BI Norwegian Business School - campus Oslo

GRA 19703

Master Thesis

Thesis Master of Science

Do stocks outperform Treasury bills?

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Start: 15.01.2019 09.00

Finish: 01.07.2019 12.00

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Do stocks outperform Treasury bills?

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Hand-in-Date:

July 1, 2019

Program: Master of Science in Business

Major in Finance

Acknowledgement

This thesis marks the end of my masters degree study at BI. I would like to thank my supervisor Paul Ehling and Michael Soukup for the support and guidance throughout the thesis.

Abstract

This thesis highlights the important role of positively skewed short horizon stock returns, and the effect of compounding on the long-term return distribution. I show that the majority of individual common stocks deliver a lifetime buy-and-hold return less than the accumulated one-month Treasury bill rate over matched horizons, and that they often are negative - *the results help explain why poorly diversified active strategies often will underperform market averages.*

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1 Introduction

Mehra and Prescott (1985) where the first to draw attention to the magnitude of equity premium and a dozens of papers has since then explored what is later referenced as the *"equity premium puzzle"*. Evidence that stock market returns outperforms risk-less returns in the long run is based on broadly diversified stock portfolios. The general recommendation, as Sharpe (1970) once stated:

if markets is efficient and investors are privy to no special information or predictive power, what should he do? First, and most important: diversify.

This thesis is focused on returns of individual stocks - borrowing the method of Bessembinder (2018). I rely on the database of *Center for Research in security prices* (CRSP), assessing monthly common stock returns, listed on NYSE, AMEX, and Nasdaq exchanges between July 1926 to November 2018. The data consist of 25,900 companies, each with their own unique ID number (*PERMCO*), whereby some have multiple share classes (*PERMNO* = 26,544), which I refer to as stocks.

While other studies have focused on the skewness in short horizon, such as Simkowitz and Beedles (1978), finding that positively skewed stock returns decreases with diversification. I instead focus on what Bessembinder (2018) first brought up, namely, the magnitude and consequence of positively skewed mean monthly returns when compounded over longer horizons. I demonstrate how positively skewed monthly stock returns propagates into the distribution of long-term returns when compounded over extended periods, and show how this affect the stocks performance - comparing them to various benchmarks.

I find that the majority of monthly stock returns contained in CRSP's database underperforme one-month Treasury bill rate over matched horizons, while more than half fails to deliver positive returns. The results shows that the Individual stocks' return distribution is positively skewed (12.48) and that the distribution skewness increase with the length of compounding. For instance, at the lifetime buy-and-hold horizon, the skewness is 150.34, while the median is negative - implying that the midpoint of the return distribution is negative, thus an increased probability to obtain negative returns when less diversified, although there are a few but extremely large returns. Moreover, the results shows that the majority of individual common stocks deliver a lifetime buy-and-hold return (inclusive dividends) below one-month Treasury rate over matched horizon, and slightly less than half provide with positive returns. The most frequent lifetime buy-and-hold return outcome is a loss of 100% (when rounded to the nearest 5%).

Since the stocks' median lifespan is rather short (seven-and-a-half years), I asses the long-term performance by conducting a bootstrap simulation. A single-stock strategy, whereby one stock is selected at random each month from 1926 to 2018, and linked over the full 92 years - repeated 20.000 times. The obtained distribution shows possible outcomes and are compared to various benchmarks. I find that the single-stock strategy fails to exceed the value-weighted return by 96.38% of the time (not including fees and transaction costs) and underperform one-month Treasury bill rate by 73.37% of the time. Slightly more than half deliverers negative returns, implying that the observed positive mean excess returns for the broad equity portfolios is actually attributable to relatively few stocks.

I asses to what extent wealth creation is concentrated by measuring the individual stocks wealth creation compared to the aggregate wealth creation in US public stock market. Wealth creation is defined as the accumulated return in excess to what is earned if the invested capital instead had earned one-month Treasury bill rate. The result shows that the accumulated lifetime wealth generated for shareholders since July 1926 to November 2018, by the 25,900 firms, is $34.8 trillion. Whereby five firms (Apple, Microsoft, Exxon, Amazon, and Alphabet) account for slightly more than 10% of the wealth created. The top-performing 85 firms, or 0.33% of 25,900 firms, collectively accounts for slightly more than 50% of the wealth creation. In fact, the top-performing 4.41% firms, collectively accounts for all the net wealth creation accumulated in the US stock market since 1926, while the remaining 95.59% firms generated wealth less than one-month Treasury interest rate.

In spite that most stocks generated negative lifetime excess returns, the results need not to be conflicting with the implication of standard asset pricing models - assuming that investors are risk-averse. These models emphasize a positive mean expected return, while the results obtained imply a negative median excess return.

Thus the results rather challenge the assumption that most individual stocks generates positive time series excess returns, highlighting the consequence of positively skewed monthly stock returns and how this affect the probability distribution of returns when compounded over longer horizons.

The results obtained highlights the fact that non-diversified portfolios in addition to have higher variance, carry a higher risk of failing to include the few stocks that generate large enough returns to enhance more modest or offset negative returns. Moreover, measures of performance, such as mean, portfolio variance, and Sharpe ratio are often based on the assumptions that returns are normally distributed. While it might hold for shorter horizons, my results show that the distribution is positively skewed for longer horizon returns.

Moreover, the results show that stocks entering CRSP's database in more recent decades, tend to underperforme one-month Treasury bill rates more frequently over their lifetime than prior decades. The findings are consistent with Fama and French (2004) who show that an increase of new listings post 1979, due to increased supply of equity, allowed for more risky stocks with higher asset growth and lower profitability to list - causing a sharp decline in survival rates. Others studies with complementing findings is Noe an Parker's (2005) "winner take all", associated with the internet economy, and Gullron et al. (2018), finding a more concentrated industry followed by abnormally large returns for those who succeed in recent years.

Early stage investments, such as venture capital is typically more risky and skewed, they often deliver negative returns, while a few generates large returns. However, these characteristics is not only confined to pre-Initial Offering investments, but also to the return distribution of longer term returns to investments in public equity - particularly smaller firms and firms listed in recent decades.

2 Literature review

In this section I present the literature connected to my research question, namely, ”Do stocks outperform Treasury bills?”. I start by presenting the research by Bessembinder (2018), highlighting the importance of positively skewed monthly stock returns, followed by a brief presentation of other contributions in the field.

2.1 Skewed distribution of returns

Borrowing the method from Bessembinder (2018), my results show the same trends as his results. He found that most stocks generated lifetime buy-and-hold returns less than what is earned by holding one-month US Treasury bills or value-weighted returns over matched horizons, implying that the positive mean excess returns observed for broad equity portfolios are attributable to relative few stocks. He argued that by holding a large enough portfolio, the small percentage of stocks with huge returns is enough to offset more frequent and negative returns - as my results supports. Moreover, Bessembinder (2018) emphasized the effect of compounding on skewed monthly stock returns, highlighting how this affect the distribution of stock returns in the long-term. His results help explain why poorly diversified active strategies most often lead to returns below market averages, and highlights the trade-off between the probability of large returns and increased risk of failing to exceed market averages, when the investor holds less diversified portfolios. Following Banz’s (1981) empirical study, suggesting that small firms provide higher risk adjusted returns, on average, compared to large firms - commonly known as *”The Small Firm Effect”*. One would anticipate that individual stocks would outperform the value weighted market more often. However, both Bessembinder (2018) and I obtained results suggesting that the single-stock strategy more frequently fails to exceed value-weighted market returns and one-month Treasury bill rate over the full period from 1926-2016 and 1926-2018.

Although diversification is supported by a wide range of studies and by the Capital asset pricing model (CAPM) of Sharpe (1970), Lintner (1965), and Mossin (1966), others has shown that diversification is not necessarily desirable for all investors. Simkowitz and Beedles (1978) found that investors holds less than perfectly diversified portfolios, a phenomenon contradicting with the frequently shared advice.

Moreover, they argued that if positive skewness is a desirable characteristic of return distributions, then diversification which destroys skew, can help explain why investors do not perfectly diversify. The contradiction might be the result of the inadequacy of the traditional two-parameter framework (CAPM model). Even in a perfect frictionless market, Simkowitz and Beedles (1978) found that for some investors, the exact number of assets they should hold in their portfolio is a function of each individual's skewness/variance awareness. Those more concerned with skewness should hold relatively small (large) number of assets in their portfolios.

In addition to Simkowitz and Beedles (1978) contribution, others such as Krauss and Litzenberger (1976) found empirical evidence suggesting that investors have an aversion to variance and a preference for skewness. The findings support more recent experimental evidence that most individuals have concave utility functions, displaying decreasing absolute risk aversion (Gordon, Paradis, & Rorke, 1972). Suggesting that prior empirical findings of Friend and Blume (1970), Black, Jensen and Scholes (1972) and Fama and MacBeth (1973), interpreted as inconsistent with the traditional theory can be attributed to misspecification of the CAPM by omission of systematic (nondiversifiable) skewness. The model by Krauss and Litzenberger (1976) imply a negative return premium for the cowskewness of stock returns with market returns. Barberis and Huang (2008) studied the pricing implications of cumulative prospect theory - paying particular attention to its probability weighting component. They found that cumulative prospect theory indeed have a novel prediction, namely that the asset's own skewness can be priced. Thus, a positive skewed security can be "overpriced" and earn a negative average excess return. Said differently, firm-specific skewness imply negative return premium.

3 Data

The study relies on the database of *Center for Research in Security Prices* (CRSP), gathered from *Wharton Research Data Services* (WRDS) (2016, accessed January 5, 2019), and the database of Kenneth R. French (2016, accessed January 5, 2019). While the former provides data of common stock returns listed on NYSE, Amex, and Nasdaq exchange, the latter contains data of US Treasury Bill (TB) returns. The frequency of the datasets is at monthly basis and over matched horizon ranging from July 1926 to November 2018.

3.1 Common Stock Returns and Treasury Bill Return

The returns gathered from WRDS is specified as *Common Stock Return* using share code (SHRCD): 10, 11, and 12, where the first digit indicates ordinary common shares and the second digit refers to whether they where further defined or not. In addition to the stocks' SHRCD, I include the stocks' company name (COMNAM), share class (PERMNO), company ID (PERMCO), price (PRC), return (RET), shares outstanding (SHROUT), delisting code (DLSTDCD), delisting return (DLRET), date (ym), value weighted return (vwretd), and equal weighted return (ewretd). The RETs includes dividend payments, thus, total stock return from one month to the next is given as follow:

$$\text{Total Stock Return} = \frac{P_1 - P_0 + D}{P_0}$$

Where P_0 is the price at time zero (buy price), P_1 is the price a month from now (sell price), and D is the dividend (if any) in this period.

