Volume Title: The Microstructure of Foreign Exchange Markets

Volume Author/Editor: Jeffrey A. Frankel, Giampaolo Galli, Alberto Giovannini, editors

Volume Publisher: University of Chicago Press

Volume ISBN: 0-226-26000-3

Volume URL: http://www.nber.org/books/fran96-1

Conference Date: July 1-2, 1994

Publication Date: January 1996

Chapter Title: Risk and Turnover in the Foreign Exchange Market

Chapter Author: Philippe Jorion

Chapter URL: http://www.nber.org/chapters/c11361

Chapter pages in book: (p. 19 - 40)

1 Risk and Turnover in the Foreign Exchange Market

Philippe Jorion

The foreign exchange market is the largest and fastest-growing financial market in the world. Yet the microstructure of the foreign exchange market is only now receiving serious attention. As described in table 1.1, daily turnover in the foreign exchange market was $880 billion as of April 1992. To put these numbers in perspective, consider the following data: as of 1992, *daily* U.S. GNP was $22 billion; *daily* worldwide exports amounted to $13 billion; the *stock* of central bank reserves totaled $1,035 billion, barely more than one day's worth of trading. The volume of trading can also be compared to that of the busiest stock exchange, the New York Stock Exchange (NYSE), about $5 billion daily,[1] or to that of the busiest bond market, the U.S. Treasury market, about $143 billion daily (*Federal Reserve Monthly Review* [April 1992]).

Since the advent of flexible exchange rates in the early 1970s, the foreign exchange market has been growing at a record rate. Figure 1.1 compares the volume of world exports to the volume of trading in deutsche mark (DM) currency futures, both expressed on a daily basis. I use futures volume because futures markets provide the only reliable source of daily volume information even if they account for only a small fraction of the foreign exchange market. The figure shows that, since the early 1970s, trading in deutsche mark futures has increased much faster than the volume of world trade. This reflects the overall growth in the foreign exchange market, where turnover has increased from $110 billion in 1983 to $880 billion in 1992.

Because transaction volume is many times greater than the volume of trade flows, it cannot be ascribed to the servicing of international trade. To illustrate

Philippe Jorion is professor of finance at the Graduate School of Management of the University of California, Irvine.

Thanks are due to participants in the NBER conference for useful comments. Partial financial support was provided by the Institute for Quantitative Research in Finance.

1. Average volume is 250 million shares, with an average price per share of about $20.00.

Table 1.1 Daily Turnover in the Foreign Exchange Market (billions of dollars)

Market	April 83	April 86	April 89	April 92
London (8:00 A.M.–16:00 P.M., GMT)	...	90	187	300
New York (14:00 P.M.–22:00 P.M., GMT)	34	59	129	192
Tokyo (23:00 P.M.–7:00 A.M., GMT)	...	48	115	126
Singapore	...	...	55	76
Zurich	...	...	57	68
Hong Kong	...	...	49	61
Germany	...	...	...	57
Paris	...	...	26	36
Canada	...	9	15	22
Total[a]	110	206	640	880

[a]Volume for all countries may not add up to total owing to omissions, gaps in reporting, and double counting. GMT = Greenwich Mean Time.

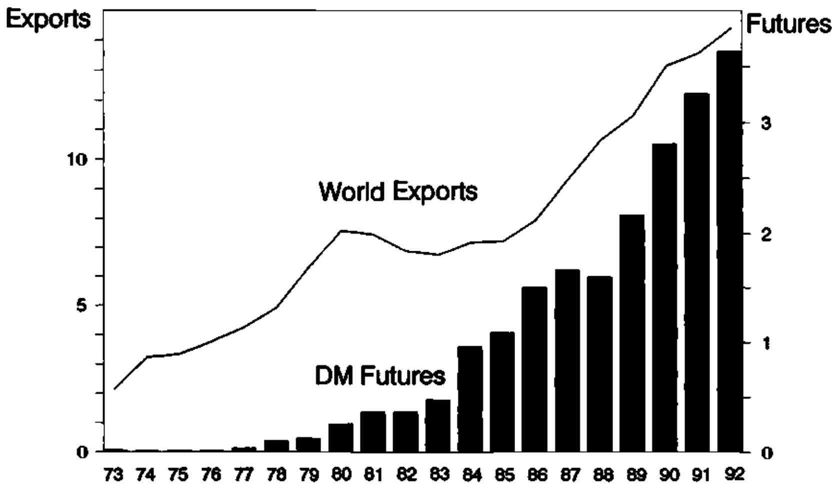

Fig. 1.1 Comparison of daily volume—billions of dollars

this point, table 1.2 describes the changing patterns of activity in the New York foreign exchange market. Over time, activity in the Canadian dollar has dwindled to about 5 percent of the market; given that Canada is the largest trading partner of the United States, trade cannot be the prime determinant of turnover in a currency. It is also interesting to note that the share of the Dutch gulden has fallen sharply after 1980; this is due to the pegging of the gulden to the mark, which, after March 1979, allowed traders to cross-hedge efficiently and more cheaply with the mark. These two examples suggest that volatility and turnover are correlated: low turnover is associated with the low volatility of the Canadian dollar or of a cross-rate.

Table 1.2 **Breakdown of Foreign Exchange Market Turnover by Currency (percentage terms, New York market)**

Currency	1969	1977	1980	1983	1986	1989
German mark	17.0	27.3	31.7	32.5	34.2	33.0
Japanese yen	2.0	4.3	10.2	22.0	23.0	25.0
British pound	45.0	17.0	22.8	16.6	18.6	15.0
Swiss franc	7.0	13.8	10.1	12.2	9.7	12.0
Canadian dollar	21.0	19.2	12.3	7.5	5.2	...
French franc	...	6.3	6.8	4.4	3.6	...
Dutch gulden	...	5.7	1.9	1.6	1.4	...
Belgian franc	...	1.5	1.0	.4	...	...
Italian lira	...	1.1	.9	.8	...	...
Other	...	2.8	2.2	2.1	4.4	15.0
Total (%)	100	100	100	100	100	100
Total ($billion)		5	23	34	58	129

Previous academic literature has viewed the positive correlation between volume and volatility as reflecting joint dependence on a common directing variable or event. This common "mixing" variable represents the random number of daily equilibria, due to new information arriving to the market. According to this class of models, known as the mixture of distribution hypothesis (MDH), unexpected risk and unexpected volume are positively correlated through their dependence on an information-flow variable.

In addition, Tauchen and Pitts (1983) show that expected turnover may change over time and increases with the number of active traders, with the rate of information flows, and with the amount of trader disagreement. This is consistent with the idea that, since trading reflects capital transactions, turnover must be driven by heterogeneous expectations combined with volatility.

