Canadian and US Capitalization and Equal Weight Indexes: the Perspective of a Canadian Investor

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Abstract

A typical Canadian investor will have investments in Canadian stocks, as well as some exposure to international markets. We consider a prototypical example of an Canadian investor who has an annually rebalanced portfolio consisting of 30% Canadian T-bills, 35% capitalization weighted TSX index, and 35% capitalization weighted CRSP index. We examine 75 years of historical data, with all returns in CAD and inflation adjusted. Based on block bootstrap resampling of the historical data, we find that a portfolio which replaces the Canadian capitalization weighted TSX index by an equal weight TSX index stochastically dominates the original portfolio.

1 Introduction

Global capitalization weighted indexes are dominated by US stocks. However, recently there have been concerns raised about this concentration in the US market, see e.g. Odeh and Fuchs (2025); McDougall (2025).

A consensus is forming that

- there is an overconcentration in technology stocks,
- due to US government deficit spending, inflation is a high risk.

There is theoretical and empirical evidence which suggests that capitalization weighted indexes are prone to overcentration in a small number of high performance stocks, which results in poor median returns (Plyakha et al., 2014; Tljaard and Mare, 2021; Bessembinder, 2018; Farago and Hjalmarsson, 2023; Forsyth, 2024). Equal weight strategies have been suggested as robust alternatives to competing approaches (DiMeguel et al., 2009; Edwards et al., 2018). Block bootstrap resampling of historical returns suggests that equal weight portfolios can ameliorate concentration risk (Farago and Hjalmarsson, 2023; Forsyth, 2024) and inflation risk (Forsyth, 2022a; Ni et al., 2024).

Equal weight strategies look attractive based on long term asset returns. However, in recent years, capitalization weighted US stock indexes have outperformed equal weight indexes (Tljaard and Mare, 2021; Forsyth, 2022b). However, if we are concerned with the concentration risk of

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capitalization weighted indexes, and inflation risk, going forward, equal weight indexes are worth examining.

There have been few studies of the effect of equal weight strategies in the context of a Canadian investor, who will typically have some investments in international stocks as well as Canadian equities. Since international capitalization weighted indexes are dominated by US stocks, we will, as a first approximation, consider a Canadian investor who has holdings only in Canadian and US indexes.

The objective of this article is to examine the effect of equal weight portfolios from the perspective of a Canadian investor.

2 Data

For US data, we use the Center for Research in Security Prices (CRSP) value-weighted (capitalization weighted) stock index, and the CRSP equal weight index.[1] These indexes are total return indexes, including all dividends and distributions.

For Canadian data, we use the Canadian Financial Markets Research Centre (CFMRC)[2] value-weighted (capitalization weighted) Canadian equity index, and the CFMRC equal-weighted Canadian equity index. Again, both these indexes are total return indexes, and include all securities in the TSX database. We also use the Canadian 30-day T-bill index, also provided by CFMRC. All data sets were retrieved at monthly intervals.

We convert the US indexes to Canadian dollars. All the indexes are then inflation adjusted using the Canadian CPI index. Consequently, all indexes are in real Canadian dollars. One unfortunate aspect of the Canadian data is that it is only available for all of these Canadian indexes as of November 1950. As a result, the data range for all indexes is 1950:11-2024:12.

We will use the following acronyms in this paper

Can EqlWT : Canadian equal weight index,

Can CapWt : Canadian capitalization weight index,

US EqlWt : US equal weight index,

US CapWt : US capitalization weight index,

Can T-bill : Canadian 30-day T-bill.

Figure 2.1 shows the historical index values for the stock indexes. Summary statistics for these indexes over the period 1950:11-2024:12 are given in Table 2.1. We remind the reader that all indexes are in real (CPI adjusted) Canadian dollars.

3 Performance by Decade

Figure 3.1 shows the annualized return by decade for the various indexes. The annualized return over the last five years is also shown.

[1]Specifically, the results we present were calculated based on data from Historical Indexes, ©2020 Center for Research in Security Prices (CRSP), The University of Chicago Booth School of Business. Wharton Research Data Services (WRDS) was used in preparing this article. This service and the data available thereon constitute valuable intellectual property and trade secrets of WRDS and/or its third-party suppliers.

