How Is Macro News Transmitted to Exchange Rates?

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Abstract

This paper tests whether macroeconomic news is transmitted to exchange rates via induced transactions, and if so, what share occurs via transactions versus traditional direct adjustment of price. We identify the link between order flow and macro news using a heteroskedasticity-based approach. This involves jointly testing (1) whether macro news flow increases order flow volatility and (2) whether the induced order flow has signed (first moment) effects on the exchange rate. The answer to both questions is yes: in both daily and intra-daily data, order flow is considerably more volatile when macro news is flowing, and these signed orders have the theoretically predicted effects on the exchange rate's direction. Of news' total price effect, induced order flow accounts for two-thirds, with direct news effects accounting for one-third. In terms of total exchange rate variation, the order flow channel brings news' explanatory power up to 30 percent, versus estimates in the 1–5 percent range from existing literature, helping to resolve the puzzle of missing news effects.

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How Is Macro News Transmitted to Exchange Rates?

In macroeconomic models of exchange rates, news maps directly into prices. The effect of news on currency demands in these models is common knowledge and transactions—though perhaps engendered by the change in exchange rates—play no role in causing the change. In microeconomic models of asset prices, in contrast, transactions do play a causal role in price determination (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 test whether any part of the effect of news on exchange rates is transmitted via transactions and, if so, what share is transmitted that way versus the traditional direct channel.

That transactions might play a role is motivated by recent empirical work demonstrating a link between signed transaction volume (order flow) and signed exchange rate changes.[1] In the models employed by these papers, order flow affects exchange rates as a proximate determinant. The underlying determinant, which theory labels information, is not specified, nor is it directly tested. This leaves open the nagging question of what really drives the order flow. This paper is an attempt to address that question by examining whether macroeconomic news might be a determinant of signed transaction volume. This question is distinct from whether unsigned volume is determined by news, a well-established property of many speculative markets (see, e.g., Fleming and Remolona 1999).[2]

We estimate a trading model that distinguishes three sources of exchange-rate variation. The first source mirrors traditional models—macro news that is

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[1] This evidence is from both micro (i.e., single marketmaker) and macro (marketwide) studies. See, e.g., Payne (1999), Rime (2000), Evans and Lyons (2002a) and Evans (2002). Order flow is the cumulation over time of *signed* trades. Trades are signed according to whether the initiator is buying or selling. (The marketmaker posting the quote is the non-initiating side.) A large empirical literature within finance shows that signing trades this way provides considerable explanatory power (see, e.g., the reviews in Madhavan 2000 and Lyons 2001).

[2] Idiosyncratic portfolio rebalancing in response to news is consistent with an effect on volume. However, under rational expectations, given that immediate adjustment in price is unbiased, on average good news for the dollar should not produce positive (or negative) order flow; i.e., one would not expect a relative increase in executed transactions initiated by dollar buyers. We return to this issue below when discussing potential simultaneity bias.

impounded in price immediately and directly (i.e., with no role for transacted order flow). The second source is the indirect effect of news via induced order flow.[3] The third source is order flow unrelated to public news (such as that due to banks' changing risk tolerances, firms' changing hedging demands, or individuals' changing liquidity demands; see, e.g., Evans and Lyons 2002a). We find that for the DM/$ market, all three sources of exchange rate variation are significant. The flow of transacted orders between marketmakers (our measure of order flow) varies considerably with macro news flow, such that roughly two-thirds of the effect of macro news on exchange rates is transmitted via order flow, the remainder being the direct effect of news. This is consistent with our finding that, though order flow is always important for determining exchange rates, it is even more important when news is flowing than when it's not (contrary to intuition from macro models). With both channels operating, news accounts for about 30 percent of total price variance, which is an order of magnitude larger than findings from past work (more below).

Though the literature linking exchange rates to news is vast, we are the first to our knowledge to use order flow to sort out the relationship. The existing literature has two branches: the first attempts to explain the direction of exchange-rate changes (first moments) and the second, later branch attempts to explain exchange-rate volatility (second moments). A common finding of the first branch is that, at least at the daily 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).[4] 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.[5] This work

[3] That this channel might be operative is another reminder that order flow and demand are not one to one. To clarify, consider a simple counter-example. In the common-knowledge tradition of exchange rate economics, when positive public news arrives, demand increases, causing price to increase—without any flow of transacted orders occurring or needing to occur. This is incompatible with demand and order flow being one to one: the demand shift does not generate any order flow at the new price.

[4] 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).

[5] 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 (2002). The latter two papers are especially

finds that arrival of scheduled announcements does indeed produce the largest exchange-rate changes. On the other hand, though major announcements dominate the volatility picture within short release windows, the ability of these fundamentals to account for volatility changes overall is lower than that of less fundamental features such as time-of-day effects and ARCH (Andersen and Bollerslev 1998).[6]

Our paper departs from earlier work on macro news in two main ways. First, we consider a broader set of macro news events. Scheduled announcements account for about 10 percent of the macro news arrivals we obtain from the Reuters Money Market Headline News screen. (The median number of macro news arrivals per day in our sample is 11.) This allows us to test whether this wider set of news types affects the processes for transactions and returns in ways not examined previously. At the same time, including a broad set of news types requires a change in estimation strategy because it is not possible to measure ex-ante expectations for most of them (e.g., a report on the Headline News screen of an official stating that the trade deficit is unsustainable). This leads to the second of our main departures from earlier work: like Rigobon and Sack (2002), we depart from the event-study approach and adopt instead an approach based on the state dependent heteroskedasticity.[7] Specifically, we identify (via GMM) the relative importance of direct and indirect effects from news by allowing the variances of shocks to order flow and price to depend separately on the rate of news arrival. These second moment conditions identify our model and answer the central question before us, namely, whether order flow plays a role in transmitting news to exchange rates. This approach, as in Rigobon and Sack (2002), does not require measurement of news' unanticipated component; it requires the weaker assumption that one can distinguish periods in which the variance of macro news flow is relatively high. We use news arrivals for this purpose.

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relevant in that they use direct measures of order flow in fixed income markets. Green (2002), for example, finds evidence that asymmetric information increases following public macro announcements.

[6] Accounting for volatility changes and accounting volatility levels of are not the same. For example, abnormal volatility in response to heightened news arrivals may dissipate rapidly, but trading induced by past news arrival can continue to contribute to normal volatility (a point we return to below).

[7] See the discussion in Rigobon and Sack (2002) comparing the merits of the event-study and heteroskedasticity approaches. Omitted variable bias in event-study analysis is simply a manifestation of a point made above, namely, that event effects are often swamped by other factors affecting price.

Before delving into details, it is worthwhile recognizing the big picture into which this paper fits. The vast event-study literature noted above that addresses news effects on exchange rates has in many instances been quite successful in explaining signed exchange rate variation *within event windows*, but remains relatively unsuccessful in accounting for total variation. A good example at the daily frequency is Klein (1991), who regresses signed exchange rate changes on signed trade-balance news and finds that news can explain about 40 percent of exchange rate changes on those days. This is a lovely result. But remember that trade balance news arrives monthly. That means that roughly 95 percent of exchange rate variation is not included in the regression (20 of 21 trading days per month). Thus, an R^2 statistic of 40 percent is still accounting for less than 3 percent of total exchange rate variation. A good example from the intraday event-study literature is Andersen et al. (2003). They too find within-event-window R^2's that are genuinely impressive. But as they note (p. 50), summing the amount of time in all of their five-minute post-event intervals accounts for only 0.2 percent of their full sample period (e.g., roughly one five-minute interval per day). Even if R^2's within event-windows were 100 percent, the total exchange rate variation being explained in their case would be about 2 percent (the extra factor of 10 coming from a conservative assumption that variance increases when news arrives by a factor of 10).[8] In our paper, based on a much broader sample of macro news events, and allowing for an indirect order flow channel, we find that news' power to explain total exchange rate variation is an order of magnitude higher at roughly 30 percent.

The remainder of the paper is in four sections. Section 1 describes our data and presents some descriptive statistics. Section 2 presents daily analysis of the three sources of price adjustment. Section 3 presents intra-daily analysis of the three sources. Section 4 concludes.

[8] That security-return volatility is not constant over time is documented by French and Roll (1986). Our daily-frequency example from Klein (1991) could include two adjustments in this respect: exchange rate volatility over weekends is not zero, which lowers his overall explanatory power, but announcement days tend to have higher volatility than non-announcement days, which raises his explanatory power. Neither of these adjustments is large enough to alter the basic message. Our intraday example from Andersen et al. (2003) is conservative: their R^2s within event windows are generally below 50 percent (see their Table 2) and variance increasing by a factor of 10 is high as well (only for the Employment Report, the highest-impact announcement, does instantaneous variance increase by a factor as large as 10; see Andersen and Bollerslev 1998, page 249).

1. Data and Descriptive Statistics

Our empirical strategy is two pronged, encompassing two data frequencies and two complementary approaches to how macro news is transmitted to exchange rates. The first approach applies at the daily frequency, the second at intraday frequencies (in our case, five-minute observations). Daily analysis of exchange rate variation is interesting because daily changes in nominal exchange rate are, to a first approximation, 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 these are rapidly dissipating price effects). This martingale property at the daily frequency does not apply to intraday prices, which exhibit mean reversion, as we shall show. The upshot is that disentangling different sources of daily exchange rate variation provides a solid indication of decompositions at frequencies more familiar to macroeconomists (e.g., monthly). But daily analysis does not convey the rich intraday structure of news effects. Nor is it suited to addressing whether news makes order flow more or less important in exchange rate determination. For these we turn to intraday analysis.

Our order flow and price data are drawn from time-stamped, tick-by-tick transactions in the largest spot market—DM/$—over a four-month period, May 1 to August 31, 1996 (full 24-hour trading day). The data source is the same as that in Evans (2002) and we refer readers there for additional detail. The transactions are from the Reuters Dealing 2000-1 system. At the time of our sample, Dealing 2000-1 was the most widely used electronic dealing system: according to Reuters, over 90 percent of the world's bilateral transactions between DM/$ marketmakers took place through the system.[9] For every trade executed on D2000-1, our data set includes a time-stamped record of the transaction price and a bought/sold indicator. The bought/sold indicator allows us to sign trades for measuring order flow.

For our daily analysis, Δp_t is the change in the DM transaction price for purchases of dollars from 5 pm BST (British Summer Time) on day t-1 to 5 pm BST on

[9] At the time of our sample, transactions between marketmakers accounted for about 75 percent of total trading in major spot markets. This 75 percent breaks into two transaction types—direct (bilateral) and brokered (multilateral). Direct trading accounted for about 60 percent of trades between

day t.[10] When a purchase transaction does not occur precisely at 5 pm, we use the immediately preceding purchase price. Daily order flow x_t is the difference between the number of trades initiated by dollar buyers and the number initiated by dollar sellers over the same time interval (in hundred thousands, negative sign denotes net dollar sales).[11] For our five-minute returns, which we denote Δp_i, we also use the immediately preceding transaction when no transaction occurs precisely at the five minute mark. (With roughly 1 million transactions per day, the preceding transaction is generally only seconds earlier.) Five-minute order flow x_i is defined similarly to x_t but over the five-minute interval matching Δp_i.

Our news data come from the Reuter's Money Market Headline News screen (source: Olsen Associates). These screens are standard equipment on FX trading desks and are used for high frequency monitoring by non-marketmaker participants as well. We cleaned the raw news data by excluding news items of the following four types: (i) announcements of upcoming known holidays, (ii) announcements that a scheduled release would take place (e.g., "Monthly employment report due out tomorrow"), (iii) duplicate announcements (the same news is repeated with a slight change in wording), and (iv) announcements referring to the dollar/DM exchange rate. The first three of these filters are intended to distill information that is truly incremental.[12] The fourth is intended to protect against feedback from exchange rates to macro news flow (e.g., an announcement that the dollar/DM exchange rate had been volatile that morning would be a clear problem for interpreting macro news flow as exogenous; there weren't, however, any actual announcements with such clear simultaneity with exchange rates). In all, the four filters excluded less than 10 percent of news arrivals.

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marketmakers and brokered trading accounted for about 40 percent. For more detail on this Reuters Dealing System see Lyons (2001) and Evans (2002).

[10] Using prices from purchase transactions (i.e., transactions at the ask) eliminates return reversals that would arise in prices that bounce randomly from bid to ask.

[11] In direct trading between marketmakers, orders sizes are standardized, so variation in size is much smaller than variation in the size of individual customer-marketmaker trades. Note too that using measures of order flow based on numbers of transactions rather than size is common in work on equity markets, even when both measures are available (see, e.g., Hasbrouck 1991). Our data set does include total dollar volume over our sample, which allows us to calculate an average trade size, which we use below to interpret the estimated coefficients.

Our daily frequency variable A_t is the number of news arrivals relating to U.S. or German macroeconomics between 5:01 pm BST on day t-1 and 5 pm BST on day t. The five-minute analogue of A_t is denoted A_i. The dummy variable A_i takes the value of one if there was a news arrival (U.S. or German) during the previous five minutes. In our four-month sample, there are 515 five-minute windows in which at least one news arrival occurs (the total number of five-minute windows is 11,473). We use this dummy-variable approach in the five-minute data because there are few instances of more than one news arrival during a single five-minute observation window (in 29/515 there were two arrivals and in 4/515 there were three.) Arrivals in the raw news data recorded after 20:00 hrs and before 6:30 (BST) are quite rare and typically refer to previous news events within the heart of the trading day. For this reason we do not include the few news arrivals that occur in this time interval in our sample.

As noted, our methodology allows us to consider a much wider set of macro news types.[13] This is important because our four-month sample limits our ability to partition the news arrivals (e.g., isolating individual news types, such as Unemployment Claims). Though there is no ready measure of ex-ante expectations for more than 80 percent of this full news set, there is a subset for which a commonly used measure of expectations exists, namely the subset of scheduled announcements (that measure being survey responses provided by Money Market Services and used extensively in foreign exchange event studies). We obtained these survey data from Money Market Services so that we could measure innovations for the announcement subset more accurately and compare our results from this subset to results from the much larger set of unscheduled news events. This provides an indication of the statistical power gained by extending the definition of “news” beyond scheduled announcements for which expectation proxies exist. Another partitioning for which our sample provides some statistical power is separating U.S. from German news. Results for these two partitions are presented in the next

[12] If a larger sample of news items caught by these three filters were available, this would provide an interesting test for over-reaction.

[13] A wider set of news types is also considered by Eddelbuttel and McCurdy (1998), though their focus is the effect of news flow on exchange rate volatility, not the joint dynamics of news, signed order flow,

section. It will be clear from the actual news items (see Figure 2) that partitioning into positive and negative news (for the dollar) would be difficult to do objectively. Indeed, that is in some sense the genesis of this paper: the same exercise is difficult for marketmakers as well.

Table 1 presents descriptive statistics for the variables used in our daily analysis (upper panel) and intraday analysis (lower panel). For the daily analysis these variables include news flow A_t, price changes Δp_t, and order flow between marketmakers x_t. The median number of daily news arrivals is 11, 8 of which pertain to Germany. As noted, these news events extend well beyond the scheduled announcements that are the focus of most past work. Our intraday analysis includes a variable not included in the daily analysis, namely n_i, the total number of trades over each five-minute interval. This variable accounts for dependence on trading intensity in the intraday model, as we shall see. Note that intraday price changes display (negative) autocorrelation, but only at lag one. Thus, future price changes cannot be predicted from past changes beyond a five minute horizon—a result confirmed by the ARMA model estimates in Evans 2002 (i.e., price changes follow an MA(1)). Order flow, at least at the five-minute frequency, is much more persistent. (Order flow exhibits virtually no persistence at the daily frequency.)

