Does the oil market learn about analyst accuracy?

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ABSTRACT

We study the relationship between analyst supply forecasts and futures returns in the crude oil market. We find that, in the 15 minutes immediately following the revelation of forecast errors, prices rise (fall) when forecasts have been too high (low). Investors seem to react more strongly to the forecasts of analysts who have been most accurate in the past, indicating that they may learn which analysts are best. Specifically, prices adjust more strongly to the initial forecasts issued by accurate analysts and then correct more aggressively to their forecast errors when actual supplies are announced.

Keywords: Analyst, forecast, learning

JEL: D83, G12, G14

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Introduction

Our study seeks to contribute to the discussion of the value of financial analysts and investors' reactions to information discovered by them. Specifically, we address whether the market reacts to analyst information, whether analyst forecast error affects price, and whether the market learns over time which analysts are most accurate. We select as our test setting the crude oil futures market. Because of the economic size of this market and its unprecedented activity in recent years, financial analysts' forecasts of oil supply (and hence equilibrium price) may have a substantial economic impact and potentially play an important role in price determination. Furthermore, the crude oil futures market centers around a single underlying asset that all analysts seek to forecast. On the other hand, equity analysts must study a variety of stocks, making it difficult to compare the informational advantages of one analyst to another. In this simpler but economically significant experimental setting, we find that analyst supply forecasts significantly impact the price of crude oil products. Forecast errors are likewise reflected in price significantly and do so within 15 minutes following the announcement of true supply. This impact overrides that which arises from the supply announcement itself. We also find that more accurate analysts generate a larger reaction, inducing larger price movements in response to forecasts and larger corrections when forecast errors are realized. In essence, we find that information generated by analysts is important to price determination and that the market seems to learn which analysts are best.

Much empirical work has been aimed at examining the sensitivity of markets to analyst forecasts and forecast errors. Post-announcement price drift is well documented in the earnings forecasting literature; indeed, Kanungo (2004) finds that stock prices are more reactive to forecast errors than to earnings themselves. Stickel (1992) further finds that those analysts with the best ex-ante reputations have the largest market impact. In his paper, he concludes that market participants do know the identities of the best analysts and respond accordingly. However, he finds that this is only true in upward revisions and not in downward ones perhaps owing to transactional difficulties in shorting. Sorescu and Subrahmanyam (2004) similarly finds that more experienced analysts receive the largest price reactions, particularly in the long-run where as Chen, Francis, and Jiang (2005) determine that both the accuracy of earnings forecasts and length of track record increase market reactive-ness, though that study focuses on first-time analysts. Mikhail, Walther, and Willis (2001), on the other hand, find the opposite. Splitting firms up by coverage, they find that firms covered by more accurate, more experienced analysts show less pronounced post-announcement drift. In summary, though post announcement drift is well documented, the issue of whether investors learn about the accuracy of analysts elicits less agreement. In these studies, however, idiosyncratic events affecting specific equities in the cross-section may cloud conclusions.

Our study contributes to this discussion on several levels. As aforementioned, the crude oil futures market lacks many of the potentially confounding variables extant in studies of traded equities. First, crude oil futures traders can create long or short positions with equal ease and may do so without additional costs associated with the borrowing of securities. In addition, because all participants trade the same underlying, there are no firm-specific risk components that may complicate evaluations. Moreover, oil is a commodity whose price is determined principally from the balance of supply and demand.[1] Equities are claims to residual payments and hence derive value from a complex tradeoff of risk and return over a stream of potentially perpetual cash-flows. Finally, the high frequency nature of our price data coupled with the precision of our time stamps allows us to investigate returns at the minutely horizon so we are able to isolate the immediate impact of forecast errors. Studies of longer horizon returns are potentially unable to avoid the

[1] There may be some option value and convenience yield that is positive and in excess of the risk-free rate given the normal state of backwardation for oil futures.

inclusion of confounding information events occurring within the return window. We believe that these characteristics make the oil market a cleaner environment in which to investigate the role of analysts and market sensitivity to their information. Along these same lines, Athanassakos and Kalimipalli (2004) studies the smaller, less liquid, natural gas storage market and finds that market participants recognize differences in ability among gas analysts and hence place more emphasis on lead analysts than on other analysts or on the consensus.

In this study, we find that prices react significantly to forecasts in the period before true supply is announced. We further find that, when true supply (and hence forecast error) is revealed, prices adjust immediately, principally within the first 15 minutes following announcement. These effects are more significant than reactions to the supply announcement itself. We then measure the sensitivity of prices to each analyst individually and find that the reaction is larger for firms with higher past accuracy, implying that the market adjusts their reactions to analyst forecasts based on past performance. In other words, investors learn which forecasts to follow.

The remainder of this paper is organized as follows: Section 1 describes our datasets. Section 2 proposes an empirical methodology and results. Section 3 addresses robustness checks and alternate explanations. Section 4 concludes.

1. Data and Markets

Data for this study come from two sources: price and transaction data are obtained from Olsen Data & Associates, and Department of Energy (DOE) supply reports and analyst forecasts are manually collected from Bloomberg. Our data is collected on a weekly basis and our study spans the period from June 2003 to March 2005, resulting in a total time series of 96 weeks.

