FX Spreads and Dealer Competition across the 24-Hour Trading Day

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This study examines the impact of competition on bid-ask spreads in the spot foreign exchange market. We measure competition primarily by the number of dealers active in the market and find that bid-ask spreads decrease with an increase in competition, even after controlling for the effects of volatility. The expected level of competition is time varying, highly predictable, and displays a strong seasonal component that in part is induced by geographic concentration of business activity over the 24-hour trading day. Our estimates show that the expected addition of one more competing dealer lowers the average quoted spread by 1.7%.

The foreign exchange (FX) market is highly liquid, economically important, and associated with a unique combination of features which makes studying bid-ask spread determination in this environment attractive. The FX market is open 24 hours a day, 7 days a week with dealer competition and trading activity varying greatly over a calendar day, as the level of business activity in different geographic regions ebb and flow. The FX market also has a decentralized multidealer structure, where dealers and customers have oligopolistic relationships. FX dealers in major currencies have access to well-developed interdealer markets, on average handle large trading volume, and operate in a largely unregulated environment.[1]

The purpose of this article is to examine the effects of dealer competition on bid-ask spreads in the spot FX market. The impact of dealer competition on bid-ask spreads has received scant attention in empirical studies of the FX

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[1] For example, in 1995 FX trading volume was estimated to be $1.2 trillion per day by the Bank for International Settlements (BIS) “Central Bank Survey of Foreign Exchange and Derivatives Market Activity, 1995” [BIS (1996)].

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market by Glassman (1987), Booth (1988), Bollerslev and Melvin (1994) and Bessembinder (1994). Yet many empirical studies of multidealer equity markets, such as Stoll (1978b), Ho and Macris (1985), Laux (1995), Wahal (1997), and earlier studies surveyed in Cohen et al. (1979) support the importance of competition in bid-ask spread determination.[2]

We examine the relation between bid-ask spreads and dealer competition using the spot deutschmark/dollar (DM/$) tick-by-tick quotes of FX dealers for a recent calendar year. The level of competition is primarily measured by the number of dealers active in the market. We interpret the time-varying bid-ask spread and number of active dealers as short-run equilibrium outcomes that result from random deviations around the long-run level of customer order flow (demand for liquidity services) and long-run dealer entry and exit, which is driven by profit maximization (supply of liquidity services). In the short run, variation in the number of dealers is caused by idiosyncratic customer order flow, current dealer inventory positions, current and near-term market depth and inventory risk considerations.

In the FX market, fluctuations in geographically concentrated customer order flow over different portions of the day result in systematic differences in dealer activity levels and quote volatility, which exhibit both static seasonal patterns as well as predictable short-run dynamics. For example, the number of active dealers varies substantially across the 24-hour clock. In addition, there are predictable daylight savings time, weekend, and end-of-month regularities. After taking these seasonalities into account, short run serial correlations remain in the data that are also predictable by market participants. Unlike most extant FX studies, we explicitly model the wide range of seasonalities and predictable short-run dynamics found in these data to control for the predictable effects of time-varying order flow and the number of active dealers on market conditions.

Most previous studies of FX spreads focus on the effect of exchange rate volatility, employing a variety of FX volatility measures. For example, Glassman (1987), Boothe (1988), Bollerslev and Melvin (1994), and Bessembinder (1994) proxy for exchange rate volatility by using variables such as price volatility of an FX futures contract or the conditional variance of the spot exchange rate estimated from a GARCH model. FX volatility is presumed to impact bid-ask spreads by positively affecting dealer risk bearing. In contrast, this study jointly examines how competition and FX volatility affect bid-ask spreads. Moreover, FX volatility is measured by the variance of bid-ask midpoint quotes within each 15-minute time interval. This measure captures both time-series variability in FX rates as well as cross-sectional disagreement among dealers regarding the current FX rate.

[2] With the exception of Wahal, this evidence is limited by the infrequency of changes in the number of dealers typically found in U.S. stock market studies.

The remainder of the article is organized as follows. Section 1 reviews the theoretical basis of the relations among spread, competition, and volatility. Section 2 contains a description of the interbank FX market and details the FX data sources and statistical properties. Section 3 presents preliminary empirical evidence. It contains perfect foresight model estimates and evidence on seasonalities. Section 4 develops a conditional expectation model, explains our estimation procedures, presents model estimates, and details our sensitivity analysis. Section 5 summarizes the evidence and presents our conclusions.

1. Theories of Spread, Competition, and Volatility

On a theoretical level, many market microstructure models of spread determination such as Stoll (1978a), Ho and Stoll (1983), Laux (1991), Biais (1993), and Glosten (1994) show that competition is a prime determinant of bid-ask spreads under a variety of market conditions. While none of these market microstructure models exactly captures the conditions present in the FX market, their general properties are strongly suggestive of the importance of dealer competition on bid-ask spread determination. We review the major properties of several of these models below.

Ho and Stoll analyze a centralized capital market with competing risk-averse dealers but without privately informed traders. They show that a dealer's spread is a positive function of transaction size, dealer risk aversion, and the security's return variance. They also show that as the number of dealers rises, the spread between the best bid and ask quotes (the inside spread) falls, though the spreads of individual dealers do not.

Biais considers a fragmented market with competing risk-averse dealers who do not observe their competitors' quotes. Instead, dealers only know the probability distribution of their competitors' possible inventory positions. Biais demonstrates that as the number of dealers rises, the bid-ask spreads of individual dealers fall because the expected best bid and ask quotes of the competing dealers are more competitive.

In another recent study, Glosten examines a centralized market characterized by an electronic limit order book, where limit orders can be interpreted as quotes being placed by competing dealers. In this market risk-neutral dealers observe the quotes of their competitors and bear adverse selection from trading with privately informed investors. Glosten shows that as the number of active dealers rises, the spread of each individual dealer falls.

Dealer spreads also can vary if dealers have differential access to information on the state of the market. In the FX market small banks see little of the aggregate order flow, while large banks observe a much greater portion of this order flow. Large banks tend to quote more aggressively than small banks due to their information advantages with regards to aggregate customer order flow. Consequently, when a significant number of large banks is in the market, we expect more aggressive pricing of liquidity services. This behavior puts added competitive pressure on other dealers interested in offering liquidity services to reduce their spreads. Thus the makeup of the active dealers or the fraction of large dealers active in the market can affect the level of dealer competition.

Aggregate dealer activity also impacts expected inventory costs of individual dealers. Since a dealer's ability to lay off unwanted inventory is positively related to expected market depth, customer order flow and the number of active dealers in nearby future periods should reduce a dealer's expected inventory costs. It follows that an increase in dealer activity is expected to lower individual dealer bid-ask spreads, by increasing competition and market depth. This is consistent with the properties of the inventory-based models of dealer quote behavior, such as Stoll (1978), Ho and Stoll (1983), and Laux (1995), where greater trading activity leads to lower expected inventory and, thus, lower spreads.

Our prior discussion indicates that both dealer activity and exchange rate volatility are related to inventory considerations. However, a lack of dealer inventory data severely limits directly testing the effect of dealer inventories on FX bid-ask spreads. Two studies that examine this issue are Bessembinder (1994), who estimates an inventory cost of carry effect by regressing interest rate differentials on spread, and Lyons (1995), who uses proprietary inventory data of a single dealer over a five-day period. Theory predicts that idiosyncratic inventory experiences induce individual dealers to alter both their bid and ask quotes, typically in the same direction, to reduce inventory accumulation.[3] If a dealer does not want to increase his/her position materially in either currency, then less aggressive bid and ask quotes are offered, which results in a higher spread.[4]

Since the value of a dealer's inventory is directly dependent on the FX rate, a rise in FX price volatility causes a rise in dealer inventory risk as well. In this situation dealers have incentives to raise spreads so as to lessen the probability of experiencing large unanticipated inventory accumulation and to compensate for bearing more inventory risk, as predicted in models of dealer behavior by Ho and Stoll (1983) and Biais (1993). We use a price volatility measure which captures both the time-series and cross-sectional characteristics of exchange rate volatility.

FX trading occurs through many alternative trading systems and, more importantly, employs alternative quote and transactions information systems. In this decentralized environment, dealers exclusively handle differing portions of aggregate order flow, and can internally match customer

[3] In our empirical analysis we examine spread dispersion as one proxy for differences in dealer inventory objectives and evaluate whether our results are sensitive to its inclusion. This estimation is presented at the end of our study as a robustness check.

[4] Bollerslev and Melvin (1994) document that such a rise in spread occurs frequently.

orders or accommodate them through internal inventory adjustments without resorting to trading on the interdealer market. This trading environment produces heterogeneous dealer expectations of FX rates, which are likely to persist as long as no single transparent market price exists. Increased disagreement among dealers as to the "true" exchange rate is hypothesized to also raise the time-series measure of FX price volatility.

In summary, there are theoretical reasons why the number of active dealers, their identity, and price volatility should impact bid-ask spreads. These motivations involve dealer competition and inventory risk considerations. Furthermore, several market microstructure models posit that these market characteristics jointly determine spreads. Thus we ultimately wish to jointly examine the effects of these variables on the choice of dealer spreads.

2. Description of Foreign Exchange Market and Data

2.1 Market structure

The FX market is a decentralized telephone market with no common trading floor or single trading system. There is no single regulatory body in this market, though individual countries can impose some restrictions on banks situated within its borders. FX trading activity is concentrated in the world's major financial centers.[5] A highly active interdealer market has developed to reduce the adverse impacts of idiosyncratic order flow on individual dealers. Spot FX trading activity in DM/$s is heavy, with 66% represented by interdealer trades.[6] The interdealer market is made up of several hundred commercial banks and other institutions located throughout the world who offer to make two-sided quotes to other active dealers in return for receiving the same service.[7] Trades of these dealers are not made public, nor are they currently available in machine-readable form.

Because of the decentralized nature of the FX market, no transaction price or volume data for the broad market is available. Dealers' major sources of information about the current state of the market are their broker boxes, which announce the volume and prices of anonymous interdealer transactions as well as dealers' direct contacts with their own customers, an information source which varies in importance across dealers. In addition, most dealers participate in one or more quote screen systems, of which the largest are Reuters, Telerate, Knight Ridder, and Minex. Dealer quotes on these systems are indicative, but once the quotes are confirmed by phone they are generally viewed as good for transactions of at least $2 million and

[5] For a more extensive description of the major institutional features of the FX market, see Goodhart (1988), Tygier (1988),and Burnham (1991).