Figures 1 and 2 provide more perspective on the announcement data. Figure 1 shows the sample distribution for all news arrivals (both U.S. and German) by 30-minute interval. Figure 2 provides a list of all the arrivals in the first three days of the sample (19 in total). These news events clearly extend well beyond scheduled announcements.[14] (Including only the latter would leave many trading days in our sample without a single news event.)

Are these news arrivals just noise? We prefer to let the data speak: if they are pure noise then their arrival rate should not be correlated with variation in exchange rates or order flow. We will test this—and soundly reject it. We would also

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and signed price movements. Berry and Howe (1994) use the number of public releases as a news flow measure to address equity market volume and volatility.

[14] Our filters did not exclude the third news arrival because it is an interpretation of the second, not simply a restatement. The filters did not exclude the eighth arrival because in Germany (unlike the U.S.) the timing of this type of release is not regular. Arrival of this type of information can certainly affect the timing of participants' position taking. The actual realization of the German Industrial Production noted in the eighth arrival never made it onto the News Screen—we do not know why.

stress that noisy data is a much more significant problem for a paper whose main result is negative, since that negative result could stem from the noise. The findings in this paper are, in contrast, positive.

Figure 3 presents an important first look at whether news arrival is correlated with order flow volatility. It presents a scatter plot of the number of news arrivals per day (A_t) against the daily variance of returns and order flow. (To measure the two realized variances more precisely, we use a measure of integrated variance based on a five-minute sampling frequency.[15]) From the figure there is clearly a relationship: the variances of both returns and order flow are higher when the flow of macro news is higher. It is well known in the literature that there is a positive link between the variance of returns and the arrival of scheduled announcements. Here we are documenting a positive link with macro news, a much larger category of public information. That said, of the two relationships, the positive link between news flow and the variance of order flow is the more novel. Our daily model gives this positive link more structure, to which we turn in the next section.

Figure 4 is a counterpart of Figure 3, but at the intraday frequency. It presents a first look at whether order flow volatility remains elevated following news for a sustained period. The answer is clearly yes: order flow variance remains significantly elevated for about two hours, and reaches its peak only after 60-90 minutes. This aligns nicely with the time pattern for the variance of price changes (Panel II). The estimates in both cases are from regressions of the form:

$$y_i = \sum_{j=-12}^{36} b_j D_{i-j} + \sum_{j=1}^{48} a_j T_{i,j} + \eta_i$$

where D_i is a dummy variable that takes the value of 1 when a news event occurs in period i, and zero otherwise. The figure shows the estimates of b_j and the 95% confidence bound. To control for volatility's intraday pattern, the terms $T_{i,j}$ are time dummies that take the value of one when observation i occurs within the j^{th} 30-minute window on each day. (Here y_i is the integrated variance of order flow and the integrated variance of prices changes, both computed over a 30-minute window ending in period i.)

We offer two final points regarding data. First, recent institutional changes in the trading of major spot markets should not be viewed as rendering our analysis obsolete. Specifically, since the time of our sample in 1996, trading between marketmakers has migrated significantly from bilateral trading (the source of our data) to brokered trading over the EBS and Reuters Dealing 2000-2 systems (see BIS 2002). These changes do not render our analysis obsolete for two reasons. First, bilateral trading between marketmakers accounts for the lion's share of total trading through virtually all of the floating-rate era (i.e., post Bretton Woods, which collapsed in the early 1970s). That the FX market is now more oriented toward brokered trading does not render the type of data we use here obsolete for uander-standing post Bretton Woods floating rates. Second, though it is true that the specific order flow data we use is now a smaller share of the total, this does not imply that order flow analysis is less useful going forward. Strategies for order flow measurement and capture will need to change (e.g., extracting it from electronic broker systems). But the role of order flow in conveying information, in theory and in practice, transcends market structure. The types of information that order flow conveys—particularly types with persistent price effects—are unlikely to change radically as the FX market changes over time. Put another way, the underlying information structure of this market has more to do with the properties of the asset being traded than it does with market structure per se. Order flow should continue to convey dispersed information that needs to be aggregated and subsequently impounded in price. The methodology we introduce here is more robust than a cursory look at market structure might suggest.

The second final point regarding the data is that our four-month sample should not be viewed as small. If this were a paper on scheduled announcements, then the sample would indeed be small. But as a paper on macro news, one that encompasses 856 separate news arrivals, concern about insufficient observations is not compelling. True, all four-month periods are not the same in terms of major economic surprises. But why this should significantly cloud the degree to which order flow transmits macro news to prices is not clear. And one certainly cannot rely on existing theory in this area to make a good case one way or the other.

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[15] See the Appendix for details on these integrated variance measures.

2. Daily Analysis: Direct vs Indirect Effects from News

Our daily analysis relies heavily on the portfolio shifts model of trading developed in Evans and Lyons (2002a). Accordingly, rather than review that model's details, our presentation focuses on ways this paper extends that earlier framework. We base our daily analysis on the portfolio shifts model because it serves three important purposes. First, the model clarifies how and why causation can run strictly from order flow to price. Within microstructure theory more broadly, this direction of causality is the norm (e.g., Glosten and Milgrom 1985 and Kyle 1985). Second, the model clarifies why price determination should depend most directly on a particular type of order flow, namely, the flow of orders between marketmakers. (This measure of flow is the most transparent to the marketmakers and therefore plays the most important role in updating their beliefs.) This feature of the model corresponds well to reality and produces estimable equations because this type of flow data is available (largely because this type of trading occurs electronically, unlike data on trades between marketmakers and the public). Third, the earlier version of the portfolio shifts model provides underlying economics for why price effects from order flow should persist. The basic reason is that flow innovations provide signals about stochastic portfolio shifts (such as those due to changing hedging demands by a subset of agents). These portfolio shifts must be reabsorbed in equilibrium by the rest of the market, so if the shifts are persistent, the effects on price are persistent too. Cao, Evans, and Lyons (2003) provide empirical evidence that significant, permanent effects of order flow on price are indeed present (in the same data we analyze here).

This paper's extension of the portfolio shifts model introduces macro news arrivals whose implications for the exchange rate are not common knowledge.[16] Specifically, the information in news has two components. The first component is a common-knowledge (or "mean") part: all agents agree what the first part's impact on the exchange rate should be. (This will be the source of the direct effects on the

[16] An earlier version of this paper provides formal treatment of this change in information structure. Though the change is fundamental, it does not involve a fundamental change in the analytics, so we omit it here to conserve space. A copy of that earlier version is available at faculty.haas.berkeley.edu/ lyons/MacroNewsOld.pdf.

exchange rate.) The second component is the part whose implication for the exchange rate is not common knowledge. Suppose, for example, that all agents do not have access to the same technology for transforming the macro data into an exchange rate forecast. The information in this second part is thus dispersed throughout the economy and for price-setting marketmakers to aggregate it, they need to learn from the public trades that are induced by it.[17]

The model produces three basic channels through which information affects prices. The first is the traditional direct channel for public information: the common-knowledge part of macro news is reflected instantaneously in price, a process that does not rely in any way on the flow of transacted orders. The second channel is for the part of news that is not common knowledge: information in the induced order flow is impounded in price as the flow is realized. The third is the channel for information in other types of order flow, i.e., order flow unrelated to macro news flow (such as trades motivated by shocks to individuals' hedging demands or shocks to banks' effective risk aversions due to capital constraints, etc.).

The model leads to the following empirical specification for daily price changes and order flow:

$$\Delta p_t = \alpha x_t + \xi_t + \kappa_t \tag{1}$$

$$x_t = e_t + \eta_t \tag{2}$$

where Δp_t is the change in the exchange rate (DM/$) from the end day t-1 to end day t and x_t is order flow between marketmakers realized over the same period. The parameter α captures the price impact of order flow, i.e., it reflects the information content of order flow (the assumption of a constant price-impact parameter is relaxed below). Prices and order flow are subject to four shocks representing different sources of information hitting the market: ξ_t, κ_t, e_t, and η_t. These shocks are mean zero, mutually uncorrelated, and serially uncorrelated. The ξ_t and κ_t

[17] 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. But news often induces follow-on trading by end-user customers, whose trading responses are not instantaneous, and these trades, when realized, induce knock-on trades between marketmakers.

shocks represent information that is impounded in price directly. ξ_t is the common knowledge effect of macro news arrivals on the exchange rate. κ_t represents other factors directly impounded in prices, i.e., factors unrelated to both order flow or macro news events (possibly noise). Order flow is driven by the e_t and η_t shocks. The e_t shocks represent order flow effects from macro news arrivals—the non-common-knowledge effect of the news. Shocks to order flow that are unrelated to macro news (i.e., portfolio shifts arising from other sources such as changing risk tolerances or hedging) are represented by the η_t shocks.

Does it make sense that the common-knowledge effect of macro news arrivals ξ_t should be orthogonal to the order flow innovations e_t and η_t? This is clearly important for identifying our model, so let us address it in more detail. That public information—understood to have common-knowledge implications—does not affect order flow is a working premise with a long history in empirical finance, dating back at least to the work of Hasbrouck (1991), and serving as the basis for much important work by various authors since then (see, e.g., Madhavan, Richardson, and Roomans 1997 and the survey in Madhavan 2000). To understand why it makes sense, it is important to distinguish clearly between order flow, which is signed, and volume, which is unsigned (i.e., cannot be negative). It is quite plausible that public news should induce trade in assets (due, perhaps, to portfolio rebalancing). But trade in assets is volume, not order flow. On average, the signed order flow implications of common-knowledge price adjustments are zero: the new price, if it is a market-clearing price, should not systematically favor imbalances of sell orders over buy orders, or vice versa. Thus, there should not be a correlation between bad public news for the DM and subsequent net DM sell orders, so long as the update of the market price is rational (and this point is robust to whether the price change induces any portfolio rebalancing).

To the above specification we add one last feature: room for contemporaneous returns to enter the order flow equation (2). Within the motivating theory, an effect of returns on order flow is not optimal. But as an empirical matter, estimating an overly restrictive model is not necessary. Specifically, we enrich the model in equations (1) and (2) to the following:

$$\Delta p_t = \alpha x_t^* + \xi_t + \kappa_t \quad (3)$$

$$x_t = x_t^* + x_t^+ \quad (4)$$

$$x_t^* = e_t + \eta_t \quad (5)$$

$$x_t^+ = \phi \Delta p_t \quad (6)$$

This specification includes an additional component of order flow, x_t^+, which is driven by contemporaneous returns. Though as econometricians we observe only the composite order flow x_t, the parameter ϕ governing x_t^+ is easily estimated within our GMM framework.

The estimation strategy in our daily analysis relies on identification through conditional heteroskedasticity. The key conditioning variable is the number of macro news arrivals between the end of day t-1 and the end of day t, A_t. We allow the variance of the ξ_t and e_t shocks to increase with the number of news arrivals:

$$Var(\xi_t) = \omega(A_t) \quad \text{and} \quad Var(e_t) = \sigma(A_t) \quad (7)$$

where $\sigma(0) = \omega(0) = 0$, with $\sigma'(.) \geq$ and $\omega'(.) \geq 0$. This specification implies that neither the ξ_t nor the e_t shocks affect prices on days when there are no news arrivals. (Moreover, we do not introduce effects on the conditional means of either returns or order flow, an assumption we examine empirically below.) The shocks κ_t and η_t are independent of news, so their variances are unrelated to A_t. We assume these variances are constant:[18]

$$Var(\kappa_t) = s_\kappa \quad \text{and} \quad Var(\eta_t) = s_\eta \ . \quad (8)$$

[18] It is well known that return variances are not constant over time. But this is not what we are assuming: the assumption here is that these variances are constant once one has controlled for order flow and news flow. In any case, we test this empirical restriction when implementing the model.

To estimate the model described in equations (3) – (8) we specify linear forms for the variance functions $\sigma(A_t)=\sigma A_t$ and $\omega(A_t)=\omega A_t$, which we later subject to diagnostic testing. The six parameters of the model $\{\alpha,\sigma,\omega,\phi,s_\kappa,s_\eta\}$ are estimated by the Generalized Method of Moments (GMM), with conditions on second moments playing the central role in identification. (Estimation details are described in the Appendix.) The answer to the central question of this paper—does order flow help to transmit macro news to exchange rates—amounts to a test of whether the parameters σ and α are positive (i.e., σ governs the impact of news on order flow variance and α governs the signed impact of order flow on prices). The relative importance of the direct and indirect news channels can be determined from the relative sizes of the estimated parameters ω and σ.

To illustrate how identification through heteroskedasticity is achieved in the model, consider how the two key parameters α and ϕ relate to the covariance between price changes and order flow. Equations (5)-(8) imply the following expression for that covariance:

$$Cov(\Delta p,x) = \alpha(1+\alpha\phi)Var(e+\eta) + \phi Var(\xi+\kappa).$$

Identification is achieved by considering how the moments in the data change with macro news flow. (The Appendix provides the full set of moment conditions used in estimation.) In particular, the arrival of macro news affects both terms on the right-hand side: from equation (7), both Var(e) and Var(ξ) increase, where the former is the indirect order-flow effect on price and the latter is the direct effect on price. The resulting change in Cov(Δp,x) depends on the values of α and ϕ. While this link alone is insufficient to identify α and ϕ, these parameters also determine how macro news affects the variances of order flow and price changes. Taken together, data on changes in Cov(Δp,x), Var(Δp), and Var(x) that are induced by daily variation in news arrival A_t (through A_t's impact on Var(e) and Var(ξ)) are sufficient to identify all the parameters of the model.[19]

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[19] The covariance equation above also clarifies why positive values of α or ϕ could in principle account for the positive *unconditional* covariance between price changes and order flow. The estimates determine whether this covariance arises because order flow has a positive price impact or because

There are at least two reasons why contemporaneous returns might enter the daily order flow equation.[20] The first is aggregation bias. As we show in the Appendix (end of "Intraday Analysis" section), when the intraday relationship between order flow and returns has an extended intertemporal structure, then the simple sums that daily data represent cannot capture the relationship fully. In this case, time-aggregated order flow x_t is not quite the right measure to include as a regressor in equation (1). As a result, joint estimation of equations (5) through (8) will produce a non-zero ϕ. The second reason why contemporaneous returns might enter the daily order flow equation is intraday feedback trading.[21] (In daily data, intraday feedback trading would appear contemporaneous.) If intraday returns do not follow a martingale then individuals might rationally choose a feedback strategy. For example, if intraday returns exhibit reversals (and they do, as we show), then negative feedback trading would be the rational response.

Though our specification in equations (3)-(6) address reverse causality (from returns to order flow), there is another causality issue we have not yet addressed: Can positive macro news cause an increase in both order flow and price (with no causality from order flow to price)? This is essentially the same question we addressed above when examining whether the common knowledge effect from macro news ξ_t should be orthogonal to our model's order flow innovations. Recall from that discussion that positive news that systematically increases signed order flow would be inconsistent with rational expectations. The reason is because—under rational expectations—public information is impounded in price instantaneously. At the new price, which fully impounds the public information, there is no longer

price changes feedback positively into order flow. We also estimated a version of the model where total order flow x is included in equation (3), as opposed to the non-feedback-driven flow x*. Estimates from this alternative specification are not substantially different from those we report in Table 2.

[20] At the daily frequency, order flow and lagged returns in our data are uncorrelated, so we do not lose generality by including only contemporaneous returns in the order flow equation.