[2]`https://www.cfmrc.org/`

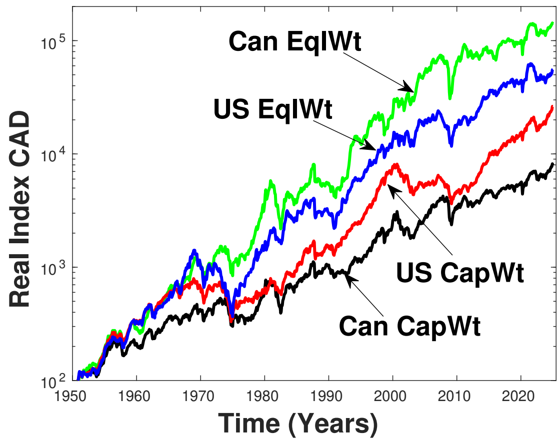


Figure 2.1: *Comparison of capitalization and equal weighted indexes, Canadian and US, 1950:11-2024:12. Source: CRSP and CFMRC. All results are in real (inflation adjusted) CAD. Log scale on y-axis.*

Observe that, for a Canadian investor, there have been two very bad decades for the US CapWt index. The 1970's resulted in negative returns for a Canadian investor in the US CapWt index, while the Can EqlWt index had excellent returns. The effect was even more pronounced during the 2000-2010 decade. This was a disaster for a Canadian investor in the US CapWt index. In this case, we can attribute this to the financial crisis, which had more of an effect in the US compared to Canada. In addition, the Canadian dollar appreciated considerably compared to the US dollar.

It is interesting to see that the performance of the Can EqlWt and the Can CapWt are similar over the period 2020:1-2024:12, in contrast to the US CapWt and US EqlWt. In fact, over the period 2025:1-2025:12, the total return of the $S\&P$ TSX equal weight index was 40%, compared to the 31% return of the $S\&P$ total return TSX capitalization weight index (in nominal CAD).[3]

However, over the last fifteen years, both the Can CapWt and Can EqlWt indexes have underperformed their US counterparts (from the perspective of a Canadian investor). Nevertheless, it would appear that the Can EqlWt index is a useful counterweight to the US CapWt index, in times of financial stress.

4 Portfolios

We consider a prototypical Canadian investor, who has an overall 70-30 stock/bond split. It could be argued that a Canadian investor should simply invest in a world-wide portfolio, with weights based on international market capitalization. However, there is a well-documented home bias.[4]

We consider an Benchmark portfolio with 35% Can CapWt, 35% US CapWt, and 30% Can T-bills. This portfolio would be a conventional approach, using capitalization weighted Canadian and US indexes.

However, from Table 2.1 and Figure 3.1, it would appear that the Can EqlWt index is worthy of consideration. Consequently, as an alternative to the Benchmark portfolio, we consider a portfolio replacing the 35% Can CapWt by 35% Can EqlWt. We label this portfolio as the EqCan strategy.

[3] `https://www.spglobal.com/spdji/en/indices/equity/sp-tsx-composite-equal-weight-index`

[4] This is not altogether irrational, since Canadian investors are less exposed to exchange rate risk, investing in Canadian indexes.

	Can T-bill	Can CapWt	Can EqlWt	US CapWt	US EqlWt
Descriptive Statistics Data: Monthly Real Log Returns, 1950:11 to 2024:12 ($N = 891$) Annualized					
Geometric Return	0.013	0.059	0.098	0.075	0.085
Arithmetic Return	0.014	0.070	0.114	0.085	0.100
Volatility	0.016	0.150	0.178	0.139	0.172
Sharp Ratio	N/A	0.380	0.564	0.515	0.504
Correlation Matrix					
	Can T-bill	Can CapWt	Can EqlWt	US CapWt	US EqlWt
Can T-bill	1.000	0.085	0.056	0.140	0.112
Can CapWt	0.085	1.000	0.878	0.742	0.726
Can EqlWt	0.056	0.878	1.000	0.608	0.724
US CapWt	0.140	0.742	0.608	1.000	0.860
US EqlWt	0.112	0.726	0.724	0.860	1.000

TABLE 2.1: *Descriptive statistics for monthly real log returns from 1950:11 to 2024:12. All return series are measured in real CAD. Source: CRSP and CFMRC.*

The detailed weights are given in Table 4.1.

