Exchange Rate Fundamentals and Order Flow

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Abstract

This paper addresses whether transaction flows in foreign exchange markets convey information about fundamentals. We begin with a GE model in the spirit of Hayek (1945) in which fundamental information is first manifest in the economy at the micro level, i.e., in a way that is not symmetrically observed by all agents. With this information structure, induced foreign exchange transactions play a central role in the aggregation process, providing testable links between transaction flows, exchange rates, and future fundamentals. We test these links using data on all end-user currency trades received by Citibank over 6.5 years, a sample sufficiently long to analyze real-time forecasts at the quarterly horizon. The predictions are borne out in four empirical findings that define this paper's main contribution: (1) transaction flows forecast future macro variables such as output growth, money growth, and inflation, (2) transaction flows forecast these macro variables significantly better than spot rates do, (3) transaction flows (proprietary) forecast future spot rates, and (4) though proprietary flows convey new information about future fundamentals, much of this information is still not impounded in the spot rate one quarter later. These results indicate that the significance of transaction flows for exchange rates extends well beyond high frequencies.

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Introduction

Exchange rate movements at frequencies of one year or less remain unexplained by observable macroeconomic variables (Meese and Rogoff 1983, Frankel and Rose 1995, Cheung et al. 2002). In their survey, Frankel and Rose (1995) describe evidence to date as indicating 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 (2002) comprehensive study concludes that "no model consistently outperforms a random walk."

This paper addresses this long-standing puzzle from a new direction. Rather than attempting to empirically link exchange rates directly to macro variables, we address instead the microeconomic mechanism by which information concerning macro variances is impounded in exchange rates by the market. One way to frame our approach is via the present value relation, in which the log spot exchange rate s_t is expressed as the sum of two terms; the present value of measured fundamentals f_t^{M}, and the present value of unmeasured fundamentals f_t^{U} :

$$s_t = (1-b)\sum_{i=0}^{\infty} b^i \mathbb{E}_t f_{t+i}^{\mathrm{M}} + (1-b)\sum_{i=0}^{\infty} b^i \mathbb{E}_t f_{t+i}^{\mathrm{U}}, \tag{1}$$

where $0 < b < 1$ is a discount factor, and $\mathbb{E}_t$ is the conditional expectations operator using market information in period t.

Empirical analysis of equation (1) is hampered by two factors. First, researchers only have data on a subset of the macro variables that could conceivably drive exchange rates, measured fundamentals f_t^{M}. Second, some of the information used in forming market expectations, $\mathbb{E}_t f_{t+i}^{\mathrm{M}}$ and $\mathbb{E}_t f_{t+i}^{\mathrm{U}}$, is typically unavailable. Consequently, empirical analysis of the link between spot rates and macro variables must be based on

$$s_t = (1-b)\sum_{i=0}^{\infty} b^i \widehat{\mathbb{E}}_t f_{t+i}^{\mathrm{M}} + \xi_t, \tag{2}$$

where $\widehat{\mathbb{E}}_t f_{t+i}^{\mathrm{M}}$ denotes the econometric estimates of market forecasts, and ξ_t represents the "unexplained" portion of the spot rate:

$$\xi_t = (1-b)\sum_{i=0}^{\infty} b^i \mathbb{E}_t f_{t+i}^{\mathrm{U}} + (1-b)\sum_{i=0}^{\infty} b^i (\mathbb{E}_t - \widehat{\mathbb{E}}_t) f_{t+i}^{\mathrm{M}}. \tag{3}$$

The poor performance of empirical models linking exchange rates to macro variables implies that movements in ξ_t dominate changes in the estimated present value of measured fundamentals (i.e. the first term on the right in equation 2). Equation (3) shows that these movements could originate from variations in the present value of unobserved fundamentals. This is the motivation behind research that looks to expand the set of variables that act as fundamentals. As yet, this effort has not resulted in much empirical success. An alternative approach is suggested by the second term in (3). Differences between the market's forecasts of measured fundamentals and econometric estimates of these forecasts could also account for the large movements in ξ_t. It is this possibility that motivates the analysis in this paper.

Our approach focuses on the gap between the information sets of the econometrician and the market. Specifically, we address whether microeconomic information that is available to the market, but not available to the econometrician, is helpful in forming estimates of market expectations, $\mathbb{E}_t f^{\mathrm{M}}_{t+i}$. We recognize that a positive finding is not itself a resolution of the Meese-Rogoff determination puzzle. It is instead an investigation of what may be a missing link in that puzzle. This analysis complements the recent results of Engel and West (2004). They find that spot rates have forecasting power for future measured fundamentals as the equation (1) predicts. Our purpose is to suggest another channel through which the theory behind (1) might find support. More specifically, we investigate whether transaction flows convey information useful in forecasting future fundamentals to the market-makers who quote foreign exchange prices. We shall argue that any information conveyed by transaction flows is incremental to the information contained in the observed history of macro variables used in econometric estimates of $\mathbb{E}_t f^{\mathrm{M}}_{t+i}$. Consequently, if transactions flows do indeed convey information about fundamentals to market-makers, these flows will provide a measure of the variations in $(\mathbb{E}_t - \widehat{\mathbb{E}}_t) f^{\mathrm{M}}_{t+i}$.

Our empirical analysis is related to earlier research by Froot and Ramadorai (2002), hereafter F&R. These authors examine the statistical relationships between real exchange rates, excess currency returns, real interest differentials, and the transaction flows of institutional investors. The empirical analysis we present differs from F&R in three important respects. First, we make no assumption about the long run behavior of the real exchange rate. By contrast, the variance decompositions F&R use are based on long run purchasing power parity. Second, we analyze transaction flows from different user segments that span demand for foreign currency, not just institutional investors. Our results indicate that the transaction flows from different segments convey different information, so including flows from all segments is empirically important for understanding the links between flows, exchange rates and fundamentals. Third, our analysis incorporates real-time estimates of the fundamental macro variables. These estimates correspond to the macro data that was available to market participants at the time rather than the values that only became available months later. The use of these real-time estimates allows use to examine the relationship between flows and fundamentals with much greater precision than would be otherwise possible.

The information conveyed by transaction flows is not concentrated "insider" information, but rather information that is dispersed around the economy and aggregated by the market (Hayek 1945). In text-book models, such information does not exist: relevant information is either symmetric economy-wide, or, sometimes, asymmetrically assigned to a single agent—the central bank. And, as a result, no textbook model predicts that market-wide transaction flows should drive exchange rates. In this paper we develop a two country general equilibrium model in which information is dispersed. This model produces a present value representation for the equilibrium exchange rate like equation (1), from a framework that incorporates optimizing households that make consumption and portfolio decisions, a realistic set of asset markets, and financial intermediaries who quote security prices and fill household orders for financial assets. The presence of financial intermediaries distinguishes this model from other general equilibrium models and allows us to study how dispersed information becomes embedded in exchange rates in detail. This analysis builds on Evans and Lyons (2004), but here we focus on the empirical implications. In particular, we show that the presence of dispersed information about fundamentals leads to a concurrent correlation between changes in spot rates and transaction flows that match the data. More strikingly, the model predicts that order flow should have superior forecasting power for *future* fundamentals than current spot rates. Related to this result, the model clarifies why dispersed information about fundamentals becomes impounded in spot rates only slowly.

The second half of the paper contains our empirical results. Consistent with the predictions of the model, we find that:

1. transaction flows forecast *future* exchange rates changes, and do so more effectively than forward discounts,

2. transaction flows forecast subsequent macroeconomic variables such as money growth, output growth, and inflation, and

3. in cases where transaction flows convey significant new information about future fundamentals, much of this information is still not impounded in the exchange rate itself three months later.

While these results represent a qualitative departures from the results of earlier exchange rate research using micro data, we think they hold much more significance from a macro perspective. For example, they direct attention away from understanding the ξ_t term in (2) as "missing fundamental variables" like the FX risk premium, and away from bubbles and behavioral explanations (without, of course, ruling these possibilities out). The results also indicate that information aggregation takes place on a macroeconomic time-scale, rather than on the ultra-high frequency time scale that one might imagine applies to the frenzied world of trading. Rather, the picture that emerges is nuanced, emphasizing flows of dispersed information, but within a framework for how exchange rates are determined that extends existing macro models.

The rest of the paper is organized as follows. Section 1 presents the model. Section 2 derives the main implications of the model's equilibrium that are the focus of the empirical analysis. Section 3 describes the data. Section 4 presents our empirical results. Section 5 concludes.

1 The Model

In this section we describe the structure of the model. There are two countries, each populated by a large number of households. For concreteness we shall refer to the home and foreign countries as the US and Europe. The Dollar (\$) and Euro (€) will therefore denote the home and foreign currencies. Our primary focus will be on the behavior of the spot nominal exchange rate, S_t, which we define as the home price of foreign currency, or specifically, the Dollar price of Euros (\$/€). We will also refer to the real exchange rate:

$$Q_t \equiv S_t P_t^* / P_t,$$

where P_t^* and P_t are respectively the consumer price indices in Europe and the US. With these definitions, a depreciation in the value of the Dollar corresponds to a rise in S_t. A depreciation in the real value of the Dollar corresponds to a rise in Q_t and represents an increase in the price of European consumer goods relative to US goods.

Below, we first describe the preferences and constraints facing US and European households. Next, we discuss how firms set the prices of consumer goods. Finally, we describe how financial intermediaries act as market-makers in world financial markets. Readers more interested in our empirical results, could proceed to Section **??** where we present the theoretical implications of the model that are the focus of our empirical analysis.

1.1 Households

Each country is populated by a continuum of households arranged on the unit interval [0,1]. We assume that half the households live in each country, and use the index $z \in [0, 1/2)$ to denote households in the home country, the US, and $z^* \in [1/2, 1]$ to denote households in the foreign country, Europe. All households derive utility from consumption and real balances.

Preferences for US households are given by:

$$\mathbb{U}_{z,t} = \mathbb{E}_t^{\text{H}} \sum_{i=0}^{\infty} \delta^i \left\{ \tfrac{1}{1-\gamma} C_{z,t+i}^{1-\gamma} + \tfrac{\chi}{1-\gamma} \left(\frac{M_{z,t+i}}{P_{t+i}} \right)^{1-\gamma} \right\}, \tag{4}$$

where $0 < \delta < 1$ is the discount factor, and $\gamma \geq 1$. $\mathbb{E}_t^{\text{H}}$ denotes expectations conditioned on US household information, $\Omega_{z,t}$ for $z \in [0, 1/2)$. $M_{z,t}$ is the stock of Dollars held by household z, and $C_{z,t}$ is a CES consumption index defined by:

$$C_{z,t} = \left(\left(C_{z,t}^1\right)^{\frac{\theta-1}{\theta}} + \left(C_{z,t}^2\right)^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}, \tag{5}$$

where $C_{z,t}^j$, $j = \{1, 2\}$ is the consumption of good j by household z in period t. The corresponding US price index is

$$P_t = \left(\left(P_t^1\right)^{1-\theta} + \left(P_t^2\right)^{1-\theta} \right)^{\frac{1}{1-\theta}}, \tag{6}$$

where P_t^j is the Dollar price of good j.

Households can hold a variety of financial assets. In particular we assume that US households can hold one-period bonds denominated in Dollars, $B_{z,t}$, or Euros $B_{z,t}^*$. US households can also hold a portfolio of (nominally) risky assets, with dollar value $A_{z,t}$, that may comprise domestic stocks, foreign stocks and derivatives such as forward contracts and options. We will not keep track of the individual asset holdings within $A_{z,t}$, but will denote the dollar return on the risky portfolio between t and $t+1$ as $\exp(r_{t+1})$. With these assumptions, the US household's budget constraint is

$$P_t^{\text{B}} B_{z,t} + S_t P_t^{\text{B}^*} B_{z,t}^* + A_{z,t} + M_{z,t} = B_{z,t-1} + S_t B_{z,t-1}^* + \exp(r_t) A_{z,t-1} + M_{z,t-1} - P_t C_{z,t} \tag{7}$$

At the beginning of each period, US households observe the return on their assets, r_t, and the prices of consumer goods P_t^1 and P_t^2 set by firms. They also see the spot exchange rate, S_t, and the prices of US and European one–period bonds, P_t^{B} and $P_t^{\text{B}^*}$, quoted by financial intermediaries. With this information, US households make their period$-t$ consumption and portfolio allocation choices. In particular, US households choose consumption $C_{z,t}^j$, and the portfolio shares $\alpha_{z,t}^{\text{B}^*} \equiv S_t P_t^{\text{B}^*} B_{z,t}^* / P_t W_{z,t}$, $\alpha_{z,t}^{\text{A}} \equiv A_{z,t} / P_t W_{z,t}$ and $\alpha_{z,t}^{\text{M}} \equiv M_{z,t} / P_t W_{z,t}$ where $W_{z,t}$ is the value of wealth at the beginning of period t, to maximize (4) subject to (7).

The first order conditions associated with this optimization problem are:

$$C_{z,t} \quad : \quad \mathbb{E}_t^{\mathrm{H}}\left[\delta\left(\frac{C_{z,t+1}}{C_{z,t}}\right)^{-\gamma}\frac{P_t}{P_{t+1}}\exp(i_t)\right]=1, \tag{8a}$$

$$\alpha_{z,t}^{\mathrm{M}} \quad : \quad \left(\frac{M_{z,t}}{P_tC_{z,t}}\right)^{-\gamma}=\frac{\exp(i_t)-1}{\chi\exp(i_t)}, \tag{8b}$$

$$\alpha_{z,t}^{\mathrm{A}} \quad : \quad \mathbb{E}_t^{\mathrm{H}}\left[\delta\left(\frac{C_{z,t+1}}{C_{z,t}}\right)^{-\gamma}\exp\left(r_{t+1}-i_t\right)\right]=1, \tag{8c}$$

$$\alpha_{z,t}^{\mathrm{B}^*} \quad : \quad \mathbb{E}_t^{\mathrm{H}}\left[\delta\left(\frac{C_{z,t+1}}{C_{z,t}}\right)^{-\gamma}\frac{S_{t+1}P_t}{S_tP_{t+1}}\exp(i_t^*)\right]=1. \tag{8d}$$

Here i_t and i_t^* are the US and European nominal interest rates implied by the prices of one-period bonds: $i_t \equiv -\ln P_t^{\mathrm{B}}$ and $i_t^* \equiv -\ln P_t^{\mathrm{B}^*}$. The derivation of these first order conditions and the other mathematical details of the model can be found in the Appendix.

The preferences and constraints facing European households are defined in an analogous manner. In particular, Europeans choose consumption and portfolios to maximize

$$\mathbb{U}_{z^*,t}=\mathbb{E}_t^{\mathrm{H}*}\sum_{i=0}^{\infty}\delta^i\left\{\tfrac{1}{1-\gamma}C_{z^*,t+i}^{1-\gamma}+\tfrac{\chi}{1-\gamma}\left(\frac{M_{z^*,t+i}^*}{P_{t+i}^*}\right)^{1-\gamma}\right\}, \tag{9}$$

subject to

$$\frac{P_t^{\mathrm{B}}B_{z^*,t}}{S_t}+P_t^{\mathrm{B}^*}B_{z^*,t}^*+A_{z^*,t}+M_{z^*,t}^*=\frac{1}{S_t}B_{z^*,t-1}+B_{z^*,t-1}^*+\exp(r_t^*)A_{z^*,t-1}^*+M_{z^*,t-1}-P_t^*C_{z^*,t},$$

for $z^*\in[1/2,1]$ where r_t^* is the nominal return (in Euros) on the foreign asset portfolio, with nominal value $A_{z^*,t}^*$ at the start of period t. P_t^* is the European price index:

$$P_t^*=\left(\left(P_t^{*1}\right)^{1-\theta}+\left(P_t^{*2}\right)^{1-\theta}\right)^{\frac{1}{1-\theta}}, \tag{10}$$

where P_t^{*j} is the Euro price of good j. The first order conditions characterizing the consumption and portfolio decisions of European households are analogous to those in (8).

1.2 Firms

There are two firms, one producing each good. Each firm has monopoly power in the US and European market for its good. We assume that firms set prices in each market optimally given local demand for the good, the costs of production, and the costs of changing prices. Since our theoretical results are not dependent on the exact form of this price-setting problem, we do not model it in any detail. We simply note that our model can accommodate Calvo-style price-setting (Calvo, 1983) so that consumer prices are sticky, or the presence of non–traded inputs into the distribution of consumer goods as in Corsetti, Dedola and Leduc (2003). The only feature we shall emphasize is that segmentation in the markets for consumer goods is sufficient for deviations from the law of one price to exist for consumer goods.

To see how the price-setting decisions of firms determine the real exchange rate, let $Q_t^j \equiv S_t P_t^{*j}/P_t^j$ denote the relative price in dollars at which firm j sells goods in Europe relative to the US. Using this definition to substitute for P_t^{*j} in the European price index gives

$$\begin{aligned} P_t^* &= \frac{1}{S_t}\left(\left(P_t^1 Q_t^1\right)^{1-\theta} + \left(P_t^2 Q_t^2\right)^{1-\theta}\right)^{\frac{1}{1-\theta}}, \\ &= \frac{P_t Q_t^1}{S_t}\left(\frac{1+\left(P_t^2 Q_t^2/Q_t^1 P_t^1\right)^{1-\theta}}{1+\left(P_t^2/P_t^1\right)^{1-\theta}}\right)^{\frac{1}{1-\theta}}, \end{aligned}$$

Taking logs and a first-order approximation to the term on the right hand side around the point where $Q_t^1/Q_t^2 = 1$ and $P_t^2/P_t^1 = \Upsilon$ gives:

$$\ln Q_t \cong \varphi \ln Q_t^1 + (1-\varphi)\ln Q_t^2, \tag{11}$$

where $\varphi = 1/(1+\Upsilon^{1-\theta}) > 0$.

