Is the Price of Crude Responsive to Macroeconomic News? A Test of the Stock-Flow Hypothesis

Arjun Chatrath
University of Portland
5000 N. Willamette Blvd.
Portland, OR 97203
chatrath@up.edu

Hong Miao*
Colorado State University
Fort Collins, CO 80523
Hong.Miao@business.colostate.edu

Sanjay Ramchander
Colorado State University
Fort Collins, CO 80523
Sanjay.Ramchander@business.colostate.edu

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Abstract

A recent study indicates that the daily price of crude oil is mostly unresponsive to macroeconomic news, at times exhibiting response-coefficients that carry the "wrong sign". The study concludes that the price of crude oil is predetermined to macro aggregates, and hence determined in a flow demand and flow supply framework. We make the economic argument that inferences on commodity price determination should be drawn from news responses only after the standard tests are subject to inventory (or stock) controls. Using both daily and intraday data for crude oil, and using rudimentary tools to isolate perceived inventory levels, we test for the stock-flow hypothesis for crude oil. We find only weak evidence on the role of inventory levels for crude oil. We also assess the extent to which the dynamics of the dollar plays in the results, and find its role to be limited. Overall, the prior conclusion that crude oil is priced primarily in a flow-environment is supported by our data. The initial (intraday) response in energy prices to macro news appears to be the result of noise trading.

JEL codes C32, D5, E37, Q41, Q43.

* Corresponding author.

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1 Introduction

The stock/flow distinction in demand and supply analysis has been pursued by economists since the 1950s (e.g., Clower (1954), Clower and Bushaw (1954), Baumol (1962) and Harrison (1980)). When demand and supply are treated as pure flow concepts, inventories are not relevant to price behavior. However, when they are treated as stock-flow concepts, inventories can induce both short-term and long-term effects in prices.[1] While economists agree on the importance of inventories in commodity price behavior, a strange dichotomy arises in comparing the assumptions by empiricists and market regulators – the role of stocks is often presumed to be minor in empirical work, and yet is

[1]/ A commonly employed example of a pure flow demand/supply market is that for day-labor. An example of a pure stock demand/supply market is that for painting by the old "Dutch-Masters" (e.g., Sexton, Clower, Graves and Lee (1992)). An intuitive example of a stock-flow market is the market for automobiles, where demand drives production, but dealership inventories play visible role in pricing.

central to the thesis of regulatory action. For instance, empirical work on the origins and transmission of energy price shocks disregards the potential for instantaneous feedback between the economy and the prices of commodities such as crude oil (e.g., Bernanke, Gertler and Watson (1997), Balke, Brown, and Yucel (2002), Kilian and Park (2009) and Herrera and Pesavento (2009)).[2] These studies implicitly assume that prices are predetermined with respect to macroeconomic aggregates. This assumption will not be valid if stock variables are important in price formation. On the other hand, commodity market regulators appear to take the opposite approach, assuming an important role of stock in all commodities. For instance, regulators of futures markets impose blanket limits on the number of contracts that may be held by a trader ("position limit") with the view that, when left unregulated, manipulators will build large stocks, and use futures contracts to squeeze the market.[3] To our knowledge, there is no systematic attempt by the exchanges to determine the stock- versus flow orientation of the commodities regulated.

In a recent study, Kilian and Vega (2011) offer an interesting, albeit indirect, test on the stock-versus-flow orientation for commodities. The authors run regressions of crude oil and gasoline returns on the surprise components of several types of U.S. macroeconomic announcements. The regressions produce anemic coefficients and R^2s, with some of the surprise coefficients exhibiting the "wrong sign". The unresponsiveness of daily returns to economic surprise is interpreted by the authors as being consistent with each (and consequently all) of the following: (a) energy prices are predetermined with

[2] / See Kilian and Vega (2011) for a more extensive discussion.

[3]/ The financial crisis of 2007-2009 has rejuvenated an old debate on position limits, with several law makers urging the Commodity Futures Trading Commission (CFTC) to "aggressively" implement limits where they don't currently exist (e.g.,"Commodity Traders, Investors Face New Regulatory Risks", Reuters, January 2011).

respect to macroeconomic aggregates; (b) crude and gasoline are consumption goods, and not investment assets; and (c) crude and gasoline prices are determined by flow supply and flow demand. While Kilian and Vega (henceforth KV) take a novel approach to addressing questions regarding price determination (and the nature of the commodity) for crude and gasoline, their study has an important shortcoming. Namely, in treating a macro news surprise as a singular variable, they fail to explicitly allow for news responses to vary with the state of stock demand and stock supply (i.e., stock variables). In other words, their support for the notion that energy prices are determined in a flow-demand/supply environment is obtained from tests that are predisposed to supporting this finding.

The purpose of this paper is to provide a general framework to obtain a stock-flow distinction for commodities. We make a case that stronger inferences on commodity price determination can be drawn if the standard tests are subject to stock controls. Specifically, when supply and demand are treated as pure flow concepts, it is presumed that stock is not important in price determination. The equilibrium price in this case is determined by current production and consumption flows, not by perceptions on future changes to production and consumption. In short, we may expect such commodities to be unresponsive to "news" on macroeconomic indicators. On the other hand, if a commodity's price is determined in a stock-flow economy, the response of stock demand is allowed to play an important role in short run price dynamics. Importantly, *excessive* levels of inventory could influence the price path in ways that may be otherwise interpreted as being counterintuitive. Therefore, in the context of empirical studies that examine price behavior in a demand and supply framework, a failure to recognize the stock-contingent nature of the responses could lead one to inaccurately portray the commodity as a pure consumption good traded in a flow demand/supply framework.

Following KV, we first examine the unconditional response of crude oil to macro news surprises. However, in a marked departure from prior studies, we extend this framework with carefully calibrated controls that proxy for excess stock demand in order to more accurately weigh in on the price determination of crude oil. It appears from casual observation that the stock-flow concept ought to apply to this commodity; it is a fairly homogenous and storable commodity with a very liquid futures contract that caters to stock building in a surplus market. [4] As an example of the vast inventories, over period 1990-2009, the ratio of crude inventories to the lagging 2-month disposition of crude averaged 8.3 (SD of 1.2).[5] It is not surprising, therefore, that market observers construe a strong role for large financial institutions and hedge funds, especially those taking physical ownership of oil, in influencing the price of oil in the short run.[6] Oil producers themselves are commonly perceived to manage inventories with the focus on influencing

[4]/ It is no coincidence that the locations of the two largest oil futures markets, New York for the NYMEX, and Antwerp-Rotterdam-Amsterdam area for the International Petroleum Exchange, happen to hold disproportionately large quantities of discretionary stocks.

[5]/ Also striking is that the coefficient of variation of the weekly percentage changes in inventories (33.8) is three times larger than the coefficient of variation for weekly percentage changes in disposition (10.8). These figures do not factor in the US Governments Strategic Petroleum Reserves (SPR). Calculations are based on weekly data on production, imports, exports, and ending inventories provided by the Department of Energy.

[6]/ For example, a news journal reported in 2004 that Morgan Stanley had acquired a large warehousing facility near Amsterdam, and Goldman Sachs had bought 10 million barrels of oil. The article also noted an internal study by a large European oil company that estimated that speculators were adding between 15% to 20% to the price of oil at that time (The Times (UK), September 12, 2004).

prices.[7] Whatever the foundations of such perceptions, it is widely believed that crude stocks significantly impact energy prices.

Using both daily and intraday data for crude oil, we examine whether the sensitivity of crude oil prices to macroeconomic shocks are contingent on the stock variables prevailing prior to the news release. For the purpose of benchmarking our results, we first conduct standard tests to establish the aggregate sensitivity of crude oil prices to macroeconomic surprises. Next, we conduct tests that attempt to decompose price responses by stock variables, which we proxy by two measures: (i) the ratio of inventories to smoothed-disposition – an inverse proxy of excess stock demand, and (ii) the convenience yield (yield), obtained in standard fashion using the term structure of crude futures prices. The yield is a widely accepted proxy for tightness (high yield) and excesses (low yield) in inventories (e.g., Hull (2008)). Regressions are conducted with macroeconomic surprises being conditioned on the level of these stock variables prevailing the day before the announcement is publicly released.

In order to add robustness to our results, we also examine the extent to which the wrongly-signed coefficients from the regression of crude returns on macroeconomic surprises are a manifestation of a proxy effect arising from the dollar's response to macro news. . This is important since the interplay between the dollar exchange rate's response to U.S. macroeconomic news (e.g., Andersen, Bollerslev, Diebold and Vega (2003) and Faust, Rogers, Wang and Wright (2007)) combined with its inverse relationship with

[7]/ A dramatic example is found in the in the late 2008. As the price of oil plunged in a worsening economy (from about $150 in July to $35 in December), producers/suppliers preferred to set their supertankers adrift the Atlantic, delaying their inevitable delivery in Cushing, Oklahoma, a major cross-roads for pipelines. The noted perceived benefit was that limiting the visible stock would contain the price declines in the face of deteriorating economic indicators (The New York Times, January 15, 2009).

crude oil prices (Golub (1983)) can potentially influence the commodity's price response. The results from this analysis would help us identify whether the weak responses of the crude oil prices crude oil are the result of a dollar-induced proxy effect. In particular, we examine whether the response coefficients for crude oil substantially change when the dollar's response to the macro news is removed from the prices.

Our results are summarized as follows: (i) We fail to detect an important role for stock variables in the daily and intraday price responses to macroeconomic indicators. (ii) Controls for the dollar are deemed unimportant to the results. Specifically, the counterintuitive and weak response coefficients persist even when crude prices are measured in foreign currency terms. (iii) While we do find stronger responses in crude prices when high frequency intraday data are employed, the responses are not statistically significant when the post-news event window is expanded to 30 minutes. The micro effects to macro news are attributed to noise trading. Overall, our findings support and strengthen the conclusions reached in KV that the price of crude oils is predetermined with respect to macro aggregates, and determined in a flow demand/supply framework.