In previous work, the positive correlation between risk and turnover was derived from ex post measures. Given the substantial amount of time variation in risk and turnover, however, it is crucial to distinguish between expected and unexpected volatility. This paper measures expected volatility from options on deutsche mark currency futures traded on the Chicago Mercantile Exchange (CME) over the period 1985–92. For a given market price, inverting the appropriate pricing model yields an *implied standard deviation* (ISD). It is widely believed that ISDs are the market's best estimate of future volatility. After all, if it were not the case, one could devise a trading strategy that could generate profits by trading in mispriced options.

This study also investigates bid-ask spreads in spot markets. The literature on spreads identifies inventory costs as one of the main components of spreads. Higher volatility means, ceteris paribus, that dealers face the risk that the exchange rate will move unfavorably while the position is held. Although this risk might be diversifiable in theory, in practice active currency dealers effectively focus on one currency only and therefore worry about idiosyncratic risk. As a result, when volatility increases, so should the spread, which reflects the compensation that dealers expect for taking on currency risk. Again, to test this hypothesis, it is crucial to distinguish between expected and unexpected volatility. ISDs should provide better volatility forecasts than time-series models.

This paper is organized as follows. The literature on the turnover-risk relation, on the spread-risk relation, and on measuring risk from options is reviewed in section 1.1. Section 1.2 describes the data. The measurement of expectations for volume and risk from time-series data is presented in section 1.3. Section 1.4 discusses how implied volatilities are derived from option prices. Empirical results are presented in section 1.5. Finally, section 1.6 contains some concluding observations.

1.1 Literature Review

1.1.1 Turnover and Risk

The domestic microstructure literature has long been concerned with the relation between turnover and risk. This relation is important for several reasons. First, it provides insight into the structure of financial markets by relating new information arrival to market prices. Also, it has implications for the design of new futures contracts; a positive relation suggests that a new futures contract can succeed only when there is "sufficient" price uncertainty with the underlying asset, which cannot be effectively cross-hedged with other contracts. Finally, the price-volume relation has a direct bearing on the empirical distribution of speculative prices.

The mixture of distribution hypothesis (MDH), first advanced by Clark (1973), assumes that price variability and volume are both driven by an unobserved common directing variable. Indeed, numerous studies have reported a strong contemporaneous correlation between volume and volatility.[2] Cornell (1981) provides considerable empirical evidence on how pervasive the relation is for eighteen futures contracts. Grammatikos and Saunders (1986) analyze foreign currency futures contracts and find that detrended volume is positively related to variability. At the same time, there are secular increases in volume, without corresponding increases in volatility.

These observations have been brought together in a seminal paper by Tauchen and Pitts (1983). The authors present a model where the volatility-volume relation can take two forms: (1) as the number of traders grows, market prices, which can be considered as an average of traders' reservation prices, become less volatile because averaging involves more observations; (2) with a fixed number of traders, higher trading volume reveals higher disagreement

2. Karpoff (1987) provides a survey of the evidence in the futures and equity markets.

among traders and is thus associated with higher price variability. This link is stronger when new information $\tilde{I}$ flows to the market at a higher rate.

Formally, market prices P and volume V are modeled as

$$\Delta\tilde{P} = \sigma_1 \sqrt{\tilde{I}}\tilde{z}_1, \tag{1}$$
$$\tilde{V} = \mu_2\tilde{I} + \sigma_2\sqrt{\tilde{I}}\tilde{z}_2,$$

where $\tilde{z}_1$ and $\tilde{z}_2$ are independent $N(0,1)$ variables, and $\tilde{I}$ represents the random number of daily equilibria, due to new information arriving to the market.

In the above, the variance term σ_1^2 depends both on the variance of a "common" noise component σ_0^2, agreed on by all traders, and on the variance of the "disagreement" component, ψ^2 scaled by the number of active traders N: $\sigma_1^2 + \psi^2/N$. Volatility of prices then increases with the rate of information flow I, increases with the common noise σ_0, increases with trader disagreement ψ, and decreases with the number of active traders N.

As for the volume parameters, these can be written as $\mu_2 \div \psi N$ and $\sigma_2^2 \div \psi^2 N$. Turnover then increases with the rate of information flow I, with trader disagreement ψ, and with the number of active traders N.

Because both ΔP^2 and V depend on the mixing variable I, their covariance is positive and equal to $\sigma_1^2\mu_2$ Var (I). At the transaction level, however, V and ΔP are independent. These relations can be summarized as

$$\begin{aligned} &\mathrm{Var}(\Delta\tilde{P}) = (\sigma_0^2 + \psi^2/N)\cdot E(\tilde{I}),\\ &E(\tilde{V}) \div \psi N \cdot E(I),\\ &\mathrm{Cov}(\Delta\tilde{P}^2, \tilde{V}) \div (\sigma_0^2 + \psi^2/N)\,\psi N \cdot \mathrm{Var}(\tilde{I}).\end{aligned} \tag{2}$$

However appealing, this model has the severe limitation that the mixing variable is unobservable. In addition, the unknown parameters σ_0, ψ, and N most likely change over time, especially when long horizons are considered. Testing the model involves making specific assumptions for the distribution of unobserved variables. Assuming a lognormal distribution for I and a logistic model for the number of traders, Tauchen and Pitts (1983) estimate the model for Treasury bill futures. They find that the model matches general trends in the data reasonably well.[3]

The main empirical confirmation of the model is the fact that, as predicted by the theory, variance and volume are positively correlated. Additional evidence can be found from controlled experiments. Batten and Bhar (1993), for instance, explore the $V - \Delta P^2$ relation for yen futures across the International Money Market (IMM), during U.S. trading hours, and the Singapore International Monetary Exchange (SIMEX), during Asian trading hours. They find that the volume-volatility correlation is similar across the IMM and the SIMEX

3. Another approach is by Richardson and Smith (1994), who conduct GMM (generalized method of moments) tests of the model by focusing on moments and cross-products of ΔP and V.

markets. Given that the volume of trading is much larger on the IMM, they conclude that information emanating from Japan must have a large effect on trading.

Another piece of evidence is by Frankel and Froot (1990), who consider the relation between the dispersion of survey forecast, volatility, and volume of trading. They find that dispersion, proxying for the parameter ψ, Granger-causes both volume and volatility, which provides some support for the MDH.

In this context, implied volatilities may prove more informative than time-series models since forecasts of $\mathrm{Var}(\Delta\tilde{P})$ include forecasts of the common noise component, σ_0, of the disagreement parameter ψ, of the number of traders N, and of the expected information flow $E(\tilde{I})$. Simple time-series models are less likely to be able to capture variation in these parameters.

