Forecasting Exchange Rate Fundamentals with Order Flow

Latest Version: July 2009

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Abstract

We study the macroeconomic information conveyed by transaction flows in the foreign exchange market. We present a new genre of model for the concurrent empirical link between spot prices and transaction flows that produces two new implications for forecasting: (i) transaction flows should have *incremental* forecasting power for future fundamentals relative to current spot prices and fundamentals, and (ii) transaction flows should have forecasting power for *future* excess returns if the information conveyed affects the risk premium. Both predictions are borne out empirically. Transaction flows in the EUR/USD market forecast GDP growth, money growth, and inflation. They also forecast future exchange rate returns, and this occurs via the information that flows carry concerning the future of the macro variables that drive the risk premium.

Keywords: Exchange Rate Dynamics, Microstructure, Order Flow.
JEL Codes: F3, F4, G1

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[1]This paper previously circulated under the title "Exchange Rate Fundamentals and Order Flow." We thank the following for valuable comments: Charles Engel, Michael Moore, Anna Pavlova, Andrew Rose, Eric van Wincoop, Clara Vega and seminar participants at the NBER (October 2004 meeting of IFM), Board of Governors at the Federal Reserve, European Central Bank, London Business School, University of Warwick, University of Michigan, Chicago GSB, UC Berkeley, Bank of Canada, International Monetary Fund, and Federal Reserve Bank of New York. Both authors thank the National Science Foundation for financial support.

Introduction

Exchange rate movements at frequencies of one year or less remain unexplained by macroeconomic variables (Meese and Rogoff 1983, Frankel and Rose 1995, Cheung et al. 2005). In their survey, Frankel and Rose (1995) conclude that "no model based on such standard fundamentals ... will ever succeed in explaining or predicting a high percentage of the variation in the exchange rate, at least at short- or medium-term frequencies." Seven years later, Cheung et al.'s (2005) comprehensive study concludes that "no model consistently outperforms a random walk."

We address this core puzzle in international economics from a new angle. Rather than attempting to link ex-post macro variables to exchange rates directly, we focus instead on the intermediate market-based process that impounds macro information into exchange rates. In particular, we theoretically and empirically examine the idea that exchange rates respond to the flow of information concerning future macroeconomic conditions conveyed via the trades of end-users in the foreign exchange market. The results reported below strongly support for this idea. More generally, they provide an example from the world's most liquid financial market of how asset prices embed information concerning future macroeconomic conditions via a market-based process.

Our theoretical analysis is based a new genre of exchange rate model that incorporates elements of monetary macro models (e.g., Engel and West 2006, Engel et al. 2007 and Mark 2009), and the elements of currency trading found in microstructure models (Evans and Lyons 1999). Our model incorporates two key features: First, only some of the macro information relevant for the current spot exchange rate at any point in time is known publicly. Other information is present in the economy, but exists in a dispersed microeconomic form in the sense of Hayek (1945). Second, the spot exchange rate is literally determined as the price of foreign currency quoted by foreign exchange dealers. As a consequence, dealers find it optimal to vary their spot rate quotes as they revise their forecasts of future macroeconomic fundamentals in response to the information they learn from their transactions with other agents. The model not only provides a theoretical basis for the strong empirical link between spot rates and transaction flows concurrently (see, for example, Evans and Lyons 2002a & 2002b), it also delivers two new implications for forecasting: First, transaction flows should have *incremental* forecasting power for future fundamentals relative to current spot rates and fundamentals. Second, dealers may use this information rationally to adjust the risk premium they embed in their future spot rate quotes. When this is the case, transaction flows will have forecasting power for *future* excess returns.

We investigate these empirical predictions using a data set that comprises USD/EUR spot rates, transaction flows and macro fundamentals over six and a half years. The transaction flows come from Citibank. We employ a novel empirical strategy that decomposes future realizations of macro variables, such as GDP growth, into a sequence of weekly information flows. These information flows are then used to test whether transaction flows convey incremental information about future macroeconomic conditions. This strategy provides more precise estimates of the information contained in transaction flows than traditional forecasting regressions – a fact reflected in the strong statistical significance of our findings. In particular we find that:

1. Transaction flows in the USD/EUR market have significant forecasting power for future information flows concerning GDP growth, money growth, and inflation in both the US and Germany over horizons ranging from two weeks to two quarters. These findings strongly indicate that transaction flows contain significant information about future GDP growth, money growth, and inflation.

2. Transaction flows have incremental forecasting power beyond that contained in the history of exchange rates and other asset prices/interest rates.

3. Transaction flows forecast about 14 percent of future exchange rate returns at a monthly horizon via the information they carry concerning future macroeconomic conditions. This level of forecasting power is at least 4-5 times larger than that of the forward discount. It suggests that the market uses the macro information in transaction flows to adjust the risk premium embedded in spot rate quotes.

To our knowledge, these findings and those in this paper's earlier version (Evans and Lyons 2004a) are the first to link transaction flows to macro fundamentals in the future and also to the dynamics of the foreign exchange risk premium. In contrast to the forecasting focus of this paper, Evans (2009) documents the links between *current* macro fundamentals, flows and exchange rates. Taken together, these findings provide strong support for the idea that exchange rates vary as the market assimilates dispersed macroeconomic information from transaction flows.

Our analysis is related to several strands of the international finance literature. From a theoretical perspective, our model includes two novel ingredients: dispersed information and a micro-based rationale for trade in the foreign exchange market. Dispersed information does not exist in textbook models: relevant information is either symmetric economy-wide, or, sometimes, asymmetrically assigned to a single agent – the central bank. As a result, no textbook model predicts that market-wide transaction flows should drive exchange rates. In recent research, Bacchetta and van Wincoop (2006) examine the dynamics of the exchange rate in a rational expectations model with dispersed information. Our model shares some of the same informational features, but derives the equilibrium dynamics from the equilibrium trading strategies of foreign exchange dealers and agents. This feature also distinguishes the model from our earlier work in Evans and Lyons (1999, 2005) where we studied exchange rate dynamics in models with exogenous transactions flows. Here we show that endogenously determined transaction flows can only convey information to dealers in an equilibrium where information is incomplete.

From a empirical perspective, our analysis is closely related to the work of Engel and West (2005). They find that spot rates have forecasting power for future macro fundamentals, as text-book models predict. Indeed, our model makes the same empirical prediction. The novel aspect of our analysis, relative to Engel and West (2005), is that we investigate the specific mechanism under which the exchange rate responds to transaction flows because they induce a change in "the market's" expectations about future fundamentals. From this perspective, our findings should be viewed as complementing theirs. Our analysis is also related to earlier research by Froot and Ramadorai (2005), hereafter F&R. These authors examine VAR relationships between real exchange rates, excess currency returns, real interest differentials, and the transaction flows of institutional investors. In contrast to our results, they find little evidence that these flows can forecast fundamentals. Our analysis differs from F&R in three respects. First, our empirical methods provide more precise estimates of the information contained in transaction flows than traditional forecasting regressions/VARs. Second, we analyze transaction flows that fully span the demand for foreign currency, not just institutional investors. This facet of our flow data proves to be empirically important. Third, we require no assumption about exchange rate behavior in the long run, whereas the variance decompositions F&R use rely on long-run purchasing power parity.

The remainder of the paper has three sections. Section 1 presents the theoretical model. Section 2 describes our strategy for estimating the forecasting power of transaction flows. We then present the data and our empirical results. Section 3 concludes.

1 The Model

This section presents a micro-based model of exchange rate dynamics that identifies how information relevant for forecasting future macroeconomic conditions becomes embedded in the spot exchange rate. The model has three essential elements. First, the spot rate is determined as the price in the foreign exchange market as quoted by dealers. In this respect, the model incorporates features of the trading models in Evans and Lyons (1999 & 2004b). Second, and unlike those earlier trading models, the model identifies order flow endogenously. It does so by using the portfolio choices of end-users, i.e., agents whose primary activity lies outside the foreign exchange market. These choices are driven by current macroeconomic conditions in a manner consistent with recent research on open economy models of portfolio choice (e.g., Evans and Hnatkovska 2005, Van Wincoop and Tille 2007, and Devereux and Sutherland 2006), and exchange rate models incorporating Taylor rules (e.g., Engel and West 2006 and Mark 2009). Third, dealers and agents have different and incomplete information about the current state of the macroeconomy. It is the richness of this information structure that produces the novel implications of the model for the behavior of exchange rates, order flow, and the forecasting power of these variables for future macroeconomic conditions.

1.1 Structure

Our economy comprises two countries populated by a continuum of risk-averse agents indexed by $n \in [0,1]$, and D risk-averse dealers who act as market-makers in the spot market for foreign currency. We refer to home and foreign countries as the US and Europe, so the log spot exchange rate, s_t, denotes the dollar price of euros. The only other actors in the model are the central banks (i.e., the Federal Reserve (FED) and the European Central Bank (ECB)), who conduct monetary policy by setting short-term nominal interest rates.

1.1.1 Dealers

The pattern of trading in actual foreign exchange markets is extremely complex. On the one hand, foreign exchange dealers quote prices at which they stand ready to buy or sell foreign currency to agents and other dealers. On the other, each dealer can initiate trades against other dealers' quotes, and can submit both market and limit orders to electronic brokerages. We will not attempt to capture this trading activity in any detail. Instead, we focus on the price dealers quote at the start of each trading week. In particular, we assume that the log spot price quoted by all dealers at the start of week t is given by

$$s_t = \mathbb{E}_t^{\mathrm{D}} s_{t+1} + \hat{r}_t - r_t - \delta_t, \tag{1}$$

where $\mathbb{E}_t^{\mathrm{D}}$ denotes expectations conditioned on the common information available to all dealers at the start of week t, Ω_t^{D}. This information set includes r_t and $\hat{r}_t$, which are the one-week dollar and euro interest rates set by the FED and ECB, respectively. (Hereafter we use hats, "ˆ", to denote European variables.) The last term on the right, δ_t, is a risk premium – positive is added return on euro holdings – that dealers choose to manage risk efficiently. This risk premium is determined below as a function of dealers' common information, Ω_t^{D}.

In the currency trading models of Lyons (1997) and Evans and Lyons (1999 & 2004b), the spot exchange rate is determined by the Perfect Bayesian Equilibrium (PBE) quote strategy of a game between the dealers played over multiple trading rounds. Our specification in equation (1) incorporates three features of the PBE quotes in these trading models: First, each dealer quotes the same price to agents and other dealers. Second, quotes are common across all dealers. Third, all quotes are a function of common information, Ω_t^{D}. It is important to realize that our specification in (1) does not implicitly restrict all dealers to have the same information. On the contrary, dealers will generally possess heterogenous information, which they use in forming their optimal trading strategies. However, in so far as our focus is on the behavior of the spot rate (rather than dealer trading), equation (1) implies that we can concentrate our attention on the part of dealers' information that is common, Ω_t^{D}.

Equation (1) says that the price quoted by all dealers at the start of week t is equal to the expected payoff from holding foreign currency until the next week, $\mathbb{E}_t^{\mathrm{D}} s_{t+1} + \hat{r}_t - r_t$, less a premium, δ_t. In models of currency trading, the size of this premium is determined by the requirements of efficient risk-sharing. More specifically, in an economy where their is a finite number of risk-averse dealers and a continuum of risk-averse agents of sufficient mass, dealers will choose δ_t such that their expected holdings of risky currencies at the end of week t are zero. This implication of risk-sharing accords well with the actual behavior of dealers, who are restricted on the size of their overnight positions (Lyons 1995).

To implement this risk-sharing implication, we assume that all dealers are located in the US. They therefore choose the risk premium, δ_t, such that their expected holdings of euros at the end of week t equal zero. These holdings are determined by the history of order flow from all agents. In particular, let x_{t+1} denote the aggregate of all orders from agents for euros received by dealers during week t,[2] so $I_{t+1} = -\sum_{i=0}^{\infty} x_{t+1-i}$ denotes the euro holdings of all dealers at the end of week-t trading. Efficient risk-sharing requires that dealers choose a value for δ_t such that

$$\mathbb{E}_t^{\mathrm{D}} I_{t+1} = 0. \tag{2}$$

Clearly, this restriction makes δ_t a function of dealers' common information, Ω_t^{D}.[3]

Recent exchange rate research by Engel et al. (2007) stresses the importance of identifying expected future interest rates consistent with their use as policy instruments by central banks. With this in mind we assume that dealers' interest rate expectations incorporate a view on how central banks react to changes in the macroeconomy. In particular, we assume that

$$\mathbb{E}_t^{\mathrm{D}}(\hat{r}_{t+i} - r_{t+i}) = (1+\gamma_\pi)\mathbb{E}_t^{\mathrm{D}}\left(\Delta\hat{p}_{t+1+i} - \Delta p_{t+1+i}\right) + \gamma_y \mathbb{E}_t^{\mathrm{D}}\left(\hat{y}_{t+i} - y_{t+i}\right) - \gamma_\varepsilon \mathbb{E}_t^{\mathrm{D}} \varepsilon_{t+i}, \tag{3}$$

for $i > 0$, where γ_π, γ_y, and γ_ε are positive coefficients. Equation (3) says that dealers expect the future differential between euro and dollar rates to be higher when: (i) the future difference between

[2] We identify the order flow from week-t trading with a subscript of $t+1$ to emphasize the fact that dealers cannot use the information it conveys until the start of week $t+1$.

[3] This implication of efficient risk-sharing also applies if dealers are distributed in both countries. In this case, I_{t+1} represents the US dealers' holding of euros minus the euro value of EU dealers' dollar holdings at the end of week-t trading. Efficient risk-sharing now requires that the expected value of the foreign currency holdings of all dealers are equalized, i.e. $\mathbb{E}_t^{\mathrm{D}} I_{t+1} = 0$, after dealers have had the opportunity to trade with each other. By assuming that all dealers are located in the US, we are simply abstracting from the need to model intradealer trade.