[6] According to the April 1995 survey of FX activity by the BIS (1996), the spot market accounts for 44% of overall FX market trading activity.

[7] For a more extensive description of the interbank market, refer to Lyons (1995).

as much as $10 million in the case of large dealers. These indicative quotes are likely to be representative for small retail customers, but more aggressive quotes are generally available to large customers and other dealers. These quote screen systems are the major source of information for bank customers interested in the current state of the spot FX market.[8] Our study is based on data from the largest of these quote screen vendors, the Reuters FXFX quote screen.

2.2 Data description

We study spot FX rates for the most actively traded currency pair, the DM/$ exchange rate. Our quote data are obtained from Olsen & Associates and consist of all spot quotes that appeared on the Reuters quote screen system during the October 1, 1992–September 29, 1993 observation period.[9] The data include both bid and ask quotes, a code identifying the individual bank dealer by the branch office where the quote originated and a time stamp.[10] The live quote data were collected, checked, and coded for likely errors and reorganized into individual currency files by Olsen & Associates. We exclude quotes coded by Olsen & Associates as likely errors.[11]

We focus on the business week when trading activity is especially active. Weekend quotes are excluded from our analysis due to the very low average activity level. Given the large number of individual quotes in the dataset, we find it useful to aggregate the tick-by-tick information within adjacent 15-minute intervals and characterize market conditions and quote behavior across these intervals. This approach minimized the frequency of cells with no or few observations, while allowing for relatively fine measurement of time-of-day effects. As a result, there is a maximum of 96 quarter-hour periods per day over 261 weekdays in our one-year observation period, yielding 25,056 quarter-hour periods. However, the number of observations differs since several of our variables require at least two bid and ask quotes to exist within the period, while others require only one observation. The use of lagged variables in the analysis further reduces the actual number of

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[8] Goodhart, Ito, and Payne (1996) examine the relation between the indicative quotes on the Reuters FXFX quote screen with the transactions on the newly opened Reuters 2000-2 electronic interdealer trading system for a seven-hour period in June 1993. They examine five-minute time intervals and find that the quote screen system mirrors the electronic interdealer system with regards to midpoint quotes and their volatility, while spreads tend to be wider and vary less frequently on the quote screen. While intriguing, this evidence pertains to a different segment of the FX market, the interdealer market rather than the retail market, both of which are of interest.

[9] Quotes in the Reuters FXFX screen can underrepresent dealer activity in some regional markets. This is primarily a concern for the Tokyo market, where Japanese dealers heavily use the Minex system. Goodhart and Demos (1990) also observe that some dealers reduce quote frequency in heavy trading periods.

[10] A number of studies have recently explored this data including Baillie and Bollerslev (1990), Goodhart and Demos (1990), Muller et al. (1990), Goodhart and Figliuoli (1991), Bollerslev and Domowitz (1993), Dacorogna et al. (1993), Bollerslev and Melvin (1994), and Andersen and Bollerslev (1998).

[11] For further details on this error coding process, see Muller et al. (1990).

usable observations. We also aggregate quote information within 15-minute intervals using equal dealer weights. To create dealer weights, the multiple quotes by a single active dealer are first averaged to obtain a single value, then these remaining values are averaged equally, one for each dealer. We also aggregate quote information by treating each quote within 15-minute intervals as an independent observation (which we define as quote weighted data) and examine how our results are affected.

Reuters time stamps each quote based on Greenwich Mean Time (GMT). We realign these time stamps by moving them back three hours to allow Monday morning trading in Australia and New Zealand to be treated as such. Given our timing convention and the exclusion of weekend periods due to low trading activity, our trading day starts in the Antipodes, then moves to Asia, Europe, and finally North America. We end the trading week in North America because Asian and European dealers with excess inventory at the end of their normal Friday trading day will continue to trade until they reach an acceptable inventory position. However, this isn't an option for North American dealers on late Friday afternoons. We next turn to the definitions of our key variables.

The mean spread is defined as the average of the differences between the paired bid and ask quotes of individual dealers within the 15-minute interval. This measure differs from many other studies, which focus on the inside spread. Given the decentralized nature of the FX market with its lack of time priority and time-varying decay rates on quotes, no meaningful measure of inside spread is available. While individual dealer spreads can take on a limited number of values across the trading day, the mean dealer spread per period has a wide range of values, which depends on the number and composition of the dealers active in a particular 15-minute period. However, as we show below, even the spreads of the largest dealers vary substantially over the 24-hour day.

Dealer activity is measured by the number of dealers entering quotes per 15-minute period. This proxies for dealer supply of liquidity services to the retail market, but is also indirectly influenced by short-run deviations from expected customer order flow. This is our primary proxy for dealer competition. In addition, dealer activity is associated with market depth and thus the ease with which dealers can lay off unwanted inventory. We alternatively use the number of quotes as a measure of dealer activity, which treats the entry of each quote as independent, even when multiple quotes are entered by the same dealer. We also examine whether there is a measurable difference in the impacts of active quoting behavior between large and small dealers.

Exchange rate (midpoint) volatility is measured by the standard deviation of the individual bid-ask quote midpoints occurring within an interval. This variable has a time-series interpretation as a measure of fluctuations in the market exchange rate over a short time interval and a cross-sectional interpretation as a measure of heterogeneous dealer expectations. In interpreting this variable, we explicitly recognize both these properties which have reinforcing impacts. Further, this price uncertainty can exist even when all dealers quote the same spread. Nevertheless, in more volatile periods the price uncertainty interpretation is likely to be dominant, since arbitrage activity by better informed dealers would limit the effects of heterogeneous dealer expectations.[12]

2.3 Descriptive statistics

Table 1 presents basic descriptive statistics of the dataset. The mean number of quoting dealers is 16.5, with a range of 0 to 41. The mean number of quotes per 15-minute period is 58.4, with a range of 0 to 147. We define large dealers as the top 10 DM/$ dealers for retail customers and the top 5 interbank DM/$ dealers based on trading volume for 1992 and/or 1993.[13] We classify all branches of the same bank dealer as a single dealer. The mean numbers of large and small dealers are 4 and 12, respectively, where large banks represent 28% of the dealer market. Using dealer weighted data and after multiplying spread and volatility by 1,000, the mean quoted spread is .818, and the mean exchange rate volatility level is .373, both measured on a DM/$ basis. Similar results are found when we use quote weights, where we treat each pair of bid and ask quotes as independent.

Our review of market microstructure theories suggests that spreads are positively related to price volatility and negatively related to competition, measured by dealer activity. Dealer activity can also proxy for future market depth, where greater depth lowers a dealer's expected inventory costs. We expect exchange rate volatility to rise as the composition of active dealers changes over time with a large-scale entry of dealers. Increased volatility can occur with the aggregation of new order flow from a large number of entering dealers, reflecting their idiosyncratic inventory experiences and heterogeneous expectations. This is likely to produce a positive correlation between exchange rate volatility and dealer activity.

To further our understanding of the contemporaneous relations across these variables, we examine their bivariate linear relations by estimating their simple correlations. Contemporaneous correlations for the overall sample and for our major variables are presented in Table 2. We find that these

[12] During our sample period, FX volatility is not attributed to German or U.S. Central Bank intervention in either the FX market or the domestic bond markets based on an examination of the 20 largest periods of exchange rate volatility. We find no evidence of German or U.S. government intervention in the FX market at these times. We do find two cases of interest rate cuts by the Bundesbank and one case of a widening in the currency fluctuation bands of the European exchange rate mechanism. Overall there is little evidence directly relating FX volatility to Central Bank intervention.

[13] This is based on retail customer assessments and dealer assessments, respectively, as reported in *Euromoney* (1992–1993 issues). FX dealers classified as large are ABN Amro, BankAmerica, Bankers Trust, Barclays, Chase Manhattan, Chemical, Citibank, Commerzbank, Deutsche Bank, Dresdner, HSBC/Midland, JP Morgan, and Union Bank of Switzerland. Some bank dealers in the Olsen database have unknown identities and we classify them as such.

Table 1
Summary statistics

Variable	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Number of quotes	25,056	58.417	43.113	0	147
Number of dealers	25,056	16.497	9.912	0	41
Large dealers	25,056	4.188	2.319	0	11
Small dealers	25,056	11.709	7.690	0	33
Percentage of large dealers	24,228	0.280	0.139	0	1
Percentage of small dealers	24,228	0.681	0.145	0	1
Quote-weighted sample					
Bid-ask spreads	24,228	0.807	0.137	0.300	6.000
Price volatility	23,877	0.484	0.312	0	5.723
Dealer-weighted sample					
Bid-ask spreads	24,228	0.818	0.125	0.300	6.000
Price volatility	23,801	0.373	0.246	0	5.921

The sample data consist of spot DM/$ exchange rate quotes posted on the Reuters FXFX quote screen during October 1, 1992 to September 29, 1993. The sample period is divided into 25,056 quarter-hour intervals and all Saturdays and Sundays are excluded from the dataset. In the quote-weighted sample, all quotes are included. In the dealer-weighted sample, all quotes belonging to the same dealer regardless of branch office are summarized by their mean. Bid-ask spread for each interval is the mean of all the differences in the paired ask and bid quotes within the interval. Price volatility for each interval is the standard deviation of midpoint quotes within the interval. Spread dispersion for each interval is the standard deviation of spreads within the interval. Bid-ask spread and price volatility are multiplied by 1,000.

contemporaneous relations of spread with dealer activity and exchange rate volatility are consistent with our earlier analysis, where we hypothesized that mean spreads would be negatively related to dealer activity and positively related to exchange rate volatility. We observe that the number of quotes and the number of dealers (total, large or small) are very highly correlated and the correlations of either the number of dealers or the number of quotes with any of the other variables is very similar. We also find that exchange rate volatility is positively related to dealer activity. The correlations of large and small dealers with overall dealer activity are very high. In particular, we see that small dealers are highly correlated with dealer activity at the .99 level, while large dealers have a positive but smaller correlation of .87 with overall dealer activity. The correlations of dealer activity with the percentages of large and small dealers are a much smaller −.34 and .35, respectively, indicating that dealer composition is not simply a linear function of the number of dealers, but instead reflects other economic influences as well. On the other hand, the correlations of bid-ask spread with the percentage of large and small dealers are −.005 and .002, respectively, indicating little direct relation between spreads and these two measures of dealer composition. Hereafter we treat the number of dealers as the primary measure of competition. In unpublished work we have used the number of quotes as an alternative dealer activity measure. The results obtained from using the number of quotes are very similar to those estimated when we use the number of dealers as our measure of competition.

