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How is macro news transmitted to exchange rates?[☆]

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Abstract

Macro news can affect currency prices directly and indirectly via order flow. Past research shows that the direct effects of scheduled macro news account for less than 10% of daily price variance. This paper shows that the arrival of macro news can account for more than 30% of daily price variance. Two features of our analysis account for this finding: (1) We consider the broad spectrum of macro news items that market participants observe, not just scheduled announcements. (2) We allow the arrival of news to affect prices indirectly via its impact on the volatility of order flow. Our analysis shows that order flow variations contribute more to currency price dynamics following the arrival of public macro news than at other times. This is not consistent with news effects being common knowledge that is impounded in price directly. Roughly two-thirds of the total effect of macro news on the DM/$ exchange rate is transmitted via order flow.

JEL classification: F31; G12; E44

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1. Introduction

All textbook models of currency pricing imply that public news determines prices directly: Currency demand shifts are common knowledge and any related transactions play no role in causing the change. In microeconomic models of asset prices, transactions do affect prices causally (e.g., Glosten and Milgrom, 1985;

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Kyle, 1985). The causal role arises because transactions convey information that is not common knowledge. This paper examines whether transactions transmit macroeconomic news to currency prices and how this channel compares with the direct channel.

We examine the impact of macro news on currency prices at intradaily and daily frequencies. We begin at the five-minute frequency. Estimates of our intraday model using interdealer order flows show that, while order flow contributes significantly to changing currency prices at all times, it contributes more to changing prices immediately after news arrival.[1] This is inconsistent with the textbook view that macro news effects are common knowledge and therefore impounded in currency prices without any order flow role. It suggests, instead, that macro news triggers trading that reveals dispersed information, which in turn affects currency prices.

Our daily analysis provides further evidence that trading on news reveals incremental information. The daily model distinguishes three sources of currency price variation. The first source mirrors traditional models—macro news that is impounded immediately and directly. The second source is the indirect effect of news on price via induced order flow. The third source is order flow that affects price but is unrelated to public news (possibly induced by banks' changing risk tolerances, firms' changing hedging demands, or individuals' changing liquidity demands; see, e.g., Evans and Lyons, 2002a). We find that all three sources of deutchemark/dollar price variation are significant. The arrival of macro news increases order flow variance significantly, with the result that roughly two-thirds of the effect of macro news on currency prices is transmitted via order flow, the remainder being the direct effect of news. This is consistent with the intraday finding that order flow is most important for determining currency prices during periods immediately following news arrival. With both the direct and indirect channels operating, we find that macro news accounts for 36% of total daily price variance. This is more than three times the explanatory power found in previous studies.

Though the literature on news and currency prices is long-standing, until recently it had not used quantities (order flow) to sort out the relation. The literature has two branches: a first-moment branch that addresses price-change direction and a second-moment branch that addresses price volatility. A common finding of the first-moment branch is that directional price effects from scheduled macro announcements are difficult to detect at the daily frequency; they are swamped by other factors. Intraday event studies, such as Andersen, Bollerslev, Diebold, and Vega (2003), do find statistically significant effects, particularly for employment and money-supply announcements.[2] The second-moment branch on volatility effects from news is partly a response to difficulty in finding news effects on return first moments.[3] This work finds that announcements do produce the largest price changes.

Our analysis differs from both branches of the literature in two important respects. First, we consider the full set of news items that are observed on news screens by market participants (the set constituting Reuters Money Market Headline News). This set includes the scheduled announcements concerning macroeconomic variables that have been the focus of earlier research and unscheduled news that account for the majority of items appearing on news screens each day. Second, we model in detail how information in a news item can be transmitted to prices via its affects on order flow and, more specifically, on order flow volatility. This indirect transmission mechanism is new to the literature and turns out to be empirically important.

The distinguishing feature of our analysis is easily understood with the aid of an example. Suppose a scheduled macro economic announcement on US Gross Domestic Product (GDP) growth is greater than the

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[1] Order flow is the cumulation over time of signed trades, where trades are signed according to whether the initiator is buying or selling (the marketmaker posting the quote is the noninitiating side). Order flow's role in determining currency prices is documented by Payne (2003), Rime (2000), Evans and Lyons (2002a, b), and Evans (2002), among many others. Flows from individual end-user segments in currency markets are addressed in Lyons (2001), Froot and Ramadorai (2005), and Evans and Lyons (2007), among others. Order flow is similarly important for prices in bond markets, which share many informational and structural features with currency markets (see, e.g., Green, 2004; Fleming, 2003; Brandt and Kavajecz, 2004).

[2] See also, for example, Cornell (1982), Engel and Frankel (1984), Hakkio and Pearce (1985), Ito and Roley (1987), Hardouvelis (1988), Klein (1991), and Ederington and Lee (1995). For bond markets, see Fleming and Remolona (1997) and Balduzzi, Elton, and Green (2001).

[3] See, for example, Goodhart, Hall, Henry, and Pesaran (1993), DeGennaro and Shrieves (1997), Andersen and Bollerslev (1998), and Melvin and Yin (2000). For bond markets, see Fleming and Remolona (1999), Bollerslev, Cai, and Song (2000), and Huang, Cai, and Wang (2002).

expectations of market participants. Furthermore, assume that everyone agrees that unexpectedly high US GDP growth represents good news for the international value of the dollar. If everyone agrees that GDP growth is x percent higher than expected and, as a result, the dollar is y percent more valuable in terms of Japanese yen, dealers will immediately quote a yen/dollar rate that is y percent higher. This is the standard mechanism through which news directly impacts on currency prices. Now suppose that everyone agrees that the GDP announcement represents good news for the dollar, but that there are diverse opinions as to how large the appreciation should be. Under these circumstances, the initial rise in the yen/dollar spot rate could be viewed as too large by some market participants and too small by others. Those who view the rise as too small will place orders to purchase the dollar, while those who view the rise as too large will place orders to sell. In aggregate, the balance of these trades represents the order flow that dealers use to further revise their spot rate quotes. In particular, positive (negative) order flow signals that the initial yen/dollar spot rate was below (above) the balance of opinion among market participants concerning the implications of the GDP announcement for the value of dollar. We term this process of price adjustment via order flow the "indirect channel". Notice that good news for the dollar need not translate into positive order flow. Good news can be associated with either positive or negative order flow depending on how dealers' initial adjusted quotes relate to the balance of opinion concerning the implications of the news. Rather, the indirect channel is operable when diverse views exist about the implications of a news item that creates volatility in order flow, which in turn feeds through to changes in currency prices.

Our finding that macro news accounts for more than 30% of price variance helps to resolve a big puzzle in international finance: the news puzzle. The puzzle is that even the most comprehensive studies of news effects on currency prices account for less than 10% of total price variation. A good example at the daily frequency is Klein (1991). He regresses foreign currency (FX) price changes on trade balance news and finds that news explains about 40% of price changes on those days. This is an impressive finding. However, because trade balance news arrives monthly, roughly 95% of FX price variation is not included in the regression (20 of 21 trading days per month). Thus, an R^2 statistic of 0.4 implies that less than 3% of total price variation is accounted for. Andersen, Bollerslev, Diebold, and Vega (2003) also report impressive R^2 statistics within their event windows (in this case, intraday windows). But as they note (p. 50), summing the amount of time in all of their five-minute, post-event windows accounts for only 0.2% of their full sample period (e.g., roughly one five-minute interval per day). Under the conservative assumption that news arrival causes variance to increase by a factor of ten, their findings imply that news accounts for no more than 2% of the total price variation. We estimate the contribution of macro news to be more than 30% because we consider a much broader set of macro news items and examine both the direct and indirect channels.

The two papers most closely related to our own are Green (2004) and Love and Payne (2004). Green studies the bond market and uses spread decompositions to show that announcements induce a significant increase in informational trading. Information asymmetry increases following the release of public information in a way consistent with, for example, the skilled information processor models of Kim and Verrecchia (1994, 1997)—see also Kandel and Pearson (1995). Green neither models how news effects the order flow process nor addresses the degree to which news can account for total price variation. Love and Payne (2004) address the currency market and, like our paper, use order flow to study the effects of macro news. Their focus, though, is different. They analyze whether the direction of instantaneous price effects from news is contemporaneously correlated with the direction of order flow. Though it is not clear why this correlation should be present in a rational expectations setting, they do find that it is significant and positive. Like Green, they do not address whether total price variation can be explained based on induced order flow variance.

Our empirical strategy is based on the state-dependent heteroskedasticy methods developed by Rigobon and Sack (R&S, 2004). This approach is a natural one given our focus on how news affects order flow volatility. Specifically, we identify the relative importance of direct and indirect news effects by allowing news to affect the variances of order flow and price differently. Another advantage of the R&S method is that it does not require data on ex ante expectations. This is important because the only data on ex ante expectations that is available comes from surveys about scheduled announcements. The R&S method allows us to work with all of the news items that participants actually observe on the Reuters trading screen. It requires the weaker assumption that one can identify changes in the variance of macro information shocks. To ensure the robustness of our results, we model these variance changes in several different ways in both the intraday and daily analysis.

The remainder of the paper is in four sections. Section 2 describes our data and presents some descriptive statistics. Section 3 presents the intraday analysis. Daily analysis is presented in Section 4. Section 5 concludes.

2. Data and descriptive statistics

Our order flow and price data are drawn from time-stamped, tick-by-tick transactions in the deuschmark/dollar (DM/\$) spot market over a four-month period, May 1 to August 31, 1996. The transactions are from the Reuters Dealing 2000-1 system, which operates 24 hours a day, seven days a week. Excluding weekends and a feed interruption caused by a power failure, there are 80 full trading days in the sample. Importantly, Dealing 2000-1 is a bilateral interdealer system on which a dealer requests a quote from another dealer and, when received, generally has only a few seconds to act before the quote is retracted. This type of data avoids the stale quote problem that can cloud inferences about causality when news arrives because, unlike limit orders, these quotes are always very short-lived, are generally not extended at moments of anticipated public news arrival, and are generally retracted at moments of unanticipated news arrival. In 1996 at the time of our sample, Dealing 2000-1 was the most widely used electronic dealing system—according to Reuters, over 90% of the world's bilateral transactions between DM/\$ dealers took place through the system. Transactions between dealers accounted for about 75% of total trading in major spot markets at the time. This 75% breaks into two transaction types: direct (bilateral) and brokered (multilateral). Direct trading accounted for about 60% of trades between marketmakers and brokered trading accounted for about 40%. (For more detail on this Reuters Dealing System, see Lyons, 2001, and Evans, 2002; the latter includes details on data collection and statistical properties.) For every trade executed on Dealing 2000-1, 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.

Our intraday analysis uses transaction prices, order flow and trade intensity measured over fixed intervals of five minutes. We denote the last DM price for the purchase and sale of dollars in interval i as p_i^{ASK} and p_i^{BID}, respectively. (The preceding transaction is only seconds before the end of each five-minute interval during regular trading hours.) Interdealer order flow, x_i, is the difference during interval i between the number of trades initiated by dealers buying dollars and the number initiated by dealers selling dollars.[4] Similarly, we measure trade intensity, n_i, by the unsigned number of interdealer transactions during interval i. Although the Dealing 2000-1 system permits trading 24 hours a day, in practice the vast majority of trading activity is concentrated between 7 am and 5 pm British Summer Time (BST) (see Evans, 2002). Our intraday analysis focuses on price and order flow dynamics while there is continuous trading activity in the market. In other words, we study how prices p_i^{ASK} and p_i^{BID} change between the end of consecutive five-minute periods. Over our four month sample there are 15,034 five-minute windows of consecutive trading activity.

Our daily analysis uses transaction prices and order flow measured once each trading day (i.e., Monday through Friday excluding holidays). Daily versions of each data series are denoted with subscript t. For the daily price, p_t, we use the last DM price for the purchase of dollars before 5 pm BST each trading day. Daily order flow, x_t, is the same as five-minute order flow x_i save that it spans the time difference between 5 pm on trading days $t-1$ and t. Trading intensity on day t, n_t, is defined as the number of transactions over the same daily interval. Order flows and trade intensity are cumulated over weekends and holidays.

The primary source of our news data is the Reuters Money Market Headline News screen (archived by Olsen Associates). These screens are standard equipment on FX trading desks and are used for high frequency monitoring by nondealer participants as well. Reuters collects news reports from approximately 150 bureaus around the world. Each report must be approved by an economics editor at Reuters before it appears as a

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[4] In direct trading between marketmakers, order sizes are standardized, so variation in size is much smaller than variation in the size of individual trades between marketmakers and their end-user customers. Also, using measures of order flow based on numbers of transactions instead of 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.

news item on the Headline screens. The presence of this editorial process means that all the news items in our data set were viewed as containing newsworthy economic information. At the same time, competition between Reuters, Bloomberg, and Dow Jones ensures that editorial decisions minimize publication delay. We impose a further layer of editorial screening by excluding from our data set news items of the following four types: (1) reports of upcoming known holidays, (2) reports that a scheduled data release will take place (e.g., "Monthly employment report due out tomorrow"), (3) duplicate reports (the same news is repeated with a slight change in wording), and (4) reports referring to the DM/$ price or market. The four filters exclude less than 10% of news arrivals. The first three filters are intended to distill information that is truly incremental.