The remainder of the paper is organized as follows. Section II paper presents a theoretical backdrop to the role of inventories in news responses. Here we examine possibility that the counter-intuitive coefficients in KV are a function of stock variables. Section III presents the data and the development of the variables employed in the empirical work. Section IV reports on the results from alternate specifications of the macroeconomic news responses. Section V concludes the paper.

2 Stock-flow commodities and the potential for complex responses to news

To better motivate our variables and empirical framework, we summarize the standard elements of equilibrium and stability for stock-flow commodities that are now familiar in the literature. The viewpoint on market equilibrium that has long dominated economic literature treats supply and demand as rates of flow (flow demand and flow supply). This is not surprising given the importance of flows in the two pillars of economics, the theory of the firm, where the emphasis is on the equilibrium rate of production, and the theory of the household that focuses on the equilibrium rate of consumption. However, ever since the contributions of Clower (1954), Clower and Bushaw (1954), Hadar (1965), Ackley (1983), Harrison (1980), and others, it is now widely acknowledged that a more complete understanding of both equilibrium and disequilibrium behavior of prices requires an explicit incorporation of stock variables.[8]

We employ the framework in Clower and Bushaw (1954) given its generality. Denote the flow demand function as $d(p)$, the flow supply function as $s(p)$, and the stock demand function as $D(p)$. Just as $d(p)$ is inversely related to prices, $D(p)$ is also downward sloping since a high (low) commodity price would require greater (smaller) amount of wealth to be set aside for inventory. However, unlike $d(p)$, at a moment in time, the stock demand function represents a constant set of values for variables such as expected income, expected storage costs, and expected prices are held constant. If any of these values were to change, the position of the stock demand function would shift. The

[8]/ The stock-flow framework has been used to explain prices in various markets including currency (Faruqee (1996)), real estate (Wheaton (1999)), and durable goods (Barsky et al., (2007)).

excess flow demand is given by $x(p) = d(p) - s(p)$, which may be positive, negative or zero. For a non-perishable commodity such as crude oil, the commodity stock can be increased only by new production and imports (flow supply components), and decreased only by consumption (by refineries) and exports (flow demand components). Therefore, for some t_0 in t, the stock supply is given by $S \equiv S^0 + \int_{t_0}^{t}(s-d)dt$, where S^0 is the stock at time t_0. The excess demand can then be represented by

$$X(p) \equiv D(p) - S^0 + \int_{t_0}^{t} x(p)dt. \qquad (1)$$

Equation 1 characterizes the price dynamic of a stock-flow commodity to be a function of both excess flow demand and excess stock demand. At the most basic level, this function can be assumed to be linear. If we are concerned with a very localized behavior of the system, we can approximate the function by $\frac{dp}{dt} = f(x, X) = \alpha x + \beta X$, where α and β are constants. A flow-oriented commodity will be distinguished by $\beta = 0$, a stock-oriented commodity by $\alpha = 0$, and a stock-flow commodity by $\alpha \neq 0, \beta \neq 0$.

Defining $\frac{dp}{dt} = q$, at equilibrium at instant t_0 we must have $\frac{dp}{dt} = 0$ and $\frac{dq}{dt} = 0$. Clower and Bushaw (1954) show the (now familiar) necessary and sufficient conditions for a price p to obtain equilibrium to be $x^0 = 0 \; and \; X^0 = 0$ if $\beta \neq 0$, and $x^0 = 0$ if $\beta = 0$. In other words, the equilibrium for a stock- or stock-flow oriented commodity is obtained if and only if both, excess flow demand *and* excess stock demand disappear. A flow oriented commodity requires only that the excess flow demand vanish. Moreover, the stability of the stock-flow equilibrium (in which prices tend to return to the equilibrium if disturbed) requires that excess flow demand as well as excess stock demand varies in a normal way with commodities price (for instance, where the excess demand function is downward sloped). Similarly, the conditions for price oscillations (instability of another kind) will be more easily met in a stock-flow environment than either a flow or a stock environment alone.

Now consider the elements stock-flow equilibrium in context of the empirical framework in KV. For the response coefficients to have any particular meaning for establishing the nature of the commodity (flow or stock-flow), the market must be assumed to be in equilibrium just prior to the release of information on the macroeconomic indicator M at t_0. At t_0 we can use the framework, $\frac{dp}{dt} = \gamma M,$ to establish whether the equilibrium is disturbed. The finding in support of the null that the price is not responsive to $M(\gamma = 0)$ at t_0 is interpreted in KV as confirmation of $\beta = 0$, that we are dealing with a flow oriented commodity. The presumption here is that any stock-variable will be caught out by the nature of γ, since it reacts to news in a predictable way. However, when we recognize that the response coefficient from the regression actually represent an aggregation of responses from multiple events (across multiple states of $X^0(p)$), a finding in support of the null (aggregate γ=0) cannot tell us anything definitively about either β or X^0. This is because stock variables do not always respond to news in a predictable way.

For instance, Mass (1978, 1980) explains the unusual behavior of hog prices in 1971 via the role of stocks. In that year, the price of corn rose dramatically due to a blight in the Midwest. Most market observers anticipated that hog prices would rise, since the rising marginal cost of hog production (principally corn feed) would deter production.

Instead, hog prices fell for about a year. The higher cost of holding inventory deterred stock demand, brought greater quantities of hogs to market, and thereby suppressed prices. Jumps in the cost of storage could thus be a major source of instability in short term prices (also see Meadows (1970)). The role of cost-shocks has similarly been implied in the behavior of finished-goods inventories for a wide range of durable and nondurable goods transportation equipment, machinery, textiles, and petroleum and coal products (e.g., Blinder (1986), and Maccini, Moore, and Schaller (2004)).[9]

For crude oil, we can find similar examples of storage costs influencing stock-demand behavior, even before the cost increases are experienced. The Department of Energy estimates that the cost of storing a barrel of crude in the early 1990s was about $4 if storage space was rented, representing approximately 10% of the price of the commodity.[10] Importantly, this cost of storage is known to rise with scarcity of storage. Therefore, when inventories are running high, *expectations* of further increases in inventories (due, for instance, to larger imports or domestic production) may dampen stock demand. This was the case in late 2008, when in the face of a sharply declining economy, the storage facilities in Cushing, Oklahoma were pushed to capacity. The lack of storage facilities (floating or otherwise) and the rising storage costs (relative to prices) compelled many long futures contract holders to settle their contracts in lieu of taking delivery.[11] Such inventory dynamics could play a role in the wrong-signed response

[9]/ Blinder (1986) suggests that inventory responses to cost-shocks might explain the higher variation in production than in sales for a wide variety of goods. Maccini et al. (2004), among others, show that shocks in real interest rates impact inventories.

[10]/ For instance, see U.S. Energy Information Administration, www.eia.doe.gov/pub/oil_gas/petroleum/analysis_publicatins/oil_market_basics/stocks_text.htm.

coefficients. In the face of good economic data, refiners tend to ramp up orders for delivery by their suppliers, and producers respond by ramping up production. If "speculative inventories" are already high at this time, stock holders may unload inventories anticipating capacity and storage-cost issues. In summary, very high inventory levels could prompt short-run price declines even amidst positive economic data. To the extent to which inventory levels muddy the response coefficients is an empirical question that can be more directly answered by a framework such as $\frac{dp}{dt} = \sum_i^I \gamma_i M_i X_i^0$, where X_i^0 represents the excess stock demand at state i.

3 Data and Measures

3.1 Data Description

Our data primarily relate to crude oil prices (spot and futures), macroeconomic announcements, and crude inventories and disposition. Crude prices are sampled on a daily and intraday basis. The daily data cover the period January 1990 through December 2009 and include both, the West Texas Intermediate (WTI) spot price, and futures price from the nearby contract traded at the New York Mercantile Exchange (NYMEX). The WTI data are end-of-day and FOB at Cushing Oklahoma, and are obtained from the U.S. Energy Information Administration of the Department of Energy (EIA-DOE). A corresponding futures price series is obtained by following the standard procedure of rolling over the nearby contract on the last day of each pre-expiration month. The intraday price data are tick-by-tick futures prices for light sweet crude oil for the period

[11]/ This "Cushing Effect" was widely thought to depress NYMEX crude prices in late 2008 (e.g., M. Zhou, MarketWatch, January 12, 2009.)

January 2005 through December 2009, and are obtained from the Futures Industry Institute.[12] The intraday data spans both open outcry and electronic trading.[13] The time series are constructed for the nearby contract with rollover contingent on intraday trading activity.[14] The futures prices are sampled at 1, 5, 10 and 30-minute intervals to construct returns and volatility measures.

We also employ 19 sets of monthly macroeconomic announcements obtained from Bloomberg. These announcements, listed in Table 1, are often highlighted as important in the behavior of financial markets in the US.[15] The data include the news release time (U.S., EST), the consensus (median) forecasts, and the release figures of the macroeconomic variables. The macroeconomic announcements are separated into four categories depending on the time of each announcement. There are 10 announcements at 8:30 am, 2 at 9:15 am, 6 at 10:00 am, and 1 at 2:00 pm. With the exception of Nonfarm Payrolls and Unemployment Rate which are usually released together at part of the Job Report on Friday, most of the other announcements are fairly evenly distributed through weekdays.

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[12]/ Our choice of sample period is constrained by the fact that intraday prices corresponding to the earliest announcements (at 8:30 am) are available only since the mid-2000s.

[13]/ The Chicago Mercantile Exchange group provides both open outcry (pit) and electronic (Globex) trading in oil futures. The open outcry trading hours for light sweet crude oil is Monday through Friday 9:00 am – 2:30 pm. Trading is also offered simultaneously (side-by-side trading) on the Globex electronic trading platform that operates Sunday through Friday, 6:00 pm – 5:15 pm. The tick-by-tick raw futures data specify the time, to the nearest second, and the exact price of the futures transaction.

