Can fear beat hope? A story of GARCH-in-Mean-Level effects for Emerging Market Country Risks*

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Abstract

Upon winning the 2002 presidential elections, event that considerably increased the Brazilian country risk levels and volatility, Lula celebrated by declaring: "hope has beaten fear". Extending Une and Portugal (2004), the aim of this paper is twofold: to empirically test the interrelations between country risk conditional mean ("hope") and conditional variance ("fear") and cast light on the role of country risk stability in the conduction of macroeconomic policies in developing small open economies. We compare the forecasting performance of various alternative GARCH-in-Mean-Level models for n-step conditional volatility point forecasts of the Brazilian country risk estimated for the period May 1994 - February 2005. The results support the idea that both hope and fear play important roles in the Brazilian case and confirms that hope and fear act in the same direction.

Keywords: nonlinear GARCH, GARCH-in-Mean-Level effect, country risk, fear of disruption, forecast performance.
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1 Introduction

In 2002, when the polls started indicating that the traditional leftist politician Lula da Silva was likely to win the Brazilian presidential elections, both Brazilian sovereign spreads and exchange rates started to hike up. The country risk reached historical record highs since Lula was then perceived as a long date market-unfriendly candidate that might abort or even reverse major ongoing economic reform programmes. By then, the market asked itself whether that Lula-fear crisis would cause Brazil to follow Argentina's fate of debt default. When Lula eventually won the elections and the markets believed in the newly elected president's commitment to the reforms under course, Lula celebrated by declaring: "hope has beaten fear".

But, from an econometric perspective, what does it mean? In the country risk literature, the expected mean of country sovereign spreads denote the perceived macroeconomic fundamentals of a country. As in some languages, e.g. Portuguese and Spanish to name a few, the word "hope" has the same translation as "expectation", we are interpreting "hope" as the expected mean of country risk spreads. And since "fear" is often associated with uncertainty and hence volatility, this paper extends the anaylsis of Une and Portugal (2004) by considering whether conditional variance improves the specification of the conditional mean and whether the conditional mean improves the specification of the conditional variance. Translating Lula's words into econometrics might lead us to believe that the parameter of the conditional mean as a weakly exogenous variable in the conditional variance equation is statistically different from zero and positive.

The question is of paramount importance for the correct specification of country risk models and helps obtaining a broader picture of the dynamic and feedback effects among levels and volatilities present in such models. In order to formally evaluate the interrelations between hope and fear, we estimated various alternative GARCH models for the Brazilian country risk for the period May 1994 and February 2005. These models should tackle multiple sources of non-linearities as well as GARCH-in-Mean effects and GARCH-in-Mean-Level effects, in line with Karanasos et al. (2004) and others. If such dynamic and feedback effects are significant, they should improve the forecasting performance of such models. So, apart from in-sample fit statistics, the models are also evaluated in terms of their out-of-sample forecasting performance for 1-step-ahead, 25-step-ahead and 50-step-ahead point forecasts of the Brazilian country risk conditional volatility. The results not only support the idea that both hope and fear do play important

roles in the Brazilian case in the long run, but also confirm that hope and fear have been acting in the same direction.
This paper is organized as follows. In Section 2, we describe the data. In Section 3, we detail the empirical models to be used, the recursive procedure used in the specification of the models, estimation of parameters and how out-of-sample forecasts were obtained as well as discuss the criteria of evaluation used in order to compare point forecasts of conditional variances. Section 4 provides the empirical results and Section 5 concludes.

2 The Data

We used 2673 daily observations of EMBI Plus Brazilian Stripped Sovereign Spread, computed in basis points and available by JP Morgan. The series runs the period from May 26, 1994, through February 3, 2005. The last 250 observations of the sample were kept as a holdback period in order to evaluate the forecasting performance of the different specifications. Missing data due to non-trading days were disregarded. The data were transformed to the traditional approximate percent changes by taking first differences of the logarithms multiplied by 100. Due to this transformation, the estimation sample loses one observation. Figure 1 provides a plot of the original and transformed series.

The transformed series displays three big volatility clusters. According to Une and Portugal (2004), the first two clusters are respectively dated as: 1) December 7, 1994 through June 14, 1995; and 2) October 24, 1997 through July 2, 2005. These two clusters are accounted for by the Tequila Crisis in the first case and a sequence of consecutive crises that hit Brazil in the second (Asian Crisis, Russian Crisis, Brazilian Crisis). The third cluster is due to the Brazilian electoral crisis. Une and Portugal (2004) could date its beginning - April 24, 2002 - but not the end since their whole sample ended in September 27, 2002. As Table 1 shows, the series of interest is heavily skewed to the right and leptokurtic.

3 Specification of Empirical Models

Une and Portugal (2004) showed that confidence crises in emerging markets, just like currency crises, may be caused when fear switches to a higher regime, leading to sudden stops of capital inflows. According to the authors, under certain conditions, the switch of uncertainty among agents to a higher regime, measured by greater conditional variance, irrespective of the level of expected macroeconomic fundamentals, might trigger a process when it is valid to speculate on this country's sovereign bonds and raise the country risk. A question still unanswered is why uncertainty among agents might switch to a higher regime irrespective of the conditional mean. Here we approach this question by considering dynamic effects of the volatility in the mean equation as well as feedback effects by also incorporating the mean dynamics in the variance equation of univariate GARCH based models.

The motivation for this approach stems from similar applications in the inflation literature. On the one hand, Friedman (1977) and Ball (1982) believe that higher inflation rates lead to higher inflation volatility. On the other hand, Cukierman and Meltzer (1986) argue that higher inflation volatility leads to higher inflation rates. Karanasos et al (2004), by applying an AR-GARCH-M-L model to the US Consumer's Price Index, prove that both hypotheses fit the data well, even though the in-mean effect (the volatility parameter in the conditional mean equation) might prevail over the level effect (the mean parameter in the conditional variance equation).

Next, we describe the empirical models used as well as the details of the recursive specification of the models.

