Working Paper Series

Estimation of Multiple Time Series with Volatility

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NO. 2016 – 13

October 2016

Abstract

Volatility in multiple time series influences parameter estimates resulting to deterioration in model fit in non-volatile segments. Block bootstrap and BLUP are embedded into the backfitting algorithm to estimate multiple time series models with common autoregressive parameter with data observed under temporary volatility. Simulation studies exhibited robustness of the estimates, predictive ability of the fitted model is superior during the non-volatile periods of the time series. While predictive ability deteriorates when the time series are very short or when they are nearly non-stationary, it still provides better predictions compared to some common time series models.

Keywords: multiple time series, volatility, block bootstrap, backfitting

1. Introduction

Prices of individual stocks in a market exhibit similar behavior, usually driven by a reaction to nationwide or international phenomena such as an upgrade in the country's credit rating or global financial crisis (Philippine Star, 2014; Guinigundo, 2010). This can be represented by multiple time series that share common autoregressive patterns. Various modeling procedures for this class of multiple time series have been developed through the years, there has been limited resources in robust modeling algorithms.

Theoretically, stocks traded in a market are valued based on the worth and performance of the companies that they represent (Demirakos et al., 2004). However, actual prices exhibit considerable dependencies on exogenous factors (Nazir et al., 2014). Stocks are bought and sold based on two factors, buyers' and sellers' perception of how much such stocks will be worth in the future and their need for liquid assets. The first factor are associated with events that have nothing to do with the operational performance of individual companies, such as the development of sociopolitical unrest in the country, which can cause stock market investors to lose confidence in the market itself and sell their positions. For example, stocks on the Stock Exchange of Thailand commonly fell after the military's declaration of martial law (Aneez and Jantraprap, 2014). The second factor can be considered as almost independent of individual companies' performance, but is affected by nationwide concerns like prevailing interest rates. When rates are low, people rely more on credit and less on cash, and have greater incentive to invest surplus cash on stocks, thereby driving stock prices up. This demonstrates that stocks easily follow shared common autoregressive patterns that can be represented in a model with an autocorrelation parameter.

Veron Cruz and Barrios (2014) estimated a multiple time series model that have common autoregressive patterns using the hybrid of maximum likelihood estimation and best linear unbiased predictors in a backfitting algorithm. While each of the N time series are assumed to have similar pattern throughout its generation, some observed time series are often influenced by stylized facts like volatility, a series of aberrant observations caused by sudden occurrence of events that are relevant to the time series observed, (Campano, 2012). The unaccounted presence of volatility in time series has been known to significantly impact the ability of existing models to accurately describe characteristics of the series, noted (Campano, 2012). Conditional heteroscedasticity assumption has been used account for volatility in time series, but Politis (2007) pointed the inherent unsuitability of this approach to time series modeling in various practical contexts. In this context, Campano (2012) developed a robust method for estimating the stationary part of a univariate time series through the integration of a block bootstrap procedure and an AR-sieve into a forward search algorithm.

We develop in this paper an estimation procedure for multiple time series data that exhibits volatile behavior through a hybrid of block bootstrap procedure and EBLUP in the backfitting framework. The method extends the approach in Veron Cruz and Barrios (2014) to address the issue of volatility. Campano (2012) provided empirical evidence that block bootstrap procedure is capable of producing robust estimates of single time series model parameters in the presence of temporary volatility.

2. Analysis of Multiple Time Series

Arellano and Bond (1991) considered multiple time series as panel data are estimated the autoregressive parameter α and the individual time series effects η_i in the model $y_{it} = \alpha y_{it-1} + \eta_i + v_{it}$ using generalized method of moments. Assuming absence of serial correlation, Arellano and Bond (1991) posited that lagged y values (two or more periods) can be used as valid instruments for equations in first differences. Thus, parameters can be estimated using $m = \frac{(T-2)(T-1)}{2}$ linear moment restrictions. Arellano and Bond (1991) further noted low bias of parameter estimates (4%-6%) across different parameter values for α. However, the algorithm diverges when the time series length is greater than the number of time series in the panel. Veron Cruz and Barrios (2014) provided an alternative to the Arellano-Bond procedure in such situations. The procedure used backfitting algorithm similarly used in the estimation of spatio-temporal models, see for example Landagan and Barrios(2007), Dumanjug et al., (2010), Campano and Barrios (2011), Bastero and Barrios (2011).