1.1 Olsen Data

The specific asset used to measure oil prices is the Light Sweet Crude futures contract traded on NYMEX (ticker: CL).[2] This is the largest, most liquid, and most price-transparent contract traded on physical commodities. Traded at a nominal contract size of 1,000 barrels, CL provides for either physical or cash settlement and is more liquid and more easily traded than crude oil itself. Bid-ask spreads are 2.5 cents (or roughly 5 bp).[3] Olsen Data & Associates provides transaction data including time (by second) and price for a variety of contract maturities of CL. We consider here only the contract with the closest expiration, that is, the near-term future, because it exhibits nearly twice the trading activity of farther-term contracts. Furthermore, the near-term contract also embeds the least interest rate risk as it has the shortest duration. The specificity of the time stamp allows us to match weekly forecast errors with trading surrounding the DOE supply change announcement.

1.2 Supply and Forecast Data

We collect our supply and forecast data from Bloomberg which records the DOE's "Weekly Petroleum Status Report" (WPSR) when it is released at 10:30 AM each Wednesday.[4] This report is prepared by the Energy Information Administration and includes a detailed summary of the supply of petroleum products in the United States measured in millions of barrels, both in

[2] Intuition and simple arbitrage arguments imply that futures price changes should match consistently with changes in spot. Chinn, LeBlanc, and Olivier (2005) finds that oil futures are in fact an unbiased estimator of future spot prices and outperform time-series models. Coimbra and Soares (2004) shows that futures outperform macroeconomic models as estimators for future spot prices.

[3] The combination of the regular and the "e-miNY" contracts (ticker: QM) allow for liquid trading at both the institutional and individual levels. QM trades a contract size of 500 barrels, allows for cash settlement, and has a bid-ask spread of 4 cents.

[4] In any week where there is a holiday, the report is delayed to Thursday at 10.30 AM. Historical archives of this data are available on the Department of Energy's website: www.eia.doe.gov. We get our DOE reports from Bloomberg though they are available to the public through a number of media outlets.

commercial inventories and the Strategic Petroleum Reserves (SPR). The focus of analyst forecasts, and hence of this study, is on the former. WPSR supplies are calculated by the DOE based on representative supply, product stock, process input, and production numbers collected from selected petroleum companies.[5] For the purposes of our study, we assume the WPSR to deliver an accurate measure of supply and will henceforth refer to them as "actual". Analysts' forecasted supply changes are likewise manually collected from Bloomberg and verified for accuracy. Though most forecasts are finalized and released early in the week, to ensure the freshness and consistency of these forecasts at the time of forecast error calculation, we record them as of 10 A.M. each Wednesday. In all, we investigate forecasts of changes in crude oil, gasoline, and distillate (petrochemicals such as heating oil, certain plastics, etc) supplies from 43 financial institutions. Crude oil consists of a mixture of substances which must be separated in order to become useful products such as gasoline and heating oil. As such, crude oil prices may be closely related to the supplies of its refined products. For example, when gasoline supplies are low, the market may foresee excess demand for crude derived from strong demand from down-stream producers of gasoline. This prompts investors to drive up the price of crude. Hence, we test price effects resulting from crude oil alone as well as those resulting from the cumulative effects of crude oil, gasoline, and distillates. Virtually all analysts in our data set provide forecasts for all three supplies. Figure 1 illustrates the historic supply levels of the three separately and in aggregate scaled to 6/1/2003 levels. It also shows the relationship between these supplies and the price of CL. Note that the three supplies are not closely correlated to one another or to CL. Crude oil supplies seems to be negatively correlated with the supplies of both gasoline and distillates, perhaps because

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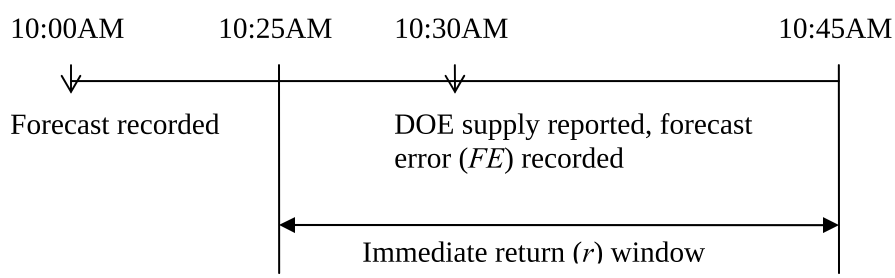
[5] A full description of the supply data collection process may be found at:

http://www.eia.doe.gov/pub/oil_gas/petroleum/data_publications/weekly_petroleum_status_report/historical/2005/2005_12_21/pdf/appendixa.pdf crude oil must be processed (consumed) in order to produce gasoline and/or distillates.

We calculate weekly forecast error, *FE*, as the forecasted change in supply minus actual change in supply. As can be seen in the graph presented in Figure 2, oil prices react significantly to supply forecast errors and do so in a relatively short window of time following the DOE announcement. On the contrary, oil returns are less pronounced before and after this window. As such, we define "immediate return" (r) as the return between 10:25 AM and 10:45 AM, encompassing the announcement time and a short period after. This window suffices to capture the lion's share of returns that occur as a result of forecast error and, as aforementioned, focusing on this relatively short return window substantially reduces the likelihood of other confounding events occurring within the event window. The timing of events, then, is:



In order to get a preliminary understanding of what drives oil prices, the following time-series regression is evaluated:

$$r_t = \alpha + \beta_{crude}\overline{FE}_{crude,t} + \beta_{gas}\overline{FE}_{gas,t} + \beta_{dist}\overline{FE}_{dist,t} + \beta_{gov}G_{tot,t} + \varepsilon \qquad (1)$$

