



## Winter Holts Oscillatory Method: A New Method of resampling in Time Series

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### ABSTRACT

*The core proposition behind this research is to create innovative methods of bootstrapping that can be applied in time series data. In order to find new methods of bootstrapping, various methods were reviewed; The data of automotive Sales, Market Shares and Net Exports of the top 10 countries which includes China, Europe, United States of America (USA), Japan, Germany, South Korea, India, Mexico, Brazil, Spain and, Canada from 2002 to 2014 were collected through various sources which includes UN Comtrade, Index Mundi and World Bank. The findings of this paper confirmed that Bootstrapping for resampling through winter forecasting by Oscillation and Average methods give more robust results than the winter forecasting by any general methods.*

**Keywords:** Winter Holts Oscillatory Method, bootstrapping, resampling.

### Introduction

In econometrics, bootstrapping can be defined as a procedure for assigning the measures of accuracy to the sample estimates. It refers to estimation of the sampling-distribution of any statistics using very simple and easy methods. It is, furthermore, a broader class of re-sampling methods. This method is used to gauge the properties of an estimator; whereby the standard selection for an approximating-distribution is the empirical distribution of the observed data.

The aim of this research is to develop a new method of bootstrap re-sampling in the time-series. Bootstrapping is the method firstly presented under independent conditions. This method is however ineffective when it comes to the dependent data. Currently, the assessment of population characteristics is greatly advanced than it used to be, mostly aiding to the framework of time-series. There have also been huge improvements in the re-sampling methods of the dependent data, as several alterations of the various bootstrap techniques have been offered, which are applicable to the dependent data, and their implementation has helped the researchers overcome the difficulties of forecasting using a time-series. Furthermore, various software are being utilized to reach monthly and even yearly forecasts,

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by determining the confidence intervals using the theory of time series while further contrasting the methods with those of bootstrapping.

The methods of re-sampling lay as conservatory to the simulation. Previously, re-sampling was simulated using computers, in-order to generate samples which are large in number. Then-after, the researchers investigate and outline the different sample patterns. The distinct feature of this methodology is that the researchers initiate with a data-set of observations, rather than just a theoretical probability distribution.

Furthermore, re-sampling can either be parametric or non-parametric. The non-parametric re-sampling is significant, since it allows the researchers to deal with single and/or multiple assumptions, associated to the estimator.

Davison and Hinkley (1997) repeatedly take new samples from the old ones, rather than proposing assumptions about the population. The data is sampled with replacement, which allows for the generation of new samples. New samples only have values, already present in the original data set. In bootstrapping, the distribution is calculated by the possible estimation of the interest. Using this method, common statistics along with the new statistics were studied, since there is no need to put forward assumptions about the population. Generally, thousands of samples are taken by using the sampling method, with replacements from the original dataset.

Efron and Tibshirani (1993) discuss the two approaches to bootstrapping: parametric and nonparametric. The parametric approach refers to the arbitrary samples that are drawn for a designated probability density function. On the contrary, the nonparametric approach refers to the hundreds or thousands of resample that are drawn with supersession; whereby each resample comprises of an equivalent size as that of the pristine sample. When applied to a multivariate case, the bootstrap component or the factor analysis are usable for determining number of factors, in order to retain and/or replicate the pattern/structure coefficients.

According to Beran and Ducharme (1991), bootstrapping is a calculation technique used for the distribution of test statistics by re-sampling the data or a model, as determined from the dataset. Bootstrapping identifies the statistical distribution and assigns approximations which are more reliable, in contrast to the first order asymptotic theory. If the dataset is derived from random-sampling, then the parametric model or the simple-random-sampling can be used to apply the bootstrap. The distribution of statistics, under the parametric-model sampling, can furthermore be found using the empirical approach.

A time series is a sequence of consecutive data-points spaced out over regular time intervals. Initially, the study of time series comprises with the description of remarkable progression, which brings forth a detailed illustration of the data. When a time-series is designed, regular patterns are repeatedly set-up; whereby, the cause and effect associations can come to be elucidated by these regular patterns. Ordinary parts include the trend, recurring changes, cyclic cause, and arbitrariness. The additional feature is the predictability and forecast the of the future series' values, on the premise of its listed history and the determination of the forecast intervals (Alonso, Pena, & Romo, 2002).

Rather than assuming every aspect of the population, the original samples are repetitively taken from the previous samples (Davison & Hinkley, 1997). The data is further sampled with the substitution permits in-order to produce a diverse range of original samples. The original samples, comprising the values of the new data-set, have prior existence. In the bootstrapping method, the analysis of distribution is done to compute possible approximations of the concern; whereby, both the general statistics and new-statistics are studied. Since there is no requirement to create hypotheses about the population, generally a thousand samples are generated by employing sampling-with-replacement approach from the new set of data. This study also intended to contribute new method of resampling specifically

for the data which are so speak as time series while focusing on common statistics and new statistics to get an innovative approach of resampling.

### **Few popular approaches of bootstarping**

#### **Block bootstrap**

An approach based on simulation to approximate the distribution of test statistics (Härdle, Horowitz & Kreiss, 2003).

#### **Non-overlapping block bootstrap**

The correlation in the observational blocks and comparatively weedy among blocks (Cordeiro & Neves, 2006).

#### **Moving block bootstrap**

It performs re-sampling of blocks of repeated observations at an instance (Liu & Singh, 1992).

#### **Circular block bootstrap**

It is used to wrap up the data in a loop and create supplementary blocks by employing the interpretation of the circularly defined means (Politis & Romano, 1992).

#### **Stationary block bootstrap**

From the given panel time series this method utilizes time series blocks whose length is random as compared to the blocks that have fixed length (Politis & Romano, 1992).

#### **Sieve bootstrap**

The phenomenon initially fits the parametric models and proceeds with re-sampling from remaining data (Bühlmann, 1997).

### **Literature Review**

Bootstrap is the method that is used for computing the distribution of test statistics; whereby the distribution can be achieved through re-sampling the data as assessed from the data set (Efron, 1979). The bootstrapping method mainly pinpoints the statistical distribution, and presents estimations that are extremely consistent; unlike the theory of first-order-asymptotic. Furthermore, if the set of data is randomly selected from the sample, then the method of bootstrap is feasibly implemented with the utilization of parametric-model or random-sampling. It can further determine the statistical distribution from empirical distribution of bootstrap method from the parametric model sampling (Beran & Ducharme, 1991).

Bootstrapping is a technique used to achieve the estimations of statistics. The method is simple to use but requires several computations in order to determine the population parameters. However, a bootstrap cannot be applied directly, since a bootstrap does the sampling using replacement. After the replacement, the bootstrap-sample is different from the initially generated sample. Moreover, while some of the data gets retained and repeated, the rest is replaced. This specific method allows for the generation of countless samples in a timely and effective manner (Efron, 1979).

The situation gets more and more complex especially when the data is in time series; factually, the bootstrap re-sampling should be employed to capture the data generation

process (DGP) of the dependence-structure. Moreover, researchers can also make use of the ARMA model for the execution of bootstrapping. Parametric model reduces the data generation process (DGP) of the dependence structure to random sampling. In the specified conditions, the bootstrap has is fundamentally similar to the data-set chosen randomly from the distribution sample.

However, if the data is in time series, then the approach of implementing the bootstrap re-sampling is ineffective since the data-set is randomly sampled from the distribution (Bose, 1988, 1990).

Truncated geometric bootstrap technique is another non-metric bootstrap method employed for the time-series data, and is uniform in nature (Politis & Romano, 1992). This method replicates the new or definite model by holding the theory of stationarity of the real time-series, during the simulation of time series re-sampling. The simulated time series is produced through the process of re-sampling, with distinct sizes of blocks occurring randomly at every point. The size of each random block has an abridged geometric distribution with an appropriate fixing probability. The bootstrapping technique is used to generate the re-sampling blocks of data by substitution, in order to generate the simulated time-series as having a real time-series. Similarly, the calculation of statistics is done based on the original set of data, in the re-sampling data series. Two leading components of this technique are the production of samples (with assistance of the bootstrap method), and the approximation of statistics (on the samples of bootstrap) as though put on a loop.