1.1.2 Bid-Ask Spreads

Microstructure theory implies that bid-ask spreads reflect three different types of costs: (1) order-processing costs; (2) asymmetric-information costs; and (3) inventory-carrying costs. Order-processing costs cover the cost of providing liquidity services and are probably small given the size of transactions in the foreign exchange market and the efficiency with which transactions are consummated. Asymmetric-information costs are relevant in the stock market, where corporate officers have access to inside information and analysts actively research firm prospects; given that there is little inside information to trade on in the foreign exchange market, this component is probably small for the foreign exchange market.[4] Finally, inventory-carrying costs are due to the cost of maintaining open positions in currencies and can be related to forecasts of price risk, interest rate costs, and trading activity.

When price volatility increases, risk-averse traders increase the spread in order to offset the increased risk of losses. Glassman (1987) reports that spreads increase with recent volatility. Bollerslev and Melvin (1994) and Bessembinder (1994) have also looked at the role of uncertainty in determining bid-ask spread. They find that spreads are positively correlated with GARCH expected volatility. An interesting question is whether volatility forecasts implied in option prices provide a better measure of risk.

Regarding the second component of inventory-carrying costs, interest rate costs, Bessembinder (1994) reports that using term structure information as a proxy for the cost of investing capital in short-term investments has little effect on the spread. Therefore, this component will be ignored here.

Finally, the third component of inventory-carrying costs involves trading activity. As shown in Glassman (1987) and Bessembinder (1994), there is evidence that, when markets are less active (as before the weekend or a holiday),

4. Lyons (1995), however, showed that marketmakers change prices in response to the perceived informativeness of the quantity transacted. Lyons argues that this finding "calls for a broader conception of what constitutes private information." Perhaps private information consists of information about order flows or price limits.

spreads tend to increase. I will thus include variables representing weekend or holiday. Trading activity is also measured by trading volume. Previous authors have shown that spreads are positively correlated with trading volume. Empirically, however, trading volume is highly autocorrelated, implying that movements in volume can be forecast. In addition, expected and unexpected volume can have a different effect on bid-ask spreads. Cornell (1978) argues that spreads should be a decreasing function of volume because of economies of scale leading to more efficient processing of trades and because of higher competition among marketmakers. Therefore, *expected* trading volume should be negatively related to spread. Easley and O'Hara (1992) formally develop a model implying such a relation. Unexpected trading volume, however, reflects contemporaneous volatility through the mixture of distribution hypothesis and should be positively related to bid-ask spreads.

1.1.3 Implied Volatility

There are only a few studies using the information content of implied standard deviation (ISD) in the foreign exchange market. This is due to the fact that option trading started only in 1982 on the Philadelphia Stock Exchange and in 1984 on the Chicago Mercantile Exchange. It is only now, after ten years, that there may be sufficient data to perform time-series tests with any statistical power.[5]

Scott and Tucker (1989) relate the ISD to future realized volatility and report some predictive ability in ISDs measured from Philadelphia Stock Exchange (PHLX) currency options, but their methodology does not allow formal tests of hypotheses.[6] Wei and Frankel (1991) and Jorion (1995) test the predictive power of ISDs by matching ISD with the realized volatility over the remaining days of the option contract. They find that ISDs appear to be biased predictors of future volatility but also outperform time-series models.

Even though ISDs should be construed as a volatility forecast for the remaining life of the option, this paper considers only the information content of ISDs for the next trading day. Presumably, better results could be obtained by focusing on short-term options or measuring an instantaneous value of the volatility by extrapolating the term structure of volatility to a very short horizon.[7]

5. Lyons (1988) used option ISDs over 1983–85 to test whether expected returns on currencies are related to ex ante volatility and found that ISDs can explain some of the movement in expected returns, although he did not test the model restrictions.

6. Scott and Tucker (1989) present one OLS regression with five currencies, three maturities, and thirteen different dates. Because of correlations across observations, the usual OLS standard errors are severely biased, thereby invalidating hypothesis tests.

7. The problem with short-term options is that their "vega" decreases sharply as the option approaches maturity, which implies that ISDs will be measured less accurately, especially if a large fraction of the time value is blurred by bid-ask spreads.

1.2 Data and Preliminary Evidence

The futures and option data are taken from the Chicago Mercantile Exchange's closing quotes for deutsche mark (DM) currency futures and options on futures over January 1985–February 1992.[8] This represents more than seven years of daily data, or 1,811 observations. I chose deutsche mark futures given that this is the most active currency futures contract.

The volume of trading is taken as the total volume of daily trades in deutsche mark contracts.[9] Although the level of futures trading volume is much less than that of the over-the-counter market, it serves as a proxy for the total interbank trading volume. In markets where both spot and futures trading volume can be observed, the two are highly correlated.

Data for the bid-ask spreads comes from DRI, up to December 1988, after which the data are collected from Datastream. It should be noted, however, that these quotations are much less reliable than the futures data. Futures data are carefully scrutinized by the exchange because they are used for daily settlement and therefore less likely to suffer from clerical measurement errors. In contrast, institutions reporting bid-ask quotes have no incentive to check the numbers provided; in some instances, there were obvious errors in the data, which have been corrected. Also, the bid-ask spreads reported are only indicative quotes and do not necessarily represent actual trades; banks tend to quote "wide spreads" in order to make sure that all customer transactions fall into the reported spread.

Implied volatilities were obtained from contracts with the usual March-June-September-December cycle. On the first day of the expiration month, which is the time around which most rollovers into the next contract occur, the option series switches into the next quarterly contract.[10] Daily returns are measured as the logarithm of the futures prices ratio for the underlying futures contract. This generates a time series of continuous one-day returns and implied volatility. Although the implied volatility is strictly associated with the volatility over the remaining life of the contract, it presumably also contains substantial information for the next day volatility.

Table 1.3 presents preliminary regressions with volume and volatility. Standard errors are heteroskedastic consistent, using White's (1980) procedure. The top panel reports results from regressing log volume on a time trend. The relation is strong and significant. Trading activity increases with time, reflecting

8. Options on futures started to trade in January 1984, but volume was relatively light in that year. In addition, there were price limits on futures, which were removed on 22 February 1985.

9. The face value of one contract is DM 125,000. Volume is thus measured in deutsche marks, although turnover could also be measured in dollars.

10. Some error might be imparted in implied volatilities if options trade with a bid-ask spread or if option hedging entails costs. Leland (1985) shows how costs tend to increase the observed ISD. Given the very low costs of transacting in the foreign exchange markets, however, the bias is very small.

Table 1.3 **Unconditional Regressions with Volume and Variance**

	Regressors			
Model	Constant	Time	Volume	R^2
Volume	9.903	.00036*		.186
	(234.44)	(9.72)		
Variance	.707	−.00010		.002
	(7.53)	(−1.08)		
Variance	−8.626		.904*	.096
	(−8.21)		(8.62)	
Variance	−10.892	−.00052*	1.171*	.132
	(−8.74)	(−5.50)	(9.17)	

Note: Regressions of log volume and variance on a time trend and log volume. Volume is the number of contracts traded daily; variance is measured as the squared log return on the nearby futures contract. The period is January 1985–February 1992 (1,811 observations). Asymptotic t-statistics are in parentheses. Standard errors are heteroskedastic consistent.

