The predictive power of dollar-real call options implied volatility*

Daniel Augusto Motta§

RESUMO

Estudos empíricos anteriores ressaltam a relação entre eventos de estresse em mercados financeiros e volatilidade implícita em opções, indicando que grandes flutuações nos preços dos ativos financeiros seriam antecipadas por um aumento significativo na volatilidade implícita. Nesse artigo, testa-se o poder de previsão da volatilidade implícita em opções cambiais de compra com relação à forte desvalorização cambial no Brasil em janeiro de 1999. Além disso, analisa-se se a volatilidade implícita em opções cambiais de compra pode ser considerada como um melhor estimador de grandes flutuações comparativamente aos tradicionais modelos de séries de tempo. Finalmente, analisa-se a racionalidade no mercado nacional de derivativos.

Palavras-chave: crise cambial, volatilidade implícita, teste de causalidade de Granger, racionalidade.

ABSTRACT

Previous empirical researches pointed out the relation between stress events in financial markets and implied volatility in option prices, indicating that large movements in asset prices would be preceded by significant increases in implied volatility. In this short paper, I will test the predictive power of US$-R$ call options implied volatility regarding the huge exchange rate devaluation in Brazil in January of 1999. Furthermore, I analyse the issue of whether US$-R$ call options implied volatility may be considered as a better estimator of large-magnitude returns than standard time series models. Finally, I analyse whether there is rationality in Brazilian derivatives market.

Key words: currency crisis, implied volatility, Granger causality test, rationality.

JEL Classification . F47, G13, G1

* A previous version was presented at the *Primeiro Encontro Brasileiro de Finanças* on July 2001. I am in debt with Professors José Evaristo dos Santos, Frank de Jong and Pedro Valls Pereira for their helpful and clarifying suggestions. Furthermore, I gratefully acknowledge comments by three anonymous referees. As usual, I assume full responsibility for any remaining error in this paper.

§ Partner of Tectrain Consulting, MA in Financial Economics at FGV-EAESP and PhD student in Economics at USP.

Recebido em setembro de 2001. Aceito em abril de 2002.

1 Introduction

In financial markets, the ability to predict second moments has been useful in several ways, such as financial risk control, asset management and hedging of derivative securities. Actually, since the usual assumption of standard risk management procedures regarding independently and identically normally distribution for asset returns generally does not hold, the ability to forecast and anticipate large movements in asset prices has been crucial to risk managers and traders. In particular, implied volatilities in option prices have been argued to contain powerful information about future volatility which is not captured by statistical models built upon past returns.

On one hand, Malz (2000) pointed out the predictive power of implied volatility models and the absence of additional information provided by historical volatility models. Jorion (1995), Xu and Taylor (1995), Christensen and Prabhala (1998) and Fleming (1998) concluded that implied volatilities are upward-biased estimators of future volatility, but outperform standard historical volatility models. Finally, Amin and Ng (1997) argued that implied volatility contains more information about future volatility than standard time-series models, but the explanatory power of implied volatilities is enhanced by the use of historical information.

On the other hand, Lamoureux and Lastrapes (1993), Canina and Figlewski (1993) and Day and Lewis (1992) found very disappointing results for implied volatility models, showing that implied volatility has no correlation with future volatility and it does not incorporate the information contained in recent observed volatility. Hull and White (1998) pointed out the predictive power of GARCH models in conjunction with historical simulation. Bates (1991, 2000) concluded that skew may be a more sensitive predictor of market stress than implied volatility. Finally, Bollen, Gray and Whaley (2000) argued that regime-switching models capture the dynamic of exchange rates better than alternative time-series models.

As regards to Brazil, Andrade and Tabak (2001) concluded that implied volatility in Dollar-Real call options obtained from a simple option pricing model, although an upward-biased estimator of future volatility, does provide information about volatility over the remaining life of the option which is not present in past returns.

Alternatively, implied volatility is also used as a credibility test of fixed-exchange rate regimes. Guimarães and Silva (2000) - using Merton (1976) option pricing model in substitution of traditional Black-Scholes (1973) option valuation formula - showed that expected exchange rate devaluation was significantly below the effective devaluation occurred in January of 1999. Besides, Campa, Chang and Refalo (1999) applied the implied probability density function

(PDF)[1] for expected future exchange rates, measuring the credibility of the crawling peg and target zone regimes governing the exchange rate.

This paper contributes to the growing literature on the use of call options to anticipate currency crisis, such as Rocha and Moreira (1998), Campa and Chang (1996) and Malz (1996), contrasting measures of devaluation risk not based on options, such as Münch (1998a, 1998b), Bertola and Svensson (1993) and Engel and Hamilton (1990).

Intuitively, given some market expectation regarding the inability of Central Bank of Brazil to sustain the exchange rate regime under growing speculative attacks, agents would hedge their exposure to exchange rate variability by operating with options on dollar-real future prices and, hence, the increasing implied volatility would anticipate huge future movements in dollar-real spot prices.

The main motivation of this research is simply to test whether implied volatility contains information about future large-magnitude returns. Specifically, the paper focuses on the predictive power of Dollar-Real calls implied volatility in anticipating Brazilian exchange rate crisis in January of 1999, applying Granger causality test. Furthermore, based on Wei and Frankel (1991), I analyse whether there is strong rationality (that is, implied volatility is an unbiased estimator of the subsequent realised exchange rate volatility) or weak rationality (that is, market participants can predict the direction of the change in exchange rate volatility) in Brazilian derivatives market.

2 Brazilian exchange rate crisis: some stylised facts

The Real Plan - introduced in December 1993 in Brazil - controlled inflationary process after the failure of previous plans based solely on wage and price controls, tax hikes and freezing of bank deposits. Basically, the plan directly addressed the problem of inflationary expectations, creating a new currency called Real, promoting the privatisation of state-owned enterprises, diminishing fiscal deficit and implement some institutional reforms. Certainly, exchange rate stabilisation was a fundamental part of Real Plan.[2]

1 See Ait-Sahalia and Lo (1998) for a nonparametric estimation of the PDF implicit in option prices. See also Hutchinson, Lo and Poggio (1994), Hansen and Jagannathan (1991) and Ross (1976) for the nonparametric estimation of alternative models.

2 See Fraga (2000) and Souza (2000) for a careful analysis of the Real Plan and the impact of recent exchange rate depreciation over Brazilian economy.

In practice, while announcing broader "maxibands", the Central Bank followed a crawling peg system, in which the Real gradually depreciated, but remained within a "miniband" surrounding a depreciating central rate. In March 1999, upper (0,93 R$/US$) and lower (0,88 R$/US$) bands were established. Since then, they were adjusted on four occasions - June 22, 1995; January 30, 1996; February 18, 1997; January 19, 1998 -, allowing the Real to depreciate at a controlled rate.

However, the increased volatility generated by the turmoil in international financial markets with Asian crisis in July 1997 and Russian crisis in August 1998, coupled with the difficulty of Brazilian government in committing to some of the structural reforms, led to wide speculation on the viability of the Brazilian exchange rate regime.[3] After the beginning of some speculative attacks, the government announced another realignment of the maxibands on January 12, 1999. During the following date, after the Real depreciation above the upper of the new band, the government decided to abandon the system and to adopt a flexible exchange rate regime.

This paper aims to investigate the predictive power of dollar-real call option implied volatility in anticipating this huge exchange rate depreciation in 13th of January of 1999.