EU and US inflation, $\Delta\hat{p}_{t+1} - \Delta p_{t+1}$, is higher, (ii) the difference between the EU and US output gaps, $\hat{y}_t - y_t$, widens, or (iii) when the real exchange rate, $\varepsilon_t \equiv s_t + \hat{p}_t - p_t$, depreciates. The first two terms are consistent with the widely-accepted view that central banks react to higher domestic inflation and output by raising short-term interest rates. The third term captures the idea that some central banks can be expected to react to deviations in the spot rate from its purchasing power parity level (i.e., the real exchange rate, ε_t), a notion that finds empirical support in Clarida, Galı, and Gertler (1998). We should emphasize that equation (3) embodies an assumption about how dealers' expectations concerning future interest rates are related to their expectations concerning macro variables (e.g., inflation and output), rather than an assumption about whether central banks actually follow particular reaction functions, such as a Taylor-rule.

Dealers have access to both private and public sources of information. Each dealer receives private information in the form of the currency orders from the subset of agents that trade with them, and from the currency orders they receive from other dealers. In currency trading models, the mapping from dealers' individual information sets to the common information set for all dealers, Ω_t^{D}, is derived endogenously from the trading behavior of dealers. We will not consider this complex process here. Instead, we characterize the evolution of Ω_t^{D} directly under the assumption that a week's worth of trading is sufficient to reveal the size of the aggregate order flow from agents to all dealers. Thus, all dealers know the aggregate order flow from week-t trading, x_{t+1}, by the start of week $t+1$.[4]

Dealers receive public information in the form of macro data releases and their observations on short-term interest rates. To characterize this information flow, let z_t denote a vector of variables that completely describe the state of the macroeconomy in week t. This vector contains short-term interest rates, r_t and $\hat{r}_t$; prices, p_t and $\hat{p}_t$; the output gaps, y_t and $\hat{y}_t$; and other variables. A subset of the these variables, z_t^o, are contemporaneously observable to all dealers and agents. We assume that the other elements of z_t only become publicly known via macro data releases with a reporting lag of k weeks. The presence of the reporting lag is an important feature of our model and accords with reality. For example, data on US GDP in the first quarter is only released by The Bureau of Economic Analysis several weeks into the second quarter, so the reporting lag for US output can

[4]This assumption is consistent with the equilibrium behavior of currency trading models and the available empirical evidence. In the PBE of the Evans and Lyons (1999) model, all dealers can correctly infer aggregate order flow from agents before they quote spot rates at the end of each trading day because intraday interdealer trading is informative about the currency orders each dealer receives from agents. Empirical support for this feature of the PBE comes in two forms. First, as Evans and Lyons (2002b & 2002a) show, aggregate order flows from intraday interdealer trading account for between 40 and 80 percent of the variation in daily, end-of-day, spot rate quotes. This would not be the case if dealers were unable to make precise inferences about aggregate customer order flows from interdealer trading before they quoted spot rates at the end of each day. Second, the variation in daily end-of-day spot rate quotes cannot be forecast by aggregate interdealer order flow on prior trading days (see, for example, Sager and Taylor 2008). If it took several days worth of interdealer trading before dealers could make accurate inferences concerning the aggregate order flow from agents, interdealer order flow would have forecasting power for future changes in quotes.

run to more than 16 weeks.

With these assumptions, the evolution of dealers' common information is given by

$$\Omega_t^{\mathrm{D}} = \left\{ z_t^o, z_{t-k}, x_t, \Omega_{t-1}^{\mathrm{D}} \right\}, \tag{4}$$

where $\{z_t^o, z_{t-k}\}$ identify the source of the public information flow, and x_t identifies the source of the information flow observed by all dealers.

1.1.2 Agents and the Macroeconomy

Since our aim is to examine how macroeconomic information is transmitted to dealers, there is no need to describe every aspect of agents' behavior. Instead, we focus on their demand for foreign currency. In particular, we assume that the demand for euros in week t by agent $n \in [0,1]$ can be represented by

$$\alpha_t^n = \alpha_s \left(\mathbb{E}_t^n \Delta s_{t+1} + \hat{r}_t - r_t \right) + h_t^n, \tag{5}$$

where $\alpha_s > 0$ and $\mathbb{E}_t^n$ denotes expectations conditioned on the information available to agent n after observing the spot rate at the start of week t, Ω_t^n. Equation (5) decomposes the demand for euros into two terms. The first is the (log) excess return expected by the agent, $\mathbb{E}_t^n \Delta s_{t+1} + \hat{r}_t - r_t$, the second is a hedging term, h_t^n, that represents the influence of all other factors. This representation of foreign currency demand is very general. For example, it could be derived from a mean-variance portfolio choice model, or from an OLG portfolio model such as in Bacchetta and van Wincoop (2006). In these cases, the h_t^n term identifies the expected returns on other assets and the hedging demand induced by the exposure of the agent's future income to exchange rate risk. Alternatively, the representation in (5) could be derived as an approximation to the optimal currency demand implied by an intertemporal portfolio choice problem, as in Evans and Hnatkovska (2005). In this case the h_t^n term would also incorporate the effects of variations in the agent's wealth.

Without loss of generality, we assume that $h_t^n = \alpha_h z_t^n$, for some vector α_h, where z_t^n is a vector of variables that describes the observable microeconomic environment of agent n. This environment includes publicly observable macro variables, such as interest rates, and the micro data that influences all aspects of the agent's behavior. The agent's environment is linked to the state of the macroeconomy by $z_t^n = z_t + v_t^n$, where $v_t^n = [v_{i,t}^n]$ is a vector of agent-specific shocks with the property that $\int_0^1 v_{i,t}^n dn = 0$ for all i. We can now use (5), to write the aggregate demand for euros by agents as

$$\alpha_t \equiv \int_0^1 \alpha_t^n dn = \alpha_s (\overline{\mathbb{E}}_t^n s_{t+1} - s_t + \hat{r}_t - r_t) + h_t, \tag{6}$$

where $h_t \equiv \int_0^1 h_t^n dn = \alpha_h z_t$ is the aggregate hedging demand and $\overline{\mathbb{E}}_t^n$ denotes the average of agents' expectations: $\overline{\mathbb{E}}_t^n s_{t+1} = \int_0^1 \mathbb{E}_t^n s_{t+1} dn$.

Like dealers, each agent has access to both private and public sources of information. The former comes in the form of information about the microeconomic environment, z_t^n. Each agent also receives public information about the macroeconomy from macro data releases, the short-term interest rates set by central banks, and from the spot exchange rate quoted by dealers. The evolution of agent n's information can therefore be represented as

$$\Omega_t^n = \left\{ z_t^o, z_{t-k}, s_t, z_t^n, \Omega_{t-1}^n \right\}, \tag{7}$$

for $n \in [0, 1]$.

Two points need emphasis here. First, in accordance with reality, agents do not observe aggregate order flow, x_t. Order flow is a source of information to dealers not agents. Second, and most importantly, we do not assume that any agent has private information about the *future* the microeconomic environments they will face or *future* macroeconomic conditions. Exchange rates will only have forecasting power for future macroeconomic variables insofar as dealers can extract useful information about *current* macro conditions from agents' currency orders.

All that now remains is to characterize the behavior of the macroeconomy. In an open economy macro model this would be done by aggregating the optimal decisions of agents with respect to consumption, saving, investment, and price-setting in a manner consistent with market clearing given assumptions about productivity, preference shocks, and the conduct of monetary/fiscal policy. Fortunately, for our purposes, we can avoid going into all this detail. Instead, it suffices to identify a few elements of the z_t vector, and to represent its dynamics in a reduced form. Specifically, we assume that the inflation, interest, price and output differentials comprise the first four elements of z_t,

$$z_t' = [\ \Delta\hat{p}_t - \Delta p_t, \quad \hat{r}_t - r_t, \quad \hat{p}_t - p_t, \quad \hat{y}_t - y_t, \quad ..., \quad ...\ ],$$

and that the dynamics of z_t can be written as

$$z_t = A_z z_{t-1} + B_u u_t, \tag{8}$$

for some matrices A_z and B_u, where u_t is a vector of mean zero serially uncorrelated shocks. We should emphasize that this representation of the macroeconomic dynamics is completely general because we have not placed any restrictions on the other variables included in the z_t vector. Evans and Lyons (2004b) provides a detailed description of the equilibrium dynamics of an open economy macro model with a similar structure.

1.2 Equilibrium

In equilibrium information flows from dealers to agents via their spot rate quotes, and from agents to dealers via order flow. Figure 1 shows the timing of events and the flows of information within each week. At the start of week t, all dealers and agents receive public information in the form of data releases on past economic activity, z_{t-k}, and observations on other macro variables including the short-term interest rates set by central banks, $z_t^o = \{r_t, \hat{r}_t, ..\}$. Each agent n also receives private information concerning his or her current microeconomic environment, z_t^n. Next, all dealers use their common information, Ω_t^{D}, to quote a log spot price, s_t, that is observable to all agents. Each agent n then uses their private information, Ω_t^n, to place a foreign currency order with a dealer, who fills it at the spot rate s_t. For the remainder of the week, dealers trade among themselves. As a result of this activity all dealers learn the aggregate order flow, x_{t+1}, that resulted from the earlier week$-t$ trades between agents and dealers.

Week	Event	Information Flow to Dealers	Information Flow to Agents
t			
	Data released on past macroeconomic activity and	z_{t-k}	z_{t-k}
	Central Banks set interest rates	z_t^o	z_t^o
	Each agent n observes her microeconomic environment		z_t^n
	Dealers quote log spot price		s_t
	Agents initiate trade against dealers' quotes producing aggregate order flow, which becomes known to all dealers via interdealer trading	x_{t+1}	
$t+1$			

Figure 1: Model Timing and Information Flows

In equilibrium the aggregate order flow received by dealers during week-t trading must equal the aggregate change in the demand for euros across all agents:

$$x_{t+1} = \alpha_t - \alpha_{t-1}. \tag{9}$$

This market-clearing condition implies that x_{t+1} is a function of the microeconomic environments facing all agents in weeks t and $t-1$, and their expectations concerning future excess returns which are based on agents' private information, Ω_t^n and Ω_{t-1}^n as shown in equation (6).

Equilibrium spot rate quotes satisfy (1) subject to the restriction in (2) that identifies the risk premium and dealer expectations concerning future interest rates in (3). In particular, combining

(1) with (3) and iterating forward assuming that $\lim_{i\to\infty}\mathbb{E}_t^{\mathrm{D}}\rho^i s_{t+1}=0$ gives

$$\mathbb{E}_t^{\mathrm{D}} s_{t+1}=\mathbb{E}_t^{\mathrm{D}}\sum_{i=1}^{\infty}\rho^i(m_{t+i}-\delta_{t+i}), \tag{10}$$

with $\rho\equiv 1/(1+\gamma_\varepsilon)<1$, where $m_t=\gamma_\pi\left(\Delta\hat{p}_{t+1}-\Delta p_{t+1}\right)+\gamma_y\left(\hat{y}_t-y_t\right)+\frac{1-\rho}{\rho}(p_t-\hat{p}_t)$. Equation (10) identifies dealers' expectations for next week's spot rate in terms of their forecasts for macro fundamentals, m_t, and the risk premium, δ_t. Substituting this expression into (1) gives the following equation for the equilibrium spot rate:

$$s_t=\hat{r}_t-r_t+\mathbb{E}_t^{\mathrm{D}}\sum_{i=1}^{\infty}\rho^i m_{t+i}-\mathbb{E}_t^{\mathrm{D}}\sum_{i=0}^{\infty}\rho^i\delta_{t+i}. \tag{11}$$

The three terms on the right of equation (11) identify different factors affecting the log spot rate that dealers quote at the start of week t. First, the current stance of monetary policy in the US and EU affects dealers' quotes via the interest differential, $\hat{r}_t-r_t$, because it directly contributes to the payoff from holding euros until week $t+1$. Second, dealers are concerned with the future course of macro fundamentals, m_t. This term embodies dealers' expectations of how central banks will react to macroeconomic conditions when setting future interest rates. The third factor arises from risk-sharing between dealers and agents as represented by the present and expected future values of the risk premium. This risk-sharing implication is unique to our micro-based model, and plays an important role in the analysis below.

Recall that dealers choose the risk premium so that $\mathbb{E}_t^{\mathrm{D}} I_{t+1}=0$, where I_{t+1} denotes their aggregate holdings of euros at the end of week-t trading. By definition, $I_{t+1}=I_t-x_{t+1}$, so the market clearing condition in (9) implies that $I_{t+1}+\alpha_t=I_t+\alpha_{t-1}=I_1+\alpha_0$. For clarity, we normalize $I_1+\alpha_0$ to zero, so the efficient risk-sharing condition in (2) becomes $0=\mathbb{E}_t^{\mathrm{D}}\alpha_t=\alpha_s$ $\mathbb{E}_t^{\mathrm{D}}(\overline{\mathbb{E}}_t^n s_{t+1}-s_t+\hat{r}_t-r_t)+\mathbb{E}_t^{\mathrm{D}} h_t$. Combining this expression with the fact that $\mathbb{E}_t^{\mathrm{D}}\Delta s_{t+1}+\hat{r}_t-r_t=\delta_t$ from equation (1), gives

$$\delta_t=\mathbb{E}_t^{\mathrm{D}} s_{t+1}^e-\alpha_s^{-1}\mathbb{E}_t^{\mathrm{D}} h_t, \tag{12}$$

where $s_{t+1}^e=s_{t+1}-\overline{\mathbb{E}}_t^n s_{t+1}$. Thus, the dealers' choice for the risk premium depends on their estimates of the aggregate hedging demand for euros, $\mathbb{E}_t^{\mathrm{D}} h_t$, and the average error agents make when forecasting next week's spot rate, s_{t+1}^e. Intuitively, dealers lower the risk premium when they anticipate a rise in the aggregate hedging demand for euros because the implied fall in the excess return agents' expect will offset their desire to accumulate larger euro holdings. Dealers also reduce the risk premium to offset agents' desire to accumulate larger euro holdings when they are viewed as being too optimistic (on average) about the future spot rate; i.e. when $\mathbb{E}_t^{\mathrm{D}} s_{t+1}<\mathbb{E}_t^{\mathrm{D}}\overline{\mathbb{E}}_t^n s_{t+1}$.

