

Currency Orders and Exchange Rate Dynamics: An Explanation for the Predictive Success of Technical Analysis

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ABSTRACT

This paper documents clustering in currency stop-loss and take-profit orders, and uses that clustering to provide an explanation for two familiar predictions from technical analysis: (1) trends tend to reverse course at predictable support and resistance levels, and (2) trends tend to be unusually rapid after rates cross such levels. The data are the first available on individual currency stop-loss and take-profit orders. Take-profit orders cluster particularly strongly at round numbers, which could explain the first prediction. Stop-loss orders cluster strongly just beyond round numbers, which could explain the second prediction.

EXCHANGE RATE RESEARCH HAS BROUGHT to light a robust but unexplained result: Technical analysis is useful for predicting short-run exchange rate dynamics. This is true for a wide variety of technical trading tools, including visual patterns, trend identification formulas, trend reversal signals, and genetic algorithms.¹ The one potential explanation for this phenomenon familiar to exchange-rate economists—central bank intervention—does not survive rigorous scrutiny (Neely (2000) and Osler (2002)). The ability of some technical methods to predict high-frequency exchange rate movements contrasts with the predictive difficulties of structural exchange-rate models. Beginning with Meese and Rogoff (1983), researchers have consistently found that structural models fail to outperform random walk models at predicting short-run exchange rate movements out of sample (Frankel and Rose (1995), Faust, Rogers and Wright (2001)).

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¹For visual patterns see Chang and Osler (1999) and Lo, Mamaysky, and Wang (2000); for trend identification formulas, see Dooley and Shafer (1984) and Levich and Thomas (1993); for trend-reversal signals, see Osler (2000, 2002); for genetic algorithms, see Neely, Weller, and Ditmar (1997) and Neely and Weller (2000).

Technical analysts have long asserted that their predictions work because orders are clustered. According to one technical analyst respected within the field: "A support zone represents a *concentration of demand*, and a resistance zone a *concentration of supply*" (Pring (1985), p. 185, italics in the original). Economists typically view the idea skeptically, since the clustering of order flow is not predicted by theoretical models. Nevertheless, research indicates that stock market limit orders cluster, and that round numbers are a favored cluster point (Osborne (1962), Niederhoffer (1965, 1966), Harris (1991), Cooney, VanNess, and VanNess (2000), Kandel, Sarig, and Wohl (2001)).

This paper examines order clustering in currency markets using the first available data on stop-loss and take-profit orders. These orders, which differ structurally from limit orders (as described in the text), are market or "at best" orders conditional on rates hitting a certain level. A stop-loss (take-profit) buy order instructs the dealer to purchase currency once the market rate rises (falls) to a certain level; sell orders are defined accordingly. The data include 9,655 orders with an aggregate value in excess of \$55 billion, and cover three currency pairs—(1) dollar-yen, (2) dollar-U.K. pound, and (3) euro-dollar. The orders were placed at National Westminster Bank, a large dealing bank, from August 1, 1999, through April 11, 2000. The paper shows that currency stop-loss and take-profit orders cluster strongly at round numbers (e.g., \$1.4300/£, ¥123.50/\$), consistent with the clustering found for equity limit orders.

Based on order-clustering patterns in executed orders, I propose an explanation for two widely used predictions of technical analysis: (1) downtrends (up-trends) tend to reverse course at "support" and "resistance" levels, which can be identified *ex ante* and which are often round numbers; and (2) trends tend to be unusually rapid after rates cross support and resistance levels. In stock markets, limit order clustering per se has been used to explain a tendency for trends to reverse at round numbers (Niederhoffer and Osborne (1966)). In currency markets, explanations for price dynamics must be based on *differences* in clustering patterns across order types, because the influence of stop-loss and take-profit orders would be offsetting if the orders clustered similarly. This paper highlights two differences in clustering patterns. First, executed take-profit orders cluster more strongly at round numbers ending in 00 than do stop-loss orders. Thus order clusters at such levels would tend to be dominated by take-profit orders. Since exchange rates generally rise in response to a preponderance of buy orders, and vice versa (Evans and Lyons (1999), Rime (2000), Evans (2001), Lyons (2001)), trends would be likely to reverse when they hit take-profit-dominated order clusters at round numbers, fulfilling technical analysts' first prediction. Second, stop-loss buy orders cluster at rates just above round numbers; stop-loss sell orders cluster just below round numbers; there are no similar asymmetries for take-profit orders. Thus, clusters just beyond round numbers dominated by stop-loss orders could propagate existing trends consistent with technical analysts' second prediction.

Theory suggests that exchange rates might respond differently to clusters of take-profit orders than they do to order flow on average. The average exchange rate response to order flow could be due to "information effects," in which dealers

respond to the news conveyed by individual orders. If only information effects are operative, however, there should be no average effect of take-profit order clusters on exchange rates: The unconditional expected size of each cluster, equal to average cluster size, should have no effect on rates because it conveys no news. The surprise component should have zero mean itself, and, since the effects of positive and negative take-profit order surprises should be symmetric, there should also be zero mean effect on exchange rates. The connection between order flow and exchange rate changes need not reflect information effects exclusively, however. It could also reflect “inventory effects,” in which order flow generates inventory adjustments among dealers, which in turn generate a price response if the instantaneous elasticity of currency demand is finite (O’Hara (1995)). Alternatively, the effect of order flow could reflect a downward sloping long-run demand for currency, which in turn could be generated by heterogeneous agents dealing with assets for which there are no perfect substitutes (Harris and Gurel (1986)). If inventory or downward demand effects are operative, clusters of take-profit orders should affect exchange rates in a manner consistent with the estimated response of exchange rates to aggregate order flow. Osler (2002) demonstrates that exchange rates do tend to reverse course at round numbers, suggesting that information is not the only connection between order flow and exchange rates.²

This paper also considers why orders might cluster at round numbers. It seems unlikely that the use of round numbers is intended to balance the costs of negotiating precise prices against the benefits of such prices (Grossman et al. (1997)). This is because large orders, which benefit the most from precise pricing, are more likely to be placed at round numbers than small orders. Evidence presented here is consistent with the communication efficiency hypothesis—that agents choose round numbers to minimize time and error in their communication with dealers (Grossman et al. (1997)). Evidence also supports the hypothesis that agents prefer certain numbers for purely behavioral reasons (Yule (1927)), possibly because they are easiest to process cognitively (Goodhart, Ito, and Payne (1996), Kandel et al. (2001)). Once the patterns of order clustering are established, they may be self-reinforcing even in the presence of rational speculative activity.

To my knowledge, this is the first empirical paper to analyze positive feedback trades at the individual trade level. A number of theoretical papers have examined how stop-loss orders and other forms of positive feedback trading, such as portfolio insurance, might affect price dynamics. These papers consistently conclude that positive feedback trading may increase volatility (Grossman (1988), DeLong et al. (1990), Frankel and Froot (1990), Krugman and Miller (1993), and Grossman and Zhou (1996)). Genotte and Leland (1990) show that markets will have a tendency to move discontinuously, or crash, if large but unanticipated amounts of stop-loss trading are triggered at certain levels. As shown below, the preconditions for discontinuous price action are satisfied in currency markets:

² Osler (2002) shows that exchange rates do behave as predicted by technical analysts, while the present paper suggests why exchange rates behave that way. Note that the exchange rate’s average response to stop-loss orders could be nonzero even if information effects are the only ones operative (note 19).

Stop-loss orders cluster strongly, and the magnitude of individual clusters cannot be fully anticipated by the market since information about orders is not publicly available. Osler (2002) provides evidence that stop-loss orders contribute to large, rapid, self-reinforcing price moves, or “price cascades.”

The paper has three sections and a conclusion. Section I provides background information on stop-loss and take-profit orders (jointly, “price-contingent orders”), and describes the data. Section II, the core of the paper, documents the clustering patterns of requested execution prices and discusses how they could explain technical analysts’ predictions that exchange rates tend to reverse course at round numbers and to trend strongly after crossing such numbers. Section II also notes that order clustering at round numbers could be self-reinforcing even in the presence of rational speculators. Section III compares the implications of limit orders for stock markets with the implications of price-contingent orders for exchange rates. Section IV summarizes the analysis in and suggests some broad implications for short-run exchange rate behavior.

I. Currency Orders: Background

Stop-loss and take-profit orders are widely used in the foreign exchange market. Indeed, many practitioners recommend their use. For example, a widely read trading manual advises: “Stops placement is one of the most essential aspects of successful commodity trading. Protective stops are a highly recommended trading technique” (Murphy (1986), p. 342). Despite their common use in the foreign exchange market, stop-loss and take-profit orders are not included in standard theoretical models of that market, and have not heretofore been examined empirically. This section begins by providing background information that may serve as a useful context for later statistical work. It then describes the data.

