

Excerpts on Causality: Order Flow To Exchange Rate Changes

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Though the direction of causality in our model runs from order flow to price (as is true of microstructure theory generally), there is a popular alternative hypothesis that involves reverse causality, namely feedback trading. This section examines whether feedback trading can account for our results.

We begin with some perspective. Most models of feedback trading are based on non-rational behavior of some kind, making them less appealing to many economists on a priori grounds. Models of feedback trading that do not rely on non-rational behavior generally require that returns be forecastable using the first lag of returns, which is not a property of major floating exchange rates (and is not a property of our hourly data either—see Table 1, row iii). Accordingly, the class of feedback trading models that might be relevant here is the non-rational class.¹

Existing empirical evidence on feedback trading in foreign exchange is scant. Valid instruments for identifying returns-chasing order flow have not been employed and it is not clear which variables would qualify. One piece of relevant evidence is provided by Killeen et al. (2001). Using daily data on foreign exchange order flow, they find that order flow Granger causes returns but returns do not Granger cause order flow. This evidence is purely statistical, however, and applies at the daily frequency, so its message (though suggestive) is not definitive for the issue in this paper.

Our approach here is to pose and address the following question: Suppose intra-hour (i.e., contemporaneous in hourly data) positive-feedback trading is

¹ Whether the non-rational class is intellectually appealing is not an issue we could hope to resolve here. We simply offer the fact that immense amounts of money are at stake when dealing in foreign exchange

present, under what conditions could it account for the key moments of our data? To address this question, we decompose measured order flow Δx_h into two components:

$$(7) \quad \Delta x_h = \Delta x_h^* + \Delta x_h^{fb}$$

where Δx_h^* denotes exogenous order flow from portfolio shifts as identified in our model, and Δx_h^{fb} denotes contemporaneous order flow due to feedback trading, where:

$$(8) \quad \Delta x_h^{fb} = f \Delta p_h .$$

The sign of the parameter f that most people have in mind for explaining our results is positive, i.e., positive feedback trading (based on the positive coefficients on contemporaneous order flow in the price-change equations in Table 1).

Next, suppose the true structural model can be written as:

$$(9) \quad \begin{aligned} \Delta p_h &= \mathbf{b}_{11} \Delta x_h^* + \mathbf{b}_{12} \Delta p_{h-1} + \mathbf{h}_h^p \\ \Delta x_h^* &= \mathbf{b}_{21} \Delta x_{h-1}^* + \mathbf{b}_{22} \Delta p_{h-1} + \mathbf{h}_h^x \end{aligned}$$

Notice that the equations in (9) are valid reduced-forms from our model that could be estimated by OLS if one had data on Δx_h^* . However, if feedback trading is present (i.e., $f \neq 0$), estimates of (9) using measured order flow, Δx_h , will suffer from simultaneity bias.

We can evaluate the size of this bias by estimating (7) – (9) as a whole system of equations. Specifically, we can combine (7) – (9) into a bivariate system for price changes and measured order flow. The dynamics of this system depend on seven parameters: $f, \mathbf{b}_{11}, \mathbf{b}_{12}, \mathbf{b}_{21}, \mathbf{b}_{22}$, and the variances of \mathbf{h}_h^p and \mathbf{h}_h^x . These parameters can be estimated by GMM using sample estimates of the covariance

at major banks (the source of our data). These banks take the evaluation of traders' performance and decision making very seriously.

matrix for the vector $[\Delta p_h, \Delta x_h, \Delta p_{h-1}, \Delta x_{h-1}]$, as described more fully in the appendix. In broad terms, the feedback trading alternative predicts that (1) the coefficient \mathbf{b}_{11} on exogenous order flow will be smaller than those in Table 1, if not zero, and (2) the coefficient on feedback trading \mathbf{f} will be positive and significant.

The GMM estimates are reported in Table 4. The last row of the table reports the estimate of the feedback parameter, \mathbf{f} : the estimate is negative and statistically insignificant. Thus, insofar as there is any empirical evidence of feedback trading in our data, it points to the presence of negative rather than positive feedback trading. Moreover, estimates from the price equation show that our causal interpretation of the order flow's impact on price (based on our model) remains intact: the estimate of \mathbf{b}_{11} is slightly larger than those in Table 1 and remains highly statistically significant, in contrast to what the feedback trading alternative predicts.