Equation (11) provides an approximation to the log real exchange rate in terms of the relative prices firms set for the goods they sell in European and US markets. If consumer goods could be freely and instantaneously moved between countries, goods arbitrage would ensure that $Q_t^j = 1$. Under these conditions, firms could in effect only set prices in one market, and purchasing power parity would prevail. By contrast, we assume that the presence of transactions and/or other costs segments consumer goods markets so that Q_t^j may differ from one. Deviations from the law of one price induced by the price-setting decisions of firms are the source of real exchange rate variations in the model. This is consistent with the empirical evidence reported by Engel (1999) and others.

1.3 Financial Intermediaries

There are D dealers, indexed by d, that act as intermediaries in four financial markets: the home money and bond markers, and the foreign money and bond markets. As such, each dealer quotes prices at which they stand ready to buy or sell securities to households and other dealers. Dealers also have the opportunity to initiate transactions with other dealers at the prices they quote. Thus, unlike standard international macro models, the behavior of the exchange and interest rates are determined by the securities prices dealers choose to quote as the solution of a utility maximization problem. We therefore begin by considering the preferences and constraints that characterize of the optimization problem facing dealers.

For the sake of simplicity, we assume that all dealers are located in the US. The preferences of dealer d are given by:

$$\mathbb{E}_t^{\mathrm{D}} \sum_{i=0}^{\infty} \delta^i \tfrac{1}{1-\gamma} C_{d,t+i}^{1-\gamma}, \tag{12}$$

where $\mathbb{E}_t^{\mathrm{D}}$ denotes expectations conditioned on the dealer's period t information, $\Omega_{d,t}$, and $C_{d,t}$ represents dealer d's consumption of goods 1 and 2 aggregated via the CES function shown in (5). Note that dealer preferences only differ from those of households in that real balances have no utility value. As a consequence, dealers will not hold currency in equilibrium (as an asset class, currencies are dominated by bonds) and act solely as intermediaries between households and central banks in the money markets. The importance of this feature will become apparent when we derive the equations that determine exchange rates below.

At the beginning of period t, each dealer d quotes a price $\tilde{S}_{d,t}$ at which he is willing to buy or sell foreign currency. He also quotes prices at which he is willing to buy or sell one period pure discount bonds — $\tilde{P}^{\text{B}}_{d,t}$ and $\tilde{P}^{\text{B}^*}_{d,t}$ respectively. All prices are good for any quantity and are publicly observed. Then each dealer receives orders for bonds and currency from a subset of households. Household orders are only observed by the recipient dealer and so represent a source of private information. Then each dealer quotes prices for foreign currency and bonds in the interdealer market: $S_{d,t}$, $P^{\text{B}}_{d,t}$ and $P^{\text{B}^*}_{d,t}$. These prices, too, are good for any quantity and publicly observed, so that trading with multiple partners (e.g., arbitrage trades) is feasible. Based on these interdealer quotes, each dealer then chooses the amount of foreign currency, $T^{\text{B}*}_{d,t}$, he wishes to purchase (negative values for sales) by initiating a trade with other dealers. Interdealer trading is simultaneous and, to the extent trades are desired at a quote that is posted by multiple dealers, those trades are divided equally among dealers posting that quote. Finally, each dealer chooses the amount of home and foreign currency, $T^{\text{M}}_{d,t}$ and $T^{\text{M}^*}_{d,t}$, they wish to purchase from the central banks.

The quote and trading decisions of dealers must respect two constraints: the flow constraints implied by market clearing and the dynamic budget constraint describing the evolution of their asset holdings. The flow constraint for trades initiated by households and other dealers is given by:

$$\tilde{P}^{\text{B}}_{d,t}O^{\text{B}}_t + P^{\text{B}}_{d,t}T^{\text{B}}_t + T^{\text{M}}_t + O^{\text{M}}_t + S_{d,t}\left(P^{\text{B}^*}_{d,t}T^{\text{B}^*}_t + T^{\text{M}*}_t\right) + \tilde{S}_{d,t}\left(\tilde{P}^{\text{B}^*}_{d,t}O^{\text{B}^*}_t + O^{\text{M}*}_t\right) = 0, \tag{13}$$

where O^v_t denotes an incoming order to purchase asset v from a household, and T^v_t is an incoming order to purchase asset v from a dealer. For trades initiated by dealer d, the flow constraint is:

$$P^{\text{B}}_tT^{\text{B}}_{d,t} + T^{\text{M}}_{d,t} + S_t\left(P^{\text{B}^*}_tT^{\text{B}^*}_{d,t} + T^{\text{M}*}_{d,t}\right) = 0. \tag{14}$$

Notice that the prices for bonds and foreign currency in this equation (i.e., P^{B}_t, $P^{\text{B}^*}_t$ and S_t) are the prices the dealer is quoted by others in the market. The dynamic budget constraint of dealer d is given by:

$$\begin{aligned} &M_{d,t} + P^{\text{B}}_tB_{d,t} + S_t\left(M^*_{d,t} + P^{\text{B}*}_tB^*_{d,t}\right) + A_{d,t} + P_tC_{d,t} \\ &\qquad = B_{d,t-1} + M_{d,t-1} + S_t\left(B^*_{d,t-1} + M^*_{d,t-1}\right) + \exp\left(r_{d,t}\right)A_{d,t-1} + \Pi_{d,t}, \end{aligned} \tag{15}$$

where $M_{d,t}, M^*_{d,t}B_{d,t}, B^*_{d,t}$ and $A_{d,t}$ respectively denote dealer d's holdings of home and foreign currency bonds, and other assets at the end of period t trading. $r_{d,t}$ is the return on dealer d's other assets, and $\Pi_{d,t}$ is his period-t trading profit:

$$\begin{aligned} \Pi_{d,t} \quad = \quad &\left(\tilde{P}^{\text{B}}_{d,t} - P^{\text{B}}_t\right)O^{\text{B}}_t + \left(\tilde{S}_{d,t}\tilde{P}^{\text{B}^*}_{d,t} - S_tP^{\text{B}^*}_t\right)O^{\text{B}^*}_t + \left(\tilde{S}_{d,t} - S_t\right)O^{\text{M}^*}_t \\ &+ \left(P^{\text{B}}_{d,t} - P^{\text{B}}_t\right)T^{\text{B}}_t + \left(S_{d,t}P^{\text{B}^*}_{d,t} - S_tP^{\text{B}^*}_t\right)T^{\text{B}^*}_t + \left(S_{d,t} - S_t\right)T^{\text{M}^*}_t. \end{aligned} \tag{16}$$

The problem facing dealer d is to choose prices, $\{\tilde{S}_{d,t}, \tilde{P}^{\text{B}}_{d,t}, \tilde{P}^{\text{B}^*}_{d,t}, S_{d,t}, P^{\text{B}}_{d,t}, P^{\text{B}^*}_{d,t}\}$, trades, $\{T^{\text{B}}_{d,t}, T^{\text{B}^*}_{d,t}, T^{\text{M}}_{d,t}, T^{\text{M}^*}_{d,t}\}$, and consumption, $C_{d,t}$, to maximize expected utility (12) subject to (13) - (16). This problem can be conceptually separated into two parts. The first concerns the optimal choice of $\{T^{\text{B}}_{d,t}, T^{\text{B}^*}_{d,t}, T^{\text{M}}_{d,t}, T^{\text{M}^*}_{d,t}\}$ given the bond and currency orders of households and the prevailing set of prices quoted by other dealers, $\{S_t, P^{\text{B}}_t, P^{\text{B}^*}_t\}$.

This decision takes the form of a portfolio allocation problem which the Appendix describes in detail. The second part of the dealer's problem concerns the optimal choice of quotes, $\{\tilde{S}_{d,t}, \tilde{P}^{\text{B}}_{d,t}, \tilde{P}^{\text{B}^*}_{d,t}, S_{d,t}, P^{\text{B}}_{d,t}, P^{\text{B}^*}_{d,t}\}$. In our trading environment, the optimal quotes for dealer d are given by:

$$S_{d,t} = \tilde{S}_{d,t} = S_t = \mathcal{F}_s(\Omega^{\text{D}}_t), \tag{17a}$$

$$P^{\text{B}}_{d,t} = \tilde{P}^{\text{B}}_{d,t} = P^{\text{B}}_t = \mathcal{F}_{\text{B}}(\Omega^{\text{D}}_t), \tag{17b}$$

$$P^{\text{B}*}_{d,t} = \tilde{P}^{\text{B}*}_{d,t} = P^{\text{B}*}_t = \mathcal{F}_{\text{B}^*}(\Omega^{\text{D}}_t). \tag{17c}$$

where $\Omega^{\text{D}}_t = \cap_d \Omega_{d,t}$ is the information set common of all dealers at the beginning of period t. The functions $\mathcal{F}_s(.)$, $\mathcal{F}_{\text{B}}(.)$ and $\mathcal{F}_{\text{B}^*}(.)$ (described below) map elements of this information set into a common quote for foreign currency, home bonds and foreign bonds. Equation (17) shows that optimal quotes have three features. First, the prices quoted to households by each dealer are the same as those quoted to other dealers. Second, quotes are common across all dealers. Third, all quotes are functions of common information.

To see why optimal quotes must have these features, consider how the choice of spot rate quote affects $\Pi_{d,t+1}$ via the last term, $(S_{d,t} - S_t)\,T^{\text{M}*}_t$, in equation (16). Suppose dealer d quotes a price $S_{d,t} > S_t$ prior to the start of interdealer trading. Because all quotes are observable and are good for any amount, incoming orders for foreign currency will be negative ($T^{\text{M}*}_t < 0$) as dealers attempt to make arbitrage profits. Under these circumstances, $(S_{d,t} - S_t)\,T^{\text{M}*}_t$ has limiting value of $-\infty$. Similarly, if $S_{d,t} < S_t$, arbitrage trading will generate an incoming flow of foreign currency orders (i.e., $T^{\text{M}*}_t > 0$) so $(S_{d,t} - S_t)\,T^{\text{M}*}_t$ will again have a limiting value of $-\infty$. As the terms in the second row of (16) show, the only way to avoid similar arbitrage losses via bond trading is for $P^{\text{B}}_{d,t} = P^{\text{B}}_t$ and $P^{\text{B}*}_{d,t} = P^{\text{B}*}_t$. Thus, optimal interdealer quotes must be common across dealers to avoid the (expected utility) losses associated with arbitrage. This requires that quotes be a function of information that is known to all dealers, Ω^{D}_t. A similar arbitrage argument applies to the prices dealers quote to households $\{\tilde{S}_{d,t}, \tilde{P}^{\text{B}}_{d,t}, \tilde{P}^{\text{B}^*}_{d,t}\}$. Again, these quotes are publicly observed and households are free to place orders with several dealers. Consequently, all dealers must quote the same prices to avoid arbitrage trading losses. In this environment, competition between dealers will ensure that households receive the same quotes as dealers.[2]

2 Equilibrium

An equilibrium in this model is described by: (i) a set of dealer quotes for the prices of bonds and foreign currency, and consumer prices set by firms that clear markets, given the consumption and portfolio choices of households and dealers; and (ii) a set of consumption and portfolio rules that maximize expected utility of households and dealers, given the prices of bonds, foreign currency and consumer goods. In this section we examine specific aspects of this equilibrium that will guide the empirical analysis that follows. In particular, our focus will be on how information concerning the state of the macro economy is transmitted to dealers via

[2] To illustrate a form this competition could take, suppose the common currency quote offered to households, $\tilde{S}_t$, is less than the quote offered to dealers, S_t. In this situation dealer d could offer households a contract that paid $\psi(S_t - \tilde{S}_t)$ per Euro ordered with $0 < \psi < 1$ if $S_t - \tilde{S}_t > 0$ and zero otherwise. This option contract would create trading gains for dealer d at the expense of other dealers because households would have a strong incentive to place positive Euro orders with him and negative orders elsewhere. The only way for dealers to insulate themselves against this form of competition is to quote $\tilde{S}_t = S_t$.

trade in financial markets. Because dealers set the prices of bonds and foreign currency, this transmission process is central to understanding the dynamics of interest rates and exchange rates.

While our model can accommodate differences in the information available to individual households and dealers, we shall keep things simple by assuming that all agents within a given group (US households, European households and dealers,) have the same information. We denote these three information sets as Ω_t^{H}, $\Omega_t^{\text{H}^*}$, and Ω_t^{D}, respectively. With this simplification, we can use a representative agent within each of these three groups to describe their behavior.

2.1 Exchange and Interest Rates

In Section (1.3) we argued that utility maximizing dealers will quote common prices for currency and bonds based on information they *all* possess before trading starts each period. We now turn to the question of how these quotes are related to dealer's information Ω_t^{D}. This will pin down the equilibrium dynamics of the spot exchange rate together with home and foreign interest rates.

The mapping from dealer's information Ω_t^{D} to quotes is identified in the following proposition.

Proposition 1 *In an equilibrium where; (i) dealers choose not to take open foreign exchange positions, and (ii) the risk–adjusted return on dealer's other assets equals zero, the log price for foreign currency quoted by all dealers is*

$$s_t = \left(\tfrac{1}{1+\eta}\right) \mathbb{E}_t^{\text{D}} \sum_{i=0}^{\infty} \left(\tfrac{\eta}{1+\eta}\right)^i f_{t+i}, \tag{18}$$

where exchange rate fundamentals, f_t, are defined as

$$f_t \equiv c_t^* - c_t + m_t - m_t^* + q_t. \tag{19}$$

Dealers also quote common prices for US and European bonds that satisfy:

$$-\ln P_t^{\text{B}} \equiv i_t = i - \frac{1}{\eta}\mathbb{E}_t^{\text{D}}\left(m_t - p_t - c_t\right), \tag{20a}$$

$$-\ln P_t^{\text{B}*} \equiv i_t^* = i - \frac{1}{\eta}\mathbb{E}_t^{\text{D}}\left(m_t^* - p_t^* - c_t^*\right), \tag{20b}$$

where m_t, m_t^*, c_t and c_t^* represent the log aggregate of Dollars, Euros, US consumption and European consumption respectively (i.e., $m_t = \ln \int_z m_{z,t} dz$). i and η are positive constants.

The Appendix provides a detailed derivation of these equations and the results reported in the propositions that follow. Here, we provide some intuition. First, consider the bond price quotes in (20). Because households are the sole holders of their national currencies, dealers quote prices that equate the aggregate demand for currency from households with the expected stock of currency. Notice that (20) constitute standard money market equilibrium conditions except for the presence of the terms involving dealer expectations, $\mathbb{E}_t^{\text{D}}$. Dealers quote bond prices without precise knowledge of household consumption plans, so the actual currency orders they receive may differ from what was expected. Recall that dealers can offset the effects of any unexpected currency orders by trading with central banks, so they never find themselves with unwanted currency balances at the end of trading in each period.

Equation (18) plays a central role in our analysis. It shows that the log price of foreign currency quoted by all dealers is equal to the present value of fundamentals, f_t. There are two noteworthy differences between this specification and the exchange rate equations found in traditional monetary models. First, the definition of fundamentals in (19) includes the difference between foreign and home consumption rather than income. This arises because household preferences imply that the demand for national currencies depends on consumption rather than income. Second, equation (18) shows that fundamentals affect the spot rate only via dealers' expectations. This is a particularly important feature of the model: Since the current spot rate is simply the common price of foreign currency quoted by dealers before trading starts, it must only be a function of information that is common to all dealers at the time, Ω_t^{D}. This means that all exchange rate dynamics in our model are driven by the evolution of dealers' common information.

What are the roles of conditions (i) and (ii)? Condition (i) restricts attention to an equilibrium where there is no incentive for dealers to manipulate the market. In an equilibrium where dealers wanted to keep a long position in foreign currency, for example, there would be a strong incentive to quote currency prices that were "too low", so spot rates would not solely reflect dealers expectations regarding current and future fundamentals. Condition (i) not only rules out this possibility, but also ensures that our equilibrium is consistent with the evidence in Lyons (1995) and Bjonnes and Rime (2004) showing the low incidence of open currency positions among actual dealers. Condition (ii) plays a similar role - it simply eliminates a risk premium term from the definition of fundamentals. Relaxing this condition would not materially affect our analysis.

2.2 Transaction Flows

We now consider the implications of Proposition 1 for transaction flows. In particular, our aim is to identify the components that contribute to household order flow in the international currency and bond markets.

Let x_t denote aggregate household order flow defined as the dollar value of aggregate household purchases of European bonds during period t trading. The contribution of US households to this order flow is $S_t\left(B^*_{z,t} - B^*_{z,t-1}\right) = \alpha^{\text{B}^*}_{z,t} P_t W_{z,t} \exp\left(i^*_t\right) - S_t B^*_{z,t-1}$ where $\alpha^{\text{B}^*}_{z,t}$ denotes the desired share of European bonds in the US households' wealth. Similarly, European households contribute $S_t\left(B^*_{z^*,t} - B^*_{z^*,t-1}\right) = \alpha^{\text{B}^*}_{z^*,t} S_t P^*_t W_{z*,t} \exp\left(i^*_t\right) - S_t B^*_{z^*,t-1}$. Market clearing requires that aggregate holdings of European foreign bonds by dealers and households sum to zero, so that $B^*_{d,t-1} + B^*_{z^*,t-1} + B^*_{z,t-1} = 0$. Hence, aggregate order flow can be written as

$$x_t = \left[\alpha^{\text{B}^*}_{z,t}\lambda_t + \alpha^{\text{B}^*}_{z*,t}\left(1-\lambda_t\right)\right]\mathbb{W}_t \exp\left(i^*_t\right) + S_t B^*_{d,t-1}, \tag{21}$$

where $\mathbb{W}_t \equiv W_t + S_t P^*_t W^*_t$ and $\lambda_t \equiv W_t/\mathbb{W}_t$. Thus, order flow depends upon the portfolio allocation decisions of US and European households (via $\alpha^{\text{B}^*}_{z,t}$, and $\alpha^{\text{B}^*}_{z^*,t}$), the level and international distribution of household wealth (via $\mathbb{W}_t$ and λ_t) and the outstanding stock of foreign bonds held by dealers from last period's trading, $B^*_{d,t-1}$. These elements imply that order flow contains both pre-determined (backward-looking) and non-predetermined (forward-looking) components. The former are given by the level and distribution of wealth, the latter by the portfolio shares because they depend on households' forecasts of future returns. We formalize these observations in the following proposition.