[21] That feedback trading is even feasible on average, given that in our data marketmakers are on both sides of every transaction, is not obvious. In equilibrium, marketmakers would anticipate these inter-marketmaker feedback trades and would seek to undo the effects on their positions. Clearly, this would not be possible via trading only with other marketmakers: somebody has to take the other side of these trades. Might end-user customers be taking the other side, i.e., engaging in negative feedback on average? This is possible, but not very satisfying intellectually. Osler (2003) reports evidence on the types of orders non-marketmakers actually submit. For evidence on the currency transaction flows of institutional investors, a specific class of non-marketmaker, see Froot and Ramadorai (2002).

motivation for dollar buying relative to dollar selling.[22] The change in price level may induce trading at the new price (i.e., unsigned volume). But on average good news for the dollar will not produce positive order flow in the aggregate at the new price (a relative increase in transactions initiated by dollar buyers).

The theory on which we base our empirical models is subtler. Part of the public news maps directly into price, as in the traditional story. (This is the shock ξ_t, which surely corresponds to what 33 percent of marketmakers have in mind when they state that the FX market adjusts to news in less than 10 seconds; see Cheung and Chinn 2001). But if to some degree market participants are drawing different inferences from common macro data, then price-setting marketmakers need to clear the market by determining the inferences of others (which they cannot know a priori). How do they learn them? The answer from microstructure theory is that they learn over time from the sequence of submitted orders. In this case, price adjusts instantaneously to the marketmaker's rational expectation of the market's interpretation, and then goes through a period of gradual adjustment caused by the sequence of transacted orders. This possibility has never been directly tested in foreign exchange markets.[23]

Daily Results

We turn to the empirical model in equations (5) through (8) for sorting out the direct versus indirect (via order flow) effects of news. The full empirical model embeds six parameters, $\alpha, \omega, \sigma, \phi, s_\kappa,$ and s_η. The parameter α captures the price impact of order flow. For the central question of this paper—how is macro news transmitted to exchange rates—the key parameters are ω and σ. ω governs the direct effect of news on price: the greater the number of news arrivals A_t the higher

[22] One way to produce this non-causal correlation between order flow and price changes is if market-makers are able to execute dollar purchases against other marketmakers before price adjusts to the public information. But this would require irrationality on the part of the quoting marketmaker: by not instantaneously impounding the public information in price he is permitting trades at "stale" prices, clearly a losing proposition. (This type of staleness is more of an issue with data from limit-order trading since existing orders may not be monitored continuously.)

[23] This statement now deserves a caveat because subsequent to public distribution of our paper, another paper has addressed the same issue; see Love and Payne (2002). See also a preceding paper by Melvin and Yin (2000) that shows that super-normal news flow produces super-normal quote arrivals (and also super-normal return volatility).

the variance of this component of daily returns. σ governs the direct effect of news on order flow: the greater the number of news arrivals A_t the higher the variance of this component of daily order flow.[24] The variance s_κ reflects the component of daily returns not explained by order flow or news. The variance s_η reflects the component of daily order flow not explained by news.

Table 2 reports GMM parameter estimates together with standard errors calculated from the asymptotic covariance matrix (allowing for heteroskedasticity).[25] The table reports estimates for specifications using the flow of all news arrivals lumped together (labeled All News) and also with the U.S. and German news introduced separately. In both specifications the estimate of the price-impact parameter α is positive, as the theory predicts, and statistically significant. (Its size corresponds to a price impact of roughly 50 basis points per $1 billion in order flow.) The parameter ϕ, which captures the contemporaneous effect of returns on order flow, is negative and significant. Recall that we offered two reasons why a negative relationship might exist here: temporal aggregation bias and negative feedback trading (on average) by marketmakers. We address these hypotheses in more detail in our intraday analysis. (At this stage, let us simply add that it is comforting that these results regarding news effects are robust to including a role for ϕ. The overall news results are essentially unchanged when we restrict ϕ equal to zero.) With all news arrivals lumped together, both of the key parameters ω and σ are significant and correctly signed (positive), implying that both direct and indirect effects of news on price are present. When U.S. and German news events are introduced separately (last column), both of the ω estimates are significant and correctly signed (positive). Also, the effect of German news on order flow volatility (σ_g) is positive and significant. The effect of U.S. news is of similar size but is not significant at the five

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[24] Though the derivation for model equation (1) does not call for order flow lags, whether they are relevant empirically is a legitimate concern. The daily analysis in Evans and Lyons (2002a) shows, however, that order flow lags are insignificant when included in this specification. Indeed, our order flow measure shows no persistence in daily data, nor do daily returns, so we are not omitting any variables that a non-structural VAR approach would identify as significant.

[25] Though not reported, we estimated the model allowing the price-impact parameter α to vary linearly with the number of announcements: the coefficient on the incremental announcement effect was positive but not significant. We also tested whether announcement effects on the variance of order flow might be non-linear (by modeling the variance of e_t as σA_t^γ), but found no evidence of this either.

percent level. (Recall that the median number of daily German news arrivals is nearly three times that for U.S. news arrivals.) In both specifications, the two (unconstrained) variance parameters s_κ and s_η are quite significant. The next rows of the table report Wald statistics for various parameter restrictions. The first two of these rows show that in the unrestricted model (i.e., with U.S. and German news separated), the null that the direct and indirect news channels are insignificant are strongly rejected. From the third row, the restriction that both of the ω and σ coefficient pairs are equal cannot be rejected, which provides support for the restricted specification in the All News column.

Important summary statistics are provided in the final rows of Table 2. The three rows labeled with $R^2_{\Delta p}$ present the fraction of total variance in price attributable on average to the direct and indirect effects of news. In both cases ("All News Together" and "US/German News Separate") the indirect channel through order flow is roughly twice the size of the direct effect: about 20 percent versus about 10 percent, respectively.[26] The final row presents the P-value for the test that the direct effect is larger than the indirect effect. In the restricted (All News Together) model, the hypothesis that the direct effect is larger is rejected at about the 1 percent level. (Recall that the restrictions on that model are not rejected.)

To summarize, we do indeed find that order flow helps transmit macro news to exchange rates. Roughly 20 percent of the daily movements in spot rates can be linked to macroeconomic news through the indirect order-flow channel. Through the direct (traditional) channel, macro news accounts for about 10 percent of daily price movements.[27] Given rejection of the test for whether $R^2_{\Delta p}(direct) > R^2_{\Delta p}(indirect)$, we conclude that at least half of the effect of macro news on the exchange rate is

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[26] Given that much of the past work on news and exchange rates implicitly assumes that the indirect channel is not present, we also estimate our daily model with the (rejected) restriction that σ equals zero. We find that the $R^2_{\Delta p}$ from the direct channel rises above 10 percent, but only to 13.6 percent, i.e., it does not rise to anywhere near the 29 percent we find for both channels. This may help explain why the explanatory power of news in our model is relatively high (see too the analysis below of the subset of scheduled announcements).

[27] Noise in our measurement of news arrivals may bias down our estimates of the total percentage of price variance from news flow, but it is not obvious why this should bias our estimates of the *relative* importance of the direct and indirect channels. With respect to the possible biasing down of the total percentage, note that our results are positive in this respect (i.e., we find a large percentage relative to existing literature); eliminating the bias, if it exists, would only make our result more striking.

transmitted via order flow. Finally, let us provide a big-picture accounting from these point estimates. The analysis in Evans and Lyons (2002a) shows that about 60 percent of daily DM/$ price variation is due to order flow and about 40 percent is due to other factors. The results in Table 2 shed light on both of these pieces. They suggest that order flow's 60 percent breaks into 20 percent that is induced by macro news and 40 percent that is not news induced. The 40 percent due to other factors in that earlier work breaks into 10 percent from the direct effect of macro news and 30 percent that remains unaccounted for.

Robustness

In this subsection we consider several potential robustness issues. First, we provide some further analysis of the feedback-trading hypothesis. Suppose one thought that observed order flow is the sum of exogenous order flow x_t^*, and a "feedback" component proportional to the change in price expected in the *future*:

$$x_t = x_t^* + \phi E[\Delta p_{t+1} | \Delta p_{t-1}]$$

In this case, measured order flow might respond to past price changes because those changes lead to revision in feedback traders' forecasts of future price changes. One way to test whether this ϕ equals zero is to consider the instrumental variables (IV) regression:

$$x_t = \phi \Delta p_{t+1} + a_1 x_{t-1} + a_2 x_{t-2} + \ldots\ldots. v_t$$

where Δp_{t-1} can be used to instrument for Δp_{t+1}. When estimated, we find that the IV ϕ estimates are insignificantly different from zero. Though not obvious, this is in fact what one would expect because in these data future price changes are unpredictable based on past price changes alone (see the autocorrelations in Table 1). There is simply no evidence here to suggest that past price changes should generate current order flow because they forecast future returns.

Our second robustness issue is the following question: Are our results due to our use of a broad measure of macro news rather than the much smaller set of scheduled announcements? To address this we turn to the subset of our news data that represents scheduled macroeconomic announcements, the subset for which we have ex-ante survey expectations for measuring announcement innovations. We focus on four U.S. announcements in particular, all of which are consistently among the most important in past event studies: Non Farm Payroll, Durable Goods, Trade Balance, and Unemployment Claims.[28] We create a set of standardized forecast errors using the sample standard deviations of the measured innovations. Then, for each day in the sample we construct an index A_t equal to the sum of the absolute standardized forecast errors. Then we re-estimate our model in Table 2 using this alternative measure of macro news flow. The results from this version of the model are in Appendix Table 1.

The results are similar in some ways to those in Table 2, but quite dissimilar in other ways. They are similar in that the parameter ϕ is still negative and still significant. The key parameters ω and σ are also still positive and significant (at the 4 and 6 percent levels, respectively). The big difference is in the bottom line: the variance ratios are 0.014 for the direct channel and 0.028 for the indirect channel (All News Together case), implying that these scheduled announcements account for only about 4 percent of total exchange rate variance. Thus, using this more limited measure of news accounts for far less of the daily price variance than the full set of Reuter's Money Market Headline News. This is consistent with past work, which shows that scheduled announcements account for less that 10 percent of daily price variance. Thus, it does appear that using news rather than just scheduled announcements helps account for our finding that a large share of volatility is due to public information arrival.

Appendix Table 1 also speaks to a related robustness check: might our use of macro news rather than the subset of scheduled announcements account for the indirect channel (via order flow) being twice as important for exchange rate variance as the direct channel (i.e., roughly 20 of 30 percent)? Note that the ratio of indirect to direct effects in Appendix Table 1 remains about the same as those in

[28] We select these announcements to give the "scheduled announcement" model a greater chance of success. In fact, results from including all the scheduled U.S. announcements for which survey expectations are available are even poorer than the results we report, presumably because most of these other announcements are insignificant for exchange rates (as shown in earlier work). For German announcements, there is little empirical basis for selecting the more significant announcement types so we include all those announcements for which we have survey expectations.

Table 2, namely 2 to 1, suggesting that the relative importance of the indirect channel is not due to our use of all news arrivals.

As a final type of robustness check we turn to regression analysis to examine the sources and form of heteroskedasticity. We consider (i) the extent to which news flow can account for the conditional variance of returns and order flow and (ii) whether the linear specifications of the variance functions $\sigma(A_t)$ and $\omega(A_t)$ in our baseline model are warranted. As described in the Appendix, we test for news-related heteroskedasticity by regressing the daily conditional variance of returns on a constant and the daily news flow A_t. We perform the same regression for the daily conditional variance of order flow. We find a significant direct effect of news on the conditional variance of prices (see Appendix Table 2). We also find a significant direct effect of news on the conditional variance of order flow. The first of these two results is consistent with existing literature. The second is new, though, and quite important to the economics underlying our model. (Both results are consistent with the visual evidence in the scatter plots in Figure 3.) Regarding potential non-linearity in the news-flow effects on the variance functions $\sigma(A_t)$ and $\omega(A_t)$, we find no evidence that squared news-flow terms should be included in the regression (see the "Non-Linear" column in Appendix Table 2).

To summarize the robustness results above, we find that our use of news rather than the much smaller set of scheduled announcements is important for explaining a large fraction of exchange rate variation. Our use of news is also important for understanding why the model explains so much exchange rate variation relative to existing literature. In contrast, our use of news does not appear to be important for the result that the indirect macro news channel is at least as important as the direct channel. In addition, our regression analysis finds a strong effect of news flow on order flow volatility: the order flow process is not orthogonal to public news, as rational expectations modeling of public news would predict. Finally, our regression results support the linear specifications we adopt in our GMM model and corroborate that both direct and indirect price effects from news are present.

3. Intraday Analysis

Our second approach complements the daily analysis above by examining intraday data, specifically five-minute data. We have seen from Figure 4 that order-flow and price responses to news are significant for up to two hours. Clearly, higher-frequency structure is present. How to capture it is less clear. There are two powerful reasons, why a simple high-frequency implementation of our daily model is not appropriate. First, variance estimates from ultra-high-frequency data over separate 5-minute windows are going to be quite noisy. Indeed, Evans (2002) shows that ultra-high-frequency variance estimation is picking up primarily variation in the *cross-section* of prices (across marketmakers) rather than time-series variation. This is clearly not what our earlier model is designed to address. (See also Zhou 1996 for an analysis of how quickly signal-to-noise ratios decay when increasing sampling frequency above five minutes.)

The second reason our daily model is not appropriate at high frequency is sequencing complexity. Figure 5 clarifies that even when causality runs wholly from order flow to prices, the response of price to order flow in ultra-high frequency data can be split into three phases, one where price adjustment precedes interdealer order flow, one where they are concurrent, and one where price adjustment follows interdealer order flow. (Recall that this paper's empirical analysis uses order flow measured from interdealer trades.) To understand why, consider the first event in the process of foreign exchange trading—the desire to transact on the part of the non-dealer customer. This is not the order flow we measure, however. Trades between marketmakers (measured by x_i) are temporally downstream from the initial customer order. If, for example, some information conveyed by customer orders is impounded in price when customer orders are executed, then price is adjusting *before* trades between marketmakers are induced, despite the fact that order flow—the customer order—is driving the price change (this is modeled, for example, in Evans 2001, pages 48-49). The bottom line is that the temporal link between our order flow measure x_i and price changes should involve both leads and lags. In this setting, methods that rely on strict temporal ordering to judge directions of influence are likely to be misleading (e.g., event-study methods).

Beyond the rather striking intraday results in Figure 4, where does this leave us? There are three topics on which the following analysis sheds light. First, we want to know whether news arrival alters the importance of order flow in exchange rate determination. For example, if order flow explains about 60 percent of daily variation in DM/$ rates on average (Evans and Lyons 2002a), is this explanatory power lower at times of macro news arrival? (The idea being that public news arrival is precisely when standard models would assert that order flow is not necessary to move price.) This question is best addressed with intraday analysis. Second, intraday analysis allows us to draw conclusions that are conditional on the horizon over which price effects last. For example, the price effects from news-related flow that we identify in daily data may in fact be rather transitory. (If so, their relevance to macroeconomists is much reduced.) This same analysis provides estimates of how much price variation at different horizons comes from order flow shocks, and how this changes with news arrival. Third, at high frequency we have sufficient statistical power to estimate the processes for both returns and order flow as state dependent. For example, allowing the price impact of order flow—an inverse measure of market "liquidity"—to depend on overall trading activity, or the arrival of news, enriches the allowable dynamics considerably.

Our intraday model, designed for use in five-minute data, is based on the same underlying economic environment as our daily model. In particular, it extends the empirical model in Evans (2002). This model takes the form:

$$\Delta p_i = B(L)v_i + \varepsilon_i \tag{9}$$

$$x_i = \tilde{C}(L)v_i \tag{10}$$

where now we use the subscript i to denote the five-minute frequency. Here, v_i represents dispersed information shocks, i.e., bits of information that are first manifested in order flow and then subsequently impounded in price. The dynamic responses of prices and order flow to these dispersed information shocks are determined by the lag polynomials $B(L)$ and $\tilde{C}(L)$. The other term in the price equation corresponds to common-knowledge news ε_i. (The shock ε_i includes both the ξ_t and κ_t shocks from the daily model. Our intraday analysis is aimed at questions for which it is not necessary to distinguish these.) The v_i and ε_i shocks are mutually independent and serially uncorrelated.

