SHEEP IN WOLVES' CLOTHING?

Speculators and Price Volatility in Petroleum Markets

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Abstract

The 1990s have been a decade of upheaval in international financial markets. Much of the responsibility for financial instability has been placed on speculators, particularly hedge funds. Speculative capital has been characterized as "hot money," with capital flows driven by "herding" and "contagion" among players in foreign-exchange, stock, bond, and commodity markets.

Policies to deal with financial instability by weakening, or even disabling speculation, have been based largely on anecdote, convenience (speculators have long served as scapegoats for various problems), and ideology, rather than careful analysis. Part of the problem arises from the secrecy with which speculators operate. Since speculative trading cannot easily be observed, it is difficult to assess speculators' contribution, if any, to financial volatility.

This paper looks at speculative behavior in one of the largest, and most volatile, international financial markets, petroleum derivatives. It utilizes a large, detailed database on individual trader positions in crude-oil and heating-oil futures markets. The paper is exploratory, focusing on measuring and assessing the tendency of speculators to herd.

Two theories behind rational herding behavior are examined – the *asymmetric information* view (poorly-informed traders make decisions based on observing well-informed traders, rather than market fundamentals) and the *monitoring/incentive* view (institutional investors make decisions knowing that their incentives are based on performance relative to a benchmark such as mean returns for a group). These theories generate different predictions regarding the types of speculators most likely to herd.

The evidence does not support the view that herding among speculators as a group is widespread in this market. In contrast, evidence in favor of a moderate degree of herding among one group of speculators, commodity-fund managers. the evidence is supportive of the monitoring/incentive theory, but not the asymmetric-information theory.

…I explained to you the instability of [stock] prices and the reasons therefore…and discussed the frenzy and foolishness of speculation. …As there are so many people who cannot wait to follow the prevailing trend of opinion, …they think only of doing what others do and following their examples...

-- excerpted from de la Vega [1688]

I. Introduction

The past few years have witnessed the worst turmoil in the international financial system in the post-War era. The "Tequila Crisis" of the mid 1990s was followed by the "Asian Crisis" and the "Russian Crisis" of the late 1990s. Views about the causes of financial turmoil, as well as proposed solutions, are numerous. One perspective focuses on "fundamentals" -- alleged weaknesses in social, political, and economic systems. An alternative view is that crises are generated by the financial system itself, arising from "speculative excess," "contagion," or "herding" – all terms that suggest that the underlying fundamentals are basically sound. In this view, speculators "panicked," reacting to bad news in one market by pulling their funds out of other markets in geographic or economic proximity.[1]

This paper focuses on the second perspective, seeking to assess speculators' role in

[1] Sanger [1998] is an example from the popular press.

financial turmoil. If speculators indeed exacerbate (or even cause) financial instability, then society would benefit from policy measures restricting their activity. Such measures are many and varied, ranging from the "Tobin Tax" on speculative activity proposed by Nobel-prize winner James Tobin, to stricter government regulation, to closing down markets entirely. The objective is to "throw sand in the wheels of international finance" (Eichengreen et al [1995], Haq et al [1996]). Conversely, if speculation serves to mitigate volatility, then trading should be encouraged.

Researchers, however, face substantial challenges in testing theories that view speculators as necessary to the functioning of the international financial system against those that see them as unnecessary at best, and destructive at worst. These challenges are of two types. First, most speculative behavior goes unseen -- neither policymakers nor researchers are typically privy to information regarding speculator decisions and actions, which are private. Only the consequences of speculator behavior are observable.

Second, many such consequences can be explained equally well by theories that assume that speculators are responsible for market turmoil, and by those based solely on fundamentals. For example, Thailand's problems may have precipitated the Asian crisis through economic linkages of trade and investment with its neighbors, rather than through the contagion widely described as behind the crisis. Consequently, there is little hard evidence on either speculators' actions or their consequences, leaving policy to be made on the basis of anecdotes and ideology.

As exemplified in the quotation above, controversy over the behavior of speculators in financial markets goes back to the early days of trading. Claims that self-interested speculative behavior is detrimental (to markets for the underlying commodity) fall into three categories.[2]

First, speculators engage in "positive feedback trading," entering markets when fundamentals are strengthening (thus driving prices up even higher), and bailing out when they weaken, putting further downward pressure on prices. Such behavior can drive prices away from fundamental values, a process sometimes referred to as a "bubble" in the modern finance literature.[3] Second, speculators manipulate the market.[4] Third, speculators trade by watching each other, rather than market fundamentals, a phenomenon referred to as "herding." When each speculator rushes to buy what others are buying and sell when others are selling, the resulting "stampede" can exacerbate volatility arising from shocks to supply and demand. Because of the current interest in

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[2] Any trader with enough capital can affect a market by building up a large enough position, but in general such positions cannot be liquidated profitably. Speculative behavior detrimental *ex ante* to a trader's own self-interest is not discussed here.

[3] For a discussion of bubbles, see the symposium in the Spring 1990 issue of the *Journal of Economic Perspectives*, especially Flood and Hodrick [1990].

[4] "Manipulation" here refers to 1) traders with market power affecting prices by spreading false news regarding their intentions or behavior, 2) traders with inside information about market fundamentals making false announcements regarding factors likely to affect market fundamentals, 3) traders buying up the stock of the commodity in inelastic supply, and reselling it at a monopoly profit (e.g., the Salomon brothers Treasury Bond corner of 1991; see Jordan and Jordan [1996]), or 4) delivery squeezes, wherein traders accumulate larger forward positions than the available supply of the cash commodity, and demand delivery.

herding, this last phenomenon provides the focus of this paper.

