Do Currency Markets Absorb News Quickly?

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Abstract

This paper addresses whether macro news arrivals affect currency markets over time. The null from macro exchange-rate theory is that they do not: macro news is impounded in exchange rates instantaneously. We test this by examining the effects of news on subsequent trades by end-user participants (such as hedge funds, mutual funds, and non-financial corporations). News arrivals induce subsequent changes in trading in all of the major end-user segments. These induced changes remain significant for days. Induced trades also have persistent effects on prices. Currency markets are not responding to news instantaneously.

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Do Currency Markets Absorb News Quickly?

This paper addresses an important null hypothesis within exchange rate theory: that macro news is impounded in exchange rates instantaneously. As an empirical matter, this is typically understood to mean a matter of seconds, or perhaps minutes, but certainly contained within the day of news arrival. This is consistent with the views of currency dealers as well: roughly 70% of the dealers surveyed by Cheung and Chinn (2001) respond that the effects of announcements are absorbed by the market within 1 minute. We test this hypothesis by examining the effects of news on subsequent currency trades by end-user participants (such as hedge funds, mutual funds, and non-financial corporations). We find that news arrivals induce subsequent changes in trading behavior in all of these major end-user segments. These induced changes in trading remain significant for days. Induced trades also have persistent effects on prices. These findings provide strong evidence that currency markets are not responding to news instantaneously.

Our basis for pursuing whether induced trades might prolong the absorption of news comes from recent empirical work demonstrating a tight link between signed transaction volume (order flow) and signed exchange rate changes.[1] This link is not predicted by macro exchange rate theory, but it is predicted by an alternative modeling framework from microstructure finance. In this micro-based framework, transactions play a central, causal role in price determination (see, e.g., Glosten and Milgrom 1985, Kyle 1985). The causal role arises because transactions convey information that is not common knowledge. In this paper, we address whether the tight link between price adjustment and order flow that exists in general might also be playing a role in how currency markets absorb news.

Most of the existing literature linking exchange rates to news is event-study based, and does not address how transaction quantities respond to news (i.e., it addresses the link between news and price in isolation). This literature has two branches. The first addresses the direction of exchange-rate changes (first moments) and the second, later branch addresses exchange-rate volatility (second moments). A common finding of the first branch is that, at least at the daily

[1] This evidence is from both micro (i.e., single marketmaker) and macro (marketwide) studies. On the micro side, see, e.g., Lyons (1995) and Bjonnes and Rime (2004). On the macro side, see, e.g., Evans and Lyons (2002a,b), Payne (2003), Osler (2004), and Bjonnes, Rime, and Solheim (2004). Order flow is the cumulation over time of signed trades, where trades are signed according to whether the initiating side is buying or selling. (The marketmaker posting the quote is the non-initiating side.)

frequency, directional effects from scheduled macro announcements are difficult to detect because they are swamped by other factors affecting price. Intraday event studies do find statistically significant effects, particularly for employment and money-supply announcements (Andersen et al. 2003).[2] The second, later branch of this literature—which focuses on news effects on volatility—is partly a response to early difficulty in finding news effects on first moments.[3] This work finds that arrival of scheduled announcements does indeed produce the largest exchange-rate changes. Nevertheless, the ability of these fundamentals to account for overall volatility changes is lower than that of less fundamental factors such as time-of-day effects and ARCH (Andersen and Bollerslev 1998).

A more recent literature has emerged that addresses the currency market's response to news as a joint quantity/price response (Carlson 2002, Danielsson et al. 2003, Evans and Lyons 2003). Carlson (2002), for example, takes a case-study approach and analyzes a single macro announcement arrival. He finds that market characteristics were affected for hours following the arrival. (For example, liquidity remained significantly below normal—and below its ex ante state—for about 2 hours.) The case-study approach leaves open the question of how systematic these prolonged market effects are, and whether they might extend beyond the day of news arrival. The work of Danielsson et al. (2003) and Evans and Lyons (2003) provides less intraday resolution than Carlson, but these papers do examine multiple news arrivals over periods of months, and thereby do provide a sense for whether quantity responses to news are systematic. (Both papers find, for example, that roughly half of the transmission of news to prices actually operates through induced order flows.) Nevertheless, limited sample sizes only months long mean that both of these papers have to aggregate across arrivals of very different news types. The limited sample sizes also restrict them to examining only those induced transaction effects that occur intraday—neither paper addresses whether the absorption of news is prolonged over more extended periods.

Our paper departs from earlier work in three main ways. First, our analysis is based on the induced trades of currency-market end users. All three of the papers noted in the previous paragraph use quantity data that reflects trades between marketmakers only (i.e., interbank

[2] 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).
[3] See, for example, Goodhart et al. (1993), DeGennaro and Shrieves (1997), and Andersen and Bollerslev (1998). See also the work on bond prices and announcements, e.g., Fleming and Remolona (1999), Balduzzi et al. (2001), Fleming (2002), and Green (2004). The latter two papers are especially relevant in that they use direct measures of order flow in fixed income markets. Green (2004), for example, finds evidence that asymmetric information in the Treasury bond market increases following public macro announcements.

trades).[4] This is relevant for the question that we address because, relative to end users, market-maker reactions to news are unlikely to be as protracted. Second, our data span over 6 years, a much longer sample than is used in existing work on the joint quantity/price response to news. This allows us to treat individual announcement types separately, without aggregating them into composite news measures. We find, in fact, that different announcement types have quite different effects on induced transactions, which is consistent with the findings of earlier work that addresses the news/price link in isolation. Third, and also related to the sample length, we are able to address whether the market's absorption of news is genuinely protracted, which here we take to mean that it extends beyond the intraday dynamics addresses elsewhere.

The remainder of the paper is in four sections. Section 1 describes our data and presents descriptive statistics. Section 2 addresses identification, specifically, our approach to identifying effects of news on trades and prices. Section 3 presents our analysis of how news affects trades and prices beyond the arrival day. Section 4 concludes.

1. Data and Descriptive Statistics

This paper uses transaction data on end-user customers, which is a qualitative departure from other micro-approach analysis of exchange rates and news. These data are from Citibank and cover all of the customer trades that Citibank executed in the USD/EUR market from April 11, 1993 to June 30, 1999.[5] (Prior to the euro's launch in January, 1999, these trades correspond to the trades of all the euro component currencies against the USD; Citibank provided us with the data already aggregated.) Citibank is among the top three currency marketmakers worldwide, with a market share for end-user customers around 10 percent (major currencies against the dollar). These transactions data are daily aggregates—intraday data were not available to us. (Any trades with end-users that are executed over a weekend—relatively rare—are included in Monday order flows, so each trading week has five days.) Days begin in this dataset at 00:00 GMT. This timing applies to both the end-user transactions and to the daily log exchange rate changes (the latter also from Citibank). Henceforth, we shall refer to daily log exchange rate changes as "returns". (Prior to the Euro's launch, exchange rates for the euro against the dollar

[4] Moreover, these other micro-approach papers consider only aggregate trade processes, whereas we analyze end-user trades at a disaggregated level, i.e., six different segments.

