy sector funds; and funds on the Thomson database with a fund name that includes “ener” or “oil” or “gas” (“ener” covers most foreign versions of energy). Thomson does not have an IOC related to energy.

The final “Energy Fund” sample contains 105 unique funds with non-missing assets data in at least one year during the period 1995-2005. Overall, the Energy Funds are more diversified than the Metals Funds. On average, the Energy Funds’ holdings in firms in SIC 1311 are only

13.18%,[17] and their holdings in firms in the "Oil and Gas Extraction" industry (SIC = 13) are only 34.56%. Over 50% of the holdings of the Energy Funds are in equities of firms in industries outside SIC 13, compared to only 15% of the holdings of the Metals Funds outside SIC 10. The Energy Funds' other equity holdings are primarily in SIC 2911 ("Petroleum Refining"), SIC 3533 ("Oil Field Machinery"), SIC 6719 ("Holding Companies, Not Elsewhere Classified"), SIC 4922 ("Natural Gas Transmission"), SIC 4911 ("Electric Services"), SIC 4931 ("Electric and Other Services Combined"), SIC 4923 ("Natural Gas Transmission and Distribution"), SIC 3492 ("Fluid Power Valves and Hose Fittings"), and SIC 2879 ("Pesticides and Agricultural Chemicals, Not Elsewhere Classified"), with over 100 funds having holdings in each of these industries.

[17] Firms with an SIC of 1310, which is undefined, are classified as SIC 1311 given that SICs 1312-1319 are undefined.

Appendix B: Summary of control variables

Summary of control variables used throughout the analysis. We draw the control variables for the determinants of institutional ownership from four sources: Del Guercio (DG, 1996), Falkenstein (F, 1996), Gompers and Metrick (GM, 2001), and Hong and Kacperczyk (HK, 2007).

Name	Description	Source
Log(SIZE)	Natural log of the market value of equity (in $ thousands) as of December 31, year t.	GM, HK,
SIZE_MV_LAG	Natural log of the market value of equity (in $ thousands) as of December 31, year t-1.	DG, F
MB	Market value of equity divided by common book equity as of December, year t.	
Log(MB)	Natural log of market value of equity divided by common book equity as of December 31, year t.	GM, HK
Log(MB)_LAG	Natural log of market value of equity divided by common book equity as of December 31, year t-1.	
Log(PRICE)	Stock price as of December 31, year t.	DG, GM
Log(PRICE)_LAG	Stock price as of December 31, year t-1.	F
INVPRICE	Inverse of stock price as of December 31, year t.	HK
MKTBETA	Calculated using Dimson's (1979) correction.	HK*****
Log(DIVYLD)	Natural log of annual dividend yield as of December 31, year t.	GM
DIVYLD_LAG	Annual dividend yield as of December 31, year t-1.	
TURNOVER	Natural log of average monthly turnover during year t.	GM
TURNOVER_LAG	Natural log of average monthly turnover during year t-1	DG, F*
AVGRET	Average monthly return during year t.	HK**
RETVOL	Standard deviation of daily firm returns during year t.	HK
RETVOL_LAG	Standard deviation of daily firm returns during year t-1.	F***
Log(RETVOL)	Natural log of standard deviation of daily firm returns during year t.	GM****
FIRMAGE	Natural log of the number of months from the CRSP start date to December 31, year t.	DG, F, GM
S&P500 DUM	Indicator variable = 1 if the firm is in the S&P 500 index as of December 31 of year t, and = 0 otherwise.	DG, GM, HK
NASDAQ DUM	Indicator variable = 1 if the firm is traded on the NASDAQ exchange according to CRSP and = 0 if it is traded on the NYSE/AMEX.	HK
PRICE DUM	Indicator variable = 1 if the firm has a share price of less than $5 at the start of the calendar year.	

* Falkenstein estimates regressions for 1991 and 1992 (pooled) and volume is measured in 12/90. GM use quarterly observations and volume is measured during the month prior to the beginning of the quarter.