II. Herding

Herding is a widespread social phenomenon (e.g., buying books because they are on best-seller lists), and the past decade has seen considerable progress in the development of theoretical models of herding behavior, both in general and in financial markets in particular.[5] The finance literature has developed two hypotheses regarding types of traders mostly likely to engage in herding behavior. These hypotheses generate different predictions, allowing us to construct tests that can distinguish between them.

The *information-asymmetry hypothesis* views herding as rational behavior by relatively poorly-informed traders, who watch their better-informed brethren, and attempt to take similar positions, or follow similar trading strategies based on past public information (e.g., trend extrapolation).[6] If this hypothesis is true, then the "smart money" – often identified with institutional investors -- is least likely to herd, because of greater (or faster, or more accurate) access to information and capability for analysis of its price implications. Individual investors are more likely to herd,[7] especially those physically

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[5] See Devenow and Welch [1996] for a survey of the literature.

[6] In this context, "rational" in the sense that it leads to higher expected returns for poorly-informed traders than acting on their own information. "Poorly informed" refers to the condition wherein some market participants have access to information regarding changes in market fundamentals more rapidly or cheaply than others.

[7] As an example from the trade press, Briese [1994, p.38] observes that "…some market books recommend following the large speculators under the theory that they must be pretty good traders to get that large." He also

present on the floor of the exchange, who can most readily observe the behavior of other traders. The few papers in the herding literature (discussed below) have not been able to examine the trading behavior of this group of individual investors.

In contrast, the *monitoring/incentive hypothesis* predicts that institutional investors are the group most likely to herd. Institutional investors are subject to industry benchmarking – e.g., fund managers' assessment and incentives are typically based on their performance relative to other managers – and will thus try to avoid standing out from the herd [Scharfstein and Stein 1990]. An effective way to do so is to buy what other fund managers are buying, etc.

Of course, these two hypotheses are not mutually exclusive. institutional investors and individuals can be herding amongst themselves at the same time, but for different reasons. Similarly, neither group need be herding. These possibilities are examined in the empirical section below.

Empirical analysis, however, has been limited to a few recent papers. Analysis of herding requires disaggregated (investor-level) data; typically, the only such data available are those collected by governments in the course of financial regulation. With one exception, the few studies in this area [Lakonishok et al 1992, Choe, Kho and Stulz 1999, Kim and Wei 1999, Wermers 1999] analyze decisions to buy and sell stocks by

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notes the counterargument that "the growth of these funds (the large speculators) can be attributed more to a knack mutual-fund and pension-fund managers.

The limitations of studies based on fund managers' security investments are of two types. First, in the case of U.S. stock markets, funds are required to report their holdings on a quarterly basis, which may work well for investor protection, but creates problems for research.[8] For example, if one fund dumps its foreign stock in late April, and another does the same in mid-June, the concept of "herding" is severely stretched, probably beyond the concept of imitative behavior that causes concern.[9]

Even apart from the time-horizon, this type of data does not allow researchers to distinguish herding from actions based on changes in political or economic "fundamentals;" i.e., developments in the real side of the economy. Continuing the example above, if the two pension fund managers see their overseas investments faring poorly, they may decide to invest elsewhere. They might not even know of decisions by others to do likewise, much less be trying to follow the herd.

The one article comprising the exception [Kodres and Pritsker 1996] analyzes data collected by the U.S. Commodity Futures Trading Commission (CFTC) on the daily

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for fundraising than trading."

[8] The underlying data are collected under the U.S. Securities and Exchange Act of 1934 and the Investment Company Act of 1940, which regulate mutual and pension funds.

positions of large players in options and futures markets.[10] The authors studied the behavior of financial institutions in foreign-exchange, eurocurrency, and other financial markets during the period 1992-1994, but were not able to get around the second problem. They thus could not ascertain whether the tendency of some financial institutions to act similarly was due to herding or parallel response to new public information.[11]

This paper takes advantage of a similar CFTC database, covering the period 1993-1997 for a particularly important, simple, and volatile international commodity market, petroleum. Petroleum provides an ideal natural laboratory for analyzing speculative behavior, for several reasons. First, it accounts for the single largest good moving in international trade, comprising 10 to 25 percent of the value of world trade (depending on oil prices).

Second, the bulk of derivatives trading in the oil market takes place on commodity

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[9] In the case of the Korean Stock Exchange (KSE), such reporting is monthly [Kim and Wei 1999]. Choe, Kho, and Stulz [1999] analyze daily data on purchases and sales on the KSE, but cannot distinguish traders, making interpretation of herding measures problematic.

[10] In addition, a few studies have examined the behavior of a single speculator, or the accounts of a single brokerage house; the generality of their results is difficult to assess. Jordan and Meiselman [1996] provide a survey.

[11] It should be noted that doubts have been raised regarding the relevance of information asymmetry in commodity markets, where private information is assumed to be less important than in equity markets. Ito et al [1998] find evidence of information asymmetry in the foreign-exchange (FX) market, showing that the end of restrictions on lunch-hour FX trading in Tokyo in 1994 was associated with higher variance of the ¥/$ exchange rate, despite the unchanged flow of public information. Manaster and Mann [1996] find evidence of information asymmetry among market-makers trading futures contracts in the pits of the Chicago Mercantile Exchange. Evidence supporting such

exchanges, in contrast to derivatives of financial instruments (e.g., interest rates and exchange rates), where the over-the-counter (OTC) market dominates trading, making it more difficult to draw general conclusions regarding speculative behavior from futures data.[12]

Third, the oil market has long been volatile. Speculators have been blamed for exacerbating "energy crises," and proposals have been made to curtail their activity (see Weiner [1998], and references therein). A recent series of articles in the trade press have related speculative activity to price fluctuations in petroleum markets.[13] Utilizing CFTC *Commitments of Traders* (COT) data (described below), they demonstrate a strong correlation between aggregate non-commercial net open interest and oil prices.