[14]/ Specifically, we consider the daily tick count for the front and first back-month contracts and rollover to the next contract when the daily tick count of the back-month contract exceeds the daily tick count of the current front month contract.

[15]/ These are predominantly the same set of announcements used by researchers such as Ederington and Lee (1993) in their examination of interest rates and foreign exchange futures markets (also see Andersen, Bollerslev, Diebold and Vega, 2003; Balduzzi, Elton and Green, 2001; Simpson and Ramchander, 2004), and by Killian and Vega (2011) in examining energy prices.

Finally, we use crude inventory and disposition data provided by the EIA-DOE. These data represent weekly ending domestic stocks (excluding Strategic Petroleum Reserves), U.S. exports of crude oil, U.S. imports and exports of crude oil, and domestic production. These are reported each Friday. Weekly disposition is obtained by taking the difference between the prior stocks and ending stocks while adding net imports and production during the interval in question.

3.2 Measures

In order to investigate the impacts of macroeconomic news on the crude oil market, we employ the measures described below.

A. Signed and Standardized Surprises

For each announcement, the surprise component is measured as the difference between the actual released values and the median predications from the survey conducted by Money Market Services (MMS) on the previous Friday. Surprises are signed such that positive surprises represent stronger-than-expected growth. However, for the Unemployment Rate and Change in Nonfarm Payrolls, both of which are countercyclical indicators, the sign of the surprises is flipped so that positive surprises reflect stronger-than-expected growth for these as well. The surprises are then standardized by their respective standard deviation. Let $A_{i,t}$ denote the released value of an announcement of type i at t, and $E_{i,t}$ denote the ex-ante expectation (i.e., the median prediction) of this release. The standardized surprise is defined as $s_{i,t} = \frac{A_{i,t}-E_{i,t}}{\sigma_i}$, where σ_i is the sample standard deviation of the surprise component, $A_{i,t} - E_{i,t}$. Because σ_i is a constant for each announcement, this standardization affects neither the statistical significance of the estimated response coefficients nor the fit of the regressions compared to the results based on the raw surprises.

B. Return and Volatility

Daily returns are given by $R_t = 100 \times (logP_t - logP_{t-1})$, where P_t represents the price at the close of trading on day t. Intraday returns during an interval (t_{i-1}, t_i) on day t is calculated using the open and close prices in the interval as $R_{t_i} = 100 \times (logP_{c,t_i} - logP_{o,t_{i-1}})$, where, P_{c,t_i} and $P_{o,t_{i-1}}$ represent the close and open price during the interval on day t. For intraday data, we employ the cumulative-intraday-squared-return measure of volatility introduced by Anderson and Bollerslev (1998a). The integrated volatility during an interval (t_{i-1}, t_i) is given by

$$\sigma_{t_i} = \sqrt{RV_{t_i}} = (\sum_{j=1}^{n} R_j^2)^{1/2},$$

where σ_{t_i} is the volatility measure, RV_t is the realized variance, or the cumulative intraday squared return, and n is the number of (return) observations during that period of time. We sample the data at 1-minute frequency. Thus, when examining volatility at 10 minute intervals, the realized variance is the sum of ten 1-minute squared returns.[16]

C. Stock Variables

Excess stock demand (equation (1)) is not directly observable. However, we are able to observe its manifestation in the spread between spot and futures prices. Moreover, we

[16]/ The realized volatility estimator has been justified based on the quadratic variation theorem, which implies that when asset prices are observed without errors, this estimator provides consistent estimates of integrated volatility of the underlying price process (e.g., Mancino and Sanfelici (2009)). Barndorff-Nielsen and Shepard (2001) show that realized volatility is less subject to measurement error and provides estimates that are less noisy.

are able to observe the supply and disposition components of equation (1). We proxy stock variables via two alternate formulations:

Convenience yield: From the Theory of Storage (e.g., Brennan, 1958), the current futures price of a good to be delivered (T-t) years from now is given by $F_{t,T} = P_t e^{(r_t+u_t)(T-t)}$, where r_t is the interest rate for that maturity, u_t is the percentage warehousing costs, and P_t is the spot price. When holders are reluctant to swap the product for the futures contract, however, this "cost-of-carry" relationship no longer holds. The reluctance to swap inventories is thought to arise from the ability to profit from temporary shortages in the commodity (e.g., Hull (2008)). The ensuing distortion in the cost-of-carry model is referred to as the convenience yield. Given the lack of data on storage costs, we employ the truncated formulation:

$$y_t = \frac{\ln(\frac{P_t}{F_{t,T}})}{T-t} + r_t. \qquad (2)$$

The convenience yield (yield) reflects the market's expectation on the future availability of the commodity. The greater the perception of inventory shortages, the higher is the yield. In contrast, if holdings are high, the convenience yield will be low and even negative. It is noteworthy that crude oil is most widely cited as having extreme variations in yield (e.g., Gibson and Schwartz (1990) and Litzenberger and Rabinowitz (1995)). Since the yield represents the reluctance to given up stocks at the current price, it also represents perceptions on excess stock demand. For instance, when convenience yields are negative, an excess of stocks is perceived. Under the stock-flow framework, if the perceived oil inventory level matters to how markets behave on news, the response coefficients ought to be sensitive to the level of the yield. Correspondingly, if we find the response coefficients to be sensitive to the level of the yield, the notion that oil is determined in the conventional flow demand and flow supply environment would be flawed.

Having obtained “nearby y_t” using the WTI price, the nearby NYMEX contract price, and the 1-month LIBOR, we develop ten dummy variables, each representing a decile for the variable. Similarly, we use the 2nd nearby NYMEX contract price, and the 3-month LIBOR to obtain the “next-to-nearby y_t”, and ten dummy variables for deciles for this variable. The two sets of dummies are found to be almost identical, indicating a consistency in the message from the futures term structure on the state of inventory tightness. We employ the nearby yield dummies in this study.

Standardized supply: We can observe the stock supply and flow demand and flow supply components of equation (1) using the DOE data. Stock supply at time *t* is simply the inventory level, and also represents the total supply at that instant. Disposition (flows of consumption and production) between day *t-i* and *t* is given by

$$\delta_t = S_{t-i} - S_t + z_{t-i,t} + m_{t-i,t} - e_{t-i,t}, \quad (3)$$

where S_t represents the stock on day *t*, and $z_{t-i,t}$, $m_{t-i,t}$, and $e_{t-i,t}$ represent the domestic production, imports, and exports, respectively, over the interval $t - i$ to t.

Since stock is not likely to be a stationary variable, we standardize week ending stocks with the disposition over the prior eight weeks. Let $\delta_{t,8}$, …., $\delta_{t,1}$ represent the disposition for week $t-8, \ldots, t-1$ respectively. Our standardized supply variable at the end of week *t* is

$$S_t^* = S_t / \sum_{i=1}^{8} \delta_{t,i}. \quad (4)$$

Having obtained S_t^* for the sample, we again develop ten dummy variables, each representing a decile for S_t^*. The dummies from (4) and (2) form the stock variables in our study of price responses to macroeconomic indicators. In both cases, when stock supply is extremely high, news that would support future increases in inventories is expected to result in a low or negative response in excess stock demand (wrong-signed response coefficients are expected).

4 Results

A. Daily responses of returns and dollar-adjusted returns

The first set of results is from the regression customarily employed to obtain response coefficients (e.g., KV),

$$r_{i,t} = a + bM_{i,t} + \varepsilon_{i,t}, \quad (5)$$

where $r_{i,t}$ represents daily returns corresponding to the i^{th} macro indicator, and $M_{i,t}$ is the standardized and signed surprise relating to that indicator. The results are reported in Table 2A. The coefficients for WTI (cash returns) confirm the evidence of weak crude responses reported in KV. For only two macroeconomic surprises, Capacity Utilization and Housing Starts do we find significance at our cut-off threshold of 10%. The largest return response is for Housing Starts – a mere 0.40% to a 1-SD surprise. Five of the nineteen coefficients are negatively signed, though only Personal Income is significant. Not surprisingly, the R^2 is very low, ranging from 0 to 0.0167. The coefficients for NYMEX (futures returns) similarly point to weak responses to macroeconomic surprises. Only one coefficient is statistically positive – Personal Consumption. Five of the NYMEX coefficients are negative, though only that for Advanced Retail Sales is significant. The R^2 ranges from 0 to 0.016. The differences in the NYMEX results and the WTI results, albeit minor, indicate that they are not "perfect substitutes" for crude price data.[17] In summary, the results in 2A confirm the patterns document in KV. That is, we find very weak responses, at times counterintuitive, to economic news surprises.

Table 2A here

It is possible that the weak results are manifestation of the dollar-proxy effect. Since the dollar values respond positively (negatively) to good (bad) macroeconomic data (e.g., Andersen, Bollerslev, Diebold and Vega (2003) and Faust, Rogers, Wang and Wright (2007)), and since the price of an imported commodity is negatively related to the dollar's strength, the evidence in Table 2 may not clearly point to a lack of responsiveness of crude. Specifically, a finding of very different coefficients from those reported in Table 2A would suggest a meaningful dollar-proxy effect, which might explain the wrong-signed coefficients. However, this finding would certainly inhibit additional interpretation of the crude oil's behavior around announcements.