3.1 Empirical Models

In order to estimate the dynamic effects of the conditional variance of the EMBI Plus Brazil Sovereign Stripped Spreads, we examine six classes of GARCH-in-mean based models, in line with Engle et al. (1987). So, for all models, we use an AR(1) specification for the conditional mean [1] and the contemporaneous conditional variance [2] defined next. For each model, three

[1] The lag order p of the auto-regressive components, where $p \in \{0, \ldots, 20\}$, was chosen by minimising the Akaike and Schwartz Information Criteria

[2] Among the three possible specifications of the conditional variance - conditional standard deviation, conditional variance and conditional variance in log (log(Var)) - we chose log(Var) since it minimised the Akaike and Schwartz Information Criteria

error distribution were assumed for the errors: Gaussian, Student t and Generalized Error Distribution (GED).

The different parametric specifications for the conditional variance evaluated include the original basic GARCH model (Bollerslev, 1986), the Threshold GARCH (TGARCH) model (Zakoian, 1994, Glosten, Jagannathan and Runkle, 1993), the Asymmetric Exponential GARCH (AEGARCH) model (Nelson, 1991), the Power GARCH (PGARCH) model (Taylor, 1986, Schwert, 1989, Ding et. al, 1993) and the Component GARCH (CGARCH) and Threshold Component GARCH (TCGARCH) model (Engle and Lee, 1999)[3].

The order of lagged squared residuals and lagged conditional variances of the various GARCH-based models was chosen to be (1,1) also by minimising the information criteria. However, as is, various of the specifications could not obtain serially uncorrelated or homoscedastic standardised errors due to the presence of some outliers, even for the Gaussian GARCH(1,1) [4]. In order to deal with these outliers [5], we detected the largest absolute standard residual of the Gaussian GARCH(1,1) model and we constructed a dummy variable that assumed the value of one in such observation and zero otherwise, to be plugged in the conditional mean equation. In order to avoid the multimodality problem in the presence of outliers (Doornik and Ooms, 2003), we also included the dummy variable lagged one period in the conditional variance equation. If, even after the inclusion of the dummies, the GARCH(1,1) model has not obtained white noise errors, the process of detecting the largest absolute standard residual should continue. This procedure does not differ considerably from (Doornik and Ooms, 2004). Eventually, the detection of only four additive outliers (December 21, 1994; October 23, 1997; May 18, 1998; and January 4, 2000), entering the conditional mean and conditional variance equations, allowed obtaining serially uncorrelated and homoscedastisc errors[6].

In order to detect the level feedback mechanism, we follow the estimation by including the lagged conditional mean in the variance equation in

[3] For a deeper discussion on the properties of alternative GARCH-in-Mean models, see Karanasos and Kim (2000)

[4] Hansen and Lunde (2001) confirmed the claim that no other GARCH model “beats” a GARCH(1,1) model for exchange rate data.

[5] For more information on the selection of nonlinear GARCH models, in the presence of outliers, see Tolvi (2001).

[6] Une and Portugal (2004) also had to include dummy variables to account for additive outliers - October 23, 24 and 27, 1997 - in the mean equation.

the GARCH-in-Mean based models, which in turn were estimated after the plain GARCH based models. This produces a GARCH-in-Mean-Level model (Karanasos et al., 2004).

3.2 Recursive Estimation and Forecast

Following Siliverstovs and van Dijk (2003), we estimated the above specified models on an expanding window of observations, starting with 05/27/1994–02/04/2004 and ending with 05/27/1994–02/03/2005. The first window loses one observation since we allow for one order of auto-regressive terms in the mean equation, having a sample size of 2421 observations. For each of the windows, we compute one-step-ahead, 25-step-ahead and 50-step-ahead point forecasts of the conditional mean. This procedure yields $P_n = P - (n-1)$forecasts, where $P = 250$ and $n \in \{1, 25, 50\}$.

In order to evaluate the models, apart from in-sample fit statistics, we also compare the n-step-ahead forecasts, since if the dynamic and feedback effects are significant and should be correctly specified, they must also improve the forecasting performance of the various model. If a certain model $\mathcal{M}_i$ obtains $\left\{\widehat{h}_{t-n}^{(i)}\right\}_{t=R+n}^{R+P}$, i.e. a sequence of P_n conditional volatility point forecasts n-steps-ahead, where R stands for the window estimating in-sample size. The associated forecast error of such model $\mathcal{M}_i$ is denoted $e_{t|t-n}^{(i)} = h_t - \widehat{h}_{t-n}^{(i)}$. Based on this error, we evaluate the Mean Squared Forecast Error[7], MSFE $= \sum_{t+n}^{R+P} \left(h_t - \widehat{h}_{t-n}^{(i)}\right)^2$. Instead of applying realized variance[8], for simplicity, we used the traditional squared returns (in our case, the square of the percentage changes) adopted in the common practice as a proxy for the conditional variance present in the sample, since it is a non-observable variable.

One of the most widespread tests used in order to compare point forecasts obtained by different models is the Diebold-Mariano test (Diebold and Mariano, 1995). Let $d_t \equiv \widehat{h}_{t-n}^{(i)} - \widehat{h}_{t-n}^{(j)}$. If $\mathcal{M}_i$'s point forecasts are significantly different from those of a $\mathcal{M}_j$, then $E[d_t] \neq 0$, which means d_t is not covariance-stationary. The Diebold Mariano (DM) statistic is:

[7]Hansen and Lunde (2001) employ five other different loss functions in order to rank the best conditional variance models

[8]For further discussion on which proxy to be used for the conditional variance, see Martens et al. (2004), Hansen et al. (2003), among others.

$$DM = \frac{\overline{d}}{\sqrt{\widehat{V\left(\overline{d}\right)}}} \xrightarrow{d} N(0,1), \tag{1}$$

where $\overline{d}$ represent the sample mean of $\{d_t\}_{t=R+n}^{R+P}$. If d_t is not serially correlated up to order $n-1$, then $\widehat{V\left(\overline{d}\right)}$ can be proxied by the sample variance γ_0 weighted by $P_n - 1$; otherwise, Harvey, Leybourne and Newbold (1997) recommend using the following modified DM stastistic,

$$MDM = \frac{\overline{d}}{\sqrt{\frac{(\gamma_0+2\gamma_1+...+2\gamma_q)}{\left[P_n+1-2n+P_n^{-1}n(n-1)\right]}}} \xrightarrow{d} t_{P_n-1}, \tag{2}$$

if $\{d_t\}_{t=R+n}^{R+P}$ is serially correlated up to order $q-1$. The MDM statistic follows a Student t distribution with $P_n - 1$ degrees of freedom.