Veron Cruz and Barrios (2014) estimated the common autoregressive parameter ϕ and the random effects for individual time series λ_i of N time series, each of length T, in two phases. The goal of the first phase was to obtain an initial (biased) estimate for ϕ by ignoring other components of the model. The second phase used the initial estimate of ϕ to estimate λ_i, estimate of ϕ is then refined in an iterative process until convergence. Veron Cruz and Barrios (2014) observed that the estimator has strong predictive ability and estimates of ϕ and λ_i's have minimal bias for a wide variety of simulation settings. The estimator performs well across different values of ϕ, except when the value is near nonstationarity. The predictive ability of the estimator improved as the length of the time series increased and was robust to the number of time series included in the analysis (N). Predictive ability was not affected by the distribution of the λ_i's (Normal or Poisson), but was affected by the variance of the error term when the coefficient of variation for the distribution of the λ_i's was very high. The algorithm was able to provide reasonable estimates for cases where the Arellano-Bond estimator typically diverged (T>N), and produced results that were comparable to the Arellano-Bond estimator when T≤N.

Volatility results to heteroskedasticity hence, commonly represented by conditionality upon an exogenous variable, such as the variance of the dependent variable depending on the variance of one or more of its predictor variables (Campano, 2012). Small changes in the variance of the predictor variable may be magnified in the variance of the dependent variable (Campano, 2012). Volatility in time series estimation has traditionally been dealt with using autoregressive conditional heteroskedastic (ARCH) and generalized autoregressive conditional heteroskedastic (GARCH) models (Bollerslev, 1986; Nelson, 1991; Enders, 2004; Brooks, 2014). ARCH models assume a functional relationship between the variance of the error terms and the actual sizes of the lag time periods' error terms (Enders, 2004). When an autoregressive moving average model is assumed for the variance of error terms, the model becomes a generalized ARCH or GARCH model (Enders, 2004). As explained by Nelson (1991),for each time point t in a series, ARCH models assign a scalar prediction error ξ_t, a vector of parameters *b,* a vector of predetermined variables x_t, and the variance of ξ_t given information at time t as σ_t^2. ARCH/GARCH procedures model σ_t^2 as linear in lagged values of $\xi_t^2 = \sigma_t^2 z_t^2$ where $z_t \sim N(0,1)$ for all t.

3. Multiple Time Series with Volatility

Following the postulated model in Veron Cruz and Barrios (2014), consider N time series each of length T, sharing a common autocorrelation parameter ϕ, the multiple time series model is given by

$$Y_{i,t} = \phi Y_{i,t-1} + \lambda_i + \varepsilon_{i,t}\,,\ \lambda_i \sim N\left(\mu_i, \sigma_{\lambda_i}^2\right),\ i = 1,2..N; t = 1,2..T \qquad (1)$$

The noise process $\{\varepsilon_{i,t}\}$ behaves as $\varepsilon_{i,t} = h_t v_t$ where $v \sim N(0,1)$ and $\{h_t^2\}$ is a sequence of volatilities characterized as some function of past realizations.

In stock market analysis, ϕ can represent the common effect that some regulatory policies of the country's stock exchange induce on the behavior of the stocks, e.g., interest rate policy. It can also represent some sociopolitical characteristics of the country that affect the desirability of investments in stocks. On the other hand, the λ_i's can represent the collection of factors internal to specific companies represented in the stock market that likewise affect the stock price, such as their total capitalization or net revenue.