Table 4**Feedback Trading Model**

$$\begin{aligned}\Delta x_h &= \Delta x_h^* + f \Delta p_h \\ \Delta p_h &= \mathbf{b}_{11} \Delta x_h^* + \mathbf{b}_{12} \Delta p_{h-1} + \mathbf{h}_h^p \\ \Delta x_h^* &= \mathbf{b}_{21} \Delta x_{h-1}^* + \mathbf{b}_{22} \Delta p_{h-1} + \mathbf{h}_h^x\end{aligned}$$

Price Change Equation Order Flow Equation

<u>Coefficient on</u>		
Δx_h^*	0.262 (14.93)	
Δp_{h-1}	-0.232 (-3.73)	0.190 (0.37)
Δx_{h-1}^*		0.147 (2.00)
$Var(\mathbf{h}_h)^{1/2}$	13.604 (14.64)	24.163 (30.52)
Feedback Parameter: f	-0.563 (-0.37)	

* T-statistics in parentheses. Estimated using GMM (see appendix for details).

5.3 Causality

Under our model’s null hypothesis, causality runs strictly from order flow to price. Accordingly, under the null, our estimation is not subject to simultaneity bias. (We are not simply "regressing price on quantity," as in the classic supply-demand identification problem. Quantity—i.e., volume—and order flow are fundamentally different concepts.) Within microstructure theory more broadly, this direction of causality is the norm: it holds in all the canonical models (Glosten and Milgrom 1985, Kyle 1985, Stoll 1978, Amihud and Mendelson 1980), despite the fact that price and order flow are determined simultaneously. The important point in these models is that price innovations are a function of order flow innovations, not the other way around.² That said, alternative hypotheses do exist under which causality is reversed. The following taxonomy frames the causality issue, and identifies specific alternatives under which causality is reversed, so that the merits of these alternatives can be judged in a disciplined way.

Theoretical Overview

The timing of the order-flow/price relation admits three possibilities, depending on whether order flow precedes, is concurrent with, or lags price adjustment. We shall refer to these three timing hypotheses as the *Anticipation* hypothesis, the *Pressure* hypothesis, and the *Feedback* hypothesis, respectively. As we shall see, reverse causality becomes a clear problem only under the Feedback hypothesis, and in that case only under certain conditions.

² Put differently, order flow in these models is a proximate cause. The underlying driver of order flow is non-public information (information about uncertain demands, information about payoffs, etc.). Order flow is the channel through which this type of information is impounded in price.

Within each of the three hypotheses—Anticipation, Pressure, and Feedback—there are also variations. Under the Anticipation hypothesis, for example, order flow can precede price adjustment because prices adjust fully only after order flow is commonly observed—in low-transparency markets like foreign exchange, order flow is not commonly observed when it occurs (Lyons 1996). Order flow might also precede price because price adjusts only after some piece of news anticipated by order flow is commonly observed (e.g., the short-lived private information in Foster and Viswanathan 1990).

Under the Pressure hypothesis the two main variations correspond to microstructure theory’s canonical model types—information models and inventory models. In information models, observing order flow provides information about payoffs (Glosten and Milgrom 1985, Kyle 1985). In inventory models, order flow alters equilibrium risk premia (Stoll 1978, Ho and Stoll 1981).³

Under the Feedback hypothesis, order flow lags price because of feedback trading. Negative-feedback trading is systematic selling in response to price increases, and buying in response to price decreases (e.g., Friedman’s celebrated “stabilizing speculators”). Positive-feedback trading is the reverse. Variations on the Feedback hypothesis are distinguished by whether this feedback trading is rational (an optimal response to return autocorrelation) or behavioral, meaning that it arises from systematic decision bias (DeLong et al. 1990, Jegadeesh and Titman 1993, Grinblatt et al. 1995).

Under the Pressure hypothesis, causality runs from order flow to price, despite their concurrent realization.⁴ Causality also runs from order flow to price under most variations of the Anticipation hypothesis. This is true, for example, under the variation noted above where order flow is not commonly observed, and

³ Within this inventory-model category, there is an additional distinction between price effects that arise at the marketmaker level (canonical inventory models) and price effects that arise at the marketwide level, due to imperfect substitutability (e.g., our Portfolio Shifts model). In the case of price effects at the marketmaker level, these effects are often modeled as changing risk premia. But sometimes, largely for technical convenience, models are specified with risk-neutral marketmakers who face some generic “inventory holding cost.”