A. Background

As suggested by its name, a stop-loss order often represents an attempt to limit losses on a given position. Likewise, a take-profit order often represents an attempt to capture profits that might otherwise disappear. However, an order can be defined as a stop-loss or take-profit order even if the agent placing it has no open currency position. The defining criteria for the order book are simply the direction of the trade (buy/sell) and whether the requested execution rate is above or below the market rate when the order is placed.

Stop-loss and take-profit orders differ structurally from limit orders, which have long been common in stock markets and are also used in some brokered currency transactions. A stop-loss or take-profit order *requires* the dealer to execute a transaction of a given size once the market reaches a certain price; the execution price may be less favorable than that requested.³ A limit order

³ Despite the decentralized nature of currency markets, dealers learn about many executed trades from voice brokers, who call out dealt prices, or through the electronic brokers EBS and Reuters Dealing 2000–2, which display a recent dealt price.

indicates that the customer is *willing* to transact at a particular price or better. If the market reaches the price specified in a limit order, the customer may not trade the full amount if there is insufficient market demand or supply at the desired price. The difference between the order types can be summarized this way: With stop-loss and take-profit orders, the amount to be traded is fixed but the execution rate is fully flexible. With limit orders, the amount to be traded is flexible but the execution rate is largely fixed.

Dealers actively seek price-contingent order flow, which is useful to them in three ways. First, it generates income via bid-ask spreads. Second, it provides private information about likely exchange-rate movements (Osler (2002)). Third, it allows them to manage risk. Suppose the rate is 1.4300, and the dealer has on his book a large take-profit sell order at 1.4310. The dealer can with relative safety open a short position at 1.4300, knowing that if the rate moves unfavorably he can buy the currency from the customer and cap his losses at 0.0010 per unit. In essence, any agent placing a take-profit order gives an option to the dealer, an observation that also holds for limit orders (Harris (1998)). In Lyons' (2001) taxonomy of the transparency of information, a dealer's price-contingent order book constitutes pretrade order flow information that is available only to the dealer.

In the academic literature, the use of price-contingent orders, and especially stop-loss orders, is often associated with imperfect rationality, either formally (Dybvig (1988)) or informally (DeLong et al. (1990), Krugman and Miller (1993)). Market participants reinforce this association when they point out that price-contingent orders are often used to control speculators' own perceived tendencies to time inconsistency.⁴ However, traders list other uses of stop-loss and take-profit orders that could be rational given certain realities of the foreign exchange market: patient traders, nontrivial trading frictions, costly information, and agency problems. I discuss these matters briefly.

Many foreign exchange market customers are "patient," in the sense that they are indifferent to the time of a transaction within a given window (Admati and Pfleiderer (1988), Harris (1998)). Patient customers, which include investment houses (Tschoegl (1988)) as well as goods and services trading firms, choose whether to trade immediately or to wait, hoping to trade later at a more favorable rate.⁵

Given the decision to wait, a customer faces another choice: He could actively monitor the market and call a dealer at the appropriate time, or he could place a price-contingent order with a dealer and let the dealer monitor the market. If the

⁴ One such tendency is known by academics as the "disposition effect": Individuals tend to hold onto losing positions longer than they hold winning positions, which is a money-losing strategy (Shefrin and Statman (1985), Odean (1998), Grinblatt and Keloharju (2000)). This would only explain the use of stop-loss orders. One might wonder why placing a price-contingent order would provide self-discipline, since agents can cancel orders before execution. The answer to this question presumably lies in the behavioral realm.

⁵ For stop-loss and take-profit orders, the costs of waiting do not include the winner's curse problem associated with limit orders (Foucault (1999), Hollifield, Miller, and Sandas (2001)), because execution is at market rates.

agent chooses to monitor the market himself, he incurs monitoring costs and also incurs risks associated with trading frictions, specifically the time required to place and execute an order. Because exchange rates change so rapidly (often more frequently than once per second), the time delay involved in placing and executing market orders imparts significant price risk.⁶ The market's high speed also makes monitoring costly, since it requires one's full attention. The high cost of market monitoring can also explain why price-contingent orders are sometimes used to hedge banks' own options positions (many options dealers do not choose to monitor the spot market) and why the bank's own spot dealers use price-contingent orders (it is costly for them to monitor the market at night).⁷

Currency dealers' use of price-contingent orders can also be traced to principal-agent problems between individual dealers and their employing institutions (Bensaid and De Bandt (2000)). To reduce their risk, foreign-exchange-dealing banks typically assign overnight loss limits to each dealer, which effectively require the dealers to protect overnight positions with stop-loss orders.

B. Data

The data comprise stop-loss and take-profit orders placed at NatWest Markets, a large foreign-exchange-dealing bank, in three currency pairs—dollar-yen, dollar-U.K. pound, and euro-dollar—from August 1, 1999, through April 11, 2000. All customer orders and the bulk of in-house orders are included.⁸ The bank keeps track of these orders in an electronic order book, which facilitates order management across time zones and allows detailed record-keeping. Information about each order includes its time of placement, requested execution rate, and order amount, as well as the desk within the bank at which it was listed. If an order is executed, the data also specify its time of execution and execution rate; otherwise, the data specify the last time at which the order was handled by the electronic order system (e.g., to shift responsibility for the order from the London to the New York office).

⁶ Payne (2000) reports that there were around 30,000 transactions in dollar-mark on Reuters Dealing 2000 during one week of October 1997.

⁷ Options dealers typically open a hedge position in the spot or forward markets at the same time they open an options position, in order to neutralize their directional risk. Though the size of the perfect hedge varies over time, transaction costs are nonzero, so options dealers adjust their hedges discretely. Everything else equal, the appropriate time for adjusting a hedge can be mapped to the level of the underlying spot or forward rate. This provides a natural motivation for using price-contingent orders. Likewise, certain "exotic" currency options are best hedged with stop-loss orders (Malz (1995)).

⁸ A few customer orders (roughly 10) were excluded due to errors in data entry. I also excluded 28 doubly price-contingent orders (orders that only become active once another order is executed), since these orders were never activated. At the suggestion of the bank, the set of in-house orders was adjusted to make the data more representative of the marketwide population of in-house orders, by excluding in-house orders with near-zero likelihood of execution at the time they were placed. In practice, this meant excluding 14 orders with requested execution rates farther from the market rate, at time of placement, than any of the customer orders (with the exception of two outliers).

There are 9,655 orders with an aggregate value in excess of \$55 billion, of which 43 percent were in dollar-yen, 33 percent in euro-dollar, and the rest in dollar-U.K. pound (24 percent). Twenty-eight percent were executed, 70 percent were deleted, and the rest remained open at the end of the sample period. On an average day, 48 new price-contingent orders were placed. Order placements for dollar-yen peaked during the Asia afternoon/London morning, and order placement for dollar-pound and euro-dollar peaked during the London afternoon/New York morning. Most orders were open for less than one day (71.6 percent). The number of open orders typically peaked at about 10 a.m. New York time, when there were on average 159 open orders in total; there was an overall peak for order execution at around the same time. As is true for interdealer trades (Evans (2001)), most price-contingent orders were executed during the roughly 10-hour interval spanning the Asian afternoon through the London afternoon/New York morning.

Orders were fairly evenly distributed by type (Table I): Take-profit orders were 57.4 percent of total orders, and the value of take-profit orders was 55.2 percent of total order value. There was also an even distribution between buy and sell orders; buy orders represent 49.1 percent of orders and of order value.⁹ The average order size was \$5.78 million and the median order size was \$3.0 million—figures that are somewhat higher than the average deal size of \$2.5 million estimated by Goodhart et al. (1996), and which roughly bracket the average trade sizes of \$3.9 million reported in Evans and Lyons (1999) and \$4 million reported in Bank for International Settlements (1999). Large orders had a statistically significant tendency to be placed farther away from current market rates than other orders, to stay open longer, and to be executed less frequently.¹⁰

Customers placed an estimated 72.8 percent of orders (Table I); the majority of these were placed by financial institutions (Table II).¹¹ The customer orders, which represent the first individual customer orders available for academic study, should be broadly representative of the marketwide population of customer orders, since the bank deals with every major type of customer—financial institutions, corporate customers, hedge funds, central banks, and wealthy individuals—from all over the world. The other customer orders data available for research describe only executed orders, aggregated on a daily basis, and do not specify the type of order—market order, stop-loss, or take-profit (Lyons (2001)). The data most often used to analyze high-frequency exchange rates—indicative quotes or transactions information from brokers—exclusively

⁹ A “buy” order is taken to be an order in which the dealer is instructed to buy the “commodity” or denominator currency of a given currency pair, as the exchange rate is conventionally quoted. The commodity currency is the dollar for dollar-yen, the pound for dollar-pound, and the euro for euro-dollar.