We estimate Model (1) in two phases. The iterative process in the first phase is implemented for each block (equal length) formed from the time series. Phase 1 of the algorithm is implemented to obtain estimates of ϕ and the λ_i's.

1.) Ignoring $\phi Y_{i,t-1}$, estimate λ_i as $\hat{\lambda}_i$ using best linear unbiased prediction (BLUP) method.

2.) Compute residuals by subtracting each $\hat{\lambda}_i$ from $Y_{i,t}$.

3.) Estimate $\hat{\phi}_i$'s by conditional least squares on each of the residual time series obtained from the previous step. This will result to N estimates for ϕ. Resample from these N estimates to obtain the bootstrap estimate $\hat{\phi}^{BS}$ of ϕ.

4.) Compute new residuals: $r_{i,t}^{re} = Y_{i,t} - \hat{\phi}^{BS} Y_{i,t-1}$.

5.) Update estimates of λ_i from the model : $r_{i,t}^{re} = \lambda_{i,t} + \varepsilon_{i,t}$.

6.) Given these $\hat{\lambda}_i$'s, compute new residuals: $r_{i,t}^{ar} = Y_{i,t} - \hat{\lambda}_i$.

7.) Update estimates of $\hat{\phi}^{BS}$ using the residual time series $r_{i,t}^{ar}$'s.

8.) Using the new $\hat{\phi}^{BS}$, iterate the process from step 4 until convergence.

The second phase of the estimation algorithm starts from N sets of estimates for ϕ and the λ_i's, where we resample to generate the final estimates of ϕ and λ_i's.

The blocks of the time series are formed to isolate parts of the multiple time series that experienced volatility. The first phase of the procedure aims to find estimates for the parameters in each of the blocks. Steps 1 to 3 are used to find initial, possibly biased estimate of ϕ. This estimate is used in Step 4 to obtain residual time series then used to obtain estimates of λ_i's in Step 5. With these estimates, residuals are again computed in Step 6 to remove the contribution of individual effects, leaving only the autocorrelation parameter ϕ which is estimated in Step 7 through autoregression on the residual time series. This estimate is then used to refine the estimates of λ_i's which are in turn used to further refine the estimate for ϕ until convergence for each block. Volatility in the multiple time series should have been isolated in only a few blocks, thus, block bootstrap procedure can control the influence of volatility on the final parameter estimates.

4. Simulation Studies

Verify robustness of the estimation procedure, we designed a simulation study. Different settings for the parameters of the multiple time series were considered. Following Veron Cruz and Barrios (2014), μ_i's were generated from $U(50{,}100)$ and $\sigma^2_{\lambda_i}$'s were based on pre-set coefficients of variation. This facilitates the generation of λ_i's from $N(\mu_i, \sigma^2_{\lambda_i})$. N time series of length 2T were built by generating ε_i with preset parameters, setting ϕ and then computing for $Y_{i,t} = \phi Y_{i,t-1} + \lambda_i + \varepsilon_{i,t}$ .The first half of the generated time series was discarded to minimize the influence of initialization. To induce volatility for each time series, a random start m of the volatile period was determined. The random start was selected based on a pre-set range and volatility was generated for a pre-set duration described as a percentage p of the time series length. From $t = m, m+1, \dots, m+pT$, elements of the series were replaced by $Y_{i,t} = h_{i,t} v_{i,t}$, where v_t was generated as $N(0,1)$ and $h_{i,t} = \sqrt{0.1 + 0.5 Z^2_{i,t-1}}$, where $Z_{i,t-1}$ is the lag value of the original $Y_{i,t}$. The volatility behavior is assumed to be similar across N time series.