3 Data description and the calculus of implied volatility

The primary data of this study, provided by BM&F, are daily dollar-real future contracts and daily dollar-real call options close prices from 02 January 1998 to 12 December 1999. Dollar-real calls at BM&F are of the European style, and mature on the first business day of the corresponding month of expiration. Furthermore, the data set includes daily dollar-real spot prices (PTAX) and CDI interest rate both provided by the Central Bank of Brazil.

The time path of daily dollar-real spot price and daily dollar-real spot returns are shown in Graph 1 and Graph 2, respectively, in which the huge exchange rate depreciation of 13th of January 1999 is clearly evident. Naturally, before this exchange rate crisis, daily dollar-real spot prices were allowed to vary only within the exchange rate miniband for which daily returns were insignificantly small.

3 According to the classical Krugman (1979, 1991) speculative models, under fundamental inconsistencies between monetary and fiscal policies, speculative attacks on fixed exchange rate regimes or target zones are not only possible, but are inevitable. See Toledo (1999) for the application of these speculative models to Brazilian exchange rate crisis in January 1999. Alternatively, Obstfeld (1994) developed a model in which crisis result from the interaction of rational private economic actors and a government that pursues well-defined policy goals, and arbitrary expectational shifts can turn a fairly credible exchange-rate peg into a fragile one.

By using the prices of the dollar-real future contract expiring in the same day of the call option contract, implied volatility can be computed by numerically solving Black-Scholes (1973) formula for options on future contracts as suggested by Black (1976). Then, the implied volatility for an at-the money call option can be obtained by estimating the liner regression suggested by Mcbeth and Merville (1979).[4]

According to Andrade and Tabak (2001), it is important to select the closest-to-the-money call option for two main reasons.[5] First, using Garman and Kohlhagen (1983) model, it can be shown that under usual circumstances the closest-at-the-money option for each expiration date is the one whose price is more sensitive to the volatility of the underlying asset. Second, there is an apparent inconsistency of recovering a volatility forecast from an option pricing model of the Black-Scholes family, which assumes known and constant volatility.[6]

The implied volatility of daily dollar-real call options and the standard deviation of daily dollar-real spot prices are shown in Graph 3. Naturally, the time path of standard deviation of daily dollar-real spot prices before January 1999 is perfectly consistent with the depreciation rate adopted by the Central Bank of Brazil. Nevertheless, both the implied volatility and the standard deviation series abruptly increase by January 1999. Clearly, realised volatility is less volatile than implied volatility in option prices, which may be considered as empirical evidence that implied volatility models overpredict the magnitude of realised volatility.[7]

Table 1 summarises the descriptive statistics for both daily dollar-real spot price return (measured by the first difference of exchange rate level) and implied volatility in dollar-real call options.[8] Specifically, as shown in Graph 4, dollar-real spot price return has both skewness

---

4 See Poteshman (2000) for a careful analysis of the econometric methodology used in implied volatility models. See also Poon and Granger (2001) for an extensive review of volatility forecasting models based either on implied volatility in option prices and on historical price information.

5 I selected those call options with time to maturity higher or equal to six days.

6 According to Feinstein (1989), under assumption that volatility is uncorrelated to returns, linearity turns Black-Scholes implied volatility into a virtually unbiased estimator of future volatility for those options - considering the class of stochastic volatility option pricing models introduced by Hull and White (1987) - which assumes that either investors are indifferent towards volatility risk or risk is non-systematic.

7 Rationality tests will provide econometric support for this tendency of implied volatility to overpredict realised volatility. Actually, according to Poon and Granger (2001), this bias can be generalised as a common characteristic of implied volatility models.

8 I also perform the model with both dollar-real spot price returns and implied volatility in logarithmic, but it was not possible to obtain better econometric results.

and kurtosis. Jarque-Bera test rejects null hypothesis of normality for both dollar-real spot price return and implied volatility. Fortunately, non-stationarity in dollar-real spot price return is rejected by Augmented Dickey-Fuller test at 5% significance level.

4 Granger causality approach

As suggested by Malz (2000), one way to test whether implied volatility foreshadows returns is to perform Granger causality tests. Briefly, a time series y is said to cause another time series x if past values of y help to predict the current value of x. In other words, according to Hamilton (1994), a variable y fails to Granger cause x if, for all $s > 0$, the mean squared error of a forecast of x_{t+s} based on $(x_t, x_{t-1}, ...)$ is the same as the MSE of a forecast of x_{t+s} that uses both $(x_t, x_{t-1}, ...)$ and $(y_t, y_{t-1}, ...)$.[9] It follows that a standard test for causality is to set a lag length k and carry out the ordinary least squares regression:

$$x_t = \sum_{i=1}^{k} \alpha_i x_{t-i} + \sum_{i=1}^{k} \beta_i y_{t-i} + \xi_t \ , \ \mathrm{t} = 1, \dots, \mathrm{T} \tag{1}$$

and test the null hypothesis H_0. $\beta_1, \beta_2, \dots \beta_k = 0$, that is, y fails to Granger cause x. The test can be performed by running a second OLS regression:

$$x_t = \sum_{i=1}^{k} \gamma_i x_{t-i} + v_t, \ \mathrm{t} = 1, \dots, \mathrm{T} \tag{2}$$

Under H_0. $\beta_1, \beta_2, \dots, \beta_k = 0$, the test variable

$$\lambda(x,y) = \frac{\sum_{t=1}^{T} \hat{v}_t^2 - \sum_{t=1}^{T} \hat{\xi}_t^2}{\sum_{t=1}^{T} \hat{\xi}_t^2} \left(\frac{T-2k-1}{k} \right) \tag{3}$$

9 For further aspects of Granger causality tests, see also Maddala and Kim (1998), Geweke, Meese and Dent (1983), Pierce and Haugh (1977) and Granger (1969). According to Greene (1997), there is an essential complication in these causality tests since there is no theory behind the formulation, that is, the tests are predicted on a model that may, in fact, be missing either intervening variables or additional lagged effects that should be present but are not.

has an asymptotic F(k, T-2k-1) distribution as T$\rightarrow\infty$, where $\hat{\xi}_t$ and $\hat{\nu}_t$ are the residuals from the linear regressions (1) and (2), respectively. If $\lambda(x.y)$ exceeds the critical value of the F distribution for the specified confidence level, H_0 is rejected. Intuitively, as pointed out by Malz (2000), if including past values of y significantly improves a forecast of x, $\lambda(x.y)$ will be large and the hypothesis that y fails to Granger cause x is rejected.

As suggested by Malz (2000), I assumed adjustments occurs within one trading week, since markets react extremely quickly to arriving news events, but not to expectations about future events.[10] Thus, the unrestricted regression equation estimated is the following:

$$r_t^2 = \pi + \sum_{i-1}^{5} \alpha_i r_{t-i}^2 + \sum_{i=1}^{5} \beta_i \sigma_{t-i} + u_t \tag{4}$$

where r_t denotes the return from time t-1 to t, and σ_t the time t at-the-money implied volatility. The null hypothesis is that of non-causality, that is, $\beta_i = 0$, $i = 1, \ldots, 5$. Naturally, if the null hypothesis is rejected, it is evidence that implied volatility does cause r_t^2 [11]

Furthermore, in order to investigate whether implied volatility is a better predictor of large-magnitude returns than historical volatility, I perform the unrestricted regression using historical volatility rather than implied volatility:

$$r_t^2 = \pi + \sum_{i-1}^{5} \alpha_i r_{t-i}^2 + \sum_{i=1}^{5} \beta_i \upsilon_{t-i} + u_t \qquad (5),$$

where $\upsilon_t = \sqrt{\frac{1}{250}\sum_{i=1}^{250} r_{t+1-i}^2}$

10 In fact, the performance of the model could not be significantly improved by incorporating additional lags.

11 According to Malz (2000), by using squared returns, it is possible to focus the analysis on kurtosis instead of skewness, which implies that positive and negative large price movements are equally modelled.