Two broad comparisons will be tested. First, all six model's forecasts, for the three distribution errors and three different forecast horizons, incorporating just the GARCH-in-Mean effects or GARCH-in-Mean-Level effects, will be compared against a benchmark GARCH(1,1). All models are controlled for outliers by the previously discussed intervention dummies. If both kinds of effects are significant they should improve the conditional variance forecasts. Second, the specifications with GARCH-in-Mean and GARCH-in-Mean-Level effects might also be very similar to one another, so the MDM tests are also applied in order to test whether the forecasts produced by these latter models are statistically different.

4 Empirical Results

Table 2 shows the log-likelihood, AIC and BIC information criteria of each estimated specification. Also, Table 2 displays the estimated parameters of the variables of interest – the log of the conditional variance in the mean equation and the lagged level in the conditional mean equation. Despite the fact that the benchmark model with which all other competing models are to be compared is the Gaussian GARCH(1,1) model with the dummies, the original Gaussian GARCH(1,1) model is displayed so that the improvement over the latter could be visualised. All models, but the original Gaussian GARCH(1,1) model, present serially uncorrelated and homoscedastic standard errors.

In general, the inclusion of the in-mean effect did not considerably minimise the information criteria, augmented the log-likelihood nor it has proved to be statiscally different from zero. The most noteworthy exceptions seem to be the AEGARCH models, whose information criteria, log-likelihood are considerably better than the benchmark Gaussian GARCH(1,1) model and the inclusion of the in-mean effect is pretty stable, be it or not with feedback effects in the variance equation. Notwithstanding, the vast majority of the other GARCH-based specifications would deny any significant in-mean effect. This would indicate that fear cannot beat hope.

Regarding the level effect in the conditional variance equation, the converse happens. Most of the specifications would deem such parameter significant, and only TGARCH models would marginally reject the null hypothesis that such parameter equals zero[9]. In general, when the level effect is taken into account, the information criteria diminishes, the log-likelihood of the models increases in comparison to the Gaussian GARCH(1,1) model. Likewise, the in-mean effect parameter is not significant, as discussed above, but for the AEGARCH models and the Gaussian specification of the PGARCH model.

Since log-likelihoods and information criteria seem to be equivalent in size, another way to compare and evaluate such specifications is by analysing their forecasting performance. Theoretically, the models with the best specification should forecast better than the other models. Table 3, present the MSFEs, discussed in the last section, and the ratio of the latter to the benchmark Gaussian GARCH(1,1)'s MFSE of the 1-step-ahead, 25-step-ahead and 50-step-ahead point ratio forecasts of all models. Table 3 provides a better picture of the models' performance. In general, the inclusion of the in-Mean and the Level effects does not improve much the 1-step-ahead point forecasts, but a very different conclusion could be drawn from the 25-step-ahead point forecasts, and especially the 50-step-ahead forecasts. The variance of the ratios (not shown in the table) is greater the more steps ahead are forecast. The exact opposite happens to the MSFEs.

If we rank the various specifications according to the smallest MSFE within

[9]These are the only specifications where the estimated lagged level parameter has negative sign

each forecast horizon, it is possible to see that the inclusion of in-Mean and Level effects considerably improves the forecasting performance of the models in terms of the MSFEs for 25-step-ahead and 50-step-ahead forecasts. When only the in-mean effect is considered, the average rank for 1-step-ahead forecasts lowers from 28 to 27; and for 50-step-ahead forecasts the average rank lowers from 34 to 33. But, when both effects are considered, the average rank for 1-step-ahead foreacasts keeps the same average rank as before while for 50-step-ahead models the average rank more than halves.

With such evidence, we apply the formerly discussed MDM tests in Tables 4 and 5. First, we compared all models to the benchmark Gaussian GARCH(1,1) model in Table 4. In general, 25 and 50-step-ahead forecasts produce a much smaller MSFE than 1-step-ahead forecasts. As the comparison of in-sample statistics and MFSEs already indicated, the MDM tests statistically confirm that by only including the in-Mean effect, for any forecast horizon, the forecasting performance does not improve. However, the inclusion of the level effect considerably improves the forecasting performance for 25 and 50 steps-ahead point forecasts.

Then, instead of having the Gaussian GARCH(1,1) model as benchmark, the second round of MDM tests consisted of analysing whether a GARCH-in-Mean-Level should be adequate in the conditional variance specification over the GARCH-in-Mean specification. The MDM statistics also confirmed that incorporating Level-effects improves the GARCH-in-Mean models. Overall, the models with best forecasting performances tended to be the same ones that were able to adequately specify both conditional mean and data: the AEGARCH models.

What could be extracted from all that? On one hand, in spite of correctly identifying that confidence crises in emerging markets like Brazil should occur when volatility switches to a higher regime, Une and Portugal (2004) could not exactly distinguish why that could happen. What these data and results show is that when the perceived macroeconomic fundamentals of such economies are expected to deteriorate in the long run, the conditional mean of the bond spreads rises as speculators pour out sovereign bonds in the secondary market and with it the conditional volatility raises to a higher pattern. That is why the higher variance regime estimated by Une and Portugal (2004) occurs exactly in periods of increasing. Since the significant level parameter in the conditional variance equation has positive sign, when the spreads raise, the uncertainty raises as well, being the converse also possible. So, when the market started believing Lula would not default on the Brazilian foreign debt, fear consequently eased due to a lower level of spreads. From the econometric point of view, Lula was not wrong after all.