We consider an investor with initial wealth of 1000 (arbitrary units), who rebalances annually to the weights in Table 4.1. The investment horizon is 10 years. This scenario is summarized in Table 4.2.

	Benchmark	EqCan
Can T-bill	0.30	0.30
Can CapWt	0.35	0.0
Can EqlWt	0.0	0.35
US CapWt	0.35	0.35
US EqlWt	0.0	0.0

TABLE 4.1: *Rebalancing weights.*

Investment horizon T	10 years
Initial Investment	1000
Annual Cash Injection	zero
Rebalancing frequency	1 year
Benchmark weights	Table 4.1
EqCan weights	Table 4.1

TABLE 4.2: *Scenarios*

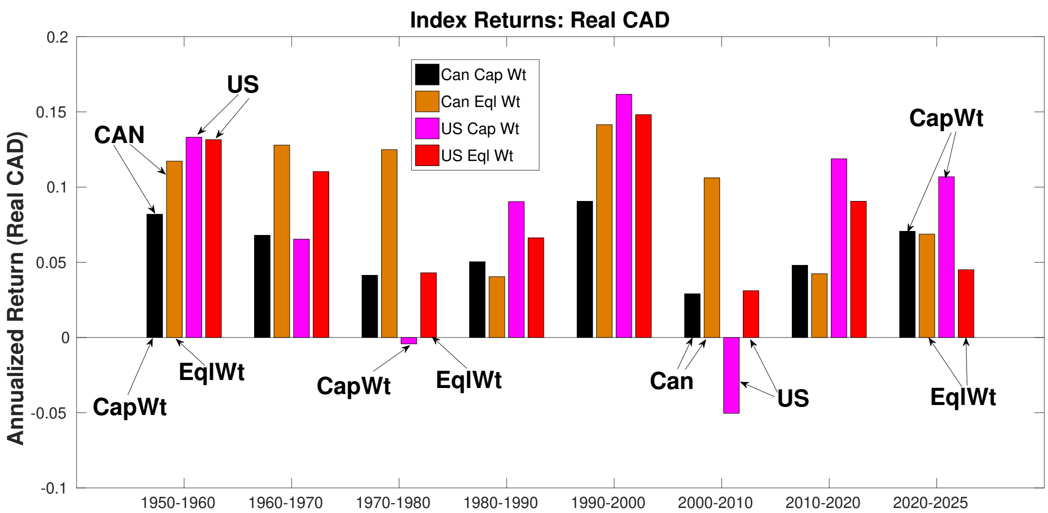


FIGURE 3.1: *Performance by decade, 1950:11 to 2024:12. Source: CRSP and CFMRC. All results are in real (inflation adjusted) CAD.*

5 Stationary Block Bootstrap Resampling

A standard practitioner approach for evaluating historical investment strategies uses rolling periods. However, this is statistically suspect, due to high correlations between overlapping rolling year periods. This approach has been superseded by stationary block bootstrap resampling (Politis and Romano, 1994; Cogneau and Zakalmouline, 2013; Dichtl et al., 2016; Cavaglia et al., 2022; Simonian and Martirosyan, 2022; Anarkulova et al., 2022; 2025). This method involves repeatedly drawing randomly sampled blocks of returns of random size (length), with replacement, from the original data series. The block size follows a geometric distribution with a specified expected block size.

Sampling the data in blocks accounts for serial correlation in the data series. A key parameter is the expected blocksize. We will present bootstrap results using an expected blocksize of one year. This choice for blocksize is discussed in Appendix A.

Detailed pseudo-code for block bootstrap resampling is given in Forsyth and Vetzal (2019).

6 Comparison of Portfolios

Based on 10^5 block bootstrap resamples, Table 6.1 shows summary statistics for the Benchmark and EqCan portfolios. We denote the investor wealth at time T by W_T. We can see that for every statistic except standard deviation, EqCan is superior to the Benchmark. The $std[W_T]$ of EqCan is signifcently larger than for the Benchmark. However, in this case, this is due to larger right skew[5] of the terminal wealth distribution of EqCan, which most investors would consider a desirable statistic. Perhaps this demonstrates that standard deviation is not a particularly useful risk measure, in general, since it penalizes upside as well as downside.

Figure 6.1 shows the percentiles the portfolio wealth through time. At each percentile, the wealth of EqCan is larger than the Benchmark, for every rebalancing time. From an examination of the $95th$ percentile, we can see that the right skew for EqCan, compared to the Benchmark, increases with time.

