WP 2008-19
September 2008

Working Paper

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by

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ABSTRACT

We study the impact of analyst forecasts on prices to determine whether investors learn about analyst accuracy. Our test market is the crude oil futures market. Prices rise when analysts forecast a decrease (increase) in crude supplies. In the 15 minutes following supply realizations, prices rise (fall) when forecasts have been too high (low). In both the initial price action relative to forecasts and in the subsequent reaction relative to realized forecast errors, the price response is stronger for more accurate analysts. These price reactions imply that investors learn about analyst accuracy and trade accordingly.

Our study seeks to investigate the impact of financial analysts' forecasts on asset prices. In addition, we explore investors' ability to learn about analyst performance and adjust their trading accordingly. 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. If the answer is negative, one might question whether analyst performance is important from the firm's perspective. Why spend good money maintaining strong analysts if the market fails to react to them and your investors do not learn or care about their accuracy? Several studies of equity market analysts discuss analyst forecast accuracy. However, equity analysts must study a variety of stocks and a variety of factors that impact price, making it difficult to compare the informational advantages of one analyst to those of another. Furthermore, equity studies executed at the daily (or longer) horizon potentially admit confounding information events. Many stocks are also difficult or impossible to short sell, potentially skewing return studies. We select as our test setting the crude oil futures market. The crude oil futures market centers around a single underlying asset that all analysts seek to forecast. In addition, crude prices are principally determined by supply and demand, making analyst supply forecasts directly relevant. Our data allows us to investigate price movements immediately following information release thus drastically reducing the likelihood of confounding events. Finally, oil futures may be shorted without additional costs, and 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. In this simpler but economically important setting, we find that analyst supply forecasts have an impact on the price of crude oil products. Price significantly reflects forecast errors and does 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 literature. 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 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 find that more experienced analysts receive the largest price reactions, particularly in the long-run, whereas Chen, Francis, and Jiang (2005) determine that both the accuracy of earnings forecasts and length of track record increase market reactivity 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 work related to commodities, Athanassakos and Kalimipalli (2004) study the smaller, less liquid, natural gas storage market and find 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 summary, though post-announcement drift is well documented, the issue of whether investors learn about the accuracy of analysts elicits less agreement.

In our more straight-forward test market, 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 the announcement. These effects are more significant than reactions to the supply announcement itself. We then measure the sensitivity of prices to each individual analyst and find that the reaction is larger for firms with higher past accuracy, implying that the market adjusts its reaction 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 I describes our datasets. Section II proposes an empirical methodology and results. Section III addresses robustness checks, and Section IV concludes.

I. Data and Markets

Data for this study comes from two sources: price and transaction data is 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.

I.A Olsen Data

The specific asset used to measure oil prices is the Light Sweet Crude futures contract traded on NYMEX (ticker: CL).[1] 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).[2] Olsen Data & Associates provides transaction data including time (by second) and price for a variety of contract maturities of CL. The specificity of the time stamp allows us to match weekly forecast errors with trading surrounding the DOE supply change announcement. 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.[3] Furthermore, the near-term contract also embeds the least interest rate risk as it has the shortest duration.

I.B 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 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 WPSR supplies 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. on Wednesday.

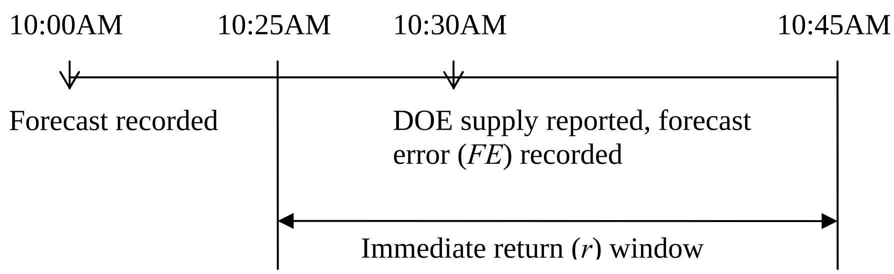
In all, we investigate forecasts of supply changes in crude oil, gasoline, and distillates (petrochemicals such as heating oil, certain plastics, etc.) from 17 financial institutions. Crude oil consists of a mixture of substances which must be separated in order to become useful products such as gasoline 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 each of the three supplies is negatively correlated with CL, as would be expected from simple economic arguments (supply increases, prices fall). Their sum is also negatively correlated to CL, a fact that is expounded upon in Figure 2. We also find that crude oil supplies are negatively correlated with the supplies of both gasoline and distillates, which is sensible since crude oil must be processed (consumed) in order to produce gasoline and distillates.