The focus of these articles is on well-capitalized speculators ("funds") – commodity pools and hedge funds – and whether these funds have a positive or negative effect on market volatility. If the funds can be characterized as "smart money," undertaking extensive analysis on possible changes in future industry, macroeconomic, political, etc.

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information asymmetry in the over-the-counter (OTC) petroleum forward market can be found in Phillips and Weiner [1994].

[12] Roughly 99 percent of FX derivatives trading is OTC -- $990 billion out of $1002 billion per day in April 1998 [Bank for International Settlements (BIS), 1999]. While no organization surveys OTC activity in petroleum, BIS [1999, Table E-41] estimates $250 billion notional value outstanding in OTC contracts in commodities other than precious metals as of June 1998 (metals and petroleum account for about 98 percent of OTC activity in commodities [World Bank, 1999]). If the ratio of OTC trading activity to notional outstandings is the same for commodity contracts as for interest-rate contracts, daily OTC non-precious-metal commodity turnover would be about $1.4 billion. Daily turnover in NYMEX oil and gas futures contracts alone was about $2.5 billion in June 1998. Adding turnover in NYMEX options contracts and IPE futures and options would increase the disparity still further.

conditions and their likely consequences for prices, their presence would help smooth market adjustment to these changes. In contrast, if funds represent "dumb money" – herding sheep, buying and selling because others are doing so, or noise traders chasing price trends, they would tend to exacerbate volatility.

The articles in the trade press tend to view the funds' behavior as volatility-increasing.[14] Trade-press accounts are not always coherent, however; e.g., Dale and Zyren [1996] claim that aggregate data show that funds are price followers (termed "sheep" by *PIW* [1995]) rather than an influence on prices. Even if their analysis showed such to be the case (which it does not, as pointed out by Krapels [1996], who notes "occasionally there is a wolf under that wool"), their reassuring interpretation (that funds should not be a policy concern because they are price followers, rather than price leaders) is the opposite of the one suggested by economic theory. If these be sheep, then one is safer among wolves!

Finally, using petroleum allows us to get around the problem noted above – distinguishing herding from parallel responses to news regarding fundamentals. Doing so

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[13] See especially Arnold [1995], Dale and Zyren [1996], Keefe [1996], Krapels [1996, 1999], *Petroleum Intelligence Weekly* [1995], and Verleger [1995].

[14] For example, Krapels [1999], who claims, "The cost [of speculation in futures markets], as the academic literature has begun to recognize but as practitioners in financial markets have long known in their bones, is volatility;" and "Of the hundreds of fund managers and commodity traders, the vast majority are 'systems traders,' relying upon the analysis of price trends for their trading decisions, and paying little if any attention to the fundamentals of the markets in which they are trading."

requires that the scholarly literature have a good handle on these fundamentals, which is indeed the case for commodities, but problematic for stocks, interest rates, and exchange rates.

III. Empirical Analysis

A. Data

The Commitments of Traders (COT) data consists of the open (i.e., end-of-trading-day) positions of large players in options and futures markets, and is collected by the CFTC, which regulates options and futures trading on commodity exchanges in the United States. While the trade press and forecasters have begun to focus on COT data only in the past few years,[15] the large-trader reporting requirements date back to the Grain Futures Act of 1922.[16]

As part of its market surveillance function, the CFTC requires large traders to report their open positions on a daily basis.[17] The term "large" refers to the size of a trader's open positions in a given contract, and varies across commodities – 150 contracts in the case of

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[15] Examples from the futures-industry trade press include Briese [1994], Krapels [1996], and Cavaleti [1996]. Examples from the petroleum-industry trade press include Arnold [1995], Verleger [1995], and Keefe [1996].

[16] The Act required traders in grain futures to report large positions to the exchanges on which they traded; these reports were then passed on to the Grain Futures Administration, part of the U.S. Department of Agriculture. The current system, whereby large traders and their brokers must report directly to the regulatory authority, was established under the Commodity Exchange Act. Regulation of futures markets, including large-trader reporting requirements, was extended beyond agricultural commodities in 1974, when the CFTC was created. McDonnell and Freund [1983] provide a historical and legal account.

gasoline, 250 in the case of heating oil, 300 in the case of crude oil.[18]

The COT data classify reporting market participants into categories (individual trader identities are blinded for confidentiality). Participants are deemed to be "commercial" if they are active in cash markets for the given commodity, and "noncommercial" otherwise.[19] Noncommercials are the group usually identified as speculators; their behavior often attracts considerable scrutiny.

Use of aggregate COT data for analysis of speculator performance dates back at least as far as Houthakker [1957], who examined month-end position data for wheat, corn, and cotton for the period 1937-1952.[20] A few researchers have had access to the underlying daily position data, disaggregated by individual trader, but with the exception of the study discussed above by Kodres and Pritsker [1996] (who did not look at speculator behavior),

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[17] Thus the COT data cannot be used to examine intraday trader behavior.