Parameter values were selected to cover factors that had previously been found by Veron Cruz and Barrios (2014) to affect either predictive ability or bias of parameter estimates. For ϕ, two values were considered, first is where external factors have moderate effect on time series values (ϕ=0.5) and the second is where they have an overwhelming effect (ϕ=0.95), this is also a near-nonstatistionary scenario. Hypothetically, in the context of the stock market, the second situation can only occur if all of the companies in the market were under singular control, which is not the case for any of the existing stock markets in the world at present. Nonetheless, this setting was included in order to evaluate the method at boundary conditions. Three settings of the CV were used, representing different types of stocks. The values of the CV were used to compute the variance of the individual time series as a fraction of their mean, with a CV of 5% indicating that the variance used was 5% of the mean and a CV of 100% indicating that the variance used was equal to the mean. Low CV time series represented stable stock markets that do not shift in price so drastically within short periods of time and high CV time series represent stock markets that are much more unstable in their day-to-day prices.

Likewise, duration of volatility was varied in order to address the effect of this on bias of parameter estimates as noted by Campano (2012) for single time series. Five possible settings were considered for volatility occurrence. For the "Beginning" setting, volatility was set to begin randomly anywhere in the first 10% of data points of each time series. For the "Middle" setting, this was shifted to the middle 10% of the series and for the "End" setting, volatility randomly started from the last 20% to the last 10% of each series for 10% duration and the last 30% to the last 20% for the 20% duration. Under the "Differing" setting, the volatile period for each time series began at some random point in the first 75% of the series. Finally, the "None" setting contained no volatile period. The first three settings under volatility occurrence cover volatility situations that affect the entire set of time series during the same time period. In the stock market context, this represents situations with a national scope. On the other hand, the "Differing" setting considers sudden volatility that can occur for specific companies in the stock market, such as from the circulation of rumors that a company is engaging in "creative accounting" practices to bloat their revenues.

A total of 972 settings were implemented, each combination was replicated 100 times. Two methods were used to estimate the parameters of the multiple time series across each of these settings: the original procedure used in Veron Cruz and Barrios (2014), and the new procedure that integrated the block cutting technique used in Campano (2012). Outcomes from these two procedures were labeled as "Original," and "Hybrid" accordingly. Results from each of these methods were evaluated using MAPE of predictions for the entire time series and for only the non-volatile part of the series, and mean absolute bias of parameter estimates from pre-determined values.

5. Results and Discussion

Consistent with Veron Cruz and Barrios (2014), Table 1 shows that the original backfitting algorithm is able to provide good predictions based on MAPE, except when simultaneously, the variance of the error term is high and coefficient of variation is 100%. Bias for estimates of ϕ was small across all settings, while the bias for the estimates of λ_i's was small except for when the time series near non-stationary (ϕ =0.95). The hybrid algorithm comparable in terms of predictive ability with the original algorithm across all settings, except for when ϕ =0.95 where the hybrid algorithm failed to converge. Furthermore, bias of the hybrid model for estimates of ϕ and the λ_i's were also inferior from the estimates of the original algorithm in general, and worsen further for shorter time series lengths. Table 2 shows that these results hold even when the number of time series is increased to 150. These indicates that when there is no volatility present in the multiple time series, the original algorithm is superior to the hybrid algorithm (predictive ability and bias of parameter estimates).

Table 1: No Volatility (n=60)

Settings				Hybrid				Original			
σ^2_εz	CV of μ_i	ϕ	T	MAPE	% Bias of $\hat{\phi}$	%Bias of $\hat{\lambda}$L	# of Non-converging	MAPE	% Bias of $\hat{\phi}$	%Bias of $\hat{\lambda}$L	# of Non-converging
1	0.05	0.5	1000	0.56	4.94	4.98	0	0.56	0.63	0.63	0
5	0.05	0.5	1000	2.77	5.01	5.03	0	2.79	0.74	0.77	0
10	0.05	0.5	1000	5.61	5.01	5.02	0	5.60	0.63	0.72	0
1	0.05	0.95	1000	0.07	3.83	72.75	87	0.06	1.65	31.24	0
5	0.05	0.95	1000	0.29	4.05	76.64	97	0.28	1.67	31.76	1

