Simulation of Swiss Market Index (SMI) for the First 20 Years in the 21st Century and Weekly and Monthly Average from 1990 to 2010 with Random Walk

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Abstract: This is the continuation of our series of studies on use the random walk model to simulate stock indices in order to provide evidence to verify the efficient market hypothesis (EMH). In this study, our simulation is directed to the Swiss Market Index (SMI). However, we expand our approach not only to the SMI in the first 20 years in the 21st century, but also to the period from 1990 to 2010 by using daily, weekly and monthly close prices because our previous experience shows the volatility is the obstacle to set the command in Monte Carlo algorithm correctly. The results not only confirm what we found in our previous studies that the random walk model can simulate the SMI, but also provide fresh evidence on simulation on the moving average.

1 INTRODUCTION

The Swiss Market Index (SMI) is an important and useful benchmark, which is composed of 20 most important companies in Switzerland. It attracts many investors/institutions and funds, not only because it includes some world famous and renowned companies such as ABB, Credit Suisse, Nestlé, Novartis, Roche, Swiss Life, and UBS, but also it serves as a thermometer for the health of Swiss economy and those companies. Fairly enough, the SMI is not as important as the stock indices such as CAC40 and DAX in major European economy, but the SMI has still been studied since early days (Ranaldo, 2001, Thorbecke, 2018, Kato, 2018).

As a matter of modeling, the SMI is subject to many mathematical and statistical studies (Tenreiro Machado, 2012, Fallahgoul, et al., 2019, Dudukovic, 2014), and online software analyses, for instance, V-Lab Analyses (V-Lab Analyses, 2021). However, to the best of our knowledge, the random walk model as an important analytical tool has yet to apply to the investigation on SMI.

Random walk was proposed to support the efficient market hypothesis (EMH) (Boya, 2019, Urquhart 2016, McGroarty 2016), which was mainly verified using statistical tools, for example, variance ratio test, unit root test, autocorrelation test, and run test (Lo, 1988, MacKinlay, 1988, Liu, 1991, He, 1991, Deo, 2003, Richardson, 2003, Chow, 1993, Denning, 1993, Aktan, et al., 2019). Over recent years, our group attempted to verify this hypothesis with the random walk simulations on stock indices (Yan, 2011, Wu, 2011, 2020, 2021). Although our studies in conjunction with other studies provide us with new insights into this issue, a solid conclusion still cannot be drawn. This is because many technical details, which are absolutely unexpected, appear during the studies. This nevertheless requires more studies to increase our first-hand experience. Hence, we employ the random walk model to simulate the SMI for the first 20 years in the 21st century.

2 MATERIALS AND METHODS

2.1 SMI Data

In Yahoo Finance (Yahoo Finance, 2021), the SMI includes daily open, high, low, close, adjusted close prices, and volume for download. Two sets of data were used in this study.

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(1) The first 20 years in the 21st century includes 5029 trading days. In consistent with our previous studies (Yan, Wu, 2011, 2020, 2021), we divide this period of 20 years into five segments: (i) 5029 trading days the segment from 2001 to 2020, (ii) 3767 trading days for segment from 2006 to 2020, (iii) 2508 trading days for segment from 2011 to 2020, (iv) 1255 trading days for segment from 2016 to 2020, and (v) 252 trading days for segment for 2020.

(2) The daily, weekly and monthly close prices from November 9, 1990 to July 30, 2010 include 4968 daily close prices, 1030 weekly close prices, and 237 monthly close prices.

2.2 Classical Random Walk

The classical random walk (Feller, 1968) is quite simple and straightforward. It is a path in x, y coordinates, where the movement starts from the origin and each step along the x-axis takes either 1/–1 along the y-axis. Historically, 1/–1 was generated by tossing a fair coin, but nowadays 1/–1 is generated by any computer program using the command to generate a series of random numbers. If a random number is larger or smaller than its previous one, then we round the random number into 1/–1. Currently the most popular algorithm to generate random numbers is the Monte Carlo method.

