Crude Oil Price Movements and Institutional Traders

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Abstract

We analyze the role of hedge fund, swap dealer and arbitrageur activity in the crude oil market. Using confidential position data on institutional investors, we first analyze the linkages between trader positions and fundamentals. We find that these institutional positions reflect fundamental economic factors within each market. Subsequently, we adopt a Markov regime-switching model with time varying probabilities and find institutional positions contribute incrementally to the probability of regime changes displaying the synchronization patterns modeled in Abreu and Brunnermeier (2002; 2003). Conditioning on hedge fund activity and arbitrageur activity significantly improves our probability estimates, demonstrating that institutional positions can be useful in determining whether price trends resembling bubble patterns will continue or reverse.

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1. Introduction

Recent episodes of commodity price changes have rekindled the debate about whether speculative activity affects commodity prices. A significant body of work shows that fundamental supply and demand affect market prices,[1] while other works argue that excessive speculation can lead prices to depart from fundamentals. Some argue that "massive passive" index investors or rampant speculation by hedge funds (both examples of the "financialization" in commodity markets) have created excessive volatility or irrational prices. Empirically, it is difficult to disentangle these two effects, given that speculators are likely to condition trades on fundamental supply and demand considerations as well. In this paper we exploit detailed daily trading data to isolate unexplained speculative position changes and relate these trades to the continuation or reversal of price changes.

We find broad evidence that macroeconomic announcements and news affect trader positions across all types of traders—including merchants, manufacturers, producers, swap dealers and hedge funds. We consider the unexplained component of position changes to stem from reflect trading strategies, market expectations, private beliefs (speculative or otherwise) and or private information of the institutional traders we analyze.

Using the unexplained component of trading—position changes that are not related to the fundamental macroeconomic variables that we employ--we find that

[1] See, for instance, U.S. Interagency Task Force (2008), Kilian (2008a; 2008b), Kilian and Hicks (2009), Hamilton (2009a; 2009b), Smith (2009) and Kilian and Murphy (2010). Brunetti, Büyükşahin and Harris (2015) and Büyükşahin and Harris (2011) show that the hedge funds and swap dealers largely react to past-day futures price changes.

aggregate hedge fund position changes are significantly related to the reversal of crude oil price trends. This evidence is consistent with Abreu and Brunnermeier (2002), where the synchronization of speculative positions leads to price reversals.

Notably, unexplained aggregate position changes of merchants, manufacturers, producers and floor brokers contribute significantly to price continuations while swap dealer trades are largely unrelated to either continuations or reversals. These results show that swap dealers, representing "massive passive" index fund investors have no discernable effect on price continuations or reversals in the crude oil market, despite the growth in commodity index funds during our sample.

Our work builds on Kilian and Vega (2011), who identify macroeconomic announcements that affect WTI crude oil prices. We consider these announcements together with several other macroeconomic variables to study whether trader positions are driven by crude oil market fundamentals. Similar to their results, we confirm strong linkages between institutional trader positions and fundamentals.

Our work is related to the growing literature on crude oil prices and volatility. Kilian and Murphy (2012 and 2014) develop a structural model where they are able to identify speculative shocks and they show that these shocks have no impact on oil prices. Likewise, Brunetti, Buyiksahin and Harris (2016) and Knittel and Pindyck (2016) find little evidence that "financialization" or speculation over the past decade led to excessive volatility or prices that deviated from fundamentals.

Other studies purport to demonstrate that speculation or "financialization" either holds the potential for, or actually does lead to excessive volatility and/or prices decoupled from fundamentals. Sockin and Xiong (2014) develop a theoretical model where an increase of speculative activity may generate the wrong belief that there is a higher demand for commodities. Using extrapolated data from CFTC reports, Singleton (2014) finds a correlation between commodity index trader (CIT) positions and oil returns at 13 week horizon.[2]

Our findings that groups of institutional traders contribute to price reversals adds to our understanding of the how institutions affect markets. While Griffin, Harris, Shu, and Topaloglu (2011) provide compelling evidence that institutional trading drove the rise and fall of tech stocks at the turn of the century, our results suggest that synchronization risk (modeled by Abreu and Brunnermeier (2002, 2003)) also plays a role in oil market price reversals.

As our laboratory we analyze futures on crude oil, a market that has experienced significant price swings in recent years.[3] Importantly, the crude oil market reflects characteristics modeled in Abreu and Brunnermeier (2002, 2003) , with a significant number of competitive, rational arbitrageurs (hedge funds) which, given the complexities of determining supply and demand, are likely to become sequentially aware of any price deviation from fundamental value. Additionally,

[2] Since there is not a direct measure of commodity index trading (CIT) in crude oil, Singleton (2014) uses the so-called Masters hypothesis to compute a measure. In a series of papers Irwin (and Sanders) shows that this computation is simply wrong. Hamilton and Wu (2014) provide evidence that Singleton's results only hold for a very short period of time and are most likely driven by increased correlations during the crisis.

[3] Crude oil, for instance, rose from $32 per barrel in 2003 to over $145 in July 2008 before falling to $35 by December 2008 during our sample period (see Figure 1).

both long and short positions in futures markets expose hedge funds to significant holding costs, given the real cash flows associated with mark-to-market margins.

These institutions potentially bring market moving information to futures markets. Hedge funds, for instance, apply complicated modeling techniques for trading, applying proprietary valuation models to take both short and long positions in futures. Likewise, swap dealers bring both over-the-counter (OTC) and commodity index order flow into the organized exchange. Their net OTC positions may represent distilled order flow from knowledgeable clients as well.

Notably, both hedge funds and swap dealers have gained market share (in terms of open interest) in futures markets. In crude oil, hedge fund market share has doubled from 20 to 40 percent while swap dealer positions almost quadrupled from 2000 to 2010 (Büyükşahin, Haigh, Harris, Overdahl, and Robe, 2010). Long commodity index fund positions grew from an estimated $9 billion in 2000 to almost $300 billion in 2012 (according to the CFTC's Index Investment Data).

Empirically, we identify detailed trader positions from the CFTC's Large Trader Reporting System[4] and apply Markov switching models (conditioning on unexplained trader positions) as a systematic approach to modeling futures price data. We recursively generate daily probabilities in the model to allow for multiple breaks and regime shifts in the data generating process.[5] Many authors have argued that nonlinear processes model the behavior of financial variables better

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[4] The CFTC audits the data and produces weekly public Commitments of Traders for four trader groups (*producer/merchants, swap dealers, managed money traders (hedge funds),* and *other non-commercials*). Our data separately identifies producer, manufacturer, dealer, swap dealer, hedge fund, floor trader, arbitrageur and non-reportable subcategories.

[5] Markov regime switching models can also capture fat tails, asymmetries, autocorrelation, volatility clustering and mean reversion in financial asset series (see Blazsek and Downarowicz, 2009).

than linear processes—e.g. Brock (1993), Hsieh (1993) and Hamilton and Susmel (1994). We find the Markov switching approach accommodates well the linkages between unexplained position changes of market participants and price trends and reversals.

The existence of different market regimes has important implications for market regulators, portfolio managers, and liquidity providers alike. Market regulators concerned about long-term trends, reversals and bubbles in market prices might more effectively implement policy choices with a better understanding of regimes and the determinants of regime switching. Portfolio managers can adopt regime dependent strategies to maximize risk-adjusted returns in this setting as well.[6] In addition, liquidity providers, who learn from order flow, might more effectively manage inventories with better information about the transition probability of regime changes.

The remainder of the paper is organized as follows. In section 2 we describe the data in detail. Section 3 analyzes the relationship between institutional investor positions and fundamentals. Section 4 presents the Markov regime modeling strategy we adopt and discusses the main results. Section 5 concludes the paper.

2. Data

We analyze futures contracts that represent one of the most important commodity, crude oil, which has experienced significant price swings during our

[6] Alexander and Dimitriu (2005) note that regime switching strategies can be defined by regime dependent returns distributions, exposure to underlying risk factors, and/or alphas. Hedge funds are perhaps most likely to implement dynamic switching strategies such as a long/short equity strategy.

sample period. We collect both daily futures prices and trader positions from January 5, 2000 through November 25, 2011. We concentrate on the six largest categories of market participants: hedge funds, swap dealers, merchants (which include wholesalers, exporters-importers, shippers, crude oil marketers, etc.), manufacturers (which include fabricators, refiners, etc.), producers, and floor brokers. We analyze hedge fund positioning since hedge funds are considered some of the most sophisticated traders in financial markets. Furthermore, hedge funds represent the largest (based on open interest) non-commercial market share in these markets.[7] We analyze swap dealer positions since swap dealers handle both sophisticated OTC and commodity index trades. Merchants, manufacturers and producers are the most important hedgers in the crude oil market.

We consider both the nearby contract (closest to delivery) and all contract maturities. Although most of liquidity concentrates in the nearby contract, there is evidence (Büyükşahin, Haigh, Harris, Overdahl, Robe, 2010) showing that longer maturity contracts may contain important information. Many of these contracts are actively traded on a daily basis. Our goal is to capture all possible dynamics in the crude oil market across the entire term structure of maturities.