For a clearer picture as to what drives returns, we evaluate the following regression in which forecast error (*FE)* is the forecasted change in supply minus the actual change in supply:

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

We regress returns on forecast errors measured relative to the mean forecast ($\overline{FE}$)[6] of supply i (crude, gasoline, distillates, and the sum of the three) and while controlling for aggregate supply change (G_{tot}). The β's in this regression describe price reactivity to forecast error. We speculate that these coefficients are positive. For example, suppose analysts forecast +1000 barrels of supply change. 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 back to pre-forecast levels. Hence, the relationship between returns and *FE* would be positive. Because of the liquidity afforded in this market, we posit that the price reaction to *FE* should be nearly immediate. 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. There is very little return activity before the event window and, following this initial jump, subsequent price movements do not seem to reverse the initial reaction—returns are relatively flat for the rest of the trading day. 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 short window suffices to capture the lion's share of returns that occurs as a result of forecast error while substantially reducing the likelihood of other confounding events occurring within the event window. The timing of events, then, is:



The test results presented in Figure 2 confirm our initial intuition that prices are significantly related to forecast error. 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 which is communicated by crude alone. R-squared is nearly three times as high when looking at the sum of all three supplies compared to crude oil alone. Because of this, results in the paper will focus on the aggregate forecast error for the three supplies FE_{tot}. Also, note that oil returns react to forecast errors and not to the actual supply change itself. β_{gov} is not significant and the inclusion of actual change in supply does not provide additional explanatory power to our regression.

Summary statistics on supply changes and analyst forecast errors appear in Figures 3 and 4. We calculate these statistics for both the change in number of barrels and the percent change in total inventory. Regardless of the measure used, forecast errors appear to be close to Normally distributed. In addition, there do not seem to be large outliers that might otherwise skew regression results. However, close inspection of these graphs 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. 2061 for gasoline) and 3263 (vs.

1996 for distillates), respectively. However, when measured by percent change in total supply, distillate supplies and forecast errors are most diffuse with standard deviations of 1.893% (vs. 1.008% for gasoline) and 1.652% (vs. 1.041%), respectively. In light of this finding, we execute all tests in this study using supply change measured in barrels as well as in percent change.

II. 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 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 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 different analysts' forecasts.

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 additional regression specifications, a two-stage and a one-stage, that test if more accurate analysts' forecast errors induce larger price corrections ex-post. If analysts do not initially react to forecasts ex-ante, one would not expect to see price correction ex-post. In the tests presented below, our default specification is to pool all forecasts, but controls for firm- and time- fixed effects are also presented. Results are qualitatively identical unless otherwise noted.

II.A Ex-ante Regression

First, we test the price-conditioning process ex-ante. We hypothesize that more accurate analysts' forecasts elicit larger pre-announcement price movement. To test this, we first regress returns on forecasts in a rolling window of 20 weeks. We define the ex-ante return ($\tilde{r}_t$) to be the return from open to close on Tuesday. For each company, we regress the returns in times *t* to *t+19* on forecasts during the same period. In order to ensure a representative measure for $\tilde{\beta}_t$ 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 that firm's forecasts. Specifically, we evaluate:

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

Put simply, we are testing if the market responds to forecasts, which are released prior to the true supply announcement on Wednesday morning. As forecasts can be changed throughout the course of the week, we investigate the return over the day closest to the 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. When analysts forecast increasing supply, the market reacts by pushing prices down. The more accurate are the analysts, the more reliable this relationship.

We also calculate for each firm at each point in time an ex-ante 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.

Table I shows summary statistics for each of these measures organized into accuracy quintiles. The most accurate firms are those with the highest *Acc*, defined as "Q1". Looking at the columns labeled "Beta (Ex-ante)," we find that, in aggregate, beta is negative. This implies that as forecasts increase, prices decrease. Moreover, we find that more accurate firms tend to have more negative coefficients. That is, prices fall farther in response to positive forecasts for more accurate analysts. This relationship is nearly monotonic, especially when measured by percent change, and the difference in average beta for Q1 and Q5 is significantly negative.

