Exchange Rate Response to Macro News: Through the Lens of Microstructure

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Abstract

This study investigates the micro effects of macro news using customer price-contingent orders (i.e. stop-loss and take-profit orders) data from a large foreign exchange dealing bank in the pound/dollar market. Results reveal that price-contingent order placement intensifies 3 to 5 hours prior to the news events. I examine the link between this surge in order placement and the exchange-rate jump following the announcement. I find that price-contingent orders can enhance our ability to explain post-release exchange-rate returns by half. Furthermore, the estimated effect of orders is orthogonal to the news surprises. This implies that there may be a component of the news response that purely reflects institutional features such as order types and not necessarily the public information itself.

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1. Introduction

News is an important source of exchange-rate volatility. Indeed, Evans and Lyons (2003) find that news accounts for about thirty percent of total price variance. In earlier studies[1], and more recently in Andersen et al. (2003, 2005), it is presumed that the response to news is entirely a reaction to its information content. That is, the exchange-rate response is monotonically related to the surprise component of the news through its effects on expected future exchange rates or on discount rates. These news studies do not attempt to trace the mechanism through which news brings about an exchange-rate change. In a world of rational expectations and perfectly shared information, the news could theoretically bring about an instantaneous change without any unusual trading activity. However, recent empirical studies indicate that trading activity is an important link between news and its associated exchange-rate response. Love and Payne (2002), for example, estimate that on average over half of the price adjustment to news comes via order flow. Evans and Lyons (2003) further suggest that about two-thirds of the increase in exchange-rate volatility associated with new public information is transmitted indirectly via order flow, with the rest being the direct impounding of news into prices with no need for trading.

In this paper, I suggest that the exchange rate's response to scheduled news announcements, and in particular, the component of the response mediated through order flow, does not entirely reflect the announcements' information content. Instead, there may be a component of the response that purely reflects order flow and is orthogonal to the information itself. This order flow is specifically the price-contingent order flow, in which a trade's execution is contingent upon the rate reaching a pre-specified threshold. More explicitly, a stop-loss buy (sell) order instructs the dealer to purchase the currency once the market rate rises (falls) to a certain level; a take profit buy (sell) instructs the dealer to buy the currency when the market rate falls (rises) to the threshold level. Stop-loss orders, which involve positive feedback trading, can create rapid, self-reinforcing price movements. Osler (2005) provides evidence of such "price cascades" using the clustering patterns of stop-loss orders around round numbers to identify the points where they are likely to be triggered. As suggested by their name, stop-loss orders can be used to protect existing positions. They can also be used to hedge options positions and to ensure that new positions are opened in a timely manner. These orders are primarily used by financial end-users.

[1] See also, for example, Cornell (1982), Engel and Frankel (1984), Hakkio and Pearce (1985), Ito and Roley (1987), Hardouvelis (1988), Klein (1991), and Ederington and Lee (1995).

Take-profit orders, on the other hand, which generate negative-feedback trading, are not triggered in waves and hence do not result in price cascades. They are primarily used by commercial end-users, i.e. importers and exporters, who trade for non-speculative reasons and have some flexibility in timing their trades (Bessembinder 1994, Foucault 1999).

Stop-loss and take-profit orders are not included in any exchange-rate models and were not discussed in the foreign exchange literature until Osler (2003). Nonetheless the relevance of order form to price movements is familiar to those in finance. Easley and O'Hara (1991), for example, develops a model in which stop-loss orders increase the probability of large, discrete price movements.

The significance of stop-loss and take-profit orders in the macro news context stems from the rapid reaction of exchange rates to news releases; in fact, the market absorbs the majority of the news within 5 minutes (Andersen et al. (2003), Cheung and Chinn, (2001)). These large moves can be expected to trigger price-contingent orders, which could in turn modify the quality of the overall response. If stop-loss orders dominate the triggered orders, the response could be magnified. If take-profit orders dominate, the response could be muted.

The paper elucidates this interplay between the institutional features of the currency market and the fundamental macroeconomic information flow. The investigation has two main pieces. First, I examine order placement patterns in the hours prior to economic announcements. Second, I examine the effects of price-contingent orders on the exchange-rate response to news. I carry out the analysis using 21 months of pound/dollar price-contingent orders provided by the Royal Bank of Scotland (RBS, formerly NatWest Markets) and data on the U.S. scheduled macroeconomic news announcements.

Regarding news-related patterns in order submission, my main result is that stop-loss order placement intensifies substantially in the hours leading up to the announcement time. By contrast, take-profit order placement remains normal before the news release but intensifies four hours afterwards. This pattern is fully consistent with agent rationality. Given the dramatic and rapid potential exchange-rate response to news, investors may wish to protect existing positions by ensuring that their losses will not greatly exceed a given amount. Carrying out a deal always takes time due to the sequence of events necessary to complete the transaction, and when dealers are busy in the post-announcement period it could take even more time. By placing stop-loss orders *before* the news events, they can be assured of liquidating their position quickly when their loss limit is reached. Customers wishing to take profits, on the other hand, will rationally prefer to wait until the rate has stopped moving. Since announcements are followed by sudden drastic exchange-rate jumps, it is quite possible that the market price goes beyond an order's specified price (below the price for the buy order or above the price for the sell order). Customers looking to take profits are therefore wise to delay submitting take-profit orders until the market calms down. This is exactly what we see in the data.

To analyze the effects of price-contingent orders on the exchange-rate's response to news, I first estimate a contemporaneous news response model that measures the exchange-rate's five-minute reaction to news surprises normalized by their standard deviation. The estimated news coefficients are similar to those in Andersen et al. (2003). Then, I augment this baseline model by adding excess stop-loss and take-profit orders, measured as the difference between orders placed in three hours previous to news events and normal level of orders placed during those hours.[2]

The results indicate that price-contingent order flow makes a substantial contribution to the exchange-rate's response to news. In particular, stop-loss orders intensify the reaction of exchange rates to news, as one would anticipate. Take-profit orders have no statistically significant effect. The lack of significance is not surprising in light of the absence of any tendency for agents to intensify the placement of these orders before the news.

When orders are included in the returns regression our ability to explain post-release exchange-rate returns rises by 12 percent. Furthermore, as news become more surprising, the impact of the excess stop-loss orders increases. I interpret this in terms of price cascades. Big surprise events tend to generate large price reactions, creating a wave of stop order executions, which in turn intensifies the overall exchange-rate response to news. Allowing for such interactions between news surprise size and price-contingent order flow increases the explanatory power of the baseline model more than half.

Interestingly, the estimated effect of the news surprises themselves is robust to the inclusion of order variables. This reflects the orthogonality of order placement to the news itself, which I document separately. Together, these results indicate that a substantial portion of the exchange-rate's response to news is unrelated to the information content of that news.

The paper also tests for asymmetry in the response to "good" news and "bad" news. Consistent with Andersen et al. (2003), I find only weak evidence for asymmetry.

The paper is structured as follows. Section 2 describes the data. Section 3 explains the intraday patterns in order placement. Section 4 presents the statistical methodology and the main

[2] I apply the same model to four and five hour intervals and found qualitatively similar results although the magnitude of order coefficients declines slightly as the length of the intervals increases. See the robustness check section for coefficient estimates.

results. Section 5 tests for asymmetries in the price response to news. Section 6 provides robustness checks. Section 7 concludes.

2. Data: Currency Orders and News

A. Currency Orders: Background and Descriptive Statistics

1. Background

Stop-loss and take-profit orders are price-contingent orders. The execution of these orders is contingent upon the rate crossing a pre-specified threshold. More specifically, a stop-loss buy (sell) order instructs the dealer to purchase currency once the market rate rises (falls) to a certain level; a take-profit buy (sell), on the other hand, instructs a dealer to buy the currency when the exchange rate falls (rises) to the threshold level. Stop-loss orders are associated with positive feedback trading since price declines (rises) trigger execution of stop-loss sell (buy) orders, which contribute to the downward (upward) trend in prices. By contrast, take-profit orders involve negative feedback trading since price declines (rises) trigger execution of take-profit buy (sell) orders, which halts or reverses the initial downward (upward) movement in prices. Price-contingent orders are executed at the market rate and the requested amount is inevitably filled, albeit at a possibly worse price than that specified in the order[3].

The term aggregate order flow, as used here, will refer to more than just stop-loss and take-profit orders, it includes limit orders and deals. Deals comprise the majority of all trades and involve one agent—either a customer or another dealing bank—trading at a quote provided by a dealer. Hence, with a deal, there is no "order" as normally defined (Osler and Savaser 2004). The share of executed price-contingent market orders in total deal flow is small (about 5% or less, according to practitioner estimates). However, since the foreign exchange market is the biggest in the world, on the order of 1.9 trillion dollars in daily turnover, even a small share of the deal flow sums to a massive amount (BIS 2004). Furthermore, these orders can generate amplified price effects distinguishable from other order forms as demonstrated in Easley and O'Hara (1991), Osler (2005). Easley and O'Hara (1991) models the effect of price-contingent orders on security market performance and shows that stop-loss orders increase the probability of large price movements. By demonstrating their clustering pattern around round numbers, Osler (2005) provides evidence from currency markets that stop-loss orders can create rapid, self-reinforcing price movements.

[3] This is where price-contingent orders differ from limit orders. Price-contingent orders have a flexible requested price, and a fixed amount. A limit order, however, does not necessarily fill the requested amount if there is not enough supply at the specified rate.

2. Descriptive Statistics:

The orders data are provided by the Royal Bank of Scotland. It includes 10,413 orders with an aggregate value in excess of $61.7 billion. The data cover all pound/dollar orders in two distinct periods: September 8, 1999 through April 11, 2000 and 12 June, 2001 through 20 September, 2002. During this time, the bank received an average of 21 new price-contingent orders per day in the pound/dollar currency pair. The dataset presents information about each order's time of placement, requested execution rate, and order amount. Twenty eight percent of orders were actually executed, the rest were either deleted or remained open at the end of the sample period.

Stop-loss orders constitute 48 percent of all orders in the sample. The distribution between buy and sell orders for pound/dollar pair is also even (Table 2a). However, there is an asymmetry between stop-loss and take-profit orders regarding the buy-sell ratios: The share of sell (sell dollars) orders is 53% in stop-loss and 44% in take-profit sample. These figures are in line with the observed strength of pound vis-à-vis the dollar in the sample period. During this time, the US entered into a recessionary period and pound (along with the Swiss Frank) appeared as a safer alternative to the US dollar, creating an increase in demand for the sterling. Consequently, more sell orders are placed in the stop-loss category to limit losses due to the downward market trend. The opposite is true for the take-profit category due to the option-like properties of these orders. In bad times, placing a take-profit buy is more profitable since it gives the investor the opportunity to enter the market at a favorable lower rate.

The majority of orders, 61 percent, were placed by customers; of these, two thirds were placed by financial customers (Table 3a). Since this dealing bank is a large player in the U.K. pound market, which transacts with every major type of customer, the orders placed with the bank should be representative of the market-wide population of customer orders. Osler (2003) states that price-contingent orders executed for customers may represent on the order of 15 percent of all customer business[4].

This paper investigates the high frequency price-adjustment to macro news given the characteristics of price-contingent orders. This renders the "near" orders the primary focus of the study. Therefore, orders placed farther away from the market rate are excluded from the dataset since these orders have no immediate price consequence due to their near-zero likelihood of

[4] This figure is based on the finding that the customer orders account for 61 percent of all price-contingent orders (Table 3a) and also on the informal estimates given by the bank, stating that customer deals represent on the order of 20 percent of all deals at this bank (by value) and that executed price-contingent orders represent on the order of five percent of deal flow (Osler 2002).

execution at the time of their placement. The distance of an order from the market rate is compared against the standard deviation of daily absolute exchange-rate changes, which is 0.004 in this sample. If the difference between the trigger rate and the market rate at the time of submission exceeds 0.004, the observation is considered as "far" and dropped from the sample[5]. The descriptive statistics of the near orders are qualitatively similar to those of the full-sample, except that near orders have a much higher rate of execution than far orders (Table 2b and 3b).

The exchange-rate quotes corresponding to the orders in the bank's record book are from Reuters. They are computed as the mid-point of the bid and ask prices sampled at five-minute intervals.