*Significantly different from zero at the 5 percent level.

the increasing number of traders. The second panel finds a negative but weak correlation between variance and the time trend. In the third panel, variance is found to be strongly contemporaneously correlated with volume; these results are in line with most of the volume-volatility literature. Finally, the fourth panel shows that risk is positively correlated with volume and at the same time negatively correlated with the time trend. This is generally consistent with the Tauchen-Pitts model, where the disagreement component of risk decreases because of averaging over an increasing number of traders. These results, however, should be explored further by distinguishing between expected and unexpected volatility.

1.3 Measuring Expectations

1.3.1 Time-Series Model for Volatility

Expected volatility is measured using a simple but robust time-series model, the GARCH(1,1) model.[11] The GARCH model, developed by Engle (1982) and extended by Bollerslev (1986), posits that the variance of returns follows a deterministic process, driven by the latest squared innovation and by the previous conditional variance:

$$(3) \qquad R_t = \mu + r_t, \quad r_t \sim N(0, h_t), \quad h_t = \alpha_0 + \alpha_1 r_{t-1}^2 + \beta h_{t-1},$$

where R_t is the nominal return, r_t is the de-meaned return, and h_t is its conditional variance, measured at time t. To ensure invertibility, the sum of parame-

11. For evidence on the GARCH(1,1) model applied to exchange rates, see, e.g., Hsieh (1989).

Table 1.4 Modeling Volatility

$R_t = \mu + r_t, \quad r_t \sim N(0, h_t), \quad h_t = \alpha_0 + \alpha_1 r^2_{t-1} + \beta h_{t-1}$[a]

Model	μ	α_0	α_1	β	Log-Lik.	$\chi^2(2)$
Normal	.0304	.619*			6,187.23	
	(1.64)	(30.04)				
GARCH	.0299	.027*	.0785*	.8802*	6,242.09	109.71
	(1.65)	(4.50)	(4.53)	(72.26)		[.000]

[a]Where R_t is defined as the return on currency futures, expressed in percentages, and h_t is the conditional variance of the innovations. The period is January 1985–February 1992. Asymptotic t-statistics are in parentheses; p-values are in square brackets. The χ^2 statistic tests the hypothesis of significance of added GARCH process.

*Significantly different from zero at the 5 percent level.

Table 1.5 Modeling Volume

Stationarity: $\Delta \log (V_t) = a + bt + \phi_1 \log (V_{t-1}) + u_t$;

ARMA: $\log (V_t) = a + bt + \varepsilon_t, \quad \varepsilon_t = \phi_1\varepsilon_{t-1} + \phi_2\varepsilon_{t-2} + \theta_1 u_{t-1} + u_t$[a]

Model	Constant	Time	ϕ_1	ϕ_2	θ_1	R^2
Stationarity	4.3781	.00017	−.442*			.2186
	(23.65)	(11.50)	(−23.72)			
ARMA	9.8942	.00037*	1.306*	−.335*	.852*	.4625
	(133.54)	(5.21)	(31.32)	(9.68)	(27.13)	

[a]Time-series model for log (V), where V is the number of contracts traded daily. The period is January 1985–February 1992. Asymptotic t-statistics are in parentheses.

*Significantly different from zero at the 5 percent level.

ters $(\alpha_1 + \beta)$ must be less than unity; when this is the case, the unconditional, long-run variance is given by $\alpha_0/(1 - \alpha_1 - \beta)$.

Estimates of the GARCH(1,1) process are presented in table 1.4. In line with previous research, I find that the GARCH model is highly significant, with a $\chi^2(2)$ statistic exceeding 100. This is much higher than the 1 percent upper fractile of the chi square, which is 9.2. There is no question, therefore, that realized volatility does change over time. The process is persistent but also stationary, with values of $(\alpha_1 + \beta)$ around 0.96. This number implies that a shock to the variance has a half-life of log(0.5)/log(0.96), which is about seventeen days. The conditional variance generated by this model will be taken as the time-series forecast of risk. Note that the GARCH model will be given the benefit of the doubt, by using "ex post" parameter values estimated over 1985–92, whereas ISDs have access only to past information.

1.3.2 Time-Series Model for Volume

To model expected volume, one must first assess whether volume is stationary. If not, first differences should be taken. To test for trend stationarity, I regress the daily change in volume on a trend and the lagged volume:

(4) $$\Delta \log(V_t) = a + bt + \phi_1 \log(V_{t-1}) + u_t.$$

Estimates of the regression are presented in table 1.5. The t-statistic on ϕ_1 is -23.7, which is much lower than the 5 percent critical value of -3.40 reported by Dickey and Fuller (1979). Therefore, there is strong mean reversion in detrended volume, and we can apply time-series models assuming stationarity to the level of log volume.

To measure expected volume, the trend model is estimated simultaneously with an ARMA process:

(5) $$v_t \equiv \log(V_t) = a + bt + \varepsilon_t, \quad \varepsilon_t = \phi_1\varepsilon_{t-1} + \phi_2\varepsilon_{t-2} + \theta_1 u_{t-1} + u_t.$$

An ARMA(2,1) process appears to provide a parsimonious fit since upper-order terms are not significant. The time-series model allows us to decompose the volume into an expected component, $E_t(v_{t+1})$, and an error process u_t.

Estimates of the ARMA process are presented in table 1.5. The ARMA coefficients are highly significant, as is the time trend coefficient. There was a marked upward trend in the number of future contracts traded over 1985–92, implying an annual growth of 9 percent. When measured in dollars, the volume of trading has grown at an annual average rate of 19 percent over this period.

1.4 Computing Implied Volatilities

Implied volatilities are derived from the Black (1976) model for European options on futures:

(6) $$c = [FN(d_1) - KN(d_2)]e^{-r\tau}, \quad d_1 = \frac{\log(F/K)}{\sigma\sqrt{\tau}} + \frac{\sigma\sqrt{\tau}}{2},$$
$$d_2 = d_1 - \sigma\sqrt{\tau},$$

where F is the futures rate, K is the strike price, τ is the time to option expiration, r is the risk-free rate (taken as the Eurodollar rate), and σ is the volatility. Note that the futures contract might expire later than the option contract, in which case F is related to the spot through a cost-of-carry relation involving the time to expiration of the futures contract.

