

Price Dynamics, Price Discovery and Large Futures Trader Interactions in the Energy Complex

Michael S. Haigh, Jana Hranaiova and James A. Overdahl

Office of the Chief Economist

U.S. Commodity Futures Trading Commission

Abstract

The role, performance and impact of large speculative traders (primarily managed money traders) in derivatives markets is of interest to practitioners, regulators and academics alike. Using a unique set of data from the Commodity Futures Trading Commission (CFTC) we study the relationship between futures prices and the positions of managed money traders (MMTs), commonly known as hedge funds, for the natural gas and crude oil futures markets. We also examine the relationship between the positions of MMTs and positions of other categories of traders (e.g., floor traders, merchants, manufacturers, commercial banks, dealers) for the same markets. Our results suggest that on average, MMT participants do not change their positions as frequently as other participants, primarily those who are hedgers. We find that there is a significant correlation (negative) between MMT positions and other participant's positions (including the largest hedgers), and results suggest that it is the MMT traders who are providing liquidity to the large hedgers and not the other way around. We find that most of the MMT position changes in the very short run are triggered by hedging participants changing their positions. That is, the price changes that prompt large hedgers to alter their positions in the very short run eventually ripple through to MMT participants who will change their positions in response. We also find no evidence of a link between price changes and MMT positions (conditional on other participants trading) in the natural gas market, and find a significantly negative relationship between MMT position changes and price changes (conditional on other participants trading) in the crude oil market.

Working Paper (comments welcome)

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**Corresponding author: Dr. Michael S. Haigh, Senior Economist, Three Lafayette Centre, 1155 21st Street, NW, Washington, DC 20581. ph: 202-418-5063; fax: 202-418-5660; e-mail: mhaigh@cftc.gov. A special thanks to Steven Cho for providing the data used in this study. The views expressed in this paper are those of the authors only and do not reflect the views of the CFTC or its staff.*

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I. Introduction

The role of speculators in the futures markets has been, and continues to be, the source of considerable controversy. One large category of speculative traders in particular - managed money traders (MMTs), commonly known as hedge funds - has drawn considerable attention from regulators, academics, investors and from the general public. Much of the attention has focused on the concern that MMTs exert a disproportionate and destabilizing effect on derivative markets which may ultimately lead to higher trading costs.

The Commodity Futures Trading Commission (CFTC) collects position level trading data on the composition of open interest across all futures and futures options contracts traded in the United States. A highly aggregated subset of this data set is released to the public through the CFTC's Commitments of Traders (COT) report. COT data can be viewed across highly aggregated categories such as "commercial" and "non commercial." The non commercial category includes participants who are not involved in the underlying cash business, and are thus referred to as speculators. It is this group of speculators who are collectively assumed by the public as being the MMTs. As such, these data are heavily scrutinized and have been used extensively by academics, practitioners and regulators alike to evaluate the role of MMTs on the derivatives markets.

Although studies that have employed COT data have made important contributions, researchers utilizing broadly aggregated data have been forced to make assumptions about the composition of each classification. Such research using the highly aggregated data should be interpreted with caution because these studies have been unable to form precise and accurate categorizations of traders. Indeed, using such data restricts the researcher's ability to accurately evaluate the interactions between specific groups of traders (e.g., floor brokers and traders, managed money traders, dealers/merchants, investment banks, pension funds, manufacturers, etc). Users of COT data are also unable to assess the effect of individual trader group positions on the price level.

To address these limitations, we use highly disaggregated, narrowly defined, position level participant data and for the first known time employ them in a new framework to analyze the relationship between MMTs' position changes with other participant position changes and the price changes in the market in which they

trade.¹ In particular, we employ Directed Acyclic Graph (DAG) method which, to date, has been surprisingly underutilized in the finance fields.² DAG methods allow us to examine the causal pattern of contemporaneous trading and pricing relationships in the futures market, based off the familiar Vector Autoregression Model (VAR). Critically, the DAG analysis allows us to address the construction of the data-determined orthogonalization on contemporaneous innovation covariance. This is vital in providing sound inference in innovation accounting (Swanson and Granger, 1997), which is used here to assess the dynamic relationships between participants and prices. This assessment of both the degree of interconnectivity and direction of causation within the trader categories and their influence on price will have important implications for both market participants and regulators alike and will shed light on the role that MMTs play in the futures industry.

Our specific research objectives are as follows: first, we build upon a previous CFTC study (CFTC, 1994) by simply assessing the proportion of open interest (OI) that each narrowly defined participant category contributes. Second, within each participant category we analyze the trading characteristics of each individual participant in that particular group. Specifically, we analyze which category's participants trade more frequently and which categories tend to hold positions longer. Third, we analyze the relationships between the participant categories and prices using the DAG methodology to decipher the causal linkages amongst these categories and the prices for the markets in which they trade. This allows us to address the question of who responds to price innovations, who demands liquidity and who provides liquidity in contemporaneous time. Fourth, using innovation accounting techniques (forecast error variance decomposition) we partition the proportion of the movements in a variable's forecast (forecast of changes in participant positions and prices) due to its own 'shocks' versus shocks from other variables. Lastly, using impulse response simulations we are able to identify which variable (when there is a large change in that variable) causes the greatest degree of volatility in the other variables.

¹ It should also be noted that the CFTC's surveillance staff regularly use position level data to monitor the trading activities of all individual traders and trader groups, including MMTs. A few studies have employed a disaggregated form of the CFTC's data (e.g, Kodres and Pritsker (1996)) but they have addressed different questions to the ones posed here (see literature section).

² Only a handful of papers have employed DAG analysis in finance. Examples include: Bessler and Yang (2003) and Haigh and Bessler (2004).

Our empirical findings provide insights into the price discovery process in futures markets. We find that large speculative categories, specifically MMTs do not trade as actively as most other participants (hedgers) in the market but they do provide liquidity to large hedgers who ‘cause’ a change in MMTs’ positions (large hedgers appear to demand liquidity). Changes in MMTs’ positions are a reaction to price changes as opposed to a cause of price changes (that is, they react to price moves rather than create them). Indeed, it is a change in the price level that prompts a change in hedgers’ positions which then prompts a response in managed money positions.

The remainder of this study is organized as follows. Section II provides an overview of the CFTC’s Large-Trader Reporting System (LTRS) and lays out our definition of the MMT trader category. Section III provides an overview of the studies that have used CFTC (COT) data. Section IV describes the position level data used in this study. Section V discusses some descriptive statistics on the trader positions and Section VI describes the DAG theory and the other empirical methods used. Section VII discussed the results. Conclusions and suggestions for further research questions are contained in Section VIII.

II. The CFTC’s Large-Trader Reporting System (LTRS)

The CFTC monitors U.S. futures and options markets through its market surveillance program. Since 1922, the main surveillance tool used by the CFTC and its predecessor agencies has been the Large Trader Reporting System (LTRS). Under the rules authority of the Commodity Exchange Act (CEA), the CFTC collects and retains position level data from large traders who own or control positions on a U.S. futures market above a specific reporting threshold. The purpose of this surveillance system is to help the CFTC identify potential concentrations of market power within a market and to enforce speculative position limits. Under the LTRS, clearing members, futures commission merchants (FCMs), foreign brokers and other traders file daily electronic confidential reports with the CFTC.³ These reports show the futures and options positions of the reporting traders that hold positions above specific levels set by the CFTC.⁴ The total amount of all the traders’

³ These rules and regulations are published in Title 17, Chapter I of the Code of Federal Regulations.

⁴ Large trader reporting levels include, for example, Wheat (100 contracts), Natural Gas (175 contracts), Crude oil (350 contracts), 10-year Treasury notes (1,000 contracts), and Euro (400 contracts).

positions reported to the CFTC represents approximately 70 – 90% of total open interest in any market, the remainder being smaller traders who do not meet reporting thresholds. Occasionally, the CFTC will raise or lower the reporting levels in specific markets with the objective of striking a balance between maximizing effective surveillance and minimizing the burden on market participants.

Commercial versus Non-Commercial Category

When a reportable trader is identified to the CFTC, the trader is classified either as a “commercial” or “non-commercial” trader. A trader’s reported futures position is determined to be commercial if the trader uses futures contracts for the purposes of hedging as defined by CFTC regulations. Specifically, a reportable trader gets classified as commercial by filing a statement with the CFTC (using the CFTC Form 40) that it is commercially “...engaged in business activities hedged by the use of the futures and option markets.” However, to ensure that the traders are classified consistently and with utmost accuracy, CFTC market surveillance staff in the regional offices checks the forms and re-classifies the trader if they have further information about the trader’s involvement with the markets.

A reportable participant may be classified at the CFTC as non-commercial in one market and commercial in another market but cannot be classified as both in the same market. Having said this, a multi-functional organization that has multiple trading entities may have each entity classified separately. For instance, a financial institution trading Treasury Notes futures contracts might have a money management unit whose trading positions are classified as being non-commercial and have a banking unit that is classified as commercial. Non-reportable positions (NRP’s) represent the participants, whose commercial and non-commercial classification is not known. The NRP participants’ share of the total open interest is arrived at by subtracting total long and short reportable positions from the total interest.

Commitment of Traders Report

The first COT report, which utilizes data from the LTRS, and provides a summary of the percent of OI held by the commercial, non-commercial and NRP categories, was first published on June 30, 1962. According to the CFTC, this report was proclaimed as “another step forward in the policy of providing the public with current and basic data on futures markets operations.” Over the years the COT has improved the reporting and

currently provides a breakdown of each Tuesday's open interest for markets in which 20 or more traders hold positions equal to or above the reporting levels established by the CFTC. The weekly COT reports are currently released every Friday at 3:30 p.m. Eastern time and the information released is aggregated to the commercial, non-commercial and NRP level. Despite this high degree of aggregation, many studies have utilized these data (e.g., Hartzmark (1991), simply because less aggregated data have not been available.

Categories within the Commercial and Non-Commercial Categories

Information released to the public in the form of the COT is highly aggregated, but the LTRS enables the CFTC surveillance team to monitor the largest individual participants in a market. CFTC staff can monitor an individual participant's pattern of positions over a specified time period in a particular market, or an individual's participant's pattern across different markets over a specified time frame. In addition, the surveillance team may monitor a particular group of participants. It is these groupings or trader categories within the Commercial and Non-Commercial Categories and individual traders within these groupings that we analyze in this study. Active groupings of participants vary across contract markets but an exhaustive list can be found in Table 1.

Managed Money Traders

A major concern in recent years is the role that large, organized futures participants play in the derivative markets. These participants go by a variety of names: pools, managed money participants, professional trading advisors, managed money investors and hedge funds. Large hedge fund complexes – those with assets greater than \$100 million are in fact, commodity pools and a clear majority of these hedge funds (those with over \$1 billion in assets) are either advised or operated by CFTC registered Commodity Trading Advisors (CTAs) and or/ Commodity Pool Operators (CPOs) (McCarty, 2004).⁵

⁵ A commodity pool is defined as an investment trust, syndicate or a similar form of enterprise engaged in the business of trading pooled funds in futures and options contracts. A commodity pool therefore, is similar to a mutual fund company or any investment company in the security industry, except that it invests pooled money in the futures and options markets. Like their securities counterparts, a commodity pool operator (CPO) might invest in certain markets, such as financial markets, like foreign currency, treasury bonds or stock index futures, or commodity markets like cocoa, coffee and sugar. Unlike operators of mutual funds, however, commodity pools may be either long or short derivative contracts. The principle objective of the CPO is that it provides smaller investors the opportunity to invest in futures and options markets with greater diversification whilst having access to professional trading management. The CPO is the institution that solicits funds from others for the purpose of pooling the funds for use in investing in derivative interests. The commodity-

Table 1. Grouping of Participants in Commercial and Non-Commercial Categories.