[5] Osler (2003) also obtains data on FX customer trades directly from a private bank. Her focus is stop-loss and take-profit orders. She shows that clustering of these orders at particular prices helps to explain two familiar predictions from technical analysis, namely that (1) trends tend to be reversed at support and resistance levels and (2) trends tend to gain momentum if support and resistance levels are breached.

are synthesized from the underlying bilateral rates against the dollar, using the respective weights in the euro.)

Advantages of the data are many. First, the data span more that six years, so analysis of announcements that arrive only monthly is possible. Second, the data include both spot and forward trades, but are netted of any trades in FX swaps (because FX swaps do not have net order flow implications—they correspond to offsetting purchases and sales). Third, and perhaps most importantly, the data are split into three customer-type categories: non-financial corporations—henceforth "Corporations", unleveraged financial institutions (primarily mutual funds)—henceforth "Investors", and leveraged financial institutions (primarily hedge funds)—henceforth "Traders".[6] At Citibank over this period, the total end-user trading volume in USD/EUR across the three categories is roughly equal (for additional detail on relative volumes across segments in these data, see Lyons 2001). In addition to the three-segment breakdown by participant type, the dataset also distinguishes customer trades that were executed with Citibank's US-based marketmakers versus those executed elsewhere within Citibank's global trading operation (referred to as "non-US"). Thus, the end-user transactions are partitioned into six non-overlapping segments, corresponding to three participant types times two trade locations.

Our announcement data are from International Money Market Services (MMS). These include real-time data on both expected and announced macro variables, from which we construct time series of macro news. Our sample includes 30 US and 13 German scheduled announcements. (For a list, see the second column of Table 2.) The expectation for each announcement is based on the median response from a survey of approximately forty money managers on the Friday of the week before the announcement. These data have been used in many earlier studies (see, for example, Urich and Watchel 1984, Balduzzi et al. 2001, and Andersen et al. 2003). We follow this literature by constructing for each announcement a time series of standardized news. Specifically, the standardized news in announcement *i* on day *t* is:

$$n_{i,t} = \frac{V_{i,t} - E_{i,t}}{\hat{\sigma}_i} \tag{1}$$

[6] A natural question is where the trades of central banks appear. The source of these data is reluctant to disclose the specifics. Though not addressed here, the source bank does maintain a fourth category of customer called "miscellaneous." This fourth category is likely to include any central bank trades for which the source bank was the counterparty. (Trading volume within this fourth category is quite small relative to volume in the three main categories, consistent with the fact that central bank trades in the USD/EUR market were quite small over this period relative to private trades.)

where $V_{i,t}$ is the value announced for variable *i*, $E_{i,t}$ is the survey expectation of $V_{i,t}$, and $\hat{\sigma}_i$ is the sample standard deviation of $V_{i,t} - E_{i,t}$ across announcement days *t*.[7] The arrival day for both US and German announcements is known in advance, and in the case of the US, the exact timing within the day is known in advance as well. We set $n_{i,t} = 0$ on days for which no announcement is scheduled.

Though the daily frequency of our data do not permit intraday analysis, there is an important advantage to daily analysis that deserves note: daily data provide a solid indication of price effects at lower frequencies (i.e., those more familiar to macroeconomists, such as monthly) because the daily frequency is the highest at which the nominal exchange rate can be reliably described as a martingale. Any empirical model that explains daily price increments is therefore relevant for explaining exchange rate levels at long horizons (i.e., one cannot sensibly argue that daily price movements are rapidly dissipating). This martingale property at the daily frequency does not apply to intraday prices, which exhibit mean reversion (see, e.g., Evans 2002).

Descriptive Statistics

Table 1 presents descriptive statistics for the main variables that we model below, specifically, the daily exchange rate return, the aggregate daily end-user order flow, and the six disaggregated end-user order-flow segments. Δp_t denotes the difference between the log spot rate (\$/€) at the end of days *t* and *t*-1, and Δx_t^j denotes the order flow for euros from segment *j* during day *t* (i.e., negative order flow denotes sales of the currency in the denominator of the price quote, here, sales of euros). Note from row 1 that there is no evidence of unconditional serial correlation in daily FX returns (p-values in parentheses). This means that for news to have prolonged effects on prices, it must come from conditioning on order flows. In contrast, there is some evidence of autocorrelation (positive) in the order flow segments; the autocorrelation coefficients are small, but many are highly statistically significant. From the correlation matrix, we see that order flow segments are not particularly strongly correlated among themselves at the daily frequency. But order flows are strongly correlated with returns (less so, however, than interdealer data; see Evans and Lyons 2002a).

Figure 1 provides complimentary evidence on the relation between the different order flow segments. Panel A shows that order flows executed at US and non-US locations diverge

[7] The Fed Funds Rate is one of our news items. Announcements about Fed Funds come from the series constructed by Brandt et al. (2001), kindly provided by Kenneth Kavajecz. Expectations for the Funds rate come from the MMS

quite significantly in the last two years of the sample. The origins of this divergence can be seen in Panels B–D. Corporate order flows for the euro have been generally negative, but much more so at non-US than US locations. By contrast, Investor order flows were generally positive, but the rise in order flow from non-US Investors led US Investors by several years. (We shall refer to investor flow executed outside the US as coming from non-US Investors, though strictly speaking, we cannot distinguish the location of the Investor from the location of the trade execution; similarly for the other segments.) Order flow originating from US and non-US Traders diverge sharply after 1995. The message conveyed by Figure 1 is that the low daily correlations between the different order-flow segments reported in Table 1 translate into sizable cumulative differences over months and years.

2. Identifying News Effects on Trades and Prices

One can think of the information in news as having two components. The first component is a common-knowledge (or "mean") part: all agents agree about the appropriate impact of this first part on the exchange rate. In macro models of news in currency markets, this first part is the whole story: it fully characterizes the instantaneous adjustment of exchange rates to news. The second component is the part whose implication for the exchange rate is not common knowledge. It is this second part that is impounded in exchange rates via induced trading. Suppose, for example, that all agents do not have access to the same technology for transforming macro data into an exchange rate forecast (see, e.g., Sims 2003 for a model of limited capacity for processing macro information). The resulting inferences drawn are not known by the marketmakers a priori. How do marketmakers aggregate the information in these inferences? The answer from microstructure theory is that they learn from the sequence of submitted orders over time. In this case, price adjusts instantaneously to the marketmaker's rational expectation of the market's interpretation (this is the first of the two components), and then goes through a period of gradual adjustment caused by the sequence of transacted orders.[8]

With respect to response delays, remember that the announcements that we address here are scheduled, so participants can plan their responses (conditional on realizations) in advance. This is likely to lower response lags considerably relative to unscheduled news. In this sense, our

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survey.