Alternatively, since the *RiskMetrics* methodology using and exponentially-weighted moving average (EWMA) model[12] has been argued to be a superior predictor of near-term volatility to equally-weighted volatility estimates, I perform the following unrestricted regression:

$$r_t^2 = \pi + \sum_{i-1}^{5} \alpha_i r_{t-i}^2 + \sum_{i=1}^{5} \beta_i \upsilon_{RM\,t-i} + u_t \quad (6),$$

where, $\upsilon_{RM,t} = \sqrt{\sum_{i=1}^{250} \delta^{t-i} r_{t+1-i}^2}$ and $\delta = 0{,}94$

The econometric results[13] are presented in Table 3. Clearly, based on AIC and BIC criteria, implied volatility model does provide better results than equally-weighted and exponentially-weighted moving average models. However, as shown in Table 2, implied volatility fails to Granger cause daily dollar-real spot price returns.[14]

Finally, in order to analyse whether EWMA volatilities provide incremental information over implied volatility model, I perform the following unrestricted equation containing both lagged implied volatilities and lagged *RiskMetrics* volatilities:

$$r_t^2 = \pi + \sum_{i-1}^{5} \alpha_i r_{t-i}^2 + \sum_{i=1}^{5} \beta_i \upsilon_{RM\,t-i} + \sum_{i=1}^{5} \gamma_i \sigma_{t-i} + u_t \quad (7)$$

The results in Table 4 indicate that EWMA estimates provide little incremental information over implied volatility estimates, since coefficients are almost identical and both AIC and BIC criteria are higher than estimates of implied volatility model.

12 According to Malz (2000), EWMA models are closely related to GARCH models, but computationally simpler. See the seminal paper of Bollerslev (1986), in which it is interestingly argued that the econometric structure of GARCH models would correspond to some sort of adaptive learning mechanism.

13 Newey and West (1987) covariance matrix was used to correct for heteroskedasticity.

14 Granger causality test can only provide truthful results if series are white noise. On contrary, one should perform cointegration analysis between both series. Fortunately, as shown in Table 1, dollar-real spot price returns are stationary based on Augmented D-F test.

Therefore, it might be concluded that implied volatility model is superior to historical price information models and that exponentially-weighted moving average model does not provide incremental information over implied volatility. Actually, these results are aligned with international evidence in support of implied volatility models. Poon and Granger (2001) pointed out that implied volatility model does provide more accurate volatility forecasts than historical price information models, although Black-Scholes formula does not allow for important statistical features of asset prices such as stochastic volatility, volatility and price jumps, mean reversion in price and volatility and tail thickness. Malz (2000) also found empirical evidence in support of implied volatility models for several exchange rate markets, suggesting a warning signal for stress events based on implied volatility dynamics.[15]

However, based on Table 2 and Table 3, the implied volatility model has some shortcomings such as negative coefficients for some lagged variables and the absence of Granger causality between implied volatility and realised exchange rate volatility. Furthermore, according to the Chow test presented in Table 2, there is no evidence of a structural break in 13th January 1999 despite the huge exchange rate devaluation shown in Graph 1 and Graph 2.

5 Strong rationality versus weak rationality

Based on Granger causality test developed in last section, one could erroneously conclude that implied volatility contains no predictive power regarding future realised exchange rate volatility. In fact, following Wei and Frankel (1991), it is fundamental to distinguish between strong rationality and weak rationality. The strong rationality hypothesis tested is that market-anticipated standard deviation is an unbiased estimator of the subsequent realised one, that is, the market not only get the direction of change correctly, but also get the magnitude of change correctly on average. On the other hand, the weak rationality simply requires that market participants are forward-looking and can predict the direction of the change in exchange rate volatility.

To test the null hypothesis of strong rationality for the implied volatility model, I perform the Wald test for coefficient restrictions.[16] Specifically, defining the null hypothesis as vector β=1,

15 Actually, there is an international controversy regarding whether implied volatility is indeed superior to historical simulation models. Figlewski (1997), for instance, argues that frictions in the market such as bid-ask spread, non-continuous trading and serial correlation will cause the observed transaction price to differ from the equilibrium market price and, consequently, implied volatility in option prices would be biased.

16 See Greene (1997) for further technical details of Wald test for coefficient restrictions.

I test whether implied volatility is an unbiased predictor of future realised exchange rate volatility.[17] As shown in Table 2, the null hypothesis is rejected at 5% level and the estimates are all smaller than one, suggesting that market participants tend to overpredict the magnitude of volatility. Therefore, implied volatility is a biased predictor of realised exchange rate volatility.

However, there are two main shortcomings that could invalidate the test. First the error term may not be white-noise, since option contracts with overlapping time to maturity would cause serial correlation. To overcome this problem, observations with overlapping horizons were excluded before the Wald test reported in Table 2. Second, the error term in equation (4) may not have a normal distribution. The Jarque-Bera test, reported in Table 5, rejects the null hypothesis of normality for OLS residuals. Besides, both skewness and kurtosis are significantly different from the respective values under normal distribution.[18]

Naturally, it would be disturbing to conclude that market participants are so foolish that their volatility forecasts are completely irrelevant to subsequent realised volatility. Thus, I analyse a weaker version of rationality, which requires that traders are forward-looking and can predict the direction of the change in exchange rate volatility. I performed the non-parametric test developed by Henriksson and Merton (1981) which is robust even in the presence of non-normality of residuals and non-stationarity of conditional probabilities over time. The null hypothesis is that the implied volatility in option prices is useless as a forecast of the future exchange rate volatility, that is, the implied volatility model fails to beat the random walk (which predicts that the expected change is always zero) as a description of realised volatility.

Let p_1 be the conditional probability of making successful forecast when the realised standard deviation in the subsequent period decreases or does not change, and p_2 the conditional probability of making successful forecast when the realised standard deviation increases. That is, $p_1 = P\left[\Delta\sigma \leq 0 \mid \Delta r^2 \leq 0\right]$ and $p_2 = P\left[\Delta\sigma > 0 \mid \Delta r^2 > 0\right]$. Furthermore, let n_1 be the number of times $\Delta r^2 \leq 0$ and n_2 the number of times $\Delta r^2 > 0$. Naturally, $N = n_1 + n_2$ is the total sample size. Then, let m_1 be the number of successful forecasts in the sample when $\Delta r^2 \leq 0$ and m_2 the number of unsuccessful forecasts when $\Delta r^2 > 0$ It follows that $M = m_1 + m_2$ is the total number of times $\Delta\sigma \leq 0$ in the entire sample. By definition, $p_1 = E\left(m_1/n_1\right)$ and $p_2 = 1 - E\left(m_2/n_2\right)$

17 I also performed a less conservative Wald test defining the following null hypothesis: vector $\alpha = \pi = 0$ and vector $\beta = 1$. Once more, as shown in Table 2, the null hypothesis is rejected at 5% level.

18 Furthermore, as pointed out by Christensen *et al.* (2002), telescoping overlap problem in options data can invalidate the strong rationality test.