3.1.1 Cleaning and merging of Common Stock Returns and Treasury Bills

Six minor changes and a assumption was made before running the models; (1) whenever DELRET and RET is present, I compute the return as follow: $(1 + RET_t) * (1 + DELRET_t)$. On occasions when RET is missing and DLRET is present, RET is replaced using DLRET, (2) due to missing prices, an average of the bid/ask price for the trading day is given by CRSP's database - marked with a minus sign (-). Because of this, I take the absolute value of all prices, (3) where price is missing I use the previous price multiplied by RET, $(P_{t-1}) * (1 + RET_t)$, and if they are both missing, I simply use the previous price, assuming no changes, (4) Since one-month TB return is given in percentage-point, I divide TB return by 100 to match the given percentage level from CRSP, and merge the two datasets by date, (5) the excess return (exret) is computed as the difference between RET and TB rate, $RET_t - TB$, (6) market capitalization (mktcap) is computed as, $PRC_t * SHROUT/1000$ (change of unit). The *mktcap* is then lagged, replacing all first entries of PERMNOs with NaNs, such that the previous PERMNO's mktcap is not mistakenly used for the next PERMNO in the data set.

4 Methodology

To answer the research question, I examine individual stocks' performance over various horizons and provide with an in depth understanding of their performance by resampling the obtained data covering the period from 1926-2018. I reveal the actual gain or loss for hypothetical investors who reinvest dividends but otherwise do not alter their position, and compare the results to holding one-month Treasury bill over matched horizon - as well as other market benchmarks. The statistics used is relative basic - mean, median, standard deviation and skeweness, whereby a detailed description of the computations and its interpretation can be found in the appendix, along with the descriptions of the resampling method (exhibit 2). Moreover, a benchmark case is made, showing multiple hypothetical return distribution metrics, using a constant mean (0.5%) and standard deviations ranging from 0-20% - identical and independent distributed. Inferences on actual return performance is made using 6 different samples: starting with (1) all individual common stocks that has appeared in CRSP's database since 1926 to 2018, (2) by the stocksfinal listing status - i.e., still trading, merged/exchanged/or liquidated, and delisted by exchange, (3) all stocks distributed into ten equal-sized buckets (bins) based on their market capitalization, (4) sample based on decade of initial appearance, (5) bootstrapped Stock return - showing performance of a single-stock strategy, as well as value-weighted portfolios, showing performance under various diversification range, and lastly, (6) individual stocks' lifetime wealth creation since 1926.

5 Results

The section is divided into 7 separate but connected statistical studies: 1) benchmark case, (2) buy-and-hold returns of individual common stocks over various horizons, (3) Lifetime buy-and-hold, by the stocks' final listing status, (4) Lifetime buy-and-hold returns - sorted by market capitalization, (5) Lifetime buy-an-hold returns, by decade of stocks' initial appearance, (6) Bootstrapped portfolio returns - selected at random each month, and finally, (7) Aggregate wealth creation.

5.1 Benchmark case

Table 1 displays metrics presenting the distribution of single-period excess returns that are distributed log-normally. The draws are from a constant distribution, i.e., the returns are independent and identical distributed across time, with a mean of 0.5%. I simulate investment horizons of one, five, and ten years, with standard deviations (SD) ranging from 0-20%.

Standard Deviation of monthly returns	0.00%	2.00%	4.00%	6.00%	8.00%	10.00%	12.00%	14.00%	16.00%	18.00%	20.00%
Horizon (years)	Panel A: skewness of buy-and-hold returns										
1	0.00	0.188	0.344	0.556	0.778	0.959	1.272	1.455	1.815	1.882	2.253
5	0.00	0.439	0.935	1.418	2.185	3.504	4.3	6.594	7.62	7.926	11.183
10	0.00	0.678	1.428	2.156	3.715	5.543	13.321	15.835	35.286	75.168	69.499
	Panel B: Median of buy-and-hold returns										
1	6.2%	6.0%	5.3%	4.4%	2.5%	0.7%	-1.8%	-5.9%	-7.5%	-12.1%	-15.9%
5	34.9%	33.4%	28.9%	21.0%	12.3%	0.2%	-11.8%	-25.3%	-38.5%	-51.4%	-61.4%
10	81.9%	77.7%	66.2%	49.7%	27.8%	3.6%	-23.1%	-44.4%	-61.4%	-75%	-85.5%
	Panel C: Percentage of buy-and-hold returns that are positive										
1	100%	80.3%	64.7%	58.3%	53.5%	50.5%	48.3%	44.9%	44.4%	42.5%	40.5%
5	100%	96.9%	79.7%	66.2%	57.0%	50.1%	44.4%	39.6%	34.9%	30.7%	28.1%
10	100%	99.6%	87.5%	72.5%	61.2%	51.3%	42.0%	35.4%	29.6%	24.2%	20.2%
	Panel D: Ninety-ninth percentile buy-and-hold return										
1	6.2%	24.4%	44.5%	66.8%	92.1%	119.3%	151.8%	182.4%	227.4%	257.3%	298.2%
5	34.9%	89.2%	164.1%	241.6%	363.7%	522.2%	642.2%	835.8%	967.9%	1187.4%	1358.1%
10	81.9%	193.9%	362.5%	577.1%	827.2%	1170.3%	1563.5%	2106.3%	1899.0%	2424.3%	2640.8%

Table 1: Benchmark: multi-period returns, when single-period returns are distributed normally

From the left column in ***Panel A*** one can observe that riskless returns, i.e., returns with $\sigma = 0$, have a skewness of zero and that the skewness is positive at an increasing rate as we move over to more risky returns. As risk and compounding horizon increase, the more skewness is induced into the distribution. For instance, when risk is modest, i.e., $\sigma = 0.02$, the skewness range from 0.188 at the one-year horizon to 0.678 at the ten-year horizon, implying that skewness is proportional to the square root of the number of elapsed periods. Furthermore, when risk is high, i.e., $\sigma = 0.20$, the skewness range from 2.253 at the one-year horizon, to 69.499 at the ten-year horizon. As explained in appendix (exhibit 2.2.1), the increase in skewness is associated with a median return which is less than the mean buy-and-hold return. A study by Fama and French (2018) shows similar results, using monthly US stock market returns ranging from 1926-2016. They found a skewness of 0.16 at the monthly horizon, compared to 6.11 at the 30-year horizon.

The results obtained in ***Panel B*** shows that the median buy-and-hold return at the annual horizon is declining at a monotonic rate as the returns are getting more risky. Going from no risk, $\sigma = 0\%$, to moderate risk, $\sigma = 10\%$, and high risk, $\sigma = 20\%$, the median declines from 6.2% to 0.7% and -15.9%, respectively. The same trend can be observed for the five-years buy-and-hold: when there is no risk, the median is 34.9%, compared to when there is some risk, the median is 0.2%, and when returns are risky, the median is -51.4%. At the decade buy-and-hold horizon, the median is 81.9% when there is no risk, 3.6% when there is some risk, and -85.5% when the risk is high.

The effect of skewness is further translated into ***Panel c***; when returns are risky but at a low rate ($0 \leq \sigma \leq 4\%$), the percentage of positive returns are increasing with the time of compounding and close to 100%. This is due to the impact of mean excess return (expected monthly stock return of 0.5%) that has a grater effect than the skewness induced by compounding for shorter periods. For instance, when $\sigma = 4\%$, one can observe that the percentage of positive returns increase from 64.7% at the one-year horizon, to 87.5% at the ten-year horizon. However, this effect decreases with higher risk. For instance, the turning-point in this case is when $\sigma > 10\%$. When $\sigma = 12\%$, we can observe that the percentage of positive returns reduces from 48.3% at the one-year horizon, to 42.0% at the ten-year horizon.

Panel D presents the 99th percentile buy-and-hold returns at the extremes. The results obtained shows a trend, at each horizon, the 99-percentile return is increasing with a higher risk (σ) and the time of compounding. For instance, at the annual and ten-year buy-and-hold horizon, when σ is 2%, 10% or 20%, the 99th percentile buy-and-hold return is 24.4%, 119.3%, and 298.2% at the annual horizon, compared to 193.9%, 1170.3%, and 2640.8% at the decade horizon.

The results obtained in table 1 imply that when risk is low ($\sigma < 12\%$), the median is positive and increasing with the time of compounding. However, as risk increase ($\sigma \geq 12\%$) the magnitude of return variation and compounding affect the median in the opposite direction. The median change sign and become increasingly negative as the compounding horizon extends. The effect of riskiness and compounding can be observed by the distribution skewness, holding the horizon constant while the riskiness increase and when the time of compounding (horizon) increase while holding the risk constant, both affects the distribution skewness positively. Thus, when risk is high, the effect of skewness induced by compounding has an greater effect than the accumulated effect of positive mean. The decline in median return at each horizon when risk is high, is offset by only a small probability of increasingly large returns, thus the rate of positive returns drops.

5.2 Buy-and-hold over various horizons

The results presented in ***Table 2*** include all individual common stocks that has appeared in CRSP's database since July 1926 to November 2018. I report returns of monthly, annual, decade and lifetime by the arithmetic mean, buy-and-hold mean, and geometric mean - as well as the distribution median, standard deviation, and skewness. The individual stock returns are compared to zero and to holding one-month Treasury bill interest rate, value-weighted, and equal-weighted market returns over matched periods. Annual and decade investment horizons are based on full calendar periods starting from January (or first appearance) to December (or delisting) the following year or decade. Stocks that pertain to shorter period are included to avoid survivorship bias and are equally compared to the benchmarks. The pooled distribution of monthly stock returns reflect both time series and cross sectional variation.

