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IFC
ISBN 978-625-97685-0-2

PressAcademia Procedia YEAR 2024 VOLUME 20

13TH ISTANBUL FINANCE CONGRESS, December 23, 2024 Istanbul, Turkiye.

MEASURING THE SENSITIVITY OF DIFFERENT MONTE CARLO MODELS IN FORECASTING AIRLINE STOCK PRICES

DOI: 10.17261/Pressacademia.2024.1925
PAP- V.20-2024(11)-p.56-65

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To cite this document
Olcen, O., (2024). Measuring the sensitivity of different Monte Carlo models in forecasting airline stock prices. PressAcademia Procedia (PAP), 20, 56-65.
Permemant link to this document: http://doi.org/10.17261/Pressacademia.2024.1925

ABSTRACT

Purpose- Monte Carlo Models are widely utilised by scientific research in a variety. Two research models are argued and designed regarding the Quasi and Pseudo Monte Carlo models in this paper.
Methodology- The main research questions are formed here as "Which Monte Carlo model can give more effective results to USA Airline investors?". There is a utilisation problem of Monte Carlo Models by investors. The research also will help to fill this gap. On the other hand, Sobol and Halton sequences are utilized to develop Quasi Monte Carlo Model.
Findings- Quasi-Monte Carlo Models are given more real results than Pseudo Monte Carlo Models, especially in high number (5000) iterations. The results are specifically important for investors. The main disadvantage of the research is a random timespan that is out of a crisis or special event.
Conclusion- According to research results of bias (the approximation to reality), the Quasi-Monte Carlo Model gives more efficient results than the Pseudo Monte Carlo Model regarding accuracy and sensitivity. Investors in the American Air Carriers financial market should be aware of this important reality.

Keywords: Monte Carlo models, American Airlines, stock prices
JEL Codes: B26, 018, R11

1. INTRODUCTION

It is an undeniable and clear reality that investors should have some special mental, sentimental and emotional abilities to complete their strategic survival and evolution in complex financial markets and environments. In light of the arguments of the Efficient Market Hypothesis, it can be stated clearly that investors should have different information structures and tools to forecast the current situation of markets. Technical analysis, financial statement analysis, and econometric analysis are important financial tools for analysing different market levels regarding the amount of correct, deep and comprehensive information and knowledge.

This paper aims to measure the impact forecasting power of the different Monte Carlo models with different numerical sequences such as Halton, Sobol and Random sequences or numbers. The main causes of the selection of the financial market of USA airlines are counted as i) Vulnerability of this financial market to systematic or idiosyncratic financial, managerial and operational shocks, ii) The impacts of the oil prices, forex rates and other variables easily can be observed on the return structure of American air carriers financial prices although there are strict and sound hedging policies. Besides these, aviation is under great change, which can be named as an evolution with the impacts of the political, technological and economic variables. For example, a security problem like the 9/11 attacks can change a lot of the market variables in aviation or redefine the market structure as a whole including financial managerial and corporate structures. On the other side, a Monte Carlo simulation can present a lot of new information, if a correct structure designs it. In this context, it is expected to be hard to forecast or model a simulation considering the hard structure of American Air carriers' financial markets. However, benefits from Quasi and Pseudo Monte Carlo Simulations that are reasoned from Halton, Sobol and Random sequences, these problems are to be solved in this analysis. Also, the paper aims to complete a research gap on the efficiency of the different Monte Carlo Models in the forecasting of financial prices of USA Aircarriers by investors.

2. LITERATURE REVIEW

Monte Carlo analysis is a powerful tool in many fields of mathematics, physics and engineering. It is known that the algorithms based on this method give statistical estimates for any linear function of the solution by performing random sampling of a certain random variable whose mathematical expectation is the desired function (Atanassov and Dimov, 2008: 1477). In designing a Monte Carlo analysis, the scenarios or cases are very important. For example, Glasserman et al. (2001) show the importance of scenario creation in constructing a Monte Carlo VAR analysis. The logic of a Monte Carlo method forms with different types, Bonate (2001:16) argues that the sampling distribution of the model parameters (inputs) must be defined a priori, for example, a normal distribution with mean μ and variance σ^2. Monte Carlo simulation repeatedly simulates the model, each time drawing a different random set of values (inputs) from the sampling distribution of the model parameters, the result of which is a set of possible outcomes (outputs) and underlines the critical importance of Random Number generation. At the same time, Random Number Generation is called as Pseudo-random Generators. Nonetheless, Ferson (1996: 990) underlines the problems of the Monte Carlo methods underlying 4 important emphases; i) Like most methods based on probability theory, Monte Carlo methods are data-intensive. Consequently, they usually cannot produce results unless a considerable body of empirical information has been collected, or unless the analyst is willing to make several assumptions in the place of such empirical information. ii) Although appropriate for handling variability and stochasticity, Monte Carlo methods cannot be used to propagate partial ignorance under any frequentist interpretation of probability. iii) Monte Carlo methods cannot be used to conclude that exceedance risks are no larger than a particular level. iv) Finally, Monte Carlo methods cannot be used to effect deconvolutions to solve back calculation problems such as often arise in remediation planning. There are different methodologies for the creation of Monte Carlo Models such as the Method of Maximum Likelihood, the Method of Moments and Nonlinear Optimisation (Raychaudhuri, 2008).