According to Henriksson and Merton (1981), a necessary and sufficient condition for the market's forecast to be useless is that $p_1 + p_2 = 1$, since a random walk process would have $p_1=1$ and $p_2=0$. Under the null hypothesis $p_1 + p_2 = 1$, $p_1 = E(m_1/n_1) = E(m_2/n_2)$ It follows that the probability distribution for m_1 has the form os a hypergeometric distribution and is independent of both p_1 and p_2.

$$P(m_1 = x \mid n_1, n_2, M) = \frac{\binom{n_1}{x}\binom{n_2}{M-x}}{\binom{N}{M}} \tag{8}$$

Fortunately, a normal distribution approximation is possible for the hypergeometric distribution by using the mean and the variance of the hypergeometric distribution, both indicated in Table 6. Once more, I exclude option contracts with overlapping maturity time. As shown in Table 6, the required m_1 to reject the null hypothesis is equal to 136, when a normal approximation is used to compute the test statistic. Since the actual value of m_1 is 139, the null hypothesis that implied volatility is useless is rejected at 5% level.

Therefore, even though the strong version of rationality is rejected by parametric regression method, the weaker version of rationality based on a non-parametric test is not rejected. As suggested by Wei and Frankel (1991), market participants could improve their forecasts of future realised volatility by putting more weight on the long-run average.

6 Conclusions

This paper contributes to the growing literature about the predictive power of implied volatility in anticipating large price movements, contrasting alternative models based on past returns such as EWMA and historical simulation models. As pointed out by Andersen and Bollerslev (1998), the choice among implied volatility or models built on past returns reflects the controversial econometric debate between time series analysis and structural econometric models.[19]

19 According to Hamilton (1994), structural econometric analysis requires much stronger assumptions about the relation between x and y, while time series analysis simply requires that the process should be ergodic for second moments. The difference arises because structural models seek the effect of x on y, and time series analysis only concern is forecasting, for which it does not matter whether it x that causes y or y that causes x. However, when the moments of the data have changed over time in fundamental ways, assumptions regarding covariance-stationary and ergodic are not valid and, hence, better forecasts can emerge from careful structural analysis.

I have presented some empirical evidence regarding Brazilian exchange rate crisis, which indicates implied volatility as a superior predictor of daily dollar-real spot price movements, based on AIC and BIC criteria, in comparison with equally-weighted and exponentially-weighted moving average volatility models. However, the implied volatility model presented some shortcomings such as negative coefficients for some lagged exogenous variables and the absence of Granger causality between implied volatility and realised exchange rate volatility.

Then, I analyse whether there is strong or weak rationality in Brazilian derivatives market. Although the strong version (that is, the market not only get the direction of change correctly, but also get the magnitude of change correctly on average) was rejected by the Wald test, the weak rationality (that is, market participants are forward-looking and can predict the direction of the change in exchange rate volatility) was supported by a non-parametric test based on normal approximation of a hypergeometric distribution.

The main conclusion of this paper is that implied volatility does help traders to anticipate future exchange rate volatility, although implied volatility is an upward-biased estimator and does not Granger cause realised exchange rate volatility.

Finally, before concluding that the rejection of both Granger causality and strong rationality could be illustrating either some kind of inefficiency regarding Brazilian derivatives market or the credibility of Brazilian exchange rate regime despite all external and internal adverse shocks until 13th January 1999, one should ask whether traders in Brazilian financial markets were hedging their exposure to exchange rate variability by really operating with dollar-real option contracts. Actually, as shown in Graph 5, the traded volume of Brazilian government bonds linked to dollar (mainly, NBC-E and NTN-D) were systematically higher than the accumulated traded volume of dollar-real option contracts, except for January 1999. Thus, the unsatisfactory performance of implied volatility model in anticipating realised exchange rate volatility may be an evidence of the predominance of Brazilian government bonds linked to dollar over dollar-real call options as a hedge instrument for exposure to exchange rate variability.[20]

Concluding, regime-switching models such as suggested by Bollen, Gray and Whaley (2000), Andersen *et al.* (2001) and Pereira and Almeida (2001) definitely constitute a great avenue for further developments.[21] Furthermore, as pointed out by Christensen (2002), im-

20 I am grateful to Frederico Turolla and José Luciano da Costa for this important insight.

21 Although there is no empirical evidence of structural break based on Chow test, which is less robust than regime-switching models. This comparative analysis is out of the scope of this paper.

plied volatility series usually present a telescoping overlap problem, which might be solved by using GMM approach as suggested by Chernov (2001). Alternatively, West and Cho (1994) suggest univariate non-parametric volatility forecasting models. Finally, as suggested by Campa, Chang and Refalo (1999) and performed by Wei and Frankel (1991), it would be useful to examine multivariate models that incorporate correlation structure across different assets, different countries and across time.

References

Ait-Sahalia, Y.; Lo, A. W. Nonparametric estimation of state-price densities implicit in financial asset prices. *Journal of Finance*, v. 53, n. 2, p. 499-547, 1998.

Amin, K., Ng, V. Inferring future volatility from the information in implied volatility in eurodollar options: a new approach. *Review of Financial Studies*, 10, p. 333-67, 1997

Andersen, T. G.; Bollerslev, T.; Diebold, F X., Labys, P. Modelling and forecasting realized volatility. Wharton University, Financial Institutions Center, *Working Paper*, 2001.

Andersen, T. G., Bollerslev, T. Answering the skeptics: yes, standard volatility models do provide accurate forecasts. *International Economic Review*, v. 39, n. 4, p. 885-905, 1998.

Andrade, S. C. de; Tabak, B. M. Is it worth traking dollar/real implied volatility? Banco Central do Brasil, *Working Paper 15*, March 2001.

Bates, D. S. The crash of '87: was it expected? The evidence from options markets. *Journal of Finance*, v. 46, n. 3, p. 1009-44, 1991.

_______. Post-'87 crash fears in the S&P 500 futures options market. *Journal of Econometrics*, 94, p. 181-238, 2000.

Bertola, G.; Svensson, L. E. O. Stochastic devaluation risk and the empirical fit of target-zone models. *American Economic Review*, 82, p. 520-36, 1993.

Black, F., Scholes. The valuation of options and corporate liabilities. *Journal of Political Economy*, 81, p. 307-27, 1973.

Black, F Fact and fantasy in the use of options. *Financial Analysts Journal*, p. 36-72, Aug. 1976.

Bollen, N. P. B., Gray, S. F., Whaley, R. E. Regime switching in foreign exchange rates: evidence from currency option prices. *Journal of Econometrics*, 94, p. 239-76, 2000.

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

Campa, J. M., Chang, P. H. K. The forecasting ability of correlations implied in foreign exchange options. *Journal of International Money and Finance*, 17, p. 855-80, 1998.

Campa, J. M., Chang, P. H. K., Refalo, J. F. An options-based analysis of emerging market exchange rate expectations: Brazil's Real Plan, 1994-1999. NBER, *Working Paper 6929*, 1999.

Canina, L.; Figlewski, S. The informational content of implied volatility. *Review of Financial Studies*, 6, p. 659-81, 1993.

Chernov. Implied volatility as forecasts of future volatility, time varying risk premia and returns variability. *Columbia Business School Working Paper*, 2001.

Christensen, B. J., Hansen, C. H., Prabhala, N. R. *The telescoping overlap problem in options data*. Atlanta: American Finance Association, 2002.

Christensen, B. J., Prabhala, N. R. The relation between implied and realized volatility. *Journal of Financial Economics*, 50, p. 125-50, 1998.