B. Macroeconomic News

The news data provided by Money Market Services (MMS) consist of the declared values of macroeconomic fundamentals along with the forecasts of the traders in anticipation of those releases. Matching the orders dataset, the news data cover the period from September 8, 1999 through April 11, 2000 and 12 June, 2001 through 20 September, 2002. This study focuses on U.S announcements scheduled for 8:30 EST. All 8:30 announcements are included in the analysis (Table 1). Since most of the important macroeconomic news is announced at 8:30, this constraint does not limit the relevance of the results[6].

There are legitimate concerns regarding the redundancy of some of these news items. For instance, PPI declaration always precedes that of CPI. Since the two series are highly correlated, the new information content of the latter is typically quite low compared to PPI. Andersen et al. (2003) shows that only a handful of the macro news announcements (payroll employment, durable goods orders, trade balance, initial unemployment claims, NAPM index, retail sales, consumer confidence, and advance GDP) have statistically significant price effects (Table 1). Hence, the general practice in the macro news literature is to focus primarily on these significant news releases (Chaboud et al., 2004, Love and Payne, 2002). Therefore, my main results apply to the significant announcement sample which contains all the 8:30 news that were found to be significant by Andersen et al. (2003) for the pound/dollar currency pair. The unrestricted sample results are reported as a robustness check.

[5] I also exclude all trades during weekends and major holidays due to unusually light volume: December 24-December 26, December 31-January 2, Good Friday, Easter Monday, Memorial Day, Labor Day, Thanksgiving and the following day, and July 4 (or, if this is on a weekend, the day on which the Independence Day holiday is observed).

[6] With 21 months of price-contingent orders data, there are not enough observations to conduct statistical analysis of other scheduled announcement times since only one or two news series are released at those times. 10:00 EST is an exception with a total of 5 releases and is analyzed in the robustness check section.

To measure the unexpected component of each announcement, which is the part that matters for price adjustment, I calculate the standardized news surprise as follows:

$$News_{kt} = \frac{A_{kt} - E_{kt}}{\hat{\sigma}_k} \tag{1}$$

where A_{kt} is the announced value of indicator k, E_{kt} is the market expected value of indicator k, which is measured as the median forecast from the MMS survey, and $\hat{\sigma}_k$ is the sample standard deviation of A_{kt} - E_{kt}. Every Friday MMS collects the forecasts of about forty money managers regarding all the indicators scheduled to be released the following week.

3. Intraday Patterns in Price-Contingent Order Placement

In this section, I discuss why people place price-contingent orders in general and especially around macro news announcements by focusing on intraday order placement patterns. The well-known finding regarding these patterns is that investors place more orders on announcement days. This is shown in Figure 1, which plots the average number of orders placed with the bank for six hours before and after the 8:30 announcements. The mean number of orders placed on days when there are no 8:30 announcements is also shown as a benchmark (henceforth, called the "no-announcement days").

On an average announcement day, the bank receives a total of 22 stop-loss and take-profit orders. On no-announcement days, this number is 20. In the restricted sample of near orders, the corresponding figures are 10 and 8 respectively[7]. Since the orders in this study constitute only a small subset of the entire market (about 5% or less), an educated guess for the market-wide averages would be around 200 and 160 with 40 extra orders on announcement days. These statistics imply that the increase in *near* order placements is the driving force behind the rise in overall order submission on announcement days and confirms the appropriateness of the far order cutoff used above.

The key result of the section is that the two order types follow different intraday patterns. Figures 2 and 3, which disaggregate orders into stop-loss and take-profit categories, portray this behavior: Stop-loss order placement intensifies substantially 3-5 hours before the news event; once the news is announced, the surge disappears immediately[8]. This is consistent with the protective and speculative motivations of the financial end-users, who typically place stop orders to avoid costs associated with transacting a deal after the news releases. Take-profit orders, on

[7] The difference in daily totals is statistically significant at the 1% level for near orders and at the 10% level for the full sample.
[8] Stop-loss order submission is higher relative to the benchmark on announcement days before 8:30 and this is statistically significant at the 1% level (except the 1-hour interval immediately preceding the release).

the other hand, do not appear to intensify prior to news releases reflecting the risk of these orders being picked off by the news-induced exchange-rate jump at an inferior price. We see that take-profit order placement picks up only after the news-induced volatility dampens (Figure 3).

One important determinant that gives rise to the observed intraday order placement patterns is the characteristics of the investors. Commercial investors, for instance, are mostly exporters and importers who frequently need to carry out currency conversions to make payments on specific due dates. Provided that the transaction occurs within the day they specify, these firms can wait to transact if they think they can get a better price (Admati and Pfleiderer 1988; Harris 1998; Osler 2002). Due to the nature of their business, it is costly for them to monitor the market actively and carry out a deal at the appropriate time. Besides, carrying out any deal takes time: First, a customer calls a salesperson requesting a two-way quote. The sales person relays the request to the interbank dealers, who provide a two-way quote based on market conditions, their own inventory position, and other relevant information. The sales person then communicates the quote to the customer, who chooses whether to buy at the quoted offer, sell at the quoted bid, or decline to deal altogether (Osler, 2003). Instead, commercial customers delegate this duty to the dealer by placing price-contingent orders. Moreover, monitoring the market is costly even for financial end-users. A small lag in placement or execution can result in significant price risk because of the high speed of the market. Hence, the common rationale of reducing monitoring costs and trading frictions underlies the use of price-contingent orders by commercial and financial investors alike.

The types of orders investors typically place depend on the nature of their business. For instance, financial customers place more stop-loss orders relative to take-profit orders (Table 3b). This behavior is partly due to their protective and speculative motives and partly due to the frequent use of overnight loss limits by financial customers. Loss limits are assigned to dealers by their employing institutions to avoid principal-agent problems since employers who invest in risky assets have to rely on the expertise of the dealers who have only limited liability (Bensaid and De Bandt 2000).

Commercial end-users, on the other hand, place more take-profit orders. The option-like properties of take-profit orders make them attractive for these investors, whose execution needs are not as immediate as financial customers (Foucault 1999). To illustrate this point, suppose there is a conversion that needs to be made for a payment on a specific date and suppose that the firm places a buy order below the current market price. If the rate decreases to the requested rate sometime within the day, the corporate customer is better off placing a take-profit buy order instead of just placing a market order at 9:00am when they first come in the office. As soon as the market rate reaches the requested rate, the customer takes the profit and leaves the market with enough currency to make its payment on its due date. Commercial customers do not have to transact immediately. They trade immediacy with the possibility of a trade at a better price by using take-profit orders.

The significance of stop-loss and take-profit orders in the macro news context stems from the rapid reaction of exchange rates to news releases. Andersen et al. (2003) shows that returns adjust to news very fast, within 5 minutes, whereas exchange-rate volatility adjusts only gradually after an hour. Therefore, financial investors, who primarily care about the returns - as opposed to levels- of exchange rates would prefer to trade immediately following an announcement. This way, they can take advantage of the sudden jump in the exchange rate. However, because carrying out a deal in the post-announcement period takes time due to the sequence of events necessary to complete the transaction, these investors tend to place their orders, which are mainly stop-loss orders, *before* the news events. This way, they can be assured of entering the market quickly, which is exactly what we see in Figure 2.

Contrary to financial customers, commercial investors' primary concern is the exchange-rate level at which their transaction occurs. They are not in a rush to enter the market immediately following the news release since they are not driven by the sudden news-induced jump in return. Therefore, commercial customers, who typically place take-profit orders, do not seek to submit orders *before* announcements. Moreover, it is not in their interest to do so. News announcements are followed by sudden drastic exchange-rate jumps. Hence, it is quite possible that the market price goes beyond the specified order price (below the price for the buy order or above the price for the sell order) creating the risk of the take-profit order being "picked-off" at an inferior price[9]. In such a situation, it would be a better strategy to wait until the market calms down, which is what we observe in Figure 3.

4. Exchange Rates, Fundamentals and Price-Contingent Orders

A. Impact on Returns: Directional Effects

In this section, I estimate the contribution of the rise in pre-announcement order flow to the subsequent exchange-rate movements. First, I begin with a baseline model which treats the news surprise as the only source of exchange-rate variation. Then, I add signed price-contingent

[9] For a more detailed discussion of the risk of being picked off in the context of limit orders, see Foucault (1999), Carlson and Lo (2004).

order variables, measured as the difference between orders placed in three hours prior to the news events and the normal level of orders placed during those hours:

$$R_t = \alpha + \sum_{k=1}^{6} \beta_k D_{kt} News_{kt} + \eta_t \tag{2}$$

$$R_t = \alpha + \sum_{k=1}^{6} \beta_k D_{kt} News_{kt} + \beta_{sls}(SLS_t - TPB_t) + \beta_{slb}(SLB_t - TPS_t) + \varepsilon_t \tag{3}$$

Here, R_t is the 5-minute log return from 8:30 to 8:35 on any given news day t. $News_{kt}$ is the standardized news corresponding to announcement k at day t (k = 1, …,6 (Table 1)). D_{kt} is equal to 1 if announcement k is released on day t, zero otherwise. SLS-TPB represents the number of stop-loss sell minus take-profit buy orders, in excess of the no-announcement day sample average, placed *within* 3 hours before the announcement. SLB-TPS is defined similarly. A more general regression equation, which includes SLS, SLB, TPS, TPB separately, seems better a priori; I use this method to save degrees of freedom. This is a concise method of grouping the order variables which are activated by a given directional move. An exchange-rate decline triggers stop-loss sells and take-profit buys rendering stop-loss buys and take-profit sells irrelevant. Since these two order types pull in opposite directions, the *net* effect is the difference between them. Depending on whether the news surprise is one that tends to appreciate or depreciate the currency, I impose a zero restriction on the irrelevant orders. For instance, if the news surprise is positive (i.e. indicative of currency appreciation), then the stop-loss sell and take-profit buys assume the value zero. Therefore, in this specification, the respective expected signs of SLB-TPS and SLS-TPB parameters are positive and negative. OLS regressions and standard errors are calculated with Newey-West correction for autocorrelation and heteroskedasticity.

Table 4 provides estimates from the baseline and Andersen et al. (2005) specifications as a reference point. In the latter, authors have enough statistical power to run the following regression on each individual announcement separately:

$$R_t = \beta_k \, News_{kt} + \varepsilon_t \tag{4}$$

The contemporaneous news response estimates and R^2's in Andersen et al. (2005) are based on futures markets spanning 10 years, from 1992 to 2002. The news estimates here are consistently at the same order of magnitude as theirs and in some instances almost exactly identical to the coefficients they report (e.g. retail sales). Furthermore, our results accord well with their finding that employment news has the largest price impact. A one-standard deviation nonfarm payroll employment surprise tends to depreciate (if negative) the dollar against the pound by 0.085 percent in the baseline model and 0.098 percent in Andersen et al. (2005). Trade balance and GDP advance release are the other two news items with the strongest price effect.

In the orders-augmented regression, we see that an additional stop-loss sell in excess of take-profit buy orders tends to depreciate the dollar against the pound by 0.025 percent. This is larger than the effect of a one-standard deviation increase in jobless claims. The negative and significant coefficient is consistent with the expected sign of the net stop-loss sell order. Net stop-loss buy orders have the expected positive coefficient, but lack the statistical significance at the 10% level. I discuss this asymmetry later in section 5.

Price-contingent orders are most influential when the news is most surprising. Large news surprises tend to generate large exchange rate reactions and trigger the execution of stop-loss orders. Due to the positive feedback trading effect, once these orders are triggered, they propagate the initial trend, which then leads to the execution of more stop-loss orders generating an even bigger price movement. To test this hypothesis, I interact the stop-loss orders with the six surprise size variables creating 12 variables spanning two directions per each of the 6 news items. Then, I add them to the order-augmented specification in equation 3. The results reveal that interaction terms are significant for the news announcements with greatest impact—payroll employment and trade balance. Therefore, in Table 4, I report those interaction coefficients only. Price-contingent order flow intensifies the impact of news considerably: A one-standard deviation increase in U.S. employment surprise, if negative, exacerbates the depreciation of the dollar against the pound due to a stop-loss sell order by 0.226 percent. Hence, the slight decline in the individual estimates of the employment and stop-loss sell orders compared to the order-augmented regression is more than compensated by the large interaction coefficient.