2.3 SMI in Pattern of a Random Walk

In fact, we can let SMI mimic the classical random walk by means of comparison between trading days, that is, if an SMI close in a trading day is larger or smaller that in its previous trading day, then we consider it as 1/–1. With trading date as x-axis and 1/–1 as y-axis, we can pace an SMI in pattern of a random walk. This SMI pathway in x, y coordinates can compare with the random walk generated by the Monte Carlo method, which can generate different random walks with different seeds. Clearly, the best simulation needs a seed which can generate a random walk as approximate to the SMI in pattern of a random walk as possible. Therefore the entire becomes to search for such the best seed. Our previous studies (Yan and Wu, 2011, 2020, 2021a,b,c) show that we need at least to search 100 000 seeds ranged from 0 to 10 using SigmaPlot (SPSS Inc., SigmaPlot, 2002) in order to find a seed, which, though not the best, is satisfactory.

Table 1: Procedure to compose a random walk simulation.

Date	SMI Close Price	Compare Previous Close Price	Random Walk in 1 or–1 Pattern	Generated Random Number	Compare Preceding Random Number	Random Walk in 1 or–1 Pattern	Generated Random Number	Random Walk in Decimal Pattern
Jan 3, 2020	10699.82		0	–0.02686		0	84.8911	10699.82
Jan 6, 2020	10665.41	–1	–1	0.84546	1	1	–14.31492	10685.51
Jan 7, 2020	10686.8	1	0	–0.7544	–1	0	36.62705	10722.13
Jan 8, 2020	10652.16	–1	–1	0.9241	1	1	–96.3666	10625.76
Jan 9, 2020	10650.97	–1	–2	0.51223	–1	0	–34.41585	10591.35
Jan 10, 2020	10639.49	–1	–3	–0.15068	–1	–1	57.08906	10648.44
Jan 13, 2020	10622.41	–1	–4	0.39615	1	0	–76.11688	10572.32
Jan 14, 2020	10655.82	1	–3	0.75981	1	1	59.3287	10631.65
Jan 15, 2020	10670.74	1	–2	–0.82084	–1	0	20.01103	10651.66

2.4 Random Walk in Decimal Pattern

The limitation of classical random walk in simulation is obvious because the SMI is the decimal data although we can artificially change the SMI in a pattern of 1/–1. Evidently, the classical random walk needs to be decimally digitalized, that is, we can directly use the generated random number to compose a random walk in x, y coordinates: each trading day goes along the x-axis and each generated number goes along the y-axis.

3 RESULTS AND DISCUSSION

We explain how to compose the random walk simulations in both 1/–1 and decimal patterns in Table 1. Columns 1and 2 do not require an explanation. Column 3 is the comparison of sequential SMI closes in column 2 with 1/–1 for larger or smaller than previous SMI close. Column 4 is the SMI in the 1/–1 pattern by means of the addition of each value in column 3. Column 5 is the random numbers generated by SigmaPlot. Column 6 is the comparison of sequential random numbers in column 5 with 1/–1 for larger or smaller than previous value. Column 7 is the classical random walk by means of the addition of each value in column 6. Column 8 is the random numbers generated by SigmaPlot with the upper/lower ranges of standard deviations of SMI close in 2020. Column 9 is the random walk in the decimal pattern by means of the addition of each value in column 8. Comparisons can be made between columns 4 and 6 for the 1/–1 pattern, and between columns 2 and 9 for the decimal pattern.

Figure 1 is the comparison between SMI close and random walk simulation in the 1/–1 pattern for 2020. Clearly, the simulation is very close to the SMI.

Figure 2 is the comparison between SMI close and random walk simulation in the decimal pattern for 2020. Clearly, the simulation is not as good as that in Fig. 1, but the simulation is reasonably fine. This demonstrates the difficulty in the simulations in the decimal pattern because of too many choices leading too much computational time and the exhausting seeds for Monte Carlo algorithm.