With these preliminary results in mind, we evaluate the two-stage regression as follows:

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

The resulting $\tilde{\gamma}$ from this regression represents the relationship between ex-ante 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 II Panel A, we find that prices seem to react more significantly to the forecasts of more accurate analysts in the period before actual supplies are announced. Coefficients are negative and significantly so, even when controlling for firm-fixed effects, implying that investors react more (less) as firms improve (decrease) their accuracy over time. Method of forecast measurement, by barrels or by percent change, does not seem to affect results.

II.B Two-Stage Ex-post Regression

We now repeat the previous two-stage regression using immediate returns and forecast errors in order to test ex-post effects. If investors condition prices on the forecasts of the most accurate analysts, prices should correct most aggressively in response to their forecast errors. To measure this response, 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 induces prices to increase when actual supplies are found to be lower than forecasts (positive forecast error). From the columns labeled "Beta (Ex-Post)" found in Table I, we can see that, in aggregate, beta is in fact positive. We also find that more accurate analysts exhibit more positive coefficients, indicating that more accurate analysts elicit a larger return response to their forecast errors. The difference in means for Q1 and Q5 is calculated and found to be significantly positive. Again, this relationship is nearly monotonic, especially when *FE* is measured in percent change.

We then evaluate the second stage of our regression 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 ex-ante accuracy, as is consistent with our main proposition. Results presented in Table II

Panel B confirm this conjecture, as γ is positive and significant. That is, investors respond with more sensitivity to forecast errors from firms whose analysis has 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.

II.C One-Stage Ex-post Regression

Finally, 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's past analysis has been very inaccurate, their perceived signal 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 β is not, investors condition prices on accuracy-adjusted forecasts and not on forecasts alone.

As can be seen in Table II 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.

III. 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 equally weight 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 price to forecast error. Re-running all of our tests, we find that results are not materially affected. In addition, we re-run all first-stage regressions with the additional inclusion of the mean forecast error for all firms on the right-hand side. However, we find that the resulting measures of price reactivity to firm-specific forecasts and forecast errors are still significantly related to previous accuracy. In fact, t-stats are the same sign throughout, with slightly lower magnitudes. Qualitative conclusions remain unchanged. We also apply alternate specifications for the accuracy measure, 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.

IV. 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 an asset whose value can be directly connected to analyst information through simple economic arguments. Papers studying equity market analysts, particularly those that focus on cross-sectional effects, may be hindered by idiosyncratic components. Study of the oil market is not affected by such concerns. The market is also liquid and can be traded equally easily in both the long and short directions. The inability to short as easily as long in the equity market is a potential factor that generates asymmetric affects. Our test, again, is free from such concerns. Furthermore, the high-frequency nature of our data allows us to investigate immediate price reactions and to isolate the market's response to analysts from other possible trade-inducing events. 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 investors react to forecasts of the aggregate supply of crude oil, gasoline, and distillates. We also find that prices correct immediately for forecast errors. We further discover 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. This holds 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 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 regarding 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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[1] Intuition and simple arbitrage arguments imply that futures price changes should match consistently with changes in spot. Chinn, LeBlanc, and Olivier (2005) find that oil futures are in fact an unbiased estimator of future spot prices and outperform time-series models.

Coimbra and Soares (2004) show that futures outperform macroeconomic models as estimators for future spot prices.

[2] The combination of the regular and "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.

[3] NYMEX contracts expire at the end of trading 3 business days before the 25th of each month. Since our tests focuses on trading immediately surrounding supply announcements, they should not be significantly affected by expiration effects.

[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.