[18] The reporting threshold is designed to capture about two-thirds of a contract's open interest; for example, during the period covered by our database, large traders in heating-oil futures accounted for an average of 66 percent of the long open interest, and 77 percent of the short open interest [Ederington and Lee 1998].

[19] It should be noted that the commercial group includes financial institutions that may hedge on customers' behalf, as well as laying off some of their own exposure to oil prices arising from writing OTC contracts such as swaps and options.

[20] Aggregate COT data are released biweekly by the CFTC. For a survey of research on speculator performance in futures markets (through analysis of COT and other data), see Jordan and Meiselman [1996]. The sole published article on trader performance in petroleum markets analyzes individual transactions in the OTC forward market in Brent blend crude oil [Phillips and Weiner 1994].

none has examined herding.[21]

The database examined here covers the three widely traded NYMEX petroleum contracts – sweet crude oil, heating oil, and New York Harbor gasoline -- and was made available by the CFTC as part of a U.S. Department of Energy (USDOE) study on the effects of speculation on heating-oil markets.[22] These contracts accounted for over 99 percent of petroleum trading on the exchange during the 46-month period (963 trading days) covered by the database, June 1993 through March 1997. Trading volume averaged roughly 25 million contracts per year for crude oil, and 7-8 million contracts for heating oil and gasoline (see Table 1).

{insert Table 1 about here}

In this paper, I examine the crude oil contract, and one of the smaller contracts, heating

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[21] Hartzmark [1987,1991] used disaggregated data to examine trading profitability in nine agricultural and financial futures contracts over the period 1977-1981. Leuthold, Garcia, and Lu [1994] repeated Hartzmark's study for pork-belly futures traded on the Chicago Mercantile Exchange over the period 1982-1990. Chang, Pinegar, and Schacter [1997] used COT position data to infer trading volume by large speculators, and related it to price volatility in five agricultural and financial futures markets.

[22] The database contains roughly 1.25 million records, each corresponding to an open position in a single contract and maturity for a single reporting trader on a single day. For the purpose of this paper, open positions were aggregated over maturities (e.g., open positions in the January, February, March, etc. heating-oil futures contracts were combined for each trader each day). Ederington and Lee [1998] provide further details.

oil, where the unusual behavior by speculators was alleged to have occurred.[23] During this time period, there were 1308 large traders (380 commercial, 928 noncommercial) active in NYMEX crude oil contracts, and 700 (277 commercial, 423 noncommercial) active in the heating oil contracts. The great majority of the large traders active in crude oil (which has almost three times more trading volume and open interest) were active in heating oil as well.[24]

The CFTC database breaks down noncommercial positions as follows. **CPO**s (**commodity-pool operators**) are the equivalent of mutual funds in the securities industry – firms that collect customer funds and use them to invest in futures and options markets. **CTA**s (**commodity trading advisors**) are firms that advise investors (both individuals and CPOs) on trading decisions, or make such decisions on their clients' behalf.

FCMs (**futures commission merchants**) are the equivalent of stockbrokers — firms that accept customer funds and orders to buy and sell futures and options. **IBs (introducing brokers)** are firms that accept customer orders, but do not accept funds, instead acting as intermediary between customers and FCMs. **APs (associated persons)** are individuals

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[23] In response to pressure from USDOE over heating-oil price increases, the chairman of Amerada Hess pointed to speculators as responsible [Sullivan 1996, Turner 1996]. The USDOE study was undertaken in response to these claims.

[24] Recall that "active" here refers to end-of-day open positions exceeding the CFTC's reporting threshold, need not be related to volume traded. To be in the database, a trader must have carried an open position in at least one day during the period covered. Studies of futures markets utilizing individual-trade data indicate that locals account for a large percentage of total trades [Manaster and Mann 1996].

who work for firms in the futures industry -- FCMs, IBs, CPOs, or CTAs.

FBs and **FT**s (**floor brokers** and **floor traders**) are "locals" – members of the exchange or seat lessors who execute trades on the floor; the former transact for customers (some for their own accounts as well), the latter only for themselves.[25]

The above groups must register with the CFTC, and are subject to oversight by the National Futures Association, the self-regulatory body of the U.S. futures industry. In contrast, **Hedge Funds** are private investment vehicles (typically limited partnerships), and under certain conditions may be able to avoid regulatory requirements regarding registration, record maintenance, and disclosure.[26] **Managed Money** refers to managers of funds broader than commodity pools. **Undesignated traders** are (unregulated) off-floor individuals or firms transacting for their own accounts, designated as "customers" below.

In order for a position to be classified in the database as belonging to a CTA, FB, FCM, or IB, it must be a "house account;" trades executed for customers are classified by customer type. Table 2 provides a breakdown on the number of noncommercial traders

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[25] The term "local" is often restricted to those who trade solely for their own account.

[26] These conditions pertain to whether the hedge fund is registered in the USA, is marketed to US investors, is marketed only to "qualified eligible participants," and the extent of the fund's activities in markets regulated by the CFTC. See International Monetary Fund [1998], Fung and Hsieh [1999] for details.

by registration type.

{insert Table 2 about here}

B. Herding Measures

The essence of herding behavior is traders changing their positions in the same direction. As noted above, the tendency of traders to move in the same direction at the same time is a necessary, but not sufficient condition for herding, because such parallel movements may be reactions to changes in common information sets. The simplest measures for capturing the tendency of traders to buy or sell when others are doing likewise are a) counts of traders buying and selling at the same time, and b) correlation across traders of changes in open position.