Table 2
Contemporaneous correlations

Variable	Number of quotes	Number of dealers	Large dealers	Small dealers	Large dealers (%)	Small dealers (%)	Bid-ask spread	Price volatility
Number of quotes	1	0.929	0.805	0.915	−0.319	0.323	−0.236	0.212
Number of dealers	0.929	1	0.870	0.988	−0.335	0.352	−0.247	0.241
Large dealers	0.805	0.870	1	0.786	0.043	−0.003	−0.214	0.226
Small dealers	0.915	0.988	0.786	1	−0.424	0.449	−0.240	.237
Large dealers (%)	−0.319	−0.335	0.043	−0.424	1	−0.911	0.015	−0.079
Small dealers (%)	0.323	0.352	−0.003	0.449	−0.911	1	−0.011	0.105
Bid−ask spread	−0.245	−0.272	−0.248	−0.261	−0.005	0.002	1	0.274
Price volatility	0.304	0.319	0.292	0.315	−0.115	0.146	0.227	1

The upper triangle of the correlation matrix contains the correlations for the dealer-weighted sample. The lower triangle of the correlation matrix contains the correlations for the quote-weighted sample. The sample data consist of spot DM/$ exchange rate quotes posted on the Reuters FXFX quote screen during October 1, 1992 to September 29, 1993. The sample period is divided into 25,056 quarter-hour intervals and all Saturdays and Sundays are excluded from the dataset. In the quote-weighted sample, all quotes are included. In the dealer-weighted sample, all quotes belonging to the same dealer, regardless of branch office, are summarized by their mean. Bid-ask spread for each interval is the mean of all the differences in the paired ask and bid quotes within the interval. Price volatility for each interval is the standard deviation of midpoint quotes within the interval.

3. Empirical Analysis

3.1 Preliminary evidence—perfect foresight results

As preliminary evidence on the determinants of bid-ask spreads in the DM/$ FX market, we regress bid-ask spreads on the number of dealers and exchange rate volatility. By using ex post realizations, we implicitly assume that market participants have perfect foresight about the explanatory variables when bid-ask spreads are determined. The estimates obtained from these regressions are presented in Table 3. The reported standard errors are robust to conditional heteroscedasticity. We find that bid-ask spreads fall with a rise in the number of dealers and the fraction of large dealers, while they rise with an increase in the fraction of small dealers. These results are preserved even after we control for exchange rate volatility. In addition, they show that after controlling for the changes in FX volatility, the dealer competition variable maintains its significant impact on bid-ask spreads. Finally, it is interesting to observe that increasing the percentage of large dealers lowers spreads, while increasing the percentage of small dealers raises spreads, which is consistent with large banks being more aggressive than small banks in the pricing of liquidity services.

Table 3
Spreads, competition, and volatility: perfect foresight estimates

	1	2	3	4	5	6	7
Constant							
Coefficient	0.873	0.898	0.829	0.768	0.823	0.857	0.769
Std. error	0.002	0.005	0.010	0.002	0.002	0.005	0.009
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of Dealers							
Coefficient	−0.003	−0.004	−0.004		−0.004	−0.004	−0.004
Std. Error	0.000	0.000	0.000		0.000	0.000	0.000
p value	0.000	0.000	0.000		0.000	0.000	0.000
% Large Dealers							
Coefficient		−0.069				−0.092	
Std. Error		0.016				0.015	
p value		0.000				0.000	
% Small Dealers							
Coefficient			0.074				0.091
Std. Error			0.014				0.013
p value			0.000				0.000
Price Volatility							
Coefficient				0.128	0.165	0.165	0.164
Std. Error				0.004	0.005	0.005	0.005
p value				0.000	0.000	0.000	0.000
$\bar{R}^2$	0.06	0.06	0.07	0.08	0.17	0.18	0.18

The table presents the results of regressing bid-ask spreads on competition and price volatility variables. The sample data consist of spot DM/$ exchange rate quotes posted on the Reuters FXFX quote screen during October 1, 1992 to September 29, 1993. The sample period is divided into 25,056 quarter-hour intervals and all Saturdays and Sundays are excluded from the dataset. All quotes belonging to the same dealer regardless of branch office are summarized by their mean within each interval. Bid-ask spread for each interval is the mean of all the differences in the paired ask and bid quotes within the interval. Price volatility for each interval is the standard deviation of midpoint quotes within the interval. Bid-ask spread and price volatility are multiplied by 1,000. All standard errors are robust with respect to conditional heteroscedasticity.

Examining Table 3 further, we see that having both the number of dealers and exchange rate volatility in the regression explains about 17% of the variability in bid-ask spreads. If we also include the percentage of large or small dealers, we can explain an additional 1% of spread variability. However, it is important to recognize that the explanatory variables are not known ex ante, but can be predicted with some accuracy. For example, market participants know that certain banks enter and exit the FX market at certain times of the day. Therefore we have to account for seasonalities in the FX market as well as predictable short-run time-varying expectations. Furthermore, the explanatory power of this perfect foresight model is overstated, given that similar seasonalities in spreads and the explanatory variables exist. We address the importance of these issues below.

3.2 FX seasonality effects

Few FX market studies carefully examine seasonality patterns in the quote data. Two major exceptions are studies by Goodhart and Demos (1990) and Andersen and Bollerslev (1998), which both emphasize the importance of these regularities. In fact, Andersen and Bollerslev argue in their study of intraday return volatility that accounting for intraday seasonalities is crucial to accurate estimation of conditional volatility of spot FX rates. Accounting for seasonalities is especially important for our competition measure since the entry and exit of dealers is highly regular over the 24-hour trading day.

Goodhart and Demos (1990) identify four market regimes within a 24-hour DM/$ trading period. Our 15-minute indicators can capture the normal patterns produced by these four overlapping market regimes, although they are much more flexible. We also introduce four indicators to account for the drop-off in trading activity on bank holidays in these four major market centers. We define a holiday to occur in the Pacific when banks are closed in Sidney; in Asia when banks are closed in two or more of its major trading centers: Hong Kong, Singapore, and Tokyo; in Europe when banks are closed in two or more of its major trading centers: Frankfurt, London, Paris, and Zurich; and in North America when banks are closed in New York.[14] The sources for bank holidays are various annual issues of *JP Morgan's World Holiday and Time Guide* (1992, 1993).

Bank dealers generally try to reduce their net FX exposure to zero near the end of each trading day and especially at the end of the business week.[15] Reduced FX exposure is also sought near the end of the month when many banks calculate their FX departments' profit and loss statements. These varying dealer inventory objectives should also be reflected in fewer quotes and higher spreads at the end of these calendar periods. Weekend and month-end effects are taken into account by introducing indicator variables for the last 7.5 hours of Friday, the first 3 hours of Monday, and the entire last weekday of the month.[16] Daylight savings time is introduced in Europe and North America by adding an indicator for the three quarter-hour periods prior to the normal start of trading in these regional markets.[17] These indicator variables allow us to characterize the typical daily seasonals in the

[14] Holiday indicators take on a value of one over the 15-minute intervals 90–96 and 1–37 for holidays in Australia, intervals 10–43 for holidays in Asia, intervals 33–76 for holidays in Europe, and intervals 64–95 for holidays in the United States, and a value of zero in all other intervals. These 15-minute intervals are based on sampling from the Olsen database. These holiday intervals are also adjusted for daylight savings time.

[15] Glassman (1987) and more recently Bessembinder (1994) report evidence of a late Friday rise in spreads which they attribute to a reluctance on the part of dealers to take additional currency positions which they cannot easily lay off before the weekend.

[16] In instances when Friday is a holiday, the Friday dummy definition is applied to Thursday.

[17] Three 15-minute intervals rather than four are used based on sampling the normal start times for dealer quote activity of European and U.S. dealers over standard time and daylight savings time.

Table 4
Seasonalities in spreads, dealer activity, and volatility

Indicator	Bid-ask spread			Number of dealers			FX volatility		
variable	Coeff.	Std. Error	p value	Coeff.	Std. Error	p value	Coeff.	Std. Error	p value
DFRI	0.053	0.004	0.000	−2.900	0.124	0.000	0.012	0.010	0.231
DMON	0.085	0.016	0.000	−0.798	0.152	0.000	0.010	0.013	0.437
DMM	0.007	0.003	0.036	−1.100	0.141	0.000	−0.005	0.007	0.457
DHP	0.068	0.017	0.000	−2.712	0.329	0.000	−0.029	0.011	0.006
DHA	−0.019	0.018	0.278	−1.754	0.502	0.000	0.016	0.019	0.404
DHE	0.127	0.019	0.000	−8.364	0.365	0.000	−0.042	0.010	0.000
DHN	−0.025	0.008	0.002	−2.960	0.284	0.000	−0.063	0.009	0.000
DSTE	−0.048	0.006	0.000	0.842	0.314	0.007	−0.027	0.009	0.004
DSTN	−0.019	0.005	0.000	4.393	0.323	0.000	0.129	0.024	0.000
$\bar{R}^2$	0.23			0.79			0.12		

The table presents the estimates from separately regressing bid-ask spreads, number of dealers, and price volatility on seasonal indicator variables. The indicators are for 96 intraday periods, Friday closing time (DFRI), Monday opening time (DMON), last day of the month (DMM), Pacific holidays (DHP), Asian holidays (DHA), European holidays (DHE), North American holidays (DHN), shift due to daylight-saving time in Europe (DSTE), and shift due to daylight-saving time in North America (DSTN). The sample data consist of spot DM/\$ exchange rate quotes posted on the Reuters FXFX quote screen during October 1, 1992 to September 29, 1993. The sample period is divided into 25,056 quarter-hour intervals and all Saturdays and Sundays are excluded from the dataset. All quotes belonging to the same dealer regardless of branch office are summarized by their mean within each interval. Bid-ask spread for each interval is the mean of all the differences in the paired ask and bid quotes within the interval. Price volatility for each interval is the standard deviation of midpoint quotes within the interval. The 96 coefficients are shown graphically in Figures 1–3. Bid-ask spread and price volatility are multiplied by 1,000. All standard errors are robust with respect to conditional heteroscedasticity.