Proposition 2 *The utility-maximizing choice of portfolios by US and European households implies that aggregate order flow may be approximated by*

$$x_t \cong \phi \nabla \mathbb{E}_t^{\mathrm{H}} s_{t+1} + \phi^* \nabla \mathbb{E}_t^{\mathrm{H}^*} s_{t+1} + o_t, \tag{22}$$

with $\phi, \phi^* > 0$, *where* $\nabla E_t^{\omega} \varkappa_{t+1} \equiv E_t^{\omega} \varkappa_{t+1} - E_t^{\mathrm{D}} \varkappa_{t+1}$ *for* $\omega = \{\mathrm{H}, \mathrm{H}^*\}$ *and* o_t *denotes terms involving the distribution of wealth and dealer's bond holdings.*

Equation (22) describes the second important implication of our model. It relates order flow to the difference between households' forecast for the future spot rate, $E_t^{\omega} s_{t+1}$ for $\omega = \{\mathrm{h}, \mathrm{h}^*\}$, and dealers' forecasts, $E_t^{\mathrm{D}} s_{t+1}$. In particular, there will be positive order flow for European bonds if households are more optimistic about the future value of the Euro than dealers so that $\nabla E_t^{\omega} s_{t+1} > 0$ for $\omega = \{\mathrm{H}, \mathrm{H}^*\}$.

To understand why differences in expectations play this role, we need to focus on how households choose their portfolios. In the appendix we show that the optimal share of US household wealth held in the form of European bonds is increasing in the expected log excess return, $\mathbb{E}_t^{\mathrm{H}} \Delta s_{t+1} + i_t^* - i_t$. Now when dealers' foreign currency quotes satisfy (18) and (19), the log spot rate also satisfies $\mathbb{E}_t^{\mathrm{D}} \Delta s_{t+1} + i_t^* - i_t = 0$. We can therefore write the excess return on European bonds expected by US households as

$$\mathbb{E}_t^{\mathrm{H}} \Delta s_{t+1} + i_t^* - i_t = \mathbb{E}_t^{\mathrm{D}} \Delta s_{t+1} + i_t^* - i_t + \nabla \mathbb{E}_t^{\mathrm{H}} s_{t+1} = \nabla \mathbb{E}_t^{\mathrm{H}} s_{t+1}.$$

Thus, when US households are more optimistic about the future value of the Euro than dealers, they expect a higher excess return on European bonds. These expectations, in turn, increase the desired fraction of US household wealth in European bonds, so US households place more orders for European bonds with dealers at the start of period$-t$ trading. Optimism concerning the value of the Euro on the part of European households (i.e. $\nabla \mathbb{E}_t^{\mathrm{H}^*} s_{t+1} > 0$) contributes positively to order flow in a similar manner.

Of course household portfolio choices are also affected by risk. The effects of risk, the distribution of wealth and dealer's bond holdings on order flow are summarized by o_t in (22). These terms will not vary significantly from month to month or quarter to quarter under most circumstances, and so will not be the prime focus of the analysis below. We shall concentrate instead on how the existence of dispersed information, manifest through the existence of the forecast differentials, $\nabla \mathbb{E}_t^{\mathrm{H}} s_{t+1}$ and $\nabla \mathbb{E}_t^{\mathrm{H}^*} s_{t+1}$, affects the joint behavior of order flow, spot rates and fundamentals.

2.3 Transaction Flows and Fundamentals

Propositions 1 and 2 show that spot rates are determined by dealer expectations regarding fundamentals, while order flow reflects (in part) differences between household and dealer expectations for future spot rates. We now turn to the question of how order flow is related to fundamentals. For this purpose we need to characterize the equilibrium dynamics of fundamentals.

Let y_t denote the vector that describes the state of the economy at the start of period t. This vector includes the variables that comprise fundamentals (i.e. consumption, money stocks and the real exchange rate) as well as those variables needed to describe production, and the distribution of wealth across households and dealers. In Evans and Lyons (2004), we describe in detail the equilibrium dynamics of a model with a similar structure. Here our focus is on the empirical implications of the model, so we present the equilibrium dynamics in reduced form:

$$\Delta y_{t+1} = A\Delta y_t + u_{t+1}, \tag{23}$$

where $\Delta y_t \equiv y_t - y_{t-1}$ with u_{t+1} a vector of mean zero shocks. This specification for the equilibrium dynamics of the state variables is completely general, yet it allows us to examine the link between order flow and fundamentals in a straightforward way.

We start with the behavior of spot rates. Let fundamentals be a linear combination of the elements in the state vector: $f_t = Cy_t$. When dealers quote spot rates according to (18) in Proposition 1, and (23) describes the dynamics of the state vector y_t, the spot rate can be written as

$$s_t = \pi \mathbb{E}_t^{\text{D}} \mathbf{y}_t, \tag{24}$$

where $\mathbf{y}_t' \equiv [y_t', \Delta y_t']$ and $\pi \equiv C\imath_1 + \frac{\eta}{1+\eta} C(I - \frac{\eta}{1+\eta} A)^{-1} A\imath_2$, with $y_t = \imath_1 \mathbf{y}_t$ and $\Delta y_t = \imath_2 \mathbf{y}_t$. π is a vector that relates the log spot rate to dealers' current estimate of the state vector $\mathbf{y}_t$. We can now write the US forecast differential as:

$$\begin{aligned} \nabla \mathbb{E}_t^{\text{H}} s_{t+1} &= \pi \left(\mathbb{E}_t^{\text{H}} \mathbb{E}_{t+1}^{\text{D}} \mathbf{y}_{t+1} - \mathbb{E}_t^{\text{D}} \mathbb{E}_{t+1}^{\text{D}} \mathbf{y}_{t+1} \right) \\ &= \pi \left(\mathbb{E}_t^{\text{H}} \mathbb{E}_{t+1}^{\text{D}} \mathbf{y}_{t+1} - \mathbb{E}_t^{\text{D}} \mathbf{y}_{t+1} \right). \end{aligned} \tag{25}$$

Suppose that US households collectively know as much about the state of the economy as dealers do. Under these circumstances, the right hand side of (25) is equal to $\pi \mathbb{E}_t^{\text{H}} \left(\mathbb{E}_{t+1}^{\text{D}} - \mathbb{E}_t^{\text{D}} \right) \mathbf{y}_{t+1}$. In other words, the forecast differential for future spot rates depends on households' expectations regarding how dealers revise their estimates of the future state, $\mathbf{y}_{t+1}$. As one might expect, this difference depends on the information sets, Ω_t^{H} and Ω_t^{D}. Clearly, if $\Omega_t^{\text{H}} = \Omega_t^{\text{D}}$, then $\mathbb{E}_t^{\text{H}} \left(\mathbb{E}_{t+1}^{\text{D}} - \mathbb{E}_t^{\text{D}} \right) \mathbf{y}_{t+1}$ must equal a vector of zeros because $\left(\mathbb{E}_{t+1}^{\text{D}} - \mathbb{E}_t^{\text{D}} \right) \mathbf{y}_{t+1}$ must be a function of information that is not in Ω_t^{D}. Alternatively, suppose that households collectively have superior information so that $\Omega_t^{\text{H}} = \{\Omega_t^{\text{D}}, \upsilon_t\}$ for some vector of variables υ_t. If dealers update their estimates of $\mathbf{y}_{t+1}$ using elements of υ_t, then some elements of $\left(\mathbb{E}_{t+1}^{\text{D}} - \mathbb{E}_t^{\text{D}} \right) \mathbf{y}_{t+1}$ will be forecastable based on Ω_t^{H}.

We formalize these ideas in the following proposition.

Proposition 3 *If US and European households are as well-informed about the state of the economy as dealers, so that $\Omega_t^{\text{D}} \subset \Omega_t^{\text{H}}$ and $\Omega_t^{\text{D}} \subset \Omega_t^{\text{H}^*}$, then US and European forecast differentials for spot rates are*

$$\nabla \mathbb{E}_t^{\text{H}} s_{t+1} = \pi\kappa(\mathbb{E}_t^{\text{H}} \mathbf{y}_{t+1} - \mathbb{E}_t^{\text{D}} \mathbf{y}_{t+1}), \tag{26a}$$

$$\nabla \mathbb{E}_t^{\text{H}^*} s_{t+1} = \pi\kappa^*(\mathbb{E}_t^{\text{H}^*} \mathbf{y}_{t+1} - \mathbb{E}_t^{\text{D}} \mathbf{y}_{t+1}), \tag{26b}$$

and order flow follows

$$x_t = \phi\pi\kappa \nabla \mathbb{E}_t^{\text{H}} \mathbf{y}_{t+1} + \phi^* \pi\kappa^* \nabla \mathbb{E}_t^{\text{H}^*} \mathbf{y}_{t+1} + o_t. \tag{27}$$

The intuition behind Proposition 3 is straightforward. If US households are collectively as well-informed about the future state of the economy as dealers, then $\nabla \mathbb{E}_t^{\text{H}} s_{t+1} = \pi \mathbb{E}_t^{\text{H}} \left(\mathbb{E}_{t+1}^{\text{D}} - \mathbb{E}_t^{\text{D}} \right) \mathbf{y}_{t+1}$, so the forecast differential depends on the speed at which US household expect dealers to assimilate new information concerning the future state of the economy. We term this the pace of information aggregation. If dealers learn nothing new about $\mathbf{y}_{t+1}$ from period$-t$ trading, $\mathbb{E}^{\mathrm{D}}_{t+1}\mathbf{y}_{t+1} = \mathbb{E}^{\mathrm{D}}_{t}\mathbf{y}_{t+1}$. Hence, if US households expect that period$-t$ trading will reveal nothing new to dealers, $\mathbb{E}^{\mathrm{H}}_{t}\left(\mathbb{E}^{\mathrm{D}}_{t+1} - \mathbb{E}^{\mathrm{D}}_{t}\right)\mathbf{y}_{t+1} = 0$ and there is no difference between dealer and household forecasts of future spot rates. Under these circumstances, there is no information aggregation so κ and κ^{*} are equal to null matrices. Alternatively, if households expect dealers to assimilate information from period$-t$ trading, the forecast differentials for spot rates will be non-zero. In the extreme case where period-t trading is sufficiently informative to reveal to dealers all that households know about the future state of the economy, $\left(\mathbb{E}^{\mathrm{D}}_{t+1} - \mathbb{E}^{\mathrm{D}}_{t}\right)\mathbf{y}_{t+1}$will equal $\mathbb{E}^{\omega}_{t}\mathbf{y}_{t+1} - \mathbb{E}^{\mathrm{D}}_{t}\mathbf{y}_{t+1}$ for $\omega = \{\mathrm{H},\mathrm{H}^{*}\}$. In this case, the pace of information is fast so κ and κ^{*} equal the identity matrices. Under other circumstances where the pace of information aggregation is slower, the κ and κ^{*} matrices will have many non-zero elements. (Exact expressions for κ and κ^{*} are provided in the Appendix.)

Equation (27) combines (22) from Proposition 2 with (26). This equation expresses order flow in terms of forecast differentials for the future state of the economy and the speed of information aggregation. Since fundamentals represent a combination of the elements in $\mathbf{y}_{t}$, (27) also serves to link dispersed information regarding future fundamentals to order flow. In particular, if households have more information about the future course of fundamentals than dealers, and dealers are expected to assimilate at least some of this information from transactions flows each period, order flow will be correlated with variations in the forecast differentials for fundamentals.

It is important to realize that the household orders driving order flow in this model are driven solely by the desire to optimally adjust portfolios. Households have no desire to inform dealers about the future state of the economy, so the information conveyed to dealers via transaction flows occur as a by-product of their dynamic portfolio allocation decisions. The transactions flows associated with these decisions establish the link between order flow, dispersed information, and the speed of information shown in equation (27).

One aspect of our model deserves further clarification. Our model abstracts from informational heterogeneity at the household level, so Ω^{H}_{t} and $\Omega^{\mathrm{H}^{*}}_{t}$ represent the information sets of the representative US and European households. This means that the results in Proposition 3 are derived under the assumption that representative households have strictly more information than dealers ($\Omega^{\mathrm{D}}_{t} \subset \Omega^{\mathrm{H}}_{t}$ and $\Omega^{\mathrm{D}}_{t} \subset \Omega^{\mathrm{H}^{*}}_{t}$). Clearly this is a strong assumption. Taken literally, it implies that every household knows more about the current and future state of the economy than any given dealer. Fortunately, our central results do not rely on this literal interpretation. To see why, suppose, for example, that each household receives a money demand shock and is thereby privately motived to trade foreign exchange. In this setting, no household would consider itself to have superior information. But the aggregate of those realized household trades would in fact convey information about the average household shock, i.e., the state of the macroeconomy. For the sake of parsimony, we have not modelled heterogeneity at the home and foreign household levels. Instead, we assume that households in any given country share the same information about the macroeconomy. Extending the model to capture heterogeneity is a natural extension, but not one that would alter the main implications of our model that are the focus of the empirical analysis below.

3 Data

Our empirical analysis utilizes a new data set that comprises end-user transaction flows, spot rates and macro fundamentals over six and a half years. The transaction flow data is of a fundamentally different type and it covers a much longer time period than the data used in earlier work (e.g., Evans and Lyons 2002a,b) The difference in type is our shift from inter-marketmaker order flow to end-user order flow. By end users we are referring to three main segments: non-financial corporations, investors (such as mutual funds and pension funds), and leveraged traders (such as hedge funds and proprietary traders). Though inter-marketmaker transactions account for about two-thirds of total volume in major currency markets, they are largely derivative of the underlying shifts in end-user demands. Our data on the three end-user segments include all of Citibank's end-user trades in the largest spot market, the USD/EUR market, over a sample from January 1993 to June 1999.[3] Citibank's end-user market share in these currencies is in the 10-15 percent range; no other bank has a larger market share in these currencies.

There are many advantages of our end-user data. First, the data are simply more powerful, covering much longer time spans. Second, because these 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; those not covered by extant end-user data sets are empirically quite important for exchange rate determination, as we show below.[4] Fourth, because the data are disaggregated into segments, we can address whether the behavior of these different flow measures is similar, and whether the information conveyed by each, dollar for dollar, is similar.

Our empirical analysis also utilizes new high-frequency real-time estimates of macro fundamentals for the US and Germany: specifically GDP growth, CPI inflation, and M1 money growth. By "real time", we mean estimates that correspond to actual macroeconomic data available at any given time. It is, of course, these actual information sets, and the expectations that derive from them, that pin down asset pricing, not the sequence of revised values that become available many months later that make up standard macro time-series.[5]

A simple example clarifies the difference between a real time estimate of a macro variable and the data series usually employed in empirical analysis. Consider a variable $\mathbb{Z}$ that summarizes economy-wide information during month τ, that ends on day $\mathrm{M}(\tau)$, with value $\mathbb{Z}_{\mathrm{M}(\tau)}$. Data on the value of $\mathbb{Z}$ is released on day $\mathrm{R}(\tau)$ after the end of month τ with a reporting lag of $\mathrm{R}(\tau)-\mathrm{M}(\tau)$ days. Reporting lags vary from month to month because data is collected on a calendar basis, but releases issued by statistical agencies are not made on holidays and weekends. For quarterly series, such as GDP, reporting lags can be as long as several months.

Real-time estimates of $\mathbb{Z}_{\mathrm{M}(\tau)}$ are constructed using the information in a specific information set. Let Ω_i denote an information set that only contains data known at the start of day i. The real-time estimate of $\mathbb{Z}_{\mathrm{M}(\tau)}$ is defined as

$$\mathbb{Z}_{\mathrm{M}(\tau)|i} \equiv E[\mathbb{Z}_{\mathrm{M}(\tau)}|\Omega_i] \qquad \text{for } \mathrm{M}(\tau-1) < i \leq \mathrm{M}(\tau).$$

[3] 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.

[4] Froot and Ramadorai (2002), consider the transactions flows associated with portfolio changes undertaken by institutional investors. Osler (2003) examines end-user stop-loss orders.

[5] The importance of this distinction has been emphasied by Faust, Rogers, and Wright (2003).

The real-time estimates have two important attributes. First, if the variables in Ω_i are a subset of the variables known to market participants on day i, the real-time estimate of $\mathbb{Z}_{\mathrm{M}(\tau)}$ can be legitimately used as a variable affecting market actively on day i. Standard times series values for macro variables do not have this feature. In particular, because the value of $\mathbb{Z}_{\mathrm{M}(\tau)}$ is released with a reporting lag, this value cannot be used to construct a measure of fundamentals that was known to all market participants during month τ. The second attribute of the real-time estimates concerns the frequency with which macro data is collected and released. Many series are collected on a monthly basis and released with a reporting lag of generally no more than one month. Other series, notably GDP growth, are constructed on a quarterly basis and the reporting lag runs to several months. The use of real-time estimates allows us to relate the behavior of exchange rates and order flow to macro variables on a weekly or even daily frequency.