We can get a sense of this proxy-problem by rerunning regression (5) employing "dollar-adjusted returns". For this purpose we rerun (5) using the alternate return measure,

$$r_t^* = 100 \times (log(P_t/e_t) - \log(P_{t-1}/e_{t-1})),$$

where e_t is the trade-weighted dollar index. The results are reported in Table 2B. The results show a very marginal impact of the dollar on the crude response coefficients. For

[17]/ Spot prices are known to be more responsive (volatile) than futures prices. Samuelson (1965) shows that futures price volatility will be inversely related to time-to-maturity of the contract (now known as the Samuelson hypothesis). By construction, the NYMEX data has a larger "futures" component at the beginning of the month, and a larger spot component at the end of the month.

instance, the negative coefficient for Personal Income and Advanced Retail Sales remains almost unchanged and even fortified. Some coefficients that showed significance in Table 2A do not do so here. However, there are no remarkable inconsistencies between the two tables that would indicate an important dollar-induced proxy-effect in the response coefficients for crude returns. More important to our study, the "wrong signed" coefficients remain unexplained by the strength of the dollar.

Table 2B here

B. Daily responses decomposed by convenience yield

To examine the importance of stock variables in the response-coefficient, we estimate a set of regressions where the standardized and signed surprises are binned by deciles based on the level of convenience yield. We estimate the regression

$$r_{j,t} = c + \sum_{i=1}^{10} c_i d_{i,t}^{y} M_{j,t} + \varepsilon_{i,t}^{y}, \qquad (6)$$

where $d_{i,t}^{y}$ are dummy variables, each representing a decile for the yield-level ($d_{1,t}^{y}$ represents the lowest yield) over the sample.[18] If high inventories explain the wrong-signed coefficients, we should find them clustered in c_1 and c_2 more than in c_9 or c_{10}. More generally, if the response coefficients are systematically different across the high-inventory, we would have found evidence against the notion that stock variables do not matter in the dynamics of crude prices. To provide a sense of the importance of the stock variables, we compare the adjusted-R^2s from equation (6) with those from an alternate estimation that employs dummies based arbitrarily on sampling interval. Specifically, for the purpose of obtaining a comparative adjusted-R^2 we estimate the regression,

[18] / The coefficients are not materially changed when (6) is estimated without the intercept.

$r_{i,t} = a + \sum_{i=1}^{10} a_i D_{i,t} M_t$, where D_i represents ten dummy variables, each corresponding to one of the sample-intervals: 1990-1991, 1992-1993, …, 2008-2009.

The results in Table 3 relate to WTI cash returns. The results from NYMEX crude returns are fairly similar, and are omitted in the interest of brevity. The response-coefficients show no systematic clustering across the convenience yield dummies. For instance, we find three significant, negative coefficients for c_1, but also find such coefficients for c_{10}. The wrong-signed coefficients appear to be scattered across the convenience yield-spectrum. Similarly, there is no systematic pattern for positive coefficients. The weak explanatory power is confirmed via a comparison of the last two columns. The arbitrary-decomposition, described above, produces adjusted-R^2s that are at least equal to those from equation (6) for majority of the announcements. Overall, the convenience-yield is unable to explain the weak results we report in Table 2.[19]

Table 3 here

C. Daily responses decomposed by Relative Inventories

In an alternate surprise-decomposition, we employ the smoothed-relative-inventory described in (4). We estimate the regression

$$r_{i,t} = c + \sum_{i=1}^{10} c_i d_{i,t}^I M_{j,t} + \varepsilon_{i,t}^I, \quad (7)$$

[19]/ The coefficients from the estimation of (6) using NYMEX returns are only slightly more in line with expectations. There are multiple negative coefficients in c_1 and c_2, and we do find a relative absence of negative coefficients in c_9 and c_{10}. However, the response coefficients are mostly insignificant, even for high convenience yield (low inventory) levels. As with the results in Table 3, the adjusted-R^2s from the arbitrary decomposition of the surprises are often greater than those from the convenience yield decomposition. In a separate set of regressions, we employ the WTI and NYMEX returns calculated from dollar-adjusted prices. Neither of the patterns in Table 3 are materially altered. The results from these alternate estimations are available from the author.

where $r_{i,t}$ represents daily returns corresponding to the i^{th} macro indicator, $M_{i,t}$ is the standardized and signed surprise relating to that indicator, and $d_{i,t}^{I}$ are the dummy variables, each representing a decile of the relative inventories (d_1^I represents the highest level of relative inventories). As with the convenience-yield decompositions, if high inventories explain the wrong-signed coefficients, we should find them clustered in c_1 and c_2 more than in c_9 or c_{10}.

The results in Table 4 relate to WTI cash returns. No systematic patterns for the response coefficients emerge across the inventory spectrum. We find significant and negative coefficients in the majority inventory-deciles. Positive coefficients are similarly scattered. Moreover, as in Table 3, significant coefficients are rare. The adjusted-R^2s ranges from 0 to 0.045 and are often lower than the adjusted-R^2 (Adj-$R^2(T)$) the arbitrary decomposition of the surprises.[20]

In summary, the results from the inventory-decomposition regressions are comparable to those from the convenience-yield regressions. Taken together, the results in Table 3 and Table 4 point away from our original proposition that stock variables might explain the apparent unresponsiveness of crude prices to macroeconomic indicators. On a broader front, we are unable to reject the null that crude prices are determined by flow demand and flow supply.

Table 4 here

[20]/ The results for NYMEX crude returns are similar and are not reported.

D. Intraday Responsiveness

The question remains on whether crude prices respond in the very short run, and if they do, it will be of some interest to also evaluate the question of the speed of price reversal. To address these questions, we first estimate equation (5) using five-minute returns for the NYMEX futures contract over the interval, 2005-2009. These results are reported in Table 5. The coefficients are positive and significant for four of the nineteen announcements. The significant coefficients, Retail Sales, Nonfarm Payrolls, Consumer Confidence, and NAPM, have been generally shown to be among the most response-inducing announcements for stocks, bonds, and exchange rates (e.g., Boyd, Hu and Jagannathan (2005); Balduzzi, Elton and Green (2001), and Simpson, Ramchander and Chaudhry (2005)). The Adjusted-R^2s for these announcements are a respectable 0.25, 0.30, 0.18, and 0.076, respectively. None of the coefficients in Table 5 are significant and negative. In short, there appears to be a fairly strong and instantaneous response to surprises.

Table 5 here

To address the question of speed of price reversal, we examine the patterns in return volatility across three intervals following the announcements. Specifically, realized volatility (RV) discussed in Section III is computed for 5 minutes, 10 minutes, and 30 minutes after each announcement. Their values are then compared to the realized volatility over the same time-intervals but from non-announcement days. These results are reported in Table 6.

The first column of results relate to the RV over five minutes. There are seven announcements that carry significant responses based on the Welch tests against the control figures.[21] Similar to the findings in Table 5, Retail Sales, Nonfarm Payrolls, and NAPM illicit significant variability when compared to the control RV. We also find significant variability for five minutes following Durable Goods Orders, Personal Consumption, PPI, and the Unemployment Report. The fourth column relates to the RV over ten minutes. Here we find only three significant values for RV – for Nonfarm Payrolls, Personal Consumption, and the Unemployment Report. It appears that the majority of the response is reversed for most of the macro indicators within just 10 minutes of the announcements. The seventh column displays the RVs computed over thirty-minute intervals. None of the values are different from the control figures. It appears that all of the price response for all the announcements is reversed within thirty minutes.

Table 6 here

5 Conclusions

This paper examines the price response behavior of crude oil in the framework of a stock-flow distinction. Killian and Vega (2011) employ regressions of returns on macroeconomic news surprises to distinguish the orientation of commodities. Upon

[21]/ Unlike the standard ANOVA tests of equality in means, the Welch statistic does not require equality in variance between the comparison samples. The Welch's t-statistic is given by $t = (k_1 - k_2)/\sqrt{\sigma_1^2/N_1 + \sigma_2^2/N_2}$, where k_i, σ_i^2 and N_i are the sample mean, variance and size, and the degrees of freedom is approximated by $\omega = \frac{(\sigma_1^2/N_1+\sigma_2^2/N_2)^2}{(\sigma_1^4/(N_1^2(N_1-1))+(\sigma_2^4/(N_2^2(N_2-1))}$ (Welch (1947).

finding that the returns of crude oil and gasoline are unresponsive to macroeconomic surprises, the authors conclude that these commodities are flow-oriented. We suggest an alternate method that explicitly allows stock variables to influence the commodity's responsiveness to macro indicators. The empirical behavior of stock-flow oriented commodities suggest that price responses to news may appear to be weak (and even specious) on aggregate, but can be real and significant when sorted by the state of the commodity supply. Specifically, commodities can at times be expected to respond with the "wrong sign" when inventories are excessive, as was the case of the hog market in the 1971.

We present a framework where the sensitivity of crude oil prices to macroeconomic surprises is contingent on the stock variables prevailing during the time of the announcements. For the purpose of our empirical study, the state of the stock variables is alternately proxied by (i) the ratio of inventories to smoothed-disposition ("inventory-ratio"), and (ii) the convenience yield. Regressions of crude oil returns on surprises that are binned according to the level of these stock variables form the basis for our conclusions on commodity orientation.

Our results indicate that the state of crude stock variables is not an important factor in explaining the commodity's price responsiveness to macroeconomic indicators. These results are robust to the inclusion of dollar values – specifically, the counterintuitive and weak response coefficients persist even when crude prices are measured in foreign currency terms. Finally, when we switch our examination to high-frequency trading data, we find that responses of crude prices are both swift and significant, but show strong signs of price reversal. The observed price reaction dissipates quickly when the news-event window is expanded to 30 minutes thus leading us to conclude that the initial response to macro news may be the result of noise trading. Thus, by offering a more comprehensive and persuasive economic argument we are able to support and strengthen the conclusions reached in KV that crude prices are predetermined to macro aggregates, and that the commodity is primarily determined in a flow demand/supply framework.

It would be instructive to note that the simple empirical framework presented in this paper may also be employed for other commodities. This approach would be useful to futures market regulators who have a tendency to be undiscriminating across commodities in establishing position limits. We suggest that a more systematic approach is required to distinguish among commodities based on their stock-flow orientation.