On the other hand, when uncertainty shifts to a higher regime without an equal increase of levels it is not a sufficient condition - though necessary - for a confidence crisis to occur in an emerging market. All this process can only be perceived in long forecast horizons (25 or 50 steps ahead) since such effects are close to be non-existant in the short run.

5 Conclusion

This paper sought to extend Une and Portugal (2004) by connecting better the dynamics and feedback effects among conditional mean and conditional variance of country risk. When Lula won the 2002 presidential elections, which had brought considerable increase in the Brazilian country risk levels and volatility, Lula celebrated by declaring: "hope has beaten fear". Interpreting the country risk conditional mean as "hope" and conditional variance as "fear", we compared the forecasting performance of various alternative GARCH-in-Mean-Level models for n-step conditional volatility point forecasts of the Brazilian country risk estimated for the period May 1994 - February 2005. The results support the idea that both hope and fear play important roles in the Brazilian case — even though hope has a greater impact on fear than fear on hope — and confirms that hope and fear act in the same direction. Lula was not wrong after all, at least in the long run. Understanding if such dynamics and feedback behaviour is also present under a Markov switching regime approach is under analysis by the authors.

References

[1] Ball, L. (1992). "Why does high inflation raise inflation uncertainty".*Journal of Monetary Economics*, V.29, pp.371–388.

[2] Bollerslev, T. (1986). "Generalized Autorregressive Conditional Heteroskedasticity".*Journal of Econometrics*, V.31, pp.307–327.

[3] Cukierman, A. and Meltzer, T. (1986). "A theory of ambiguity, credibility, and inflation under discretion and asymmetric information".*Econometrica*, V.54, pp.1099–1128.

[4] Diebold, F. and Mariano, R.S. (1995). "Comparing predictive accuracy". *Journal of Business & Economic Statistics*, Jul., V.13, n.3, pp.253–260.

[5] Ding, Z., Granger, C.W.J. and Engle, R.F. (1993). "A long memory property of stock market returns and a new model". *Journal of Empirical Finance*, V.1, pp.83–106.

[6] Doornik, J.A. and Ooms, M. (2003). "Multimodality in the GARCH regression model". *Nuffield Economics Discussion Papers*, Oxford University, Nuffield College, Department of Economics, n. 2003/w20.

[7] Doornik, J.A. and Ooms, M. (2004). "Outlier detection in GARCH models". Mimeo.

[8] Engle, R.F. and Lee, G.G.L. (1999). "A permanent and transitory component model of stock return volatility". In *Cointegration, Causality, and Forecasting. A Festschrift in Honour of Clive W.J. Granger*, Chapter 20, pp. 475–497. Oxford: Oxford University Press.

[9] Engle, R.F., Lilien, D.M. and Robins, R.P. (1987). "Estimating time varying risk premia in the term structure: the ARCH-M model". *Econometrica*, V.55, pp.391–407.

[10] Friedman, T. (1977). "Inflation and unemployment". *Journal of Political Economy*, V.85, pp.451–472.

[11] Glosten, L.R., Jaganathan, R. and Runkle, D. (1993). "On the relation between the expected value and the volatility of normal excess return on stocks". *Journal of Finance*, V.48, pp.1779–1801.

[12] Hansen, P.H. and Lunde, A. (2001), "A forecast comparison of volatility models: does anything beat a GARCH(1,1)?". *Brown University Working Papers*, Brown University, Department of Economics, n. 2001/04.

[13] Hansen, P.H., Lunde, A. and Nason, J.M. (2003), "Choosing the best volatility models: the model confidence set approach". *Federal Reserve Bank of Atlanta Working Papers*, Federal Reserve Bank of Atlanta, n. 2003/28.

[14] Harvey, D., Leybourne, S.J. and Newbold, P. (1998), "Tests for forecast ecompassing". *Journal of Business & Economic Statistics*, Apr., V.16, n.2, pp.254–259.

[15] Karanasos, M., Karanassou, M. and Fountas, S. (2004), “Analyzing US inflation by a GARCH model with simultaneous feedback”. *WSEAS Transactions on Information Society & Applications*, Aug., V.1, n.2, pp.767–772.

[16] Karanasos, M., Kim, J. (2000), “Alternative GARCH-in-Mean models: an application to the Korean stock market”. *Discussion Papers in Economics*, University of York, Department of Economics and Related Studies, n. 2000/25.

[17] Martens, M., van Dijk, D. and de Pooter, M. (2004), “Modelling and forecasting S&P 500 volatility: long memory, structural breaks and nonlinearity”. *Tibergen Institute Discussion Paper*, Erasmus Universiteit Rotterdam, Tinbergen Institute, n. TI 2004-067/4.

[18] Nelson, D.B. (1991). “Conditional heteroskedasticity in asset returns: a new approach”.*Econometrica*, V.59, pp.347–370.

[19] Schwert, W. (1989). “Stock volatility and crash of ’87”.*Review of Financial Studies*, V.3, pp.7–102.

[20] Siliverstovs, B. and van Dijk, D. (2003). “Forecasting industrial production with linear, nonlinear, and structural change models”.*Econometric Institute Reports*, Erasmus Universiteit Rotterdam, Tinbergen Institute, n. EI 2003-16.

[21] Taylor, S. (1986). *Modelling Financial Time Series*, New York: John Wiley & Sons.