There are numerous methods of bootstrapping such as re-sampling from the sample, which approximates the variance as having field trials through the use of the bootstrapping method as has been proposed by (Gulesserian & Kejriwal, 2013). Furthermore, different methods have been used for testing the hypotheses through the use of re-sampling based methods.

The forecasting process is significant since it considers the performance of the time-series within the history, along-with its endurance as within the future. Due to this reason, the selection of the model is exceptionally significant, while also substantially defining the performance of time-series. This process regulates the trend and seasonality, as has been shown in the figure below (Archibald & Koehler, 2003).

Amongst the forecasting models, perhaps the most distinct model is that of Holt-Winters. The Holt-Winters technique was taken into account and was proved as the best suited model for the specified set of data. Cordeiro and Nerves (2003) state that the formation of this model consists of subsequent algorithmic equations that aid in the approximation of seasonal factors and trends. The equations are used to determine the curved-values at the period-end after seasonality adjustment at time  $t$ . Furthermore, curved seasonal index for  $s$  periods is used to determine the value of trend at a time  $t$  for the given constant. The equation of forecast is the sum of all these factors (Politis & Romano, 1992).

As compared to other methods, this does not maintain data on each and every of the previous records. Thus, it is best fitting to the progression of a series, while entailing the latest observations.

The bootstrap method is a computer-based demanding method (Efron & Tibshirani, 1993). It offer results in conditions when the traditional approaches fail. However, the traditional approach of bootstrapping does not regard the forms of dependent data, as in the time-series where the ordering or the series of dependent-data ought to be unbroken throughout the re-sampling method. In the recent times, however, the strategies of re-sampling for the dependent-data have been significantly refined (Lahiri, 2003). The majority is regarded as sections of the blocks of data, specifying that the dependence organization in each of the sections might be constant. There are diverse variants of interference that vary within the means as the blocks are created (Olatayo, Amahia, & Obilade, 2010).

The block bootstrap is a simulation-based approach, used to approximate the distribution of test statistics. It is used to generate bootstrap-samples by re-sampling the data at random; which furthermore creates the empirical distribution-function as linked to it. The bootstrap method gives expansion to the asymptotic approximations where the data are scattered identically and separately. Nevertheless, the performance of this new process is more satisfactory, as compared to the time-series data with serial correlation (Politis & Romano, 1992).

The block bootstrap is commonly used to recover the accuracy of bootstrap, for the time-series data. It can maintain the arrangement of the new time-series inside a block, by dividing the data into several blocks. Nevertheless, the precision of block-bootstrap is subject to the selection of block-length. The appropriate block length depends on the sample-size, the data generation process, and the statistics under consideration. The block bootstrap method is used when there lay a correlation in the system data (Politis & Romano, 1992).

Therefore, the remaining re-sampling was unsuccessful because since it lacks the capability to repeat the correlation factor in data. The block bootstrap strives to repeat the correlation through re-sampling, regardless of the data-blocks. Generally, the block bootstrap has been employed with the correlation factor of data in the time-series; it can moreover also be employed with the data correlated in groups.

The method of non-overlapping block bootstrap separates and transforms time series into blocks. Politis and Romano (1992) argue that there lay random samples of blocks, which are chosen randomly with replacement from the observations. Once the blocks are combined, the bootstrap-sample is generated. The non-overlapping block bootstrap method considers the correlation in the blocks of observations.

The method of moving block bootstrap performs re-sampling of the blocks with repeated observations. Consequently, the reliable structure of new the observations is maintained inside the each block. This method of moving block bootstrap was introduced so that the information can be distributed into the overlapping blocks of length (Kunsch, 1989; Liu & Singh, 1992). Moreover, since there are series of observations for the different blocks of length, the blocks are randomly drawn with replacement from these blocks-of-length. Subsequently, these blocks are aligned in an order based on their extraction source, and result in the bootstrap observations. This bootstrap observation operates with the dependent data, but observations that are bootstrapped are not fixed within their structural limits. However, it has been revealed that randomly changing the block length helps overcome this limitation.

The method of circular block bootstrap is an expansion of the preceding method. This approach is used to warp the data in the form of loop and create supplementary blocks by instituting interpretation of the circularly defined means. The method of circular block is used to re-sample the overlapping and sporadically extensive blocks of length  $l$ . As the circular-block-bootstrap re-samples the blocks from this set with the same probability, the new observations namely,  $X_1, \dots, X_n$  get the same weight in the circular block bootstrap. This feature differentiates the circular-block-bootstrap from the preceding methods as that of the moving-block-bootstrap and the non-overlapping-block-bootstrap, which undergo edging effects. The circular-block-bootstrap allows blocks to recur again as the data reaches its end-point, thereby warping the data back to its start (Liu & Singh, 1992).

The stationary-block-bootstrap is comparatively distinct from the previous methods of the block-bootstrap, since it utilizes blocks whose length is random, instead of blocks with fixed lengths (Carlstein, 1986). This form of re-sampling technique is used to calculate the approximation-errors, and helps create areas for the parameters that are dependent on the stationary observations. This technique is a comprehensive one, since it creates the blocks of blocks for distribution of the stationary sequence observations. It allocates the creation of re-sampling blocks from the set of observations, in order to create a pseudo-time series

(Carlstein, 1992). Furthermore, it is essential that the re-sampled pseudo time-series be stationary, in the stationary-bootstrap. Not only the stationary-block-bootstrap is stationary, it moreover holds other functionalities: it is also used to re-sample the blocks of random length whereby the length of every block includes a geometric distribution (Politis & Romano, 1994).

The sieve-bootstrap is a new bootstrap-method used to fit the parametric models and subsequently perform re-sampling from the remaining samples (Buhlmann, 1997). Nevertheless, the model is selected adaptively in contrast of a fixed model. The sample bootstrap is held stationary and does not lead to any organized dependence. Furthermore, what makes the sieve-bootstrap distinct from the formerly mentioned methods is that it assumes zero sub-samples from the new data.

Considering that a sample is  $(X_1, \dots, X_m)$ , the method of autoregressive is approximate; while the remaining is adjusted in such a manner that their empirical cumulative distribution function is achieved. The attained empirical cumulative distribution function is distributed independently and identically. In such context, bootstrap error series and bootstrap series are produced simultaneously. An individual may observe that sieve-bootstrap is non-parametric in its nature, even if the method is formed the basis of a sieve bootstrap (DeLurgio, 1998).

Moreover, the model that is used to filter the remaining series is known as AR(p) model. There are countless applications for the method of sieve bootstrap (Zagdanski, 1999). Zagdanski (1999) achieved forecast intervals for the stationary time-series that might occur in the future observations. Zagdanski (1999) further defined the structure of the top linear forecaster, for the estimation of values of the future time-series. The method of sieve-bootstrap is presented as offering reliable approximates of the conditional distribution in order to calculate the future values of the specified observation-data.

Furthermore, the situation is a lot more challenging when the data is in time-series, since a bootstrap re-sampling, which can capture the structural dependence of data the generation process (DGP), needs to be applied. If the parametric approach is applied then the ARMA model could be utilized to decrease the DGP of the random sampling. In the given situation, the bootstrap has an ability that is equally essential to the randomly selected dataset from the distributed sample. If the dataset is in time-series then the methods of applying the bootstrap re-sampling are generally ineffective; in contrast to the dataset randomly sampled from the distribution (Bose, 1988, 1990).

Olatayo, Amahia, and Obilade (2010) argue that researchers could even utilize a non-metric bootstrapping method, known as the truncated geometric bootstrap-technique. This technique is stationary in nature, particularly for the time-series data. In this specific method, the original model is replicated by conserving the stationary theory of actual time-series in the resample simulated time-series. The simulated time-series is produced through the re-sampling of different random-sized blocks at every truncation. The span or size of each random block has a truncated geometric distribution with an attached suitable probability. This technique contributes to the formation of re-sampling blocks of data to random sampling with simultaneous replacement to figure simulated time series. Regarding the actual time series, it is necessary to re-perform calculation of the statistics, based on the new re-sampled time series dataset. The two main components of this method are the construction of samples with the help of bootstrapping and estimation of statistics on the bootstrap samples by applying loop.