⁴ This does not imply that price cannot influence order flow. Price does influence order flow in microstructure models (both for the usual downward sloping demand reason, and because agents learn from price). It is still the case that—in equilibrium—price innovations are functions of order flow innovations, not vice versa. Our Portfolio Shifts model is a case in point.

therefore affects price with a delay. One way to examine this variation of the Anticipation hypothesis is by introducing lagged order flow to our Portfolio Shifts model. Rows 1 and 3 of Table 2 present the results of this regression: lagged order flow is insignificant. At the daily frequency, lagged order flow is already embedded in price.⁵

Under the Feedback hypothesis, causality can go in reverse, that is, from price to order flow.⁶ With negative-feedback trading, a la Friedman's stabilizing speculators for example, the direction of causality is reversed. However, in this case one would expect an order-flow/price relation that is *negative*; we find a positive relation, so this type of feedback trading cannot account for our results. If instead positive-feedback trading were present and significant, then one would expect order flow in period t to be positively related to the price change in period $t-1$. In daily data, this corresponds to Δx_t being explained, at least in part, by Δp_{t-1} . If our order-flow coefficient in Table 1 is picking up this daily-frequency positive feedback, then including lagged price change Δp_{t-1} in the Portfolio-Shifts regression should weaken, if not eliminate, the significance of order flow.

Rows 2 and 4 of Table 2 present the results of this regression. Past price change does not reduce the significance of order flow, and is itself insignificant. These results run counter to the positive-feedback hypothesis at the daily frequency.

⁵ As another check along these lines, we also decompose contemporaneous order flow into expected and unexpected components (by projecting it on past order flow). In our model, all order flow Δx is unexpected, but this need not be the case in the data. We find, as the model predicts, that order flow's explanatory power comes from its unexpected component.

⁶ Note that the Feedback hypothesis does not imply that causality runs wholly in reverse. For example, the Feedback hypothesis does not rule out that feedback trading can affect prices.

Table 2

Portfolio shifts model: Alternative specifications

$$\Delta p_t = \beta_1 \Delta(i_t - i_t^*) + \beta_2 \Delta x_t + \beta_3 \Delta x_{t-1} + \eta_t$$

$$\Delta p_t = \beta_1 \Delta(i_t - i_t^*) + \beta_2 \Delta x_t + \beta_3 \Delta p_{t-1} + \eta_t$$

	$D(i_t - i_t^*)$	Dx_t	Dx_{t-1}	Dp_{t-1}	Diagnostics		
					R^2	Serial	Hetero
DM	0.40	2.16	0.29		0.65	0.76	0.39
	(0.36)	(0.18)	(0.19)			0.48	0.03
	0.42	2.17		0.11	0.66	0.60	0.38
	(0.35)	(0.18)		0.07		0.44	0.01
Yen	2.48	2.90	-0.20		0.47	0.07	0.55
	(0.91)	(0.36)	(0.35)			0.41	0.84
	2.64	2.98		-0.13	0.48	0.21	0.52
	(0.91)	(0.36)		(0.09)		0.63	0.81

The dependent variable Δp_t is the change in the log spot exchange rate from 4 pm GMT on day t-1 to 4 pm GMT on day t (DM/\$ or ¥/\$). The regressor $\Delta(i_t - i_t^*)$ is the change in the one-day interest differential from day t-1 to day t (* denotes DM or ¥, annual basis). The regressor Δx_t is interdealer order flow between 4 pm GMT on day t-1 and 4 pm GMT on day t (negative for net dollar sales, in thousands). Estimated using OLS. Standard errors are shown in parentheses (corrected for heteroskedasticity in the case of the DM). The sample spans four months (May 1 to August 31, 1996), which is 89 trading days. The Serial column presents the p-value of a chi-squared test for residual serial correlation, first-order in the top row and fifth-order (one week) in the bottom row. The Hetero column presents the p-value of a chi-squared test for ARCH in the residuals, first-order in the top row and fifth-order in the bottom row.