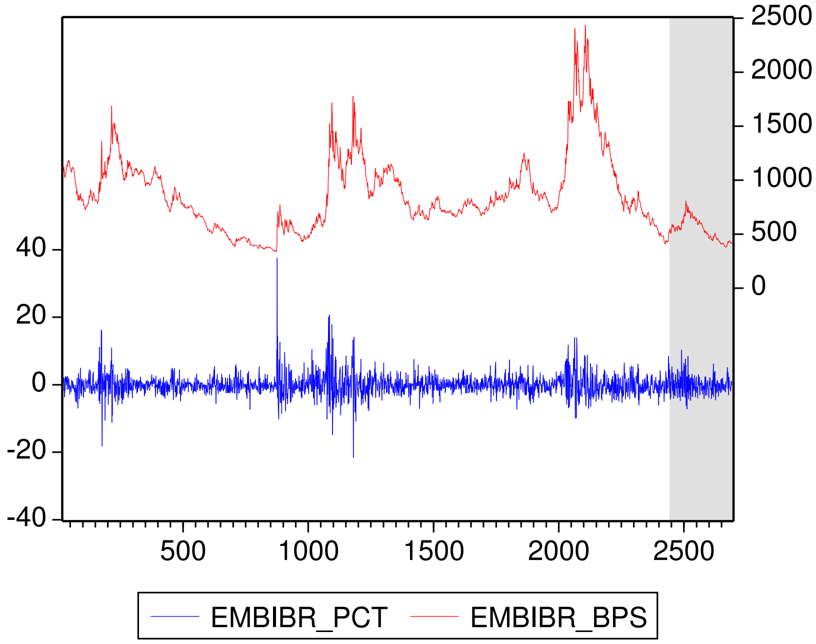
[22] Tolvi, J. (2001), “Nonlinear model selection in the presence of outliers”. *Research Reports*, University of Turku, Department of Economics, n. 90.

[23] Une, M.Y. and Portugal, M.S. (2004), “Fear of disruption: a Markov switching regime model for the Brazilian country risk conditional volatility”. In *Proceedings of the 9th Annual Meeting of the Latin American and Caribbean Economic Association (LACEA 2004)*, San José, Costa Rica, November 2004.

[24] Zakoian, J.M. (1994). “Threshold Heteroskedastic Models”.*Journal of Economic Dynamics and Control*, V.18, pp.931–944.

A Tables and Figures

Figure 1: EMBI Plus Brazilian Sovereign Stripped Spread



Notes: EMBI Plus Brazilian Sovereign Stripped Spread for the period May 27, 1994 through February 2, 2005. In the upper part, EMBIBR_BPS denotes the original series in basis points. In the lower part, EMBIBR_PCT denotes the transformed series in percent changes (100*log-difference). The shaded area is the holdback out-of-sample period used for forecast exercises.

Table 1: **Summary statistics** — EMBI Plus Sovereign Stripped Spreads of Brazil

	Basis Points	Percent Changes
No. of Obs.	2422	2421
Mean	877.7394	-0.029555
Median	810.9590	-0.163714
Maximum	2436.016	37.59119
Minimum	336.9290	-21.65645
Standard Deviation	348.3697	3.077393
Skewness	1.244408	1.336922
Kurtosis	5.289189	17.94843
Jarque-Bera	1156.464 (0.000)	23262.29 (0.000)

Notes: Original series in basis points spans the following period - May 27, 1994 through February 4, 2005. The transormed series loses one observation.

Table 2: **Parameter estimation** — GARCH-in-Mean and GARCH-in-Mean-Level

Model	LL	AIC	SC	log(GARCH)	p-value	EMBIBR_PCT(-1)	p-value
GARCH_N	-5573.22	4.608	4.620				
GARCH_N_D	-5495.61	4.546	4.562				
GARCH_T_D	-5478.88	4.533	4.552				
GARCH_GED_D	-5478.30	4.532	4.551				
TGARCH_N_D	-5478.12	4.532	4.551				
TGARCH_T_D	-5463.28	4.521	4.542				
TGARCH_GED_D	-5464.55	4.522	4.543				
AEGARCH_N_D	-5480.80	4.534	4.553				
AEGARCH_T_D	-5465.39	4.522	4.544				
AEGARCH_GED_D	-5466.32	4.523	4.545				
PGARCH_N_D	-5494.85	4.546	4.565				
PGARCH_T_D	-5476.15	4.531	4.553				
PGARCH_GED_D	-5477.63	4.533	4.554				