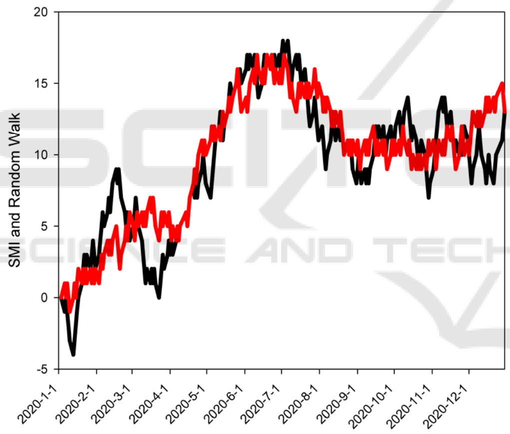

Figure 1: The SMI in 2020 in 1/–1 pattern (black line) and its simulation (red line) generated by random walk in 1/–1 pattern using the seed of 3.15054.

In our previous studies (Yan, Wu, 2011, 2020, 2021), we used to detail the difference between figures in order to indicate the impact of Covid-19 pandemic and financial crisis. However, we will not repeat these details in this study because these events not only affect the stock markets similarly but also can be considered as random events due to their unexpectedness. Therefore, importance is to simulate the stock indices under these unexpected and unpredictable random events rather than to detail what occurs in figures.

Figures 3, 4, 5 and 6 are the comparison between SMI close and random walk simulation in the decimal pattern from 2016, from 2011, from 2006 and from 2001 to 2020. These figures as the figures in our previous studies (Yan, Wu, 2011, 2020, 2021) demonstrate the possibility to use a random walk model to simulate the stock indices, but the suitability is limited to short period of time because the simulation for a short period of time is usually better than the simulation for a long period of time. However, if we dive into the depth of simulation, we found that the random walk is not time-dependent, but rather than volatility-dependent. The unexpected and unpredictable events essentially sharply increase the volatility of stock. This makes difficulty in random walk simulation because the random walk is based on the generated random numbers, whose command sets four parameters, number to generate, upper/lower ranges and seeds. How to the upper/lower ranges is crucial.

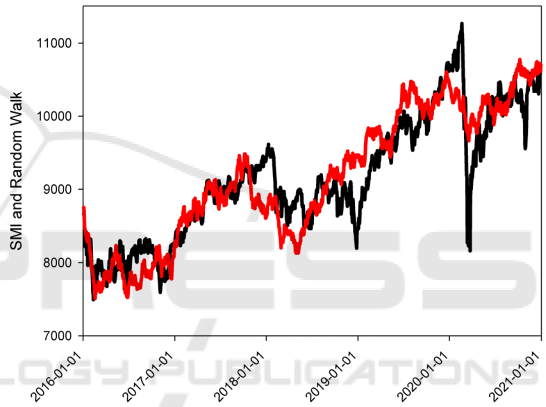

Figure 3: The SMI from 2016 to 2020 (black line) and its simulation (red line) generated by random walk in decimal pattern using any of three seeds from 3.75113 to 3.75115.

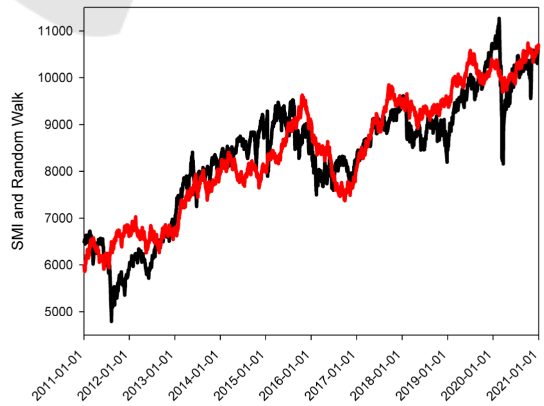

Figure 4: The SMI from 2011 to 2020 (black line) and its simulation (red line) generated by random walk in decimal pattern using the seed of 3.76679.

With increasing our experience in this type of simulations, we consider that the minimization of the volatility is perhaps a way to go around the difficulty in choice of upper/lower ranges. Another possible approach could use different seeds for different periods of time. However, this type of simulations seems to contradict to our understanding on simulation.

In order to minimize the volatility, we consider the approach of moving average, which can smooth the fluctuations of the SMI in our study.