Panel A: Individual stocks, monthly horizon (N=3,671,121)					
Variable	Mean	Median	SD	Skewness	%Positive
BH Return, T-bill	0.0037	0.0039	0.0026	0.6529	92.7%
BH Return, stock	0.0112	0.0000	0.1821	12.484	48.49%
	%>T-bill		%>VW Mkt return		%>EW Mkt return
BH Return, stock	47.82%%		46.28%		45.85%
Panel B: Individual stocks, annual horizon (N=324,800)					
Variable	Mean	Median	SD	Skewness	%Positive
Sum stock Return	0.1266	0.1188	0.6225	3.0073	62.80%
BH Return, T-bill	0.0424	0.0439	0.0319	0.6612	96.63%
BH Return, stock	0.1477	0.0527	0.8242	20.6493	55.79%
Geometric Return, stock	-0.0025	0.0049	0.0796	4.1715	55.79%
	%>T-bill		%>VW Mkt return		%>EW Mkt return
BH Return, stock	51.7%		44.46%		42.42%
Panel C: Individual stocks, decade horizon (N=62,020)					
Variable	Mean	Median	SD	Skewness	%Positive
Sum stock Return	0.7509	0.6493	1.5056	1.1758	73.99%
BH Return, T-bill	0.3075	0.1652	0.3586	1.8808	99.15%
BH Return, stock	1.2453	0.1759	5.4303	21.2211	57.05%
Geometric Return, stock	-0.015	0.0036	0.0994	-7.0273	57.05%
	%>T-bill		%>VW Mkt return		%>EW Mkt return
BH Return, stock	50.68%		37.67%		33.97%
Panel D: Individual stocks, lifetime horizon (N=26,544)					
Variable	Mean	Median	SD	Skewness	%Positive
Sum stock Return	1.5448	1.033	2.8542	1.371	71.32%
BH Return, T-bill	1.1125	0.3374	2.281	4.2052	99.83%
BH Return, stock	187.1552	-0.03	13462.634	150.3424	49.35%
Geometric Return, stock	-0.031	-0.0004	0.1278	-6.3162	49.35%
	%>T-bill		%>VW Mkt return		%>EW Mkt return
BH Return, stock	42.5%%		30.72%		25.96%

Table 2: CRSP common stock returns at various horizons

Panel A reports the statistics of the pooled distribution, consisting of 3,671,121 monthly stock returns (RET). The result shows that the mean monthly stock return (1.12%) is slightly larger than the mean monthly Treasury bill (TB) return (0.37%). Compared to the benchmarks, the slight majority (51.51%) of the monthly stock returns provide a negative return and only 47.82% delivers a return that exceeds the one-month TB rate. Moreover, it is noteworthy that the stocks' monthly returns are highly variable, with $\sigma = 18.21\%$ and a skewness of 12.484 implying a few but large outliers to the right side of the distribution. Before including the delisting returns (DLRET), the skewness of RETs was found to be 6.44, compared to 12.84 after including DLRET (see appendix: exhibit 1, for detailed description). I find this observation surprising because Bessembinder (2018) obtained a skewness of 6.96, close to mine before including the DLRET. To my knowledge, we differentiate only in terms of the size of the sample, whereby his results rely on the CRSP database from July 1926 to December 2016 - two years less than my sample. Further investigation points at several extreme return events, caused by extreme DELRETs and thus a high positive skewness (exhibit 1: table 9). For instance, two of the most extreme DELRETs are 4700% and 3176.4%, respectively. On one hand, including these extreme DLRETs will affect the skewness greatly, but on the other hand, an exclusion might induce biases to the probability distribution of monthly stock returns. I consider the extreme return events as relevant and important to this study, thus I will continue with the inclusion of all DLRETs .

Panel B and C, reports the summary statistics of annual and decade horizon. The total number of buy-and-hold returns (N) obtained in the annual distribution is 324,800, whereas decade distribution contains 62,020 decade buy-and-hold returns. As demonstrated in table 1 (*Benchmark case*), a variation of 18.21% at the monthly horizon should induce a higher skewness into the distribution of buy-and-hold returns as the time of compounding increase. This seems to be the case, the skewness increase considerably from monthly to annual buy-and-hold horizon. However, to my surprise, the difference between annual buy-and-hold skewness (20.65) and decade buy-and-hold skewness (21.22) is small. An examination of the median lifetime, reveals that at least half of the CRSP common stocks have a lifetime, less than, or equal to 7.5 years - some new listings others delisted within these years. Thus, the relative shy increase in skewness, compared to the *Benchmark case*, is attributable to the time of compounding. Moreover, the mean and median of buy-and-hold returns is 14.77% and 5.27% at the annual horizon, and 124.53% and 17.59% at the decade horizon. The rate of positive buy-and-hold returns at the annual horizon is 55.79% and 57.05% at the decade horizon. Moreover, only 51.7% of annual buy-and-hold return exceeds one-month TB and slightly less (50.68%) at the decade horizon.

In **Panel D** I report the lifetime returns of 26,544 stocks, starting from July 1926 (or first appearance) to December 2018 (or delisting month and year). The lifetime mean of buy-and-hold return is $18,715.52\%$, whereas the arithmetic mean is 154.48%. The effect of compounding can be observed both in the median and the skewness. The lifetime buy-and-hold median and skewness is -3.0% and 150.342, compared to the sum-median and skewness of 103.3% and 1.371. The percentage delivering positive returns are 71.32% by sum returns and 49.35% by buy-and-hold returns. Moreover, only 42.5% buy-and-hold returns outperforms one-moth TB bill and a even lower rate (30.72%) exceeds value-weighted market average.

Returns obtained in panel B, C and D are plotted into a frequency distribution ranging from -100% to 5000%. Returns do not exceed -100% because investors have limited liability. At the annual horizon, returns are rounded to the nearest 2%, whereas for decade and lifetime returns it is rounded to the nearest 5%.

The most frequent observation in ***Figure 1*** is returns of 0%, followed up by smaller but approximately equal-sized spikes at -100% and 100%. The skewness can be observed as the line stretching far out to the right, where there are numerous, but not very frequent observations above 100%. Extending the buy-and-hold horizon to decade, ***Figure 2*** reports that the most frequent return observation is -100%, followed up by smaller spikes at approximately -50%, 0%, and 100%. The results

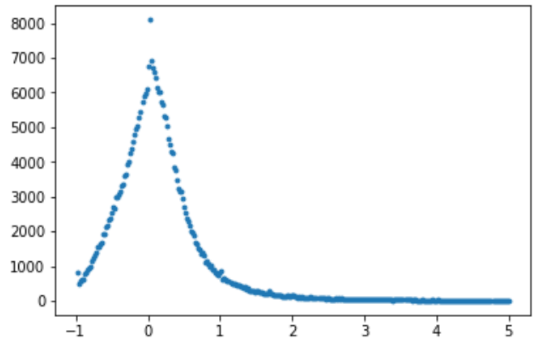

Figure 1: Annual BH (rounded to .02)

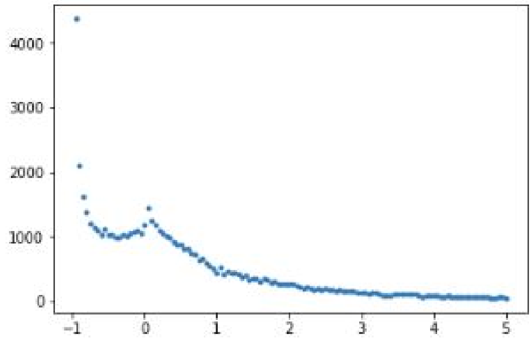

Figure 2: Decade BH (rounded to .05)

indicate that 0% return occurs more frequent than the other two spikes and the distribution appears to be asymmetric compared to the normal distribution. ***Figure 3*** shows similar trends, but with only one peak - loss of 100%. The distribution is as expected, highly skewed, with a lot but

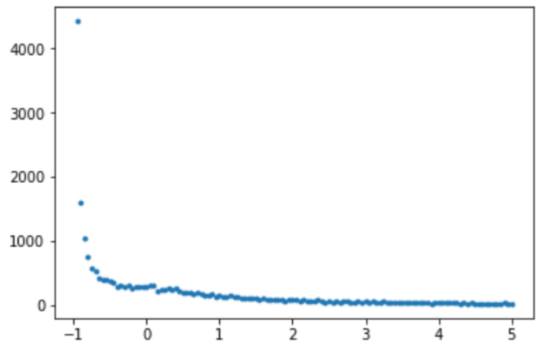

Figure 3: Lifetime BH (rounded to .05)

less frequent observations, stretching far out to the right. The results obtained in panel B, C and D match the results obtained in Table 1, *Benchmark case*. The high volatility and compounding of monthly stock returns induce positive skewness into the distribution of returns. The results obtained shows that at the lifetime horizon, the accumulated positive mean might give an overoptimistic expectation when the skew is high and the median negative. The dispersion between expected buy-and-hold return (mean) and actual performance of individual stocks, can be explained by the frequency of negative returns and the small percentage of stocks that delivers large returns - observed in figures above. To answer the question raised, *"Do stocks outperform Treasury bills?"*, the majority (57.5%) do not outperform TB returns over their lives and only 49.35% is positive. In fact, the reason that the broad stock market outperforms TB returns over longer horizons, is shown to be attributable to relatively few stocks that generates large enough returns to enhance moderate or offset slightly more frequent and negative returns.

5.3 Outcomes by delisting status

Table 3 presents the summary statistics of lifetime buy-and-hold returns for three different samples. The samples drawn are based on the individual stocks' delisting code (DLSTCD), thus enabling additional information tied to their listing status. The first of three digits indicates still active (1), merged/exchanged/or liquidated (2, 3, or 4), or delisted by exchange (5). Although stocks still active should have 1 as its first DLSTCD digit, none did with the exception of two stocks. Thus, I assume when otherwise is not indicated by the DLSTCD, the stocks is still active.

Panel A: Stocks that did not delist (N=4265)					
Variable	Mean	Median	SD	Skewness	%Positive
Sum stock Return	2.8810	1.9777	3.5084	1.033	81.76%
BH Return, stock	1044.9471	0.5761	33550.3949	60.3758	62.3%
Geometric Return, stock	-0.0036	0.0041	0.039	2.793	62.3%
	%>T-bill		%>VW Mkt return		%>EW Mkt return
BH Return, stock	57.85%		37.4%		34.65%
Panel B: Stocks that merged, exchanged, or liquidated (N=12,954)					
Variable	Mean	Median	SD	Skewness	%Positive
Sum stock Return	2.2952	1.6755	2.362	1.3782	91.42%
BH Return, stock	39.4686	1.0204	699.7204	59.5188	73.65%
Geometric Return, stock	0.0053	0.0076	0.0293	-10.0093	73.65%
	%>T-bill		%>VW Mkt return		%>EW Mkt return
BH Return, stock	63.14%		47.02%		38.79%
Panel C: Stocks delisted by exchange (N=9325)					
Variable	Mean	Median	SD	Skewness	%Positive
Sum stock Return	-0.1087	-0.4912	2.3401	2.7386	38.62%
BH Return, stock	-0.0137	-0.9205	20.2212	55.3266	9.67%
Geometric Return, stock	-0.0932	-0.0409	0.1964	-3.9675	9.67%
	%>T-bill		%>VW Mkt return		%>EW Mkt return
BH Return, stock	6.81%		5.03%		4.16%

Table 3: Lifetime buy-and-hold by final listing status

Panel A displays the statistics of lifetime returns, generated by 4,265 individual stocks assumed to be *still active*. The most desirable outcome is found within this group - a lifetime buy-and-hold mean of $104,494\%$. This might not come to any surprise, given that the sampled stocks most likely pertain to the majority of stocks which has contributed with the largest returns. The percentage of lifetime buy-and-hold that exceeds zero is 62.3%, while 57.85% exceeds the TB returns over the same horizon. The distribution skewness (60.38) is empirical important because while the mean is more than $100,000\%$, the median is considerably smaller, 57.61%. Thus, even for the still active sample, only the minority (34.65%) contribute with a buy-and-hold return exceeding the value weighted return.

