Informed Trading in the WTI Oil Futures Market

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ABSTRACT

The weekly release of the U.S. inventory level by the DOE-EIA is known as the market mover in the U.S. oil futures market. We uncover suspicious trading patterns in the WTI futures markets in days when the inventory level is released that are higher than market forecasts: there are significantly more orders initiated by buyers in the two hours preceding the official release of the inventory level, with a drop in the average price of –0.25% ahead of the news release. This finding is consistent with informed trading. We also provide evidence of an asymmetric response of the oil price to oil-inventory news, and highlight an over-reaction that is partly compensated in the hours following the announcement.

Keywords: Insider trading, WTI crude oil futures, Intraday data, Inventory release

https://doi.org/10.5547/01956574.40.2.orou

1. INTRODUCTION

This paper provides evidence of suspicious trading patterns consistent with informed trading in the West Texas Intermediate (WTI) oil futures market on the days when the announcement of the U.S. crude oil stock level by the Department of Energy contrasts with the expectations of energy analysts collected in Bloomberg's inventory survey. Our results reveal significant order imbalances, with a majority of buyer-initiated trades in the two hours preceding the announcement of positive surprises—changes in inventories that are larger than expected—at 10: 30 a.m. on Wednesday.[1] The findings are robust to alternative definitions of the surprise and the measures of order imbalance considered. Our results have important implications, as the WTI futures market is the leading market with respect to price discovery (see the recent evidence in Elder et al. (2014)) and the most-traded futures commodity contract worldwide.

The inventory level is known to be a central variable for the determination of oil prices, as highlighted in early theoretical contributions such as Deaton and Laroque (1996), Pindyck (1994, 2001), Geman and Nguyen (2005), Pirrong (2009) or more recently Kilian and Lee (2014), Kilian and Murphy (2014), Smith et al. (2015) and Knittel and Pindyck (2016). As noted in Kilian and Murphy (2014): "[...] any expectation of a shortfall of future oil supply relative to future oil demand not already captured by flow demand and flow supply shocks necessarily causes an increase in the demand for above-ground oil inventories and hence in the real price of oil." (p. 455) Inventories

1. All times in the paper are eastern standard times (EST).

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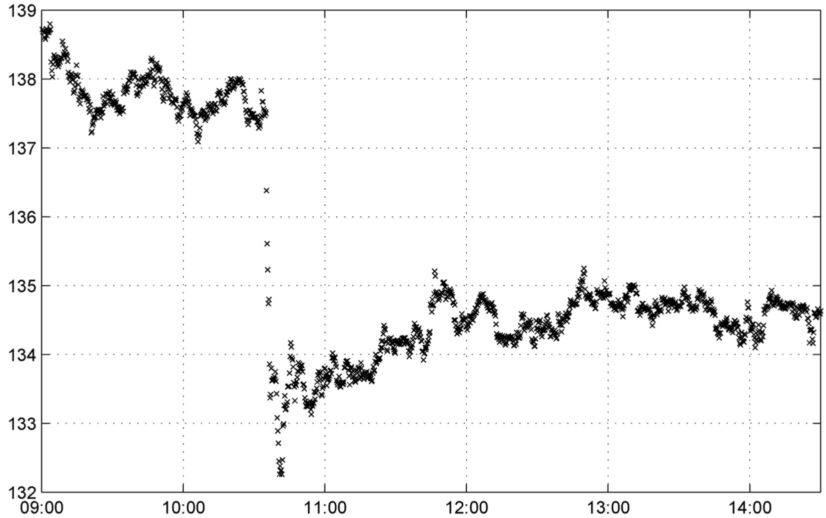
Figure 1: The oil price on July 16th 2008. The oil-inventory announcement was higher than expected.



may also be related to precautionary demand, as highlighted by Kilian (2008, 2009) and Alquist and Kilian (2010).

It is hence not surprising that weekly announcements about the level of oil stocks in the U.S. are eagerly anticipated by the financial community[2] Of course, changes in oil inventories are endogenous with respect to the economy. Hence, the relationship between changes in oil inventories and changes in the price of oil may not be causal.[3] Moreover, this relationship may be unstable over time (see, e.g., Kilian and Park (2009) and Fattouh et al. (2013)).

This impact of the EIA announcement release on oil prices is illustrated in Figure 1, where we plot the transaction prices over the day of July 16th 2008. The Bloomberg median forecast for this day was a drop of 2.2 million barrels, with individual forecasts by oil experts going up to –3.9 million barrels. The actual reported value was instead a rise in stocks of 2.952 million barrels, which greatly surprised the market and led to a drop in price of almost 6 dollars in the few minutes following the release at 10: 35 a.m.

Apart from inventory announcements, there has been substantial research on the impact of non-oil-specific news on oil prices. For example, using daily data, Kilian and Vega (2011) find no evidence of an impact of macro news on oil prices and, as such, oil prices are contemporaneously exogenous. This result has important implications for the ordering of the oil price variable in multivariate models such as vector-autoregressive models when the impact of shocks has to be investigated. Chatrath et al. (2012) confirm these findings using intraday data. Rosa (2014) and Basistha and Kurov (2015) analyze the impact of monetary surprises on oil prices using intraday data. As such, they can identify the effect of surprises at the exact time when they occur. Datta et al. (2014) provide evidence that events of various types can significantly affect on the conditional distribution of returns measured by the option-implied density. Berk and Rauch (2016) investigate the impact of Commodity Futures Trading Commision (CFTC) announcements on oil prices.

2. Bloomberg (2013), Wall Street Journal (2015)..

3. Studies providing descriptive statistics about the relationship between oil price changes and changes in oil inventories include Bjursell et al. (2015) and Elder et al. (2013). Similar evidence for the gas market appears in Chiou-Wei et al. (2014). In a related study, Linn and Zhu (2004) consider the volatility surrounding the release of the gas-storage report.

It is well-known, however, that the largest impact on oil prices comes from the weekly inventory news release by the DOE-EIA about petroleum reserves in the U.S., which is the most anticipated piece of news in the oil market. Recent research has thus focused on the impact of this release of the stock level.[4] Bu (2014) is one attempt to assess the impact of inventory shocks on both oil prices and oil volatility. This work, however, uses daily data, a frequency at which a phenomena taking place over a few minutes might well not be visible. Halova Wolfe and Rosenman (2014) consider the impact of the oil-inventory news on both oil and gas prices and volatility. They use intraday data, but focus on the specific time of announcements, thereby ignoring the periods around the time of the release. Bjursell et al. (2015) also make use of intraday data to investigate the association between inventory shocks and price jumps, and provide evidence that these, mainly large jumps, often appear at the time of the news release. Elder et al. (2013) also use intraday data to detect intraday jumps in oil prices. The authors provide evidence that jumps often coincide with the release of either macro-news or oil-inventory news, showing the importance of fundamentals in the determination of oil prices beyond speculative motivations.[5] Finally, Ye and Karali (2016) consider the informational content of inventory shocks, looking at both EIA and API releases over the short August 2012–December 2013 time period. They find no significant, or at best a weakly significant, price impact of the API and that the market mover for oil is indeed the EIA release. In contrast to our study, the authors only focus on the impact of the news and not on potentially suspicious trading patterns before the official release time.[6] In what follows, we identify days with significant inventory surprises when the difference between the expectation (Bloomberg survey) and the realized value is "sufficiently large" on these days.[7]

Our work takes a different approach, building on recent contributions by Irvine et al. (2007), Christophe et al. (2010), Blau and Wade (2012) and Bernile et al. (2016), where the focus is on the detection of information leakage before official announcements. In contrast with previous work such as Ederington and Lee (2002), these papers go beyond the simple analysis of return patterns to assess the possibility of leakage by taking into account order imbalance as a symptom of informed trading. We also base our analysis on order imbalance to draw conclusions about the likelihood that market participants trade on private information. To our best knowledge, this is the first time such an analysis is pursued for some commodity markets.