The real-time estimates used here are conceptually distinct from the real-time *data* series studied by Croushore and Stark (2001), Orphanides (2001) and others. A real-time data series comprises a set of historical values for a variable that are known on a particular date. This date identifies the vintage of the real-time data. For example, the value for $\mathbb{Z}_{\mathrm{M}(\tau)}$ released on day $\mathrm{R}(\tau)$, $\mathbb{Z}_{\mathrm{M}(\tau)|\mathrm{R}(\tau)}$, represents the first vintage of real-time data for $\mathbb{Z}$ from month τ. The conceptual distinction between real-time data and estimates can be further examined with the identity

$$\mathbb{Z}_{\mathrm{M}(\tau)|\mathrm{R}(\tau)} - \mathbb{Z}_{\mathrm{M}(\tau)|i} \equiv \left(\mathbb{Z}_{\mathrm{M}(\tau)|\mathrm{M}(\tau)} - \mathbb{Z}_{\mathrm{M}(\tau)|i}\right) + \left(\mathbb{Z}_{\mathrm{M}(\tau)|\mathrm{R}(\tau)} - \mathbb{Z}_{\mathrm{M}(\tau)|\mathrm{M}(\tau)}\right).$$

This expression decomposes the difference between the real-time data value and estimate for $\mathbb{Z}_{\mathrm{M}(\tau)}$ into two components. The first is the difference between the real time estimate of $\mathbb{Z}_{\mathrm{M}(\tau)}$ at the end of month τ and the estimate on a day earlier in the month. The importance of this component should generally decline as i nears the end of the month. The second component is the difference between the value for $\mathbb{Z}_{\mathrm{M}(\tau)}$ released on day $\mathrm{R}(\tau)$ and the real-time estimate of $\mathbb{Z}_{\mathrm{M}(\tau)}$ at the end of the month. This term identifies the impact of information concerning $\mathbb{Z}_{\mathrm{M}(\tau)}$ collected by the statistical agency before the release date that was not part of the $\Omega_{\mathrm{M}(\tau)}$ information set. The importance of this component depends on how much is learnt in retrospect over the reporting lag about the behavior of $\mathbb{Z}_{\mathrm{M}(\tau)}$ by the statistical agency, and how much more information the agency has concerning $\mathbb{Z}_{\mathrm{M}(\tau)}$ at the end of the month relative to $\Omega_{\mathrm{M}(\tau)}$.

In this paper we construct real time estimates of GDP growth, consumer price inflation, and M1 growth for the US and Germany using an information set Ω_i spanned by 35 macro series. These series come from a database maintained by Money Market News Services that contains details of each data release. For the US estimates we use the 3 US quarterly GDP releases and the monthly releases on 18 other US macro variables. The German real-time estimates are computed using the monthly releases on 14 German macro variables. It is important to note that these specifications for Ω_i only include macro data from regular releases made by US and German statistical agencies. As such, our real time estimates are computed using a specification for Ω_i that represents a strict subset of the information available to financial market participants at the time. A detailed description of the quasi-maximum likelihood procedure used to compute the real-time estimates can be found in Evans (2005).

Figure 1 provides some visual evidence on the difference between the real-time estimates of GDP and the series of GDP data releases for the US. The graph displays two noteworthy features. First, the real-time estimates (shown by the solid plot) display a much greater degree of volatility than the cumulant of the

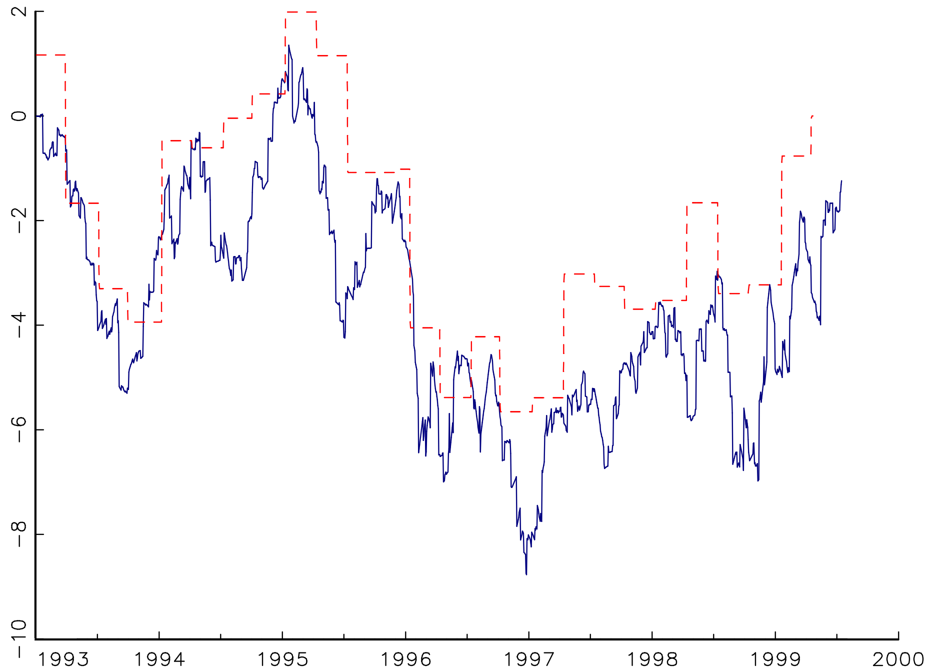

Figure 1: Real-time estimates of log US GDP (blue line) and cumulant of GDP releases (red dashed line).

data releases (shown by the dashed plot). This volatility reflects how inferences about current GDP change as information arrives in the form of monthly data releases during the current quarter and GDP releases referring to growth in the previous quarter. The second noteworthy feature concerns the vertical gap between the plots. This represents the difference between the real-time estimates and the ex post value of log GDP based on data releases. This gap should be insignificant if the current level of GDP could be precisely inferred from contemporaneously available data releases. Figure 1 shows this to be the case during the third and forth quarters of 1995. During many other periods, the real-time estimates were much less precise.

In the analysis that follows, we shall consider the joint behavior of exchange rates, order flows and the real-time estimates of macro variables at the weekly, monthly and quarterly frequency. Over the 6 year span of our data, the weekly analysis provides a much greater degree of precision in our statistical inferences concerning the high frequency link between flows, exchange rates and macro variables than would be otherwise possible.

4 Empirical Analysis

In this section we examine the empirical implications of Propositions 1 - 3. First, we consider the implications of our model for the correlation between order flows and changes in spot exchange rates. Next, we examine the links between spot rates and fundamentals. We then focus on the forecasting power of order flows for fundamentals. Our model identifies conditions under which order flow should have incremental forecasting power beyond spot rates, and we find strong empirical support for this prediction in the data. Finally, we consider the pace of information aggregation.

4.1 The Order Flow/Spot Rate Correlation

Evans and Lyons (2002a,b) show that order flows account for between 40 and 80 percent of the daily variation in the spot exchange rates of major currency pairs. We now provide a structural interpretation of this finding using the results in Propositions 1 - 3.

Recall that when dealers' foreign currency quotes satisfy (18) and (19) in Proposition 1, the log spot rate satisfies $\mathbb{E}_t^{\mathrm{D}}\Delta s_{t+1}+i_t^*-i_t=0$. Combining this restriction with the identity $\Delta s_{t+1}\equiv\mathbb{E}_t^{\mathrm{D}}\Delta s_{t+1}+s_{t+1}-\mathbb{E}_t^{\mathrm{D}}s_{t+1}$ gives

$$\begin{aligned}\Delta s_{t+1} &= i_t-i_t^*+s_{t+1}-\mathbb{E}_t^{\mathrm{D}}s_{t+1},\\ &= i_t-i_t^*+\pi\left(\mathbb{E}_{t+1}^{\mathrm{D}}\mathbf{y}_{t+1}-\mathbb{E}_t^{\mathrm{D}}\mathbf{y}_{t+1}\right),\end{aligned} \tag{28}$$

where the second line follows from the relation between the spot rate and state vector described by equation (24). Thus, Proposition 1 implies that the rate of depreciation is equal to the interest differential plus the revision in dealer forecasts concerning the future state of the economy between periods t and $t+1$. This forecast revision is attributable to two possible information sources. The first is public information that arrives right at the start of period $t+1$, before dealers quote s_{t+1}. The second is information conveyed by the transactions flows during period t. It is this second information source that accounts for the correlation between order flow and spot rate changes in the data as Proposition 4 shows.

Proposition 4 *When dealer quotes for the price of foreign currency satisfy (18), and order flow follows (27), the rate of depreciation can be written as*

$$\Delta s_{t+1}=i_t-i_t^*+b\left(x_t-\mathbb{E}_t^{\mathrm{D}}x_t\right)+\zeta_{t+1}. \tag{29}$$

ζ_{t+1} *represents the portion of* $\pi\left(\mathbb{E}_{t+1}^{\mathrm{D}}\mathbf{y}_{t+1}-\mathbb{E}_t^{\mathrm{D}}\mathbf{y}_{t+1}\right)$ *that is uncorrelated with order flow, and* b *is a projection coefficient equal to*

$$\frac{\pi\mathbb{CV}\left(\mathbf{y}_{t+1},o_t\right)}{\mathbb{V}(x_t)}+\frac{\phi\pi\mathbb{V}\left(\nabla\mathbb{E}_t^{\mathrm{H}}\mathbf{y}_{t+1}\right)\kappa'\pi'}{\mathbb{V}(x_t)}+\frac{\phi^*\pi\mathbb{V}\left(\nabla\mathbb{E}_t^{\mathrm{H}^*}\mathbf{y}_{t+1}\right)\kappa^{*\prime}\pi'}{\mathbb{V}(x_t)}, \tag{30}$$

where $\mathbb{V}\left(.\right)$ *and* $\mathbb{CV}(.,.)$ *denote the population variance and covariance.*

Inspection of expression (30) reveals that the observed correlation between order flow and the rate of depreciation can arise through two channels. First, if the distribution of wealth and dealer bond holdings affect both order flow (via o_t in equation 22) and has forecasting power for fundamentals, order flow will be correlated with the depreciation rate through the first term in (30). Since there is little variation in o_t from month to month or even quarter to quarter, it is unlikely that this channel accounts for much of the order flow/spot rate correlation we observed at a daily or weekly frequency. The second channel operates through the transmission of dispersed information. If household expectations for the future state vector differ from dealers' expectations, and information aggregation accompanies trading in period t, both the second and third terms in (30) will be positive. Notice that the depreciation rate is correlated with order flow in this case not just because households and dealers hold different expectations, but also because households expect some of their information to be assimilated by dealers from the transactions flows they observe in period t. In this sense, the correlation between order flow and the depreciation rate informs us about both the existence of dispersed information and the pace at with information aggregation takes place.

Now we turn to the empirical evidence. Table 1 presents the results of regressing excess currency returns, $\Delta s_{t+1} + i_t^* - i_t$, on order flows from different end-users. We present results for returns measured over one day, one week and one month, with order flow cumulated over the same horizon. Two points emerge from the table. First, the coefficient estimates are quite different according to the origin of the order flow. This finding is consistent with the idea, formalized by Proposition 4, that the correlation between the depreciation rate and order flow depends (in part) on the information differential driving transactions. While it seems reasonable that the trades initiated by different sets of end-user are associated with different information differentials, our model is not rich enough to exactly account to the pattern of coefficient estimates we observe. The second noteworthy point concerns explanatory power. Notice that the R^2 statistics increase with the horizon. The explanatory power of flows for concurrent returns is substantial: at the monthly frequency, the R^2 statistic when all flow segments are included is 30 percent.[6] We also find that end-user flows convey information beyond that in the inter-marketmaker flows used in Evans and Lyons (2002a,b). When both types of flow are included in a regression of daily excess returns, we are able to reject the null hypothesis that the coefficients on end-user flows are zero at the 1 percent level.

The results in Table 1 provide preliminary evidence that is consistent with the theoretical links between exchange rates, order flow and fundamentals implied by our model. We now turn to a more detailed inspection of the link between spot rates and fundamentals.

4.2 Spot Rates and Fundamentals

We shall examine the link between spot rates and fundamentals in two ways. First we examine the model's implications for forecasting fundamentals with spot rates. Second, we study whether our model can account for the apparent lack of cointegration between the spot rates and fundamentals (see, for example, Engel and West 2004).

The model's implications for forecasting fundamentals with spot rates follow straightforwardly from Proposition 1. In particular equation (18) can be rewritten as

$$s_t = \mathbb{E}_t^{\mathrm{D}} f_t + \mathbb{E}_t^{\mathrm{D}} \sum_{i=1}^{\infty} \left(\tfrac{\eta}{1+\eta} \right)^i \Delta f_{t+i}. \tag{31}$$

Thus, the log spot rate quoted by dealers differs from dealers' current estimate of fundamentals by the present value of future changes in fundamentals.

One implication of (31) is that the gap between the current spot rate and estimated fundamentals, $s_t - \mathbb{E}_t^{\mathrm{D}} f_t$, should have forecasting power for future changes in fundamentals. This can be formally shown by

[6] Froot and Ramadorai (2002) also find stronger links between end-user flows and returns as the horizon is extended to 1 month; their flow measure is institutional investors, however, not economy-wide.

Table 1: Contemporaneous Regressions for Excess Returns

Horizon	Corporate		Traders		Investors		R^2	χ^2
	US	Non-US	US	Non-US	US	Non-US		(p-value)
1 day	-0.155	-0.240					0.015	15.133
	(0.113)	(0.067)						(0.001)
			0.174	0.204			0.024	21.791
			(0.055)	(0.060)				(0.000)
					-0.047	0.369	0.044	38.261
					(0.120)	(0.060)		(0.000)
	-0.147	-0.214	0.153	0.194	-0.029	0.353	0.078	75.465
	(0.107)	(0.064)	(0.054)	(0.056)	(0.121)	(0.059)		(0.000)
1 week	-0.118	-0.469					0.061	32.070
	(0.138)	(0.083)						(0.000)
			0.349	0.114			0.077	27.965
			(0.069)	(0.096)				(0.000)
					-0.005	0.523	0.105	37.728
					(0.154)	(0.086)		(0.000)
	-0.167	-0.358	0.275	0.069	-0.051	0.447	0.195	111.527
	(0.133)	(0.077)	(0.064)	(0.090)	(0.143)	(0.080)		(0.000)
1 month	0.065	-0.594					0.129	22.434
	(0.266)	(0.126)						(0.000)
			0.389	0.166			0.103	8.750
			(0.135)	(0.225)				(0.013)
					-0.091	0.719	0.205	34.636
					(0.215)	(0.119)		(0.000)
	0.120	-0.376	0.214	-0.074	0.000	0.583	0.299	58.424
	(0.185)	(0.102)	(0.137)	(0.196)	(0.208)	(0.130)		(0.000)

Notes: The table reports coefficient and standard errors from regressions of excess returns measured over one day, week and month, on order flows cumulated over the same horizon. The left hand column report χ^2 statistics for the null that all the coefficients on order flow are zero. Estimates are calculated at the daily frequency. The standard errors correct for heteroskedastic and the moving average error process induced by overlapping forecasts (1 week and 1 month results).

considering the projection:

$$\Delta f_{t+h} \quad = \quad \beta_s \left(s_t - \mathbb{E}_t^{\mathrm{D}} f_t\right) + \varepsilon_{t+h}, \tag{32}$$

where
$$\beta_s \quad = \quad \sum_{i=1}^{\infty} \left(\tfrac{\eta}{1+\eta}\right)^i \left\{\mathbb{CV}(\mathbb{E}_t^{\mathrm{D}} \Delta f_{t+i}, \mathbb{E}_t^{\mathrm{D}} \Delta f_{t+h}) / \mathbb{V}\left(s_t - \mathbb{E}_t^{\mathrm{D}} f_t\right)\right\},$$

and $\varepsilon_{t+\tau}$ is the projection error that is uncorrelated with $s_t - \mathbb{E}_t^{\mathrm{D}} f_t$. The projection coefficient β_s provides a measure of the forecasting power of $s_t - \mathbb{E}_t^{\mathrm{D}} f_t$ for the change in fundamentals h periods ahead.

Now suppose that we attempt to forecast the same change in fundamentals with $s_t - f_t$. In this case the projection is

$$\Delta f^m_{t+\tau} \quad = \quad \hat{\beta}_s \left(s_t - f_t\right) + \hat{\varepsilon}_{t+\tau}, \tag{33}$$

where $$\hat{\beta}_s \quad = \quad \beta_s \frac{\mathbb{V}\left(s_t - f_t\right)}{\mathbb{V}\left(s_t - f_t\right) + \mathbb{V}(f_t - \mathbb{E}^{\mathrm{D}}_t f_t)}.$$

When dealers have incomplete information about the current level of fundamentals, $\mathbb{V}\left(f_t - \mathbb{E}^{\mathrm{D}}_t f_t\right) > 0$, and $\hat{\beta}_s$ will be pushed below β_s. This is a form of attenuation bias that arises because the use of f_t rather than $\mathbb{E}^{\mathrm{D}}_t f_t$ in the forecasting equation introduces an errors-in-variables problem. Of course mis-measurement is not in itself a new idea - many papers have recognized that an incomplete definition of fundamentals may be contributing to the poor forecasting performance of spot rates. Here, however, the errors-in-variables problem occurs not because realized fundamentals are mis-measured, but because spot rates are determined by dealers' real-time estimates of fundamentals that may differ significantly from f_t.

A similar errors-in-variables problem plagues tests for the presence of cointegration between the spot rate and fundamentals. To see why, we rewrite equation (31) as:

$$s_t - f_t = \mathbb{E}^{\mathrm{D}}_t \sum_{i=1}^{\infty} \left(\tfrac{\eta}{1+\eta}\right)^i \Delta f_{t+i} - \left(f_t - \mathbb{E}^{\mathrm{D}}_t f_t\right).$$

According to this equation, s_t and f_t should be cointegrated when: (i) f_t follows a non-stationary $I(1)$ process, and (ii) the dealers' error in estimating the current level of f_t is stationary $I(0)$. When dealers observe money stocks and consumer prices, $f_t - \mathbb{E}^{\mathrm{D}}_t f_t$ will be a function of their errors in estimating household consumption. Uncertainty about household consumption decisions may therefore contribute to the dynamics of $s_t - f_t$. A simple example provides useful intuition on the potential size of this contribution.