Commercial		Non-Commercial	
Code	Description	Code	Description
18	Co-Operative	AP	Associated Person
AD	Dealer/Merchant	CPO	Commodity Pool Operator
AM	Manufacturer	CTA	Commodity Trading Advisor
AO	Agricultural/Natural Resources – Other	FB	Floor Broker
AP	Producer	FCM	Futures Commission Merchant
AS	Commodity Swaps/Derivatives Dealer	FT	Floor Trader
FA	Arbitrageur or Broker/Dealer	IB	Introducing Broker
FB	Non U.S. Commercial Bank	MM	Managed Money
FC	U.S. Commercial Bank		
FD	Endowment or Trust	NRP	No Registration
FE	Mutual Fund		
FF	Pension Fund		
FG	Insurance Company		
FH	Hedge Fund		
FM	Mortgage Originator		
FO	Financial – Other		
FP	Managed Account or Pool		
FS	Financial Swaps/Derivatives Dealer		
FT	Corporate Treasurer		
LF	Livestock Feeder		
LO	Livestock – Other		
LS	Livestock Slaughterer		
Managed Money Traders			
	CPO		Commodity Pool Operator
	CTA		Commodity Trading Advisor
	AP		Associated Person
	MM		Managed Money

FA and FS have recently been combined into category AS.

Although there is no legal definition of what a hedge fund is, and there is no official database for hedge funds, certain organizations publish an annual list of the largest hedge fund complexes. For example, Institutional Investor Magazine publishes annually the largest 100 hedge fund complexes by assets under management.⁶ From this list, the CFTC has analyzed the rankings since 2002 and concluded that the vast majority of these funds were operated or advised by CFTC registrants. Indeed, in 2002, 55 of the top 100 hedge fund complexes were operated or advised by CFTC registrants with the numbers increasing to 65 in 2003 and 69

trading advisor (CTA) actually manages the accounts and funds invested in the CPO and is the equivalent of an investment advisor in the securities world.

⁶ See Institutional Investor website. www.institutionalinvestor.com

in 2004.⁷ It is clear that many of the large Commodity pools, CPO and CTA's are generally considered to be hedge funds and hedge fund operators.

The official term used by the CFTC in regulatory matters to describe the activities of managed futures activities is commodity pool. However, in this study, the group of managed money traders was defined to include all registered Commodity Pool Operators (CPOs), registered Commodity Trading Advisors (CTAs), Associated Persons (APs) controlling customer accounts. In addition, for the purposes of this study, market surveillance staff at the CFTC also identified other participants who were not registered in a particular category but were known to be 'managed money participants (MM)' and so these were also included. We therefore include all these categories of participants that manage money, and collectively call these groups Managed Money Traders (MMTs) (see bottom of Table 1). Only CPOs and CTAs in the Non-Commercial category were included because the inclusion of the CPOs and CTAs from the commercial category may have been for some purpose other than that of a speculative managed money trader. To include these traders would have included activity that was very different in nature from the type of trading activity this study is designed to address.

Section III. Literature Review

Information contained in the CFTC's COT data has been used extensively to examine a number of policy and financial microstructure issues. One popular area of study addresses the relationship between large trader positions and the price level (volatility) and indeed, reports of this link are often quoted in the popular press but often such reporting is not based on any solid empirical evidence. As such, several researchers have employed the COT data to gather empirical evidence to test competing theories regarding large trader positions and price volatility. The researchers do however generally acknowledge that the results obtained from using the highly aggregated data are not ideal, and as such, the results should be interpreted with caution.

Brorsen and Irwin (1987) estimate the quarterly open interest of futures funds and find no significant relationship between price volatility and positions, and Brown, Goetzmann, and Park (1998) estimate monthly

⁷ Focusing on the top 25 hedge funds, CFTC registered CPOs and/or CTAs were in 18 of the top 25 (72%) in 2002, 17 of the top 25 (68%) in 2003, and 18 of the top 25 (72%) in 2004 with 6 out of the top ten in 2004 being registered with the CFTC (McCarty, 2004).

hedge fund positions in currency markets around the time of the Asian financial crisis in 1997 and find no link between positions of funds and falling currency values. In a 1994 CFTC study (which built on a 1991 study) Granger Causality tests were undertaken to measure the temporal lead-lag relationship between managed money and daily settlement prices. In 5 of the 13 markets studied by the CFTC a relationship was found between price changes and positions but causation could not be established.⁸ Irwin and Yoshimaru (1999) studied MMT positions and found no significant relationship between positions and prices and Fung and Hsieh (2000) studied hedge fund exposures during a number of major events and concluded that hedge fund trading did not cause prices to deviate from their economic fundamentals. Irwin and Holt (2004) found a small but positive relationship between trading volume and volatility but concluded that the relationship was entirely consistent with either private information (Clark, 1973) or the noise trader hypothesis (De Long et al, 1990).

A second set of studies using CFTC data focuses on ‘herding’ in futures markets whereby traders take similar positions simultaneously or following one another (Kodres, 1998). Kodres and Pritsker (1996) and Kodres (1998) investigated herding behavior for the largest traders (including hedge funds) for 11 futures markets and Weiner (2002) focused on hedge funds trading in the heating oil market.⁹ The studies had the same conclusion: there is evidence of herding in some markets amongst hedge funds but the herding typically explains less than 10 percent of the variation in changes in positions. Related to these papers, another set of studies evaluated whether traders rely on positive feedback strategies. Kodres (1994) found that a significant minority employed feedback strategies more frequently than could be explained by random chance. Dale and Zryen (1996) also found evidence of positive feedback strategies amongst non commercial traders in energy and Treasury bond futures markets and Irwin and Yoshimaru (1999) found evidence of positive feedback trading strategies in half of the 36 futures markets they studied.

One final area of analysis using COT data is the study of returns by futures speculators. Early studies on speculator returns have utilized brokerage records which tend to record only the transactions of very small

⁸ In the 2005 NYMEX study, using Granger Causality tests with non-COT data they found that price volatility was causing hedge fund participation and not the other way around.

⁹ Ederington and Lee (2002) use a data set on groups of traders provided by the CFTC and conduct an analysis on who trades futures (within the commercial and non commercial groups) and also analyze what types of trades each group generally places (spreads, outright etc).

traders thus making generalizations difficult (see for example, Stewart (1949), Hieronymous (1971) and Ross (1975)). Other studies that have used end of month large trader records (see Houthakker (1957) and Rockwell (1967)) had no option but to make simplifying assumptions about traders' behavior. These assumptions restricted the ability of these studies to accurately assess the performance of traders and examine the distribution of trader returns. While these studies included a much broader sample of traders over a long time period, and the data used (provided by the CFTC) broke down traders into either non-commercial or commercial categories, the data reported was limited to positions of traders on just one day of the month and also aggregated across contract maturity months and across traders.

More recently, in an attempt to resolve the controversy over speculator returns, several researchers have built on the early work that utilized CFTC data and have, utilized data sets that included positions of large individual traders provided by the CFTC, but that were usually unavailable for academic research. These data sets enabled Hartzmark (1987), for instance, to study trader behavior in nine different markets over a 4 ½ year period. Hartzmark, studied the trading behavior of commercials (hedgers) and non-commercials (speculators) as an entire group and found that commercials (hedgers) are more profitable, whilst speculators earn negative or zero profits. Hartzmark (1991) also demonstrates that even though some traders make significant profits, these profits are generated by pure luck. Leuthold, Garcia and Lu (1994) extended Hartzmark's work but focused on just one market (frozen pork bellies) over a longer period of time. The rationale behind this focusing on this market was that it has generally been considered highly speculative and would therefore provide a more robust test of the speculator return theories. Leuthold et al. find that some traders within this category generated significant profits and those profits were not a result of luck but rather the result of significant forecasting ability of the traders.

By combining a unique dataset that generally is not available for research and by using state-of-art econometric techniques we contribute to the literature by addressing, in a more precise way, the role that MMTs play in today's energy futures markets and what impact, if any, they have on other participants and prices in the markets in which they trade. We now turn to a discussion of the data used in our analysis.

IV. Data

Daily position data utilized in this study runs from 8/4/2003 – 8/31/2004 for the Natural Gas and Crude Oil futures and options markets. The first set of data provides a breakdown of all trader participation by categories (see table 1) in the futures and options markets on a daily basis. The data details whether the group of traders is commercial or non-commercial and aggregates the number of traders within each group and enables us to analyze the relationships amongst these categories. A second set of data is a disaggregated version of the first data set and contains trading activity of every participant with each trading group (a much larger database) and it is this data that is used to analyze the trading patterns within each category.

The data sets include nearby futures and options trading activity and nearby futures prices (because this usually reflects the majority of open interest in a contract) and all futures and options trading activity for all months combined. Delta adjusted options positions (both short and long) are calculated for both the nearby and all-months-combined positions.¹⁰ Summary statistics from options markets are compared to similar statistics from futures markets.

V. Descriptive Statistics on Positions of Traders

Percent of Open Interest Held by Different Trader Categories

To investigate the participation rate of MMTs and other participants in the markets we first calculated each category's share of OI. Tables 2 and 3 show the percent of OI held by each participant category for futures and options (delta adjusted) for the natural gas and crude oil markets, respectively. For instance, focusing on table 2, MMTs, on average, held 18.17% of the long side of open interest in the nearby (upper value) futures market and 29.85% of the short side of OI in the same contract.¹¹ The figures in bold represent positions of

¹⁰ For each option position the delta of that position is obtained whereby the delta calculates the expected change in an option's price given a one-unit change in the price of the underlying futures contract. The number of options contracts at a particular strike and futures maturity is then multiplied by that specific delta value and then enables us to obtain the equivalent futures position. This method is used by exchanges to monitor correct margin requirements of traders and CFTC surveillance staff to monitor correct position limits. Here we use the delta equivalent positions to assess the relationship between position changes and price movements. We can therefore combine all futures and options positions to just futures and futures equivalent positions making the question easier to tackle.

¹¹ Note: although MMTs have sizable positions in both the long and short side over this year, it should not be assumed on the basis of these data that MMTs necessarily have offsetting positions. These data are averages over the one year period. Indeed, the average position by all MMTs was short 5613 in the nearby contract over the year (this figure is not shown in the table). A further avenue of research would be to calculate the average greater side position (CFTC, 1994). For

MMTs in all contracts other than the nearby, and the lower italic figures represent the percent of open interest in all contracts combined. For instance, MMT held 9.11% of the long side of all open option positions.

Table 2. Percent of Open Interest Held by Participant Categories for Natural Gas

Trader Category	As % of Total Open Interest				Average Futures Daily Open Interest	Average Options Daily Open Interest
	Futures		Options			
	Long	Short	Long	Short		
AD	28.57	24.60	30.58	30.78	47867.34	46243.27
	35.49	41.52	34.62	33.93	302588.26	199413.92
	<i>34.42</i>	<i>38.98</i>	<i>33.67</i>	<i>33.15</i>	<i>350455.60</i>	<i>245657.19</i>
AM	2.87	3.35	3.70	5.05	47867.34	46243.27
	3.99	2.64	3.02	3.32	302588.26	199413.92
	<i>3.79</i>	<i>2.78</i>	<i>3.12</i>	<i>3.64</i>	<i>350455.60</i>	<i>245657.19</i>
AO	8.07	2.89	2.00	0.93	47867.34	46243.27
	8.85	3.43	2.35	0.77	302588.26	199413.92
	<i>8.67</i>	<i>3.34</i>	<i>2.30</i>	<i>0.82</i>	<i>350455.60</i>	<i>245657.19</i>
AP	2.38	3.57	0.44	0.61	47867.34	46243.27
	2.95	2.39	0.16	0.23	302588.26	199413.92
	<i>2.83</i>	<i>2.58</i>	<i>0.20</i>	<i>0.29</i>	<i>350455.60</i>	<i>245657.19</i>
AS	9.15	12.33	15.74	14.75	47867.34	46243.27
	10.23	12.81	18.11	17.71	302588.26	199413.92
	<i>10.17</i>	<i>12.73</i>	<i>17.71</i>	<i>17.26</i>	<i>350455.60</i>	<i>245657.19</i>
FA	0.25	0.29	0	0	47867.34	46243.27
	0.73	0.22	0	0	302588.26	199413.92
	<i>0.66</i>	<i>0.23</i>	<i>0</i>	<i>0</i>	<i>350455.60</i>	<i>245657.19</i>
FBT	4.44	3.69	22.00	23.41	47867.34	46243.27
	7.95	8.78	18.34	20.33	302588.26	199413.92
	<i>7.40</i>	<i>8.04</i>	<i>19.08</i>	<i>20.90</i>	<i>350455.60</i>	<i>245657.19</i>
FS	0.89	0.17	0.27	0.30	47867.34	46243.27
	0.33	0.28	0.67	0.77	302588.26	199413.92
	<i>0.44</i>	<i>0.26</i>	<i>0.61</i>	<i>0.70</i>	<i>350455.60</i>	<i>245657.19</i>
MMT	18.17	29.84	9.61	9.53	47867.34	46243.27
	12.91	17.77	8.96	9.19	302588.26	199413.92
	<i>13.91</i>	<i>19.72</i>	<i>9.11</i>	<i>9.23</i>	<i>350455.60</i>	<i>245657.19</i>
NRP	6.39	5.19	12.40	11.96	47867.34	46243.27
	4.60	4.25	12.12	12.58	302588.26	199413.92
	<i>4.91</i>	<i>4.36</i>	<i>12.27</i>	<i>12.57</i>	<i>350455.60</i>	<i>245657.19</i>