We now combine (11) with (12) to identify the information spot rate quotes convey to agents:

$$s_t = \hat{r}_t - r_t + \mathbb{E}_t^{\mathrm{D}} \sum_{i=1}^{\infty} \rho^i m_{t+i} + \tfrac{1}{\alpha_s}\mathbb{E}_t^{\mathrm{D}} \sum_{i=0}^{\infty} \rho^i h_{t+i} - \tfrac{1}{\rho}\mathbb{E}_t^{\mathrm{D}} \sum_{i=1}^{\infty} \rho^i s_{t+i}^e. \tag{13}$$

Here we see that spot rates embed dealers' expectations about future macro fundamentals, m_t, current and future aggregate hedging demands, h_t, and agents' future average forecast errors, s_t^e. These expectations are conditioned on dealers' common information set, Ω_t^{D}, which includes past order flows (i.e., x_{t-i}, for $i \geq 0$) that were not observed by agents. Thus, insofar as these past flows carry price-relevant information to dealers, the quoted value of s_t will convey incremental information to agents that they can use in determining their week$-t$ currency orders.

Agents' currency orders convey information to dealers via order flow. In particular, since dealers know the history of order flow and $\alpha_{t-1} = \sum_{i=0}^{\infty} x_{t-i}$ by market clearing, $\alpha_{t-1} \in \Omega_t^{\mathrm{D}}$. Consequently, unexpected order flow from week-t trading is $x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1} = (\alpha_t - \alpha_{t-1}) - \mathbb{E}_t^{\mathrm{D}}(\alpha_t - \alpha_{t-1}) = \alpha_t - \mathbb{E}_t^{\mathrm{D}} \alpha_t$. Substituting for α_t in this expression using (6) and (12) gives

$$x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1} = h_t - \mathbb{E}_t^{\mathrm{D}} h_t + \alpha_s(\overline{\mathbb{E}}_t^n s_{t+1} - \mathbb{E}_t^{\mathrm{D}}[\overline{\mathbb{E}}_t^n s_{t+1}]). \tag{14}$$

Thus unexpected order flow contains new information about the hedging demand, h_t, and about the average of agents' spot rate forecasts, $\overline{\mathbb{E}}_t^n s_{t+1}$. Both of these factors depend on the microeconomic environments agents face in week t. As a consequence, order flow during week t carries more timely information about the current state of the economy – not the future state – than is available from the most recent macro data releases. This key feature of our model lies behind the empirical implications we analyze below.

To this point we have identified the equilibrium spot rate, risk premium and unexpected order flow relative dealers' and agents' expectations. A complete description of the equilibrium requires the identification of these expectations. For this purpose, we introduce a new vector, $Z_t = [\ u_t', \ \ u_{t-1}', \ \ ..., \ \ u_{t-k-1}', \ \ z_{t-k}'\ ]'$, that contains the information that is *potentially* available to dealers and agents about the state of macroeconomy in week t, z_t, and about the shocks to the economy over the past $k+2$ weeks, $\{u_t,\ u_{t-1}, ...u_{t-k-1}\}$. The dynamics of Z_t are easily derived from equation (8) and may be written as

$$Z_t = AZ_{t-1} + Bu_t. \tag{15}$$

We can now describe the equilibrium of the model.

Proposition *In equilibrium, there exists vectors Λ_s and Λ_δ such that the log spot rate, risk premium and unexpected order flow in week-t trading satisfy*

$$s_t = \Lambda_s \mathbb{E}_t^{\mathrm{D}} Z_t, \qquad \delta_t = \Lambda_\delta \mathbb{E}_t^{\mathrm{D}} Z_t, \tag{16a}$$

$$\textit{and} \qquad x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1} = \alpha_t = \alpha_s \Lambda_\delta (Z_t - \mathbb{E}_t^{\mathrm{D}} Z_t), \tag{16b}$$

where $E_t^{\mathrm{D}} Z_t = \Phi^{\mathrm{D}} Z_t$ for some matrix Φ^{D}, and Z_t follows (15).

The Appendix provides a detailed derivation of this proposition. Here we emphasize three features. First, the equilibrium encompasses the special case where the flow of public information provides dealers and agents with complete information about the current state of the economy. This is the information structure found in standard macro exchange rate models. It implies that $Z_t = \mathbb{E}_t^{\mathrm{D}} Z_t$, so dealers can anticipate order flow with complete precision: $x_{t+1} = \mathbb{E}_t^{\mathrm{D}} x_{t+1}$. Under these circumstances, dealers set the risk premium to a level that insures that their foreign currency holdings are always at their optimal risk-sharing level of zero. And, as a consequence, actual order flow, x_{t+1}, is also zero. Thus, the presence of incomplete information concerning the current state of the economy not only accords with reality but is also a necessary condition for the existence of (non-zero) order flows.

Second, the equilibrium provides a structural explanation for the strong relationship between high-frequency variations in spot rates and contemporaneous order flows documented by Evans and Lyons (2002a & 2002b) and many others (see Osler 2008 for a recent survey). According to our model, this relationship exists because order flows during week t convey information to dealers that is incorporated into their estimates of potentially available information Z_{t+1} at the start of week $t+1$. More specifically, combining the identity, $s_{t+1} = \mathbb{E}_t^{\mathrm{D}} s_{t+1} + (s_{t+1} - \mathbb{E}_t^{\mathrm{D}} s_{t+1})$, with equations (1) and (16a) gives

$$s_{t+1} - s_t = r_t - \hat{r}_t + \delta_t + \Lambda_s (\mathbb{E}_{t+1}^{\mathrm{D}} - \mathbb{E}_t^{\mathrm{D}}) Z_{t+1}. \tag{17}$$

Since the first three terms on the right hand side are known to dealers at the start of week t, changes in the log spot rate, $s_{t+1} - s_t$, will be correlated with unexpected order flow, $x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1}$, insofar as the latter is correlated with the revision in dealers' expectations, $(\mathbb{E}_{t+1}^{\mathrm{D}} - \mathbb{E}_t^{\mathrm{D}}) Z_{t+1}$. Evans (2009) provides a detailed examination of this correlation.

The third feature we wish to emphasize concerns the long run relationship between order flow and spot rates. Equations (9) and (16b) imply that $x_{t+1} = \alpha_s \Lambda_\delta (Z_t - \mathbb{E}_t^{\mathrm{D}} Z_t) - \alpha_s \Lambda_\delta (Z_{t-1} - \mathbb{E}_{t-1}^{\mathrm{D}} Z_{t-1})$, so any permanent shock to an element of Z_t has no long-run effect on order flow: The shock may initially affect elements of $Z_t - \mathbb{E}_t^{\mathrm{D}} Z_t$ and $Z_{t-1} - \mathbb{E}_{t-1}^{\mathrm{D}} Z_{t-1}$, and so have a short-run impact; but once dealers learn about its macroeconomic effects, they adjust the risk premium so that its impact on subsequent order flow vanishes. At the same time, the shock can have a long-run effect on the spot rate. Equation (16a) implies that $s_t = \Lambda_s Z_t - \Lambda_s(Z_t - \mathbb{E}_t^{\mathrm{D}} Z_t)$, so a permanent shock to elements of Z_t can affect the spot rate via the first term long after its macroeconomic impact has been learnt by dealers. In sum, therefore, our model does not imply that there should be any cointegrating (long-run) relationship between the aggregate flow of agents' foreign currency orders cumulated through time and macro variables or the spot rate.

2 Empirical Analysis

In this section we examine the implications of our model for forecasting future macroeconomic conditions. First we derive a key testable implication of our model regarding the forecasting power of spot rates and order flow for macro variables. We then describe the data used to estimate these forecast relationships and present our empirical results.

2.1 Identifying the Forecasting Power of Spot Rates and Order Flow

The forecasting power of spot rates and order flows come from difference sources. Spot rates have forecasting power in our model because dealers' quotes include their expectations concerning the future course of macro variables and risk premia. This is clearly seen by rewriting (13) as

$$s_t - f_t = \textstyle\sum_{i=1}^{\infty} \rho^i \mathbb{E}_t^{\mathrm{D}} \eta_{t+i}, \tag{18}$$

where $\eta_t \equiv \gamma_\pi \left(\Delta \hat{p}_{t+1} - \Delta p_{t+1}\right) + \gamma_y \left(\hat{y}_t - y_t\right) - \delta_t$, and $f_t \equiv \hat{r}_t - r_t - \mathbb{E}_t^{\mathrm{D}} \left(\hat{p}_{t+1} - p_{t+1}\right) - \delta_t$. Dealers' quotes are affected by both current macroeconomic conditions, f_t, and the expected course of future inflation, output gaps and the risk premia via $\mathbb{E}_t^{\mathrm{D}} \eta_{t+i}$. As a consequence, $s_t - f_t$ will have forecasting power for any future macro variable, $\mathcal{M}_{t+\tau}$, if dealers' forecasts, $\mathbb{E}_t^{\mathrm{D}} \mathcal{M}_{t+\tau}$, are correlated with $\mathbb{E}_t^{\mathrm{D}} \eta_{t+i}$.

The forecasting power of order flows comes from the information they convey to dealers. Order flow from week-t trading will have forecasting power for $\mathcal{M}_{t+\tau}$ if the information in $x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1}$ induces dealers to *revise* their forecasts for $\mathcal{M}_{t+\tau}$ between the start of weeks t and $t+1$. Under these circumstances, order flows from week-t will have *incremental* forecasting power for $\mathcal{M}_{t+\tau}$ beyond that contained in $s_t - f_t$.

We can clarify this distinction between the forecasting power of spot rates and order flows with the aid of a projection of $\mathcal{M}_{t+\tau}$ on a constant, $s_t - f_t$ and $x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1}$:[5]

$$\mathcal{M}_{t+\tau} = \beta + \beta_s (s_t - f_t) + \beta_x (x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1}) + \zeta_{t+\tau}, \tag{19}$$

[5] We assume throughout that all these variables are covariance stationary so that the unconditional moments presented below are well-defined.

where $\zeta_{t+\tau}$ is the mean-zero projection error that identifies the component of $\mathcal{M}_{t+\tau}$ that is uncorrelated with both $s_t - f_t$ and $x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1}$. Since these terms are uncorrelated with each other, the projection coefficients are given by

$$\beta_s = \frac{\mathbb{CV}(\mathcal{M}_{t+\tau}, s_t - f_t)}{\mathbb{V}(s_t - f_t)} \qquad \text{and} \qquad \beta_x = \frac{\mathbb{CV}(\mathcal{M}_{t+\tau}, x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1})}{\mathbb{V}(x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1})}, \tag{20}$$

where $\mathbb{CV}(.,.)$ and $\mathbb{V}(.)$ denote the unconditional covariance and variance operators, respectively. Combining these expressions with (18) and the identity $\mathcal{M}_{t+\tau} = \mathbb{E}_t^{\mathrm{D}} \mathcal{M}_{t+\tau} + (\mathbb{E}_{t+1}^{\mathrm{D}} - \mathbb{E}_t^{\mathrm{D}})\mathcal{M}_{t+\tau} + (1 - \mathbb{E}_{t+1}^{\mathrm{D}})\mathcal{M}_{t+\tau}$ gives

$$\beta_s = \frac{\mathbb{CV}(\mathbb{E}_t^{\mathrm{D}} \mathcal{M}_{t+\tau}, \sum_{i=i}^{\infty} \rho^i \mathbb{E}_t^{\mathrm{D}} \eta_{t+i})}{\mathbb{V}(s_t - f_t)} \qquad \text{and} \qquad \beta_x = \frac{\mathbb{CV}((\mathbb{E}_{t+1}^{\mathrm{D}} - \mathbb{E}_t^{\mathrm{D}})\mathcal{M}_{t+\tau}, x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1})}{\mathbb{V}(x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1})}. \tag{21}$$

To interpret the expressions in (21), recall that $\rho = 1/(1+\gamma_\varepsilon)$ where γ_ε identifies the sensitivity of the expected interest differential, $\mathbb{E}_t^{\mathrm{D}}(\hat{r}_{t+i} - r_{t+i})$, to variations in the expected real exchange rate, $\mathbb{E}_t^{\mathrm{D}} \varepsilon_{t+i}$. Plausible values for γ_ε should be positive but small (Clarida, Galı, and Gertler 1998), so ρ should be close to one. This being the case, the expression for β_s indicates that $s_t - f_t$ will have greater forecasting power when dealer expectations, $\mathbb{E}_t^{\mathrm{D}} \mathcal{M}_{t+\tau}$, are strongly correlated with their forecasts for expected inflation and/or output gaps over long horizons. In contrast, the expression for β_x shows that the forecasting power of order flow only depends on the information it conveys to dealers concerning $\mathcal{M}_{t+\tau}$. Recall from (14) that $x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1}$ conveys information about h_t and $\overline{\mathbb{E}}_t^n s_{t+1}$ – two factors that embed more timely information about the current state of the economy than is available to dealers from other sources. The expression for β_x shows that order flows will have incremental forecasting power when dealers find this information relevant for forecasting the future course of $\mathcal{M}_t$.