A number of other factors give us confidence that our analysis is not significantly exposed to feedback from the DM/$ market to macro news flow. The potential here is that increased volatility in the DM/$ price creates incentives for reporters to initiate news items to explain it, which are then posted to the Headline screen. Our fourth filter helps to protect against this form of endogeneity insofar as the news item makes reference to the DM/$ market. The well-defined editorial process described also helps protect against spurious news creation. Perhaps most important, the Headline screen is used by traders in many markets (money markets, bond markets, currency markets, and others), so the audience is much wider than just the DM/$ market. We find the hypothesis of feedback to news flow patently strained when it comes to our analysis at the five-minute frequency.

The estimation strategy we adopt in both our intraday and daily analysis does not require that every news item be equally important. All we require is that the news data can be used to identify variations in the flow of macro news hitting the FX market. For this purpose we construct several different measures of macro news flow: one based on the arrival rates of US news items only, one based on German items only, and one based on the arrival of both US and German items. We also use measures from the subset of releases that are scheduled. Here we combine the Reuters data with survey data on exante expectations (provided by Money Market Service) for 28 US variables and 12 Germany variables to compute measures of news flow from unexpected announcements.[5] We use these different measures of macro news flow to check the robustness of our estimation results. In particular, because the arrival of scheduled news is by definition immune to possible feedback from FX price volatility to the arrival of unscheduled news, comparing results using all news versus scheduled news allows us to empirically investigate whether feedback is present.

Table 1 presents descriptive statistics for the variables used in intraday and daily analyses. The upper rows of Panel A report sample statistics for the daily change in FX prices multiplied by one hundred, Δp_t, and the level of interdealer order flow x_t. The distribution of daily price changes is dispersed. The 5'th and 95'th percentile changes represent percentage changes of -0.78 and 0.45, respectively, in the DM purchase price of a dollar. There is no detectable serial correlation in either price changes or order flow at the daily frequency: The estimated first-order autocorrelation in the Δp_t and x_t series are 0.015 and -0.035, respectively and both are statistically insignificant. The remaining rows in Panel A report statistics on four of our measures of macro news flow. A_t^{US} and A_t^{GM}, respectively, denote the number of US and German news items appearing on the Reuters Headline screen between 5:01 pm BST on day $t-1$ and 5 pm BST on day t. A_t^{ALL} is the daily arrival rate of all news computed as $A_t^{\mathrm{US}}+A_t^{\mathrm{GM}}$. A_t^{S} denotes the arrival rate for the subset of scheduled news, defined as the number of scheduled releases between 5:01 pm BST on day $t-1$ and 5 pm BST on day t. As the table shows, the median arrival rate for German news is four times the rate for US news. It seems unrealistic, a priori, that information about the German economy is being disseminated to the public on average at four times the rate of information concerning the US economy. In our analysis we examine whether A_t^{GM} and A_t^{US}, respectively, overstate and understand the true arrival rate for news. Also, the arrival rates for A_t^{ALL} are considerably higher than the rate for scheduled news, A_t^{S}. This observation serves to emphasize the point that scheduled news is not the only real-time source of public information available to market participants.

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[5] The US announcements are for Business Inventories, Capacity Utilization, Unemployment Claims, Consumer Confidence, Construction, Consumer Prices, Credit, Durable Goods, Existing Home Sales, Factory Orders, GDP, the GDP Deflator, the Trade Balance, Housing Starts, Industrial Production, Leading Indicators, M1, M2, M3, NAPM, Nonfarm Payroll Employment, Personal Consumption Expenditure, Personal Income, the Producer Price Index, Retail Sales, the Budget Deficit, the Unemployment Rate, and the Federal Funds Rate. The German announcements are for the Current Account, Employment, GDP, Import Prices, Industrial Production, M3, Manufacturing Orders, Manufacturing Output, Retail Sales, the Trade Balance, Wholesale Prices, and the Cost of Living.

Table 1
Sample Statistics

The sample is May 1 to August 31, 1996. Δp_t is one hundred times the change in the last deutschmark (DM) purchase price for dollars between 5:00 pm on day t and day $t-1$. x_t is the total interdealer order flow over the same time interval. A_t^{US} and A_t^{GM} are, respectively, the number of macro news arrivals observed on the Reuters Money Market Headline News screen relating to the US and Germany between 5:00 pm on day t and day $t-1$. A_t^{ALL} denotes the total number of news items, $A_t^{\mathrm{US}}+A_t^{\mathrm{GM}}$, and A_t^{S} is the total number of scheduled news items arriving over the same time interval. Schedule announcements are listed in footnote 5. In Panel B, Δp_i is one hundred times the change in price (DM purchase price for dollars) between the end of interval i and $i-1$. x_i and n_i are the order flows and total number of trades in interval i, respectively. Autocorrelations are computed by Generalized Method of Moments as in Evans (2002), and the P-values reported in parenthesis are calculated from Wald tests of the null hypothesis of a zero correlation (allowing for conditional heteroskedasticity).

	Minimum	5%	25%	50%	75%	95%	Maximum	Standard Deviation	Skewness	Kurtosis
A. Daily data										
Δp_t	−2.07	−1.19	−0.38	0.03	0.34	0.69	1.24	0.59	−0.81	3.85
x_t	−449	−308	−61	8	91	186	339	136.4	−0.58	4.54
A_t^{US}	0	0	1	2	5	7	9	1.80	1.20	3.76
A_t^{GM}	0	2	6	8	12	18	22	5.01	0.48	2.89
A_t^{ALL}	0	2	9	11	15	21	27	5.70	0.33	2.82
A_t^{S}	0	0	1	2	4	6	10	2.12	1.14	4.23
B. Intraday data										
Δp_i	−0.79	−0.14	−0.03	0.00	0.03	0.13	0.5	0.08	−0.21	7.42
x_i	−72	−9	−2	0	3	9	69	5.56	0.09	12.60
n_i	2	2	30	60	105	220	1060	78.34	3.28	22.43
Autocorrelations										
Lag =		1	2	3	4	5	6	12	18	24
Δp_i		−0.31	−0.00	−0.00	−0.00	−0.00	0.00	0.00	0.00	0.00
		(<0.01)	(0.35)	(0.76)	(0.79)	(0.68)	(0.23)	(0.69)	(0.60)	(0.64)
x_i		0.23	0.10	0.09	0.08	0.06	0.06	0.03	0.02	0.00
		(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.01)	(0.65)

Panel B of Table 1 presents descriptive statistics for prices, order flow, and trade intensity measured at the five-minute frequency. The sample statistics for $\Delta p_i^{\mathrm{ASK}}$ and $\Delta p_i^{\mathrm{BID}}$ are almost identical, so we report only those for $\Delta p_i^{\mathrm{ASK}}$ (i.e., the change the DM price for the last purchase of dollars in interval $i-1$ and interval i multiplied by one hundred). As one would expect, the range of price changes and order flows at the five-minute frequency are much smaller than at the daily frequency. One noteworthy feature of these statistics concerns the distribution of trade intensity, n_i. While the median trade intensity in our sample is 60 trades per interval (i.e., 12 trades per minute), the distribution for n_i indicates that the pace of trading is occasionally much higher. Evans (2002) shows that some of the variations in trade intensity can be related to the shift from predominantly Asian-based to US-based dealers as the trading day progresses. However, on a particular day, variations in trade intensity can differ significantly from this seasonal pattern. From the lower portion of Panel B, we see a sharp difference from the daily frequency statistics: Both price changes and order flows are serially correlated at high (intraday) frequencies. Transaction price changes display significant negative autocorrelation, but only at lag one, while order flow appears serially correlated at up to 18 lags. Negative first-order serial correlation in the transaction price changes is not due to bid-ask bounce because the prices here are all ask prices. Instead it reflects the decentralized nature of trading on the Dealing2000-1 system. Our transaction prices are not the prices quoted by a single dealer, instead they represent the prices at which a sequence of particular trades took place between any pairs of dealers using the D2000-1 system. Evans (2002) shows that negative serial correlation in price changes can arise in this situation if the lack of transparency in interdealer trading permits the existence of bid and ask quote distributions at a particular time without introducing arbitrage opportunities. Because interdealer trading on Dealing2000-1 lacks transparency (details of each trade remain the private information of the trading parties), we allow for the presence of quote distributions in our intraday analysis and thereby account for the serial correlation properties of price changes.

We track the arrival of news at the five-minute frequency with dummy variables. The dummy variable A_i takes the value of one if either a US or German news item appears on the Reuters screen during interval i. At least one news arrival occurs in 515 out of the 15,034 consecutive trading windows. 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, numbers that proved insufficient to get mileage from a multi-valued dummy). We also make use of analogous dummies for all German news, all US news, and all scheduled US news, denoted, respectively, by A_i^{GM}, A_i^{US}, and A_i^{S}.

3. Intraday analysis

Our intraday analysis is based on a model for the joint dynamics of FX prices and order flows estimated at the five-minute frequency. Information is impounded into FX prices via two channels. The first is the direct channel through which the arrival of new common knowledge information leads dealers to change the FX prices they quote. The transmission of information into FX prices via this channel is direct and instantaneous. The second channel, the indirect channel, operates via order flow. In this case the arrival of information is first manifest in the trading decisions of individuals because the information is dispersed. Once dealers observe the ensuing order flow, they adjust their FX quotes to reflect the new information embedded in the pattern of trading. Thus, order flow is the medium by which dispersed information becomes embedded into FX prices.

Our intraday analysis focuses on the relative importance of the direct and indirect information channels in the period immediately following the arrival of news. The motivation for this focus is straightforward: If macro news primarily comprises new common knowledge information, as is traditionally assumed, we should find evidence that the direct channel accounts for most of the FX price variation over intervals that include the news arrival. Conversely, if the arrival of macro news triggers revelation of dispersed information, possibly reflecting diverse views about price implications, we should find that the indirect channel dominates. We quantify the relative importance of the direct and indirect channels from a decomposition of the variance in FX price changes.

3.1. The model

Our intraday model extends the empirical model in Evans (2002) to account for the effects of news arrivals. At the heart of the model are the following equations:

$$\Delta p_i = B(L)\xi_i + \varepsilon_i \quad \text{and} \tag{1}$$

$$y_i = C_y(L)\xi_i, \tag{2}$$

where Δp_i is the change in the spot price of FX between the end of periods $i-1$ and i, and y_i is the order flow initiated by end-users during period i. Eq. (1) shows how prices respond to two types of news: common knowledge news shocks, ε_i, and dispersed information shocks, ξ_i. We assume that these shocks are mutually independent and serially uncorrelated conditioned on the state of the market in period i. The ε_i shocks represent unambiguous price-relevant news that is simultaneously observed by everyone and so are impounded fully and instantaneously into the price of FX. Dispersed information shocks represent, in aggregate, the bits of information contained in the trades of individual agents. This information is first manifested in the order flow, y_i, and then subsequently impounded in price. End-user order flow is the difference between the purchase and sales of dollars initiated by end-users at dealer FX quotes. The dynamic responses of prices and order flow to these dispersed information shocks are determined by the lag polynomials $B(L)$ and $C_y(L)$.

Three features of our specification deserve note. First, Eq. (1) describes the dynamics of transactions prices, p_i, defined as the market-wide average price at which transactions take place at time i. Second, the assumed independence between the common knowledge and dispersed information news shock implies that, conditioned on the state of the market, common knowledge news has no effect on order flow. This assumption has 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). Intuitively, any revision in price due to common knowledge news should establish a new market-clearing price that does not systematically favor subsequent imbalances of sell orders over buy orders, or vice versa. For example, there should not be a correlation between bad public news for the DM and subsequent net DM sell orders, so long as the initial update of the market price is unbiased. (This has nothing to do with the behavior of unsigned trading volume. Our model does not restrict how common knowledge news affects volume through, say, portfolio rebalancing.) The third feature concerns the dynamics of end-user order flow y_i. We assume that end-users' demand for foreign currency is imperfectly elastic, so any imbalance in order flow (i.e., $y_i \neq 0$) requires price adjustment to achieve market clearing. Consequently, all order flow is, at least temporarily, price relevant.[6] Under rational expectations, this information is summarized in current and past dispersed information shocks, but it remains unrelated to common knowledge news shocks, as shown in Eq. (2).