Day, T., Lewis, C. Stock market volatility and the information content of stock index options. *Journal of Econometrics*, 52, p. 267-87, 1992.

Engel, C., Hamilton, J. D. Long swings in the dollar: are they in the data and do markets know it? *American Economic Review*, v. 80, n. 4, p. 689-713, 1990.

Feinstein, S. The Black-Scholes formula is nearly linear in s for at-the-money options; therefore implied volatilities from at-the-money options are virtually unbiased. Federal Reserve Bank of Atlanta, *Working Paper*, 1989.

Figlweski, S. Forecasting volatility using historical data. New York University, *Financial Markets, Institutions and Instruments*, v. 13, n. 1, 1997

Fleming, J. The quality of market volatility forecasts implied by S&P 100 index option prices. *Journal of Empirical Finance*, 5, p. 317-45, 1998.

Fraga, A. Monetary policy during the transition to a floating exchange rate: Brazil's recent experience. Finance Development, *IMF Publication Services*, v. 37, n. 1, 2000.

Garman, M. B., Kohlhagen, S. Foreign currency option values. *Journal of International Money and Finance*, 2, p. 231-38, 1983.

Geweke, J., Meese, R., Dent, W. Comparing alternative tests of causality in temporal systems: analytic results and experimental evidence. *Journal of Econometrics*, 21, p. 161-94, 1983.

Granger, C. W. J. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, 37, p. 424-38, 1969.

Greene, W. H. *Econometric analysis*. Third Edition. 1997.

Guimarães, B. V., Silva, M. E. *A possibilidade de saltos no câmbio implícita nos prêmios das opções*. 2000. Mimeografado.

Hamilton, J. D. *Time series analysis*. Princeton University Press, 1994.

Hansen, L. P.; Jagannathan, R. Implications of security market data for models of dynamic economies. *Journal of Political Economy*, 99, p. 225-62, 1991.

Henriksson, R., Merton, R. On market timing and investment performance - statistical procedures for evaluating forecasting skills. *Journal of Business*, v. 54, n. 4, 1981.

Hull, J., White, A. The pricing of options on assets with stochastic volatilities. *Journal of Finance*, v. 5, n. 2, p. 281-300, 1987

_______ Incorporating volatility updating into the historical simulation method for value-at-risk, *Journal of Risk*, v. 1, n. 1, p. 5-19, 1998.

Hutchinson, J. M., Lo, A. W., Poggio, T. A nonparametric approach to the pricing and hedging of derivative securities via learning networks. *Journal of Finance*, 49, p. 851-89, 1994.

Jorion, P. Predicting volatility in the foreign exchange market. *Journal of Finance*, v. 1, n. 2, p. 507-28, 1995.

Krugman, P. R. A model of balance of payments crises. *Journal of Money, Credit and Banking*, 11, p. 311-25, August 1979

_______ Target zones and exchange rate dynamics. *Quarterly Journal of Economics*, 116, p. 669-82, August 1991.

Lamoureux, C., Lastrapes, W. Forecasting stock return variance: toward an understanding of stochastic implied volatilities. *Review of Financial Studies*, 6, p. 293-326, 1993.

Maddala, G. S., Kim, I. M. *Unit roots, cointegration and structural change*. Cambridge University Press, 1998.

Malz, A. Option-based estimates of the probability distribution of exchange rates and currency excess returns. Federal Reserve Bank of New York, *Working Paper*, 1996.

_______ Do implied volatilities provide early warning of market stress? *RiskMetrics Journal*, 1, p. 41-60, 2000.

McBeth, J. D., Merville, L. J. An empirical examination of the Black-Scholes call option pricing model. *Journal of Finance*, v. 34, n. 5, p. 1173-86, 1979

Merton, R. C. Option pricing when underlying stock returns are discontinuous. *Journal of Financial Economics*, 3, p. 125-44, 1976.

Münch, I. P. *Bandas de câmbio, expectativas de desvalorização, volatilidade e crescimento econômico*: uma análise comparativa entre o Brasil e outros países emergentes. 1988a. Tese (Doutorado em Economia) Fundação Getúlio Vargas.

_______ Bandas de câmbio e expectativas de desvalorização: um teste de credibilidade aplicado a Brasil, México, Rússia, Venezuela, Tailândia e Hong Kong. *Revista Brasileira de Economia*, v. 52, n. 4, p. 637-73, 1998b.

Newey, W. K., West, K. D. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, v. 55, n. 3, p. 703-8, 1987.

Obstfeld, M. The logic of currency crises. Banque de France, *Cahiers Economiques et Monetaires*, 43, p. 189-213, 1994.

Pereira, P. V., Almeida, N. M. *Modelos de mudança de regime*: uma aplicação em finanças empíricas. Primeiro Encontro Brasileiro de Finanças, 2001.

Pierce, D. A., Haugh, L. D. Causality in temporal systems: characterization and a survey. *Journal of Econometrics*, 5, p. 265-93, 1977

Poon, S. H.; Granger, C. Forecasting financial market volatility - a review. *SSRN Working Paper*, June, 2001.

Poteshman, A. M. Forecasting future volatility from option prices. *SSRN Working Paper*, December 2000.

Rocha, K. M. C., Moreira, A. R. B. Credibilidade da política cambial e as opções cambiais. *Pesquisa e Planejamento Econômico*, v. 28, n. 3, p. 509-30, 1998.

Ross, S. Options and efficiency. *Quarterly Journal of Economics*, 90, p. 75-89, 1976.

Souza, A. M. Os efeitos de uma desvalorização cambial para uma economia aberta. FEA-USP, *Monografia*, 2000.

Toledo, J. E. C. de. Políticas econômicas e estabilização no Plano Real. *Revista de Economia Aplicada*, v. 3, n. Especial Plano Real, p. 61-77, março 1999.

Wei, S. J., Frankel, J. A. Are option-implied forecasts of exchange rate volatility excessively variable? NBER, *Working Paper 3910*, 1991.

West, K. D., Cho, D. The predictive ability of several models of exchange rate volatility. NBER, *Working Paper 152*, 1994.

Xu, X., Taylor, S. J. Conditional volatility and the informational efficiency of the PHLX currency options market. *Journal of Banking & Finance*, 19, p. 803-21, 1995.

Appendix

Table 1
Basic Descriptive Statistics

	Exchange Rate (level)	Exchange Rate (first difference)	Implied Volatility
Range	490	466	467
Missing Values	30	54	53
Mean	1.4856349	0.00104020627103	0.01057997085572
Standard Deviation	0.3467837	0.01223405394888	0.01534546441124
Minimum	1.11650	-0.0844281495	0.00068351927
Maximum	2.13470	0.0891719745	0.18717244271
Skewness*	0.216 (0.110)	2.094 (0.113)	
7.000 (0.113)			
Kurtosis*	-1.783 (0.220)	24.555 (0.226)	63.229 (0.225)
ADF test	-2.630323760	-7.912843246**	-0.621204943
Jarque-Bera****	68.24090 ***	13450.75***	75160.1 ***

Notes: *The numbers in brackets denote the standard deviation of skewness and kurtosis, respectively.

** Null hypothesis of unit root rejected at 5%.

*** Null hypothesis of normality rejected at 5%.

**** Jarque-Bera statistic = $T\{[S^2/6]+[(K-3)^2/24]\}$, where T is the sample size, S the skewness and K the kurtosis. Under null hypothesis of normality, the test has a chi-square distribution with 2 degrees of freedom. The critical value at 5% level is 5.991. The critical values of S and K to reject the null hypothesis of normality at 5% level are 0.05207 and 4.0414, respectively.