Suppose that fundamentals follow a random walk, $\Delta f_{t+1} = v_{t+1}$ where v_{t+1} is an i.i.d. mean zero shock that is uncorrelated with f_t and elements of Ω^{D}_t. If dealers receive a noisy signal of f_t every period equal to $f_t + \zeta_t$ where ζ_t is another i.i.d. mean zero shock, then their estimates of f_t will follow:

$$\mathbb{E}^{\mathrm{D}}_t f_t = \mathbb{E}^{\mathrm{D}}_{t-1} f_{t-1} + \varphi\left(f^c_t + \zeta_t - \mathbb{E}^{\mathrm{D}}_{t-1}\left(f^c_{t-1}\right)\right),$$

where $\varphi^{\mathrm{D}} \equiv \frac{\mathbb{V}^{\mathrm{D}}_t(f_t)}{\mathbb{V}^{\mathrm{D}}_t(f_t) + \mathbb{V}^{\mathrm{D}}_t(\zeta_t)}$. Combining this equation with $\Delta f_{t+1} = v_{t+1}$, we find that the estimation error follows an AR(1) process:

$$f_t - \mathbb{E}^{\mathrm{D}}_t f_t = (1-\varphi)\left(f_{t-1} - \mathbb{E}^{\mathrm{D}}_{t-1} f_t\right) + (1-\varphi)\, v_t - \varphi^{\mathrm{D}} \zeta_t. \tag{34}$$

Notice that the autoregressive coefficient in this process approaches unity as the variance of the noise rises. Thus, dealers' estimation errors will be more persistent when the information they receive about the current level of fundamentals is less precise.

The implications of our model for forecasting fundamentals and the behavior of $s_t - f_t$ are now clear. If dealers have imprecise information about fundamentals that follows a non-stationary process, the estimation errors $f_t - \mathbb{E}_t^{\mathrm{D}} f_t$ may be extremely persistent and the sample variance of $f_t - \mathbb{E}_t^{\mathrm{D}} f_t$ very large.[7] As a consequence, there may be a significant degree of attenuation bias in the estimating β_s from the fundamentals forecasting projection (32). In terms of cointegration, while $f_t - \mathbb{E}_t^{\mathrm{D}} f_t$ is stationary, so that s_t and f_t are indeed cointegrated, realizations of $f_t - \mathbb{E}_t^{\mathrm{D}} f_t$ in any sample may appear non-stationary so that conventional tests reject cointegration between s_t and f_t. The failure to find cointegration stems not from using the wrong definition of fundamentals, f_t. Rather, it results from the fact that dealers use $\mathbb{E}_t^{\mathrm{D}} f_t$ to set spot rates and the difference between f_t and $\mathbb{E}_t^{\mathrm{D}} f_t$ can be very persistent.

Table 2: Real-Time Estimates and Errors

A: Cointegration	US			German		
Results	Output	Prices	Money	Output	Prices	Money
Coefficient.	0.880	1.056	1.020	0.873	0.667	0.980
Standard Error	0.025	0.008	0.002	0.026	0.024	0.006
p–value	(0.001)	(0.001)	(0.068)	(0.000)	(0.001)	(0.002)
B: Error Autocorrelations						
Lag = 1 Day	0.980	0.950	0.896	0.984	0.987	0.947
1 Week	0.904	0.749	0.483	0.920	0.934	0.765
1 Month	0.620	0.495	0.192	0.693	0.750	0.343
2 Months	0.369	0.493	0.109	0.386	0.662	0.133
1 Quarter	0.209	0.511	0.118	0.212	0.573	0.066

Notes: The upper panel reports the results from the cointegrating regression of the real time estimate of the fundamental variable on its ex post value. The reported standard errors are computed by Dynamic OLS in daily data (1682 observations) with 10 leads and lags to correct for finite sample bias. Standard errors contain an MA(10) correction for residual serial correlation. The p-values are for the hypothesis that the cointegration coefficient equals unity. The lower panel reports daily autocorrelations for the real-time errors, defined as the difference between the ex post and real-time estimate of the fundamental variables.

Table 2 examines the time series properties of the expectational errors associated with different fundamental macro variables. The upper panel reports the results from the cointegrating regression of the real-time estimate of the fundamental variable on its own ex-post value, i.e., it addresses the expectational error $f_t - \mathbb{E}_t^{\mathrm{D}} f_t$. (The reported standard errors are computed by Dynamic OLS in daily data with 10 leads and lags to correct for finite-sample bias. Standard errors contain an MA(10) correction for residual serial correlation.) The p-values reported in parentheses are for the hypothesis that the cointegration coefficient equals unity. Note that this is rejected in five of the six cases at the one-percent level, suggesting that elements of $f_t - \mathbb{E}_t^{\mathrm{D}} f_t$ contain a unit root. The lower panel reports daily autocorrelations for the real-time errors, defined as the difference between the ex-post value and real-time estimate of the fundamental variables. These remain quite high, even at the one-quarter horizon, for many of the variables, which is consistent with the persistence argument above. We view these cointegration-test results as offering promising prospects for resolving the puzzle of no-cointegration between exchange rates and fundamentals highlighted in past work.

[7] Although equation (34) is derived under the assumption that fundamentals follow a random walk, the basic intuition of the example carries over to cases where fundamentals follow more general non-stationary I(1) processes.

4.3 Forecasting Fundamentals with Spot Rates and Order Flow

Our model shows that order flow should have forecasting power for future spot rates when households' transaction flows convey information about future fundamentals that is news to dealers. This interpretation of the order flow/price change correlation implies that order flow should have forecasting power for future fundamentals.

Proposition 5 *When dealer quotes for the price of foreign currency satisfy (18), and order flow follows (27), changes in future fundamentals are related to spot rates and order flows by*

$$\Delta f_{t+h} = \beta_s \left(s_t - \mathbb{E}_t^{\mathrm{D}} f_t\right) + \beta_x \left(x_t - \mathbb{E}_t^{\mathrm{D}} x_t\right) + \epsilon_{t+h}, \tag{35}$$

where $\epsilon_{t+\tau}$ is the projection error. β_s is the projection coefficient identified in (32) and β_x is equal to

$$\frac{\mathbb{CV}\left(o_t, \Delta f_{t+h}\right)}{\mathbb{V}\left(x_t - \mathbb{E}_t^{\mathrm{D}} x_t\right)} + \frac{\phi\pi\kappa\mathbb{V}\left(\nabla\mathbb{E}_t^{\mathrm{H}}\mathbf{y}_{t+1}\right)\left(A^{h-1}\right)' C'\imath_2'}{\mathbb{V}\left(x_t - \mathbb{E}_t^{\mathrm{D}} x_t\right)} + \frac{\phi^*\pi\kappa^*\mathbb{V}\left(\nabla\mathbb{E}_t^{\mathrm{H}^*}\mathbf{y}_{t+1}\right)\left(A^{h-1}\right)' C'\imath_2'}{\mathbb{V}\left(x_t - \mathbb{E}_t^{\mathrm{D}} x_t\right)}.$$

The intuition behind Proposition 5 is straightforward. Recall from (31) that $s_t - \mathbb{E}_t^{\mathrm{D}} f_t$ is equal to the present value of future changes in fundamentals. The first term in (35) is therefore a function of dealers' information at the start of period t, Ω_t^{D}. Period-t order flow will have incremental forecasting power of future changes in fundamentals, beyond $s_t - \mathbb{E}_t^{\mathrm{D}} f_t$, when it conveys information about Δf_{t+h} that is not already known to dealers (i.e. in Ω_t^{D}). The expression for β_x shows that this will happen when: (i) the distribution of wealth and dealer bond holdings affect order flow and have forecasting power for fundamentals, and (ii) when there is dispersed information concerning future fundamentals and the information aggregation accompanies period-t trading. Proposition 4 showed that order flow would be correlated with the depreciation rate under these same conditions. Thus, if our theoretical rationale for the results in Table 1 holds true, we should also find that order flow has incremental forecasting power for future changes in fundamentals.

Assessing the empirical evidence on this prediction is complicated by the fact that we don't have data on $\mathbb{E}_t^{\mathrm{D}} f_t$. Proposition 5 establishes the conditions under which order flow has incremental forecasting power for fundamentals beyond the power in $s_t - \mathbb{E}_t^{\mathrm{D}} f_t$. Does this mean that order flow should also have incremental forecasting power relative to $s_t - f_t$? Unfortunately, this question cannot be answered theoretically. If the introduced measurement error of $f_t - \mathbb{E}_t^{\mathrm{D}} f_t$ is uncorrelated with order flow, then attenuation bias will only affect β_s. Under these circumstances, the forecasting power in $s_t - \mathbb{E}_t^{\mathrm{D}} f_t$ will be understated but order flow will continue to have forecasting power via β_x. There is, however, no good reason why $f_t - \mathbb{E}_t^{\mathrm{D}} f_t$ and order flow should be uncorrelated. In this case, the estimates of both β_s and β_x will be affected by measurement error and it is conceivable that the estimate of β_x will be close to zero. Thus, as a theoretical matter, order flow could appear not to have incremental forecasting power relative to $s_t - f_t$, even though it does relative to $s_t - \mathbb{E}_t^{\mathrm{D}} f_t$.

With this caveat in mind, we first conduct Granger Causality tests for a set of macro variables considered fundamental across a wide range of modeling traditions: GDP growth, M1 money growth, and CPI inflation.[8]

[8] We focus on output growth here, rather than consumption growth as in the model, for two reasons: we want comparability with past work and we have more confidence in the integrity of the available data.

For consistency with earlier studies (for example, Engel and West 2004), we do not use the real-time estimates of these macro variables, but rather the ex-post values released by the US and German statistical agencies. For this reason, our Granger Causality tests involving GDP growth are based on a VAR estimated at the quarterly frequency, while the tests involving money growth and inflation use VARs estimated in monthly data. All the VARs include one lag of the depreciation rate, the macro variable, a the six order flow segments.

Table 3: Granger Causality Significance Levels

Variable to be Forecast	Forecasting Variable	
	Order Flows	Exchange Rate
Money Growth—US	0.00	0.72
Output Growth—US	0.00	0.01
Inflation—US	0.47	0.09
Money Growth—Germany	0.79	0.72
Output Growth—Germany	0.44	0.96
Inflation—Germany	0.00	0.71

Notes: Table presents marginal significance levels of tests whether end-user flows Granger cause three macro variables: output growth, money growth, and inflation. The tests are based on a monthly-frequency VAR for money and inflation, and a quarterly-frequency VAR for output growth. All the VARs include one lag of each of the following: the rate of exchange-rate depreciation, the macro variable, and the 6 end-user flow segments.

The results in Table 3 show that order flow forecasts all three of these variables at the one percent level. Interestingly, the spot rate itself is able to forecast only one of these three variables – GDP growth – at the one percent level. Moreover, we find no evidence of Granger causality going the opposite direction for either order flow or the spot rate. In sum, the results in Table 3 provide an initial indication that there is fundamental information in the end-user order flows.

To examine the forecasting power of order flow in more detail, we next consider forecasting regressions of the form:

$$\Delta^h \mathrm{y}_{t+h} = a_1 \Delta^k \mathrm{y}_t + a_2 \Delta^k s_t + \textstyle\sum_{n=1}^{6} \omega_j x_{j,t}^k + \eta_{t+h}, \tag{36}$$

where $\Delta^h \mathrm{y}_{j+h}$ denotes the $h-$period change in the macro variable y ending at $t+h$, $\Delta^k s_t$ is the rate of depreciation between $t-k$ and t, and $x_{j,t}^k$ is the order flow from segment j in periods $t-k$ to t. We estimate this equation in weekly data using the real-time estimates of GDP, M1 and prices as the macro variables. Estimates from this regression allow us to address three questions: (i) what is the incremental forecasting power in order flow? (ii) how does this forecasting power change with the forecasting horizon? and (iii) is order flow able to forecast the measure of fundamentals relevant for exchange rate determination, dealers' real-time estimates?

Table 4 presents the results from estimating (36) in weekly data with horizons h ranging from one month to two quarters. We report results where k is set equal to h, but our findings are not sensitive to the number of cumulation weeks k. There are a total of 284 weekly observations in our sample period, so there are 35 non-overlapping observations on the dependent variable at our longest forecasting horizon. In each cell of the table we report the R^2 statistic as a measure of forecasting power and the significance level of a chi-squared test for the joint significance of the forecasting variables. These test statistics are corrected for conditional heteroskedasticy and the moving-average error structure induced by the forecast overlap using the Newey-West estimator.

The results in Table 4 clearly show that order flow has considerable forecasting power for all of the six macro variables, and this forecasting power is typically a significant increment over the forecasting power of the other variables considered. Consider, for example, the case of US GDP growth. At the two-quarter forecasting horizon, order flow produces an R^2 statistic of 24.6 percent, which is significant at the one-percent level. In contrast, forecasting US output growth two months out using both past US output growth and the spot rate produces an R^2 statistic of only 9.6 percent, a level of forecasting power that is insignificant at conventional levels. In general, the forecasting power of order flow is greater as the forecasting horizon is lengthened.

These results contrast quite sharply from the findings of Froot and Ramadorai (2002). They found no evidence of a long run correlation between real interest rate differentials (their measure of fundamentals) and the transaction flows of institutional investors. One likely reason for this difference is the wider span of end-users generating the order flows in our data. As the coefficient estimates in Table 1 indicate, transactions from different end-user segments appear to convey different information. Another likely reason concerns the way we measure macro fundamentals. Figure 1 showed that the real-time estimates of GDP display a good deal of high frequency volatility. This volatility represents the daily arrival of information and is characteristic of the other real-time estimates we use (i.e. inflation and money growth). We have also seen from Table 2 that there is considerable persistence in the real-time estimation errors (i.e. the elements of $f_t - \mathbb{E}_t^{\mathrm{D}} f_t$). These observations indicate that forecasting changes in the elements of f_t is a different proposition than forecasting the changes in $\mathbb{E}_t^{\mathrm{D}} f_t$. However, it is the changes in $\mathbb{E}_t^{\mathrm{D}} f_t$ that are relevant for the expectations regarding future spot rates that drive order flows.

Table 4: Forecasting Fundamentals

	US Output Growth				German Output Growth			
Forecasting Variables	1 month	2 months	1 quarter	2 quarters	1 month	2 months	1 quarter	2 quarters
Output	0.002	0.003	0.022	0.092	0.004	0.063	0.089	0.006
	(0.607)	(0.555)	(0.130)	(0.087)	(0.295)	(0.006)	(0.009)	(0.614)
Spot Rate	0.001	0.005	0.005	0.007	0.058	0.029	0.003	0.024
	(0.730)	(0.508)	(0.644)	(0.650)	(0.002)	(0.081)	(0.625)	(0.536)
Output and Spot Rates	0.003	0.007	0.031	0.096	0.059	0.083	0.099	0.033
	(0.802)	(0.710)	(0.287)	(0.224)	(0.007)	(0.021)	(0.024)	(0.709)
Order Flows	0.032	0.080	0.189	0.246	0.012	0.085	0.075	0.306
	(0.357)	(0.145)	(0.002)	(0.000)	(0.806)	(0.227)	(0.299)	(0.000)
All	0.052	0.086	0.199	0.420	0.087	0.165	0.156	0.324
	(0.383)	(0.195)	(0.011)	(0.000)	(0.021)	(0.037)	(0.130)	(0.000)
	US Inflation				German Inflation			
Forecasting Variables	1 month	2 months	1 quarter	2 quarters	1 month	2 months	1 quarter	2 quarters
Inflation	0.003	0.024	0.005	0.053	0.007	0.037	0.053	0.024
	(0.461)	(0.146)	(0.487)	(0.213)	(0.402)	(0.067)	(0.040)	(0.232)
Spot Rate	0.005	0.007	0.013	0.016	0.081	0.000	0.000	0.033
	(0.351)	(0.419)	(0.391)	(0.457)	(0.000)	(0.962)	(0.858)	(0.305)
Inflation and Spot Rates	0.007	0.028	0.015	0.060	0.088	0.038	0.053	0.051
	(0.505)	(0.352)	(0.636)	(0.441)	(0.002)	(0.214)	(0.112)	(0.364)
Order Flows	0.025	0.050	0.116	0.212	0.050	0.116	0.178	0.271
	(0.773)	(0.629)	(0.052)	(0.000)	(0.429)	(0.010)	(0.025)	(0.000)
All	0.031	0.082	0.124	0.240	0.127	0.158	0.258	0.511
	(0.788)	(0.151)	(0.010)	(0.000)	(0.005)	(0.021)	(0.005)	(0.000)
	US Money Growth				German Money Growth			
Forecasting Variables	1 month	2 months	1 quarter	2 quarters	1 month	2 months	1 quarter	2 quarters
	0.071	0.219	0.253	0.329	0.050	0.111	0.122	0.041
Money Growth	(0.009)	(0.000)	(0.000)	(0.000)	(0.023)	(0.005)	(0.017)	(0.252)
	0.021	0.001	0.003	0.005	0.002	0.044	0.036	0.065
Spot Rate	(0.054)	(0.778)	(0.732)	(0.619)	(0.558)	(0.031)	(0.123)	(0.343)
	0.086	0.220	0.267	0.333	0.050	0.130	0.129	0.080
M Growth and Spot Rates	(0.002)	(0.000)	(0.000)	(0.000)	(0.075)	(0.004)	(0.040)	(0.403)
	0.034	0.119	0.280	0.424	0.026	0.082	0.152	0.578
Order Flows	(0.466)	(0.239)	(0.026)	(0.000)	(0.491)	(0.147)	(0.037)	(0.000)
	0.096	0.282	0.417	0.540	0.074	0.175	0.284	0.624
All	(0.056)	(0.000)	(0.000)	(0.000)	(0.244)	(0.020)	(0.001)	(0.000)

Notes: The table reports the R^2 from the forecasting regression for the fundamental listed in the header of each panel using the forecasting variables reported on the left. The regressions are estimated in weekly data (284 observations). Significance levels for χ^2 statistics testing the null hypothesis of no predictability (corrected for heteroskedasticity and the forecast horizon overlap) are reported in parentheses. The weekly estimates of fundamentals are real time estimates based on the history of macro announcements.