[5] This can be seen by comparing the 5^{th} and 95^{th} percentiles of both terminal distributions.

Strategy	E[W_T]	Median[W_T]	W_T : 5^{th} percentile	W_T : 95^{th} percentile	ES(5%)	std[W_T]
Benchmark	1816	1746	994	2878	858	583
EqCan	2167	2046	1097	3657	936	800

TABLE 6.1: 10^5 *Stationary block bootstrap simulations, rebalanced yearly.* W_T *denotes total investor wealth at* $t = T$. *Asset weights in Table 4.1). Scenario in Table 4.2. Data Source: CRSP and CFMRC, 1950:11-2024:12. All indexes are in CAD, inflation adjusted. ES(5%) is the mean of the worst 5% of the outcomes. Expected blocksize one year.*

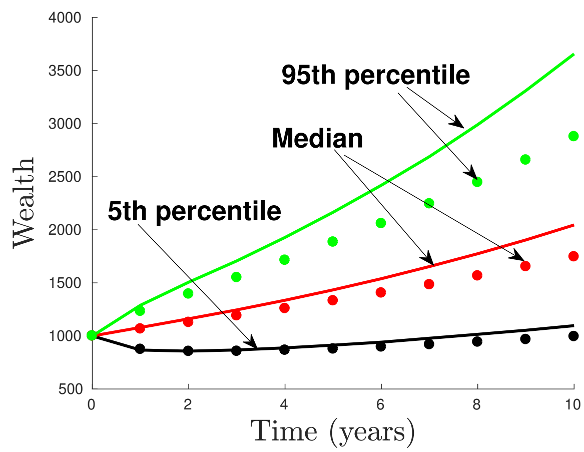


FIGURE 6.1: *Percentiles of wealth through time. Line: EqCan, symbols: Benchmark, yearly rebalancing. Asset weights in Table 4.1). Scenario in Table 4.2. Data Source: CRSP and CFMRC, 1950:11-2024:12.* 10^5 *stationary block bootstrap simulations, expected blocksize one year. All results are in real (inflation adjusted) CAD.*

Figure 6.2(a) compares the cumulative distribution functions (CDFs) for the Benchmark and EqCan portfolios. The CDF curve for EqCan plots below the CDF for the Benchmark (except at the two endpoints, where the curves overlap). This indicates that portfolio EqCan stochastically dominates (to first order) the Benchmark portfolio. The significance of this is easily seen in Figure 6.2(b), where we plot $1 - CDF$ on the y-axis. If we examine any point on the x-axis ($x = X$), we can see that $Prob[W_T > X]$ for EqCan is larger than $Prob[W_T > X]$ for the Benchmark. This means that any rational investor, who prefers more rather than less, will choose EqCan over the Benchmark portfolio.[6]

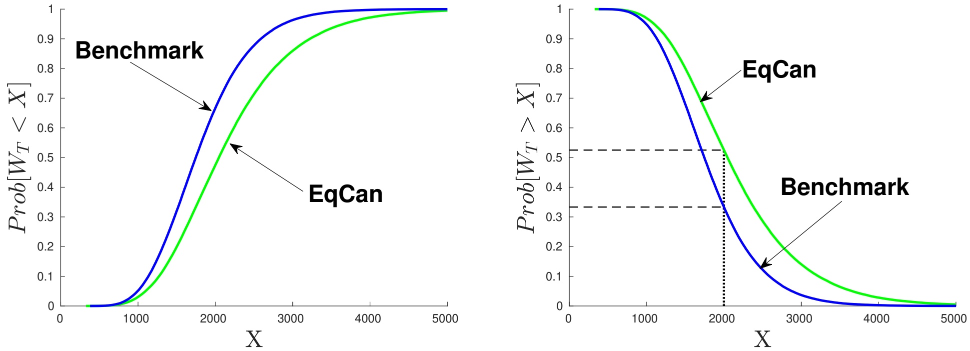
7 Pathwise comparison

We have established that EqCan stochastically dominates the Benchmark, assuming the validity of bootstrap resampling. However, this does not imply that, along each stochastic path an investor would be better off with EqCan compared to the Benchmark portfolio.[7]

A more strict comparison of EqCan and the Benchmark can be determined by examining the

[6]This will be true for any investor with a non-decreasing, but otherwise arbitrary, utility function.