Eqs. (1) and (2) allow us to identify three channels through which the arrival of macro news could affect the dynamics of price and order flows. First, when the macro announcement contains a common knowledge component, it affects prices instantaneously via the ε_i shock. This direct channel is operable when everyone agrees on the price implications of the announcement. Second, when a macro announcement is viewed by different agents as having different price implications, its effects on prices and order flow manifest via the ξ_i shocks: Although everyone observes the same announcement, different views about the mapping from macro data to FX prices represent dispersed information that is relevant for equilibrium prices. Third, the arrival of a macro announcement can affect the process through which dispersed news is impounded into prices, by which we mean the lag polynomials. We allow for this by permitting $B(L)$ and $C_y(L)$ to vary with the arrival of news announcements.

3.1.1. *Empirical specification*

Estimation of our intraday model is complicated by two factors. First, our data are on market-wide order flow between dealers, x_i, not the end-user order flows, y_i. We must be careful to distinguish these different order flows if we are to account for the temporal impact of dispersed information. Second, our model needs to accommodate forms of state-dependency beyond the arrival of macro news.

Prices in the data set come in two forms. If a dealer initiating a transaction 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 equals the bid quote given by the other dealer. We refer to this as the DM sale price for dollars, p^{BID}. Evans (2002) finds evidence that lack of transparency in direct dealer trading allows for an equilibrium price distribution, as opposed to a strict law of one price. To formalize this idea, our intraday model assumes that equilibrium in the market at a particular 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, respectively. These observed prices are related to the average transaction price, p_i, defined in Eq. (1), by

$$p_i^o = p_i + \eta_i^o, \tag{3}$$

for $o = \{\text{ASK}, \text{BID}\}$. η_i^{ASK} and η_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. We assume that observed prices are drawn randomly and independently from the cross-sectional distributions of purchase and sale prices every period, so that η_i^{ASK} and η_i^{BID} are serially uncorrelated and independently distributed.

The second complication arises from the distinction between the interdealer and end-user order flows. The order flow measure in our data set is derived from trades initiated between dealers. These trades are temporally downstream from the trades initiated by end-users against dealer quotes. As a result, a dispersed information shock ξ_i can affect prices and end-user order flows before it shows up in interdealer order flow. Dealers could

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[6] Our elasticity assumption does not imply that shocks to order flow necessarily have permanent price effects. It is possible that some shocks to order flow affect prices only while the associated inventory imbalance is being spread among dealers (see Cao, Evans, and Lyons, 2006). In this special case, some of the individual coefficients in $B(L)$ differ from zero, but their sum equals zero.

adjust their price in the face of an end-user order induced by ξ_i before initiating trades in the interdealer market for risk sharing or speculative motives. Thus, price changes could appear temporally prior to changes in interdealer order flow even though they represent a response to earlier end-user order flow. We allow for this possibility by assuming that the interdealer order flow we measure is a distributed lag of end-user order flow:

$$x_i = C_x(L)y_{i-m}, \tag{4}$$

where, again, $C_x(L)$ is a polynomial in the lag operator. In this specification, it takes at least m periods before imbalances in end-user orders for FX show up in interdealer order flow (where m could be zero).

The link between end-user order flow and interdealer order flow in Eq. (4) is consistent with the predictions of theoretical models of multiple-dealer markets, such as the simultaneous trade model of Lyons (1997). In that model, the optimal strategy for a dealer is to initiate trade with other dealers in proportion to the end-user order flow he receives. Eq. (4) weakens this prediction by assuming that interdealer order flow is proportional to a distributed lag of end-user flows. Allowing for richer dynamics makes sense here because the degree of transparency assumed by the simultaneous trade model is higher than that present on the Dealing 2000-1 system. Lower transparency gives individual dealers the ability to adjust their quotes in response to incoming end-user flows without creating opportunities for arbitrage. Empirical studies of individual dealer behavior (e.g., Lyons, 1995) show that this is exactly what they do. Consequently, our empirical specification needs to accommodate dealer strategies in which incoming end-user order flow triggers a change in quotes before impacting on interdealer order flow.[7]

Combining Eq. (4) with Eqs. (1) and (2), we can now represent the dynamics of prices and interdealer order flow by:

$$\Delta p_i = D(L)x_i + \varepsilon_i \quad \text{and} \tag{5}$$

$$x_i = C(L)\xi_{i-m}, \tag{6}$$

where $D(L) = B(L)L^{-m}C(L)^{-1}$ and $C(L) = C_x(L)C_y(L)$. Although the polynomial $D(L)$ could take many forms depending on the dynamic responses of price and interdealer order flow to dispersed information shocks, in general it includes both negative and positive powers of L (corresponding to leads and lags of x_i) when $m>0$. Our model estimates are based on a sixth-order specification for $D(L)$ that links Δp_i to interdealer order flows from x_{i+4} to x_{i-1}. This specification is supported by a series of diagnostic tests reported in Evans (2002). It implies that a dispersed information shock could impact end-user orders and prices up to 20 minutes before it affects interdealer order flow (i.e., $m = 4$). Similarly, we specify the form of $C(L)$ so that the time series properties implied by Eq. (6) match those in the data. As in Evans (2002), we find that interdealer order flow is well characterized by an AR(10) process, so we specify $C(L)$ as $(1-\sum_{j=1}^{10} c_j L^j)^{-1}$.

Finally, we incorporate the effects of macro news. We treat the arrival of news as changing the state of the market. Following Evans (2002), we also allow the dynamics of prices and order flow to vary with trading intensity. Including trading intensity as a state variable is important for accommodating the pronounced time-dependence in volatility shown by Andersen and Bollerslev (1998). Let S_i denote the state of the market in period i. We assume that S_i depends on trading intensity in period i, n_i, and the arrival of news during the past three periods, A_i, A_{i-1}, and A_{i-2}. (The dummy variable A_i equals one if a macro news arrives during period i.) We incorporate state-dependency into the price and order flow dynamics via the polynomial $D(L)$ and the error variances. Specifically, $D(L)$ is replaced by $D(L,S)$, a state-dependent sixth-order polynomial:

$$D(L,S) = d_1(n,\bar{A})L^{-4} + d_2(n,\bar{A})L^{-3} + \cdots + d_5(n,\bar{A}) + d_6(n,\bar{A})L, \tag{7}$$

where $\bar{A}_i \equiv \max\{A_i, A_{i-1}, A_{i-2}\}$ with state-dependent coefficients $d_j(.,.)$. Thus, $d_6(n,1)$ is the coefficient on lagged order flow x_i when trade intensity equals n and news arrived in the past 15 minutes. We also allow for

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[7] One implication of our specification in Eq. (4) is that price changes have forecasting power for future interdealer order flow when $m>0$. This does not mean that dealers could forecast future order flow in real time. No dealer had access to the sequence of transaction prices we have in our data set. Consequently, the lead-lag relation between price changes and order flow in the reduced form equations of our model are not attributable to feedback trading from transaction prices to order flow by dealers.

state-dependence in the error variances, $Var(\varepsilon_i|S_i) = \Omega_\varepsilon(n_i, A_i)$, $Var(\xi_i|S_i) = \Omega_\xi(n_i, A_i)$, and $Var(\eta_i^{\text{ASK}}|S_i) = Var(\eta_i^{\text{BID}}|S_i) = \Omega_\eta(n_i, A_i)$. State-dependence in the coefficients and variances is modeled as

$$d_j(n, \bar{A}) = \underline{d}_j(\bar{A})\mathrm{e}^{(-n/500)} + \overline{d}_j(\bar{A})[1 - \mathrm{e}^{(-n/500)}] \quad \text{and} \tag{8}$$

$$\Omega_j(n, A) = \underline{\varpi}_j(A)\mathrm{e}^{(-n/500)} + \overline{\varpi}_j(A)[1 - \mathrm{e}^{(-n/500)}], \tag{9}$$

where $\underline{d}_j(0)$, $\overline{d}_j(0)$, $\underline{\varpi}_j(0)$, and $\overline{\varpi}_j(0)$ are the parameters to be estimated for observations without a news arrival, and $\underline{d}_j(1)$, $\overline{d}_j(1)$, $\underline{\varpi}_j(1)$, and $\overline{\varpi}_j(1)$ when there is a news arrival. These functional forms make $d_j(.)$ and $\Omega_j(.)$ smooth monotonic functions of trade intensity and are similar to the transition functions used in nonlinear time-series models (Potter, 1999). They bound the coefficients between $\underline{d}_j(\bar{A})$ and $\overline{d}_j(\bar{A})$, and the variances between $\underline{\varpi}_j(A)$ and $\overline{\varpi}_j(A)$ as trade intensity varies between zero and ∞.

Several aspects of our specification for state-dependency deserve comment. First, while specialized with respect to variations in trading intensity, the functional forms in Eqs. (7)–(9) do not appear unduly restrictive when we subject our model to specification tests. Second, no evidence exists that variations in trading intensity or the arrival of news affect the dynamics of order flow via $C(L)$. Thus, we do not incorporate state-dependency in this polynomial to avoid an unnecessary proliferation in parameters. Third, our specification places minimal restrictions on how the arrival of news affects the error variances and the link between order flow and price dynamics. Importantly, we do not restrict how the coefficients in $D(L, S)$ or the error variances change following the arrival of news. Consequently, our specification does not impose a prior about how the arrival of macro news affects the relative importance of the direct and indirect information transmission channels. Finally, our specification makes no distinction between the arrival of US news, German news, scheduled news, or unscheduled news. A_i equals one when any news arrives during period i. We recognize that this assumption could be too restrictive. For example, the information transmission process following the arrival of scheduled US news could differ from that following other news items.

3.1.2. Estimation

The model is estimated using the Generalized Method of Moments (GMM) technique developed in Evans (2002). The moment conditions used to estimate the parameters of the order flow process are

$$0 = \mathrm{E}[\xi_i \otimes z_i^x] \quad \text{and} \tag{10}$$

$$0 = \mathrm{E}[\{\xi_i^2 - \Omega_\xi(S_i)\} \otimes z_i^x], \tag{11}$$

where $\xi_i = x_{i+4} - \sum_{j=1}^{10} c_j x_{i+4-j}$ and $\Omega_\xi(S_i)$ is the conditional variance of ξ_i specified in Eq. (9). [Hereafter, we use S_i not n_i and A_i as the argument of the error variances, $\Omega(.)$.] If the order flow process is correctly specified, a dispersed information shock ξ in period i should be uncorrelated with interdealer order flow x in periods $i+3$ and earlier. Similarly, the difference between ξ_i^2 and the conditional variance should be uncorrelated with current or past trade intensity and order flows. We employ $\{x_{i+3}, \ldots, x_{i-6}\}$ and four lagged values of ξ_i as elements of the instrument vector z_i^x in Eq. (10). In Eq. (11) the instrument vector contains a constant, $\mathrm{e}^{(-n_i/500)}$ and A_i. With this choice of instruments, Eqs. (10) and (11) represent 17 moment restrictions on 14 parameters $[\{c_j\}_{j=1}^{10}, \underline{\varpi}_\xi(0), \underline{\varpi}_\xi(1), \overline{\varpi}_\xi(0)$ and $\overline{\varpi}_\xi(1)]$.

