South African Economic Risk Stabilization in Heterogeneous Bi-lateral FX Markets

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Abstract

The purpose of this study is to model the nonparametric realized volatility of the futures contract as traded in domestic U.S. markets for exchange involving the South African rand and the U.S. dollar (ZAR). The study embraces a Bayesian regularization radial basis function (RBF) artificial neural network (ANN) to model the complex volatility patterns. The modeling characteristics revealed by the Kajiji-4 RBF ANN provide significant new information about the role of FX trading behavior within the bilateral mineral alliances of the two economies. In addition to conditional volatility and trade-weighted state variables, both U.S. and South African based news proxies prove to be important determinants of volatility. Additionally, the daily time-scale reveals evidence of heterogeneous trading across the bilateral trade dimensions. This latter finding suggests that future research may yet identify a significant trading rule for the ZAR contract.

I. Introduction

It is widely known that high frequency volatility of FX market contracts is best modeled by complex nonlinear functions. To date, the literature has proposed a number of alternative methods to best model the state variables that drive high frequency volatility patterns in futures and futures options FX contracts. With increased availability to high-frequency data, research has been able to more clearly separate its focus on parametric and nonparametric returns volatility. Andersen, Bollerslev, and Diebold (2002) have noted that current research methods have increasingly moved away from hard-to-estimate parametric models in favor of more flexible and computationally simple nonparametric alternatives. This trend, they argue, will provide support for continued research efforts at exploiting volatility information in high frequency data as well as providing an impetus to model and forecast multivariate environments of financial consequence.

One of the more promising nonparametric methods employed to model FX futures contract volatility falls under the domain of artificial neural networks (ANN). Hornik, Stinchcombe, and White (1989) provide significant evidence about the ability of ANN models to approximate any Borel measurable function to any degree of accuracy. Not surprisingly, the literature is rich with studies that offer various enhancements to the ANN topology to better exploit this method as a financial time-series modeling tool. By way of example, Malliaris and Salchenberger (1996); Niranjan (1997); Hutchinson et al., (1996) and Kajiji (2001) have each focused on incorporating enhancements to dampen noise-related error inflation in a technique that is employed in this study – the radial basis function neural network (RBF).

In this paper we focus on modeling the realized returns volatility of the futures contract written against the South African Rand exchange (ZAR) against the United States dollar as traded on the U.S. Chicago Board to Trade (CBOT). The modeling process proceeds from a U.S. perspective. We rely upon stylized facts that argue realized returns are robust with respect to the use of high-frequency data at the daily level or greater is sufficient to separate the expected return component from the occurrence of an innovation in the volatility series. As such, we conjecture that the realized volatility of the U.S traded instrument can be modeled by conditional volatility and latent state variables that proxy the release of regularly scheduled news as well as non-scheduled releases of news. Of explicit issue here is whether the U.S. based-trader is joined by other traders around the globe in their reaction to news releases. Of course, in a completely homogeneous market all traders react immediately to the news component.

In the absence of homogeneous trading of the ZAR, trading results can be quite onerous to the domestic policy officials in the South African base currency home market. When market participants in different parts of the world are able to produce a separate time-scale on which they react to jumps inducing news, then in the absence of optimally specified forecasting models it is possible for these traders to induce market-beating trade methodologies. Of course, a trading rule that exists undetected by the broad market for any length of time may result in an unintended and uninformed transfer of wealth. We specifically investigate whether bilateral trade between the U.S. and South Africa may lead to FX market inefficiency of heterogeneous trading.

The paper proceeds by introducing the role and appropriateness of the Kajiji-4 radial basis function (RBF) artificial neural network (ANN) as the nonparametric modeling procedure of choice. Additionally, the paper reports the results of the GARCH(1,1) volatility model when applied to the ZAR contract. Conditional volatility estimates will play a key role in the specification of state-input variables provided to the Kajiji-4 method.