Note: Upper figure represents shares based on the nearby contract, the middle figure (bold) based on all other contracts (except the nearby), and the lower (italic) figure includes all contracts combined. ^a Options are Delta Adjusted Option Positions. AD = Dealer/Merchant, AM = Manufacturer, AO = Agricultural and Natural Resource, AP = Producer, AS = Commodity Swaps/Derivatives Dealer, FA = Arbitrageur or Broker/Dealer, FBT = Floor Broker or Floor Trader, FS = Financial Swaps/Derivatives Dealer, LF = Livestock Feeder, MMT = Managed Money Trader, NRP = No Registration. FA and FS have recently been combined into category AS.

example, imagine a market where Dealers/Merchants 20% of the long side and zero short side on day 1, but switched to 0% long and 20% short on day 2. The average greater side position would be 20% as compared to an average long and short position of 10% each. Moreover, we do not analyze any spread trading by MMT or any other participant group. The omission of spread positions is one limitation on the power of our results.

Table 3. Percent of Open Interest Held by Participant Categories for Crude Oil

Trader Category	As % of Total Open Interest				Average Futures Daily Open Interest	Average Options Daily Open Interest
	Futures		Options			
	Long	Short	Long	Short		
AD	18.69	24.04	15.94	22.98	148236.50	56107.33
	34.96	21.72	21.31	28.92	477637.40	211693.43
	<i>30.79</i>	<i>22.21</i>	<i>20.24</i>	<i>27.85</i>	<i>625873.91</i>	<i>267800.76</i>
AM	7.21	21.46	2.94	7.09	148236.50	56107.33
	7.75	8.89	1.34	2.43	477637.40	211693.43
	<i>6.84</i>	<i>12.77</i>	<i>1.67</i>	<i>3.19</i>	<i>625873.91</i>	<i>267800.76</i>
AO	0.70	0.28	0.20	0.34	148236.50	56107.33
	0.49	0.21	0.08	0.15	477637.40	211693.43
	<i>0.56</i>	<i>0.23</i>	<i>0.10</i>	<i>0.19</i>	<i>625873.91</i>	<i>267800.76</i>
AP	9.32	11.84	10.02	14.33	148236.50	56107.33
	12.80	12.39	14.72	15.89	477637.40	211693.43
	<i>11.98</i>	<i>11.87</i>	<i>13.84</i>	<i>15.70</i>	<i>625873.91</i>	<i>267800.76</i>
AS	12.00	4.46	12.77	16.01	148236.50	56107.33
	12.62	28.75	17.35	21.39	477637.40	211693.43
	<i>12.85</i>	<i>22.79</i>	<i>16.28</i>	<i>20.32</i>	<i>625873.91</i>	<i>267800.76</i>
FA	0.20	0.06	0.10	0.15	148236.50	56107.33
	0.18	0.09	0.05	0.03	477637.40	211693.43
	<i>0.19</i>	<i>0.08</i>	<i>0.06</i>	<i>0.06</i>	<i>625873.91</i>	<i>267800.76</i>
FBT	2.33	6.78	33.00	18.07	148236.50	56107.33
	6.73	9.26	25.14	16.61	477637.40	211693.43
	<i>5.45</i>	<i>8.73</i>	<i>26.98</i>	<i>16.94</i>	<i>625873.91</i>	<i>267800.76</i>
FS	0.11	0	0.05	0.16	148236.50	56107.33
	0.49	0.13	0.17	0.40	477637.40	211693.43
	<i>0.40</i>	<i>0.10</i>	<i>0.14</i>	<i>0.36</i>	<i>625873.91</i>	<i>267800.76</i>
MMT	27.35	7.34	7.18	5.42	148236.50	56107.33
	12.76	6.16	6.08	4.12	477637.40	211693.43
	<i>17.26</i>	<i>6.57</i>	<i>6.37</i>	<i>4.40</i>	<i>625873.91</i>	<i>267800.76</i>
NRP	6.58	7.11	13.26	10.70	148236.50	56107.33
	4.04	5.80	11.61	7.93	477637.40	211693.43
	<i>4.81</i>	<i>6.07</i>	<i>12.01</i>	<i>8.50</i>	<i>625873.91</i>	<i>267800.76</i>

Note: Upper figure represents shares based on the nearby contract, the middle figure (bold) based on all other contracts (except the nearby), and the lower (italic) figure includes all contracts combined. ^a Options are Delta Adjusted Option Positions. AD = Dealer/Merchant, AM = Manufacturer, AO = Agricultural and Natural Resource, AP = Producer, AS = Commodity Swaps/Derivatives Dealer, FA = Arbitrageur or Broker/Dealer, FBT = Floor Broker or Floor Trader, FS = Financial Swaps/Derivatives Dealer, LF = Livestock Feeder, MMT = Managed Money Trader, NRP = No Registration. FA and FS have recently been combined into category AS.

The dominant participant in terms of open interest in the natural gas market is the dealer/merchant category (the first category in table 2). Focusing on the long side of the nearby futures contract, dealer/merchants represented 28.57% of the open interest. They, like MMTs represent a sizeable portion of the open interest on the short side (24.60%), but were long over the course of the year by an average of 2,043 contracts.¹² As can be seen from the adjusted option categories, MMTs when compared to the dealer/merchant and floor broker categories hold relatively small positions in the option markets.

In the crude oil market (table 3), MMTs represented approximately 17.26% of open interest in all futures contracts combined on the long side, and about 7% on the short side. Their share of open interest is the greatest in the nearby contract (27.35% on the long side and 7.34% on the short side). MMTs were basically long over this period holding, on average, 34,773 contracts (not shown in table). The largest 'short' over this time period was the manufacturing category holding 21.46% of the open interest in the nearby contract. Indeed, this category held, on average, a short position of 29,855 contracts on a given day (not shown). Dealers/merchants also significantly contribute to the level of open interest holding 18.69% and 24.04% of the nearby long and short positions respectively. The average dealer position was short 8,461 contracts (not shown in table) over the course of the year. Relative to dealers/merchants, producers, commodity swaps/derivatives dealers, floor brokers/traders and NRPs, MMTs held a relatively small share of open interest in the options markets.

Number of Traders Holding Positions

Understanding the share of open interest held by each category is informative but says nothing about the number of participants in the market and the level of activity of these participants. Tables 4 and 5 address this issue. The upper and lower panels of table 4 illustrate the number of unique participants (in the nearby futures markets) in each category, the average number of different participants with open positions on any day in each category, and the maximum and minimum number of participants on a given day over the course of the year. Focusing on MMTs in natural gas, we observe 147 unique participants in that category, of which 65.66 held a large position open on an average day. The smallest number of participants observed was 47 and the largest 81.

¹² These data are excluded to conserve space but are available upon request.

Dealer/merchants, despite having fewer unique participants, have a greater presence in the market with 70.56 participants with open positions on an average day. The minimum number of traders in this category is also greater than that for MMTs (57).

In the crude oil market we see a similar picture– but here there are more MMT participants (276) and on average 79.70 of these are present each day. The minimum number present is 52 and the maximum number is 100, depending on the contract expiration month. Dealer/Merchants also have a significant daily average presence with 61 traders on average and with the minimum number present equaling 52 and the maximum equaling 70. Recall that the manufacturer category commanded a significant share of open interest in the nearby contract (21.46% of the short side). Evidence from the lower panel of table 5 suggests that there are just 30 unique participants in this market over this time period and 16.88 participants are present on an average day. This suggests that the traders in this category hold very large positions.

Table 4. Number of Participants Holding Positions: Natural Gas

Participant Category	Total number of ‘Unique’ Participants Over the Time Period	Number of Participants Holding Positions on any given day		
		Average (St Dev)	Minimum	Maximum
AD	106	70.56 (5.13)	57	81
AM	13	6.00 (1.28)	4	9
AO	42	28.06 (2.10)	22	32
AP	21	11.49 (1.03)	8	14
AS	21	16.60 (1.08)	14	18
FA	3	1.96 (0.99)	1	3
FBT	85	37.92 (3.50)	31	47
FS	2	2.00 (0.00)	2	2
MMT	147	65.66 (7.24)	47	81
NRP	192	44.77 (6.38)	25	57

Note: Number of unique participants counts the total number of unique traders within each category that were observed over the time period, whilst the average gives an idea of the typical presence of that category on an average day. AD = Dealer/Merchant, AM = Manufacturer, AO = Agricultural and Natural Resource, AP = Producer, AS = Commodity Swaps/Derivatives Dealer, FA = Arbitrageur or Broker/Dealer, FBT = Floor Broker or Floor Trader, FS = Financial Swaps/Derivatives Dealer, LF = Livestock Feeder, MMT = Managed Money Trader, NRP = No Registration. FA and FS have recently been combined into category AS.

Table 4. cont. Number of Participants Holding Positions: Crude Oil

Trader Category	Total number of 'Unique' Traders Over the Time Period	Number of Participants Holding Positions on any given day		
		Average (St Dev)	Minimum	Maximum
AD	106	61.03 (4.50)	52	70
AM	30	16.88 (1.80)	13	21
AO	17	5.24 (1.82)	2	9
AP	18	12.53 (2.11)	8	16
AS	25	15.76 (2.07)	12	20
FA	1	1.00 (0.00)	1	1
FBT	89	40.00 (4.37)	32	53
FS	1	1.00 (0.00)	1	1
MMT	172	79.70 (14.14)	52	100
NRP	276	55.75 (20.44)	29	114

Note: Number of unique participants counts the total number of unique traders within each category that were observed over the time period, whilst the average gives an idea of the typical presence of that category on an average day. AD = Dealer/Merchant, AM = Manufacturer, AO = Agricultural and Natural Resource, AP = Producer, AS = Commodity Swaps/Derivatives Dealer, FA = Arbitrageur or Broker/Dealer, FBT = Floor Broker or Floor Trader, FS = Financial Swaps/Derivatives Dealer, LF = Livestock Feeder, MMT = Managed Money Trader, NRP = No Registration. FA and FS have recently been combined into category AS.

Participation in the Market

Data from the LTRS provides details on end-of-day positions. It is therefore impossible to understand intraday trading patterns from these data. We are, however, able to observe the frequency at which participants within each category change their daily positions. Table 5 sheds light on this issue. First we define 'active participants'. These are participants that changed their positions more than 25 days out of the sample. Very active participants on the other hand are defined as participants that also traded more than 75% of their total days in the market (see footnote of the table 5 for an example). Focusing on the dealer/merchant category in the natural gas market we see that 81 (76% of the 106 participants identified previously in Table 4) are active and 39 (37%) are very active. The 81 active participants, on average traded many more times than 25 days, they actually traded, on average, 152.9 days, or 69.9% of the days in the market. The very active participants traded 215.1 days or 91.4% of the total days in the market.