Our paper is the first to focus on the possibility of information leakage before the inventory announcements, and to show that the trading patterns are consistent with informed trading. We specifically examine the trading activity around the weekly inventory announcements in the front-month WTI oil futures contract traded on the New York Mercantile Exchange (NYMEX) over the 2007–2014 period. The U.S. Department of Energy makes an announcement about the level of oil inventories each Wednesday at 10: 30 a.m. We investigate potential trading by informed investors in the hours preceding the official news release. We use intraday data to calculate order imbalances

4. News is defined as announcement minus expectation (see Chapter 7 in Kilian and Lütkepohl (2017)). In this way, news is defined as a shock and the two terms will be used interchangeably in the rest of the text.

5. Hamilton (2009), Büyüksahin and Harris (2011), Alquist and Gervais (2013), Kilian and Murphy (2014), Kilian and Lee (2014), Knittel and Pindyck (2016) and Bunn et al. (2017) are examples of contributions discussing the relationship between oil prices and speculation. In their survey on the role of speculation in oil markets, Fattouh et al. (2013) conclude that there is no reliable evidence that financial speculation is a significant determinant of the price of oil.

6. There is similar for non-energy commodities such as the orange juice (Baur and Orazem, 1994) or corn (Lehecka et al., 2014). The focus is again on the price reaction to scheduled announcements, while we look at both the price *and* the trading pattern in the *pre-announcement* period.

7. A definition of what is meant by "sufficiently large" is given in Section 3.1 and robustness analysis around this definition is provided in Section 4.4.

over short intervals (2 or 5 minutes) and show that there are significant order imbalances in days when the news release contains surprising inventory-level information. This pertains when the actual stock level is higher than expected (a positive surprise). The bulk of order imbalances occurs around the beginning of the open outcry trading session when liquidity is sufficiently high.

Our results can be taken as providing preliminary evidence that the inventory level released by the DOE each Wednesday is known by some market participants who are able to benefit from their insider position to make money with the news. More generally, our results call into question the overall informational efficiency of the most liquid commodity market in the world. We should, nevertheless, be careful in interpreting these findings. While our results are consistent with the presence of informed trading, they do not explicitly demonstrate it. In particular, some traders may have superior ability in either predicting the inventory level to be released and/or in analyzing the ongoing information flow about oil supply and demand conditions.[8]

The rest of the paper is organized as follows. The next section reviews the issue of insider trading in the specific case of commodity markets. Section 3 presents the price and inventory data and provides preliminary evidence of the diffusion of private information on the oil price before the official release time. Section 4 is then devoted to the empirical analysis, where order-imbalances are formally related to surprises. The last section concludes and discusses the implication of our findings, as well as avenues for future research.

2. INSIDER TRADING IN COMMODITY MARKETS

Grossman (1986) discusses the potential interest in insider trading in futures markets. On the one hand, insider trading can be liquidity-enhancing but can also, on the other hand, reduce liquidity and markedly affect the viability of futures markets. Leland (1992) corroborates these effects, adding that insider trading does help to integrate information into prices. Outside investors, nevertheless, can lose significantly. John and Lang (1991), building on early work by Pettit (1972), analyze the impact of earnings announcements in the stock market.[9] More recently, Hirshleifer et al. (1994) and Brunnermeier (2005) have developed theories of the utilization of private information in trading and conclude that short-lived informational advantages can lead to significant profits for insiders.

These high potential profits are naturally a source of concern for regulators. Indeed, "insider trading" is generally regarded as an illegal activity. However, this term covers both illegal and legal trading activities, depending on the nature of the market (equities, commodities) and regional trading rules. In equity markets, legal insider trading refers to corporate insiders (officers, directors or employees) trading their own securities within the boundaries of company policy and regulations governing overall trading. For instance in the U.S., corporate insiders must report their trades to the SEC. Insider trading in equity markets is broadly prohibited in all countries with stock markets. Insider-trading laws were first established in the United States (1934), then in France (1967) and finally appeared much later in some developed countries such as Germany (1994).[10]

8. Some traders may benefit from better due diligence, which is now very sophisticated. For instance, Verstein (2016) reports the use of helicopters with infrared cameras flying around storage facilities in Oklahoma in order to estimate oil reserves.

9. Earnings are, of course, one of the most important items of news for individual stock prices, and have been the subject of intense research in financial economics in recent years.

10. See Bhattacharya and Daouk (2002) for a survey of insider-trading law enactment and their different enforcement across the world. See also Bhattacharya (2014) for a general discussion of insider trading in equity market.

In commodity-futures markets, the illegal nature of insider trading is less obvious than in equity markets. It is clear that having private information can give a trader an unfair advantage in commodity futures markets. If the trader hears about an important event before the public, he holds a short-lived information advantage from which he can possibly profit by for instance selling short in the hope of buying more cheaply later. But it is not because this is unfair that it is illegal. Actually, insider trading using misappropriated governmental information remained legal until 2010, and insider trading on information obtained outside of the government is still allowed on commodity futures markets. The reason for the latter is that futures markets are hedging markets: their purpose is to protect buyers and sellers from unexpected price movements which represent commercial risk. As hedging decisions are linked to commercial positions that potentially affect commodity prices, it seems difficult to prohibit insider trading on information obtained outside of the government. In other words, the commercial risks depend on material information that hedgers hold. As such, the prohibition of insider trading would be in opposition to the essential nature of commodity futures markets.

This difference between securities and commodity futures probably explains why the U.S. only recently banned insider trading using non-public information from government sources in commodity futures market, with the approval of the U.S. Financial Reform Law in July 2010.[11] This post-2008 reform includes a section dealing with insider trading using data on commodities that practitioners used to coin the "Eddie Murphy rule".[12] This section of the 2010 Financial Reform Law illustrates the effort to standardize CFTC and SEC rules, but received a cold reception from commodity traders for two main reasons. First, they were concerned that the wording of the Law would prevent them from trading on their own information that they had previously reported to the government (USDA, DOE and CFTC) and which was not yet released. Second, they fear that government analysts would be prevented from answering questions from private-sector analysts and traders. Due to the nature of commodity futures markets, the proposed legislative text has been tweaked in order to prevent curbs on information exchange.

Despite there being no historical evidence of USDA or DOE leaks in recent decades, the "Eddie Murphy" rule serves the market and public by protecting market participants and promoting market integrity. There have, however, been past experiences of insider-trading scandals in commodity markets. The most notable one dates back to 1905 and involved a trader and a USDA statistician. Since this scandal, weekly and monthly report preparation has been increasingly secured by the USDA: locked doors, closed window shades, armed guards, and criminal penalties for staff who leak. The EIA has also adopted increasingly strict procedures since the last mistake of May 29th 2008. At that time, the oil price was $130 a barrel and the EIA briefly released its weekly inventory report online before the scheduled time. Warned by web robots, informed traders profited from this mistake and the data quickly spread via instant messages. The EIA website was recording 5,000 hints a second around the time of the report release. In the end, no traders were punished as this was a mistake by the EIA.