[8] From our observations of how the FX market absorbs macro news in practice, some price adjustment by marketmakers does indeed occur rapidly, though generally not a lot, and this initial adjustment involves little apparent role for flow. This is the part of the market response that corresponds most closely to the Cheung and Chinn (2001) survey result noted in the first paragraph (in our judgment). But informal observation also makes it clear that news regularly induces follow-on trading by end-user customers, whose trading responses are not instantaneous.

tests for whether market responses to news are protracted are conservative tests. Note, too, that the model that we present below is capturing average responses (i.e., the total average response, including the induced order flow effects). This is distinct from second-moment effects, i.e., effects on volatility. In fact, in response to news, order flow and price are also (jointly) more volatile, which adds a dimension to the first-moment analysis that we do here. Addressing directly these second-moment effects would take us too far afield from our central question, so we do not address it within this paper.

The Empirical Model

Our aim is to study the impact of news announcements on spot rates and order flows in the days following the announcement. For this purpose, we model the daily dynamics of prices and order flows as a 7-variable, kth-order VAR:

$$\begin{bmatrix} \Delta p_t \\ \Delta x_t^1 \\ \vdots \\ \Delta x_t^6 \end{bmatrix} = A_1 \begin{bmatrix} \Delta p_{t-1} \\ \Delta x_{t-1}^1 \\ \vdots \\ \Delta x_{t-1}^6 \end{bmatrix} + A_2 \begin{bmatrix} \Delta p_{t-2} \\ \Delta x_{t-2}^1 \\ \vdots \\ \Delta x_{t-2}^6 \end{bmatrix} + \ldots + A_k \begin{bmatrix} \Delta p_{t-k} \\ \Delta x_{t-k}^1 \\ \vdots \\ \Delta x_{t-k}^6 \end{bmatrix} + \begin{bmatrix} e_t \\ u_t^1 \\ \vdots \\ u_t^6 \end{bmatrix}, \tag{2}$$

where Δp_t denotes the difference between the log spot rate (\$/€) at the end of days t and t-1, and Δx_t^j denotes the order flow for euros from segment j during day t. Daily innovations to the spot rate and the 6 order flows are denoted by e_t and u_t^j, respectively. These innovations are driven, in part, by macro announcements according to:

$$e_t = \sum_{i=1}^{M} \beta_i \, n_{i,t} + \xi_t \, , \tag{3}$$

$$u_t^j = \sum_{i=1}^{M} \beta_i^j n_{i,t} + \zeta_t^j \qquad j = 1, 2, \ldots 6, \tag{4}$$

where M is the number of announcement types (43 in our case) and $n_{i,t}$ is the standardized signed news arising from announcement i on day t (equation 1). The ξ_t and ζ_t^j shocks represent the sources of spot rate and order flow innovations that are uncorrelated with news announcements. These shocks may be correlated. For example, shocks to order flow during the day may lead marketmakers to revise their quoted prices. Alternatively, unexpected price movements during the day may induce a change in order flow (via feedback trading). Our model does not restrict the correlation between the ξ_t and ζ_t^j shocks.

The effects of announcements are identified by the β coefficients: β_i identifies the average effect of signed news in announcement *i* on the log spot rate, while β_i^j identifies the average effect of signed news on the j^{th} order flow segment. Notice that none of the coefficients identify the intra-day transmission mechanism through which the spot rate and order flow changes take place. For example, news may affect the spot rate directly because it induces marketmakers to change their quotes. News may also affect spot rates indirectly because marketmakers change their quotes in response to induced order flow. Our model does not distinguish between these direct and indirect transmission channels (see Evans and Lyons 2003 for a model that does distinguish them). The β_i coefficient simply identifies the total daily effect of the i^{th} news item. Similarly, β_i^j coefficient indicates the total daily effect of news on order flow.

Our model enables us to focus on three issues: (i) If news affects order flow, do the effects persist beyond the day of the announcement? (ii) If news affects spot rates, are all the effects confined to the day of the announcement? (iii) Do news-induced order flows generate price movements after the announcement day?

All of these questions can be readily addressed by computing impulse response functions. Specifically, we can trace out the impact of the news in announcement *i* on the spot rate and order flows using the estimates of β_i and β_i^j, together with the VAR coefficients in the A_k matrices. For example, let $\{\hat{B}_k\}_{k=0}^{\infty}$ denote the sequence of matrices that define the vector moving average representation of the estimated VAR (with $\hat{B}_0 = I$), and let $\hat{b}_i{}' = [\hat{\beta}_i, \hat{\beta}_i^1, \ldots \hat{\beta}_i^6]$ be the vector of estimated β coefficients for the news in announcement *i*. The estimated impact of a one standard deviation news shock on the exchange rate return *k* periods after the announcement is given by the first row of $\hat{B}\hat{b}_i$, while the impact on the j^{th} order flow is given by row j+1 of $\hat{B}\hat{b}_i$.

To determine the statistical significance of our estimated impulse responses, we conduct a series of Monte Carlo experiments. Each experiment imposes a particular null hypothesis on the β coefficients used in generating pseudo data samples (e.g., that there are no systematic news effects beyond the day of news arrival). Let $\hat{\beta}^0$ denote the matrix of estimated β coefficients under the null (specified below). We compute Monte Carlo p-values under the null as follows: First we draw a sequence for $\{\tilde{\xi}_t, \tilde{\zeta}_t^1 \ldots \tilde{\zeta}_t^6\}_{t=1}^T$ from $N(0, \hat{\Sigma})$, where $\hat{\Sigma}$ is the estimated covariance matrix of $\{\xi_t, \zeta_t^1 \ldots \zeta_t^6\}$ and T is the number of trading days in our sample. We then combine these pseudo shocks with the actual data on news and $\hat{\beta}^0$ to compute a set of VAR innovations under the null according to equations (3) and (4). From these innovations, we use equation (2) together with the estimates of the VAR coefficients in A_k to generate a pseudo time series for Δp_t and Δx_t^j (the pre-sample estimates of Δp_t and Δx_t^j are set equal to zero). With this generated data, we next estimate the VAR and the β coefficients with the null hypothesis imposed. From these estimates, we then compute the impulse response functions. The Monte Carlo distribution under the null is constructed from the empirical distribution of the impulse responses computed from 1000 pseudo data sets.

3. News Effects on Trades and Prices Beyond the Arrival Day

Our main results are presented in a series of five tables, Tables 2-6. Table 2 reports our estimates of the β coefficients from the model in equations (2)-(4), i.e., the coefficients that determine the average effects of news arrivals on innovations in our VAR. Table 3 describes the dynamics of segment order flows over the days following news arrival (in the form of impulse responses). Table 4 addresses the dynamics of segment order flows in a different way: it presents the variance of order flow due to news as a percentage of the order-flow variance due to all shocks. Tables 5 and 6 parallel Tables 3 and 4: they describes return dynamics, first as impulse responses (Table 5), and then in the form of the ratio of return variance due to news relative to return variance due to all shocks.