MMTs despite having more participants than the dealer category (147 vs. 106) are far less active. Indeed, 68 participants are classified as active (46%) and 22 (15%) as very active. In fact, only the

manufacturer and NRP categories had lower proportions (38% and 22%) of active participants. The MMT active participants traded, on average, 104.8 days, and only one category, NRP, had less trading activity by its ‘active’ participants. As a percent of all trading days, MMTs have low activity rates. Interestingly, we see an almost identical story for MMTs in the crude oil market with only NRP having a lower proportion actively trading (17%). Indeed, despite MMTs having the third highest number of very active participants (28, but only 16% of the total), they are only active 86 days on average, just one day more than the least very active category (agricultural and natural resource traders).

As mentioned previously, the LTRS only collects end-of-day position data and so we can say nothing here of intraday activity. However, this analysis has shown that many MMT traders are not trading every day and hold positions for several days and even months before making any change. Most other trading categories change their positions on a much more frequent basis.¹³

Table 5. Participation in the Market : Natural Gas

Participant category	# of participants		# active days		% active days	
	active	very active	active	very active	active	very active
AD	81 (76%)	39 (37%)	152.9	215.1	69.9	91.4
AM	5 (38%)	3 (23%)	159.6	217.3	73.0	97.1
AO	29 (69%)	7 (17%)	105.2	213.6	47.6	90.8
AP	15 (71%)	5 (24%)	106.9	156.4	57.3	86.6
AS	20 (95%)	8 (38%)	159.1	229.5	67.5	91.2
FA	3 (100%)	1 (33%)	105.0	107.0	62.8	82.3
FBT	41 (48%)	24 (28%)	167.4	226.9	71.9	90.8
FS	2 (100%)	1 (50%)	182.5	254.0	67.6	94.1
MMT	68 (46%)	22 (15%)	104.8	172.4	55.1	88.6
NRP	42 (22%)	18 (9.4%)	93.8	136.0	65.8	91.7

AD = Dealer/Merchant, AM = Manufacturer, AO = Agricultural and Natural Resource, AP = Producer, AS = Commodity Swaps/Derivatives Dealer, FA = Arbitrageur or Broker/Dealer, FBT = Floor Broker or Floor Trader, FS = Financial Swaps/Derivatives Dealer, LF = Livestock Feeder, MMT = Managed Money Trader, NRP = No Registration. FA and FS have recently been combined into category AS.

¹³ A change in position is documented if a participant’s number of outstanding contracts differs from a previous position. Of course, it is possible that a participant traded contracts intraday but ended with precisely the same number of contracts so it looked like they did not trade. We ignore the likelihood of this occurring but acknowledge it is possible. In a recent study by the New York Mercantile Exchange (2005) the exchange found that hedge funds hold positions significantly longer than the rest of the market, which, they say, supports the conclusion that Hedge Funds are non-disruptive source of liquidity to the market.

Table 5. cont. Participation in the Market : Crude Oil

Participant category	# of participants		# active days		% active days	
	active	very active	active	very active	active	very active
AD	74 (70%)	35 (33%)	150	217	69	92
AM	20 (67%)	12 (40%)	151	200	77	96
AO	8 (47%)	2 (12%)	74	107	54	85
AP	13 (72%)	9 (50%)	177	219	78	96
AS	20 (75%)	15 (60%)	171	206	81	94
FA	1 (100%)	1 (100%)	119	119	99	99
FBT	58 (65%)	42 (47%)	139	162	80	92
FS	1 (100%)	1 (100%)	254	254	94	94
MMT	85 (49%)	28 (16%)	104	168	55	86
NRP	48 (17%)	17 (6%)	83	131	60	92

Active = participants that actively traded for more than 25 days, very active = participants that also traded more than 75% of their total days (270) in the market. For example, a participant may be in the active group because he changed his positions on 25 days, but if he held passive large positions in the market for an additional 75 days (thus was in the market for a total of 100 days), he will not qualify as a very active trader as his active days constitute only 25% of the total days. Figures in parenthesis represent percent of active and very active traders of the total number of unique traders (from Table 4). # active days and % active days represent averages across participants in each trading category. % active days is the number of active days as percent of total number of days in the market.

Correlations of Trading Positions

Our preliminary analysis of interactions begins with simple correlation analysis between participants' changes in positions. This preliminary analysis provides some intuition into the DAG analysis. Bilateral correlation coefficients with significance levels are reported for the categories of participants in both the natural gas and crude oil markets in table 6. The column labeled MMT illustrates the correlations between MMT futures trading positions. Perhaps surprising is the high degree of negative correlation between the MMTs and the others with the strongest connection between the two largest participants (in terms of open interest) – dealers/merchants and MMTs. Indeed, Figure 1 plots the changes between these two large categories (the upper panel plots all commercial vs. all non commercials). The graph illustrates the consistent strength in their relationships. In the crude oil market (lower panel of table 6) we see a similar negative relationship in the futures markets for MMT with the other categories. The two largest hedgers (dealers/merchants and manufacturers) are plotted against MMT in Figure 2. As can be seen manufacturers and dealers/merchants are very highly (negatively) correlated with MMT. However, correlation says nothing of causation and it is to that issue that we now turn.

Table 6. Correlations of Changes in Positions in Futures for Natural Gas Participants

	AD	AM	AO	AP	AS	FA	FBT	FS	MMT	NRP
AD	-	0.440***	0.315***	0.376***	0.413***	0.135**	0.06	0.260***	-0.910***	0.349***
AM		-	-0.180***	0.750***	0.100	0.086	-0.04	-0.478***	-0.456***	-0.104*
AO			-	-0.212***	0.340***	0.270***	0.268***	0.571***	-0.460***	0.470***
AP				-	0.091	0.055	-0.127**	-0.502***	-0.365***	-0.149**
AS					-	0.119**	0.119**	0.181***	-0.568***	0.131**
FA						-	0.100*	0.093	-0.232***	0.240***
FBT							-	0.152**	-0.270***	0.250***
FS								-	-0.320***	0.621***
MMT									-	-0.518***
NRP										-

*, **, *** indicates significance at the 1%, 5% and 10%, respectively. AD = Dealer/Merchant, AM = Manufacturer, AO = Agricultural and Natural Resource, AP = Producer, AS = Commodity Swaps/Derivatives Dealer, FA = Arbitrageur or Broker/Dealer, FBT = Floor Broker or Floor Trader, FS = Financial Swaps/Derivatives Dealer, MMT = Managed Money Trader, NRP = No Registration. FA and FS have recently been combined into category AS.

Correlations of Changes in Positions in Futures for Crude Oil Participants

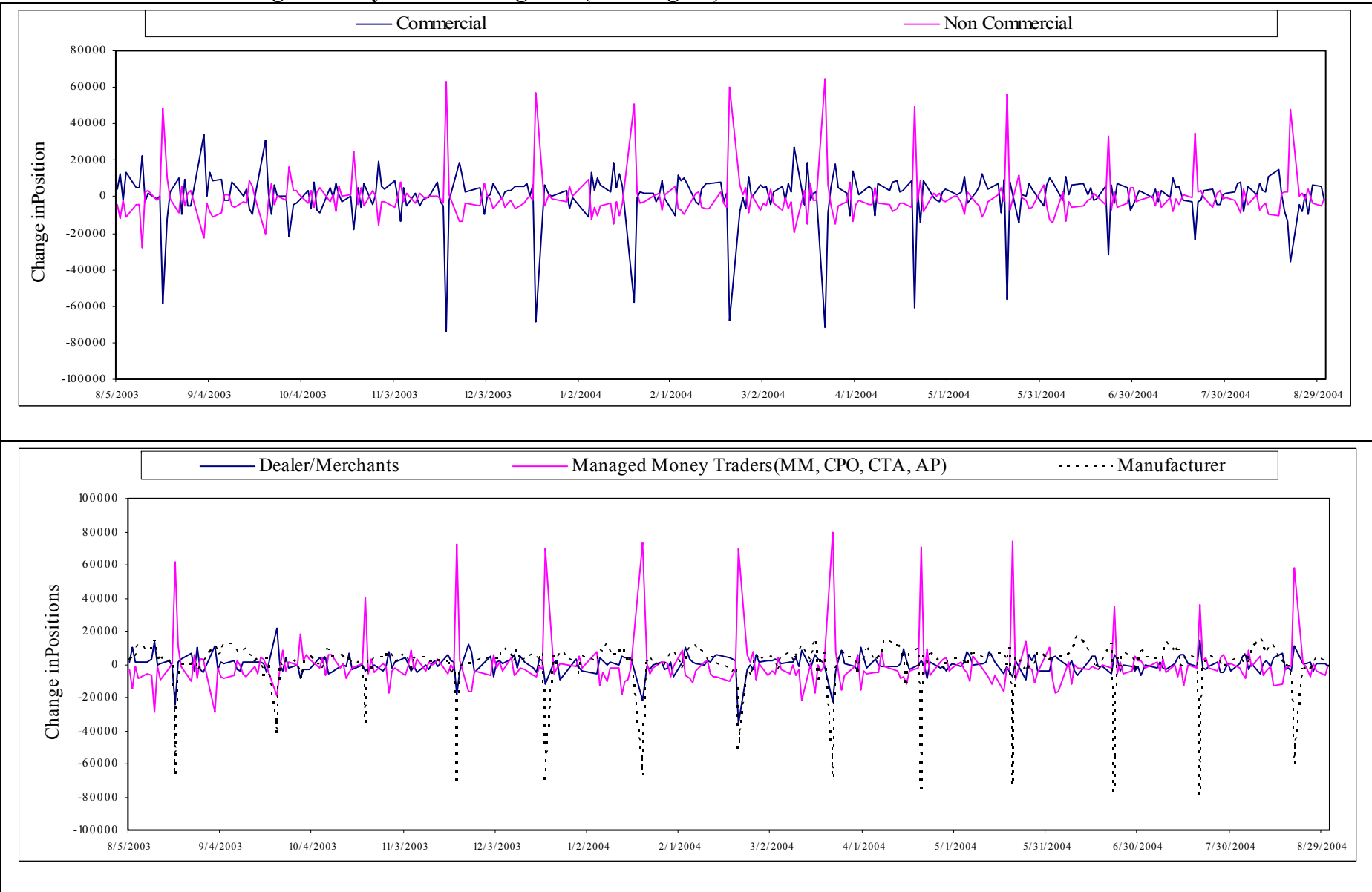
	AD	AM	AO	AP	AS	FA	FBT	FS	MMT	NRP
AD	-	0.284***	-0.124**	-0.010	-0.083	-0.110*	0.436***	-0.163***	-0.619***	0.048
AM		-	-0.537***	-0.419***	-0.825***	-0.287***	0.722***	-0.576***	-0.861***	-0.177***
AO			-	0.120**	0.560***	0.010	-0.496***	0.317***	0.482***	0.090
AP				-	0.377***	0.321***	0.255***	-0.212***	0.122**	0.184***
AS					-	0.240***	0.537***	-0.592***	0.602***	0.291***
FA						-	-0.255***	0.212***	0.219***	0.068
FBT							-	-0.255***	-0.810***	0.032
FS								-	0.532***	0.011
MMT									-	-0.080
NRP										-

*, **, *** indicates significance at the 1%, 5% and 10%, respectively. AD = Dealer/Merchant, AM = Manufacturer, AO = Agricultural and Natural Resource, AP = Producer, AS = Commodity Swaps/Derivatives Dealer, FA = Arbitrageur or Broker/Dealer, FBT = Floor Broker or Floor Trader, FS = Financial Swaps/Derivatives Dealer, MMT = Managed Money Trader, NRP = No Registration. FA and FS have recently been combined into category AS.