According to Chen and Hong (2007), the utilization of Monte Carlo Methods in financial management is formed by three steps as such i) generating sample paths, evaluating the payoff along each part, and calculating an average to obtain estimation. Financial decision analysis, financial risk assessment, financial risk management, financial portfolio management and optimisation, and financial strategic planning can be realised with Monte Carlo Methods. In classical evaluation criteria, a Monte Carlo method can be described regarding two dimensions such as data conformity, congruence of the analytical model and validation of the Mathematical model (Nawrocki, 2001: 93).

Halton sequences and Sobol sequences are assumed to distribute randomness (random walk) in space in an order, so a wide utilization example in probability science (Berblinger and Schlier, 1991; Halton, 1992; Sanaç ve Karçı, 2005). Also, in a Monte Carlo simulation context, the utilization of different sequences such as Faure, Halton and Vander Corput means the derandomization of the accuracy of the estimate (Weeraisnghe et al, 2016). In parallel with them, In essence, they are the production sequences with the utilisation of base numbers. Halton sequences are low discrepancy sequences, so reaching the numbers is relatively easy with practical computer algorithms (Dong and Lemieux, 2022; Drukker and Gates, 2006; Faure and Lemieux, 2007). On the other side, there are different ways to create a Halton sequence as in the randomized version of Wang and Hickernell (2000). Especially in financial calculations, Halton sequences give successful results (Faure and Lemieux, 2015). Train (1999) finds that the impacts of Halton sequences can change depending on the sampling largeness.

Sobol sequences are also low discrepancy sequences in the quasi-Monte Carlo approach (Faure and Lemieux, 2016). Like Halton sequences, Sobol sequences are products of development in computer science (Renardy et al., 2021). According to Gomez-Perez et al. (2013) and Kucherenko (2008), Sobol sequences, which are subjected to a quasi-Monte Carlo approach with a deterministic point set and especially, utilize financial calculations such as calculating and pricing financial derivatives (Harase, 2019) and insurance (Kreinin and Kucherenko, 2021) to increase sensitivity. Dimov et al. (2023) utilize the Sobol sequences for the calculation of air pollution depending on their high sensitivity. The utilization of sequences as such Sobol sequences in the Monte Carlo approach increases the impact of accuracy (Owen, 2020; Atanassov and Ivanovska, 2022)

3. THE DATA AND METHODOLOGY

Research data (the stock prices) is taken from investing.com for 10 big airlines in the USA. January, February, March and April months of 2018 are selected randomly. The research steps can be argued as follows. i) Three Monte Carlo algorithms are set for this database under the names of Quasi and pseudo-Monte Carlo Methods benefiting from standard deviation and mean values of the monthly database on Excel program, and ii) Quasi-Monte Carlo Algorithms are utilised with the Sobol and Halton sequences, one dimension (Matlab package program is used in the production of this sequences.) for 500, 1000 and 5000 iterations. At the end of the analysis, bias will be calculated for each month. Therefore, the approximation of different Monte Carlo Methods to the reality will be analysed for investors.

4. FINDINGS AND DISCUSSION

The findings can be tabled for different Monte Carlo Methods for ten airline companies' prices. In the first three tables, there are the mean, variance and standard deviation results of Pseudo Monte Carlo results for 500, 1000 and 5000 iterations of ten USA Airline Companies. The last column belongs to differences between the Monte Carlo Model Mean and an average of the stock price monthly.

Table 1: Pseudo Monte Carlo Results for 500 Iterations

Monte Carlo Model	Mean	Variance	Standard Deviation	Difference by mean
JANUARY				
AAL-500	54.8740324	6.650322255	2.578821873	0.028824747
ALGT-500	159.7196129	45.77666675	6.765845605	0.075625149
ALK-500	69.82080436	16.14344816	4.017891009	0.044909923
DAL-500	57.1797921	4.258142425	2.063526696	0.023065042
HA-500	38.09339707	1.033803659	1.016761358	0.011364837
JBLU-500	21.73389512	0.642871364	0.801792594	0.008962026
LUV-500	63.58447414	4.465931017	2.113274951	0.023621103
SAVE-500	43.889216	4.295110236	2.072464773	0.023164948
SKW-500	53.4909031	4.376205703	2.091938265	0.023382612
UAL-500	71.61429502	21.1623284	4.60025308	0.051419268