** GM use quarterly observations and current quarter and previous 9-month returns to capture momentum effects.

*** DG use the lag of the inverse of the standard deviation of returns.

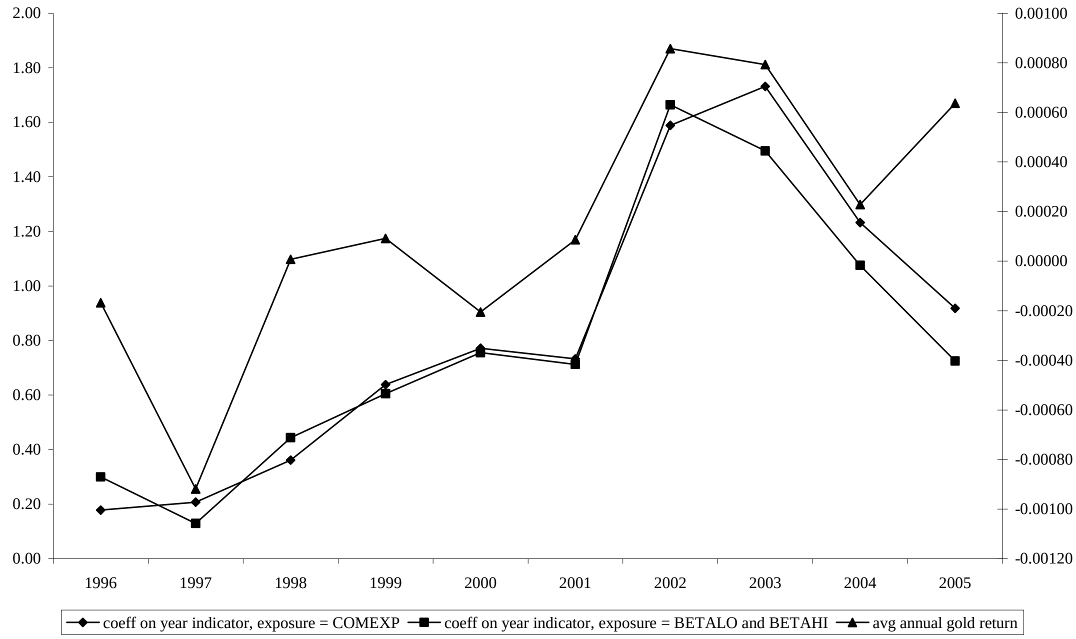
**** GM use the natural log of variance rather than the standard deviation.

***** HK use the firm's industry beta.

Figure 1. Average Commodity Returns and Year Indicator Variables

Plots of average daily returns on gold (Panel A) and oil and gas (Panel B) in each calendar year (scale on right axis), together with coefficient estimates on the year indicator variables from the models discussed in Table 2 for the full sample of gold firms and oil and gas firms (scale on left axis).