[7]Given two portfolios which initially cost the same, then if one portfolio gives a higher terminal value along every path, compared to the other portfolio, then this would be an arbitrage opportunity.



(a) CDF (b) $1 - CDF$.

FIGURE 6.2: *CDF curves at $T = 10$ years. Asset weights in Table 4.1). W_T denotes the total investor wealth at $t = T$. Scenario in Table 4.2. Data Source: CRSP and CFMRC, 1950:11-2024:12.* 10^5 *stationary block bootstrap simulations, expected blocksize one year. All results are in real (inflation adjusted) CAD.*

pathwise comparison of these two strategies. Denote the total wealth in portfolio Benchmark by W^{bench}, and the total wealth in portfolio EqCan by W^{EqCan}. We will consider the statistics of (W^{EqCan}/W^{bench}) along each path. EqCan outperformance, along any path, is indicated if $(W^{EqCan}/W^{bench}) > 1.0$

Table 7.1 shows the summary statistics for the ratio (W^{EqCan}/W^{bench}) at $T = 10$ years. ES(5%) is the expected shortfall at the five per cent level, i.e. the mean of the worst 5% of the outcomes. The Omega ratio (Keating and Shadwick, 2002) for this pathwise test, at level L is defined as

$$
\begin{aligned}
\Omega(L) &= \frac{\int_L^\infty (1 - F(R_T))\ dR_T}{\int_{-\infty}^L F(R(T)\ dR_T} \ ; \ F(R_T) \text{ CDF of } R_T \\
&= \frac{E[\max(R_T - L, 0)]}{E[\max(L - R_T, 0)]} \\
& \qquad R_T = \frac{W_T^{EqCan}}{W_T^{bench}} \ .
\end{aligned} \tag{7.1}
$$

The Omega ratio is a measure of upside versus downside, with respect to the level L. Since we are interested in pathwise outperformance of W^{EqCan} compared to W^{bench}, we will examine $\Omega(L)$, with $L = 1$.

We can see from Table 7.1 that, along any path, the 5^{th} percentile of the wealth of the buy and hold portfolio is about 92% of the rebalanced portfolio, while at the 95^{th} percentile, $(W_T^{EqCan}/W_T^{bench})$ is 1.5. This indicates a better upside, compared to the downside, for buy and hold. This is also reflected in the Omega ratio, which is illustrated in Figure 7.1. Figure 7.2 shows the percentiles of (W^{EqCan}/W^{bench}) through time.

8 Extra Costs with Equal Weight Indexes

It could be argued that the results presented so far are not reflective of real-world equal weight ETFs. Equal weight portfolios may generate additional costs and fees due to frequent rebalancing. We explore the sensitivity to such costs by artificially reducing the returns of the Can EqlWt index by $50 - 100$ bps per year, in Appendix B. Obviously, the outperformance of the CanEq portfolio

$E[(W_T^E/W_T^b)]$	(W_T^E/W_T^b) Median	(W_T^E/W_T^b) 5^{th} percentile	(W_T^E/W_T^b) 95^{th} percentile	ES(5%)	Omega (L=1)
1.188	1.1655	0.9479	1.5041	0.9035	30.41

Table 7.1: *Statistics for $(W_T^E/W_T^b) = (W_T^{EqCan}/W_T^{bench})$ at $T = 10$ years. W^{EqCan} denotes the total wealth in portfolio EqCan, while W^{bench} denotes the total wealth in the Benchmark portfolio. ES(5%) is the mean of the worst 5% of the outcomes of (W^{EqCan}/W^{bench}). The Omega ratio for (W^{EqCan}/W^{bench}) is defined in equation (7.1). Asset weights in Table 4.1). Scenario in Table 4.2. Data Source: CRSP and CFMRC, 1950:11-2024:12. 10^5 stationary block bootstrap simulations, expected blocksize one year. All results are in real (inflation adjusted) CAD. Outperformance along a path is indicated if $(W_T^{EqCan}/W_T^{bench}) > 1$.*