Figure 1. Comparing Changes in Position between the Non-Commercial & Commercial Categories (upper figure) & Dealer/Merchants & Managed Money Trader Categories (lower figure): Natural Gas



Figure 2. Comparing Changes in Positions between the Non-Commercial & Commercial Categories (upper figure) & Dealer/Merchants & Manufacturer & Managed Money Trader Categories (lower figure): Crude Oil



VI. Empirical Methods

Directed Graphs, the PC Algorithm

The application of Directed Acyclic Graphs (DAGs) follows the theoretical work of Pearl (2000) and the TETRAD algorithms in Spirtes, Glymour and Scheines (2000) and readers are directed to these papers for a complete overview of the theory. Briefly stated, a directed graph is a picture representing causal flow among or between a set of variables. In this paper we apply the PC algorithm in TETRAD to build a DAG on the innovations from a Vector Autoregressive Regression (VAR) model of the variables.

The PC algorithm starts with a complete undirected graph, G on the vertex set \mathbf{Z} . The complete, undirected, graph shows an undirected line between each of the variables in the system (each variable in \mathbf{Z}). Lines connecting each of the variables are sequentially removed based on zero or partial (conditional) correlation. The conditioning variable(s) on the removed lines between two of the variables is called the “sepset” of the variables whose line has been removed (for vanishing zero order conditioning information the sepset is the empty set). Edges are directed by considering triples $X - Y - Z$, such that X and Y are adjacent as are Y and Z , but X and Z are not adjacent. Direct lines between triples: $X - Y - Z$ as $X \rightarrow Y \leftarrow Z$ if Y is not in the sepset of Z and X . If $X \rightarrow Y$, Z and Y are adjacent, Z and X are not adjacent, and there is no arrowhead at Y , then orient $Y - Z$ as $Y \rightarrow Z$. If there is a directed path from X to Y , and a line between X and Y , then direct $(X - Y)$ as: $X \rightarrow Y$. In applications, Fisher’s z (see Appendix on Directed Graphs) is used to test whether conditional correlations are significantly different from zero.

Vector Autoregressive Models and Innovation Accounting

Whereas ‘structural’ econometric models are well suited to tackle questions at static equilibria before and after a shock, they are not particularly well suited to tackle issues of what unfolds between the pre and the post shock equilibria. VAR econometric models impose as few as possible *a priori* theoretical restrictions and allow any of the regularities in the data to reveal themselves. Indeed, Hamilton (pp. 324 – 27) noted that a VAR model may be considered a reduced form of a structural econometric model. In particular, the VAR econometric model allows us to undertake innovation

accounting on the residuals. Innovation accounting includes both an analysis of forecast error decompositions and also impulse response simulations. Innovation accounting therefore provides information on how 1) individual participants positions and prices influence the market; 2) the strength of the relationships amongst the positions and prices; 3) magnitude of a response from a change in a position or change in price; 4) pattern of response as a result of the change; and 5) direction of the response. Detailed derivations and summaries of VAR econometric methods are provided by Hamilton (chapter 11) and are not outlined here.

VII. Empirical Results

As we have numerous participants in each market (and some do not command a significant share of the open interest) we define separate categories to for the largest hedgers and speculators and pool all the other commercial and non-commercial participants together. Specifically, in the natural gas market we focus on the dealers/merchant category, MMTs, and the other two broad categories – the rest of commercials and non-commercials. Commercials here include all hedgers except dealers/merchants and non-commercials include all speculators except MMTs. For the crude oil market, we include one other large hedger group – the manufacturer group. Such a grouping keeps our models parsimonious but still allows us to study specific large participants.¹⁴

The VAR framework was chosen over a Vector Error Correction (VEC) model suggested by Johanesen and Juselius (1991, 1992) in this paper because cointegration was not an issue. Specifically, as the variables studied here (changes in positions and changes in prices) are all stationary (results of tests are excluded to conserve space but are available upon request) they cannot, by definition be cointegrated. The optimal lag length is based on the Akaike Information Criterion (AIC), which determined that a one lag structure was optimal for both the natural gas and the crude oil markets.¹⁵

¹⁴ An alternative to using OI to decide on groupings of participants is to employ cluster analysis to systematically group participants. This is an avenue of further research.

¹⁵ Granger and Newbold (pp. 99 – 101) caution against the exclusive reliance on Q (portmanteau) statistics to test for the model's adequacy. Accordingly, Dickey Fuller (DF) unit roots tests were also conducted on each of the VAR equation's residuals since the stationarity of these residuals provides verification of the models adequacy.

The strengths of the relationships amongst the variables in the VAR can be described through standard innovation accounting techniques, but critical in such an analysis is the treatment of contemporaneous innovation correlation. Indeed, most studies employing VAR's have yet to fully address the problem associated with the contemporaneous relationships among variables. Despite this, innovation accounting techniques require that a causal assumption about contemporaneous correlation be made. Early work in this area employed the Choleski factorization, with more recent applications concentrating on a 'structural' factorization suggested by Bernanke (1986) and Sims (1986) simply because researchers may not view the world as being recursive (Cooley and Leroy (1985)). The solution that we adopt here is the factorization procedure known as the Bernanke ordering. Specifically, write the vector of innovations (ϵ) from the estimated VAR model as $\mathbf{A}\epsilon_t = \mathbf{v}_t$, where \mathbf{A} is a $n \times n$ matrix (where n = number of variables) and \mathbf{v}_t is a $n \times 1$ vector of orthogonal shocks.

As illustrated by Doan (1992, pp. 8 – 10), a factorization is identified if there is no combination of i and j ($i \neq j$) for matrix \mathbf{A} where both $\{a_{ij}\}$ and $\{a_{ji}\}$ are non-zero where $\{a_{ij}\}$ is an element i,j of matrix \mathbf{A} in this instance. In this paper, we employ the algorithm presented in Spirtes et al. (1993) in order to place zeros in the \mathbf{A} matrix.

Results from DAGs: Natural Gas

Innovations from our VAR give us the contemporaneous innovations correlation matrix, $\Sigma(\hat{v}_t)$, where \hat{v}_t are the elements of the correlation matrix on innovations from the VAR. DAG theory points out that the off-diagonal elements of the scaled inverse of the $\Sigma(\hat{v}_t)$ matrix are in fact the negatives of the partial correlation coefficients between the corresponding pair of variables given the remaining variable(s) in the matrix (Whittaker 1990, p.4). To illustrate, suppose we are interested in computing the conditional correlation between innovations in MMT participants and price changes given innovations with dealers/merchants in the natural gas market and computing the conditional correlation between

Additionally we do not detect any evidence of remaining ARCH effects (at the one percent level). In sum both VAR models seem well specified.

innovations in MMT and price changes given innovations with both changes in dealers/merchants positions and changes in manufacturers' positions in the crude oil market. The off-diagonal elements of the scaled inverse of the $\Sigma (\hat{v}_t)$ matrix (after multiplying by minus one so we get the correct sign of the partial correlations), denoted by $\Sigma^* (\hat{v}_t)$, where the * indicates that we have scaled and corrected for the sign of the inverse matrix for the natural gas market is as follows:

$$\Sigma_{NG}^* (\hat{v}_t) = \begin{bmatrix} 1.000 & & \\ -0.905 & 1.000 & \\ 0.1824 & -0.065 & 1.000 \end{bmatrix}.$$

The matrix $\Sigma_{NG}^* (\hat{v}_t)$ is the 3 x 3 matrix of partial correlations with lower triangular elements associated with dealers/merchants, MMTs and price changes. For example, the partial correlation between dealers/merchants and MMT given innovations in prices is -0.905. Fisher's z test (see appendix) can be applied to test whether the partial correlation is significantly different from zero (and in this case it is). The partial correlation between MMTs and price changes, given innovations in dealers/merchant changes, is -0.065 and this is not statistically different than zero.¹⁶ On the other hand there is a significant and positive relationship between dealers/merchants and prices (0.1824). This result, suggests that there is no link between MMTs and price volatility (recall we are using changes, so, for example, a large change in MMT positions, either more short or more long, results in no effect on price changes). There is a positive association between changes in dealers/merchants positions and price changes.

The theory of DAGs as outlined in Spirtes et. al (1993) provides a robust algorithm for removing edges between the variables studied here and also directs causal flow (causality) information amongst the variables. Based on the correlation matrix, causal flows between contemporaneous innovations from each of the trader categories and price level are assigned. The PC algorithm starts with a complete undirected

¹⁶ The unconditional correlation between MMT innovations and price innovations (not conditional on dealers/merchants) is -0.2399 – significant at the one percent level. Unlike the unconditional correlations the partial correlations 'purge' out the effect of other participants (price) influence of the relationship between the two variables.

graph (like the one illustrated in figure 3a) whereby innovations in each market are connected together. The PC algorithm then begins to remove edges based on simple correlations and then the next step of removing edges is based on the partial correlations.

The information flows from the causal pattern suggested by the PC algorithm for the natural gas market are intriguing. Focusing first on figure 3b we observe that indeed, the largest speculative category (MMT) provides liquidity to the market and enhances the price discovery function. Specifically, MMTs appear to be, in econometric terms, an information sink – they do not cause any other participant to change their position in contemporaneous time (on the same day) but rather, information flows towards them rather than away. Moreover, price changes appear to be exogenous – they are not caused by any single category of participant (although joint demand and supply of contracts by all participants clearly affects the change in price). Changes in positions of dealers/merchants, all other commercial positions and all other non-commercials prompt a response in MMT positions.¹⁷ Dealers/merchants ‘cause’ all other non-commercials and commercials to change their positions in contemporaneous time (same day). It seems therefore that the dealer/merchant category prompts changes in other categories and is a dominant source of information provision. Moreover, it is the change in the price level that prompts the dealers/merchants to alter their position in contemporaneous time.

¹⁷ For example, in a falling market, finding the lower prices attractive, dealers may wish to lock in lower prices (buy contracts) to hedge future cash market purchases. Responding to the same market information, MMTs will sell, providing liquidity to dealers, but they too are also responding to the same fundamental information. The direction of the causality implies information from dealers (and hence the market) flows to MMTs and they respond by changing their positions. DAG’s are based on contemporaneous correlation and so this causal link is for the very short run. Longer term relationships are investigated below in the innovation accounting section.

Figure 3a. Undirected Edges in the Natural Gas Market

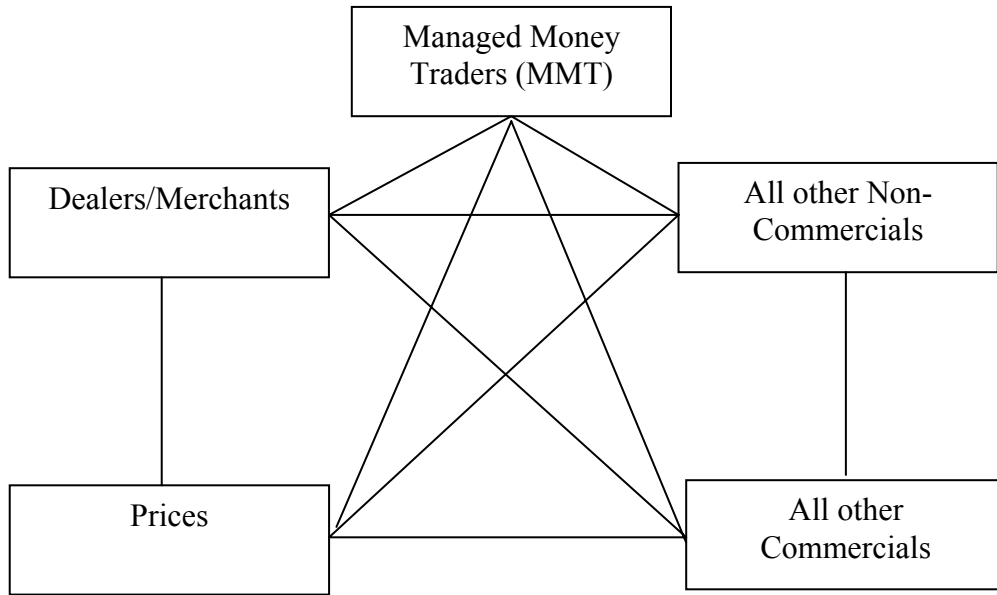
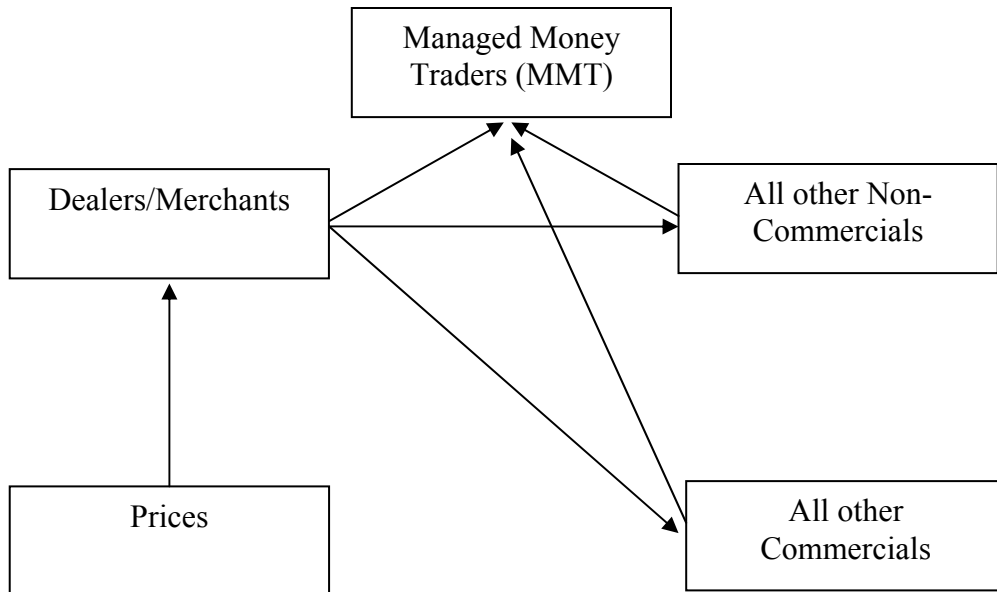