There are two key identifying assumptions: rational expectations (as before) and imperfect substitutability across different-currency assets. To understand the first, note that we require orthogonality between the common-knowledge news shock ε_i and the dispersed information shock v_i. This orthogonality derives from the rational expectations restriction that common-knowledge news shocks are impounded fully and instantaneously in price (see the discussion of causality within the daily model). The second identifying assumption maintains that all order flow x_i represents dispersed information. Imperfect substitutability together with rational expectations is sufficient to ensure this: with imperfect substitutability (i.e., aggregate foreign exchange demand that is imperfectly elastic), all order flow conveys information that is price relevant since all order flow requires price adjustment to achieve market clearing.[29] (The rational expectations assumption ensures this information is dispersed rather than public.) Based on this specification in equation (10) we shall address whether our intraday estimates are consistent with an aggregation-bias explanation for the negative estimates of ϕ (reported in Table 2).

As noted above, in ultra-high frequency data it is important to account for the timing of dispersed information shocks relative to the timing of the order flow we measure—interdealer flow (Figure 5). Trades between dealers are temporally downstream from initial customer orders. At the same time, trades between dealers can also precede price adjustment, for example, if those interdealer trades provide a signal for subsequent public information that will affect price on arrival. Our model needs to capture this fact that the temporal link between order flow x_i and price changes can involve both leads and lags.

[29] In the extreme of perfect substitutability, in contrast, order flow *can* include components that are price irrelevant. It is perhaps best to think of the dispersed information shock v_i in equation (10) as a composite shock that includes any information relating to narrowly defined fundamentals as well as information relating to portfolio balance effects on price.

To develop an estimable model, we proceed in two steps. First, we assume that the lag polynomial in the order flow equation, $\widetilde{C}(L)$, can be written as $L^m C(L)$ where $C(L)^{-1}$ exists (an autoregressive process). m denotes the number of (five-minute) periods between the first effects on price from a typical customer order and its subsequent effect on order flow between marketmarkers, x_i. With these assumptions we can rewrite equation (9) as

$$\Delta p_i = D(L)x_i + \varepsilon_i , \tag{11}$$

where $D(L) = B(L)L^{-m}C(L)^{-1}$. The polynomial $D(L)$ may take many forms depending on the dynamic responses of price and order flow to dispersed information shocks. Notice though that if $m > 0$ (consistent with the timing illustrated in Figure 4) then $D(L)$ should contain both leads and lags (because the polynomials $B(L)$ and $C(L)^{-1}$contain only non-negative powers of L). Based on the many tests presented in Evans (2002), we follow that paper in using a six-term polynomial: $D(L) = d_1 L^{-4} + d_2 L^{-3} + ... + d_6 L$ as our basic specification. Similarly, we find that the dynamics of order flow are well characterized if $C(L)^{-1}$ is an AR(10). In both cases, coefficient estimates on further leads/lags for price changes, and lags for order flow, are not statistically significant when more general specifications are estimated (see Evans 2002 for further diagnostics supporting these specifications). The specification for $D(L)$ allows a customer order to begin to have an impact on price up to 20 minutes before it affects order flow between marketmakers (i.e., m = 4).

The second step is to test whether the lag polynomials and the error variances are dependent on macro news having arrived. Evans (2002) reports strong evidence of dependence on trading intensity, n_i, measured as the number of transactions in observation window i. (Including trading intensity as a state variable is important for accommodating the pronounced time dependence in volatility documented by Andersen and Bollerslev 1998.) Here we extend the analysis by including macro news arrival as an additional state variable. Specifically, we construct dummy variables A_i^* and A_i that take the value of one if there was a news arrival (either U.S. or German) during the previous 15 or 5 minutes respectively.[30] The results in Appendix Table 3 shows that there is strong evidence for state-dependence in the return equation polynomial $D(L)$, with respect to both A_i^* and n_i, but not the order flow polynomial $C(L)^{-1}$. There is also strong evidence of heteroskedasticity related to A_i and n_i in the error variances.

These results point to the need to incorporate state-dependence into our intraday model. To this end, we consider an extension of (9) where $D(L)$ is replaced by $D(L, n_i, A_i^*)$, a state-dependent 6th order polynomial:

$$D(L,n,A^*) = d_1(n,A^*)L^{-4} + d_2(n,A^*)L^{-3} + ... + d_5(n,A^*) + d_6(n,A^*)L \ ,$$

with state-dependent coefficients $d_j(n,A^*)$. Thus, $d_6(n,A^*=1)$ is the coefficient on lagged order flow when trade intensity equals n and news arrived in the past 15 minutes $(A^*=1)$. We also allow for heteroskedasticity in the error variances, $Var(\varepsilon_i) = \Sigma_\varepsilon(n_i, A_i)$ and $Var(v_i) = \Sigma_v(n_i, A_i)$. State-dependence in the coefficients and variances is modeled as:

$$d_j(n,A^*) = d_j(0,A^*)\exp(-n/\gamma) + d_j(\infty,A^*)[1-\exp(-n/\gamma)] \tag{12}$$

$$\Sigma_j(n,A) = \Sigma_j(0,A)\exp(-n/\gamma) + \Sigma_j(\infty,A)[1-\exp(-n/\gamma)] \tag{13}$$

where $d_j(0,0)$, $d_j(\infty,0)$, $\Sigma_j(0,0)$, and $\Sigma_j(\infty,0)$ are the parameters to be estimated for observations without a news arrival, and $d_j(0,1)$, $d_j(\infty,1)$, $\Sigma_j(0,1)$, and $\Sigma_j(\infty,1)$ when there is a news arrival. Although these functional forms are somewhat specialized with respect to variations in trading intensity, they do not restrict how the flow of

[30] As noted, we use a dummy variable approach because the arrival of more than one news arrival during any 5-minute window is uncommon. (746 of 856 news items have no other news item in the same 5-minute window; in 49 cases there are two news arrivals in the same window and in 4 cases there are three arrivals. In no case are there more than three arrivals.) Note too that for our intraday analysis, there is no scope for using survey-measured expected values for scheduled announcements (to measure surprises) because even for monthly announcements there are only four forecast errors in our sample for each announcement type.

news affects price and order flow dynamics. Nor do they appear unduly restrictive when we subject our model to specification tests below.

Intraday Results

Table 3 presents GMM estimates of the intraday model. One measure of the importance of state-dependence in the price change dynamics is the sum of the order flow coefficients $D(1,n,A^{*})$. This measures the long run impact of order flow on the price level. The estimated $D(1,n,A^{*})$ varies considerably with both trading intensity and macro news flow. This is consistent with the findings of our state-dependence tests. It also accords well with the non-parametric evidence on state-dependence in hourly price change data reported in Evans and Lyons (2002b). The variation in the estimates of $D(1,n,A^{*})$ also underlines how the analysis of intraday data brings greater resolution to the study of return and order flow dynamics.

Before addressing the implications of our estimates, we examine a number of diagnostic tests (see Appendix Table 4). First, we examine the null hypothesis of no state-dependence in $D(1,n,A^{*})$. Consistent with our earlier results, this hypothesis is strongly rejected with respect to trade intensity and macro news flow. Second, we consider LM-type tests for mis-specification in the estimated $d_j(n,A^{*})$ and $\Sigma_j(n,A)$ functions. None of these tests are statistically significant suggesting that the estimated model has captured well the state-dependence related to trading intensity and news flow. Third, we examine whether the model captures all the heteroskedasticity in the data. Here we find evidence of some residual ARCH effects. So, while the model does appear to capture the state-dependent dynamics of prices and order flow with respect to trading intensity and news flow, it does not account for all the sources of heteroskedasticity. As a final diagnostic, we examine whether the estimated intraday model can account for the negative estimates of ϕ found in the daily model (i.e., from the specification in equation 6 that $x_t^{+} = \phi\Delta p_t$). Under the null of our intraday model, time-aggregated (i.e., daily) order flow x_t is only approximately equal to the correct measure of order flow that should be present in equation (1). Moreover, as the appendix shows, estimates of the intraday model imply that the approximation error is negatively correlated with daily price changes. In other words, the negative estimates of ϕ can arise through time-aggregation of the price and order flow dynamics that are described by our intraday model.

We now turn to the point of this section: How is the information in macro news transmitted to prices? To answer this question we use the GMM estimates to compute the fraction of price variance attributable to dispersed information across different market states. Specifically, our estimates allow us to write price changes as:

$$\Delta p_i = B(L, n_i, A_i^*) v_i + \varepsilon_i$$

where $B(L,n,A^*) = D(L,n,A^*) L^4 C(L)$. Using this equation, we can compute the fraction of the variance in a k-period price change due to v_i shocks for a given level of trade intensity and news flow. Table 4 shows that this fraction increases with trade intensity and horizon (as in Evans 2002). More importantly, however, there is a marked difference in the contribution depending on whether news arrives. For all trade intensities and horizons, dispersed information contributes more to the variance of price changes when news has arrived. Indeed, comparison of the first and second panels shows that order flow accounts for two to three times as much price variance when news has arrived. Thus, order flow is *more* important in exchange rate determination when news arrives, not less. The p-values for the hypothesis that there is no increase in the ratio, shown in the lower panel, are all small, particularly at the 5-minute horizon and in the limit as the horizon approaches infinity.

Robustness

In this subsection we consider several potential robustness issues at the intraday frequency. The first concerns the possibility of feedback trading. The last section of the appendix addresses whether in this empirical return environment feedback trading could possibly produce profits on average. There we consider feedback trading rules of a rather general form (equation A5) and examine profit outcomes from Monte Carlo simulations. Based on typical trade sizes in this market and reasonable levels of trading intensity, we find that strategies within the broad class we consider produce trading losses of about $1 million per month on average, with probabilities of monthly losses of about 60 percent. Moreover, these estimates are conservative in that they take no account of transaction costs (neither in terms of price impact nor spreads).

That feedback trading would not be profitable in this environment does not (for many people) rule out its presence. For these people we construct a lower bound on price variance due to order flow shocks by including only those price effects from flow that occur after flow. (We do this despite the message from Figure 4 that some order flow between dealers *should* lag price adjustment, even when causality is running wholly from order flow—end-user order flow—to price.) These lower-bound results are presented in Appendix Table 5 (following the same format as Table 4). As expected, by this measure order flow contributes less to the variance of prices unconditionally. But there is still strong evidence that order flow contributes more to the variance of prices in the presence of macro news. The essential finding in Table 4 is therefore robust to extreme views on the prevalence of feedback trading.

4. Conclusions

This paper extends the literature on exchange rates and public news in three main ways. First, our analysis is the first to address the presence of an indirect channel through which public news affects exchange rates (the question in the title). Second, methodologically we depart from existing literature by using identification based on heteroskedasticity, à la Rigobon and Sack (2002), rather than the event-study approach. Third, our methodology accommodates a much wider set of news events than the scheduled macro announcements that are the focus of event studies. Indeed, this third feature transforms the nature of the paper: it should be viewed as addressing news, not scheduled announcements.

To address the indirect channel, we test whether macroeconomic news is transmitted to exchange rates via induced transactions and if so, what share occurs via transactions versus the traditional direct channel. Our model distinguishes three sources of exchange-rate variation. The first source mirrors traditional models—public news that is impounded in price immediately and directly (i.e., with no role for order flow). The second source is an indirect effect of public news that operates via induced order flow. The third source of exchange rate variation is caused by order flow that is unrelated to public news arrival. No previous work has disentangled these three sources empirically.

Using DM/$ data from 1996, we find that all three sources of price variation are significant. Our point estimates at the daily frequency imply that about two thirds of the price effect from macro news is transmitted via order flow, with the remaining one third being the direct impounding of news in price. Unconditionally, the total effect accounts for about 30 percent of long-horizon exchange rate variance. We reject the null that the direct channel is the more important, implying that the indirect channel accounts for at least half of the effect of macro news on the DM/$ rate. These daily results are consistent with those at the five-minute frequency. In particular, our five-minute results in Table 4 show that when news arrives there is a 100-200 percent increase in the importance of order flow in price determination. This is inconsistent with the "macroeconomic" prior that order flow should be *less* important when public news arrives. These intraday results apply consistently when conditioning on both trading intensity and price-impact horizon.

More broadly, our results can be understood using the following spectrum. On one pole, price-setting marketmakers observe macro news, instantly calculate the exchange-rate implication, and instantly adjust all their prices by the same amount. On the other pole of the spectrum, marketmakers observe macro news but have no idea how to interpret it, or how the rest of the market will interpret it. Instead, they wait to observe any induced trades and set their prices and expectations based on the interpretations embedded therein. The first of these two poles represents all of current macro theory on exchange rates. Our results suggest instead that the world is nearer to the second pole. Note, though, that this pole does not imply irrationality: It may be rational for participants to draw different inferences from common macroeconomic data if, for example, agents observe common data with different prior beliefs (perhaps based on different information sets). In any event, whether this is rational is beyond the scope of this paper. We would simply emphasize that the phenomenon is not limited to the FX market: think, for example, of forecasts of the whole stock market, where these forecasts, too, should be based on common economy-wide data (Harris and Raviv 1993).

Why does this paper find that roughly 30 percent of total volatility comes from news whereas past work finds that announcement effects account for less than 5 percent? We offer three possible reasons. First, we consider macro news rather than just scheduled announcements. This explanation is consistent with our finding that when we estimate our model on scheduled announcements only (the more limited set used by others, for which survey expectations are readily available) we find they account for only 4 percent of total volatility. Second, we adopt a heteroskedasticity approach that mitigates a source of measurement error, in that it does not rely on measuring ex-ante news expectations (in contrast to the event-study approach). Third, we use a less restrictive model in the sense that we allow for an indirect channel and we allow flow responses to dispersed information to persist over extended periods. Event studies impose window lengths that constrain response times, typically less than one hour in intraday analysis. In practice, response times for some end-user customers, which includes time to reflect and, in many cases, time to build consensus among multiple decision-makers, surely extend beyond an hour.[31] This idea links rather naturally to the analysis in Andersen et al. (2003): they find that the impact effect of announcements on price—the first moment effect—is over quite quickly, whereas the effect on volatility is not immediate, with the full "impact" effect on volatility occurring only after about an hour (their Table 3). This is a lovely match with our finding in Figure 4 that effects on order flow and return variance reach their peak only after 60-90 minutes. Future analysis might address whether rates of volatility decay that differ across announcements provide an indicator of relative interpretation difficulty.

There is a second question, beyond the question in the title, that motivates this paper: What drives the order flow? Finding answers to this question that go beyond the traditional answers of "information" and "risk sharing" is a crucial—perhaps the crucial—challenge to microstructure research. This paper is one approach to answering this question. Results here suggest that about 1/3 of order

[31] Carlson (2002), for example, finds that in response to a public macro announcement, liquidity in an electronic interbank trading system (Reuters 2000-2) remained significantly below normal (and below its ex ante state) for about 2 hours. Even if *average* effects from news are reflected in prices quickly, as in Andersen and Bollerslev (1998) and Cheung and Chinn (2001), this does not imply that total effects are reflected quickly. Average effects may correspond to the direct, or rational expectations channel, which one would expect to be reflected more quickly than indirect, order-flow mediated effects.

flow and its resulting explanatory power comes from macro news (i.e., news-related flow accounts for about 20 percent of daily return variation, whereas all flow accounts for about 60 percent—on the latter, see Evans and Lyons 2002a). The bottom-line in accounting for daily return variation is then: 10 percent direct news effects, 20 percent news-related flow, 40 percent news-unrelated flow, and 30 percent still unaccounted for (rounded figures).