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Table 1. U.S. News Announcements, 1/1990 -12/2009

The monthly macroeconomic news announcements employed in this study are listed by announcement time. The Mean and Std.Dev represent the average and standard deviation of the raw surprises, the difference beween the actual and survey figures.

					Raw Surprise	
Time	Announcement	OBS	Source	Dates	Mean	Std.Dev
8:30	Advanced Retail Sales	240	BC	1/1990-12/2009	-0.0163	0.6011
	Business Inventory	240	BC	1/1990-12/2009	0.0442	0.2757
	Change in Nonfarm Payrolls	240	BLS	1/1990-12/2009	-19.4813	105.7431
	Consumer Price Index	240	BLS	1/1990-12/2009	-0.0075	0.1371
	Durable Goods Orders	240	BC	1/1990-12/2009	-0.0079	2.8101
	Housing Starts	240	BC	1/1990-12/2009	0.0089	0.0841
	Personal Consumption	239	BC	1/1990-12/2009	0.0259	0.2688
	Personal Income	240	BEA	1/1990-12/2009	0.0475	0.2628
	Producer Price Index	240	BLS	1/1990-12/2009	-0.0119	0.4273
	Trade Balance	240	BEA	1/1990-12/2009	0.1563	4.2401
	Unemployment Rate	240	BLS	1/1990-12/2009	-0.0252	0.1473
9:15	Capacity Utilization	240	FRB	1/1990-12/2009	0.0060	0.3442
	Industrial Production	240	FRB	1/1990-12/2009	-0.0085	0.3286
10:00	Business Inventories[22]	240	BC	1/1990-12/2009	0.0442	0.2757
	Construction Spending	240	BC	1/1990-12/2009	0.0823	1.0074
	Factory Orders	240	BC	1/1990-12/2009	0.0429	0.6824
	Leading Indicators	240	CB	1/1990-12/2009	0.0078	0.1715
	NAPM	239	NAPM	1/1990-12/2009	-0.0437	2.0108
	New Home Sales	240	BEA	1/1990-12/2009	7.0796	61.0123
14:00	Treasury Budget Statement	240	TD	1/1990-12/2009	1.0277	11.9747

Note: Bureau of Labor Statistics (BLS), Bureau of the Census (BC), Bureau of Economic Analysis (BEA), Federal Reserve Board (FRB), National Association of Purchasing Managers (NAPM), Conference Board (CB), Treasure Department (TD)

[22] Business inventory data are released either at 8:30 am or 10:00am. Starting from December 2005, these data are released 10:00am.

Table 2A. Standard Regressions using Daily Returns, 1990-2009

The statistics are from the regression,

$$r_{i,t} = a + bM_{i,t} + \varepsilon_{i,t},$$

where $r_{i,t}$ alternately represents daily WTI returns and NYMEX futures returns corresponding to the i^{th} macro indicator, and $M_{i,t}$ is the standardized and signed surprise relating to that indicator. [a,b] and [c] represent significance levels of 1%, 5%, and 10%,respectively.

Time	Announcement	WTI (cash market) returns			NYMEX nearby contract returns			Nobs
		$\hat{\beta}_i$	(t-stat)	R^2 (%)	$\hat{\beta}_i$	(t-stat)	R^2 (%)	
8:30	Advanced Retail Sales	-0.21	(-1.39)	0.80	-0.19[c]	(-1.64)	1.12	240
	Change in Nonfarm Payrolls	0.12	(0.94)	0.38	0.10	(0.85)	0.31	240
	Consumer Price Index	-0.04	(-0.23)	0.02	-0.05	(-0.44)	0.08	240
	Durable Goods Orders	-0.12	(-0.66)	0.19	-0.08	(-0.60)	0.15	240
	Housing Starts	0.40[c]	(1.70)	1.21	0.19	(1.56)	1.02	240
	Personal Consumption	0.21	(1.31)	0.74	0.23[c]	(1.93)	1.61	239
	Personal Income	-0.32[c]	(-1.94)	1.60	-0.12	(-0.85)	0.32	240
	Producer Price Index	-0.17	(-0.84)	0.30	-0.07	(-0.41)	0.07	240
	Trade Balance	0.20	(1.22)	0.62	0.05	(0.38)	0.06	240
	Unemployment Rate	0.11	(0.85)	0.31	0.14	(1.21)	0.63	240
9:15	Capacity Utilization	0.29[b]	(2.00)	1.67	0.17	(1.39)	0.81	240
	Industrial Production	0.19	(1.30)	0.71	0.12	(1.01)	0.43	240
10:00	Business Inventories	0.07	(0.50)	0.10	0.09	(0.84)	0.30	240
	Construction Spending	0.27	(1.61)	1.10	0.21	(1.41)	0.33	240
	Factory Orders	-0.09	(-0.57)	0.14	-0.12	(-0.88)	0.33	240
	Leading Indicators	0.28	(1.51)	0.95	0.01	(0.07)	0.00	240
	NAPM	0.01	(0.07)	0.00	-0.08	(-0.52)	0.12	239
	New Home Sales	0.22	(1.32)	0.73	0.03	(0.21)	0.83	240
14:00	Treasure Budget Statement	0.12	(0.67)	0.19	0.04	(0.31)	0.04	240

Table 2B. Standard Regressions using Daily Dollar-Adjusted Returns, 1990-2009

The statistics are from the regression

$$r_{i,t}^{*} = a + bM_{i,t} + \varepsilon_{i,t},$$

where $r_{i,t}^{*}$ represents dollar-adjusted returns corresponding to the i^{th} macro indicator, and $M_{i,t}$ is the standardized and signed surprise relating to that indicator. Dollar adjusted returns for both the WTI and the NYMEX futures contract are given by $r_t^{*} = 100 \times (log(P_t/e_t) - \log(P_{t-1}/e_{t-1}))$, where e_t is the trade-weighted dollar index at the end of day t. [a, b] and [c] represent significance levels of 1%, 5%, and 10%, respectively.

Time	Announcement	WTI (cash market) returns			NYMEX nearby contract returns			Nobs
		$\hat{\beta}_i$	(t-stat)	R^2 (%)	$\hat{\beta}_i$	(t-stat)	R^2 (%)	
8:30	Advanced Retail Sales	-0.26[c]	(-1.69)	1.19	-0.23[c]	(-1.69)	1.19	240
	Change in Nonfarm Payrolls	-0.04	(-0.30)	0.04	-0.10	(-0.75)	0.24	240
	Consumer Price Index	-0.03	(-0.17)	0.01	-0.02	(-0.14)	0.01	240
	Durable Goods Orders	-0.16	(-0.84)	0.30	-0.09	(-0.65)	0.18	240
	Housing Starts	0.38	(1.63)	1.12	0.26	(1.23)	0.64	240
	Personal Consumption	0.22	(1.31)	0.76	0.19	(1.31)	0.75	239
	Personal Income	-0.35[b]	(-2.00)	1.74	-0.14	(-0.86)	0.32	240
	Producer Price Index	-0.14	(-0.65)	0.18	-0.18	(-0.93)	0.36	240
	Trade Balance	0.13	(0.75)	0.23	0.08	(0.52)	0.12	240
	Unemployment Rate	0.20	(1.48)	0.94	0.22	(1.59)	1.08	240
9:15	Capacity Utilization	0.22	(1.46)	0.89	0.27[b]	(1.97)	1.62	240
	Industrial Production	0.11	(0.75)	0.24	0.17	(1.23)	0.64	240
10:00	Business Inventories	0.07	(0.51)	0.11	0.03	(0.25)	0.03	240
	Construction Spending	0.25	(1.46)	0.91	0.08	(0.39)	0.07	240
	Factory Orders	-0.11	(-0.68)	0.20	-0.17	(-1.11)	0.52	240
	Leading Indicators	0.26	(1.32)	0.73	0.14	(0.77)	0.25	240
	NAPM	-0.08	(-0.46)	0.09	0.09	(0.43)	0.08	239
	New Home Sales	0.22	(1.29)	0.71	0.05	(0.39)	0.06	240
14:00	Treasure Budget Statement	0.14	(0.78)	0.26	0.10	(0.64)	0.17	240

Table 3. Response-Coefficients for WTI crude from Regressions with Surprises Decomposed by Convenience-Yields

The regression results are from the estimation of

$$r_{i,t} = c + \sum_{i=1}^{10} c_i d_{i,t}^{y} M_{j,t} + \varepsilon_{i,t}^{y} ,$$

where $r_{i,t}$ represents daily WTI returns corresponding to the i^{th} macro indicator, $M_{i,t}$ is the standardized and signed surprise relating to that indicator, and $d_{i,t}^{y}$ are the dummy variables for convenience-yield deciles. The Adjusted-$R^2(T)$ in the final column is intended for comparative purposes, and provides the explanatory power of an "arbitrarily" decomposition of the data. It is from the from the WTI returns regression, $r_{i,t} = a + \sum_{i=1}^{10} a_i D_{i,t} M_t$, where D_i $(i=1,..10)$ represent dummy variables, each corresponding to one of the 10 sample-intervals: 1990-1991, 1992-1993, …, 2008-2009. [a,b] and [c] represent significance levels of 1%, 5%, and 10%, respectively.