FX market, which represent long-run predictable patterns in the FX trading environment.

We estimate these FX seasonality effects by ordinary least squares (OLS) using our various seasonal indicators as previously defined but without an intercept term.[18] We find that mean spread, dealer activity, and exchange rate volatility all exhibit substantial variability across time of day, weekends, month ends, daylight savings time, and holidays in major trading centers. This can be seen from Figures 1–3 for the quarter-hour seasonals and Table 4 for the nonintraday seasonal indicators.

We observe in Figure 1 that mean bid-ask spreads are at their maximum around the Tokyo lunch hour but stay relatively high throughout most of the Asian trading period and are lowest in the overlap of the Asian and European trading period. Spreads then gradually rise as the Asian dealers exit and this occurs even as early North American dealers enter. They continue to rise through the North American afternoon but then begin falling in the Pacific market period. Spreads are at their lowest in the early hours of the Pacific market segment, presumably due to a low rate of order flow and therefore a low information flow which reduces exchange rate volatility. Overall we

[18] All the standard errors are adjusted for conditional heteroscedasticity.

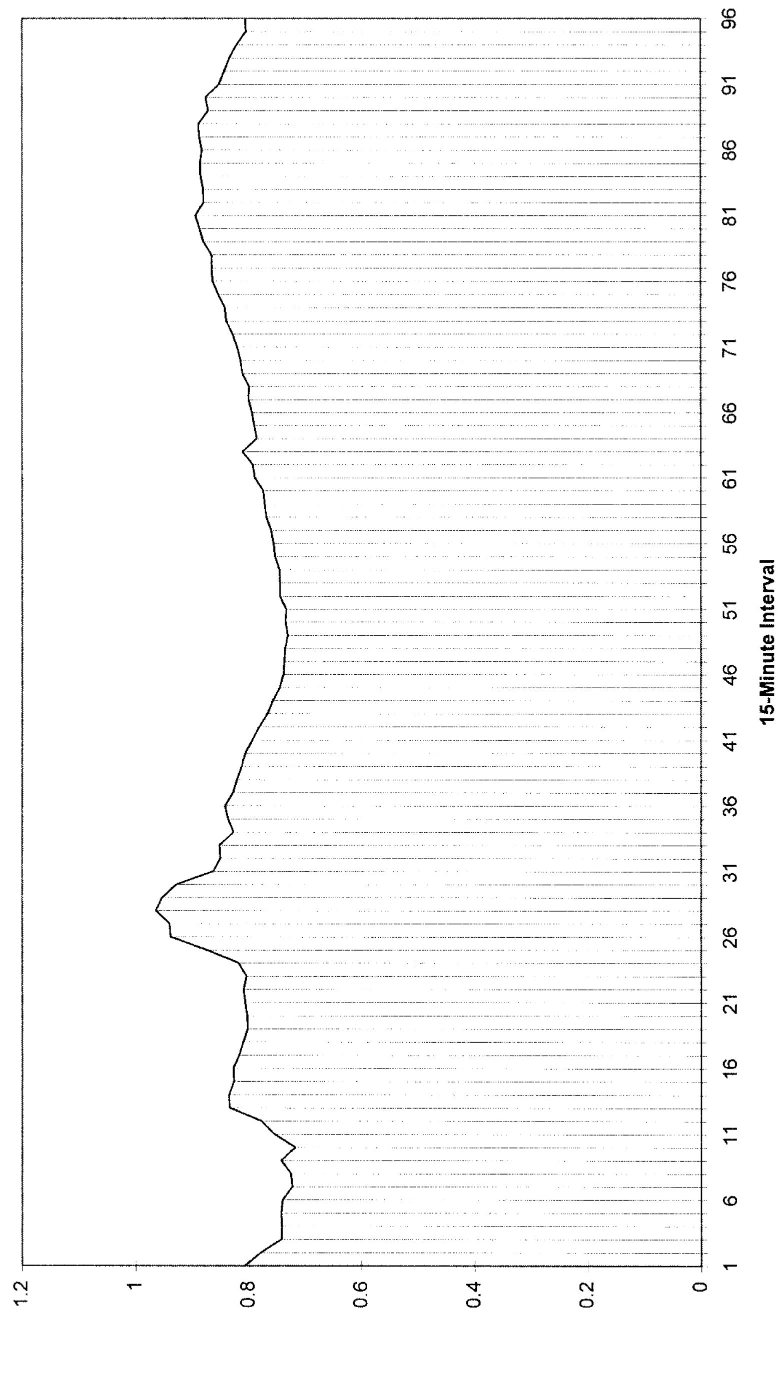

Figure 1
Bid-ask spreads: quarter hourly coefficients (mean spreads × 1,000)

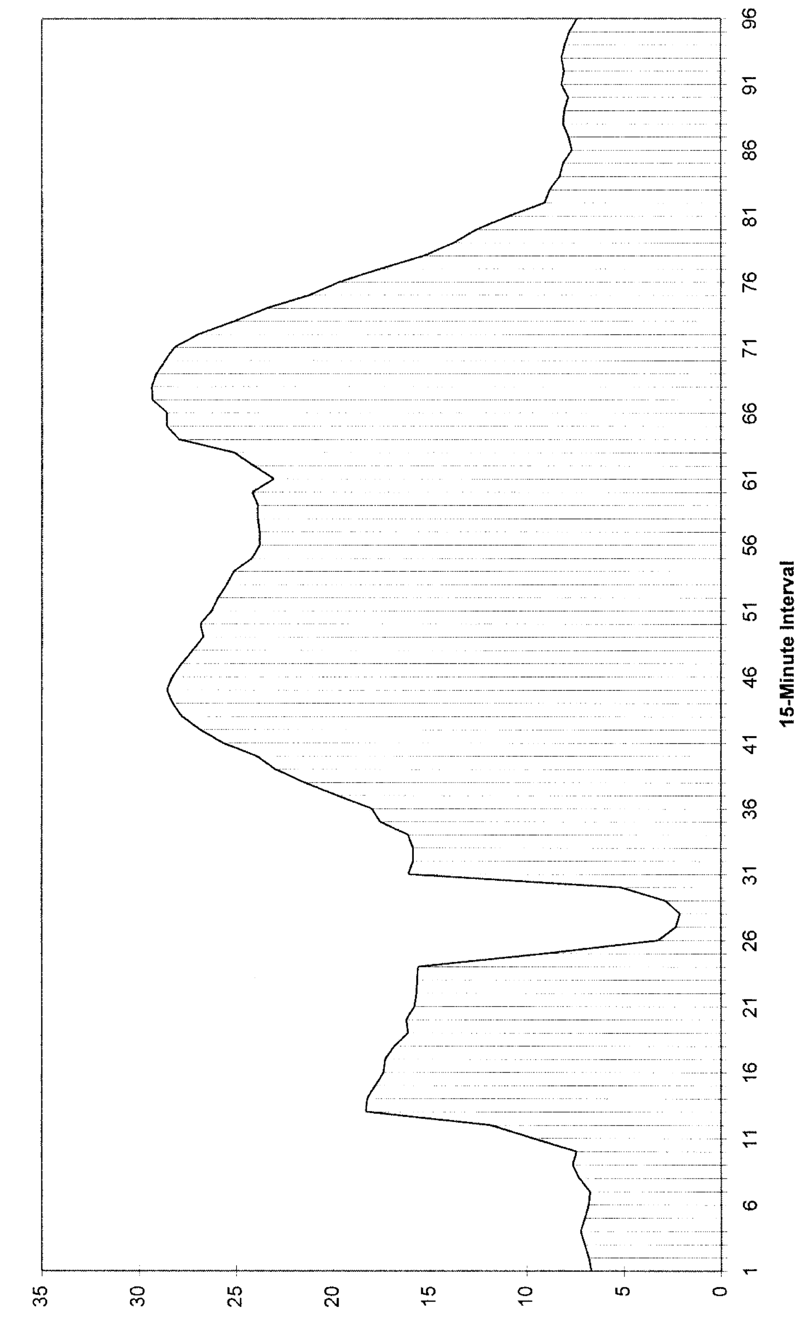

Figure 2
Number of active dealers: quarter hourly coefficients

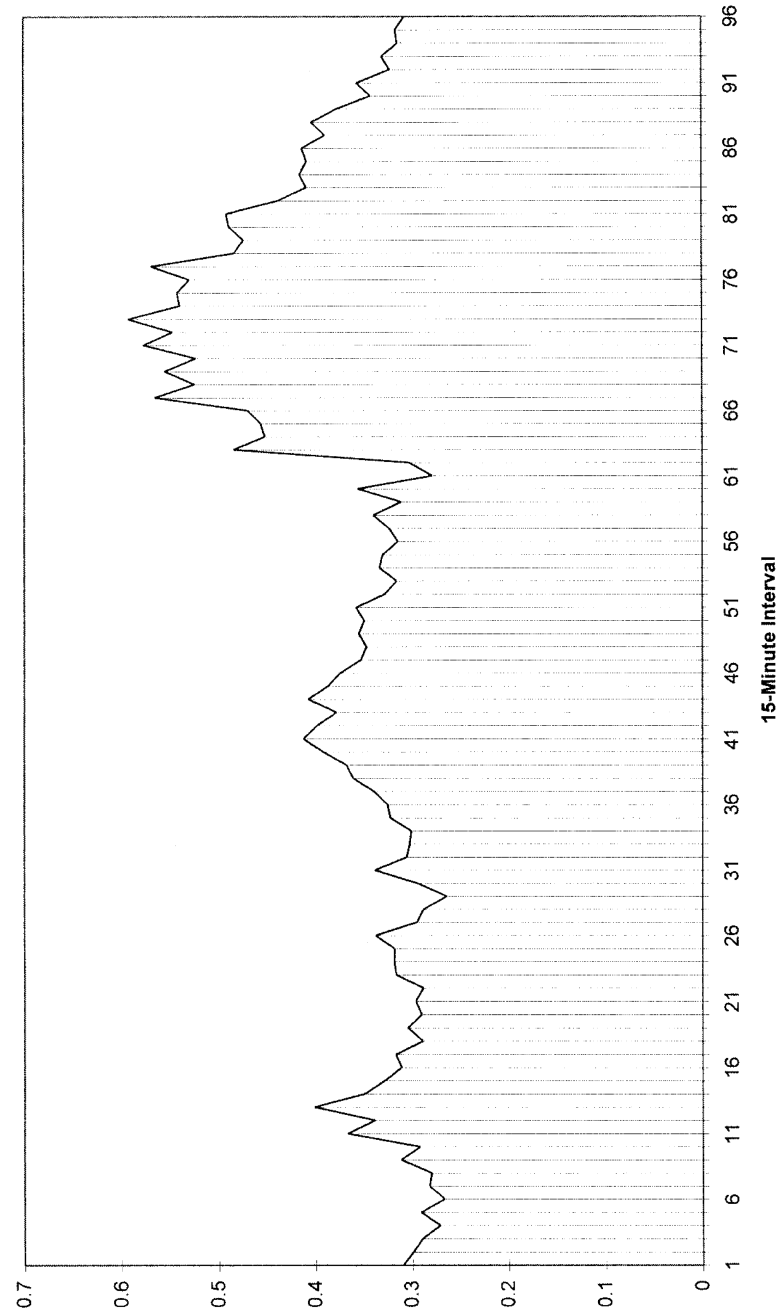

Figure 3
Price volatility: quarter hourly coefficients (standard deviation of midpoint quotes × 1,000)