We regress immediate returns on forecast errors measured relative to the mean forecasts[6] of crude, gasoline, and distillates and on aggregate supply changes (G_{tot}). The β's in this regression describe price reactivity to forecast error in supplies. We speculate that these coefficients are positive. To understand the intuition behind this reaction, consider an example where analysts forecast +1000

[6] We use median forecast errors as well and arrive at the same findings.

barrels of total supply in aggregate. The market should note the increase in supply and reduce prices. Suppose then that the true supply is revealed to have zero change in supply, yielding FE=1000. Prices, having already reacted to forecasts, should rise. Hence, the relationship between returns and FE would be positive. In fact, we find that coefficients are positive and significant for crude, gasoline, and distillates implying that returns are higher (lower) when supplies are lower (higher) than expected. Importantly, these effects seem not to be overlapping, indicating that gasoline and distillate supplies deliver additional information regarding crude oil prices over-and-above that communicated by crude alone. The r-squared when looking at all three supplies is nearly triple that of crude oil alone. Because of this, results in the paper will focus on the aggregate forecast error for all three supplies FE_{tot}. Also, note that oil returns react to forecast errors and not simply to the actual supply change itself as β_{gov} is not significant.

Summary statistics on supply changes and analyst forecast error calculated as both the change in number of barrels as well as the percent change in total inventory appear in Figures 3 and 4. Though the two figures look similar, close inspection finds that, when measured by number of barrels, crude oil supply changes and forecast errors are the most diffuse with standard deviations of 3262 (vs 2276 for distillates) and 1995 (vs 1291), respectively. However, when measured by percent change in total supply, distillates supplies and forecast errors are most diffuse with standard deviations of 1.893% (vs 1.15% for crude) and 1.058% (vs 0.717%), respectively. In light of this finding, we execute all tests in this study using supply change measured in barrels as well as measured as a percent change.

2. Empirical Methodology and Results

Having determined that prices react to forecast error, it is sensible to conclude that investors care about the forecast error of analysts and might learn, over time, which analysts are most adept. We postulate that, if analysts are known to be accurate, investors will condition price on their forecasts and price reactions to their forecast errors should likewise be large. The opposite should be true of inaccurate analysts. We test price reactions before true supply is revealed to determine whether prices conform to analyst information, and then examine prices after the supply announcement to see if prices should equilibrate to reflect actual supply information. If investors do not learn about the accuracy of analysts from their past performance, oil prices should not react differently to forecast error for different analysts.

Specifically, we propose three testing methodologies. We first execute a test of investor reaction to forecasts and investigate returns prior to the announcement of true supply, seeking to determine if investors react more strongly to the most accurate analysts' forecasts ex-ante. Then, we present two regression specifications, a two-stage and a one-stage, that test if more accurate analysts' forecast errors induce larger price reactions ex-post. In the tests presented below, our default specification is to pool all forecasts, but individual firm tests as well as controls for firm- and time- fixed effects are also presented. Results are qualitatively identical unless otherwise noted.

2.1 Ex-ante Regression

First, we test the price-conditioning process ex-ante. We hypothesize that more accurate analysts' forecasts will elicit larger pre-announcement price movement. To test this, we first regress returns on forecast in a rolling window of 20 weeks. That is, at any time *t*, we regress the return from the open to close on Tuesday ($\tilde{r}_t$) in times *t* to *t+19* on each company's forecast errors during the same period. In order to ensure a representative measure for $\widetilde{\beta}_t$ we require at least 10 matched pairs of $\tilde{r}_t$ and *FE* in the 20-week window. This generates, for each firm, a time series of betas describing how aggressively prices react to forecasts. In the first stage, we calculate:

$$\tilde{r}_t = \alpha + \tilde{\beta}_t(F_t) + \varepsilon$$

In other words, we are testing if the market responds to the forecast, which is released throughout the course of the week, before the true supply is realized on Wednesday morning. As forecasts can be changed throughout the course of the week, we choose to investigate the return over the day closest to announcement, Tuesday, to ensure that we capture price movements responding to the most recent forecasts.[7] In this regression, we conjecture that coefficients should be negative. That is, when analysts forecast too much supply, prices should fall. Then, in the second stage, we evaluate:

$$\tilde{\beta}_t = \alpha + \tilde{\gamma} Acc_t + \varepsilon$$

We calculate for each firm at each point in time an accuracy measure *Acc* as follows:

$$Acc_t = \frac{1}{\sum_{t-10}^{t-1} |FE_t| / N}$$

N is the number of dates for which a forecast error is calculable in the period from *t-10* to *t-1*. Put simply, *Acc* is the inverse of the moving average absolute value of forecast errors over the past 10 periods. To ensure consistency and reliability, we include only those points at which 5 or more past *FE*'s exist.

The resulting $\tilde{\gamma}$ from this regression represents the relationship between accuracy and the coefficient of market response to *F*. If $\tilde{\gamma}$ is negative, the market conditions prices more on the forecasts of firms with higher accuracy. As can be seen in Table 1 Panel A, we find that prices do seem to react significantly to forecasts in the period before actual supplies are announced. Coefficients are negative and significantly so, even when controlling for firm-fixed effects. Method of aggregation, by barrels or by percent change, does not seem to affect results. The most accurate analysts induce the largest return response to their forecasts in the period.