Effects of News Arrivals on VAR Innovations

Table 2 reports the estimates of the β coefficients using innovations from a second-order VAR (where the order of the VAR was determined using the BIC information criterion). The column labeled #N shows the number of announcements over the 6+ year sample period. To interpret the "Returns" column, note that a positive shock of one standard deviation to non-farm employment (announcement 23) leads to a 24 basis point appreciation of the dollar (reduces the dollar price of a euro). Beyond non-farm employment, which is the biggest coefficient in the Return column, nine other news items have a significant impact on spot rates at the 5% level. Andersen et al. (2003) also find that news concerning non-farm employment has the largest impact of spot rates, but their intra-day estimate using a 5-minute sampling frequency is approximately half the size found here. (One possibility for this discrepancy is that our estimate also incorporates the impact on returns from news-generated order flows that occur the same day.) As a rule, more news items have significant effects on order flows than on returns. For example, news about non-farm employment has a large and statistically significant impact on order flow from US traders. To interpret these "Order Flow" columns, note that a positive shock of one standard deviation to non-farm employment induces US-trader sales of euros (purchases of Dollars) equal to approximately \$29m.

To investigate whether announcement effects on the log spot rate are stable over time, we compared the β_i coefficients across the two halves of the sample. Specifically, we augmented equation (3) to take the form:

$$e_t = \sum_{i=1}^{M} \beta_i n_{i,t} + \sum_{i=1}^{M} \delta_i D_t n_{i,t}$$

where D_t is a dummy variable equal to one in the second half of the sample, zero otherwise, so that δ_i measures the change in β_i across the sub-samples. We could not reject the null of $\delta_i = 0$ at the 5 percent level for any of the announcements. Though this may seem inconsistent with evidence that currency markets tend to change the variables they focus on over time, note that our analysis is at the daily frequency, whereas evidence of changing focus variables is from intraday event studies (see, e.g., Bacchetta and van Wincoop 2004). It is possible that changes in announcement impact effects, which is what the event studies capture, were offset within the day by changes in indirect price effects via induced order flow, leaving the announcements' total price impact at a daily frequency relatively stable. In any event, there is no evidence in our sample that the price-impact of announcements changed significantly at the daily frequency.

Order Flow Dynamics Following News

Table 3 describes the dynamics of segment order flows over the days following news arrival (in the form of impulse responses). Since there are 43 news items and 6 flow segments to consider for each, we narrow our focus to those 18 news items that have a significant impact on order flow on the day of the announcement (at the 5 percent level, from Table 2). For each news item meeting this criterion, the table reports the impulse response of the order flow registering the largest initial impact. The table also reports the p-value for the null hypothesis that the news item has no immediate impact on the order flow segment. These p-values are computed from the Monte Carlo experiments described above with the restriction that $\beta_i^j = 0$ for all *i* and *j*. (Note that while $\beta_i^j = 0$ under this null, news can still affect order flows on the days following an announcement if the news affects spot rates and the effects feed through to order flow via some form of feedback trading.) In all but two cases (Fed funds news and Preliminary GDP news), news has a significant impact on order flow on at least one day following the announcements. In most cases, the cumulative effect of the news on order flow (shown in the last column) is also highly statistically significant.[9]

Though we have not modeled why delayed trading in response to announcements should be more pronounced for certain end-user segments, it is noteworthy that the delayed responses in Table 3 tend to concentrate on the non-financial corporations and on the traders, rather than on the investors. In only 2 of the 18 cases was the investors category the one that registers the largest initial impact (versus 8 occurrences each for the non-financial corporations and traders categories). And in both of those cases, the delayed order flow response tends to be concentrated on day one or day two after the announcement, rather than extending through day three and day four after the announcement. This may result from the fact that the investor category is dominated by mutual funds, which tend not to engage in active currency management, making their currency trades less sensitive to specific news arrivals (both contemporaneously and over time).

Table 4 addresses the dynamics of segment order flows in terms of the ratio of order-flow variance from news relative to order-flow variance from all shocks. Specifically, the table reports how news shocks contribute to the variance of segment order flows over five days, starting with the day of the announcement (i.e., one trading week). The set of news shocks and order flow segments that we present are the same as those in Table 3. Announcement news is a non-trivial source of daily variance in several of the order flow segments, particularly in the case of GDP and consumption expenditures. The prolonged effects of news on some of the flow segments shows up in the variance contributions 2–4 days after the announcement. To summarize, the evidence in Tables 3 and 4 indicates that news does indeed affect order flows, and that the effects persist for several days beyond the day of the announcement.

Return Dynamics Following News

Do the news-induced order flows affect price? This question is addressed in Tables 5 and 6. These two tables parallel Tables 3 and 4: they describes return dynamics, first as impulse responses (Table 5), and then as the ratio of return variance due to news relative to return variance due to all shocks. Specifically, Table 5 addresses the question of whether the impact of

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[9] These effects arise because order flows segments have forecasting power for other segments, not because individual segments are strongly autocorrelated (see Table 1). Granger causality tests (unreported) show eight cases of statistically significant cross-segment Granger causality (out of 6×5=30 possible cases of order flow segment *j* Granger causing order flow segment *i*).

news on returns persists beyond the day of the announcement. For perspective, recall from Table 1 that there is no evidence of unconditional serial correlation in Δp_t, so one would not expect to see any spot rate changes on days following announcements in the absence of order flow effects on returns. Granger causality tests (unreported) show that lagged values of Δp_t have no forecasting power for subsequent Δp_t (the p-value is 0.363). In contrast, order flows from US Traders and US Investors do have forecasting power for Δp_t: the p-values are 0.002 and 0.079, respectively. This raises the possibility that news can have persistent effects on returns beyond the day of the announcement via the long-lasting effects documented in Tables 3 and 4.[10]

Table 5 focuses on the return dynamics induced by those news items whose immediate price impact is statistically significant (at the 5% level, from Table 2). The table reports the impact of news on Δp_t on the four days following the announcement (expressed as a percentage of the impact on the announcement day). Thus, negative numbers reflect subsequent reversal over the days following the initial news shock. For example, in the period following a positive shock of one standard deviation in unemployment claims, the euro depreciated by approximately 17% of the initial impact effect. The table also reports the p-value for the null hypothesis that the news item has no immediate impact on any order flow segment. As above, these p-values are computed from the Monte Carlo experiments with the restriction that $\beta_i^j = 0$ for all i and j. Under this null, news can only affect returns on the days after an announcement via its impact on spot rates on the announcement day.

The last column reports the cumulative response over the four days following the announcement. In every case where the cumulative response appears significant at the 5% level, its sign is negative. This indicates that the prolonged absorption of news identified by the model tends to imply a systematic partial reversal of the initial price-impact. These reversals are largest in the case of US news concerning unemployment claims and the trade balance.

Table 6 reports how news contributes to the variance of daily returns over five days, starting with the day of the announcement. As above, we report variance decompositions only for the shocks studied in the spot rate impulse response functions. News about non-farm employment makes a far larger contribution to the variance of daily returns on the day of the announcement than news about the other items. Innovations to spot prices from all sources do not make a sizable contribution to the variance of returns on the days that follow. (Recall from Table 1 that

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[10] This is not a violation of standard definitions of market efficiency: the market as a whole cannot condition on these Citibank data—they are proprietary.

there is little serial correlation in Δp_t.) However, insofar as they make some contribution, news shocks account for a sizable fraction.