According to some analysts, the probability of information leakage from government offices such like the USDA or the DOE is extremely slim (Futures Magazine, 2010). However, given that some Fed officials were recently concerned by the suspicious use of insider information (Wall

11. This Financial Reform Law is over 2,000 pages long and represents a sweeping attempt to prevent future financial crises.

12. This refers to the film "Trading Places" where two commodity brokers, Eddie Murphy and Dan Aykroyd, make a profit on the frozen orange juice market using a stolen orange crop report from the U.S. Department of Agriculture (USDA).

Street Journal, 2016), information leakage from the DOE remains, in the light of our results, a concern.

3. DATA AND PRELIMINARY DATA ANALYSIS

Our empirical analysis requires two types of data: information on inventory announcements and market expectations, and oil futures prices at high-frequency. Our choice of the January 2007–October 2014 period is dictated by the electronic trading in Globex from September 2006 onwards, thereby making the nature of the market very different from this date.[13] We thus decided to exclude the period before January 2007.

3.1 Inventory announcements, expectations and surprises

Information on the inventory level is generally released each Wednesday at 10: 30 a.m., except when the Wednesday corresponds to a holiday—in which case the announcement is made on the Thursday or possibly the Friday. The release is made by the U.S. Energy Information Administration (EIA), which is the statistical and analytical agency within the U.S. Department of Energy (DOE). This weekly announcement is coined the "Weekly Petroleum Status Report" (WPSR), and includes many figures relating to the oil market such as field production, imports and exports, inputs and production at refineries and blending terminals, production from gas-processing plants and fractionators, and inventories at refineries, terminals, pipelines, and fractionators. The report covers the 50 States and the District of Columbia.[14] We here only consider the change in the total petroleum stocks for the U.S., excluding Strategic Petroleum Reserves. This change in stocks is calculated using company submissions for the week ending at 7: 00 a.m. the preceding Friday.

It is important to note here that the EIA does not pre-release/embargo this data to any outside entities.[15] As such, our case is different from that in Bernile et al. (2016), where Federal Open Market Committee (FOMC) scheduled announcements are pre-released to media companies for analysis before public release. Our investigation then covers a longer period—several hours—before the announcement and is not confined to any predetermined period.

We define surprises using the weekly Bloomberg's survey that is conducted with the participation of a dozen experts in the oil industry. For the period February 7th 2007 to October 22nd 2014, we have data on 402 announcements with a mean number of experts of 13.14. The minimum and maximum number of experts is 8 and 19, respectively, making the calculation of statistical values feasible. Over our study period, 55 analysts representing 49 firms that are invested in oil trading delivered forecasts. We also collect the exact time release, the date and individual forecasts from experts from the Bloomberg database.[16] This allows us to measure the gap between the prediction and the actual value, and thus whether to classify an announcement as a surprise. Table 1 reports the

13. The recent contribution by Raman et al. (2016) emphasizes the change in trading practices after the start of the electronic Globex platform.

14. Further information about the full content of the WPSR can be found on the EIA website at: http://www.eia.gov/petroleum/supply/weekly/pdf/wpsrall.pdfhttp://www.eia.gov/petroleum/supply/weekly/pdf/wpsrall.pdf.

15. We thanks employees at the EIA for confirming this point. Our results about price and trading patterns before announcements are then not the product of possible leakage due to pre-release.

16. In a few instances, the release is made at 10: 35 a.m. or 11: 00 a.m. We take this into account in our analysis and analyze price and trading relative to the announcement time. In some Figures, we report time rather than time relative to news release for clarity. The reader should be aware that in the case of delayed announcement, the reported time is not exact.

Table 1: Summary statistics of U.S. oil inventory actual values and analysts' forecast errors

	N	Mean*	Std dev.*	Median*	Min*	Max*
Actual values	402	124.97	3846.58	466.50	–11120.00	10013.00
Median estimates	402	241.73	1740.00	750.00	–4950.00	3200.00
Forecasting errors	402	–116.76	3255.74	94.50	–10120.00	9033.00
Absolute forecasting errors	402	2533.28	2048.39	1990.50	11.00	10120.00

Notes: * Thousands bbl.
The table reports sample statistics of oil inventories for the period between February 7th 2007 and October 22nd 2014. "Actual values" refer to the EIA actual oil inventory data, "Median estimates" are the median forecasts from the weekly Bloomberg survey, "Forecasting errors" are the difference between the actual value and the median forecast of each weekly oil inventory, and "Abs forecasting errors" are the absolute value of this difference.

Table 2: Summary statistics for U.S. oil-inventory surprises

	Year	2007	2008	2009	2010	2011	2012	2013	2014	Total
	No. of news items	47	53	51	52	52	52	52	43	402
3σ	NoSUR	37	40	40	43	40	41	39	32	312
	SUR	10	13	11	9	12	11	13	11	90
	PosSUR	3	8	5	4	5	6	5	7	43
	NegSUR	7	5	6	5	7	5	8	4	47
	% NoSUR	78.72%	75.47%	78.43%	82.69%	76.92%	78.85%	75.00%	74.42%	77.61%
	% SUR	21.28%	24.53%	21.57%	17.31%	23.08%	21.15%	25.00%	25.58%	22.39%
	% PosSUR	6.38%	15.09%	9.80%	7.69%	9.62%	11.54%	9.62%	16.28%	10.70%
	% NegSUR	14.89%	9.43%	11.76%	9.62%	13.46%	9.62%	15.38%	9.30%	11.69%
4σ	NoSUR	40	46	46	48	47	47	46	37	357
	SUR	7	7	5	4	5	5	6	6	45
	PosSUR	3	4	2	2	1	4	2	5	23
	NegSUR	4	3	3	2	4	1	4	1	22
	% NoSUR	85.11%	86.79%	90.20%	92.31%	90.38%	90.38%	88.46%	86.05%	88.81%
	% SUR	14.89%	13.21%	9.80%	7.69%	9.62%	9.62%	11.54%	13.95%	11.19%
	% PosSUR	6.38%	7.55%	3.92%	3.85%	1.92%	7.69%	3.85%	11.63%	5.72%
	% NegSUR	8.51%	5.66%	5.88%	3.85%	7.69%	1.92%	7.69%	2.33%	5.47%

Notes: The table shows the sample statistics for oil-inventory surprises (SUR) over the period February 7th 2007 to October 22nd 2014. SUR refers to the actual inventory announcement being +/–3 or 4 standard deviations away from the median forecast of the weekly Bloomberg survey. A positive surprise (PosSUR) is defined as a forecasting error over +3 or +4 standard deviations and a negative surprise (NegSUR) as a forecasting error over –3 or –4 standard deviations. NoSUR refers to all the other cases where the actual inventory is in the range between the lowest and highest economists' estimates, or not much over this range.

summary statistics for the actual values, forecasts and forecast errors. As can be seen, the forecast is, on average, slightly optimistic and the variability of realized values and forecasting errors is fairly large.

We rely on these survey forecasts, as there is no traded instrument that would allow us to infer market expectations (as in the case of interest rate futures for FOMC meetings). In our baseline analysis, we define a surprise as an actual value that is over three standard deviations from the median forecast in the Bloomberg survey: we call these '3σ surprises'.[17] At the end of the empirical section, we show that our results are robust to alternative definitions of surprises.