Panel A: Gold



Panel B: Oil and Gas

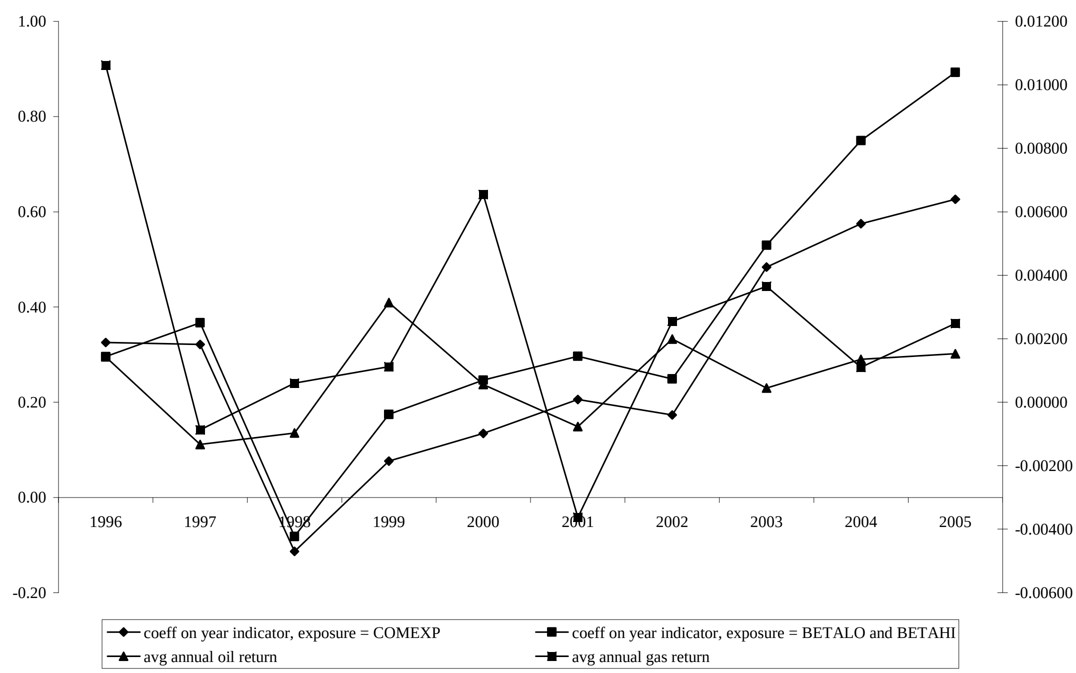


Table 1. Summary of commodity firm samples and exposure measures

Summary of commodity firm samples and exposure measures. Panel A reports the number of firm year observations in the gold and oil and natural gas industry samples. Panel B reports daily returns and the standard deviation of daily returns for the underlying commodity associated with each industry and the correlations of the commodity returns with the market return. We use the quoted daily spot prices on gold bullion (dollars per troy oz.); natural gas at the Henry Hub (dollars per MMBtu); and West Texas Sweet crude oil (dollars per barrel) from Datastream. Panel C reports descriptive statistics for the estimated exposures (*COMEXP*). Panel D reports the results of regressions examining the relation between firm level cumulative abnormal returns and *COMEXP* around days in which there are extreme price shocks in the underlying commodity markets. We classify a date as extreme if the daily return is greater than (less than) the 99th (1st) percentile of the return series for each commodity over the period 1995 to 2005.

	Gold	**Oil and gas**	
Panel A: Sample			
SIC Code(s)	1040; 1041	1311	
Total number of firms	78	199	
Number of foreign firms	60	45	
Total firm-year observations	344	999	
Panel B: Commodity prices			
Commodity	Gold Bullion ($/Troy oz.)	Henry Hub ($/MMBtu)	West Texas Sweet ($/Barrel)
Daily return	0.0133%	0.2617%	0.0723%
Daily Std Dev	0.7859%	6.7444%	2.3919%
Correlation with market	-0.0562	0.0137	-0.0073
Panel C: Firm Exposures (COMEXP)			
Mean	2.2587	0.2415	
Std Dev	1.4711	0.3288	
Skewness	0.2723	1.8592	
Minimum	-2.5878	-1.0459	
25%	1.2479	0.0527	
Median	2.0742	0.2170	
75%	3.2072	0.3987	
Maximum	8.3264	4.0980	
Panel D: Relation between cumulative returns and COMEXP around commodity price shocks			
Response coefficients:			
Positive events	0.0205	0.0280	0.0323
(t-values)	(3.31)	(4.50)	(5.27)
Negative events	-0.0154	0.0063	-0.0371
(t-values)	(-4.13)	(0.70)	(-5.60)