Gulesserian and Kejriwal (2013) there are several method of bootstrap, for instance, re-sampling from the sample and estimation of variance with field-trials by using the bootstrap method.

## Hypotheses

**H<sub>1</sub>:** Bootstrapping for resampling through winter forecasting by Oscillation method gives more robust result than the winter forecasting by general method.

**H<sub>2</sub>:** Bootstrapping for resampling through winter forecasting by Average method gives more robust result than the winter forecasting by general method.

## Research Methods

### Method of Data Collection, Sampling & Re-Sampling of collected samples

The data/ sample of Automobile production, automobile Sales, Market Share and Net Exports of top 10 countries which includes China, Europe, United States of America (USA), Japan, Germany, South Korea, India, Mexico, Brazil, Spain and, Canada from 2002 to 2014, was collected through multiple websites such as eikon, index mundi, world bank, etc.

For re-sampling the Oscillation and Average methods were selected to bootstrap the collected sample

### Research Model used for Oscillation Method

$$z_t = \mu + \sum [x_t \cos(2\pi ft) + x_t \sin(2\pi ft)]$$

Where,

$\mu$  = Average of time series variable

$x_t$  = Time series variable

$\cos$  &  $\sin$  = Trigonometric Functions

$\pi = 3.14$  (Constant)

$f$  = frequency

$t$  = time

### Research Model used for Average Method

$$z_t = \frac{(x_t + x_{t+1})}{n}$$

### Econometrical tool applied for testing hypotheses

Holt Winter Forecast (additive method) was deployed to evaluate the hypotheses framed. The test is generally utilized for time series data since it assists in forecasting values for future/ proceeding events and analyzing trend of values occurred in past.

### New bootstrapping procedure and findings of the paper

In order to find out the new methods of time series bootstrapping, the sales, market shares and the net exports of automotive were taken for the period from 2002-2014 for top 10 automotive producing nations. For all of the stated outlined series the oscillatory series were created for the years 2002-2008, through deploying the following equation (Madalla 1992).

$$z_t = \mu + \sum [x_t \cos(2\pi ft) + x_t \sin(2\pi ft)]$$

For all same stated series the series of central tendency (arithmetic mean procedure) for the years 2002-2008 were also created via using the equation mentioned below as used by (Carlson, 1971).

$$z_t = \frac{(x_t + x_{t+1})}{n}$$

After transforming the original series for 2002-2008 of auto motive sales, auto motive market shares and auto motive net exports, via oscillatory and average methods for all top ten auto motive nations, winter holt procedure were used to forecast the proceeding coefficients for all stated variables for the years 2009-2014. A care full investigation further revealed that projections of the sample for oscillation and average for the years 2009-2014 were closed to the projection of sample through general method for the same period of 2009-2014 of the stated variables as it is confirmed by coefficients of dispersion and trend analyses via line chart, i.e. when the winter holt method was deployed on the original data for the period of 2002-2008 of stated variables for forecasting the forecasted annual values for the period 2009-2014, the arrived forecasted annual values for this period were not better off than the forecasted annual values through the winter holt procedure by oscillatory and average methods, thus we remained failed to reject our hypotheses for all top ten automotive producing nations (as mentioned in tables 1-10), which are

**H<sub>1</sub>:** Bootstrapping for resampling through winter forecasting by Oscillation method gives more robust result than the winter forecasting by general method.

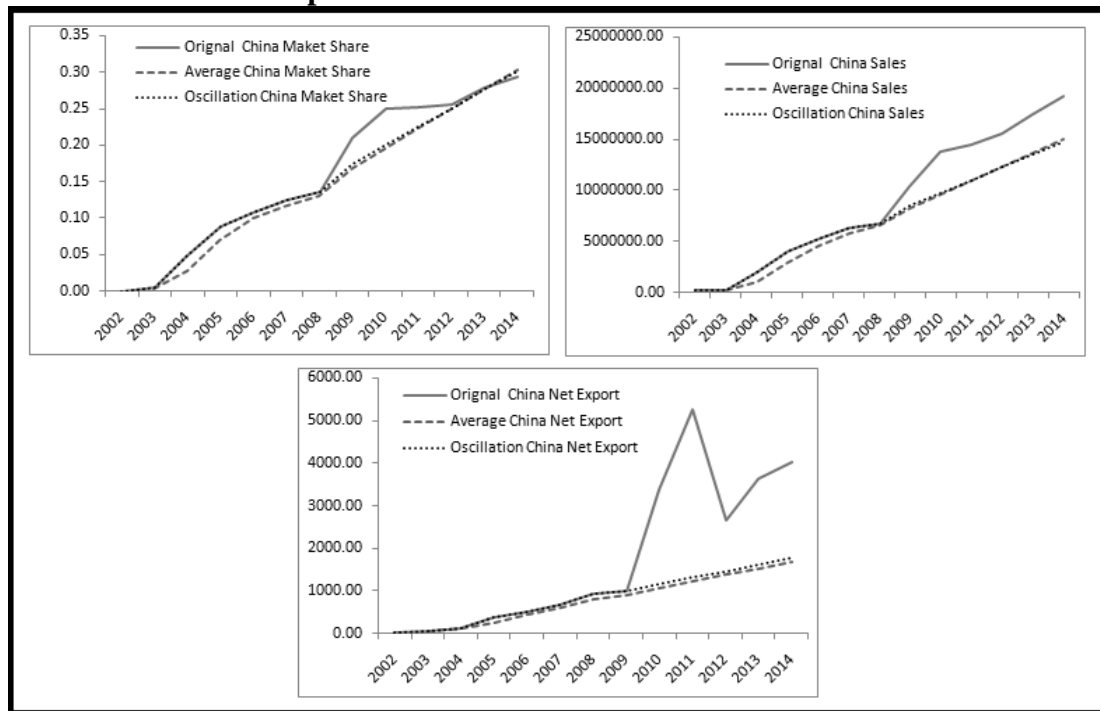
**H<sub>2</sub>:** Bootstrapping for resampling through winter forecasting by Average method gives more robust result than the winter forecasting by general method.

**Table 1: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of China**

Year	Original China Market Share	Average China Market Share	Oscillation China Market Share	Original China Sales	Average China Sales	Oscillation China Sales	Original China Net Export	Average China Net Export	Oscillation China Net Export
2002	0		0	182707		182124	25		25
2003	0.01	0	0.01	191872	187290	191259	67	46	67
2004	0.05	0.03	0.05	1914958	1053415	1908840	125	96	125
2005	0.09	0.07	0.09	3971101	2943030	3958413	373	249	372
2006	0.11	0.1	0.11	5175961	4573531	5159424	510	442	508
2007	0.13	0.12	0.12	6297538	5736750	6277417	678	594	676
2008	0.14	0.13	0.14	6755609	6526574	6734025	924	801	921
		<b>Forecasted Values</b>			<b>Forecasted Values</b>			<b>Forecasted Values</b>	
2009	0.21	0.17	0.17	10331315	8241124	8498587	998	917	998
2010	0.25	0.2	0.2	13757794	9594750	9751394	3381	1073	1151
2011	0.25	0.22	0.22	14472416	10948377	11004201	5265	1229	1304
2012	0.26	0.25	0.25	15495240	12302003	12257009	2654	1386	1457
2013	0.28	0.28	0.28	17460066	13655629	13509816	3649	1542	1611
2014	0.29	0.3	0.3	19205782	15009256	14762623	4018	1698	1764
<b>Average</b>	0.257	0.237	0.237	15120436	11625190	11630605	3328	1308	1381
<b>Dispersion</b>	-	-0.020	-0.020	-	-3495246	-3489831	-	-2020	-1947