For the nearby contract, before maturity (the expiration date), most market participants typically avoid deliver issues and roll over their positions from the nearby contract to the next-to-nearby contract. This behavior generates seasonality in the position data. To mitigate these problems, we adopt a roll-over strategy and switch to the new contract when the open interest of the nearby contract falls below

[7] Where non-commercial refers to traders with limited or no interest in producing, consuming, storing, or transporting the underlying commodity.

the open interest of the next-to-nearby contract. In this regard, our roll-over strategy also avoids price and position changes generated by delivery considerations at or near contract expirations. When we consider all contract maturities, positions are constructed such that seasonality and delivery distortions are uninfluential.

2.1. Futures Market Return Data

We compute rate of returns in two ways. First, we calculate daily returns based on daily settlement (closing) prices of the nearby contract. We construct daily returns as $r_t^{front} = p_t^{front} - p_{t-1}^{front}$, where p_t^{front} is the natural logarithm of the settlement price in day *t*. When we switch contract from the nearby position to the next-to-nearby position, p_t^{front} and p_{t-1}^{front} refer to the next-to-nearby contract. We refer to these rate of returns as the *front month* returns. Second, we account for all contract maturities traded on a given day and construct the daily price as the weighted average of each maturity contract settlement price and use as weights the open interest of each contract. We refer to those prices as p_t^{all} and to the returns as r_t^{all}.[8]

Table 1, rows one and two, report summary statistics for the return processes. Mean daily crude oil returns are positive with r_t^{all} having higher daily returns (both mean and median) and lower standard deviation than r_t^{front}. This is to be expected since the averaging of r_t^{all} is smoothing the time series. The

[8] The last week of trading of the nearby contract is always excluded in the computation of r_t^{all}.

unconditional distribution is non-Gaussian with negative skew and kurtosis in excess of three (results not reported).

Figure 1 depicts prices and returns for the front maturity and for all maturities. It is possible to distinguish periods of high volatility (during the recent crisis) and periods of low volatility. In particular, high volatility is associated with prices falling.

2.2. Market Participant Positions

The CFTC collects data on the positions of large traders that hold positions above CFTC-specified levels.[9] Total trader positions reported to the CFTC represent approximately 70 to 90 percent of total open interest in any market, with the remaining open interest representing smaller (non-reportable) traders. The CFTC classifies each reporting trader based on self-reported business models.

In this paper we concentrate on the six largest categories of market participants in the crude oil market, including commodity swap dealers and hedge funds. Although there is no formal definition of a hedge fund in the Commodity Exchange Act, we classify Commodity Pool Operators, Commodity Trading Advisors and Associated Persons who may control customer accounts as hedge funds. We also include other CFTC market surveillance staff-identified participants known to be managing money in our hedge fund category. We cross-reference this list of hedge funds with press reports to directly confirm that these traders are generally or specifically considered to be hedge funds or hedge fund operators.

[9] These large trader reporting levels are 350 contracts for crude oil.

In commodity markets swap dealers play an important role. Swap dealers use derivative markets both to manage their price exposure originating from their over-the-counter (OTC) business and to manage their transactions with commodity index funds. These funds are often employed by large institutions that seek diversification by investing in commodities. For this reason commodity index funds hold significant long-only positions, especially in near-term futures contracts. Over our sample, as commodity index funds have experienced significant growth, swap dealer participation has grown concurrently. Merchants, manufacturers and producers are the largest hedgers in the crude oil market. Finally, floor brokers are the traditional members of the exchange that facilitate transactions on the pit.[10] These market participants are believed to convey important information to the market.

We analyze positions on both futures and options (delta adjusted) on futures and compute the net total positions as the difference between long (futures and options) and short (futures and options). We construct these positions for the front nearby contract and for all contract actively traded. We consider both futures and options positions because we are interested in the overall exposure of institutional investors in the crude oil market. However, our results are robust to considering only futures net positions.

Table 1 shows descriptive statistics for the positions of each market participant group.

- Merchants hold net short positions. This is in line with traditional hedging strategies implemented by these market agents. Comparing positions in the

[10] Open outcry trading of crude oil on the all CME Group platforms has ceased on July 2nd 2015.

front month to those on all maturities, the overall short position of merchant drops from 50,000 contract to below 45,000. This indicates that merchants partially counterbalance their short positions in the front month with long position in longer maturity futures and options. The standard deviation of all maturities positions is more than double that of the front month.

- Manufacturers and producers also hold net short positions. Similar to merchants, these market participants are traditional hedgers. Unlike merchants, manufacturers and producers hedge along the term structure – i.e. the mean and median positions are larger for all maturities than for the front month.
- Floor brokers have relatively small net positions. This is to be expected since these market participants facilitate trading on the pit and usually do not carry large inventories. The standard deviation of floor broker positions is the largest (relative to the mean) among all trader categories, indicating that these market participants may convey information to the market.
- Swap dealers hold large net long positions in the front maturity contract. However, these positions become close to zero when considering all maturities contracts. We conjecture that swap dealers use the front month to manage their transactions with commodity index funds and the longer maturities to manage their price exposure originating from their over-the-counter (OTC) business.
- Hedge funds are on average net long. Their long position is much larger in all maturities contracts then in the front month, implying that these

sophisticated investors use the entire curve to get exposure in the crude oil market.

Table 2 shows the participation rate of each trader category as percentage of the total open interest broken down by long and short positions. Table 2 shows that hedge funds hold positions on both sides of each market in more or less equal amounts. As expected, swap dealers hold mainly long positions, with nearly 40 percent of long positions in the front maturity. Merchants, manufacturers and producers hold predominantly short positions that reach up to 47 percent of the market.

Figure 2 depicts the quarterly participation rate of each market participant, computed as the sum of futures and options long and short positions divided by two.

- Merchants have similar participation rates in the front maturity as in all maturities, indicating that they concentrate their position in the front month.
- Manufacturers have only a fraction of their exposure in the front maturity. Most of the exposures is in all other maturities. A similar picture emerges for producers. These market participants use the entire term structure to hedge their positions in the cash business.
- Floor brokers have low participation rates in the front maturity but they are more active when considering all maturities.
- Participation rates for swap dealers, at the beginning of our sample, is similar in both the front month and all maturities contracts. However, starting from 2005, the front month becomes the dominant contract perhaps due to the CIT demand.

- Hedge funds, from 2000 until 2004, have exposures on all maturities but since 2005, they concentrate their exposures in the front maturity contract.
- Overall, Figure 2 indicates that when studying the trading behavior of institutional traders in the crude oil market, it is important to account for all positions across the term structure and not those only in the front maturity contract.

3. Market Fundamentals and Institutional Investor Positions

In futures markets, market fundamentals related to the supply and demand of the underlying asset play an important role in the pricing of contracts.[11] Fundamentals are also likely to influence trader positioning as well. To separate the role of fundamental factors from trader positioning net of these factors, we run regressions of change in trader positions on fundamentals. The goal is twofold, first we would like to gauge the extent to which institutional investors impound fundamentals into their aggregate positions. The residuals of these regressions represent trading strategies, market expectations, believes, private information or speculative behavior of the institutional traders we analyze. We will use these residuals in the transition probabilities of the model in section 5 to understand whether and how (residual) trader positions contribute to the probability of the crude oil market of being in a bullish or bearish regime with high and low volatilities. In this regard, fundamentals represent information while "unexplained" positions represent a measure of information processing.[12]

The fundamental variables that we consider are as follows. We first consider the Aruoba-Diebold-Scotti (ADS, 2009) business conditions index, designed to track real U.S. business conditions.[13] The ADS index is an accurate measure of the current state of the U.S. real economy. The second fundamental variable we consider is the TED spread—the difference between the interest rates on interbank loans and short-term U.S. government debt. The TED spread is an indicator of

[11] Recent examples include Kilian (2008a; 2008b), Kilian and Hicks (2009). and Kilian and Murphy (2010).
[12] Kim and Verrecchia (2004; 2007) model the dual nature of information and information processing abilities among traders.
[13] ADS index data is available from the Federal Reserve Bank of Philadelphia.

perceived credit risk in the economy, with an increase in the TED spread indicating increased U.S. counterparty risk. The third fundamental variable we consider is the MSCI world stock market index, representing the major stock markets around the world.[14] While the ADS index and the TED spread mainly refer to the U.S. economy, the MSCI index proxies for global fundamental factors. The fourth variable we consider is the 10-year expected inflation estimate provided by the Federal Reserve Bank of Cleveland.

- We also considered the inventory of petroleum and other energy liquids published by the U.S. Energy Information Administration. There is evidence that inventories play an important role in the crude oil market. We consider inventories excluding the Strategic Petroleum Reserve (SPR) – Petroleum stocks maintained by the Federal Government for use during periods of major supply interruption.
- Kilian and Vega (2011) consider a wide range of macroeconomic announcements and study how crude oil prices react to the unexplained component of these announcements.[15] For daily data, they find that three announcements have some impact on crude oil prices. These are: the Government Budget Deficit, core CPI and Housing starts (the number of privately owned new houses (technically housing units) on which construction has been started in a given period). In our

[14] The MSCI World Index is comprised of 1,500 world stocks from 24 developed countries and is commonly used as a benchmark for global stock funds. The index is available in local currency and U.S.$, and with or without dividends reinvested.

[15] The unexplained component of the announcements is computed as the difference between the actual announcement and market expectations.

analysis we add these three announcements to capture how fundamentals affect trader positions.

Lastly, to account for the possible seasonality in trader positions, we use a Fourier Transform of order 5.