Finally, it would be heroic indeed for us to assert that causality between order flow and exchange rates is strictly one directional. It is, almost surely, two directional, at least under some circumstances.[32] That said, as a theoretical matter the portfolio shifts model underlying our analysis provides a clear formalization of one-directional causality, even in the face of public information. As an empirical matter, we allowed for the potential presence of reverse causality but found no evidence of the most commonly offered form, namely positive-feedback trading. Moreover, existing micro evidence of causality running from order flow to prices in stock, bond, and FX markets is so strong that there is no case for believing that causality runs wholly, or even largely, in reverse (for micro evidence in stocks and bonds see the survey by Madhavan 2000). Rather, we have presented many types of broadly complementary evidence that, together, make a strong case that indirect effects of news, via transactions, do indeed affect exchange rates. This evidence includes different data frequencies, different horizons, different identifying assumptions, etc. The story that emerges from the ensemble of evidence is clear, new, and substantial: by opening the order-flow channel, the ability of news to account for total exchange rate variation rises from the 1-5 percent found previously to roughly 30 percent, a sizable step in resolving the distressing puzzle of missing news effects.

[32] One possible channel of reverse causality is when exchange rate changes are large enough to induce distress at some institutions, causing them to sell into falling markets (and vice versa) for risk management purposes.

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Table 1: Sample Statistics

A: Daily Data

	Δp_t	x_t	$\lvert\Delta p_t\rvert$	$\lvert x_t\rvert$	News Arrivals US: A_t^{us}	News Arrivals German: A_t^{g}	News Arrivals Total: A_t
5%	-11.9	-308	0.1	5	0	2	2
25%	-3.8	-61	1.4	28	1	6	9
50%	0.3	8	3.7	83	2	8	11
75%	3.4	91	5.9	140	5	12	15
95%	6.9	186	11.9	319	7	18	21
Max	12.4	339	20.7	449	9	22	27
Min	-20.7	-449	0.0	0	0	0	0
Sdt. Dev.	5.9	136.4	3.8	97.9	2.2	5.1	6.0
Skewness	-0.8	-0.6	1.5	1.5	0.7	0.5	0.2
Kurtosis	3.8	4.5	6.1	4.9	2.6	3.0	2.6

B: 5-Minute Data

	Δp_i	x_i	$\lvert\Delta p_i\rvert$	$\lvert x_i\rvert$	n_i
5%	-1.4	-9	0.0	0	2
25%	-0.3	-2	0.1	1	6
50%	0.0	0	0.3	3	12
75%	0.3	3	0.7	5	21
95%	1.3	9	1.7	12	44
Max	5.0	69	7.9	72	212
Min	-7.9	-72	0.0	0	2
Sdt. Dev.	0.8	5.6	0.6	4.2	15.5
Skewness	-0.2	0.1	2.2	3.2	3.4
Kurtosis	7.4	12.6	10.8	22.9	23.2

Autocorrelations (p-values)

	Lag=1	2	3	4	5	6	12	18	24
Δp_i	-0.305	-0.010	-0.004	-0.003	-0.004	0.013	0.004	0.018	0.004
	(0.00)	(0.35)	(0.76)	(0.79)	(0.68)	(0.23)	(0.69)	(0.06)	(0.64)
x_i	0.231	0.105	0.093	0.077	0.060	0.058	0.027	0.023	0.004
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.65)

Notes: Sample covers four months from May 1 to August 31, 1996. Δp_t is 1000 times the change in the last DM purchase price for dollars between 4:00 pm on day t and day $t-1$. x_t is the total interdealer order flow over the same time interval. Δp_i and x_i are the corresponding price changes and order flows during 5-minute interval i, and n_i is the total number of trades, A_t^{us} and A_t^{g} are respectively the number of macro news arrivals observed on the Reuters Money Market Headline News screen relating to the US and Germany between 4:00 pm on day t and day t-1. Autocorrelations are computed from five-minute data by GMM, and the p-values are calculated from Wald tests of the null hypothesis of a zero correlation (allowing for conditional heteroskedasticity). There are 11,473 five-minute observations for the intraday analysis.

Table 2: Daily Model Estimates

$$\Delta p_t = \alpha x_t^* + \xi_t + \kappa_t \quad \text{with} \quad VAR(\xi_t) = \omega A_t \text{ , } VAR(\kappa_t) = s_\kappa$$

$$x_t = x_t^* + x_t^+ \quad \text{with} \quad x_t^* = e_t + \eta_t \text{, } VAR(e_t) = \sigma A_t \text{ , } VAR(\eta_t) = s_\eta \text{, } x_t^+ = \phi \Delta p_t$$

	All News Together		**US/German News Separate**	
Parameters	Estimate	Std. Err.	Estimate	Std. Err.
α	0.031	(0.002)	0.031	(0.002)
ϕ	-2.051	(0.172)	-2.048	(0.172)
s_κ	81.375	(10.714)	78.729	(9.761)
s_η	3.795	(0.502)	3.774	(0.493)
ω	2.791	(0.690)		
σ	0.168	(0.034)		
ω_{us}			4.896	(1.781)
ω_g			2.342	(0.912)
σ_{us}			0.176	(0.090)
σ_g			0.166	(0.039)
Wald Tests:			Statistic	P-value
$\omega_{us} = \omega_g = 0$			68.081	(0.000)
$\sigma_{us} = \sigma_g = 0$			25.230	(0.000)
$\omega_{us} = \omega_g$ & $\sigma_{us} = \sigma_g$			2.069	(0.355)
Variance Ratios	Ratio	Std. Err.	Ratio	Std. Err.
$R^2_{\Delta p}(direct)$	0.094	(0.037)	0.126	(0.036)
$R^2_{\Delta p}(indirect)$	0.232	(0.062)	0.205	(0.054)
$R^2_{\Delta p}(total)$	0.326	(0.069)	0.331	(0.068)
P-value: direct>indirect		(0.013)		(0.080)

Notes: The table reports GMM parameter estimates and asymptotic standard errors (corrected for heteroskedasticity) in parentheses. The Wald statistics are for the null hypothesis listed; p-values are reported in parentheses. The standard errors reported for the variance ratios are computed from a Monte Carlo experiment with 5000 replications. $R^2_{\Delta p}(direct)$ and $R^2_{\Delta p}(indirect)$ are the fraction of the daily variance in prices attributed to news arrival via the direct and indirect channels (i.e., via ξ_t and e_t, respectively). The p-value in the last line is for the null hypothesis that $R^2_{\Delta p}(direct) > R^2_{\Delta p}(indirect)$ and is calculated from the Monte Carlo experiment.

Table 3: Intraday Model Estimates (GMM)

$\Delta p_i = D(L, n_i, A_i^*)x_i + \varepsilon_i + \omega_i - \omega_{i-1}$ with $Var(\varepsilon_i) = \Sigma_\varepsilon(n_i, A_i)$, $Var(\omega_i) = \Sigma_\omega(n_i, A_i)$

$C(L)^{-1} x_i = v_i$ with $Var(v_i) = \Sigma_v(n_i, A_i)$

Price Eq.: No News Arrival

	x_{i+4}	x_{i+3}	x_{i+2}	x_{i+1}	x_i	x_{i-1}
Coefficients in $D(L,0,A_i^*=0)$	0.029	0.025	0.028	-0.047	-0.113	-0.034
	(0.024)	(0.057)	(0.233)	(0.052)	(0.025)	(0.033)
Coefficients in $D(L,\infty,A_i^*=0)$	0.127	0.275	0.543	0.629	-0.22	-0.062
	(0.106)	(0.210)	(0.716)	(0.186)	(0.078)	(0.101)

	$\Sigma_\varepsilon(0,0)$	$\Sigma_\varepsilon(\infty,0)$	$\Sigma_\omega(0,0)$	$\Sigma_\omega(\infty,0)$	$D(1,0,0)$	$D(1,\infty,0)$
	0.000	0.010	0.002	0.000	-0.113	1.293
	(N/A)	(<0.001)	(<0.001)	(N/A)	(0.030)	(0.106)

Price Eq.: News Arrival

	x_{i+4}	x_{i+3}	x_{i+2}	x_{i+1}	x_i	x_{i-1}
Coefficients in $D(L,0,A_i^*=1)$	-0.022	0.074	0.054	-0.131	0.002	-0.066
	(0.045)	(0.046)	(0.042)	(0.046)	(0.044)	(0.043)
Coefficients in $D(L,\infty,A_i^*=1)$	0.278	-0.018	0.256	0.858	-0.449	0.091
	(0.153)	(0.139)	(0.131)	(0.133)	(0.107)	(0.114)

	$\Sigma_\varepsilon(0,1)$	$\Sigma_\varepsilon(\infty,1)$	$\Sigma_\omega(0,1)$	$\Sigma_\omega(\infty,1)$	$D(1,0,1)$	$D(1,\infty,1)$
	0.000	0.006	0.002	0.000	-0.089	1.015
	(N/A)	(0.002)	(<0.001)	(N/A)	(0.070)	(0.209)

Order Flow Eq.

	x_{i-1}	x_{i-2}	x_{i-3}	x_{i-4}	x_{i-5}	x_{i-6}
Coefficients in $C(L)^{-1}$	0.210	0.036	0.048	0.033	0.019	0.025
	(0.014)	(0.013)	(0.012)	(0.012)	(0.011)	(0.011)

	x_{i-7}	x_{i-8}	x_{i-9}	x_{i-10}
	0.015	0.017	-0.016	0.020
	(0.010)	(0.012)	(0.010)	(0.008)

	$\Sigma_v(0,0)$	$\Sigma_v(\infty,0)$	$\Sigma_v(0,0)$	$\Sigma_v(\infty,1)$
	0.000	0.032	0.000	0.032
	(N/A)	(0.002)	(N/A)	(0.034)

Notes: GMM estimates with asymptotic standard errors in parenthesis corrected for conditional heteroskedasticity and an MA(1) error term. (Coefficients and standard errors in the first two panels are multiplied by 100.) The state-dependent polynomial in the price equation is $D(L, n_i, A_i^*) = d_1(n_i, A_i^*)L^{-4} + d_2(n_i, A_i^*)L^{-3} + \ldots + d_6(n_i, A_i^*)L$ where A_i^* is a dummy variable equal to one if there was a macro news arrival during the previous 15-minutes (i.e. 3 observation windows). State-dependency in the coefficients and variances is modeled as:

$$d_j(n_i, A_i^*) = d_j(0, A_i^*)\exp(-n_i/\gamma) + d_j(\infty, A_i^*)(1-\exp(-n_i/\gamma))$$

$$\Sigma_j(n_i, \lambda) = \Sigma_j(0, A_i)\exp(-n_i/\gamma) + \Sigma_j(\infty, A_i)(1-\exp(-n_i/\gamma))$$

where $\gamma = 100$, and A_i is a dummy variable equal to one if there was a news arrival during the previous 5-mintues.

Table 4: Percentage Price Variance From Order Flow Shocks

News Arrival

Trade intensity n	Horizon (minutes) 5	30	60	120	∞
10	5.123	12.137	13.597	15.072	15.497
	(0.955)	(3.282)	(3.924)	(4.580)	(4.768)
20	7.981	15.754	17.101	18.380	18.734
	(1.941)	(5.593)	(6.399)	(7.158)	(7.367)
30	11.214	19.163	20.358	21.448	21.742
	(3.192)	(7.949)	(8.887)	(9.737)	(9.965)

No News Arrival

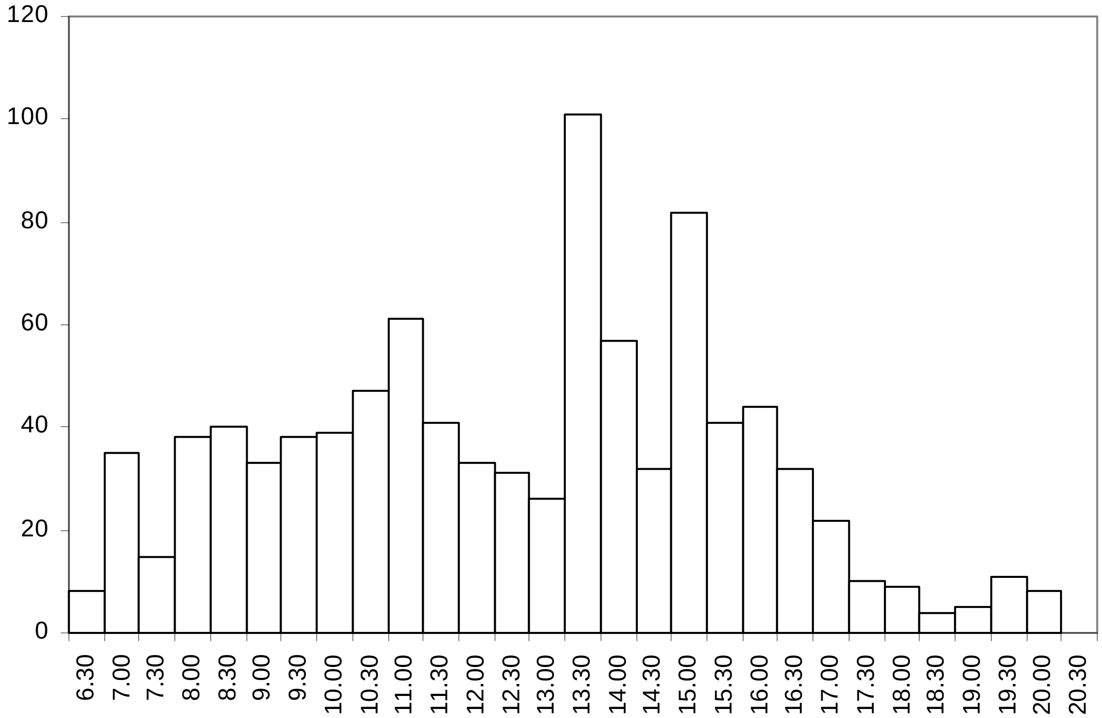
Trade intensity n	Horizon (minutes) 5	30	60	120	∞
10	1.436	2.314	2.118	1.863	1.775
	(0.822)	(1.837)	(2.343)	(3.005)	(0.304)
20	3.808	7.475	7.957	8.454	8.599
	(0.968)	(2.048)	(2.378)	(2.728)	(0.508)
30	7.173	14.862	16.129	17.307	17.628
	(1.244)	(2.676)	(2.948)	(3.203)	(0.964)

P-values: No increase in variance ratio

Trade intensity n	Horizon (minutes) 5	30	60	120	∞
10	0.006	0.005	0.009	0.014	<0.001
20	0.003	0.022	0.029	0.037	0.001
30	0.013	0.124	0.147	0.165	0.018

Notes: Estimated from five-minute data (model in Table 3). The upper two panels report the percentage of price variance over various horizons due to order flow shocks, given trade intensity n, with and without concurrent news arrival. (From Table 1, the median number of trades n per five-minute interval is 12 and the 75th percentile is 21.) The standard errors reported in parenthesis in the upper panels, and p-values shown in the lower panel are calculated from 5000 Monte Carlo draws from the estimated asymptotic distribution of the GMM estimates.