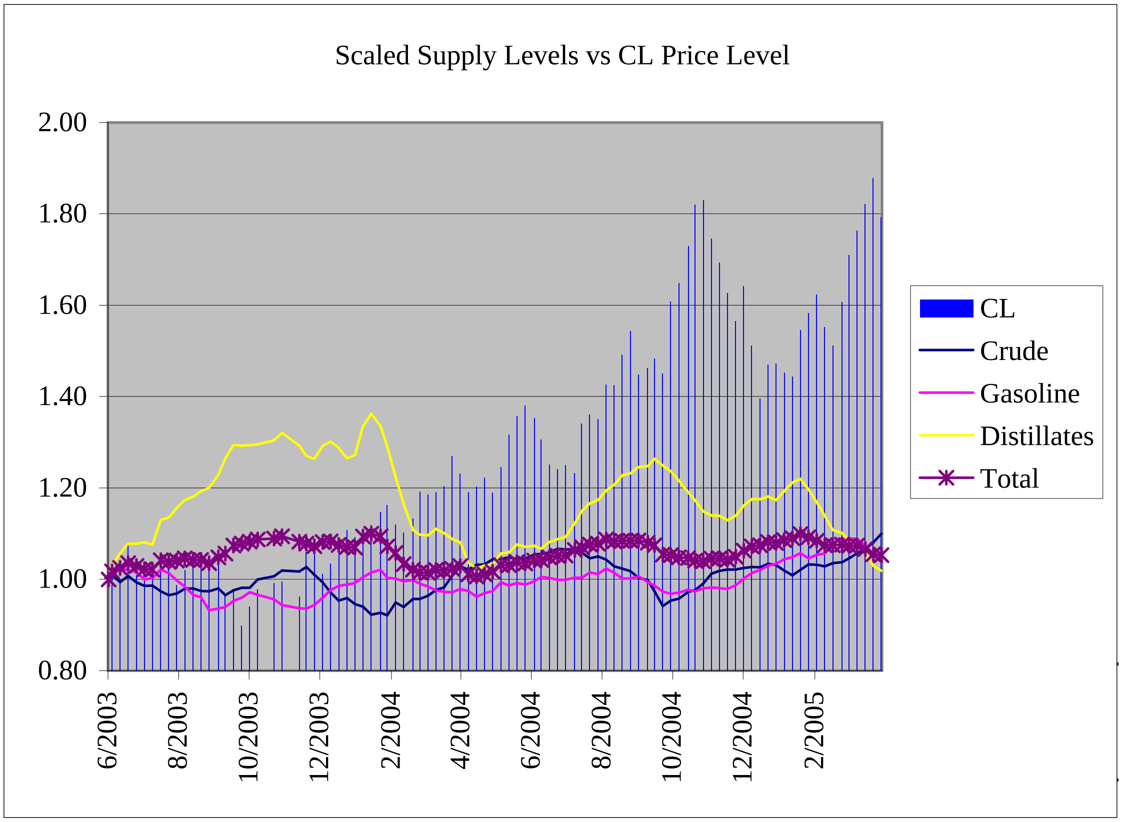
[5] A full description of the supply data collection process may be found at: http://www.eia.doe.gov/pub/oil_gas/petroleum/data_publications/weekly_petroleum_status_report/historical/2005/2005_12_21/pdf/appendixa.pdf

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

[7] Casual observation and anecdotal evidence find that, in most cases, final forecasts are released on Tuesday. We, however, repeat all tests using the return accumulated over Monday and Tuesday and find no qualitative differences.

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.