Parameters of the price process are computed from moments using the bivariate process for purchase and sales prices, Δp_i^{ASK} and Δp_i^{BID}, respectively. Combining Eq. (3) with Eq. (5) and our specification for $D(L, S)$ gives

$$\Delta p_i^o = \sum_{j=1}^{6} \{\underline{d}_j(\bar{A}_i)\mathrm{e}^{(-n_i/500)} + \overline{d}_j(\bar{A}_i)(1 - \mathrm{e}^{(-n_i/500)})\} x_{i+5-j} + u_i^o, \tag{12}$$

where $u_i^o \equiv \varepsilon_i + \eta_i^o - \eta_{i-1}^o$ for $o = \{\text{ASK}, \text{BID}\}$. This equation describes the state-dependent relation between actual transactions prices and interdealer order flow implied by our model. The composite error term, u_i^o, follows an MA(1) process and $Cov(u_i^{\text{ASK}}, u_i^{\text{BID}}) = \Omega_\varepsilon(n_i, A_i)$. We account for this error structure in the moment conditions used to estimate the parameters of the price process:

$$0 = \mathrm{E}[u_i^o \otimes z_i^p], \tag{13}$$

$$0 = \mathrm{E}[\{(u_i^o)^2 - \Omega_\varepsilon(S_i) - \Omega_\eta(S_i) - \Omega_\eta(S_{i-1})\} \otimes z_i^p], \tag{14}$$

$$0 = \mathrm{E}[\{u_i^o u_i^{\text{\o}} - \Omega_\varepsilon(S_i)\} \otimes z_i^p], \tag{15}$$

$$0 = \mathrm{E}[\{u_i^o u_{i-1}^o + \Omega_\eta(S_{i-1})\} \otimes z_i^p], \tag{16}$$

$$0 = \mathrm{E}[u_i^o u_{i-1}^{\text{\o}} \otimes z_i^p], \tag{17}$$

$$0 = \mathrm{E}[u_i^o u_{i-2}^o \otimes z_i^p] \quad \text{and} \tag{18}$$

$$0 = \mathrm{E}[u_i^o u_{i-2}^{\text{\o}} \otimes z_i^p], \tag{19}$$

for $o, \text{\o} = \{\text{ASK}, \text{BID}\}$ and $\text{\o} \neq o$. The moment restriction in Eq. (13) exploits the assumed orthogonality between the instruments, z_t^p, and both the common knowledge news and idiosyncratic shocks. The other restrictions in Eqs. (14)–(19) are derived from the moving average structure of the composite error. In particular, Eqs. (14) and (15) focus on the variance of $\{u_i^{\text{ASK}}, u_i^{\text{BID}}\}$, while Eqs. (16)–(19) focus on the autocovariance. For example, in Eqs. (18) and (19) we exploit the fact that, under an MA(1) process, all the autocorrelations in the composite errors at lag two are zero. We use $\{x_{i+j},\ \mathrm{e}^{(-n_i/500)}x_{i+j},\ \bar{A}_i x_{i+j},\ \bar{A}_i \mathrm{e}^{(-n_i/500)} x_{i+j}\}_{j=-1}^{4}$ as instruments in Eq. (13), and $\{1, \mathrm{e}^{(-n_i/500)}, A_i\}$ in Eqs. (14)–(19). This instrument choice gives us 81 moment restrictions on the 32 parameters of the prices process $(\{\underline{d}_j(0), \underline{d}_j(1), \overline{d}_j(0), \overline{d}_j(1)\}_{j=1}^{6}$ and $\{\underline{\omega}_j(0), \underline{\omega}_j(1), \overline{\omega}_j(0), \overline{\omega}_j(1)\}_{j=\varepsilon,\eta})$.

In standard time-series applications, GMM estimates of the parameter vector θ are found by minimizing a quadratic form constructed from the sample analogues of the moment conditions implied by the model. In this application, estimation is complicated by the fact that the gap between successive purchases or sales or both occasionally spans many minutes. In these cases there is no record of an FX purchase or sale in the observation interval. For the purpose of computing our estimates, we designate the price and order flow observations from these periods as missing and we construct sample moments without these observations. Specifically, let $\mathrm{E}[m_{i,j}(\theta)] = 0$ denote condition j among the moment conditions shown in Eqs. (10), (11) and Eqs. (13)–(19) and let $\Lambda = \{i_1, .i_2 \ldots i_T\}$ be the set of observations for which none of the elements in $m_{i,j}(.)$ for all j is missing. We compute the sample analogue to condition j as $\bar{m}_j(\theta) = T^{-1}\sum_\Lambda m_{i,j}(.)$. The GMM estimates of θ are then found by minimizing

$$Q(\theta) = \bar{m}(\theta)' W^{-1} \bar{m}(\theta), \tag{20}$$

where $\bar{m}(\theta) = [\bar{m}_1(\theta), \bar{m}_2(\theta), \ldots,]'$. Our model specification implies that the moments include observations on order flow and price changes over 15 periods of continuous trading (i.e., 75 minutes). Consequently, data from the periods of intermittent trading that occur before 7 am or after 5 pm BST on trading days are excluded from our estimation sample. Nevertheless, this leaves us with a large sample of $T = 11,473$ observations from which to compute the moments $\bar{m}(\theta)$.

We follow the standard practice of first setting the weighting matrix W equal to the identity to obtain consistent estimates of θ. These estimates, $\tilde{\theta}$, then are used to compute a consistent estimate of the optimal weighting matrix, $\tilde{W}$. We construct $\tilde{W}$ using the Newey and West (1987) estimator for the covariance of $m_{i,j}(\theta)$ incorporating a correction for MA(1) serial correlation. This estimate of the covariance matrix allows for the fact that the model fails to completely account for the heteroskedasticity in prices and order flow. The GMM estimates, $\hat{\theta}$, are found by minimizing Eq. (20) with $W = \tilde{W}$. The asymptotic covariance matrix of the resulting estimates is $\hat{V} = [\hat{G}\tilde{W}^{-1}\hat{G}']^{-1}$, where $\hat{G} = \partial\bar{m}(\hat{\theta})/\partial\theta'$.

We examine the performance of our estimated model with a series of diagnostic tests. In particular, we use a chi-squared test to examine the validity of an auxiliary set of moment conditions implied by our model but not used in estimation. Let $\bar{m}_{\mathrm{II}}(\theta)$ denote a vector of K_{II} sample moments, comprising the K_{I} moments used to find the GMM estimates, and $K_{\mathrm{II}} - K_{\mathrm{I}}$ auxiliary moment conditions implied by the model. Following Hayashi (2000), we construct the test statistic by first finding the GMM estimates of θ, denoted $\hat{\theta}_{\mathrm{II}}$, from the set of K_{II} moments. These estimates are found with the two-step procedure described above using the Newey and West estimator from the first step to construct the weighting matrix, $\tilde{W}_{\mathrm{II}}$. Next, we construct the submatrix of $\tilde{W}_{\mathrm{II}}$ corresponding to the original K_{I} moments, $\tilde{W}_{\mathrm{I}}$. We then find an alternative set of GMM estimates, $\hat{\theta}_{\mathrm{I}}$, by minimizing Eq. (20) with $W = \tilde{W}_{\mathrm{I}}$. Finally, we form the test statistic

$$C \equiv T\bar{m}_{\mathrm{II}}(\hat{\theta}_{\mathrm{II}})' \tilde{W}_{\mathrm{II}}^{-1} \bar{m}_{\mathrm{II}}(\hat{\theta}_{\mathrm{II}}) - T\bar{m}(\hat{\theta}_{\mathrm{I}})' \tilde{W}_{\mathrm{I}}^{-1} \bar{m}(\hat{\theta}_{\mathrm{I}}), \tag{21}$$

where T denotes the number of nonmissing elements used to construct $\bar{m}_{\mathrm{II}}(\theta)$. Under the null hypothesis that the auxiliary moment conditions are satisfied, the C statistic has an asymptotic chi-squared distribution with $K_{\mathrm{II}} - K_{\mathrm{I}}$ degrees of freedom. We use this test below to examine the adequacy of our specification for the state-dependent coefficients and error variances.

3.1.3. *Model estimates*

Table 2 presents GMM estimates of the intraday model. In specifications where all the variance parameters were left unrestricted, the estimates of $\underline{\omega}_{\varepsilon}(A)$, $\underline{\omega}_{\xi}(A)$, and $\overline{\omega}_{\eta}(A)$ were close to zero (i.e., <0.0001), so the table reports estimates where these parameters are restricted to zero. With these restrictions imposed, there are 40 parameters to be estimated from a total of 98 moment restrictions, so our estimates are derived from a model with 58 over-identifying restrictions. The Hansen (1982) J-statistic computed from our GMM estimates is 68.645, which implies a P-value of 0.160 for the null of a correctly specified model.

Panel A of Table 2 reports the parameters for the state-dependent order flow polynomial, $D(L,S)$. A comparison of the estimated state-dependent coefficients in rows (i) and (ii) and rows (iii) and (iv) shows that trade intensity has differing effects on the price-impact of order flow depending on the arrival of news. This is most easily seen in the right-hand column where we report the sum of the coefficients in different market states. These estimates have two noteworthy features. First, the long-run impact of order flow on prices is much larger when trading intensity is high $[\sum_j \underline{d}_j(.) < \sum_j \overline{d}_j(.)]$. Second, controlling for trading intensity, the arrival of news slightly reduces the long-run impact of order flow $[\sum_j d_j(\bar{A} = 1) < \sum_j d_j(\bar{A} = 0)$, except at the very lowest trade intensities]. Further evidence on the importance of state-dependency is provided by the four test statistics shown at the bottom of the panel. Here we report the results of Wald tests for the following coefficient restrictions: $\underline{d}_j(0) = \overline{d}_j(0)$, $\underline{d}_j(1) = \overline{d}_j(1)$, $\overline{d}_j(1) = \overline{d}_j(0)$, and $\underline{d}_j(1) = \underline{d}_j(0)$ for $j = \{1, \ldots, 6\}$. As the table shows, there is strong statistical evidence against all of these restrictions. These findings are consistent with the nonparametric evidence on state-dependence in hourly price change data reported in Evans and Lyons (2002b). Love and Payne (2004) also find evidence that the price impact of order flow varies according to the arrival of scheduled macroeconomic news. Our results show that it is important to accommodate state-dependency with respect to both the arrival of news and variations in trading intensity.

Parameter estimates from the order flow equation are reported in Panel B. Many of the coefficients are highly statistically significant, indicating that there is a good deal of serial correlation in intraday order flow. The table also reports the estimate of $(1 - \sum_j c_j)^{-1}$, which measures the cumulative long-run effect of dispersed information on order flow. The estimate of 1.69 indicates that the cumulative effect of a dispersed information shock is approximately 70% greater than its initial impact.

Panel C of Table 2 reports the estimated parameters of the state-dependent error variances. The estimated values for $\underline{\omega}_{\eta}(A)$ imply that the standard deviation of the idiosyncratic shocks slowly falls from approximately 0.04 to 0.01 as n varies from 2 to 1,000. Thus, the cross-sectional dispersion of transactions prices falls as trade intensity increases, as in Evans (2002), but we find no evidence that dispersion depends on the arrival of news. The estimates of $\overline{\omega}_{\varepsilon}(A)$ indicate how the volatility of common knowledge shocks varies with trade intensity and the arrival of news. The estimated standard deviation of common knowledge shocks rises from approximately 0.01 to 0.09 as n varies between 2 and 1,000 when news is absent and from 0.01 to 0.07 when news arrives. The estimated standard deviation of dispersed information shocks also increases with trade intensity; from 0.01% to 0.17% as n varies between 2 and 1,000, whether or not news arrives.

Two implications of these estimates deserve emphasis. First, under normal trading conditions, much of the observed volatility in high-frequency transactions prices is attributable to the dispersion of prices that characterizes market activity at a particular time. Failure to account for this feature of the data would leave our analysis of how news arrivals affect prices and order flow flawed. Second, our estimates show only how the arrival of news affects price and order flow dynamics for a given level of trade intensity. If the arrival of news changes trade intensity, as it does, the total impact of news on prices and order flow reflects both the direct

Table 2
Generalized Method of Moments (GMM) estimates of the intraday model

The table reports GMM estimates with asymptotic standard errors in parentheses corrected for conditional heteroskedasticity and an MA(1) error term. News arrival is denoted by A_i and $\bar{A}_i$, with $\bar{A}_i = \max\{A_i, A_{i-1}, A_{i-2}\}$, where $A_i = 1$ if there was a news arrival during the previous five-minutes. Coefficients and standard errors in Panel A are multiplied by one hundred. *P*-values are reported in parentheses below the Wald statistics in Panel A. For the variance parameters, *P*-values are not reported in cases in which unrestricted parameter estimates were <0.0001 because these parameters were restricted to zero.