2. The RBF ANN with Prior Information and Regularization

The objective of the RBF ANN is to combine a hidden layer of radial units that model a Gaussian response surface into a network of outputs. Since these functions are non-linear, it is not actually necessary to have more than one hidden layer to model any shape of function. With sufficient radial units the RBF design will always produce an efficient modeling of any function. But, the method does not exist without limitations. Stylized facts have emerged from RBF implementations that report extrapolation inaccuracies when data points are far from the training set. Because it is sufficient to use a linear combination of these outputs (i.e. a weighted sum of the Gaussians), RBF networks are generally constructed as a supervised least squares based method that is first applied to a training set as a means of deriving the optimal weighting values. The supervised learning function may be stated as,

$$y = f(x) \tag{1}$$

where, y the output vector is a function of x the input vector with n number of inputs.

Alternatively, the supervised learning function can be restated as the following linear model,

$$f(x_i) = \sum_{j=1}^{m} w_j h_j(x) \tag{2}$$

where, *m* is the number of basis functions (centers), *h* is the hidden units, *w* is the weight vectors, and i = 1..*K* output vectors (target variables). The flexibility of *f* and its ability to model many different functions is inherited from the freedom to choose different values for the weights.

Note that the RBF mapping function may be restated as a Tikhonov's (1977) regularization equation. Tikhonov regularization adds a weight decay parameter to the error function to penalize mappings that are not smooth. Traditionally, iterative techniques are used to compute the weight decay parameter [see Orr (1996; 1997)]. But, iterative techniques have known drawbacks. In addition to being computationally burdensome, iterative methods lack specificity, as they require an initial estimate for the regularization parameter. Computational experience suggests that when iterative methods are employed, it is not uncommon to experience local minimum, or to produce inflated residual sums of squares when the weight decay parameter goes to infinity.

Kajiji (2001) reasoned that an optimally derived regularization estimate would reduce the "curse" of dimensionality and thereby assist in achieving a reduction in noise-induced inflation in the residual sum of squares. Through the use of a closed-form solution method for the estimation of an optimal ridge regression parameter when enhanced by Bayesian prior information set, Kajiji implemented a parallel extension to the RBF topology as a means by which to derive the initial estimate of the regularization parameter.[1] Hemmerle (1975) proposed an alternative closed-form solution to the estimation of the ridge-regression parameter by offering a modification to the original Hoerl and Kennard (1970) iterative method. Further, Hemmerle's method produced a vector of optimized ridge parameters unlike a single non-optimized ridge parameter of Hoerl and Kennard. By contrast, Crouse et al.(1995) produced an algorithm that further enhanced the prediction ability of the Hoerl and Kennard single ridge parameter by adding a prior information matrix. In tests of algorithmic efficiency Kajiji found her extension to the regularization parameter modeled complex nonlinear financial time series with a consistently smaller fitness function MSE than did the non-optimized iterative-based RBF with regularization. Although Kajiji presented four alternative RBF algorithms (Kajiji-1 to Kajiji-4), we postulate that the Kajiji-4 algorithm is a sufficiently reasonable method to model high frequency financial time series.

3. Conditional Volatility and the ZAR Futures Contract

3.1 Data

The models reported in this section are based on realized returns obtained from daily closing quotes on the futures contract against the dollar exchange with the South African Rand. In addition, daily data on futures for the dollar trade-weighted index (DX), the U.S. Treasury bond (TB), and COMEX gold are observed. From the South African market, returns on the 10-year and 20-year government bond yield provide behavioral economic content from the base country market. All data are obtained from Global Financial Data (www.globalfindata.com). Finally, returns of spot platinum prices obtained from the London Platinum and Palladium Market (LPPM) complete the data set. The sample period is from October 2, 2000 to June 21, 2002 inclusive resulting in 428 observations for each variable.

[1] See Crouse, R. H., C. Jin, et al. (1995). "Unbiased Ridge Estimation with Prior Information and Ridge Trace." Communication in Statistics **24**(9): 2341-2354. for details.