Although panel A provides more desirable outcomes, a higher rate of outperformance to benchmarks is found in ***Panel B*** - firms that *merged/exchanged/ or liquidated*. The number of firms contained in this category is 12,954, and the results shows that almost 74% delivered a positive return, while 63% exceeds holding one-month TB over the same horizon. Moreover, 47% exceeded value weighted market return and almost 39% exceeded equal weighted return over the same period of time. The mean and median is $3,946\%$ and 102% (respectively), with a skewness of 59.52. The dispersion between mean and median is large but the distance between them are narrowed down compared to stocks still trading. A larger median imply that the probability of obtaining a positive return is greater but at the same time, a lower expected return due to lower volatility and skew.

The last panel, ***Panel C***, displays the summary statistics of 9,325 stocks - delisted by exchange. The buy-and-hold mean and median of these stocks are 1.37% and -92%,. Although the distribution skewness of buy-and-hold returns is smaller (55.33) compared to the prior panels, only 6.81% outperforms TB return, 5% exceeds value weighted average, and 4% exceeds equal weighted average. The poor performance is connected to the highly negative median, implying a greater amount of negative returns - Only 9.67% lifetime buy-and-hold returns exceeds zero.

Although *stocks still* trading provides the largest mean lifetime return, a higher rate of returns exceeding zero and other market averages are found with stocks that *merged/exchanged/or liquidated*. This did not come as a surprise, as being acquired is typically value-enhancing. Although the majority of stocks in both category provides lifetime buy-and-hold returns that exceeds one-month TB rates, they both fail to deliver returns exceeding market averages. As the result shows, the highest rate of underperfomance is attributable to stocks that delisted by exchange. However, the results are less applicable unless the investors are able to foresee the category a stock belong to in advance.

5.4 Outcomes by firmsize and decade of initial appearance

Table 4 presents the summary statistics of 26,544 stocks at the monthly, annual, and decade horizon. The stocks are divided into 10 equal-sized groups (firmsize) based on the stocks' market capitalization (mktcap), the month prior to the interval. The groups are displayed in an ascending order, i.e., I start with the smallest firmsize, preceding with increasingly large firmsizes. If the mktcap happened to be *NaN*, the next and first available *mktcap* is used to determine the stock's firmsize. Lifetime performance is not examined due to the method used, i.e., a stock's mktcap at the time of listing cannot provide reliable data about its future (long-term) performance.

Panel A: Individual stocks, monthly horizon							
Group (market cap)	Mean	Median	Skewness	%>0	%>T-bill	%>VW return	%>EW return
1	0.04	-2.24e-07	7.073	44.51%	42.43%	42.8%	42.45%
2	0.0187	-5.33e-07	4.207	46.87%	44.73%	42.81%	42.36%
3	0.0179	-5.67e-08	11.675	48.62%	46.46%	43.71%	43.12%
4	0.02	1.00e-07	29.113	50.19%	48.03%	44%.83	44.09%
5	0.0203	0.003	5.682	51.35%	49.25%	45.59%	44.93%
6	0.0208	0.009	2.04	52.7%	50.56%	46.59%	45.83%
7	0.0215	0.0119	2.173	53.76%	51.54%	47.44%	46.52%
8	0.0221	0.0157	1.343	55.31%	53.00%	48.51%	47.51%
9	0.0216	0.0183	1.187	56.6%	54.11%	49.18%	48.14%
10	0.0197	0.0188	0.0683	57.62%	54.82%	49.02%	48.22%
Panel B: Individual stocks, annual horizon							
Group (market cap)	Mean	Median	Skewness	%>0	%>T-bill	%>VW return	%>EW return
1	0.246	-7.54e-07	16.22	48.4%	45.18%	41.53%	39.87%
2	0.17	7.24e-07	29.532	50.37%	47.11%	41.44%	39.75%
3	0.141	0.014	14.734	51.51%	48.08%	42.02%	40.28%
4	0.141	0.029	8.361	53.2%	49.51%	43.18%	41.68%
5	0.1383	0.045	4.631	54.74%	51.07%	44.64%	42.3%
6	0.131	0.053	3.42	55.65%	51.86%	45.07%	42.8%
7	0.129	0.066	3.237	57.36%	53.28%	45.7%	43.56%
8	0.128	0.079	3.094	59.5%	54.92%	46.58%	44.19%
9	0.131	0.095	4.643	62.28%	57.29%	47.58%	45.12%
10	0.122	0.098	10.273	64.76%	58.54%	46.81%	44.64%
Panel C: Individual stocks, decade horizon							
Group (market cap)	Mean	Median	Skewness	%>0	%>T-bill	%>VW return	%>EW return
1	1.676	-0.161	19.0	44.25%	39.45%	30.42%	27.30%
2	1.321	-0.017	14.583	49.43%	43.94%	32.98%	29.77%
3	1.117	0.028	11.088	50.97%	45.33%	34.98%	31.45%
4	1.078	0.036	12.917	51.59%	46.17%	35.42%	32.9%
5	1.012	0.083	9.724	53.57%	47.89%	35.81%	33.16%
6	1.133	0.148	11.942	56.48%	50.46%	38.73%	35.55%
7	1.142	0.207	5.566	58.79%	52.3%	39.2%	36.15%
8	1.183	0.275	9.112	61.62%	55%	40.83%	37.31%
9	1.25	0.394	8.315	67.16%	59.35%	44.18%	38.87%
10	1.535	0.71	10.347	76.28%	66.72%	44.06%	37.28%

Table 4: Individual common stocks' buy-and-hold returns, sorted by firmsize

The results obtained in ***Panel A*** shows that the small firms delivers a larger mean monthly buy-and-hold return (4%) than big firms (1.97%). Moreover, the findings suggest that the small decile groups tend to be more positively skewed than the big decile groups and underperforms more frequently. The results might be anticipated based on prior simulations - small firms tend to have a higher return volatility, thus obtains more skewness when compounded. For instance, at the decade horizon (Panel C), the distribution skewness of small firms is 19.0 while the distribution skewness of big firms is 10.347. The higher return volatility of small firms and the effect of compounding impacts the distribution skewness in a more positive direction, consequently the result is that small firms underperforms more frequently. The majority (55.75%) of small firms fails to match zero and only 39.45% exceeds one-month TB rate. In contrast, the majority of big firms delivers a positive mean return (76.28%) and exceeds one-month TB rate (66.72%). Although the big decile group stocks is less skewed, the distribution skewness still manifest itself in the frequency of underperformance to the market averages. The percentage that outperforms value-weighted market returns are 49.02% at the monthly horizon, 46.81% at the annual horizon, and 44.06% at the decade horizon.

Stocks' lifetime buy-and-hold, by decade, is presented in ***Table 5***. The results obtained are based on the date of the stocks' initial appearance in the CRSP database through its delisting or end of sample (December 2018). The initial decade can be observed at the left column, right next to it, N, is the number of firms that entered the CRSP database during that decade. Note that the six moths in 1926 is assigned to the first decade, i.e., from 1927 to 1936, and the two years from 2017-2018 is assigned to the last decade, ranging from 2007 to 2016. The mean decade return is matched with zero, holding one-month TB and to other market averages.

Panel A: Lifetime buy-and-hold returns, by decade of initial appearance								
Initial Decade	N	Mean	Median	Skewness	%>0	%>T-bill	%>VWMkt return	%>EW return
1926-1936	915	4616.38	6.01	27.97	72.46%	67.43%	31.80%	10.27%
1937-1946	251	1170.83	28.81	7.45	91.63%	86.06%	44.22%	19.12%
1947-1956	249	419.78	13.96	8.38	91.16%	87.15%	39.76%	25.30%
1957-1966	1596	85.73	1.39	13.02	74.00%	61.53%	44.99%	28.45%
1967-1976	4475	28.38	0.56	15.92	60.38%	46.39%	42.64%	28.76%
1977-1986	5174	9.98	-0.51	41.34	39.39%	31.91%	21.14%	22.88%
1987-1996	6885	3.44	-0.24	17.43	45.30%	39.83%	26.58%	25.16%
1997-2006	4198	1.32	-0.48	50.44	40.38%	37.26%	28.85%	23.73%
2007-2018	2801	0.28	-0.10	7.32	44.45%	43.41%	31.88%	36.88%

Table 5: Lifetime buy-and-hold returns, by decade of initial appearance

The earliest decade (1926-1936) include 915 stocks that either where already listed at the initiation of CRSP coverage, or, listed during the decade. Over the next 20 years, only 500 stocks entered the CRSP common stock database, followed by 1,596 stocks during 1957-1966. The results shows a significant jump in entries during 1967-1976, a total of 4,475 stocks entered the database, whereby 2,828 is attributable to the inclusion of Nasdaq stocks in the CRSP database. Fama and French (2004) connected the increase in number of entries during 1980-2001 to the increased supply of equity capital. Suggesting that a lower cost of capital allowed weaker firms and firms with more distant expected payoffs to enter the public equity market. The cross-section profit became negatively skewed, while asset growth positively skewed (Fama & French, 2004). Moreover, they reported a sharp decline in survival rates, finding no trends for mergers during this period, Fama and French (2004) believed that it could be connected with poor performance by the newly listed stocks. They argued that higher return dispersion is attributable to increased dispersion of profitability and growth - a consequence of increased skewness connected to the flood of small new lists in the decades post 1979.

Although they did not report on mean or standard deviation of returns, my results shows an increase in return skewness during 1977-1986. From 15.92 the decade prior, to 41.34 during 1977-1986, then a slight drop to 17.43 during 1987-1996, before a significant increases to 50.44 during 1997-2006. The findings supports the argument of Fama and French (2004), showing a clear increase in positive skewness accompanied by a negative median. During 1977-1986, the median is -51%, the following decade -24%, and lastly during 1997-2006 a median of -48%. For comparison, the decades prior provided the smallest median, 56%, during 1967-1976 and the biggest median, 2881%, during 1937-1946. Moreover, the majority failed to outperform both value-weighted and equal-weighted market returns over their lifetime. The worst performing decade was during 1977-1986, with its 21.14% above value-weighted average and best performance during 1957-1966, 44.99%. Compared to equal-weighted average, the best performing decade was during 2007-2018, with its 36.88%, and the worst performance, 10.27% during 1926-1936. Examining the performance compared to one-month Treasury Bill, the underperformance is attributable to the stocks that entered the CRSP database after 1976. The decades prior to 1977 contributed with returns largely above 50% with the exception of 46.39% during 1967-1976. The decades after contributed with only, 31.91% during 1977-1986, 39.83% during 1987-1996, 28.85% during 1997-2006, and 36.88% during 2007-2008.