The preceding discussion suggests that we empirically investigate the forecasting power of spot rates and order flows for a macro variable $\mathcal{M}_t$ by estimating β_s and β_x from a regression of $\mathcal{M}_{t+\tau}$ on a constant, $s_t - f_t$ and $x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1}$. Of course, to implement this approach we need data on these variables over a sufficiently long time span to estimate the moments in β_s and β_x with precision. Unfortunately, this is unlikely to be the case in practice. Our data on order flows covers six an a half years – a longer time span than any other comparable data set – but it does not contain many observations on standard macro variables such as output and inflation across a variety of macroeconomic conditions. Consequently, the available time series on $\mathcal{M}_t$, $s_t - f_t$ and $x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1}$ are unlikely to have must statistical power for detecting the true values of β_s and β_x. To address this problem, we implement a novel procedure that estimates the components of β_s and β_x.

Let $\Omega_t \subset \Omega_t^{\mathrm{D}}$ denote a subset of the information available to dealers at the start of week t that includes $\mathcal{M}_t$. Without loss of generality we can write

$$\mathcal{M}_{t+\tau} = \sum\nolimits_{i=-t}^{\tau-1} \mathcal{E}_{t+i} + \mathbb{E}[\mathcal{M}_{t+\tau}],$$

where $\mathcal{E}_t = \mathbb{E}[\mathcal{M}_{t+\tau}|\Omega_{t+1}] - \mathbb{E}[\mathcal{M}_{t+\tau}|\Omega_t]$ is the week-t flow of information into Ω_{t+1} concerning $\mathcal{M}_{t+\tau}$, and $\mathbb{E}[\mathcal{M}_{t+\tau}] = \mathbb{E}[\mathcal{M}_{t+\tau}|\Omega_0]$ denotes the unconditional expectation. Substituting this expression into (20) gives

$$\beta_s = \sum\nolimits_{i=-t}^{\tau-1} \beta_s^i \qquad \text{and} \qquad \beta_x = \sum\nolimits_{i=-t}^{\tau-1} \beta_x^i, \tag{22}$$

where β_s^i and β_x^i are the coefficients from the projection:

$$\mathcal{E}_{t+i} = \beta^i + \beta_s^i(s_t - f_t) + \beta_x^i(x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1}) + \xi_{t+i}. \tag{23}$$

Our strategy is to estimate this projection for different horizons i using estimates of $\mathcal{E}_t$ obtained from a time series model (described below). Unlike the underlying macro time series, $\mathcal{M}_t$, these estimates can be computed at a high enough frequency for us to estimate β_s^i and β_x^i with precision given the time span of our data. Of course, this increase in precision comes at a cost. Statistically significant estimates of β_s^i and β_x^i imply that $s_t - f_t$ and $x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1}$ have forecasting power for the flow of information used to revise future expectations concerning $\mathcal{M}_{t+\tau}$. However, (22) shows that this must be true at some horizon(s), i, if $s_t - f_t$ and $x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1}$ truly have forecasting power for $\mathcal{M}_{t+\tau}$. In sum, therefore, when we test the statistical significance of horizon-specific β_s^i and β_x^i we are examining a necessary condition for the existence of forecasting power in spot rates and order flows.

To implement our procedure, two data issues need addressing. Since (23) includes unanticipated order flow, $x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1}$, it appears that we need data on both x_{t+1} and dealers' information, Ω_t^{D}, in order to estimate β_x^i. Fortunately, an implication of our model makes this unnecessary. Recall that dealers choose the risk premium such that $\mathbb{E}_t^{\mathrm{D}} \alpha_t = 0$, and $x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1} = \alpha_t - \mathbb{E}_t^{\mathrm{D}} \alpha_t$ because $\alpha_{t-1} \in \Omega_t^{\mathrm{D}}$. Combining these expressions with the market clearing condition in (9) gives $x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1} = \sum_{i=0}^{\infty} x_{t+1-i}$. Thus, the requirement of efficient risk-sharing on the dealers' choice of risk premium implies that unexpected order flow can be identified from the cumulation of current and past order flows, $\tilde{x}_{t+1}$. The second issue concerns the identification of the macro information flows, $\mathcal{E}_{t+i}$. We discuss this in the next subsection.

2.2 Data

Our empirical analysis uses a data set that includes end-user transaction flows, spot rates, interest rates and macro fundamentals over six and a half years. The transaction flow data differ in two important respects from the data used in earlier work (e.g., Evans and Lyons 2002a & 2002b). First, they cover a much longer time period; January 1993 to June 1999. Second, they come from transactions between end-users and a large bank, rather than from inter-bank transactions. Our data cover transactions with three end-user segments: non-financial corporations, investors (such as mutual funds and pension funds), and leveraged traders (such as hedge funds and proprietary traders). The data set also contains information on trading location, US versus Non-US. From this we construct order flows for six segments: trades executed in the US and non-US for non-financial firms, investors, and leveraged traders. Though inter-bank transactions accounted for about two-thirds of total volume in major currency markets at the time, they are largely derivative of the underlying shifts in end-user currency demands. Our data include all the end-user trades with Citibank in the largest spot market, the USD/EUR market, and the USD/EUR forward market.[6] Citibank had the largest share of the end-user market in these currencies at the time, ranging between 10 and 15 percent. The flow data are aggregated at the daily frequency and measure in $m the imbalance between end-user orders to purchase and sell euros.

There are many advantages of our transaction flow data. First, the data are simply more powerful, covering a much longer time span. Second, because the underlying trades reflect the world economy's primitive currency demands, the data provide a bridge to modern macro analysis. Third, the three segments span the full set of underlying demand types. We shall see that those not covered by extant end-user data sets are empirically important.[7]

In the analysis that follows we consider the joint behavior of exchange rates and order flows at the weekly frequency. The weekly timing of the variables is as follows: We take the log spot rate at the start of week t, denoted by s_t, to be the log of the offer rate (USD/EUR) quoted by Citibank at what is generally the end of active trading on Friday of week $t-1$ (approximately 17:00 GMT). This is also the point at which we sample the week$-t$ interest rates from Datastream. In our analysis

[6] Before January 1999, data for the Euro are synthesized from data in the underlying markets against the Dollar, using weights of the underlying currencies in the Euro. Data on end-user transactions are only available from Citibank in this synthesized form, so we cannot study the end-user transactions in individual currencies. That said, transactions before 1999 are dominated by transactions in the Deutschemark/Dollar. Evans and Lyons (2002a) found that 87% of the market-wide interdealer transactions between the Dollar and the underlying currencies in the Euro involved trades in the Deutschemark/Dollar. This study also showed that Deutschemark/Dollar order flow was the most significant determinant of daily spot rate changes in the other underlying currencies. Furthermore, the weekly rates of depreciation in the individual currency/Dollar pairs are highly correlated with the weekly depreciation in the Deutschemark/Dollar between January 1993 to December 1998: the median correlation is 0.95.

[7] Froot and Ramadorai (2005) consider the transactions flows associated with portfolio changes undertaken by institutional investors. Osler (2003) examines end-user stop-loss orders.

below depreciation rates and interest rates are expressed in annual percentage terms. The week-t flow from segment j, x_j, is computed as the total value in \$m of euro purchases initiated by the segment against Citibank's quotes between the 17:00 GMT on Friday of week $t-1$ and Friday of week t. Positive values for these order flows therefore denote net demand for euros.

Table 1: Order Flow Summary Statistics

	Corporate		Hedge		Investor	
	US	Non-US	US	Non-US	US	Non-US
A:						
Mean	-16.8	-59.8	-4.1	11.2	19.4	15.9
Standard Deviation	108.7	196.1	346.3	183.4	146.6	273.4
Autocorrelations						
ρ_1	-0.037	0.072	-0.021	-0.098	0.096	0.061
ρ_2	-0.040	0.089	0.024	0.024	-0.024	0.107
ρ_4	0.028	-0.038	0.126	0.015	-0.030	-0.030
ρ_8	-0.028	0.103	-0.009	0.083	-0.016	-0.014
B: Cross-Correlations						
Corporate Non-US	-0.084*					
Traders US	0.125**	-0.136**				
Traders Non-Us	0.035	-0.026	0.066			
Investors US	-0.158**	0.035	0.045	0.083*		
Investors Non-US	-0.029	-0.063	0.159**	-0.032	0.094*	

Notes: The table reports weekly-frequency statistics for order flows from end-user segments cumulated over the week between January 1993 and June 1999. The last four rows of panel A report autocorrelations ρ_i at lag i. Statistical significance for the cross-correlations at the 10% and 5% levels is denoted by "*" and "**".

Summary statistics for the weekly order flow data are reported in Table 1. The statistics in panel A display two noteworthy features. First, the order flows are large and volatile. Second, they display no significant serial correlation. At the weekly frequency, then, the end-user flows appear to represent shocks to the foreign exchange market arriving at Citibank. Panel B reports the cross-correlations between the six flows. These correlations are generally quite small, ranging from approximately -0.16 to 0.16, but several are statistically significant at the 5 percent level. Insofar as these order flows convey information to dealers, individual segments should not be viewed as carrying entirely separate information.

We consider the forecasting power of spot rates and order flows for three standard variables, GDP growth, CPI inflation, and M1 growth, both in the US and Germany.[8] The flow of macro information for each of these variables is identified using the real-time estimation method developed in Evans (2005). To understand how these information flows are estimated, let $\mathcal{M}_{\text{Q}(i)}$ denote US GDP growth in quarter i that ends on day $\text{Q}(i)$ and let $\mathcal{R}_d$ denote the vector of scheduled US macro data releases on day d. The individual data releases in $\mathcal{R}_d$ vary from day to day, but the identity of upcoming releases is known in advance because release dates for each variable follow a preset schedule. $\mathcal{R}_d$ includes monthly series like Nonfarm Payroll as well as the "Advance", "Preliminary" and "Final" GDP data for quarter i that are released on three days after $\text{Q}(i)$.

The real-time estimation method combines a time-series model for the daily increments to GDP growth, $\Delta\mathcal{M}_d$, where $\mathcal{M}_{\text{Q}(i)} = \sum_{d=\text{Q}(i)+1}^{\text{Q}(i)} \Delta\mathcal{M}_d$; with a set of signaling equations that relate the data releases in $\mathcal{R}_d$ to contemporaneous growth in GDP. For example, the Nonfarm Payroll release is related to GDP growth during the month that the payroll data is collected. The resulting system of equations is written in state space form:

$$\mathcal{Z}_d = A_d\mathcal{Z}_{d-1} + V_d \qquad \text{and} \qquad \mathcal{R}_d = C_d Z_d + U_d, \tag{24}$$

where $\mathcal{Z}_d$ is the state vector on day d that includes current and lagged values of $\Delta\mathcal{M}_d$. V_d and U_d are vectors of serially uncorrelated shocks. The matrices A_d and C_d vary deterministically over each quarter to accommodate the preset sequence of releases in $\mathcal{R}_d$ and the temporal aggregation of $\Delta\mathcal{M}_d$ into quarterly GDP growth. They also contain the parameters of the time series process for $\Delta\mathcal{M}_d$ and the signaling equations. These parameters are estimated by maximum likelihood with the aid of the Kalman Filter applied to (24). The real time estimate on day d of GDP growth in the current quarter i is defined as $\mathbb{E}[\mathcal{M}_{\text{Q}(i)}|\Omega_d]$ for $d \leq \text{Q}(i)$, where Ω_d comprises the history of data releases, $\{\mathcal{R}_{d-i}\}_{i\geq 0}$. Estimates of $\mathbb{E}[\mathcal{M}_{\text{Q}(i)}|\Omega_d]$ are computed from $\mathbb{E}[\mathcal{Z}_d|\Omega_d]$ using the Kalman Filter evaluated at the maximum likelihood parameter estimates. The real-time estimates of CPI inflation and M1 growth are computed in a similar manner. A detailed description of the real-time estimation procedure is presented in Evans (2005).

In our analysis below we use information flows for the six macro variables estimated at a weekly frequency. For example, in the case of GDP growth, the information flow in week t is computed as $\mathcal{E}_t = \mathbb{E}[\mathcal{M}_{\text{Q}(i)}|\Omega_{\text{W}(t)}] - \mathbb{E}[\mathcal{M}_{\text{Q}(i)}|\Omega_{\text{W}(t-1)}]$ where $\text{W}(t)$ denotes the last day of week t, and $\text{W}(t) \leq \text{Q}(i)$. For the US variables, the information set, Ω_d, includes the 3 quarterly releases on US GDP

[8] Although Citibank's data on end-user flows are primarily driven by Deutschemark/Dollar transactions before the adoption of the Euro, we recognize the possibility that the end-user flows in the other underlying currencies could have carried incremental information relevant to the determination of other European interest rates that was uncorrelated with Germany's GDP and CPI. If this is the case, the empircal results we report below may understate the degree to which end-user flows in the Deutschemark/Dollar carry incremental information concerning Germany's GDP and CPI.

and the monthly releases on 20 other US macro variables. The information flows for the German variables are computed using a specification for Ω_d that includes the 3 quarterly release on German GDP and the monthly releases on 8 German macro variables.[9] All series come from a database maintained by Money Market News Services (M.M.S.) that contains details of each data release. Notice that the information flows we compute use specifications for Ω_d that make $\Omega_{\mathrm{W}(t-1)}$ a subset of the information available to dealers at the start of week t.

The statistical properties of the macro information flows are summarized in Table 2. Panel A shows that all the information flows have sample means close to zero and display little serial correlation. None of the autocorrelations are significant at the 5 percent level. Panel B reports the cross-correlations between the six information flows. Because the three US (German) flows are computed from the same set of US (German) data releases, it is not surprising to see some significant correlations between the US flows and between the German flows. However, none of the cross correlations are particularly large. This signifies that the data releases convey information with different relevance for different variables. For example, the Nonfarm Payroll release may induce a significant revision in the real-time estimate of GDP growth but have little impact on the real-time estimate of inflation. From this perspective, it appears that our six information flows convey distinctly different macro information.