Figure 7 shows the comparison of simulations on SMI daily, weekly and monthly average from 1990 to 2010. As can be seen, the simulations based on the 1/–1 pattern are worse than the decimal pattern in general. This shortage could be attributed to the extreme small probability for such a long period of time.

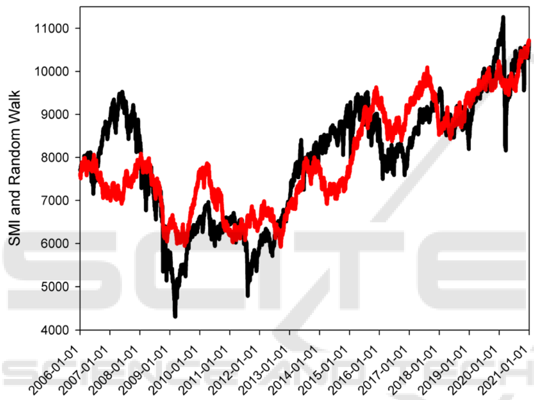

Figure 5: The SMI from 2006 to 2020 (black line) and its simulation (red line) generated by random walk in decimal pattern using the seed of 1.25267.

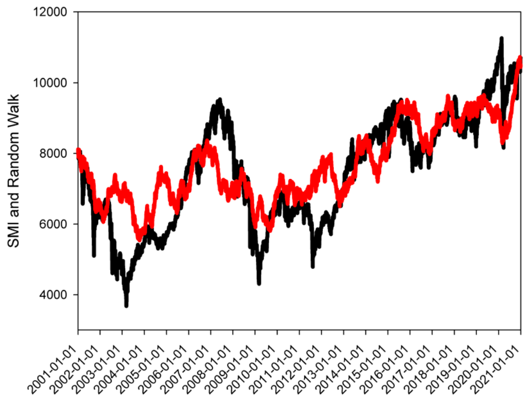

Figure 6: The SMI from 2001 to 2020 (black line) and its simulation (red line) generated by random walk in decimal pattern using the seeds of 1.45015.

As we know that the probability for a perfect fit for the 1/–1 pattern is ½n (Yan, Wu, 2011, 2020, 2021), where n is the number of points along the x-axis in x, y coordinates. In such cases, the probabilities for 2020 is ½252, for the daily close from 1990 to 2010 is ½4968, for weekly close prices from 1990 to 2010 is ½1030, for monthly close prices is ½237. Clearly these probabilities are very difficult to achieve.

4 CONCLUSIONS

In this study, we continue our efforts to verify the EMH with simulation on the SMI. Moreover, we attempt to simulate the SMI in its weekly and monthly average in order to reduce the volatility, which is due to unexpected random events. The results not only confirm what we found in our previous studies, but also shed lights on the simulation based on the moving average. Thus, it opens a new frontier for the simulations in the future.

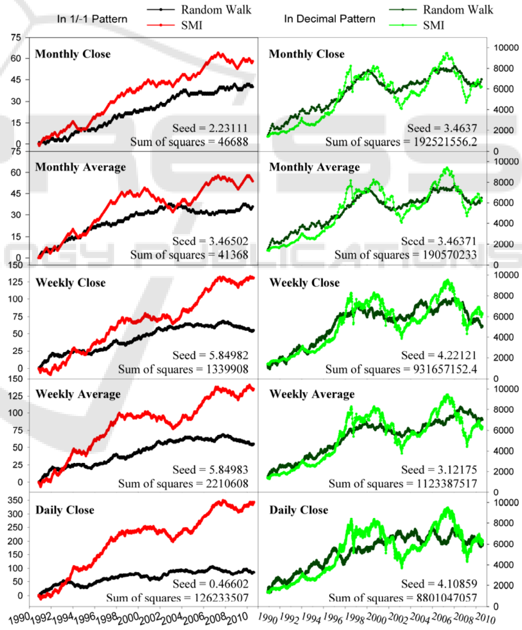

Figure 7: Comparison of simulations on SMI daily, weekly and monthly average from 1990 to 2010.

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