Overall, including interaction terms improves the explanatory power of the base line models considerably: The adjusted-R^2 increases from 26 percent to 40 percent enhancing our ability to explain price adjustment to news by more than half.

An alternative way of test whether stop-loss order effect depends on how surprising the announcement is, is to partition the sample into two according to the *size* of the standardized news surprises. On days with more than one announcement released at the same time, the surprise variables are aggregated using their estimated news response coefficients as weights to account for possible counteracting price effects. If the absolute value of the standardized surprise variable is smaller (larger) than the sample median, the observation belongs to the small (large) surprise sample. Table 5 shows that the estimated effect of stop-loss sell orders in excess of buy orders is 0.049 percent for large surprises but only 0.008 percent for the small ones. This difference in effect is statistically significant at the 1 percent level and provides further support for the claim that stop-loss orders tend to generate larger price movements when news is most surprising.

The novelty in Table 5 is that news coefficients are also larger in the large news sample. One might conjecture that larger news coefficients in the large surprise sample are proxying for the orders in "stock", which are not captured by SLS-TPB and SLB-TPS. Our focus variables measure the flow of orders within 3 hours prior to the news events. Yet, larger surprises tend to trigger not only orders placed just before the announcements but also the ones that were already waiting in the books. Since the dataset does not include execution times, estimating the price effect of the orders in stock explicitly is not possible, but the bigger news coefficients in the large surprise sample provides one possible interpretation of how these orders may factor in to our analysis of post-announcement exchange-rate returns.

The results further suggest that the component of the response mediated through price-contingent order flow, does not entirely reflect the announcements' information content. The estimated news coefficients are robust to the inclusion of order variables into the baseline specification. Furthermore, in OLS regressions of news surprises on price-contingent orders, the estimated coefficients are all insignificant indicating that these orders do not help predict the news (Table 6). Also, the contemporaneous news response estimates reported in Andersen et al. (2005) are consistently at the same order of magnitude with those found in this study (Table 4). These findings suggest that price-contingent orders can complement the conditional mean specification presented in earlier studies, and also that the part of the price reaction captured by these orders are orthogonal to macro news surprises.

The coefficient estimates, though substantial, constitute a lower bound for stop-loss orders' price impact. The order series come from a single bank as opposed to the entire bank population. Due to this measurement error in the order variable, its coefficient is biased toward zero. Theoretically, this also biases the coefficients of the other explanatory variables as well, although in unknown directions. However, in this case, the stability of the news surprise coefficients over various different specifications, indicate that measurement error in the order variable is not a significant source of bias in other right-hand variable estimates. Similar measurement error concerns might also arise for news surprise variables. However, as long as the incorrectly measured variables are uncorrelated with each other, their coefficient estimates are attenuated (Garber and Klepper (1980)). Hence, orthogonality of news variables to order flow suggests that there is attenuation bias in the estimated order coefficients.

B. Absolute Returns

There is a sizable exchange-rate jump subsequent to news announcements as noted in Cheung and Chinn (2000) and Andersen et al. (2003). This is also documented in our sample in Figure 4, which plots mean absolute returns in each 5-minute interval of the day, averaged separately across announcement and no-announcement days.

In this section, I test whether the price-contingent order effect found in first moments also exists in second moments as well. I estimate how much the *types* of orders placed before a news announcement contributes to the *size* of the ensuing exchange-rate jump. A stop-loss order is a conditional instruction for the dealer to follow the market trend whereas a take-profit order is an instruction to go against it. Therefore, regardless of the sign, stop orders, on average, should be associated with larger exchange-rate moves and take-profit orders with smaller exchange rate moves.

The baseline model, which treats the news surprise size as the only source of exchange-rate volatility, and the orders-augmented model are as follows:

$$|R_t| = \alpha + \sum_{k=1}^{6} \beta_k D_{kt} \, |News_{kt}| + \eta_t \tag{5}$$

$$|R_t| = \alpha + \sum_{k=1}^{6} \beta_k D_{kt} \, |News_{kt}| + \beta_{sl} SL_t + \beta_{tp} TP_t + \varepsilon_t \tag{6}$$

Here, SL_t and TP_t denote the *excess* stop-loss and take-profit orders placed within 3 hours before the announcement time. OLS regressions and standard errors are calculated with Newey-West correction for autocorrelation and heteroskedasticity.

Table 7 contains the news surprise coefficients from the baseline model. The estimates show that the unanticipated component of the macronews releases explains 21 percent of the variation in absolute exchange-rate returns. News about payroll employment, in particular, has the largest price impact among all 8:30 announcements, a finding confirmed by the previous literature. The table also includes the Andersen et al. (2003) estimates of the contemporaneous volatility response to news. Despite the modeling and time period differences[10], these estimates

[10] Andersen et al. (2003) proxies the intraday exchange-rate volatility by the absolute value of the residuals from a regression of 5-minute returns on lagged returns and news surprise variables. They, then, estimate “5-minute exchange-rate volatility as driven partly by the volatility over the day containing the 5-minute interval in question, partly by news S_{kt}, and partly by a calendar effect pattern consisting largely of intraday effects that capture the high-frequency rhythm of deviations of intraday volatility from the daily average”. Their findings are based on interbank dealer data spanning 1992-1998.

provide a useful benchmark for comparing news surprise coefficients and confirm that our control variable estimates are similar in magnitude to the coefficients they report.

Order-augmented specification in Table 7 shows that stop-loss orders are positively correlated with the size of the ensuing exchange-rate jump. An additional unit of stop-loss order placed within 3 hours prior to the news release increases the absolute returns by 0.016 percent. Take-profit orders, on the other hand, are found to be statistically insignificant. This is not surprising in light of the absence of any tendency for agents to intensify the placement of these orders before the news. Here, too, the coefficients of order variables are biased towards zero due to the measurement error in the explanatory variables.

The interaction coefficients in Table 7 provide further support for the observation that price-contingent orders are most influential when the news is most surprising. The adjusted R^2 of the baseline, augmented and the interactions models are 0.21, 0.24 and 0.32 respectively. This implies that, on average, stop-loss order placement in the hours preceding news events enhance our ability to explain post-release exchange-rate volatility by 14 percent. Once the interaction between surprise size and stop-loss orders are taken into account, this figure rises to 52 percent (due to the 0.11 increase over the baseline goodness of fit).

Orthogonality of macro news surprises to the order variables is still valid in the context of absolute returns (Table 8). There is no significant change to the direction or the magnitude of the news effects when order variables are included to the baseline specification providing further support for this claim.

C. How long does the price-contingent order effect persist?

The analysis so far has demonstrated that the surge in stop-loss order placement in the hours preceding news events explains the *immediate* post-release exchange-rate returns. In this section, I examine how long this effect lasts by focusing on cumulative returns. To measure persistence, I replace the dependent variable in equation (3) with 15, 30, 45 and 60-minute cumulative returns, respectively (Table 9). I find that the price effect of stop-loss sell orders is at its peak at the 30-minute horizon disappearing only after 45 minutes.

I also test whether large surprises, which are more likely to entail price cascades, are associated with prolonged stop-loss order effects, by estimating the cumulative returns going forward in the large and small surprise sample separately (Table 10a and 10b). The results reveal that the stop-loss sell orders have a substantial effect on cumulative returns beyond *two hours* when news are most surprising. For small surprise events, the price impact of orders disappears much more quickly, after half an hour. This highlights the role that stop-loss trading can play in producing persistent price effects in currency markets.

5. Is there an asymmetric response to macro news releases?

Throughout the analysis, there is a recurring observation: While the coefficients of net stop-loss sell orders are significant both economically and statistically, stop-loss buy orders have negligible price impact. Normally, both order types, buys and sells, should be contributing to the subsequent exchange rate move symmetrically since exactly the same price adjustment mechanism puts the chain of events into motion, which eventually triggers the orders.

In this section, I will discuss why the estimated coefficients reveal such an asymmetry. Part of the reason can be attributed to the macroeconomic developments of the period under analysis. The dataset used here spans September 8, 1999 through April 11, 2000 and June 12, 2001 through September 20, 2002, which includes both the expansion and the recession times of the U.S. economy[11]. After the first quarter of 2001, the U.S. economy went into a recession period. During this time, pound (along with the Swiss Frank) appeared as a safer alternative to the US dollar, creating an increase in demand for the sterling.

While there have been some fluctuations in the parity consistent with growth forecast and productivity growth differentials between the United Kingdom and the United States, the pound continued its strength vis-à-vis the dollar in the interval studied here (BIS 2004). Since 2/3rd of the days in the dataset overlaps with the US recessionary period, on average, more stop-loss sell orders could be triggered during this time than stop-loss buys orders. Furthermore, bank's customers placed more stop-loss sell orders compared to stop-loss buys to protect themselves from the declining value of the dollar (Table 2a and 2b). Hence, the previous regression results might merely reflect this asymmetry in the dataset.

An alternative explanation to the question of why the price impact of stop-loss sell orders is larger compared to stop-loss buy orders lies in the news asymmetry literature (Conrad et al., 2001; Veronesi, 1999; Barberis et al.1998). This literature suggests that bad news in "good times" should have an unusually large impact. Particularly, Veronesi's rational-expectations equilibrium approach to the subject also implies that good news in bad times increases an asset's price but by less than it would in a present-value model due to the increased state risk factor. If

[11] I follow the NBER and the Andersen et al. (2005) recession definition, i.e., recession begins when there are three consecutive monthly declines in non-farm payroll employment and ends when there are three consecutive monthly increases in non-farm payroll employment. The recession dates remain unchanged if industrial production is used instead of the payroll employment statistics as the definition variable.

so, then the Veronesi model explains why we see significant coefficients associated with stop-loss sell orders but not with stop-loss buy orders in this particular sample, which is predominantly composed of recessionary days. Furthermore, another testable implication of this model is that if bad news in good times lead to unusually large initial price reaction, then this would translate into more stop-loss sell orders being triggered and more exchange-rates to be crossed, hence resulting in a larger estimated coefficient for stop-loss sell orders in the expansionary times than in recessionary times.

To test the validity of these two arguments, I partition the dataset into two based on the recession beginning date, February 28, 2001, reported by the NBER and define a dummy variable ***Exp*** which takes on the value 1 if the day is in the expansionary period and zero else. Table 11 reports the results from the following regression specification:

$$R_t = \alpha + \sum_{k=1}^{6} \gamma_k [Exp_t * D_{kt} * News_{kt}] + \sum_{k=1}^{6} \beta_k [D_{kt} * News_{kt}] + \gamma_{sls}[Exp_t * SLS - TPB_t] \\ + \beta_{sls}[SLS - TPB_t] + \gamma_{slb}[Exp_t * SLB - TPS_t] + \beta_{slb}[SLB - TPS_t] + \varepsilon_t \tag{7}$$

Exp_t*$News_{kt}$ represents the interaction between the expansion dummy variable and the standardized news surprise coefficient associated with announcement k at time t. Exp_t*SLS-TPB_t and Exp_t*SLB-TPS_t capture the effect of the net stop-loss sell and buy orders on a given day in the expansionary period. The other variables' definition remains the same as in the previous specifications.

The results show that an additional unit of stop-loss sell order depreciates the dollar against the pound by 0.03 percent in expansionary times (Table 11). Although the corresponding figure is smaller for the recession sample (0.02 percent) as predicted by the Veronesi model, the difference is not statistically significant. Hence, there is no evidence of news asymmetry reflected on the price-contingent order coefficients. Similarly, there is no significant difference between the expansion and recession coefficients associated with news variables aside from the trade balance announcement, which is larger in the expansion period. This is understandable since during expansionary times imports tend to grow. Hence, a narrower trade deficit than expected during periods of economic growth might surprise investors more than it would in recessionary times leading to a larger appreciation.

Stop-loss buy order coefficients become statistically significant at the 5% level and are of the same magnitude as their stop-loss sell counterparts in the expansion sub-sample. As predicted by the news asymmetry models, the stop-loss buy orders' contribution to post-release price movements remains negligible in the recession period. Hence, the Veronesi approach may provide an explanation for the weak price impact of the stop-loss buy orders: The recession days outnumber the expansion days in the sample, and therefore, the full sample specifications do not reflect significant coefficients for the stop-loss buy orders.