¹⁰ The lower likelihood of execution for large orders seems to be entirely due to the larger average gap between market rate and requested execution rate rather than to any tendency for large orders to be deleted more swiftly. For orders placed within one percent of the market rate but ultimately deleted, the average time open did not differ significantly between large and small orders. Indeed, among all orders placed within one percent of the market rate, the fraction that were actually executed is higher for large than small orders.

¹¹ Whether the order is placed by a customer or the bank itself is inferred from the desk placing the order. The bank suggests the error in this estimate is not likely to be large.

Table I
Descriptive Information on Stop-loss and Take-profit Orders

The table describes all stop-loss and take-profit orders for three currency pairs—dollar-yen, dollar-U.K. pound, and euro-dollar—placed at a major foreign exchange dealing bank over August 1, 1999, through April 11, 2000. There are 9,655 orders with aggregate value in excess of \$55 billion. The symbol * (**) indicates significance at the five (one) percent level.

	All Orders	Stop-loss	Take-profit	Z-Stat. , SL vs. TP	Large Orders (\geq \$30 Mill.)	Small Orders (<\$30 Mill.)	Z-Stat. , Lg. vs. Sm.
Number of orders	9,655	3,935	5,720		243	9,412	
Share of orders	100.0	42.6	57.4		2.5	97.5	
Size (\$ Mill.)							
Mean	5.78	6.35	5.39	3.63**	55.4	4.50	Not relevant
Median	3.00	3.24	2.12	10.81**	43.0	2.99	
Dist. to mkt. (%)							
Mean	0.92	0.91	0.93	0.52	2.43	0.88	10.32**
Median	0.53	0.43	0.68	8.08**	1.75	0.52	11.67**
Days Open							
Mean	3.79	3.42	4.05	2.39**	10.6	3.6	5.70**
Median	0.56	0.46	0.59	9.72**	0.8	0.6	5.73**
Share(s) executed	27.9	28.3	29.9	1.71*	20.2	29.5	2.88**
Share(s) placed by customers	72.8	64.1	78.8	15.9**	57.2	73.2	55.3**

Table II
Further Descriptive Information of Stop-loss and Take-profit Orders

The table lists the sources of all stop-loss and take-profit orders for three currency pairs—dollar-yen, dollar-U.K. pound, and euro-dollar—placed at a major foreign-exchange-dealing bank during August 1, 1999, through April 11, 2000. There are 9,655 orders with aggregate value in excess of \$55 billion. If orders amounts were not originally measured in dollars, the dollar value represents the original order amount adjusted by the requested execution rate. “Other” customer orders are orders from all sources placed in Tokyo and orders intended to hedge customer options positions. “Internal” orders are those placed by agents within the bank.

	Number of Orders	Percent of Orders	Dollar Value of Orders (\$ Billions)	Percent of Order Value
All orders	9,655	100.0	55.9	100.0
Customer orders	7,027	72.8	335.8	64.0
Fin. inst.	5,357	55.5	27.6	49.4
Non-fin. inst.	770	8.0	4.9	8.8
Other	900	9.3	3.3	5.9
Internal	2,628	27.2	20.1	36.0

describe interbank transactions (Goodhart and Payne (1996), Goodhart et al. (1996), Goodhart, Chang, and Payne (1997), Evans and Lyons (1999), Rime (2000), and Evans (2001)).

Customer orders are generally considered the main driving force for short-run exchange rate dynamics (Lyons (2001)). As noted by Yao (1997, p. 6), “dealers

emphasize the importance of customer trades because without them their view and understanding of the market would be limited. Moreover, customer trades generate the majority of trading profits for most FX dealers.” Price-contingent orders executed for customers may represent on the order of 15 percent of all customer business, given the following three observations: (1) customer deals represent on the order of 20 percent of all deals at this bank (by value), according to the bank; (2) customer orders account for 64 percent of all price-contingent orders (by value; Table II); and (3) the bank estimates informally that executed price-contingent orders represent on the order of five percent of deal flow. Trader comments suggest that a large fraction of all price-contingent orders, possibly greater than half, are kept in mind but never formally placed with dealers.

II. Technical Analysis and the Distribution of Orders

This section first presents the two predictions of technical analysts that are the focus of the paper. It then documents the clustering patterns of stop-loss and take-profit orders, and explains how these patterns could generate exchange-rate dynamics consistent with those predictions. Finally, it discusses why the dynamics might persist.

A. Two Predictions of Technical Analysis

Most active currency market participants use technical analysis (Allen and Taylor (1992), Lui and Mole (1998)). The two predictions on which this paper focuses are among those used most widely.

Prediction 1: Downtrends (uptrends) tend to reverse course at support (resistance) levels that can be identified ex ante.

According to one major technical analysis manual, “[S]upport is a level or area on the chart under the market where buying interest is sufficiently strong to overcome selling pressure. As a result, a decline is halted and prices turn back again. ... Resistance is the opposite of support” (Murphy (1986), p. 59). Osler (2000) shows that support and resistance levels distributed to customers by six private firms successfully identify points where exchange rates are likely to reverse course.

Prediction 2: Trends tend to be unusually rapid after rates cross support and resistance levels that can be identified ex ante.

“A breakout occurs when the [price] moves outside the trendline or channel. It indicates that there’s been an important shift in supply and demand. When confirmed, it should be acted on immediately” (Hardy (1978), p. 54). Brock, Lakonishok, and LeBaron (1992) show that breakouts beyond recent highs and lows help predict stock market trends.

Technical analysts stress the importance of round numbers as support and resistance levels. “There is a tendency for round numbers to stop advances or declines ... [R]ound numbers ... will often act as ‘psychological’ support or resistance levels. ... Traders tend to think in terms of important round numbers ... as price objectives and act accordingly” (Murphy (1986), p. 67). Among support

and resistance levels for currencies distributed by technical analysts to their customers, 96 percent end in 0 or 5, and 20 percent end in 00 (Osler (2000)).

Osler (2002) provides empirical support for predictions (1) and (2) by showing that exchange rates reverse course upon reaching round numbers more frequently than they reverse at other numbers, and that exchange rates tend to trend rapidly after crossing round numbers. The tendency to reverse course upon reaching round numbers is short-lived: Behavior is once again indistinguishable from average within an hour in most cases. The rapid trends associated with crossing round numbers remain statistically significant for at least two hours. In addition, Osler (2002) shows that there is no support, either empirical or conceptual, for the two other potential explanations from the literature for these unusual behaviors—central bank intervention and chaotic exchange-rate processes. The analysis uses minute-by-minute exchange rate quotes taken during New York trading hours for the period January 1996 through April 1998 for three currencies—dollar-yen, dollar-U.K. pound, and dollar-mark. Results, which are generally consistent across the three currencies, are based on bootstrap tests in which exchange rate behavior near round numbers is compared with exchange rate behavior at arbitrary numbers (Efron (1979, 1982)).¹²

In currency markets, the concept of a round number is only well defined because of two quotation conventions. First, market makers consistently quote rates in the three currency pairs as follows: (1) yen per dollar, (2) dollars per pound, and (3) dollars per euro. Second, these rates are consistently quoted to a fixed number of significant digits. For dollar-pound and euro-dollar (dollar-yen) there are four (two) digits to the right of the decimal point. Below, the paper will refer repeatedly to the “final two significant digits” of exchange rates; this means the two digits at the right end of the rate as conventionally quoted. Existing exchange rate models, in which the key economic variable is always the log of the exchange rate, implicitly assume the irrelevance of quotation conventions.

B. Order Clustering

To explain their predictions, technical analysts often appeal to unevenness in order flow. Edwards and Magee (1997), the most widely known source in this field, define support as “buying, actual or potential, sufficient in volume to halt a downtrend in prices for an appreciable period,” and resistance as “selling, actual or potential, sufficient to satisfy all bids and hence stop prices from going higher for a time” (p. 211).

Order clustering at round numbers, one potential source of uneven flow, has been documented for stock market limit orders. Kandel et al. (2001) show that limit orders submitted by Israeli investors at IPO auctions cluster at prices ending in 0 and 5. In U.S. stock markets, limit orders also cluster at prices ending in

¹²The analysis of Osler (2002) applies to intraday data. While most historical applications of technical analysis have been at longer horizons, this probably reflects data availability. Technical analysts assert explicitly that their principles apply at any frequency. For example, “Regardless of the ‘periodicity’ of the data in your charts (i.e., hourly, daily, weekly, monthly, etc.), the basic principles of technical analysis endure. ... Opportunities exist in any time frame” (Achelis (2001)).

0 and 5, with stronger clusters at numbers ending in 0 (Harris (1991)). Before the shift to decimal pricing (completed in April 2001), limit order prices not at whole numbers clustered most strongly at the halves, and secondarily at the other even eighths (Osborne (1962), Niederhoffer (1965, 1966), Harris (1991)).