10	0.05	0.95	1000				100	0.56	1.71	32.43	6
1	1	0.5	1000	5.55	5.01	5.06	0	5.91	0.64	0.78	0
5	1	0.5	1000	35.51	4.96	5.60	0	32.32	0.63	1.35	0
10	1	0.5	1000	46.56	5.15	14.35	0	40.40	0.67	2.04	0
1	0.05	0.5	400	0.57	12.45	12.51	0	0.55	1.41	1.42	0
5	0.05	0.5	400	2.81	12.60	12.63	0	2.76	1.43	1.46	0
10	0.05	0.5	400	5.64	12.30	12.51	0	5.61	1.44	1.52	0
1	0.05	0.5	100	0.68	51.66	52.28	0	0.56	5.19	5.21	0
5	0.05	0.5	100	2.94	51.71	52.22	0	2.77	4.88	4.92	0
10	0.05	0.5	100	5.88	51.41	51.75	0	5.58	4.61	4.70	0

Table 2: No Volatility (n=150)

Settings				Hybrid				Original			
$\sigma^2_{\varepsilon}Z$	CV of μ_i	ϕ	T	MAPE	% Bias of $\hat{\phi}$	%Bias of $\hat{\lambda}$L	# of Non-converging	MAPE	% Bias of $\hat{\phi}$	%Bias of $\hat{\lambda}$L	# of Non-converging
1	0.05	0.5	1000	0.56	4.99	5.00	0	0.56	0.60	0.60	0
5	0.05	0.5	1000	2.78	4.98	5.00	0	2.78	0.56	0.58	0
10	0.05	0.5	1000	5.63	5.03	5.11	0	5.61	0.59	0.68	0
1	0.05	0.95	1000	NaN	NaN	NaN	100	0.06	1.65	31.34	5
5	0.05	0.95	1000	NaN	NaN	NaN	100	0.28	1.71	32.47	8
10	0.05	0.95	1000	NaN	NaN	NaN	100	0.56	1.69	32.11	14
1	1	0.5	1000	4.13	5.02	5.07	0	4.81	0.60	0.75	0
5	1	0.5	1000	27.49	5.05	7.23	0	24.38	0.56	1.29	0
10	1	0.5	1000	51.29	5.18	6.25	0	40.53	0.57	3.02	0
1	0.05	0.5	400	0.56	12.64	12.76	0	0.55	1.26	1.27	0
5	0.05	0.5	400	2.80	12.61	12.77	0	2.78	1.37	1.39	0
10	0.05	0.5	400	5.64	12.56	12.72	0	5.60	1.29	1.41	0
1	0.05	0.5	100	0.67	51.77	52.44	0	0.56	4.75	4.77	0
5	0.05	0.5	100	2.93	51.92	52.41	0	2.77	4.97	5.03	0
10	0.05	0.5	100	5.87	51.66	52.02	0	5.59	4.72	4.74	0

We compare in Table 3 overall performance of the original and hybrid algorithms across settings where volatility is present. The hybrid algorithm is superior over the original algorithm in terms of MAPE for 29.17% of the settings based on MAPE for the entire time series. With only the non-volatile part of the time series, the MAPE generated from the hybrid algorithm is lower than those generated by the original algorithm in 88.43% of the settings. As shown from Table 4, the MAPE generated by both the original algorithm and the hybrid algorithm for the entire length of the multiple time series are very high. Thus, the supposed advantage of the original algorithm in comparison with the hybrid as shown in Table 3 is not meaningful. The poor predictive ability of the two algorithms is expected given the presence of volatility in the multiple time series and is not the main interest in this study. Rather, our goal is robustness of the estimated model from the effect of volatility, so that it can be used in appropriate characterization of the non-volatile segments of the time series. In Table 4, the hybrid algorithm consistently outperforms the original algorithm. While Table 4 only shows results for when volatility occurs at the beginning of the time series, results are similar for when volatility occurs at the middle or at the end of the time series. The advantage of the hybrid algorithm is further emphasized in Table 5, which shows the distribution of the differences in the MAPE generated for the non-volatile part of the time series by the two algorithms in various settings. The hybrid algorithm outperformed the original algorithm in terms of MAPE for the non-volatile part of the series by at least 5% in 261 of 645 settings, while the original was only able to dominate the hybrid in 12 of the settings.