A. Price equation: $\Delta p_i = \sum_{j=1}^{6}\{\underline{d}_j(\bar{A}_i)\mathrm{e}^{-n_i/500} + \overline{d}_j(\bar{A}_i)(1-\mathrm{e}^{-n_i/500})\}x_{i+5-j} + \varepsilon_i$

	$\bar{A}$	$\underline{d}_1(.)$	$\underline{d}_2(.)$	$\underline{d}_3(.)$	$\underline{d}_4(.)$	$\underline{d}_5(.)$	$\underline{d}_6(.)$	$\sum_j \underline{d}_j(.)$
(i)	0	0.029	0.025	0.028	−0.047	−0.113	−0.034	−0.113
		(0.024)	(0.057)	(0.233)	(0.052)	(0.025)	(0.033)	(0.030)
(ii)	1	−0.022	0.074	0.054	−0.131	0.002	−0.066	−0.089
		(0.045)	(0.046)	(0.042)	(0.046)	(0.044)	(0.043)	(0.070)

	$\bar{A}$	$\overline{d}_1(.)$	$\overline{d}_2(.)$	$\overline{d}_3(.)$	$\overline{d}_4(.)$	$\overline{d}_5(.)$	$\overline{d}_6(.)$	$\sum_j \overline{d}_j(.)$
(iii)	0	0.127	0.275	0.543	0.629	−0.220	−0.062	1.293
		(0.106)	(0.210)	(0.716)	(0.186)	(0.078)	(0.101)	(0.106)
(iv)	1	0.278	−0.018	0.256	0.858	−0.449	0.091	11.015
		(0.153)	(0.139)	(0.131)	(0.133)	(0.107)	(0.114)	(0.209)

Wald tests

	$\underline{d}_j(0) = \overline{d}_j(0)$	$\underline{d}_j(1) = \overline{d}_j(1)$	$\overline{d}_j(1) = \overline{d}_j(0)$	$\underline{d}_j(1) = \underline{d}_j(0)$
(v)	216.083	19.096	20.896	11.953
	(<0.001)	(0.004)	(0.002)	(0.063)

B. Order flow equation: $x_i = \sum_{j=1}^{10} c_j x_{i-j} + \xi_{i-4}$

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	$(1-\sum_{j=1}^{10} c_j)^{-1}$
(i)	0.21	0.036	0.048	0.033	0.019	0.025	0.015	1.688
	(0.014)	(0.013)	(0.012)	(0.012)	(0.011)	(0.011)	(0.010)	(0.070)

	c_8	c_9	c_{10}
(ii)	0.017	−0.016	0.020
	(0.012)	(0.010)	(0.008)

C. Variance parameters: $\Omega_j(n, A) = \underline{\omega}_j(A)\mathrm{e}^{-n_i/500} + \overline{\omega}_j(A)(1-\mathrm{e}^{-n/500})$

		Shock types					
		Idiosyncratic		Common knowledge		Dispersed information	
	A	$\underline{\omega}_\eta(.)$	$\overline{\omega}_\eta(.)$	$\underline{\omega}_\varepsilon(.)$	$\overline{\omega}_\varepsilon(.)$	$\underline{\omega}_\xi(.)$	$\overline{\omega}_\xi(.)$
(i)	0	0.002	0.000	0.000	0.010	0.000	0.032
		(<0.001)			(<0.001)		(0.002)
(ii)	1	0.002	0.000	0.000	0.006	0.000	0.032
		(<0.001)	–		(0.002)		(0.034)

effect of news and the indirect effects associated with the induced change in trade intensity. (We examine the combined effects of news in Table 4.)

One important aspect of the model concerns the link between end-user order flow and interdealer order flow. Our estimated specification in Eq. (6) assumes that the dispersed information in a news announcement shows up in interdealer order flow with up to a 20-minute delay. We can test the validity of this assumption by regressing the squared residuals from the order flow equation [i.e., $\hat{\xi}^2_{i-4}$ from estimates of Eq. (6)] on current and lagged values of the news dummies $\{A_i, A_{i-1}, \ldots, A_{i-6},\}$ and trade intensities $\{n_i, n_{i-1}, \ldots, n_{i-6}\}$. According to our model, none of the coefficients on A_i through A_{i-3} should be significant because dispersed information contained in period-*i* news should show up only in the variance of interdealer order flow in period $i-4$. This prediction is confirmed in the data. None of the individual coefficients on A_i through A_{i-3} is statistically significant, and the *P*-value for the null that all four are zero is 0.568. By contrast, a joint test for the significant of the coefficients on A_{i-4} through A_{i-6} has a *P*-value of 0.011. This is strong evidence supporting our empirical specification.

Our specification for the intraday model imposes many more moment conditions than were used in GMM estimation. Table 3 provides diagnostics in the form of *C*-tests on a selection of these additional moment conditions. The tests in Column (1) look for state-dependency in the order flow polynomial $C(L)$. For this purpose we compute *C*-statistics for restrictions of the form $\mathrm{E}[\xi_i x_{i+4-j} \mathrm{z}_i] = 0$ for $j = \{1, 2, \ldots, 10\}$, where z_i equals n_i, A_i^{US}, and A_i^{S} in rows (i), (ii), and (iii), respectively. These moment conditions do not hold if, contrary to the assumption of our model, the serial correlation in order flow varies with either trade intensity, the arrival of US news, or the arrival of scheduled news. The tests reported in Column (2) look for misspecification in the estimated form of the $D(L, S)$ polynomial. In this case the restrictions being tested take the form $\mathrm{E}[u_i^o \mathrm{z}_i x_{i+5-j}] = 0$ for $j = \{1, 2, \ldots, 6\}$, where $u_i^o \equiv \varepsilon_i + \eta_i^o - \eta_{i-1}^o$ for $o = \{\text{ASK}, \text{BID}\}$. These tests look for evidence of state-dependency in $D(L, S)$ beyond that implied by functional form in Eqs. (7) and (8). Similarly, the *C*-tests in Columns (3)–(5) look for evidence of misspecification in the error variances. The moments being tested here take the form of $\mathrm{E}[\varkappa_i \mathrm{z}_i] = 0$, where $\varkappa_i$ is the unexpected squared realization of the shock in period i [i.e., $\varkappa_i \equiv u_i^o u_i^o - \Omega_\varepsilon(n_i, A_i)$ in Column (3), $\varkappa_i \equiv \xi_i^2 - \Omega_\xi(n_i, A_i)$ in Column (4), and $\varkappa_i \equiv u_i^o u_{i-1}^o + \Omega_\eta(n_{i-1}, A_{i-1})$ in Column (5)]. Row (iv) reports *C*-tests for third-order residual autoregressive conditional heteroskedasticity (ARCH) by testing moment conditions of the form $\mathrm{E}[\varkappa_i \varkappa_{i-j}] = 0$ for $j = \{1, 2, 3\}$.

As the table shows, none of the test statistics in Rows (i)–(iii) is significant at the 5% level. In particular, there is no evidence from the tests in Row (i) that the functional forms in Eqs. (7)–(9) are unduly restrictive. The results in Rows (ii) and (iii) address the question of whether there should be a distinction in our model between the arrival of US and German news or scheduled and unscheduled news. The median (daily) arrival rate for German news is four times the rate for US news. Some of this difference could be attributable to institutional features, such as the distribution of news bureaus supplying Reuters, that are unrelated to the pace at which price-relevant information becomes known. In particular, the arrival rate of German news items on the Headline screens could overstate the true pace at which price-relevant German news arrives. In this case, our specification using the A_i dummy overstates how the dynamics of prices and order flow change immediately following the arrival of price-relevant news. The *C*-statistics in Row (ii) test for this form of misspecification using the arrival of US news as an instrument. None of the statistics is significant at the 5% level. Differences between the arrival of scheduled and unscheduled news could pose similar problems. For

Table 3
Diagnostics for the intraday model

The table reports *C*-tests for a set of auxiliary moment conditions implied by the model. In Column (1) the restrictions take the form $\mathrm{E}[\xi_i x_{i+4-j} z_i] = 0$ for $j = \{1, 2, \ldots, 10\}$. The restrictions in Column (2) are $\mathrm{E}[u_i^o z_i x_{i+5-j}] = 0$ for $j = \{1, 2, \ldots, 6\}$, where $u_i^o \equiv \varepsilon_i + \eta_i^o - \eta_{i-1}^o$ for $o = \{\text{ASK}, \text{BID}\}$. In Columns (3)–(5) the restrictions are $\mathrm{E}[\varkappa_i z_i] = 0$, where $\varkappa_i \equiv u_i^o u_i^o - \Omega_\varepsilon(n_i, A_i)$ in Column (3), $\varkappa_i \equiv \xi_i^2 - \Omega_\xi(n_i, A_i)$ in Column (4), and $\varkappa_i \equiv u_i^o u_{i-1}^o + \Omega_\eta(n_{i-1}, A_{i-1})$ in Column (5). The instruments z_i are n_i, A_i^{US}, A_i^{S}, and $\varkappa_{i-j}$ for $j = \{1, 2, 3\}$ in rows (i)–(iv) respectively. *P*-values are reported in parentheses.

Instrument: z_i	(1) $C(L)$	(2) $D(L, S)$	(3) $\Omega_\varepsilon(S)$	(4) $\Omega_\xi(S)$	(5) $\Omega_\eta(S)$
(i) Trade intensity n_i	2.624	0.371	0.737	0.200	0.134
	(0.989)	(0.999)	(0.391)	(0.655)	(0.714)
(ii) US news A_i^{US}	1.731	19.083	0.950	1.731	0.019
	(0.188)	(0.087)	(0.330)	(0.188)	(0.891)
(iii) Scheduled news A_i^{S}	17.905	13.084	3.904	2.307	1.660
	(0.084)	(0.363)	(0.068)	(0.129)	(0.198)
(iv) Residual ARCH			17.543	30.123	8.190
			(0.001)	(<0.001)	(0.042)

example, if the ratio of common knowledge to dispersed information in scheduled news is higher on average than in nonscheduled news, the price and order flow dynamics following the arrival of scheduled news could differ from the dynamics following the arrival of other news. The C-statistics in Row (iii) are designed to look for evidence of this form of misspecification. None are significant at the 5% level. In sum, these diagnostic tests suggest that the estimated model adequately accounts for the effects of varying trade intensity and the arrival of news on the dynamics of transaction prices and interdealer order flow.

The model is less successful in accounting for all the heteroskedasticity in the error processes. The C-tests for third-order residual ARCH are significant at the 5% level. An inspection of the estimated residuals shows that these residual ARCH effects are concentrated at lag one. In fact, if we omit this moment from our C-test, we cannot reject the null of no residual heteroskedasticity. We have accounted for this feature of the data in our estimates and tests by constructing the GMM weighting matrix from the Newey and West estimator with an MA(1) serial correlation correction.

3.1.4. *News arrival and intraday dynamics*

We now examine how the information in macro news is transmitted to prices. For this, we use our model estimates to compute a variance decomposition for price changes across different market states. First, we use our estimates to write the change in average transaction price as

$$\Delta p_i = B(L, S_i)\xi_i + \varepsilon_i, \tag{22}$$

where $B(L,S) = D(L,S)C(L)L^m$. The state-dependent coefficients in $B(L,S)$ identify how dispersed information affects prices and can be computed from our estimates of the coefficients in $D(L,S)$ and $C(L)$. We can also use Eq. (22) to decompose the variance of price changes into different theoretical components. In particular, consider the k-period price change between period $i-k$ and i: $\Delta^k p_i \equiv \sum_{j=0}^{k-1}\Delta p_{i-j}$. Substituting for Δp_i with Eq. (22), gives

$$\Delta^k p_i = \sum_{j=0}^{k-1}\varepsilon_{i-j} + \sum_{j=0}^{k-1} B(L, S_{i-j})\xi_{i-j}, \tag{23}$$

which implies that

$$Var(\Delta^k p_i|\{S_{i-j}\}_{j=0}^{k-1}) = \sum_{j=0}^{k-1}\Omega_\varepsilon(S_{i-j}) + \sum_{j=0}^{k-1} B(L, S_{i-j})^2\Omega_\xi(S_{i-j}). \tag{24}$$

Eq. (24) provides a decomposition of the variance of price changes conditioned on the state of the market during the last k periods. The first component on the right-hand side is the variance contribution of common knowledge shocks; the second, the contribution of dispersed information shocks operating via order flow. State-dependency in the error variances and lag polynomial $D(L,S)$ of our model allows the contribution of each variance component to vary with changes in trade intensity and the arrival of macro news. We now use the model estimates to quantify these effects.

Order flow is much more important in price determination when macro news arrives. Table 4 reports the estimated contribution of dispersed information to the variance of price changes over horizons of five, 30, and 60 minutes (i.e., $k = \{1, 6, 12\}$) when trading intensity is at four different levels (i.e., $n = \{25, 50, 100, 150\}$ per five-minute interval). Row (i) in each panel reports the contribution for a given level of trade intensity in the absence of macro news. (The statistics in parenthesis are standard errors associated with these estimates computed from the asymptotic distribution of the GMM estimates by the delta-method.[8]) Consistent with the results in Evans (2002), these statistics show that the contribution of dispersed information to price variance rises with trade intensity and horizon. The contribution of dispersed information in the presence of macro news is reported in Row (ii). These statistics incorporate direct effects of news arrival via the five- and

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[8] Specifically, let $R^k(\theta, n, A)$ denote the contribution of dispersed information shocks equal to $\{\sum_{j=0}^{k-1} B(L,S)^2\Omega_\xi(S)\}\{\sum_{j=0}^{k-1}\Omega_\varepsilon(S) + \sum_{j=0}^{k-1} B(L,S)^2\Omega_\xi(S)\}^{-1}$ given a constant level of trading intensity n, and the presence or absence of macro news, $A = \{1, 0\}$. We estimate the standard error of $R^k(\theta, n, A)$ as the square root of $\nabla R^k(\hat{\theta}, n, A)'\hat{V}\nabla R^k(\hat{\theta}, n, A)$, where $\nabla R^k(.)$ is the gradient vector with respect to θ and $\hat{V}$ is the estimated covariance matrix of the GMM estimates, $\hat{\theta}$.