We estimate the following equation

$$\Delta Z_{i,t} = \gamma_0 + \gamma_1 ADS_t + \gamma_2 TED + \gamma_3 \Delta \ln(MSCI_t) + \gamma_4 \Delta EI_t + \gamma_5 Inventories_t + \sum_{k=1}^{3} \gamma_{5+k} Surprice_{k,t} + \sum_{j=1}^{5} \left(a_j sin(2j\pi t) + b_j cos(2j\pi t) \right) + u_{i,t} \quad (1)$$

where $\Delta Z_{i,t}$ is the daily change of institutional investor i on day t – the change in position represent the daily trading activity of market participants—we standardize position changes so that increases and decreases among position changes are with respect to their averages over the entire sample period; $\Delta \ln(MSCI_t)$ is the daily compounded rate of return of the MSCI index; expected inflation is non-stationary and hence we use the first difference; also inventories are non-stationary and we use the first difference; $Surprice_{k,t}$ is the difference between the macro announcement and market expectations for Government Budget Deficit, core CPI and Housing starts. It is important to note that in section 5 we adopt a regime switching approach. As it will be clear from the results in section 5, the regime switching model clearly provides a better fit for the futures returns. For trader positions we also adopt a non-linear approach and estimate regime switching models. However, there was no improvement in the fit and standard information criteria select the linear model over the non-linear one.

Table 3 reports regression estimates of equation (1). For the front maturity contract, merchant position changes are positively linked to the TED spread. This implies that when the credit risk in the US economy increases, merchants hedge more. Merchant position changes, front maturity and all maturities, are also negatively related to the world stock market index, as worldwide economic fundamentals improve, merchants hedge less. For the front maturity contract, merchant position changes are negatively linked to inventories and positively linked to the surprise announcements of housing start. When inventories are growing, merchants decrease their hedging positions perhaps to account for a possible reduction in demand. By the same token, when house starts is increasing hedging activity of merchants also increase to account for an expected increase in demand of oil.

For the front maturity contract, manufacturer position changes are positively linked to the ADS index which indicates that as economic conditions improve, crude oil demand is also expected to grow and manufacturers increase their hedging positions. Similar to merchants, when credit conditions deteriorate, manufacturers increase their hedging activity. When considering all maturities, manufacturer position changes are negatively linked to the world fundamentals as captured by the MSCI index. Interestingly, a positive surprise in CPI reduces hedging activity by manufacturers, this reaction may be due to the fact that a positive surprise in inflation may indicate that prices, including those of crude oil, are increasing and hence there is less need for hedging (merchants, manufacturers and producers are exposed to a reduction in price of crude oil).

For the front maturity contract, producer position changes are positively linked to the ADS economic condition index and the TED spread. As economic conditions improve, crude oil demand is also expected to grow and producers increase their hedging positions. When the credit risk in the US economy increases, producers hedge more. Similar to merchants and manufacturers, producers hedge less when the world stock market index (MSCI) has positive returns. When inventories are growing, producers decrease their hedging positions perhaps to account for a possible reduction in demand. A positive surprise in the budget deficit increases hedging activity of producers. For the front maturity contract, producer position changes seem not to be linked to economic fundamentals.

Positions changes of floor brokers and traders seems not to be linked to economic fundamentals. The role of these agents is to intermediate between demand and supply on the pit. Their position may be neutral with respect to fundamentals – it might be linked to idiosyncratic information on the crude oil market as we shall see in the next section. This is confirmed by the very low R^2.

Swap dealer position change in the front maturity contract is linked to most fundamentals considered in equations (1). As economic conditions improve, swap dealers reduce their investment in the crude oil market. CITs are looking for diversification opportunities and demand for diversification drops when economic conditions improve. In the front maturity, fundamentals explain more than 50% of the variation in swap dealer positions. Interestingly, position changes in all maturity contracts seem not to be linked to fundamentals. Perhaps, swap dealers are using longer maturity contracts to hedge price exposures in the front month and, more in general, in their portfolios hence neutralizing the effects of fundamentals.

Hedge fund position changes are linked to fundamentals. In particular, when the world stock market improves, hedge funds activity in crude oil increases, while an increase in inventories, reduces hedge funds trading activity in credo oil. Overall, however, fundamentals explain very little of the variation in hedge fund activity.

Overall, it seems that hedgers trading activity is linked to demand effects (as captured by the ADS and the TED spread). Speculative positions of swap dealers in the front maturity contract are heavily linked to fundamentals, but this is not the case for swap dealers all maturities and for hedge funds, front month and all maturities.

4. Regime Switching Modeling

4.1 The Model

Figure 1 shows several dynamics in the price of crude oil. At the beginning of our sample and until mid-2008, crude oil price increase first steadily and then dramatically. During the financial crisis there was a sudden drop followed by steady increase followed by another drop. We can distinguish between two different regimes in financial markets—increasing and declining prices—which exhibit different (unconditional) mean returns and which may also have different return variances. Bear markets are typically associated with higher volatility levels, for instance Hamilton and Susmel (1994) and Dueker (1997).[16] In addition, asset returns have been shown to exhibit leptokurtosis, volatility clustering and heteroskedasticity. Econometrically, the GARCH model is able to capture these stylized facts rather well.

Gray (1996) and Dueker (1997) introduce Markov regime switching in the GARCH framework

$$
\begin{aligned}
y_t &= \mu(S_t) + \sum_{j=1}^{k} \theta_j X_{j,t} + \varepsilon_t \\
\varepsilon_t &= \sigma_t u_t \qquad u_t \sim i.i.d.\, N(0,1) \\
\sigma_t^2(S_t, S_{t-1}, \dots, S_0) &= \omega(S_t) + \sum_{j}^{p} \alpha_j(S_{t-j})\varepsilon_{t-j}^2 + \sum_{j}^{q} \beta_j(S_{t-j})\sigma_{t-j}^2(S_{t-1}, \dots, S_0).
\end{aligned}
\tag{2}
$$

[16] Brunetti, Büyükşahin and Harris (2010) demonstrate the strong link between bear markets and volatility for five futures markets, including crude oil, corn and equity index futures studied here.

Where y_t represent returns at time t for crude oil dependent upon $X_{j,t}$, the exogenous and/or lagged j variables for the conditional mean. The innovation term, ε_t, is normally distributed.[17] To simplify, we assume the parameter vector θ_j in the conditional mean equation is constant (i.e. it does not switch according to the Markov process) but this assumption can be easily relaxed. The constant in the conditional mean equation, μ, is allowed to switch between two regimes—positive mean, (μ_1) which are accompanied by relatively low volatility, and negative mean, (μ_0) which are accompanied by relatively high volatility, so that

$$\begin{gathered}\mu(S_t) = \mu_1 S_t + \mu_0(1 - S_t)\\ S_t \in \{0,1\} \quad \forall t\\ Pr(S_t = 0|S_{t-1} = 0) = p_{00}\\ Pr(S_t = 1|S_{t-1} = 1) = p_{11}\end{gathered}$$

The volatility literature demonstrates that the GARCH(1,1) model is able to fully capture the volatility dynamics of asset returns—e.g. Andersen and Bollerslev (1998) and Hansen and Lunde (2005). Our data confirm this result for the crude oil futures markets. Therefore, in what follows we concentrate on the GARCH(1,1) case. The conditional variance, σ_t^2, in Equation (2) is a function of the entire history of the state variable S_t. This is due to the autoregressive term, σ_{t-j}^2, in the conditional variance equation—see Dueker (1997), Cai (1994), and Hamilton and Susmel (1994). Following Dueker (1997), we approximate the entire history using only the two most recent values of the state variable, a procedure that is parsimonious with evaluating the likelihood function and making the conditional variance, σ_t^2, a function only of the current (S_t) and the previous states (S_{t-1}). By

[17] Dueker (1997) adopts a student-t distribution for the error term. When we assume a student-t distribution for the innovations the estimated degrees of freedom are very high, so we adopt a normal distribution.

integrating out S_{t-1}, the conditional variance for the GARCH(1,1) can therefore be written as

$$\sigma_t^2(a,b) = \omega(S_t = a) + \alpha[\varepsilon_{t-1}^2(S_{t-1} = b)] + \beta\sigma_{t-1}^2(S_{t-1} = b). \tag{3}$$

Equation (3) allows the constant in the conditional variance equation to switch, which, in turn, allows the unconditional variances to switch across regimes.[18]

In this basic setup the transition probabilities are constant, which we deem overly restrictive. Indeed we are interested specifically in whether transition probabilities depend on the trading activity of market participants. For this reason, we introduce time varying probabilities modeled as probit functions of unexplained trader positions from our fundamental macroeconomic regressions above, denoted by $u_{i,t}$

$$Pr(S_t = 0|S_{t-1} = 0, u_{i,t-1}) = p_{00,t} = \Phi(u'_{i,t-1}\varsigma) \tag{4}$$
$$Pr(S_t = 1|S_{t-1} = 1, u_{i,t-1}) = p_{11,t} = \Phi(u'_{i,t-1}\upsilon) \tag{5}$$

Here Φ denotes the cumulative density function of the normal distribution, and ς and υ are parameters that capture how the transition probabilities vary in response to investor positioning. This approach estimates the conditional probability of being in a given regime at time *t+1* given the information available at time *t*.