2.2 Two-Stage Ex-post Regression

We now repeat the previous two-stage regression using immediate returns and forecast

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[7] Casual observation and anecdotal evidence find that, in most cases, final forecasts are released on Tuesday.

errors in order to test ex-post effects. If investors condition prices on the forecasts of the most accurate analysts, prices should correct aggressively in response to forecast errors. Specifically, in the first stage, we calculate the following regression:

$$r_t = \alpha + \beta_t FE_t + \varepsilon$$

The coefficient β represents the sensitivity of oil prices to the forecast error of a given firm at time t. A positive β implies that ex-ante over-estimation of supplies will induce prices to increase as actual supplies are found to be lower. We then regress these reactivity measures on accuracy to see if the most accurate firms generate the most sensitivity as follows:

$$\beta_t = \alpha + \gamma Acc_t + \varepsilon$$

The γ from this regression represents the relationship between accuracy and the coefficient of market response to *FE*. If γ is positive, the market reacts more to firms with higher accuracy as is consistent with our proposition. Results presented in Table 1 Panel B confirm this conjecture as γ is positive and significant. That is, investors respond with more sensitivity to forecasts errors from firms who have been more accurate in the past. Findings are the same whether we aggregate based on change in number of barrels or on percentage change and are robust to controls for both time- and firm- fixed effects.

2.3 One-Stage Ex-post Regression

Here, we investigate the relationship between analyst forecasts and prices in a signaling framework. Consider that forecasts (and resulting forecast error) are information signals that analysts send to investors. We conjecture that these signals, however, are attenuated by previous accuracy. If a firm is very inaccurate, the perceived forecast error is zero and constant. Their forecasts should not affect returns. In other words, if past performance is poor, investors ignore subsequent information signals. To capture this, we regress returns on weighted forecast errors, using our accuracy measure to attenuate *FE*. Specifically, we evaluate the following:

$$r_t = \alpha + \gamma Acc_{tot,t} * (FE_t) + \beta(FE_t) + \varepsilon$$

Put simply, we are attempting to measure the marginal impact of accuracy on how the forecast error signal *FE* is transmitted to returns. In this setup, if γ is positive and significant, investors react to more accurate firms more strongly than inaccurate ones. If γ is positive and while β is not, investors condition prices on accuracy-adjusted forecasts and not on forecasts alone.

As can be seen in Table 1 Panel C, we find that γ is positive and significant while β is not. In other words, the accuracy adjusted forecast error is a significant determinant of price reaction while forecast error itself is not. Investors seem to adjust their perception of forecast error based on the past accuracy of the analysts. As is consistent with the findings of the rest of this section, investors seem to condition price most closely on the forecasts of accurate analysts, and as a result, when errors are realized, price correction is also more pronounced for more accurate analysts. Again, this is true even when controlling for firm-fixed effects.

3. Robustness Checks

We execute several robustness checks. Unless otherwise noted, none yield appreciable differences and our conclusions are unaffected. Numerical results and testing specifics are available upon request.

For all of our regressions, in calculating aggregate *FE*, we have equally weighted the three supplies. As a robustness check, we also try weighting the forecast errors for each supply by the in-sample betas calculated in Section 1.2, that is, the empirically derived sensitivity of prices to forecast error. Re-running all of our tests, we find that results are not materially affected. We apply alternate specifications of the accuracy measure as well, measuring it as the inverse standard deviation, inverse variance, and rank order of forecast errors. In each case, we arrive at the same qualitative finding: more accurate firms induce a larger surprise response.

We furthermore control for autocorrelation. Durbin-Watson coefficients are about 1.86

indicating that auto-correlation is not a significant concern in our tests. Nonetheless, we calculate Newey-West t-stats for our pooled regressions to control for both auto-correlation and heteroskedasticity and likewise note no important differences in significance levels or qualitative understanding.

4. Conclusion

In this paper, we investigate the impact of analyst forecasts and investors' ability to learn in a relatively transparent and straight-forward information setting. By focusing our attention on the crude oil futures market, we study a real asset whose value can be directly connected to analyst information through simple economic arguments. This market is also very liquid and the precision of our data allows us to isolate price effects that specifically arise from the information of the analysts and their forecast errors. As such, we believe that our study avoids some of the confounding factors that cloud other studies of this kind and lends a unique voice to the discussion.

We find that oil futures prices react immediately to forecast errors in the aggregate supply of crude oil, gasoline, and distillates. We further find that investors seem to learn which analysts are most accurate and react most strongly to those analysts, conditioning prices on their forecasts ex-ante and reacting immediately to their forecasting errors ex-post. We find this to hold true in a number of different testing specifications and through a variety of statistical checks. Left unanswered, however, is the exact mechanism through which these price reactions are proliferated. One possible counter-explanation is that those firms that tend to be most accurate also tend to have the largest trading desks. In that case, larger price impact on the part of accurate firms could be self-fulfilling, though this would still be consistent with our intuition on learning. It is also curious that crude oil supplies alone do not seem to explain oil futures returns. Perhaps a more complex set of interactions is necessary to fully explain the relationships between supply and price examined here. Since gasoline seems to be an important factor, electricity prices/supplies or other downstream products may have similar explanatory power. Without addressing these issues, it suffices here to state that we find oil futures prices to be intimately related to the aggregate supply of oil products and that investors recognize this relationship. They seem to trade on the forecasts of analysts in this field and further seem to learn which analysts are most accurate.