find that mean spreads on a typical day range between .70 and .97 on a 1,000 DM/$ basis or between 0.05% and 0.07% of the spot price.[19]

Figure 2 presents dealer activity, which varies greatly across the day. We observe relatively low activity in early morning in the Pacific, followed by much greater activity beginning in period 13 as major Asian dealers enter the market. There is a lull in trading over the Tokyo lunch hour, followed by increasing activity as European dealers begin entering around period 33.[20] Dealer activity tapers off around period 50 with the onset of the European lunch hour and the continued exit of Asian dealers. Activity steadily increases with the entry of North American dealers beginning around period 64. By period 70, European traders begin exiting the market and are soon followed by East Coast–based North American dealers, leaving a low level of dealer activity over the remainder of the trading day. A similar pattern is uncovered for the number of quotes per quarter hour. Exchange rate volatility also exhibits a significant intraday pattern, which is observable from Figure 3. Overall, volatility varies from a low of less than .0003 to .0006 at the daily high.

The remaining nine seasonality parameter estimates are shown in Table 4, along with the standard errors, which are robust to conditional heteroscedasticity. We find that all nine seasonality parameters are statistically significant in the number of dealers equation, while in the exchange rate volatility equation only five of the seasonal parameters are significant, with four being negative. In the spread equation, all the seasonality parameters are statistically significant except one. The signs of all the significant parameter estimates for dealer activity are consistent with expectations; holidays and weekends reduce trading. Interestingly, the seasonal patterns observed for bid-ask spreads, dealer activity, and exchange rate volatility are quite distinct as seen from Table 4 and Figures 1–3.

3.3 Quote behavior of a large dealer

While the seasonal patterns in the aggregate data are pronounced, a question remains as to their cause. Are these patterns primarily the result of variability in the composition of active dealers, who individually exhibit highly stable quote patterns, or are they also due to variability in quote patterns by individual dealers across the day? To address this question, we plot spreads and related variables across the day for a single large dealer, Deutsche Bank, in Figures 4–6.[21] The figures plot the 96 quarter-hour coefficients obtained

[19] This is similar to the median spread estimate of 1.0 reported by Bollerslev and Melvin (1994).

[20] The Japanese Ministry of Finance prohibited Tokyo banks from trading over this period during our sample period and other Asian markets appear to take their lunch hours within this same period.

[21] This examination is limited because many quotes are coded with an unknown institution designation (about 11.6% of the time). In analyzing Deutsche Bank dealer activity, we use dealer code 55 which is used for all Deutsche Bank branches and find that these quotes represent 7.6% of all quotes in the database.

by regressing each of the dependent variables shown in Figures 4–6 on all the seasonal variables included in Table 4 along with the 96 quarter-hour indicators. Figure 4 presents the number of quotes by this single large dealer across the day. It indicates that Deutsche Bank quotes most heavily in the European market segment, but is fairly active in the Asian market as well. Figure 5 presents the percentage of total quotes represented by Deutsche Bank across the day. We see even more variability but similar patterns for overall quote activity.

Figure 6 presents spread levels across the day for Deutsche Bank. It is noteworthy that spreads are highest in the Pacific and Asian market segments, are lower in the European segments, and lowest in the North American segment, where competition is especially intense. It is also noteworthy that spreads rise in periods 1–11 when Asian dealers begin to place FX quotes at the start of the Asian trading day, rise again at the Tokyo lunch hour, and rise further in period 70–76 when North American dealers begin trading. This suggests that spreads initially rise with the influx of new dealers and presumably an influx of order flow and new information, but thereafter spread tends to drop due to increased dealer competition.

In the remainder of the article our analysis is conducted at the aggregate dealer level with deseasonalized data. Conceptually the seasonal patterns in dealer spreads and activity represent the long-run equilibrium of aggregate supply and demand for dealer services. In addition, there are short-run deviations in market conditions that tend to be serially correlated and are captured by the conditional expectations. While joint estimation of the seasonalities and our conditional expectation model of dealer spreads would be preferred, this involves an excessive number of parameters which precludes convergence of our model estimators. Instead, we first extract the seasonality effects in the data and then estimate a system of equations described below.

4. Conditional Expectation Model and Estimates

4.1 Model

The results in the previous section show the importance of accounting for deterministic components in dealer spreads (S), dealer activity (A), and exchange rate volatility (V). More generally, expectations of these variables are formed conditional on all available information and not just seasonal indicators. Therefore, although unobservable, we know that market expectations are functions of the current information set. We assume that the conditional expectations of the market variables are linear functions of this information set. Next, we restrict our information set to the recent history

This calculation excludes data for September 1993 where missing dealer codes were frequent.