Denote by $\hat{\boldsymbol{\xi}}_{t|t}$ the *(N × 1)* vector of conditional probabilities and define $\boldsymbol{\eta}_t$ as the *(N × 1)* vector of the conditional density of returns y_t conditional on S_t and S_{t-1}.[19] Following Hamilton (1994), the optimal forecast at each time *t* is computed by iterating the following equations

[18] Following Dueker (1997), $\omega(S_t)$ is parameterized as $\gamma(S_t)\cdot\omega$ such that $\gamma(S_t = 1)$ is normalized to unity.
[19] Given that the Markov process has 2 states, $N = 4$.

$$\hat{\xi}_{t|t} = \frac{(\hat{\xi}_{t|t-1} \odot \boldsymbol{\eta}_t)}{1'(\hat{\xi}_{t|t-1} \odot \boldsymbol{\eta}_t)}$$
$$\hat{\xi}_{t|t+1} = \boldsymbol{P}_{t+1} \cdot \hat{\xi}_{t|t}$$

where **1** denotes the unit vector, $\boldsymbol{P}_{t+1}$ is the $(N \times N)$ Markov transition probability matrix and $\odot$ denotes element-by-element multiplication. In this framework, $\boldsymbol{P}_{t+1}$ is time varying as function of market participant positions. This approach allows us to compute the probability of moving from one regime to the other (and vice versa) in period *t+1* given the trading behavior of market participants at time *t*.

We estimate the parameters by maximizing the following likelihood function

$$ln[L_t(a,b)] = -\frac{1}{2} ln[\sigma_t^2(a)] - \left[\frac{\varepsilon_{t-1}^2(a)}{2\sigma_t^2(b)}\right] - ln[\sqrt{2\pi}] \qquad (6)$$

where $a \in \{0,1\}$ relates to $S_t \in \{0,1\}$ and $b \in \{0,1\}$ relates to $S_{t-1} \in \{0,1\}$ (see Hamilton, 1994).

4.2 Parameter Estimates

We utilize detailed position data to estimate the model in equation (6) above. Importantly, we use the residuals from equation (1) to capture private information and/or trading strategies of institutional traders. Indeed we are interested specifically in whether price continuations and reversals (the transition probabilities) depend on trading activity from hedge funds, swap dealers and hedgers.

Table 4 presents the results. The first two columns refer to the model with constant transition probabilities. Before commenting further the results, it is important to note that a simple GARCH(1,1) model with no regime switching, generates log-likelihoods of -7502 and -6638 for the front maturity and all maturities rate of returns, respectively, indicating that the regime switching approach we adopt provides a much better fit for crude oil returns and volatility. The first two column indicate that one regime (regime 0) is characterized by a positive rate of return (i.e. increasing prices) while the other regime (regime 1) is characterized by negative returns (i.e. decreasing prices). The volatility in regime 1, when prices are decreasing, is about 11 and 9 times larger (γ) with respect to regime 0 for the front maturity and all maturities, respectively. This is in line with previous research in stock markets (e.g. Maheu and McCurdy, 1999; and Cunado, Gil-Alana, and Perez de Gracia, 2008). On average, daily price changes are much smaller during upward price movements (regime 0), suggesting that the market goes up more smoothly than it goes down. As demonstrated by the parameter estimates of α and β, the volatility process is persistent—consistent with the classic result in the GARCH literature—but stationary ($\alpha + \beta < 1$).

In the rest of the table we allow the transition probabilities to be time-varying as a function of institutional trader behavior – the residual from equation (1). Our analysis is effectively incorporating traders' activity indirectly in the conditional probability of moving between the two regimes.

Merchants significantly enter transition probability P_{11} only for the all maturities return process. The coefficient is positive indicating that merchants trading activity across the entire term structure of crude oil futures increases the probability of remaining in the high volatility regime with decreasing prices. The log-likelihood notably improves when we allow the transition probabilities to be time-varying.

Manufacturers have a positive and significant coefficient in both P_{00} and P_{11} for the all maturities crude oil returns. The probability of remaining in a given regime increases with merchants trading activity.

Producers are significant in P_{00} with a positive coefficient indicating that the trading activity of these market participants increases the probability of remaining in the low-volatility regime with increasing prices.

Merchants, manufacturers and producers exhibit similar results in terms of sign and magnitude of the estimated coefficient, and in terms of goodness of fit (see log-likelihood values). Overall we find that hedgers, as represented by merchants, manufacturers and producers, increase the probability of crude oil prices and volatility of staying in the same regime. This implies that these market participants, which represent the very large majority of hedgers in this market, do not contribute to price reversals.

Floor brokers have a positive and significant coefficient in the transition probabilities of the front maturity contract. Also these market participants increase the probability of the crude oil market of remaining in a given regime.

Swap dealers in the front maturity contract largely represent passive index fund investors who hold commodities mainly for diversification purposes. Consistent with this fact, swap dealer net positions are not significantly related to the transition probabilities—their positions generally bring no incremental information to our model. This is also true when considering all maturities contracts. It seems that swap dealer trading activity does not provide any valuable information to the transition probabilities. In fact, the values of the log-likelihood are the lowest among all institutional traders.

Hedge fund positions significantly decrease the likelihood of remaining in the same regime, evidence that hedge funds largely serve to stabilize futures markets.[20] Also, in terms of information, the value of the log-likelihood is the highest for hedge funds indicating that these market participants bring additional information about price reversals.

4.3 Transition Probabilities: A forecasting exercise

We would like to explore whether the transition probabilities, conditional on traders' behavior, can help forecasting switching from one regime to the other. To do so, we estimate the model in equation (6) from the beginning of our sample, January 2000, until December 2003. We then compute and store the transition probabilities for the first out-of-sample day using equations (4) and (5). We do this recursively, adding a day to the estimation window.

Figure 3 displays the price of crude oil along with the time series of transition probability estimates – we report the 44-day moving average of the transition probabilities. We concentrate on $p_{10,t}$ which represents the probability of switching from the high volatility state to the low volatility state. $p_{10,t}$ is particularly important since represents the probability of moving from a turbulent state (crisis) to a calm state where prices are increasing and volatility is moderate.

[20] Similar evidence is found in Brunetti, Büyükşahin, and Harris (2010) and Boyd, Büyükşahin, Harris, and Haigh (2009).

Figure 3 shows that the probability of moving from a turbulent state, regime 1, to a more stable state, regime 0, conditional on merchant trading behavior. This probability averages about 10 percent but it decreases considerable during the financial crisis. Merchant trading behavior reduces the probability of moving to a less volatile state during the 2008-2009 financial crisis. A similar behavior is evident for manufacturers and producers. In line with the estimated parameters in Table 4, these market participants increase the probability of remaining in the same state ($p_{10,t} = 1 - p_{11,t}$) or, alternatively, reduce the probability of moving to state 0.

For merchants, manufacturers and producers, Figure 3 reports $p_{10,t}$ for the all maturities contract. The results of the front maturity contract are in line with what reported but less strong.

Trading activity of floor brokers also reduces the probability of moving from the high volatility regime a low volatility regime. For floor brokers we only report results for the front maturity contract since the transition probability for all maturities contract does not seem to be much affected by the trading activity of floor brokers.

Swap dealers trading activity does not seem to have any impact on transition probabilities. This is in line with the results in Table 4.

Hedge funds are the only institutional traders that seems to increase the probability of moving from the high volatility regime to the low volatility regime. Notably, in January 2009 this probability jumps from 7 percent to 22 percent, an indication that the conditional probability (based on hedge fund positions) of a crude oil price reversal was expected. Note that the transition probabilities we estimate only indicate the conditional probability of moving from one regime to another based on recent hedge fund positioning. It would be incorrect to interpret these results as evidence that hedge funds move the market. Rather, these results suggest that aggregate hedge fund position changes reflect information processing by hedge funds incremental to fundamental market information that is useful in estimating the probability of future price reversals. Similar results apply to $p_{10,t}$ for all maturities.[21]

5. Conclusions

In recent years many assets including crude oil experienced sustained price increases followed by sudden price decreases. At the same time, hedge funds, swap dealers and arbitrageurs dramatically increased their activity in these markets.

We first analyze the relationship between trader positions and fundamentals and find significant evidence that fundamentals drive both trader positions.

In the spirit of Abreu and Brunnermeier (2002; 2003) where synchronization risk affects price patterns, we exploit the confluence of these events to explore whether institutional positioning is useful in predicting the continuation or reversal of price trends in financial markets. We propose a Markov switching process between low volatility and high volatility markets conditioned on the positions of institutional traders. We find hedge fund activities add incrementally to the transition probabilities that we estimate, suggesting that information processing by hedge

[21] We do not report results for p_(01,t), the probability of moving from a low volatility regime to a high volatility regime. These results are not so clear cut as those for p_(10,t).

funds also contributes to the probability of continuations and reversals in these markets evidence consistent with synchronization behavior among equity market arbitrageurs as modeled by Abreu and Brunnermeier (2002; 2003). Conversely, swap dealer positioning is largely unrelated to the probability of transitioning between bull and bear markets, consistent with the diversification goals of traders using swap dealers for exposure to commodity markets. Hedgers, on the other hand, seem to facilitate the persistence in regimes.

Our results indicate that trader positioning can be useful in predicting the transition probability of moving between regimes. We believe the Markov switching approach that we apply represents an important step toward a better understanding of price patterns of crude oil. Although not directly addressing the existence or causes of asset bubbles, we find that institutional positions are informative (in the conditional sense) about the transition probabilities between high and low volatility regimes.