For a given option price, inverting the pricing model yields an *implied standard deviation.* Because Beckers (1981) showed that using at-the-money options was preferable to various other weighting schemes, only at-the-money calls and puts are considered here. In addition, these are the most actively traded and therefore the least likely to suffer from nonsimultaneity problems. On any given day, one computes the ISD as the arithmetic average of that obtained from the two closest at-the-money call and put options. These options have the highest "vega," or price sensitivity to volatility, and therefore should provide the most accurate estimates of volatility. Averaging over one call and one put lessens the effect of bid-ask spreads and of possible nonsynchronicity between futures and option prices.

Since CME options are of the American type, using a European model introduces a small upward bias in the estimated volatility. This bias is generally small for short-maturity options.[12] For instance, with typical parameter values, using a European model overestimates a 12 percent true volatility by reporting a value of about 12.02 percent.[13] The difference, however, is less than half of typical bid-ask spreads when quoted in terms of volatility and thus barely economically significant.

Another potential misspecification is that the Black-Scholes model is inconsistent with stochastic volatilities. If volatility changes in a deterministic fashion, ISD can be construed as an average volatility over the remaining life of the option. But, if volatility is stochastic, there is more than one source of risk in options, and the arbitrage argument behind the Black-Scholes option pricing model fails.

Recent papers by Hull and White (1987), Scott (1987), and Wiggins (1987) have examined the pricing of options on assets with stochastic volatility. The general approach to pricing options in these papers is to treat the volatility as a random state variable. In order to derive tractable results, the innovations in volatility and returns are generally assumed to be uncorrelated; prices are then calculated by Monte-Carlo simulation. Scott (1988) and Chesney and Scott (1989), for instance, present a careful empirical analysis of the random variance model (implemented on a Cray supercomputer) and find that the random variance model actually provides a worse fit to market prices than the Black-Scholes model using ISDs.[14] For U.S. stock options, differences are on the order only of \$0.02, much lower than typical bid-ask spreads of \$0.05–\$0.25. Duan (1995) extends the risk-neutral valuation to the case where logarithmic returns follow a GARCH process. Under some combination of preferences and distribution assumptions, he derives a GARCH option-pricing model, but the magnitude of the bias, computed by simulations, is very small, at most \$0.10–\$0.15 for at-the-money options on a \$100 underlying asset.

Because options with stochastic volatility are priced using Monte-Carlo

12. The bias depends on the difference between U.S. and foreign interest rates. When U.S. rates are higher than foreign rates, the American premium on spot currency options is close to zero for calls and positive for puts. Jorion and Stoughton (1989) compare market prices of American PHLX (Philadelphia Stock Exchange) and European CBOE (Chicago Board Options Exchange) options and find that differences are minor, essentially undistinguishable from bid-ask spreads. Adams and Wyatt (1987) and Shastri and Tandon (1986) use numerical procedures to show that biases in measured implied volatilities are generally minor for short-term at-the-money options.

13. With a futures prices of \$0.50, a strike price of 50, a U.S. interest rate of 6 percent, 50 calendar days to expiration, and a true volatility of 12 percent, the values of an American and a European call are 0.8799 and 0.8786, respectively. Inverting the American call value using a European model yields an apparent volatility of 12.02 percent. With the same parameters but 95 days to expiration, the estimated volatility is 12.04 percent. With 5 days to expiration, it is 12.00 percent.

14. Melino and Turnbull (1990) compare option prices derived from Black-Scholes and a stochastic volatility model, using parameters derived from the time-series process, and find that the stochastic volatility model provides a better fit to options than the standard model using historical volatility. They do not, however, consider a Black-Scholes model with implied volatility.

Table 1.6 **Comparison of Volatility Regressions**

$R^2_{t+1} = a + b_1\sigma_t^{2,\,\mathrm{ISD}} + b_2h_{t+1} + b_3E_t(v) + c[v_{t+1} - E_t(v)] + \varepsilon_{t+1}$†

	Slopes on:				
a	ISD	GARCH	$E(v)$	$v - E(v)$	R^2
−.117	1.192*				.0464
(.095)	(.182)				
.164		.724*			.0243
(.071)		(.126)			
.113			.598*		.0304
(.063)			(.079)		
−.123	1.150*	.051			.0465
(.094)	(.243)	(.159)			
−.659	1.153*	.037	.053		.0467
(1.051)	(.243)	(.160)	(.104)		
−.237		.741*	.038	1.540*	.1737
(.989)		(.119)	(.098)	(.122)	
−1.201			.178	1.532*	.1493
(.999)			(.098)	(.122)	
−.628	.906*	.206	.055	1.500*	.1873
(.985)	(.220)	(.148)	(.097)	(.116)	

†Variance over next day is related to forecast variance from option implied standard deviation (ISD), σ_t^{ISD}. GARCH(1,1) forecast, h_{t+1}, expected log volume from ARMA time-series model, $E_t(v)$, and unexpected log volume over next day, $[v_{t+1} - E_t(v)]$. The period is January 1985–February 1992. Heteroskedastic-consistent standard errors are in parentheses.

*Significantly different from zero at the 5 percent level.

methods, no published research has ever recovered the implied (instantaneous) standard deviation from a stochastic volatility model. Recently, however, Heston (1993) has developed a closed-form solution that efficiently computes option values under stochastic volatility. To implement this model, the researcher requires knowledge of additional parameters, including those describing the time-series process for the volatility, as well as the price of volatility risk.

In summary, although stochastic volatility models are theoretically more appealing than the standard Black-Scholes approach, they have severe shortcomings. Besides computational costs, the estimation of many additional parameters introduces elements of uncertainty. In the debate between purists and empiricists, my view is that the Black-Scholes approach, a simple and robust model, provides a sufficient approximation to ISDs.

1.5 Empirical Results

The mixture of distribution hypothesis postulates a positive relation between volume and volatility for a given number of traders. To capture this relation, I estimate a regression of the squared return on expected variance and an innovation component:

$$R_{t+1}^2 = a + bE_t(R_{t+1}^2) + c[v_{t+1} - E_t(v_{t+1})] + \varepsilon_{t+1}. \quad (7)$$

The advantage of this approach is that slow changes in σ_0, ψ, and N may be captured by the rational forecast $E_t(R_{t+1}^2)$. In the above regression, we expect the coefficient c to be positive. Lamoureux and Lastrapes (1990) apply a GARCH model to a sample of twenty stocks and find that GARCH effects disappear once volume is included as an exogenous variable. They interpret this evidence as support for the hypothesis that GARCH effects are a manifestation of the time dependence in the rate of information arrival to the market.

This, however, assumes that the best available forecasts of volatility are generated by a GARCH model. In fact, better forecasts may be available from the option markets. The issue is whether the correlation between volatility and volume remains in the presence of *implied volatilities*. If not, the usefulness of the mixing model would be in serious doubt.