Table 2 shows the summary statistics for surprises. In the total sample of 402 announcements over the February 2007–October 2014 period, there are 90 surprises (22.39%), of which 43 are positive and 47 are negative. This is sufficient to carry out a statistical analysis of surprises. The

17. Our definition is different from that in Halova et al. (2014). The latter define a surprise as the difference between the actual value and the median forecast, while we define the surprise as a categorical variable which takes the value one in case of a surprise and zero otherwise. In other words, while Halova et al. (2014) estimate the magnitude of the surprise we focus on *whether* the announcement is a surprise or not.

Figure 2: Number of 3σ surprises vs. no surprise by week-of-the-year

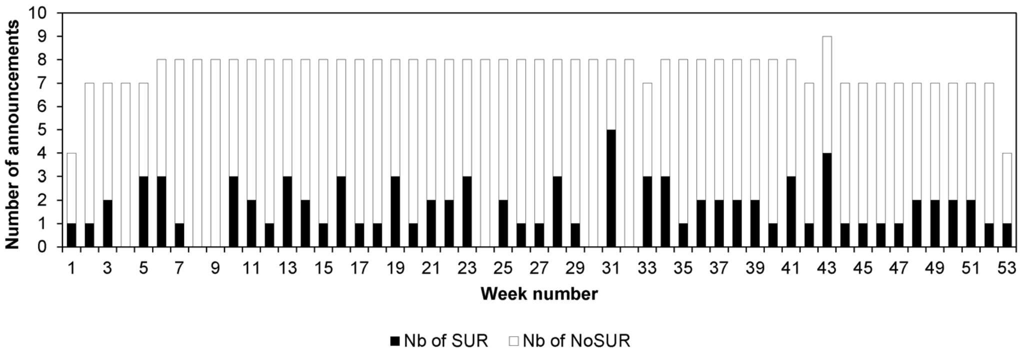
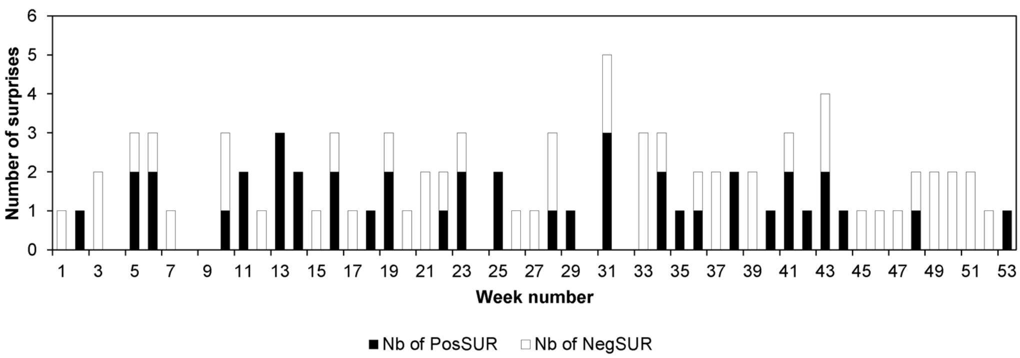


Figure 3: Number of 3σ positive surprises vs. negative surprises by week-of-the-year



number of yearly surprises in Table 2 is quite stable, as is the ratio of yearly positive to negative surprises. Each year, there are 3 to 8 positive or negative surprises. We also do not see any particular trend over the sample, with surprises not being clustered in particular years. To further examine the occurrence of surprises, Figures 2 and 3 respectively plot the number of surprises and the number of positive vs. negative surprises by week number. Again, there is no particular pattern: surprises do not appear in certain periods of the year, and neither do positive or negative surprises. We thus conclude that the econometric analysis does not need to consider year or week effects, or any seasonal correction, to take into account particular time patterns in surprises, despite the well-known seasonality in inventory levels over the year.

An alternative to the EIA release is the inventory news reported by API every Tuesday afternoon at 4: 30 p.m.[18] The API announcement takes place before the EIA release but after the experts have been interviewed by Bloomberg to carry out its survey. As such, the informational content of the API report might affect the surprise or non-surprise characteristic of the EIA announcement the next day. This may not be very likely, as recent research (Ye and Karali, 2016) has found that the API report has only little informational content.[19] Note that, in addition, any informational content

18. If Monday is a Federal holiday, the reports are released on the Wednesday afternoon.

19. This finding is supported by oil-market practitioners who are doubtful about the value added of the API survey. In Bloomberg (2013), the chief market strategist at Confluence Investment Management in St. Louis says: "You can go to jail if you don't contribute to the DOE and if you contribute bad numbers they can sue you. The API asks its members to contribute. The members sometimes don't, and sometimes they give the API incomplete numbers." The article further mention that "Valero Energy Corp., the San Antonio-based biggest independent refiner in the U.S., is not a member of the API and doesn't

in the API report would mean that some of the announcements that we categorize as surprises are in fact not so, thereby having a marginal effect on our overall results. Our results are thus conservative with respect to the definition of surprises.

3.2 WTI futures prices

Our price data are the transaction prices for the WTI futures (ticker: CL) quoted on the NYMEX—part of the Chicago Mercantile Exchange (CME) Group from 2008 onwards—for the period covering all the announcements. Futures contracts used to be traded both on the electronic market—electronic trading began in September 2006—through CME Globex and ClearPort, and via an open outcry session.[20] The open outcry session used to cover the 9: 00 a.m.–2: 30 p.m. period from Monday to Friday, while the electronic market was open 6: 00 p.m.–5: 00 p.m. from Sunday to Friday. All WTI futures contracts are quoted in U.S. dollars per barrel, and the contract unit is 1,000 barrels with a delivery point at Cushing, Oklahoma.[21]

We choose WTI futures for two reasons. First, WTI and Brent futures continue to be the world benchmark for crude oil (Elder et al., 2014), although this status is now called into question in recent research using high-frequency (intraday) data (see Liu et al. (2015) and the references therein). Second, together with Brent traded on the ICE, the WTI today is the world's most liquid crude oil contract (both contracts trade around 150 million units a year) and was twice as liquid as the ICE-Brent over the 2007–2014 period (see Halova Wolfe and Rosenman (2014)). This is also the most-traded commodity futures over the world in value. This liquidity is also visible in the number of daily transactions. Over our analysis period, the daily number of transactions on the front-month contract is about 90,000, ensuring reasonable liquidity at all times of the day.[22] As such, WTI futures should attract informed traders who are strongly incited to trade in deep markets to limit the price impact of their orders—if the transaction has a significant impact on the market price, the informational advantage could be unprofitable—and to enjoy low transaction costs. We then consider WTI futures for their liquidity and the ability of most traders to hold positions at competitive cost in this market.

As is common for the analysis of the futures prices of a given commodity, we use a continuous series of futures prices by considering the front-month futures contract and switching to the next front-month contract once the latter's trading volume exceeds the former. As such, we are certain to look at the most liquid WTI contract available for trading in the market at every point in time. In addition, the front-month contract is the quickest to reflect available information and to react to new information, thereby being the most desired way in which informed traders can benefit from private information.