CGARCH_N_D	-5533.49	4.578	4.597				
CGARCH_T_D	-5484.10	4.538	4.559				
CGARCH_GED_D	-5471.53	4.528	4.552				
TCGARCH_N_D	-5485.14	4.540	4.563				
TCGARCH_T_D	-5465.80	4.524	4.551				
TCGARCH_GED_D	-5490.50	4.544	4.568				
GARCH_N_D_M	-5496.20	4.547	4.566	-0.011	0.878		
GARCH_T_D_M	-5479.10	4.534	4.555	-0.010	0.887		
GARCH_GED_D_M	-5478.50	4.533	4.555	-0.029	0.691		
TGARCH_N_D_M	-5478.60	4.533	5.555	0.057	0.455		
TGARCH_T_D_M	-5463.50	4.522	4.546	0.037	0.645		
TGARCH_GED_D_M	-5464.90	4.523	4.547	0.015	0.850		
AEGARCH_N_D_M	-5479.30	4.534	4.555	0.161	0.032		
AEGARCH_T_D_M	-5464.60	4.523	4.546	0.114	0.079		
AEGARCH_GED_D_M	-5465.90	4.524	4.548	0.100	0.124		
PGARCH_N_D_M	-5495.60	4.547	4.569	0.000	0.998		
PGARCH_T_D_M	-5476.50	4.532	4.556	0.001	0.989		
PGARCH_GED_D_M	-5477.90	4.534	4.558	-0.020	0.784		
CGARCH_N_D_M	-5534.20	4.579	4.601	-0.039	0.614		
CGARCH_T_D_M	-5484.3	4.539	4.563	-0.057	0.449		
CGARCH_GED_D_M	-5495.9	4.548	4.572	-0.080	0.273		
TCGARCH_N_D_M	-5528.20	4.575	4.599	-0.050	0.546		
TCGARCH_T_D_M	-5467.0	4.526	4.555	-0.016	0.833		
TCGARCH_GED_D_M	-5470.2	4.529	4.558	-0.047	0.522		
GARCH_N_D_M_L	-5486.3	4.540	4.561	0.028	0.716	0.164	0.000
GARCH_T_D_M_L	-5470.1	4.527	4.551	0.019	0.807	0.155	0.000
GARCH_GED_D_M_L	-5471.4	4.528	4.552	-0.003	0.972	0.156	0.000
TGARCH_N_D_M_L	-5477.6	4.533	4.557	0.054	0.521	-0.096	0.115
TGARCH_T_D_M_L	-5462.4	4.522	4.548	0.032	0.690	-0.116	0.129
TGARCH_GED_D_M_L	-5463.9	4.523	4.549	0.011	0.893	-0.112	0.139
AEGARCH_N_D_M_L	-5471.3	4.528	4.552	0.171	0.016	0.043	0.000
AEGARCH_T_D_M_L	-5458.1	4.518	4.544	0.137	0.054	0.045	0.000
AEGARCH_GED_D_M_L	-5459.2	4.519	4.545	0.116	0.103	0.043	0.000
PGARCH_N_D_M_L	-5478.8	4.534	4.558	0.137	0.059	0.049	0.004
PGARCH_T_D_M_L	-5464.6	4.523	4.550	0.097	0.175	0.050	0.023
PGARCH_GED_D_M_L	-5465.8	4.524	4.551	0.078	0.274	0.050	0.021
CGARCH_N_D_M_L	-5485.7	4.541	4.567	0.035	0.660	0.166	0.000
CGARCH_T_D_M_L	-5465.9	4.525	4.554	0.003	0.965	0.093	0.006
CGARCH_GED_D_M_L	-5471.0	4.529	4.558	0.002	0.978	0.157804	0.000
TCGARCH_N_D_M_L	-5481.0	4.538	4.567	0.017	0.835	0.258	0.000
TCGARCH_T_D_M_L	-5458.3	4.520	4.551	-0.027	0.735	0.267	0.000
TCGARCH_GED_D_M_L	-5462.7	4.523	4.555	-0.042	0.596	0.272	0.000