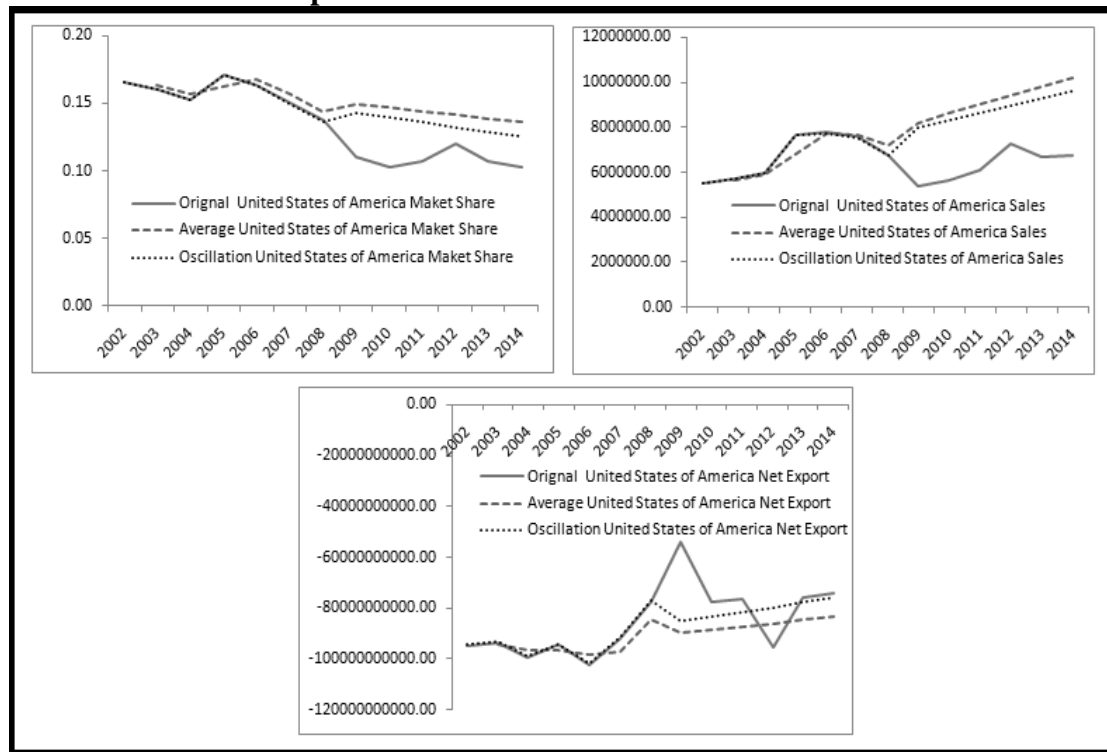
**Figure 1: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of China**



**Table 2: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of USA**

Year	Original USA Market Share	Average USA Market Share	Oscillation USA Market Share	Original USA Sales	Average USA Sales	Oscillation USA Sales	Original USA Net Export	Average USA Net Export	Oscillation USA Net Export
2002	0.17		0.17	5518933		5501300	-94775113219		-94472306732
2003	0.16	0.16	0.16	5722213	5620573	5703931	-93426415073	-94100764146	-93127917677
2004	0.15	0.16	0.15	5993937	5858075	5974786	-99100786438	-96263600756	-98784159425
2005	0.17	0.16	0.17	7659983	6826960	7635509	-94325692321	-96713239380	-94024321734
2006	0.16	0.17	0.16	7761592	7710788	7736794	-102086175212	-98205933767	-101760009882
2007	0.15	0.16	0.15	7562334	7661963	7538172	-91508363355	-96797269284	-91215994134
2008	0.14	0.14	0.14	6769107	7165721	6747480	-77227896328	-84368129842	-76981153199
		Forecasted Values			Forecasted Values			Forecasted Values	
2009	0.11	0.15	0.14	5400890	8209469	8001000	-53873799213	-89851209040	-85292057937
2010	0.1	0.15	0.14	5635432	8610076	8328466	-77470286931	-88549224139	-83387720178
2011	0.11	0.14	0.14	6089403	9010682	8655931	-76266370778	-87247239237	-81483382420
2012	0.12	0.14	0.13	7241900	9411289	8983396	-95131285407	-85945254336	-79579044662
2013	0.11	0.14	0.13	6677652	9811896	9310862	-75494411212	-84643269434	-77674706904
2014	0.1	0.14	0.13	6709446	10212502	9638327	-73707666157	-83341284533	-75770369146
Average	0.108	0.143	0.135	6292454	9210986	8819664	-75323969950	-86596246787	-80531213541
Dispersion	-	0.035	0.027	-	2918532	2527210	-	-11272276837	-5207243592

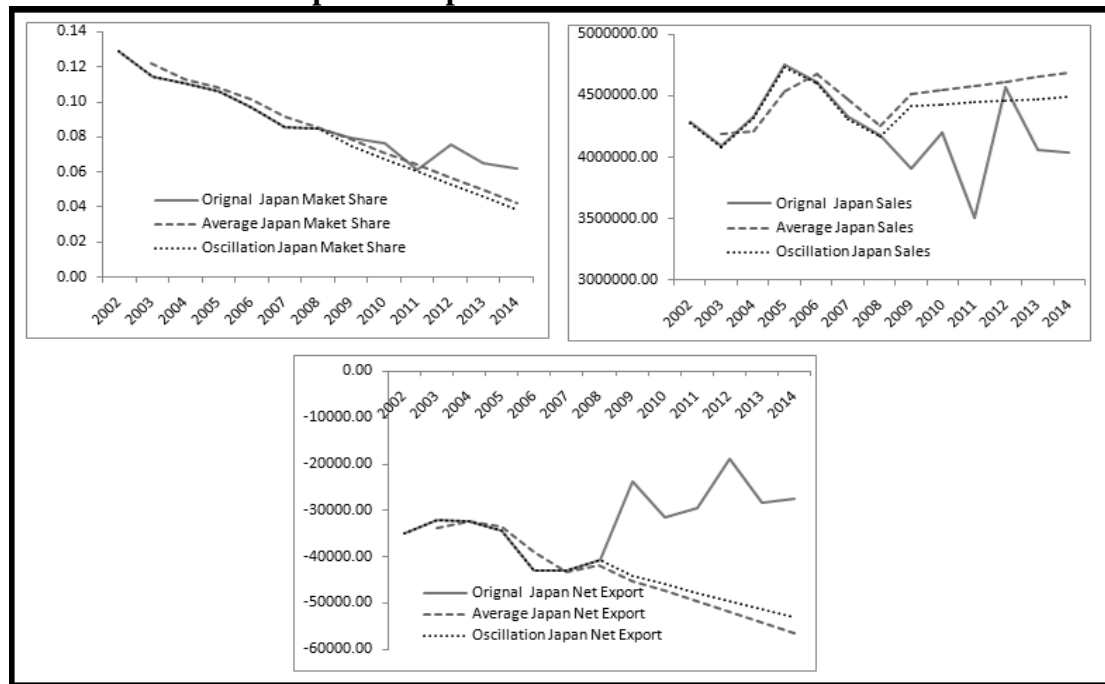
**Figure 2: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of USA**



**Table 3: Table 3: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of Japan**

Year	Original Japan Market Share	Average Japan Market Share	Oscillation Japan Market Share	Original Japan Sales	Average Japan Sales	Oscillation Japan Sales	Original Japan Net Export	Average Japan Net Export	Oscillation Japan Net Export
2002	0.13		0.13	4292719		4279003.76	-35015		-34903.13
2003	0.11	0.12	0.11	4095091	4193905	4082007.18	-32167	-33591	-32064.23
2004	0.11	0.11	0.11	4334120	4214605.5	4320272.49	-32402	-32284.5	-32298.48
2005	0.11	0.11	0.11	4748482	4541301	4733310.6	-34483	-33442.5	-34372.83
2006	0.1	0.1	0.1	4612318	4680400	4597581.64	-43161	-38822	-43023.1
2007	0.09	0.09	0.09	4325508	4468913	4311688	-43118	-43139.5	-42980.24
2008	0.08	0.09	0.08	4184266	4254887	4170897.27	-40727	-41922.5	-40596.88
		Forecasted Values			Forecasted Values			Forecasted Values	
2009	0.08	0.08	0.07	3905310	4513028.4	4415301.75	-23834	-45160.53	-44268.11
2010	0.08	0.07	0.07	4203181	4547512.16	4430028.58	-31784	-47434.88	-46040.89
2011	0.06	0.06	0.06	3509036	4581995.91	4444755.42	-29753	-49709.22	-47813.67
2012	0.08	0.06	0.05	4572333	4616479.67	4459482.25	-19029	-51983.56	-49586.46
2013	0.06	0.05	0.05	4064577	4650963.43	4474209.08	-28377	-54257.9	-51359.24
2014	0.06	0.04	0.04	4033183	4685447.19	4488935.92	-27660	-56532.25	-53132.02
Average	0.070	0.060	0.057	4047937	4599238	4452119	-26740	-50846	-48700
Dispersion	-	-0.010	-0.013	-	551301	404182	-	-24107	-21961