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Table 1: Summary Statistics

This table presents the distribution of daily returns and trader positions for the nearby crude oil futures contracts from January 2, 2003 through March 19, 2009. Daily returns are calculated as the difference in the natural logarithm of daily prices (in %). *Front maturity* only considers the price of the nearby contract. We switch from the nearby contract to the next-to-nearby contract when the open interest of the nearby contract falls below that of the next-to-nearby contract. *All maturities* considers all contract maturities traded on a given day. The price is constructed as weighted average of each contract price weighted by the open interest.

Positions refer to the daily change in closing net futures and options positions (number of contracts). *Front maturity* refers to futures and options positions on the nearby contract only. *All maturities* refers to futures and options positions on all contracts available for trading in a given day.

Number of Observations: 2964					
	Mean	Median	Max	Min	Std. Dev.
Returns (%)					
Front maturity	0.017	0.085	13.345	-16.544	2.365
All maturities	0.047	0.092	9.835	-12.782	1.979
Merchant					
Front maturity	-50,227	-49,178	32,641	-146,601	35,250
All maturities	-44,904	-30,958	90,551	-206,337	79,448
Manufacturer					
Front maturity	-20,863	-19,730	14,033	-59,984	12,348
All maturities	-25,529	-26,911	28,789	-64,976	17,583
Producer					
Front maturity	-7,621	-7,800	12,053	-30,511	6,638
All maturities	-9,787	-10,819	16,042	-33,587	9,191
Floor Broker					
Front maturity	-1,166	-503	10,987	-16,831	3,331
All maturities	898	542	18,658	-21,134	-11,640
Swap Dealer					
Front maturity	72,230	64,777	193,253	-9,695	39,238
All maturities	4,589	2,261	102,950	-107,205	56,141
Hedge Fund					
Front maturity	6,087	6,853	90,328	-93,504	30,229
All maturities	72,502	60,304	318,133	-36,555	62,026

Table 2: Long/Short Percentage of Open Interest

This table presents the distribution of long and short trader positions as a percent of total open interest for crude oil futures contracts from January 2, 2003 through March 19, 2009. Positions refer to the daily change in closing net futures and options positions (number of contracts). *Front maturity* refers to futures and options positions on the nearby contract only. *All maturities* refers to futures and options positions on all contracts available for trading in a given day.

Crude Oil Number of Observations: 2964 (%)						
	Median		Max		Min	
	Long	Short	Long	Short	Long	Short
Merchant						
Front maturity	9	30	42	59	1	8
All maturities	12	30	38	61	2	9
Manufacturer						
Front maturity	1	10	11	13	0	3
All maturities	22	47	73	89	1	3
Producer						
Front maturity	1	8	11	29	0	1
All maturities	17	47	57	87	1	6
Floor Broker						
Front maturity	4	6	10	16	0	0
All maturities	20	21	53	52	8	7
Swap Dealer						
Front maturity	39	6	60	21	2	1
All maturities	23	17	44	26	6	2
Hedge Fund						
Front maturity	23	19	48	50	2	1
All maturities	26	28	71	77	7	3

Table 3: Trader positions and fundamentals

$$\Delta Z_{i,t} = \gamma_0 + \gamma_1 ADS_t + \gamma_2 TED_t + \gamma_3 \Delta\ln(MSCI_t) + \gamma_4 \Delta EI_t + \gamma_5 Inventories_t + \sum_{k=1}^{3} \gamma_{5+k} Surprise_{k,t} + \sum_{j=1}^{5} \left(a_j sin(2j\pi t) + b_j cos(2j\pi t)\right) + u_{i,t}$$

$\Delta Z_{i,t}$ is the daily change of institutional investor i on day t; $\Delta\ln(MSCI_t)$ is the daily compounded rate of return of the MSCI index; ΔEI_t is the first difference of expected inflation; also inventories are non-stationary and we use the first difference; Budget Deficit, Core CPI and Housing Starts are is the difference between the macro announcements and market expectations. Robust standard errors in parenthesis. ** and * indicate 5% and 10% significance levels, respectively.

	Merchant		Manufacturer		Producer		Floor Broker		Swap Dealer		Hedge Fund	
	Front Maturity	All Maturities	Front Maturity	All Maturities	Front Maturity	All Maturities	Front Maturity	All Maturities	Front Maturity	All Maturities	Front Maturity	All Maturities
γ_0	-1.5888 (1.7661)	0.5392 (1.1212)	4.6657** (0.6866)	-0.7371 (0.6347)	0.4221 (0.3316)	0.0756 (0.3123)	-0.3867 (0.2492)	0.2287 (0.2237)	2.8807* (1.5227)	-0.4568 (1.5986)	-7.4180** (1.8053)	0.2360 (1.8992)
ADS_t	2.1695 (2.4983)	0.2343 (0.2157)	2.4033** (0.8340)	0.1393 (0.6105)	0.8235** (0.3346)	0.1534 (0.3158)	-0.0039 (0.2680)	-0.2675 (0.2545)	-3.4122* (1.8956)	-0.1823 (1.4706)	-0.7294 (1.9447)	0.6031 (1.7988)
TED_t	0.0634** (0.03347)	-0.0207 (0.0192)	0.0210* (0.0113)	0.0144 (0.0103)	0.0160** (0.0057)	-0.0020 (0.0052)	0.0037 (0.0044)	-0.0070 (0.0050)	-0.0544* (0.0300)	0.0053 (0.0272)	-0.0341 (0.0272)	0.0160 (0.0300)
$\Delta\ln(MSCI_t)$	-2.1548** (0.9698)	-3.8067** (0.6987)	-0.3751 (0.3827)	-1.2568** (0.4059)	-0.6423** (0.2054)	-0.4133** (0.1979)	0.2019 (0.1941)	0.6487** (0.2731)	2.3068** (0.9280)	-0.0384 (1.1537)	5.2857** (1.2623)	8.5744** (1.8206)
ΔEI_t	-4.6540 (3.3164)	-3.6727 (34788)	0.5378 (1.3860)	-0.1701 (1.5225)	-0.1879 (0.6713)	-0.4466 (0.7529)	-0.6926 (0.6812)	-0.2894 (0.8005)	1.2667 (2.8192)	-5.2782 (3.6666)	6.5001 (5.2041)	10.376* (5.9575)
Inventories	-0.0077 (0.0350)	-0.0037* (0.0021)	-0.0085 0.0146	0.0056 (0.0119)	-0.0148** (0.0071)	0.0024 (0.0067)	0.0044 (0.0053)	0.0047 (0.0042)	0.0885** (0.0295)	0.0215 (0.0258)	-0.0681** (0.0337)	-0.0549* (0.0325)
Budget Deficit	3.8560 (2.6652)	5170.6 (3479.1)	-0.6174 (0.7922)	0.8336 1.1505	1.4622** (0.7697)	0.4978 (0.7486)	-0.3244 (0.6616)	-1.0597 (0.7613)	-2.2774* (1.1669)	-0.8638 (3.1833)	-5.7148** (2.7570)	-5.2473 (3.8557)
Core CPI	5.8412 (5.1973)	1.6588 (4.3930)	-1.5250 (1.9788)	-4.8048** (2.2581)	0.6086 (1.130)	0.5875 (1.7493)	0.4792 (1.6523)	0.3033 (2.3796)	-6.2108* (3.7167)	-1.2521 (4.7672)	-2.4538 (5.5578)	7.4428 (5.9089)
Housing start	0.0041 (0.0048)	0.0086* (0.0050)	-0.0022 (0.0022)	-0.0031 (0.0027)	-0.0003 (0.0012)	-0.0028 (0.0018)	-0.0027 (0.0018)	-0.0026 (0.0023)	-0.0003 (0.0039)	-0.0051 (0.0065)	0.0053 (0.0052)	0.0068 (0.0052)
R^2 (%)	24.2	22.8	22.9	27.2	12.1	6.03	2.88	2.54	50.5	7.82	2.78	2.99

Table 4: Regime Switching Estimates

This table presents results of the Markov switching model estimating the transition probability between high volatility bear markets (μ_0) and low volatility bull markets (μ_1)

$$y_t = \mu_t + \sum_{j=1}^{k} \theta_j X_{j,t} + \varepsilon_t; \text{ where}$$
$$\mu_t = \mu_1 S_t + \mu_0 (1 - S_t)\ S_t \in \{0,1\} \quad \forall t, \text{ and}$$
$$\sigma_t^2(S_t) = \omega(S_t) + \alpha[\varepsilon_{t-1}^2(S_{t-1})] + \beta\sigma_{t-1}^2(S_{t-1}),$$
$$p_{00,t} = \Phi(\mathrm{u}'_{i,t-1}\varsigma),\ p_{11,t} = \Phi(\mathrm{u}'_{i,t-1}\upsilon)$$

where y_t is the daily returns and σ_t^2 is the conditional GARCH(1,1) variance for the crude oil futures contracts from January 5, 2000 through November 25, 2011. We assume the parameter vector θ_j in the conditional mean equation is constant across regimes. $\mathrm{u}'_{i,t-1}$ are either the unexplained standardized daily closing net futures and options positions changes for the front maturity and for all maturities. The first two columns refer to the model with only a constant in the transition probabilities. $\omega(S_t)$ is parameterized as $\gamma(S_t) \cdot \omega$ such that $\gamma(S_t = 1)$ is normalized to unity. **, and * indicate significance at 5% and 10% significance level, respectively.