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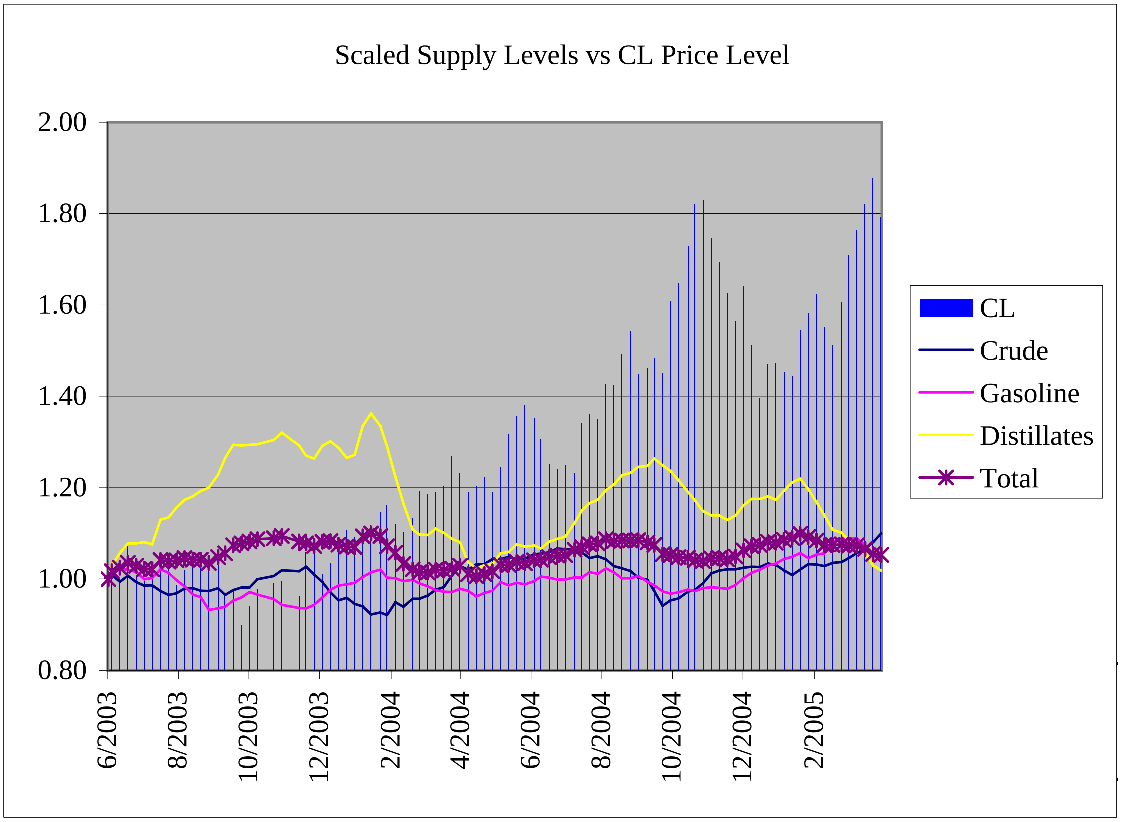
Figure 1: Supply Correlations and their Relation to Price

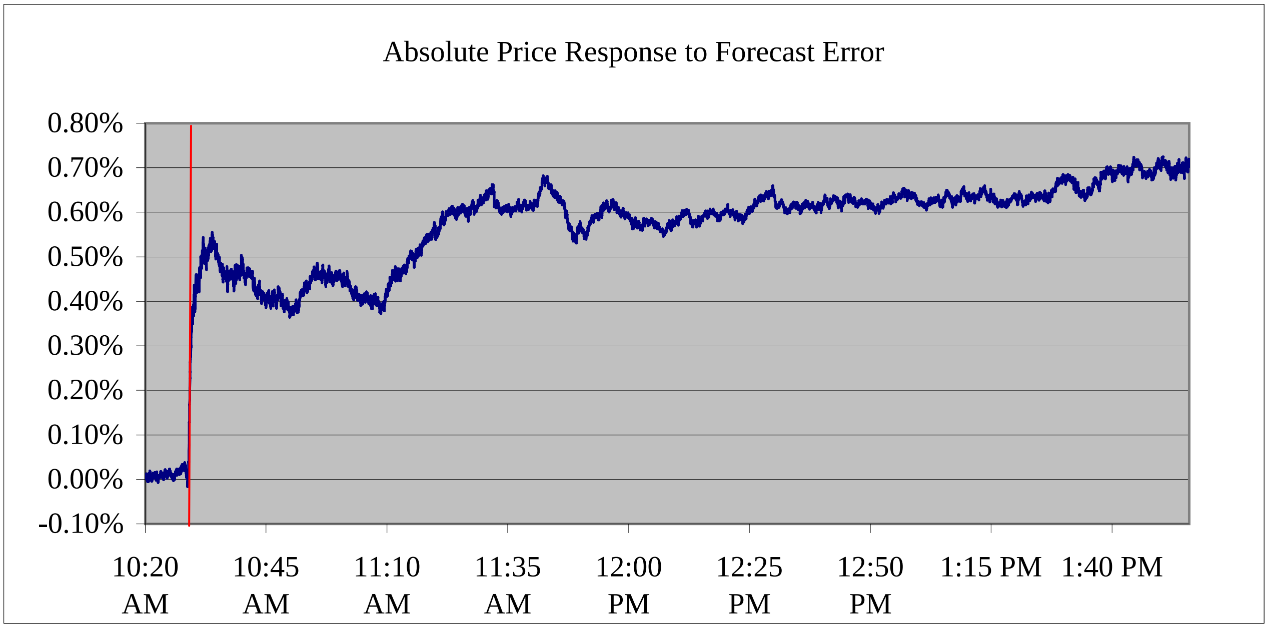
This figure illustrates the relative relationships between the three supplies examined in this study: crude oil, gasoline, and distillates. Included as well is the price of crude oil, proxied by the near-term futures contract CL. Crude supply is found to be negatively correlated to gasoline and distillates. The total of the three supplies as well as crude oil supply alone are negatively correlated with price.