As an additional robustness test, we investigate non-linearity, focusing in particular on whether returns and order flows might depend nonlinearly on past returns. Our linear VAR does not account for the possibility that market responses might depend on the size of the news surprise. For example, an announcement that immediately induces a large price move may trigger large additional order flows, and even price cascades (perhaps due to stop-loss orders; see Osler 2004). Since our data are daily, we cannot investigate this at the intradaily frequency. To address it with our daily data, we re-estimate the VAR including 2 lags of squared returns in each equation, and then test for the joint significance of the two additional terms (Wald test). These tests show no evidence of nonlinearity in the return equation and no evidence in 5 of the 6 order flow equations (all marginal significance levels above 10 percent). The exception is the equation for order flow from non-US corporations, where the significance level is 4.6%. (With 14 additional variables, a purely spurious finding that one of the 14 is significant at the 5 percent level would not be surprising.) Overall, then, there is little evidence of nonlinearity in the daily dynamics of the returns/flows system.

4. Conclusions

This paper extends the literature on exchange rates and news in three main ways. First, no other paper has addressed news using the trades of end-user customers. Indeed, most papers in this area do not consider that prices and quantities are joint processes (i.e., they address the link between news and price in isolation). Recent papers that do address these joint dynamics focus exclusively on trades between marketmakers—i.e., interbank trades—rather than on trades of end users (Carlson 2002, Danielsson et al. 2003, Evans and Lyons 2003).[11] This is relevant for the question that we address because, relative to end users, marketmaker reactions to news are unlikely to be as protracted. Second, on the methodological front, we introduce a novel identification approach for isolating news shocks and their effects on trades and prices (specifically, our projection of the VAR innovations on news shocks). Third, our results provide forceful evidence that currency markets are still absorbing news after several days. By "still absorbing" we mean that end-user trades are still being induced, and these induced trades are having persistent effects on prices.

[11] Moreover, these other micro-approach papers consider only aggregate trades processes, whereas we analyze end-user trades at a disaggregated level, i.e., six different segments.

To understand how the market impact of news can be protracted, it is helpful to distinguish *average* news effects from *total* news effects. Average effects correspond to the direct (or "rational-expectations") channel for price impact, which one would expect to be reflected immediately, i.e., more quickly than indirect, order-flow-driven effects. Even if average effects from news are reflected in prices quickly, as found many past papers (e.g., Andersen and Bollerslev 1998 and Cheung and Chinn 2001),[12] this does not imply that total effects are reflected quickly. Rather, participants' macro views evolve continually, and trades induced by those evolving views hit the market over extended periods. This idea links rather naturally to the analysis in Andersen et al. (2003): they find that the impact effect of announcements—the average signed effect on price—is absorbed quite quickly, whereas the initial effect on volatility is only partial, rising over time (and hour or more) and only later decaying.

But why, specifically, might response lags be so long as to seem at first blush non-rational? Based on conversations with bank practitioners, we offer the following conjectures. Consider first the non-financial corporations. The treasury group within a corporation may have a currency "strategy meeting" only, say, once per week. Moreover, continuous monitoring of currency markets often involves specialized labor and significant labor costs. When monitoring does occur, it is typically not performed by the ultimate decision maker, adding to response lags. Investors (i.e., primarily mutual funds) face many of the same considerations. Few mutual funds engage in ultra-high-frequency currency management, so individual news arrivals are unlikely to alter their portfolio allocations (until they have accumulated to a change in "view"). Though their currency trades are also affected by inflows/redemptions from underlying investors, this mechanism is unlikely to operate at ultra-high frequencies either. Finally, consider the traders (i.e., primarily hedge funds). Though a natural candidate for ultra-high-frequency strategies, in fact, those active in major currencies tend to respond more to how a bit of news affects their larger strategy; most (but certainly not all) do not engage in tactical intraday reallocations to news.

What implications can be drawn from these results? First, the event-study approach to measuring news effects, which is employed by virtually every paper in this large literature, does not appear well-suited to capturing the total effect of news, given the protracted market absorp-

[12] Recall from the introduction the Cheung and Chinn (2001) finding that roughly 70% of the currency dealers believe that announcement effects are absorbed within 1 minute. As noted in their paper, the survey design allowed the respondents to interpret the question their own way. We take the finding to mean that the dealer's world returns to "normal" very quickly, where normal is a state in which order flow is the main force driving prices. This interpretation squares well with our findings.

tion identified here. This under-estimate of total effects may be linked to what is arguably the central puzzle in this literature—the puzzle of missing news effects, i.e., that past measures of average news effects can account for only around 3 percent of total exchange rate variation (Evans and Lyons 2003). Second, prices are affected by these protracted, news-related trades, suggesting that markets are not treating them as inconsequential. (Put differently, the market is not identifying these induced trades as pure "animal spirits" and willingly taking the other side at existing prices.) Third, we cannot rule out the possibility that the induced trades are in fact non-rational. If the market as a whole is not large enough to absorb non-rational trades at existing prices, or if the market cannot distinguish them from other trades that convey information, then prices can be affected, despite the lack of any macro information content. Further work will be needed to distinguish this non-rational interpretation from other possibilities. From our perspective, there are in fact three main hypotheses that further work will need to discriminate: (1) news-induced trades are rational and convey incremental information about the true state of the macro-economy; (2) news-induced trades are rational, but are motivated by risk management—e.g., portfolio rebalancing—rather than macro information; and (3) news-induced trades are non-rational in some way, perhaps corresponding to the distinct cognitive biases identified within behavioral finance. Distinguishing among these three hypotheses is an important frontier for micro-based research on exchange rates.

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Table 1: Sample Statistics

		Mean	Std.	Skew	Kurt.	ρ_1	ρ_2	ρ_3
Returns								
	Δp_t	-0.009	0.544	0.149	4.691	-0.022	0.003	-0.011
						(0.448)	(0.918)	(0.658)
<u>Order Flows</u>								
Corporations								
US	Δx_t^C	-3.424	45.555	-1.650	19.692	0.075	0.053	-0.035
						(0.018)	(0.060)	(0.255)
Non-US	Δx_t^{C*}	-11.879	81.666	0.573	11.440	0.033	0.045	0.028
						(0.192)	(0.091)	(0.286)
Traders								
US	Δx_t^T	-0.783	138.745	0.502	15.426	0.114	0.046	0.001
						(0.003)	(0.076)	(0.967)
Non-US	Δx_t^{T*}	2.257	82.462	0.400	7.598	-0.025	-0.023	-0.029
						(0.506)	(0.397)	(0.212)
Investors								
US	Δx_t^I	3.821	59.977	-1.946	33.632	0.063	0.023	0.031
						(0.048)	(0.437)	(0.188)
Non-US	Δx_t^{I*}	3.170	112.391	2.472	40.441	0.068	0.038	0.027
						(0.003)	(0.070)	(0.175)
Aggregate								
	Δx_t	-4.940	226.073	0.677	9.418	0.098	0.059	0.026
						(0.001)	(0.016)	(0.310)

Correlation Matrix

	Δp_t	Δx_t^C	Δx_t^{C*}	Δx_t^T	Δx_t^{T*}	Δx_t^I	Δx_t^{I*}	Δx_t
Δp_t	1.000							
Δx_t^C	-0.034	1.000						
Δx_t^{C*}	-0.102	0.020	1.000					
Δx_t^T	0.131	0.033	-0.048	1.000				
Δx_t^{T*}	0.102	-0.014	-0.038	-0.012	1.000			
Δx_t^I	0.070	-0.031	0.014	-0.063	0.021	1.000		
Δx_t^{I*}	0.192	-0.013	-0.022	0.038	-0.011	0.067	1.000	
Δx_t	0.178	0.209	0.319	0.601	0.339	0.265	0.521	1.000

Notes: Exchange rate returns, Δp_t , are calculated as the daily change in the natural log of the spot price ($/€) x 100, Δx_t^j denotes the daily order flow for euros by segment *j* in millions of euros. The statistics reported below ρ_i are the sample autocorrelations at lag *i*. P-values for the null hypothesis of no autocorrelation are reported in parenthesis. The sample spans the period 4/11/93 – 6/30/99, and includes observations on 1682 trading days.