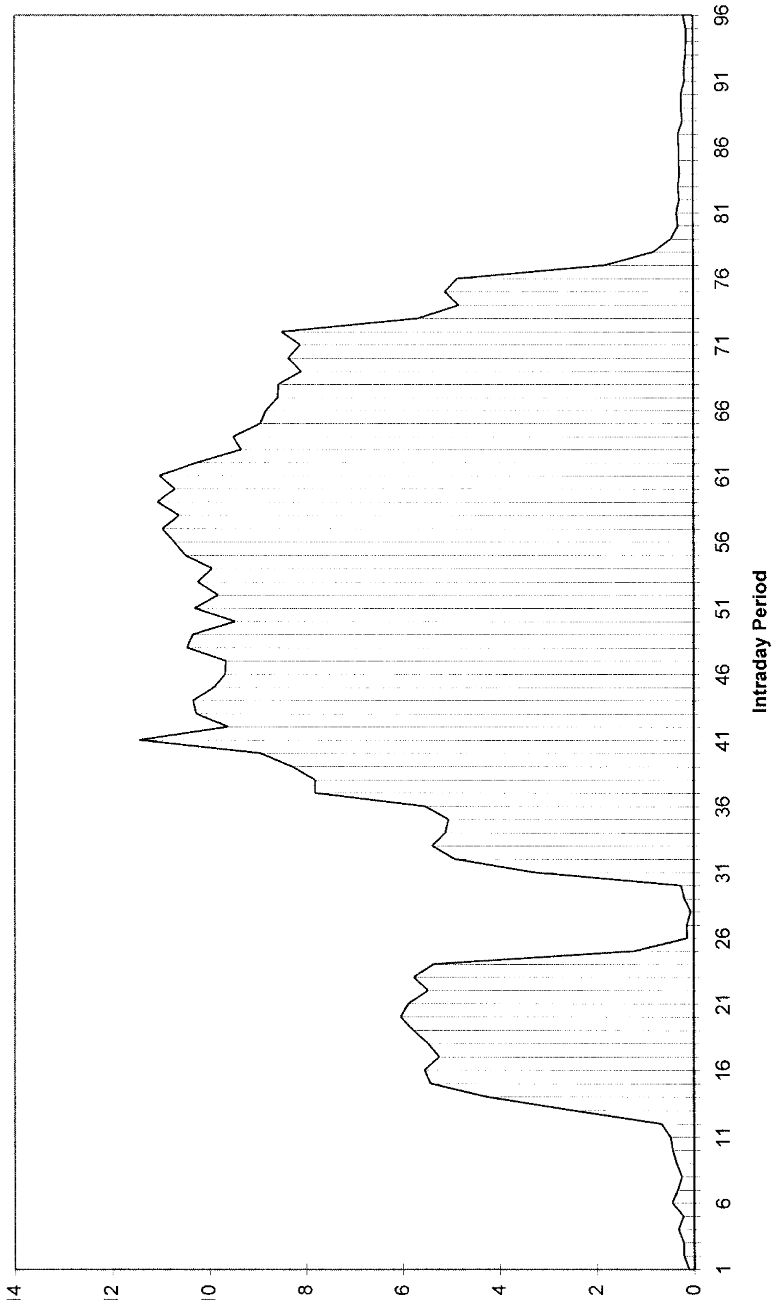

Figure 4
Number of quotes of Deutsche Bank

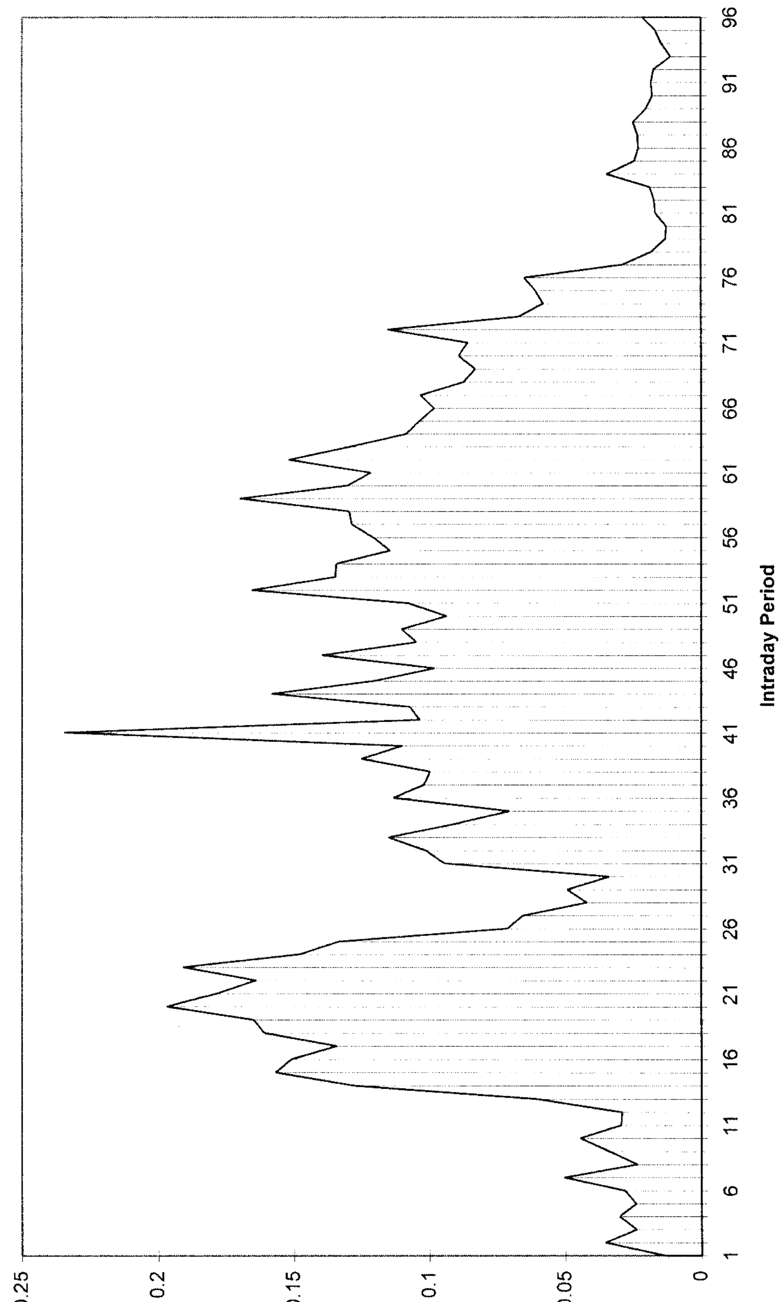

Figure 5
Percentage of total dealer quotes posted by Deutsche Bank

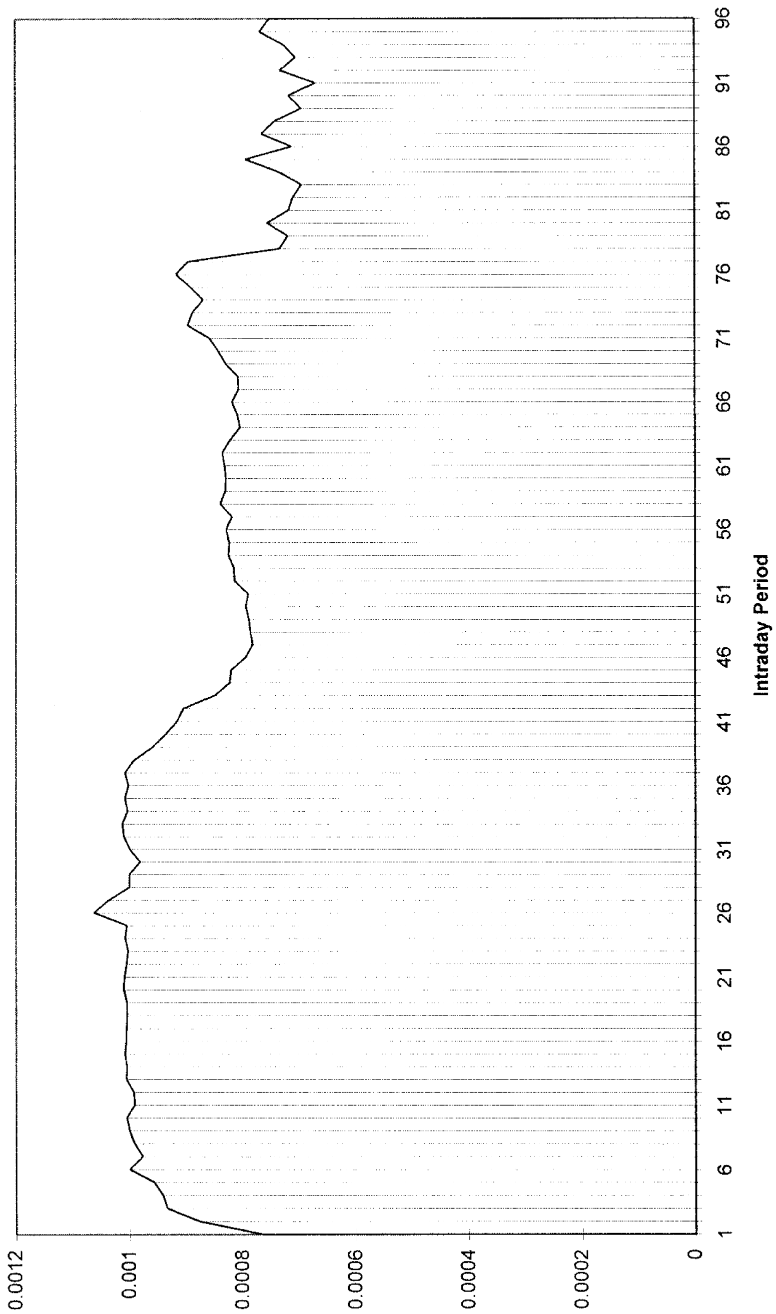

Figure 6
Quoted spreads of Deutsche Bank

of spreads, dealer activity, and exchange rate volatility. Finally, we consider the best linear projection of the market variables on the restricted information set. This results in the following vector autoregressive representation for the variables:

$$\begin{aligned} S_t &= E[S_t \mid \bar{I}_{t-1}] + e_t^s = \gamma^s + \sum_{i=1}^{k} s_i^s S_{t-i} \\ &\quad + \sum_{i=1}^{k} a_i^s A_{t-i} + \sum_{i=1}^{k} v_i^s V_{t-i} + e_t^s \end{aligned} \tag{1}$$

$$\begin{aligned} A_t &= E[A_t \mid \bar{I}_{t-1}] + e_t^a = \gamma^a + \sum_{i=1}^{k} s_i^a S_{t-i} \\ &\quad + \sum_{i=1}^{k} a_i^a A_{t-i} + \sum_{i=1}^{k} v_i^a V_{t-i} + e_t^a \end{aligned} \tag{2}$$

$$\begin{aligned} V_t &= E[V_t \mid \bar{I}_{t-1}] + e_t^v = \gamma^v + \sum_{i=1}^{k} s_i^v S_{t-i} \\ &\quad + \sum_{i=1}^{k} a_i^v A_{t-i} + \sum_{i=1}^{k} v_i^v V_{t-i} + e_t^v \end{aligned} \tag{3}$$

where $E[\cdot \mid \bar{I}_{t-1}]$ is the expectation operator conditional on the specified information $\bar{I}_{t-1}$ that is available at time $t-1$ and the residuals, e_t^s, e_t^a, and e_t^v, are innovations in market expectations at time t.

Equations (1)–(3) are highly general in that our three market variables are assumed to be jointly determined and the characterization is not based on any specific economic theory, but is consistent with a wide set of possible models. We have conditioned the expectations on a subset of the full information set. The choice is determined by the need to obtain a parsimonious formulation, by data availability, and by our estimation results, which show that the lagged predetermined variables are economically meaningful, as they have material predictive power. The conditional expectation property $E[E(\cdot \mid I_{t-1}) \mid \bar{I}_{t-1}] = E(\cdot \mid \bar{I}_{t-1})$ for $\bar{I}_{t-1} \subset I_{t-1}$ guarantees that any subset of the known information set may be used in conditioning expectations.

The distributions of the innovations e_t^s, e_t^a, and e_t^v in Equations (1)–(3) have several important properties. First, they are orthogonal to the lagged dependent variables and have zero means. The orthogonality property forms the basis of our estimation procedure. Second, the innovations may be serially correlated. For example, the dealer participation variable A_t may be affected by private information trading, which is a possibility not directly captured by Equation (2). The dealer activity innovation e_t^a can include this information, and if private information trading is serially correlated, then e_t^a also would be. In general, the innovations include information used by market participants, but which is ignored by our conditional expectations due to data and other limitations noted above. Our estimation method is robust to possible serial correlation in the projection errors. Third, the conditional covariances of the residuals are functions of the available information and may result in conditional heteroscedasticity. We account for the possible presence of conditional heteroscedasticity of an unknown form in our choice of estimation method.

Having specified the short-run expectation structure of our variables, we next specify the economic environment within which we examine these expectations. Our three variables are treated as jointly dependent and linearly related. Thus the relation between the three can be written as

$$aE[S_t \mid I_{t-1}] + bE[A_t \mid I_{t-1}] + cE[V_t \mid I_{t-1}] = \phi,$$

where ϕ is an arbitrary constant term which could be zero. Conditioning the relation on a finer information set $\bar{I}_{t-1}$, the equation can be expressed as

$$E[S_t \mid \bar{I}_{t-1}] = \gamma + aE[A_t \mid \bar{I}_{t-1}] + \beta E[V_t \mid \bar{I}_{t-1}]$$

or

$$S_t = \gamma + \alpha E[A_t \mid \bar{I}_{t-1}] + \beta E[V_t \mid \bar{I}_{t-1}] + e_t^s, \tag{4}$$

where $\gamma = \phi/a$, $\alpha = -b/a$, and $\beta = -c/a$. Therefore the parameters of the equations that describe the short-run expectations are intimately related to the economic model which describes the market environment.[22] Specifically, simultaneous estimation of Equations (2)–(4) is needed. We hypothesize that the parameter estimate for α is negative, reflecting the negative effects of competition on bid-ask spread, and the parameter estimate for β is positive, reflecting the positive effect of volatility in dealer inventory values on spreads.