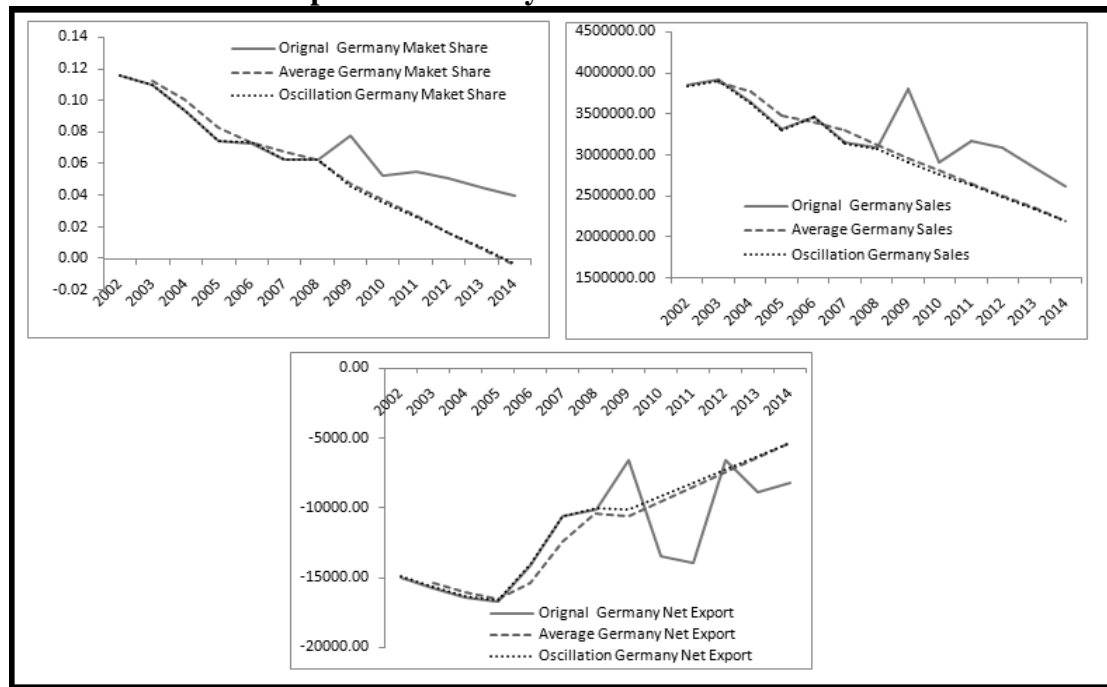
**Figure 3: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of Japan**



**Table 4: Table 4: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of Germany**

Year	Original Germany Market Share	Average Germany Market Share	Oscillation Germany Market Share	Original Germany Sales	Average Germany Sales	Oscillation Germany Sales	Original Germany Net Export	Average Germany Net Export	Oscillation Germany Net Export
2002	0.12		0.12	3852434		3840125.47	-15002		-14954.07
2003	0.11	0.11	0.11	3915095	3883764.5	3902586.27	-15798	-15400	-15747.53
2004	0.09	0.1	0.09	3640584	3777839.5	3628952.33	-16419	-16108.5	-16366.54
2005	0.07	0.08	0.07	3319259	3479921.5	3308653.97	-16739	-16579	-16685.52
2006	0.07	0.07	0.07	3467961	3393610	3456880.86	-14185	-15462	-14139.68
2007	0.06	0.07	0.06	3148163	3308062	3138104.62	-10624	-12404.5	-10590.06
2008	0.06	0.06	0.06	3090040	3119101.5	3080167.32	-10118	-10371	-10085.67
		Forecasted Values			Forecasted Values			Forecasted Values	
2009	0.08	0.05	0.05	3807175	2961820.6	2910651.66	-6598	-10650.1	-10203.15
2010	0.05	0.04	0.04	2916259	2809850.34	2768476.33	-13467	-9582.27	-9233.62
2011	0.06	0.03	0.03	3173634	2657880.09	2626301	-13982	-8514.44	-8264.08
2012	0.05	0.02	0.02	3082504	2505909.83	2484125.67	-6617	-7446.61	-7294.55
2013	0.05	0.01	0.01	2849772	2353939.57	2341950.34	-8847	-6378.79	-6325.01
2014	0.04	0	0	2616519	2201969.31	2199775.01	-8249	-5310.96	-5355.48
Average	0.055	0.025	0.025	3074311	2581895	2555213	-9627	-7981	-7779
Dispersion	-	-0.030	-0.030	-	-492416	-519097	-	1646	1847

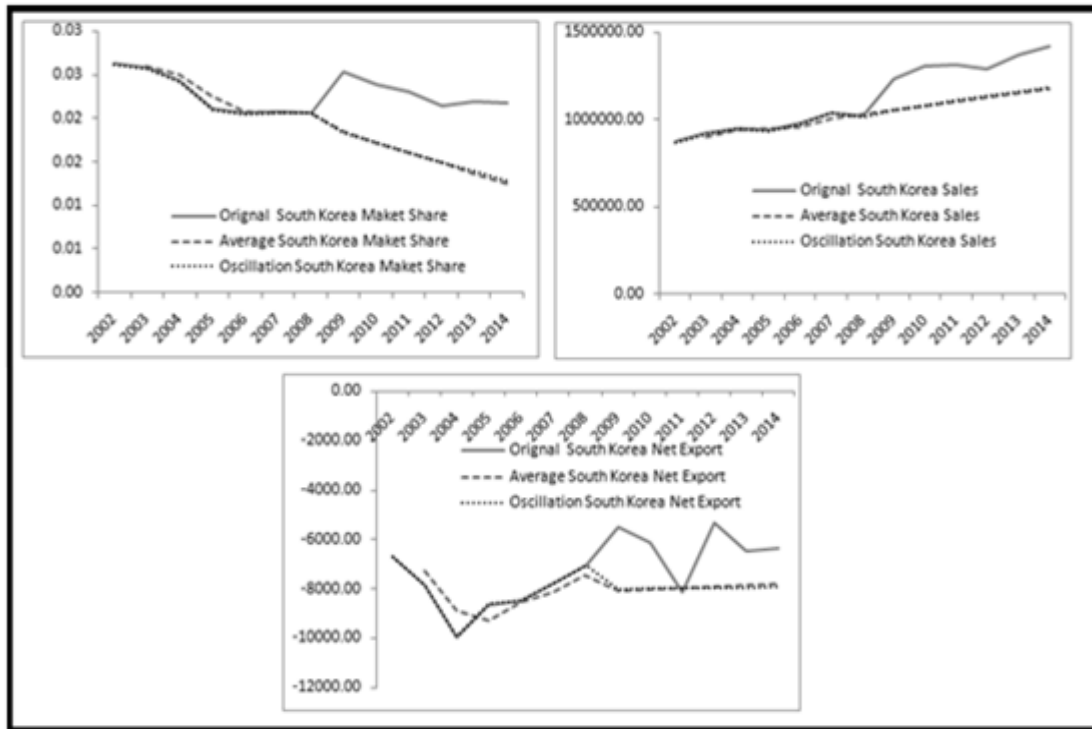
**Figure 4: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of Germany**