3.2 Modeling Conditional Volatility

The GARCH model was first developed to model data at the daily frequency level or greater. The stylized facts report volatility persistence in high frequency financial data. Although several studies are not supportive of the GARCH framework when applied to high frequency data [see Andersen and Bollerslev(1994), Guillaume et al. (1994), Ghose and Kroner (1995), and Dacorogna et al. (1998)], stylized facts report that memory effects are short-lived and generally weakly explained by ex-post squared returns (realized volatility). By contrast, the use of daily intervals (and lower) supports a finding of long-lived volatility memory. Andersen and Bollerslev (1997) resolve the apparent conflict. Importantly, they show that standard GARCH models are capable of predicting close to fifty percent of the variance in the latent one-day ahead volatility factors (when using a continuous-time stochastic volatility framework based upon cumulative squared intra-day returns[2]).

The weak-form GARCH model of Bollerslev (1986) generalized the original autoregressive conditional heteroscedasticity (ARCH) model of Engle (1982). For a time series variable x_t, the model is expressed as:

$$x_t = \sigma_t z_t \tag{3}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 x_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{4}$$

where $z_t \sim NID(0,1)$, for $\alpha_0, \alpha_1 \geq 0$ and $t = 1...T$. The model implies that $x_t \,|\, \Omega_{t-1} \sim N(0, \sigma_{t-1}^2)$. The model is particularly useful in financial research as it permits x_t to be leptokurtotic; a fact that infers the model's ability to capture stylized seasonality (or, volatility clustering).

[2] For more on the subject of the GARCH framework see the review in Dash and Kajiji (2001).

4. Estimation Results

4.1 Descriptive Statistics

Table I provides descriptive statistics computed from daily observations over the study period. Presented in the table are results on the following daily characteristics: one-day return, volatility (%), and conditional volatility. Although the returns pattern for the ZAR shows negative lags up to 10 days, a closer view of the sequence demonstrates the decreasing monotonic nature of the lag trough day 3. The second day lag is just slightly smaller than the one day lag (-0.069 versus -0.061). However, by the third day, the lag has fallen considerably to -0.017. For this analysis, we consider the effective lag period to be slightly greater than 2 days. We note that one-day volatility shows a positive lag of approximately the same magnitude for up to 3 days. At lag 4 both the return and volatility lags show a noticeable depreciation. As expected, conditional volatility is initially strong with a constant and steady lessening of importance as the lag increases.

Table I: Descriptive Statistics

	Descriptive Statistics		Autocorrelations						
	Mean	Std. Dev	Lag1	Lag2	Lag3	Lag4	Lag5	Lag7	Lag10
1-day return	0.000817	0.012452	-0.069	-0.061	-0.017	0.086	-0.079	0.114	-0.007
1-day volatility (%)	0.051868	0.125935	0.985	0.953	0.912	0.864	0.811	0.702	0.545
Conditional Volatility	0.000152	0.000289	0.924	0.819	0.744	0.698	0.656	0.546	0.448

Figure 1 provides a descriptive view of the daily ZAR returns volatility. It is immediately evident that the ZAR contract is characteristic of time-varying volatility. Except for January 1999 the volatility patterns in the daily returns present a pattern that is well documented for high frequency data. Volatility is persistent but is clearly changing over the sample period. At first volatility shows signs of weakening. This is followed by a noticeable jumps, which in turn is followed by an increasing volatility until the end of the study period.

4.2 GARCH Estimate

Conditional volatility is estimated by applying GARCH(1,1) to the daily returns. Parameters α_1 and β were subjected to the typical stationarity constraint. This constraint is necessary and sufficient to examine a finite, time-independent variance of the innovations process. The reported χ^2 statistic of the GARCH estimate confirms that a GARCH process is describing a statistically significant amount of the conditional variance in returns. The results presented in Table II of this study are consistent with GARCH(1,1) results applied to daily data as reported in all prior research.[3] Stated differently, the GARCH results confirm that the ZAR realized daily volatility is stationary, but does change over time.