In conclusion, the evidence regarding the presence of asymmetric response to news in the pound/dollar market is mixed: The news asymmetry explains well the weak price impact of stop-loss buy orders in the full sample and the strong price effect of the same variable in the expansion sub-sample. On the other hand, the presence of an asymmetric response to news necessitates that the stop-loss sell orders effect be larger in the expansion sample compared to the recession sample (since the arrival of bad news in "good times" trigger stop-loss sell orders, which in turn should have an unusually large impact). However, the findings of this study do not support the last argument. Furthermore, the asymmetry captured directly by the news surprise coefficients themselves is also negligible. This is in line with the findings of Andersen et al. (2003), who show that the evidence for news asymmetry in currency markets is weak.

6. Robustness Checks

The significance of stop-loss orders is not limited to the three-hour interval discussed above. The price effect of orders placed within 4, 5 and 6 hours prior to the announcement time still remains significant. Yet, stop-loss orders placed within 3 hours prior to the announcement time have the largest statistically significant impact on the return size (Figure 5). After three hours, the effect dies out gradually, becoming statistically insignificant at the 24-hour interval. It is not surprising that the stop order placement three and four hours prior to the news release has the largest impact on the return size: In this study, the currency pair under analysis is the dollar/pound, and the majority of the order submission in preparation for the 8:30 EST U.S. macro news events takes place during the busy London morning hours, which correspond to the significant intervals mentioned above. Stop-loss orders placed within one hour and within two hours prior to the announcement time, however, are consistently found to be statistically insignificant. This is due to the relatively fewer number of orders placed in such short intervals, which translate into a lot of zeros in the SL_t and TP_t series. Similar results apply to the signed orders as well (Figure 6).

The cutoff determining whether an order is far away from the market rate is defined earlier as one standard deviation of the absolute daily exchange rate changes. If the distance between the requested execution rate and the market rate at the time of the placement exceeds one standard deviation, that order is considered as a "far" order and therefore, excluded from the original sample. In this section, I investigate the sensitivity of the results to a change in this cutoff. If the orders within two standard deviations of the market rate are included in the sample, the effect of price-contingent orders decreases in both the absolute return and the signed return regressions. This is an expected outcome since less of the orders in the sample will actually be executed and hence the overall magnitude and significance of the stop-loss and take-profit orders diminishes (Figures 7a, 7b and Figure 8). If, on the other hand, the orders within half a standard deviation of the market rate are included in the sample, the price impact of price contingent orders increases (Figures 9a, 9b and Figure 10). This implies that the results reported in the earlier sections constitute a lower bound for the effect of price-contingent orders. As the cutoff used for filtering out the far orders becomes more and more restrictive, the price impact of stop-loss orders becomes larger (Table 12), yet the adjusted-R^2 is the highest in regression (3) in Table 12 indicating that orders that are placed within one standard deviation from the market rate constitute a more appropriate representation of the actually executed orders than the other two groups.

Another important robustness check relates to the announcement sample used in this study. Not all announcements generate a statistically significant price impact. This can be due to the timing of the announcement or the traders' belief that news regarding real variables is more influential than nominal variables (Cheung and Chinn, 2001). Based on an extensive dataset which covers six years, Andersen et al. (2003) find that for the pound/dollar pair, the significant 8:30 announcements are unemployment, durable goods, trade balance, retail sales, jobless claims and GDP advance releases. Therefore, in this study, I focused on these six news items only. This is the general practice in the macro news literature where research is primarily concentrated on major news releases with significant price impact (Love and Payne, 2002; Chaboud et al., 2004; Hautch and Hess, 2001).

The question of whether including all 8:30 announcements into the analysis would change the previous results can arise nonetheless. In theory, this should, on average, reduce the magnitude of the stop-loss orders' effect on post-release returns: Less significant announcements imply smaller news surprises, which lead to smaller initial price reactions, which in turn, trigger fewer stop-loss orders. Hence, overall, the price impact of stop-loss orders will be more modest compared to the results from the significant announcement sample. This dilution effect is indeed what Tables 13 and 14 show. The estimated net stop-loss coefficients from both the absolute and signed return regressions are smaller and adding the price-contingent order variables increase the adjusted R^2 by 1% in the signed and by 2% in the absolute return specifications. These are smaller increments compared to the previous sections' findings. Nonetheless, even in samples that include all announcement types, an additional stop-loss order placed before the announcement intensifies the post-release price move by 0.01 percent, which implies that the effect is comparable to that of the jobless claims reports announced weekly.

The effect of price-contingent orders prevails at other U.S. announcement times, too. However, only one or two news series are released at those times making it hard to conduct statistical analysis with 21 months of order data. At 10:00 EST, a total of five news items are released (construction spending, consumer confidence, factory orders, NAPM index and new home sales). Andersen et al. (2003) finds that out of the five, only construction spending, consumer confidence and NAPM index have statistically significant price impact. Hence, I analyze the effect of price-contingent orders on the days of these three news releases. Table 15 suggests that an additional net stop-loss sell order, placed within an hour of the 10 o'clock announcements, tends to depreciate the dollar against the pound by .045 percent. This confirms the previous result that price-contingent order flow has substantial effects on post-release returns. It is not surprising to see a lower the adjusted R^2 in this case since 10 o'clock announcements are less significant in their price impact compared to big news events such as GDP or unemployment, which are released at 8:30 EST. As before, estimated news coefficients are similar to those reported in Andersen et al. (2003) and are robust to the inclusion of order variables.

One might also wonder whether the length of the sample, which spans a total of 21 months, is a cause of concern for the validity of the news variable t-statistics since the dataset contains 21 observations for each monthly announcement. As a check on the robustness of the results, I also performed all of the empirical work using bootstrapped standard errors with no change in any of the qualitative results although the coefficients of advanced GDP were no longer significant).

7. Conclusion

In this study, I examine whether the post-release exchange rate movements are linked to pre-announcement price-contingent order placements and if so, how much they contribute to the following exchange-rate jump. I find that investors with rational timing incentives intensify their stop order submissions prior to news releases and that this surge in placement enhances our ability to explain the following exchange rate jump by more than half. This particular finding is relevant for improved high-frequency volatility estimation since a better understanding of conditional mean jumps is essential for modeling purposes.

In addition, the results reveal that the component of the news response captured by price-contingent orders might be independent of the announcement's information content. This suggests that news-induced price-contingent order placements can have significant impact on exchange-rates without necessarily conveying incremental information about the state of the macroeconomy.

The results also extend the recent findings in the exchange-rate literature, which suggest that order flow volatility remains elevated hours even days after the macronews announcements (Andersen et al. 2003, Evans and Lyons 2005). According to these studies, investors continue to evaluate and interpret the new information by carrying out post-announcement transactions. Since investors can use price-contingent orders to prepare for scheduled announcements conditional on the outcome and take positions accordingly in advance, an increase in the placement of these orders might be associated with reduced order flow volatility following the news releases. Exploring this relationship between price-contingent orders and post-announcement volatility persistence will be the prime candidate for future research.

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Table 1: U.S. News Announcements

The table lists the US macroeconomic news announcements that are released at 8:30 EST over September 8, 1999 through April 11, 2000 and June 12, 2001 through September 20, 2002.

Announcement	Frequency	Source[1]	Units[2]
1- GDP (Advance)*	Quarterly	BEA	% change qoq
2- GDP (Preliminary)	Quarterly	BEA	% change qoq
3- GDP (Final)	Quarterly	BEA	% change qoq
4- Nonfarm Payroll Employment*	Monthly	BLS	Thousands
5- Retail Sales*	Monthly	BC	Change %
6- Durable Goods Orders*	Monthly	BC	Change %
7- Business Inventories	Monthly	BC	Change %
8- Trade Balance*	Monthly	BEA	$ Billions
9- Producer Price Index	Monthly	BLS	Change %
10- Consumer Price Index	Monthly	BLS	Change %
11- Housing Starts	Monthly	BC	Millions of units
12- Index of Leading Indicators	Monthly	CB	Change %
13- Personal Consumption	Monthly	BEA	Change %
14- Personal Income	Monthly	BEA	Change %
15- Initial Unemployment Claims*	Weekly	ETA	Thousands

[1]Bureau of Labor Statistics (BLS), Bureau of the Census (BC), Bureau of Economic Analysis (BEA), Conference Board (CB), Employment and Training Administration (ETA)

[2] Expressed at an annualized rate.

*Asterisks refer to the announcements that are included in the significant announcement sample in this study. The selection is based on whether Andersen et al. (2003) found statistically significant price impact associated with the given news item.

Table 2.a: Descriptive Information on Stop-Loss and Take-Profit Orders

The table describes the stop-loss and take-profit orders for the pound-dollar currency pair processed by a major foreign exchange dealing bank over September 8, 1999 through April 11, 2000 and June 12, 2001 through September 20, 2002. There are 10,413 orders with aggregate value in excess of $61 billion.

		All Orders	Stop-Loss	Take-Profit
Number Orders		10,413	5,020	5,393
Share of Orders		100.0	48.2	51.8
Size ($ Mill.):	**Mean**	5.92	5.89	5.96
	Median	3.58	4.01	3.10
Dist. To Mkt. (%):	**Mean**	1.13	1.11	1.14
	Median	0.52	0.53	0.51
Share of buy orders (%)		52	47	56
Share Executed (%)		27.78	23.45	31.82

Table 2.b: Descriptive Information on Stop-Loss and Take-Profit Orders (Excluding Far Orders)

The table describes the stop-loss and take-profit orders that lie within one standard deviation of the daily market rate for the pound-dollar currency pair processed by a major foreign exchange dealing bank over September 8, 1999 through April 11, 2000 and June 12, 2001 through September 20, 2002. The reason for focusing on this subset of orders is that only those orders, which are near the market rate can be triggered and thus have a high frequency price impact. In this subset, there are 4,281 orders with aggregate value in excess of $23 billion.

		All Orders	Stop-Loss	Take-Profit
Number Orders		4,281	2,081	2,200
Share of Orders		100.0	48.61	51.39
Size ($ Mill.):	**Mean**	5.54	5.49	5.60
	Median	3.61	4.27	3.11
Dist. To Mkt. (%):	**Mean**	0.23	0.24	0.23
	Median	0.24	0.24	0.23
Share of buy orders (%)		49	43	54
Share Executed		41.37	37.29	45.23

Table 3.a: Sources of Stop-Loss and Take-Profit Orders

The table lists the stop-loss and take-profit orders for the pound-dollar currency pair processed by a major foreign exchange dealing bank over September 8, 1999 through April 11, 2000 and June 12, 2001 through September 20, 2002. There are 10,413 orders with aggregate value in excess of $61 billion. "Other" customer orders are orders from unidentified desks within the bank. "Internal" orders are those placed by agents within the bank.

	Number of Orders	**Percent of Orders**	**Dollar Value of Orders ($ Billions)**	**Percent of Order Value**
All Orders	**10,413**	**100.0**	**61.7**	**100.0**
Customer Orders	**6,347**	**61.0**	**33.9**	**54.9**
Fin. Inst.	4,181	40.2	22.0	35.7
Non-Fin. Inst.	2,109	20.3	11.8	19.1
Other	57	0.5	0.1	0.1
Internal	**4,066**	**39.0**	**27.8**	**45.1**

Table 3.b: Sources of Stop-Loss and Take-Profit Orders (Excluding Far Orders)

The table lists the stop-loss and take-profit orders that lie within one standard deviation of the daily market rate for the pound-dollar currency pair processed by a major foreign exchange dealing bank over September 8, 1999 through April 11, 2000 and June 12, 2001 through September 20, 2002. The reason for focusing on this subset of orders is that only those orders, which are near the market rate can be triggered and thus have a high frequency price impact. There are 4,281 orders with aggregate value in excess of $23 billion. "Other" customer orders are orders from unidentified desks within the bank. "Internal" orders are those placed by agents within the bank.