Figure 3b. Directed Edges in the Natural Gas Market



Results from DAGs: Crude Oil

For the crude oil market, the off-diagonal elements of the scaled inverse of the $\Sigma(\hat{v}_t)$ matrix are as follows:

$$\Sigma_{CO}^*(\hat{v}_t) = \begin{bmatrix} 1.000 & & & \\ -0.220 & 1.000 & & \\ -0.758 & 0.001 & 1.000 & \\ -0.917 & 0.286 & 0.611 & 1.000 \end{bmatrix}$$

The matrix $\Sigma_{CO}^*(\hat{v}_t)$ is the 4 x 4 matrix of partial correlations with lower triangular elements associated with MMTs' position changes, price changes, dealer/merchant change in positions and manufacturer changes in positions in the crude oil futures market. The conditional partial correlation between innovations in MMT changes in net position and changes in prices is -0.220, which is significant at the one percent level of significance. This result, albeit a simple one is again consistent with the belief that MMTs do not negatively impact the markets by increasing price volatility (recall again, we are using changes, so, for example, a large change in MMT positions, either more short or more long, results in a smaller change in prices in this case). Here we see a negative correlation and this finding may be consistent with the notion that in providing liquidity, volatility is dampened. The correlation between innovations in the change in MMTs' positions and dealer/merchants given innovations in changes in prices and changes in manufacturer positions is also negative (-0.758) and significant.¹⁸ The partial correlation between changes in manufacturer positions and changes in prices given innovations in changes in dealer/merchants and MMT positions is positive (0.286) and significant at the 1% level

¹⁸ For example, in a rising market, hedgers may sell futures contracts in order to offset risk (they find the price attractive and wish to lock in the higher price). MMTs also see the rising market and buy contracts and in doing so, takes the other side of the hedger's demand for selling. Without the liquidity provided by the MMTs, not only would the hedger's incur more price slippage (driving prices for their short positions further down) but would quiet possibly be unable to fill the orders that they would like to.

suggesting once again that large hedgers tend to change positions in the same direction. Overall, evidence from both markets seems to suggest that the link between position changes and prices is connected in the commercial sector (the large hedgers) and price volatility increases may be attributed to this sector and not the MMT sector.

The upper panel on figure 4 illustrates the undirected graph for the crude oil market. The same categories of participants are included in this analysis along with one other category – manufacturers (that hold a significant portion of the open interest). The lower panel illustrates the directed graph. Interestingly, we see that this market exhibits a similar pattern to the natural gas market. In econometric terms, MMT acts as a ‘near’ sink responding to changes in positions of dealers/merchants, manufacturers, and the composite hedger category “all other commercials”. In this case, MMT appears to ‘cause’ all the other non commercial categories. Like the case of natural gas, price changes cause changes in dealer/merchant positions who, in contemporaneous time prompt a change in MMT positions.

In summary, evidence from DAGs applied to both energy markets tells the same story – price changes cause changes in dealer/merchant positions in contemporaneous time that combined with other large categories influence changes in managed money positions. Moreover, evidence from the conditional partial correlations suggests that 1) there is no evidence of MMT causing volatility (natural gas) and 2) there is a negative relationship between changes in MMT positions (given changes in other participants) and the price changes in crude oil.

Results from Innovation Accounting: Natural Gas

Forecast Error Decompositions

The forecast error decompositions tell us the proportion of the movement in a variable due to its own influence versus influences from other variables. The forecast error decompositions allow us to consider which participant positions and prices in these markets are statistically exogenous or endogenous to each other at differing forecast horizons. Forecast error decompositions based on the DAGs are provided in table 7 for natural gas.

Figure 4a. Undirected Edges in the Crude Oil Futures Market

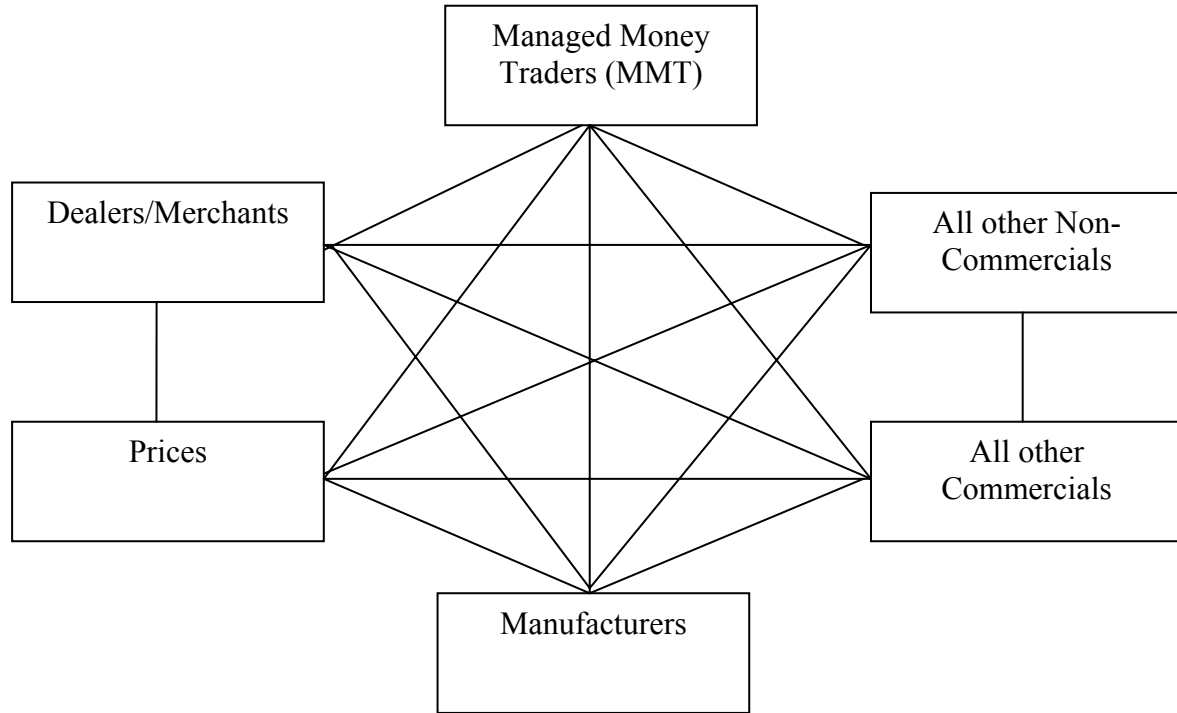
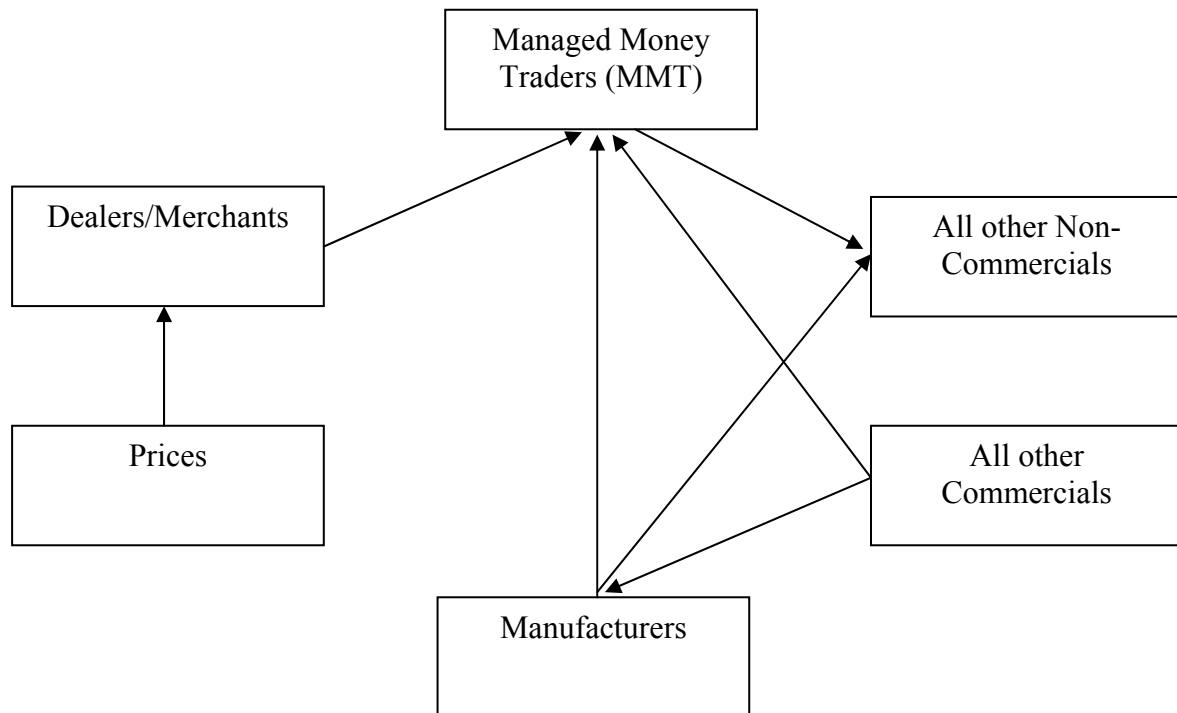


Figure 4b. Directed Edges in the Crude Oil Futures Market



In this study, we provide horizons for 1, 2 (short run) and 5 days (long run). The first column in the output is the standard error of the forecast for each series and the remaining columns illustrate the error decompositions, which should add to 100 (but may not due to rounding). Looking first at the forecast decomposition for MMT in the natural gas market, we see that this participant category is heavily influenced by the dealer/merchant category. In fact, almost 67% of the variation of MMT positions is explained by this aggregate hedging category after one day. Commercials account for between 17.73% and 19.08% of the variation in MMT from 1 – 5 days and the non commercials explain about 4%. Recall from the DAG analysis all three of these categories caused MMT in contemporaneous time but it is clear that the dealer/merchant category has the strongest effect. Price changes on the other hand have little direct effect as they did in the DAG analysis.