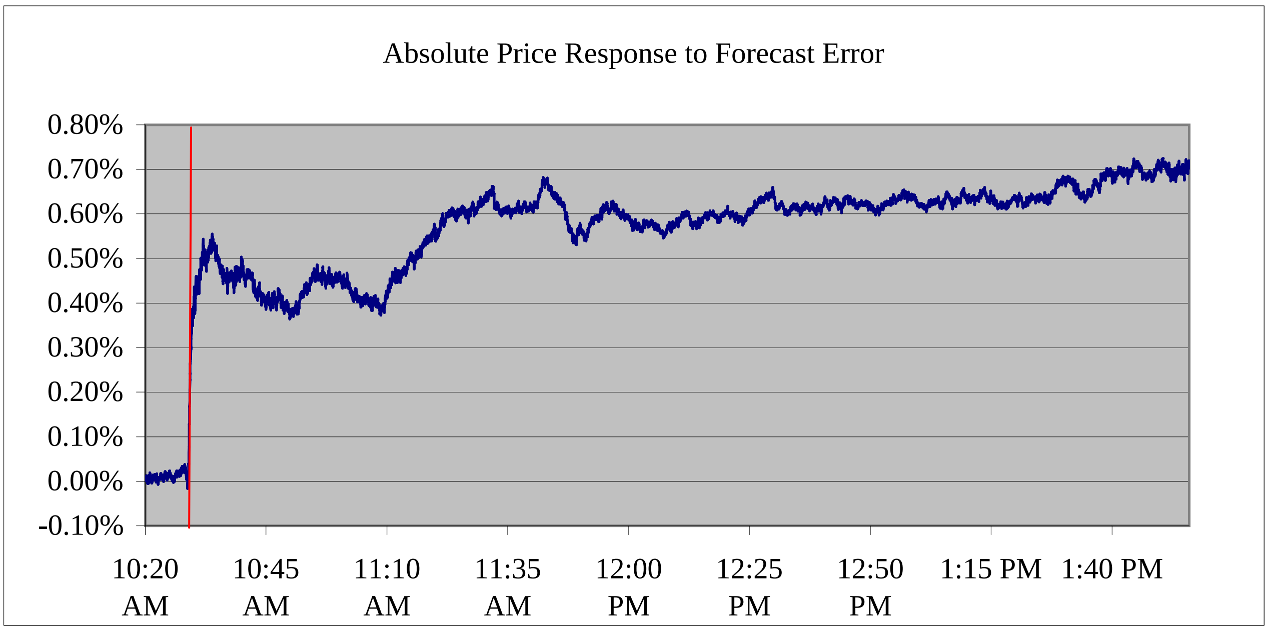


Correlation Matrix

	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 aggregate supply exhibits the strongest effect. Data is collected from June 2003 to March 2005.