Figure 1: Sample Distribution of News Arrivals



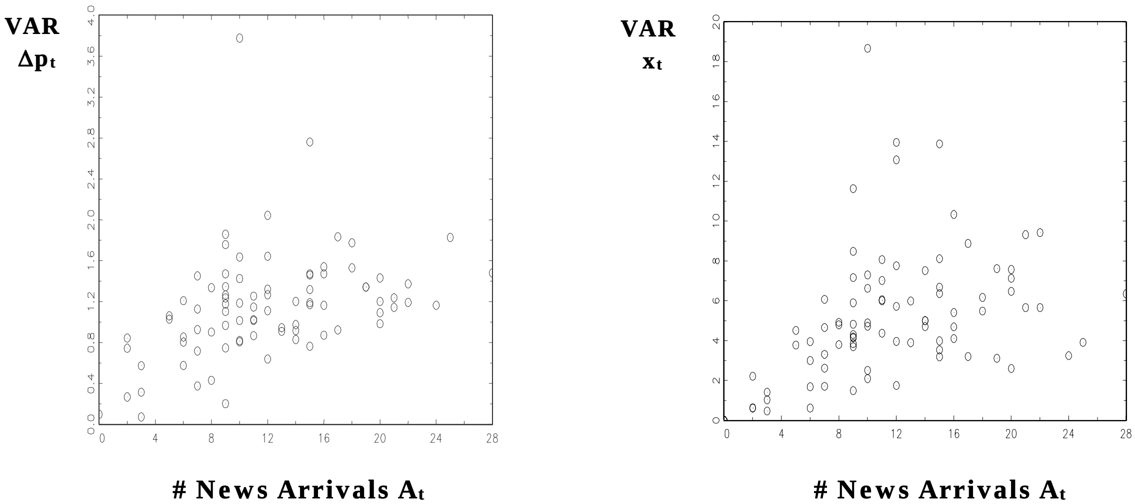
Notes: Distribution of all news arrivals by 30 minute interval starting at the interval centered at 6:30 BST and ending at the interval centered at 20:00 BST. Sample: May 1 to August 31, 1996. Data on news arrivals are from the Reuters Money Market Headline News screen.

Figure 2: Macro News Sample

Date	Time	News
05/01/96	13:05:22	MARCH U.S. LEADING INDICATORS SHOW ECONOMY EASING
05/01/96	14:00:50	U.S. MARCH CONSTRUCTION SPENDING ROSE 3.1 PCT
05/01/96	14:10:14	MARCH U.S. CONSTRUCTION SPENDING REBOUNDS STRONGLY
05/02/96	6:05:18	GERMAN MARCH IMPORT PRICES CLIMB 0.3 PCT M/M
05/02/96	8:33:10	BUNDESBANK DOES NOT PLAN NEWS CONFERENCE TODAY
05/02/96	9:48:20	GERMAN CALL MONEY FALLS BACK TO 3.30/40 PCT
05/02/96	10:50:08	BUNDESBANK LEAVES INTEREST RATES UNCHANGED
05/02/96	10:51:56	GERMAN MARCH INDUSTRIAL OUTPUT DATA DUE 1130 GMT
05/02/96	12:30:40	U.S. JOBLESS CLAIMS FELL IN LATEST WEEK
05/02/96	12:31:00	U.S. Q1 1996 REAL GDP ROSE 2.8 PCT
05/02/96	14:00:30	U.S. MARCH FACTORY ORDERS ROSE 1.5 PCT
05/02/96	15:01:54	U.S. Q1 GDP SURGE SEEN JUST A BLIP IN MODEST TREND
05/02/96	15:10:32	GERMAN EMPLOYER TO OPPOSE ANTI-WAGE DUMPING LAW
05/03/96	9:56:32	GERMAN CALL MONEY EASES SLIGHTLY AHEAD OF WEEKEND
05/03/96	12:30:38	U.S. APRIL NON-FARM PAYROLLS ROSE 2,000
05/03/96	12:31:00	U.S. MARCH PERSONAL INCOME ROSE 0.5 PCT
05/03/96	12:38:44	U.S. JOBLESS RATE LOWER BUT LABOR MARKET LOOKS WEAK
05/03/96	13:42:16	MARCH US INCOME DATA SHOW MODEST GROWTH, INFLATION
05/03/96	14:00:16	U.S. MARCH HOUSING COMPLETIONS ROSE 5.1 PCT

Notes: The figure shows the macro news arrivals on the first 3 days of our sample (May 1 to May 3, from the total sample from May 1 to August 31, 1996). Time is measured as British Standard Time (BST).

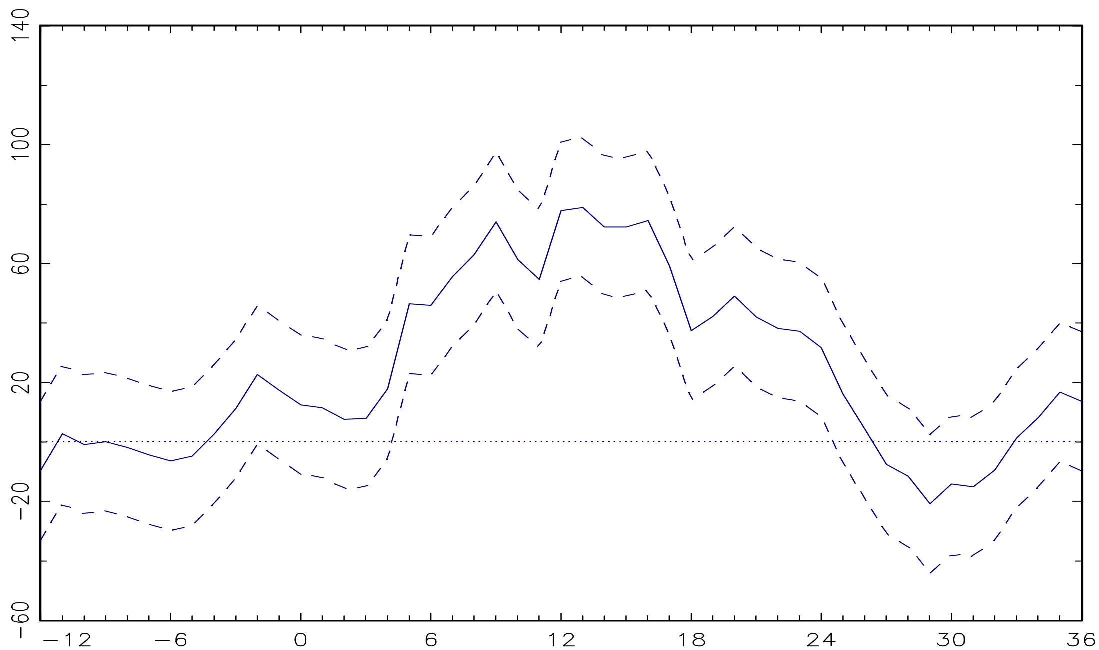
Figure 3: Daily Price and Order Flow Volatility



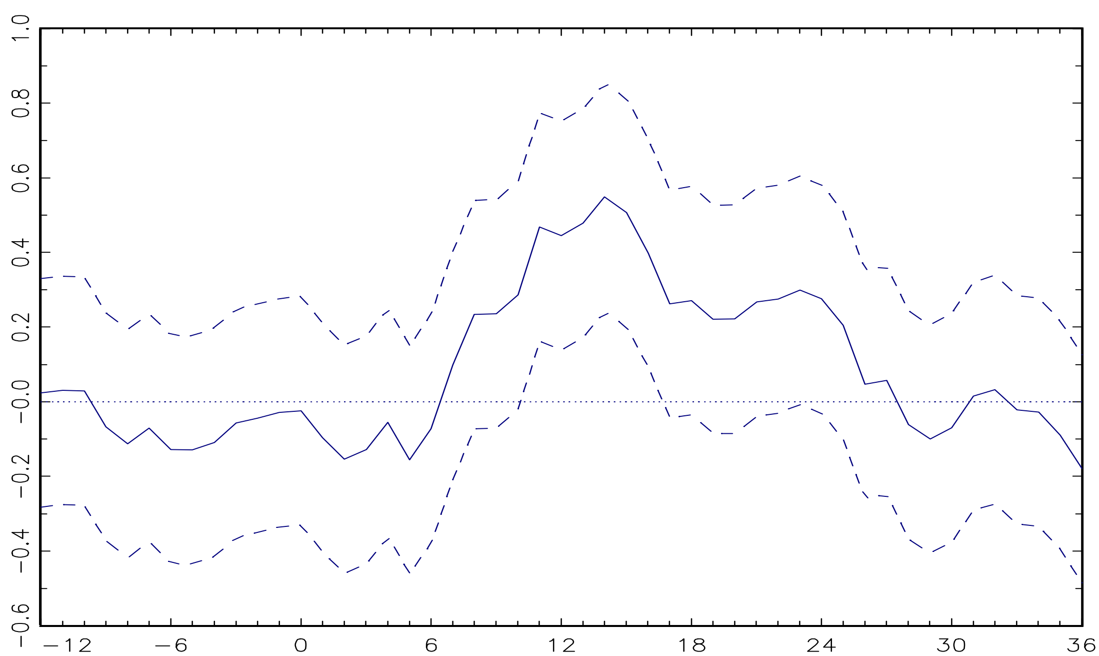
Notes: Daily data from May 1 to August 31, 1996. Data on news arrivals A_t are from the Reuters Money Market Headline News screen. Daily realized variances for Δp_t and x_t are integrated variance measures based on a five-minute sampling frequency (Andersen et al. 2001).

Figure 4

I: Excess Variance of Order Flow

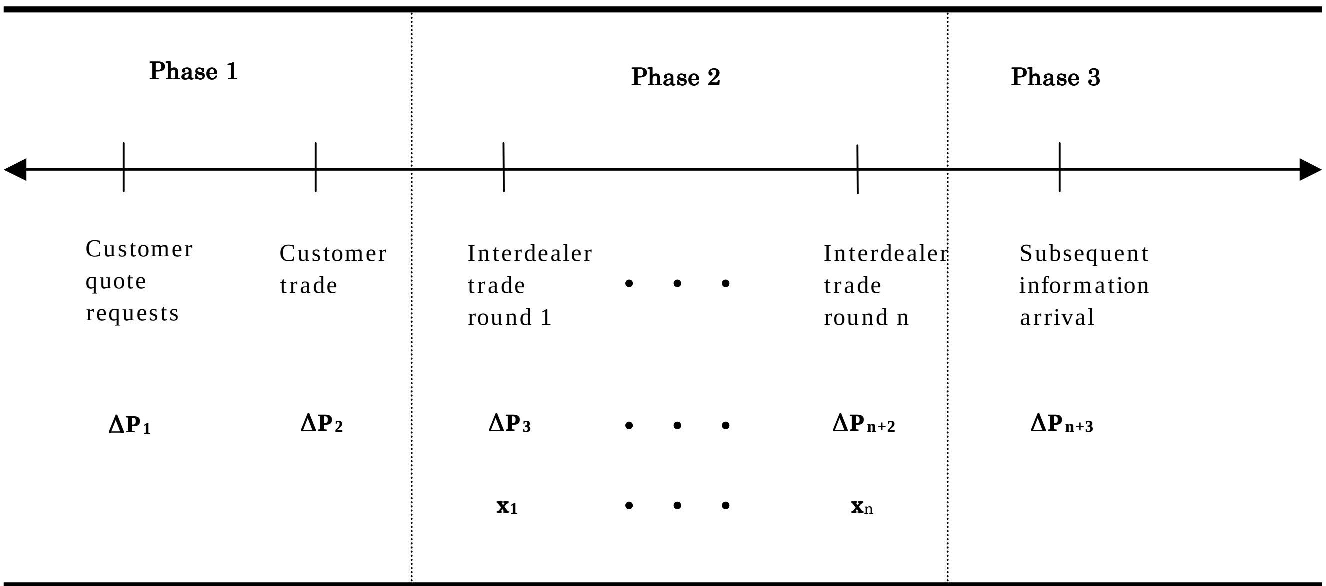


II: Excess Variance of Price Changes



Notes: Panels I and II show the average excess volatility of order flow and price changes (x1000) spanning the period from 1 hour (12 periods) before the news event to 3 hours (36 periods) afterwards. The term "excess" here means netted of the average intraday volatility pattern, as described in the text. The dashed lines show the 95% confidence band associated with the estimates.

Figure 5: Time-line of Information Flow at Ultra-High Frequencies



Notes: The response of price to order flow in ultra-high frequency data can be split into three phases, one where price adjustment precedes interdealer order flow, one where they are concurrent, and one where price adjustment follows interdealer order flow. (Recall that this paper's empirical analysis uses order flow measured from interdealer trades.) In the first phase, price is responding to the orders received by dealers from non-dealer customers (ΔP_1 and ΔP_2). Price impact in this phase occurs before the induced interdealer trading (the latter involving both risk-sharing and speculative motives.) But all price impact does not occur in phase one because customer trades are not publicly observable. In the second phase, interdealer order flows x_i induced by the customer order—which are more transparent than the customer order—become the causal driver of additional price adjustment. The third phase includes price changes due to subsequent information arrival that is correlated with the initial customer trade (i.e., for which the initial customer trade provides a signal).

Rationales for the various stages of price adjustment come from multiple sources. The first price change shown above, ΔP_1, is addressed by Jones and Lipson (1999): when customers call various banks for quotes, often the banks know something about the trade's direction. So even banks that do not receive the order have learned something about it before it is executed, and some of this information becomes impounded in price before execution. The second of the phase-one price changes, ΔP_2, is analyzed by Evans (2001, especially pages 48-49): when customer orders arrive, some adjustment in market price occurs immediately, i.e., before any interdealer trading; but, due to low transparency, not all. Turning to the phase-2 causal link between (rounds of) interdealer order flow and price changes ΔP_3 through ΔP_{n+2}, for detail see, e.g., Lyons (1997). The phase-3 link between price change and lagged order flow is standard within the large literature on information-based models of trading.

Appendix Table 1

Daily Model Estimates with Scheduled Announcements

$$\Delta p_t = \alpha x_t^* + \xi_t + \kappa_t \quad \text{with} \quad VAR(\xi_t) = \omega A_t \,,\ VAR(\kappa_t) = s_\kappa$$

$$x_t = x_t^* + x_t^+ \quad \text{with} \quad x_t^* = e_t + \eta_t \,,\ VAR(e_t) = \sigma A_t \,,\ VAR(\eta_t) = s_\eta \,,\ x_t^+ = \phi \Delta p_t$$

	All News Together		US/German News Separate	
Parameters	Estimate	Std. Err.	Estimate	Std. Err.
α	0.031	(0.002)	0.031	(0.002)
ϕ	-2.036	(0.175)	-2.028	(0.174)
s_κ	108.725	(5.596)	108.582	(5.639)
s_η	5.506	(0.381)	5.477	(0.379)
ω	8.523	(5.019)		
σ	0.415	(0.267)		
ω_{us}			13.979	(11.636)
ω_g			7.815	(4.871)
σ_{us}			0.648	(0.664)
σ_g			0.379	(0.265)
Variance Ratios	Ratio	Std. Err.	Ratio	Std. Err.
$R^2_{\Delta p}(direct)$	0.014	(0.009)	0.018	(0.011)
$R^2_{\Delta p}(indirect)$	0.028	(0.020)	0.025	(0.018)
$R^2_{\Delta p}(total)$	0.042	(0.026)	0.044	(0.026)

Notes: The table reports GMM parameter estimates and asymptotic standard errors (corrected for heteroskedasticity) in parentheses. The index A_t is constructed as the sum of the absolute standardized forecast errors associated with scheduled macro announcements on each day. We include U.S. announcements on: Non Farm Payroll, Durable Goods, Trade Balance, and Unemployment Claims, and German announcements on: the Current A/C, Employment, GDP, Import Prices, Industrial Production, M3, Manufacturing Orders, Manufacturing Output, Producer Prices, Retail Sales, the Trade Balance, Whole Sale Prices, and the Cost of Living Index. The standard errors reported for the variance ratios are computed from a Monte Carlo experiment with 5000 replications. $R^2_{\Delta p}(direct)$ and $R^2_{\Delta p}(indirect)$ are the fraction of the daily variance in prices attributed to news arrival via the direct and indirect channels (i.e., via ξ_t and e_t, respectively).