**Table 5: Table 5: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of South Korea**

Year	Original South Korea Market Share	Average South Korea Market Share	Oscillation South Korea Market Share	Original South Korea Sales	Average South Korea Sales	Oscillation South Korea Sales	Original South Korea Net Export	Average South Korea Net Export	Oscillation South Korea Net Export
2002	0.03		0.03	873581		870789.91	-6709		-6687.56
2003	0.03	0.03	0.03	921675	897628	918730.25	-7851	-7280	-7825.92
2004	0.02	0.02	0.02	951219	936447	948179.86	-9986	-8918.5	-9954.09
2005	0.02	0.02	0.02	941483	946351	938474.96	-8651	-9318.5	-8623.36
2006	0.02	0.02	0.02	977140	959311.5	974018.04	-8512	-8581.5	-8484.8
2007	0.02	0.02	0.02	1040372	1008756	1037048.01	-7835	-8173.5	-7809.97
2008	0.02	0.02	0.02	1020457	1030414.5	1017196.64	-7082	-7458.5	-7059.37
		Forecasted Values			Forecasted Values			Forecasted Values	
2009	0.03	0.02	0.02	1234618	1052533.33	1058018.8	-5537	-8080.47	-8008.47
2010	0.02	0.02	0.02	1308326	1078071.05	1083079.29	-6168	-8021.05	-7994.7
2011	0.02	0.02	0.02	1316320	1103608.76	1108139.79	-8179	-7961.64	-7980.92
2012	0.02	0.01	0.02	1293585	1129146.48	1133200.28	-5350	-7902.22	-7967.14
2013	0.02	0.01	0.01	1373316	1154684.19	1158260.78	-6512	-7842.81	-7953.36
2014	0.02	0.01	0.01	1422221	1180221.9	1183321.28	-6384	-7783.4	-7939.59
Average	0.022	0.015	0.017	1324731	1116378	1120670	-6355	-7932	-7974
Dispersion	-	-0.007	-0.005	-	-208353	-204061	-	-1577	-1619

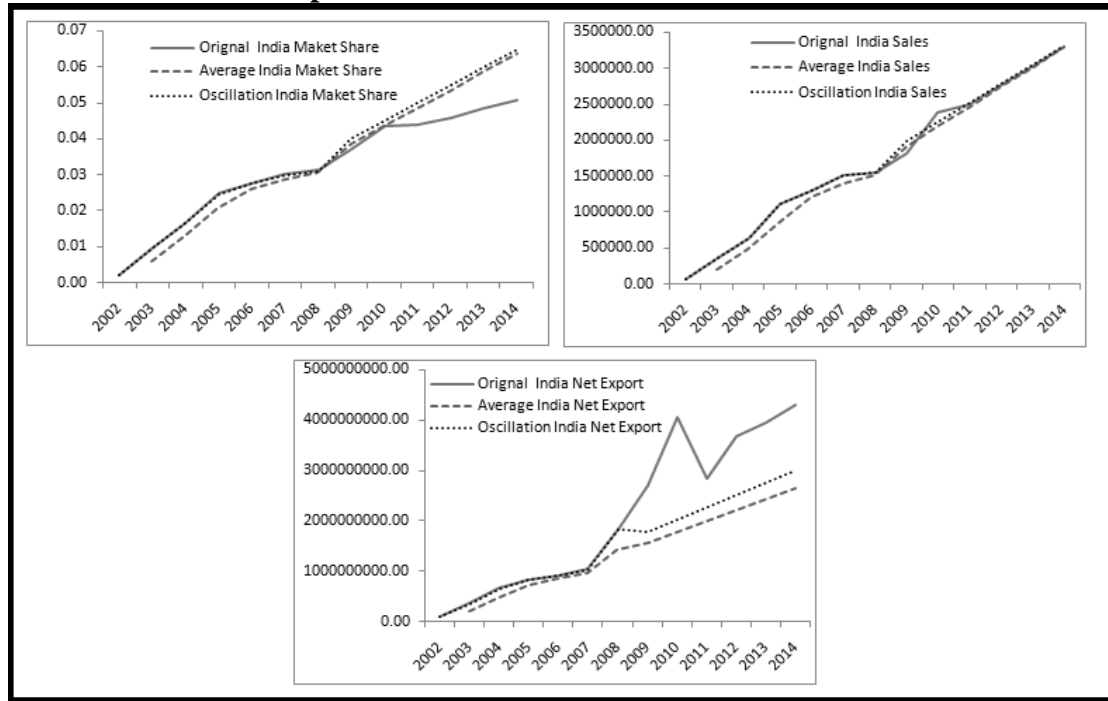
**Figure 5: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of South Korea**



**Table 6: Table 6: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of India**

Year	Original India Market Share	Average India Market Share	Oscillation India Market Share	Original India Sales	Average India Sales	Oscillation India Sales	Original India Net Export	Average India Net Export	Oscillation India Net Export
2002	0		0	67691		67475	91088787		90797758
2003	0.01	0.01	0.01	348480	208086	347367	349872226	220480507	348754384
2004	0.02	0.01	0.02	646644	497562	644578	650151443	500011835	648074209
2005	0.02	0.02	0.02	1106863	876754	1103327	822669360	736410402	820040931
2006	0.03	0.03	0.03	1311373	1209118	1307183	918788164	870728762	915852636
2007	0.03	0.03	0.03	1511812	1411593	1506982	1033936588	976362376	1030633161
2008	0.03	0.03	0.03	1545414	1528613	1540476	1829916100	1431926344	1824069518
		Forecasted Values			Forecasted Values			Forecasted Values	
2009	0.04	0.04	0.04	1816878	1922997	1988318	2705719306	1551379955	1787081979
2010	0.04	0.04	0.05	2387197	2199485	2252634	4049311186	1769111360	2031058810
2011	0.04	0.05	0.05	2510313	2475974	2516950	2833804094	1986842765	2275035641
2012	0.05	0.05	0.05	2773516	2752462	2781265	3661754700	2204574169	2519012471
2013	0.05	0.06	0.06	3041590	3028950	3045581	3936671913	2422305574	2762989302
2014	0.05	0.06	0.06	3305701	3305439	3309897	4298470901	2640036979	3006966133
Average	0.045	0.050	0.052	2639199	2614218	2649108	3580955350	2095708467	2397024056
Dispersion	-	0.005	0.007	-	-24981	9908	-	-1485246883	-1183931294

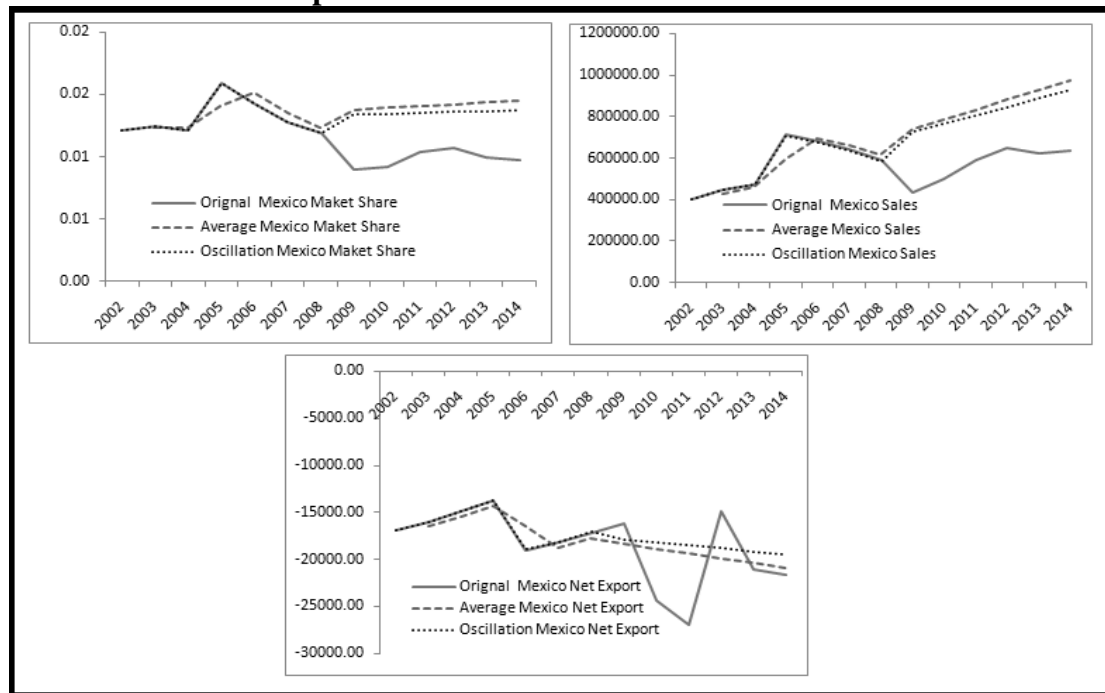
**Figure 6: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of India**