Researchers suggest a number of reasons for order clustering. Harris (1991) suggests that market participants use a subset of the available prices to simplify their negotiations. Grossman et al. (1997) suggest that some clustering is appropriate in every market. “The optimal minimum tick will be smaller than the unit of trade typically used during periods of normal trading activity. If market participants typically used the minimum tick as the unit of trade, then the market would lack the flexibility to reduce the minimum tick to allow for smaller units of trade when appropriate” (p. 26). To explain how individual cluster points are selected, Goodhart and Curcio (1991), Kandel et al. (2001), and Yule (1927) suggest that people simply prefer round numbers. A number of factors could contribute to this preference. First, Grossman et al. (1997) provide what I call the “communication efficiency” hypothesis, when they note that precision is costly because it raises both the time required to communicate prices and the potential for communication errors. Second, the preference could be related to cognitive efficiency, that is, the ease with which numbers can be remembered and mentally manipulated. Finally, the preference could be even more basic. As early as 1927, Yule identified a “human tendency to select and identify with round numbers (0s), halves (5s), quarters, and even numbers” (Mitchell (2001), p. 408); Yule implies that this tendency derives from deeper in the human psyche than a cognitive cost–benefit analysis.

Orders clustering at round numbers is evident in currency markets. To identify round numbers, let M_{ij} be the last two digits in the requested execution rate of order j in currency i (X_{ji}), and let A_i be an adjustment factor that is 1000 for dollar-pound and euro-dollar, and 100 for dollar-yen: $M_{ij} = \text{modulo}(X_{ji}A_i; 100)$. Figure 1 plots the overall frequency distribution of M_{ij} for all orders in all currencies. If requested execution rates did not cluster, these frequencies would be roughly uniform at 1.0 percent. Instead, the pattern of frequencies has high spikes at round numbers. The single greatest cluster is at levels ending in 00 (such as ¥123.00/\$, \$0.9100/€, or \$1.6700/£), where 9.9 percent of order value is placed. There are also clusters, of declining magnitude, at levels ending in 50, at other levels ending in 0, and at levels ending in 5. There is no special tendency for rates to cluster at levels ending in 25 or 75. Though relatively few orders have requested execution rates ending in digits other than 0 or 5, there are some intriguing preferences within this latter group: 2 and 8 are favored over 3 and 7, which, in turn, are favored over 1, 4, 6, and 9.^{13,14}

¹³ Marginal significance for the comparison between the joint frequency of orders at 2 and 8 on the one hand, and at 3 and 7 on the other hand, is 0.000 (z -statistic 10.9). Marginal significance for the comparison between joint frequencies at 3 and 7 on the one hand, and at 1, 4, 6, and 9 on the other hand, is also 0.000 (z -statistic 8.3).

¹⁴ Two additional observations strengthen the parallel between order clustering in stock and currency markets. First, clustering is stronger for stocks traded in dealer markets, whose structure is closest to the foreign exchange market, than for exchange-traded stocks. Second, limit orders are most similar to take-profit orders, which show the tiering of clusters more prominently than stop-loss orders (Figure 3A–D).

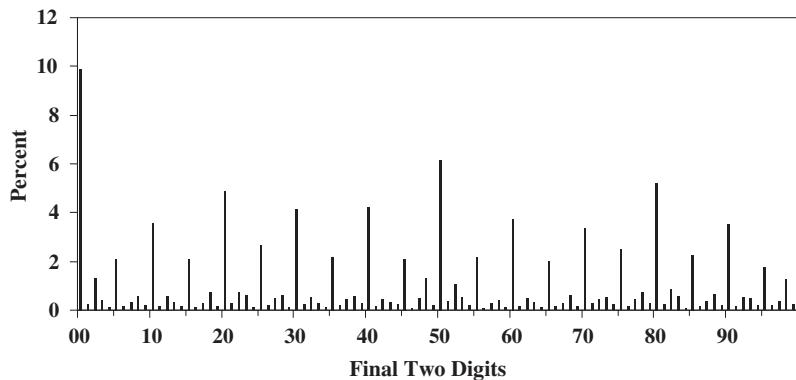


Figure 1. Placed orders, distribution of final two digits of requested execution rates. The figure shows the frequency distribution of requested execution rates for stop-loss and take-profit orders, looking only at the final (right-hand) two digits. (For an order with execution rate \$1.4321/l, ¥143.21/\$, or \$0.9821/0, the last two significant digits were 21.) The underlying data include 9,655 orders with aggregate value in excess of \$55 billion. These represent all stop-loss and take-profit orders for three currency pairs—dollar-yen, dollar-U.K. pound, and euro-dollar—processed by a major dealing bank during August 1, 1999, through April 11, 2000.

The hypothesis that the overall distribution is consistent with the uniform can be rejected at far beyond the 0.01 percent level using the Anderson–Darling test (D’Agostino and Stephens (1986)).¹⁵ With the full sample of 9,655 orders, any individual frequency above 1.17 percent or below 0.83 percent differs significantly from one percent at the five percent significance level (using the binomial distribution). The frequencies for all levels ending with 0 or 5 surpass the higher critical value, and the frequencies for all levels ending in 1, 3, 4, 6, 7, and 9, fall below the lower critical value. Frequencies for most levels ending in 2 and 8 fall below the lower critical value.

Some but not all the reasons for order clustering reviewed above seem relevant to the clustering of stop-loss and take-profit orders. All the preferences are consistent with Yule’s “pure preference” hypothesis. The preference for numbers ending in 00 relative to all other numbers is also consistent with both the communication efficiency hypothesis and the cognitive efficiency hypothesis. However, communication efficiency seems unlikely to be a complete explanation for the clustering phenomenon, since levels ending in 5 (or halves or quarters when prices are quoted in eighths) are preferred to all other levels that do not end in 0, though these other levels are equally costly in terms of communication efficiency. The preference for levels ending in 5, and other subsidiary preferences such as that for 2 and 8 over 1 and 9, are consistent with the cognitive efficiency hypothesis. Further evidence consistent with a behavioral component to agents’ preferences among numbers is presented in Section III.

¹⁵The Anderson–Darling test statistic is 74.6 on a scale of $(0, \infty]$; the critical value for 0.01 percent significance is 8.0.

The ease-of-negotiation hypothesis does not seem relevant to currency order clustering. This hypothesis predicts that larger orders should be less likely than small orders to be placed at round numbers, because the benefits of precision rise with order size while the costs of negotiation are relatively invariant to order size (Grossman et al. (1997)). However, the data do not support this prediction: 14.4 percent of large order value (with large orders defined as having dollar value at or above \$30 million) was placed at rates ending in 00, a figure that is statistically significantly higher than the 9.4 percent figure for other orders.

Since our intent is to examine the impact of stop-loss and take-profit orders on exchange rates, it is most important to focus on the subset of such orders that were actually executed, and to weight those orders by their values. As shown in Figure 2, the pattern of order clustering among executed orders weighted by value is qualitatively similar to the pattern for all placed orders, but less pronounced. For example, the frequency of orders with requested execution rates ending in 00, which is 9.9 percent in Figure 1, is only 7.2 percent in Figure 2. This difference can be traced to two aspects of agents' order placement strategies already noted. First, large orders have a stronger tendency to cluster at round numbers than small orders. Second, large orders tend to be placed farther from the current market rate than other orders, where they are less likely to be executed.

C. Differences between Stop-loss and Take-profit Orders

The clustering of executed stop-loss and take-profit orders at round numbers, while suggestive of the order clustering cited by technical analysts, cannot explain their predictions. The four types of orders included in the aggregate—(1) stop-loss buy, (2) take-profit buy, (3) stop-loss sell, (4) take-profit sell—could each potentially affect rates differently. To account for exchange rate dynamics one

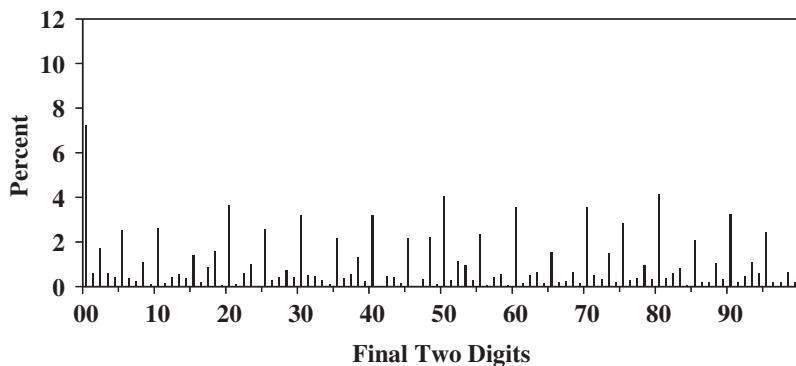


Figure 2. Executed order value, distribution of final two digits of requested execution rates. The figure shows the frequency distribution of requested execution rates of executed price-contingent orders, looking only at the final (right-hand) two digits. (For an order with execution rate \$1.4321/l, ¥143.21/\$, or \$0.9821/0, the last two significant digits were 21.) Orders are weighted by dollar value. The underlying data include 2,694 executed orders with aggregate value of \$14.7 billion, processed by a major dealing bank during August 1, 1999, through April 11, 2000.