		Low CY (high inventories)								High CY (low inventories)			
Surprise	c	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	Adj-R^2	Adj-$R^2(T)$
ARS	0.05	-0.87[a]	-0.02	-0.38	-0.11	0.50	0.29	-0.30	0.49	0.63	0.40	2.46	4.43
CNP	-0.04	0.32	0.21	-0.56	-0.12	1.04[c]	-0.20	0.57[c]	0.19	0.00	-0.05	0.00	0.91
CPI	-0.02	-0.23	0.51	0.06	-0.41	0.37	0.80	0.09	-0.70	-0.25	-0.36	0.00	0.00
DGO	0.02	-0.20	0.33	-0.62	-0.02	-0.05	-0.35	0.74	-0.08	-0.15	-0.40	0.00	0.00
HS	-0.16	0.03	0.40	-0.18	0.65	0.60	-0.18	-0.20	0.28	0.30	1.27[b]	0.00	0.71
PC	0.00	0.63[c]	0.83	-0.37	0.03	0.25	0.52	-0.23	1.01	-1.47[c]	-0.06	0.73	4.93
PI	0.03	-0.75[c]	0.11	0.29	0.30	-0.48	-0.25	-0.35	-0.09	-0.86	-5.48[a]	5.10	5.23
PPI	0.13	0.96	0.03	0.79	0.12	0.18	0.10	-1.39[b]	-0.48	-0.99[c]	-0.63	0.65	0.12
TB	-0.06	0.25	0.16	0.10	0.75	0.17	-0.34	-1.12	0.58	1.42	0.47	0.00	0.00
UR	-0.03	-0.26	-0.56	-0.03	0.11	-0.19	0.49	0.19	0.20	-0.20	0.30	0.00	0.00
CU	0.07	0.04	0.25	0.66[b]	0.45	1.08[b]	-0.34	0.83	0.30	0.77	-0.41	1.46	4.51
IP	0.09	-0.17	-0.21	0.78	-0.14	1.32[b]	-0.23	0.60	-0.16	0.40	-1.23[b]	4.23	4.49
BI	0.02	0.74	-0.14	0.53	0.10	-0.65	-0.62	0.24	0.18	-0.44	-0.74	0.07	0.00
CS	0.08	1.75[b]	0.48	0.37	0.48	1.27[b]	-0.10	-0.34	-0.36	0.06	-1.29	2.64	2.59
FO	0.15	-2.05[b]	0.12	-0.82	-0.73	-0.30	-0.47	-0.46	0.30	0.51	2.19[a]	4.89	0.78
LI	-0.19	1.36[a]	1.21	-0.27	-0.45	-0.55	-0.09	-0.08	-0.35	0.49	0.02	3.69	3.39
NAPM	0.15	-1.11	0.40	-1.38[c]	0.28	-0.10	-0.02	0.35	0.13	-0.15	0.97	0.00	0.00
NHS	0.06	0.77[c]	0.20	-0.10	0.13	-0.46	0.11	0.38	-0.25	0.75	0.23	0.00	0.00
BST	-0.22	0.63	0.14	-0.33	-0.77	-0.34	0.77	0.27	-0.01	0.64	-0.03	0.00	0.00

Table 4. Response-Coefficients for WTI crude with Surprises Decomposed by Smoothed Relative Inventories
The regression results are from the estimation of

$$r_{i,t} = c + \sum_{i=1}^{10} c_i d_{i,t}^{I} M_{j,t} + \varepsilon_{i,t}^{I},$$

where $r_{i,t}$ represents daily WTI returns corresponding to the i^{th} macro indicator, $M_{i,t}$ is the standardized and signed surprise relating to that indicator, and $d_{i,t}^{I}$ are the dummy variables for the smoothed-relative-inventory deciles. The Adjusted-$R^2(T)$ in the final column is intended for comparative purposes, and provides the explanatory power of an "arbitrarily" decomposition of the data. It is from the from the WTI returns regression, $r_{i,t} = a + \sum_{i=1}^{10} a_i D_{i,t} M_t$, where D_i *(i=1,..10)* represent dummy variables, each corresponding to one of the 10 sample-intervals: 1990-1991, 1992-1993, …, 2008-2009. [a,b] and [c] represent significance levels of 1%, 5%, and 10%, respectively.

Surprise	C	High Relative Inventories					Low Relative Inventories					Adj-R^2	Adj-$R^2(T)$
		c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}		
ARS	0.00	0.74	-0.70	-0.61[b]	0.46	0.12	-0.03	-0.14	0.48	0.41	-0.26	0.00	4.43
CNP	0.00	0.54	-0.52	-0.15	-0.22	0.65[c]	-0.06	-0.04	0.31	0.55	0.06	0.00	0.91
CPI	-0.05	-0.46	-0.88	0.01	0.33	0.11	0.00	-0.42	0.59	1.06[b]	-0.84[c]	1.27	0.00
DGO	0.10	-0.50	-0.38	0.20	-0.19	0.23	-0.11	0.12	0.00	2.07[b]	-0.61	0.00	0.00
HS	-0.13	-0.27	0.77	-0.92	2.36[a]	0.67	-0.73	0.55	0.15	0.65	0.12	1.27	0.71
PC	0.05	0.51	-0.20	-0.43	-0.08	0.63	0.32	0.24	0.37	0.65	0.12	0.00	4.93
PI	0.02	0.74	0.11	0.33	-1.64[b]	-0.20	-0.75[c]	-1.60[b]	-0.22	-0.14	-0.60	2.03	5.23
PPI	0.11	0.93	-1.45[b]	-0.35	0.67	-0.83	0.18	-0.33	-0.77	-0.08	0.72	1.56	0.12
TB	-0.14	0.61	-0.94	2.60[a]	0.18	-0.97	0.16	0.17	-0.29	-0.27	1.49[b]	2.44	0.00
UR	-0.01	-0.09	-0.06	0.22	0.34	0.79[b]	-0.10	-0.04	0.09	-0.15	0.09	0.00	0.00
CU	0.12	-1.04[b]	0.68	0.51	0.84[c]	0.31	0.65	-0.37	0.28	0.95[a]	-0.40	4.54	4.51
IP	0.12	-0.58	0.69	0.26	-0.03	0.32	0.87	-0.16	0.08	0.68[b]	-0.44	1.14	4.49
BI	0.03	-0.33	-0.13	1.15[c]	-0.26	0.36	0.11	-0.15	-0.14	0.35	0.29	0.00	0.00
CS	0.10	0.05	0.48	0.09	0.21	-0.36	0.08	0.02	0.40	0.01	1.40[a]	0.00	2.59
FO	0.17	-0.68	0.66	0.71	-0.70	-0.01	-0.20	0.34	-0.37	0.20	-0.90[b]	0.85	0.78
LI	-0.30	-0.49	0.24	1.35[b]	-0.27	0.02	-0.56	0.39	-0.88	0.12	1.64[a]	4.26	3.39
NAPM	0.16	-0.95	0.16	-0.20	0.63	0.77	-0.32	-0.20	0.42	-0.01	-0.85	0.00	0.00
NHS	0.02	-0.46	0.88[b]	0.60	0.15	1.85	-0.19	-0.88[b]	-0.09	-0.07	0.34	3.25	0.00
BST	-0.20	-1.28	1.47[c]	-0.33	1.17	0.05	-0.54	1.41	-0.98	0.55	0.20	0.00	0.00

Table 5. Intraday (5-minute) Response-Coefficients for NYMEX Crude, 2005-2009

The statistics are from the regression,

$$r_{i,t} = c + \sum_{i=1}^{10} c_i M_{i,t} + \varepsilon_{i,t},$$

where $r_{i,t}$ alternately represents daily WTI returns and NYMEX futures returns corresponding to the i^{th} macro indicator, and $M_{i,t}$ is the standardized and signed surprise relating to that indicator. [a,b] and [c] represent significance levels of 1%, 5%, and 10%, respectively.

Time	Announcement	$\hat{\beta}_i$	(t-stat)	Standard p-value	R^2 Percent	Nobs
8:30	Advanced Retail Sales	0.1433[a]	(4.44)	0.00	25.41	60
	Change in Nonfarm Payrolls	0.2852[a]	(5.01)	0.00	30.57	59
	Consumer Price Index	0.0281	(1.10)	0.28	2.09	59
	Durable Goods Orders	0.0331	(1.00)	0.32	1.73	59
	Housing Starts	0.0436	(1.61)	0.11	4.35	59
	Personal Consumption	-0.0470	(-1.31)	0.19	2.88	60
	Personal Income	-0.0076	(-0.34)	0.73	0.20	60
	Producer Price Index	0.0422	(1.46)	0.15	3.54	60
	Trade Balance	0.0317	(1.23)	0.22	2.54	60
	Unemployment Rate	-0.0849	(-1.24)	0.22	2.65	59
9:15	Capital Utilization	0.0074	(0.26)	0.80	0.12	59
	Industrial Production	-0.0047	(-0.16)	0.87	0.05	59
10:00	Business Inventories	-0.0216	(-0.71)	0.48	0.98	53
	Consumer Confidence	0.1628[a]	(3.59)	0.00	18.20	60
	Construction Spending	0.0570	(1.43)	0.16	3.40	60
	Factory Orders	0.0049	(0.12)	0.91	0.03	59
	Leading Indicators	0.0052	(0.16)	0.88	0.04	60
	NAPM	0.0880[a]	(2.18)	0.03	7.57	60
	New Home Sales	0.0349	(0.95)	0.34	1.55	60
14:00	Budget Statement Tentative	0.0185	(0.49)	0.62	0.43	59

Table 6. Volatility Responses: Evidence of Rapid Reversals

The table reports the realized volatility (RVOL) between the release time and five minutes-, 10 minutes-, and 30 minutes after news-arrival (RVOL(0,5), RVOL(0,10) R(0,30), respectively). The control sample includes all the days without any news announcements. The Welch t-tests and the corresponding p-values are for the null hypothesis that the release of news has no impacts on the realized volatilities. $H_0: RVOL_{Event} = RVOL_{Control}$, the means of the realized volatility in the control and event sample are the same. [a,b] and [c] represent significance levels of 1%, 5%, and 10%, respectively.