The exogenous feature of the change in price level as shown by the DAG analysis is also confirmed by the forecast error decompositions. Price changes explain 100% of its own variation after one day and very little variation in its movement comes from any other category. In fact, MMT explains just 6% of the price change total variation after 6 days. There appears to be a modest (at best) amount of feedback from MMT to prices after several days but the effect is fairly trivial and the argument that a change to MMTs' positions causes excessive volatility appears to be not consistent with the data. The aggregate hedging category 'commercial' seems to have its own variation explained by itself (about 57%) and the dealer/merchant category. Non-commercials are almost entirely exogenous explaining almost 100% of its variation after 1 day. The influence of the dealers/merchants on non-commercial positions in contemporaneous time dies out within the day. Lastly, dealers are also exogenous after one day and price change has very little effect on the change in their positions despite the fact that price changes were the sole influence in the change in their positions on the same day.

Table 7. Forecast Error Decompositions for Natural Gas

Decomposition of Variance for MMT

Day	St. Error	MMT	Price	Comms	Non Comm	Dealer/Merchant
1	1.21	11.22	0.03	17.73	4.24	66.79
2	1.25	12.47	0.10	19.08	4.01	64.34
5	1.25	12.52	0.10	19.08	4.01	64.29

Decomposition of Variance for Series Price

Day	St. Error	MMT	Price	Comms	Non Comm	Dealer/Merchant
1	0.03	0.00	100.00	0.00	0.00	0.00
2	0.04	5.49	91.89	0.72	0.35	1.55
5	0.04	6.06	90.89	0.94	0.39	1.72

Decomposition of Variance for Series All other Comms

Day	St. Error	MMT	Price	Comms	Non Comm	Dealer/Merchant
1	6.49	0.00	0.02	56.94	0.00	43.05
2	6.53	0.01	0.08	56.73	0.56	42.62
5	6.53	0.04	0.09	56.71	0.57	42.59

Decomposition of Variance for Series All other Non Comms

Day	St. Error	MMT	Price	Comms	Non Comm	Dealer/Merchant
1	1.14	0.00	0.00	0.00	99.54	0.46
2	1.16	0.17	0.29	4.02	95.06	0.45
5	1.16	0.21	0.30	4.02	94.95	0.53

Decomposition of Variance for Series Dealers

Day	St. Error	MMT	Price	Comms	Non Comm	Dealer/Merchant
1	1.70	0.00	0.04	0.00	0.00	99.96
2	1.79	3.19	0.27	2.23	0.02	94.30
5	1.80	3.44	0.27	2.31	0.02	93.95

Notes: The decompositions for each step ahead are given for a Bernanke factorization of contemporaneous covariances, which treats each price series as exogenous in contemporaneous time. The justification for this is based on the DAG on observed innovations from the VAR model described in Section VI. The decompositions may not sum to one hundred in each row due to rounding. MMT = Managed Money Trader, Comms = All commercials except dealers/merchants, Non-Comms = All non-commercials except MMTs.

Impulse Response Analysis

Impulse responses are presented here as a matrix of graphs with each element of the matrix corresponding to the response of one variable to a one time shock in another variable. The impulse responses allow us to trace out the time path of the various shocks on the variables contained in the VAR

system (see Sims (1980)). On the horizontal axis of each graph is the number of days after the shock, here 5 days. Here all responses are standardized to account for differences in units of measurement (prices versus positions for example) and this normalization allows for comparisons of relative responses across all the variables. Thus, all responses are measured in terms of standard deviations.

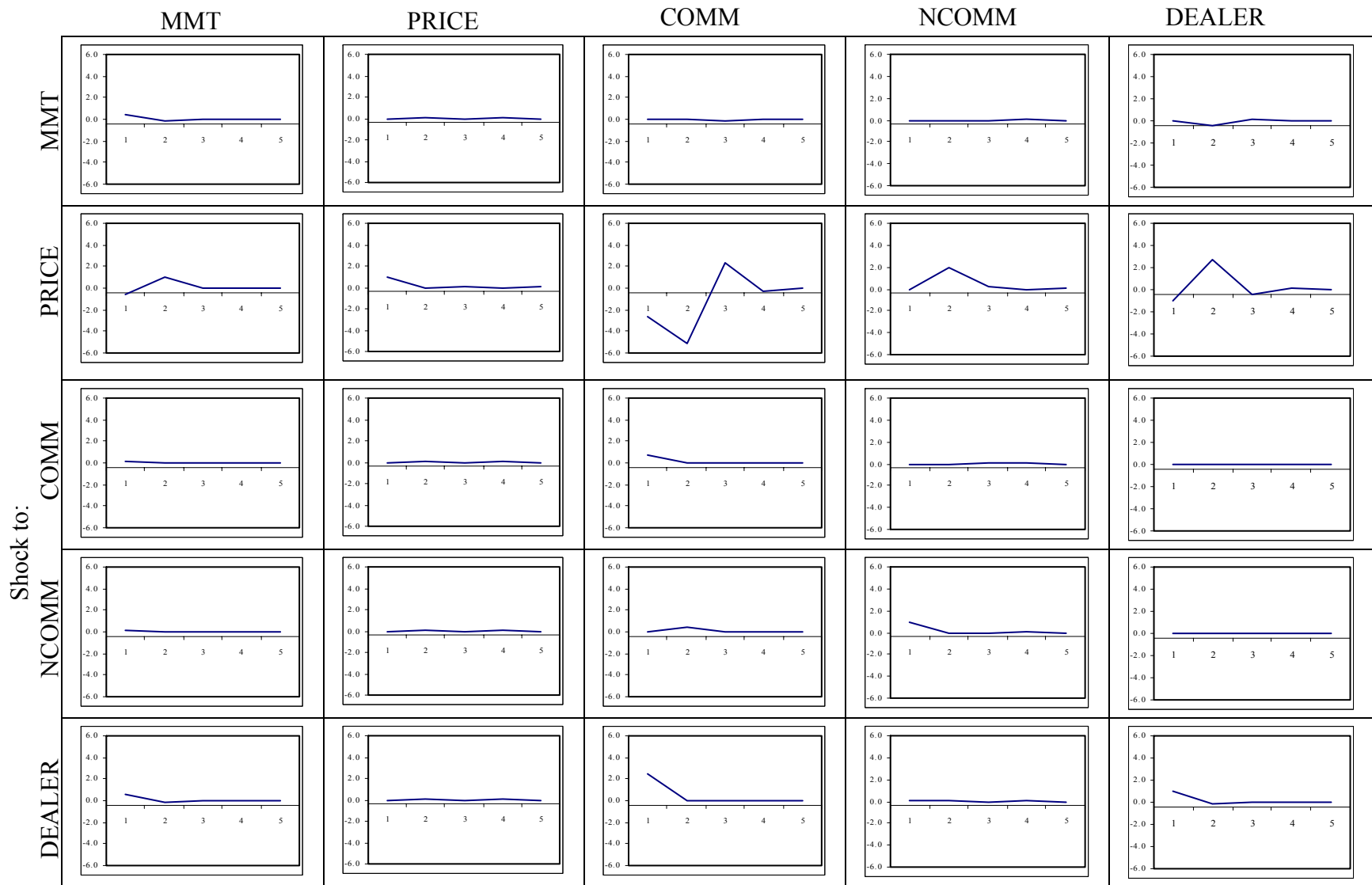
Figure 5 illustrates the responses in the natural gas market. The upper row of the figure illustrates the responses of MMT position changes, price changes, changes in positions of commercials, non commercials and dealers/merchants to a one standard deviation shock to changes in MMT positions.¹⁹ As can be seen, there is very little response from all variables; price changes, for example (the second element of that row) are basically irresponsive. The DAG analysis and the forecast error decompositions both illustrated that price changes were not affected by the change in MMT positions and the impulse responses suggest the same. When price changes are shocked (2nd row), MMT trading position changes are not immediately affected (like in the DAG analysis) but after approximately 2 days MMTs increase their position changes by about one standard deviation. MMT position changes appear to respond to price changes after a lag, suggesting that MMTs are price takers.²⁰ Dealers/merchants (the last entry on the second row) also respond positively and immediately as they did in the DAG analysis but to a greater extent (2 standard deviations). The effect dies out after three days. The commercial category responds the most to changes in the prices. With a one standard deviation increase in price changes the commercial hedging category changes considerably – by about 2 standard deviations on the first day and then by almost five standard deviations by the second day but then the change dies out after 4 days.

¹⁹ For natural gas the largest change (short) in one day was 29,071 contracts, the largest change (long) in one day as 26,139. The mean was 42 (not surprisingly close to zero given the switch from long to short). The standard deviation was 5,003 contracts. For crude oil the largest change (short) was 29,107, the largest change (long) was 79,693 contracts. The mean change was -142 contracts. The standard deviation was 15,179.

²⁰ This does not imply necessarily that when prices are increasing, positions are increasing as we are focusing on price changes in this simulation. For example, with a positive shock to price changes even though the response by MMT appears ‘positive’ this might actually reflect a change to a larger short position (relative to the change in the prices). Recall however, that we did find a positive correlation between prices (in levels and first differences) and MMT positions.

Figure 5. Impulse responses over 5 days from one standard deviation positive shocks for Natural Gas.

Response of:



The commercial and the noncommercial categories do not cause much of a response in the other categories. A one standard deviation shock to the dealer category (bottom row) solicits a two standard deviation response in the commercial category but that effect dissipates after 2 days of trading.

Results from Innovation Accounting: Crude Oil

Forecast Error Decompositions

Turning our attention to the crude oil market we can see that dealers/merchants, all other commercials and the large manufacturer category influences changes in MMT positions – just as we saw in the DAG illustration. Their individual effects seem to be consistent over the time horizon with the most influence coming from the aggregate category of all other commercials. As was the case with natural gas, our results (Table 8) indicate that price changes in the crude oil market are 100% exogenous and they are basically only influenced by the manufacturer category. This effect becomes trivial at about 2% in 5 days. The commercial category is exogenous at 100% after 1 day (recall this category was not influenced by any other category in the DAG analysis) and is only slightly influenced by changes in MMT positions within 2 and 5 days.

The non-commercial category in the crude oil market was significantly influenced in contemporaneous time in the DAG analysis by the MMTs and manufacturers and indeed MMTs explain about 30% of the variation of the position changes over longer horizons. The remaining variation is explained by position changes in other categories. The non-commercial category appears to be the most influenced over time by other participant positions. This was not the case in the natural gas market. Dealers/merchants in the crude oil market are fairly well insulated from the influence of other participant categories but prices do explain a modest amount of the changes in their positions (almost 4% after 5 days). Most variation for manufacturers comes from itself (about 40%) and the commercial category (60%). The influence of the commercial category on manufacturers is consistent with the DAG analysis.