To test the information content of various forecasts, table 1.6 reports regres-

Table 1.7 **Comparison of Bid-Ask Spread Regressions**
$S_t = a + b_1\sigma_t^{2,\text{ISD}} + b_2h_{t+1} + b_3E_{t-1}(v) + c[v_t - E_{t-1}(v)] + dD_t + \varepsilon_t$[†]

	Slopes on:					
a	ISD	GARCH	$E(v)$	$v - E(v)$	Fri./Hol.	R^2
.040	.1055*					.1728
(.004)	(.0084)					
.061		.0705*				.1095
(.004)		(.0082)				
.085			.0020			.0001
.003			.0036			
.038	.0914*	.0170				.1761
(.005)	(.0093)	(.0086)				
.152	.0897*	.0212*	−.0113*			.1792
(.042)	(.0093)	(.0095)	(.0043)			
.084			.0021	.0078		.0019
(.037)			(.0036)	(.0062)		
.149	.0886*	.0220*	−.0114*	.0016	.0108*	.1850
(.042)	(.0093)	(.0095)	(.0043)	(.0058)	(.0032)	

[†]Bid-ask spread measured in deutsche marks is related to forecast variance from option implied standard deviation (ISD), σ_t^{ISD}, GARCH(1,1) forecast, h_{t+1}, expected log volume from ARMA time-series model, $E_{t-1}(v)$, unexpected log volume $[v_t - E_{t-1}(v)]$, and Friday-holiday dummy variable D_t. The period is January 1985–February 1992. Heteroskedastic-consistent standard errors are in parentheses.

*Significantly different from zero at the 5 percent level.

sions of the one-day squared return against several predetermined variables:

(8) $$R^2_{t+1} = a + b_1\,\sigma_t^{2,\mathrm{ISD}} + b_2 h_{t+1} + b_3\,E_t(v) + \varepsilon_{t+1},$$

where σ_t^{ISD} is the option IDS, h_{t+1} is the GARCH forecast using information up to time t, and $E_t(v)$ is the expected volume, also measured at time t. All predetermined variables—the implied variance, the GARCH forecast, and the expected volume—are positively, and significantly, related to future risk. More interestingly, when pitting all three forecasts against each other, only the implied variance appears significant. Note that these results are particularly impressive since the GARCH model was given the benefit of the doubt, using "ex post" parameter values estimated over 1985–92. In contrast, ISDs have access only to past information.

The table also shows that ISDs are nearly unbiased forecasts of the next day's variance, with the slope coefficients generally close to unity. ISDs, in theory the best forecast of volatility over the remaining life of the option, are also proving to be useful short-term forecasts.

Focusing on volume, regressions of risk on expected and unexpected volume indicate that the strongest association appears between risk and unexpected volume, as predicted by the Tauchen-Pitts model. The last regression in the table uses the three predetermined variables as well as the unexpected volume variable. The positive relation between risk and unexpected volume is still strong, as predicted by the information-flow model. However, in contrast with the Lamoureux-Lastrapes results, measures of ex ante risk are still significant. Even when volume measures are included, the GARCH forecast is still sig-

Table 1.8 **Using Spreads to Forecast Volatility**
$R^2_{t+1} = a + b_1\sigma_t^{2,\mathrm{ISD}} + b_2 h_{t+1} + b_3 E_t(v) + b_4 S_t + \varepsilon_{t+1}$†

	Slopes on:				
a	ISD	GARCH	$E(v)$	Spread	R^2
.449				1.623*	.0055
(.067)				(.702)	
.130		.685*		.560	.0249
(.030)		(.133)		(.696)	
−.107	1.187*	.058		−.411	.0468
(.101)	(.223)	(.163)		(.577)	
−.610	1.189*	.045	.050	−.398	.0469
(1.056)	(.222)	(.166)	(.104)	(.578)	

†Variance over next day is related to forecast variance from option implied standard deviation (ISD), σ_t^{ISD}. GARCH(1,1) forecast, h_{t+1}, expected log volume from ARMA time-series model, $E_t(v)$, and bid-ask spread, S_t. The period is January 1985–February 1992. Heteroskedastic-consistent standard errors are in parentheses.

*Significantly different from zero at the 5 percent level.

nificant. This suggests that expected volatility captures some of the time variation in the information-flow variable.

Next, table 1.7 reports various regressions of the bid-ask spread S_t against the same variables as in table 1.6 above. The most general setup is

$$(9) \qquad S_t = a + b_1\sigma_t^{2,\mathrm{ISD}} + b_2h_{t+1} + b_3E_{t-1}(V_t) + c[V_t - E_{t-1}(V_t)] + dD_t + \varepsilon_t,$$

where variables are defined as above, and D_t is a dummy variable set to one on a Friday or before a holiday. The first two regressions show that the spread is significantly positively related to measures of risk, separately taken as the implied variance and the GARCH variance; the spread is not related to expected volume. When comparing GARCH and implied volatilities, we again find that there is little information content in GARCH forecasts besides that in implied volatility. Finally, the bottom of the table reports the results using all regressors, the Friday/holiday indicator, three predetermined variables, and unexpected volume. Confirming previous research, spreads increase on a Friday or before a holiday. Spreads also increase with implied and GARCH variances but decrease with expected volume, as predicted. These results confirm that bid-ask spreads reflect inventory-carrying costs that primarily depend on price uncertainty and trading activity.

Finally, table 1.8 investigates whether the spread contains information above and beyond that in other risk forecasts. The full regression is

$$(10) \qquad R_{t+1}^2 = a + b_1\sigma_t^{2,\mathrm{ISD}} + b_2h_{t+1} + b_3E_t(v_{t+1}) + b_4S_t + \varepsilon_{t+1}.$$

The first panel, using the spread as the only regressor, shows that the spread is a significant leading indicator of volatility. However, in the full regression reported at the bottom of the table, the coefficients b_2, b_3, and b_4 are all insignificantly different from zero. This confirms that neither GARCH forecasts, nor expected volume, nor spreads, have any information content beyond that in ISDs. Options appear to embody all economically relevant information for future risk.

1.6 Conclusions

Many elements of the microstructure of the foreign exchange market depend critically on perceived risk. Bid-ask spreads should increase with inventory-carrying costs, which depend on risk forecasts. Volume is positively correlated with volatility through the mixture of distribution hypothesis.

The premise of this paper was that risk measures contained from option prices, ISDs, provide superior forecasts for exchange rate volatility. Indeed, the paper reports that ISDs are markedly superior to the current state of the art in time-series volatility forecasting; GARCH models appear to contain no information besides that in ISDs. Neither do expected volume or bid-ask spreads.

Further, ISDs also dominate all other risk measures for the purpose of explaining bid-ask spreads.