Notes: LL = Log-likelihood; AIC = Akaike Information Criteria; SC = Schwartz Information Criteria; log(GARCH) means the logarithm of the variance in the conditional mean equation; EMBIBR_PCT(-1) means the lagged mean in the conditional variance equation; the endings _N, _T, _GED, _D, _M and _L respectively stand for Gaussian, Student t, Generalised Error Distribution, Dummy Intervention, GARCH-in-Mean effect and GARCH-in-Mean-Level effect.

Table 3: Mean Squared Forecast Errors and Ratio to Gaussian GARCH(1,1) with intervention

Modelo	1-step-ahead			25-step-ahead			50-step-ahead			Average
	MSFE	Ratio	Rank	MSFE	Ratio	Rank	MSFE	Ratio	Rank	Rank
GARCH_N	128.3767			147.6556			119.979			
GARCH_N_D	124.6828	1.000	23	142.3741	1.000	39	107.0399	1.000	45	36
GARCH_T_D	124.3339	0.997	7	143.9567	1.011	49	109.1026	1.019	49	35
GARCH_GED_D	124.3986	0.998	9	143.0113	1.004	46	107.7474	1.007	47	34
TGARCH_N_D	126.8356	1.017	50	138.6453	0.974	22	103.3966	0.966	24	32
TGARCH_T_D	126.4247	1.014	46	138.8524	0.975	25	102.3461	0.956	20	30
TGARCH_GED_D	126.7194	1.016	49	138.8124	0.975	23	103.4488	0.966	25	32
AEGARCH_N_D	125.147	1.004	31	138.5743	0.973	21	102.4743	0.957	23	25
AEGARCH_T_D	125.4438	1.006	36	138.3505	0.972	17	102.3176	0.956	19	24
AEGARCH_GED_D	125.3242	1.005	34	138.475	0.973	20	102.3884	0.957	21	25
PGARCH_N_D	124.5884	0.999	20	141.5586	0.994	32	105.0651	0.982	34	29
PGARCH_T_D	124.4338	0.998	12	142.0276	0.998	35	105.0742	0.982	35	27
PGARCH_GED_D	124.4178	0.998	10	141.4331	0.993	31	104.4003	0.975	30	24
CGARCH_N_D	126.1837	1.012	43	142.638	1.002	42	106.9434	0.999	43	43
CGARCH_T_D	127.5828	1.023	53	147.5652	1.036	53	116.4895	1.088	54	53
CGARCH_GED_D	125.2049	1.004	32	142.1571	0.998	37	106.1908	0.992	39	36
TCGARCH_N_D	124.552	0.999	18	142.793	1.003	44	105.5125	0.986	37	33
TCGARCH_T_D	124.295	0.997	6	144.37	1.014	50	106.5503	0.995	41	32
TCGARCH_GED_D	125.2313	1.004	33	142.4206	1.000	41	104.5627	0.977	31	35
GARCH_N_D_M	124.7596	1.001	25	142.2852	0.999	38	106.9567	0.999	44	36
GARCH_T_D_M	124.3788	0.998	8	143.9281	1.011	48	109.0832	1.019	48	35
GARCH_GED_D_M	124.4604	0.998	15	142.8489	1.003	45	107.5856	1.005	46	35
TGARCH_N_D_M	126.5585	1.015	48	138.8182	0.975	24	103.7934	0.970	27	33
TGARCH_T_D_M	126.3322	1.013	45	139.4153	0.979	28	104.1892	0.973	28	34
TGARCH_GED_D_M	126.5494	1.015	47	138.9551	0.976	26	103.6871	0.969	26	33
AEGARCH_N_D_M	124.5751	0.999	19	138.392	0.972	19	102.4039	0.957	22	20
AEGARCH_T_D_M	124.9137	1.002	29	138.2618	0.971	16	102.2489	0.955	17	21
AEGARCH_GED_D_M	124.872	1.002	28	138.3624	0.972	18	102.2838	0.956	18	21
PGARCH_N_D_M	124.6136	0.999	21	141.5907	0.994	33	105.0558	0.981	33	29
PGARCH_N_T_M	124.4537	0.998	13	142.008	0.997	34	104.9741	0.981	32	26
PGARCH_N_GED_M	124.4305	0.998	11	141.3934	0.993	30	104.36	0.975	29	23
CGARCH_N_D_M	126.232	1.012	44	142.0838	0.998	36	106.1174	0.991	38	39
CGARCH_T_D_M	125.6614	1.008	39	142.7185	1.002	43	106.7629	0.997	42	41
CGARCH_GED_D_M	125.936	1.010	42	142.3757	1.000	40	106.3733	0.994	40	41
TCGARCH_N_D_M	125.5792	1.007	37	143.7122	1.009	47	105.3644	0.984	36	40
TCGARCH_T_D_M	124.5027	0.999	17	141.0339	0.991	29	109.8013	1.026	50	32
TCGARCH_GED_D_M	123.2016	0.988	2	139.1383	0.977	27	101.7178	0.950	16	15
GARCH_N_D_M_L	124.7551	1.001	24	131.8132	0.926	7	93.86472	0.877	8	13
GARCH_T_D_M_L	124.489	0.998	16	132.735	0.932	9	94.75853	0.885	10	12
GARCH_GED_D_M_L	124.6589	1.000	22	132.3593	0.930	8	94.40152	0.882	9	13
TGARCH_N_D_M_L	127.5215	1.023	52	145.6136	1.023	52	112.2744	1.049	51	52
TGARCH_T_D_M_L	127.0115	1.019	51	148.446	1.043	54	115.7388	1.081	53	53
TGARCH_GED_D_M_L	128.1022	1.027	54	145.5298	1.022	51	112.5089	1.051	52	52
AEGARCH_N_D_M_L	123.8076	0.993	3	124.6398	0.875	3	85.54436	0.799	3	3
AEGARCH_T_D_M_L	124.2002	0.996	4	123.4694	0.867	1	83.80868	0.783	1	2
AEGARCH_GED_D_M_L	124.2123	0.996	5	124.3484	0.873	2	85.15319	0.796	2	3
PGARCH_N_D_M_L	124.8218	1.001	27	128.9184	0.905	5	89.73186	0.838	5	12
PGARCH_N_T_M_L	125.0967	1.003	30	128.4856	0.902	4	89.09809	0.832	4	13
PGARCH_N_GED_M_L	124.7885	1.001	26	129.0242	0.906	6	89.86042	0.840	6	13
CGARCH_N_D_M_L	123.0453	0.987	1	132.9877	0.934	10	93.68715	0.875	7	6
CGARCH_T_D_M_L	125.3916	1.006	35	133.6432	0.939	12	95.01588	0.888	11	19
CGARCH_GED_D_M_L	125.9162	1.010	41	133.4567	0.937	11	95.38561	0.891	12	21
TCGARCH_N_D_M_L	124.4586	0.998	14	134.9525	0.948	13	95.85729	0.896	13	13
TCGARCH_T_D_M_L	125.5995	1.007	38	135.9233	0.955	15	97.48256	0.911	14	22
TCGARCH_GED_D_M_L	125.7117	1.008	40	135.3659	0.951	14	99.02446	0.925	15	23
No Effects	125.3222	1.005	28.4	141.5564	0.994	34.8	105.6139	0.9867	34.3	32.5
GARCH-in-Mean Effects	125.1117	1.003	27.2	140.9623	0.990	32.3	105.1533	0.9824	32.9	30.8
GARCH-in-Mean Level Effects	125.1993	1.004	26.8	133.4284	0.937	15.4	95.7331	0.8944	15.3	19.2

Notes: MSFE = Mean Squared Forecast Error; Ratio = $MSFE^{(i)}/MSFE_{GARCH\_N\_D}$; Rank denotes the forecast horizon rank order; the endings _N, _T, _GED, _D, _M and _L respectively stand for Gaussian, Student t, Generalised Error Distribution, Dummy Intervention, GARCH-in-Mean effect and GARCH-in-Mean-Level effect.

Table 4: Modified Diebold Mariano Test against Gaussian GARCH(1,1) with intervention