The fact that the median return is negative for decades following 1977, can be connected to the changes in characteristics of the firms brought to the public equity market in more recent decades, accompanied by a sharp decline in survival rates. The flood of small firms entering the equity stock market post-1977 is contained in the top five groups. The results shows that the positive distribution skewness of individual stock return pertains to all decile groups, however smaller firms tend to underperform benchmarks more frequently.

5.5 Bootstrapped portfolio simulations

The CRSP dataset contains return of 26,544 stocks pertaining to 92 calendar years, from 1926-2018. However, the lifetime of individual common stocks tend to be considerably shorter. The results obtained shows that the median life span of a common stock is only 7.5 years, while the 90th percentile life span is 28 years - only 38 stocks where present under the full 92 years (Appendix: exhibit 2.2.7.1). Thus, to obtain evidence of long-term performance I adopted a bootstrap simulation, a procedure where one or more stocks are picked at random each month over the full 92 years and linked together by 1-year, 10-year, life (92-year). For annual and decade, I repeated the procedure 5000 times, whereas for lifetime I repeated the procedure 20,000 times. The process provides me with a large enough return distribution of possible outcomes, yielding an average close to the expected value, following the *Law of large numbers* (Davidson, 2018, p.187-192). The portfolios exceeding one stock is value-weighted by their market capitalization (Appendix: exhibit 2.2.7) using one, five, twenty-five, fifty, or one-hundred stocks. The results obtained shows the long-term performance of individual stocks ranging from July 1926 to December 2018, ignoring any transaction costs.

	1-year horizon			10-year horizon			Life (92-year) horizon		
	Mean	Median	Skewness	Mean	Median	Skewness	Mean	Median	Skewness
Bootstrapped single-stock position									
Holding return	0.163	0.038	8.871	2.532	0.285	81.667	9290.43	-0.12	101.74
$\% > 0$	53.45%			56.38%			49.01%		
$\% > T - bill$	50.63%			48.01%			26.03%		
$\% > VWmkt$	42.75%			29.54%			3.41%		
Bootstrapped 5-stock portfolio, value weighted									
Holding return	0.132	0.107	0.998	1.945	1.246	4.69	9737.37	1090.78	23.55
$\% > 0$	64.48%			83.88%			99.9%		
$\% > T - bill$	60.10%			72.3%			96.46%		
$\% > VWmkt$	47.22%			40.68%			22.15%		
Bootstrapped 25-stock portfolio, value weighted									
Holding return	0.123	0.126	0.088	1.864	1.455	1.656	7553.24	3770.86	6.88
$\% > 0$	70.23%			96.28%			100%		
$\% > T - bill$	65.19%			87.17%			99.9%		
$\% > VWmkt$	49.09%			45.73%			37.67%		
Bootstrapped 50-stock portfolio, value weighted									
Holding return	0.121	0.13	-0.105	1.846	1.467	1.079	7084.77	4572.35	4.05
$\% > 0$	71.51%			98.63%			100%		
$\% > T - bill$	66.51%			90.82%			100%		
$\% > VWmkt$	49.43%			47.5%			42.93%		
Bootstrapped 100-stock portfolio, value weighted									
Holding return	0.12	0.133	-0.226	1.831	1.466	0.854	6639.01	5083.01	3.19
$\% > 0$	72.37%			99.62%			100%		
$\% > T - bill$	67.44%			93.17%			100%		
$\% > VWmkt$	49.86%			49.04%			46.53%		

Table 6: Bootstrapped stock portfolios, July 1926 to November 2018

The results in ***Table 6*** imply that the single-stock position is profitable on average with a mean accumulated return of 16.3% at the annual horizon, 253.2% at the decade horizon, and 929,043% at the lifetime (full 92 years). Not surprisingly, the single-stock buy-and-hold distribution is highly skewed. At the annual buy-and-hold horizon the distribution skewness is 8.871, at decade horizon 81.667, and lifetime horizon 101.174. While the increase in skew is anticipated based on the previous findings, what might come as an surprise is the poor performance of the single-stock strategy. In accordance to *The small-firm effect* by Banz (1981) one might anticipate the single-stock strategy to outperform benchmarks that include larger stocks in the long-term more frequently. In fact, only 49.01% generated a positive 92-year return, while the majority, 73.97%, failed to provide returns exceeding one-month treasury bill, and only 3.41% provided returns exceeding value-weighted returns.

The results in table 6 verifies that the skewness of accumulated returns decreases considerably as the number of stocks in the portfolio increase. At the annual horizon, the skewness decreases from 8.87 for single-stock strategy to 0.998 for 5-stock portfolio, and 0.088 for 25-stock portfolio. While stock portfolio of 50 and 100 stocks is negatively skewed by -0.105 and -0.226, respectively - possibly connected to heterogeneity in the timing of earnings announcement dates (Albuquerque, 2012). On one hand, the results imply that short-horizon skew of single-stock strategy can be eliminated by diversification, but on the other hand, stays positive at longer horizon although more diversification is introduced to the portfolio. Moreover, the rate of underperfomance decrease as more stocks are included into the portfolio, also reflected in the decreased distribution skewness. For instance, at the decade horizon, with single-stock, 5-stock, 25-stock, 50-stock, and 100-stock, the rate of buy-and-hold returns that exceeds the one-month Treasury bill increase from 56.38% (with single-stock), to 83.88%, to 96.28%, to 98.63%, and with 100 stock to 99.62%. At all buy-and-hold horizons and although well diversified, the rate of underperformance is always above 50% when compared to value-weighted. For instance, at the decade horizon, the rate of returns that exceeds value-weighted average for 25-stock portfolio is 45.736%, and at the full 92-years 49.04%. The result is relevant because active managers often is measured relative to value-weighed benchmarks such as the SP 500. Moreover, the returns are without any transaction cost, which would yield even less return to the investor. The results reflects the positively skewed distribution of returns at short horizon and help explain why poorly diversified, active mangers, underperform the broad stock market more than half of the time.

5.6 Lifetime wealth creation

Evidence so far shows that most individual common stocks in the US fails to deliver lifetime buy-and-hold returns exceeding one-month Treasuries over matched horizon. The results in this section highlights to what extent the value creation is concentrated, and how the outperformance of the overall market is attributable to large returns earned by the few stocks. Wealth creation is defined as the accumulated return in excess to what is earned if the invested capital (measured as individual companie's market capitalization) instead had earned one-month Treasury bill rate since 1926. The degree of concentration is measured as the individual company's wealth creation , divided by the aggregate wealth creation in the US public stock market.

Table 7 display the net lifetime wealth creation generated by the top 50 companies of total 25,900 companies (PERMCO) and their cumulative percentage contribution to the total net stock market wealth creation. Lifetime wealth creation is defined as the individual stocks value creation above one-month TB rate from initial appearance to delisting or end of 2018. Dichev (2007) noted that investors in general do not reinvest dividends but rather fund new equity issuance and reinvest proceeds earned from the investments. Thus, obtaining a high buy-and-hold return might not reflect large value creation for investors in aggregate and vice versa. For instance, if a stock's share price at the time of delisting is $0, then the buy-and-hold return of this stock yields a loss of 100%, regardless of the fact that the stock may have payed dividends to its shareholder prior to the delisting. Thus, in contrast to the previous assumption, that investors reinvest dividends, I instead compute the aggregate value creation for investors. I use the stocks' market capitalization as the initial wealth invested, and multiply this by wealth creation above one-month TB rate, each month since its initial appearance (earliest 1926) to its delisting (or November 2018). Similarly, the total dollar wealth creation is measured at the company level (PERMCO), across share classes (PERMNO), as the sum of wealth creation each month by the 25,900 firms in excess (or loss) to one-month Treasuries (see formula in appendix: exhibit 2.2.7).

The result shows that the 25,900 companies, collectively, generated $34.8 trillion in wealth for investors, measured as of November 2018. The largest wealth creation is provided by two relatively young firms, namely, APPLE INC with its $1.104 trillion (generated over 455 months) and Microsoft CORPS with $1.035 trillion (generated over just 392 months). EXXON MOBIL CORP generated $999.4 billion and is the third largest value generating firm for shareholders, followed by AMAZON COM INC ($788.8 billion), JOHNSON JOHNSON ($533.2 billion), INTERNATIONAL BUSINESS MACHS COR ($501.98 bilion), BERKSHIRE HATHAWAY INC DEL ($473.2 billion), WALMART INC ($468.7 billion), and ALTRIA GROUP ($463.4 billion). Of the ten firms, only three have been generating value since July 1926 or over the full 1109 months, namely, EXXON MOBILE CORP, INTERNATIONAL

BUSINESS MACHS COR, and ALTRIA GROUP.