	Number of Orders	**Percent of Orders**	**Dollar Value of Orders ($ Billions)**	**Percent of Order Value**
"All Orders"	**4,281**	**100.0**	**23.7**	**100.0**
Customer Orders	**2,732**	**63.8**	**14.6**	**61.7**
Fin. Inst.	1,757	41.0	9.4	39.7
Non-Fin. Inst.	968	22.6	5.2	21.9
Other	7	0.2	0.0	0.1
Internal	**1,549**	**36.2**	**9.1**	**38.3**
"Stop-Loss Orders"	**2,084**	**100.0**	**11.4**	**100.0**
Customer Orders	**1,213**	**58.2**	**6.1**	**53.5**
Fin. Inst.	974	46.7	5.1	44.7
Non-Fin. Inst.	238	11.4	1.0	8.8
Other	1	0.1	0.0	0.0
Internal	**871**	**41.8**	**5.3**	**46.5**
"Take-Profit Orders"	**2,264**	**100.0**	**12.6**	**100.0**
Customer Orders	**1,550**	**68.5**	**8.6**	**68.3**
Fin. Inst.	803	35.5	4.4	34.9
Non-Fin. Inst.	741	32.7	4.2	33.4
Other	6	0.3	0.0	0.0
Internal	**714**	**31.5**	**4.0**	**31.7**

Table 4: Impact on Returns: Signed Effects

The dependent variable is *5-minute Returns*, the 5-minute pound-dollar log return from 8:30-8:35. The base currency is the dollar. *Employment, Durable Goods, Trade Balance, Retail Sales, Jobless Claims and GDP Advance* represent the standardized news surprise variables corresponding to each major US macroeconomic announcement released at 8:30 EST. In regression 2-4, *SLS-TPB* (*SLB-TPS)* denote the number of stop-loss sell (buy) orders in excess of take-profit buy (sell) orders placed 3 hours before the announcement time. The remaining variables are the interactions between the order variables defined above and the two most significant news items—unemployment and trade balance. Heteroskedasticity and autocorrelation robust t-statistics are in parentheses. The last column presents the contemporaneous news response coefficients and R^2 from Andersen et al. (2005). The estimates are based on futures returns from 1992-2002.

5-minute Returns	Baseline	News and Orders	News, Orders, Interactions	Orders Only	*Andersen et al. (2005)*
	(1)	(2)	(3)	(4)	*(5)*
Employment	0.085**	0.085**	0.066**		*0.098***
	(2.09)	(2.03)	(2.45)		*(R^2=0.16)*
Durable Goods	0.027	0.027*	0.027*		*0.038***
	(1.61)	(1.78)	(1.73)		*(R^2=0.17)*
Trade Balance	0.069***	0.068***	0.073***		*0.049***
	(3.18)	(3.04)	(4.57)		*(R^2=0.16)*
Retail Sales	0.042***	0.039***	0.040***		*0.042***
	(3.00)	(2.84)	(2.79)		*(R^2=0.15)*
Jobless Claims	-0.013***	-0.012**	-0.013***		*-0.017***
	(-2.64)	(-2.45)	(-2.60)		*(R^2=0.04)*
GDP Advance	0.063***	0.068***	0.067***		*0.054***
	(2.70)	(3.17)	(3.01)		*(R^2=0.22)*
SLS-TPB		-0.025***	-0.021**	-0.028***	
		(-3.18)	(-2.44)	(-3.19)	
SLB-TPS		0.009	0.007	0.013	
		(1.10)	(0.89)	(1.36)	
Employment x SLS			0.226***		
			(2.57)		
Trade Balance x SLS			-0.020		
			(-0.67)		
Employment x SLB			-0.019		
			(-0.56)		
Trade Balance x SLB			0.130***		
			(3.51)		
Adjusted R^2	0.26	0.29	0.40	0.04	‡
N. of Observations	162	162	162	162	

The symbols ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level, respectively.
‡ Individual R^2's are given separately for each announcement.

Table 5: Directional Effects: Small vs. Large Surprises

The dependent variable is *5-minute Returns*, the 5-minute pound-dollar log return from 8:30-8:35. The base currency is the dollar. *Employment, Durable Goods, Trade Balance, Retail Sales, Jobless Claims and GDP Advance* represent the standardized news surprise variables corresponding to each major US macroeconomic announcement released at 8:30 EST. In regression 2 and 4, *SLS-TPB* (*SLB-TPS)* denote the number of stop-loss sell (buy) orders in excess of take-profit buy (sell) orders placed 3 hours before the announcement time. The sample is divided into two depending on whether the absolute value of the weighted standardized news surprises is smaller or larger than the sample median. Heteroskedasticity and autocorrelation robust t-statistics are in parentheses.

	Small Surprise		Large Surprise	
	Baseline	News, Orders	Baseline	News, Orders
	(1)	(2)	(3)	(4)
Employment	-‡	-‡	0.113**	0.112**
	-	-	(2.06)	(1.97)
Durable Goods	0.003	0.006	0.034*	0.035**
	(0.24)	(0.42)	(1.81)	(2.02)
Trade Balance	0.010*	0.009*	0.073*	0.072*
	(1.70)	(1.74)	(1.85)	(1.71)
Retail Sales	0.014	0.013	0.044***	0.040***
	(0.70)	(0.72)	(2.99)	(2.90)
Jobless Claims	-0.005	-0.005	-0.021**	-0.019**
	(-1.34)	(-1.38)	(-2.26)	(-2.12)
GDP Advance	-‡	-‡	0.066***	0.070***
	-	-	(2.81)	(3.21)
SLS-TPB		-0.008***		-0.049***
		(-2.62)		(-4.21)
SLB-TPS		-0.003		0.007
		(-0.70)		(0.53)
Adjusted R^2	0.01	0.06	0.24	0.30
N. of Observations	81	81	81	81

The symbols ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level, respectively.

‡All Employment and GDP Advance announcements during the period under analysis here are associated with large news surprises, hence, in the small surprise sample, the these variables are absent.

Table 6: Orthogonality – Signed News and Orders

The dependent variables, *Employment, Durable Goods, Trade Balance, Retail Sales, Jobless Claims and GDP Advance,* represent the standardized news surprise variables corresponding to each major US macroeconomic announcement released at 8:30 EST. *SLS-TPB* (*SLB-TPS)* denote the *total* number stop-loss sell (buy) orders in excess of take-profit buy (sell) orders placed 3 hours before the announcement time. Heteroskedasticity robust t-statistics are reported in parentheses.

	SLS-TPB	***SLB-TPS***	Adjusted R^2	N. of Observations
Employment	-0.14	-0.01	0.01	21
	(-0.56)	(-0.02)		
Durable Goods	-0.09	0.18	0.04	20
	(-0.29)	(0.89)		
Trade Balance	-0.01	0.13	0.02	22
	(-0.05)	(0.57)		
Retail Sales	0.32	0.28	0.09	21
	(0.81)	(1.02)		
Jobless Claims	0.11	-0.02	0.01	93
	(1.24)	(-0.32)		
GDP Advance	0.17	-0.74	0.31	7
	(0.24)	(-1.57)		

The symbols ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level, respectively.

Table 7: Contemporaneous Volatility Response

In regressions 1-4, the dependent variable is *Absolute 5-minute Returns*, the absolute value of the 5-minute pound-dollar return from 8:30-8:35. The base currency is the dollar. *Abs_Employment, Abs_Durable Goods, Abs_Trade Balance, Abs_Retail Sales, Abs_Jobless Claims and Abs_GDP Advance* represent the absolute values of the standardized news surprise variables corresponding to each major US macroeconomic announcement released at 8:30 EST. *SL* and *TP* denote the number of stop-loss and take-profit orders placed 3 hours before the announcement time respectively. Heteroskedasticity and autocorrelation robust t-statistics are in parentheses. Regression (5) provides the Andersen et al. (2003) estimates of the contemporaneous response of exchange-rate volatility to news.

Absolute 5-minute Returns	Baseline	News and Orders	News, Orders, Interactions	Orders Only	*Andersen et al.(2003)*
	(1)	(2)	(3)	(4)	*(5)*
Abs_Employment	0.074**	0.073**	0.053**		*0.058***
	(2.03)	(2.06)	(2.09)		
Abs_Durable Goods	0.021*	0.014	0.017		*0.017***
	(1.78)	(1.06)	(1.25)		
Abs_Trade Balance	0.030**	0.024*	0.026**		*0.023***
	(2.41)	(1.69)	(1.96)		
Abs_Retail Sales	0.036***	0.034***	0.035***		-‡
	(2.72)	(2.52)	(2.61)		
Abs_Jobless Claims	-0.004	-0.004	-0.004		*0.003***
	(-0.74)	(-0.84)	(-0.72)		
Abs_GDP Advance	0.049**	0.053**	0.050**		-‡
	(2.18)	(2.32)	(2.22)		
SL		0.016***	0.017**	0.017***	
		(2.79)	(1.84)	(2.89)	
TP		0.002	0.001	0.002	
		(0.55)	(1.38)	(0.46)	
Abs_Employment x SL			0.071***		
			(2.74)		
Abs_Durable Goods x SL			-0.001		
			(-0.72)		
Abs_Trade Balance x SL			-0.001		
			(-0.69)		
Abs_Retail Sales x SL			-0.027		
			(-1.25)		
Abs_Jobless Claims x SL			-0.001		
			(-0.71)		
Abs_GDP Advance x SL			0.368		
			(1.02)		
Adjusted R^2	0.21	0.24	0.32	0.04	-‡
N. of Observations	162	162	162	162	

The symbols ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level, respectively.
‡ The R^2 and the coefficients of ***Abs_Retail Sales*** and ***Abs_GDP Advance*** are missing from the Andersen et al. (2003) regression as the authors report only four of the major news' coefficients.

Table 8: Orthogonality – News and Orders

The dependent variables, *Abs_Employment, Abs_Durable Goods, Abs_Trade Balance, Abs_Retail Sales, Abs_Jobless Claims and Abs_GDP Advance,* represent the absolute values of the standardized news surprise variables corresponding to each major US macroeconomic announcement released at 8:30 EST. *SL* and *TP* denote the number of stop-loss and take-profit orders placed 3 hours before the announcement time respectively. Heteroskedasticity and autocorrelation robust t-statistics are in parentheses.

	SL	***TP***	Adjusted R^2	N. of Observations
Abs_Employment	0.35	-0.09	0.00	21
	(1.39)	(-0.34)		
Abs_Durable Goods	0.38	-0.03	0.07	20
	(1.44)	(-0.44)		
Abs_Trade Balance	0.23	-0.08	0.08	22
	(1.27)	(-0.75)		
Abs_Retail Sales	0.04	-0.24	0.00	21
	(0.28)	(-1.03)		
Abs_Jobless Claims	-0.03	-0.02	0.00	93
	(-0.36)	(-0.82)		
Abs_GDP Advance	-2.98	0.38	0.00	7
	(-1.26)	(0.95)		

The symbols ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level, respectively.

Table 9: Persistence — Cumulative Returns

The dependent variables are the cumulative pound-dollar log returns from 8:30-8:45, 8:30-9:00, 8:30-9:15 and 8:30-9:30. The base currency is the dollar. *Employment, Durable Goods, Trade Balance, Retail Sales, Jobless Claims and GDP Advance* represent the standardized news surprise variables corresponding to each major US macroeconomic announcement released at 8:30 EST. *SLS-TPB* (*SLB-TPS)* denote the number of stop-loss sell (buy) orders in excess of take-profit buy (sell) orders placed 3 hours before the announcement time. Heteroskedasticity and autocorrelation robust t-statistics are in parentheses.

Returns	**Payroll Employment**	**Durable Goods**	**Trade Balance**	**Retail Sales**	**Jobless Claims**	**GDP Advance**	**SLS-TPB**	**SLB-TPS**	Adj-R^2
15-min	0.067*	0.037*	0.067**	0.043***	-0.01	0.069**	-0.020**	0.008	0.14
	(1.66)	(1.71)	(2.04)	(3.14)	(-1.54)	(2.02)	(-2.05)	(0.69)	
30-min	0.073	0.063***	0.057	0.055***	-0.019**	0.021	-0.031**	-0.003	0.12
	(1.36)	(2.77)	(1.55)	(2.85)	(-2.46)	(0.38)	(-2.38)	(-0.14)	
45-min	0.101*	0.055***	0.058	0.058**	-0.025***	-0.024	-0.028*	-0.009	0.10
	(1.73)	(2.76)	(1.54)	(2.36)	(-2.57)	(-0.44)	(-1.86)	(-0.51)	
60-min	0.094	0.044***	0.040	0.038	-0.019*	-0.024	-0.026	-0.011	0.04
	(1.59)	(2.59)	(0.76)	(1.38)	(-1.63)	(-0.39)	(-1.45)	(-0.48)	

The symbols ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level, respectively.