4.4 Estimating the Speed of Information Aggregation

The results in Table 4 support the idea that order flow contains dispersed information about the future values of fundamental macro variables. While this finding is consistent with theoretical mechanism driving exchange rate dynamics in our model, it does not tell us anything about the pace of information aggregation. Recall that it is the combination of dispersed information on the one hand, and the pace of information aggregation on the other, that produces the qualitatively new possibilities for exchange rate dynamics.

To quantify the pace at which the market aggregates macro information, we estimate the following regression:

$$\Delta^{13}\mathrm{y}_{t+13} = \gamma_0 + \sum_{i=0}^{5} \alpha_i \Delta \mathrm{y}_{t-i} + \sum_{i=0}^{\#w} \delta_i \Delta s_{t+i} + u_{t+13}, \tag{37}$$

where $\Delta^{13}\mathrm{y}_{t+13}$ denotes the quarterly change in a given fundamental variable (i.e., 13 weeks), #w denotes the number of "learning weeks", and Δs_{t+i} denotes the change in the spot exchange rate over week $t+i$. The idea here is that exchange rate changes should progressively impound more information about the fundamental y_t.

The first column of Table 5 presents the R^2 statistic from regression (37) for different numbers of learning weeks (denoted $R^2_{\Delta p}$). Given that exchange rate changes should progressively impound more fundamental information, one would expect the $R^2_{\Delta p}$ to increase as the number of learning weeks is increased. This is in fact what we find for each of the six variables though the increase is often not significant. The column labeled "Sig. I" reports p-values for the joint significance of the coefficients using a chi-squared test corrected for heteroskedasticity and the forecast overlap.

The incremental information in order flow is expressed in columns three and four of each of Table 5's panels. Column three presents the proportional increase in R^2 when order flow is added to the regression. That is, we estimate:

$$\Delta^{13}\mathrm{y}_{t+13} = \gamma_0 + \sum_{i=0}^{5} \alpha_i \Delta \mathrm{y}_{t-i} + \sum_{i=0}^{\#w} \delta_i \Delta s_{t+i} + \sum_{j=1}^{6} \omega_j x_{j,t} + u_{t+13},$$

where $x_{j,t}$ is the quarterly order flow from segment j. Column three then presents the statistic $\triangledown R^2_{\Delta p} \equiv (R^2_{\Delta p,x}/R^2_{\Delta p}) - 1$, where $R^2_{\Delta p,x}$ is the R^2 statistic from the regression above. P-values for the joint significance of the coefficients in this augmented regression are reported in the column labeled "Sig. II" (again corrected for heteroskedasticity and the forecast overlap).

If the information conveyed to dealers by order flow concerning fundamentals is impounded in the exchange rate, the statistics in the third column should fall as the number of learning weeks increase. Moreover, if one expected this information to be fully reflected in the exchange rate by, say, three weeks, then one would expect the column-three statistic to shrink to zero when the number of learning weeks is set to three. The most striking finding displayed in Table 5 is that in every case these statistics do not shrink to zero, or even close to zero, even after 12 weeks. Yes, information in order flow is getting impounded into exchange rates over time, but a lot of that information is still not impounded a quarter later. For example, a coefficient in the third column, 12-week row, of 1.0 would imply that a quarter later, the exchange rate alone is impounding only half the fundamental information that order flow and the exchange rate together convey. There should be no presumption that these statistics would shrink to zero if we considered longer horizons. The rate at which the macro variable is changing may match the pace of information aggregation in the market so that the statistics we see here could be quite representative of those derived from longer-horizon forecasts.

Table 5: Tests for the Speed of Information Aggregation

	US Output Growth				German Output Growth			
	$R^2_{\Delta p}$	Sig. I	$\nabla R^2_{\Delta p}$	Sig. II	$R^2_{\Delta p}$	Sig. I	$\nabla R^2_{\Delta p}$	Sig. II
Learning Weeks								
0	0.157	(0.119)	0.981	(0.020)	0.077	(0.003)	1.745	(0.016)
3	0.187	(0.009)	0.860	(0.016)	0.078	(0.917)	1.697	(0.023)
6	0.201	(0.003)	0.805	(0.008)	0.080	(0.986)	1.683	(0.018)
9	0.203	(0.010)	0.794	(0.004)	0.080	(0.999)	1.672	(0.019)
12	0.219	(0.001)	0.743	(0.000)	0.084	(0.998)	1.556	(0.018)
	US Inflation				German Inflation			
	$R^2_{\Delta p}$	Sig. I.	$\nabla R^2_{\Delta p}$	Sig. II.	$R^2_{\Delta p}$	Sig. I	$\nabla R^2_{\Delta p}$	Sig. II
Learning Weeks								
0	0.021	(0.303)	5.728	(0.014)	0.012	(0.144)	23.035	(0.001)
3	0.022	(0.978)	5.648	(0.012)	0.012	(0.997)	22.747	(0.001)
6	0.032	(0.760)	3.751	(0.014)	0.031	(0.356)	8.743	(0.001)
9	0.066	(0.077)	1.580	(0.030)	0.034	(0.514)	8.451	(0.001)
12	0.080	(0.026)	1.155	(0.073)	0.051	(0.353)	5.381	(0.000)
	US Money Growth				German Money Growth			
	$R^2_{\Delta p}$	Sig. I	$\nabla R^2_{\Delta p}$	Sig. II	$R^2_{\Delta p}$	Sig. I	$\nabla R^2_{\Delta p}$	Sig. II
Learning Weeks								
0	0.256	(0.086)	0.540	(0.030)	0.147	(0.011)	1.505	(0.002)
3	0.263	(0.513)	0.577	(0.024)	0.155	(0.343)	1.370	(0.005)
6	0.275	(0.244)	0.563	(0.017)	0.168	(0.118)	1.195	(0.009)
9	0.289	(0.069)	0.528	(0.018)	0.203	(0.000)	0.840	(0.016)
12	0.290	(0.152)	0.539	(0.013)	0.247	(0.000)	0.527	(0.048)

Notes: $R^2_{\Delta p}$ denotes the R^2 statistic from the regression

$$\Delta^{13} y_{t+13} = \gamma_0 + \sum_{i=0}^{5} \alpha_i \Delta y_{t-i} + \sum_{i=0}^{\#w} \delta_i \Delta s_{t+i} + u_{t+13}$$

where $\Delta^{13} y_{t+13}$ denotes the quarterly change in the fundamental (listed in the header of each sub-panel) and #w denotes the number of "learning weeks". P-values for the joint significance of the δ_i coefficients (corrected for heteroskedasticity and the forecast overlap) are reported in the column headed Sig. I. $\nabla R^2_{\Delta p}$ shows the proportional increase in R^2 when order flow is added to the regression. Specifically, let $R^2_{\nabla p,x}$ denotes the R^2 statistic from the regression

$$\Delta^{13} y_{t+13} = \gamma_0 + \sum_{i=0}^{5} \alpha_i \Delta y_{t-i} + \sum_{i=0}^{\#w} \delta_i \Delta s_{t+i} + \sum_{j=1}^{6} \omega_j \Delta^{13} x_{j,t} + u_{t+13}$$

where $\Delta^{13} x_{j,t}$ is the quarterly order flow from segment j. $\nabla R^2_{\Delta p} = (R^2_{\nabla p,x} / R^2_{\Delta p})$-1. P-values for the joint significance of the ω_i coefficients (corrected for heteroskedasticity and the forecast overlap) are reported in the column headed Sig. II.

Taken together, the results in Tables 4 and 5 provide strong evidence in support of the economic mechanisms that drive exchange rates in our model. In fact, our results sharply contradict the traditional assumption that little or no information dispersion exists. Instead, they point to the presence of dispersed, fundamental-related information in order flow, and an information aggregation process that operates on a macroeconomic time scale, not in minutes, hours, or days.

One implication of these surprising findings is the order flow should have *forecasting* power for spot rate changes. If the information aggregation process takes time, then order flows should have forecasting power for future changes in spot rates over the corresponding learning period. To examine this possibility, Table 6 reports the results of estimating forecasting regressions for excess returns:

$$\Delta^h s_{t+h} + i_t^{*h} - i_t^h = \delta_0 + \sum_{j=1}^{6} \delta_j x_{j,t}^h + \omega_{t+h}, \tag{38}$$

where i_t^{*h} and i_t^h are respectively the h-period nominal interest rates on Euro and Dollar deposits. The regressions are estimated at the daily frequency with horizons h of one week to one month.

Table 6 shows that many coefficients in forecasting regression (38) are statistically significant. This is particularly so for the coefficients on US corporate and long-term investor order flows. The results are also striking in terms of the degree of forecastability as measured by the R^2 statistics. Order flows have more forecasting power as the horizon increases, reaching 19 percent at the one month horizon. This is a striking degree of forecastability. By comparison, the R^2 statistics from Fama-type regressions (where the rate of depreciation is regressed on the interest differential) are generally in the 2-4 percent range. Of course the order flows in our regressions represent the flow of private information received by dealers in the market. So our forecasting results should not be interpreted as evidence that excess foreign currency returns can be easily forecast using data that was publicly available. Rather the degree of forecastability underlines the quantitative importance of the slow pace of information aggregation associated with exchange rate dynamics.

Could the results in Table 6 stem from the restrictions we impose on the interest differential in equation (38)? To address this question, we also estimated (38) with the addition of $i_t^h - i_t^{*h}$ as a right hand side variable. This specification effectively relaxes the unit coefficient restriction on the interest differential in predicting the depreciation rate, a restriction that is overwhelming rejected by a vast empirical literature. The estimates from the amended regression are almost identical to those in Table 6. In particular, the coefficient on the interest differential is small and statistically insignificant, while the coefficients on order flow and the R^2 statistics are essentially unchanged. These findings indicate that the results in Table 6 are indeed robust. They also show that in this data set there is no evidence of forward discount bias once we account for the effects of order flows on the rate of depreciation.

Table 6: Forecasting Regressions for Excess Returns

Horizon	Corporate		Traders		Investors		R^2	χ^2
	US	Non-US	US	Non-US	US	Non-US		(p-value)
1 week	1.119	-0.061					0.027	10.243
	(0.365)	(0.170)						(0.006)
			0.045	0.205			0.003	0.983
			(0.162)	(0.225)				(0.612)
					-0.652	0.222	0.015	6.003
					(0.304)	(0.183)		(0.050)
	1.074	-0.008	-0.071	0.039	-0.421	0.247	0.037	16.207
	(0.363)	(0.189)	(0.161)	(0.228)	(0.309)	(0.196)		(0.013)
2 weeks	1.243	-0.067					0.069	13.403
	(0.363)	(0.155)						(0.001)
			0.098	0.230			0.009	1.787
			(0.155)	(0.209)				(0.409)
					-0.785	0.203	0.042	9.791
					(0.276)	(0.145)		(0.007)
	1.124	-0.004	-0.013	0.063	-0.536	0.207	0.092	24.352
	(0.356)	(0.172)	(0.143)	(0.209)	(0.273)	(0.161)		(0.000)
3 weeks	1.262	-0.041					0.104	16.261
	(0.341)	(0.142)						(0.000)
			0.097	0.190			0.011	1.532
			(0.155)	(0.190)				(0.465)
					-0.864	0.170	0.071	12.247
					(0.271)	(0.120)		(0.002)
	1.111	0.014	-0.005	0.024	-0.626	0.184	0.143	30.195
	(0.313)	(0.150)	(0.138)	(0.196)	(0.258)	(0.143)		(0.000)
1 month	1.179	-0.051					0.119	18.041
	(0.306)	(0.133)						(0.000)
			0.090	0.135			0.010	1.116
			(0.160)	(0.173)				(0.572)
					-0.965	0.131	0.110	15.434
					(0.264)	(0.109)		(0.000)
	0.985	-0.008	0.001	-0.038	-0.762	0.146	0.185	33.629
	(0.259)	(0.137)	(0.136)	(0.182)	(0.242)	(0.128)		(0.000)

Notes: The table reports coefficient and standard errors from regressions of excess returns measured over 1, - 3 weeks and 1 month on lagged order flows cumulated over one month. The left hand column report χ^2 statistics for the null that all the coefficients on order flow are zero. Estimates are calculated at the daily frequency using 1141 trading days in the sample. The standard errors correct for heteroskedastic and the moving average error process induced by overlapping forecasts.

5 Conclusion

This paper offers 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 view and the emerging "micro" view that associates exchange rate movements unexplained by macroeconomics as largely determined by order flows. Our approach treats the unexplained term not simply as a disturbance, or projection error, but as an information phenomenon. Specifically, we address the possibility that transaction flows in the foreign exchange market are conveying information about the present value of future fundamentals that is not captured in macro-econometric measures of fundamentals. If transaction flows reaching the market are conveying signals of future macro realizations and these signals are truly incremental to the public information, then market–makers will impound this information in exchange rates. This mechanism produces "unexplained" exchange rate variation relative to observations on traditional macroeconomic variables.

Our approach differs from the extant micro view in the literature because models offered thus far (e.g., Evans and Lyons 2002a,b) have interpreted the information conveyed by transaction flows as orthogonal to macro fundamentals. This information is viewed, instead, as relating to the other driver within the broader asset pricing literature; termed stochastic discount factors, expected returns or portfolio balance effects. Most readers of this micro literature have adopted the same view: transaction flow effects on exchange rates are about pricing errors, not about fundamentals.

In this paper we developed a simple general equilibrium model of information aggregation that provides a utility-based present value representation for exchange rates. We then used the model to show that the presence of dispersed information about fundamentals and information aggregation lead to a concurrent correlation between changes in spot rates and transaction flows that match the data. More strikingly, our model predicts that order flow should have incremental forecasting power for *future* fundamentals relative to current spot rates. We also provide theoretical perspective on the apparent lack of cointegration between spot exchange rates and standard measures of fundamentals.

We presented four main empirical findings, all of which are consistent with our model: (i) order flows forecast future macro variables such as output growth, money growth, and inflation, (ii) order flows generally forecast these macro variables better than spot rates do, (iii) order flows forecast future spot rates, and (iv) though order flows convey new information about future fundamentals, much of this information is still not impounded in the spot rate one quarter later. Together, these results have an important broad-level implication. Traditionally, people have viewed past micro-empirical findings linking transaction flows and exchange rates as reflecting a high-frequency, non-fundamental part of exchange rate determination. Our findings here suggest that the significance of transaction flows is deeper. Transaction flows appear to be central to the process by which expectations of future macro variables are impounded into exchange rates.

A Appendix

In this appendix we first provide detail on the consumption and portfolio decisions of households and dealers. We then derive the results presented in Propositions 1 - 5.

A.1 Decision-Making

A.1.1 Households

The consumption and portfolio decision facing households can be written in the form of a dynamic programming problem. In particular, US household z solves

$$\begin{aligned} J(W_{z,t}) &= \max_{\alpha^{\text{B}}_{z,t},\alpha^{\text{A}}_{z,t},\alpha^{\text{M}}_{z,t},C_{z,t}} \left\{ \tfrac{1}{1-\gamma} C_{z,t}^{1-\gamma} + \tfrac{\chi}{1-\gamma} \left(\alpha^{\text{M}}_{z,t} W_t \right)^{1-\gamma} + \delta \mathbb{E}^{\text{H}}_t J(W_{z,t+1}) \right\}, \\ & \text{s.t.} \\ W_{z,t+1} &= \exp(i_t - \Delta p_{t+1}) \left(H^{\text{M}}_{z,t+1} W_{z,t} - C_{z,t} \right), \\ H^{\text{M}}_{z,t+1} &= 1 + (\exp(\Delta s_{t+1} + i^*_t - i_t) - 1)\, \alpha^{\text{B}^*}_{z,t} + (\exp(r_{t+1} - i_t) - 1)\, \alpha^{\text{A}}_{z,t} \\ & \quad - \exp(-i_t)(\exp(i_t) - 1)\, \alpha^{\text{M}}_{z,t}, \end{aligned}$$

where $\quad W_{z,t} = \exp(i_{t-1}) B_{z,t-1}/P_t + S_t \exp(i^*_{t-1}) B^*_{z,t-1}/P_t + \exp(r_t) A_{z,t-1}/P_t + M_{t-1}/P_t$

is the value of wealth at the beginning of period t, measured in terms of the consumption index, $C_{z,t}$. $H^{\text{M}}_{z,t+1}$ is the (gross) excess return on wealth between periods t and $t+1$. This depends on the share of wealth held in foreign bonds, $\alpha^{\text{B}^*}_{z,t} \equiv S_t P^{\text{B}^*}_t B^*_{z,t}/P_t W_{z,t}$, other assets, $\alpha^{\text{A}}_{z,t} \equiv A_{z,t}/P_t W_{z,t}$, and real balances $\alpha^{\text{M}}_{z,t} \equiv M_{z,t}/P_t W_{z,t}$. Solving this problem gives the first-order conditions shown in (8).

In order to characterize the optimal portfolio choices of households, we work with log normal approximations to the first order conditions and a log linearization of the budget constraint. For this purpose, we first combine the identity $\alpha^{\text{M}}_{z,t} \equiv M_{z,t}/P_t W_{z,t}$ with the first-order condition for real balances and the definition of $H^{\text{M}}_{z,t+1}$. The budget constraint can then be rewritten as:

$$\frac{W_{z,t+1}}{W_{z,t}} = \exp(i_t - \Delta p_{t+1}) \left(H_{z,t+1} - (1 + \Gamma(i_t)) \frac{C_{z,t}}{W_{z,t}} \right),$$

where $\Gamma(i) \equiv \chi^{1/\gamma} \left(\frac{\exp(i)-1}{\exp(i)} \right)^{1-\frac{1}{\gamma}}$ and

$$H_{z,t+1} \equiv 1 + (\exp(\Delta s_{t+1} + i^*_t - i_t) - 1)\, \alpha^{\text{B}^*}_{z,t} + (\exp(r_{t+1} - i_t) - 1)\, \alpha^{\text{A}}_{z,t}.$$

Notice that the coefficient on the consumption-wealth ratio includes the $\Gamma(i_t)$ function because increased consumption raises holdings of real balances. This, in turn, reduces the growth in wealth because the return on nominal balances is zero.