Correlation Matrix					
	Crude	Gasoline	Distillates	Total	CL
Crude	1.00	-0.16	-0.34	0.15	-0.17
Gasoline	-0.16	1.00	0.28	0.60	-0.01
Distillates	-0.34	0.28	1.00	0.79	-0.04
Total	0.15	0.60	0.79	1.00	-0.12
CL	-0.17	-0.01	-0.04	-0.12	1.00

Figure 2: Price Response to Forecast Error

This figure reports price responsiveness to forecast error (FE) calculated as forecasted supply minus actual supply. The graph shows the average absolute value of price movements for oil futures (ticker: CL) on announcement days. Prices react substantially after forecast errors are realized at 10:30 AM, demarked by the vertical line. Very little price movement is observed before 10:30 and attenuated drift seems apparrent throughout the rest of the day. The table shows regression results when returns are regressed on forecast errors (FE) and aggregate supply change (Gtot). They indicate that the immediate return (change in price from 10:25 to 10:45 AM) responds significantly positively to forecast errors. When supply is lower (higher) than expected, prices rise (fall). Crude supplies alone exhibit this effect, but gasoline and distillates also exhibit significant coeffcients. Data is collected from June 2003 to March 2005.

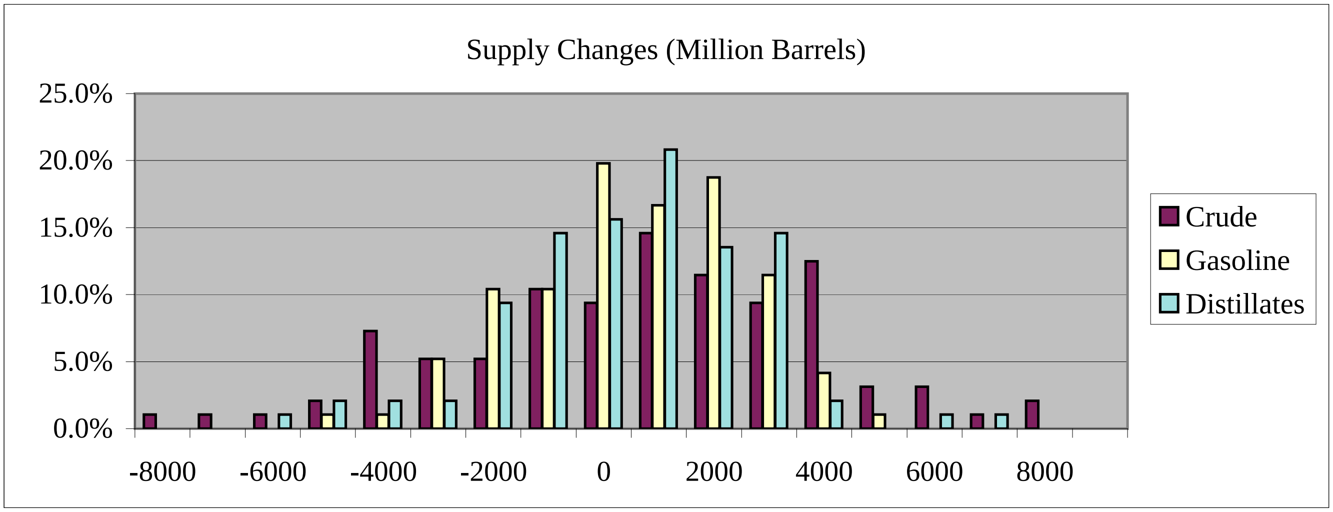


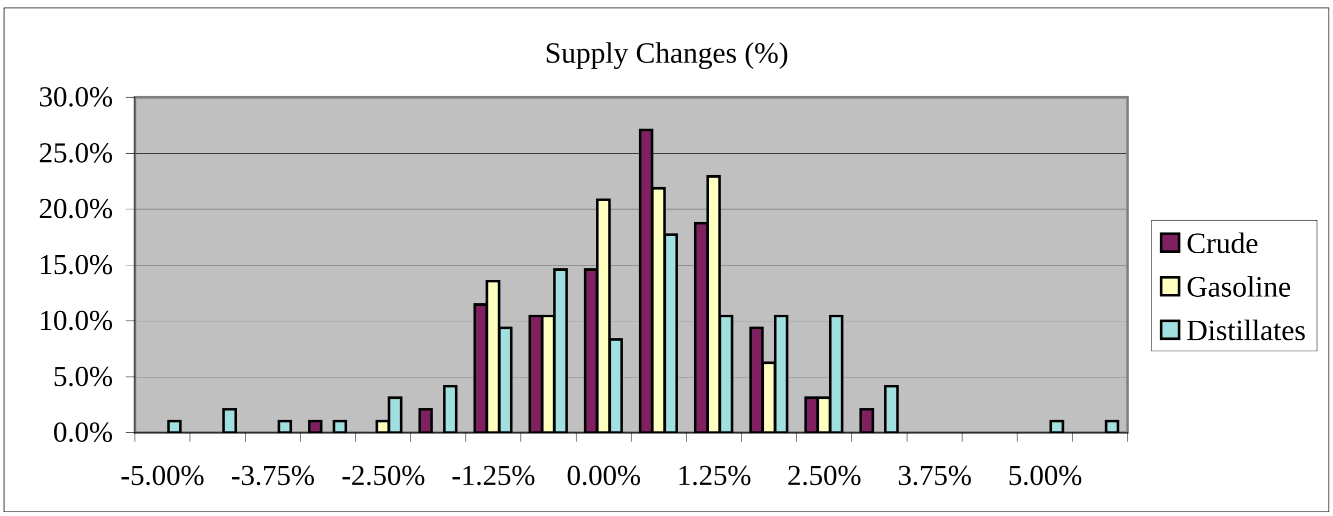
Price Reactiveness to Supply Changes
(Coefficients reported x 10^6)

	FEcrude	FEgasoline	FEdistillates	FEtot	Gcrude	Gtot	DF	R^2
Coefficient	1.622						87	0.126
(P-value)	(0.0004)							
Coefficient	2.240				-0.637		90	0.115
(P-value)	(0.0466)				(0.5173)			
Coefficient	2.196	1.548	2.948				87	0.327
(P-value)	(0.0000)	(0.0163)	(0.0001)					
Coefficient				2.210			87	0.3464
(P-value)				(0.0001)				
Coefficient				2.510		0.303	87	0.3414
(P-value)				(0.0001)		(0.5571)		

Figure 3: Supply Changes

This figure reports summary statistics regarding supply changes over our test period. Though all three supplies are similarly distributed, when measured in barrels, crude oil appears to be most diffuse. When measured in percent change of total supply, distillate supply changes appear to be the most diffuse. Supplies are recorded at 10:30 AM each announcement day over the period from June 2003 to March 2005.