Figure 1: ZAR/USD Daily Returns

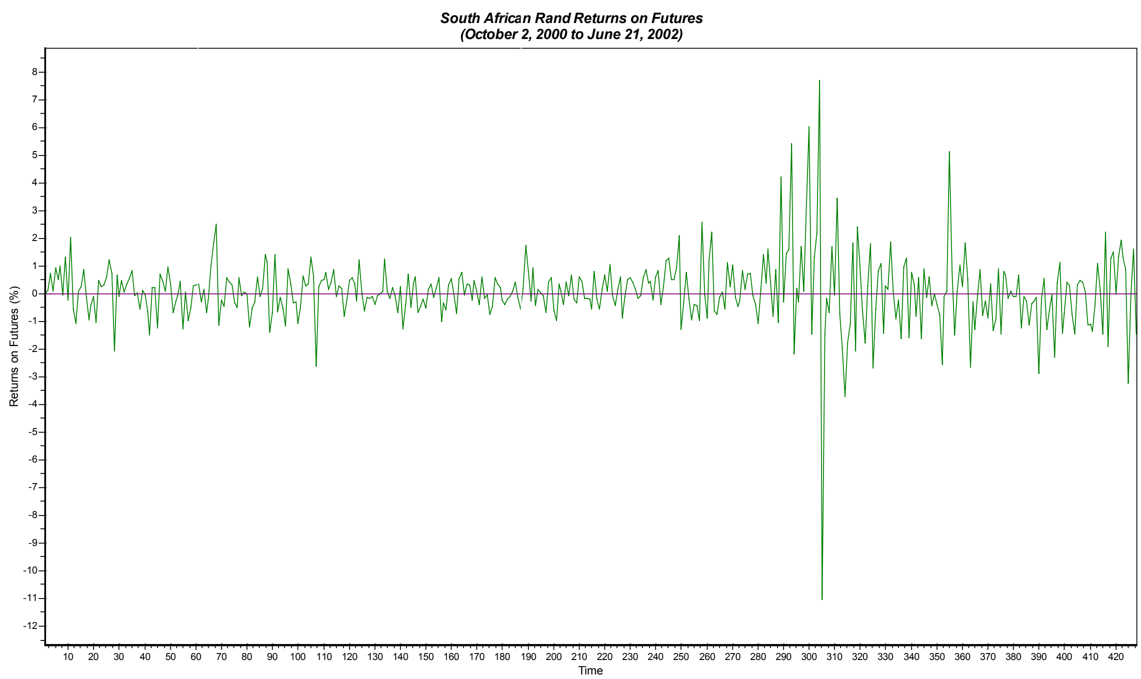

Table II: Estimation of GARCH(1,1) Process

Model	μ	α_0	α_1	β	Long-Run Volatility (% pa)	Log-Likelihood	$Pr > \chi^2$
GARCH	0.000689 (0.0599)	3.8089x10-6 (0.0145)	0.1597 (0.0001)	0.8135 (0.0001)	0.1182	1380.140	0.0001

p-values are in parenthesis

[3] OLS, Hansen-White, and GARCH estimates are obtained from version 8e of the Statistical Analysis System (SAS), North Carolina.

4.3 RBF Volatility Modeling Efficiency

It is a process of error comparison that provides the conventional wisdom for comparing the relative attractiveness of alternate ANN solutions. We examine computed MSE statistics for three subsets within the sample data. The MSE for the training, validation and fitness sub-samples are defined in equations 5 through 8 accordingly:

$$MSE_{training} = \sum_{i=1}^{t} \left(y_i - \hat{y}_i \right)^2 \Big/ t \tag{5}$$

$$MSE_{validation} = \sum_{i=t+1}^{v} \left(y_i - \hat{y}_i \right)^2 \Big/ v \tag{6}$$

$$MSE_{fitness} = \sum_{i=1}^{T} \left(y_i - \hat{y}_i \right)^2 \Big/ T \tag{7}$$

where $\text{MSE}_{training}$ is restricted to the training sub-set (T_t) and the $\text{MSE}_{validation}$ captures the out-of-sample error component ($T_{t+1}..T_v$). The $\text{MSE}_{validation}$ measure is computed over all (T) observations. The analysis provided herein relies on the interpretation of the computed fitness ($\text{MSE}_{validation}$).