PERMCO	Company name	Lifetime wealth creation ($ million)	% of Total	Cumulative % of total	Start month	End month	Life in months
7	APPLE INC	1 104 772	2.65%	2.65%	1981-01	2018-11	455
8048	MICROSOFT CORP	1 034 623	2.48%	5.13%	1986-04	2018-11	392
20678	EXXON MOBIL CORP	999 426	2.4%	7.53%	1926-07	2018-11	1109
15473	AMAZON COM INC	788 833	1.89%	9.42%	1997-06	2018-11	258
45483	ALPHABET INC	563 603	1.352%	10.78%	2004-09	2018-11	171
21018	JOHNSON & JOHNSON	533 217	1.28%	12.06%	1944-10	2018-11	890
20990	INTERNATIONAL BUSINESS MACHS COR	501 988	1,2%	13.26%	1926-07	2018-11	1109
540	BERKSHIRE HATHAWAY INC DEL	473 210	1.14%	14.395%	1976-11	2018-11	505
21880	WALMART INC	468 671	1.12%	15.52%	1972-12	2018-11	552
21398	ALTRIA GROUP INC	463 428	1.11%	16.63%	1926-07	2018-11	1109
20799	GENERAL MOTORS CORP	431 183	1.03%	17.67%	1926-07	2009-06	996
20792	GENERAL ELECTRIC CO	416 532	0.999%	18.67%	1926-07	2018-11	1109
20440	CHEVRON CORP NEW	414 009	0.99%	19.66%	1926-07	2018-11	1109
21446	PROCTER & GAMBLE CO	399 567	0,95%	20.62%	1929-09	2018-11	1071
20468	COCA COLA CO	380 968	0.91%	21.53%	1926-07	2018-11	1109
21188	MERCK & CO INC NEW	353 692	0.85%	22.38	1946-06	2018-11	870
20436	JPMORGAN CHASE & CO	340 426	0.82%	23.197%	1969-04	2018-11	596
2367	INTEL CORP	333 222	0.8%	24.0%	1973-01	2018-11	551
20606	DU PONT E I DE NEMOURS & CO	326 452	0.78%	24.78%	1926-07	2017-08	1094
20103	AT&T CORP	304 272	0.73%	25.51	1926-07	2005-11	953
5085	HOME DEPOT INC	296 971	0,71%	26.22%	1981-10	2018-11	446
7267	UNITEDHEALTH GROUP INC	295 669	0.71%	26.932%	1984-11	2018-11	409
21394	PFIZER INC	276 547	0.66%	27.6%	1944-02	2018-11	898
21305	WELLS FARGO & CO NEW	273 346	0.66%	28.25%	1963-01	2018-11	671
8045	ORACLE CORP	263 952	0.63%	28.88%	1986-04	2018-11	392
20315	BOEING CO	262 989	0.63%	29.52%	1934-10	2018-11	1010
21384	PEPSICO INC	259 313	0.62%	30.14%	1926-07	2018-11	1109
20017	ABBOTT LABORATORIES	248 872	0.6%	30.74%	1937-04	2018-11	980
52983	VISA INC	248 397	0.6%	31.33%	2008-04	2018-11	128
21177	MCDONALDS CORP	240 562	0.58%	31.91%	1966-08	2018-11	628
54084	FACEBOOK INC	237 714	0.57%	32.48%	2012-06	2018-11	78
10486	CISCO SYSTEMS INC	229 061	0.55%	33.03%	1990-03	2018-11	345
21205	3M CO	226 226	0.54%	33.57%	1946-02	2018-11	874
50700	MASTERCARD INC	215 440	0,52%	34.09%	2006-06	2018-11	150
20587	DISNEY WALT CO	213 338	0,51%	34.6%	1957-12	2018-11	732
20288	VERIZON COMMUNICATIONS INC	212 227	0,51%	35.11%	1984-03	2018-11	417
21211	MOBIL CORP	207 355	0.49%	35.61%	1927-01	1999-11	875
216	AMGEN INC	188 453	0,45%	36.06%	1983-07	2018-11	425
43613	COMCAST CORP NEW	173 042	0,42%	36.47%	2002-12	2018-11	192
20191	AMOCO CORP	172 070	0,41%	36.89%	1934-09	1998-12	772
21734	TEXACO INC	168 437	0.40%	37.29%	1926-07	2001-10	904
21401	CONOCOPHILLIPS	167 541	0,40%	37.69%	1926-07	2018-11	1109
21810	UNION PACIFIC CORP	167 001	0,40%	38.1%	1969-08	2018-11	592
21102	LILLY ELI & CO	166 824	0,40%	38.49%	1970-08	2018-11	580
20331	BRISTOL MYERS SQUIBB CO	160 574	0,39%	38.88%	1929-08	2018-11	1072
20908	H P INC	147 174	0.35%	39.23%	1961-04	2018-11	692
21886	WARNER LAMBERT CO	145 911	0,35%	39.58%	1951-07	2000-06	588
21832	UNITED TECHNOLOGIES CORP	141 446	0.34%	39.92	1929-05	2018-11	1075
3151	BANK OF AMERICA CORP	140 011	0.34%	40.26%	1973-01	2018-11	551
90	AMERICAN EXPRESS CO	139 496	0.33%	40.59%	1926-07	2018-11	40.59

Table 7: Lifetime wealth creation by Individual stocks, since 1926

As one can observe, the four largest value creating firms alone stands for slightly more than 9% of the $34.8 trillion created collectively, while the 50 firms together accounts for 40.49% over the 1926-2018 period. APPLE INC alone contributed with 2.65% of total, MICROSOFT 2.48%, EXXON MOBILE 2.4%, and AMA-

ZON COM INC 1.89% of total. The evidence imply that the value creation is in fact relatively concentrated.

In fact, plotting the cumulative percentage of net stock market wealth creation attributable to the 25,900 firms (***figure 4***), ranking them from highest to lowest wealth creation shows that the curve asymptotes at 100%. A wide range of firms contributed with wealth beyond 100% and reach a maximum at 115.59% reflecting that the gross stock market wealth creation was 15.59% larger than net wealth creation. ***Figure 5*** shows the same data but for only the 1200 firms with the largest lifetime wealth creation. The data shows that it passes through 50% with just 85 firms, and passes through 75% with 289 firms, i.e., 0.33% of all firms contributed with 50% of the accumulated net wealth creation, while 1.12% contributed with 75% of the accumulative net wealth in the period 1926-2018. The results imply that the cumulative wealth creation has become slightly more concentrated, although the cumulative wealth creation has decreased by 1.68% from the max measured by Bessembinder's (2018) in the period from 1926-2016. He found that the cumulative wealth creation reached a maximum of 117.27% and that it passed 50% and 75% with just 90 and 295 firms (respectively) of total 25,332 firms. The curve on figure 5 reaches 100% at 1141 firms, or 4.41% of the 25,380 firms contained in the sample, meaning that slightly more than 4% collectively accounted for all the net wealth creation in the US stock market during 1926-2018. Moreover, 10,894 (or 42.06%) firms has since 1926 created positive net wealth, 4.25% more firms compared to 2016 (Bessembinder, 2018). These together offset the remaining 15,006 (or 57.94%) firms' poor performance.

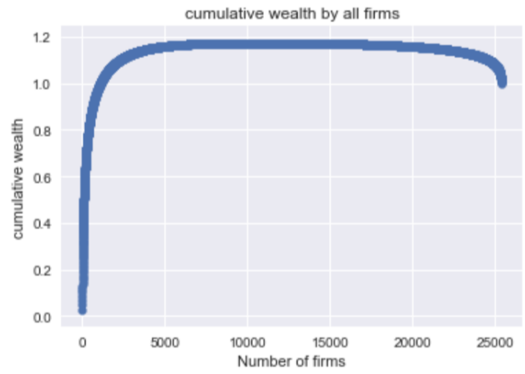

Figure 4: Cumulative %, all companies

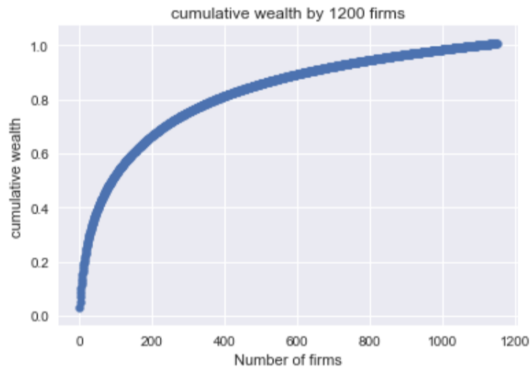

Figure 5: Cumulative %, top 1200 companies

The result shows that since 1926, 1141 firms (or 4.41%) have collectively generated net wealth equal to the overall market, while the remaining 95.59% of firms have collectively generated lifetime dollar gains below what would otherwise have been obtained had the investment instead earned one-month Treasury rate. However, although I have demonstrated that there the value creation is concentrated it is important to note that while some firms have long life span other have relatively short. In addition, firms sizes varies considerably, bigger firms tend to provide a higher rate of excess return. Moreover, the positively skewed monthly return in combination multiperiod compounding of returns induce additional skewness into the distribution of returns, possibly reinforcing each other. That is, firms with large returns tend to grow more and survive longer compared to firms with low returns who tend to exit the market.

6 Conclusion

The results shows that the majority of individual common stocks that have appeared in CRSP's database since 1926, do not outperform one-month Treasury bill interest rate over their lifetime. Of the total 26,544 stocks, only 42.5% managed to provide lifetime returns exceeding one-month Treasury rate over matched horizons, whereby slightly more than half delivers negative returns (including reinvested dividends). Moreover, evidence suggest that stocks merged/exchanged/or liquidated provided with the highest rate of outperformance (63.14%), while stocks that delisted by exchange contributed with the lowest performance rate (6.81%). However, the findings are less useful unless the investor can foresee the category a stock belongs to. The positive skewness obtained in the long-term investment distribution is attributable to both positively skewed monthly stock returns and the length of compounding. Even in the benchmark case, when returns are assumed to be normally distributed in the one-period horizon, the compounding of volatile returns over any longer horizon induces skewness into the distribution. Although the results obtained using real returns are less skewed compared to the benchmarks case - explained by a greater complexity to real returns, such as varying expected return and return volatility across stocks and over time, and that stocks might delist, which is not accounted for in the benchmark case.

I find that small firms (small market capitalization) tend to underperform one-month

Treasury bills and other market averages more frequently than large firms, and that more recent decades have a higher rate of underperformance compared to prior decades. The results supports the findings of Fama and French (2004), who showed an increase in the number of new listings accompanied with higher asset growth and lower profitability, causing a decline in survival rates. Furthermore, assessing the long-term (92 years) performance using a single-stock strategy, I find that the strategy fail to exceed one-month Treasury bill rates 73.37% of the times. Moreover, I find that increasing the number of stocks in the portfolio, both reduced the distribution skewness and improved the strategy performance - thus obtained evidence that diversification indeed improves return performance .

Turning the focus to lifetime wealth creation, I find that the stocks collectively have generated $34.8 trillion for investors, whereby the top-5 firms (Apple, Microsoft, Exxon, Amazon, and Johnson Johnson) stands for almost 11% of the net stock market gains generated. The evidence shows that wealth creation is highly concentrated, the top-289, or just one-third of 1%, collectively stands for slightly more than 50% of all net wealth creation in the stock market, and only 1141 firms, or 4.41% of all firms, collectively generated the net wealth of the overall market.

The results imply that the outperformance by the overall stock market is in fact attributable to large returns generated by relatively few stocks and underlines the importance of portfolio diversification, especially if mean and variance are metrics used to asses performance. The fact that large positive returns are generated by just a few stocks help explain why diversification works and why poorly diversified portfolios will underperform even in the absence of transaction costs and fees. I have demonstrated that the wealth creation above one-month treasury interest rate is highly concentrated, thus the chance of failing to include the few stocks that generates large returns are high when portfolios are poorly diversified. However, as Simkowitz and Beedles (1978) stated, the exact number of assets an investor should hold in their portfolio is a function of each individual's skewness/variance awareness. Those who are more concerned with skewness should hold relatively small (large) number of assets in their portfolios.