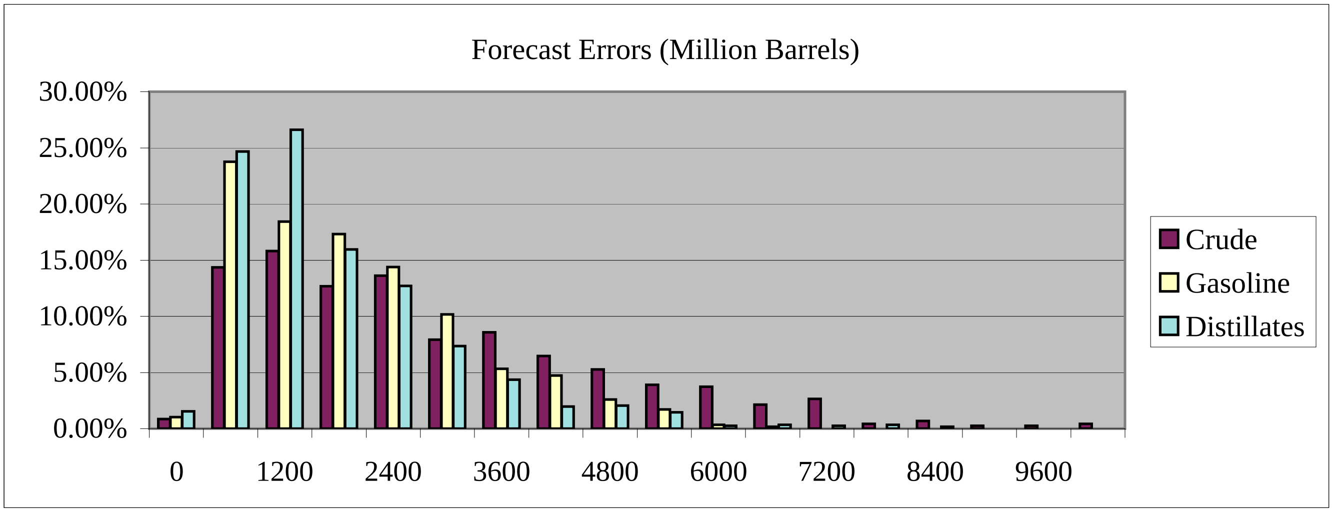


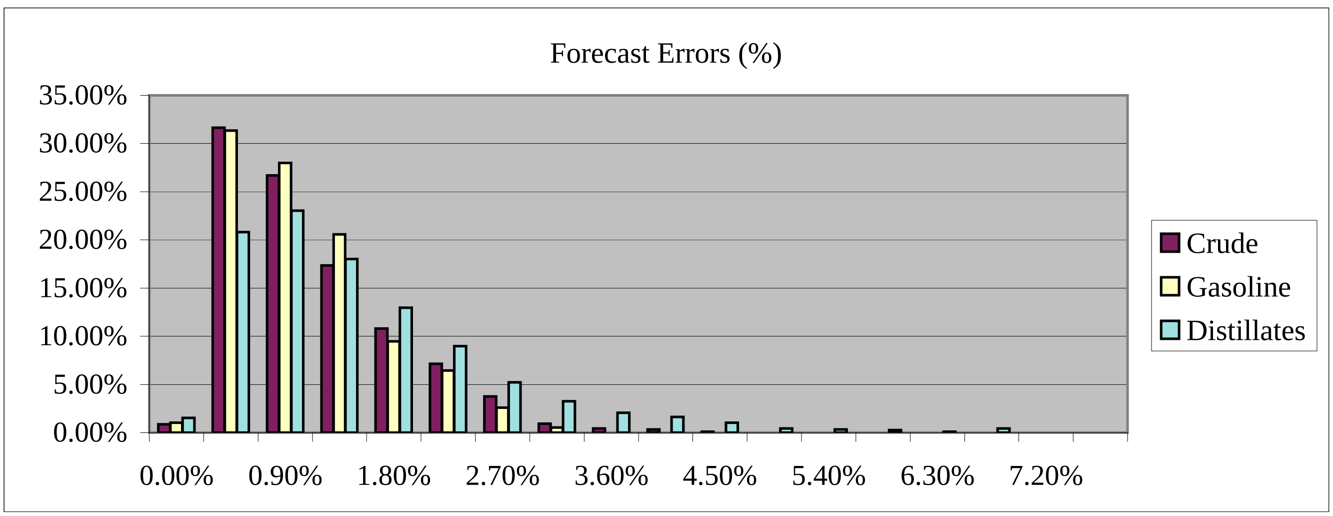
DOE Supply Change Data

	Crude Oil		Gasoline		Distillates	
	Gross	%	Gross	%	Gross	%
Mean	297	0.105%	85	0.046%	20	0.037%
Median	300	0.102%	500	0.238%	200	0.171%
SD	3262	1.150%	2061	1.008%	2276	1.893%
Max	7900	2.996%	4900	2.263%	6400	5.037%
Min	-9100	-3.266%	-5700	-2.895%	-6800	-5.191%

Figure 4: Absolute Forecast Errors

This figure presents summary statistics regarding forecast errors reported in absolute value. Again, when measured in barrels, crude oil appears to be most diffuse. When measured in percent change of total supply, distillates appear to be the most diffuse. Forecast errors are calculated as the 10:00 AM forecasted supply minus the 10:30 AM actual supply over the period from June 2003 to March 2005.





Analyst Forecast Errors

	Crude Oil		Gasoline		Distillates	
	Gross	%	Gross	%	Gross	%
Mean	2581	0.906%	1708	0.838%	1521	1.268%
Median	2100	0.716%	1500	0.729%	1200	1.001%
SD	1995	0.717%	1262	0.619%	1291	1.058%
Max	11500	4.361%	6500	3.107%	8300	6.593%
Min	0	0.000%	0	0.000%	0	0.000%

Table 1: Regression Analysis

This table presents tests of the effect of previous-period accuracy on price responsiveness. Panel A looks at forecasts (F). Panels B and C investigate forecast error (FE). Accuracy (Acc) is the inverse of the moving average absolute value of forecast errors over the previous 10 periods. Panel A presents results for a two-stage regression. First, we find calculate price responsiveness (Beta) in a 20-period rolling regression r = a + Beta*F + e where r is the return on the Tuesday preceding the announcement of