Table III: Default Parameter Settings for Kajiji-4

Model	Values
# in Overall Fitness ($T_t + T_v$)	426
# in Validation Set (T_v)	108
# in Training Set (T_t)	318
Spread Constant	1.0
Number of Centers	T_t
Maximum Centers	No specification necessary
Iteration Starting Value	Computed mathematically
Max Iterations	n/a
Max Epoch	n/a
Average Time to Solution	< 1 min
Input Layer	Standardized
Function	Gaussian

All Kajiji-4 RBF applications use the default parameter settings as identified in Table III. This restriction only permits comparison at the "default" level of algorithmic performance. Solution characteristics that differ from those reported in this study may be possible with further refinement(s) to the listed parameter settings.

4.4 RBF Model Efficiency

The Kajiji-4 nonparametric RBF ANN proved to be quite informative when applied to the problem of modeling the realized volatility of the ZAR futures contract. But no matter how efficient the algorithm, it is not always possible for a single ANN model to provide sufficient evidence to conclusively establish the relative importance of alternative state variables in the determination of FX volatility. Instead, it becomes necessary to invoke the 'preponderance of evidence' rule. When applied to alternate but closely defined ANN models, this rule implies that one may rely upon observable trends for variable inclusion to identify the best state variables for policy determination and review.

4.5 Announcement Effects and News

Evidence has been provided by Bollerslev, Cai, and Song (2000) of a domestic announcement and news effect in 30 year Treasury bond returns. However, there is no supporting evidence to sustain or extend this finding beyond the U.S. Treasury bond market. Nevertheless, lacking alternatives, we generalize and extend the findings to the South African economy by including both the returns on the 10- and 20-year government bond yields as proxies for South African macro-economic announcements and news effect. These variables are designated as 10yr, 20yr, and lag20yr, respectively. The announcement and news effect is further augmented in this study by the inclusion of a bi-lateral trade and interest scarce metals dimension. Returns for futures on gold and spot platinum are complete the definition of the announcement and news dimension for this study.

South Africa is the world's largest producer of gold. Gold mining operations in South Africa account for more than 27 percent of South African mineral revenues and slightly more than 56 percent of the mineral related labor force. The future of gold related economic activity is very much in the South African news owing to globally depressed prices for gold, increasing declining grade, deep mine levels, and the inability of producers to increase productivity by substituting factor inputs to better utilize new technology. Platinum is an equally valuable mineral. More than 80 percent of global platinum supplies, among the world's scarcest metals, are concentrated in South Africa. New mine production totals approximately 5 million troy ounces a year while, by contrast, gold mine production runs approximately 82 million ounces a year. In Figure 2, we show the relationship between gold futures and ZAR volatility. Similarly, in Figure 3, the relationship is repeated for platinum. Clearly, there is a strong correlation between ZAR volatility and the gold variable. The lack of variability in the platinum data may be owing to the reliance on spot price behavior in the EU; however, we note a distinct lack of correspondence to the high volatility inherent in the ZAR.