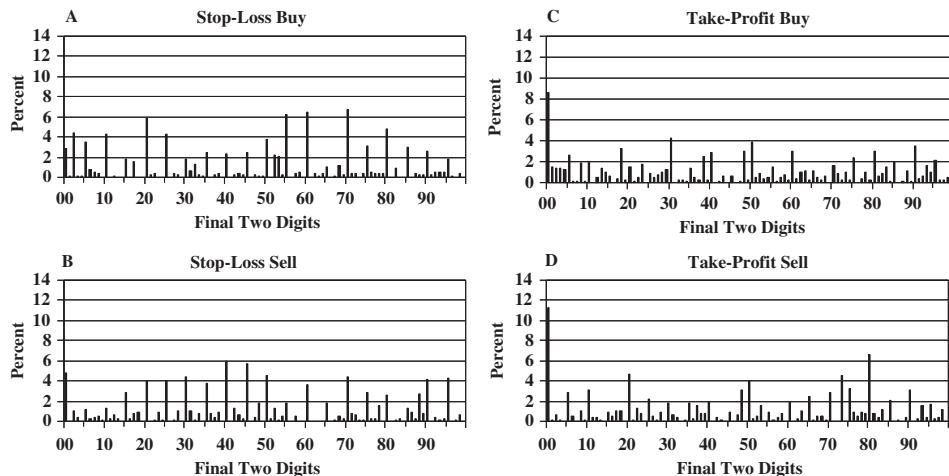


Figure 3. Executed rates by order type, distribution of final two digits of requested execution rates. The figure shows the frequency distribution of the final (right-hand) two digits of requested execution rates for all stop-loss and take-profit orders for three currency pairs—dollar-yen, dollar-pound, and euro-dollar—executed by a major dealing bank during August 1, 1999, through April 11, 2000. There are 2,694 orders with aggregate value near \$14.6 billion. Orders are aggregated across currencies and weighted by dollar value.

must examine each order type separately. Figure 3A–D shows the frequency distribution of M_{ij} for each order category. The tendency to cluster at round numbers is common to all four order types. Nonetheless, two critical asymmetries are apparent, which are summarized in Table III. I argue later that these two asymmetries could explain predictions (1) and (2). First, I document their statistical significance and their origin.

Asymmetry 1: Executed take-profit orders cluster more strongly at numbers ending in 00 than executed stop-loss orders.

Exchange rates ending exactly at 00 trigger 9.8 percent of take-profit order value but only 4.3 percent of stop-loss order value.

Statistical significance: For hypothesis testing, I use the bootstrap technique, because the underlying frequency distributions do not conform to any standard parametric distribution. (For more on the bootstrap, see Efron (1979, 1982).) The null hypothesis has two components: First, 00 is not special among rates ending in 0; second, the frequencies for rates ending in 0 have the same distribution for stop-loss and take-profit orders. The test focuses on the difference of 11.2 percentage points between the sum of the actual frequencies at 00 for executed take-profit orders (8.2 (buy) + 11.8 (sell)) and the sum of actual frequencies at 00 for executed stop-loss orders (4.4 + 4.3) (Table III).¹⁶ It is necessary to find the likelihood of observing a value as large as 11.2 under the null.

¹⁶The difference between 11.2 and the 11.3 figure one would infer from the text is due to rounding.

Table III
Requested Execution Rates near Round Numbers

The table summarizes asymmetries in the distribution of requested execution rates near round numbers ending in 00 and 50 for price-contingent orders. Underlying data are all stop-loss and take-profit orders for three currency pairs—dollar-yen, dollar-U.K. pound, and euro-dollar—executed at a major bank during August 1, 1999, through April 11, 2000. There are 2,694 orders with aggregate value near \$14.6 billion. For each entry, I take the percent of executed orders of each order type with requested execution rates ending in the indicated set of two-digit numbers, and sum them. The marginal significance represents the likelihood of observing the actual difference between orders above and below the round number, under the following null hypothesis: Agents' preferences for round numbers are consistent with those in Figure 3A–D, with a strongest preference for rates ending in (0) and successively weaker preferences for rates ending in (5), the set (2,3,7,8), and the set (1,4,6,9). However, agents' preferences do not differ significantly according to the digit preceding these numbers. For each type of order, 2,000 sums of 10 frequencies were generated, where each set included one observed frequency from rates ending in 0, one observed frequency from rates ending in 5, four observed frequencies from rates ending in 2, 3, 7, or 8, and four observed frequencies from rates ending in 1, 4, 6, or 9. From these, 1,000 differences were calculated and ranked. The ranked simulated differences provided marginal significance levels for the actual differences. Numbers in parentheses are marginal significance levels for the same tests applied to frequencies for all placed orders, weighted by order value.

	Stop-loss Orders		Take-profit Orders	
	Buy	Sell	Buy	Sell
At 00	4.4	4.3	8.2	11.8
Around 00				
90–99	7.3	8.2	11.2	10.3
01–10	17.0	6.9	9.7	7.1
Difference	9.6	–1.3	–1.5	–3.2
Marg. Sig.	0.022	0.197	0.266	0.255
Around 50				
40–49	4.8	15.0	9.1	8.3
51–60	17.0	6.7	7.6	7.6
Difference	12.2	–8.3	–1.5	–0.7
Marg. Sig.	0.005	0.000	0.264	0.461

Ten thousand sets of four numbers are chosen at random from the sample frequencies for all rates ending in 0. From each set, the first two are summed, the last two are summed, and the difference between sums is taken. The ranked absolute values of these 10,000 simulated differences provides the distribution from which to calculate the marginal significance for the observed difference under the null. That marginal significance is 0.5 percent, which indicates that executed take-profit orders are indeed more strongly concentrated at 00 than executed stop-loss orders.

Origin: Only part of this asymmetry can be traced to patterns in the initial placement of requested execution rates, in which the fraction of orders at 00 is 10.6 percent for all take-profit orders and 8.9 percent for all stop-loss orders. The difference of 1.7 percentage points, though statistically significant, is less than half the corresponding difference of 5.5 percentage points for executed order value. To explain the rest of this asymmetry, recall that the fraction of order value

at 00 is lower for executed orders than for placed orders, because larger orders are executed relatively infrequently. It turns out that the difference between placed and executed order value at 00 is greater for stop-loss than take-profit orders for two reasons. First, large stop-loss orders tend to be bigger than large take-profit orders, and small stop-loss orders tend to be smaller than small take-profit orders. Second, the fraction of large orders at 00 is larger for stop-loss than for take-profit orders. Table IV presents the details of these comparisons.

Asymmetry 2: Stop-loss buy orders are more strongly clustered above than below round numbers, and the opposite is true for stop-loss sell orders.

For example, 17.0 percent of executed stop-loss buy order value is found at rates ending in the range [01,10]; less than half as much, 7.3 percent, is found at rates ending in [90,99]. A similar asymmetry can be observed above and below 50. Executed take-profit orders exhibit no pronounced asymmetries above and below round numbers.

Statistical significance: This asymmetry is formalized by comparing the frequency of orders in the range [90,99] with their frequency in the range [01,10]; a similar comparison is undertaken for orders placed at levels above and below 50. Once again, the bootstrap technique is used and the null hypothesis has two components. The first component is that agents' preferences for round numbers are tiered into five categories: (1) all rates ending in 0; (2) all rates ending in 5; (3) all rates ending in 2 and 8; (3) all rates ending in 3 and 7; and (5) all rates ending

Table IV
Sources of Asymmetry between Stop-loss and Take-profit Orders

This table documents the size and statistical significance of two asymmetries between stop-loss and take-profit orders that help explain the lower concentration of order value at 00 for executed stop-loss than for executed take-profit orders. Underlying data comprise all stop-loss and take-profit orders for three currency pairs—dollar-yen, dollar-U.K. pound, and euro-dollar—placed at a major foreign-exchange-dealing bank during August 1, 1999, through April 11, 2000. There are 9,655 orders with aggregate value in excess of \$55 billion. Panel A: Among placed orders, large stop-loss orders tend to be bigger than large take-profit orders, and small stop-loss orders tend to be smaller than small take-profit orders. Panel B: Among placed orders, not weighted by value, the difference in concentration at 00 between large and small orders is more pronounced for stop-loss orders.