actual supply levels. Reported are gammas from the regression Beta = a + Gamma*Acc. Negative gamma implies that investors condition more on forecasts of more accurate analysts. Panel B is the same two-stage regression with first stage r` = a + Beta*FE where r` is the return calculated from 10:25 AM to 10:45 AM on Wednesday (forecast error is realized at 10:30 AM). Reported are the gammas from the regression: Beta' = a + Gamma'*Acc + e. Panel C evaluates the regression r = a+ Gamma*(Acc*FE) + Beta*FE. In Panels B and C, a positive gamma implies that investors condition more on the forecasts of more accurate analysts. All coefficients reports x10^-3.

Panel A: Ex-ante Regression Gammas

	Barrels			Percent		
	Pooled	Firm-fixed	Time-fixed	Pooled	Firm-fixed	Time-fixed
Coefficient	-7.850	-8.830	3.979	-6.800	-5.790	-0.220
(P-value)	(0.0001)	(0.0001)	(0.1501)	(0.0001)	(0.0003)	(0.9250)
DF	788	773	723	788	773	723
R^2	0.019	0.208	0.390	0.023	0.174	0.359

Panel B: Two-stage Ex-post Regression Gammas

	Barrels			Percent		
	Pooled	Firm-fixed	Time-fixed	Pooled	Firm-fixed	Time-fixed
Coefficient	3.140	1.449	5.845	7.220	5.294	7.058
(P-value)	(0.0001)	(0.0259)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
DF	788	773	723	788	773	723
R^2	0.025	0.871	0.905	0.112	0.807	0.874

Panel C: One-stage Ex-post Regression Coefficients

	Barrels				Percent			
	Pooled		Firm-fixed		Pooled		Firm-fixed	
	Acc*FE	FE	Acc*FE	FE	Acc*FE	FE	Acc*FE	FE
Coefficient	8.180	0.000	8.852	0.000	9.780	-63.880	10.670	-77.420
(P-value)	(0.0001)	(0.8392)	(0.0001)	(0.9016)	(0.0001)	(0.2111)	(0.0001)	(0.1298)
DF	950		934		950		934	
R^2	0.259		0.282		0.240		0.261	