Table 10.a: Cumulative Returns: Large Surprise Sample

The dependent variables are pound-dollar cumulative log returns. The base currency is the dollar. *Employment, Durable Goods, Trade Balance, Retail Sales, Jobless Claims and GDP Advance* represent the standardized news surprise variables corresponding to each major US macroeconomic announcement released at 8:30 EST. *SLS-TPB* (*SLB-TPS)* denote the number of stop-loss sell (buy) orders in excess of take-profit buy (sell) orders placed 3 hours before the announcement time. The sample is divided into two depending on whether the absolute value of the weighted standardized news surprises is smaller or larger than the sample median. Heteroskedasticity and autocorrelation robust t-statistics are in parentheses.

Returns	Payroll Employment	Durable Goods	Trade Balance	Retail Sales	Jobless Claims	GDP Advance	SLS-TPB	SLB-TPS	Adj-R^2
8:30-8:35	0.112**	0.035**	0.032	0.040***	-0.019**	0.07***	-0.049***	0.007	0.30
	(1.97)	(2.02)	(0.71)	(2.90)	(-2.12)	(3.21)	(-4.21)	(0.53)	
8:30-8:45	0.080	0.029	0.023	0.041***	-0.006	0.072*	-0.038**	0.010	0.10
	(1.36)	(1.36)	(0.57)	(3.25)	(-0.48)	(1.92)	(-2.07)	(0.62)	
8:30-9:00	0.109	0.061**	0.002	0.056***	-0.015	0.017	-0.040*	-0.009	0.12
	(1.55)	(2.37)	(0.05)	(2.77)	(-1.25)	(0.30)	(-1.80)	(-0.40)	
8:30-9:15	0.135*	0.061***	-0.012	0.053**	-0.019	-0.022	-0.051**	-0.009	0.17
	(1.83)	(2.85)	(-0.30)	(2.36)	(-1.17)	(-0.37)	(-2.23)	(-0.39)	
8:30-9:30	0.122	0.046**	-0.018	0.028	0.000	-0.016	-0.063***	0.000	0.10
	(1.59)	(2.47)	(-0.36)	(1.14)	(-0.02)	(-0.23)	(-2.65)	(0.01)	
8:30-9:45	0.153**	0.062***	-0.014	0.011	-0.005	-0.017	-0.074***	0.001	0.16
	(2.19)	(4.06)	(-0.32)	(0.69)	(-0.25)	(-0.17)	(-2.55)	(0.05)	
8:30-10:00	0.139*	0.087***	-0.016	-0.001	-0.025	-0.028	-0.079**	0.011	0.14
	(1.92)	(4.01)	(-0.32)	(-0.05)	(-0.83)	(-0.31)	(-2.48)	(0.45)	
8:30-10:15	0.117*	0.056	-0.006	-0.028*	-0.018	-0.023	-0.086***	0.016	0.08
	(1.85)	(1.54)	(-0.15)	(-1.70)	(-0.45)	(-0.35)	(-3.02)	(0.66)	
8:30-10:30	0.146***	0.065	0.041	-0.028	-0.024	0.014	-0.090***	0.004	0.11
	(2.62)	(1.51)	(0.92)	(-1.19)	(-0.48)	0.24)	(-3.28)	(0.13)	
8:30-10:45	0.140**	0.057	0.031	-0.04	-0.003	0.076	-0.063**	-0.016	0.04
	(2.01)	(0.97)	(0.52)	(-1.53)	(-0.06)	(0.96)	(-2.02)	(-0.43)	
8:30-11:00	0.130	0.080	0.023	-0.047	-0.019	0.04	-0.065*	-0.008	0.02
	(1.62)	(1.44)	(0.32)	(-1.16)	(-0.37)	(0.68)	(-1.85)	(-0.21)	

The symbols ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level, respectively.

Table 10.b: Cumulative Returns: Small Surprise Sample

Returns	Durable Goods	Trade Balance	Retail Sales	Jobless Claims	SLS-TPB	SLB-TPS	Adj-R^2
8:30-8:35	0.006	0.009*	0.013	-0.005	-0.008***	-0.003	0.06
	(0.42)	(1.74)	(0.72)	(-1.38)	(-2.62)	(-0.70)	
8:30-8:45	0.097***	0.047	0.137	-0.015	-0.005	-0.007	0.06
	(4.48)	(1.51)	(1.00)	(-1.56)	(-0.73)	(-0.60)	
8:30-9:00	0.080**	0.071*	0.059	-0.021	-0.023**	-0.013	0.05
	(2.87)	(1.81)	(0.32)	(-1.71)	(-2.26)	(-0.81)	
8:30-9:15	0.002	0.083*	0.269	-0.039**	-0.011	-0.021	0.03
	(0.04)	(1.92)	(1.07)	(-2.45)	(-0.66)	(-1.14)	
8:30-9:30	0.009	0.058	0.390	-0.049***	-0.002	-0.003	0.02
	(-0.20)	(0.95)	(1.63)	(-2.71)	(-0.10)	(-1.04)	

The symbols ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level, respectively.
‡All Employment and GDP Advance announcements during the period under analysis here are associated with large news surprises, hence, in the small surprise sample, the these variables are absent.

Table 11: Directional Effects: Is there an asymmetric response?

The dependent variable is *5-minute Returns*, the 5-minute pound-dollar log return from 8:30-8:35. The base currency is the dollar. *Employment, Durable Goods, Trade Balance, Retail Sales, Jobless Claims and GDP Advance* represent the standardized news surprise variables corresponding to each major US macroeconomic announcement released at 8:30 EST. In regression 1 and 2, *SLS-TPB* (*SLB-TPS)* denotes the number of stop-loss sell (buy) orders in excess of take-profit buy (sell) orders placed 3 and 4 hours before the announcement time respectively. *Exp* is a dummy variable that takes on the value 1 for days within the expansionary period. The dataset spans September 8, 1999 through April 11, 2000 and June 12, 2001 through September 20.Days following February 28, 2001constitute the recessionary period. Heteroskedasticity and autocorrelation robust t-statistics are in parentheses.

5-minute Returns	
Exp x Employment	0.079*
	(1.82)
Exp xDurable Goods	0.045**
	(2.12)
Exp xTrade Balance	0.123***
	(2.62)
Exp x Retail Sales	-0.046
	(-0.56)
Exp x Jobless Claims	0.012
	(0.61)
Exp x GDP Advance	0.035
	(0.28)
Employment	0.086*
	(1.93)
Durable Goods	0.033*
	(1.90)
Trade Balance	0.020
	(0.76)
Retail Sales	0.043***
	(2.96)
Jobless Claims	-0.017***
	(-3.20)
GDP Advance	0.074***
	(4.05)
Exp x SLS-TPB	-0.030**
	(-2.03)
SLS-TPB	-0.022**
	(-2.37)
Exp x SLB-TPS	0.031**
	(2.41)
SLB-TPS	-0.003
	(-0.27)
Adjusted R^2	0.25
N. of Observations	162

The symbols ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level, respectively.

Table 12: Robustness Checks: Far vs. Near Orders

The dependent variable is *5-minute Returns*, the 5-minute pound-dollar log return from 8:30-8:35. The base currency is the dollar. *Employment, Durable Goods, Trade Balance, Retail Sales, Jobless Claims and GDP Advance* represent the standardized news surprise variables corresponding to each major US macroeconomic announcement released at 8:30 EST. *SLS-TPB* (*SLB-TPS)* denote the number of stop-loss sell (buy) orders in excess of take-profit buy (sell) orders placed 3 hours before the announcement time. Regressions 2, 3 and 4 use price continent orders from three different samples, those that are placed within half, one and two standard deviations of the daily market rate respectively. Heteroskedasticity and autocorrelation robust t-statistics are in parentheses.

5-minute Returns	Baseline	Cutoff=0.5*σ	Cutoff=σ	Cutoff=2*σ
	(1)	(2)	(3)	(4)
Employment	0.085**	0.080**	0.085**	0.085**
	(2.09)	(2.02)	(2.03)	(2.02)
Durable Goods	0.027	0.027*	0.027*	0.028*
	(1.61)	(1.45)	(1.78)	(1.78)
Trade Balance	0.069***	0.065***	0.068***	0.064***
	(3.18)	(3.02)	(3.04)	(3.16)
Retail Sales	0.042***	0.041***	0.039***	0.041***
	(3.00)	(3.11)	(2.84)	(2.98)
Jobless Claims	-0.013***	-0.013**	-0.012**	-0.011**
	(-2.64)	(-2.34)	(-2.45)	(-2.39)
GDP Advance	0.063***	0.063***	0.068***	0.068***
	(2.70)	(2.67)	(3.17)	(2.83)
SLS-TPB		-0.029**	-0.025***	-0.013***
		(-2.08)	(-3.18)	(-1.94)
SLB-TPS		-0.011	0.009	0.003
		(-0.61)	(1.11)	(0.69)
Adjusted R^2	0.26	0.28	0.29	0.27
N. of Observations	162	162	162	162

The symbols ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level, respectively.

Table 13: Robustness Checks: All Announcements

Absolute 5-minute Returns	Baseline	3 hours	4 hours
	(1)	(2)	(3)
Abs_Employment	0.076**	0.076**	0.075**
	(2.09)	(2.13)	(2.08)
Abs_CPI	-0.005	-0.005	-0.007
	(-0.73)	(-0.73)	(-1.03)
Abs_Durable Goods	0.024*	0.02	0.023*
	(1.89)	(1.39)	(1.69)
Abs_Housing Starts	-0.007	-0.008	-0.008
	(-1.37)	(-1.52)	(-1.62)
Abs_Leading Indicators	0.004	0.005	0.003
	(0.81)	(1.17)	(0.57)
Abs_Trade Balance	0.033	0.031**	0.032***
	(1.55)	(2.32)	(2.52)
Abs_PPI	0.029**	0.031**	0.027**
	(2.05)	(2.28)	(1.85)
Abs_Retail Sales	0.035***	0.034***	0.035***
	(3.09)	(2.97)	(2.95)
Abs_Business Inventories	-0.003	0.000	0.000
	(-0.61)	(-0.03)	(-0.04)
Abs_Pers. Consumption Expenditures	-0.015***	-0.014**	-0.015**
	(-2.58)	(-2.18)	(-2.41)
Abs_Personal Income	0.039*	0.033	0.036*
	(1.87)	(1.50)	(1.70)
Abs_Jobless Claims	0.000	0.000	0.000
	(-0.06)	(0.03)	(-0.09)
Abs_GDP Advance	0.054**	0.058**	0.055**
	(2.35)	(2.45)	(2.27)
Abs_GDP Preliminary	0.015*	0.01	0.008
	(1.63)	(0.93)	(0.78)
Abs_GDP Final	0.008	0.012	0.011
	(0.96)	(1.32)	(1.22)
SL		0.010***	0.006**
		(2.56)	(1.95)
TP		0.002	0.000
		(0.90)	(0.09)
Adjusted R^2	0.21	0.23	0.23
N. of Observations	240	240	240

The symbols ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level, respectively.

Table 14: Robustness Checks: All Signed Announcements

5-minute Returns	Baseline	3 hours	4 hours
	(1)	(2)	(3)
Employment	0.080**	0.080**	0.081**
	(2.02)	(-2.00)	(-2.04)
CPI	0.005	0.004	0.007
	(0.86)	(0.66)	(1.08)
Durable Goods	0.026	0.026	0.026
	(1.49)	(1.56)	(1.55)
Housing Starts	0.003	-0.002	0.003
	(0.38)	(-0.25)	(0.31)
Leading Indicators	-0.004	-0.003	-0.017
	(-0.84)	(-0.57)	(-1.31)
Trade Balance	0.068***	0.068***	0.068***
	(3.00)	(2.96)	(2.82)
PPI	-0.012	-0.010	-0.013
	(-0.68)	(-0.54)	(-0.72)
Retail Sales	0.041***	0.040***	0.041***
	(2.86)	(2.78)	(2.92)
Business Inventories	-0.003	-0.004	-0.004
	(-0.27)	(-0.45)	(-0.43)
Personal Consumption Expenditures	-0.008	-0.005	-0.007
	(-0.82)	(-0.49)	(-0.61)
Personal Income	-0.013	-0.009	-0.014
	(-0.82)	(-0.40)	(-0.62)
Jobless Claims	-0.012**	-0.012**	-0.011**
	(-2.26)	(-2.24)	(-2.12)
GDP Advance	0.061***	0.064***	0.061***
	(2.52)	(2.79)	(2.54)
GDP Preliminary	0.012	0.011	0.016
	(0.63)	(0.49)	(0.72)
GDP Final	-0.009	-0.008	-0.007
	(-0.57)	(-0.48)	(-0.44)
SLS-TPB		-0.010*	-0.008*
		(-1.72)	(-1.87)
SLB-TPS		0.005	-0.001
		(0.69)	(-0.22)
Adjusted R^2	0.21	0.22	0.22
N. of Observations	240	240	240

The symbols ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level, respectively.