	Large SL	Large TP	Small SL	Small TP
Panel A:				
Average size (\$ mill.)	61.73	50.71	4.85	4.26
Standard deviation	60.65	30.17	4.98	5.03
Number observations	104	139	3831	5581
Test	Z = 1.702	Marg.Sig. = 0.044	Z = 5.592	Marg.Sig. = 0.000
Panel B:				
Percent orders at 00	14.42	8.77	9.35	10.64
Number observations	104	3831	139	5581
Test	Z = 1.996	Marg.Sig. = 0.023	Z = 0.480	Marg.Sig. = 0.313

in 1, 4, 6, and 9. The second component is that differences between frequencies within each preference category are random, for example, there is no special preference for 55 over 25 or 35.

For each type of order (stop-loss buy, stop-loss sell, take-profit buy, take-profit sell), I create 20,000 sums of 10 frequencies selected at random, where each set includes:

1. One of the sample frequencies for rates ending in 0,
2. One of the sample frequencies for rates ending in 5,
3. Two of the sample frequencies for rates ending in either 2 or 8,
4. Two of the sample frequencies for rates ending in either 3 or 7,
5. Four of the sample frequencies for rates ending in either 1, 4, 6, or 9.

This construction ensures that each set of 10 has the same number of entries from each preference category as the range it is intended to represent (e.g., [90,99]). Each set of 10 is summed and paired with another sum of 10; then the difference between the two sums is calculated. The ranked simulated differences provide the distribution from which to calculate the marginal significance of the observed difference under the null.¹⁷ Three of the four stop-loss asymmetries are significant at the five percent level. Overall, this indicates rejection of the null hypothesis that the distributions of executed stop-loss buy and sell orders are symmetric around 00 and 50. All four marginal significance levels for the take-profit asymmetries exceed 10 percent by comfortable margins (Table III), indicating that we cannot reject the symmetry hypothesis for executed take-profit orders.

Origin: The test just described yields qualitatively similar results when applied to the frequency distribution of all placed orders unweighted by value. Since this is the distribution that best represents agents' preferences among exchange rate levels, it appears that this second asymmetry originates in agents' preferences for order location relative to round numbers, and is not strongly related to order execution patterns.¹⁸

D. Technical Analysis

This section discusses how asymmetries (1) and (2) could explain technical analysts' predictions (1) and (2), respectively.

¹⁷ Note that this analysis assumes that there is no stronger preference for rates ending in 00 than there is for other rates ending in 0. If rates ending in 00 are excluded from the set of rates ending in 0, consistent with the Asymmetry 1 (an approach more favorable to the asymmetry hypotheses under investigation), results differ only slightly from those reported.

¹⁸ For these asymmetries around 00 and 50, marginal significance levels for placed stop-loss orders, unweighted by value, are: Buy orders around 00, 0.9 percent; sell orders around 00, 1.4 percent; buy orders around 50, 5.0 percent; sell orders around 50, 1.1 percent. Marginal significance levels for corresponding data on take-profit orders are all above 19 percent.

Asymmetry (1) and Prediction (1): The fact that take-profit orders cluster more than stop-loss orders at levels ending in 00 could explain why technical analysts predict that trends often reverse course at round numbers. To clarify this, it is helpful to note why the frequencies in Figure 3A–D might be related to exchange rate dynamics. Suppose that rates rise by one point between periods $t - 1$ and t . This rise triggers the execution of stop-loss buy and take-profit sell orders in period t . The order amounts depend in part on the last two digits of the exchange rate, kl , so let $SL^b(kl)_t$ represent the amount of active stop-loss buy orders, and $TP^s(kl)_t$ represent the amount of active take-profit sales orders, with requested execution rate kl at time t .

When these orders are executed, their effect on exchange rates should only be related to net order flow, or $SL^b(kl)_t - TP^s(kl)_t$. The unconditional expected value of this difference is related to the difference in population frequencies:

$$E[SL^b(kl)_t - TP^s(kl)_t] = s^b(kl) - t^s(kl)r]V \quad (1)$$

where $s^b(kl)$ represent the share of all stop-loss buy order value executed at levels ending in l , $t^s(kl)$ represents the corresponding proportion of take-profit sales order value, r represents the ratio of all take-profit sell order value to all stop-loss buy order value, and V represents the value of the population of executed stop-loss buy orders. Since our sample of orders is likely to be representative of the broader population of orders, and r in the sample does not differ greatly from unity (Table I), any large difference in sample frequencies should correspond to a large expected difference in executed order amounts.

To finish connecting frequencies to exchange rate dynamics, we apply recent evidence that exchange rates generally rise when buy orders dominate aggregate deal flow, and fall when sell orders dominate (Evans and Lyons (1999), Rime (2000), Evans (2001), Lyons (2001)). Suppose the exchange rate rises to a level ending in 00. Assume for convenience that deal flow unrelated to price-contingent orders nets to zero, so that price dynamics are determined by price-contingent order flow. According to the data underlying Figure 3A–D, only 4.4 percent of all stop-loss buy order value is triggered at levels ending in 00—substantially less than the 11.8 percent of take-profit sell order value triggered at such levels. Therefore, price-contingent order flow would likely be dominated by take-profit sales orders and rates should fall, reversing the previous trend and fulfilling technical analysts' first prediction.

The effect of take-profit order clusters on exchange rates might differ from the estimated effect of aggregate order flow. Microstructure theory highlights three main reasons why order flow could affect financial prices: one based on information, a second based on a downward sloping long-run demand curve for currencies, and a third based on inventories. Only the latter two connections support any average influence from take-profit order clusters to exchange rates.

Information: When order flow conveys private information about fundamental values (as in Glosten and Milgrom (1985), Kyle (1985)), then market makers will raise (lower) prices in response to informative buy (sell) orders. Order clusters are partly predictable to market players, since customers themselves place the

orders and dealers execute them. Only the surprising component of an order cluster should convey news, and, with unbiased expectations, this component should be zero, on average. If the effects of positive and negative order surprises are symmetric and if information is the only connection between order flow and exchange rates, then average effect of order clusters should be zero. The effects of take-profit order surprises are likely to be symmetric.

Downward Sloping Long-Run Demand: The long-run demand curve for an asset can be downward sloping under two sets of conditions: The first is that agents are risk averse and the asset has no perfect substitutes. In that case, an exogenous change in the asset's demand or supply can cause a permanent price change even in the absence of new information (Harris and Gurel (1986)). It is well known that the major exchange rates, of which there are only a few, are poorly correlated with each other and with other financial assets. The second set of conditions under which demand for an asset could be downward sloping is that arbitrage is limited and agents are heterogeneous. Limits to arbitrage, such as position limits for dealers, limits to portfolio allocations among institutional investors, and credit constraints (Shleifer and Vishny (1997)), certainly exist in currency markets. Agent heterogeneity can arise along many dimensions, including agents' opinion of the asset's true value and agents' risk tolerance. Substantial evidence indicates that agents in currency markets are in fact heterogeneous, at least with respect to their expected future exchange rates (Goodman (1979), Ito (1990)). In short, the conditions under which asset demand curves are downward-sloping could well be satisfied in markets for the major liquid currencies.

Inventories: Inventory models suggest that dealers will manage their inventory positions carefully, since all inventory is exposed to price risk (Amihud and Mendelson (1980), Ho and Stoll (1981)). Foreign exchange dealers, in particular, have been shown to prefer inventory levels near zero (Lyons (1995), Yao (1997), Bjonnes and Rime (2000)). Most theoretical models suggest that dealers manage inventory positions by shading prices: In currency markets, a dealer finding himself long might quote lower prices to attract buy orders and discourage sell orders. Evidence for price shading in currency markets is mixed. Lyons shows that one dealer did respond by shading prices to other dealers. Dealers analyzed in Bjonnes and Rime and Yao, however, did not shade prices to other dealers.

The absence of price shading need not imply the absence of marketwide inventory effects. The classic inventory effect models examine market makers for whom price shading is the only inventory management tool available (Amihud and Mendelson (1980), Ho and Stoll (1981)). In currency markets, dealers can also trade with other dealers. Indeed, dealers studied in Bjonnes and Rime (2000) and Yao (1997) all tended to unload excess inventory through brokered transactions with other dealers. When a dealer offloads unwanted inventory through a broker, other dealers can observe the transaction, including whether it is at the bid or the offer, and adjust their prices accordingly (Goodhart et al. (1996)). In this way, the market as a whole may adjust rates in response to an inventory imbalance, even though the individual dealer with the imbalance does not shade his rates directly.