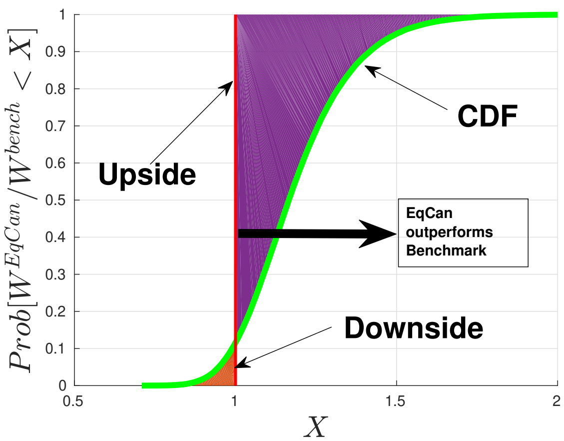


Figure 7.1: *CDF for $(W_T^{EqCan}/W_T^{bench})$ at $T = 10$ years. This is a pathwise performance measure. EqCan outperforms the benchmark, along each path, if $(W_T^{EqCan}/W_T^{bench}) > 1$. $\Omega(1)$ is the ratio of the upside area to the downside area. Asset weights in Table 4.1. Scenario in Table 4.2. Data Source: CRSP and CFMRC, 1950:11-2024:12. 10^5 stationary block bootstrap simulations, expected blocksize one year. All results are in real (inflation adjusted) CAD.*

is reduced, but it is still significant. CanEq continues to stochastically dominate the Benchmark portfolio.

9 Why does equal weight outperform?

An equal weighted index will obviously put more weight on small capitalization (cap) stocks, compared to a capitalization weighted index. Years ago, it was noted that small cap stocks seemed to perform better than one would expect. In fact, small cap portfolios were one of the original factors in the Fama-French three factor model of stock returns (Fama and French, 1992). The classic small cap paper dates from 1981 (Banz, 1981). However, once this effect becomes well known, we would expect that the outperformance of small cap stocks would be arbitraged away.

Bessembinder (2018) notes that empirical analysis suggests that most individual stocks are losers during their lifetime. Over the period 1926-2016, Bessembinder (2018) shows that most of the wealth creation in the stock market can be attributed to a small number of firms. Some interesting facts from Bessembinder (2018):

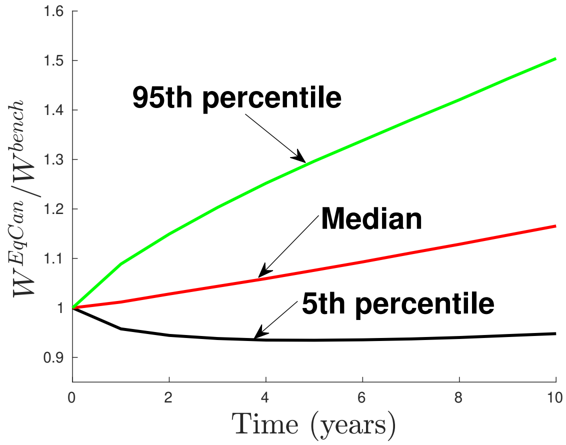


FIGURE 7.2: *Percentiles of* (W^{EqCan}/W^{bench}) *through time. This is a pathwise performance measure. EqCan outperforms the benchmark, along each path, if* $(W^{EqCan}/W^{bench}) > 1$. *Asset weights in Table 4.1. Scenario in Table 4.2. Data Source: CRSP and CFMRC, 1950:11-2024:12.* 10^5 *stationary block bootstrap simulations, expected blocksize one year. All results are in real (inflation adjusted) CAD.*

- short lifetimes: the median time that a stock is listed on the Center for Security Prices (CRSP) database (1926-2016) is less than eight years;
- poor average performance: over their lifetimes, less than 43% of stocks (including reinvested dividends) outperform T-bills;
- extreme skewness: the CRSP database holds 23,500 stocks (all stocks which traded during 1926-2016). Of these stocks, just 4% (the top lifetime performers) accounted for all the net long-term wealth creation in the stock market (i.e. accumulated value in excess of investing in T-bills). The remaining 96% of stocks collectively matched T-bill returns (some stocks exceeded T-bills, many were wealth destroyers).

Following along this theme, Farago and Hjalmarsson (2023) point out that since the return distribution of a buy and hold portfolio is highly skewed (due to the approximate log-normality of cumulative returns), small, equally weighted portfolios can be superior to the buy and hold portfolio (i.e. the capitalization weighted index) with high probability. Perhaps the most surprising result is the following:

- the CRSP data for 1976-2019 is used to generate blocks of 30 year returns. A portfolio picking 50 stocks at random, and rebalancing to equal weighting each month, beats the market (the capitalization weighted CRSP index) 96% of the time over 30 years.