To simultaneously estimate the above three equation systems, we employ Hansen's (1982) generalized method of moments (GMM). We define the vector function $h(u_t, z_t, \theta) = u_t \otimes z_t$, where $u_t = (e_t^a e_t^v \eta_t)'$ is a (3×1) vector of residuals, $\eta_t = e_t^s + \alpha e_t^a + \beta e_t^v$, and z_t is a (n $\times$1) vector of instrumental variables present on the right-hand-side of Equations (2) and (3). The GMM procedure uses the $3n$ orthogonality conditions $E[h(u_t, z_t, \theta)] = 0$ to estimate θ, the vector of parameters in Equations (2)–(4). Hansen shows that the vector of parameter estimates has the property

$$\sqrt{T}(\hat{\theta} - \theta) \xrightarrow{d} N(0, [D_0' \Omega_0^{-1} D_0]^{-1}), \tag{5}$$

where $D_0 = E[\frac{\partial h(u_t, z_t, \theta)}{\partial \theta}]$ and $\Omega_0 = E[h(u_t, z_t, \theta)h(u_t, z_t, \theta)']$. GMM is a

[22] The interdependency is typical of rational expectation models.

useful procedure for obtaining consistent estimates that are asymptotically normally distributed in the presence of serially correlated and conditionally heteroscedastic errors. To begin the nonlinear GMM estimation, we base our initial parameter values on estimates of Equations (2) and (3) derived from OLS. The starting values for the parameters α and β are obtained by estimating Equation (4) by OLS where the conditional means of A_t and V_t are obtained from separately estimating Equations (2) and (3).

The error term u_t contains projection errors that are potentially serially correlated. The covariance matrix can be adjusted for both conditional heteroscedasticity and serial correlation. However, the covariance matrix may not be positive definite when the error terms are allowed to be serially correlated. To ensure a positive definite matrix, we use the Newey and West (1987) robust estimation procedure, which assigns less weight to the higher order autocovariances. Our sensitivity analysis using autocorrelations of lags 1 and 2 indicates little sensitivity in the model's parameter estimates. Thus we report results that are robust to conditional heteroscedasticity, but assume serially uncorrelated residuals.

We also conduct a series of unit root tests to assess the stationarity of our variables, since the GMM estimation and inference procedures we use assume stationarity. We use the Dickey and Fuller (1979) unit root test and the Phillips and Perron (1988) nonparametric test.[23] Both the "t-test" and the $T(\rho - 1)$ test that we use assume six lags with and without a trend variable. Without exception, the unit root hypothesis is strongly rejected.

Before estimating our system of equations, we need to examine the effectiveness of Equations (2) and (3) in accounting for the time variation in the conditional means of A and V. This evaluation requires that we first decide on the appropriate number of lags to include in the equations. We determine the appropriate lag structure using the Schwarz criterion, where the number of lags is allowed to vary from 1 to 12 for each of the three predetermined variables. Under the Schwarz criterion we choose the number of lags that minimize the loss function $T \log(ESS) + K \log(T)$, where T is the number of observations, K is the number of lags, and ESS is the error sum of squares [Schwarz (1978)]. Using the Schwarz criterion, we find that the optimal number of lags varies between two and six, with most concentrated between four and six lags. Accordingly, we conclude that six lags are sufficient for all our predictive variables. The seasonal adjustments do not appear to alter these results. Thus we model the system of conditional mean Equations (2) and (3) as linear functions of 19 predetermined variables, namely six lagged values of dealer activity, exchange rate volatility, mean spread, and a vector of ones.

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[23] The Dickey and Fuller test assumes homoscedasticity and serially uncorrelated residuals.

4.2 Conditional expectation estimates

Table 5 reports the results of estimating the conditional means of our explanatory variables using six lags of spread, competition, and FX volatility. To estimate the model with seasonally adjusted variables, we take the residuals from the previously discussed seasonality equations. This has the effect of extracting the seasonality patterns from the dataset. We find that the past values of the three predetermined variables produce conditional mean estimates with good explanatory power, consistent with dynamically changing conditional means. Overall we find that about 40% of the variability in dealer activity can be explained in terms of the first six lags of our three predetermined variables. In contrast, we can explain 14% of the variability in exchange rate volatility.[24] Thus we find that information from the past hour and a half (six lags) is quite useful in predicting the subsequent levels of the explanatory variables. However, predicting dealer activity is much easier than predicting exchange rate volatility.

An important related question is how much of explanatory power of the perfect foresight model presented in Table 3 is due to the predetermined variables capturing the previously documented seasonalities in the data. When we estimate the conditional mean equations without seasonally adjusting the data, we find that we obtain R^2's that are roughly double those reported in Table 5.[25] This further emphasizes the need to account for the long-run predictability in the data, which represent the long-run equilibrium for dealer services, when examining the relationship between changes in bid-ask spreads and competition.

We draw three major conclusions from the estimates of the conditional mean equations in Table 5. First, the expectations of dealer activity and exchange rate volatility are time varying, even after adjusting for known seasonalities. Second, these model estimates provide useful information on the relations among our variables and their lagged values, producing evidence on the intertemporal dynamics of these three predicted variables. In contrast, our earlier evidence found in Table 2 is on the pairwise contemporaneous ex post relations, which does not bear directly on spread determination decisions because this involves multivariate and dynamic relations among the ex ante variables, as seen in Equation (4). Third, the evidence presented in Table 5 indicates that in estimating the conditional mean equations [Equations (2) and (3)], not only are each variable's prior six lags useful instruments for predicting its ex post values, but so are the other lagged predetermined variables. Thus we conclude that ignoring these conditional expectations when estimating the relation between spread and dealer competition can seriously distort the results.

[24] In addition, an extended version of the model that includes a separate equation for the proportion of large dealers can explain 8% of the variability in the proportion of large dealers.

[25] These tables can be found in our earlier working paper.

Table 5
Prediction equations

	Number of dealers			Price volatility		
Variable	Coeff.	Std. Error	*p* value	Coeff.	Std. Error	*p* value
Constant	0.008	0.023	0.729	−0.001	0.001	0.543
S{1}	−1.600	0.371	0.000	0.145	0.025	0.000
S{2}	−1.133	0.394	0.004	0.069	0.026	0.008
S{3}	0.302	0.403	0.454	0.066	0.026	0.013
S{4}	−0.308	0.396	0.436	−0.011	0.026	0.669
S{5}	0.077	0.388	0.843	0.046	0.025	0.070
S{6}	0.447	0.357	0.211	0.065	0.023	0.005
A{1}	0.404	0.007	0.000	0.002	0.000	0.000
A{2}	0.168	0.008	0.000	0.000	0.000	0.720
A{3}	0.085	0.008	0.000	0.001	0.000	0.118
A{4}	0.035	0.008	0.000	0.000	0.000	0.327
A{5}	0.032	0.008	0.000	0.002	0.000	0.002
A{6}	0.020	0.007	0.005	0.001	0.000	0.164
V{1}	0.939	0.110	0.000	0.181	0.007	0.000
V{2}	−0.192	0.112	0.087	0.075	0.007	0.000
V{3}	−0.168	0.112	0.136	0.045	0.007	0.000
V{4}	0.020	0.112	0.856	0.064	0.007	0.000
V{5}	0.053	0.112	0.637	0.034	0.007	0.000
V{6}	−0.041	0.110	0.708	0.042	0.007	0.000
$\bar{R}^2$	0.40			0.14		

The table presents the results of predicting the number of dealers and price volatility using lagged variables of bid-ask spreads, number of dealers, and price volatility. The sample data consist of spot DM/\$ exchange rate quotes posted on the Reuter FXFX quote screen during October 1, 1992 to September 29, 1993. The sample period is divided into 25,056 quarter-hour intervals and all Saturdays and Sundays are excluded from the dataset. All quotes belonging to the same dealer regardless of branch office are summarized by their mean within each interval. Bid-ask spread for each interval is the mean of all the differences in the paired ask and bid quotes within the interval. Price volatility for each interval is the standard deviation of midpoint quotes within the interval. All variables are deseasonalized using the seasonal indicators mentioned in Table 4 plus 96 quarter-hour indicators. In addition, bid-ask spread and price volatility are multiplied by 1,000. The predetermined variables are coded as X{i}, where X refers to bid-ask spread (S), dealer activity as measured by the number of dealers (A), and price volatility (V), and i refers to the lagged period. All standard errors are robust with respect to conditional heteroscedasticity.

We next estimate our ex ante model of spread determination. Table 6 reports the results of jointly estimating the parameters in the spread determination model represented by Equations (2)–(4).[26] We find that spread is significantly negatively related to predicted dealer activity and significantly positively related to predicted exchange rate volatility. More importantly, both parameter estimates are statistically significant using heteroscedasticity robust standard errors. Economically interpreting the parameter estimate for the impact of the number of dealers on spreads, we find that mean spread falls by 1.7% per additional dealer actively quoting, ceteris paribus.[27] Alternatively, if there is an increase of 10 dealers, which represents one standard

[26] With 19 instrumental variables, the GMM procedure uses 57 moment conditions in estimating Equations (2)–(4).

[27] This is measured by adjusting the parameter estimate for the prior multiplication of the spreads by 1,000 and then scaling it by the mean spread reported in Table 1.