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7 Appendix

Exhibit 1 - Cleaning and merging data

	w/o DLRET	Including DLRET
skewness	6.335	12.578

Table 8: Distribution skewness, with and without delisting return

The above table shows the monthly return skewness with and without deisting return. Observing more closely, by drawing the DELRET exceeding 1000% I obtained the following result:

PERMNO	PERMMCO	COMPNAM	DLSTCD	DLRET	RET	SHROUT
10349	101	AMFI CORP	551	47.00	47.00	1138
12141	179	ALTAIR CORP	551	31.764	31.764	1160
41276	2092	HAYWARD MANUFACTURING INC	500	16.436	19.299	1123
78536	26258	EMS SYSTEMS LTD	500	11.00	11.00	12047

Table 9: Delisting returns over 1000%

Exhibit 1: The highly positively skewed distribution of monthly stock returns are attributable to the inclusion of extreme delsing returns (DLRET) as shown in table 9. For more detailed explanation, please see Exhibit2: Methodology.

Exhibit 2 - Methodology

The statistical computations and its interpretation is presented below, followed by definitions of concepts and a description of the method used for resampling the dataset to obtain more insightful data about the stocks. I have chosen to use Python because it can handle a dataset of this size, in addition to its flexibility in building both tailored and generalized functions needed for this research. Each experiment is given a unique *experiment ID*, and thus, easily traceable.

Exhibit 2.1 - Mean, median, and standard deviation

The statistics of interest is the sum-/, buy-and hold-/, and geometric - returns' *mean, median, standard deviation (std), and skewness* over various investment horizons and using various subsamples of the dataset obtained from CRSP. While sum of individual stock returns reveals the arithmetic mean, buy-and-hold mean reveals the actual gain or loss of a hypothetical investors who reinvest dividends but otherwise do not alter their position. The sum of RET's is straight forward, $(RET_t + RET_{t+1})$, while buy-and-hold RET exceeding one month are linked using the gross return, $(1 + RET_t)$*$(1 + RET_{t+1})$*...*$(1 + RET_{t+n})$. The product of this procedure will be referenced to as *ret*. For instance, annual, decade, or lifetime *ret*s is the product of at lest 12 or more RETs. The standard mean $(\bar{x})$ describes the center of the data and is a useful metric for expectations (Miller, 2013). However, since the actual amount invested might be less relevant, I also introduce the *geometric mean*, enabling an "apple-to-apple" comparison of two or more investment options over longer horizons. The geometric mean is more appropriate when working with percentages, because it takes into account the effects of compounding and is defined as *"the nth root of the product of n numbers"*, i.e., the n set of RETs used in an experiment. Sum, buy-and-hold, and geometric mean is computed follow:

$$(1) \quad \text{Mean}(\bar{x}) = \frac{1}{n} * \left(\sum_{i=1}^{n} X_i \right) \quad , \quad (3) \quad \text{Geometric mean} = \sqrt[n]{(x_1)(x_2)\cdots(x_i)}$$

Where,

- $X_i = ret_i$
- n = Number of *ret*s

While mean is useful for observing central tendencies (expected return), they are sometimes largely affected by extreme outliers, thus the *meadian* is might be more appropriate as it is simply the mid-point of the dataset after arranging the rets from the minimum to the maximum value. For instance, in case of extreme outliers, say observations: x = 50, y = -20, and z = -21, would yield a mean of 3 but on the other hand a median of -20. The problem arise because the standard mean is not robust against extreme outliers and highlights the importance of median - using both enables a better understanding of the distribution at hand.

Other metrics essential for understanding the distribution of RETs is the *Standard deviation* (σ). It quantifies the amount of variation or dispersion of the sample RETs, and are computed as follow:

$$(2) \quad \text{Standard Deviation}(\hat{\sigma}) = \sqrt{\frac{(x - \bar{x})^2}{n - 1}}$$

Where,

- $X_i = ret_i$
- $\bar{X}$ = Sample mean/geometric mean
- n = Number of *ret*s

Standard deviation is thus the average distance between the returns and the mean (Miller, 2013), a value indicating the variation around mean . A low σ indicates that the RETs tend to be close to the mean RET, while a high σ indicates that the RETs are spread over a wide range of values.

Exhibit 2.1.1 - Skewness

The distribution *skewness* tells us how symmetrical the distribution is around the mean. For instance, a positively skewed probability distribution indicates that the tail is on the right side of the distribution. In general, when mean is to the right of median we assume that the distribution is right skewed and left skewed when the mean is to the left of the median. However, this rule of thumb might fall short when we are dealing with multimodal distributions (distribution with multiple peaks), or with distributions where one tail is long and the other fat. If the distribution is both symmetric and unimodal (one single peak), then the mean = median = mode. However, the converse is not true - a zero skewness does not imply that the mean is equal to the median. The skewness indicates to which direction and the magnitude of how far the distribution deviates from normal:

$$(3) \quad \text{skewness}(\tilde{s}) = \frac{n}{(n-1)(n-2)} \sum_{i=1}^{n} \left[\frac{(x_i - \bar{x})}{\hat{\sigma}} \right]^3$$

Where,

- $X_i = ret_i$
- $\bar{x}$ = Sample mean/geometric mean
- n = Number of *ret*s
- $\hat{\sigma}$ = Standard deviation

As the formula reveals, extreme outliers (x_i) is given a greater weight than the *ret*s close to mean. Looking at it separately, the numerator is called the third moment because we take the difference of *ret* and $\bar{x}$ to the power of three, whereas for the denominator we take the $\hat{\sigma}$ to the power of three. Therefore, what characterizes a positively skewed distribution is that it has a few but large outliers to the right of $\bar{x}$, and at the same time, the mass of the observations concentrated to the left side of $\bar{x}$ - and vice verca for negatively skewed distributions.

Exhibit 2.2 - Definitions and re-sampling

Definitions and a thorough review of the method used for resampling the dataset will be given in this section, starting with what I refer to as the benchmark case - a simulation of returns that are independent and identical distributed (IID). Next, I describe the characteristics and method used for resampling the dataset: in short, the statistical inferences are done over 5 different samples: starting with (1) all individual common stocks that have appeared in CRSP's database since July 1926 to December 2018, (2) by the stocks' final listing status - i.e., still trading, merged/exchanged/or liquidated, and delisted by exchange, (3) stocks distributed into ten equal-sized buckets (bins) based on their market capitalization , (4) sample based on decade of initial appearance, and lastly (5) bootstrapped Stock returns - value-weighted and with various portfoliosizes. Finally, I present the definition and method for obtaining lifetime wealth creation of individual commons stocks.

Exhibit 2.2.1 - Benchmark case

Hypothetical buy-and-hold returns of one, five, and decade horizons is simulated over various standard deviation (σ) ranging from 0-20%. Using python's built in function, np.random.randn, I make randomized draws from an independent and identical distributed pool of returns, where the mean monthly excess stock return (μ) is set to 0.5%, and σ are distributed lognormally. That is, $r \equiv ln(1 + R)$ is distributed normally with $\mu = 0.5\%$, and $\hat{\sigma}$ range from $0\% - 20\%$, and expected excess return, $E(R)$, equal to exp($\mu + 0.5 * \sigma^2$) -1. The median excess return, $exp(\mu) - 1$, is less than $E(R)$ for all $\sigma > 0$. Although the simulation parameters is symmetric, the lognormal distribution of simple-period returns does not have a distinct skewness, but increase monotonically, dependent only on σ. Furthermore, if the mean excess log return, $\mu = ln[1 + E(R)] - 0.5\sigma^2$, is negative, then the median simple excess return is also negative: $\sigma > 2 * ln[1 + E(R)$. This implies that more than half of single-period excess simple-returns will be negative when the excess return variance is sufficient large relative to the mean excess simple return. In this case (using $\mu = 0.5\%$), when $\sigma > 9.988\%$.

Exhibit 2.2.2 - Buy-and-hold horizons

Investment horizons exceeding one month are computed over calendar years, decades, or lifetime. For instance, an annual investment horizon starts in January and ends in December. Stocks that list or delist within the calendar interval is matched with holding US Treasury bills or other market averages over the same period of time because otherwise, by omitting these stocks, could potentially induce survivorship bias to the results. The six months in 1926 is assigned to the first calendar decade ranging from 1927 to 1936, while the last decade range from 2007 to 2018. *Lifetime* investment horizon follow the individual common stock's lifetime, earliest from July 1926 or initial appearance to December 2018 or its month of delisting. Although I focus on long-term performance, I examine shorter investment horizons for comparison.

Exhibit 2.2.3 - Sample by delisting code

The sample is determined based on the stocks delisting code (DLSTCD), where the first of three digits indicate: 1: active (or still trading), 2,3, and 4: merger, exchange, or liquidated, and 5: delisted by exchange. Thus, the statistical computation /(inferences?) are done for three different samples: The first, stocks that "Did not delist" implied by DLSTCD=100, referencing a sample containing all stocks in the interval where 0 $<=$ DLSTCD $<$ 200. The second, stocks that "merged, exchange, or liquidated", implied by DLSTCD = 400, containing all stocks in the interval where 200 $<=$ DLSTCD $<$ 500. Lastly, firms that liquidated implied by DLSTCD = 500, containing all stocks in the interval DLSTC $>=$ 500. By dividing the dataset into smaller samples (group by characteristics) that reflects important events or status of individual common stocks, I allow for comparison and detection of trends typical to the specific group. For instance, an expectation I have is that firms that gets acquired, is typically value-enhancing to investors. Thus for this group, I should find a relatively high rate of performance.

Exhibit 2.2.4 - Sample by market capitalization

The CRSP dataset is resampled into to ten buckets (bins) based on the stocks' market capitalization (firmsize) , the month prior to the calendar interval. The firmsize is determined as the stocks market capitalization computed as shares outstanding multiplied by stock's price at the time. For instance, the stock's annual buy-and-hold return is distributed into a bucket based on the stock's firmsize, December, the month prior to the calendar year. If it happens to be Nan, then the next and first fimsize is used. Each bucket contains the same amount of data (10% in each group), group 1 denotes the smallest firms and group 10 denotes the largest firms for the whole CRSP dataset ranging from July 1926 to December 2018. The results obtained is compared to zero, the accumulated one-month TB interest rate, and both value-weighted and equal weighted common stock portfolio return over matched horizons as before.