As noted earlier, rates reverse course relatively frequently at such levels, consistent with the first prediction of technical analysis (Osler (2002)). This observa-

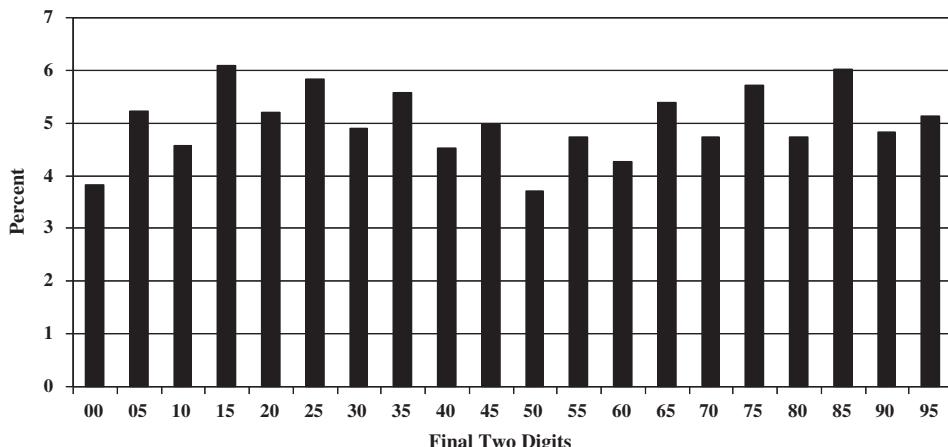


Figure 4. Exchange rate midpoints, distribution of final two digits. The figure shows the frequency distribution of exchange rate quotes, looking only at the final (right-hand) two digits. Exchange rates are the midpoint of bid and ask quotes for dollar-mark, dollar-yen, and dollar-U.K. pound, sampled at one-minute intervals between 9 a.m. and 4 p.m., New York time, from January 1996 through April 1998. Midpoints were rounded to two significant digits for dollar-yen and to four significant digits for dollar-mark and dollar-U.K. pound. Levels are grouped into five-unit buckets, with each bucket centered on the number shown on the axis.

tion suggests that the average effect of take-profit order clusters is nonzero which, in turn, suggests that noninformative order flow influences exchange rates—though it does not clarify the source of that influence.

Asymmetry (2) and Prediction (2): The large stop-loss buy (sell) order clusters just above (below) round numbers could explain why technical analysts predict that uptrends (downtrends) tend to be relatively rapid after rates cross round numbers. Suppose rates fall through \$1.4350/£ and reach \$1.4345/£; this triggers stop-loss sell and take-profit buy orders. According to the data underlying Figure 3, 4.5 percent of all executed stop-loss sell orders have an execution rate ending in 45; the corresponding percentage for executed take-profit buy orders is only 2.0. Thus price-contingent order flow would likely be dominated by sell orders. If there are marketwide inventory effects or if agents are heterogeneous, the execution of these sell orders would accelerate the existing downward trend, fulfilling technical analysts' second prediction. Osler (2002) shows that exchange rates trend rapidly after crossing round numbers, and thus conform to the second prediction of technical analysis. Osler also provides evidence that this unusual exchange rate behavior derives from stop-loss order clusters, and not from central bank intervention or any other possible source suggested in the literature.¹⁹

¹⁹ A nonzero average effect of stop-loss orders need not imply that rates respond to noninformative order flow. If price cascades occur in which stop-loss orders are executed in waves, the average (signed) exchange rate response to positive stop-loss order surprises should be larger than the (signed) response to negative responses. This asymmetry would cause the average (signed) effect of order surprises to be positive. Evidence presented in Osler (2002) suggests that such price cascades do occur in currency markets.

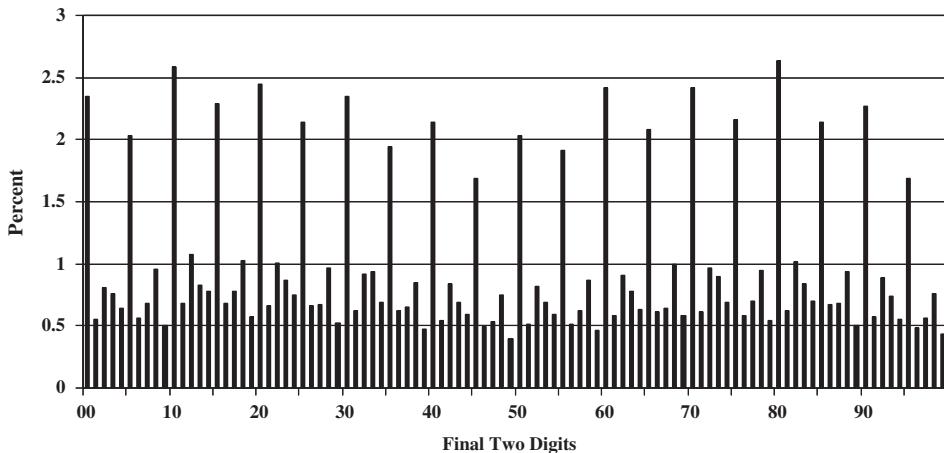


Figure 5. Exchange rate bid quotes, distribution of final two digits. The figure shows the frequency distribution of bids for three exchange rates, dollar-mark, dollar-yen, and dollar-U.K. pound, looking only at the final (right-hand) two digits. Quotes were sampled at one-minute intervals between 9 a.m. and 4 p.m., New York time, from January 1996 through April 1998.

E. Equilibrium

Friedman (1953) argues that rational speculation is always stabilizing, which is sometimes taken to imply that the constellation of order-placement and exchange-rate behaviors identified above would not persist in the face of rational, fundamentals-based speculation. On the other hand, DeLong et al. (1990) show that rational speculation need not be stabilizing. The following analysis suggests that the order placement patterns and exchange-rate behavior under analysis are self-reinforcing, and could represent a stable Nash equilibrium even in the presence of rational speculators.²⁰

Consider a patient liquidity trader with a long position who places a take-profit sell order above the market rate and a stop-loss sell order below it, knowing the unusual ways exchange rates behave at round numbers. To maximize profits, it would probably be optimal for him to place the take-profit order *exactly on* some round number: If it is placed below, but near, the round number, the trader could miss profits by having his order executed before the rate actually turns around; if the order were placed above, but near, the round number, the trader could miss profits by having no position when a trend reversal begins. It is optimal to place the stop-loss order *just below* a round number: If the order were placed above or just at the round number, the trader might have his position unwound just as prices turned around and began to move in his favor. If the order were placed far below the round number, the trader could incur an opportunity loss from failing to liquidate earlier. In short, a rational liquidity trader placing price-contingent

²⁰ Formal proof of this conjecture is beyond the scope of this work.

gent orders could well reinforce the order clustering pattern documented above.²¹

This self-reinforcing equilibrium might survive the introduction of rational fundamentals-based traders. Consider a rational trader who believes that the exchange rate is above its fundamental value. In Friedman's world (1953), the rational trader sells. In the presence of any limit to arbitrage—for example, risk aversion or position limits—the trader sells a limited amount, the rate moves part way to its long-run equilibrium, and the story ends. In the world assumed here, however, the story continues. Suppose the rate falls to a round number, where it is likely to reverse course at least briefly. If transactions costs are small and the expected reversal sufficiently large, the trader will temporarily reduce his short position and might even open a long position, thus reinforcing the rate's existing tendency to reverse course. If transactions costs are large and/or the expected reverse movement small, the trader may leave his short position unchanged, thus remaining neutral with respect to the rate's behavior.²² Whichever option the fundamentals-based trader chooses, he will not undermine the self-reinforcing pattern of order placement noted earlier, and may intensify it.

III. Limit Orders and Price-Contingent Orders

This section compares the implications of price-contingent and limit orders for asset price behavior. Since limit orders are common in U.S. stock markets and price-contingent orders are common in currency markets, it is also relevant to examine whether stock prices conform to the implications of limit orders and exchange rates conform to the implications of price-contingent orders.

A. Shared Implications: Trend Reversals

Niederhoffer and Osborne (1966) reasoned that stock prices might tend to reverse at limit order cluster points. Their logic begins with the tendency of limit orders to cluster at even eighths, just as the logic for trend reversals at take-profit cluster points begins with clustering patterns. However, the logic for trend reversals at limit orders thereafter departs from that just presented for take-profit orders. Stock prices should tend to reverse at limit-order cluster points because "limit orders act as a barrier to continued price movement" (Niederhoffer and Osborne, p. 912), not because the execution of the orders themselves propels prices backward, as would be true for take-profit orders. Suppose some firm's

²¹This logic is familiar to market participants. For example: "[A]void placing protective stops at obvious round numbers. A trader on the short side, for example, instead of putting a protective buy stop at \$4.00, would put it at \$4.01. Or, on the opposite side, a long position would be protected at \$3.49 instead of \$3.50" (Murphy (1986), p. 67, *italics in the original*).