To address the statistical power of our resulting information flow series, we compare each series' power to forecast its own subsequent data release to a forecast from professional money managers. On the Friday before each scheduled data release, M.M.S. surveys approximately forty money managers on their estimate for the upcoming release. We computed the forecast error implied by the median response from the survey as $\mathcal{M}_{\mathrm{R}} - \overline{\mathbb{E}}_{\mathrm{S}}[\mathcal{M}_{\mathrm{R}}]$, where $\mathcal{M}_{\mathrm{R}}$ is the value released on day R and $\overline{\mathbb{E}}_{\mathrm{S}}[\mathcal{M}_{\mathrm{R}}]$ is the median forecast from the survey conducted on day S $(< \mathrm{R})$. The comparable forecast error using the real-time estimates is computed as $\mathcal{M}_{\mathrm{R}} - \mathbb{E}[\mathcal{M}_{\mathrm{R}}|\Omega_{\mathrm{S}}]$. The mean and mean square error for both sets of forecasts errors are reported in Panel C of Table 2. These statistics show that the forecast errors implied by our estimated conditional expectations are comparable to those based on the M.M.S. survey. This finding provides assurance that the macro information flows are not dominated by specification error.

[9] The real-time estimates for US variables use data releases on: quarterly GDP, Nonfarm Payroll, Employment, Retail Sales, Industrial Production, Capacity Utilization, Personal Income, Consumer Credit, Personal Consumption Expenditures, New Home Sales, Durable Goods Orders, Construction Spending, Factory Orders, Business Inventories, the Government Budget Deficit, the Trade Balance, NAPM index, Housing Starts, the Index of Leading Indicators, Consumer Prices and M1. The real-time estimates for German variables use data releases on GDP, Employment, Retail Sales, Industrial Production, Manufacturing Output, Manufacturing Orders, the Trade Balance, Consumer Prices and M1.

Table 2: Summary Statistics for Macro Information Flows

	US			German		
	GDP	Inflation	M1	GDP	Inflation	M1
A:						
Mean	<0.001	<0.001	-0.006	0.002	0.002	0.022
Standard Deviation	0.200	0.030	1.379	0.526	0.806	1.454
Autocorrelations						
ρ_1	0.044	0.013	0.071	0.022	0.092	0.070
ρ_2	0.103	-0.019	0.069	-0.008	0.021	0.081
ρ_3	0.007	-0.004	0.039	-0.024	-0.029	0.125
ρ_4	0.019	0.018	0.015	-0.026	-0.049	0.133
B: Cross Correlations						
	-0.047					
	0.120**	0.048				
	0.005	-0.040	0.024			
	0.023	-0.034	0.073*	0.413**		
	0.006	0.046	0.020	-0.141**	-0.112**	
C: Forecast Comparisons						
M.M.S Mean	0.729	-0.327	0.399	0.132	-0.136	4.778
M.M.S. M.S.E	1.310	1.797	11.807	6.981	1.687	42.363
Real-Time Mean	0.190	0.054	0.033	-0.416	-0.035	-0.159
Real-Time M.S.E.	1.407	2.357	11.932	6.954	1.906	20.561

Notes: The table reports statistics for the macro information flows concerning US GDP growth, CPI inflation, and M1 growth, and German GDP growth, CPI Inflation, and M1 growth at the weekly frequency between January 1993 and June 1999; 335 weekly observations. The last four rows of Panel A report autocorrelations ρ_i at lag i. Panel C compares the mean and Mean Squared Error (M.S.E.) of real-time estimates against the real-time errors computed from M.M.S. surveys of professional money managers. Statistical significance at the 10% and 5% level is denoted by * and **, respectively.

2.3 Empirical Results

2.3.1 Macro Forecasting

We begin by examining the forecasting power of spot rates for the six macro information flows. In our model it is the difference between the current spot rate and fundamentals, $s_t - f_t$, that identifies the potential forecasting power of spot rates. We proxy this difference with the depreciation rate, Δs_t, and four interest rate spreads: the US default, commercial paper and term spreads and the German term spread. The US and German term spreads, sp_t^{T} and $\widehat{sp}_t^{\mathrm{T}}$, are computed as the difference between the 3-month and 5-year yields on government bonds. We compute the US default spread, sp_t^{D} as the difference between Moody's AAA corporate bond yield and Moody's

BAA corporate bond yield. The US commercial paper spread, sp_t^{CP}, is the difference between the 3-month commercial paper rate and the 3-month T-Bill rate. Before September 1997 we use the 3-month commercial paper rate, thereafter the 3-month rate for non-financial corporations. The spreads are computed from the interests rates on Friday of week $t-1$, and so represent information that was available to dealers at the start of week t: if they have forecasting power for the macro information flows, dealers should have been able to forecast these macro flows at the time.

We examine the forecasting power of the depreciation rate and spreads with two regressions. The first is a traditional regression where the dependent variable is the realized future macro variable. The second uses the dependent variable proposed here, namely, our macro information flow series. For the first, we regress the realized macro variable on a constant and the current values of the depreciation rate and spreads. In the case of US GDP, the regression takes the form:

$$\mathcal{M}_{\mathrm{Q}(i)} = \psi + \psi_{\mathrm{S}}(s_{\mathrm{QL}(i)} - s_{\mathrm{QL}(i-1)}) + \psi_{\mathrm{T}} sp^{\mathrm{T}}_{\mathrm{QL}(i)} + \psi_{\mathrm{D}} sp^{\mathrm{D}}_{\mathrm{QL}(i)} + \psi_{\mathrm{CP}} sp^{\mathrm{CP}}_{\mathrm{QL}(i)} + \zeta_{\mathrm{Q}(i)}, \tag{25}$$

where $\mathcal{M}_{\mathrm{Q}(i)}$ denotes the growth in GDP in quarter i that ends on day $\mathrm{Q}(i)$ and $\mathrm{QL}(i)$=$\mathrm{Q}(i-1)$+1. This regression is estimated at the quarterly frequency using the depreciation rate and spreads at the beginning of quarter i. We examine the forecasting power of the depreciation rate and spreads for inflation and M1 growth with analogous regressions estimated at the monthly frequency (i.e., we estimate a monthly version of (25) with $\mathrm{Q}(i)$ replaced by $\mathrm{M}(i)$, where $\mathrm{M}(i)$ denotes the last day of month i). When forecasting German variables we replace the three US spreads with the German term spread, $\widehat{sp}_t^{\mathrm{T}}$. All macro variables are expressed in annual percentage terms.

The second regression examines the forecasting power of the depreciation rates and spreads for the macro information flows at the weekly frequency. In this case the US regressions take the form:

$$\mathcal{E}^k_{t+k} = \beta^k + \beta^k_{\mathrm{S}} \Delta s_t + \beta^k_{\mathrm{T}} sp^{\mathrm{T}}_t + \beta^k_{\mathrm{D}} sp^{\mathrm{D}}_t + \beta^k_{\mathrm{CP}} sp^{\mathrm{CP}}_t + \xi_{t+k}, \tag{26}$$

where $\mathcal{E}^k_{t+k} = \sum_{i=0}^{k-1} \mathcal{E}_{t+i}$. The dependent variable is the the flow of information between the start of weeks t and $t+k$ concerning either GDP growth, inflation or M1 growth during the quarter or month that includes week $t+k$ (measured in annual percentage terms). As above, we replaced the three US spreads with the German spread when estimating the German regressions. Our data sample spans 335 weeks, so the estimates of (26) will be more precise provided the forecasting horizon, k, is not too long. Below we report results for $k = \{4, 13\}$ that are representative of the estimates we obtain at other horizons.

Table 3 reports the coefficient estimates from regressions (25) and (26) for the six macro variables together with asymptotic standard errors that correct for the presence of heteroskedasticity (White 1980) and the MA($k-1$) error structure induced by the overlapping forecasts in (26) (Newey and

Table 3: Forecasting Macro Information Flows

	US					German		
	Δs	sp^{D}	sp^{T}	sp^{CP}	R^2	Δs	sp^{T}	R^2
A: GDP Growth								
(i)	-0.552	-6.855***	0.386	2.097	0.274	-5.688	3.267**	0.25
	(0.574)	(2.333)	(0.333)	(1.880)		(10.736)	(1.332)	
(ii) $k = 4$	-0.018	-0.357*	0.035	0.296***	0.066	-0.266***	0.259**	0.11
	(0.029)	(0.189)	(0.025)	(0.087)		(0.076)	(0.115)	
(iii) $k = 13$	-0.049	-0.298***	0.025	0.201***	0.125	-0.014	0.266***	0.19
	(0.050)	(0.101)	(0.022)	(0.072)		(0.092)	(0.059)	
B: Inflation								
(i)	-0.072	0.046	0.024	0.073	0.033	-2.989	-0.917	0.07
	(0.073)	(0.131)	(0.017)	(0.072)		(10.010)	(0.641)	
(ii) $k = 4$	0.343	-0.698	0.448	-1.659	0.029	-0.443***	-0.088	0.09
	(0.344)	(3.014)	(0.342)	(1.485)		(0.124)	(0.143)	
(iii) $k = 13$	0.832	-0.639	0.397	-1.664	0.085	0.058	-0.118	0.01
	(0.641)	(2.350)	(0.326)	(1.176)		(0.168)	(0.135)	
C: M1 Growth								
(i)	0.732	-14.736**	1.176*	-0.969	0.163	-0.135	-6.243***	0.38
	(3.823)	(7.331)	(0.696)	(3.881)		(1.867)	(1.367)	
(ii) $k = 4$	-7.042	-4.947***	0.415***	-0.329	0.162	0.039	-1.385***	0.16
	(4.634)	(1.283)	(0.143)	(0.888)		(0.179)	(0.431)	
(iii) $k = 13$	2.662	-4.466**	0.314*	-0.359	0.217	-0.249	-1.686***	0.47
	(3.134)	(1.200)	(0.181)	(0.976)		(0.343)	(0 342)	

Notes: The table reports OLS estimates of regression (25) in line (i) and regression (26) in lines (ii) and (iii). In line (i) the dependent variable is GDP growth over the next quarter (panel A), inflation over the next month (panel B) and M1 growth over the next month (panel C). In lines (ii) and (iii) the dependent variables are the macro information flows over k weeks concerning future GDP growth (panel A), inflation (panel B) and M1 growth (panel C). The left and right hand columns report estimates using US variables and German variables, respectively. The column headers show the regressors in each regression. Asymptotic standard errors are reported in parenthesis corrected for heteroskedasticity (line i) and both heteroskedasticity and MA($k-1$) serial correlation (lines ii and iii). Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

West 1987). The table displays three noteworthy features. First, there is strong evidence in Panel A that dealers had access to information with forecasting power for real GDP growth in both the US and Germany. While the estimates of (25) in row (i) are based on just 24 observations and so should be interpreted with caution, the estimates of (26) in rows (ii) and (iii) can be reliably interpreted as indicating that dealers had access to information with forecasting power for both US and German GDP growth. In particular, the estimates indicate that sp_t^{D}, sp_t^{CP} and $\widehat{sp}_t^{\mathrm{T}}$ have significant forecasting power for the flows of future macro information concerning GDP growth over the next month ($k = 4$) and quarter ($k = 13$). The estimates in panel C indicate that the spreads have similar significant forecasting power for information flows concerning M1 growth. The second feature concerns the forecastability of inflation. In contrast to panels A and C, only one of the coefficient estimates in panel B is statistically significant. Furthermore, all of the regression R^2 statistics are much smaller than their counterparts in the other panels. Since spreads are known to have forecasting power for future inflation in other periods (e.g., Mishkin 1990), we attribute these findings to the relative stability of inflation in our data sample. Finally, we note that the depreciation rate has significant forecasting power for the information flows concerning just German GDP growth and inflation. Clearly, dealers have access to much more precise information about the future course of GDP and M1 growth than is indicated by depreciation rates alone.

We now turn to the central question: Does order flow convey new information to dealers concerning the future state of the macroeconomy? To address this question, we add the six end-user flows to the forecasting regression in (26):

$$\mathcal{E}_{t+k}^{k} = \beta^{k} + \beta_{\mathrm{S}}^{k}\Delta s_t + \beta_{\mathrm{T}}^{k} sp_t^{\mathrm{T}} + \beta_{\mathrm{D}}^{k} sp_t^{\mathrm{D}} + \beta_{\mathrm{CP}}^{k} sp_t^{\mathrm{CP}} + \sum_{j=1}^{6} \beta_j^{k}\tilde{x}_{j,t} + \xi_{t+k}, \qquad (27)$$

where $\tilde{x}_{j,t}$ is the order flow from segment j in weeks $t-k$ to t.[10] Estimates of the β_j^k coefficients will reveal whether the end user flows convey *incremental* information to dealers in week t about the future flow of macro information between weeks t and $t+k$ concerning GDP growth, inflation and M1 growth. We present the estimates of these coefficients for the one month ($k=4$) and one quarter ($k=13$) horizons in Table 4, together with Newey-West asymptotic standard errors that correct for the forecast overlap. Table 4 also reports the results of a Wald test for the joint significance of all six β_j^k coefficients.

The results in Table 4 clearly show that our end user flows carry information about the future state of the macro economy. (We do not report the other coefficients estimates from (27) to conserve space.) The estimated coefficients on five of the six flows are statistically significant at the 5 percent level in at least one of the forecasting regressions, and many are significant at the 1 percent level. The coefficients on the individual order flow segments are quite different from each other: some are positive some are negative, some appear highly significant in several equations, others in one or two. Recall that order flows are correlated across user types so no one coefficient summarizes the incremental information conveyed by an individual order flow. We therefore refrain from placing a structural interpretation on the individual estimates. That said, one clear pattern emerges from the results. The order flows collectively have more forecasting power at the one quarter ($k=13$) than one month ($k=4$) horizon. In every case, the Wald tests for the joint significance of the six

[10] Our results are robust to using order flows cumulated over the past four weeks, i.e., $t-4$ to t.