Farago and Hjalmarsson (2023) emphasize that this non-intuitive result is largely due to the equal weight rebalancing effect. They use simulations based on simple assumptions to explain this result. This rebalancing effect essentially captures the mathematical benefits of the skewed distribution of stock returns. This effect was also studied in Forsyth (2024).

10 Conclusion

We consider a prototypical Canadian investor, with holdings spread amongst Canadian T-bills, Canadian and US capitalization weighted indexes. All returns are expressed in real (inflation adjusted) Canadian dollars.

Data series	Optimal expected block size $\hat{b}$ (months)
Can T-bill	48.4
Can CapWt	2.7
Can EqlWt	6.1
US CapWt	2.1
US EqlWt	4.3

TABLE A.1: *Optimal expected blocksize $\hat{b} = 1/v$ when the blocksize follows a geometric distribution $Pr(b = k) = (1 - v)^{k-1}v$. The algorithm in Patton et al. (2009) is used to determine $\hat{b}$. Data Source: CRSP and CFMRC, 1950:11-2024:12. All indexes are in CAD, inflation adjusted.*

Based on block bootstrap resampling simulations, for a Canadian investor, replacing a capitalization weighted Canadian stock index by an equal weighted Canadian stock index greatly improves total portfolio performance.

This outperformance can possibly be explained as follows:

- reduction of concentration: equal weight indexes can outperform capitalization weighted indexes due to reduction of the concentration effect (Farago and Hjalmarsson, 2023; Forsyth, 2024),
- low correlation: the comparatively low historical correlation between the Canadian equal weight index and the US capitalization weighted index,
- decades of poor US returns: the US capitalization weighted index, from the perspective of a Canadian investor has had very poor returns over two ten year periods, out of seven historical decades). The Canadian capitalization weighted index performs well during these bad times for US investments.

Appendix

A Bootstrap Resampling

As discussed in Section 5, a key parameter for the stationary block bootstrap algorithm is the expected blocksize. Using the algorithm in Patton et al. (2009), we can estimate the expected blocksize for each time series separately, as shown in Table A.1.

Informally, the expected blocksize corresponds to the average memory length of the time series. Short term bond returns are primarily driven by policies of central banks, which generally favour gradual changes to interest rates. We can see that the expected blocksize for T-bills, from Table A.1, is about 51 months, which is consistent with intuition. On the other hand, the expected blocksize for stocks, from Table A.1, is about 3 months, indicating that, stocks show a very short memory length, which is also consistent with intuition.

Since we draw the returns in blocks simultaneously for all the time series, using a single expected blocksize, it is not clear how to estimate the blocksize for this use case. Fortunately, the results are insensitive to a wide range of expected blocksizes. This is shown in Figure A.1. On the basis of Table A.1 and Figure A.1 we use an expected blocksize of one year.

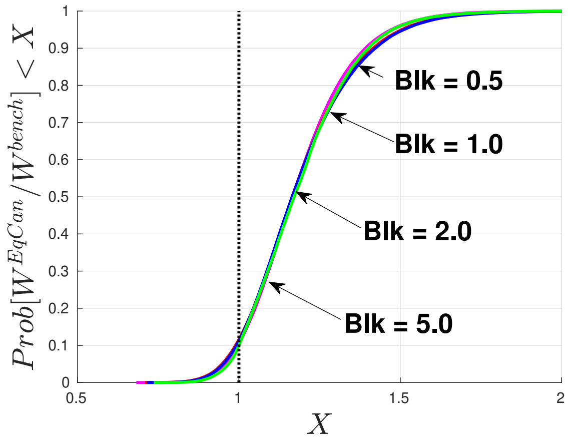


FIGURE A.1: *CDF for $(W_T^{EqCan}/W_T^{bench})$ at $T = 10$ years. This is a pathwise performance measure. EqCan outperforms the benchmark, along each path, if $(W_T^{EqCan}/W_T^{bench}) > 1$. Effect of different blocksizes, Blk is the expected blocksize in years for the stationary block bootstrap resampling method. Note that CDF curves with different blocksizes essentially overlap. $\Omega(1)$ is the ratio of the upside area to the downside area. Asset weights in Table 4.1. Scenario in Table 4.2. Data Source: CRSP and CFMRC, 1950:11-2024:12. 10^5 stationary block bootstrap simulations, expected blocksize one year. All results are in real (inflation adjusted) CAD.*