Time	Sample	Mean RVOL**(0,5)**	Welch t-Test	p-Value	Mean RVOL**(0,10)**	Welch t-Test	p-Value	Mean RVOL**(0,30)**	Welch t-Test	p-Value
8:30	*Control*	*0.1174*			*0.1204*			*0.1397*		
	ARS	**0.1802**[a]	2.7401	0.0080	0.1444	1.3952	0.1676	0.1371	-0.1429	0.8867
	CNP	**0.3464**[a]	3.9383	0.0000	**0.2101**[a]	3.5030	0.0009	0.1650	1.2330	0.2218
	CPI	0.1434	1.2006	0.2343	0.1280	0.4769	0.6349	0.1314	-0.5644	0.5740
	DGO	**0.1976**[a]	2.9379	0.0047	0.1336	0.7952	0.4294	0.1266	-0.7882	0.4331
	HS	0.1540	1.5875	0.1174	0.1324	0.6730	0.5033	0.1353	-0.2893	0.7734
	PC	**0.1908**[a]	2.8122	0.0066	**0.1610**[b]	1.9859	0.0513	0.1470	0.3842	0.7019
	PI	0.1384	1.1472	0.2553	0.1243	0.3161	0.7528	0.1362	-0.2492	0.8038
	PPI	**0.1750**[b]	2.3713	0.0209	0.1296	0.6204	0.5371	0.1362	-0.1983	0.8434
	TBGS	0.1413	1.1868	0.2395	0.1463	1.2062	0.2322	0.1482	0.4955	0.6217
	UR	**0.3407**[a]	3.7933	0.0004	**0.2074**[a]	3.3592	0.0014	0.1646	1.1973	0.2354
9:15	*Control*	*0.1503*			*0.1477*			*0.1430*		
	CU	0.1751	1.0953	0.2774	0.1596	0.5887	0.5581	0.1478	0.2264	0.8215
	IP	0.1751	1.0953	0.2774	0.1596	0.5887	0.5581	0.1478	0.2264	0.8215
10:00	*Control*	*0.2249*			*0.2206*			*0.2162*		
	BI	0.2409	0.4614	0.6467	0.2212	0.0344	0.9727	0.2248	0.3671	0.7152
	CS	0.2594	1.4232	0.1592	0.2425	1.0390	0.3026	0.2381	1.1124	0.2698
	FO	0.2585	1.2785	0.2055	0.2348	0.7325	0.4664	0.2354	1.0094	0.3162
	LI	0.2370	0.5147	0.6083	0.2361	0.6507	0.5175	0.2233	0.3931	0.6954
	NAPM	**0.2770**[b]	2.2058	0.0307	0.2516	1.5507	0.1257	0.2437	1.4210	0.1584
	NHS	0.2457	0.8794	0.3822	0.2215	0.0603	0.9520	0.1875	-0.1320	0.0358
14:30	*Control*	*0.1258*			*0.0892*			*0.0748*		
	BST	0.1542	1.1848	0.2423	0.1033	0.9061	0.3695	0.0851	0.7012	0.4866

Reviewer Tables

The tables that follow are referenced in footnotes in this paper, and are intended to demonstrate the consistency of results across specifications.

<u>This table intended for Reviewer.</u> *<u>Following Footnote 19, Table R1 provides estimates from equation (6) using NYMEX rather than WTI.</u>*

Table R1. Response-Coefficients for NYMEX crude with Surprises Decomposed by Convenience-Yields

The regression results are from the estimation of

$$r_{i,t} = c + \sum_{i=1}^{10} c_i d_{i,t}^{y} M_{i,t} + \varepsilon_{i,t}^{y} ,$$

where $r_{i,t}$ represents daily NYMEX crude returns corresponding to the i^{th} macro indicator, $M_{i,t}$ is the standardized and signed surprise relating to that indicator, and $d_{i,t}^{y}$ are the dummy variables for convenience-yield deciles. The Adjusted-R^2(T) in the final column is intended for comparative purposes, and provides the explanatory power of an "arbitrarily" decomposition of the data. It is from the from NYMEX returns regression, $r_{i,t} = a + \sum_{i=1}^{10} a_i D_{i,t} M_{i,t}$, where D_i *(i=1,..10)* represent dummy variables, each corresponding to one of the 10 sample-intervals: 1990-1991, 1992-1993, …, 2008-2009. [a,b] and [c] represent significance levels of 1%, 5%, and 10%, respectively.

		<u>Low CY (high inventories)</u>					<u>High CY (low inventories)</u>						
Surprise	c	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	Adj-R^2	Adj-R^2(T)
ARS	-0.08	-0.07	0.34	-0.06	0.81	0.34	-1.32[c]	-0.01	-0.18	0.96[b]	1.68[b]	2.93	6.13
CNP	0.00	0.41	0.37	-0.33	0.26	-0.16	0.15	-0.13	-0.39	0.37	0.05	0.00	0.00
CPI	-0.05	0.35	0.15	-0.67	0.77[c]	0.05	0.46	-0.52	-0.47	0.15	-0.52	1.64	0.00
DGO	0.12	-0.80[b]	-0.63[c]	-0.14	0.22	0.21	-0.49	-0.17	-0.13	0.55	0.66[c]	1.65	1.40
HS	0.02	0.25	0.21	0.00	0.18	-0.18	-0.07	0.44	0.20	0.13	0.55	0.00	0.00
PC	0.22[c]	0.50[c]	-0.25	0.63[c]	0.94[a]	-0.13	0.40	-0.32	-0.32	0.30	0.08	2.89	1.85
PI	0.02	-1.23[c]	-0.12	0.29	-0.01	-0.14	0.00	-0.88	-0.41	0.59	-0.14	0.00	1.25
PPI	0.00	0.51	-0.74	0.34	-0.45	-0.32	0.26	-0.86	-0.20	0.40	-0.31	0.00	0.00
TB	-0.13	0.40	-0.43	0.03	0.77	-0.08	0.06	0.33	-0.43	0.74	-0.65	0.00	0.00
UR	0.02	0.55	-0.45	-0.16	0.34	0.85[a]	0.33	-0.24	0.05	-0.01	-0.04	1.72	0.36
CU	0.06	0.00	0.00	-0.09	0.32	1.05[a]	-0.89[c]	-0.14	0.18	0.02	0.10	2.76	4.97
IP	0.08	0.39	-0.34	-0.27	-0.21	0.87[a]	-0.73	-0.04	0.17	0.17	-0.06	3.24	2.90
BI	0.00	0.29	0.08	0.06	-0.04	0.14	-0.10	0.60	0.43	-0.52	0.32	0.00	0.20
CS	0.16	1.33[a]	-0.80	0.31	-0.26	0.35	0.35	0.21	-0.11	0.29	-0.02	0.00	0.50
FO	0.13	0.31	-0.44	-1.40[a]	-0.40	-1.09	-0.03	0.56	-0.07	0.37	-0.06	1.87	0.00
LI	-0.29[c]	0.46	0.25	0.48	-0.68	-0.02	-0.13	-0.15	-0.43	0.57	-0.21	0.00	1.63
NAPM	0.19	-1.16[b]	0.53	0.29	0.05	-0.42	-0.31	0.37	-0.31	-0.16	1.12[c]	0.51	0.81
NHS	0.16	-0.21	-0.26	0.01	-1.03[c]	0.16	0.37	0.56[c]	0.11	-0.09	0.07	0.00	0.00
BST	-0.12	0.01	-1.09[b]	0.65	-0.15	1.49	0.06	0.46	1.16	-0.04	-1.05	0.29	0.57

***This Table intended for Reviewer**. Following footnote 19, below are results from the estimation of (6), but using dollar-adjusted returns.*

Table R2. Response-Coefficients for Dollar-adjusted WTI returns with Surprises Decomposed by Convenience-Yields

The regression results are from the estimation of

$$r^*_{i,t} = c + \sum_{i=1}^{10} c_i d^y_{i,t} M_{i,t} + \varepsilon^y_{i,t},$$

where $r^*_{i,t}$ represents dollar-adjusted WTI crude returns corresponding to the i^{th} macro indicator, $M_{i,t}$ is the standardized and signed surprise relating to that indicator, and $d^y_{i,t}$ are the dummy variables for convenience-yield deciles. Dollar adjusted returns are given by, $r^*_t = 100 \times (log(P_t/e_t) - \log(P_{t-1}/e_{t-1}))$, where e_t is the trade-weighted dollar index at the end of day t. The Adjusted-R^2(T) in the final column is intended for comparative purposes, and provides the explanatory power of an "arbitrarily" decomposition of the data. It is from the from the WTI regression, $r_{i,t} = a + \sum_{i=1}^{10} a_i D_{i,t} M_{i,t}$, where D_i *(i=1,..10)* represent dummy variables, each corresponding to one of the 10 sample-intervals: 1990-91, 1992-93, …, 2008-09. [a,b] and [c] represent significance levels of 1%, 5%, and 10%, respectively.