Table 4
Variance Decompostions

The table reports values for $R^k(\theta, n, A)$, the contribution of dispersed information shocks to variance of k-horizon price changes implied by the Generalized Method of Moments estimates of the intraday model given a constant level of trading intensity n, and the presence or absence of macro news, $A = \{1, 0\}$. Standard errors are in parentheses. Statistics in Rows (i)–(iii) are computed as $R^k(\theta, n, 0)$, $R^k(\theta, n+45, 1)$, and $R^k(\theta, n+65, 1)$, respectively. Cases in which the Monte Carlo P-value for the null that news arrival does not increase the contribution of dispersed news to the variance of prices is less than 10%, 5%, and 1% percent are indicated by *, **, and ***, respectively.

	Horizon (minutes)			Horizon (minutes)		
	5	30	60	5	30	60
		Trade intensity: $n = 25$			Trade intensity: $n = 50$	
(i) No news	0.631	0.989	0.758	1.436	2.314	2.118
	(1.040)	(2.811)	(3.754)	(1.327)	(2.911)	(3.621)
(ii) News	3.895**	10.280**	11.768*	5.123**	12.137**	13.597**
	(0.911)	(3.396)	(4.236)	(1.354)	(4.554)	(5.451)
(iii) Scheduled news	8.271***	16.083**	17.417*	9.868***	17.807**	19.067**
	(2.896)	(8.020)	(9.112)	(3.748)	(9.569)	(10.727)
		Horizon (minutes)			Horizon (minutes)	
		Trade intensity: $n = 100$			Trade intensity: $n = 150$	
(i) No news	3.808	7.475	7.957	7.173	14.862	16.129
	(1.359)	(2.850)	(3.303)	(1.738)	(3.747)	(4.131)
(ii) News	7.981**	15.754*	17.101*	11.214**	19.163	20.358
	(2.755)	(7.658)	(8.729)	(4.500)	(10.673)	(11.862)
(iii) Scheduled news	13.231***	21.067*	22.163*	16.679**	24.053	24.980
	(5.533)	(12.326)	(13.573)	(7.248)	(14.569)	(15.871)

15-minute announcement dummies and the indirect effects via the induced change in trade intensity. We estimate that trading intensity rises by approximately 45 trades per five-minute interval when news arrives.[9] To estimate the contribution of dispersed information we therefore use the GMM estimates of Eq. (24) with $B(L, S^{\mathrm{A}})$, $\Omega_{\xi}(S^{\mathrm{A}})$, and $\Omega_{\varepsilon}(S^{\mathrm{A}})$, where $S^{\mathrm{A}} = \{n+45, 1\}$ and n is the initial level of trade intensity shown at the top of each panel in the table. A comparison of the statistics in Rows (i) and (ii) show that, following the arrival of macro news, dispersed information contributes more to the variance of prices across all three horizons. This pattern also appears consistently across all four panels (corresponding to different initial levels of trade intensity).

We conducted a Monte Carlo experiment to assess the statistical significance of these findings. The experiment comprised the following steps: (1) draw a vector of parameter estimates $\hat{\theta}^j$ from the estimated asymptotic distribution of the GMM estimates, $N(\hat{\theta}, \hat{V}_{\theta})$; (2) use Eq. (24) and $\hat{\theta}^j$ to compute the contribution of the dispersed information shocks to the k-period price variance at trade intensity n in the absence of news ($A = \bar{A} = 0$), $R^k(\hat{\theta}^j, n, 0)$ for horizons of five, 30, and 60 minutes (i.e., $k = \{1, 6, 12\}$); (3) use Eq. (24) and $\hat{\theta}^j$ to compute the contribution to k-period price variance with news ($A = \bar{A} = 1$) at trade intensity $n^{\mathrm{A}} = n + 45$, $R^k(\hat{\theta}^j, n^{\mathrm{A}}, 1)$ for $k = \{1, 6, 12\}$; and (4) repeat steps (1)–(3) five thousand times for $n = \{25, 50, 100, 150\}$ and compute the fraction of times that $R^k(\hat{\theta}^j, n, 0) \geqslant R^k(\hat{\theta}^j, n^{\mathrm{A}}, 1)$. This procedure gives us a Monte Carlo estimate of the P-value for the null hypothesis that news arrival does not increase the contribution of dispersed news to the variance of prices. Cases in which the P-values are less than 10%, 5% and 1% are indicated in Table 4 by *, **, and ***, respectively. Based on these calculations, the increased contribution of dispersed information

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[9] This estimate is obtained from the OLS estimate of δ from the regression $n_i = \delta A_i + \sum \gamma_i \, dum_{i,\tau} + u_i$, where $dum_{i,\tau}$ is a seasonal time dummy that takes the value of one when observation i falls in the τ'th 30-minute window of a day. We estimate δ to be 44.55 with a standard error of 3.10.

shocks following the arrival of macro news is strongly significant over most horizons and initial trading intensities.

The specification tests reported in Table 3 do not suggest that the direct affects of macro news arrival vary according to whether or not the news item is scheduled. Nevertheless, scheduled news could have a different total impact because the induced trade intensity differs from the trade intensity induced by nonscheduled news. We estimate that trading intensity when scheduled US news arrives rises by approximately 65 trades per five-minute interval. Row (iii) of Table 4 shows the contribution of dispersed information in the presence of a scheduled news announcement that increases trade intensity by this amount. Because the price-impact of order flow increase with trading intensity, the estimated variance contribution of dispersed information is larger following the arrival of scheduled news than it is for the more prevalent nonscheduled items. The *P*-values computed from Monte Carlo experiments with $n^{\mathrm{A}} = n + 65$ indicate an even stronger pattern of statistical significance.

Overall, our estimates indicate that order flow contributes more to price adjustment following macro news than at other times. This is not what one would expect if macro news is primarily made up of common knowledge information that is directly impounded into FX prices. If macro news primarily transmits new common knowledge information, order flow should contribute less to price dynamics in the period following the arrival of news than at other times. By contrast, the results in Table 4 strongly suggest that the arrival of macro news triggers trading that reveals new dispersed information that affects prices indirectly. One particularly interesting aspect of our findings concerns the effects of scheduled US announcements. Because these news items contain data releases on macro economic aggregates, one might have expected that they contain a greater proportion of common knowledge to dispersed information than some of the other news items in our sample. That order flow is at least as important in price dynamics following scheduled news suggests that this common view concerning the information content of macro news is incorrect.

4. Daily analysis

Our intraday analysis shows the importance of the order flow channel as a means for impounding macro news in FX prices. We now examine implications of this for the behavior of FX prices at the daily frequency. This examination compliments our intraday analysis for three reasons. First, daily changes in FX prices are nearly a martingale (which is not true of five-minute changes). Our daily model thus sheds light on how the information contained in macro news contributes to price variation over the longer run. Second, our daily analysis provides additional perspective on results relating daily price dynamics to order flow (e.g., Evans and Lyons, 2002a). In particular, our estimates provide a breakdown of the sources of price and order flow volatility. Third, our daily analysis provides a robustness check on the results presented above. For example, we can construct measures of the daily flow of macro news in ways that were not possible at higher frequencies. The consistency of the results derived from estimates of the daily and intraday model shows that our main findings are robust to our methods for identifying the impact of macro news arrivals.

4.1. The model

Our daily model for price and order flow dynamics is made up of the following equations:

$$\Delta p_t = \alpha x_t + e_t + v_t \quad \text{and} \tag{25}$$

$$x_t = u_t + w_t, \tag{26}$$

where Δp_t is the change in the spot price of FX between 5:00 pm on day $t-1$ and 5:00 pm on day t and x_t is interdealer order flow realized over the same period. The parameter α captures the price impact of order flow at the daily horizon, i.e., it reflects information content. Prices and order flow are subject to four shocks representing different sources of information hitting the market: e_t, v_t, u_t, and w_t. These shocks are mean zero, serially uncorrelated, and mutually independent conditional on the day-t state of the market. The e_t and v_t shocks represent information that is impounded in price directly. e_t is the common knowledge effect of macro news arrivals on the price of FX. v_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 u_t and w_t shocks. The u_t shocks represent order flow effects from macro news arrivals, the dispersed information effect of the news. Shocks to order flow that are unrelated to macro news are represented by the w_t shocks (e.g., portfolio shifts arising from other sources such as changing risk tolerances or hedging).

We identify the effects of the news-related common knowledge and dispersed information shocks, e_t and u_t, through state-dependency of price changes and order flow in the second moments. Specifically, we assume that the variance of e_t and u_t on day t is increasing in the daily flow of macro news, which we measure by the number of US and German news arrivals between 5:00 pm on days $t-1$ and t, A_t^{US}, and A_t^{G}:

$$Var_t(e_t) = \Sigma_e^2(A_t^{\mathrm{US}}, A_t^{\mathrm{G}}) \quad \text{and} \quad Var_t(u_t) = \Sigma_u^2(A_t^{\mathrm{US}}, A_t^{\mathrm{G}}), \tag{27}$$

where $\Sigma_\varkappa^2(0,0) = 0$, with $\partial\Sigma_\varkappa^2/\partial A_t^k > 0$ for $\varkappa = \{e, u\}$ and $k = \{\textsc{us}, \textsc{g}\}$. Thus, on days without news, $e_t = u_t = 0$, so price changes and order flow are driven solely by the v_t and w_t shocks. These shocks are independent of news, so their variances are unrelated to A_t^k. Little evidence of state-dependency exists in the second moments of daily price changes and order flow beyond the effects of news. In particular, unlike our intraday model, there is no need to incorporate trade intensity as an additional state variable. We therefore assume that the conditional variances of the v_t and w_t shocks are constant:

$$Var_t(v_t) = \Sigma_v^2 \quad \text{and} \quad Var_t(w_t) = \Sigma_w^2. \tag{28}$$

Several features of our daily model deserve comment. First, our specification abstracts from the complex intraday dynamics of prices and order flow. Eqs. (25) and (26) imply that, by 5:00 pm GMT each day, FX prices fully reflect the information contained in order flow to that point. As a result, price change over the next 24 hours (i.e., Δp_{t+1}) are not correlated with order flow from the past 24 hours (i.e., x_t). This feature of our model is supported by the data. We show below that there is no correlation between Δp_{t+1} and x_t. Our specification also implies the absence of serial correlation in daily price changes and order flows. This, too, is consistent with the evidence reported in Section 2. A second feature of our specification concerns the price-impact parameter α. Our intraday analysis showed that the price impact of order flows varied with trade intensity and the arrival of news. This form of state-dependency in the intraday data does not appear at the daily frequency, so we do not allow for state-dependency in α. We would add that this restriction in our model means that our test of the relative importance of indirect effects is conservative. Order flow induced by news could have more price impact than the constrained equation gives it credit for. In any event, we do incorporate state-dependency into the error variances. This final feature is key to identifying the effects of macro news.

Identification of the effects of macro news is achieved by the assumption that the variance of the e_t and u_t shocks is higher on days when a greater number of news items appears on the Reuters Money Market News screen. Crucially, this assumption does not require that FX market participants view the information in each news item as equally important (which the market does not). The identifying power of this assumption does, however, depend on the absence of wild variations in the quality of Reuters' editorial judgements. For example, if the Reuters screen were flooded one day with reports containing essentially no information, but on another a few reports appeared with great economic significance, daily variations in the number of news reports would be a poor measure of the daily flow of macro news. Based on our understanding of Reuters' editorial process, this possibility seems far-fetched. That said, we recognize that no single measure identifies the daily variation in macro news flow with complete precision. Thus, in addition to measures based on the daily arrival rates for US and German news shown in Eq. (27), we also use a measure based on the subset of items that are scheduled.

4.2. Estimation

We estimate two versions of the model by the Generalized Method of Moments. Version I assumes that the variances of the e_t and u_t shocks on day t vary only with the sum of the US and German news items, $A_t^{\mathrm{ALL}} \equiv A_t^{\mathrm{US}} + A_t^{\mathrm{G}}$. Under this specification, the flow of macro news is identified by the arrival rate of both US and German news. We also allow for the possibility that daily variations in the flow of macro news could be reflected differently in the arrival rates for US and German news. Version II of our model allows the variance of e_t and u_t on day t to depend on the number of US and German news items separately. The variance functions are assumed to be linear in both versions of the model:

$$\text{Version I:}\quad \Sigma^2_{\varkappa}(A^{\mathrm{US}}_t, A^{\mathrm{G}}_t) = \sigma_{\varkappa} A^{\mathrm{ALL}}_t \quad \text{and}$$

$$\text{Version II:}\quad \Sigma^2_{\varkappa}(A^{\mathrm{US}}_t, A^{\mathrm{G}}_t) = \sigma^{\mathrm{US}}_{\varkappa} A^{\mathrm{US}}_t + \sigma^{\mathrm{G}}_{\varkappa} A^{\mathrm{G}}_t, \tag{29}$$

where $\sigma_{\varkappa}, \sigma^{\mathrm{US}}_{\varkappa}$, and $\sigma^{\mathrm{G}}_{\varkappa}$ are positive parameters for $\varkappa = \{e, u\}$. Thus, the parameters to be estimated are $\{\alpha, \Sigma^2_w, \Sigma^2_v, \sigma_e, \sigma_u\}$ in Version I and $\{\alpha, \Sigma^2_w, \Sigma^2_v, \sigma^{\mathrm{US}}_e, \sigma^{\mathrm{G}}_e, \sigma^{\mathrm{US}}_u, \sigma^{\mathrm{G}}_u\}$ in Version II.