Table 3: Summary of All Settings

	Hybrid outperforms Original				Converge at least 70%	
	MAPE	MAPE (w/o vol)	Phi (% bias)	Lhat (% bias)	Hybrid	Original
Overall	29.17%	88.43%	55.21%	59.38%	61.57%	95.83%

Table 4: MAPE with Volatility at Beginning of Time Series

Settings						Hybrid		Original	
% Volatility	$\sigma^2_\varepsilon z$	CV of μ_i	ϕ	N	T	MAPE (All Timepoints)	MAPE (w/o Volatility)	MAPE (All Timepoints)	MAPE (w/o Volatility)
10	1	0.05	0.5	60	1000	122.05	0.65	143.32	3.67
10	5	0.05	0.5	60	1000	103.87	2.79	83.83	4.21
10	10	0.05	0.5	60	1000	97.32	5.63	69.65	6.30
10	1	0.20	0.5	60	1000	78.64	0.66	125.52	3.67
10	1	1.00	0.5	60	1000	96.99	5.43	85.82	7.62
10	1	0.05	0.5	60	400	137.19	0.74	128.64	3.82
10	1	0.05	0.5	60	100	108.70	1.05	79.33	4.64
20	1	0.05	0.5	60	1000	290.17	0.93	161.38	7.77
20	5	0.05	0.5	60	1000	773.19	2.88	156.25	7.80
20	1	0.05	0.95	60	1000	158.27	0.30	155.41	7.79
20	1	0.05	0.5	150	1000	164.8	0.70	169.49	7.78

Table 5: Distribution of MAPE difference (for time series parts w/o volatility)

MAPE difference	Hybrid superior	Original superior
Less than 5%	311	18
5% to < 10%	221	7
10% to < 20%	33	4
20% and higher	7	1

In Table 3, bias for the estimates of ϕ and the λ_i's shows that the hybrid algorithm is better than the original algorithm in 55.21% of the settings for ϕ and 59.38% of the settings for the λ_i's. While this seems to indicate that the hybrid algorithm fails to produce consistently better estimates of the parameters across different settings, Table 6 shows that the relatively poor performance of the hybrid algorithm is actually almost entirely contained in multiple time series of lengths 100. This means that the original algorithm is superior over the hybrid algorithm (relative to bias) when the multiple time series common length is 100, but the hybrid algorithm is consistently superior to the original algorithm for multiple time series of lengths 400 and 1000. Furthermore, the MAPE of the hybrid algorithm for the non-volatile part of the time series remains superior compared to the original algorithm even when the time series length is 100. Table 7 shows a summary indicating that when T=1000, the hybrid algorithm outperforms the original by about 20% in bias for ϕ and by about 30% for the bias in λ_i's. This advantage is consistent across different levels of volatility, variability of the error terms, coefficients of variation, values of ϕ, and number of time series. However, consistent with Table 6, the advantage is reduced as the common length of the time series becomes shorter. While Table 7 shows results for settings where volatility is set to occur at the beginning, results are consistent for cases where volatility occur at the middle, end, and differing settings.