		Low CY (high inventories)						High CY (low inventories)				
Surprise	c	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	Adj-R^2	Adj-R^2(T)
ARS	0.06	-0.86[a]	-0.11	-0.43	-0.26	0.42	0.10	-0.29	0.31	0.55	0.45	1.56	4.43
CNP	-0.09	0.08	-0.09	-0.74	-0.42	0.69	-0.33	0.47	0.05	-0.12	-0.08	0.00	0.91
CPI	-0.02	-0.19	0.56	0.08	-0.43	0.53	0.92	-0.08	-0.83	-0.17	-0.51	0.00	0.00
DGO	0.03	-0.16	0.32	-0.61	-0.29	-0.09	-0.40	0.71	-0.17	-0.20	-0.50	0.00	0.00
HS	-0.11	-0.07	0.43	-0.23	0.63	0.72	-0.23	-0.22	0.31	0.29	1.25[b]	0.00	0.71
PC	0.03	0.82[b]	0.78	-0.42	-0.12	0.17	0.50	-0.15	1.27	-1.48[c]	-0.08	1.51	4.93
PI	0.04	-0.73[c]	0.13	0.28	0.24	-0.50	-0.19	-0.44	-0.25	-0.82	-5.20[a]	4.30	5.23
PPI	0.16	1.00	0.15	0.91	0.28	0.10	0.05	-1.28[c]	-0.73	-0.93	-0.57	0.41	0.12
TB	-0.06	-0.01	0.15	0.24	0.57	-0.17	-0.63	-1.23	0.44	1.16	0.19	0.00	0.00
UR	-0.04	0.08	-0.50	0.01	0.25	-0.02	0.63[c]	0.18	0.35	-0.25	0.25	0.00	0.00
CU	0.07	-0.01	0.31	0.62	0.17	0.92[c]	-0.42	0.79	0.29	0.70	-0.43	0.45	4.51
IP	0.10	-0.20	-0.21	0.81[b]	-0.17	1.13[b]	-0.71	0.54	-0.15	0.29	-1.15[b]	3.44	4.49
BI	-0.01	0.68	-0.05	0.48	0.12	-0.71	-0.50	0.23	0.25	-0.49	-0.86	0.00	0.00
CS	0.10	1.90[a]	0.28	0.17	0.43	1.24[b]	-0.09	-0.24	-0.40	0.12	-1.52	2.42	2.59
FO	0.17	-2.31[b]	0.12	-0.79	-0.81	-0.36	-0.49	-0.49	0.29	0.49	2.33[a]	5.03	0.78
LI	-0.16	1.56[a]	1.52[c]	-0.28	-0.67	-0.75	-0.27	-0.28	-0.34	0.37	-0.23	5.78	3.39
NAPM	0.15	-1.53	0.38	-1.50[c]	0.20	-0.25	-0.08	0.28	0.06	-0.19	0.77	0.00	0.00
NHS	0.06	0.78[c]	0.14	-0.10	0.19	-0.52	0.06	0.44	-0.14	0.69	0.42	0.00	0.00
BST	-0.20	0.61	0.32	-0.18	-0.66	-0.40	0.81	0.27	0.15	1.00	-0.03	0.00	0.00

***This Table intended for Reviewer**. Following footnote 20, below are results from the estimation of (7) using NYMEX returns.*

Table R3. Response-Coefficients for NYMEX crude with Surprises Decomposed by Smoothed Relative Inventories
The regression results are from the estimation of

$$r_{i,t} = c + \sum_{i=1}^{10} c_i d_{i,t}^I M_{j,t} + \varepsilon_{i,t}^I,$$

where $r_{i,t}$ represents daily NYMEX returns corresponding to the i^{th} macro indicator, $M_{i,t}$ is the standardized and signed surprise relating to that indicator, and $d_{i,t}^I$ are the dummy variables for the smoothed-relative-inventory deciles. The Adjusted-R^2(T) in the final column is intended for comparative purposes, and provides the explanatory power of an "arbitrarily" decomposition of the data. It is from the from the NYMEX returns regression, $r_{i,t} = a + \sum_{i=1}^{10} a_i D_{i,t} M_t$, where D_i *(i=1,..10)* represent dummy variables, each corresponding to one of the 10 sample-intervals: 1990-1991, 1992-1993, …, 2008-2009. [a,b] and [c] represent significance levels of 1%, 5%, and 10%, respectively.

		High Relative Inventories					Low Relative Inventories						
Surprise	c	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	Adj-R^2	Adj-R^2(T)
ARS	-0.11	1.08	-0.10	0.15	0.34	-0.11	0.33	-0.05	0.18	0.84[c]	-0.16	0.00	6.13
CNP	0.00	-0.03	-0.47	-0.17	-0.33	0.55	0.02	0.08	0.14	0.60	0.13	0.00	0.00
CPI	-0.12	-0.56	-0.69	-0.09	0.06	0.22	-0.12	-0.50	0.61	0.96	-0.46[b]	2.31	0.00
DGO	0.10	-0.26	-0.22	0.57	-0.25	0.30	-0.13	0.12	0.04	0.12	-0.82[c]	0.00	1.40
HS	0.06	-0.19	0.52	-0.75	0.63	0.36	-0.62	0.28	0.02	0.33	0.44	0.88	0.00
PC	0.22	0.21	-0.26	-0.58	0.42	0.50	-0.01	-0.31	0.33	0.70[c]	0.32	0.77	1.85
PI	0.05	0.72	0.17	-0.16	-0.04	-0.14	-0.23	-1.68[a]	0.26	-0.05	-0.80	1.04	1.25
PPI	-0.01	1.17[c]	-0.95[c]	-0.28	0.82[c]	-0.36	0.68	-0.77	-0.56	-0.19	0.08	1.26	0.00
TB	-0.14	-0.73	-0.83	1.21	0.21	-0.64	0.08	0.02	-0.56	-0.10	1.50[b]	0.36	0.00
UR	0.01	0.12	0.00	0.35	0.79	0.61[b]	-0.11	-0.03	0.02	-0.06	0.23	0.00	0.36
CU	0.09	-1.31[a]	0.41	0.37	0.20	-0.07	0.43	0.00	0.30	0.95[a]	-0.32	6.91	4.97
IP	0.07	-0.87[a]	0.58	0.32	-0.22	0.11	0.65	0.45	0.16	0.64[a]	-0.30	4.84	2.90
BI	-0.01	-0.19	0.22	0.78	-0.03	0.39	-0.33	-0.09	-0.01	0.50	0.26	0.00	0.20
CS	0.16	0.10	0.40	-0.01	0.22	-0.18	-0.22	-0.04	0.23	0.09	1.33[a]	0.00	0.50
FO	0.14	-0.24	0.49	0.75	-0.61	-0.27	-0.34	0.23	-0.48	0.27	-0.90[b]	1.36	0.00
LI	-0.29[b]	-0.01	-0.13	0.05	-0.06	-0.11	-0.72	0.05	-0.86[c]	0.11	0.68[c]	0.00	1.63
NAPM	0.19	-0.56	-0.03	-0.21	0.40	0.64	-0.12	-0.37	0.23	-0.17	-1.11[c]	0.00	0.81
NHS	0.12	-0.52	0.80[a]	0.21	0.22	0.48	-0.15	-0.53	-0.28	-0.55	0.22	1.92	0.00
BST	-0.15	0.00	0.80	0.97	0.63	0.10	-0.67	0.83	-0.56	0.63	-0.34	0.00	0.57

This Table intended for Reviewer*. Tables 3 and 4 (final column) provide adjusted-R^2s from "arbitrary" decompositions of the surprises. The table below provides the coefficients and adjustd-R^2 from these decompositions.*

Table R4A. WTI with Year Dummies

$$r_t = c + \sum_{i=1}^{10} c_i D_i M_t$$

Where D is a set of 10 dummy variables, each set corresponding to a time interval: 1990-1991, 1992-1993, 1994-1995, 1996-1997, 1998-1999, 2000-2001, 2002-2003, 2004-2005, 2006-2007, 2008-2009. We compare this Adjusted-R^2 with those from the "stock-variable" decompositions reported in Table 3 and Table 4.

Surprise	c	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	**Adj-R^2**
ARS	0.04	-0.08	0.20	0.28	0.55	-0.88	-0.74[a]	1.06[b]	-1.15[c]	-0.54	0.40	4.43
CNP	0.00	0.19	-0.10	-0.24	-0.11	0.12	0.19	0.08	0.17	-0.65	1.79[a]	0.91
CPI	-0.05	-0.06	0.01	-0.30	-0.52	0.62	0.11	-0.47	-0.31	-0.02	0.28	0.00
DGO	0.06	0.19	-0.24	0.11	0.23	-0.12	-0.38	-0.59	0.68	-0.13	-0.49	0.00
HS	-0.17	2.55[a]	0.39	-0.09	0.78	0.84	0.10	0.14	0.08	0.01	0.24	0.71
PC	0.07	-1.24[a]	0.33	0.09	0.41	0.06	1.36[a]	1.10[c]	-0.31	0.09	0.46	4.93
PI	0.00	-2.99[a]	0.18	-0.65	-0.69	0.00	0.60	1.22	-0.46	-0.22	-0.37	5.23
PPI	0.10	-0.95	0.16	-0.14	-1.09	-0.43	-0.78	0.25	-0.75	-0.01	1.15[c]	0.12
TB	-0.11	-1.97	0.98	1.71	0.85	-0.86	1.05	0.18	-0.41	-0.64	0.70	0.00
UR	-0.05	0.01	0.25	0.35	0.13	0.09	0.08	-0.53	0.22	-0.63	0.57[c]	0.00
CU	0.05	-0.69[c]	-0.08	0.55	0.64	1.23[b]	0.37	-0.33	0.09	-0.12	0.97[a]	4.51
IP	0.02	-1.51[a]	0.19	0.73	0.93	0.47	-0.33	-0.13	0.11	0.29	0.54[b]	4.49
BI	0.03	0.08	-0.07	0.18	-0.16	-0.22	-0.86[b]	0.26	0.39	0.14	0.91[b]	0.00
CS	0.04	-0.09	-0.11	0.51	-0.16	0.04	0.58	-0.06	0.34	0.24	2.13[a]	2.59
FO	0.18	0.54[c]	-0.15	0.31	0.09	-1.04	-0.10	-0.82	-0.56	0.28	-0.57	0.78
LI	-0.26	-0.44	0.10	-0.30	1.05	0.76	1.17[b]	0.13	0.17	-0.53	1.32[a]	3.39
NAPM	0.16	0.11	0.07	0.02	0.23	-0.95	0.30	0.82	-0.50	0.00	-0.16	0.00
NHS	0.02	-0.55	-0.25	-0.12	-0.05	0.75	0.42	0.83	0.24	0.09	0.09	0.00
BST	-0.21	0.28	-0.44	1.93	0.68	0.50	1.74[c]	0.06	1.27	0.18	-0.89[c]	0.00

Note: a, b and c indicate significance at the 1%, 5% and 10% level.