To gauge liquidity in days with announcements, Figure 4 plots the volume for days with no surprise (top panel), days with positive surprises (middle panel) and days with negative surprises (bottom panel). This Figure shows the average number of contracts traded in 5-minute intervals

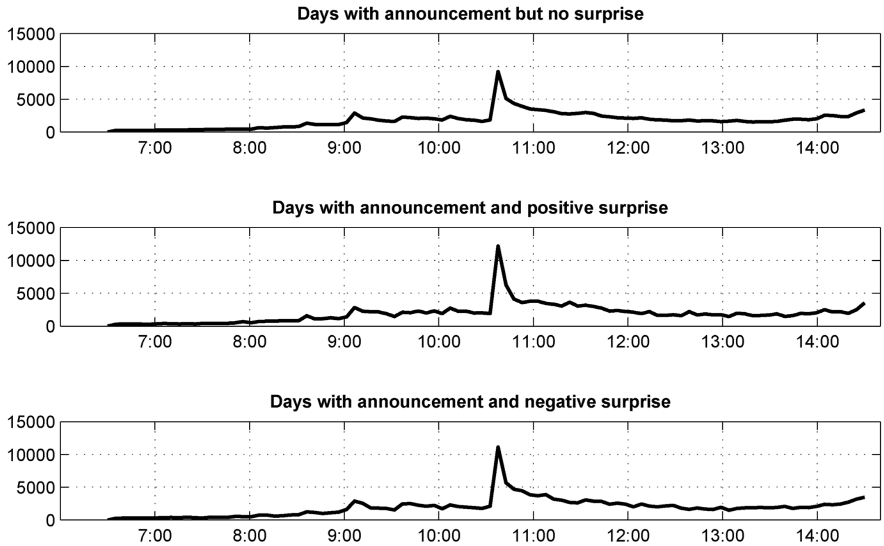
participate in the weekly survey. Valero produced 910,000 barrels a day of distillate fuel, including heating oil and diesel, in the second quarter [2013], according to the company's earnings release. That's about 20 percent of the 4.66 million barrel a day U.S. output reported by the EIA".

20. The open outcry session ceased on July 7th 2015, which was considered to be a disappointing change by historical traders (Financial Times, 2015).

21. Further specifications on WTI futures contracts can be found on the CME website at: http://www.cmegroup.com/trading/energy/crude-oil/light-sweet-crude_contractSpecs_futures.htmlhttp://www.cmegroup.com/trading/energy/crude-oil/light-sweet-crude_contractSpecs_futures.html.

22. 850,000 WTI futures and options of all maturities are traded daily. The total open interest is over 3 billions barrels.

Figure 4: Volume (number of contracts) by 5-minute interval.



during the day. All three panels reveal the same pattern: a notable rise in trading activity at around 8: 30, a larger one at 9: 00 (corresponding to the opening of the open outcry session), then a huge spike at the time of the news release and slowly-decreasing trading activity ending with a last period of relatively intense trading corresponding to the final minutes of open outcry.[23] The huge number of traded contracts at the time of the announcement shows the importance of the EIA release in resolving the uncertainty surrounding the inventory level. We can also see from Figure 4 that volume is, on average, higher on days with surprises, as market participants trade in response to the new inventory level that has just been released to adjust their positions.

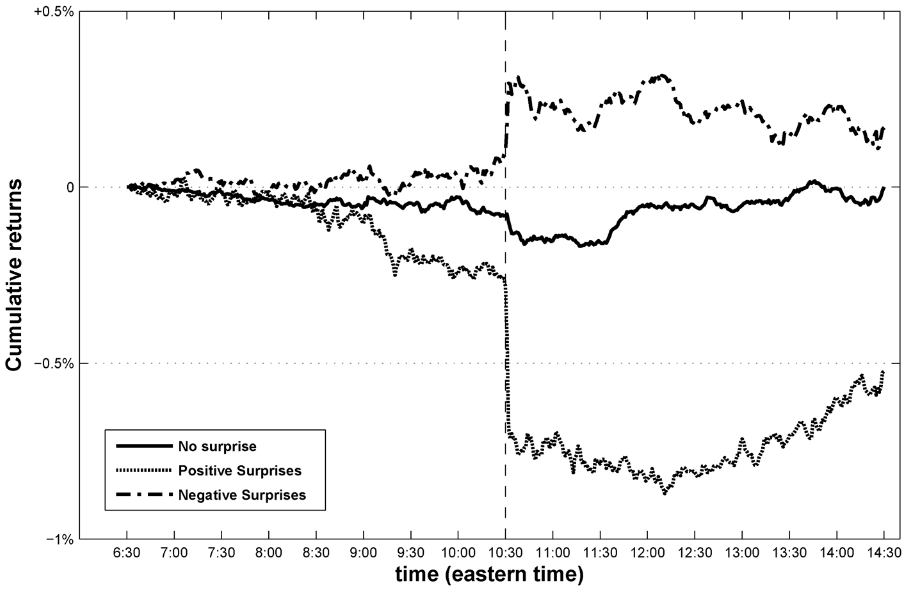
3.3 The return pattern around announcements

Our first analysis of the data focuses on the return patterns of WTI futures series in days with inventory announcements. Figure 5 plots the average cumulative returns from 6: 30 a.m. to 2: 30 p.m., distinguishing between days with no surprise, days with a 3σ positive surprise and days with a 3σ negative surprise. A number of comments can be made. First, there is no particular pattern in days with no surprise, except for a small fall in price at the time of the announcement and during the two hours before the announcement. This can be explained by our definition of a surprise, which is not perfect by nature. An inventory level in line with expectations may surprise market participants whose forecasts are different from the consensus. The negative reaction of the oil futures price in no-surprise days is due to an asymmetric feature that we will elaborate on below: the impact of positive surprises is much larger, on average, than that of negative surprises.

Second, in days with positive surprises we observe a clear run-up in returns starting at around 8: 30 a.m., i.e. two hours before the official release of the EIA inventory level. The pattern is then similar to that in Hendershott et al. (2015) and Bernile et al. (2016), who also find increasing cumulative returns ahead of news. At the time of the announcement, this anticipation leads to an av-

23. For days with no announcement, the volume pattern is similar to that found in the literature on market microstructure, i.e. higher trading volume at the start and end of the trading session and a U-shaped relationship between the start and end, consistent with Admati and Pfleiderer (1988).

Figure 5: Cumulative returns in announcement days.



erage fall in returns of 0.25%, which is to be compared with the 0.05% figure in Bernile et al. (2016) before the FOMC announcement.[24] Our result is in line with Halova Wolfe and Rosenman (2014) or Ye and Karali (2016), who also identify large price variations around surprising announcements.

Third, days with positive surprises are characterized by a large average price drop of about 0.5%—traders take short positions as inventories are larger than expected—which is partly corrected in the hours following the news release. Four hours later, the drop is half as large, i.e. 0.25%. In other words, the futures price over-reacts to the announcement. Over-reaction is the subject of intense research in behavioral finance. Recent contributions have attributed over-reactions to the general sentiment in financial markets, while earlier work argued for over-confidence, positive feedback trading or herding.[25] In our context, over-reaction may be viewed as an *efficient inefficiency* (Pedersen, 2015), as it is not clear how it could be robustly exploited for trading purposes. It, however, contrasts with the underlying assumption in Moskowitz et al. (2012) that time series momentum—persistence of returns—in financial markets is due to initial under-reaction and delayed over-reaction.

Fourth, days with negative surprises do not show any particular pattern in the pre-announcement period. At the time of the news release, we then observe a positive jump—inventories are lower than expected—which effect is much smaller in size than its counterpart for positive surprises. Specifically, the average rise is about 0.15%, which is three times smaller than that when inventories larger than expected. Negative surprises seem to have then only a limited impact on oil futures prices. Again, there is an over-reaction in the hours following the announcement, as for positive surprises, with the initial price jump being absorbed by, on average, 2: 30 p.m., i.e. at the end of the open outcry session.