Table 2. Determinants of turnover

We regress the natural logarithm of turnover (*TURNOVER*) on measures of commodity exposure and control variables consisting of: the natural logarithm of market equity, the inverse price ratio, the natural logarithm of dividend yield, average firm returns, idiosyncratic volatility, firm age, stock market betas calculated using Dimson's (1979) correction, and indicator variables for S&P 500 stocks and NASDAQ listed stocks. The model includes indicator variables for the years 1996 – 2005. Commodity price exposure is measured by the continuous variable *COMEXP* and by indicator variables that equal 1 if a firm's commodity exposure is greater (less) than the 70^{th} (30^{th}) percentile exposure (*xBETAHIGH* and *xBETALOW*, where *x* denotes commodity type). The percentiles are recalculated each calendar year. The regression is run for three samples: the full sample (denoted "Full Sample"), firms that have a market equity value greater than the 25^{th} percentile market equity value in each year (denoted "Size > 25^{th} Percentile"), and firms whose share price is greater than \$5 at the start of each calendar year (denoted "Stock Price > \$5"). Significance levels are based on a two-tailed (one-tailed) test for the control variables (exposure variables) using standard errors calculated with the Huber-White estimator of variance. Parenthetical amounts represent the p-value of a test of the difference between the coefficient estimate on *xBETALOW* and *xBETAHIGH.*

	Full Sample		Size > 25th Percentile		Stock Price > $5	
Panel A: Gold						
Intercept	-4.3451***	-4.0427***	-4.2083***	-3.6039***	0.1724	0.3914
SIZE_MV_LAG	-0.0719	-0.0691	-0.0835	-0.0841	-0.3065***	-0.3097***
Log(PRICE)_LAG	-0.0730	-0.0675	-0.3259	-0.2608	0.2631	0.2781
MKTBETA	0.0199	0.0217	0.0927	0.0632	0.0437	0.0448
Log(DIVYLD)	-0.0464**	-0.0519***	-0.0201	-0.0263	0.0148	0.0119
AVGRET	1.2586	0.9725	-1.8578	-1.5707	1.7369	1.8490
RETVOL_LAG	4.7478	3.8759	3.6377	2.3003	-4.8492	-3.8587
FIRMAGE	0.2052***	0.2065***	0.2166***	0.2286***	0.0975	0.0921
S&P500 DUM	0.7448***	0.7230***	0.6985***	0.6661***	1.3101***	1.2909***
NASDAQ DUM	0.0765	0.0895	-0.2935	-0.2850	-1.2016***	-1.2200***
COMEXP-GOLD	0.1433***		0.2259***		0.0479	
GOLDBETALOW		-0.2054		-0.3413*		-0.1482
GOLDBETAHIGH		0.3340**		0.2687*		-0.0460
Difference		0.5394		0.6100		0.1942
Test: HIGH vs LOW		(0.00)		(0.01)		(0.77)
N	295	295	216	216	125	125
Adjusted R^2	23.53%	24.26%	33.67%	33.65%	33.45%	33.00%
Panel B: Oil and gas						
Intercept	-5.5324***	-5.1843***	-4.5338***	-4.3208***	-5.6940***	-5.5043***
SIZE_MV_LAG	0.1359***	0.1136***	0.0439	0.0385	0.1354***	0.1357***
Log(PRICE)_LAG	-0.2503***	-0.2803***	-0.5462**	-0.6007***	-0.1225	-0.0972
MKTBETA	0.3539***	0.3347***	0.4178***	0.4113***	0.5280***	0.5125***
Log(DIVYLD)	0.0003	0.0018	-0.0059	-0.0039	0.0100	0.0140
AVGRET	-0.4516	-0.3195	0.2572	0.1585	-0.6964	-0.6358
RETVOL_LAG	17.1030***	17.6385***	19.6269***	20.7940***	18.3607***	19.6753***
FIRMAGE	-0.0321	-0.0279	-0.0327	-0.0292	-0.0325	-0.0267
S&P500 DUM	0.4785***	0.5108***	0.6203***	0.6097***	0.4424***	0.4256***
NASDAQ DUM	0.0579	0.0573	-0.0690	-0.0741	-0.0529	-0.0581
COMEXP-ENERGY	0.4782**		0.9356***		1.1517***	
ENERGYBETALOW		-0.3277***		-0.3631***		-0.4493***
ENERGYBETAHIGH		0.1758**		0.1620**		0.1214*
Difference		0.5035		0.5251		0.5707
Test: HIGH vs LOW		(0.00)		(0.00)		(0.01)
N	944	944	705	705	634	634
Adjusted R^2	25.27%	26.49%	26.06%	25.78%	34.07%	33.86%