The GMM estimates of the model parameters are derived from the following set of moment conditions:

$$0 = \mathrm{E}[(\Delta p_t - \alpha x_t)x_t], \tag{30}$$

$$0 = \mathrm{E}[\{\mathscr{V}_t(\Delta p_t) - Var_t(\Delta p_t)\} \otimes \mathscr{Z}_t] \quad \text{and} \tag{31}$$

$$0 = \mathrm{E}[\{\mathscr{V}_t(x_t) - Var_t(x_t)\} \otimes \mathscr{Z}_t], \tag{32}$$

where $\mathscr{Z}_t$ is a vector of instruments. The condition in Eq. (30) follows from the assumed orthogonality between the shocks to prices (e_t and v_t) and the shocks to order flow (u_t and w_t). Eqs. (31) and (32) combine the second moments of price changes and order flow implied by the model with measures of the variance of order flow, $\mathscr{V}(x_t)$, the variance of price changes, $\mathscr{V}(\Delta p_t)$. These measures are computed for each day in our sample from the five-minute intraday observations as

$$\mathscr{V}_t(\Delta p_t) = \sum_{i=1}^{T_t} \Delta p^2_{it} \quad \text{and} \quad \mathscr{V}_t(x_t) = \sum_{i=1}^{T_t} x^2_{it}, \tag{33}$$

where the subscript it denotes the ith five-minute observation on day t, and T_t denotes the number of observations with consecutive trading. $\mathscr{V}_t(\Delta p_t)$ and $\mathscr{V}_t(x_t)$ are the (uncentered) second moments of the price change and order flow process over day t, scaled by the number of five-minute intraday observations. Andersen, Bollerslev, Diebold, and Labys (2001) show that these measures are consistent nonparametric estimates of the actual moments under mild regularity conditions. They also note that, while the measures are biased when prices changes and order flow do not follow martingales in the continuous time limit, in practice these biases are very small if a large number of high frequency observations are used to compute each daily measure. This appears true in our data where the average value of T_t is 188. Estimates of $\mathscr{V}_t(\Delta p_t)$ and $\mathscr{V}_t(x_t)$ computed from Δp_{it} and x_{it} are almost identical to their counterparts using the estimated residuals from the price and order flow equations of the intraday model. The correlation between the alternative measures is greater than 0.99 for both order flow and price changes.

We use two sets of instruments to implement estimation. The instrument vector in Version I includes a constant and sum of the US and German news items, A^{ALL}_t. In Version II, we use a constant, A^{US}_t and A^{G}_t as instruments. These choices imply that the number of moment conditions in Eqs. (30)–(32)) equals the number of parameters, so the estimates come from exactly identified versions of the model. As above, we apply the standard two-step method to compute the GMM estimates (without the serial correlation correction in the weighting matrix). We also consider the adequacy of our model estimates with a set of diagnostic tests based on additional moment conditions.

In our intraday analysis there are over 11 thousand time series observations from which to compute the sample moments in the GMM objective function in Eq. (20). Here we have just 80 trading days of data from which to compute estimates of the daily model. Consequently, the GMM asymptotic distribution could be a poor approximation to the finite-sample distribution of the parameter estimates. We conducted a Monte Carlo experiment to investigate this possibility. Specifically, taking the GMM estimates of each version of our daily model, $\hat{\theta}$ (reported Table 5), we generated five thousand samples of 80 daily observations on Δp_t, x_t, $\mathscr{V}_t(\Delta p_t)$ and $\mathscr{V}_t(x_t)$ using the actual news data.[10] The GMM estimates of the model were then computed from each sample to compile a Monte Carlo distribution $\{\tilde{\theta}_j\}^{5000}_{j=1}$. We found that GMM estimates $\hat{\theta}$ are similar to the mean of the Monte Carlo distributions for both versions of our model. The largest difference was just 1.6%.

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[10] For the purpose of these calculations we assumed that daily shocks are made up of $T = 180$ independent five-minute shocks, i.e., $\zeta_t = \sum_{i=1}^{T} \zeta_{it}$ for $\zeta = \{e, v, u, w\}$ with $\zeta_{it} \sim$ i.i.d.$N(0, T^{-2} Var_t(\zeta_t))$ for each day t. We then use Eq. (33) to compute $\mathscr{V}_t(\Delta p_t)$ and $\mathscr{V}_t(x_t)$ with $x_{it} = u_{it} + w_{it}$ and $\Delta p_{it} = \alpha x_{it} + e_{it} + v_{it}$.

Table 5

Generalized Method of Moments (GMM) estimates of daily models

Panel A of the table reports GMM parameter estimates and asymptotic standard errors (corrected for heteroskedasticity) in parentheses. Panel B shows Wald tests for the coefficient restrictions listed on the left with asymptotic *P*-values reported in parentheses. The *J*-tests shown in Panel C test the moment restrictions in Eqs. (33)–(33) and the following: (i) $\mathrm{E}[(\Delta p_t - \alpha x_t)x_{t-1}] = 0$; (ii) $\mathrm{E}[(\Delta p_t - \alpha x_t)(\Delta p_{t-1} - \alpha x_{t-1})] = 0$, $\mathrm{E}[x_t x_{t-1}] = 0$; (iii) $\mathrm{E}[(\Delta p_t - \alpha x_t) \otimes \mathrm{z}_t] = 0$, $\mathrm{E}[\{\mathscr{V}_t(\Delta p_t) - Var_t(\Delta p_t)\}n_t] = 0$, and $\mathrm{E}[\{\mathscr{V}_t(x_t) - Var_t(x_t)\}n_t] = 0$, where $z_t = \{x_t n_t, x_t A_t^{\mathrm{ALL}}\}$ in Version I and $z_t = \{x_t n_t, x_t A_t^{\mathrm{US}}, x_t A_t^{\mathrm{G}}\}$ in Version II; (iv) $\mathrm{E}[\{\mathscr{V}_t(\Delta p_t) - Var_t(\Delta p_t)\}\{V_{t-1}(\Delta p_{t-1}) - Var_{t-1}(\Delta p_{t-1})\}] = 0$ and $\mathrm{E}[\{\mathscr{V}_t(x_t) - Var_t(x_t)\}\{\mathscr{V}_{t-1}(x_{t-1}) - Var_{t-1}(x_{t-1})\}] = 0$; and (v) all the moments listed in (i)–(iv). Asymptotic *P*-values are reported in parentheses.

A. Parameters

	Version I		Version II	
	Estimate	Standard Error	Estimate	Standard Error
α	0.032	(0.003)	0.032	(0.003)
σ_w^2	67.231	(11.395)	67.018	(11.282)
σ_v^2	3.530	(0.675)	3.518	(0.671)
σ_e	3.737	(0.813)		
σ_u	0.188	(0.053)		
σ_e^{US}			5.682	(2.661)
σ_e^{G}			3.358	(0.977)
σ_u^{US}			0.291	(0.147)
σ_u^{G}			0.168	(0.063)

B. Wald tests

	Version II	
	Statistic	*P*-value
$\sigma_e^{\mathrm{US}} = \sigma_u^{\mathrm{US}} = 0$	33.303	(0.000)
$\sigma_u^{\mathrm{US}} = \sigma_u^{\mathrm{G}} = 0$	13.707	(0.001)
$\sigma_e^{\mathrm{US}} = \sigma_u^{\mathrm{US}} \& \sigma_u^{\mathrm{US}} = \sigma_u^{\mathrm{G}}$	0.763	(0.683)

C. Diagnostic tests

	Version I		Version II	
	Statistic	*P*-value	Statistic	*P*-value
(i) Lagged order flow	2.502	(0.114)	2.502	(0.114)
(ii) Serial correlation				
Δp_t Eq.	0.014	(0.905)	0.014	(0.905)
x_t Eq.	0.190	(0.663)	0.190	(0.663)
(iii) State-dependency				
α	2.767	(0.251)	2.767	(0.251)
$Var(\Delta p_t)$ and $Var(x_t)$	2.479	(0.290)	2.527	(0.283)
(iv) Residual arch				
Δp_t Eq.	0.348	(0.555)	0.281	(0.596)
x_t Eq.	2.332	(0.127)	2.486	(0.115)
(v) Joint test	10.097	(0.343)	9.876	(0.361)

There are much larger differences in the estimated standard errors. The estimated asymptotic standard errors are on average 2.5 times larger than the standard errors computed from the Monte Carlo distribution in Version I of the model and 2.7 times larger in Version II. Based on these findings, it seems likely that estimated asymptotic standard errors overstate the true standard errors. Below we take the conservative approach of reporting the asymptotic standard errors.

4.2.1. Daily estimates

Panel A of Table 5 reports parameter estimates from both versions of the model with exact identification. Asymptotic standard errors allowing for residual heteroskedasticity are shown in parentheses. 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.) In Version I of the model, both variance parameters σ_e and σ_u are positive and significant at the 5% level. These estimates imply that both direct and indirect effects of news on price are present. This finding is confirmed by the estimates from Version II reported in the right-hand panel. When US and German news events are introduced separately, the estimates of σ_e^{US}, σ_e^{G}, σ_u^{US}, and σ_u^{G} are all positive and significant at the 5% level. Furthermore, as Panel B shows, Wald statistics for the null that $\sigma_e^{\mathrm{US}} = \sigma_u^{\mathrm{US}} = 0$ and $\sigma_u^{\mathrm{US}} = \sigma_u^{\mathrm{G}} = 0$ are highly significant. Panel B also shows that there is no significant evidence against the parameter restrictions imposed by Version I of the model, namely, $\sigma_e^{\mathrm{US}} = \sigma_u^{\mathrm{US}}$ and $\sigma_u^{\mathrm{US}} = \sigma_u^{\mathrm{G}}$.

To provide additional support for our specification, Panel C shows results of diagnostic tests that examine an expanded set of moment conditions. In Row (i) we report the *J*-statistic for specifications using Eqs. (30)–(32)) and $\mathrm{E}[(\Delta p_t - \alpha x_t)x_{t-1}] = 0$ as moment conditions. Our model should satisfy this additional condition because all the price impact of order flow occurs within the day. As the table shows, there is no significant evidence to reject this set of restrictions in either version of the model. The statistics in row (ii) test for the presence of (residual) serial correlation in the price change and order flow process by, respectively, adding $\mathrm{E}[(\Delta p_t - \alpha x_t)(\Delta p_{t-1} - \alpha x_{t-1})] = 0$ and $\mathrm{E}[x_t x_{t-1}] = 0$ to the conditions in Eqs. (30)–(32). Again, consistent with the assumed structure of out model, none of the *J*-statistics is statistically significant. Next, we turn to the issue of state-dependency. Our daily model assumes that trade intensity and news have no effect on α, the parameter identifying the price-impact of order flow. We examine this restriction by adding $\mathrm{E}[(\Delta p_t - \alpha x_t) \otimes \mathrm{z}_t] = 0$ to the conditions in Eqs. (30)–(32) for $\mathrm{z}_t = \{x_t n_t, x_t A_t^{\mathrm{ALL}}\}$ in Version I and $\mathrm{z}_t = \{x_t n_t, x_t A_t^{\mathrm{US}}, x_t A_t^{\mathrm{G}}\}$ in Version II, where n_t denotes trading intensity on day *t*. As the table shows, neither of the associated *J*-statistics are significant. We also check for additional state-dependency in the error variances. In this case we add $\mathrm{E}[\{\mathscr{V}_t(\Delta p_t) - Var_t(\Delta p_t)\}n_t] = 0$ and $\mathrm{E}[\{\mathscr{V}_t(x_t) - Var_t(x_t)\}n_t] = 0$ to the conditions in Eqs. (30)–(32). These additional moments examine whether the residual variance in price and order flow, unaccounted for by the arrival of news, is correlated with daily trade intensity. Once again, neither of the *J*-statistics is significant. There is no evidence that trade intensity should be present as a second state variable governing the error variances. Further evidence on the specification of the error variances is provided by the statistics in Row (iv). Here we test for residual first-order ARCH by adding $\mathrm{E}[\{\mathscr{V}_t(\Delta p_t) - Var_t(\Delta p_t)\} \times \{\mathscr{V}_{t-1}(\Delta p_{t-1}) - Var_{t-1}(\Delta p_{t-1})\}] = 0$ and $\mathrm{E}[\{\mathscr{V}_t(x_t) - Var_t(x_t)\}\{\mathscr{V}_{t-1}(x_{t-1}) - Var_{t-1}(x_{t-1})\}] = 0$ to the conditions in Eqs. (30)–(32). These specification tests also show no evidence of significant misspecification in the error variances. Finally, in Row (v), we report *J*-statistics for models using Eqs. (30)–(32) and all the additional moments. These moment conditions respectively provide nine and 11 over-identifying restrictions in Versions I and II of the model. As the table shows, neither *J*-statistic is significant at the 5% level. The parameter estimates obtained in this manner are similar to those reported in Panel A. Because the estimated standard errors are a little smaller (as one would expect), the overall pattern of statistical significance we report appears robust to the number of over-identifying restrictions used in estimation. This level of robustness is also reflected in the model-based statistics.