Of course, as in all derivatives markets, the futures contracts outstanding at any time must sum to zero – for every short, there must be a long, and it is not possible for the market as a whole to change position. Instead I examine the tendency to herd of the trader types discussed above.

1. Counts of Buyers and Sellers

Under the null hypotheses of no herding, the number of speculators buying (denoted B below) and selling (S) each day should be equal, and deviations from equality due to chance. Table 3 provides summary statistics on counts of speculator activity. The daily median (and mean) number of large speculators' changing position[27] in crude-oil futures is 28, with a maximum of 50, and minimum of 10. Analogous figures for heating-oil futures are median of 17 large speculators active, with a maximum of 42, and minimum of 3.[28]

On none of the 962 trading days (one observation is lost in calculating daily position changes) in the period were all of the large noncommercial players on the same side of the market.[29] The mean percentage buying was 48.7 percent in crude oil, 50.3 percent in heating oil.

{insert Table 3 about here}

The count measure used in the small herding literature on mutual fund managers' stock selections (Lakonishok et al [1992], Choe et al [1999], Wermers [1999]) is the absolute difference each day between the fraction of speculators buying and 50 percent (so that everyone selling and no one selling yield the same value), less an adjustment factor. The

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[27] In the absence of transaction data it is impossible to know the number of large speculators active in the markets each day. The number changing position represents a lower bound, and is referred to as the number "active" below.

[28] Low numbers often correspond to holiday periods; e.g., on 3 July 1995, a Monday prior to the U.S. Independence Day holiday, only 3 large speculators were active in heating-oil futures, and 10 in crude-oil futures.

[29] The days with the lowest percentage of large speculators buying were 26 July 1994 in crude-oil futures (3 of 23 active, or 13 percent), and 19 September 1996 in heating-oil futures (1 of 14 active, or 7 percent). The highest percentages of large speculators buying were recorded on 6 August 1993 in crude-oil futures (17 of 20, or 85 percent), and 27 January 1997 for heating-oil futures (15 of 17, or 88 percent).

adjustment factor (here labeled μ) reflects the fact that even under the null hypothesis, the expected value of an absolute difference is positive.

$$H = |B/(B+S) - 0.5| - \mu$$

$$\mu = E[|B/(B+S) - 0.5| \text{ no herding}]$$

Under the null hypothesis of no herding, μ is readily calculated, as the sample fraction buying B/(B+S) has a binomial distribution with probability of success 0.5 and number of trials = B+S. The adjustment factor declines with sample size, ranging here from 5.6 percent (sample size 50) to 25 percent (sample size 3).

Table 4 presents summary statistics on *H* for three groups of speculators – all noncommercials, CPOs, and floor brokers and traders. When all noncommercials are taken together, there is little indication of parallel movement in open positions in either crude-oil or heating-oil futures; as shown in the first and fourth columns of the table, the mean value of *H* is only 1.20 percent in the former, and 0.86 percent in the latter. The standard deviations are also small, though, and the herding estimates are statistically positive at conventional significance levels, although economically small.

{insert Table 4 about here}

The distribution of *H* is skewed, however, with large positive values possible, but large negative values bounded by the size of the adjustment factor. In crude oil, for example, the maximum value of *H* is 28.6 percent, and the minimum value, -10.5 percent. While the mean values of the herding measure are positive in both markets, both markets exhibit positive skewness, and the median values are both negative (–0.06 percent in crude oil, -0.47 percent in heating oil).

In the crude-oil market, 496 of the 962 trading days (51.6 percent) had a *negative* value of *H*, indicating that the fraction of noncommercial traders on the same side of the market was actually *closer* to 50 percent than would be expected by chance. This was even more the case in heating oil, where *H* was negative on 505 of the 962 trading days (52.5 percent).[30]

These results are in contrast to Choe et al [1999] (the only study to test on daily data), who found evidence of substantial herding by foreign investors in the Korean stock market (but recall caveat in footnote 9 above), and Wermers [1999], who found moderate herding (over calendar quarters) among U. S. mutual fund managers.

It may be the case that speculators are simply too heterogeneous for herding to be an important phenomenon for the group as a whole. To explore this possibility, herding statistics were calculated separately for CPOs and floor participants (FBs and FTs); estimates are reported in Table 4. These traders are predicted to be the most-likely herding candidates by the theories discussed above.

As managers of commodity funds, CPOs tend to be in the futures markets regularly, move investments among commodities, and be subject to similar performance assessments, making them good *a priori* herding candidates according to the monitoring/incentive theory. Moreover, the trade press characterizes most CPOs as technical traders – buying and selling futures contracts based on recent price movements, rather than analysis of likely developments in fundamentals. As long as technical-trading rules are similar across CPOs, they would tend to buy and sell at the same time.[31] Empirical research based on aggregate data from a variety of futures markets indicates that these technical systems indeed generate similar trading strategies, and that as a group CPOs tend to be positive-feedback traders, buying after price increases, and selling after declines [Irwin and Yoshimaru 1999].[32]

Floor participants (brokers and traders) are likely herding candidates according to the asymmetric-information theory, both because they can watch each other far more readily than other market participants, and because their full-time occupation as traders in the

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[30] The p-values (i.e., likelihood of getting at least this many negative values under the null hypothesis that the values of H are drawn from a population with median zero) are 17.5 percent for crude oil, and 6.5 percent for heating oil.