FEBRUARY				
AAL-500	51.81809696	3.47969146	1.865393111	0.020850407
ALGT-500	164.7366502	14.31969848	3.784137746	0.042297149
ALK-500	69.82080436	16.14344816	4.017891009	-4.971856994
DAL-500	57.1797921	4.258142425	2.063526696	-4.112949995
HA-500	37.35215849	0.968389439	0.984067802	0.010999405
JBLU-500	20.47668083	0.335790662	0.57947447	0.006477068
LUV-500	63.58447414	4.465931017	2.113274951	-5.78394782
SAVE-500	39.79816666	0.602414861	0.77615389	0.00867545
SKW-500	55.36623269	2.586940469	1.608396863	0.017977835
UAL-500	65.95102463	3.04408042	1.744729326	0.019501689
MARCH				
AAL-500	53.7842609	3.209583114	1.791530941	0.020024813
ALGT-500	171.4397415	24.65159379	4.965037139	0.055496637
ALK-500	64.1983768	3.420006017	1.849325828	0.020670815
DAL-500	55.00893212	1.447706886	1.203206917	0.013448829
HA-500	36.50959769	1.120330339	1.058456583	0.011830884
JBLU-500	21.73389512	0.642871364	0.801792594	-0.250561783
AAL-500	58.51887882	2.142100609	1.463591681	0.016359277
ALGT-500	41.88610119	6.79514272	2.606749455	0.029136907
ALK-500	56.94364682	4.241471301	2.059483261	0.023019847
DAL-500	69.30518151	2.777441299	1.66656572	0.018628016
HA-500	53.7842609	3.209583114	1.791530941	0.020024813
APRIL				
AAL-500	47.1460019	8.001234311	2.828645314	0.031617145
ALGT-500	157.3881516	157.8223112	12.56273502	0.140419804
ALK-500	63.27923487	9.568135026	3.093240215	0.034574651
DAL-500	53.58413775	1.256430626	1.120906163	0.012528914
HA-500	39.7659273	1.806945694	1.344226802	0.015025077
JBLU-500	19.68593687	0.164927934	0.406113204	0.004539325
AAL-500	54.66513931	1.063582624	1.031301423	0.011527358
ALGT-500	36.95846713	1.344677381	1.159602251	0.012961439
ALK-500	55.12646642	2.150342513	1.466404621	0.016390718
DAL-500	68.35686819	3.137437454	1.771281303	0.019798473

Table 2: Pseudo Monte Carlo Results for 1000 Iterations

Monte Carlo Model	Mean	Variance	Standard Deviation	Difference by mean
JANUARY				
AAL-1000	54.84130568	6.868243257	2.620733343	0.061551466
ALGT-1000	159.6337505	47.27669889	6.875805327	0.161487584
ALK-1000	69.76981504	16.67244454	4.083190485	0.095899249
DAL-1000	57.15360477	4.397675312	2.097063497	0.049252371
HA-1000	38.08049379	1.067679841	1.033285944	0.024268117
JBLU-1000	21.72371991	0.663937286	0.814823469	0.019137231
LUV-1000	63.55765547	4.612272822	2.14762027	0.050439766
SAVE-1000	43.86291525	4.435854502	2.106146838	0.049465706
SKW-1000	53.46435521	4.519607345	2.125936816	0.0499305
UAL-1000	71.55591519	21.85578589	4.675017208	0.1097991
FEBRUARY				
AAL-1000	51.79442406	3.593715686	1.895709811	0.044523308
ALGT-1000	164.6886274	14.78893334	3.845638223	0.090320013
ALK-1000	69.76981504	16.67244454	4.083190485	-4.920867668
DAL-1000	57.15360477	4.397675312	2.097063497	-4.086762666
HA-1000	37.33967011	1.000122096	1.000061046	0.023487786
JBLU-1000	20.46932697	0.346794014	0.588892192	0.013830929
LUV-1000	63.55765547	4.612272822	2.14762027	-5.757129157
SAVE-1000	39.78831682	0.622155085	0.788768081	0.018525285
SKW-1000	55.34582122	2.671710595	1.634536814	0.038389307
UAL-1000	65.92888302	3.143830332	1.773084976	0.041643298
MARCH				
AAL-1000	53.76152535	3.314756299	1.82064722	0.042760361

ALGT-1000	171.3767323	25.45938924	5.045729802	0.118505786
ALK-1000	64.17490781	3.532074441	1.879381399	0.044139813
DAL-1000	54.99366274	1.495146051	1.222761649	0.02871821
HA-1000	36.49616527	1.15704187	1.075658807	0.025263301
JBLU-1000	21.72371991	0.663937286	0.814823469	-0.240386579
LUV-1000	58.50030501	2.212294006	1.487378232	0.034933089
SAVE-1000	41.85302005	7.017809269	2.649114809	0.062218043
SKW-1000	56.9175108	4.3804579	2.092954347	0.049155862
UAL-1000	69.28403184	2.86845385	1.693651041	0.039777684
APRIL				
AAL-1000	47.11010478	8.263422658	2.874616958	0.067514266
ALGT-1000	157.2287234	162.9939097	12.76690682	0.299848067
ALK-1000	63.23997989	9.88166834	3.143512103	0.073829632
DAL-1000	53.56991282	1.297601958	1.139123329	0.026753851
HA-1000	39.7488683	1.866156572	1.366073414	0.032084081
JBLU-1000	19.68078306	0.170332373	0.412713428	0.009693133
LUV-1000	54.65205151	1.098434618	1.048062316	0.02461516
SAVE-1000	36.94375112	1.388740425	1.178448312	0.027677452
SKW-1000	55.10785691	2.220805985	1.490236889	0.035000228
UAL-1000	68.33438962	3.240246534	1.80006848	0.042277042