Table 8. Forecast Error Decompositions for Crude Oil

Decomposition of Variance for MMT

Day	St. Error	MMT	Price	Comms	Non Comm	Dealer/Merchant	Man.
1	0.81	24.28	0.42	40.17	0.00	12.51	22.62
2	0.82	24.52	0.42	39.97	0.30	12.30	22.48
5	0.82	24.55	0.42	39.97	0.30	12.30	22.47

Decomposition of Variance for Series Price

Day	St. Error	MMT	Price	Comms	Non Comm	Dealer/Merchant	Man.
1	0.02	0.00	100.00	0.00	0.00	0.00	0.00
2	0.02	0.11	97.49	0.11	0.05	0.11	2.14
5	0.02	0.18	97.30	0.15	0.05	0.11	2.22

Decomposition of Variance for Series All other Comms

Day	St. Error	MMT	Price	Comms	Non Comm	Dealer/Merchant	Man.
1	0.60	0.00	0.00	100.0	0.00	0.00	0.00
2	0.61	1.48	0.19	97.43	0.09	0.07	0.76
5	0.61	1.48	0.19	97.41	0.09	0.07	0.76

Decomposition of Variance for Series All other Non Comms

Day	St. Error	MMT	Price	Comms	Non Comm	Dealer/Merchant	Man.
1	0.79	29.71	0.513	23.877	18.15	15.31	12.44
2	0.80	29.85	0.896	23.272	18.32	15.63	12.05
5	0.80	29.91	0.900	23.245	18.30	15.63	12.02

Decomposition of Variance for Series Dealers

Day	St. Error	MMT	Price	Comms	Non Comm	Dealer/Merchant	Man.
1	0.65	0.00	3.24	0.00	0.00	96.76	0.00
2	0.66	1.07	3.93	0.61	0.40	93.76	0.24
5	0.66	1.06	3.93	0.66	0.39	93.65	0.27

Decomposition of Variance for Series Manufacturers

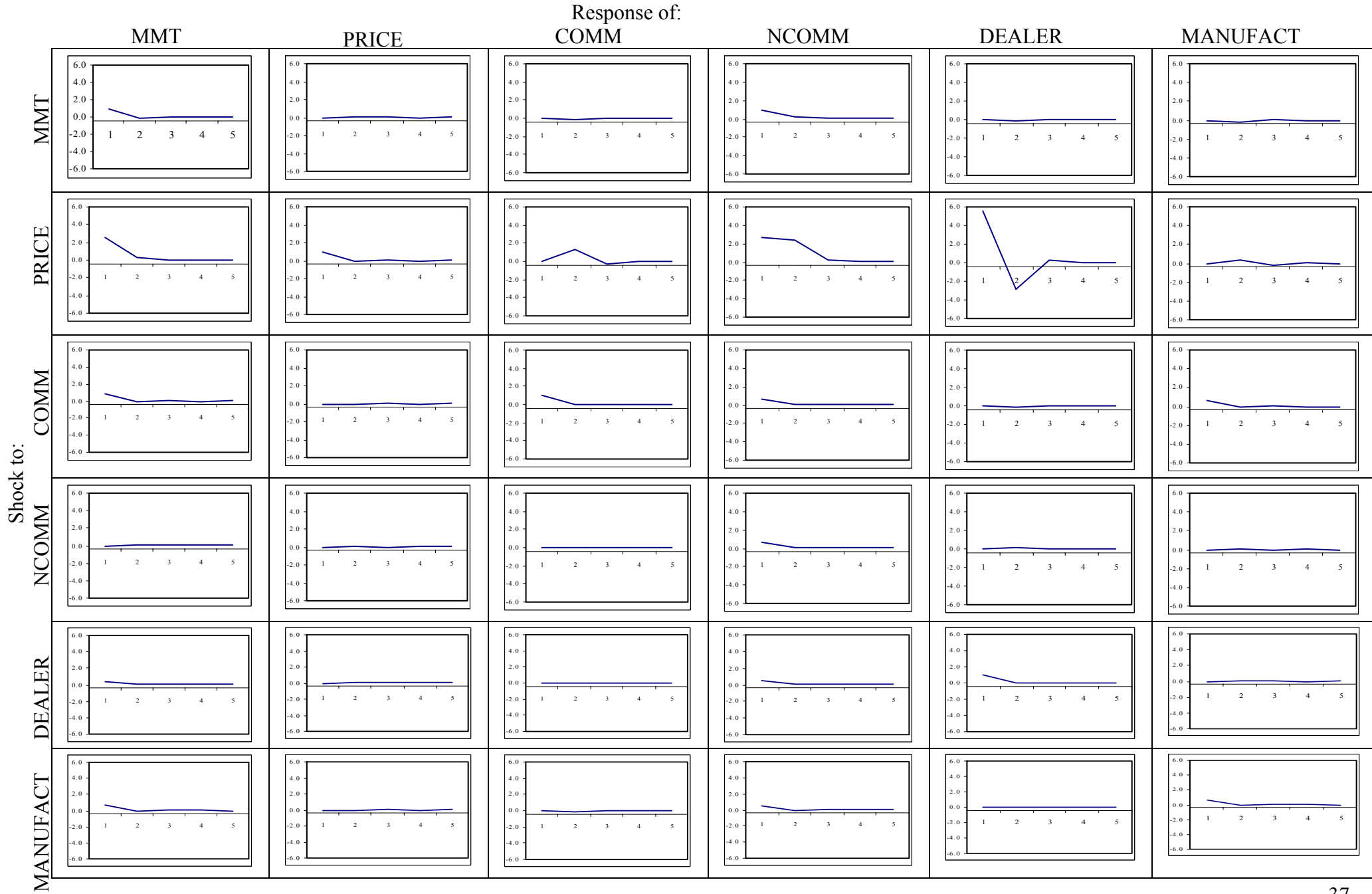
Day	St. Error	MMT	Price	Comms	Non Comm	Dealer/Merchant	Man.
1	0.52	0.00	0.00	60.04	0.00	0.00	39.97
2	0.53	2.42	0.024	58.28	0.09	0.03	39.16
5	0.53	2.42	0.032	58.28	0.09	0.03	39.15

Notes: The decompositions for each step ahead are given for a Bernanke factorization of contemporaneous covariances, which treats each price series as exogenous in contemporaneous time. The justification for this is based on the DAG on observed innovations from the VAR model described in Section VI. The decompositions may not sum to one hundred in each row due to rounding. MMT = Managed Money Trader, Comms = All commercials except dealers/merchants, Non-Comms = All non-commercials except MMTs.

Impulse Response Analysis

Turning our attention to the crude oil market and focusing on the effect of a one standard deviation shock to changes in MMTs' positions we see (from the top row of figure 6) that there is little response from any category except non-commercials – who, after one day increase positions by approximately one standard deviation. When price changes are shocked we once again see a large effect on the market. An increase in the price change triggers more than a two standard deviation increase in MMT position changes but that effect quickly dies out (2 days). As with the case of natural gas, the dealer category is strongly affected by the price changes and there is a large change in position changes (almost six standard deviations after one day) but the effect is reversed and dies out after just three days. Both non-commercials and commercials in the crude oil market respond to a price shock, but to a lesser extent than the dealers in the crude oil market and their response is also smaller relative to their one in the natural gas market. The manufacturing category is fairly unresponsive to price shocks in the short run, but there is a response from this category from shocks to the commercial position changes (about a one standard deviation increase). The commercial category does continue to influence the MMT position changes (3rd row of figure 6) beyond contemporaneous time (see DAG graph, figure 4b) but their influence on MMTs dies out after 2 days. The non commercial positions (comprised mainly of floor brokers and traders) have little affect on the market. Dealers too have little influence in the market after the current day. The DAG analysis suggested that dealers prompt changes in MMT positions in contemporaneous time and the impulse response results seem to suggest that their influence is limited to that time frame. Lastly, the manufacturing category continues to exert influence over the MMT category after one day (bottom left hand corner of figure 6), but with the exception of the non-commercials, this category has little effect on any other category.

Figure 6. Impulse responses over 5 days from one standard deviation positive shocks for Crude Oil Market.



VIII. Conclusions

In recent years, managed money traders (MMTs) have drawn considerable attention from investors, academics, regulators and the general public. The major criticism is that MMT may exert undue collective influence on the markets and thus move prices in ways that hinders the market's price discovery role, reduces the effectiveness of hedges constructed with contracts from these markets and raises trading costs. Using position level data grouped into precise categories of market participants, and using recent advances in causal modeling and time series techniques, we analyze the role of MMTs in the natural gas and crude oil futures markets.

Using basic descriptive statistics we find that while MMTs' share of open interest has grown in the energy markets studied here (especially since the last CFTC study of 1994), although MMTs' share of open interest in the options markets remains quiet low relative to other participants. We find that despite the growth in the share of open interest, MMT participants are relatively inactive, especially when compared to other participants as they do not change their positions, on average, as frequently as traders in the large hedging categories. While there is significant negative correlation between MMT positions and other participants (including the largest hedgers), results from DAG analysis suggest that it is the MMT traders that are providing liquidity to the large hedgers and not the other way around. We find that it is the price innovations that prompt large hedgers to change their positions within the same day. Price change shocks do eventually ripple through to MMT traders who will alter their position changes but most of the position changes are triggered by hedging participants. We also find no evidence of a link between price changes and MMT position changes (conditional on other participants trading) in the natural gas market, and find a significantly negative relationship between MMT position changes and price changes (conditional on other participants trading) in the crude oil market.

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Appendix

Directed Acyclic Graphs

For three variables named A, B and C, demonstrate a causal fork, A causes B and C, as: $B \leftarrow A \rightarrow C$. The unconditional connection between B and C is nonzero (both B and C have a common cause in A), but the conditional connection between B and C given knowledge of the common cause A, is zero. This is one screening off property related with causal relations: *common causes screen off associations between their joint effects*. demonstrate the inverted causal fork, A and C cause B, as: $A \rightarrow B \leftarrow C$. Here the unconditional association between A and C is zero, but the conditional connection between A and C given the common effect B is not zero. A second screening off property associated with causal relations is: *common effects do not screen off association between their joint causes*. These screening off phenomena are illustrated in the literature of *Directed Acyclic Graphs*.

A Directed Acyclic Graph (DAG) is a representation illustrating causal flow between variables through lines with and without arrowheads. Variables associated by a line are said to be adjacent. If we have a set of variables $\{A,B,C,D,E\}$: (i) the undirected graph contains only undirected lines (e.g., A — B); (ii) a directed graph contains only directed lines (e.g., $B \rightarrow C$). A DAG is a graph that contains no directed cyclic paths (an acyclic graph contains no directed path from a variable that returns to itself).

Directed Acyclic Graphs characterize conditional independence as implied by the recursive product decomposition:

$$\Pr(v_1, v_2, v_3, \dots, v_n) = \prod_{i=1}^n \Pr(v_i \mid pa_i) \quad (A1)$$

where Pr denotes probability. The symbol pa_i refers to the realization of some subset of the variables that precede (come before in a causal sense) v_i in order (v_1, v_2, \dots, v_n) . The symbol \prod refers to the multiplication operator. Pearl (1986) proposes d-separation as a graphical characterization of conditional independence and Verma and Pearl (1988) offer a proof of this proposition. D-separation characterizes the conditional independence relations given by equation (A1). If we devise a Directed Acyclic Graph in

which the variables matching to pa_i are represented as the parents (direct causes) of V_i , then the independencies implied by equation (A1) can be interpreted off the graph using the criterion of d-separation (defined in Pearl (1995)).

Definition: Let X, Y and Z be three disjoint subsets of vertices [variables] in a Directed Acyclic Graph G , and let p be any path between a vertex [variable] in X and a vertex [variable] in Y , where by 'path' we mean any succession of edges, regardless of their directions. Z is said to block p if there is a vertex w on p satisfying one of the following: (i) w has converging arrows along p , and neither w nor any of its descendants are on Z , or, (ii) w does not have converging arrows along p , and w is in Z . Further, Z is said to d-separate X from Y on graph G , written $(X \perp Y | Z)_G$, if and only if Z blocks every path from a vertex [variable] in X to a vertex [variable] in Y .

Geiger, Verma and Pearl (1990) demonstrate that there is a one-to-one association between the set of conditional independencies, $X \perp Y | Z$, and the set of triples (X, Y, Z) that satisfy the d-separation criterion in graph G . If G is a DAG with variable set V , X and Y are in V , and Z is also in V , then G linearly implies the correlation between X and Y conditional on Z is zero if and only if X and Y are d-separated given Z .

Spirtes, Glymour and Scheines (1993) have applied the concept of d-separation into the PC Algorithm (marketed as the software TETRAD II (Scheines, et al 1994) and the algorithm for building directed graphs can automatically test significance of correlations and partial correlations. The algorithm is a sequential set of commands that begin with an unrestricted graph where every variable is connected with every other variable (like the upper panels Figures 3 and 4) and proceeds step-wise to eliminate lines between variables and to direct "causal flow." Fisher's z is applied to test for significance from zero; where:

$$z(\rho(i, j | k), n) = \left[\frac{1}{2} \sqrt{n - |k| - 3} \right] \ln \left\{ \frac{|1 + \rho(i, j | k)|}{|1 - \rho(i, j | k)|} \right\}, \quad (A2)$$

and n is the number of observations used to estimate the correlations, $\rho(i, j | k)$ is the population correlation between series i and j conditional on series k (removing the influence of series k on each i and j), and $|k|$ is the number of variables (prices and positions in this paper) in k (that we condition on). If i, j and k are normally distributed and $r(i, j | k)$ is the sample conditional correlation of i and j given k , the distribution of $z(\rho(i, j | k), n) - z(r(i, j | k), n)$ is standard normal.