Appendix Table 2
Variance Regressions (Daily Data)

Equation	Regressors				Diagnostics				
	Const.	A_t	A_t^{us}	A_t^{g}	R^2	SEE	Non-linear	Serial	Hetero
Price change	70.709	3.900			0.17	48.23	0.49	0.19	0.61
	(12.271)	(0.793)						0.74	0.98
	69.404		6.033	3.367	0.18	48.27	0.57	0.21	0.64
	(11.649)		(2.220)	(1.013)				0.81	0.99
Order flow	2.911	0.212			0.13	3.02	0.45	0.00	0.00
	(0.732)	(0.050)						0.06	0.04
	2.881		0.258	0.201	0.13	3.03	0.81	0.00	0.00
	(0.697)		(0.128)	(0.067)				0.05	0.04

Notes: The table reports OLS regression coefficients with standard errors in parenthesis. The dependent variable is the integrated variance of price changes (upper panel) and the integrated variance of order flow (lower panel). (In both cases the integrated variance is calculated using a 5-minute sampling frequency.) Regressors include; the number of US news arrivals A_t^{us}, German news arrivals, A_t^{g}, and total news arrivals A_t, all on day *t*. The Non-linear column presents the p-value of a chi-squared LM test for exclusion of the squared news term (or terms, in the case where country news arrivals are separated). The Serial column presents the p-value of a chi-squared LM test for first-order (top row) and fifth-order (bottom row) serial correlation in the residuals. The Hetero column presents the p-value of a chi-squared LM test for first-order (top row) and fifth–order (bottom row) ARCH in the residuals.

Appendix Table 3

Tests for State-Dependency (Intraday Data)

Non–linearity

Equation	$\Theta(L)x_i n_i$	(p-value)	$\Theta(L)x_i A_i^*$	(p-value)
Δp^{ask}	106.311	(<0.001)	15.561	(0.016)
Δp^{bid}	97.942	(<0.001)	14.941	(0.021)
x	8.536	(0.201)	5.001	(0.544)

Heteroskedasticity

	n_i	(p-value)	A_i	(p-value)
ε_t	800.089	(<0.001)	10.341	(0.001)
ω_t^{ask}	5.628	(0.018)	0.072	(0.789)
ω_t^{bid}	3.224	(0.073)	0.251	(0.617)
v_t	6638.392	(<0.001)	16.689	(<0.001)

Notes: The upper panel reports Wald statistics and p-values for the null hypothesis of zero coefficients on the terms listed at the head of each column in models of the form:

$$z_i = \Theta(L)x_i + \Theta(L)x_i n_i + \Theta(L)x_i A_i^* + w_i \,.$$

All models were estimated by GMM allowing for heteroskedasticity and an MA(1) error structure in the case of $z_i = \Delta p_i^{ask}$ and $z_i = \Delta p_i^{bid}$. These estimates are then used to construct the Wald test. For the price change models, $\Theta(L) = \theta_1 L^{-4} + \theta_2 L^{-3} + ... + \theta_6 L$ and for order flow, $\Theta(L) = \theta_1 L + \theta_2 L^2 + ...\theta_{10} L^{10}$. A_i^* and A_i are a dummy variables equal to one if there was a macro news arrival during the previous 15-mintues (i.e. 3 observation windows) or previous 5-mintues respectively. The lower panel reports the results of Glesjer (1969) tests for heteroskedasticity in the variance of each shock using the variables listed at the head of each column. The shock v_i is the innovation to the AR(10) model for order flow, while ε_i, ω_i^{ask}, and ω_i^{bid} are the shocks from

$$\Delta p_i^{ask} = \Theta(L)x_i + \varepsilon_i + \omega_i^{ask} - \omega_{i-1}^{ask}$$

$$\Delta p_i^{bid} = \Theta(L)x_i + \varepsilon_i + \omega_i^{bid} - \omega_{i-1}^{bid}$$

which are estimated jointly by GMM.

Appendix Table 4

Diagnostics for The Intraday Model

	Statistic	*P*-value
Wald Test for $D(L,0,0) = D(L,\infty,0)$	216.083	(<0.001)
Wald Test for $D(L,0,1) = D(L,\infty,1)$	19.096	(0.004)
Wald Test for $D(L,0,1) = D(L,0,1)$	11.953	(0.063)
Wald Test for $D(L,\infty,1) = D(L,\infty,0)$	20.896	(0.002)
Test for misspecification in $D(L,n_i,A_i^*)$	0.371	(0.999)
Test for misspecification in $\Sigma_\varepsilon(n_i,A_i)$	0.737	(0.391)
Test for misspecification in $\Sigma_\omega(n_i,A_i)$	0.134	(0.714)
Test for misspecification in $\Sigma_v(n_i,A_i)$	2.514	(0.112)

Squared Residual Autocorrelations (Std. Errs.)

Residual	Lag = 1	2	3	4	5	6	12
$\varepsilon_i^2 / \Sigma_\varepsilon(n_i,A_i)$	0.089	0.039	0.053	0.162	0.029	0.060	0.020
	(0.028)	(0.020)	(0.031)	(0.136)	(0.015)	(0.021)	(0.008)
$\left(\omega_i^{ask}\right)^2 / \Sigma_\omega(n_i,A_i)$	0.067	0.015	0.015	-0.016	0.000	0.019	0.013
	(0.025)	(0.016)	(0.021)	(0.011)	(0.011)	(0.013)	(0.011)
$\left(\omega_i^{bid}\right)^2 / \Sigma_\omega(n_i,A_i)$	0.059	0.022	0.009	0.006	-0.002	0.009	0.024
	(0.024)	(0.010)	(0.012)	(0.012)	(0.009)	(0.011)	(0.014)
$v_i^2 / \Sigma_v(n_i,A_i)$	0.067	0.032	0.038	0.032	0.000	0.022	-0.009
	(0.026)	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.007)

Notes: The table reports diagnostic tests for the estimated intraday model shown in Table 3. The upper panel reports Wald tests for state-dependency in $D(L,n_i,A_i^*)$. The second panel reports LM-type tests for misspecification in the estimated $d_j(n_i,A_i^*)$ and $\Sigma_j(n_i,A_i)$ functions with respect to trade intensity n_i (A_i^* and A_i are a dummy variables equal to one if there was a news arrival during the previous 15-mintues—i.e. 3 observation windows—or previous 5-mintues respectively.) The lower panel reports autocorrelations in the standardized squared shocks.

Appendix Table 5: Lower Bound on Percentage Price Variance From Order Flow Shocks

News Arrival

	Horizon (minutes)				
Trade intensity n	5	30	60	120	∞
10	2.766	6.961	8.03	9.121	9.437
	(0.826)	(2.126)	(2.500)	(2.912)	(3.038)
20	5.165	11.028	12.27	13.454	13.783
	(1.387)	(3.006)	(3.392)	(3.782)	(3.895)
30	8.111	15.235	16.546	17.740	18.062
	(2.252)	(4.162)	(4.541)	(4.899)	(4.998)

No News Arrival

	Horizon (minutes)				
Trade intensity n	5	30	60	120	∞
10	0.903	3.191	4.078	5.202	5.58
	(0.267)	(0.922)	(1.173)	(1.490)	(0.269)
20	1.808	4.668	5.408	6.167	6.388
	(0.471)	(1.212)	(1.404)	(1.601)	(0.531)
30	2.694	5.760	6.394	6.992	7.156
	(0.696)	(1.488)	(1.653)	(1.809)	(0.852)

P-values: No increase in variance ratio

	Horizon (minutes)				
Trade intensity n	5	30	60	120	∞
10	0.002	0.006	0.010	0.019	<0.001
20	0.001	0.002	0.003	0.005	<0.001
30	0.001	0.002	0.002	0.002	<0.001

Notes: Estimated from five-minute data (model in Table 3). The upper two panels report the estimated lower bound for the percentage of price variance over various horizons due to order flow shocks, given trade intensity *n*, with and without concurrent news arrival. This lower bound is estimated using only the price effects of interdealer order flow that is temporally prior to those price effects. (From Table 1, the median number of trades *n* per five-minute interval is 12 and the 75th percentile is 21.) The standard errors reported in parenthesis in the upper panels, and p-values shown in the lower panel are calculated from 5000 Monte Carlo draws from the estimated asymptotic distribution of the GMM estimates.

Appendix

Daily Analysis

The reduced form of the model presented in (3) - (6) is:

$$\begin{aligned}\Delta p_t &= \alpha\left(e_t+\eta_t\right)+\xi_t+\kappa_t,\\ x_t &= \left(1+\phi\alpha\right)\left(e_t+\eta_t\right)+\phi\left(\xi_t+v_t\right),\end{aligned}$$

where $Var\left(\xi_t\right)=\omega A_t$, $Var\left(\kappa_t\right)=s_\kappa$, $Var\left(e_t\right)=\sigma A_t$, and $Var\left(\eta_t\right)=s_\eta$. For the model where A_t identifies all the news items in day t, ω and σ are parameters. In the model where we separate US and German news items, $A_t'=\left[A_t^{us},A_t^{g}\right]$, $\omega=\left[\omega_{us},\omega_g\right]$ and $\sigma=\left[\sigma_{us},\sigma_g\right]$. To find the GMM estimates, we first find the variances and covariance for price changes and order flow implied by the equations above:

$$\begin{aligned}Var\left(x_t\right) &= \left(1+\phi\alpha\right)^2\left(\sigma A_t+s_\eta\right)+\phi\left(\omega A_t+s_\kappa\right),\\ Var\left(\Delta p_t\right) &= \alpha^2\left(\sigma A_t+s_\eta\right)+\left(\omega A_t+s_\kappa\right),\\ Cov\left(x_t,\Delta p_t\right) &= \left(1+\phi\alpha\right)\alpha\left(\sigma A_t+s_\eta\right)+\phi\left(\omega A_t+s_\kappa\right).\end{aligned}$$

Next, we construct empirical counterparts to these theoretical moments in the form of the integrated variances and covariance from the five-minute data:

$$\mathcal{V}\left(\Delta p_t\right)=\sum_{i=1}^{288}\Delta p_{it}^2,\qquad \mathcal{V}\left(x_t\right)=\sum_{i=1}^{288}x_{it}^2,\qquad \text{and } \mathcal{CV}\left(x_t,\Delta p_t\right)=\sum_{i=1}^{288}\left(\Delta p_{it}x_{it}\right),$$

where the subscript "it" denotes the i'th. 5-minute observation on day t. The variables $\mathcal{V}\left(\Delta p_t\right),\mathcal{V}\left(x_t\right)$ and $\mathcal{CV}\left(x_t,\Delta p_t\right)$ measure the realized volatility in price changes and order flow that, under suitable conditions, provide us with unbiased and highly efficient estimates of actual volatility (see, Andersen, Bollerslev, Diebold, and Labys 2001). [$\mathcal{V}\left(\Delta p_t\right)$ and $\mathcal{V}\left(x_t\right)$

are plotted in Figure 3.]

Table 2 reports GMM estimates based on the following set of moment conditions:

$$
\begin{aligned}
0 &= E\left[\{\mathcal{V}(\Delta p_t) - Var(\Delta p_t)\} \otimes \mathcal{Z}_t\right], \\
0 &= E\left[\{\mathcal{V}(x_t) - Var(x_t)\} \otimes \mathcal{Z}_t\right], \\
0 &= E\left[\{\mathcal{CV}(x_t, \Delta p_t) - Cov(x_t, \Delta p_t)\} \otimes \mathcal{Z}_t\right], \\
0 &= E\left[\left(\Delta p_t - \tfrac{\alpha}{1+\alpha\phi} x_t\right)(x_t - \phi \Delta p_t)\right],
\end{aligned}
$$

where $\mathcal{Z}_t$ is a vector of instruments. The first three conditions imply that the difference between realized volatility any the (co)variance implied by the model is uncorrelated with each instrument. The fourth condition follows from the fact that shocks to the price equation, $\xi_t + \kappa_t$, are uncorrelated with $x_t^* = e_t + \eta_t$. In the case of the All News model, we use a constant and A_t as instruments, and when US and German news are separated we use a constant, A_t^{us}, and A_t^g.

The ratios reported in the lower panel of Table 2 are computed as

$$
\begin{aligned}
R^2_{\Delta p}(direct) &= \frac{Var_T(\xi_t)}{Var_T(\Delta p_t)} R^2_{\xi}, \\
R^2_{\Delta p}(indirect) &= \frac{\hat{\alpha}^2 Var_T(x_t^*)}{Var_T(\Delta p_t)} R^2_{e}, \\
R^2_{\Delta p}(total) &= R^2_{\Delta p}(direct) + R^2_{\Delta p}(indirect),
\end{aligned}
$$

where $Var_T(.)$ denotes the sample variance of daily observations, and a " ^" denotes the GMM parameter estimate. R^2_e and R^2_ξ identify the average contribution of news-related shocks to the integrated variance of the residuals in the order flow and price change equations and are computed as $R^2_e = \hat{\sigma}\overline{A_t}/\left(\hat{\sigma}\overline{A_t} + \hat{s}_\eta\right)$ and $R^2_\xi = \hat{\omega}\overline{A_t}/\left(\hat{\omega}\overline{A_t} + \hat{s}_\kappa\right)$, where $\overline{A_t}$ is the sample average of A_t. The standard errors associated with all the ratios are computed from a Monte Carlo simulation with 5000 replications based on the asymptotic distribution of the

GMM estimates.

Appendix Table 2 provides supplemental evidence on the daily relation between the volatility and the flow of news items. The upper (lower) panel reports results from regressions of the integrated volatility of price changes (order flow) on the daily flow of all news items, A_t, US items, A_t^{us}, and German items A_t^g. Consistent with the results in Table 2 and the visual evidence in Figure 3, all three regressors are statistically significant. We also report several diagnostics associated with these regressions. Under the column headed "Non-linear", are p-values for chi-squared LM tests excluding squared news terms. None of the tests are significant, providing support for the linear variance functions of our daily model. There is little evidence of residual serial correlation or heteroskedasticity in the price volatility regressions. In the case of order flow, the presence of residual serial correlation indicates that daily changes in the volatility of order flow are not completely accounted for by variations in the flow of news. To see whether this feature of the data materially affected our results, we re-estimated the daily model using the Newey-West weighting matrix allowing for an MA(1) error structure. The parameter estimates (and standard errors) are very similar to those shown in Table 2.

Intraday Analysis

Our analysis of the intraday data draws on Evans (2002). The data set constitutes a sequence of irregularly spaced observations on a continuous trading process. At some points in the sample, the gaps between successive trades span many minutes, while at others several trades appear with the same second-by-second time stamp. We do not attempt to directly model these irregular timing patterns. Instead, we use prices, order flow, trading intensity, and news flow measured relative to a fixed five-minute observation interval. One consequence of adopting a fixed observation interval is that there are periods of the day when no transactions take place during an interval. We designate observations from these periods as "missing". Evans (2002) describes how GMM estimation can be modified to deal with these observations and we refer interested readers to that paper for further estimation and testing details.

To estimate the intraday model, we need to be precise about the relation between the prices we observe in the data set and the equilibrium market price. Prices in the data set come in two forms. If a dealer initiating a transactions buys dollars, the transaction price equals the ask quote in DMs per dollar offered by the other dealer. We refer to this as the DM purchase price for dollars, p^{ask}. If the dealer initiating a transaction sells dollars, the transaction price will equal the bid quote given by the other dealer. We refer to this as the DM sale price for dollars, p^{bid}. Evans (2002) argues that the lack of transparency in direct dealer trading (and differences between the mechanisms for direct and brokered interdealer trading) allows for the existence of an equilibrium price distribution without introducing arbitrage opportunities.