Studies of the stock market, in contrast, find that there is not much information in ISDs. Canina and Figlewski (1993) analyze S&P100 index options and find that ISDs have little predictive power for future volatility and appear to be even worse than simple historical measures. Lamoureux and Lastrapes (1993) focus on individual stock options and find that historical time series contain predictive information over and above that of implied volatilities. My results are in sharp contrast to those of the stock option literature and may be indicative of measurement problems in the stock option market. if the arbitrage between options and the underlying stocks is costly, then there may be deviations between options and underlying stock prices. Alternatively, nonsynchronicity in the stock index value may induce measurement errors in implied volatilities. Because of the depth and liquidity of CME futures and options, traded side by side in the same market, implied volatilities are less likely to suffer from the measurement problems that affect stock options and provide better measures of forecast volatility.

The superiority of ISDs is reassuring because it indicates that option traders form better expectations of risk over the next day than statistical models, even when the latter are based on "ex post" parameter values. To some extent, these results were expected since time-series models are unable to account for events such as regular announcements of macroeconomics indicators, meeting of G-7 finance ministers, and so on. Because the timing of these events is known by the foreign exchange market, we would expect options to provide better forecasts than naive time-series models.

Using ISDs, the paper confirms the positive relation between unexpected risk and unexpected volume predicted by the mixture of distribution hypothesis. In contrast with results in the stock market, however, we find that expected variance does not disappear when volume is included in the variance equation. The paper also finds that spreads are positively correlated with expected risk. Overall, the information content of ISDs suggests that an important aspect of anticipated risk is ignored when focusing solely on time-series models of volatility.

References

Adams, P., and S. Wyatt. 1987. On the pricing of European and American foreign currency call options. *Journal of International Money and Finance* 6:315–38.

Batten, J., and R. Bhar. 1993. Volume and price volatility in yen futures markets: Within and across three different exchanges. Working paper. Sydney: Center for Japanese Economic Studies, Macquarie University.

Beckers, S. 1981. Standard deviations implied in option prices as "predictors of future stock price variability." *Journal of Banking and Finance* 5:363–81.

Bessembinder, H. 1994. Bid-ask spreads in the interbank foreign exchange markets. *Journal of Financial Economics* 35:316–48.

Black, F. 1976. The pricing of commodity contracts. *Journal of Financial Economics* 3:167–79.

Bollerslev, T. 1986. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics* 31:307–27.

Bollerslev, T., and M. Melvin. 1994. Bid-ask spreads and volatility in the foreign exchange market: An empirical analysis. *Journal of International Economics* 36:355–72.

Canina, L., and S. Figlewski. 1993. The informational content of implied volatility. *Review of Financial Studies* 6:659–81.

Chesney, M., and L. Scott. 1989. Pricing European currency options: A comparison of the modified Black-Scholes model and a random variance model. *Journal of Financial and Quantitative Analysis* 24:267–84.

Clark, P. 1973. A subordinated stochastic process model with finite variance for speculative prices. *Econometrica* 41:135–55.

Cornell, B. 1978. Determinants of the bid-ask spread on forward foreign exchange contracts under floating exchange rates. *Journal of International Business Studies* 9:33–41.

Cornell, B. 1981. The relationship between volume and price variability in futures markets. *Journal of Futures Markets* 1:303–16.

Dickey, D., and A. Fuller. 1979. Distribution of estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association* 74:427–31.

Duan, J.-C. 1995. The GARCH option pricing model. *Journal of Mathematical Finance* 1:13–32.

Easley, D., and M. O'Hara. 1992. Adverse selection and large trade volume: The implications for market efficiency. *Journal of Financial and Quantitative Analysis* 27: 185–208.

Engle, R. 1982. Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. *Econometrica* 50:987–1007.

Frankel, J., and K. Froot. 1990. Exchange rate forecasting techniques, survey data, and implications for the foreign exchange market. Working Paper no. 3470. Cambridge, Mass.: National Bureau of Economic Research.

Glassman, D. 1987. Exchange rate risk and transaction costs: Evidence from bid-ask spreads. *Journal of International Money and Finance* 6:479–90.

Grammatikos, T., and A. Saunders. 1986. Futures price variability: A test of maturity and volume effects. *Journal of Business* 59:319–29.

Heston, S. 1993. A closed-form solution for options with stochastic volatility with applications to bond and currency options. *Review of Financial Studies* 6:327–43.

Hsieh, D. 1989. Modeling heteroskedasticity in daily foreign exchange rates. *Journal of Business and Economic Statistics* 7:307–17.

Hull, J., and A. White. 1987. The pricing of options on assets with stochastic volatility. *Journal of Finance* 42:281–300.

Karpoff, J. 1987. The relation between price changes and trading volume: A survey. *Journal of Financial and Quantitative Analysis* 22:109–26.

Jorion, P. 1995. Predicting volatility in the foreign exchange market. *Journal of Finance* 50:507–28.

Jorion, P., and N. Stoughton. 1989. An empirical investigation of the early exercise of foreign currency options. *Journal of Futures Markets* 9:365–75.

Lamoureux, C., and W. Lastrapes. 1990. Heteroskedasticity in stock return data: Volume versus GARCH effect. *Journal of Finance* 45:221–29.

———. 1993. Forecasting stock-return variance: Toward an understanding of stochas-

tic implied volatilities. *Review of Financial Studies* 6:293–326.
Leland, H. 1985. Option pricing and replication with transaction costs. *Journal of Finance* 40:1283–1301.
Lyons, R. 1988. Tests of the foreign exchange risk premium using the expected second moments implied by option pricing. *Journal of International Money and Finance* 7:91–108.
———. 1995. Tests of microstructural hypotheses in the foreign exchange market. *Journal of Financial Economics* 39:321–51.
Melino, A., and S. Turnbull. 1990. Pricing foreign currency options with stochastic volatility. *Journal of Econometrics* 45:239–65.
Richardson, M., and T. Smith. 1994. A direct test of the mixture of distribution hypothesis: Measuring the daily flow of information. *Journal of Financial and Quantitative Analysis* 29:101–16.
Scott, E., and A. Tucker. 1989. Predicting currency return volatility. *Journal of Banking and Finance* 13:839–51.
Scott, L. 1987. Option pricing when the variance changes randomly: Theory, estimation and an application. *Journal of Financial and Quantitative Analysis* 22: 419–38.
Scott, L. 1988. Random variance option pricing: Empirical tests of the model and delta-sigma hedging. University of Illinois. Mimeo.
Shastri, K., and K. Tandon. 1986. On the use of European models to price American options on foreign currency. *Journal of Futures Markets* 6:93–108.
Tauchen, G., and M. Pitts. 1983. The price variability-volume relationship on speculative markets. *Econometrica* 51:485–505.
Wei, S., and J. Frankel. 1991. Are option-implied forecasts of exchange rate volatility excessively variable? Working Paper no. 3910. Cambridge, Mass.: National Bureau of Economic Research.
White, H. 1980. A heteroskedastic-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* 48:817–38.
Wiggins, J. 1987. Options values under stochastic volatility: Theory and empirical estimates. *Journal of Financial Economics* 19:351–72.