Taking logs on both sides of the budget constraint, and linearizing the right hand side around the point where the consumption-wealth ratio and home nominal interest rate are constant, gives:

$$\Delta w_{t+1} \cong i_t - \Delta p_{t+1} + k + \tfrac{1}{\rho}(h_{t+1} - \lambda i_t) - \tfrac{1-\rho}{\rho}(c_t - w_t), \tag{A1}$$

where $\rho = 1 - \mu\left(1 + \Gamma(i)\right)$, $\lambda = \frac{\mu(\gamma-1)}{\gamma(\exp(i)-1)\exp(i)}\Gamma(i)$ and $k = \ln\rho + \left(1 - \frac{1}{\rho}\right)\ln\mu + \lambda/\rho$. The sign of the λ coefficient depends on the degree of curvature in the sub-utility function. To understand why, we need to consider the two channels through which nominal interest rates affect the return on wealth via real balances. First, an increase in the interest rate lowers the excess return on wealth when real balances are a constant fraction of wealth. This can be seen from the definition of $H^{\mathrm{M}}_{z,t+1}$ above. When $\gamma < (>)\ 1$, the former (latter) effect dominates so the excess return on wealth is negatively (positively) related to the nominal interest rate. In the case of log utility ($\gamma = 1$) the effect exactly cancel, and $\lambda = 0$. Hereafter, we focus on the case where $\gamma > 1$, so that $\lambda > 0$ and excess returns are negatively related to the nominal interest rate.

Using the definition of $H_{z,t+1}$ above, we follow Campbell and Viceira (2002) in approximating the log excess return on wealth by:

$$\begin{aligned} h_{t+1} \;\cong\;& \alpha^{\mathrm{A}}_{z,t}\left(r_{t+1} - i_t\right) + \alpha^{\mathrm{B}^*}_{z,t}\left(\Delta s_{t+1} + i^*_t - i_t\right) + \tfrac{1}{2}\alpha^{\mathrm{A}}_{z,t}(1-\alpha^{\mathrm{A}}_{z,t})\mathbb{V}^{\mathrm{H}}_t\left(r_{t+1}\right) \\ &+\tfrac{1}{2}\alpha^{\mathrm{B}^*}_{z,t}(1-\alpha^{\mathrm{B}^*}_{z,t})\mathbb{V}^{\mathrm{H}}_t\left(\Delta s_{t+1}\right) - \alpha^{\mathrm{B}^*}_{z,t}\alpha^{\mathrm{A}}_{z,t}\mathbb{CV}^{\mathrm{H}}_t\left(r_{t+1}, \Delta s_{t+1}\right), \end{aligned} \tag{A2}$$

where $\mathbb{V}^{\mathrm{H}}_t(.)$ and $\mathbb{CV}^{\mathrm{H}}_t(.,.)$ denote the variance and covariance conditioned on household $z's$ period t information, $\Omega_{z,t}$. This second–order approximation holds exactly in the continuous–time limit when the spot exchange rate and the price of other assets follow Wiener processes.

We can now use (A1), (A2) and the linearized first order conditions to characterize the optimal choice of consumption, real balances and the portfolio shares $\alpha^{\mathrm{A}}_{z,t}$ and $\alpha^{\mathrm{B}^*}_{z,t}$. Combining the log linearized versions of (8c) and (8d) with (A1) and (A2) we obtain:

$$\begin{bmatrix} \alpha^{\mathrm{B}^*}_{z,t} \\ \alpha^{\mathrm{A}}_{z,t} \end{bmatrix} = \tfrac{\rho}{\gamma}\left(\Xi^{\mathrm{H}}_t\right)^{-1} \begin{bmatrix} \mathbb{E}^{\mathrm{H}}_t\Delta s_{t+1} + i^*_t - i_t + \frac{1}{2}\mathbb{V}^{\mathrm{H}}_t(\Delta s_{t+1}) - \theta^s_{z,t} \\ \mathbb{E}^{\mathrm{H}}_t r_{t+1} - i_t + \frac{1}{2}\mathbb{V}^{\mathrm{H}}_t(\Delta s_{t+1}) - \theta^r_{z,t} \end{bmatrix}, \tag{A3}$$

where
$$\theta^v_{z,t} = \gamma\mathbb{CV}^{\mathrm{H}}_t\left(c_{z,t+1} - w_{z,t+1}, v_{t+1}\right) + (1-\gamma)\,\mathbb{CV}^{\mathrm{H}}_t\left(\Delta p_{t+1}, v_{t+1}\right),$$

for $v = \{s, r\}$. The matrix Ξ^{H}_t is the conditional covariance of the vector $(\Delta s_{t+1}, r_{t+1})'$. $\mathbb{E}^{\mathrm{H}}_t\Delta s_{t+1} + i^*_t - i_t - \theta^s_{z,t}$ and $\mathbb{E}^{\mathrm{H}}_t r_{t+1} - i_t - \theta^r_{z,t}$ are the risk–adjusted expected excess returns on foreign bonds and other assets. The variance terms arise because we are working with log excess returns. $\theta^v_{z,t}$ identifies the consumption hedging factor associated with foreign bonds ($v = s$) and other assets ($v = r$).

All that now remains is to characterize the demand for real balances and the consumption wealth ratio. The former is found by log linearizing (8b):

$$m_{z,t} - p_t = \varpi + c_{z,t} - \eta i_t, \tag{A4}$$

where $\varpi \equiv \frac{1}{\gamma}\ln\chi + i\exp(i)\eta$ and $\eta = 1/\gamma(\exp(i)-1) > 0$. An approximation to the log consumption wealth ratio is found by combining (A1) with the linearized version of (8a):

$$c_{z,t} - w_{z,t} = \tfrac{\rho k}{1-\rho} + \left(1 - \tfrac{1}{\gamma}\right)\mathbb{E}^{\mathrm{H}}_t\sum_{i=0}^{\infty}\rho^{i+1}(i_{t+i} - \Delta p_{t+1+i}) + \mathbb{E}^{\mathrm{H}}_t\sum_{i=1}^{\infty}\rho^{i-1}(h_{t+i} - \lambda i_{t+i-1}).$$

We can characterize the behavior of European households in a similar way. Specifically, the linearized budget constraint for household z is:

$$\Delta w^*_{z,t+1} \cong i^*_t - \Delta p^*_{t+1} + k + \tfrac{1}{\rho}\left(h^*_{zt+1} - \lambda i^*_t\right) - \tfrac{1-\rho}{\rho}(c^*_{z,t} - w^*_{z,t}), \tag{A5}$$

where the log excess return is approximated by:

$$\begin{aligned} h^*_{zt+1} \quad &\cong \quad \alpha^{\mathrm{A}^*}_{z,t}\left(r^*_{t+1} - i^*_t\right) + \alpha^{\mathrm{B}}_{z,t}\left(i_t - \Delta s_{t+1} - i^*_t\right) + \tfrac{1}{2}\alpha^{\mathrm{A}^*}_{z,t}(1 - \alpha^{\mathrm{A}^*}_{z,t})\mathbb{V}^{\mathrm{H}^*}_t\left(r^*_{t+1}\right) \\ &\quad + \tfrac{1}{2}\alpha^{\mathrm{B}}_{z,t}(1 - \alpha^{\mathrm{B}}_{z,t})\mathbb{V}^{\mathrm{H}^*}_t\left(\Delta s^*_{t+1}\right) + \alpha^{\mathrm{A}^*}_{z,t}\alpha^{\mathrm{B}}_{z,t}\mathbb{CV}^{\mathrm{H}^*}_t\left(r^*_{t+1}, \Delta s_{t+1}\right). \end{aligned} \tag{A6}$$

The optimal portfolio shares are:

$$\begin{bmatrix} \alpha^{\mathrm{B}}_{z,t} \\ \alpha^{\mathrm{A}^*}_{z,t} \end{bmatrix} = \tfrac{\rho}{\gamma}\left(\Xi^{*\mathrm{H}^*}_t\right)^{-1}\begin{bmatrix} i_t - \mathbb{E}^{\mathrm{H}^*}_t\Delta s_{t+1} - i^*_t + \frac{1}{2}\mathbb{V}_t\left(\Delta s_{t+1}\right) - \theta^{-s}_{z,t} \\ \mathbb{E}^{\mathrm{H}^*}_t r^*_{t+1} - i^*_t + \frac{1}{2}\mathbb{V}_t\left(r^*_{t+1}\right) - \theta^{r^*}_{z,t} \end{bmatrix} \tag{A7}$$

where $$\theta^{\omega}_{z,t} = \gamma\mathbb{CV}^{\mathrm{H}^*}_t\left(c^*_{z,t+1} - w^*_{z,t+1}, \omega_{t+1}\right) + (1-\gamma)\,\mathbb{CV}^{\mathrm{H}}_t\left(\Delta p^*_{t+1}, \omega_{t+1}\right),$$

for $\omega_t = \{-s_t, r^*_t\}$ and $\Xi^{*\mathrm{H}^*}_t$ is the conditional covariance matrix for the vector $(-\Delta s_{t+1}, r^*_{t+1})'$. The demand for log real balances is given by:

$$m^*_{z,t} - p^*_t = \varpi + c^*_{z,t} - \eta i^*_t, \tag{A8}$$

and the log consumption wealth ratio by:

$$c^*_{z,t} - w^*_{z,t} = \tfrac{\rho k}{1-\rho} + \left(1 - \tfrac{1}{\gamma}\right)\mathbb{E}^{\mathrm{H}^*}_t\sum_{i=0}^{\infty}\rho^{i+1}(i^*_{t+i} - \Delta p^*_{t+1+i}) + \mathbb{E}^{\mathrm{H}^*}_t\sum_{i=1}^{\infty}\rho^{i-1}(h^*_{t+i} - \lambda i^*_{t+i-1}). \tag{A9}$$

A.1.2 Financial Intermediaries

Given the form of optimal quotes in (17), trading profits $\Pi_{d,t}$ equal zero, and the problem of choosing trades, $\{T^{\mathrm{B}}_{d,t}, T^{\mathrm{B}^*}_{d,t}, T^{\mathrm{M}}_{d,t}, T^{\mathrm{M}^*}_{d,t}\}$, and consumption, $C_{d,t}$, for dealer d can be written as :

$$\mathcal{J}_t(W_{d,t}) = \max_{\left\{\alpha^{\mathrm{A}*}_{d,t}, \alpha^{\mathrm{B}*}_{d,t}, C_{d,t},\right\}}\left\{\tfrac{1}{1-\gamma}C^{1-\gamma}_{d,t} + \beta\mathbb{E}^{\mathrm{D}}_t\mathcal{J}(W_{d,t+1})\right\}, \tag{A10}$$

s.t. $$W_{d,t+1} = \exp\left(i_t - \Delta p_{t+1}\right)\left(H_{d,t+1}W_{d,t} - C_{d,t}\right), \tag{A11}$$

where

$$\begin{aligned} H_{d,t+1} \quad &= \quad 1 + \left(\exp\left(\Delta s_{t+1} + i^*_t - i_t\right) - 1\right)\left(\alpha^{\mathrm{B}*}_{d,t} - \xi_t\right) + \left(\exp\left(r_{d,t+1} - i_t\right) - 1\right)\alpha^{\mathrm{A}}_{d,t}, \\ \alpha^{\mathrm{A}*}_{d,t}P_tW_{d,t} \quad &= \quad A_{d,t}, \\ \alpha^{\mathrm{B}*}_{d,t}P_tW_{d,t} \quad &= \quad S_tP^{\mathrm{B}^*}_t\left(B^*_{t-1} + T^{\mathrm{B}*}_{d,t} - \mathbb{E}^{\mathrm{D}}_tT^{\mathrm{B}*}_t - O^{\mathrm{B}*}_t\right), \text{ and} \\ \xi_tP_tW_{d,t} \quad &= \quad S_tP^{\mathrm{B}^*}_t\left(T^{\mathrm{B}*}_t - \mathbb{E}^{\mathrm{D}}_tT^{\mathrm{B}*}_t\right). \end{aligned}$$

$W_{d,t}$ denotes the real wealth of dealer d at the start of period t. This comprises the dealer's holding of bonds and other assets: $W_{d,t} \equiv \left(B_{d,t-1} + S_tB_{d,t-1} + \exp(r_{d,t})A_{d,t-1}\right)/P_t$. $\alpha^{\mathrm{B}*}_{d,t}$ identifies the fraction of wealth dealer d wishes to hold in foreign bonds, taking into account the orders from households and the expected orders from other dealers, $O^{\mathrm{B}*}_t + \mathbb{E}^{\mathrm{D}}_tT^{\mathrm{B}*}_t$. Notice that dealers cannot condition their own orders on the orders they receive from other dealers because interdealer trading is simultaneous. Rather period$-t$ orders must be conditioned on the orders of households, $O_t^{\text{B}*}$, and the expected orders from other traders, $\mathbb{E}_t^{\text{D}} T_t^{\text{B}*}$. $H_{d,t+1}$ is the excess return on wealth between the start of periods t and $t+1$. This return depends upon the excess return on foreign bonds, and the actual fraction of wealth held in foreign bonds at the end of period t trading, $\alpha_{d,t}^{\text{B}*} - \xi_t$, where ξ_t represents the effects of unexpected foreign bond orders from other dealers.

The first-order conditions from (A10) and (A11) are given by:

$$C_{d,t} \quad : \quad \mathbb{E}_t^{\text{D}} \left[\delta V_{t+1} C_{d,t}^{\gamma} \exp\left(i_t - \Delta p_{t+1}\right) \right] = 1, \tag{A12a}$$

$$\alpha_{d,t}^{\text{A}*} \quad : \quad \mathbb{E}_t^{\text{D}} \left[\delta V_{t+1} C_{d,t}^{\gamma} \exp\left(r_{t+1} - i_t\right) \right] = 1, \tag{A12b}$$

$$\alpha_{d,t}^{\text{B}*} \quad : \quad \mathbb{E}_t^{d} \left[\delta V_{t+1} C_{d,t}^{\gamma} \exp\left(\Delta s_{t+1} + i_t^* - i_t\right) \right] = 1, \tag{A12c}$$

where $V_t \equiv d\mathcal{J}_t(W_{d,t})/dW_{d,t}$ is the marginal utility of wealth that follows the recursion:

$$V_t = \mathbb{E}_t^{\text{D}} \left[\delta V_{t+1} \exp\left(i_t - \Delta p_{t+1}\right) H_{d,t+1} \right]. \tag{A13}$$

$\mathbb{E}_t^{\text{D}}$ denotes expectations conditioned on dealer d's information at the start of period t. Notice that this is the same information set available to dealers before quotes were chosen because quotes are functions of common period information, Ω_t^{D}. In the special case where dealers can perfectly predict the flow of incoming orders for foreign bonds (i.e., $T_{d,t}^{\text{B}*} = \mathbb{E}_t^{\text{D}} T_t^{\text{B}*}$), (A13) simplifies to $V_t = C_{d,t}^{-\gamma}$ so the consumption and portfolio decisions facing dealers take the familiar form. Under other circumstances, uncertainty about incoming bond orders affects these decisions by driving a wedge between the marginal utility of wealth and consumption.

To characterize the consumption and portfolio choices implied by (**??**) and (A13), we first approximate log budget constraint as

$$\Delta w_{d,t+1} \cong i_t - \Delta p_{t+1} + k_d + \tfrac{1}{1-\mu} h_{d,t+1} - \tfrac{\mu}{1-\mu}(c_{d,t} - w_{d,t}), \tag{A14}$$

where μ is the steady state consumption to wealth ratio, and $k_d = \ln(1-\mu) - \frac{\mu}{1-\mu}\ln\mu$. $h_{d,t+1}$ is the log excess return on wealth, which we approximate by:

$$\begin{aligned} h_{d,t+1} \quad \cong \quad & \alpha_{d,t}^{\text{B}*}\left(\Delta s_{t+1} + i_t^* - r_{t+1}\right) + \tfrac{1}{2}\alpha_{d,t}^{\text{B}*}(1-\alpha_{d,t}^{\text{B}*})\mathbb{V}_t^{\text{D}}\left(\Delta s_{t+1}\right) + \alpha_{d,t}^{\text{A}}\left(r_{d,t+1} - i_t\right) \\ & + \tfrac{1}{2}\alpha_{d,t}^{\text{A}}(1-\alpha_{d,t}^{\text{A}})\mathbb{V}_t^{\text{D}}\left(r_{t+1}\right) - \alpha_{d,t}^{\text{A}}\alpha_{d,t}^{\text{B}*}\mathbb{CV}_t^{\text{D}}\left(r_{d,t+1}, \Delta s_{t+1}\right) - \mathbb{CV}_t^{\text{D}}\left(s_{t+1}, \xi_t\right). \end{aligned} \tag{A15}$$

Combining this equation with log linearized versions of (A12a)- (A13) gives the following approximation for the log marginal utility of wealth:

$$\ln V_t \equiv v_t \cong -\gamma c_t - \varphi \tag{A16}$$

where $\varphi \equiv \mathbb{CV}_t^{\text{D}}\left(s_{t+1}, \xi_t\right)$. Substituting for v_t in the linearized first order conditions for $\alpha_{d,t}^{\text{A}*}$ and $\alpha_{d,t}^{\text{B}*}$ gives

$$\begin{bmatrix} \alpha_{d,t}^{\text{B}*} \\ \alpha_{d,t}^{\text{A}} \end{bmatrix} = \tfrac{1-\mu}{\gamma}\left(\Xi_t^{\text{D}}\right)^{-1} \begin{bmatrix} \mathbb{E}_t^{\text{D}}\Delta s_{t+1} + i_t^* - i_t + \frac{1}{2}\mathbb{V}_t^{\text{D}}(\Delta s_{t+1}) - \theta_{d,t}^{s} \\ \mathbb{E}_t^{\text{D}} r_{d,t+1} - i_t + \frac{1}{2}\mathbb{V}_t^{\text{D}}(\Delta s_{t+1}) - \theta_{d,t}^{r} \end{bmatrix} \tag{A17}$$

where $\qquad \theta_{d,t}^{\omega} = \gamma\mathbb{CV}_t^{\text{D}}\left(c_{d,t+1} - w_{d,t+1}, \omega_{t+1}\right) + (1-\gamma)\,\mathbb{CV}_t^{\text{D}}\left(\Delta p_{t+1}, \omega_{t+1}\right),$

for $\omega = \{s, r\}$ and Ξ_t^{D} is the conditional covariance matrix for the vector $(\Delta s_{t+1}, r_{t+1})'$. The log consumption-wealth ratio for dealer d is approximated by

$$c_{d,t} - w_{d,t} = \left(\tfrac{1}{\mu} - 1\right) k_d + \left(1 - \tfrac{1}{\gamma}\right) \mathbb{E}_t^{\text{D}} \sum_{i=0}^{\infty} (1-\mu)^{i+1} \left(i_{t+i} - \Delta p_{t+1+i}\right) + \mathbb{E}_t^{\text{D}} \sum_{i=1}^{\infty} (1-\mu)^{i-1} h_{d,t+i}, \quad \text{(A18)}$$

where $k_d > 0$, $1 > \mu > 0$ and $h_{d,t}$ is the log excess return on dealer's wealth.