To formalize this idea, our intraday model assumes that equilibrium in the market at a point in time is described by a distribution of purchase prices and a distribution of sales prices. Let p_i^{ask} and p_i^{bid} denote observed prices drawn randomly from the respective distributions of purchase and sales prices at time i. These observed prices are related to the average transaction price, p_i, by

$$p_i^o = p_i + \omega_i^o, \tag{A1}$$

for $o = \{ask, bid\}$. ω_i^{ask} and ω_i^{bid} are idiosyncratic shocks that identify the degree to which observed prices differ from the market-wide average. Their size depends on the identity of the dealers whose prices we observe. The model assumes that observed prices are drawn randomly and independently from the cross-sectional distributions of purchase and sale prices every period so that ω_i^{ask} and ω_i^{bid} are serially uncorrelated and independently distributed.

Combining (A1) with (9) and (11) in the text, gives us the estimable form of the model

$$\begin{aligned}
\Delta p_i^{ask} &= D(L, n_i, A_i^*)x_i + \varepsilon_i + \omega_i^{ask} - \omega_{i-1}^{ask}, && \text{(A2)}\\
\Delta p_i^{bid} &= D(L, n_i, A_i^*)x_i + \varepsilon_i + \omega_i^{bid} - \omega_{i-1}^{bid}, && \text{(A3)}\\
C(L)^{-1}x_i &= v_i. && \text{(A4)}
\end{aligned}$$

This specification extends the model in Evans (2002) with addition of both another state variable (news arrival) and the equation for order flow, and can be estimated with the same technique. We therefore refer readers to that paper for further details on how the GMM estimates reported in Table 3 are obtained. As in Evans (2002), we set γ equal to 100 for estimation (where γ is the scaling parameter in the state-dependence functions of equations 12 and 13). We also find that the unrestricted estimates of $\Sigma_{\varepsilon}(0, A)$, $\Sigma_{v}(0, A)$ and $\Sigma_{\omega}(\infty, A)$ are very close to zero, so Table 3 reports estimates where these parameters are restricted to zero. None of these restrictions materially affect the variance decompositions in Table 4.

Appendix Table 3 provides empirical motivation for the presence of state-dependence in the intraday model. The upper panel reports Wald tests for non-linearity in models of the form:

$$z_i = \theta(L)x_i + \theta_n(L)x_i n_i + \theta_A(L)x_i A_i + \varsigma_i.$$

All models are estimated by GMM allowing for heteroskedasticity and an MA(1) error structure in the case of $z_i = \Delta p_i^{ask}$ and $z_i = \Delta p_i^{bid}$. These estimates are then used to construct the Wald test. For the price change models, $\theta_j(L) = \theta_{j1}L^{-4} + \theta_{j2}L^{-3} + ...\theta_{j6}L$, and for order flow $\theta_j(L) = \theta_{j1}L + \theta_{j2}L^2 + ...\theta_{j10}L^{10}$; these specifications capture all the serial correlation in the data (see, Evans 2002 for further details). As the table shows, there is strong evidence to reject the null hypothesis of no state-dependence with respect to trading intensity and the flow of news in both the price equations, but not in the order flow equation. The lower panel reports Glesjer (1969) tests for heteroskedasticity in the shocks to the model in (A2) - (A4) estimated without state-dependence in $D(L, n_i, A_i^*)$. There is strong evidence against the null of homoskedasticity in all cases with respect to trading intensity. There is also strong evidence of heteroskedasticity related to the flow of news in the case of the ε_i and v_i shocks.

Appendix Table 4 reports diagnostics for the GMM estimates of the intraday model. The Wald test for the null of $D(L, 0, 0) = D(L, \infty, 0)$ is computed as $\nabla\hat{d}' \left[\hat{\Omega}_{\nabla d}\right]^{-1} \nabla\hat{d}$ where

$$\nabla\hat{d} = \left[\hat{d}_1(0,0) - \hat{d}_1(\infty,0), \dots, \hat{d}_6(0,0) - \hat{d}_6(\infty,0)\right]$$

and $\hat{\Omega}_{\nabla d}$ is the estimated asymptotic covariance matrix of ∇d. The other Wald tests use the coefficients in $D(L, n, A^*)$ analogously. To test for misspecification in the $d_j(n, A^*)$ and $\Sigma_j(n, A)$ functions, we use the GMM version of the LM test developed by Newey and West (1987). In the case of the $d_j(n, A^*)$ functions, we consider alternative specifications of the form $\tilde{d}_j(n, A^*) = d_j(n, A^*) + \varphi_j n$. To test the null hypothesis that $\varphi_j = 0$ for all j, we use the two-step procedure suggested by Greene (1997). First, we compute the derivative for the GMM criterion function with $\tilde{d}_j(n, A^*)$ replacing $d_j(n, A^*)$ at the GMM estimates with $\varphi_j = 0$. We then calculate the Wald statistic for the null hypothesis that this vector of derivatives equals zero. In the case of the variance functions $\Sigma_\omega(n)$ and $\Sigma_\varepsilon(n)$, the alternative specifications take the form of $\tilde{\Sigma}_\varpi(n, A) = \Sigma_\varpi(n, A) + \varphi n$, where $\Sigma(n, A) = \{\Sigma_\varepsilon(n, A), \Sigma_\omega(n, A), \Sigma_v(n, A)\}$. None of these statistics are statistically significant. This suggests that the model did manage to incorporate most of the state-dependence in return and order flow dynamics. The lower panel reports autocorrelations for the estimated shocks. The shocks are calculated from the GMM estimates and standardized as $\tilde{\varpi}_i^2 = \varpi_i^2[\hat{\Sigma}_\varpi(n_i, A_i)]^{-1}$ where ϖ_i denotes the shock in question. These statistics show there is some residual heteroskedasticity not accounted for by the state variables.

The variance decompositions reported in Table 4 are computed as follows. First we write the price change dynamics implied by the GMM estimates as

$$\Delta p_i = B(L, n_i, A_i^*)v_i + \varepsilon_i,$$

where $B(L, n, A^*) = D(L, n, A^*)L^4C(L)$. Next, we consider the k-period price change, $\Delta^k p_i \equiv \Sigma_{j=0}^{k-1}\Delta p_{i+j}$, implied by this equation:

$$\Delta^k p_i = \sum_{j=0}^{k-1} \varepsilon_{i-j} + B(L, k, n_i, A_i^*)v_i,$$

where $B(L, k, n_i, A_i^*) = \sum_{j=0}^{k-1} B(L, L^j n_i, L^j A_i^*)L^j$. Since the v_i and ε_i shocks are independent and serially uncorrelated, the variance of price changes is

$$Var(\Delta^k p_i) = \sum_{j=0}^{k-1} \Sigma_\varepsilon(n_{i-j}) + Var\left(B(L, k, n_i, A_i^*)v_i\right).$$

The upper panel of Table 4 reports the contribution of the second term to the variance of price changes for different horizons k, and trading intensities n_i with $A_i^* = A_i = 1$. The calculations use the GMM estimates of $D(L, n, A^*)$, $C(L)$, $\Sigma_\varepsilon(n, A)$ and $\Sigma_v(n, A)$ reported in Table 3. Standard errors (shown in parenthesis) are computed from 5000 Monte Carlo simulations based on the asymptotic distribution of the GMM estimates. (For the $k = \infty$ case, we note that prices can be written as $p_i = \bar{p}_i + I(0)$ terms, where $\Delta\bar{p}_i = \varepsilon_i + B(1, n, A^*)v_i$. The contribution of order flow can therefore be calculated as $B(1, n, A^*)^2\Sigma_v(n, A)/Var(\Delta\bar{p}_i)$.) The middle panel reports the analogous contributions for the case where $A_i^* = A_i = 0$. The lower panel reports the Monte Carlo p-value for the null hypothesis that there is no increase in the contribution of order flow shocks when news arrives.

Aggregation Bias

Finally, we consider whether time-aggregation of our intraday model can account for the negative estimates of ϕ in the daily model. For this we calculate $x_i^* \equiv \frac{1}{D(1)} \sum_{j=1}^{288} D(L)x_{i-j}$ where $D(L)$ is the polynomial on order flow from the model in (A2) - (A4) estimated without state-dependence. Notice that the 5:00 BST observation on x_i^* each day (i.e., $x_{t,216}^*$) should closely approximate x_t^* in the daily model. To examine whether our intraday model can account for the negative estimates of ϕ found in the daily data, we then estimate the regression

$$x_t = a_0 x_{t,216}^* + a_1 \Delta p_t + \zeta_t.$$

This regression corresponds to the combination of equations (4) and (6) of the daily model. The OLS estimate of a_0 is 0.948 while the estimate of a_1 is -1.963, close to the estimate of -2.051 found for ϕ in Table 2. Hence, yes, time aggregation in this context can indeed account for the negative estimates of ϕ in the daily model.

Feedback Trading

We examine the profitability of feedback trading rules with form

$$d_i = \psi_1 \Delta p_{i-1} + \psi_2 \Delta p_{i-2} + \psi_3 \Delta p_{i-3} + \psi_4 \Delta p_{i-4} + \psi_5 \Delta p_{i-5} + \psi_6 \Delta p_{i-6}, \tag{A5}$$

where d_i represents the purchase of dollars during period i and Δp_i is the change in the DM price of Dollars between the end of period $i-1$ and i. (Note that Δp_{i-1} contains the last observable price before trading begins in period i.) The ψ_i coefficients determine the link between the observed history of price changes and the current trading decision of a feedback trader. Our aim is to examine the profitability of following (A5) when the values for the ψ_i coefficients are chosen to be consistent with characteristics of price changes and order flow in the data. For the sake of simplicity, we ignore the transactions cost that arise from trading via bid-ask spreads. This means that the profitability estimates we calculate below overstate the actual profitability of following the feedback rules we consider.

The profitability of following (A5) is measured in terms of DMs and Dollars. Let $w_i^{DM} \equiv b_i^{DM} + p_i b_i^{\$}$ denote the DM value of wealth for the feedback trader at the start of period i. b_i^{DM} and $b_i^{\$}$ are the trader's DM and Dollar balances at the start of period i that evolve according to $b_{i+1}^{DM} = b_i^{DM} - p_i d_i$ and $b_{i+1}^{\$} = b_i^{\$} + d_i$. Combining these equations with the definition of w_i^{DM} above gives

$$w_{i+1}^{DM} = w_i^{DM} + (p_{i+1} - p_i)\left(b_i^{\$} + d_i\right) \tag{A6}$$

and

$$w_{i+1}^{\$} = \frac{p_i}{p_{i+1}} w_i^{\$} + \frac{(p_{i+1} - p_i)}{p_{i+1}}(b_i^{\$} + d_i) \tag{A7}$$

where $w_i^{\$} \equiv w_i^{DM}/p_i$ is the dollar value of wealth. We measure the profitability of the trading rule in terms of the daily return on wealth in DM's, $r^{DM} = \ln w_{288}^{DM} - \ln w_1^{DM}$, and Dollars, $r^{\$} = \ln w_{288}^{\$} - \ln w_1^{\$}$; and in terms of the daily profit in DMs, $\pi^{DM} = w_{288}^{DM} - w_1^{DM}$, and Dollars $\pi^{\$} = w_{288}^{\$} - w_1^{\$}$.

We consider two trading rules. Rule A is derived from the regression of order flow, x_i, on six lags of the change in price, $\{\Delta p_{i-j}\}_{j=1}^{6}$, estimated over the entire data sample. To derive the feedback rule for an individual trader that corresponds to the pattern of aggregate trading across the market, we assume that each transaction is for \$$\kappa$m. and that trading intensity $\bar{n}$ is constant. The value for each of the ψ_j coefficients in (A5) is then calculated as $\hat{\beta}_j \kappa/\bar{n}$, where $\hat{\beta}_j$ is the estimated regression coefficient on Δp_{i-j}. Thus, under Rule A, the predictable component of aggregate order flow $\hat{x}_i$ equals $\bar{n} d_i/\kappa$. Rule B is derived in a similar manner except the ψ_j coefficients are calculated from the regression of order flow on six lags of price changes over a single trading day. This approach allows the exact form of the trading rule to evolve over the sample. It also means that the profitability of the trading rule can be judged out-of-sample as we describe below.

Since the profitability of a trading rule varies stochastically with prices, we study the distribution of r^{DM}, $r^{\$}$, π^{DM} and $\pi^{\$}$ implied by rules A and B calculated from a Monte Carlo experiment with the following steps.

1. We simulate 1001 trading days of data on prices and order flow according to estimates of the Intraday model:

$$\begin{aligned} \Delta p_i &= \hat{D}(L, \bar{n}, 0) x_i + \varepsilon_i, \\ x_i &= \hat{C}(L) v_i, \end{aligned}$$

   with $\varepsilon_i \sim i.i.dN(0, \hat{\Sigma}_\varepsilon(\bar{n}, 0))$ and $v_i \sim i.i.d.N(0, \hat{\Sigma}_v(\bar{n}, 0))$, where "^" denotes the GMM estimates from Table 3. We set trade intensity $\bar{n}$ equal to 12 (the median value in our data sample) and assume that there are no announcements.

2. Rule A: Using the feedback coefficients ψ_j for Rule A, we compute the sequence of trades over a single day, day t, (i.e., $\{d_i\}_{i=1}^{288}$) implied by the simulated sequence of price changes. Rule B: We compute the coefficients for Rule B from the regression of order flow on lagged price changes estimated from the simulated data on day $t-1$. We then compute the sequence of trades over day t implied by the trading rule given the

simulated sequence of price changes. For both rules we assume that $\kappa = 5$ (quotes in the inter dealer market are good for trades between \$1m and \$10m).

3. We calculate $r^{\$}, r^{DM}$, $\pi^{\$}$, and π^{DM} using (A6) and (A7) for rules A and B over day t. In these calculations we assume that dealers start the day with \$100m in wealth equally split between Dollar and DM balances.

4. Starting at day $t = 2$, we repeat steps 2 and 4 1000 times to generate a distribution for $r^{\$}, r^{DM}$, $\pi^{\$}$, and π^{DM}.

	Rule A				Rule B			
	r^{DM}	π^{DM}	$r^{\$}$	$\pi^{\$}$	r^{DM}	π^{DM}	$r^{\$}$	$\pi^{\$}$
median	-1.09%	-1.64m	-1.09%	-1.09m	-0.91%	-1.37m	-0.92%	-0.92m
p-value	60.30%	60.30%	60.30%	60.30%	58.30%	58.30%	58.40%	58.40%

The table above reports the simulation results. The upper row shows the median returns and profits measured in DMs and Dollars on a monthly basis (20 trading days). The median monthly return is approximately minus one per cent across trading rules and currencies. In terms of profitability, both rules generate median loses of between DM1.4m and DM1.6m or \$1m to \$0.9m over a month. The lower row of the table reports the probability of receiving a negative return or profit each day based on the Monte Carlo distribution. These probabilities are close to 60% in all cases.

Recall that this simulation does not take into account the transactions costs (associated with the bid-ask spread) that arise from following the trading rules. As such, the results represent an upper bound on the profitability of following such a rule in the actual market. With this perspective, it seems clear that a trader would be rather fortunate to profit from following a feedback rule like (A5) consistent with the time series properties of order flow and prices. In fact, our simulation results show that such a strategy would most likely lead to significant trading losses. We have also conducted experiments where the trade size κ is set to \$2.5 and where trading intensity $\bar{n}$ is set at a higher value of 20. In both cases, a trader would suffer significant losses with a similarly high probability.