Table 4: Forecasting Macro Information Flows With Order Flows

k	Corporate US	Corporate Non-US	Traders US	Traders Non-US	Investors US	Investors Non-US	Wald p-value	R^2
A: US								
GDP Growth								
4	-0.054	-0.008	0.008	0.056	0.013	0072**	0.276	0.11
	(0.106)	(0.052)	(0.022)	(0.051)	(0.053)	(0033)		
13	0.098*	0.016	-0.026**	0.008	-0.007	-0.015	0.001	0.28
	(0.052)	(0.019)	(0.011)	(0.021)	(0.028)	(0.020)		
Inflation								
4	-2.663*	-0.048	0.259	0.622	-0.049	-0.244	0.635	0.06
	(1.470)	(0.691)	(0.313)	(0.714)	(0.800)	(0.395)		
13	-1.047**	0.271	0.317**	-0.349	-0.424	0.126	0.050	0.17
	(0.481)	(0.436)	(0.145)	(0.303)	(0.398)	(0.251)		
M1 Growth								
4	0.502	-0.353	-0.203	0.006	0.119	-0.171	0.533	0.18
	(0.594)	(0.299)	(0.161)	(0.347)	(0.441)	(0.210)		
13	0.408	-0.122	0.055	-0.521***	-0.865***	-0.195	0.002	0.44
	(0.285)	(0.153)	(0.070)	(0.202)	(0.226)	(0.131)		
B: German								
GDP Growth								
4	0.203	-0.001	0.077	-0.090	-0.112	0.117	0.354	0.15
	(0.181)	(0.097)	(0.071)	(0.091)	(0.189)	(0.107)		
13	-0.064	-0.020	0.016	-0.124***	-0.157***	-0.036	0.041	0.30
	(0.091)	(0.032)	(0.021)	(0.050)	(0.060)	(0.029)		
Inflation								
4	0.125	0.257	0.173*	-0.252	0.199	0.062	0.183	0.13
	(0.366)	(0.173)	(0.098)	(0.243)	(0.200)	(0.125)		
13	0.177	-0.044	0.007	-0.263***	-0.226**	0.075	0.035	0.20
	(0.158)	(0.064)	(0.048)	(0.098)	(0.111)	(0.056)		
M1 Growth								
4	-0.500	0.101	-0.222	0.062	0.140	-0.028	0.541	0.18
	(0.480)	(0.304)	(0.223)	(0.339)	(0.349)	(0.219)		
13	-0.258	-0.027	0.054	0.304***	0.764***	-0.294***	<0.001	0.67
	(0.215)	(0.112)	(0.080)	(0.120)	(0.184)	(0.065)		

Notes: The table reports OLS estimates of the β_j^k coefficients in regression (27) multiplied by 1000. The dependent variables are the macro information flows over k weeks concerning future GDP growth, inflation and M1 growth in the US (panel A) and Germany (panel B). Asymptotic standard errors are reported in parentheses corrected for heteroskedasticity and MA($k-1$) serial correlation. The column headed Wald reports the p-value of the Wald statistic for the null of zero coefficients on the six order flows. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

flow coefficients are significant at the 5 percent level at the quarterly horizon. Furthermore, the R^2 statistics in these regressions are on average about twice the size of their counterparts in the Table 3. By this measure, the flows contain an economically significant degree of incremental forecasting power for the macro information flows beyond that contained in the deprecation rates and spreads.

The incremental forecasting power of the six flow segments extends over a wide range of horizons. To show this, we computed the variance contribution of the flows from the estimates of (27) for horizons ranging from one week to two quarters. In particular, let $\mathcal{E}^k_{t+k} = \hat{\beta}^k + \widehat{\mathcal{E}}_{t,\Delta s} + \widehat{\mathcal{E}}_{t,x} + \hat{\xi}_{t+k}$ denote estimates of (27) where $\widehat{\mathcal{E}}_{t,\Delta s} = \hat{\beta}^k_{\mathrm{S}} \Delta s_t + \hat{\beta}^k_{\mathrm{T}} sp^{\mathrm{T}}_t + \hat{\beta}^k_{\mathrm{D}} sp^{\mathrm{D}}_t + \hat{\beta}^k_{\mathrm{CP}} sp^{\mathrm{CP}}_t$ and $\widehat{\mathcal{E}}_{t,x} = \sum_{j=1}^{6} \hat{\beta}^k_j \tilde{x}_{j,t}$. Multiplying both sides of this expression by $\mathcal{E}^k_{t+k}$ and taking expectations gives the following decomposition for the variance of the k-horizon information flow:

$$\mathbb{V}(\mathcal{E}^k_{t+k}) = \mathbb{CV}(\widehat{\mathcal{E}}_{t,\Delta s}, \mathcal{E}^k_{t+k}) + \mathbb{CV}(\widehat{\mathcal{E}}_{t,x}, \mathcal{E}^k_{t+k}) + \mathbb{CV}(\hat{\xi}_{t+k}, \mathcal{E}^k_{t+k}).$$

The contribution of the order flows is given by the second term on the right. We calculated this contribution as the slope coefficient in the regression of $\widehat{\mathcal{E}}_{t,x}$ on $\mathcal{E}^k_{t+k}$; i.e., an estimate of $\mathbb{CV}(\widehat{\mathcal{E}}_{t,x}, \mathcal{E}^k_{t+k})/\mathbb{V}(\mathcal{E}^k_{t+k})$. We also computed the standard error of this estimate with the Newey-West estimator allowing for an $MA(k-1)$ error process.

Figure 2 plots the variance contributions of the order flows together with 95 percent confidence bands for the six macro information flows for horizons $k = 1, .., 26$. In five of the six cases, the contributions rise steadily with the horizon and are quite sizable beyond one quarter. The exception is US GDP growth, where the contribution remains around 15 percent from the quarterly horizon onward. For perspective on these results, recall from Section 2.1 that order flow has incremental forecasting power for a macro variable $\mathcal{M}_{t+\tau}$ when the projection coefficient $\beta_s = \sum_{i=-t}^{\tau-1} \beta^i_x$ differs from zero, where β^i_x measures order flows' forecasting power for the flow of information at horizon i concerning $\mathcal{M}_{t+\tau}$. The plots in Figure 2 show that order flows have considerable forecasting power for the future flows of information concerning GDP growth, inflation and M1 growth at all but the shortest horizons. Clearly, then, these order flows are carrying significant information on future macroeconomic conditions.

Our analysis to this point has been based on asymptotic inference. To insure that our results concerning the forecasting power of order flows are robust, we also constructed a bootstrap distribution for the regression estimates of (27) at the one- and two-quarter horizons ($k = 13, 26$).[11]

[11] Estimates of long-horizon forecasting regressions like (25) and (26) are susceptible to two well-known econometric problems. First, the coefficient estimates may suffer from finite sample bias when the independent variables are predetermined but not exogenous. Second, the asymptotic distribution of the estimates provides a poor approximation to the true distribution when the forecasting horizon is long relative to the span of the sample. Finite-sample bias in the estimates of β^k_j is not a prime concern because our six flow segments display little or no autocorrelation and are uncorrelated with lagged information flows. There should also be less of a size distortion in the asymptotic

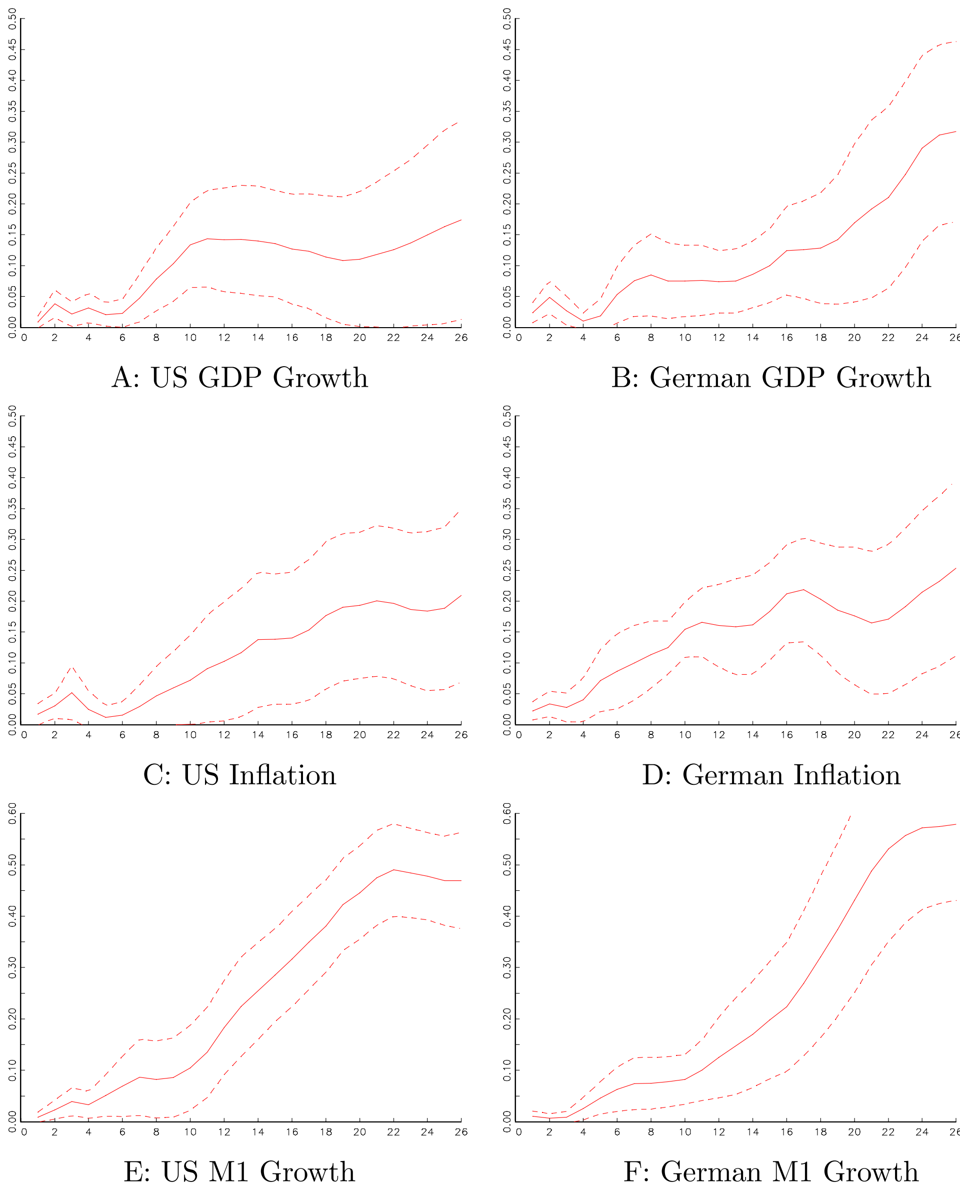

Figure 2: Estimated Contribution of Order Flows to the Variance of Future Information Flows concerning GDP growth, Inflation and M1 growth by forecasting horizon, τ, measured in weeks. Dashed lines denote 95% percent confidence bands computed as $\pm 1.96\hat{\sigma}$, where $\hat{\sigma}$ is the standard error of the estimated contribution.

The bootstrap distribution was constructed under the null hypothesis that the order flows have no incremental forecasting for the macro information flows (see Appendix for details). We found that the estimated coefficients on the end-user flows are jointly significant at the 5 percent level when compared against this distribution.

distribution than is found elsewhere. For example, Mark (1995) considered a case where the data span is less than five times the length of his longest forecasting horizon. Here, we have 11 non-overlapping observations at the 2-quarter horizon.

The results in Table 4 and Figure 2 contrast with the findings of F&R. They found no evidence of a long run correlation between real interest rate differentials and the transaction flows of institutional investors. As we noted above, this result is completely consistent with our theoretical model: Order flows can convey information to dealers about macro variables without there being any long-run statistical relationship between order flow and the variable in question. Our model also provides perspective on why the incremental forecasting power of order flows could increase with the horizon. Recall from equation (14) that unexpected order flow, $x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1}$, contains new information about the hedging demand, h_t, and about the average of agents' spot rate forecast series, $\overline{\mathbb{E}}_t^n s_{t+1}$. Insofar as these two components embed agent's expectations for monetary policy's full future path, they will convey information to dealers about the full future course of output, inflation and monetary growth, not simply at short-horizons. We present further evidence consistent with this interpretation below.[12]

2.3.2 Macro Information and the Risk Premium

If order flows convey information about future macroeconomic conditions, how do dealers use this information in determining their spot rate quotes? To address this question, recall that the equilibrium spot rate follows

$$s_t = \hat{r}_t - r_t + \mathbb{E}_t^{\mathrm{D}} \sum_{i=1}^{\infty} \rho^i m_{t+i} - \mathbb{E}_t^{\mathrm{D}} \sum_{i=0}^{\infty} \rho^i \delta_{t+i},$$

where $m_t = \gamma_\pi (\Delta \hat{p}_{t+1} - \Delta p_{t+1}) + \gamma_y (\hat{y}_t - y_t) + \frac{1-\rho}{\rho}(p_t - \hat{p}_t)$. In principle, dealers could use the information in order flows to revise their forecasts for future macro fundamentals, m_t, leaving their forecasts for the risk premium on the euro, δ_t, unchanged. This would be consistent with the class of macro models that treat the risk premium as a constant. Alternatively, dealers may find the information conveyed by order flow useful for revising their forecasts of both m_t and δ_t. In this case, order flows should have forecasting power for excess returns. For example, let $er_{t+1} = \Delta s_{t+1} + \hat{r}_t - r_t$ denote the log excess return on euros between the start of weeks t and $t+1$. Combining this definition with (1) gives

$$er_{t+2} = \delta_{t+1} + s_{t+2} - \mathbb{E}_{t+1}^{\mathrm{D}} s_{t+1} = \mathbb{E}_t^{\mathrm{D}} \delta_{t+1} + (\delta_{t+1} - \mathbb{E}_t^{\mathrm{D}} \delta_{t+1}) + (s_{t+2} - \mathbb{E}_{t+1}^{\mathrm{D}} s_{t+1}).$$

[12] After the first draft of this paper, Evans and Lyons (2004a), began circulating, Rime, Sarno, and Sojli (2007) reported other forecasting results consistent with our findings. They examined the short-term forecasting power of aggregate interdealer order flow in the USD/EUR, USD/GBP and USD/JPY markets for specific macro data releases scheduled in the next week. Their findings are based on a much shorter data sample.