Table 2: Impact of US Announcements

Announcements			Returns	Order Flows					
				Corporations		Traders		Investors	
#	Item	#N	Δp_t	US: Δx_t^C	Non-US : Δx_t^{C*}	US: Δx_t^T	Non-US: Δx_t^{T*}	US: Δx_t^{I*}	Non-US: Δx_t^{I*}
1	Bus Inv	63	0.016	-4.042	0.271	10.989	-1.062	-4.045	8.186
2	Capacity	70	0.036	-2.723	-1.303	-67.202***	-4.417	1.149	-14.498
3	Claims	323	0.051**	-1.049	-5.236	-11.165*	-0.775	-2.094	3.681
4	Confidence	78	-0.085**	-0.777	-7.642	2.810	1.753	-1.614	0.803
5	Construction	76	0.060	-0.475	10.610	-6.777	4.347	-4.308	2.162
6	CPI	48	0.043	-10.035***	-6.383	0.667	-9.309**	5.398	17.916**
7	Credit	77	-0.006	-4.457	15.969**	-10.685	1.457	20.252	-1.999
8	Durables	76	-0.014	-0.885	16.545**	6.686	-7.598	1.100	-6.101
9	Fact. Ords	72	0.073	1.837	7.698	28.464***	3.883	-0.070	0.270
10	Fed Funds	19	-0.011	-1.461	-1.330	-7.115	8.847***	-8.781	-12.561
11	GDP adv	25	-0.071	1.388	-7.685	7.797	-8.875	2.286	10.977
12	GDP fin	25	0.169	-6.919	-6.840	-75.010**	-12.677	18.697***	-11.245
13	GDP prl	24	-0.127	6.351*	-11.865	-8.439	29.183**	12.131	1.870
14	Earnings	64	-0.015	1.336	-7.127	-20.734*	-6.282	15.408*	10.414*
15	House Sts	71	-0.028	-11.642**	-2.582	-12.359	1.468	4.275	1.715
16	Ind. Prod	62	-0.090	9.369	6.467	47.809*	2.373	2.573	14.277
17	Leading	54	-0.062	-5.793	16.126***	3.724	8.194	-16.071**	-9.011
18	M1	77	0.105*	-3.191	-4.617	35.457	-12.339	-14.217	8.913
19	M2	73	-0.070	9.269	0.838	-34.419	3.883	-2.360	6.365
20	M3	68	0.061	3.874	3.842	-5.395	-11.706*	-6.976	3.588
21	NAPM	76	-0.107**	-0.314	15.150	-1.577	-1.962	2.219	-18.114
22	New Homes	77	-0.139**	9.687**	10.638	-2.769	-11.462*	-12.283	-1.983
23	NF Empl.	78	-0.239***	-0.646	4.261	-28.877**	5.736	2.248	-6.596
24	Cons.	60	-0.118**	-4.062*	-6.485	14.165	4.869	-17.800**	10.130
25	Income	63	-0.102	1.330	-9.416	-10.518	7.269	9.718	-1.901
26	PPI	66	-0.084**	-9.191	-6.970	24.842	-5.439	3.416	-6.401
27	Ret. Sales	70	-0.018	2.030	-1.992	-10.506	-2.393	1.377	-9.336
28	Budget	75	0.029	5.729*	4.206	-1.191	1.526	-5.014	-12.114
29	Trade Bal.	77	-0.117***	0.641	16.961	-6.227	1.576	3.187	-19.474*
30	Unemploy.	56	0.098*	7.877	-1.578	-21.174*	8.459	-9.400	-5.811

Table 2 (Cont.) : Impact of German Announcements

Announcements			Returns	Order Flows					
				Corporations		Traders		Investors	
#	Item	#N	Δp_t	US: Δx_t^C	Non-US : Δx_t^{C*}	US: Δx_t^T	Non-US: Δx_t^{T*}	US: Δx_t^{I*}	Non-US: Δx_t^{I*}
1	GDP	19	0.067	10.354	-3.155	-7.328	11.232*	5.788	-17.399*
2	Employ	68	0.035	-2.367	-4.741	26.249**	2.295	3.812	9.107*
3	Ret. Sales	63	-0.044	-8.553	-6.953	22.301*	-4.952	1.008	-9.670
4	Ind. Prod	74	-0.009	-1.252	0.684	-2.920	2.995	-3.129	0.226
5	Man Output	71	0.125	-1.826	17.886	24.506*	24.677	-9.510	29.380
6	Man Orders	75	-0.038	-5.009	-8.237	-28.559*	-4.628	3.800	-20.806
7	Trade Bal.	65	-0.099**	-6.021	-7.972	1.684	1.866	13.776**	7.080
8	Current a/c	76	0.003	-3.282	-8.844**	-8.237*	0.112	0.453	-4.807
9	Cost of Liv.	68	-0.024	3.451	-0.170	26.899**	-7.282	4.418	-3.297
10	WPI	65	-0.044	-2.568	1.102	-4.543	3.585	6.419*	-4.655
11	PPI	75	0.054**	0.811	-10.889***	-3.288	2.037	4.744***	3.969
12	Import Prices	70	-0.107*	-0.568	-0.401	-30.022***	-15.729*	13.333*	15.064*
13	M3	75	-0.017	-2.048	-4.184	-0.627	8.600*	0.775	-1.590

Notes: Each column reports the estimated coefficients from the regression of the VAR innovation listed at the head of the column on the 43 announcements shown on the left. Innovations are computed from a 2nd-order VAR for returns and the six order flow segments estimated in daily data over 1682 trading days. #N denotes the number of each news announcements in the sample. All announcements are standardized to have a unit variance over the sample period. "*", "**" and "***" denote statistical significance at the 10%, 5%, and 1% level respectively.