[31] The majority of CTAs, who advise or make investments for commodity pools, describe their trading strategies as "trend following" [Fung and Hsieh 1999]. See also Kolb [1997, p.105] and footnote 14 above.

exchange pits may make it difficult for them to keep up with and assess the impact of information flowing into the market.[33]

For each group, two separate assumptions were made about the likelihood of an active speculator being a buyer on a given day under the null hypothesis of no herding. First, the likelihood was assumed to be 50 percent, as above. Second, the likelihood was allowed to differ each day, in accordance with the sign patterns of changes in open position of noncommercials as a group, excluding the subgroup examined. For example, if 40 percent of non-CPO speculators were purchasers on a given day, then it was assumed that in the absence of herding, 40 percent of CPOs would be purchasers that day as well.

The justifications for the second assumption are two. First, news arriving in the market may elicit changes in net position for speculators as a group that are unrelated to herding behavior. For example, information that suggests an increase in price volatility (due to changes in fundamentals, e.g., an unexpected decline in inventory levels) may lead speculators as a group to reduce the size of their open interest. If speculators happen to be net long at the time, then fewer should buy than sell that day; the (<50) percentage

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[32] These results are based on data collected in a CFTC pilot program covering December 1988 through March 1989. The briefness of the sample period, as well as the enormous increase in fund activity in the ensuing decade raise questions about their current relevance.

[33] The problem of market-maker strategy when facing traders with potentially-superior information is at the heart of asymmetric-information models developed for equity markets (see, e.g., the textbook by O'Hara [1995]).

buying provides a benchmark for the day. Second, the second assumption is employed in the few studies in the literature, and thus allows for a direct comparison with their results.

The results for CPOs differ significantly from those of noncommercials as a group, regardless of which assumption is made regarding the daily benchmark for percentage buying. As seen in Table 4, mean (respectively, median) herding measures in crude oil were about 3 (respectively, 1) percentage points higher than would be expected by chance for the 50 percent benchmark, and about 5 (respectively, 3) percentage points higher than would be expected by chance for the benchmark used in the literature.

Moreover, CPO herding tendencies are stronger for heating oil than for crude oil. Mean (respectively, median) herding measures in heating oil were about 4 (respectively, 3) percentage points higher than would be expected by chance for the 50 percent benchmark, and about 8 (respectively, 6) percentage points higher than would be expected by chance for the benchmark used in the literature.[34]

Results for floor participants are weaker. Mean herding measures are small (<2 percent in both markets) when the 50 percent benchmark is used, large (>5 percent in both markets) when the literature benchmark is used. Median herding measures are negative

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[34] The p-value for the means and medians differing from zero are well below 1 percent in both markets, under both benchmark assumptions. The herding measure is positive on 468 of the 851 days (55 percent) in which there were at least two large CPOs active in the market using the 50 percent benchmark. The analogous figure using the literature benchmark is 517 positives out of the 851 days (61 percent).

(and statistically insignificant from zero at conventional levels) under the first benchmark, but large under the second benchmark.

The stronger results for CPOs should be viewed in the context of the relative small number active in the markets each day, however. As seen in Table 3 above, a mean and median of only 7 large CPOs are active IN crude oil, compared to about 12 floor traders, and 28 total. Corresponding figures IN heating oil are even smaller – 4 CPOs and 9 floor traders out of 17 total.

2. Correlations

The count measures examined above have the advantage of being nonparametric, and hence not relying on distributional assumptions about trader position changes. Such tests may not be very powerful, however, in part because they do not take advantage of potentially important information – the *size* of trader position changes – instead relying only on the *sign* of these changes.

In contrast, the most widely used measure of tendency toward parallel behavior, correlation, assumes position changes are normally distributed. I start by estimating correlations for commercial traders. While this paper focuses on speculator behavior, it is useful to examine the behavior of commercial participants as a benchmark against which to compare position changes by noncommercials.

A priori, there would no reason to expect herding behavior by oil companies and financial institutions that use the futures markets to hedge their (or their customers') cash positions. Rather, we would expect changes in commercials' positions to reflect changes in their underlying business, whether it be entering into agreements to make or take future delivery of crude oil or petroleum products (in the case of oil companies), or entering into swaps or adjusting hedge programs for customers (in the case of financial institutions).

In constructing a correlation table of changes in commercials' positions, we run into two problems. First, each correlation refers to a pair of traders, resulting in a large number of correlations to be calculated – for n participants, there can be up to $n(n-1)/2$ correlations, equal to 72010 in the case of crude oil, 38226 in the case of heating oil.[35] Second, the CFTC does not provide a useful industry breakdown for commercials – throwing them all in the same pool might result in inaccurately small correlations as a result of comparing participants who would be unlikely to come into contact with each other, much less herd.

Fortunately, Ederington and Lee [1998] provide an industry breakdown of the 40 largest commercials that traded heating-oil during this period. On this basis, I calculated two sets of position-change correlation matrices for heating-oil traders, one for oil companies (24 participants), the other for financial institutions (16 participants). I also constructed correlation matrices for the same group of 40 in the crude oil futures market.[36]

The results are shown in Table 5. Not surprisingly, there is scant evidence of herding among commercial participants in either the heating-oil or crude-oil futures markets. The average and median correlations are very close to zero, and differ from zero at conventional significance levels only in the case of oil companies in crude futures. All of the roughly 200 correlations calculated in the two markets for financial institutions are below 50%. Of the nearly 500 correlations in the two markets calculated for oil companies, only one exceeds 50% -- the 79% correlation between two active traders (one was active in the crude-oil futures market on 112 of the 962 days in the sample period, the other on 218 days) is based on only 4 days when both were active.