Table 6: Bias and MAPE Across Time Series Lengths

	Hybrid Superior to Original			
Length	MAPE	MAPE (w/o Volatility)	ϕ (% bias)	$\hat{\lambda}$ (% bias)
1000	28.82%	86.57%	78.82%	79.17%
400	39.24%	84.26%	86.81%	90.63%
100	19.44%	92.13%	0.00%	8.33%

Table 7: Bias Comparison (Volatility at Beginning of Time Series)

Settings						Hybrid		Original	
% Volatility	$\sigma^2_{\varepsilon}z$	CV of μ_i	ϕ	N	T	ϕ (% bias)	$\hat{\lambda}$ (% bias)	ϕ (% bias)	$\hat{\lambda}$ (% bias)
10	1	0.05	0.5	60	1000	4.92	4.24	26.72	34.07
10	5	0.05	0.5	60	1000	4.94	4.25	26.04	33.43
10	10	0.05	0.5	60	1000	5.00	4.16	25.14	32.64
10	1	0.20	0.5	60	1000	4.88	4.21	26.74	34.10
10	1	1.00	0.5	60	1000	5.06	4.45	26.00	33.80
10	1	0.05	0.5	60	400	12.61	11.66	23.97	31.62
10	1	0.05	0.5	60	100	50.80	49.50	12.02	21.29
20	1	0.05	0.5	60	1000	5.39	3.79	22.04	37.60
20	5	0.05	0.5	60	1000	5.43	3.54	21.53	37.20
20	1	0.05	0.95	60	1000	4.24	74.79	35.88	525.94
20	1	0.05	0.5	150	1000	5.23	4.29	22.02	37.58

Convergence summaries in Table 3 shows that the original algorithm generally converges more often than the hybrid algorithm, which is not surprising due to the partitioning protocol in the hybrid algorithm. Table 3 shows that the hybrid algorithm converges in at least 70% of 100 replicates, for 61.57% of the settings. However, as shown in Table 8, the hybrid algorithm's failure to converge is almost entirely contained in settings where ϕ=0.95 (near non-stationary). This convergence problem had also been previously identified for the original algorithm by Veron Cruz and Barrios (2014) for the cases where N is near of greater than T and ϕ=0.95, which is the case for the hybrid algorithm even when T=1000 since the length used for the backfitting protocol effectively becomes 100 after partitioning. Also from Table 8, it is shown that the hybrid algorithm retains its superiority over the original algorithm in terms of MAPE for the non-volatile part across different values of ϕ. While the results seem to indicate that the original algorithm is better than the hybrid algorithm at minimizing bias for estimates of the parameters when ϕ=0.95, this is because cases where the hybrid algorithm fails to converge are counted against its favor. Where the hybrid algorithm does converge, it typically provides better estimates of the parameters than the original (except when T=100).

Table 8: Summary of MAPE and Bias Across $\boldsymbol{\phi}$ Values

	Hybrid Superior to Original				Converge at least 70%	
phi	MAPE	MAPE (w/o vol)	Phi (% bias)	Lhat (% bias)	Hybrid	Original
0.5	20.37%	89.20%	63.89%	69.44%	94.21%	95.83%
0.95	37.96%	86.11%	46.53%	49.31%	28.94%	95.83%

In the presence of volatility, the hybrid algorithm performs better than the original algorithm in most settings. In the absence of volatility, the hybrid algorithm is comparable to the original algorithm in terms of MAPE, but is poorer in estimating model parameters. This is a consequence of the partitioning made on the multiple time series in the hybrid algorithm, hence, Veron Cruz and Barrios (2014) noted that parameter estimates improved as the length of the time series increases. Partitioning the time series into blocks effectively shortened the length of the multiple time series that was used in estimating parameters per block, affecting the accuracy of estimates. It is important then to verify presence of volatility before using the hybrid algorithm over the original algorithm. A test for detecting volatility similar to Campano (2012) for single time series can be considered. Thus, development of a test that can determine whether or not there is sufficient volatility in the multiple time series to make the use of the hybrid algorithm preferable over the original algorithm is necessary.