Table 3: Order Flow Dynamics

US News #	Item	Order Flow Segment	Days After Announcement 0	1	2	3	4	1 - 4
2	Capacity	Δx_t^T	-34.522	-3.629	-1.939	-0.537	-0.226	-6.331
				(0.000)	(0.009)	(0.002)	(0.052)	(0.000)
6	CPI	Δx_t^C	-8.775	-0.538	-0.922	-0.098	-0.045	-1.602
				(0.010)	(0.000)	(0.011)	(0.096)	(0.000)
7	Credit	Δx_t^{C*}	15.601	1.074	1.335	0.219	0.113	2.741
				(0.014)	(0.001)	(0.002)	(0.025)	(0.000)
8	Durables	Δx_t^{C*}	14.962	0.687	1.148	0.144	0.075	2.055
				(0.054)	(0.002)	(0.019)	(0.061)	(0.001)
9	Fact. Ords	Δx_t^T	28.732	3.543	1.001	0.312	0.189	5.045
				(0.000)	(0.128)	(0.035)	(0.134)	(0.005)
10	Fed Funds	Δx_t^{T*}	8.958	-0.557	-0.022	-0.003	0.025	-0.556
				(0.083)	(0.794)	(0.809)	(0.205)	(0.044)
12	GDP fin.	Δx_t^I	18.488	1.205	-1.555	0.086	0.179	-0.085
				(0.132)	(0.029)	(0.295)	(0.012)	(0.720)
13	GDP prl.	Δx_t^{T*}	29.868	0.710	-0.898	0.077	0.083	-0.028
				(0.273)	(0.111)	(0.279)	(0.154)	(0.893)
17	Leading	Δx_t^{C*}	15.817	1.556	0.286	0.102	0.061	2.005
				(0.006)	(0.200)	(0.076)	(0.136)	(0.007)
23	Non F Empl.	Δx_t^T	-25.998	-3.094	-3.778	-0.732	-0.555	-8.158
				(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
24	Consumption	Δx_t^I	-17.979	-1.086	1.086	0.005	-0.022	-0.018
				(0.030)	(0.013)	(0.846)	(0.313)	(0.878)
30	Unemploy.	Δx_t^C	7.806	0.378	0.962	0.079	0.097	1.516
				(0.035)	(0.000)	(0.021)	(0.005)	(0.000)
German News #	Item	Order Flow Segment	Days After Announcement 0	1	2	3	4	1 - 4
2	Employ	Δx_t^T	26.097	2.924	1.956	0.531	0.205	5.616
				(0.000)	(0.010)	(0.001)	(0.073)	(0.001)
3	Ret. Sales	Δx_t^C	-9.304	-0.189	-0.523	-0.031	-0.039	-0.782
				(0.139)	(0.010)	(0.180)	(0.084)	(0.007)
8	Current a/c	Δx_t^{C*}	-8.790	-0.123	-0.521	-0.018	-0.036	-0.698
				(0.302)	(0.002)	(0.267)	(0.077)	(0.014)
9	Cost of Liv.	Δx_t^T	27.454	3.457	0.368	0.287	0.039	4.152
				(0.000)	(0.379)	(0.026)	(0.591)	(0.005)
11	PPI	Δx_t^{C*}	-10.745	-0.696	-0.640	-0.089	-0.051	-1.476
				(0.003)	(0.001)	(0.008)	(0.023)	(0.000)
12	Import Prices	Δx_t^T	-31.306	-4.654	-1.728	-0.524	-0.394	-7.300
				(0.000)	(0.014)	(0.005)	(0.006)	(0.000)

Notes: The table reports impact on the order flow segment on days 0 to 4 following each news announcement. It presents only those 18 news items that have a significant impact on order flow on the day of the announcement (at the 5 percent level, from Table 2). For each news item meeting this criterion, the table reports the impulse response of the order flow registering the largest initial impact. Below each estimated order flow impact we report the p-value (computed by Monte Carlo simulation) for the null hypothesis that $\beta_i^j = 0$ for all *i* and *j* (i.e., of no direct impact on order flow). The order flow segments are: US corporations Δx_t^C, non-US corporations Δx_t^{C*}, US traders Δx_t^T, non-US traders Δx_t^{T*}, US investors Δx_t^I and non-US investors Δx_t^{I*}.

Table 4: Contribution of Announcements to Order Flow Variance

US News		Order Flow	Days After Announcement				
#	Item	Segment	0	1	2	3	4
2	Capacity	Δx_t^T	6.357	2.27	3.045	2.417	3.438
6	CPI	Δx_t^C	3.769	3.878	1.612	1.225	0.868
7	Credit	Δx_t^{C*}	3.608	4.626	5.778	6.217	7.038
8	Durables	Δx_t^{C*}	3.319	3.421	2.523	2.745	2.930
9	Fact. Orders	Δx_t^T	4.403	0.606	1.026	1.684	1.090
10	Fed Funds	Δx_t^{T*}	1.184	0.004	0.012	1.032	0.071
12	GDP fin.	Δx_t^I	9.718	6.908	0.765	10.451	0.148
13	GDP prl.	Δx_t^{T*}	13.159	6.556	9.173	10.996	12.628
17	Leading	Δx_t^{C*}	3.709	0.212	1.262	1.789	1.358
23	Non Farm Empl.	Δx_t^T	3.605	8.617	5.659	14.532	6.214
24	Cons.	Δx_t^I	9.189	3.369	0.003	0.157	0.116
30	Unemployment	Δx_t^C	2.982	4.222	1.057	5.827	2.063
German News		Order Flow	Days After Announcement				
#	Item	Segment	0	1	2	3	4
2	Employment	Δx_t^T	3.633	2.310	2.981	1.990	2.703
3	Ret. Sales	Δx_t^C	4.237	1.247	0.158	0.946	0.158
8	Current A/Cc	Δx_t^{C*}	1.146	0.704	0.037	0.631	0.070
9	Cost of Living.	Δx_t^T	4.02	0.082	0.873	0.073	0.540
11	PPI	Δx_t^{C*}	1.711	1.063	0.953	1.264	1.162
12	Import Prices	Δx_t^T	5.228	1.804	2.898	7.318	5.314

Notes: The table reports the variance of the order flow segment due to the news announcement (listed in the left-hand column) as a percentage of the variance due to all shocks impacting the order flow segment. (As in Table 3, it includes only those 18 news items from Table 2 that have a significant impact on order flow on the day of the announcement.) The order flow segments are: US corporations Δx_t^C, non-US corporations Δx_t^{C*}, US traders Δx_t^T, non-US traders Δx_t^{T*}, US investors Δx_t^I and non-US investors Δx_t^{I*}.