Figure 2: Gold Futures and ZAR Volatility

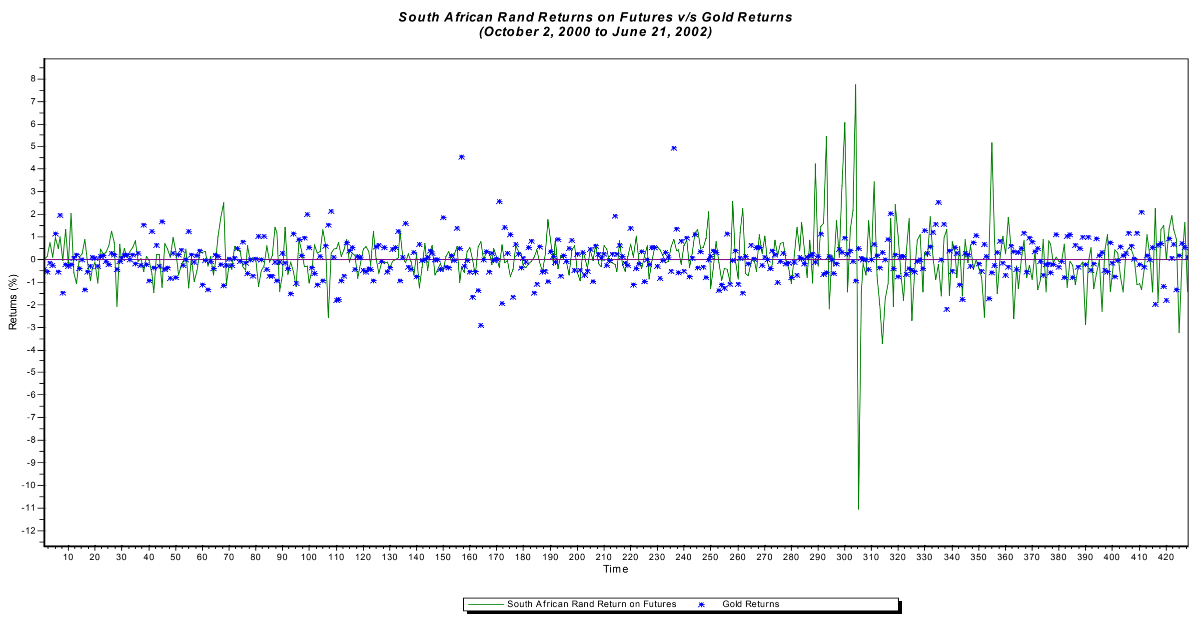

Table IV presents 18 alternative economic models ranked by the attractiveness of the computed fitness MSE. We invoke the ‘preponderance of evidence’ rule by limiting the analysis to those models that achieve an MSE no larger than 0.07. Model I in Table IV provides the most direct insight into the state variables that drive ZAR volatility on a daily time scale. As we would expect from the descriptive statistics and the graphical presentation of ZAR returns, the

GARCH dimension of conditional volatility is included in this model. Also included are the two proxies for U.S. domestic news – DX and TB. The concurrent returns from the COMEX gold futures contract are also included in this model. At this point the findings presented here confirm the stylized facts as reported in the literature regarding the global FX market. However, we note that model I also includes a non-domestic variable. The yield on the South African 20-year government bond enters this equation. This latter variable was included to serve as the non-domestic proxy for news and announcements in South Africa. Model II includes one additional state variable. The two-day lag of the ZAR realized futures volatility is the one added state variable. The reported fitness MSE value is only 0.008 points higher than that reported by model I. The evidence here clearly supports the more generalized findings gleaned from the autocorrelation analysis presented in Table I. Model III drops the two-day lag in favor of a one-day lag. There is no material difference between the computed fitness MSE values for these two models. Hence, we are inclined to accept the generality of the lagged component.