Table 15: Robustness Checks: 10:00 EST Announcements

5-minute Returns	Benchmark	Orders placed within 1 hr	Orders placed within 2 hrs	Orders placed within 3 hrs
	(1)	(2)	(3)	(4)
Construction Spending	0.025**	0.026**	0.027**	0.025**
	(2.16)	(2.02)	(2.12)	(2.11)
Consumer Confidence	0.028**	0.035**	0.034**	0.031**
	(2.29)	(2.35)	(2.30)	(2.29)
NAPM Index	0.020	0.020	0.012	0.020
	(1.21)	(1.17)	(0.55)	(1.17)
SLS-TPB		-0.045**	-0.031	-0.025
		(-2.00)	(-1.50)	(-1.43)
SLB-TPS		-0.002	-0.001	0.000
		(-0.13)	(-0.53)	(0.06)
Adjusted R^2	0.05	0.06	0.03	0.03
N. of Observations	44	44	44	44

The symbols ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level, respectively. Construction spending is measured as % change, consumer confidence and NAPM (National Association of Purchasing Managers) indices as % level.

Figure 1: Intraday Pattern of Price-Contingent Orders

This figure shows the number of price-contingent orders placed in each hour preceding and following 8:30EST, averaged across all announcement days versus the benchmark (days with no announcements). The dotted line represents the benchmark.

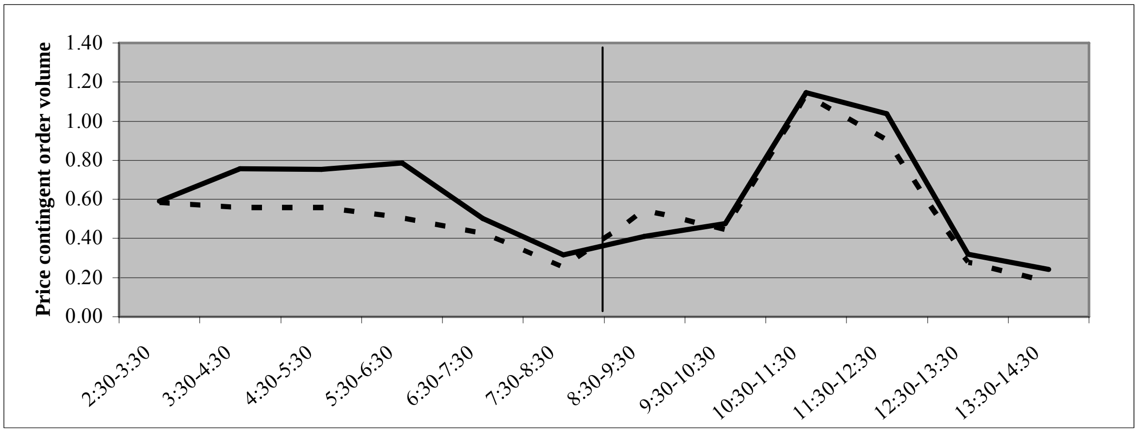

Figure 2: Intraday Pattern of Stop-Loss Orders

This figure shows the number of stop-loss orders placed in each hour preceding and following 8:30EST, averaged across all announcement days versus the benchmark (days with no announcements). The dotted line represents the benchmark.

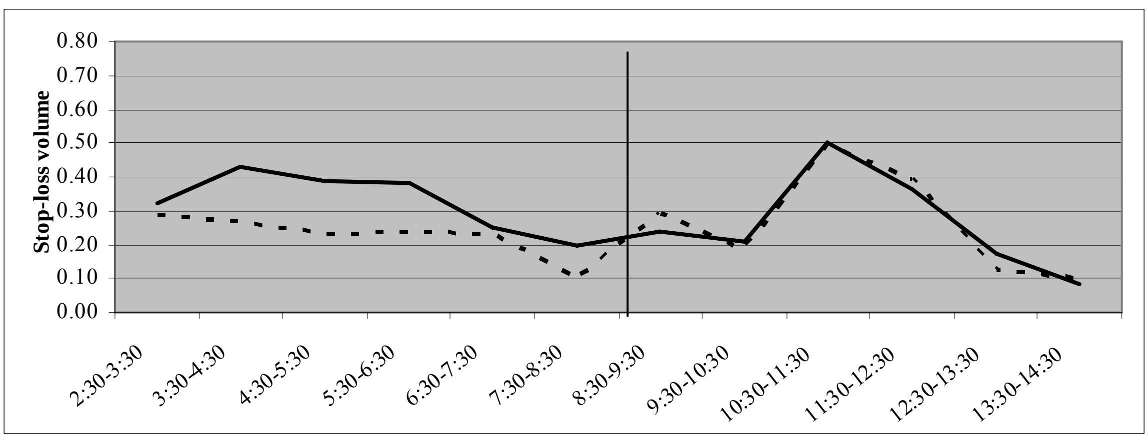

Figure 3: Intraday Pattern of Take-Profit Orders

This figure shows the number of take-profit orders placed in each hour preceding and following 8:30EST, averaged across all announcement days versus the benchmark (days with no announcements). The dotted line represents the benchmark.

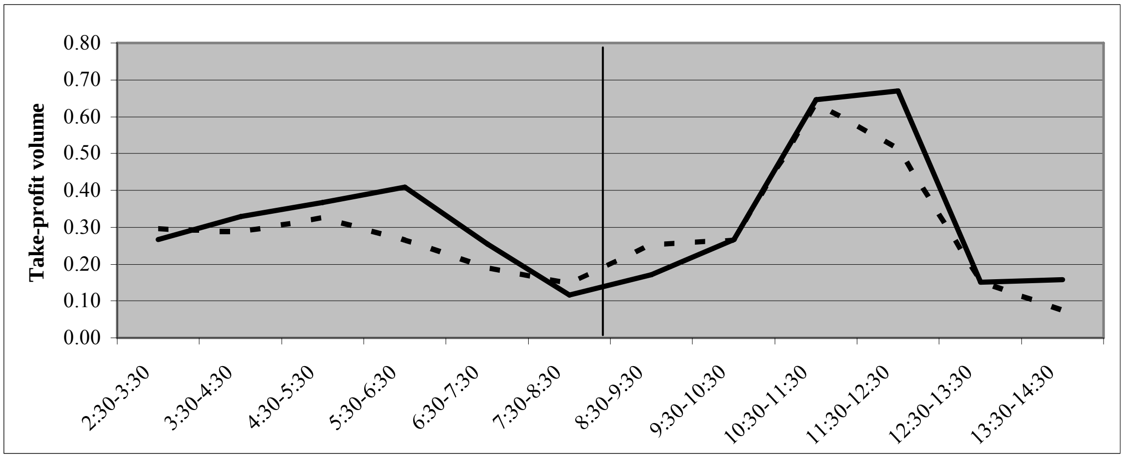

Figure 4: Intraday Pattern of Exchange-Rate Volatility

This figure plots the absolute returns in each 5-minute interval of the day, averaged across all announcement days in the sample versus the benchmark (days with no announcements). The thin line represents the benchmark. To avoid contamination from shifts in and out of day light saving time, the figure only shows the returns corresponding to U.S. daylight saving time.

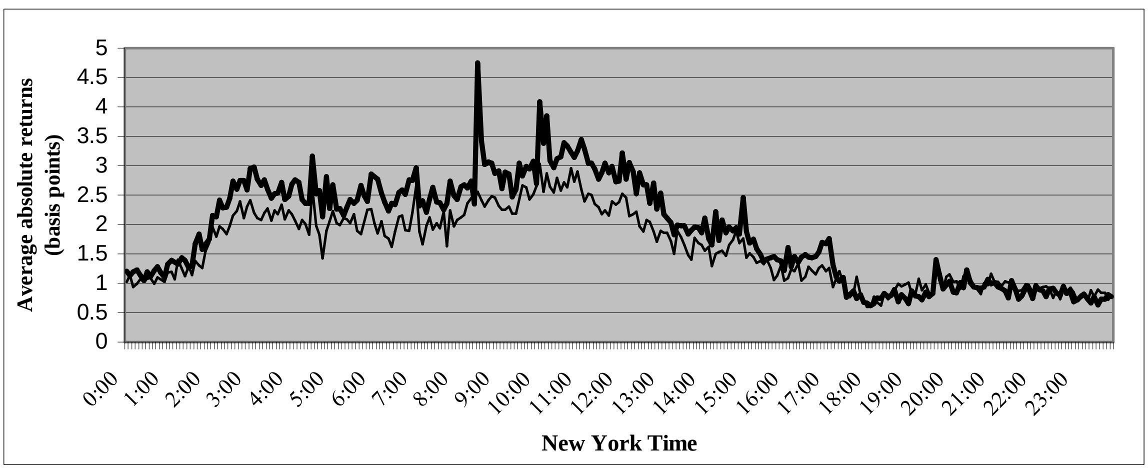

Figure 5: Impact on Return Size: Stop-Loss Orders

Figure 5 and 6 plot the estimated stop-loss and take-profit order slope coefficients respectively against the associated interval, h, from the regression equation:

$$| R_t |= \alpha + \sum_{k=1}^{6} \beta_k D_{kt} \, | News_{kt} | + \beta_{sl} SL_t + \beta_{tp} TP_t + \varepsilon_t$$

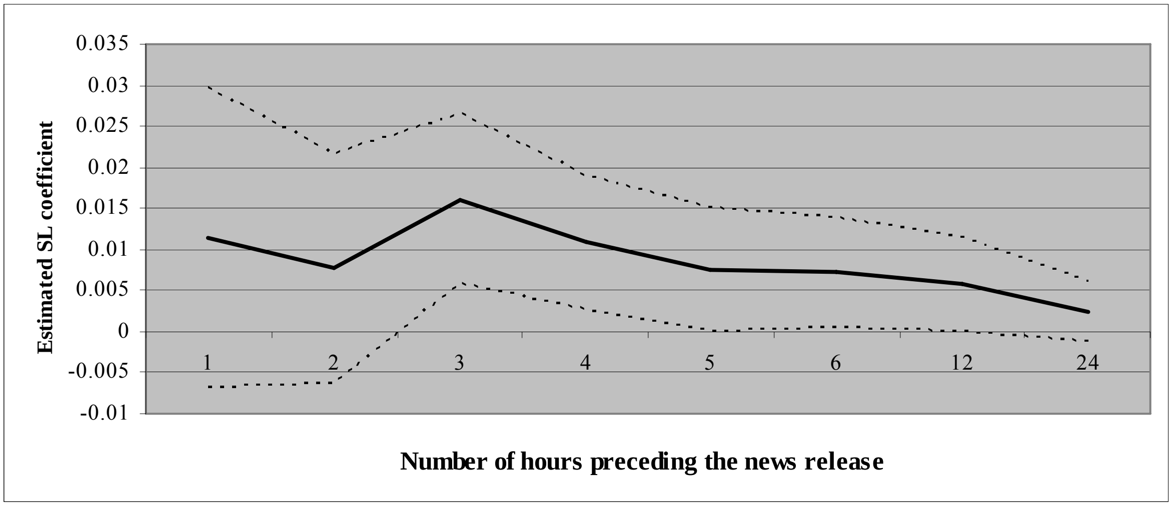

Figure 6: Impact on Returns: Directional Effects

Figure 6 plots the estimated coefficients of stop-loss sell orders (net of take-profit buys) against the associated hourly time window, h, from the signed returns regression equation:

$$R_t = \alpha + \sum_{k=1}^{6} \beta_k D_{kt} News_{kt} + \beta_{sls}(SLS_t - TPB_t) + \beta_{slb}(SLB_t - TPS_t) + \varepsilon_t$$