²²Conceivably, this analysis could help explain the following two asymmetries informally observed between currency and equity markets: (1) both technical analysis and stop-loss orders are more common in currency markets than in stock markets, (2) technical analysis seems to be more profitable in currency markets (Dooley and Shafer (1984) and Levich and Thomas (1993)) than in stock markets (Fama and Blume (1966) and Brock et al. (1992)).

share price rises to \$40, where there is a cluster of sell limit orders. Transactions will take place at \$40 until market buy orders exhaust the whole cluster of limit orders or until another sell limit order arrives at a lower price. In essence, a cluster of limit orders at a given level impedes further trending and creates more opportunities for price reversals. This effect should grow with order cluster size, which could explain the observation of Niederhoffer and Osborne that the tendency for prices to reverse course at a given price level, such as one-eighth, generally rises monotonically with the frequency with which limit orders are placed at that level.²³

B. Contrasting Implications: Financial Price Clustering

The implications of limit and price-contingent orders for financial price clustering are diametrically opposed. In markets where limit orders are substantially more common than stop-loss and take-profit orders, like U.S. stock markets, the frequency with which prices are found at limit order cluster points should be relatively high. In markets where price-contingent orders are substantially more common than limit orders, such as currency markets, the frequency with which prices are found at cluster points of price-contingent orders should be relatively low.

Stocks should be found more frequently where limit orders cluster because rates should tend to pause at such points, as suggested above. Niederhoffer (1966) shows that 58.5 percent of all NYSE transactions in 1964 took place at even eighths, a value that is statistically significantly higher than the value of 50.0 percent it would have if transactions were equally likely to take place at any level. Similarly, Kandel et al. (2001) find that IPO prices in Israel cluster disproportionately at prices ending in 0 and 5, where prices for IPO limit orders also cluster.²⁴

Exchange rates should spend relatively little time where stop-loss and take-profit orders cluster, because these orders tend to push rates away from their requested execution rates. De Grauwe and Decupere (1992) show that exchange rate quotes for dollar-mark and dollar-yen were relatively unlikely to close the day at or near round numbers between 1980 and 1990. To extend this result to a higher frequency, I use indicative quotes for dollar-mark, dollar-yen, and

²³ Kavacejz and Odders-White (2002), who join Neiderhoffer and Osborne (1966) in noting that equity limit orders cluster at important technical trading levels, suggest that the significance of those levels may lie in the associated concentration of liquidity. This insight seems likely to help explain the continued importance of technical trading in stock markets, where such trading does not seem to be profitable. However, the insight may not be directly relevant to currency markets, since stop-loss and take-profit orders are market orders when executed, and should therefore drain liquidity like equity market orders, rather than supply liquidity like limit orders. In addition, the continued reliance on technical analysis in currency markets can be readily explained by the profitability of technical trading strategies in those markets (e.g., Levich and Thomas (1993)).

²⁴ Price clustering has also been observed in the London gold market (Ball, Torous, and Tschoegl (1985)) and the market for corn and soybean futures (Stevenson and Bear (1970)). As yet there is no evidence connecting this clustering to order flow.

dollar-U.K. pound collected at one-minute intervals from 9 a.m. to 4 p.m. New York time from January 1996 through April 1998.²⁵ Figure 4 shows the frequency distribution of the final two significant digits of quote midpoints, grouped into 20 five-level buckets centered on price levels ending in 0 or 5. The overall distribution is different from the uniform at a high level of significance.²⁶ Exchange rate quotes spend relatively little time near 00 and 50, the levels at which price-contingent orders cluster most strongly: Frequencies for the rates around 00 and 50 are each statistically significantly lower than the five percent one would expect under the uniform.²⁷ This qualitative result extends to a subsidiary tendency for exchange rates to spend *more* time near levels ending in 5 than at nearby levels ending in 0, which mirrors the tendency of price-contingent orders' requested execution rates to end *less* frequently in 5 than in 0. The differences between exchange rate frequencies at adjacent buckets ending in 0 and 5 are all statistically significant at the five percent level.²⁸

The full distribution of bid prices according to the final two significant digits is shown in Figure 5, where the overall pattern of frequencies is essentially the same as that for midquotes, but shifted five points downward. The pattern for ask prices (not shown) is similar, but shifted five points upward from the pattern for midquotes. Within the broad tendency for rates to spend relatively little time at levels near 00 and 50, subsidiary patterns in the placement of dealer quotes are identical to patterns noted earlier in the placement of price-contingent orders. Dealers have a strong tendency to place bid and ask quotes at levels ending in 0 and 5, and they place quotes at levels ending in 2, 3, 7, and 8 more frequently than rates ending in 1, 4, 6, and 9. These patterns are also consistent with yen/dollar clustering at the one-digit level reported by Grossman et al. (1997), which uses tic-by-tic data. As noted there, the preference for rates ending in 0 may represent a concern for communication efficiency. The subsidiary preference for rates ending in 5, and the preference for levels ending in 2, 3, 7, and 8 over levels ending in 1, 4, 6, and 9, cannot be explained in terms of communication efficiency—and suggests the influence of behavioral factors such as cognitive efficiency or a pure preference.

²⁵ Transactions data would be ideal, but they are not available for this purpose. Fortunately, existing comparisons of quote and transactions data suggest no likely distortion in the results (Goodhart et al. (1996), Danielsson and Payne (1999)).

²⁶ The Anderson–Darling statistic for this test exceeds 39.6 (see note 15).

²⁷ The sample size here is 734,645 observations. The null hypothesis is a binomial distribution with probability five percent of an exchange rate's final two digits falling within a certain band (such as 98, 99, 00, 01, 02). The expected number of observations is 36,732.3, with standard deviation 186.8. According to the normal approximation to the binomial distribution, which is accurate for large samples in which p is close to zero, any frequency above 5.05 or below 4.95 differs significantly from 5.0 percent at the five percent confidence level.

²⁸ For each pairwise comparison, the number of observations for the second entry is taken as the total minus the number of observations for the first entry, and the frequency of the second entry is adjusted accordingly. All comparisons reject the equality hypothesis at better than the one percent significance level.

IV. Conclusions

This paper focuses on two predictions of technical analysis: (1) downtrends (uptrends) tend to reverse course at pre-identifiable support (resistance) levels, which are often round numbers; (2) trends tend to be relatively rapid after rates cross support and resistance levels. These are arguably the predictions most commonly used in the foreign exchange market, where technical analysis is so ubiquitous as to be part of the language of daily conversation. The present paper provides an explanation for this anticipated price behavior, based on a close analysis of the complete set of stop-loss and take-profit orders placed at a large foreign-exchange-dealing bank during August 1, 1999, through April 11, 2000.

The paper shows that requested execution rates for stop-loss and take-profit orders cluster at round numbers, consistent with existing evidence on limit orders in stock markets. It also shows that the pattern of clustering differs across order types and could produce the price behaviors predicted by technical analysts. Executed take-profit orders cluster more strongly at round numbers than do stop-loss orders. Since take-profit orders should tend to reverse price trends, exchange rates should tend to reverse course at round numbers when they hit take-profit-dominated order flow. Executed stop-loss buy orders cluster most strongly just above round numbers, and executed stop-loss sell orders cluster most strongly just below round numbers. Since stop-loss orders should tend to propagate price trends, exchange rate trends should be relatively rapid after the rate crosses a round number and hits stop-loss-dominated order flow.

The evidence presented here is consistent with three reasons why stop-loss and take-profit orders cluster at round numbers. First, the use of round numbers reduces the time and errors involved when customers communicate with their dealers (Grossman et al. (1997)). Second, round numbers may be easier to remember and to manipulate mentally (Goodhart and Curcio (1991), Kandel et al. (2001)). Third, humans may simply prefer round numbers, even without rational arguments for their superiority (Yule (1927)). Once the pattern of order clustering is established, it may be self-reinforcing even in the presence of rational speculators.

The clustering of orders at certain levels undermines any otherwise monotonic relation between trading intensity and information flow. A monotonically positive relation is postulated formally in Easley and O'Hara (1992) and Diamond and Verrecchia (1987), based on the intuition that trading intensity rises when there is more private information. A negative relation is suggested in Lyons (1996), based on the concept of "hot potato trading"—the process by which unwanted inventory gets passed among currency dealers. Order clustering at round numbers makes price levels, per se, an additional determinant of trading intensity.

The analysis in this paper suggests two additional lines of research. First, the clustering of price-contingent orders implies that exchange rates are path dependent. This path dependence could contribute to the "exchange-rate disconnect" problem, that is, the difficulties encountered by standard structural exchange rate models in forecasting exchange rates over short horizons (Meese and Rogoff

(1983)). Second, the clustering of price-contingent orders induces excess kurtosis, relative to the normal distribution, in price-contingent order flow. Since short-run exchange rate dynamics are apparently dominated by the influence of order flow, excess kurtosis in price-contingent order flow could contribute to excess kurtosis in high-frequency exchange rate changes.

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