Table 3: Pseudo Monte Carlo Results for 5000 Iterations

Monte Carlo Model	Mean	Variance	Standard Deviation	Difference by mean
JANUARY				
AAL-5000	54.97571238	6.851992089	2.617631007	0.072855234
ALGT-5000	159.9863825	47.164836	6.867665979	0.191144364
ALK-5000	69.97922519	16.63299534	4.078356941	0.1135109
DAL-5000	57.26115459	4.387269833	2.094581064	0.058297443
HA-5000	38.1334868	1.06515357	1.032062774	0.028724895
JBLU-5000	21.76550888	0.662366323	0.813858909	0.022651734
LUV-5000	63.66779814	4.601359578	2.145077989	0.059702899
SAVE-5000	43.97093091	4.425358686	2.103653652	0.058549956
SKW-5000	53.57338582	4.508913359	2.123420203	0.059100109
UAL-5000	71.79567771	21.80407223	4.669483079	0.129963423
FEBRUARY				
AAL-5000	51.89164727	3.585212482	1.893465733	0.052699899
ALGT-5000	164.8858544	14.75394078	3.841085885	0.106907051
ALK-5000	69.97922519	16.63299534	4.078356941	5.130277817
DAL-5000	57.26115459	4.387269833	2.094581064	4.194312481
HA-5000	37.39095915	0.997755676	0.998877207	0.027801257
JBLU-5000	20.49952884	0.345973454	0.588195081	0.016370944
LUV-5000	63.66779814	4.601359578	2.145077989	5.867271821
SAVE-5000	39.82876951	0.620682984	0.787834364	0.021927406
SKW-5000	55.42964993	2.665388976	1.632601904	0.045439405
UAL-5000	66.0198173	3.136391616	1.770986057	0.049290983
MARCH				
AAL-5000	53.85489891	3.306913149	1.818491999	0.050613192
ALGT-5000	171.6355072	25.39914897	5.039756837	0.14026907
ALK-5000	64.2712936	3.523717088	1.87715665	0.052245976
DAL-5000	55.05637319	1.491608339	1.221314185	0.033992236
HA-5000	36.55133141	1.154304157	1.074385479	0.029902842
JBLU-5000	21.76550888	0.662366323	0.813858909	0.282175544
LUV-5000	58.57658656	2.207059427	1.485617524	0.041348461
SAVE-5000	41.98888232	7.001204209	2.645978875	0.073644227
SKW-5000	57.02484988	4.37009316	2.090476778	0.05818321
UAL-5000	69.37089228	2.861666711	1.691646154	0.047082754
APRIL				
AAL-5000	47.25753213	8.243870312	2.871214083	0.079913087
ALGT-5000	157.8834858	162.6082446	12.75179378	0.354914395
ALK-5000	63.40119778	9.858287012	3.139790919	0.087388254

DAL-5000	53.62833379	1.294531661	1.137774873	0.031667128
HA-5000	39.81892862	1.861741	1.364456302	0.03797624
JBLU-5000	19.70194944	0.169929345	0.412224871	0.011473252
LUV-5000	54.70580234	1.095835577	1.046821655	0.029135671
SAVE-5000	37.00418892	1.385454482	1.177053305	0.032760345
SKW-5000	55.18428507	2.215551266	1.488472796	0.04142793
UAL-5000	68.42670778	3.232579684	1.79793762	0.050041112

The Quasi-Monte Carlo method is utilized with Sobol numbers in place of random numbers. The results in the following three tables are taken. The last column belongs to differences between the Monte Carlo model mean and real-world means.