Figure 3: Platinum Future and ZAR Volatility

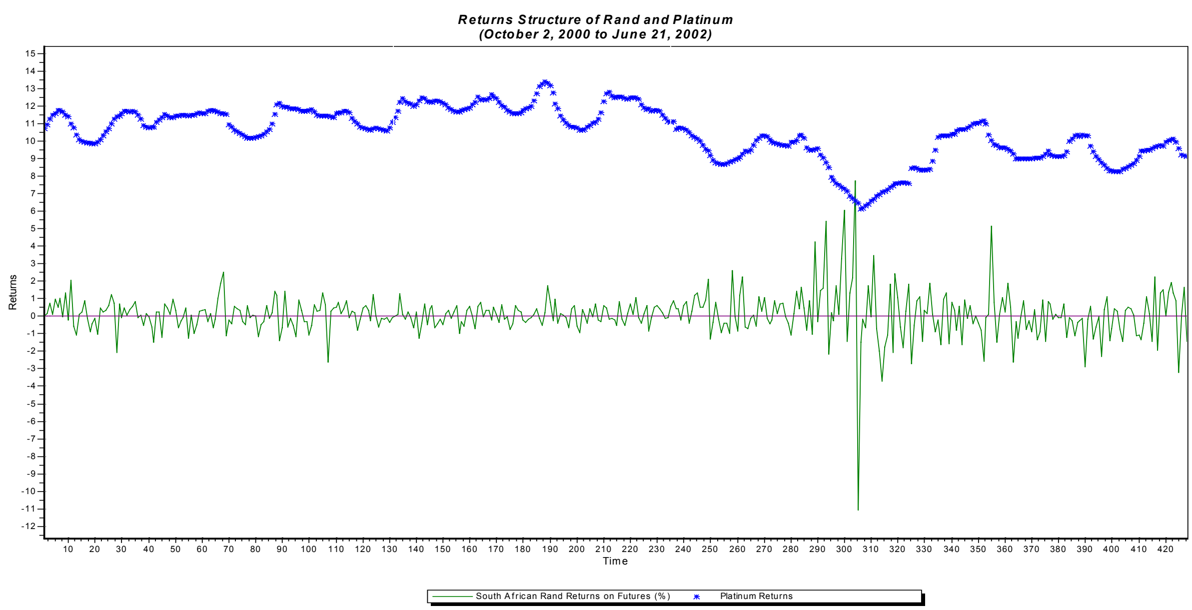

Table IV: ZAR Model MSE by Model

Model #	GARCH	DX	TB	Lag1	Lag2	20Yr	10Yr	DX Frb	Gold	Lag 20Yr	Platinum	Lag1 Platinum	Lag2 Platinum	Training	Validation	Fitness
I	I	I	I			I			I					1.5738	1.2491	0.0554
II	I	I	I		I	I			I					1.5738	1.2800	0.0562
III	I	I	I	I		I			I					1.5738	1.2445	0.0563
IV	I	I	I		I				I	I				1.5738	1.2797	0.0563
V		I			I				I	I				1.5736	1.2565	0.0617
VI		I			I	I			I	I				1.5738	1.2538	0.0625
VII	I	I	I						I	I				1.5738	1.2316	0.0670
VIII	I	I	I						I	I		I		1.5736	1.2362	0.0686
IX	I	I	I						I	I			I	1.5733	1.2314	0.0718
X	I	I	I		I	I			I					1.5738	1.1964	0.0746
XI		I	I			I			I					1.5730	1.2257	0.0749
XII	I	I	I						I	I	I			1.5736	1.2177	0.0765
XIII	I	I	I	I		I			I					1.5736	1.1875	0.0805
XIV		I				I			I					1.5722	1.2097	0.0814
XV		I				I		I	I					1.5712	1.1938	0.0854
XVI	I	I				I			I					1.5717	1.1817	0.0860
XVII			I			I			I					1.5684	1.0721	0.1163
XVIII						I		I	I					1.5664	1.0634	0.1173

4.6 Heterogeneous Trading Evidence

Models IV through VIII provide evidence of heterogeneous trading in the FX market for the U.S. traded ZAR futures contract. By definition, model IV of this group has the lowest reported fitness MSE (0.0563). This MSE value is not materially different from that produced by model III. However, model IV introduces the one-period lag on the South African news proxy (the 20-year yield on the government bond) while retaining state variables GARCH, DX, TB, and Gold. We also note that a platinum variable enters the analysis with model VIII. This model includes the one-day lag of LPPM platinum returns. While all models in this group include the one-period lag of the South African news proxy, the models differ in their specification of state variables regarding conditional volatility and the two U.S. news proxies. We note that by a preponderance of the evidence gleaned from models I through IV it is clear that the GARCH, DX, and TB dimensions contribute to unique definition of ZAR futures contract volatility.