Table 3. Determinants of ownership intensity by institutions and mutual funds

Models of commodity price exposure as a determinant of ownership intensity (LNUMGR) of institutions, mutual funds, and sector funds. Control variables include: the natural logarithm of market equity, the inverse price ratio, the natural logarithm of dividend yield, turnover, average firm returns, idiosyncratic volatility, firm age, stock market betas calculated using Dimson's (1979) correction, indicator variables for S&P 500 stocks and NASDAQ listed stocks, and year indicator variables for 1996-2005. Commodity price exposure is measured by the continuous variable *COMEXP* and by indicator variables that equal 1 if a firm's commodity exposure is greater (less) than the 70^{th} (30^{th}) percentile exposure (*xBETAHIGH* and *xBETALOW*, where *x* denotes commodity type). Significance levels are based on a two-tailed (one-tailed) test for the control variables (exposure variables) using standard errors calculated with the Huber-White estimator of variance. Parenthetical amounts represent the p-value of a test of the difference between the coefficient estimate on *xBETALOW* and *xBETAHIGH.*

	LNUMGR - Institutions		*LNUMGR - Funds*		
Panel A: Gold firms			All	Metals	Focused Metals
Intercept	-2.2684***	-2.0866***	-7.0686***	-3.3095***	-3.3427***
SIZE_MV_LAG	0.4692***	0.4773***	0.8449***	0.4348***	0.4222***
Log(PRICE)_LAG	0.0376	0.0367	-0.1389	0.0010	0.0103
MKTBETA	-0.0067	-0.0124	-0.0592	-0.0794	-0.0955
Log(DIVYLD)	-0.0057	-0.0048			
TURNOVER	0.2414***	0.2438***	-0.0735	-0.0857**	-0.0722*
AVGRET	-2.2764***	-2.4660***			
RETVOL_LAG	-2.3252	-2.9140	-5.6895*	-3.9903	-3.5253
FIRMAGE	0.0830***	0.0886***	0.0000	-0.0478	-0.0364
S&P500 DUM	0.2359***	0.2171***			
NASDAQ DUM	-0.3211***	-0.3334***			
COMEXP-GOLD	0.1060***				
GOLDBETALOW		-0.0837*	-0.0137	-0.1577	-0.1339
GOLDBETAHIGH		0.1394***	0.1505	0.0463	0.0675
Difference		0.2231	0.1642	0.2040	0.2014
Test: HIGH vs LOW		(0.00)	(0.26)	(0.08)	(0.07)
Adjusted R^2	91.25%	90.70%	73.21	58.87	60.74
N	295	295	293	293	293
Panel B: Oil and gas firms			All	Energy	Focused O&G
Intercept	-2.5223***	-2.5376***	-5.0110***	-25.8917***	-6.8973***
SIZE_MV_LAG	0.5594***	0.5602***	0.7189***	2.2774***	0.6109***
Log(PRICE)_LAG	0.1505***	0.1418***	0.0341	-0.0455	0.0458
MKTBETA	0.0358	0.0352	0.0398	-1.8782***	-0.5059***
Log(DIVYLD)	0.0109***	0.0107**			
TURNOVER	0.3329***	0.3321***	0.1709***	0.1404	0.0514
AVGRET	-2.1765***	-2.1400***			
RETVOL_LAG	-5.6628***	-5.2833***	-5.2914***	32.2795**	10.6014**
FIRMAGE	0.0892***	0.0890***	0.0433	0.3627**	0.0800
S&P500 DUM	0.0299	0.0309			
NASDAQ DUM	-0.2415***	-0.2418***			
COMEXP-ENERGY	0.1666***				
ENERGYBETALOW		-0.0292	-0.3192***	-1.3203***	-0.3540**
ENERGYBETAHIGH		0.0726**	0.1087*	-0.9915***	-0.3059**
Difference		0.1018	0.4279	0.3288	0.0481
Test: HIGH vs LOW		(0.00)	(0.00)	(0.41)	(0.75)
Adjusted R^2	89.94%	89.91%	84.16	50.98	41.90
N	944	944	912	912	912