{insert Table 5 about here}

Against this commercial benchmark I compare the behavior of commodity-pool operators in heating-oil futures, the group and market with the strongest evidence of parallel behavior based on the count tests above. During the sample period, there were 80 CPOs active in this market, but many were relatively small; the median number of days in the market was 92. Even among the ten largest (ranked by frequency of market

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[35] These numbers represent upper bounds, because correlations can only be calculated when two traders' are in the market at the same time; i.e., their position-change dates overlap.

participation), the median number of days in the market was 536, less than for the commercials. As a result, only about one third of the 3160 possible correlations among CPO position changes can be calculated.

The results are consistent with those above (see Table 6). CPOs as a group show a statistically strong, although economically slight, tendency to herd. The average correlation was about 11 percent, versus zero for both oil companies and financial institutions in the heating-oil market. About one-quarter of the 1115 correlations calculated exceed 25%; the top decile exceeds 50%, and the top 5 percent exceed 75 percent. Only 382 (35 percent) of the correlations are negative.

{insert Table 6 about here}

The high correlations tend to be among the smaller players, however; when attention is restricted to the largest 10 CPOs (measured by number of days active in the market), the herding measures are weaker. Only one of the 45 correlations among the top ten CPOs exceeds 50 percent; only five exceed 30 percent. The average and median correlations are still statistically strong although economically slight, however, at 7.2 percent and 2.2 percent respectively. Three-quarters of the 45 correlations are positive.

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[36] While all 40 large commercial traders in heating-oil futures participated in crude-oil futures as well, four of them (two from each group) were active on fewer than 10 days, and so had to be dropped from the calculations.

IV. Conclusion

This paper has assessed the extent of speculator herding in a volatile international commodity market – petroleum futures. Employing both parametric (correlation) and nonparametric (count) methods, I find little evidence of herding in heating-oil and crude-oil futures markets among noncommercial traders as a group. In contrast, there is solid evidence of parallel position changes among a subgroup of speculators, commodity-fund managers (CPOs). The extent of parallelism is moderate economically, but statistically highly significant at conventional levels (p-values much less than 1 percent).

Evidence of such behavior among floor participants is mixed, and depends on the approach adopted; however, more work is needed to understand the factors behind these results. Overall, the data provide strong support for the monitoring/incentive theory of herding behavior, and at best weak support for the asymmetric-information theory.

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TABLE 1 NYMEX futures contracts -- Aggregate statistics				
Thousand Contracts	**Crude Oil**	**Heating Oil**	**NY Harbor Gasoline**	**Other Petroleum[1]**
Trading Volume				
1993	**24869**	**8625**	**7408**	**45**
1994	**26812**	**8987**	**7471**	**45**
1995	**23614**	**8277**	**7072**	**50**
1996	**23488**	**8342**	**6312**	**54**
1997	**24771**	**8371**	**7475**	**40**
Year-end Open Interest				
1993	**412**	**185**	**137**	**2**
1994	**354**	**133**	**53**	**3**
1995	**353**	**129**	**62**	**2**
1996	**364**	**95**	**60**	**3**
1997	**413**	**152**	**101**	**2**

1. Other petroleum contracts traded 1993-1997 were propane and Gulf Coast unleaded gasoline.

TABLE 2 -- Reporting Traders: Breakdown by Type				
Number of Traders Reporting[1]	**Crude Oil**	**Heating Oil**	**Gasoline**	**Total**
Commercial	**380**	**277**	**276**	**479**
Noncommercial [2]	**928**	**423**	**446**	**1213**
Associated Person	4	5	2	6
Commodity Pool Operator	124	82	77	145
Commodity Trading Advisor	147	102	96	173
Floor Broker	128	73	80	167
Floor Trader	73	44	40	92
Futures Commission Merchant	40	26	18	51
Hedge Fund, Managed Money	133	95	86	151
Undesignated	549	196	232	750
Total	**1308**	**700**	**722**	**1692**

1. Reporting thresholds: crude oil – 300 contracts, heating oil – 250, gasoline – 150.
2. Noncommercial trader-types do not add to noncommercial totals due to multiple designations.

TABLE 3 -- DAILY COUNTS OF ACTIVE NONCOMMERCIAL TRADERS

TRADER COUNT	BUYERS	SELLERS	TOTAL (**CPO**, *FB&FT*)	PERCENT BUYERS	BUYERS	SELLERS	TOTAL (**CPO**,*FB&FT*)	PERCENT BUYERS
	CRUDE OIL				**HEATING OIL**			
mean	13.7	14.4	28.1 (**6.8**, *12.6*)	48.7	8.6	8.6	17.2 (**4.2**, *8.6*)	50.3
median	13	14	28 (**7**, *12*)	48.3	8	8	17 (**4**, *9*)	50.0
minimum/ maximum	3/32	2/31	10/50 (**0/21**, *4/23*)	13.0/85.0[1]	1/22	1/24	3/42 (**0/26**, *2/17*)	7.1/88.2[1]

1. Days with the lowest percentage of large speculators buying were 26 July 1994 in crude-oil futures (3 of 23 active), and 19 September 1996 in heating-oil futures (1 of 14 active). The highest percentages of large speculators buying were recorded on 6 August 1993 in crude-oil futures (17 of 20), and 27 January 1997 for heating-oil futures (15 of 17).