	Constant transition probabilities		Merchant		Manufacturer		Producer	
	Front Maturity	All Maturities	Front Maturity	All Maturities	Front Maturity	All Maturities	Front Maturity	All Maturities
μ_0	0.1532**	0.1945**	0.1352**	0.1546**	0.1381**	0.1587**	0.1311**	0.1589**
	(0.0498)	(0.0433)	(0.0483)	(0.0349)	(0.0394)	(0.0346)	(0.0576)	(0.0336)
μ_1	-1.1376**	-0.8639**	-1.1376*	-0.7996**	-1.1909**	-0.7991**	-1.1971**	-0.9019**
	(0.5206)	(0.4192)	(0.6103)	(0.3340)	(0.3438)	(0.2586)	(0.4095)	(0.2897)
Ω	0.2187**	0.1875**	0.1781*	0.1368**	0.1766**	0.1666**	0.1813**	0.1110**
	(0.0941)	(0.6781)	(0.1042)	(0.0550)	(0.0515)	(0.0688)	(0.0584)	(0.0365)
γ	10.963**	9.1689**	10.397*	9.5917**	10.449**	9.2618**	9.6591**	10.374**
	(4.6685)	(3.0188)	(5.1668)	(2.5095)	(2.1864)	(2.1424)	(2.3853)	(2.6853)
α	0.0182**	0.0273**	0.0130**	0.0237**	0.0293**	0.0160**	0.0191**	0.0307**
	(0.0068)	(0.0138)	(0.0034)	(0.0079)	(0.0100)	(0.0063)	(0.0026)	(0.0128)
β	0.9320**	0.9435**	0.9320**	0.9235**	0.9324**	0.9101**	0.9291**	0.9347**
	(0.0298)	(0.0269)	(0.0177)	(0.0260)	(0.0165)	(0.0262)	(0.0201)	(0.0170)
P_{00}-Const	2.6618**	2.7560**	2.1701**	2.0675**	2.1816**	2.0748**	2.2462**	2.2400**
	(0.3144)	(0.4164)	(0.1423)	(0.2136)	(0.1235)	(0.1497)	(0.2367)	(0.1448)
P_{00}-$u_{i,t-1}$			0.1703	-0.0067	-0.1154	0.2321*	0.0274	0.3793**
			(0.4039)	(0.0295)	(0.1157)	(0.1374)	(0.1408)	(0.1144)
P_{11}-Const	1.066**	1.5173**	1.0968**	1.1524**	1.1395**	1.0860**	1.1885**	1.0625**
	(0.3821)	(0.3516)	(0.3049)	(0.2352)	(0.1724)	(0.1893)	(0.2628)	(0.1691)
P_{11}- $u_{i,t-1}$			-0.2220	0.3778**	-0.3484	0.3540**	-0.1774	-0.1138
			(0.7419)	(0.1249)	(0.2291)	(0.1746)	(0.3422)	(0.2487)
θ	-0.0386**	-0.0668**	-0.0381*	-0.0629**	-0.0389*	-0.0630**	-0.0369*	-0.0654**
	(0.0189)	(0.0258)	(0.0200)	(0.0189)	(0.0235)	(0.0187)	(0.0224)	(0.0193)
Log-Lik.	-6523.3	-6022.9	-6510.8	-6008.6	-6510.9	-6008.5	-6512.7	-6008.4

Table 4: Regime Switching Estimates (continued)

	Floor Broker		Swap Dealer		Hedge Fund	
	Front Maturity	All Maturities	Front Maturity	All Maturities	Front Maturity	All Maturities
μ_0	0.1295**	0.1501**	0.1313**	0.1545**	0.1428**	0.1583**
	(0.0427)	(0.0342)	(0.0430)	(0.0482)	(0.0406)	(0.0351)
μ_1	-1.1570**	-0.7606**	-1.1347**	-0.8399**	-1.2799**	-0.8146**
	(0.4573)	(0.2380)	(0.4027)	(0.3051)	(0.3607)	(0.2408)
Ω	0.1868**	0.1579**	0.1933**	0.1395**	0.1457**	0.1228**
	(0.0555)	(0.0536)	(0.0572)	(0.0639)	(0.0524)	(0.0508)
γ	9.6957**	8.9099**	9.5823**	8.9379**	11.628**	10.670**
	(2.0599)	(1.9243)	(2.0111)	(2.7250)	(3.0425)	(3.0146)
α	0.0253**	0.0178**	0.0294*	0.0285**	0.0358**	0.0255**
	(0.0108)	(0.0072)	(0.0176)	(0.0105)	(0.0172)	(0.0130)
β	0.9300**	0.9171**	0.9280**	0.9204**	0.9400**	0.9301**
	(0.0173)	(0.0205)	(0.0170)	(0.0180)	(0.0221)	(0.0205)
P_{00}-Const	2.2443**	2.0985**	2.2164**	2.1706**	2.1714**	2.0227**
	(0.1369)	(0.1185)	(0.1613)	(0.1510)	(0.1691)	(0.1151)
P_{00}-$u_{i,t-1}$	0.1258**	-0.0214	-0.0673	0.1805	-0.1770*	-0.1329**
	(0.0605)	(0.0345)	(0.0975)	(0.2031)	(0.1071)	(0.0412)
P_{11}-Const	1.1670**	1.1002**	1.1502**	1.1548**	1.2168**	1.2232**
	(0.1885)	(0.1781)	(0.1964)	(0.2522)	(0.2110)	(0.2045)
P_{11}- $u_{i,t-1}$	0.1304**	-0.0339	0.0356	-0.1028	-0.6417**	-0.4775**
	(0.0514)	(0.0283)	(0.0669)	(0.3229)	(0.2006)	(0.1446)
θ	-0.0375*	-0.0622**	-0.0379**	-0.0624**	-0.0410**	-0.0626**
	(0.0215)	(0.0194)	(0.0187)	(0.0229)	(0.0184)	(0.0194)
Log-Lik.	-6509.8	-6010.2	-6515.2	-6011.3	-6508.9	-6006.5

Figure 1
Prices and returns.
Front maturity refers to the nearby contract. *All maturities* account for all contract maturities traded on a given day. The daily price is computed as the weighted average of each maturity contract settlement price and use as weights the open interest of each contract.

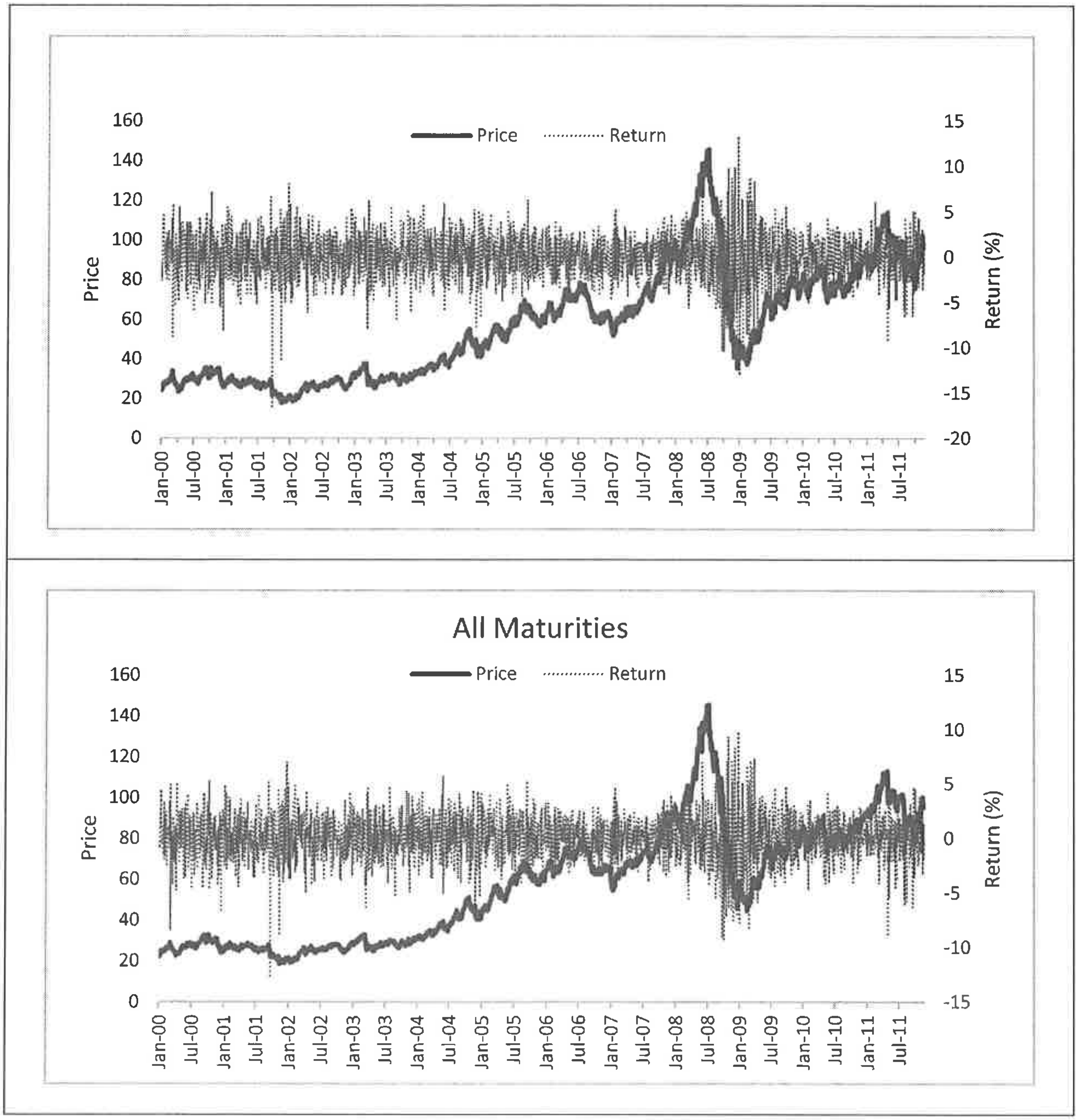


Figure 2
Participation rates of institutional investors.
Front maturity refers to futures and options positions on the nearby contract only. *All maturities* refers to futures and options positions on all contracts. Positions are computed as the sum of futures and options long and short positions, divided by two.