Figure 3: Actual and Predicted Values of Rand

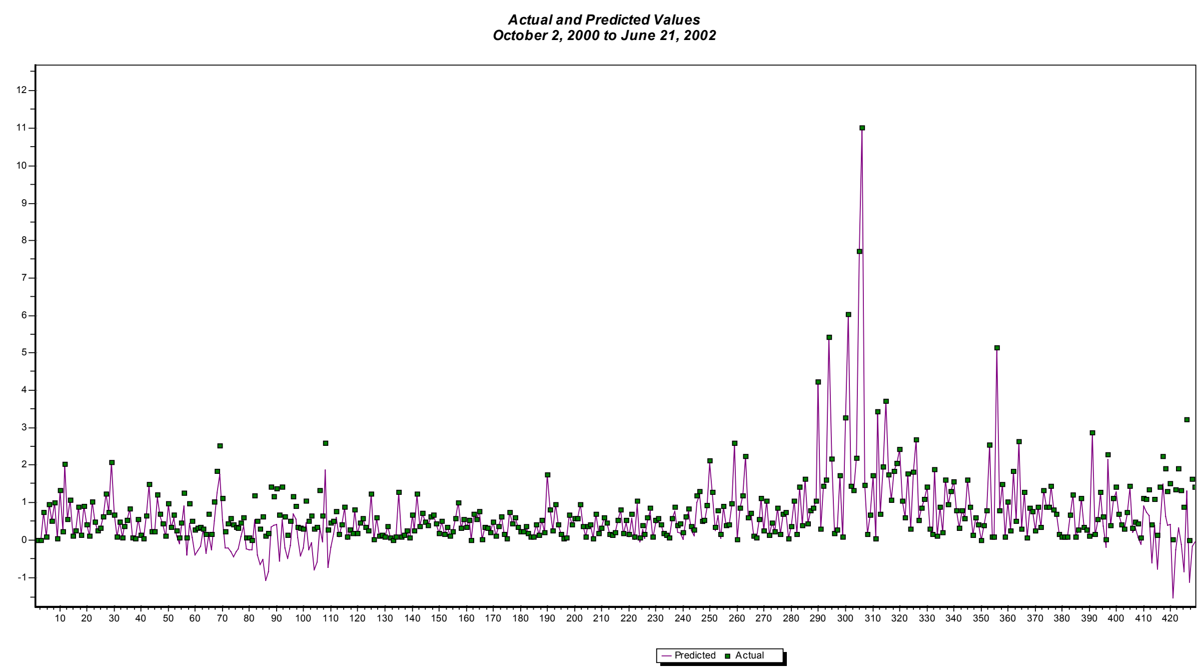

Figure 3 provides a cross-plot of actual realized volatility against the predicted outcome. Two observations may be gleaned from these two time series. First, as time passes and volatility declines by showing less dispersion among the peaks and troughs, it is clear that the Kajiji-4 algorithm is able to capture this trend with extreme precision. However, the algorithm also shows an under-prediction bias in its replication of the volatility pattern. That is, the predicted values are below the actual values despite the ability of the algorithm to match peaks and troughs on a daily basis.

5. Summary and Conclusions

This paper focused on the role of the Kajiji-4 RBF ANN to provide an efficient modeling platform when applied to daily volatility of the ZAR futures contract. As with other studies from the FX markets performed on daily returns data, we found volatility persistence with a time effect. This finding is important for two reasons. First, it suggests that a successful application of the RBF-ANN to the ZAR may warrant the application of this nonparametric method to other high frequency financial data obtained from the global FX markets. Second, the GARCH findings presented in this paper further corroborate stylized facts that report volatility for this contract, like other FX contracts, is appropriately – albeit, not completely – modeled by the ARCH style models.

The results of solving alternative RBF-ANN model specifications clearly point to the role of both conditional volatility, trade-weighted dollar effects, and U.S. news as volatility determinants. Importantly, this study augments past research by providing evidence of heterogeneous trading for the ZAR contract. The existence of a lag between 1 and 2 days is enough to suggest that traders who are 0.5 to 1.5 days removed from the U.S. market are likely to react to information that leads to significantly different trading activity. In short, a trading rule may exist for these traders. The findings presented here beg for the further interrogation of what role news (both domestic and South African) may play in shaping the daily volatility pattern of this contract. What is most evident from the outcome of this study is the need to expand future studies to examine intra-day observations. The daily time-scale did not offer the resolution needed to fully account for the effect of the lag. Until a time-scale at the hourly or greater level is introduced, it may not be completely possible to conclusively identify the existence and location of heterogeneous trading. However, sufficient evidence now exists to encourage policymakers on both continents to review how the informational content of news is released to the global trading community. Clearly, some traders are in a position to exploit news at a time when others cannot; a process that will lead to a non-optimal transfer of wealth.

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