TABLE 4 -- HERDING STATISTICS FOR NONCOMMERCIAL TRADERS

H (in percent)[1]	**CRUDE OIL**			**HEATING OIL**		
	All	**CPO**	*FB&FT*	All	**CPO**	*FB&FT*
mean	1.20	**3.24 [5.09]**	*1.11 [6.77]*	0.86	**3.86 [7.95]**	*1.78 [12.0]*
standard deviation	0.22	**0.47 [0.51]**	*0.30 [0.47]*	0.26	**0.60 [0.66]**	*0.39 [0.62]*
p-value [percent]	<0.01	**<0.01 [<0.01]**	*0.03 [<0.01]*	0.09	**<0.01 [<0.01]**	*<0.01 [<0.01]*
median	-0.06	**1.04 [2.80]**	*-0.47 [3.76]*	-0.47	**2.99 [5.80]**	*0.26 [8.44]*
days with $H > 0$	466	**517 [524]**	*462 [572]*	457	**468 [517]**	*494 [658]*
days with $H < 0$	496	**428 [421]**	*500 [390]*	505	**383 [334]**	*468 [304]*
p-value [percent]	17.5	**0.21 [0.04]**	*11.6 [<0.01]*	6.48	**0.20 [<0.01]**	*21.0 [<0.01]*

1. Figures in square brackets calculated assuming E[B/(B+S)] equals fraction of all active speculators (excluding subgroup tested) buying each day. Other figures calculated assuming E[B/(B+S)] = 50 percent for all groups each day.

Table 5 – Correlations among Commercial Players

Trading Group	**Oil Companies**		**Financial Institutions**	
Market	Crude Oil	Heating Oil	Crude Oil	Heating Oil
Participants	22	24	14	16
Median number of days active in market (out of 962 total)				
	640	913	556	741
Number of Correlations				
maximum possible	231	276	91	120
actual	224	265	84	113
positive	132	146	49	58
negative	92	119	35	55
Average	1.9%	-0.2%	1.1%	-0.3%
Standard deviation	0.7%	0.4%	1.6%	0.9%
Order statistics				
Highest	*78.8%*	*20.6%*	*38.1%*	*48.9%*
95th percentile	*17.2%*	*9.6%*	*25.8%*	*9.6%*
90th percentile	*11.6%*	*6.9%*	*13.0%*	*8.2%*
Upper quartile	*6.2%*	*3.5%*	*7.3%*	*3.9%*
Median	*1.3%*	*0.3%*	*0.7%*	*0.4%*
Lower quartile	*-2.8%*	*-3.3%*	*-3.1%*	*-4.6%*
10th percentile	*-9.0%*	*-7.4%*	*-10.0%*	*-10.2%*
5th percentile	*-14.5%*	*-12.0%*	*-14.3%*	*-15.6%*
Lowest	*-33.3%*	*-25.9%*	*-81.3%*	*-38.0%*
p-value (for zero median)	0.5%	5.5%	7.8%	42.5%

Table 6 – CPO herding in heating-oil futures		
number of CPOs		80
maximum possible number of correlations		3160
	all 80	largest 10[1]
median # of reportable days (out of 962 total)	92	536
number of correlations	1115	45
positive	725	34
negative	382	11
zero	8	0
lowest	*-100 %*	*-16.9%*
5%	*-30.4%*	*-8.0%*
10%	*-17.4%*	*-6.4%*
lower quartile	*-3.5%*	*0.2%*
median	*4.7%*	*2.2%*
upper quartile	*24.9%*	*10.7%*
90%	*50.1%*	*32.2%*
95%	*76.2%*	*38.5%*
highest	*100 %*	*51.3%*
p-value (for median = 0)	*<0.01 %*	*0.04%*
average	10.9%	7.2%
standard deviation	3.0%	2.2%
p-value (for mean = 0)	0.03 %	0.25%

1. "Largest" defined by number of days active in the market.

allowing us to estimate herding measures of two types. The first type follows the small existing literature described above, and measures the tendencies of market participants to make similar decisions (here correlation of changes in their positions in the oil futures markets, and likelihood of buying when "the herd" is buying and selling when "the herd" is selling). The second type goes beyond the existing literature to separate out time periods when information about fundamentals flowing into the market is great, and hence decisions are unlikely to be the outcome of herding behavior.

Table not used—summary statistics on speculators

	total noncommercial buyers	sellers	total active	actual percent buying	theoretical percent buying	absolute difference col S - Col T	absolute difference expected	absolute difference: observed - expected (col. U - col. V)	
CRUDE OIL									
mean	13.69	14.44	28.12	48.69%		8.86%	7.66%	1.20%	mean
std. deviation	prob(b=s)	0.0168 %		0.36%		0.2178%		0.2164%	std. deviation
median	13	14	28	48.28%		7.32%	7.47%	-0.06%	median
maximum	32	31	50	85.00%		36.96%	12.30%	28.55%	maximum
minimum	3	2	10	13.04%		0.00%	5.61%	-10.47%	minimum
positive	buyers as % of active		48.67%					466	positive
negative								496	negative
HEATING OIL									
mean	8.59	8.57	17.16	50.30%		10.90%	10.04%	0.86%	mean
std. deviation	prob(b=s)	88.105 2%		0.44%		0.2613%		0.2580%	std. deviation
median	8	8	17	50.00%		9.18%	9.82%	-0.47%	median
maximum	22	24	42	88.24%		42.86%		32.38%	maximum
minimum	1	1	3	7.14%		0.00%		-18.75%	minimum
	buyers as % of active		50.06%					457	positive
								505	negative