24. Note, in addition, that our data include 43 positive surprises over a seven and a half year period, while the sample in Bernile et al. (2016) includes only 25 surprises over the period September 1997–June 2013, i.e. about 15 years. This highlights the potential profit for insider trading around EIA news in the oil futures market as well as the importance of the phenomenon highlighted here.

25. We refer the interested reader to the survey in Barberis and Thaler (2003) for an exposition of the existing literature on, among other phenomena, over-reaction. This interesting issue is beyond the scope of the present paper.

Overall, it is clear that, *i)* for positive surprises, there is a significant run-up from 8: 30, *ii)* prices respond to surprises, meaning that news really is news and is not common knowledge, and *iii)* price over-reacts to surprises.

4. EMPIRICAL ANALYSIS

This section first presents the order-imbalance method and then the empirical results and robustness analysis with respect to alternative definitions of surprises.

4.1 Empirical method

To see whether there is trading based on private information regarding the EIA inventory announcement, we consider trading activity in the futures market in the hours before the news release. Assuming that informed traders need immediate execution to exploit their informational advantage, we imagine that they will trade at the best price offered by their counterparts. It is then common to measure informed trading by order imbalance *OI*, defined as:

$$OI = (B - S) / (B + S) \tag{1}$$

where *B* is the volume of buyer-initiated trading and *S* the volume of seller-initiated trading over a given period of time. Volume can either be defined as the number of trades or the dollar trading volume, producing *OIN* and *OID* respectively. When there is considerable variability in order size, it is better to work with *OID* so as not to overweight small trades. Hence, our baseline analysis will use *OID*.[26] The presence of informed trading will be revealed in *OI* that are significantly higher on days of surprises. Large order imbalance is a strong indication, although not a formal proof, of trading based on private information.

Our data for the WTI futures price do not indicate whether the transaction arises from a buyer or a seller. As is common for such data, we rely on the tick rule to classify transactions as buyer or seller-initiated. When the transaction price is above [below] the previous transaction price, we consider the transaction as being buyer [seller] -initiated.[27] One issue with our data is that they are stamped only to the second, meaning that several transactions can occur in one second. We follow Bernile et al. (2016) in calculating the volume-weighted price for the second of interest, and then rely on the tick rule to classify the bulk of transactions in this second.

4.2 Main findings

Figures 6 and 7 plot the *OID* computed over short intervals of 2 and 5 minutes, respectively, for the periods two and a half hours before and after a typical announcement.[28] In the top panel, we plot the *OID* for days with announcements the value of which was in line with expert

26. We have replicated the full empirical analysis using *OIN* as the measure of informed trading. The results, similar to those using *OID*, are not reported here but are available on the author's website (https://sites.google.com/site/benoitsevi/ https://sites.google.com/site/benoitsevi/).

27. Bernile et al. (2016) discuss the use of the tick rule in the context of the literature on empirical market microstructure. We refer the interested reader to their footnote 11 for further explanations.

28. We have also calculated *OIDs* for one and ten-minute intervals and obtain similar patterns. Extending the analysis period also produces similar results.

Figure 6: Order imbalances based on dollar trading volume considering 3σ surprises (2 minutes).

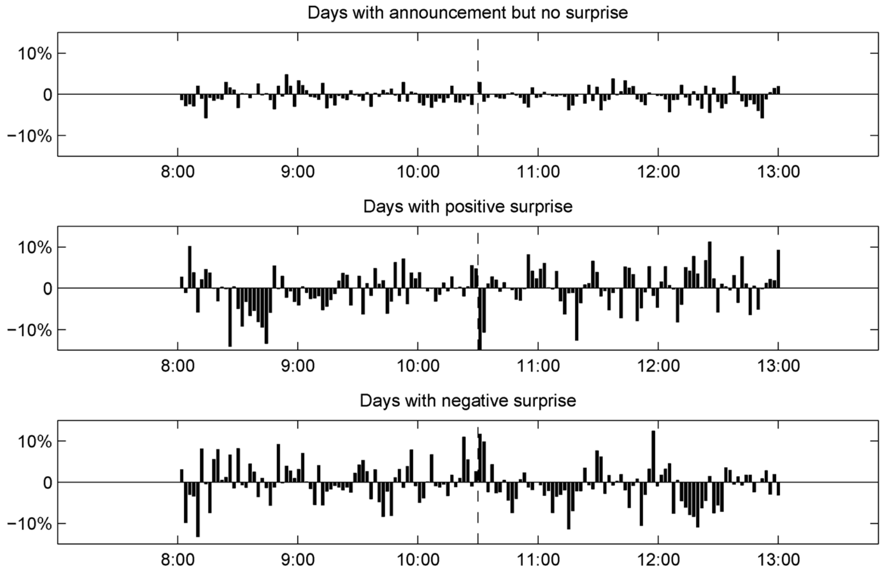
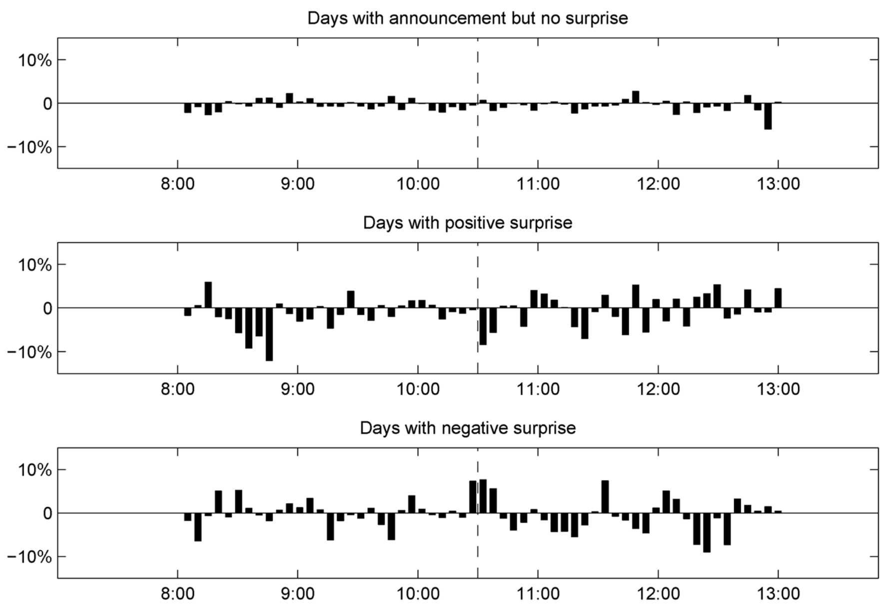


Figure 7: Order imbalances based on dollar trading volume considering 3σ surprises (5 minutes).



expectations. In the middle and the bottom panel, we analagously plot the 2 and 5-minute *OID* for positive and negative surprises, respectively.