Table 2
Statistical Tests for Implied Volatility Model

Granger causality test (five lags included)				
Null Hypothesis	Range		F-Statistic	Probability
Implied Volatility does not Granger cause Realised Exchange Rate Volatility	268		3.70606 *	0.00295
Chow breakpoint test (13th January 1999)				
	F-statistic	Probability	Log-likelihood ratio	Probability
	1.162264**	0.313883427	13.55394	0.258665436
Wald test *** (Ho: β =1)				
	F-statistic	Probability	Chi-square	Probability
	877681.494	0.0000	438840.747	0.0000
(Ho: $\pi=\alpha=0$; $\beta=1$)				
	F-statistic	Probability	Chi-square	Probability
	241667.6508	0.0000	2658344.1589	0.0000

Notes: * Null hypothesis that implied volatility does not Granger cause Realised volatility not rejected at 5%

** Null hypothesis of no structural break at 13th January 1999 not rejected at 5%

*** Both coefficient restrictions rejected at 5%.

Table 3
OLS Estimates of Alternative Volatility Forecasting Models

	Implied Volatility		Equally-weighted volatility		EWMA	
Variable	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Constant term	35526.29	0.567530	71537.16	1.254419	65326.12	0.3743
RETSQEXCH(-1)	-0.013280	-0.211070	-0.006401	-0.120314	0.005687	0.9190
RETSQEXCH(-2)	0.479904	6.622081	0.207073	3.934479	0.224284	0.0001
RETSQEXCH(-3)	0.455145	4.421991	0.434344	8.973805	0.457653	0.0000
RETSQEXCH(-4)	-0.456569	-4.193916	0.120716	2.299378	0.103418	0.0647
RETSQEXCH(-5)	-0.108223	-0.814975	-0.131206	-2.488950	-0.153913	0.0065
VOL(-1)	0.024351	3.422755				
VOL(-2)	0.000451	0.057023				
VOL(-3)	-0.014025	-1.644634				
VOL(-4)	-0.012795	-1.543268				
VOL(-5)	0.005412	0.675908				
RAIZ(-1)			-0.387386	0.6987		
RAIZ(-2)			1.077603	0.2820		
RAIZ(-3)			0.328690	0.7426		
RAIZ(-4)			-1.403116	0.1615		
RAIZ(-5)			0.137958	0.8904		
RAIZRM(-1)					-1.784928	0.0752
RAIZRM(-2)					0.057781	0.9540
RAIZRM(-3)					0.267193	0.7895
RAIZRM(-4)					1.087338	0.2777
RAIZRM(-5)					0.529035	0.5971
Adjusted R-squared	0.482453	0.254815		0.277226		
Akaike info criterion (AIC)	29.22405	29.93682		30.01464		
Schwarz criterion (BIC)		29.36834	30.05532		30.14016	

Table 4
Does EWMA Provide Incremental Information Over Implied Volatility Model?

Variable	Implied Volatility		EWMA and Implied Volatility	
	Coefficient	t-Statistic	Coefficient	t-Statistic
Constant term	35526.29	0.567530	40704.12	0.603618
RETSQEXCH(-1)	-0.013280	-0.211070	-0.019174	-0.284147
RETSQEXCH(-2)	0.479904	6.622081	0.464807	5.884826
RETSQEXCH(-3)	0.455145	4.421991	0.426208	3.751796
RETSQEXCH(-4)	-0.456569	-4.193916	-0.477964	-3.974696
RETSQEXCH(-5)	-0.108223	-0.814975	-0.092750	-0.650536
VOL(-1)	0.024351	3.422755	0.026355	3.334109
VOL(-2)	0.000451	0.057023	0.001450	0.165709
VOL(-3)	-0.014025	-1.644634	-0.013722	-1.458690
VOL(-4)	-0.012795	-1.543268	-0.012230	-1.296822
VOL(-5)	0.005412	0.675908	0.005951	0.674964
RAIZRM(-1)			0.000187	0.105235
RAIZRM(-2)			0.000415	0.251385
RAIZRM(-3)			-0.000776	-0.465504
RAIZRM(-4)			-0.001075	-0.694897
RAIZRM(-5)			0.000758	0.511607
Adjusted R-squared	0.482453	0.473424		
Akaike info criterion (AIC)	29.22405	29.34885		
Schwarz criterion (BIC)	29.36834	29.57231		

Table 5
Properties of the OLS Estimates for Implied Volatility Model

Residuals from the OLS regression (4)	
Mean	-2.361037700936
Standard deviation	0.5166101992148
Skewness	12.38482791534 (0.14
Kurtosis	185.0386021226 (0.29
Jarque-Bera	386574.0 *

Note: * Null hypothesis of normality rejected at 5% level.

Table 6
Non-parametric Test for Implied Volatility Model

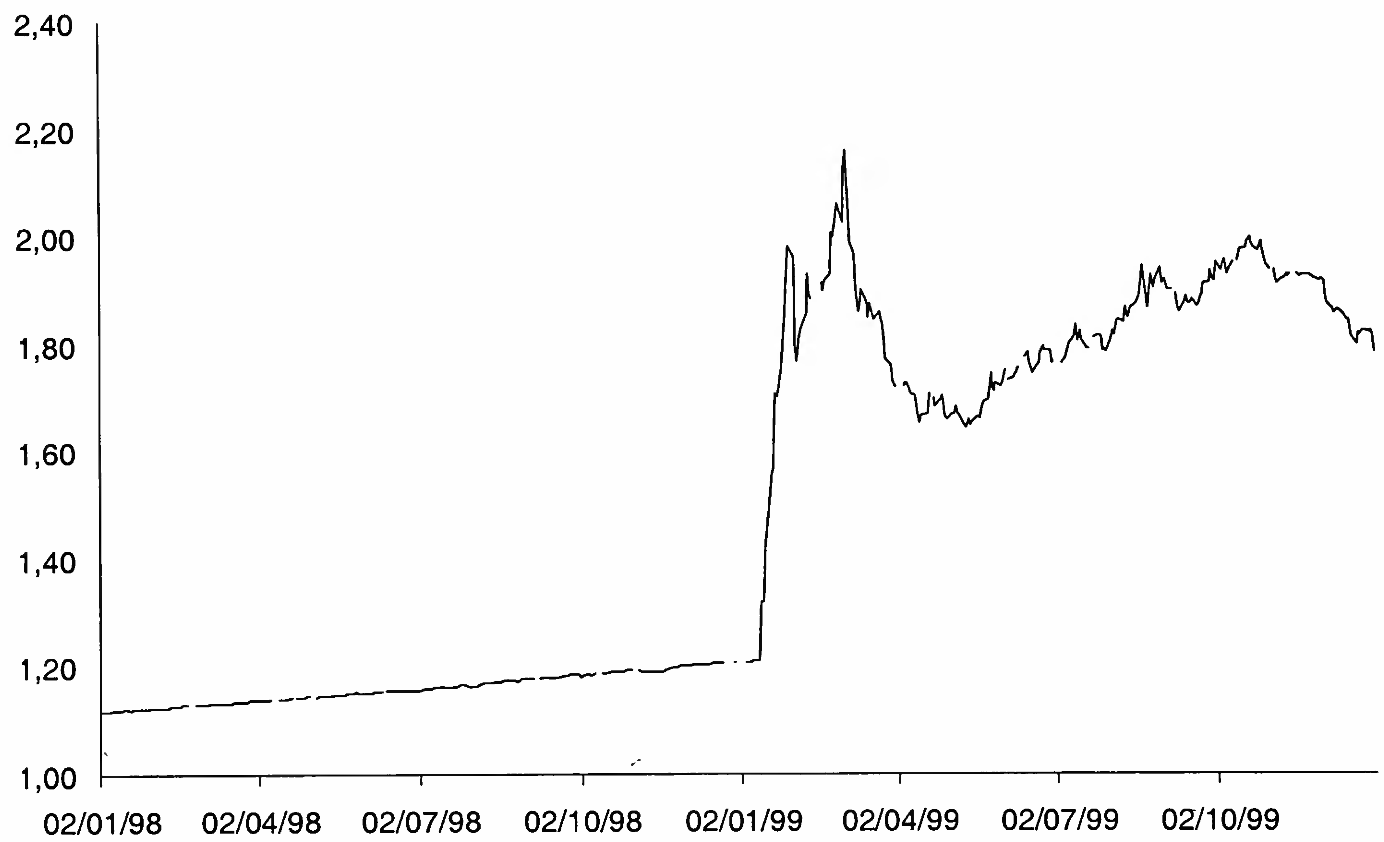
Ho : p1+p2=1 (implied volatility is useless as predictor of realised exchange rate volatility)								
N	n1	n2	M	m1	m2	p1+p2	m1 needed to reject Ho	Cut-off value (95%)
349	230	119	197	139	58	1.11695 **	136*	1.65 ***