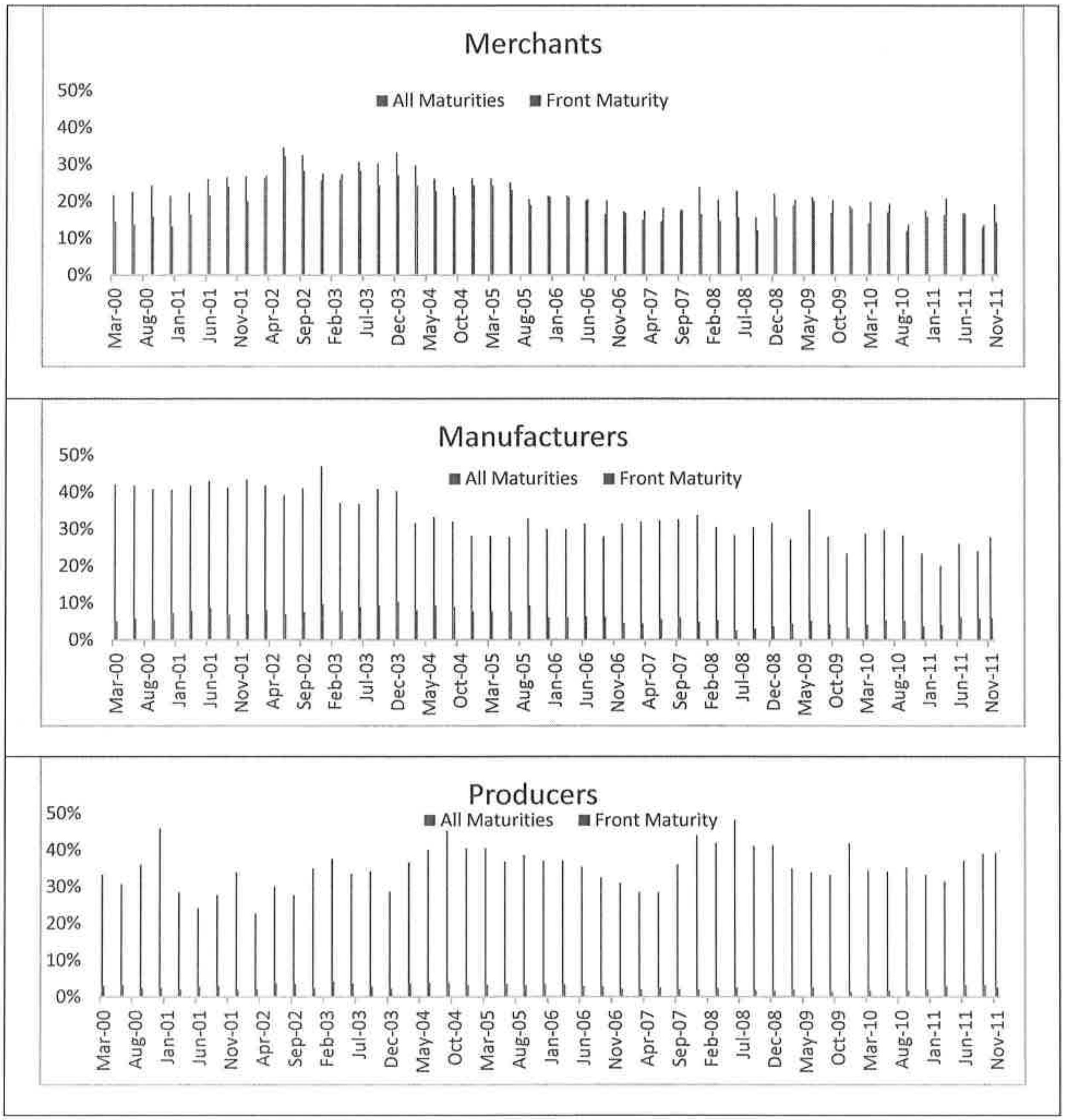


Figure 2 (continued)

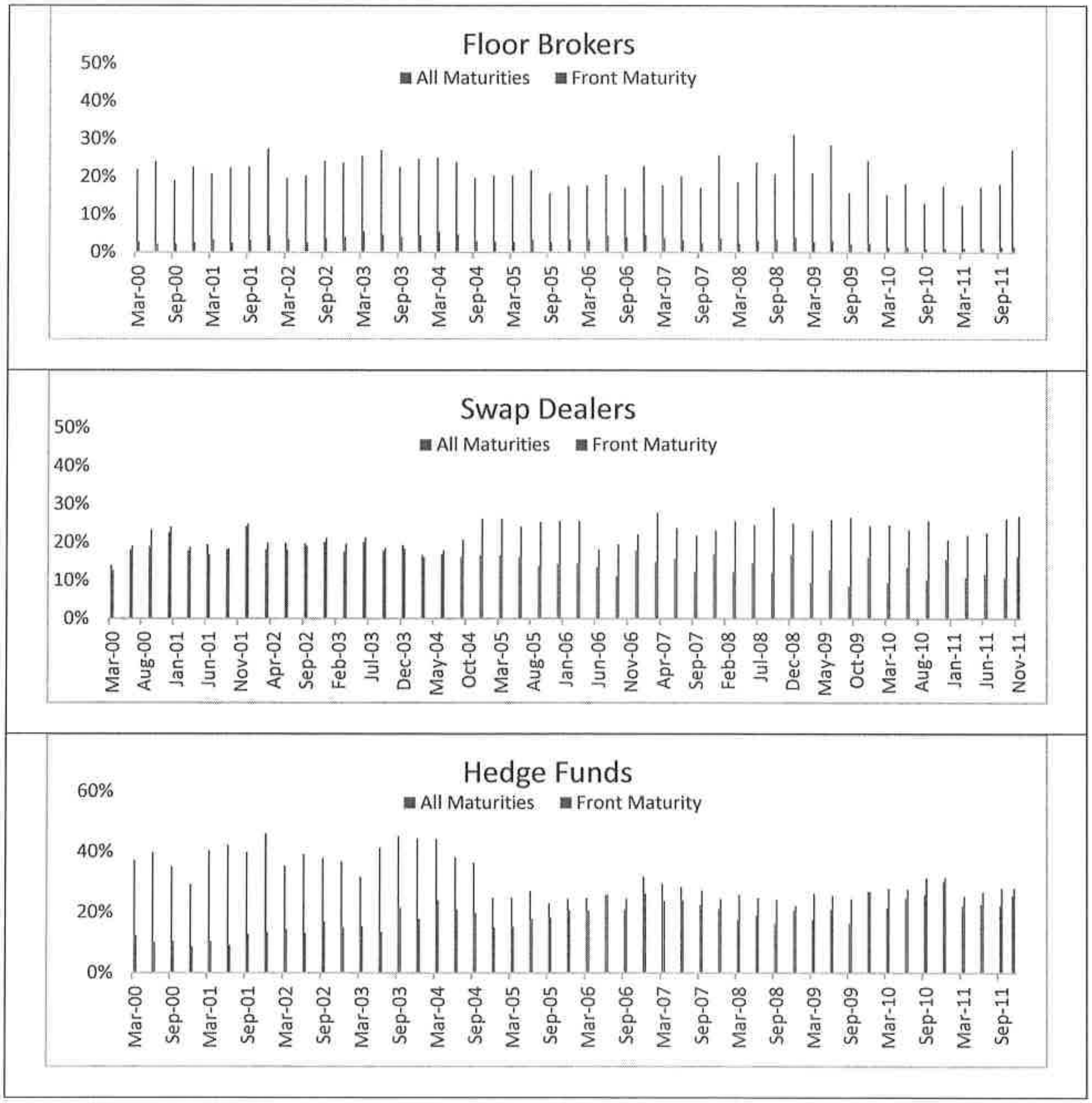
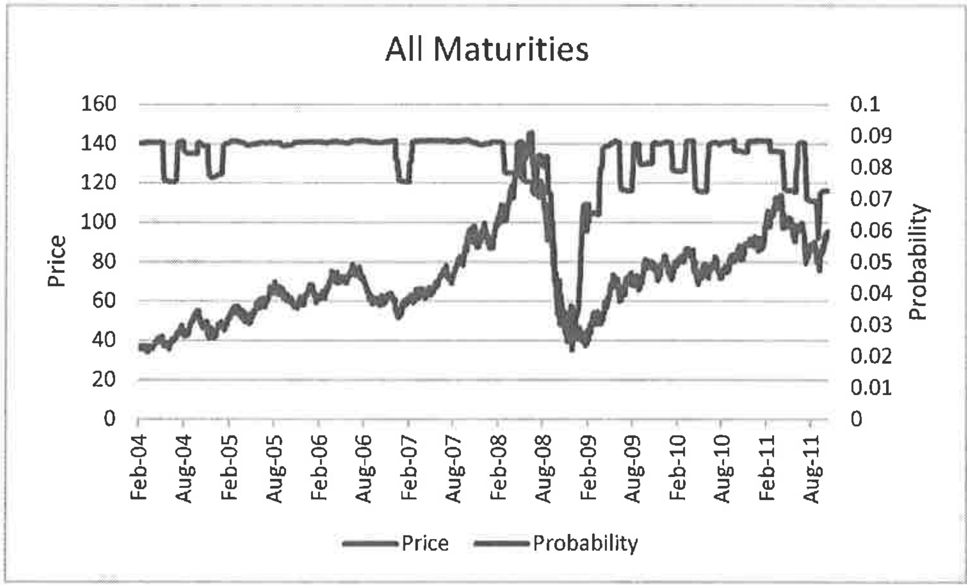