Order flow from week t trading, $x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1}$, cannot be correlated with either $\mathbb{E}_t^{\mathrm{D}}\delta_{t+1}$ or $(s_{t+2} - \mathbb{E}_{t+1}^{\mathrm{D}} s_{t+1})$, and so will have forecasting power for excess returns between weeks $t+1$ and $t+2$, when it induces dealers to revise their forecasts for the risk premium δ_{t+1}; i.e. when $\mathbb{CV}(\delta_{t+1} - \mathbb{E}_t^{\mathrm{D}}\delta_{t+1}, x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1}) \neq 0$.

We examine whether the information on future macroeconomic conditions is used to revise the risk premium embedded in dealers' quotes as follows: Let $\mathcal{E}_{t+k}^k$ now define the flow of information between the start of weeks t and $t+k$ concerning a *linear combination of macro variables.* We considered: (i) the difference between US and German GDP growth, $\Delta y - \Delta\hat{y}$; (ii) the difference between US and German inflation, $\Delta p - \Delta\hat{p}$; (iii) the difference between US and German M1 growth, $\Delta m - \Delta\hat{m}$; (iv) the growth in the US M1/GDP ratio, $\Delta m - \Delta y$; (v) the growth in the German M1/GDP ratio, $\Delta\hat{m} - \Delta\hat{y}$; and (vi) the difference between the US and German M1/GDP growth rates $(\Delta m - \Delta y) - (\Delta\hat{m} - \Delta\hat{y})$. For each combination, we first computed the predicted order flow component, $\widehat{\mathcal{E}}_{t,x}$, from the forecasting regression in (27) with $k = 13$. We then estimated

$$\Delta^\tau s_{t+\tau} = b + b_r(r_t^\tau - \hat{r}_t^\tau) + b_x\widehat{\mathcal{E}}_{t,x} + v_{t+\tau}, \tag{28}$$

where r_t^τ and $\hat{r}_t^\tau$ denote the τ-week rates on euro-dollar and euro-deutschemark deposits at the start of week t. If the order flows contain incremental information about the linear combination of macro variables over the next 13 weeks that dealers use to revise the risk premium, then the estimates of b_x should be significant. We include the interest differential on the right hand side of (28) with an unrestricted coefficient b_r to accommodate variations in the ex ante risk premia that are unrelated to order flow. If these variation are absent, b_r should equal one.

Table 5 reports the estimates of (28) for horizons $\tau = \{1, 4\}$ weeks.[13] The results are rather striking. First, the estimates of the b_x coefficients display a similar pattern across the forecast horizons. The coefficients on the components involving the GDP growth and inflation are small and statistically insignificant. By contrast, the coefficients on the components with M1 growth, M1/GDP growth and the M1/GDP growth differentials are all highly significant. This constitutes direct empirical evidence that the order flows convey information about the future course of the macroeconomy, and that dealers use this information to revise the risk premia embedded in their spot rate quotes. More specifically, the expression for the risk premium in (12) implies that

$$\delta_{t+1} - \mathbb{E}_t^{\mathrm{D}}\delta_{t+1} = (\mathbb{E}_{t+1}^{\mathrm{D}} - \mathbb{E}_t^{\mathrm{D}})(s_{t+2} - \overline{\mathbb{E}}_{t+1}^n s_{t+2}) - \alpha_s^{-1}(\mathbb{E}_{t+1}^{\mathrm{D}} - \mathbb{E}_t^{\mathrm{D}})h_{t+1},$$

[13] Because we estimate the order flow component, $\widehat{\mathcal{E}}_{t,x}$, we need to account for sampling variation when computing the standard errors of the coefficient estimates. For this purpose we use an IV procedure akin to 2SLS: We replaced $\widehat{\mathcal{E}}_{t,x}$ by $\mathcal{E}_{t+k}^k$ in (28) and then used $\widehat{\mathcal{E}}_{t,x}$ as an instrument for $\mathcal{E}_{t+k}^k$. The coefficient estimates are identical to OLS. Their standard errors are computed from the IV procedure with the Newey and West (1987) covariance estimator that allows for the presence of heteroskedasticity and an $MA(\tau - 1)$ error process.

so dealers will adjust the risk premium upward when they infer from order flow that on average agents are underestimating the future depreciation of the dollar by a larger amount; i.e., when $(\mathbb{E}^{\mathrm{D}}_{t+1} - \mathbb{E}^{\mathrm{D}}_{t})(s_{t+2} - \overline{\mathbb{E}}^{n}_{t+1} s_{t+2}) > 0$. This will happen, for example, when dealers' raise their expectations for the future path of the interest differential, $\hat{r}_{t+i} - r_{t+i}$, *relative* to the average path expected by agents. In other words, when the information in order flow leads dealers to expect a looser (tighter) future US (German) monetary policy than the average forecast outside of the foreign exchange market. Under these circumstances, order flows forecasting looser (tighter) future monetary conditions in the US (Germany) should induce dealers to raise the risk premium on the euro, with the result that the order flows forecast positive future returns on the euro. The signs of the statistically significant coefficients on the M1/GDP growth components in Table 5 are consistent with this explanation.

The second noteworthy feature concerns the R^2 statistics. They rise from less than 6 percent to 14 percent as we move from the one week to one month forecasting horizon. By comparison, the R^2 statistics from Fama-style regressions of future returns on the interest differentials alone are typically less than 3 percent. Here all the forecasting power comes from the order flow component, $\widehat{\mathcal{E}}_{t,x}$. If (28) is re-estimated without the interest differentials, the b_x estimates and R^2 statistics are essentially unchanged. Our results are also robust to imposing $b_r = 1$ as a restriction.

Of course, a logical possibility is that dealers revise the risk premium in their spot quotes in response to order flows, but part of the reason is unrelated to future macroeconomic conditions. If this is the case, order flows should have forecasting power for future (excess) returns beyond that found in $\widehat{\mathcal{E}}_{t,x}$. The right hand column of Table 5 provides statistical evidence on this possibility. Here we report the p-values of LM statistics for the null hypothesis that the residuals from (28) are unrelated to the six flows. As the table shows, the p-values are well above 5 percent in all the cases where the estimated b_x coefficients appear significant.

The results in Table 5 provide a macro-based explanation for the forecasting results first reported in Evans and Lyons (2005). There we showed that end-user flows had significant out-of-sample forecasting power for excess currency returns at the four-week horizon.[14] Our findings in Table 5 indicate that this forecasting power stems from the fact that order flows convey significant information about future macroeconomic conditions, specifically M1 and GDP growth, that dealers use to revise the risk premia they embed in their spot rate quotes. To our knowledge, this is the first piece of empirical evidence identifying the process by which macroeconomic information

[14] These findings are consistent with the results of in-sample forecasting tests. In an earlier version of this paper we showed that Citibank's order flows forecast euro returns at horizons of two to four weeks with in-sample R^2 statistics of approximately 8 to 16 percent (results available on request). We recognize that the relative merits of in-sample and out-of-sample evaluation methods are the subject of debate in the econometrics literature (Inoue and Kilian 2005), but they do not appear important in the present context.

Table 5: Forecasting Returns

$\hat{r}-r$	$\Delta y-\Delta\hat{y}$	$\Delta p-\Delta\hat{p}$	$\Delta m-\Delta\hat{m}$	$\Delta m-\Delta y$	$\Delta\hat{m}-\Delta\hat{y}$	$(\Delta m-\Delta y)$ $-(\Delta\hat{m}-\Delta\hat{y})$	R^2	LM p-value
Horizon $\tau=1$								
-0.229	-0.229						<0.01	0.249
(0.369)	(0.949)							
-0.194		-0.290					<0.01	0.202
(0.367)		(0.507)						
0.161			0.589**				0.02	0.981
(0.387)			(0.218)					
0.04				0.436**	-0.700**		0.03	0.993
(0.398)				(0.280)	(0.281)			
0.110						0.585**	0.02	0.979
(0.381)						(0.219)		
0.136						0.639**	0.06	0.571
(0.310)						(0.184)		
Horizon $\tau=4$								
-0.214	-0.094						<0.01	<0.001
(0.315)	(0.651)							
-0.200		-0.106					<0.01	<0.001
(0.327)		(0.383)						
0.248			0.709**				0.14	0.236
(0.316)			(0.156)					
0.122				0.564**	-0.799**		0.14	0.166
(0.302)				(0.193)	(0.186)			
0.186						0.697**	0.13	0.120
(0.307)						(0.162)		

Notes: The table reports coefficients and IV asymptotic standard errors from regression (28) for horizons $\tau=\{1,4\}$ weeks. $\widehat{\mathcal{E}}_{t,x}$ is the predicted component of the macro information flow estimated in (27) with $k=13$, based on the linear combination of variables listed at the head of each column. The right-hand column reports the p-value of LM statistics for the null that the regression residuals are unrelated to order flows. Standard errors correct for heteroskedasticity and the MA$(\tau-1)$ error process induced by overlapping forecasts. *, **, and *** denote significance at the 10%, 5% and 1% levels.

determines the foreign exchange risk premium.

3 Conclusion

The aim of this paper was to revisit the long-standing forecasting puzzles in exchange rate economics to determine whether the information role of order flow provides resolution. We developed a structural model for both the contemporaneous relationship between flows, rates, and fundamentals and the implied forecasting relationship. The contemporaneous relationship arises because transaction flows reveal macroeconomic information that was previously dispersed, and therefore not fully impounded in the exchange rate. The forecasting relationship arises because the same macro information revealed by flows is useful for determining the foreign exchange risk premium, generating rational forecastability in excess returns. We then examined the empirical implications of the model. We found that transaction flows have significant forecasting power for macro fundamentals – incremental forecasting power beyond that contained in exchange rates and other variables. We also showed that transaction flows have significant forecasting power for exchange rate returns. Our model provides a rational interpretation for these forecastable returns in that the macro information being revealed by flows is important for determining the foreign exchange risk premium. In sum, we find strong support for the idea that exchange rates vary as the market assimilates dispersed macro information from transaction flows.

We conclude with some perspective. Our results provide a qualitatively different view of why macroeconomic variables perform so poorly in accounting for exchange rates at horizons of one year or less. This view is different from both the traditional macro and the emerging "micro" perspectives. Unlike the macro perspective, we do not view all new information concerning macro fundamentals as being impounded from public-information sources. Much information about macro fundamentals is initially microeconomically dispersed. The market needs to assimilate implications for the spot exchange rate, and for other asset prices, via trading. It is this assimilation process that accounts for (much of) the disturbances in exchange rate equations. Our approach also differs from the extant micro perspective because models offered thus far (e.g., Evans and Lyons 2002a &2002b) have interpreted the information conveyed by transaction flows as orthogonal to macro fundamentals. Most readers of this micro literature have adopted the same view. Our findings, by contrast, suggest that transaction flows are central to the process of impounding information into exchange rates. In particular, they point to the existence of a transaction-mediated link between the foreign exchange risk premium and the macroeconomy that is new to the literature. In light of the long-standing difficulty of relating excess currency returns to conventional measures of risk (see Burnside, Eichenbaum, Kleshchelski, Rebelo, Hall, and Hall 2008 for a recent contribution), exploring this link should be a high priority for future exchange rate research.

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A Appendix

Proof of Proposition We derive the equilibrium of the model in three steps. First we conjecture how the flows of information received by dealers and agents relate to current macroeconomic conditions. Second, we use these conjectures to identify dealers' and agents' estimates of the current state of the economy. Equations for the equilibrium spot rate, risk premia and order flow are then derived from these estimates. Finally, we use these equations to verify that dealers and agents receive information in the form conjectured in the first step.