Notes: * Null hypothesis that market's forecast is useless is rejected at 5% level.

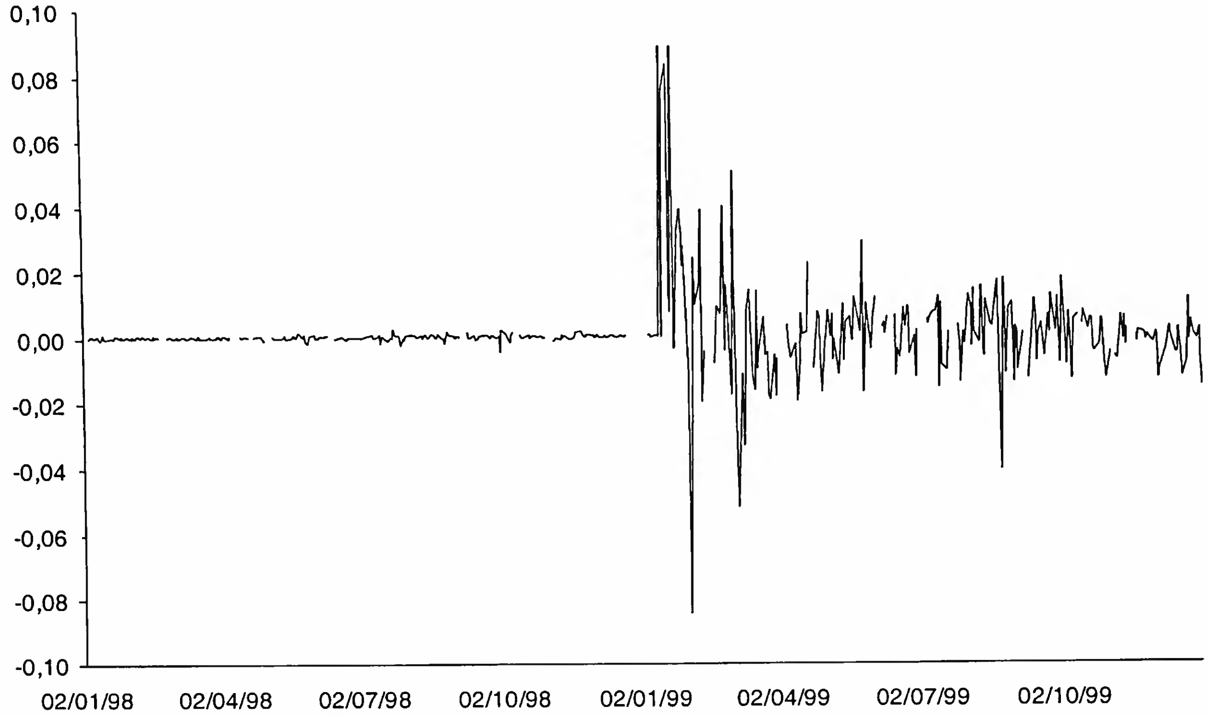
** Point estimate of (p1+p2) = (m1/n1) + (n2-m2)/n2

*** m1 needed to reject Ho = 1.65* s(m1) + E(m1), where: E(m1) = M.n1/N and $s^2(m1)$ = {[m1.n1.n2.(N-M)]/[N^2(N-1)]}

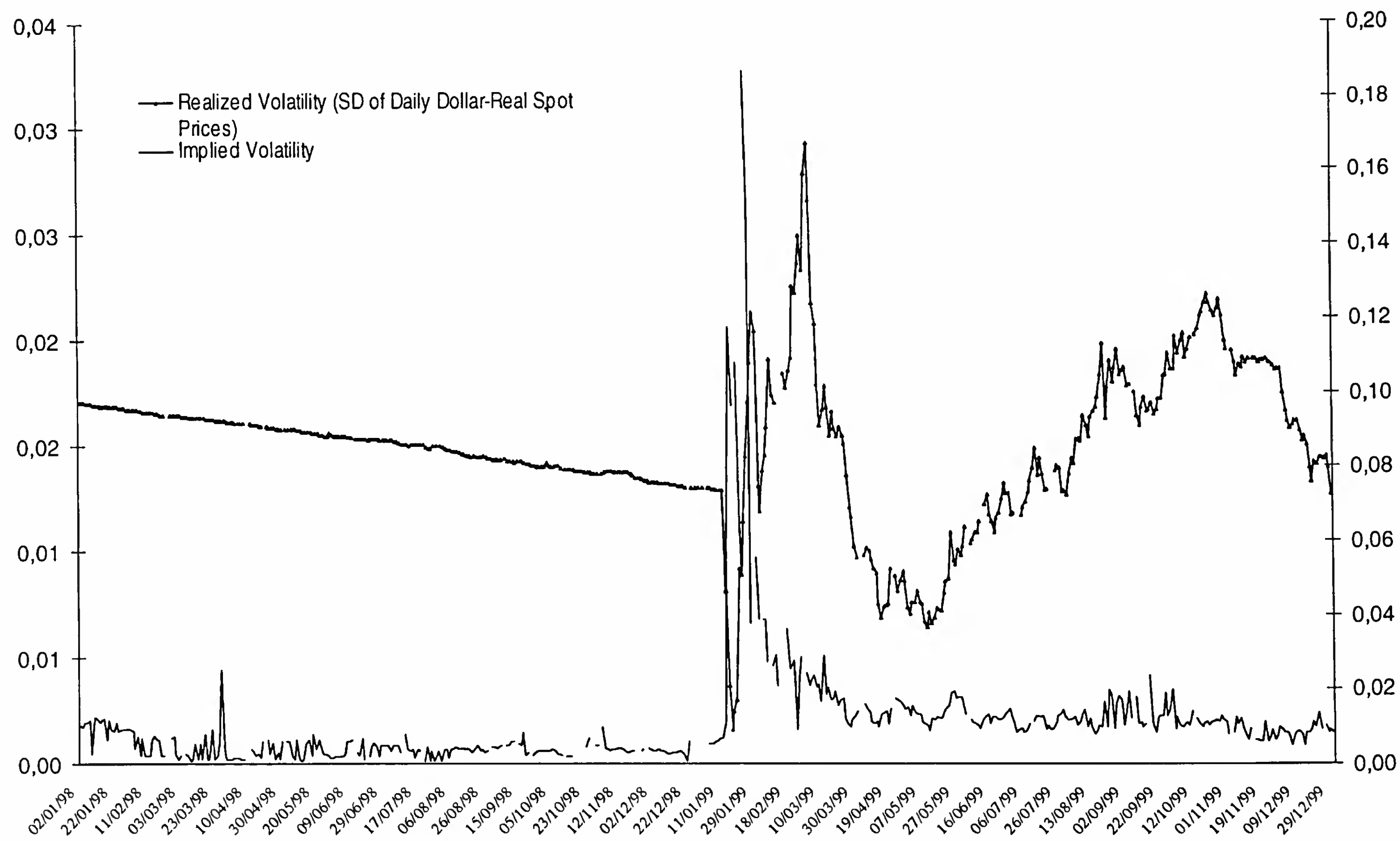
Graph 1
Time Path of Daily Dollar-Real Spot Price