A.2 Proofs of Propositions 1 - 5

Proposition 1 Under condition (i), $\alpha_{d,t}^{\text{B}*} = 0$, so (A17) becomes

$$\mathbb{E}_t^{\text{D}} \Delta s_{t+1} + i_t^* - i_t = \beta^{\text{D}} \mathbb{E}_t^{\text{D}} er_{d,t+1},$$

where $\beta^{\text{D}} \equiv CV_t^{\text{D}} \left(r_{d,t+1}, \Delta s_{t+1}\right) / V_t^{\text{D}} \left(r_{d,t+1}\right)$ and $er_{d,t+1}$ is the risk adjusted excess return on dealers' other assets equal to $r_{d,t+1} - i_t - \frac{1}{2} V_t^{\text{D}}(r_{d,t+1}) + \theta_{d,t}^r - \left(\theta_{d,t}^s - \frac{1}{2} \mathbb{V}_t^{\text{D}}(s_{t+1})\right) / \beta^{\text{D}}$. Condition (ii) restricts $E_t^{\text{D}} er_{d,t+1}$ to zero so spot rates satisfy

$$\mathbb{E}_t^{\text{D}} \Delta s_{t+1} + i_t^* - i_t = 0. \quad \text{(A19)}$$

If the interest rates implied by dealers quotes for bond prices are to be consistent with money market clearing, equations (A4) and (A8) imply that

$$\begin{aligned} \mathbb{E}_t^{\text{D}} m_{z,t} - \mathbb{E}_t^{\text{D}} p_t &= \varpi + \mathbb{E}_t^{\text{D}} c_{z,t} - \eta i_t, \quad &\text{(A20a)} \\ \mathbb{E}_t^{\text{D}} m_{z^*,t}^* - \mathbb{E}_t^{\text{D}} p_t^* &= \varpi + \mathbb{E}_t^{\text{D}} c_{z^*,t} - \eta i_t^*, \quad &\text{(A20b)} \end{aligned}$$

Rearranging these equations gives (20). Combining (A20) with (A19) gives

$$s_t = \tfrac{\eta}{1+\eta} \mathbb{E}_t^{\text{D}} s_{t+1} + \tfrac{1}{1+\eta} \mathbb{E}_t^{\text{D}} f_t.$$

Solving this equation forward and applying the law of iterated expectations gives (18).

Proposition 2 Let $er_{z,t+1}$ be the risk adjusted excess return on the other assets held by US households equal to $r_{t+1} - i_t + \frac{1}{2} \mathbb{V}_t^{\text{H}}(\Delta s_{t+1}) - \theta_{z,t}^r$. We may now rewrite the portfolio allocation equation in (A3) as

$$\alpha_{z,t}^{\text{B}*} = \tfrac{\rho}{\gamma} \Theta^{\text{H}} \left(\mathbb{E}_t^{\text{H}} \Delta s_{t+1} + i_t^* - i_t + \tfrac{1}{2} \mathbb{V}_t^{\text{H}}(s_{t+1}) - \theta_{z,t}^s\right) - \beta^{\text{H}} \Theta^{\text{H}} \mathbb{E}_t^{\text{H}} er_{z,t+1}, \quad \text{(A21)}$$

where $\beta^{\text{H}} \equiv \mathbb{VC}_t^{\text{H}} \left(r_{t+1}, \Delta s_{t+1}\right) / \mathbb{V}_t^{\text{H}} \left(r_{t+1}\right)$ and $\Theta^{\text{H}} \equiv \left(\mathbb{V}_t^{\text{H}} \left(\Delta s_{t+1}\right) - \frac{\gamma}{\rho} \left(\beta^{\text{H}}\right)^2 \mathbb{V}_t^{\text{H}} \left(r_{z,t+1}\right)\right)^{-1}$. Households know that dealers quote spot rates in accordance with (18). So the expected excess return on foreign bonds can be written as

$$\mathbb{E}_t^{\text{H}} \Delta s_{t+1} + i_t^* - i_t = \mathbb{E}_t^{\text{D}} \Delta s_{t+1} + i_t^* - i_t + \nabla \mathbb{E}_t^{\text{H}} s_{t+1} = \nabla \mathbb{E}_t^{\text{H}} s_{t+1}.$$

Combining this expression with (A21) gives us

$$\alpha_{z,t}^{\text{B}*} = \tfrac{\rho}{\gamma} \Theta^{\text{H}} \nabla \mathbb{E}_t^{\text{H}} s_{t+1} - \Theta^{\text{H}} \beta^{\text{H}} \mathbb{E}_t^{\text{H}} er_{z,t+1} - \Theta^{\text{H}} \left(\theta_{z,t}^s - \tfrac{1}{2} \mathbb{V}_t^{\text{H}}(s_{t+1})\right). \quad \text{(A22)}$$

Following the same steps for European households, we obtain

$$\alpha^{\text{B}*}_{z^*,t} = \tfrac{\rho}{\gamma}\Theta^{\text{H}^*}\nabla\mathbb{E}^{\text{H}^*}_t s_{t+1} - \Theta^{\text{H}^*}\beta^{\text{H}^*}\mathbb{E}^{\text{H}^*}_t er_{z^*,t+1} - \Theta^{\text{H}^*}\left(\theta^s_{z*,t} - \tfrac{1}{2}\mathbb{V}^{\text{H}^*}_t(s_{t+1})\right). \tag{A23}$$

Equations (A22) and (A23) show that the desired portfolio shares for foreign bonds depend on: (i) the difference in expectations regarding future sport rates between the households and dealers, (ii) the risk adjusted expected excess return on other assets, and (iii) and the risk associated with holding foreign bonds. Substituting the expressions for $\alpha^{\text{B}*}_{z,t}$ and $\alpha^{\text{B}*}_{z^*,t}$ in the order flow equation (21), and linearizing around the point where wealth is equally distributed between households and expectations are the same gives (22).

Proposition 3 Let $\Omega^{\text{H}}_t = \{\Omega^{\text{D}}_t, \upsilon_t\}$ for some vector of variables υ_t so that $\Omega^{\text{D}}_t \subset \Omega^{\text{H}}_t$. From Bayesian updating we known that

$$\begin{aligned}\mathbb{E}\left[\varkappa_{t+1}|\Omega^{\omega}_t, \upsilon_t\right] &= \mathbb{E}\left[\varkappa_{t+1}|\Omega^{\omega}_t\right] + \mathbb{B}_{\varkappa,\upsilon}\left(\upsilon_t - \mathbb{E}\left[\upsilon_t|\Omega^{\omega}_t\right]\right), \\ \mathbb{B}_{\varkappa,\upsilon} &= \mathbb{V}^{\omega}_t\left(\upsilon_t\right)^{-1}\mathbb{CV}^{\omega}_t(\varkappa_{t+1}, \upsilon_t).\end{aligned} \tag{A24}$$

for some random variable $\varkappa_{t+1}$ and information set Ω^{ω}_t. Applying this equation in the case where $\varkappa_{t+1} = \mathbb{E}\left[\mathbf{y}_{t+1}|\Omega^{\text{D}}_{t+1}\right]$, $\Omega^{\omega}_t = \Omega^{\text{D}}_t$, and $\Omega^{\text{H}}_t = \{\Omega^{\text{D}}_t, \upsilon_t\}$, gives

$$\mathbb{E}^{\text{H}}_t\mathbb{E}^{\text{D}}_{t+1}\mathbf{y}_{t+1} - \mathbb{E}^{\text{D}}_t\mathbf{y}_{t+1} = \mathbb{B}_{\mathbb{E}^{\text{D}}_{t+1}\mathbf{y}_{t+1},\upsilon_t}\left(\upsilon_t - \mathbb{E}\left[\upsilon_t|\Omega^{\text{D}}_t\right]\right).$$

In the case where $\varkappa_{t+1} = \mathbf{y}_{t+1}$, $\Omega^{\omega}_t = \Omega^{\text{D}}_t$, and $\Omega^{\text{H}}_t = \{\Omega^{\text{D}}_t, \upsilon_t\}$ we get:

$$\mathbb{E}^{\text{H}}_t\mathbf{y}_{t+1} - \mathbb{E}^{\text{D}}_t\mathbf{y}_{t+1} = \mathbb{B}_{\mathbf{y}_{t+1},\upsilon_t}\left(\upsilon_t - \mathbb{E}\left[\upsilon_t|\Omega^{\text{D}}_t\right]\right).$$

Combining these equations we obtain:

$$\mathbb{E}^{\text{H}}_t\mathbb{E}^{\text{D}}_{t+1}\mathbf{y}_{t+1} - \mathbb{E}^{\text{D}}_t\mathbf{y}_{t+1} = \kappa\left(\mathbb{E}^{\text{H}}_t\mathbf{y}_{t+1} - \mathbb{E}^{\text{D}}_t\mathbf{y}_{t+1}\right), \tag{A25}$$

where

$$\kappa \equiv \mathbb{B}_{\mathbb{E}^{\text{D}}_{t+1}\mathbf{y}_{t+1},\upsilon_t}\left(\mathbb{B}'_{\mathbf{y}_{t+1},\upsilon_t}\mathbb{B}_{\mathbf{y}_{t+1},\upsilon_t}\right)^{-1}\mathbb{B}'_{\mathbf{y}_{t+1},\upsilon_t}.$$

Now we combine (25) and (A25) to give $\nabla\mathbb{E}^{\text{H}}_t s_{t+1} = \pi\kappa\nabla\mathbb{E}^{\text{H}}_t\mathbf{y}_{t+1}$ which is (26a). Applying the same technique to the foreign forecast differential gives $\nabla\mathbb{E}^{\text{H}^*}_t s_{t+1} = \pi\kappa^*\nabla\mathbb{E}^{\text{H}^*}_t\mathbf{y}_{t+1}$ where κ^* is the foreign counterpart of κ. This is equation (26b). Substitution for $\nabla\mathbb{E}^{\text{H}}_t s_{t+1}$ and $\nabla\mathbb{E}^{\text{H}^*}_t s_{t+1}$ in (22) with these expressions gives (27).

Proposition 4 First we use (A24) with $\mathbf{y}_{t+1} = \varkappa_{t+1}$, $\Omega^{\omega}_t = \Omega^{\text{D}}_t$, and $\Omega^{\text{D}}_{t+1} = \{\Omega^{\text{D}}_t, \upsilon_t\}$ to give

$$\mathbb{E}^{\text{D}}_{t+1}\mathbf{y}_{t+1} - \mathbb{E}^{\text{D}}_t\mathbf{y}_{t+1} = \mathbb{B}_{\mathbf{y}_{t+1},\upsilon_t}\left(\upsilon_t - \mathbb{E}\left[\upsilon_t|\Omega^{\text{D}}_t\right]\right).$$

Next we combine this expression with (28):

$$\Delta s_{t+1} = i_t - i^*_t + \pi\mathbb{B}_{\mathbf{y}_{t+1},\upsilon_t}\left(\upsilon_t - \mathbb{E}\left[\upsilon_t|\Omega^{\text{D}}_t\right]\right).$$

Now note that the vector υ_t denotes the new information available to dealers between the start of periods t and $t+1$. Thus, period t order flow x_t is an element of υ_t. We can therefore write:

$$\Delta s_{t+1} = i_t - i_t^* + b\left(x_t - \mathbb{E}_t^{\mathrm{D}} x_t\right) + \zeta_{t+1}$$

where $b = \pi \mathbb{B}_{\mathbf{y}_{t+1},x_t}$ and ζ_{t+1} denotes the effect of other elements in υ_t that are uncorrelated with order flow. To see how the correlation between order flow and spot rates depends on the degree of information aggregation, we simply use (27) to substitute for x_t in the definition of $\mathbb{B}_{\mathbf{y}_{t+1},x_t}$. In particular, we first write

$$\pi \mathbb{B}_{\mathbf{y}_{t+1},x_t} \mathbb{V}_{t.}^{\mathrm{D}}(x_t) = \phi\pi \mathbb{CV}_{t.}^{\mathrm{D}}\left(\mathbf{y}_{t+1}, \nabla \mathbb{E}_t^{\mathrm{H}} \mathbf{y}_{t+1}'\right)\kappa'\pi' + \phi^*\pi \mathbb{CV}_{t.}^{\mathrm{D}}\left(\mathbf{y}_{t+1}, \nabla \mathbb{E}_t^{\mathrm{H}^*} \mathbf{y}_{t+1}'\right)\kappa^{*\prime}\pi' + \pi \mathbb{CV}_{t.}^{\mathrm{D}}\left(\mathbf{y}_{t+1}, o_t\right),$$

and use the identity $\mathbf{y}_{t+1} \equiv \mathbb{E}_t^{\mathrm{D}}\mathbf{y}_{t+1} + \mathbb{E}_t^{\omega}\mathbf{y}_{t+1} - \mathbb{E}_t^{\mathrm{D}}\mathbf{y}_{t+1} + (\mathbf{y}_{t+1} - \mathbb{E}_t^{\omega}\mathbf{y}_{t+1})$ for $\omega = \{\mathrm{H},\mathrm{H}^*\}$ to give

$$b = \mathbb{V}_{t.}^{\mathrm{D}}(x_t)^{-1}\left(\phi\pi \mathbb{V}_{t.}^{\mathrm{D}}\left(\nabla \mathbb{E}_t^{\mathrm{H}}\mathbf{y}_{t+1}\right)\kappa'\pi' + \phi^*\pi \mathbb{V}_{t.}^{\mathrm{D}}\left(\nabla \mathbb{E}_t^{\mathrm{H}^*}\mathbf{y}_{t+1}\right)\kappa^{*\prime}\pi'\right) + \mathbb{V}_{t.}^{\mathrm{D}}(x_t)^{-1}\pi \mathbb{CV}_{t.}^{\mathrm{D}}\left(\mathbf{y}_{t+1}, o_t\right).$$

Proposition 5 Consider the projection of Δf_{t+h} on $s_t - \mathbb{E}_t^{\mathrm{D}} f_t$ and the unexpected component of order flow $x_t - \mathbb{E}_t^{\mathrm{D}} x_t$:

$$\Delta f_{t+h} = \beta_s\left(s_t - \mathbb{E}_t^{\mathrm{D}} f_t\right) + \beta_x\left(x_t - \mathbb{E}_t^{\mathrm{D}} x_t\right) + \epsilon_{t+h}.$$

Order flow has incremental forecasting power when β_x differs from zero. To show that this is indeed the case, we first note that $\beta_x\left(x_t - \mathbb{E}_t^{\mathrm{D}} x_t\right) + \epsilon_{t+h}$ must equal the projection error in (32), ε_{t+h}, because $x_t - \mathbb{E}_t^{\mathrm{D}} x_t$ is uncorrelated with $s_t - \mathbb{E}_t^{\mathrm{D}} f_t$. Consequently, β_s takes the same value as it did in (32) and:

$$\beta_x = \frac{\mathbb{CV}\left(\Delta f_{t+h}, x_t - \mathbb{E}_t^{\mathrm{D}} x_t\right)}{\mathbb{V}\left(x_t - \mathbb{E}_t^{\mathrm{D}} x_t\right)}.$$

Using the identity $\Delta f_{t+h} \equiv \nabla \mathbb{E}_t^{\omega}\Delta f_{t+h} + \mathbb{E}_t^{\mathrm{D}}\Delta f_{t+h} + \left(\Delta f_{t+h} - \mathbb{E}_t^{\omega}\Delta f_{t+h}\right)$ for $\omega = \{\mathrm{H},\mathrm{H}^*\}$ to substitute for Δf_{t+h}, and (27) to substitute for order flow, we find that

$$\beta_x = \frac{\phi\pi\kappa \mathbb{CV}\left(\nabla \mathbb{E}_t^{\mathrm{H}}\mathbf{y}_{t+1}, \nabla \mathbb{E}_t^{\mathrm{H}}\Delta f_{t+h}\right) + \phi^*\pi\kappa^* \mathbb{CV}\left(\nabla \mathbb{E}_t^{\mathrm{H}^*}\mathbf{y}_{t+1}, \nabla \mathbb{E}_t^{\mathrm{H}^*}\Delta f_{t+h}\right) + \mathbb{CV}\left(o_t, \Delta f_{t+h}\right)}{\mathbb{V}\left(x_t - \mathbb{E}_t^{\mathrm{D}} x_t\right)}.$$

The final step is to substitute for Δf_{t+h} using the fact that $f_t = C y_t$.

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