Comment Bernard Dumas

Philippe Jorion's paper contains empirical tests of three hypotheses relating bid-ask spreads in the futures market for currencies, expected and unexpected volume, and price volatility. For reasons given in the paper, it is claimed that expected volume would be negatively related to spreads and unexpected volume positively related to them. A mixing variable, *I*, representing the rate at which information arrives on the foreign exchange market, further leads Jorion to hypothesize a positive relation between unexpected volume and price volatility.

Bernard Dumas is on the faculty of the Hautes Études Commerciales School of Management in France. He is a research professor at Duke University and a research associate of the National Bureau of Economic Research, the Centre for Economic Policy Research, and Delta.

I have four comments on this paper, three of which pertain to the way in which variables are measured, and one of which pertains to the manner in which the mixing variable is specified.

The Measurement of Volume

Volume in this study is the volume of trade in the futures market. Jorion points out that the futures market in foreigu exchange is a very small part of the total world foreign exchange market.

More damaging may be the observation that the futures market is not "representative" of the overall market because it is a centralized, organized market while the bulk of the market is an interbank, decentralized market in which traders cannot observe order flows and volume of trade. The way in which people channel their orders to the futures as opposed to the interbank market would presumably depend on the institutional features of the two types of markets.[1] The decision to trade on one market rather than the other is a missing variable in the theory being tested here. That missing variable may obfuscate the test of the relation between volume and price volatility.

In a very indirect attempt to estimate the severity of this problem, one could make use of the fact that futures markets in foreign exchange are not the only centralized exchange on which volume is directly observable. There exist centralized foreign exchange options markets. Jorion could measure the correlation between volume in the futures and the options markets. That measurement would, of course, leave unobserved the degree to which trades shift between organized and decentralized trading places.

The Role of the Mixing Variable in the Model Specification

This study exhibits an apparent contradiction concerning the way in which the mixing variable, I, is specified. This mixing variable is either a random variable or a random process. To keep the discussion simple, let us imagine that the derivations leading to equation set (2) of the paper remain valid under either formulation. The empirical analysis, however, needs to be adapted depending on the assumed specification.

If the mixing variable is a random variable, then, according to the third equation of equation set (2), there is indeed a constant positive covariance between unexpected volume and squared price increments, as claimed. But, under the same assumption, the first two equations in equation set (2) make it plain that (expected) volatility and expected volume are constant over time. It is then incoherent to proceed to estimate movements of these quantities, as Jorion does.

If the mixing variable follows a stochastic process, expected volume and

1. By way of analogy, see the recent work of Easley, O'Hara, and Srinivas (1994) on the choice made by informed traders to trade in the options market or in the underlying cash market.

volatility are allowed to change over time, but the relation between unexpected volume and squared price increments is not stable over time (although it always has the same sign). It is not clear then that this relation can be captured simply by measuring the cross-moment (sample covariance or sample correlation) between the observed values of these two variables. This would have to be shown.

The Measurement of Volatility in the Presence of a Mixing Variable

In this study, (expected) volatility is measured in two separate ways. One is the Black-Scholes implied standard deviation. The other measurement is based on the estimation of a GARCH process. Both the Black-Scholes model and the GARCH model are specified in real time, when in fact the presence of a mixing variable in the model being tested would require the use of a random time deformation.

Several authors have adapted the theory of option pricing to random time scales.[2] It would have been preferable to estimate real-time implied volatility on the basis of a random-time option-pricing model since, under the null hypothesis, time does flow randomly in the foreign exchange market.

GARCH models have also been extended to random times by, for example, Stock (1988). In a recent study, Ghysels and Jasiak (1994) fit a random-time GARCH model to the daily time series of the S&P500 index from 1950 to 1987. The fit of the GARCH model identifies clear accelerations of time on the stock exchange. Ghysels and Jasiak also show that the estimated volatility under time deformation follows a much smoother path than in the absence of time deformation.

Following Frenkel and Levich (1977) and many others, we have every reason to believe that the foreigu exchange market also goes through tranquil (slow time) and turbulent (fast time) periods. That aspect of the behavior of the market is neglected by Jorion when he measures volatility, even though the theory being tested specifically incorporates a mixing variable.

The Measurement of Short-Lived Volatility Changes from Medium-Term Options

In this study, Jorion endeavors to measure volatility changes on a day-to-day basis. However, when the Black-Scholes implied standard deviation is used for the purpose, the options that serve as a basis for the measurement are medium-term options (several weeks to maturity). No overnight options are available to allow the measurement of daily volatility. This difficulty is pointed out in the paper. How serious is it?

It all depends on whether volatility changes are typically short lived or long lived. If they are long lived, the problem is not as serious as it is if they are short lived.

2. In that extension, the pure arbitrage foundation of the Black-Scholes theory is lost.

The success of GARCH models in fitting financial time series is a testimony to the degree of persistence of volatility. However, there exists also evidence that volatility changes are short lived following the arrival of a piece of news. Ederington and Lee (1993), for instance, study the effect of *scheduled* macroeconomic news on the stock market. They find that the volatility is only slightly elevated for a few hours after the announcement. Donders and Vorst (1994) study the effect of firm-specific, scheduled news releases on implied stock-price volatility. They find that volatility rises steadily for a few days prior to the event date and then drops back to a normal level almost immediately.

Such evidence calls into question the method used in the present study to measure short-term volatility.

Conclusion

Having not done similar work myself, I am not in a position to ascertain whether the apparent shortcomings that I have identified are capable of overturning the results of Philippe Jorion's study. His main conclusion—that neither GARCH modeling nor the information provided by spreads of volume is capable of improving on the Black-Scholes implied standard deviation as a measurement of expected volatility—is a strong one and one that will no doubt generate a lot of interest and controversy.

References

Donders, M. W. M., and T. C. F. Vorst. 1994. The impact of firm-specific news on implied volatilities. Working paper. Erasmus University, Rotterdam.

Easley, D., M. O'Hara, and P. S. Srinivas. 1994. Option volume and stock prices: Evidence on where informed traders trade. Working paper. Cornell University.

Ederington, L. H., and J. H. Lee. 1993. How markets process information: News releases and volatility. *Journal of Finance* 48:1161–91.

Frenkel, J. A., and R. M. Levich. 1977. Transactions costs and interest arbitrage: Tranquil vs. turbulent periods. *Journal of Political Economy* 85:1209–26.

Ghysels, E., and J. Jasiak. 1994. Stochastic volatility and time deformation: An application to trading volume and leverage effects. Discussion paper. Centre de Recherche et Développement Économique, Université de Montréal.

Stock, J. H. 1988. Estimating continuous time processes subject to time deformation. *Journal of the American Statistical Association* 83:77–84.