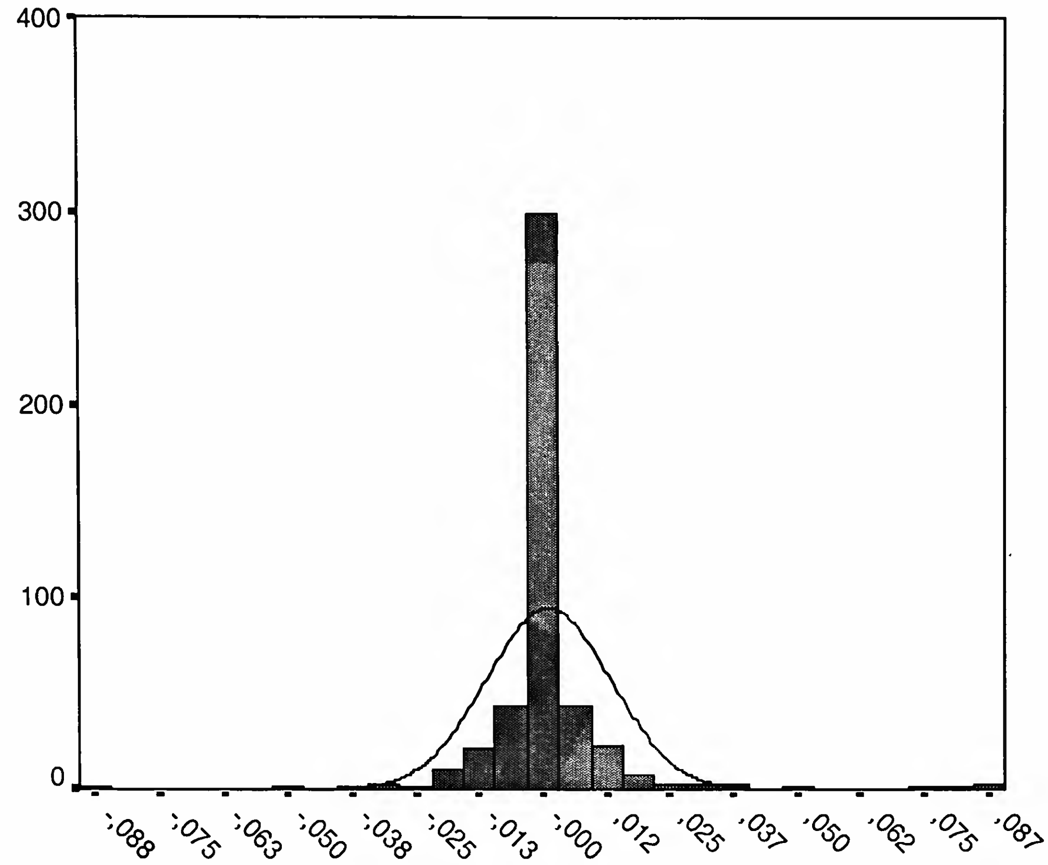
Graph 2
Time Path of Daily Dollar-Real Spot Price Returns



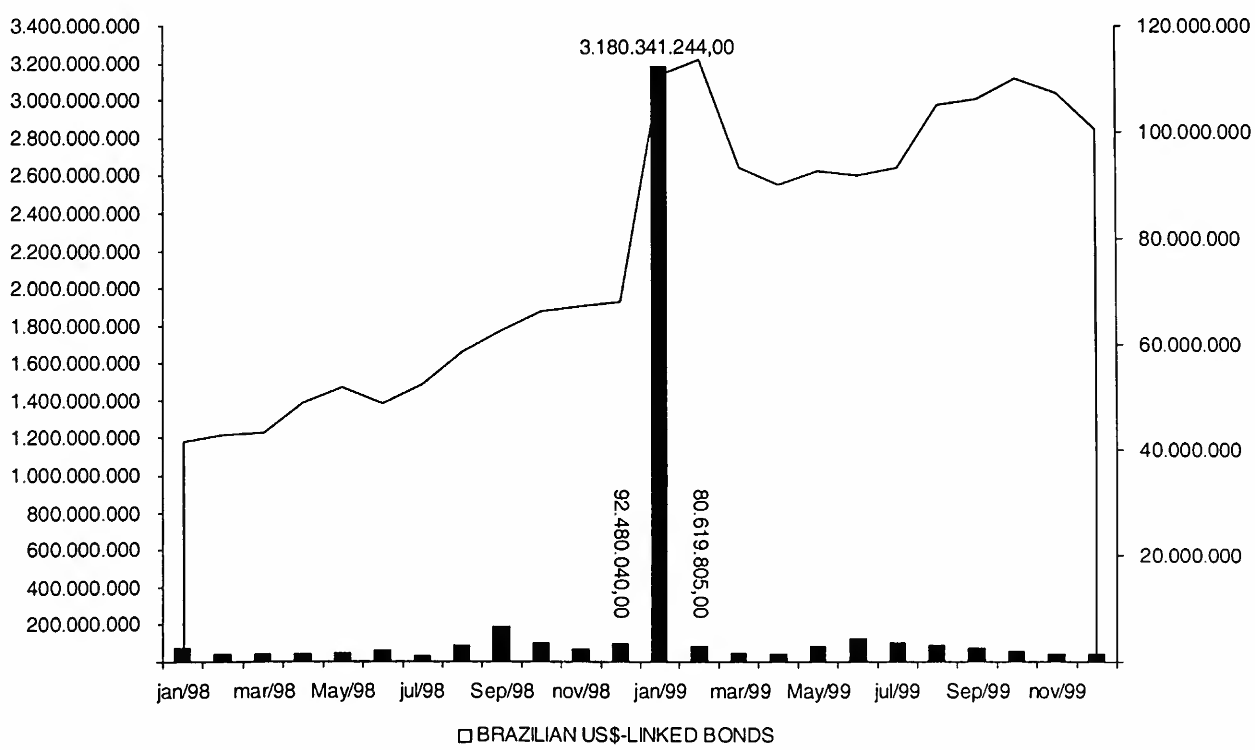
Graph 3
Implied Volatility Versus Realized Volatility for Daily Dollar-Real Call Option



Graph 4
Histogram of Daily Dollar-Real Spot Price Returns



Graph 5
Dollar-Real Call Options Versus US$-Linked Brazilian Government Bonds (R$)



Source: Central Bank of Brazil and BM&F.