Table 4. Univariate comparison of derivatives use and diversification as measures of reporting complexity

Univariate analysis of derivatives use and diversification as proxies for greater information complexity (i.e., lower transparency) associated with commodity price exposure. The proxies for derivatives use are as follows: DERIVS is an indicator variable = 1 if the firm uses derivatives; *COMMDER* is an indicator variable = 1 if the firm uses commodity derivatives; CORECOM is an indicator variable = 1 if the firm uses derivatives based on its core business (gold or oil and gas). The proxies for diversification are as follows: NUMSEG is the number of segments in which a firm operates; MULTI is an indicator variable = 1 if the firm operates in multiple segments and = 0 if the firm is a single segment firm; and DIVERSE is 1 - the degree of concentration in a single business segment, where concentration is measured using a revenue-based Herfindahl index for each firm in each year.

	Gold Sample		Oil and Gas Sample	
Panel A: Derivatives use proxies	N	Mean	N	Mean
Any derivatives (*DERIVS*)				
Low exposure firms	49	79.6%	255	51.4%
High exposure firms	60	78.3%	258	81.0%
p-value of difference		(0.87)		(0.00)
Commodity derivatives (*COMMDER*)				
Low exposure firms	49	67.3%	255	46.3%
High exposure firms	60	70.0%	258	75.2%
p-value of difference		(0.77)		(0.00)
Core commodity derivatives (*CORECOM*)				
Low exposure firms	49	65.3%	255	45.5%
High exposure firms	60	65.0%	257	75.5%
p-value of difference		(0.97)		(0.00)
Panel B: Diversification proxies				
Number of business segments (*NUMSEG*)				
Low exposure firms	64	1.5781	292	1.4760
High exposure firms	82	1.3537	282	1.2907
p-value of difference		(0.23)		(0.02)
Multi-segment indicator (MULTI)				
Low exposure firms	64	0.2188	292	0.2363
High exposure firms	82	0.1341	282	0.1419
p-value of difference		(0.19)		(0.00)
Line of business diversity (*DIVERSE*)				
Low exposure firms	64	0.1206	292	0.0959
High exposure firms	82	0.0704	282	0.0601
p-value of difference		(0.18)		(0.02)

Table 5. Determinants of ownership interest as a function of complexity of source of exposure
Models of ownership interest on proxies for commodity exposure and complexity about commodity exposure. The proxies for ownership interest are average daily share turnover (*TURNOVER)* and the number of institutional and fund managers (*LNUMGR)*. The proxies for complexity are derivatives use (*COMMDER*) and diversification (MULTI). The regression model includes year indicator variables for 1996 to 2005 and control variables as shown in Table 3. Commodity price exposure is measured by indicator variables that equal 1 if a firm's commodity exposure is greater (less) than the 70th (30th) percentile exposure (*xBETAHIGH* and *xBETALOW*, where *x* denotes commodity type). Standard errors are calculated using the Huber-White estimator of variance.