**Table 7: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of Mexico**

Year	Original Mexico Market Share	Average Mexico Market Share	Oscillation Mexico Market Share	Original Mexico Sales	Average Mexico Sales	Oscillation Mexico Sales	Original Mexico Net Export	Average Mexico Net Export	Oscillation Mexico Net Export
2002	0.01		0.01	403824		402533.78	-16972		-16917.77
2003	0.01	0.01	0.01	447003	425413.5	445574.83	-16087	-16529.5	-16035.6
2004	0.01	0.01	0.01	474953	460978	473435.53	-14926	-15506.5	-14878.31
2005	0.02	0.01	0.02	714010	594481.5	711728.74	-13830	-14378	-13785.81
2006	0.01	0.02	0.01	680946	697478	678770.38	-19109	-16469.5	-19047.95
2007	0.01	0.01	0.01	641394	661170	639344.75	-18307	-18708	-18248.51
2008	0.01	0.01	0.01	589045	615219.5	587163	-17203	-17755	-17148.04
		Forecasted Values			Forecasted Values			Forecasted Values	
2009	0.01	0.01	0.01	439120	741050.33	726473.34	-16199	-18340.1	-17906.89
2010	0.01	0.01	0.01	503748	788267.55	767429.13	-24359	-18849.34	-18238.54
2011	0.01	0.01	0.01	592101	835484.76	808384.93	-26936	-19358.59	-18570.19
2012	0.01	0.01	0.01	649333	882701.98	849340.73	-15000	-19867.83	-18901.84
2013	0.01	0.01	0.01	626097	929919.19	890296.53	-21141	-20377.07	-19233.49
2014	0.01	0.01	0.01	637484	977136.4	931252.33	-21621	-20886.31	-19565.15
Average	0.010	0.010	0.010	574647	859093	828863	-20876	-19613	-18736
Dispersion	-	0.000	0.000	-	284446	254216	-	1263	2140

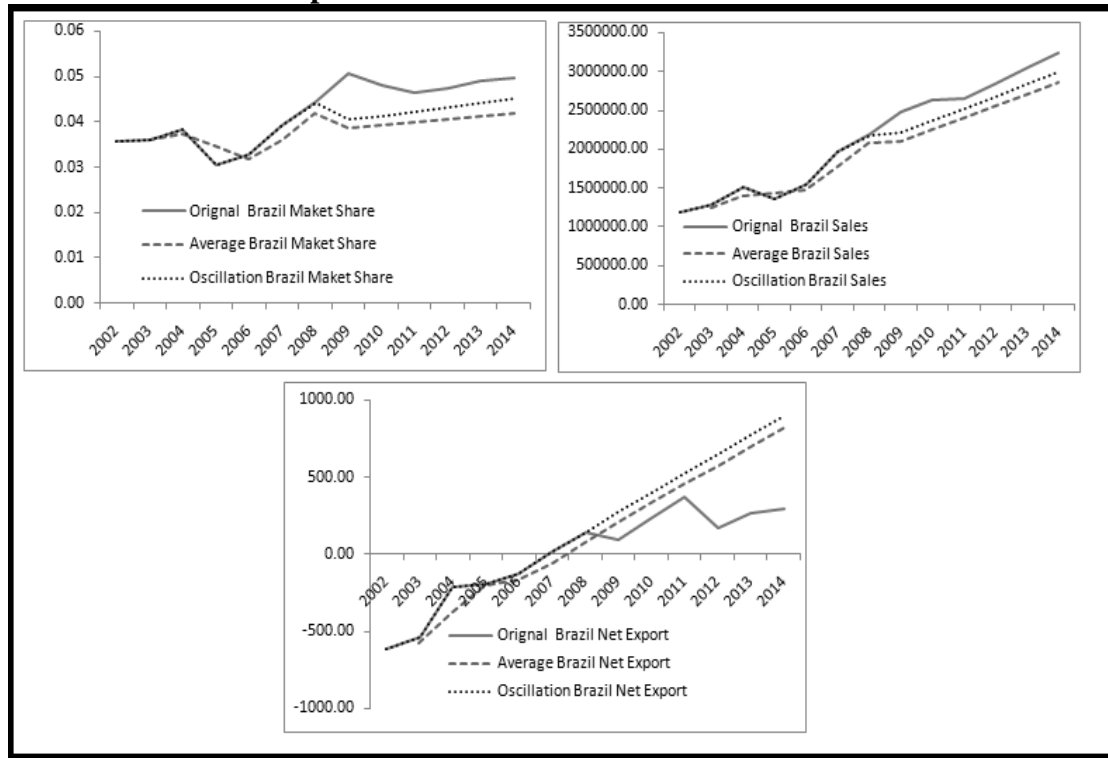
**Figure 7: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of Mexico**



**Table 8: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of Brazil**

Year	Original Brazil Market Share	Average Brazil Market Share	Oscillation Brazil Market Share	Original Brazil Sales	Average Brazil Sales	Oscillation Brazil Sales	Original Brazil Net Export	Average Brazil Net Export	Oscillation Brazil Net Export
2002	0.04		0.04	1190853		1187048.22	-615		-613.04
2003	0.04	0.04	0.04	1292583	1241718	1288453.2	-534	-574.5	-532.29
2004	0.04	0.04	0.04	1507496	1400039.5	1502679.55	-215	-374.5	-214.31
2005	0.03	0.03	0.03	1369182	1438339	1364807.46	-194	-204.5	-193.38
2006	0.03	0.03	0.03	1556220	1462701	1551247.88	-126	-160	-125.6
2007	0.04	0.04	0.04	1975518	1765869	1969206.22	15	-55.5	14.95
2008	0.04	0.04	0.04	2193277	2084397.5	2186269.48	144	79.5	143.54
		<b>Forecasted Values</b>			<b>Forecasted Values</b>			<b>Forecasted Values</b>	
2009	0.05	0.04	0.04	2474764	2099035.47	2208207.16	92	212.23	276.11
2010	0.05	0.04	0.04	2644706	2251471.12	2365626.38	232	334.28	399.43
2011	0.05	0.04	0.04	2647250	2403906.78	2523045.6	370	456.32	522.75
2012	0.05	0.04	0.04	2851540	2556342.44	2680464.82	165	578.36	646.07
2013	0.05	0.04	0.04	3062960	2708778.1	2837884.04	268.98	700.4	769.39
2014	0.05	0.04	0.05	3244614	2861213.75	2995303.26	294.8	822.45	892.71
<b>Average</b>	0.050	0.040	0.042	2820972	2480125	2601755	237	517	584
<b>Dispersion</b>	-	-0.010	-0.008	-	-340848	-219217	-	280	347