On days without surprises, *OIDs* are small over the whole period, with no particular pattern. In contrast, on days with surprises, either positive or negative, we observe large *OIDs* immediately after the announcement. This finding confirms our conclusion from the observation of the cumulative returns (Figure 5) that news release has a large impact on the oil futures price when the inventory level is different from the expected value. Note that these large *OIDs* are particularly relevant in light of the huge trading volume ($B+S$) in the oil futures market every Wednesday at 10: 30 a.m. (see Figure 4). Admati and Pfleiderer (1988) set out a theory explaining the clusters in trades during the trading session. This concentration of trading comes from the strategic behavior of liquidity and informed traders who have mutual incentives to trade at the same time. The spike in trading volume at the time of announcement, either for surprises or not, is also consistent with the search for the resolution of uncertainty. In summary, the news release is an event for the oil market, and market participants trade heavily to adjust their positions at the time the inventory level is made public.

For negative surprises (the bottom panels), the *OIDs* are much larger than for days with no surprise, but appear largely random: we cannot identify any particular pattern either in the pre- or the post-announcement periods. Conversely, in days with positive surprises, we observe *OIDs* that are mostly in line with the subsequent announcement surprise (buyer-initiated orders). In particular, in the 8: 30–9: 30 range, there are almost no positive *OID*s, which is indicative of trading on private information. Overall, the order-imbalance pattern is very consistent with the returns patterns plotted in Figure 5. We also conclude that the order imbalance somewhat predicts the content of the news to be delivered.

During the post-announcement period, while *OIDs* are small in days with no surprises, we observe the opposite pattern for days with positive and negative surprises. In the former case, the *OIDs* appear to be mainly positive—buyer-initiated transactions—which is in line with the over-reaction suggested in Figure 5. Similarly, *OIDs* are mostly negative—seller-initiated transactions—when there are negative surprises, which is also consistent with over-reaction. It should be noted, however, that large *OIDs* are partly due to lower liquidity—small ($B+S$)—in the post-announcements periods, as emphasized in Figure 4.

4.3 Statistical significance

To gauge the statistical significance of the patterns in Figures 6 and 7, we run the following regression:

$$OI_t = \alpha + \beta.I(SUR_t > 3\sigma) + \gamma.I(SUR_t < 3\sigma) + \varepsilon_t \qquad (2)$$

We regress the *OID* for day *t* over a given time interval on two indicator variables: the first for positive surprises and the second for negative surprises. In this first set of regressions, we consider '3σ surprises'. Various time intervals for the *OID* are considered in our analysis ([–240,–120], [–240, 0], [–120,–60], [–120,0], [–60,0], all times are in minutes). Such a partition of the four hours before the announcement should allow to detect periods where order imbalancess are significantly different from zero. In particular, we expect the *OIDs* to be significantly related to the indicator variables, at least in the case of positive surprises. The coefficient estimates appear in Table 3. Estimation is by ordinary least squares (OLS).[29]

The results clearly indicate a significant association between the dummy for positive surprises and the average *OID* over the 8: 30–9: 30 period. The *t*-statistic is large (3.154), revealing the existence of buyer-initiated orders before the public release of inventory levels that are higher than expected. For the extended period 8: 30–10: 29, the relationship between the dummy and *OID* also appears, but is less significant. When we extend the period over which the *OID* is calculated, we lose

29. In preliminary work, we ran regressions with a dummy variable for days with an announcement, as in Bernile et al. (2016). This did not attract a significant estimated coefficient. We thus only report results for the surprise dummies. The extended results, which are qualitatively similar to those presented here, are available upon request.

Table 3: Ordinary least squares estimates for '3σ surprises'.

Event windows	Intercept	PosSUR	NegSUR	$\beta=-\gamma$
[–240,–120]	–0.639	0.630	0.135	0.284
	(–1.412)	(0.469)	(0.105)	
[–240,0]	–0.438	–0.568	0.300	–0.899
	(–1.747)	(–0.767)	(0.420)	
[–120,–60]	0.212	**–3.529**	–0.009	**–2.449**
	(0.522)	(–3.154)	(–0.008)	
[–120,0]	–0.221	**–1.758**	0.389	**–2.231**
	(–0.820)	(–2.304)	(0.588)	
[–60,0]	–0.628	0.433	0.717	–0.528
	(–1.886)	(0.458)	(0.778)	

Notes: t-statistics are reported in parentheses and estimates that are significantly different from zero at the 5% level are highlighted in bold. The last column reports the t-statistic corresponding to the estimate of the coefficient θ in the reparametrized model dedicated to test for the linear restriction $\beta=-\gamma$.

significance. In particular, the OID during the 4-hour pre-announcement period is not significantly linked with surprises. Similarly, considering the last hour before the news release only does not lead to significant estimates for the indicator variables. As such, we conclude that order imbalance is concentrated in the hour surrounding the opening of the open outcry session.

As an additional result, we report the test statistic for the null hypothesis $H_0 : \beta = \gamma$. To do so, we rewrite the model as:

$$OI_t = \alpha + (\beta + \gamma).I(SUR_t > 3\sigma) + \gamma.(I(SUR_t < 3\sigma) - I(SUR_t < 3\sigma)) + \varepsilon_t \quad (3)$$

or:

$$OI_t = \alpha + \theta.I(SUR_t > 3\sigma) + \gamma.[I(SUR_t < 3\sigma) - I(SUR_t > 3\sigma)] + \varepsilon_t \quad (4)$$

As such, the test statistic is the t-statistic of θ in the new formulated equation as the OLS estimator is known to be invariant to linear reparametrizations. The null hypothesis can be tested using the standard t-ratio on θ in the reparametrized model.[30] The t-statistic is reported in the last column of Table 3 where we observe that the estimates are significantly different for the 8: 30–9: 30 period and, to a lesser extent, for the 8: 30–10: 29 period.

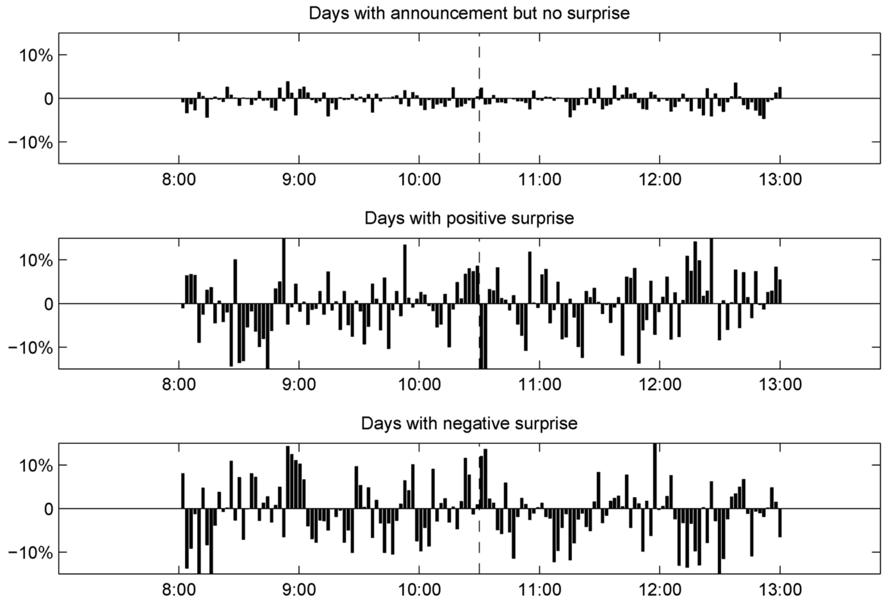
One important feature of our results is the asymmetry between positive and negative surprises. While we obtain statistically-significant estimates for inventories that are higher than expected, the estimates for lower than expected inventories reveal no abnormal order imbalance for any sub-period of the pre-announcement period. The question then arises as to why there is more order imbalance in case of positive surprises. We suggest that informed traders in the oil futures market face different situations when expecting good or bad news. In the case of good news, participants speculating on price drops and owning the commodity at the same time are naturally hedged. Conversely, when bad news is anticipated and the oil futures prices is expected to increase, speculation is more risky as hedging is not feasible.