Tablo 4: Quasi-Monte Carlo Results for 500 Iterations with a Sobol Sequence

Monte Carlo Model	Mean	Variance	Standard Deviation	Difference by mean
JANUARY				
AAL-500	54.88328482	6.484583738	2.546484584	-0.019572319
ALGT-500	159.7438878	44.63582627	6.681004885	-0.051350303
ALK-500	69.83521996	15.74112312	3.967508427	-0.030494329
DAL-500	57.18719573	4.152021521	2.037650981	-0.015661416
HA-500	38.09704506	1.008039331	1.004011619	-0.007716848
JBLU-500	21.73677183	0.626849803	0.791738469	-0.006085314
LUV-500	63.59205625	4.354631632	2.086775415	-0.016038987
SAVE-500	43.8966517	4.188068025	2.046476979	-0.015729253
SKW-500	53.49840866	4.26714244	2.065706281	-0.015877049
UAL-500	71.63080004	20.63492344	4.542567935	-0.034914245
FEBRUARY				
AAL-500	51.82478971	3.392971016	1.842001904	0.014157654
ALGT-500	164.7502271	13.96282471	3.736686327	0.028720227
ALK-500	64.84049049	1.210647376	1.100294222	0.008456878
DAL-500	53.0567607	1.720440232	1.311655531	0.010081404
HA-500	37.35568918	0.944255356	0.971728026	0.007468716
JBLU-500	20.47875989	0.327422128	0.572208116	0.004398
LUV-500	57.79188994	1.262584623	1.123647909	0.008636375
SAVE-500	39.80095138	0.587401552	0.766421263	0.005890725
SKW-500	55.37200338	2.522469055	1.588228276	0.012207146
UAL-500	65.95728446	2.968216221	1.72285119	0.01324186
MARCH				
AAL-500	53.79068865	3.129594277	1.769065934	0.013597067
ALGT-500	171.4575553	24.0372297	4.902777763	0.037682823
ALK-500	64.20501191	3.334773046	1.826136097	0.014035709
DAL-500	51.06868098	2726.321266	52.21418644	3.953699969
HA-500	36.51339527	1.092409604	1.045184005	0.0080333
JBLU-500	21.47738362	0.599223638	0.774095367	0.005949709
AAL-500	58.52412997	2.08871544	1.445238887	0.011108128
ALGT-500	41.89545382	6.625795005	2.574061966	0.019784279
ALK-500	56.95103594	4.135765873	2.033658249	0.015630728
DAL-500	69.3111609	2.708222248	1.645667721	0.012648627
HA-500	53.79068865	3.129594277	1.769065934	0.014035709
APRIL				
AAL-500	47.15615066	7.80182853	2.793175349	0.021468387
ALGT-500	157.4332248	153.8890829	12.40520386	0.095346582
ALK-500	63.29033296	9.329679138	3.054452347	0.023476566
DAL-500	53.5881594	1.225118016	1.106850494	0.008507269
HA-500	39.77075019	1.761913215	1.32737079	0.010202192
JBLU-500	19.68739394	0.160817621	0.401020724	0.003082251
AAL-500	54.66883946	1.037076148	1.018369358	0.007827202
ALGT-500	36.96262761	1.311165496	1.14506135	0.008800959
ALK-500	55.13172767	2.09675194	1.448016554	0.011129477
DAL-500	68.36322329	3.059246622	1.749070216	0.01344338

Tablo 5: Quasi-Monte Carlo Results for 1000 Iterations with a Sobol Sequence

Monte Carlo Model	Mean	Variance	Standard Deviation	Difference by mean

JANUARY				
AAL-1000	54.8922211	6.564066759	2.562043473	0.010636041
ALGT-1000	159.7673332	45.18293777	6.721825479	0.027904917
ALK-1000	69.84914298	15.93406565	3.991749698	0.016571309
DAL-1000	57.19434637	4.202913795	2.050100923	0.008510768
HA-1000	38.10056839	1.020395099	1.010146078	0.00419351
JBLU-1000	21.73955025	0.634533243	0.79657595	0.003306897
LUV-1000	63.59937929	4.408007344	2.099525504	0.008715949
SAVE-1000	43.90383332	4.239402129	2.058980847	0.008547632
SKW-1000	53.50565777	4.319445778	2.07832764	0.008627948
UAL-1000	71.64674109	20.8878504	4.57032279	0.018973191
FEBRUARY				
AAL-1000	51.82478971	3.392971016	1.842001904	0.014157654
ALGT-1000	164.7502271	13.96282471	3.736686327	0.028720227
ALK-1000	64.84049049	1.210647376	1.100294222	0.008456878
DAL-1000	53.0567607	1.720440232	1.311655531	0.010081404
HA-1000	37.35568918	0.944255356	0.971728026	0.007468716
JBLU-1000	20.47875989	0.327422128	0.572208116	0.004398
LUV-1000	57.79188994	1.262584623	1.123647909	0.008636375
SAVE-1000	39.80095138	0.587401552	0.766421263	0.005890725
SKW-1000	55.37200338	2.522469055	1.588228276	0.012207146
UAL-1000	65.95728446	2.968216221	1.72285119	0.01324186
MARCH				
AAL-1000	53.79689676	3.167954427	1.779874835	0.007388954
ALGT-1000	171.4747604	24.3318596	4.932733481	0.020477699
ALK-1000	64.20501191	3.334773046	1.826136097	0.007627322
DAL-1000	51.06868098	2726.321266	52.21418644	3.770466792
HA-1000	36.51339527	1.092409604	1.045184005	0.004365477
JBLU-1000	21.47738362	0.599223638	0.774095367	0.003233206
LUV-1000	58.52412997	2.08871544	1.445238887	0.006036408
SAVE-1000	41.89545382	6.625795005	2.574061966	0.010751225
SKW-1000	56.95103594	4.135765873	2.033658249	0.008494091
UAL-1000	69.3111609	2.708222248	1.645667721	0.00687355
APRIL				
AAL-1000	47.16595264	7.89745732	2.810241506	0.011666408
ALGT-1000	157.4767579	155.7753365	12.48099902	0.051813491
ALK-1000	63.30105183	9.444035141	3.073114892	0.012757698
DAL-1000	53.59204362	1.240134567	1.113613293	0.004623043
HA-1000	39.77540828	1.783509387	1.335480957	0.005544102
JBLU-1000	19.68880123	0.162788799	0.403470939	0.001674965
LUV-1000	54.67241319	1.049787827	1.024591542	0.004253479
SAVE-1000	36.96664593	1.32723675	1.152057616	0.00478264
SKW-1000	55.13680913	2.122452307	1.45686386	0.00604801
UAL-1000	68.36936123	3.096744505	1.759756945	0.007305437