Table 5: Return Dynamics Induced By Announcements

US News		Days After Announcement				
Item #	Item	1	2	3	4	1 to 4
3	Claims	-17.483	-5.104	-0.175	0.632	-22.130
		(0.000)	(0.020)	(0.395)	(0.101)	(0.000)
4	Confidence	-5.082	-2.849	-0.615	0.242	-8.304
		(0.173)	(0.140)	(0.157)	(0.457)	(0.083)
21	NAPM	-2.932	2.521	1.139	0.889	1.618
		(0.201)	(0.079)	(0.005)	(0.028)	(0.394)
22	New Homes	2.151	-1.453	0.322	0.252	1.272
		(0.248)	(0.161)	(0.139)	(0.245)	(0.437)
23	Non Farm Empl.	-1.769	2.031	0.347	0.567	1.176
		(0.098)	(0.012)	(0.015)	(0.001)	(0.235)
24	Cons	-2.264	-9.458	-0.972	-0.015	-12.709
		(0.291)	(0.000)	(0.017)	(0.903)	(0.002)
26	PPI	-16.992	-6.518	-0.726	0.533	-23.704
		(0.000)	(0.010)	(0.088)	(0.168)	(0.000)
29	Trade Bal	-3.089	3.167	1.098	0.888	2.064
		(0.173)	(0.032)	(0.009)	(0.019)	(0.323)
German News		Days After Announcement				
Item #	Item	1	2	3	4	1 to 4
7	Trade Bal	-11.630	2.965	-0.344	0.600	-8.409
		(0.006)	(0.083)	(0.232)	(0.120)	(0.047)
11	PPI	-0.920	-2.288	0.889	0.640	-1.680
		(0.580)	(0.098)	(0.020)	(0.065)	(0.416)

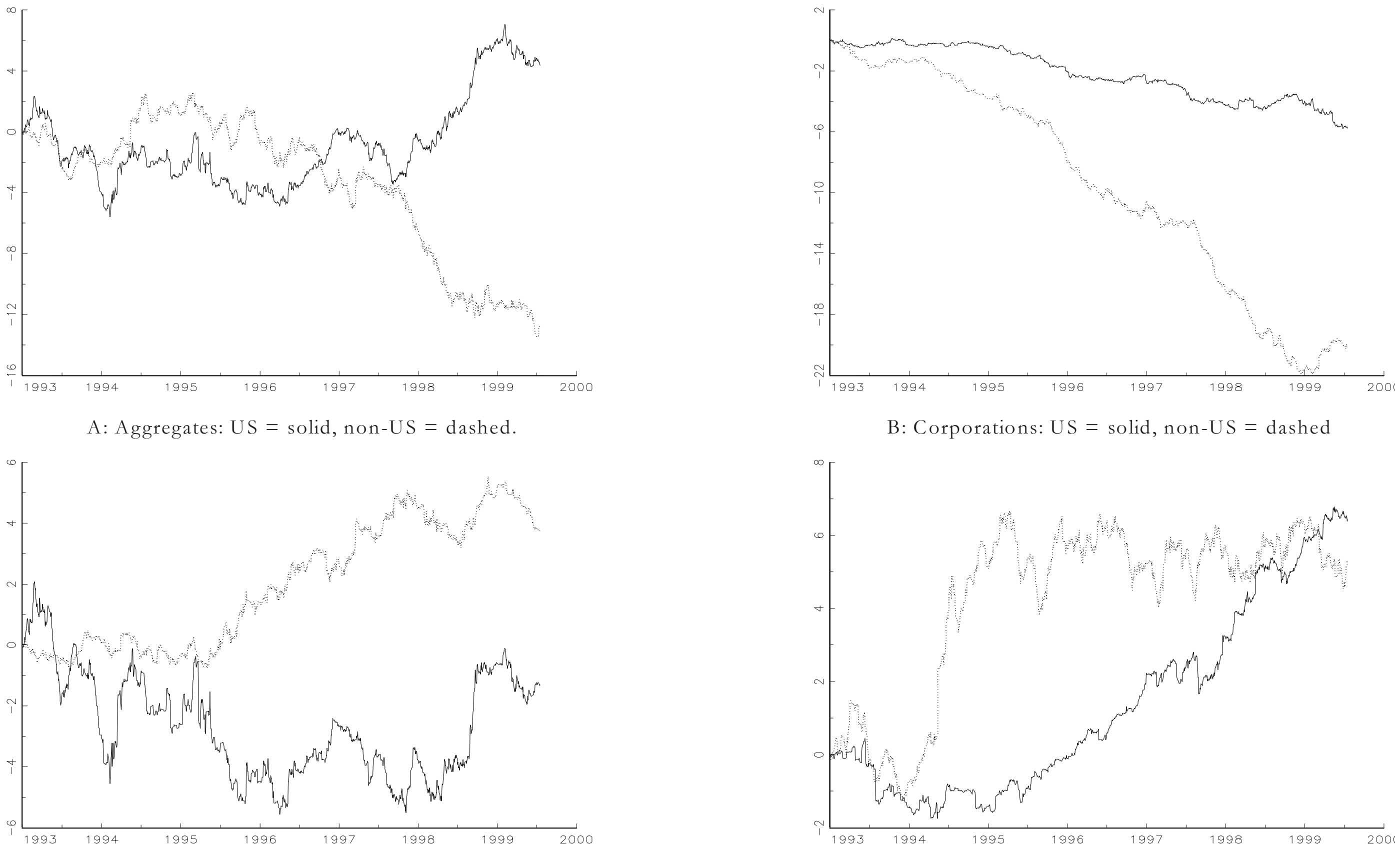
Notes: The table reports the impact on returns Δp_t on days 1 to 4 following each news announcement. It presents only those 10 news items that have a significant impact on price on the day of the announcement (at the 5 percent level, from Table 2, column 4). The price impact is report as a percentage of the price impact on the day of the announcement. Below each estimated price impact we report the p-value (computed by Monte Carlo simulation) for the null hypothesis that $\beta_i^j = 0$ for all *i* and *j*. The eight US announcements and two German announcements have immediate price impacts that are statistically significant at the 5% level as reported in Table 2.

Table 6: Contribution of Announcements to Return Variance

US News		Days After Announcement				
#	Item	0	1	2	3	4
3	Claims	0.723	0.377	0.018	0.714	0.034
4	Confidence	2.532	0.412	0.767	0.367	0.054
21	NAPM	3.952	0.503	4.105	7.732	6.027
22	New Homes	6.453	0.273	0.536	1.011	1.549
23	Non F Empl.	26.479	2.189	2.55	21.091	10.174
24	Consumption	4.203	7.534	3.177	0.002	1.304
26	PPI	2.199	1.872	0.929	1.545	0.027
29	Trade Balance	4.573	0.919	4.413	8.913	6.511
German News		Days After Announcement				
#	Item	0	1	2	3	4
7	Trade Balance	3.276	0.577	0.309	2.918	0.184
11	PPI	1.047	0.11	0.662	1.06	0.914

Notes: The table reports the variance of daily exchange rate returns due to the announcement (listed in the left-hand column) as a percentage of the variance due to all shocks. (As in Table 5, it includes only those 10 news items from Table 2 that have a significant impact on price on the day of the announcement.)

Figure 1: Order Flow Segments



A: Aggregates: US = solid, non-US = dashed.

B: Corporations: US = solid, non-US = dashed

C: Traders: US = solid, non-US = dashed

D: Investors: US = solid, non-US = dashed

Figure 1 presents cumulative net purchases of euros (in billions) over our sample for the six different end-user segments and for the aggregate. The order flow segments are: US and non-US non-financial corporations (Panel B), US and non-US traders (primarily hedge funds, Panel C), and US and non-US investors (primarily mutual funds, Panel D). Sample: April 11, 1993 to June 30, 1999.