Figure 3: Crude Oil Prices and Estimated Transition Probabilities

P_{10}: Probability of reversal from a high-volatility regime to a low volatility regime
Explanatory Variable: Merchants



P_{10}: Probability of a reversal from a high-volatility regime to a low volatility regime
Explanatory Variable: Manufacturers

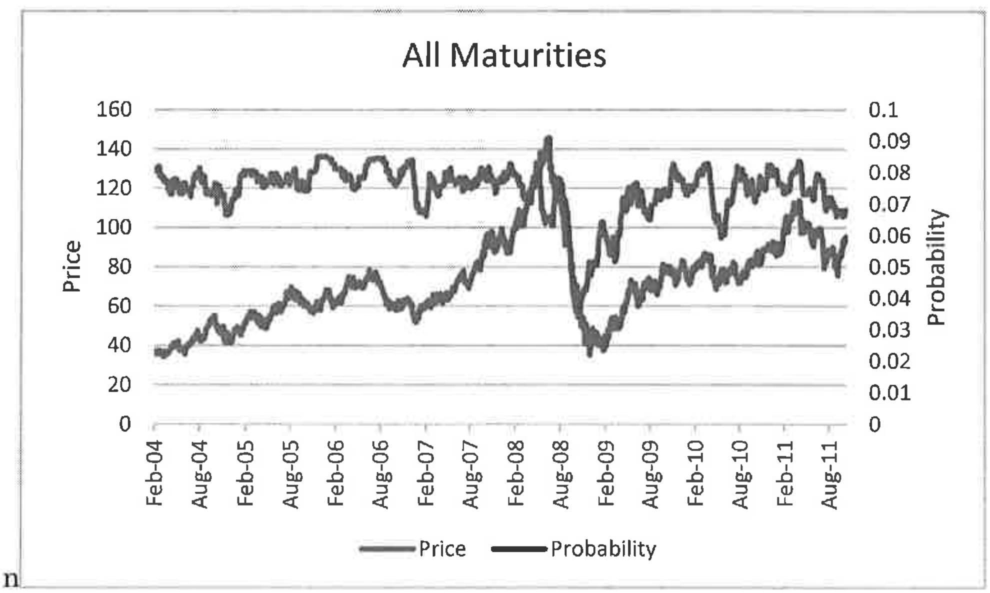


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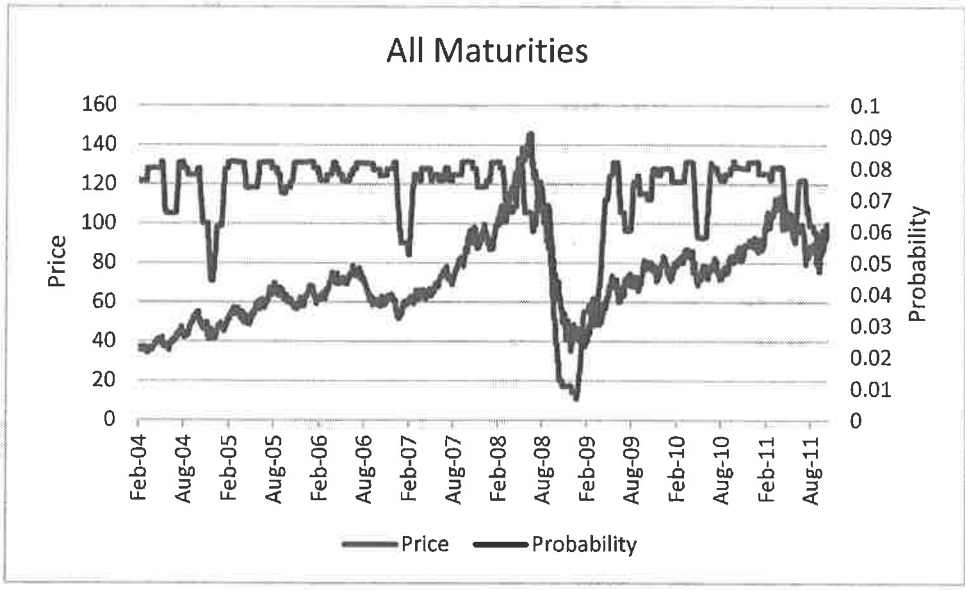
Figure 3: Crude Oil Prices and Estimated Transition Probabilities (continued)

P_{10}: Probability of reversal from a high-volatility regime to a low volatility regime
Explanatory Variable: Producers



P_{10}: Probability of a reversal from a high-volatility regime to a low volatility regime
Explanatory Variable: Floor Brokers

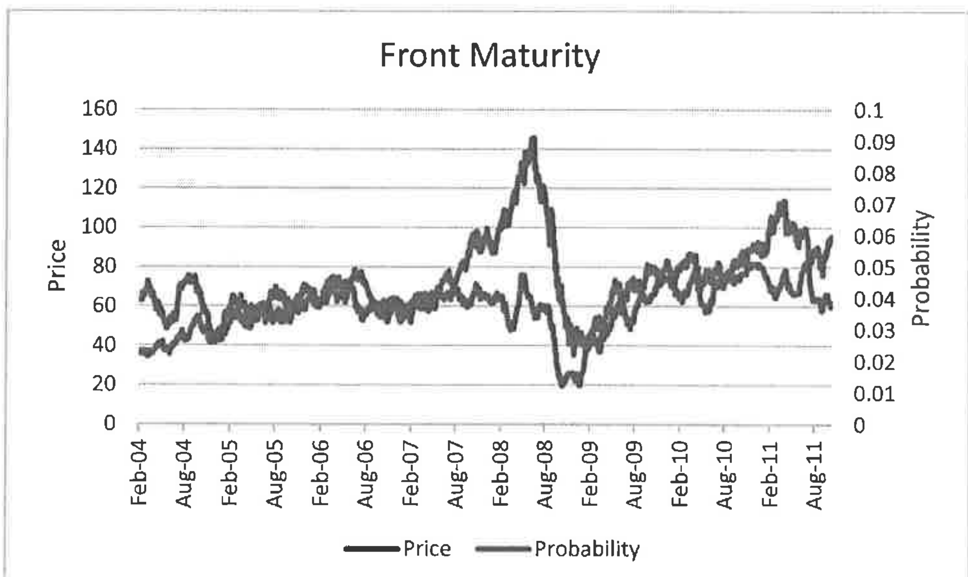
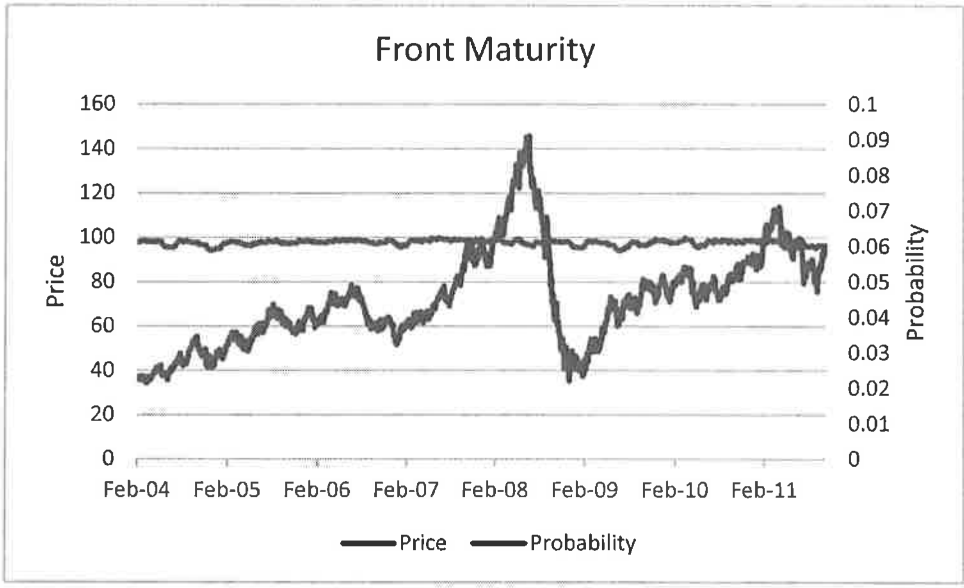


Figure 3: Crude Oil Prices and Estimated Transition Probabilities (continued)

P_{10}: Probability of reversal from a high-volatility regime to a low volatility regime
Explanatory Variable: Swap Dealers



P_{10}: Probability of a reversal from a high-volatility regime to a low volatility regime
Explanatory Variable: Hedge Funds