Table 6
Spreads, competition, and volatility: conditional expectation estimates

	Spread			Number of dealers			Price volatility		
Variable	Coeff.	Std. Error	*p* value	Coeff.	Std. Error	*p* value	Coeff.	Std. Error	*p* value
PCON	0.006	0.001	0.000						
PA	−0.014	0.001	0.000						
PV	0.975	0.031	0.000						
Constant				0.066	0.022	0.004	−0.006	0.001	0.000
S1				−1.384	0.356	0.000	0.263	0.015	0.000
S2				−1.205	0.371	0.001	0.149	0.014	0.000
S3				0.333	0.379	0.379	0.123	0.013	0.000
S4				−0.070	0.372	0.851	0.060	0.013	0.000
S5				−0.132	0.372	0.722	0.055	0.011	0.000
S6				0.468	0.345	0.175	0.057	0.011	0.000
A1				0.388	0.008	0.000	0.005	0.000	0.000
A2				0.173	0.008	0.000	0.002	0.000	0.000
A3				0.088	0.008	0.000	0.001	0.000	0.000
A4				0.038	0.008	0.000	0.000	0.000	0.147
A5				0.034	0.008	0.000	0.001	0.000	0.000
A6				0.020	0.007	0.006	0.000	0.000	0.005
V1				1.187	0.119	0.000	0.057	0.004	0.000
V2				−0.170	0.109	0.119	0.013	0.003	0.000
V3				−0.200	0.112	0.076	0.008	0.003	0.006
V4				−0.012	0.103	0.907	0.008	0.004	0.037
V5				0.021	0.103	0.838	0.000	0.003	0.937
V6				−0.122	0.100	0.220	−0.002	0.003	0.563

The table presents the results of regressing bid-ask spreads on expected number of dealers and expected price volatility. The sample data consist of spot DM/$ exchange rate quotes posted on the Reuters FXFX quote screen during October 1, 1992 to September 29, 1993. The sample period is divided into 25,056 quarter-hour intervals and all Saturdays and Sundays are excluded from the dataset. All quotes belonging to the same dealer regardless of branch office are summarized by their mean within each interval. Bid-ask spread for each interval is the mean of all the differences in the paired ask and bid quotes within the interval. Price volatility for each interval is the standard deviation of midpoint quotes within the interval. All variables are deseasonalized using the seasonal indicators mentioned in Table 4 plus 96 quarter-hour indicators. In addition, bid-ask spread and price volatility are multiplied by 1,000. Generalized method of moments is used to estimate the three equations jointly. The variables for the spread equation refer to a constant (PCON), predicted dealer activity as measured by the number of dealers (PA), and predicted volatility (PV). The predetermined variables for the number of dealers and volatility equations are coded as Xi where X refers to bid-ask spread (S), dealer activity as measured by the number of dealers (A), and price volatility (V), and i refers to the lagged period.

deviation from the mean number of dealers of 16.5, then the mean spread is expected to fall by 17%. Interpreting the exchange rate volatility parameter likewise, we see that a .025% rise in exchange rate volatility, which represents a one standard deviation increase in volatility, is associated with approximately a 30% rise in the mean spread.[28]

[28] In comparison, Bollerslev and Melvin (1994) estimate a similar relation between spread and exchange rate volatility, while ignoring the effect of dealer competition. They find that the parameter estimate for volatility is 10 times as large as the estimate we report. However, there are a number of important differences in approaches. They define volatility by a conditional variance of ask quotes derived from a GARCH process, while we use the standard deviation of dealer-weighted midpoint quotes over 15-minute intervals. They log transform their variables and estimate the relation using an ordered probit model, while we use seasonally adjusted data and GMM estimation. Also, they use only three months of quotes and do not jointly estimate the exchange rate volatility and spread equations.

Turning to the parameter estimates of the two predicted variables in Table 6, we observe that predicted dealer activity is positively correlated with its own six lags, negatively related to spread at lags 1 and 2 and positively related to midpoint volatility at lag 1. Exchange rate volatility is positively correlated with all but one of its own lags. Exchange rate volatility is also positively related to five lags of spread and to several lags of dealer activity. Comparing parameter estimates for the predicted variables in Table 6 with those in Table 5, the major differences involve exchange rate volatility, which is much more strongly related to lagged dealer activity and to lagged spreads under simultaneous estimation of Equations (2)–(4).

4.3 Robustness analysis

As a robustness check of our model specification, we take the natural logs of all our variables and reestimate the model defined by Equations (2)–(4) using GMM. We find that the estimates are qualitatively quite similar to those reported for Table 6.

Next, we reestimate our model after appending one additional explanatory variable. The additional explanatory variables we consider are the fraction of large banks active in the market and spread dispersion across dealers. This alters our system of equations in two fundamental ways. It changes the spread determination equation [Equation (4)] by adding one further conditional mean. It also adds one more conditional mean equation, requiring the estimation of a four-equation system. In this specification we include the six lags of the added explanatory variable in the conditional means of dealer competition and exchange rate volatility as well. The conditional mean equation of the added explanatory variable also includes six lags for all four endogenous variables.

We use spread dispersion as a proxy for the disparity in dealer inventory objectives and measure it by the standard deviation of the individual spreads occurring within a 15-minute interval. Spread dispersion can exist even when dealers are in complete agreement as to midpoint quotes, so that no price uncertainty exists. We differentiate between large and small dealers to examine the presence of any asymmetric behavior for these dealers. The earlier analysis suggests that larger dealers tend to have smaller spreads. Conversely, we view the fraction of small dealers as a measure of reduced competition in the FX market.

The results of expanding the model by appending an added explanatory variable are presented in Table 7 when we add either a second measure of dealer competition or a proxy for differing dealer inventory objectives. The results of estimating the extended model defined by the system of Equations (2)–(4) plus a conditional expectation equation for spread dispersion or the composition of dealers did not improve the explanatory power of the spread determination equation. More importantly, they preserve the inferences we reach with the more parsimonious model shown in Table 6.

Table 7
Conditional expectation estimates for alternative specifications

	1	2	3
Constant			
Coefficient	0.0067	0.0066	−0.0072
Standard error	0.0014	0.0014	0.0013
p value	0.0000	0.0000	0.0000
Number of dealers			
Coefficient	−0.0143	−0.0144	−0.0029
Standard error	0.0006	0.0006	0.0007
p value	0.0000	0.0000	0.0000
Price volatility			
Coefficient	0.9858	0.9796	0.2708
Standard error	0.0317	0.0314	0.0329
p value	0.0000	0.0000	0.0000
Percent large dealers			
Coefficient	−0.0118		
Standard error	0.0452		
p value	0.7948		
Percent small dealers			
Coefficient		0.0795	
Standard error		0.0450	
p value		0.0776	
Spread dispersion			
Coefficient			−2.7766
Standard error			0.1708
p value			0.0000
$\bar{\mathbf{R}}^2$	0.45	0.44	0.44

This table presents the results of regressing bid-ask spreads on expected number of dealers, expected price volatility, expected percentage of large dealers, expected percentage of small dealers, or expected spread dispersion. The sample data consist of spot DM/$ exchange rate quotes posted on the Reuters FXFX quote screen during October 1, 1992 to September 29, 1993. The sample period is divided into 25,056 quarter-hour intervals and all Saturdays and Sundays are excluded from the dataset. All quotes belonging to the same dealer regardless of branch office are summarized by their mean within each interval. Bid-ask spread for each interval is the mean of all the differences in the paired ask and bid quotes within each interval. Price volatility for each interval is the standard deviation of midpoint quotes within the interval. Spread dispersion for each interval is the standard deviation of spreads within the interval. All variables are deseasonalized using the seasonal indicators mentioned in Table 4 plus 96 quarter-hour indicators. In addition, bid-ask spread and price volatility are multiplied by 1,000. Generalized method of moments is used to estimate the spread equation reported in the table simultaneously with all the prediction equations. The estimations from the prediction equations are not reported in the table. The predetermined variables used in the prediction equations are the six lags of all the variables used in the system of equations.

We further explored whether several alternative lag structures of the endogenous variables could enhance the predictive power of the conditional means. In the first case, we try to exploit the strong daily seasonality found in all the variables that we examined by adding the lagged value of the endogenous variable for the same quarter hour on the prior trading day. We find that the additional lag has a positive and statistically significant parameter in the conditional mean equations. Yet the explanatory power of the conditional mean equations as measured by the coefficient of determination is only marginally improved.

As a second robustness evaluation, we modified our conditional expectation equations by first differencing the six lags of each of the three endogenous variables by their respective values lagged one full trading day (i.e., 96 lags earlier). We then added the level of these three predictive variables lagged one trading day. As in the prior case, the predictive variables lagged one trading day are all positive and statistically significant. However, the explanatory power of conditional mean equations falls noticeably, especially for exchange rate volatility, where it falls by more than 50%. Our conclusion from this sensitivity analysis is that, while the data exhibit strong daily seasonalities, the data also exhibit a strong degree of smoothness from period to period. This smoothness makes the prior six lags of the variables more than adequate instruments and leaves little additional predictive power for lags one day earlier.

Our conclusions are also left unaltered when we estimated our system of Equations (2)–(4) using seasonally unadjusted data. This seems to suggest that the seasonal indicators are orthogonal to the other explanatory variables. However, this is not the case. In fact, the model's insensitivity to seasonalities in these data reflects the fact that the dealer activity variables capture much of the seasonality effects in these data. To more formally examine this relation we calculate the correlation between our dealer activity variables and the time series of the parameter estimates for the 96 intraday indicator variables (the products of multiplying the 96 indicator variables with their parameter estimates from the spread equation). The simple correlation of the indicators with the number of dealers is -0.405 which is quite high, suggesting that a large fraction of the seasonalities in mean spreads is captured by dealer activity.

5. Conclusions

Quote behavior in the spot FX market for DM/$ is examined using tick-by-tick interbank quotes from Reuters FXFX screen for a one-year period. We view the FX bid-ask spread as an outcome of the interaction between institutional and behavioral factors. The institutional factors account for the structure of the FX market and the strong seasonal patterns found in dealer quote behavior which are a result of predictable shifts in FX customer order flow across time. Behavioral factors we focus on are dealer competition, dealer quotes and inventory adjustments. More specifically we examine the dynamics of dealer quote activity in light of the wide changes across time in dealer competition, the ability to lay off inventory positions, disagreements concerning the true exchange rate, and differences in dealer pricing of liquidity services. These factors have statistically significant impacts on expected spreads and we explore how they influence the choice of observed dealer spreads.

We find that bid-ask spreads in the spot FX market are positively related to predicted FX volatility and negatively related to predicted dealer activity, which we interpret as a proxy for dealer competition. Economically interpreting the parameter estimate for the number of dealers, an increase of 10 dealers causes the average spread to fall by 17%. These results are qualitatively consistent with well-known market microstructure models. We also find that spread is negatively related to the percentage of large dealers in the market, which is an additional measure of dealer competition. In addition we account for the strong seasonalities and time-varying conditional expectations of bid-ask spreads, the number of active dealers, the fraction of large dealers, and exchange rate volatility. We interpret the documented seasonalities as equilibrium outcomes of long-run predictable variation in order flow and dealer entry and exit on market conditions. The short-run conditional expectations capture the impacts of the changing supply of dealer liquidity services, the volatility in dealer inventory value, and the influences of unanticipated customer order flow. We conclude that dealer competition in the spot FX market is an important determinant of bid-ask spread.

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