Modelo	1-step-ahead		25-step-ahead		50-step-ahead	
	MDM	p-valor	MDM	p-valor	MDM	p-valor
GARCH_T_D	1.132	0.129	-2.332	0.010	-2.756	0.003
GARCH_GED_D	1.986	0.024	-2.679	0.004	-2.887	0.002
TGARCH_N_D	-0.807	0.210	2.594	0.005	2.600	0.005
TGARCH_T_D	-0.712	0.239	3.055	0.001	3.417	0.000
TGARCH_GED_D	-0.870	0.193	2.721	0.003	2.500	0.007
AEGARCH_N_D	-0.275	0.392	0.980	0.164	2.009	0.023
AEGARCH_T_D	-0.407	0.342	1.121	0.132	2.377	0.009
AEGARCH_GED_D	-0.364	0.358	0.929	0.177	2.188	0.015
PGARCH_N_D	0.194	0.423	0.628	0.265	3.363	0.000
PGARCH_T_D	0.374	0.354	0.263	0.397	2.995	0.002
PGARCH_GED_D	0.393	0.347	0.568	0.285	2.702	0.004
CGARCH_N_D	-1.127	0.130	-0.144	0.443	0.088	0.465
CGARCH_T_D	-2.353	0.010	-2.780	0.003	-3.682	0.000
CGARCH_GED_D	-0.343	0.366	0.118	0.453	0.834	0.202
TCGARCH_N_D	0.055	0.478	-0.119	0.453	0.603	0.273
TCGARCH_T_D	0.161	0.436	-0.464	0.322	0.183	0.427
TCGARCH_GED_D	-0.240	0.405	-0.013	0.495	1.170	0.122
GARCH_N_D_M	-2.062	0.020	2.452	0.007	2.085	0.019
GARCH_T_D_M	0.903	0.184	-2.428	0.008	-3.090	0.001
GARCH_GED_D_M	1.959	0.026	-2.069	0.020	-2.859	0.002
TGARCH_N_D_M	-0.816	0.208	2.671	0.004	2.340	0.010
TGARCH_T_D_M	-0.753	0.226	3.276	0.001	2.981	0.002
TGARCH_GED_D_M	-0.735	0.232	2.923	0.002	2.757	0.003
AEGARCH_N_D_M	0.068	0.473	0.999	0.159	2.312	0.011
AEGARCH_T_D_M	-0.153	0.439	1.170	0.122	2.300	0.011
AEGARCH_GED_D_M	-0.124	0.451	1.126	0.131	2.238	0.013
PGARCH_N_D_M	0.120	0.452	0.626	0.266	3.764	0.000
PGARCH_N_T_M	0.315	0.377	0.243	0.404	3.234	0.001
PGARCH_N_GED_M	0.425	0.336	0.569	0.285	2.488	0.007
CGARCH_N_D_M	-1.228	0.110	0.183	0.428	1.029	0.152
CGARCH_T_D_M	-0.605	0.273	-0.177	0.430	0.301	0.382
CGARCH_GED_D_M	-0.850	0.198	-0.001	0.500	0.729	0.233
TCGARCH_N_D_M	-0.373	0.355	-0.296	0.384	0.586	0.279
TCGARCH_T_D_M	0.086	0.466	0.385	0.350	-0.898	0.185
TCGARCH_GED_D_M	0.567	0.286	1.086	0.139	2.241	0.013
GARCH_N_D_M_L	-0.072	0.471	3.979	0.000	5.376	0.000
GARCH_T_D_M_L	0.254	0.400	3.826	0.000	4.008	0.000
GARCH_GED_D_M_L	0.027	0.489	4.370	0.000	4.756	0.000
TGARCH_N_D_M_L	-0.910	0.182	-1.374	0.085	-1.903	0.029
TGARCH_T_D_M_L	-0.791	0.215	-2.005	0.023	-2.508	0.006
TGARCH_GED_D_M_L	-1.118	0.132	-1.079	0.141	-1.513	0.066
AEGARCH_N_D_M_L	0.344	0.366	3.163	0.001	4.258	0.000
AEGARCH_T_D_M_L	0.158	0.437	3.083	0.001	4.090	0.000
AEGARCH_GED_D_M_L	0.169	0.433	2.858	0.002	4.396	0.000
PGARCH_N_D_M_L	-0.083	0.467	3.018	0.001	4.966	0.000
PGARCH_N_T_M_L	-0.241	0.405	3.235	0.001	5.116	0.000
PGARCH_N_GED_M_L	-0.058	0.477	3.163	0.001	5.553	0.000
CGARCH_N_D_M_L	1.268	0.103	3.367	0.000	6.054	0.000
CGARCH_T_D_M_L	-0.594	0.277	4.372	0.000	4.723	0.000
CGARCH_GED_D_M_L	-0.981	0.164	4.552	0.000	5.574	0.000
TCGARCH_N_D_M_L	0.078	0.469	2.490	0.007	6.200	0.000
TCGARCH_T_D_M_L	-0.234	0.408	1.880	0.031	5.203	0.000
TCGARCH_GED_D_M_L	-0.362	0.359	2.243	0.013	3.459	0.000

Notes: The endings _N, _T, _GED, _D, _M and _L respectively stand for Gaussian, Student t, Generalised Error Distribution, Dummy Intervention, GARCH-in-Mean effect and GARCH-in-Mean-Level effect.

Table 5: Modified Diebold Mariano Test against Gaussian GARCH(1,1)-in-Mean

Model	1-step-ahead		25-step-ahead		50-step-ahead	
	MDM2	p-valor	MDM2	p-valor	MDM2	p-valor
GARCH_N_D_M_L	0.005	0.498	3.950	0.000	5.312	0.000
GARCH_T_D_M_L	0.355	0.361	3.779	0.000	3.953	0.000
GARCH_GED_D_M_L	0.114	0.455	4.326	0.000	4.694	0.000
TGARCH_N_D_M_L	-0.885	0.188	-1.425	0.078	-1.956	0.026
TGARCH_T_D_M_L	-0.763	0.223	-2.052	0.021	-2.554	0.006
TGARCH_GED_D_M_L	-1.091	0.138	-1.119	0.132	-1.552	0.061
AEGARCH_N_D_M_L	0.372	0.355	3.150	0.001	4.230	0.000
AEGARCH_T_D_M_L	0.182	0.428	3.069	0.001	4.065	0.000
AEGARCH_GED_D_M_L	0.196	0.422	2.846	0.002	4.367	0.000
PGARCH_N_D_M_L	-0.037	0.485	3.009	0.001	4.934	0.000
PGARCH_N_T_M_L	-0.194	0.423	3.224	0.001	5.080	0.000
PGARCH_N_GED_M_L	-0.016	0.494	3.153	0.001	5.518	0.000
CGARCH_N_D_M_L	1.339	0.091	3.352	0.000	5.993	0.000
CGARCH_T_D_M_L	-0.536	0.296	4.332	0.000	4.659	0.000
CGARCH_GED_D_M_L	-0.939	0.174	4.525	0.000	5.502	0.000
TCGARCH_N_D_M_L	0.106	0.458	2.476	0.007	6.160	0.000
TCGARCH_T_D_M_L	-0.215	0.415	1.865	0.032	5.161	0.000
TCGARCH_GED_D_M_L	-0.336	0.369	2.230	0.013	3.445	0.000

Notes: The endings _N, _T, _GED, _D, _M and _L respectively stand for Gaussian, Student t, Generalised Error Distribution, Dummy Intervention, GARCH-in-Mean effect and GARCH-in-Mean-Level effect.