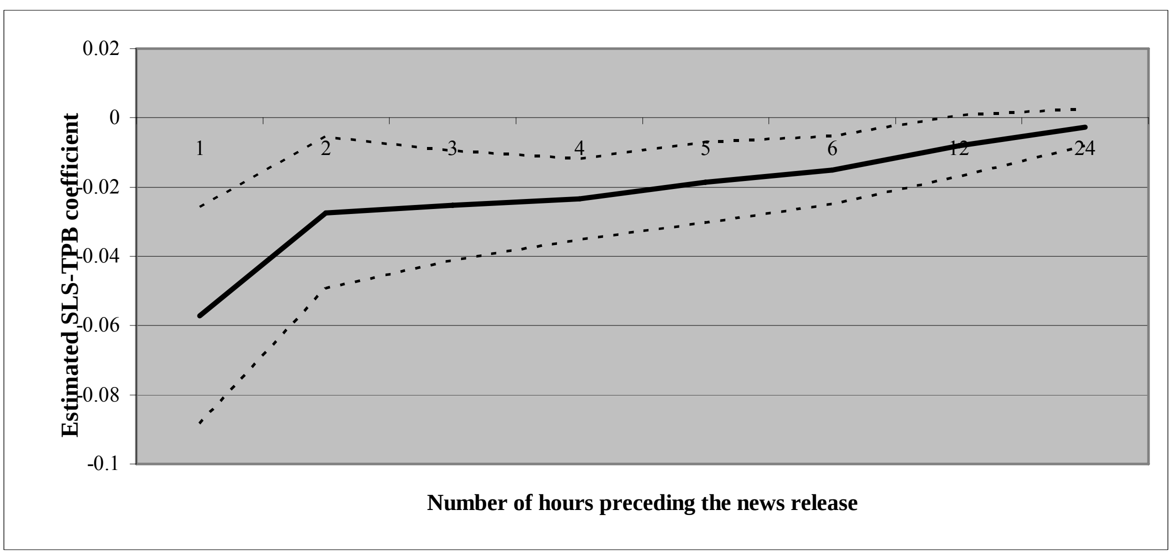

Figure 7: Estimated Stop-loss and Take-Profit Coefficients—Very Far Orders

Figures 7 (a) and (b) plot the estimated stop-loss and take-profit coefficients from the far order sample against the associated interval, h, based on the regression equation below, where far orders are those that are placed within two standard deviations away from the daily market rate at the time of the placement.

$$| R_t |= \alpha + \sum_{k=1}^{6} \beta_k D_{kt} \mid News_{kt} \mid + \beta_{sl} SL_t + \beta_{tp} TP_t + \varepsilon_t$$

Figure 7 (a)

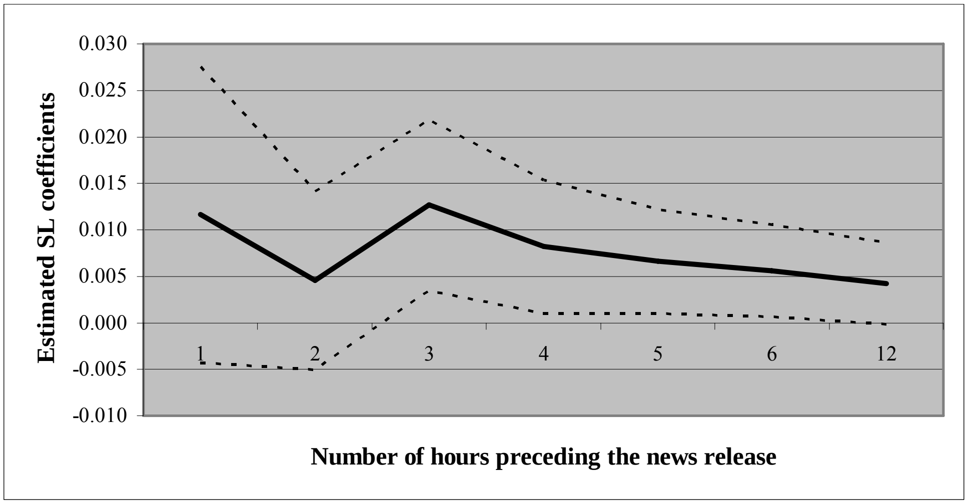

Figure 7 (b)

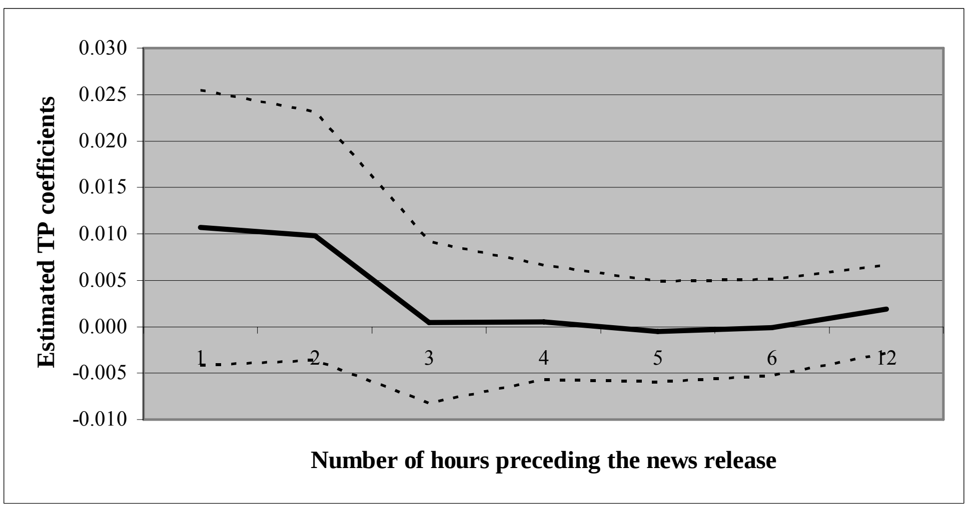

Figure 8: Estimated Stop-loss Sell Coefficients—Very Far Orders

Figure 11 plots the estimated coefficients of stop-loss sell orders (net of take-profit buys) from the far order sample against the associated interval, h, based on the regression equation below, where far orders are those that are placed within two standard deviations away from the daily market rate at the time of the placement:

$$R_t = \alpha + \sum_{k=1}^{6} \beta_k D_{kt} News_{kt} + \beta_{sls}(SLS_t - TPB_t) + \beta_{slb}(SLB_t - TPS_t) + \varepsilon_t$$

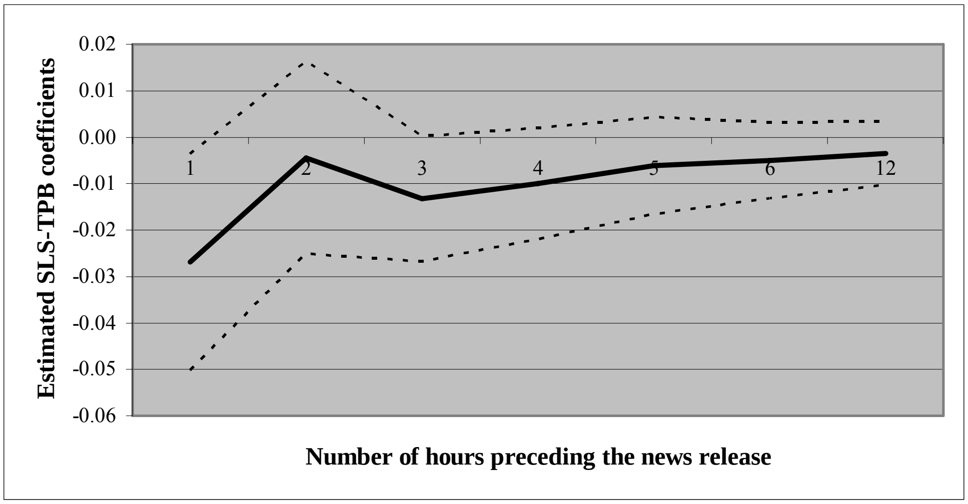

Figure 9: Estimated Stop-loss and Take-Profit Coefficients—Very Near Orders

Figures 8 (a) and (b) plot the estimated stop-loss and take-profit coefficients from the near order sample against the associated interval, h, based on the regression equation below, where near orders are those that are placed within half a standard deviation away from the daily market rate at the time of the placement:

$$| R_t | = \alpha + \sum_{k=1}^{6} \beta_k D_{kt} \, | News_{kt} | + \beta_{sl} SL_t + \beta_{tp} TP_t + \varepsilon_t$$

Figure 9 (a)

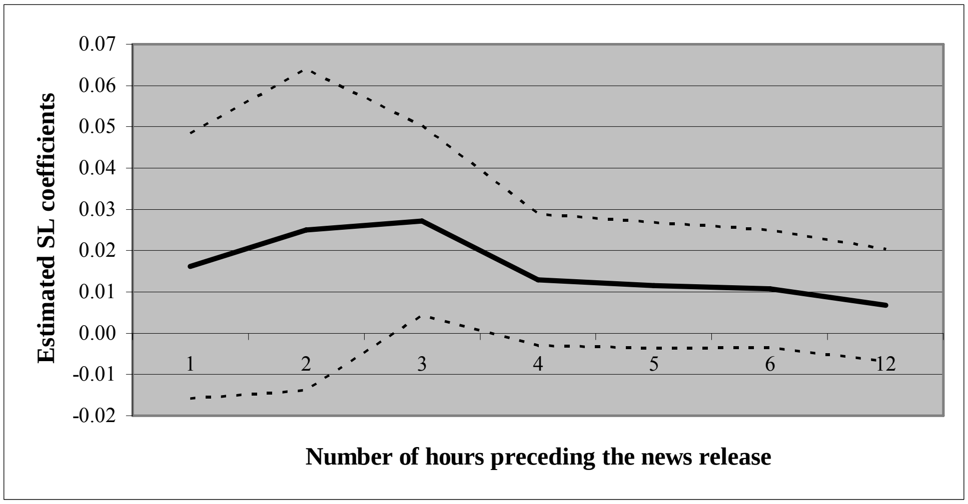

Figure 9 (b)

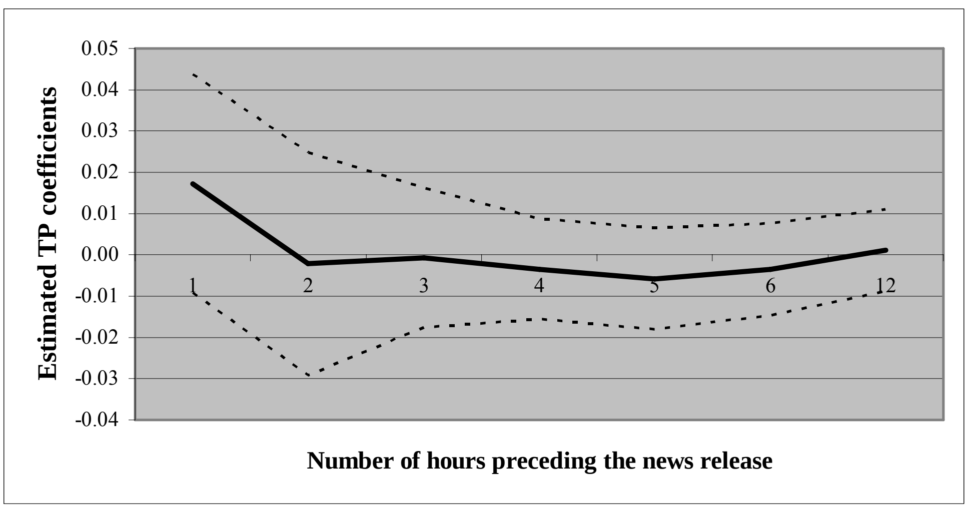

Figure 10: Estimated Stop-loss Sell Coefficients—Very Near Orders

Figure 10 plots the estimated coefficients of stop-loss sell orders (net of take-profit buys) from the near order sample against the associated interval, h, based on the regression equation below, where near orders are those that are placed within half a standard deviation away from the daily market rate at the time of the placement:

$$R_t = \alpha + \sum_{k=1}^{6} \beta_k D_{kt} News_{kt} + \beta_{sls}(SLS_t - TPB_t) + \beta_{slb}(SLB_t - TPS_t) + \varepsilon_t$$