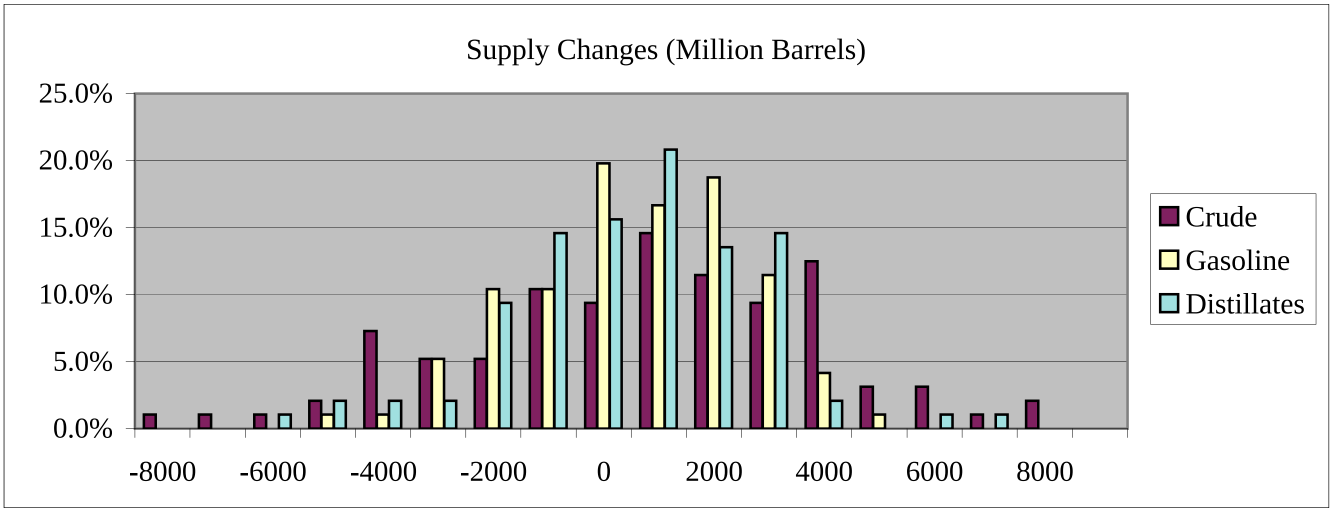


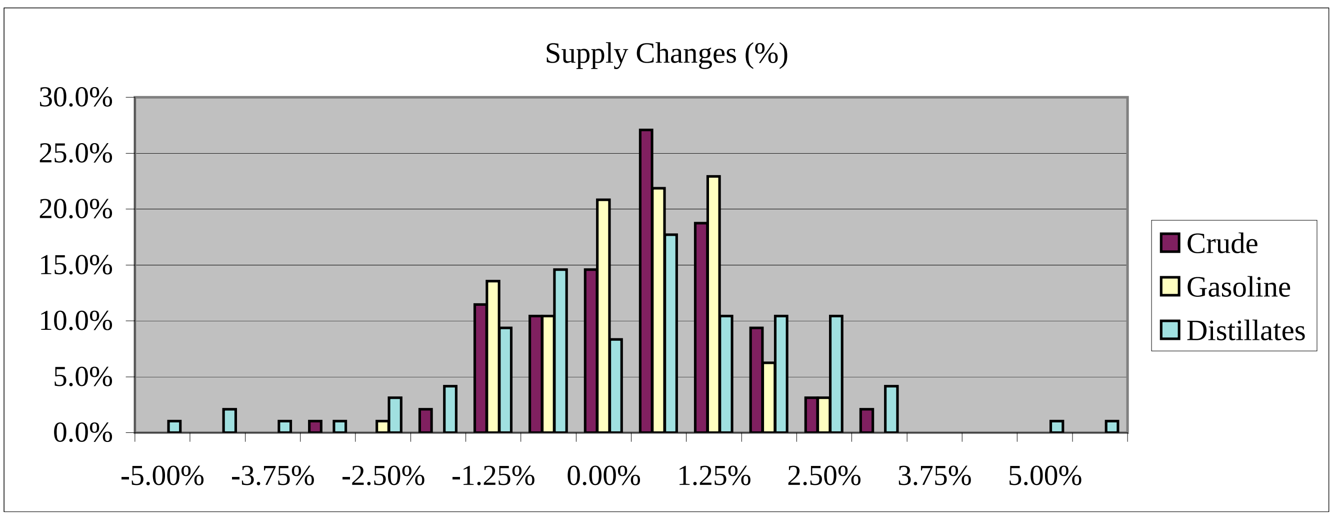
Price Reactiveness to Supply Changes
(Coefficients reported x 10^6)

	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.