**Figure 8: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of Brazil**

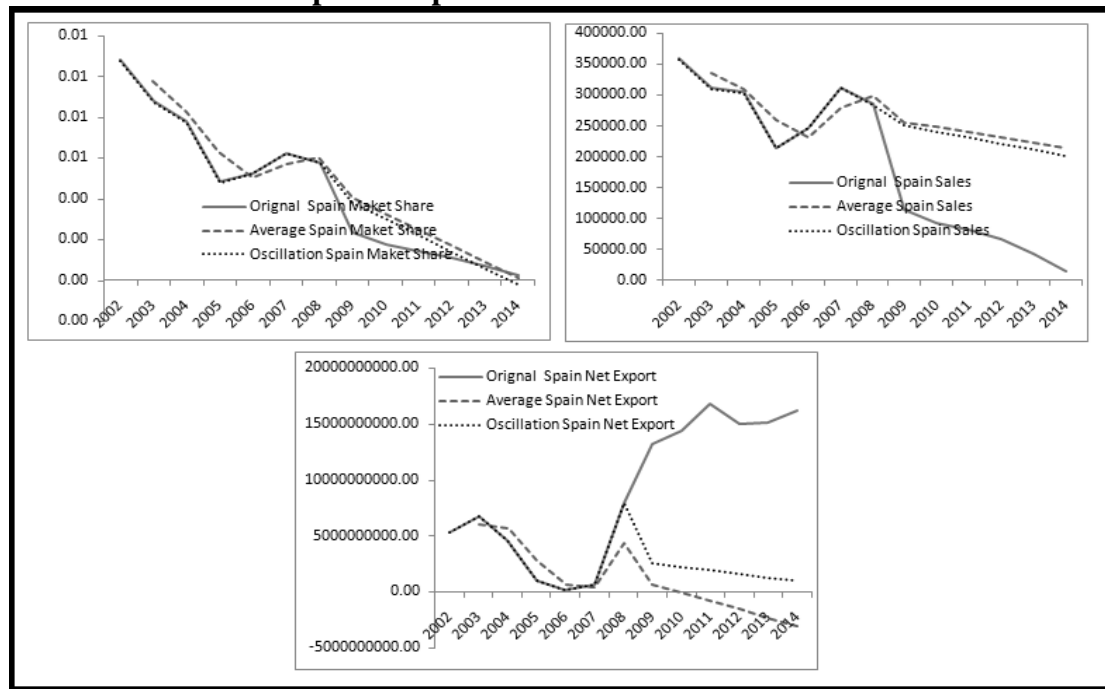


**Table 9: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of Spain**

Year	Original Spain Market Share	Average Spain Market Share	Oscillation Spain Market Share	Original Spain Sales	Average Spain Sales	Oscillation Spain Sales	Original Spain Net Export	Average Spain Net Export	Oscillation Spain Net Export
2002	0.01		0.01	359219		358071	5379812377		5362623876
2003	0.01	0.01	0.01	312119	335669	311122	6711779350	6045795864	6690335215
2004	0.01	0.01	0.01	304922	308521	303948	4572502787	5642141069	4557893641
2005	0	0.01	0	214967	259945	214280	1063386978	2817944883	1059989457
2006	0.01	0.01	0.01	247411	231189	246621	210519756	636953367	209847145
2007	0.01	0.01	0.01	312533	279972	311534	709353238	459936497	707086854
2008	0.01	0.01	0.01	285506	299020	284594	7959235234	4334294236	7933805477
		Forecasted Values			Forecasted Values			Forecasted Values	
2009	0	0	0	116016	255954	250462	13165492055	694332982	2560083322
2010	0	0	0	94441	247450	240572	14402283431	-56670257	2252904807
2011	0	0	0	81709	238946	230681	16788186729	-807673496	1945726292
2012	0	0	0	66436	230442	220791	15047950230	-1558676735	1638547777
2013	0	0	0	44472	221937	210900	15074025441	-2309679974	1331369263
2014	0	0	0	15592	213433	201010	16223445300	-3060683213	1024190748
Average	0.000	0.000	0.000	69778	234694	225736	15116897198	-1183175115	1792137035
Dispersion	-	0.000	0.000	-	164916	155958	-	-16300072313	-13324760163



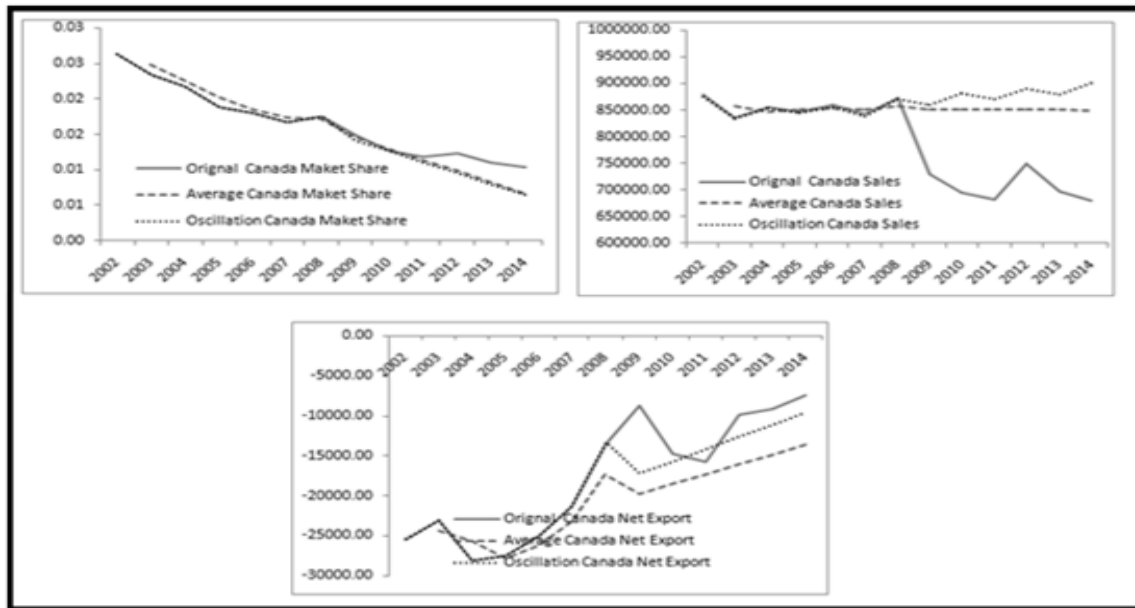
**Figure 9: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of Spain**



**Table 10: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of Canada**

Year	Original Canada Market Share	Average Canada Market Share	Oscillation Canada Market Share	Original Canada Sales	Average Canada Sales	Oscillation Canada Sales	Original Canada Net Export	Average Canada Net Export	Oscillation Canada Net Export
2002	0.03		0.03	878211		875405.12	-25497		-25415.54
2003	0.02	0.02	0.02	836230	857220.5	833558.25	-23163	-24330	-23088.99
2004	0.02	0.02	0.02	855175	845702.5	852442.72	-28163	-25663	-28073.02
2005	0.02	0.02	0.02	847436	851305.5	844728.44	-27538	-27850.5	-27450.02
2006	0.02	0.02	0.02	858826	853131	856082.05	-25088	-26313	-25007.84
2007	0.02	0.02	0.02	841585	850205.5	838896.14	-21420	-23254	-21351.56
2008	0.02	0.02	0.02	872720	857152.5	869931.66	-13390	-17405	-13347.22
		Forecasted Values			Forecasted Values			Forecasted Values	
2009	0.01	0.01	0.01	729023	851731	859007	-8718	-19796.97	-17284.17
2010	0.01	0.01	0.01	694349	850923	880370	-14729	-18557.27	-15757.56
2011	0.01	0.01	0.01	681956	851083	869445	-15808	-17317.57	-14230.96
2012	0.01	0.01	0.01	748530	850275	890808	-9907	-16077.87	-12704.35
2013	0.01	0.01	0.01	696499	850434	879883	-9078	-14838.17	-11177.74
2014	0.01	0.01	0.01	678582	849626	901246	-7384	-13598.47	-9651.14
Average	0.010	0.010	0.010	704823	850679	880127	-10937	-16698	-13468
Dispersion	-	0.000	0.000	-	145856	175303	-	-5760	-2530

**Figure 10: Forecasted values of Original, Oscillatory and Average Methods of Sales, Market Share and Net Export of Canada**



## Discussions and Conclusion

This paper contains new ideas to address the instituted gap in the available bootstrapping methods. However, various methods of bootstrapping which include parametric model sampling (Beran & Ducharme, 1991), non-metric bootstrap method /Truncated geometric bootstrap technique for time series data when time series is uniformed in nature (Politis & Romano, 1992), re-sampling from the sample, which approximate the variance (Gulesserian & Kejriwal, 2013), resampling time series via serial correlation method (Politis & Romano, 1992), the block bootstrap method (Politis & Romano, 1992), re-sampled pseudo time series stationary bootstrap method (Politis & Romano 1994) were used. Hence, this study in principle contributed the novel idea of bootstrapping the time series via resampling through winter forecasting by Oscillation and average methods and also confirmed that these two novel methods of time series bootstrapping give more robust result than the other available methods of time series bootstrapping for example winter holts method for time series bootstrapping.

## Declarations

### Competing Interests

The authors declare that they have no competing interests.

### Authors' Contribution

Subhani, M. I. was primarily involved in framing the proposition and designing the methodology of this study which includes framing hypotheses, modeling the model for bootstrapping and finalizing the epistemological outcome of this study where, Saleem, M. F. was involved in reviewing the all possible literature available for this study. Saleem, M. F. also collected the data along with the execution of the data analysis for assessing the hypotheses and proposition.

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