Tablo 6: Quasi-Monte Carlo Results for 5000 Iterations with a Sobol Sequence

Monte Carlo Model	Mean	Variance	Standard Deviation	Difference by mean
JANUARY				
AAL-5000	54.89887797	6.645045198	2.577798518	0.003979175
ALGT-5000	159.7847983	45.74034279	6.76316071	0.010439839
ALK-5000	69.8595146	16.13063827	4.016296586	0.006199689
DAL-5000	57.19967308	4.254763572	2.062707825	0.003184064
HA-5000	38.10319302	1.032983332	1.016357876	0.001568884
JBLU-5000	21.74161996	0.642361243	0.801474418	0.001237182
LUV-5000	63.60483441	4.462387284	2.112436338	0.003260827
SAVE-5000	43.9091831	4.291702049	2.071642355	0.003197856
SKW-5000	53.51105781	4.372733166	2.091108119	0.003227904
UAL-5000	71.658616	21.14553601	4.598427558	0.007098285
FEBRUARY				
AAL-5000	51.83606903	3.476930311	1.864652866	0.00287834
ALGT-5000	164.7731084	14.30833574	3.782636084	0.005839002

ALK-5000	64.84722803	1.240604926	1.113824459	0.001719336
DAL-5000	53.06479249	1.763012641	1.327784863	0.002049613
HA-5000	37.36163946	0.967621018	0.983677294	0.001518437
JBLU-5000	20.48226375	0.335524211	0.579244517	0.000894141
LUV-5000	57.79877049	1.293827364	1.137465324	0.001755829
SAVE-5000	39.80564448	0.601936843	0.775845889	0.001197621
SKW-5000	55.38172874	2.584887721	1.607758602	0.002481789
UAL-5000	65.96783416	3.041664931	1.744036964	0.002692153
MARCH				
AAL-5000	53.80152135	3.207036298	1.790820007	0.002764369
ALGT-5000	171.4875769	24.63203266	4.96306686	0.007661154
ALK-5000	64.21619407	3.417292228	1.848591958	0.002853548
DAL-5000	53.59493709	1.255433644	1.120461353	1.427443867
HA-5000	36.51979535	1.119441353	1.058036555	0.00163322
JBLU-5000	21.48212372	0.614051467	0.783614361	0.001209613
LUV-5000	58.53297974	2.140400844	1.463010883	0.002258352
SAVE-5000	41.91121583	6.789750747	2.605715017	0.004022268
SKW-5000	56.96348884	4.238105677	2.058665994	0.003177825
UAL-5000	69.32123798	2.775237389	1.665904376	0.002571545
APRIL				
AAL-5000	47.17325439	7.9948853	2.82752282	0.004364658
ALGT-5000	157.5091869	157.6970786	12.55774974	0.019384559
ALK-5000	63.30903659	9.560542674	3.092012722	0.004772933
DAL-5000	53.59493709	1.255433644	1.120461353	0.001729581
HA-5000	39.77887821	1.805511876	1.343693371	0.00207417
JBLU-5000	19.68984955	0.164797064	0.405952046	0.000626641
LUV-5000	54.67507535	1.062738667	1.03089217	0.001591319
SAVE-5000	36.96963928	1.343610374	1.159142085	0.00178929
SKW-5000	55.14059445	2.148636208	1.465822707	0.002262693
UAL-5000	68.37393354	3.134947885	1.770578404	0.002733124

The Quasi-Monte Carlo method is utilized with Halton numbers in place of random numbers. The results in the following three tables are taken. The last column gives the numerical differences between the Monte Carlo model mean and the real-world means of ten airline companies.