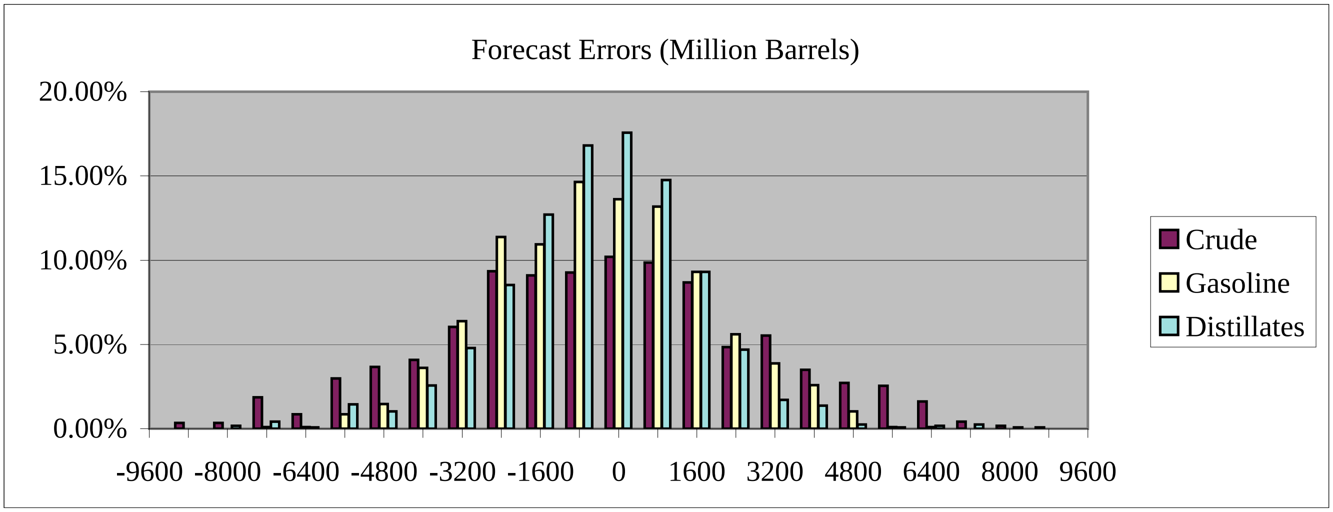


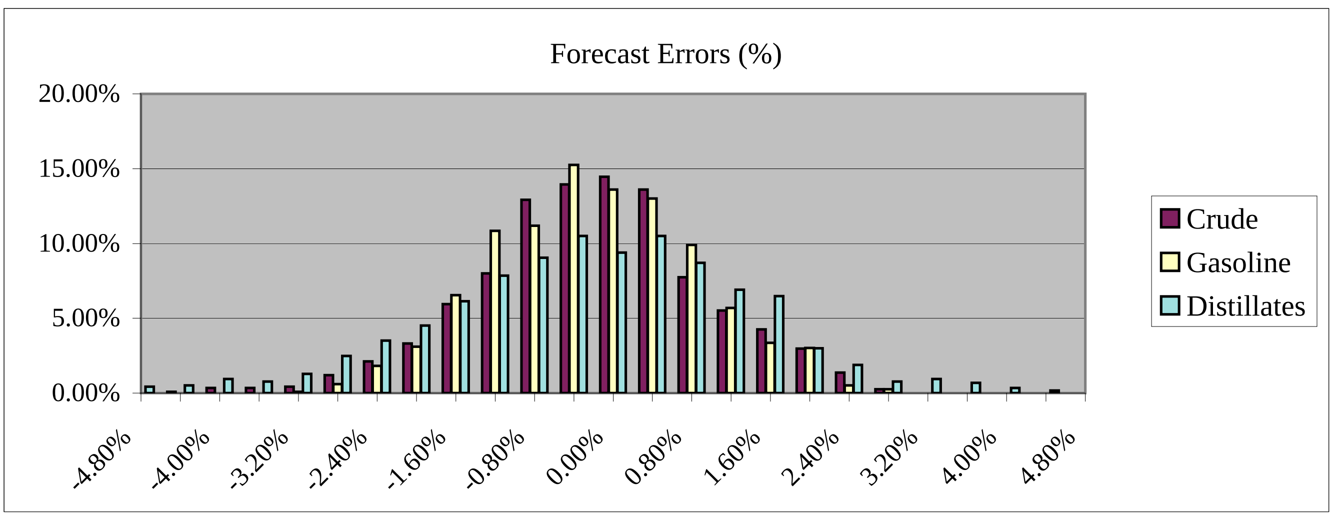
DOE Supply Change Data

	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: Forecast Errors

This figure presents summary statistics regarding forecast errors. 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. Distributions are roughly Normally distributed and there are not a substantial number of outliers. 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	8	-0.002%	89	0.040%	-13	-0.008%
Median	75	0.026%	100	0.048%	100	0.084%
SD	3263	1.156%	2123	1.041%	1996	1.652%
Max	8900	3.130%	6500	3.107%	8300	6.593%
Min	-11500	-4.361%	-6400	-2.956%	-7400	-6.410%

Table I: Quintile Analysis

This table tests the monotonicity of the relationship between accuracy and price responsiveness. Accuracy (Acc) is the inverse of the moving average absolute value of forecast errors over the previous 10 periods. Price responsiveness (Beta) is calculated in a 20-period rolling regression r = a + Beta*F + e. The return r is the return on the Tuesday preceding the announcement of actual supply levels for ex-ante tests. Betas are found to be negatively related to accuracy (meaning positive forecasts induce larger reductions in price for more accurate analysts). For ex-post tests, the return is calculated from 10:25 AM to 10:45 AM on Wednesday (forecast error is realized at 10:30 AM). Betas are found to be positively related to accuracy (meaning positive forecast errors induce larger price increases for more accurate analysts). These relationships are found to be nearly monotonic and the difference between average values for the extreme quintiles is significantly different from zero. Barrel coefficients reported x10^-6.

	Barrels			Percent		
	Acc	Beta (Ex-Ante)	Beta (Ex-Post)	Acc	Beta (Ex-Ante)	Beta (Ex-Post)
Aggregate	169.795	-0.301	1.646	30.971	-0.079	0.273
Q1	228.873	-0.565	1.708	41.808	-0.169	0.348
Q2	187.140	-0.474	1.743	35.264	-0.098	0.318
Q3	166.172	-0.703	1.853	30.884	-0.072	0.265
Q4	145.322	0.054	1.557	26.028	0.011	0.217
Q5	120.982	0.193	1.360	20.749	-0.066	0.215
Q1-Q5	107.891	-0.758	0.349	21.059	-0.103	0.133
(P-value)	(0.000)	(0.001)	(0.000)	(0.000)	(0.002)	(0.000)

Table II: 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	

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