Recall that the vector $Z_t = [\ u_t', \ \ u_{t-1}', \ \ ..., \ \ u_{t-k-1}', \ \ z_{t-k}' \ ]'$ contains the information that is *potentially* available to dealers and agents about the state of macroeconomy in week t, z_t, and that its dynamics are represented by the AR(1) process in (15): $Z_t = AZ_{t-1} + Bu_t$. Let $Z_t^{\text{D}} = [\ z_t^{o\prime}, \ \ z_{t-k}', \ \ x_t \ ]'$ and $Z_t^n = [\ z_t^{o\prime}, \ \ z_{t-k}', \ \ s_t \ \ z_t^{n\prime} \ ]'$ denote the vectors of information observed by all dealers and agent n in week t. We first conjecture that

$$Z_t^{\text{D}} = CZ_t, \qquad \text{and} \qquad Z_t^n = C^{\text{N}} Z_t + D^{\text{N}} v_t^n. \tag{A1}$$

Next, we use (15) and (A1) to characterize the behavior of $\mathbb{E}_t^{\text{D}} Z_t$ and $\mathbb{E}_t^n Z_t$. Applying the Kalman filter to (15) and (A1) gives

$$\begin{aligned}
\mathbb{E}_t^{\text{D}} Z_t &= A\mathbb{E}_{t-1}^{\text{D}} Z_{t-1} + GCA(Z_{t-1} - \mathbb{E}_{t-1}^{\text{D}} Z_{t-1}) + GCBu_t, \qquad \text{and} \\
\mathbb{E}_t^n Z_t &= A\mathbb{E}_{t-1}^n Z_{t-1} + G^{\text{N}} C^{\text{N}} A \left(Z_{t-1} - \mathbb{E}_{t-1}^n Z_{t-1}\right) + G^{\text{N}} C^{\text{N}} Bu_t + G^{\text{N}} D^{\text{N}} v_t^n,
\end{aligned}$$

where G and G^{N} are Kalman gain matrices for the dealers' and agents' inference problems. Let Σ_u and Σ_v denote the covariance matrices for u_t and v_t^n respectively. Then these gain matrices can be written as

$$G = \Sigma^{\text{D}} C' \left(C\Sigma^{\text{D}} C'\right)^{-1} \qquad \text{and} \qquad G^{\text{N}} = \Sigma^{\text{N}} C^{\text{N}\prime} \left(C^{\text{N}} \Sigma^{\text{N}} C^{\text{N}\prime} + D^{\text{N}} \Sigma_v D^{\text{N}\prime}\right)^{-1} \tag{A2}$$

where $\Sigma^i = A\left((I - G^i C^i)\Sigma^i\right) A' + B\Sigma_u B'$ for $i = \{\text{D,N}\}$. Combining these expressions with (15) gives us the following equations for the estimation errors

$$Z_t - \mathbb{E}_t^{\mathrm{D}} Z_t = \sum_{i=0}^{\infty} \{(I - GC)A\}^i (I - GC)Bu_{t-i}, \qquad \text{and} \tag{A3}$$

$$Z_t - \mathbb{E}_t^{n} Z_t = \sum_{i=0}^{\infty} \{(I - G^{\mathrm{N}}C^{\mathrm{N}})A\}^i \left\{(I - G^{\mathrm{N}}C^{\mathrm{N}})Bu_{t-i} - G^{\mathrm{N}}D^{\mathrm{N}}v_{t-i}^n\right\}. \tag{A4}$$

Because the inference problem facing all agents $n \in [0,1]$ involves the same C^{N}, D^{N} and Σ_v, matrices, G^{N} is also the same across all agents. This means that the agent-specific shocks, $\{v_{t-i}^n\}$, are the only source of heterogeneity in the estimation errors, $Z_t - \mathbb{E}_t^n Z_t$. Furthermore, under our information assumptions all the elements of $(I - GC)Bu_{t-i}$ for $i \geq k$ are in Ω_t^{D}, so no linear combination of these elements can affect $Z_t - \mathbb{E}_t^{\mathrm{D}} Z_t$. $\{(I - GC)A\}^i$ must therefore be equal to null matrices for $i \geq k$, so (A3) becomes

$$Z_t - \mathbb{E}_t^{\mathrm{D}} Z_t = \sum_{i=0}^{k-1} \{(I - GC)A\}^i (I - GC)Bu_{t-i} = \sum_{i=0}^{k-1} \Gamma_i u_{t-i} = \Theta^{\mathrm{D}} Z_t, \tag{A5}$$

because $\{u_t, u_{t-1}, ...u_{t-k+1}\}$ are elements of Z_t. Similarly, since all the elements of $(I - G^{\mathrm{N}}C^{\mathrm{N}})Bu_{t-i}$ for $i \geq k$ are also in Ω_t^n, (A4) becomes

$$Z_t - \mathbb{E}_t^n Z_t = \sum_{i=0}^{k-1} \{(I - G^{\mathrm{N}}C^{\mathrm{N}})A\}^i (I - G^{\mathrm{N}}C^{\mathrm{N}})Bu_{t-i} - \sum_{i=0}^{\infty} \{(I - G^{\mathrm{N}}C^{\mathrm{N}})A\}^i G^{\mathrm{N}}D^{\mathrm{N}}v_{t-i}^n,$$

So aggregating across agents gives

$$Z_t - \overline{\mathbb{E}}_t^n Z_t = \sum_{i=0}^{k-1} \{(I - G^{\mathrm{N}}C^{\mathrm{N}})A\}^i (I - G^{\mathrm{N}}C^{\mathrm{N}})Bu_{t-i} = \Theta^{\mathrm{N}} Z_t. \tag{A6}$$

We can thus identify dealers' and the average of agents' estimates of Z_t as

$$\mathbb{E}_t^{\mathrm{D}} Z_t = \Phi^{\mathrm{D}} Z_t \qquad \text{and} \qquad \overline{\mathbb{E}}_t^n Z_t = \Phi^{\mathrm{N}} Z_t, \tag{A7}$$

where $\Phi^{\mathrm{D}} = I - \Theta^{\mathrm{D}}$ and $\Phi^{\mathrm{N}} = I - \Theta^{\mathrm{N}}$.

We now use (A7) to derive equations for the spot rate, risk premium and order flow. For this purpose recall that $z_t' = [\ \Delta\hat{p}_t - \Delta p_t, \quad \hat{r}_t - r_t, \quad \hat{p}_t - p_t, \quad \hat{y}_t - y_t, \quad ..., \quad ...\ ]$, so $\Delta\hat{p}_t - \Delta p_t = \ell_1 z_t$, $\hat{r}_t - r_t = \ell_2 z_t$, etc., for some selection vectors, ℓ_i. Furthermore, equation (8) implies that $z_t = B_u u_t + A_z B_u u_{t-1} + A_z^2 B_u u_{t-1} + ...A_z^k z_{t-k} = \Lambda_z Z_t$, so we can write $\Delta\hat{p}_t - \Delta p_t = \ell_1 \Lambda_z Z_t = \Lambda_{\Delta p} Z_t$, $\hat{r}_t - r_t = \ell_2 \Lambda_z Z_t = \Lambda_r Z_t$, and so on. We show below that $\delta_t = \Lambda_\delta \Phi^{\mathrm{D}} Z_t$, so with the aid of (15) we can use (11) and the fact that $\mathbb{E}_t^{\mathrm{D}}[\hat{r}_t - r_t - \delta_t] = \hat{r}_t - r_t - \delta_t$ to write

$$s_t = \left\{ \Lambda_r - \Lambda_\delta + (\gamma_\pi \Lambda_{\Delta p} A + \lambda_y \Lambda_y + \tfrac{1-\rho}{\rho}\Lambda_p - \Lambda_\delta \Phi^{\mathrm{D}})(I - \rho A)^{-1}\rho A \right\} \mathbb{E}_t^{\mathrm{D}} Z_t = \Lambda_s \mathbb{E}_t^{\mathrm{D}} Z_t. \tag{A8}$$

We can now use (A7) and (A8) to write the aggregate demand for foreign currency by agents in (6) as

$$\begin{aligned} \alpha_t &= \alpha_s(\mathbb{E}_t^{\mathrm{D}} \Delta s_{t+1} + \hat{r}_t - r_t) + \alpha_s(\overline{\mathbb{E}}_t^n - \mathbb{E}_t^{\mathrm{D}}) s_{t+1} + h_t, \\ &= \alpha_s \delta_t + \alpha_s \Lambda_s \Phi^{\mathrm{D}} (\overline{\mathbb{E}}_t^n - \mathbb{E}_t^{\mathrm{D}}) Z_{t+1} + h_t. \end{aligned} \tag{A9}$$

Efficient risk-sharing implies that dealers choose δ_t such that $\mathbb{E}_t^{\mathrm{D}} \alpha_t = 0$. Combining this restriction with expression above gives the following equation for the risk premium:

$$\begin{aligned} \delta_t &= \Lambda_s \Phi^{\mathrm{D}} \mathbb{E}_t^{\mathrm{D}} (\mathbb{E}_t^{\mathrm{D}} - \overline{\mathbb{E}}_t^n) Z_{t+1} - \alpha_s^{-1} \mathbb{E}_t^{\mathrm{D}} h_t \\ &= \left\{ \Lambda_s \Phi^{\mathrm{D}} A (\Phi^{\mathrm{D}} - \Phi^{\mathrm{N}}) - \alpha_s^{-1} \Lambda_h \right\} \mathbb{E}_t^{\mathrm{D}} Z_t = \Lambda_\delta \mathbb{E}_t^{\mathrm{D}} Z_t. \end{aligned} \tag{A10}$$

(A9) can now be rewritten as

$$\alpha_t = \{\alpha_s \Lambda_s \Phi^{\mathrm{D}} A (\Phi^{\mathrm{N}} - \Phi^{\mathrm{D}}) + \Lambda_h\} (Z_t - \mathbb{E}_t^{\mathrm{D}} Z_t) = -\alpha_s \Lambda_\delta (Z_t - \mathbb{E}_t^{\mathrm{D}} Z_t). \tag{A11}$$

Since dealers know the history of order flow and $\alpha_{t-1} = \sum_{i=0}^{\infty} x_{t-i}$ by market clearing, $\alpha_{t-1} \in \Omega_t^{\mathrm{D}}$. Consequently, unexpected order flow from week-t trading is $x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1} = (\alpha_t - \alpha_{t-1}) - \mathbb{E}_t^{\mathrm{D}}(\alpha_t - \alpha_{t-1}) = \alpha_t - \mathbb{E}_t^{\mathrm{D}} \alpha_t$. Under efficient risk-sharing $\mathbb{E}_t^{\mathrm{D}} \alpha_t = 0$ so

$$x_{t+1} - \mathbb{E}_t^{\mathrm{D}} x_{t+1} = \alpha_t = -\alpha_s \Lambda_\delta (Z_t - \mathbb{E}_t^{\mathrm{D}} Z_t). \tag{A12}$$

Equations (A8), (A10) and (A12) give the expressions in the proposition.

Finally, we verify our conjecture in (A1). Combining (A11) with the market clearing condition, $x_t = \alpha_{t-1} - \alpha_{t-2}$, gives

$$x_t = \alpha_s \Lambda_\delta (Z_{t-1} - \mathbb{E}_{t-1}^{\mathrm{D}} Z_{t-1}) - \alpha_s \Lambda_\delta (Z_{t-2} - \mathbb{E}_{t-2}^{\mathrm{D}} Z_{t-2}).$$

We established in (A5) that $Z_t - \mathbb{E}_t^{\mathrm{D}} Z_t = \sum_{i=0}^{k-1} \Gamma_i u_{t-i}$. Substituting these estimation errors into the expression above gives

$$x_t = \alpha_s \Lambda_\delta \Gamma_0 u_{t-1} + \alpha_s \Lambda_\delta \sum_{i=1}^{k-2} (\Gamma_i - \Gamma_{i-1}) u_{t-i-1} - \alpha_s \Lambda_\delta \Gamma_{k-1} u_{t-k-1} = \Lambda_x Z_t, \tag{A13}$$

because $\{u_{t-1}, u_{t-1}, ...u_{t-k-1}\}$ are all elements in Z_t. Let $z_t^o = cz_t = \Lambda_o Z_t$ denote the subset of variables in z_t that are contemporaneously observed by dealers and agents. We can now use equations (A7), (A8) and (A13) to rewrite (A1) as

$$Z_t^{\mathrm{D}} \equiv \begin{bmatrix} z_t^o \\ z_{t-k} \\ x_t \end{bmatrix} = \begin{bmatrix} & & \Lambda_o & & \\ 0 & 0 & ... & 0 & I \\ & & \Lambda_x & & \end{bmatrix} \begin{bmatrix} u_t \\ u_{t-1} \\ \vdots \\ u_{t-1-k} \\ z_{t-k} \end{bmatrix} = CZ_t, \tag{A14}$$

and

$$Z_t^n \equiv \begin{bmatrix} z_t^o \\ z_{t-k} \\ s_t \\ z_t^n \end{bmatrix} = \begin{bmatrix} & & c\Lambda_z & & \\ 0 & 0 & ... & 0 & I \\ & & \Lambda_s \Phi^{\mathrm{D}} & & \\ & & \Lambda_z & & \end{bmatrix} \begin{bmatrix} u_t \\ u_{t-1} \\ \vdots \\ u_{t-1-k} \\ z_{t-k} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ I \end{bmatrix} v_t^n. \tag{A15}$$

We have thus verified our conjecture and established that the equilibrium of the model is as described by the proposition.

Bootstrap Distribution We constructed the bootstrap distribution for the regression estimates from regression (27) as follows: First we estimated a fourth-order VAR for the weekly change in log spot rate, Δs_t, the spreads ($\{sp_t^{\mathrm{T}}, sp_t^{\mathrm{D}}, sp_t^{\mathrm{CP}}\}$ for the US, $\widehat{sp}_t^{\mathrm{T}}$ for Germany) and the six flow segments, $\tilde{x}_{j,t}$. Next, for each of the six macro variables we consider, we generated a pseudo data series spanning 335 weeks for the k-week information flows, $\mathcal{E}_{t+k}^k = \sum_{i=0}^{k-1} \mathcal{E}_{t+i}$, by bootstrap sampling from the weekly estimates, $\mathcal{E}_{t+i}$.(Recall that the $\mathcal{E}_t' s$ are serially uncorrelated.) Pseudo data series for Δs_t, the spreads and $x_{j,t}$ are similarly generated by bootstrap sampling from the VAR residuals. Notice that under this data generation process, realizations of $\mathcal{E}_{t+k}^k$ are independent from the other variables. We then use the pseudo data to estimate equation (27) at the one quarter ($k = 13$) and two quarter ($k = 26$) horizons. This process is repeated 5000 times to construct a bootstrap distribution for the regression estimates under the null hypothesis that spot rates, spreads and order flows have no forecasting power for the information flows concerning our six macro variables.