Another important consideration in the use of the hybrid algorithm is its inability to converge when the autoregressive pattern is nearly non-stationary. This phenomenon was explained in Dumanjug et al. (2010) as a consequence of making use of bootstrap procedures for spatio-temporal models. Since the hybrid algorithm involves partitioning the multiple time series into shorter collections of time series, the risk of non-convergence increases.

Finally, it should be noted that the multiple time series should have a sufficient common length (at least 400) for the hybrid algorithm to provide better estimates of the parameters than the original algorithm as shown in Table 6. For short multiple time series, the partitioning protocol of the hybrid algorithm divides the time series into even shorter lengths, which contributes excessively to the bias in estimating the parameters. However, the hybrid algorithm is still able to outperform the original for short time series lengths in terms of mean absolute prediction error.

6. Conclusions

This study aimed to develop an estimation procedure for multiple time series data that exhibits volatile behavior. A hybrid of block bootstrap and BLUP embedded into the backfitting algorithm considerably improved both predictive ability and parameter estimates when volatility is present provided that the multiple time series is sufficiently long and stationary. When volatility is not present, the original algorithm (without block bootstrap) should be used instead of the hybrid algorithm since it is not vulnerable to localized non-stationarity. Thus, the development of a test that can determine whether or not a multiple time series contains enough volatility to warrant the use of the hybrid algorithm is necessary.

References

Aneez, S., and Jantraprap, V. (2014). SE Asia Stocks - Thailand falls after martial law; Jakarta on political uncertainty. Retrieved November 10, 2014 from: http://finance.yahoo.com/news/se-asia-stocks-thailand-falls-112116897.html

Arellano, M., and Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies,*58(2):277–297.

Bastero, R., and Barrios, E. (2011).Robust estimation of a spatiotemporal model with structural change. *Communications in Statistics - Simulation and Computation*, 40:448–468.

Bollerslev, T. (1986).Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, 31(3): 307–327.

Brooks, C. (2014). *Introductory Econometrics for Finance*. Cambridge: Cambridge University.

Campano, W. (2012).Robust Methods in Time Series Models with Volatility. *The Philippine Statistician*, 61(2): 83 – 101.

Campano, W., and Barrios, E. (2011).Robust estimation of a time series model with structural change. *Journal of Statistical Computation and Simulation,*81(7):909–927.

Demirakos, E., Strong, N. and Walker, M. (2004) What valuation models do analysts use? *Accounting Horizons*, 18: 221-240.

Dumanjug, C., Barrios, E., and Lansangan, J. (2010). Bootstrap procedures in a spatial-temporal model. *Journal of Statistical Computation and Simulation,* 80(7):809–822.

Enders, W. (2004).*Applied Econometrics Time Series*. NJ: John-Wiley and Sons.

Guinigundo, D. (2010). *The impact of the global financial crisis on the Philippine financial system – an assessment*. Retrieved December 20, 2014 from: http://www.bis.org/publ/bppdf/bispap54s.pdf

Landagan, O., and Barrios, E. (2007).An estimation procedure for a spatial-temporal model. *Statistics and Probability Letters,* 77, 401–406.

Nazir, M., Younus, H., Kaleem, A., and Anwar, Z. (2014). Impact of political events on stock market returns: empirical evidence from Pakistan. *Journal of Economic and Administrative Sciences,* 30(1): 60 – 78.

Nelson, D. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, 59(2): 347–370.

Philippine Star. (2014). *Bourse rallies as Moody upgrades credit rating.* Retrieved December 20, 2014 from: http://www.philstar.com/business/2014/12/12/1401963/bourse-rallies-moody-upgrades-credit-rating

Politis, D. (2007). Model-Free Versus Model-Based Volatility Prediction. *Journal of Financial Econometrics,* 5(3):358-389.

Veron Cruz, R., and Barrios, E. (2014).Estimation Procedure for a Multiple Time Series Model. *Communications in Statistics - Simulation and Computation,* 43(10), 2415 – 2431.