	TURNOVER	*LNUMGR*	*LNUMGR - Funds*		
Panel A: Gold firms		Institutions	All	Metals	Focused Metals
xBETALOW	-0.5683**	-0.2630**	-0.2539	-0.3403*	-0.3463*
xBETAHIGH	0.3181	-0.0561	0.3979*	0.1749	0.1645
Difference	0.8864	0.2069	0.6518	0.5152	0.5108
	(0.00)	(0.10)	(0.01)	(0.02)	(0.01)
COMMDER	0.1892	-0.0410	0.2423	0.0520	0.0171
COMMDER*BETALOW	0.4253	0.2447*	0.3365	0.2624	0.2988
COMMDER*BETAHIGH	0.1408	0.2902**	-0.2175	-0.0673	-0.0267
Adj R2	34.84	90.54	76.01%	57.23%	59.40%
N	237	237	231	231	231
xBETALOW	-0.2266	-0.0205	0.2772**	0.0122	0.0272
xBETAHIGH	0.3892**	0.1139**	0.0511	0.0227	0.0579
Difference	0.6158	0.1344	-0.2261	0.0105	0.0307
	(0.02)	(0.06)	(0.24)	(0.94)	(0.83)
MULTI	-0.0134	0.1106*	0.2047	0.0134	0.0526
MULTI*BETALOW	-0.3460	-0.0428	-0.4827*	-0.2450	-0.2869
MULTI*BETAHIGH	-0.4573*	-0.0024	0.1532	-0.2046	-0.2406
Adj R2	22.36%	91.41%	68.51%	52.39%	55.16%
N	222	222	220	220	220
Panel B: Oil and gas firms		Institutions	All	Energy	Focused O&G
xBETALOW	-0.4449***	0.0012	-0.3667***	-0.3352	-0.2601*
xBETAHIGH	-0.0221	0.1039	-0.0692	-0.7975*	-0.5567***
Difference	0.4228	0.1027	0.2975	-0.4623	-0.2966
	(0.01)	(0.21)	(0.02)	(0.39)	(0.14)
COMMDER	0.1909*	0.1530***	0.2480***	0.3463	-0.1617
COMMDER*BETALOW	0.2233	0.0070	0.1613	-1.6314**	-0.1406
COMMDER*BETAHIGH	0.2244	-0.0575	0.2280**	-0.3273	0.3316
Adj R2	28.98%	90.59%	84.94%	52.16%	42.56%
N	857	857	823	823	823
xBETALOW	-0.3519***	-0.0402	-0.2901***	-0.1728***	-0.1269***
xBETAHIGH	0.1689**	0.0498*	0.0787	0.0009	-0.0842**
Difference	0.5208	0.0900	0.3688	0.1737	0.0427
	(0.00)	(0.07)	(0.00)	(0.00)	(0.29)
MULTI	-0.0291	-0.1172**	0.1180	0.2190***	0.0478
MULTI*BETALOW	0.1108	0.0260	-0.0698	-0.1297	-0.0474
MULTI*BETAHIGH	0.2680	0.0589	0.1735	-0.0774	-0.0110
Adj R2	28.46%	89.79%	83.70%	64.47%	49.39%
N	877	877	848	848	848

Table 6. Determinants of institutional ownership interest by institutional owner type

Coefficient estimates from multivariate models of exposure proxies as determinants of ownership intensity by institutions classified based on fiduciary standards and monitoring incentives. Separate models are estimated for gold firms and oil and gas firms. The proxy for ownership intensity is the (log of 1 + the) number of institutions that hold the firm's stock (*LNUMGR*). Model 1 includes indicator variables for exposure greater than the 70^{th} percentile (*xBETAHIGH*) and less than the 30% percentile (*xBETALOW*) and control variables. Model 2 includes *xBETAHIGH* and *xBETALOW,* a main effect representing transparency about exposure (either derivatives use or diversification), and interaction variables between the commodity exposure metrics and the transparency metrics. The regression models include year indicator variables for 1996 to 2005 and control variables as described in Table 3. Coefficient estimates for the control variables are not presented. Standard errors are computed using Huber/White estimator of variance. Parenthetical amounts represent the p-value of a test of the difference between the coefficient estimate on *xBETALOW* and *xBETAHIGH.*