4.3. News arrival and daily dynamics

Our intraday analysis showed that dispersed information contributes more to the variance of price changes following macro news announcements than at other times. Our daily model allows us to address a distinct but equally important issue: the extent to which macro news is impounded in prices directly, via the common knowledge e_t shocks, or indirectly, via the dispersed information u_t shocks that affect prices via order flow.

To clarify this issue within the context of our daily model, consider the unconditional variance of price changes implied by our model, $Var(\Delta p_t)$. By definition, this variance can be written as $\mathrm{E}[Var_t(\Delta p_t)] + Var(E_t \Delta p_t)$, where $E_t \Delta p_t$ and $Var_t(\Delta p_t)$ denote the first and second moments of price changes conditioned on the day *t* state of the market. According to our model, the number of news arrivals has no implication for the direction of how prices change, so $E_t \Delta p_t = 0$. With the aid of Eq. (25), we can therefore write the unconditional variance as

$$Var(\Delta p_t) = \alpha^2 \mathrm{E}[Var_t(x_t)] + \mathrm{E}[Var_t(e_t + v_t)]. \tag{34}$$

The first term on the right identifies the contribution of order flow volatility to the variance of price changes. The second term identifies the contribution of information that is directly impounded into prices. Using Eqs. (26)–(28) to substitute for $Var_t(x_t)$ and $Var_t(e_t + v_t)$, we obtain

$$Var(\Delta p_t) = \mathrm{E}[\Sigma_e^2(A_t^{\mathrm{US}}, A_t^{\mathrm{G}})] + \alpha^2 \mathrm{E}[\Sigma_u^2(A_t^{\mathrm{US}}, A_t^{\mathrm{G}})] + \Sigma_v^2 + \alpha^2 \Sigma_w^2. \tag{35}$$

Eq. (35) decomposes the unconditional variance of daily price changes into four components. The first term identifies the contribution of common knowledge shocks associated with the arrival of news. We refer to this as the direct channel. The second term represents the contribution of dispersed information shocks associated with news. This term includes the price-impact coefficient α, because dispersed information affects prices via order flow. We refer to this as the indirect channel. The third and fourth terms identify the contribution of shocks that are not associated with the arrival of news; information embedded in the v_t and w_t shocks affects price via the direct and indirect channels, respectively.

Table 6 reports elements of the variance decomposition in Eq. (35) derived from the estimates of the daily model. For this purpose, the expectations terms in Eq. (35) are replaced by sample averages (i.e., $\mathrm{E}[\Sigma_\varkappa^2(A_t^{\mathrm{US}}, A_t^{\mathrm{G}})]$ is replaced by $\frac{1}{T}\sum_{t=1}^{T} \hat{\Sigma}_\varkappa^2(A_t^{\mathrm{US}}, A_t^{\mathrm{G}})$ for $\varkappa = \{e, u\}$). We also report standard errors computed by the delta-method from the estimated asymptotic distribution of the model estimates. The statistics shown in Panel A use the parameters estimated from the exactly identified models reported in panel A of Table 5. These statistics are similar to those based on the estimates derived from Versions I and II of the model with nine and 11 over-identifying restrictions.

The upper rows in Panel A of Table 6 report the contribution of dispersed and common knowledge information shocks to the unconditional variance of prices. The statistics in Row (i) report the fraction of the unconditional variance attributable to the common knowledge shocks associated with news: $\mathrm{E}[\Sigma_e^2(A_t^{\mathrm{US}}, A_t^{\mathrm{G}})]/Var(\Delta p_t)$. Estimates from both versions of the model indicate that the direct effect of news arrivals account for approximately 14% of the variance of total price changes. The estimates from Version II of the model indicate that this total is split roughly two to one between German and US news. Because German news arrives at four times the daily rate of US news on average, these estimates suggest that a typical US news item has a somewhat larger direct effect on prices than a German item. Row (ii) reports the contribution of dispersed information to the variance of prices: $\alpha^2 \mathrm{E}[\Sigma_u^2(A_t^{\mathrm{US}}, A_t^{\mathrm{G}})]/Var(\Delta p_t)$. These statistics show that the indirect effects of news arrival account for roughly 22% of the variance. Once again, the arrival of German news contributes more than twice as much as US news through this channel. Row (iii) shows the total contribution of news to the variance of prices via both channels is approximately 36%. These estimates are an order of magnitude larger than those found in event studies. Row (iv) reports the ratio of indirect to direct effects of news arrival implied by our model estimates: $\alpha^2 \mathrm{E}[\Sigma_u^2(A_t^{\mathrm{US}}, A_t^{\mathrm{G}})]/\mathrm{E}[\Sigma_e^2(A_t^{\mathrm{US}}, A_t^{\mathrm{G}})]$. As the table shows, the contribution of news via the indirect channel is roughly 60% larger than the contribution via the direct channel. These estimates clearly indicate that the indirect effects of news operating via order flow are an important component of price dynamics.

As a robustness check on these findings, we also estimate Versions I and II of our model using scheduled news. For this purpose we first computed the standardized forecast error for each of the 28 US and 12 German scheduled announcements as $\mathscr{E}_t^j \equiv (\mathscr{A}_t^j - \overline{\mathscr{A}}_t^j)/\widehat{Std}(\mathscr{A}_t^j - \overline{\mathscr{A}}_t^j)$, where $\mathscr{A}_t^j$ is the value for variable j announced on day t and $\overline{\mathscr{A}}_t^j$ is the median forecast of $\mathscr{A}_t^j$ from a survey of professional business economist conducted by Money Market Services. $\widehat{Std}(.)$ is the estimated standard error computed from data on $\mathscr{A}_t^j - \overline{\mathscr{A}}_t^j$ from January 1993 to December 1999. Our four-month sample on prices and order flows is too short to study the impact of individual scheduled announcements so we compute measures of news arrival by aggregating the absolute values of $\mathscr{E}_t^j$ each day. Specifically, we now take A_t^{X} to equal $\sum_j |\mathscr{E}_t^j|$ for all country $\mathrm{X} = \{\mathrm{US}, \mathrm{G}\}$ variables j announced on day t. According to these measures, a scheduled announcement need not constitute new information to market participants. If a prior consensus existed (at the time of the Money Market Services survey) about the announced value for item j on day t,$\mathscr{E}_t^j$ equals zero, so the announcement does not contribute to our measure of news flow, A_t^{X}.

Panel B of Table 6 reports the variance decompositions implied by estimates of the daily model using A_t^{US} and A_t^{G} computed from scheduled news. Three sets of results stand out. First, our estimates from both versions of the model imply that scheduled news accounts for approximated 20% of the unconditional

Table 6
Daily price variance decompositions

The table reports elements of the variance decomposition for price changes implied by the Generalized Method of Moments (GMM) estimates of the daily models. Rows (i)–(iv) report estimates of $\mathrm{E}[\Sigma_e^2(A_t)]/Var(\Delta p_t)$, $\alpha^2\mathrm{E}[\Sigma_u^2(A_t)]/Var(\Delta p_t)$, $(\mathrm{E}[\Sigma_e^2(A_t)]+\alpha^2\mathrm{E}[\Sigma_u^2(A_t)])/Var(\Delta p_t)$, and $\alpha^2\mathrm{E}[\Sigma_u^2(A_t)]/\mathrm{E}[\Sigma_e^2(A_t)]$. Under the Version I heading, the estimates use $A_t = A_t^{\mathrm{ALL}}$. Under the US, German, and Combined headings of Version II, A_t equals A_t^{US}, A_t^{G}, and A_t^{ALL}. Panel B reports estimates using the absolute, standardized forecast error for scheduled news. Standard errors, computed from the estimated asymptotic distribution of the GMM estimates, are reported in parentheses.

	Version I	Version II		
	Combined	US	German	Combined
A. All news				
(i) Direct	0.139	0.036	0.104	0.140
	(0.046)	(0.042)	(0.017)	(0.046)
(ii) Indirect	0.224	0.060	0.166	0.226
	(0.078)	(0.033)	(0.070)	(0.078)
(iii) Total	0.364	0.096	0.270	0.366
	(0.092)	(0.040)	(0.088)	(0.091)
(iv) Ratio (indirect/direct)	1.612	1.642	1.602	1.612
	(0.763)	(1.069)	(0.857)	(0.761)
B. Scheduled news				
(i) Direct	0.097	0.068	0.030	0.098
	(0.034)	(0.030)	(0.021)	(0.034)
(ii) Indirect	0.109	0.064	0.043	0.107
	(0.070)	(0.056)	(0.040)	(0.069)
(iii) Total	0.206	0.132	0.073	0.204
	(0.076)	(0.074)	(0.049)	(0.077)
(iv) Ratio (indirect/direct)	1.128	0.931	1.466	1.092
	(0.843)	(0.748)	(1.503)	(0.801)

variance of daily price changes. These estimates are two thirds the size of their counterparts based on the full spectrum of news in Panel A, but they are much larger than the contribution implied by event studies. Second, the contribution of scheduled news to price volatility appears more equally balanced between the direct and indirect channels than is the case of all news. The combined ratios in Row (iv) are close to unity. The third noteworthy feature concerns the difference between the effects of scheduled US and German news. Approximately two-thirds of the variance in daily price changes due to scheduled announcements can be attributed to US items and one-third to German items. This two-to-one ratio roughly matches the ratio of US to German scheduled announcements (153:74) in our sample. Our estimates also indicate that German announcements operate more via the indirect than the direct channel whereas US announcements impact prices equally via both channels.

To summarize, the results in Table 6 show that both scheduled and nonscheduled news contribute to the variance of the price changes in our sample. Our results also indicate that news items generally contain both commonknowledge information that is directly reflected in prices and dispersed information that indirectly affects prices via its impact on order flow.

5. Conclusion

This paper extends past work on FX prices and public news in three main ways. First, we address the presence of an indirect channel through which public news affects prices. Second, we use heteroskedasticity in order flow and price for identification, à la Rigobon and Sack (2004), instead of the more common event-study approach. Third, our methodology exploits the full set of macro news events piped into FX trading desks.

Our analysis of intraday data shows that order flow contributes more to changing FX prices in the period immediately following the arrival of news than at other times. This evidence pointing to the importance of the indirect channel is supported by our daily analysis: Roughly two-thirds of the effect of macro news on FX prices is transmitted via order flow, the remainder being the direct effect of news. With both the direct and indirect channels operating, we estimate that macro news accounts for 36% of total FX price variance in daily data. Given that daily prices are nearly a martingale, this finding implies that macro news is far larger contributor to longer-term price variation than previously thought.

Our daily results speak directly to the question, What drives order flow? The analysis in Evans and Lyons (2002a) splits total daily DM/$ price variation into two parts: about 60% is due to order flow and about 40% is due to other factors. The results in Table 6 shed light on both of these parts. They suggest that order flow's 60% breaks roughly into one-third (20%) that is induced by macro news and two-thirds (40%) that is not news induced. Put differently, macro news accounts for about one-third of the variance of interdealer order flow in our sample. The 40% of total price variation due to other factors breaks into about one-third (15%) from the direct effect of macro news and two-thirds (25%) that remains unaccounted for.

Finally, let us offer a wider perspective on our results. Inherent in current macro models is the view that price-setting dealers observe macro news, calculate the price implication, and instantly adjust all their FX prices by the same amount. Our results suggest that this is over-simplified. The model that emerges is one in which dealers observe macro news but have little idea how to interpret it, or how the rest of the market will interpret it. Instead, they wait to observe the trades induced and set their prices and expectations based on the interpretations embedded therein. (This view is consistent with the findings of Evans and Lyons, 2007, that FX order flow conveys information useful for forecasting macro variables.) Models with this richer informational structure could offer new insights into many of the long-standing puzzles concerning the behavior of FX prices.

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