Tablo 7: Quasi-Monte Carlo Results for 500 Iterations with a Halton Sequence

Monte Carlo Model	Mean	Variance	Standard Deviation	Difference by mean
JANUARY				
AAL-500	54.88328482	6.484583738	2.546484584	0.019572319
ALGT-500	159.7438878	44.63582627	6.681004885	0.051350303
ALK-500	69.83521996	15.74112312	3.967508427	0.030494329
DAL-500	57.18719573	4.152021521	2.037650981	0.015661416
HA-500	38.09704506	1.008039331	1.004011619	0.007716848
JBLU-500	21.73677183	0.626849803	0.791738469	0.006085314
LUV-500	63.59205625	4.354631632	2.086775415	0.016038987
SAVE-500	43.8966517	4.188068025	2.046476979	0.015729253
SKW-500	53.49840866	4.26714244	2.065706281	0.015877049
UAL-500	71.63080004	20.63492344	4.542567935	0.034914245
FEBRUARY				
AAL-500	51.82478971	3.392971016	1.842001904	0.014157654
ALGT-500	164.7502271	13.96282471	3.736686327	0.028720227
ALK-500	64.84049049	1.210647376	1.100294222	0.008456878
DAL-500	53.0567607	1.720440232	1.311655531	0.010081404
HA-500	37.35568918	0.944255356	0.971728026	0.007468716
JBLU-500	20.47875989	0.327422128	0.572208116	0.004398
LUV-500	57.79188994	1.262584623	1.123647909	0.008636375
SAVE-500	39.80095138	0.587401552	0.766421263	0.005890725
SKW-500	55.37200338	2.522469055	1.588228276	0.012207146
UAL-500	65.95728446	2.968216221	1.72285119	0.01324186
MARCH				
AAL-500	53.79068865	3.129594277	1.769065934	0.013597067

ALGT-500	171.4575553	24.03722979	4.902777763	0.037682823
ALK-500	64.20501191	3.334773046	1.826136097	0.014035709
DAL-500	55.01324905	1.411627312	1.188119233	0.009131902
HA-500	36.51339527	1.092409604	1.045184005	0.0080333
JBLU-500	21.47738362	0.599223638	0.774095367	0.005949709
AAL-500	58.52412997	2.08871544	1.445238887	0.011108128
ALGT-500	41.89545382	6.625795005	2.574061966	0.019784279
ALK-500	56.95103594	4.135765873	2.033658249	0.015630728
DAL-500	69.3111609	2.708222248	1.645667721	0.012648627
HA-500	53.79068865	3.129594277	1.769065934	0.013597067
APRIL				
AAL-500	47.15615066	7.80182853	2.793175349	0.021468387
ALGT-500	157.4332248	153.8890829	12.40520386	0.095346582
ALK-500	63.29033296	9.329679138	3.054452347	0.023476566
DAL-500	53.5881594	1.225118016	1.106850494	0.008507269
HA-500	39.77075019	1.761913215	1.32737079	0.010202192
JBLU-500	19.68739394	0.160817621	0.401020724	0.003082251
AAL-500	54.66883946	1.037076148	1.018369358	0.007827202
ALGT-500	36.96262761	1.311165496	1.14506135	0.008800959
ALK-500	55.13172767	2.09675194	1.448016554	0.011129477
DAL-500	68.36322329	3.059246622	1.749070216	0.01344338

Tablo 8: Quasi-Monte Carlo Results for 1000 Iterations with a Halton Sequence

Monte Carlo Model	Mean	Variance	Standard Deviation	Difference by mean
JANUARY				
AAL-1000	54.8922211	6.564066759	2.562043473	0.010636041
ALGT-1000	159.7673332	45.18293777	6.721825479	0.027904917
ALK-1000	69.84914298	15.93406565	3.991749698	0.016571309
DAL-1000	57.19434637	4.202913795	2.050100923	0.008510768
HA-1000	38.10056839	1.020395099	1.010146078	0.00419351
JBLU-1000	21.73955025	0.634533243	0.79657595	0.003306897
LUV-1000	63.59937929	4.408007344	2.099525504	0.008715949
SAVE-1000	43.90383332	4.239402129	2.058980847	0.008547632
SKW-1000	53.50565777	4.319445778	2.07832764	0.008627948
UAL-1000	71.64674109	20.8878504	4.57032279	0.018973191
FEBRUARY				
AAL-1000	51.83125378	3.434559435	1.853256441	0.00769359
ALGT-1000	164.7633401	14.13397023	3.759517287	0.015607222
ALK-1000	64.84435171	1.225486557	1.107016963	0.004595659
DAL-1000	53.06136364	1.74152806	1.319669678	0.005478463
HA-1000	37.35909923	0.955829309	0.977665234	0.004058669
JBLU-1000	20.48076792	0.331435416	0.575704278	0.002389973
LUV-1000	57.79583311	1.27806041	1.130513339	0.004693201
SAVE-1000	39.80364095	0.594601467	0.771104057	0.003201153
SKW-1000	55.37757689	2.553387533	1.597932268	0.00663364
UAL-1000	65.96333039	3.004598324	1.733377721	0.007195927
MARCH				
AAL-1000	53.79689676	3.167954427	1.779874835	0.007388954
ALGT-1000	171.4747604	24.3318596	4.932733481	0.020477699
ALK-1000	64.2114203	3.334773046	1.826136097	0.007627322
DAL-1000	55.01741847	2726.321266	52.21418644	0.004962482
HA-1000	36.51706309	1.092409604	1.045184005	0.004365477
JBLU-1000	21.48010013	0.599223638	0.774095367	0.003233206
LUV-1000	58.52920169	2.08871544	1.445238887	0.006036408
SAVE-1000	41.90448687	6.625795005	2.574061966	0.010751225
SKW-1000	56.95817258	4.135765873	2.033658249	0.008494091
UAL-1000	69.31693597	2.708222248	1.645667721	0.00687355
APRIL				
AAL-1000	47.16595264	7.89745732	2.810241506	0.011666408
ALGT-1000	157.4767579	155.7753365	12.48099902	0.051813491
ALK-1000	63.30105183	9.444035141	3.073114892	0.012757698