	Classified by fiduciary standards				Classified by monitoring incentives		
	Banks	*Insurance Companies*	*Invstmnt. Advisors*	*Others*	*Dedicated Owners*	*Quasi-indexers*	*Transient Investors*
Panel A: Gold firms							
xBETALOW	-0.0795	-0.0392	-0.0822	0.0989*	-0.0671	-0.0861	-0.0413
xBETAHIGH	0.0628	0.0505	0.1261**	0.0508	0.1079*	0.1232**	0.0765
Difference: HIGH–LOW	0.1423**	0.0897	0.2083***	-0.0481	0.1750**	0.2093***	0.1178*
Test: HIGH vs LOW	(0.04)	(0.17)	(0.00)	(0.48)	(0.07)	(0.00)	(0.09)
Test vs. Banks		(0.53)	(0.45)	(0.03)			
Test vs. Insurance Cos.			(0.15)	(0.09)			
Test vs. Invstmt. Advisors				(0.00)			
Test vs. Dedicated Owners						(0.70)	(0.56)
Test vs. Insurance Cos.							(0.24)
Panel A: Oil and gas firms							
xBETALOW	-0.0087	0.0061	-0.0474	0.0013	0.0128	-0.0295	-0.0575*
xBETAHIGH	0.0571	0.0435	0.0618**	0.0175	0.0955***	0.0664*	0.0845**
Difference: HIGH–LOW	0.0658	0.0374	0.1092***	0.0162	0.0827*	0.0959**	0.1420***
Test: HIGH vs LOW	(0.13)	(0.40)	(0.01)	(0.74)	(0.06)	(0.04)	(0.00)
Test vs. Banks		(0.56)	(0.31)	(0.32)			
Test vs. Insurance Cos.			(0.14)	(0.66)			
Test vs. Invstmt. Advisors				(0.06)			
Test vs. Dedicated Owners						(0.81)	(0.27)
Test vs. Insurance Cos.							(0.33)

Table 7. Determinants of sector fund ownership conditional on commodity price returns

Models of the determinants of mutual fund ownership for the gold sample and the oil and gas sample conditional on commodity price returns for the underlying commodity. The dependent variable is the (log of 1 +) the number of fund managers (*LNUMGR*). Determinants include control variables drawn from Falkenstein (1996), indicator variables for high and low exposure based on *COMEXP*, year indicator variables for 1996 - 2005, and interaction variables for good and bad return years in the underlying commodity markets. Coefficients for the control variables are not presented. Standard errors are calculated using the Huber-White estimator of variance.

	LNUMGR of gold firms			**LNUMGR of oil and gas firms**		
	All funds	Metals Funds	Focused Metals Funds	All funds	Energy Funds	Focused Oil & Gas Funds
Coefficient estimates:						
xBETALOW	-0.3623*	-0.4113**	-0.4015**	-0.4140***	0.2229	-0.0109
xBETAHIGH	-0.1368	-0.2304	-0.2059	0.0155	0.1855	0.0937
xBETALOW						
* GOODYR	0.7673***	0.6667***	0.6522***	0.1403	-3.5976***	-1.0479***
* BADYR	0.2881	0.1141	0.1719	0.1077	0.1243	0.4161*
xBETAHIGH						
* GOODYR	0.2812	0.3915*	0.3854*	0.1230	-2.1943**	-0.6151*
* BADYR	0.5630**	0.4432**	0.4414**	0.1318	-0.7091	-0.4234
Tests of differences:						
In benchmark years:						
Difference	0.2255	0.1809	0.1956	0.4295***	-0.0374	0.1046
In good years:						
xBETALOW	0.4050*	0.2554	0.2507	-0.2737**	-3.3747***	-1.0588***
xBETAHIGH	0.1444	0.1611	0.1795	0.1385	-2.0088***	-0.5214*
Difference (High – Low)	-0.2606	-0.0943	-0.0712	0.4122***	1.3659**	0.5374**
In bad years:						
xBETALOW	-0.0742	-0.2972	-0.2296	-0.3063***	0.3472	0.4052***
xBETAHIGH	0.4262**	0.1611	0.1795*	0.1473	-0.5236	-0.3297**
Difference (High – Low)	0.5004**	0.4583***	0.4091***	0.4536***	-0.8708	-0.7349***
Good vs. bad years (Good – Bad):						
xBETALOW	0.4792	0.5526**	0.4803**	0.0326	-3.7219***	-1.4640***
xBETAHIGH	-0.2818	-0.0517	-0.0560	-0.0088	-1.4852*	-0.1917
N	293	293	293	912	912	912
Adj R^2	73.58%	59.63	61.43	84.11	52.10	43.23