4.4 Robustness analysis

In preliminary work, we considered a number of alternative definitions of surprises. First, we used the quite sophisticated surprises defined as in Bernile et al. (2016) and Ye and Karali

30. This test has the additional property to account for the covariance across the estimates.

Figure 8: Order imbalances based on dollar trading volume and 4σ surprises (2 minutes).



(2016). These definitions involve preliminary regressions and are prone to the generated-regressor problem but end up identifying the same surprises as our simple definition used throughout the paper. Second, we used the surprise definition as in Andersen et al. (2003), which is $(Act_t - For_t)/\hat{\sigma}_t$ where Act_t is the released value, For_t the predicted value and $\hat{\sigma}_t$ the sample standard deviation of the surprise component $Act_t - For_t$ over the past 100 weeks. Third, we experimented with surprises defined as realized values outside the range of forecasts. All the results are very similar to those in our baseline analysis.

To save space, we here only present the results when the surprise is defined as actual values that are over four standard deviations from the median forecast: these are coined '4σ surprises'. The number of surprises drops by about a half, as can be seen in the bottom panel of Table 2. Again, we do not identify any specific pattern over the years. The number of surprises by year is between 4 and 7. We end up with a total of 23 positive surprises and 22 negative surprises over the period of interest.

Order imbalances for 2-minute intervals is plotted in Figure 8, and is quite similar to that for 3σ surprises. There is order imbalance in the selling direction for positive surprises in the 8: 30–9: 30 period. We also note a cluster of notable buyer-initiated orders around 9: 00 in days with negative surprises.

The estimates for the regression using 4σ surprises appear in Table 4. The results are quite similar to those in Table 3, where surprises are defined less strictly. The *t*-statistics are, however, lower, possibly due to the smaller number (23) of positive surprises. For the period 8: 30 – 10: 29, we fail to identify any significant relationship between *OID* and surprises, either positive or negative. Moreover, the last column of Table 4 reporting the *t*-statistic for the test of the linear restriction $\beta = \gamma$ indicates that the estimated parameters are not significantly different at any horizon with this more conservative definition of surprises. Again, the small number of 4σ surprises may account for the difficulties to reach more significant results.

Table 4: Ordinary least squares estimates for '4σ surprises'.

Event windows	Intercept	PosSUR	NegSUR	$\beta=-\gamma$
[–240,–120]	–0.592	1.519	–0.694	0.802
	(–1.413)	(0.951)	(–0.298)	
[–240,0]	–0.446	–0.116	–0.278	0.113
	(–1.891)	(–0.126)	(–0.244)	
[–120,–60]	–0.053	**–3.243**	0.375	–1.511
	(–0.145)	(–2.051)	(–0.282)	
[–120,0]	–0.305	–1.685	0.121	–1.404
	(–1.219)	(–1.572)	(–0.152)	
[–60,0]	**–0.628**	–0.140	0.157	0.176
	(–1.980)	(–0.109)	(0.133)	

Notes: t-statistics are reported in parentheses and estimates that are significantly different from zero at the 5% level are highlighted in bold. The last column reports the t-statistic corresponding to the estimate of the coefficient θ in the reparametrized model dedicated to test for the linear restriction $\beta=-\gamma$.

5. CONCLUSION

This paper has provided evidence of a clear run-up price effect of about 0.25% and large selling-initiated transactions ahead of the EIA-DOE inventory release each Wednesday, when the level to be released is higher than expected. The significant order imbalance takes place around the opening of the open outcry session, when increasing liquidity facilitates discreet trading. In addition, at that time, the news release is not too distant thereby limiting the risk for potential informed traders that other news enter the market. As such, our results derived from high-frequency data are robust to alternative definitions of surprises and are consistent with potential informed trading.

Importantly, however, we are not able to formally conclude that private information is used by insiders, as our data does not allow us to identify the channel by which this information would enter the market. Indeed, an alternative explanation for our findings is that some market participants have better information on which to form expectations or have better ability to process public information than analysts responding to Bloomberg's survey do. Despite there is no compelling evidence about such explanations, we definitely cannot rule out that possibility.

Despite our results remain open to interpretation, our analysis has a number of implications with respect to the Weekly Petroleum Status Report. First, it raises the question of whether EIA lock-up practices are really secure. This calls into question the overall security of government data raised recently in numerous media (Wall Street Journal, 2013, 2016). Second, our work also has regulatory implications, as we might wish for the worthier monitoring of oil markets around announcements to better assess the presence of insider trading. Third, the time chosen for the announcement could also be changed to limit the potential for insider trading in times of high liquidity. For instance, an announcement at 8: 30 a.m. might help to moderate the activity of insiders in the oil futures market in the pre-announcement period.

One limit of our work, which also is a possible avenue for future research, lies in the transactions that we cannot relate to traders. The use of data with the type of traders, or possibly their identity, at the tick-data level would reveal new features. Existing work such as Phillips and Weiner (1994) uses trade-level data to gauge the profit for various types of traders in the North Sea oil forward market. Using individual trade data, the authors are able to identify the types of traders that make profits, and so test the theory of insurance or information in forward trading. In the same vein, Ederington and Lee (2002) use CFTC-type data on traders' positions in the heating-oil futures market to gauge the hedging and speculative behavior of various agents. Both contributions have valuable data on trades, making their analysis innovative with respect to trader behavior in oil markets. However, they do not investigate the response of prices and/or volume to news.

Other potential lines of research include the analysis of informed trading for alternative oil-related assets such as options on futures, stocks of oil companies or the FX rates of oil-exporting countries. We have also not exploited the apparent over-reaction to news. In the vein of papers dealing with short-term contrarian strategies based on news, the economic value of these patterns could then be estimated (Jegadeesh and Titman, 1993, 1995).

ACKNOWLEDGMENTS

We wish to thank Philippe Bernard from Université Paris-Dauphine for helping us with the data from Bloomberg. We thank Rob Merriam and Mark Mayo from the Energy Information Administration (EIA) at the Department of Energy (DOE) for useful discussions about the process governing the release of the Weekly Petroleum Status Report. We wish to thank Marketa Halova Wolfe for useful comments about Bloomberg's survey of oil-market participants. Participants at the 2015 Energy and Finance Conference at Cass Business School, the 2016 International Symposium on Energy and Finance Issues at IPAG Business School, the 2017 Commodity Markets Winter Workshop in Lillehammer, the 2017 Financial Risks International Forum, the 2nd Hellenic Association of Energy Economists International Conference in Athens (2017) and the Commodity and Energy Markets Conference Annual Meeting in Oxford (2017) are also gratefully acknowledged as well as Gennaro Bernile, Eleni Gousgounis, Erik Haugom, Jianfeng Hu, Sebastian Jaimungal, Lutz Kilian, Delphine Lautier, Yannick Le Pen, Gabriel Powers, Marcel Prokopczuk, Bertrand Villeneuve and Chardin Wese Simen and two anonymous referees for useful comments that helped to improve the paper. We are, of course, responsible for all remaining errors. Both authors acknowledge financial support by Foundation "Europlace Institute of Finance" and French Energy Council.

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