DAL-1000	53.59204362	1.240134567	1.113613293	0.004623043
HA-1000	39.77540828	1.783509387	1.335480957	0.005544102
JBLU-1000	19.68880123	0.162788799	0.403470939	0.001674965
LUV-1000	54.67241319	1.049787827	1.024591542	0.004253479
SAVE-1000	36.96664593	1.32723675	1.152057616	0.00478264
SKW-1000	55.13680913	2.122452307	1.45686386	0.00604801
UAL-1000	68.36936123	3.096744505	1.759756945	0.007305437

Tablo 9: Quasi-Monte Carlo Results for 5000 Iterations with a Halton Sequence

Monte Carlo Model	Mean	Variance	Standard Deviation	Difference by mean
JANUARY				
AAL-5000	54.89887797	6.645045198	2.577798518	0.003979175
ALGT-5000	159.7847983	45.74034279	6.76316071	0.010439839
ALK-5000	69.8595146	16.13063827	4.016296586	0.006199689
DAL-5000	57.19967308	4.254763572	2.062707825	0.003184064
HA-5000	38.10319302	1.032983332	1.016357876	0.001568884
JBLU-5000	21.74161996	0.642361243	0.801474418	0.001237182
LUV-5000	63.60483441	4.462387284	2.112436338	0.003260827
SAVE-5000	43.9091831	4.291702049	2.071642355	0.003197856
SKW-5000	53.51105781	4.372733166	2.091108119	0.003227904
UAL-5000	71.658616	21.14553601	4.598427558	0.007098285
FEBRUARY				
AAL-5000	51.83606903	3.476930311	1.864652866	0.00287834
ALGT-5000	164.7731084	14.30833574	3.782636084	0.005839002
ALK-5000	64.84722803	1.240604926	1.113824459	0.001719336
DAL-5000	53.06479249	1.763012641	1.327784863	0.002049613
HA-5000	37.36163946	0.967621018	0.983677294	0.001518437
JBLU-5000	20.48226375	0.335524211	0.579244517	0.000894141
LUV-5000	57.79877049	1.293827364	1.137465324	0.001755829
SAVE-5000	39.80564448	0.601936843	0.775845889	0.001197621
SKW-5000	55.38172874	2.584887721	1.607758602	0.002481789
UAL-5000	65.96783416	3.041664931	1.744036964	0.002692153
MARCH				
AAL-5000	53.80152135	3.207036298	1.790820007	0.002764369
ALGT-5000	171.4875769	24.63203266	4.96306686	0.007661154
ALK-5000	64.21619407	3.417292228	1.848591958	0.002853548
DAL-5000	55.02052438	1.446558125	1.202729448	0.001856573
HA-5000	36.51979535	1.119441353	1.058036555	0.00163322
JBLU-5000	21.48212372	0.614051467	0.783614361	0.001209613
LUV-5000	58.53297974	2.140400844	1.463010883	0.002258352
SAVE-5000	41.91121583	6.789750747	2.605715017	0.004022268
SKW-5000	56.96348884	4.238105677	2.058665994	0.003177825
UAL-5000	69.32123798	2.775237389	1.665904376	0.002571545
APRIL				
AAL-5000	47.17325439	7.9948853	2.82752282	0.004364658
ALGT-5000	157.5091869	157.6970786	12.55774974	0.019384559
ALK-5000	63.30903659	9.560542674	3.092012722	0.004772933
DAL-5000	53.59493709	1.255433644	1.120461353	0.001729581
HA-5000	39.77887821	1.805511876	1.343693371	0.00207417
JBLU-5000	19.68984955	0.164797064	0.405952046	0.000626641
LUV-5000	54.67507535	1.062738667	1.03089217	0.001591319
SAVE-5000	36.96963928	1.343610374	1.159142085	0.00178929
SKW-5000	55.14059445	2.148636208	1.465822707	0.002262693
UAL-5000	68.37393354	3.134947885	1.770578404	0.002733124

5. CONCLUSIONS

According to research results of bias (the approximation to reality), the Quasi-Monte Carlo Model gives more efficient results than the Pseudo Monte Carlo Model regarding accuracy and sensitivity. Investors in the American Airlines market should be aware of this important reality. Thus, the main question of the research is answered and the research gap is completed. On the other side, the timespan of the research model gains importance. A strong, unexpected or undesired event can have different impacts on the Monte Carlo Model depending on the volatility structure. It is another question if the investors are vulnerable regarding rational and emotional reasoning, as it is known that variables such as sustainability, branding and corporate governance structures have impacts on investors' decisions in airline financial markets of the United States.

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