B Effect of extra costs for the Equal Weight Canadian Index

In this Appendix, we examine the effect of accounting for possible extra costs and fees associated with the Can EqlWt index. Suppose we are given an historical simple return over the period $t_i \rightarrow t_{i+1}$, denoted by R_i. Then, if the asset value at time t_i is denoted by S_i, we have that

$$\frac{S_{i+1}}{S_i} = (1 + R_i) \ . \tag{B.1}$$

In order take into account extra costs, we modify equation (B.1)

$$\frac{S^m_{i+1}}{S^m_i} = (1 + R_i)e^{-C\Delta t} \tag{B.2}$$

$$\Delta t = t_{i+1} - t_i \ , \tag{B.3}$$

where C is the annualized cost, and S_i^m is the modified asset value at time t_i.

Table B.1 shows the effect of different choices for the cost C on the summary statistics for $(W_T^{EqCan}/W_T^{bench})$. Even assuming that $C = 100$ *bps* still results in EqCan signifcently outperforming the Benchmark. Plots of the CDF curves of $(W_T^{EqCan}/W_T^{bench})$ for various values of C are shown in Figure B.1. Comparing the CDFs for W_T^{EqCan} and W_T^{bench} (not shown) for $C = 100$ *bps* continue to show that EqCan stochastically dominates the Benchmark.

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$E[(W_T^E/W_T^b)]$	(W_T^E/W_T^b) Median	(W_T^E/W_T^b) 5^{th} percentile	(W_T^E/W_T^b) 95^{th} percentile	ES(5%)	Omega (L=1)
No Reduction					
1.1880	1.1655	0.9479	1.5041	0.9035	30.41
Reduction: 50bps					
1.1666	1.1446	0.9317	1.4759	0.8884	20.57
Reduction: 100bps					
1.1457	1.1242	0.9158	1.4482	0.8734	14.06

TABLE B.1: *Statistics for* $(W_T^E/W_T^b) = (W_T^{EqCan}/W_T^{bench})$ *at* $T = 10$ *years. Effect of artificially reducing the historical annualized return of the the Can EqlWt index. ES(5%) is the mean of the worst 5% of the outcomes of* (W^{EqCan}/W^{bench})*. The Omega ratio for* (W^{EqCan}/W^{bench}) *is defined in equation (7.1). Asset weights in Table 4.1). Scenario in Table 4.2. Data Source: CRSP and CFMRC, 1950:11-2024:12.* 10^5 *stationary block bootstrap simulations, expected blocksize one year. All results are in real (inflation adjusted) CAD.*

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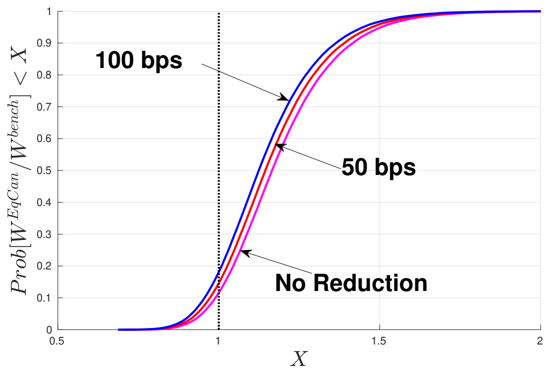

FIGURE B.1: *CDF for* $(W_T^{EqCan}/W_T^{bench})$ *at* $T = 10$ *years. This is a pathwise performance measure. EqCan outperforms the benchmark, along each path, if* $(W_T^{EqCan}/W_T^{bench}) > 1$*. Effect of artificially reducing the historical annualized return of the the Can EqlWt index. Annualized reduction in bps shown on figure. The CDFs correspond to Table B.1a. Asset weights in Table 4.1). Scenario in Table 4.2. Data Source: CRSP and CFMRC, 1950:11-2024:12.* 10^5 *stationary block bootstrap simulations, expected blocksize one year. All results are in real (inflation adjusted) CAD.*

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