Exhibit 2.2.5 - Sample by decade

This study consist of smaller 9 subsamples of the initial sample, each containing the lifetime buy-and-hold returns to stocks listed within a calendar decade. For instance, if a stock's first appearance was in March 1945, then the lifetime buy-and-hold return of this stock belongs to the sample defined as *1937-147*. The first decade covers an additional 6-months, all stocks present from before 1926 and the ones that listed at some point between 1926 to 1936. The others decades run over precise decades starting from January 1937, with one exception - the last decade. The last decade are assigned two extra years, and range from 2007-2018. The results obtained is matched to zero, holding a one-month TB, and both value-weighted and equal-weighted return over matched horizons as before.

Exhibit 2.2.6 - Single-stock strategy, using bootstrap simulation

Buy-and-hold statistics of single-stock strategy are computed over 1-year, 10-year and lifetime horizons. By one-stock strategy I mean a stock picked at random each month over the full 92 years of data. For comparison and obtaining evidence connected to the well documented effect of diversification, I also conduct a multi-stock portfolio with various sizes, where multiple stocks is picked at random each month, value weighted by their market capitalization with respect to the other stocks in the portfolio, and linked over the full 92 years. For instance, a portfolio consisting of five stocks: if stock A has a market capitalization equal to $1m and the sum of all five market caps equal $5m, then the weight of stock A is 1/5. Stocks with higher market cap carry more weight in the portfolio and conversely smaller market caps carry lower weight. This procedure is repeated each month over the full 92 years and linked together by year, decade or lifetime. The results obtained serves as possible outcomes, ignoring transaction costs and fees. I repeat the simulation 5,000 times for annual and decade horizon, and 20,000 for lifetime horizon - following the theorem of Law of Large Numbers (LLN). According to LLN, the result of performing the same experiment a large enough number of times c(Davidson, 2018, p.187-192). Since the lifetime horizon result in only one return output per simulation, and are highly variable (using only 5,000 simulations), I increase the number of simulations for this experiment. The obtained result is compared to the benchmarks as before.

Exhibit 2.2.7 - Lifetime wealth creation

Lifetime wealth creation is defined as the individual stocks' value creation above one-month TB rate from initial appearance to delisting or end of 2018. The computation performed is as follow: (1) obtain the difference between return and TB rate (exret = RET - rf), (2) multiply exret by the stocks market capitalization (mktcap), which is their respective price (PRC) multiplied by shares outstanding (SHROUT), the product of exret multiplied by mktcap is defined as dollargain (dgain), (3) create the compounded future rate (FV), which is the log of TB rate, summed cumulative at an ascending date order, and taken the exponent of. The compounded future rate (FV) is then multiplied with dgain, representing the accrued interest rate for a dgain on a given time t until December 2016, by month. Finally, the future value of dgain is then cumulative summed across months, by PERMCO, reusulting in what I refer to as *firmlifegain*.

In addition, as a reference point I also compute the *Marketlifegain* which is similar to firmlifegain, exept that I cumulative sum the dgains across PERMCOs, by month (replacing all values within the month with its total sum by month), multiply this by the the FV rate, and finally cumulative summing these across months, obtaining what is referenced as *mktlifegain*.

I assessed the wealth creation for each of the 25,900 companies using the framework by Bessembinder (2018): W_0 denotes investors initial wealth, and T the investment horizon. The investor can chose how to allocate W_0 between riskless bonds with known period (*t*) return (R_{ft}), and risky equity investment return $R_t = R_{ct} + R_{dt}$), where R_{ct} is the capital gain component of the period *t* return, and R_{dt} is the dividend component. Dividends are assumed returned to the bond account, where by the investor might make an additional time *t* investment (separate from that earned by dividend) in the risky asset in the amount of F_t (with a repurchase of shares by firm denoted by $F_t < 0$). The investor's total wealth: W_t = $B_t + I_t$ is thus the position in the risky asset (I_t) and riskless bonds (B_t), where $B_t = B_{t-1} * (1 + R_{ft}) + I_{t-1} * R_{dt} - F_t$ shows the earnings of interest, collected dividend, and change in position of the risky asset. On the other hand, $I_t = I_{t-1} * (1 + R_{ct}) + F_t$ shows the position in the risky asset, the capital gains return and any new net investment. Combined, the investors overall wealth is expressed as $W_t = B_{t-1} * (1 + R_{ft}) + I_{t-1} * (1 + R_t)$, and thus:
$W_t - W_{t-1} * (1 + R_{ft}) = I_{t-1} * (R_t - R_{ft}) \qquad (1)$

states that the investor's actual wealth at time *t*, in excess of what would have been earned had it been invested in risk-less bonds in time t_{-1}, is the product of the dollar investment in the risky asset multiplied by the asset's excess return. Moreover, letting FV_t, T denote the accumulated factor obtained by compounding forward the one-month Treasury interest rate from time *t* to *T*, the above equation can be rewritten:

$$\begin{aligned}\mathbf{W_t} - \mathbf{W_0} * \mathbf{FV_{0,T}} = \mathbf{I_0} * (\mathbf{R_1} - \mathbf{R_{f1}}) * \mathbf{FV_{1,T}} \\ + \mathbf{I_1} * (\mathbf{R_2} - \mathbf{R_{f2}}) * \mathbf{FV_{2,tT}} + .. \qquad (2) \\ + \mathbf{I_{T-2}} * (\mathbf{R_{T-1}} - \mathbf{R_{fT-1}}) * \mathbf{FV_{T-1,T}} + .. \\ + \mathbf{I_{T-1}} * (\mathbf{R_T} - \mathbf{R_{fT}})\end{aligned}$$

The left side imply the difference between between the investor's actual wealth and final wealth had the investor instead invested entirely in risk-free assets. The dollar amount on the right side of equation (2) can be found summing the future values (compounding net risky asset gains forward) of the period-by period wealth creation specified by the right side of equation (1). Each stock's value creation is computed according to expression (3), where I_t is defined as the beginning-of-period market capitalization and should thus apply to investors in aggregate. Value created prior to July 1926 is not reflected since the data only covers stocks trading or listed during July 1926 to November 2018 - included in the value creation is the Stock's delisting return.

Exhibit 2.2.7.1 - Median Lifetime and stocks present for the full 92-years

I displayed top-50 firms above is to demonstrate important points - for full coverage of results, please See excel attachment. Stocks' total number of months (*life*) is obtained by counting the months in between its *Start_month* (first appearance) to its *End_month* (last observation). The median lifetime was found using python's built in function, ranging the column *life* in an ascending order giving its mid-value back and the number of stocks present for the full 92-years obtained by extracting stocks with life equal to 1109 months

```
In [336]: print(smpl5.loc[smpl5['life'] == 1109].shape)
          print(smpl5['life'].median())
          print(np.percentile(smpl5['life'], 90))

(38, 9)
88.0
339.0
```

	Month	years	
Median	88	7.33	
99th percentile	339	28.25	height

Table 10: Median month and median years for stocks

As observed the shape of the dataframe containing stocks with months equal to 1109 is 38, i.e., a total of 38 stocks are present for the whole 92-years. The median is 88 months, divided by 12 yields 7.33 (or rounded up 7.5 years). Moreover, the 99th percentile life span is 339 months or 28.25 years, further implying that most individual stocks pertain to a relatively short horizon (less than one-third) when compared to the full 92 years of data.

Exhibit 3 - Replication of Wealth creation, by Bessembinder

For comparisonm I have created the result by Bessembinder (2018) using CRSP's databse of common stock ranging from July 1926 to December 2016. Although the lifetime wealth creation for some firms deviate slightly, the overall obtained result is in line with his.

	PERMCO	COMNAM	Wealth creation ($ million)	% of Total	Cumulative %	First_month	Last_month	life
1	20678	EXXON MOBIL CORP	1002291,365	2,98 %	2,98 %	1926-07	2016-12	1086
2	7	APPLE INC	745676,5292	2,22 %	5,19 %	1981-01	2016-12	432
3	8048	MICROSOFT CORP	629800,4142	1,87 %	7,06 %	1986-04	2016-12	369
4	20792	GENERAL ELECTRIC CO	607345,9583	1,80 %	8,87 %	1926-07	2016-12	1086
5	540	BERKSHIRE HATHAWAY INC DEL	548076,4193	1,63 %	10,50 %	1976-11	2016-12	482
6	20990	INTERNATIONAL BUSINESS MACHS COR	520240,9901	1,55 %	13,66 %	1926-07	2016-12	1086
7	20799	GENERAL MOTORS CORP	491394,3397	3,23 %	8,62 %	1926-07	2009-06	996
8	21398	ALTRIA GROUP INC	470178,2557	1,40 %	15,05 %	1926-07	2016-12	1086
9	45483	ALPHABET INC	449799,4968	1,34 %	16,39 %	2004-09	2016-12	148
10	21018	JOHNSON & JOHNSON	426209,6724	1,27 %	18,96 %	1944-10	2016-12	867
11	20440	CHEVRON CORP NEW	390555,6355	1,16 %	20,12 %	1926-07	2016-12	1086
12	21880	WAL MART STORES INC	368213,1063	1,09 %	21,22 %	1972-12	2016-12	529
13	21446	PROCTER & GAMBLE CO	354970,8623	1,05 %	22,27 %	1929-09	2016-12	1048
14	15473	AMAZON COM INC	335100,3471	1,00 %	23,27 %	1997-06	2016-12	235
15	20468	COCA COLA CO	326075,4127	0,97 %	24,24 %	1926-07	2016-12	1086
16	20606	DU PONT E I DE NEMOURS & CO	307043,4457	0,91 %	25,15 %	1926-07	2016-12	1086
17	4388	TELE COMMUNICATIONS INC NEW	297726,7825	1,48 %	29,87 %	1973-01	1999-03	315
18	21188	MERCK & CO INC NEW	286670,1659	0,85 %	26,00 %	1946-06	2016-12	847
19	21305	WELLS FARGO & CO NEW	261342,9058	0,78 %	26,78 %	1963-01	2016-12	648
20	2367	INTEL CORP	259252,1619	0,77 %	27,55 %	1973-01	2016-12	528
21	20436	JPMORGAN CHASE & CO	237431,5628	0,71 %	28,25 %	1969-04	2016-12	573
22	43613	COMCAST CORP NEW	235055,5786	0,70 %	28,95 %	2002-12	2016-12	169
23	5085	HOME DEPOT INC	230702,6472	0,69 %	29,64 %	1981-10	2016-12	423
24	21211	MOBIL CORP	230589,4813	1,06 %	33,80 %	1927-01	1999-11	875
25	21384	PEPSICO INC	224472,9708	0,67 %	30,30 %	1926-07	2016-12	1086
26	21830	U S WEST INC NEW	218928,8421	0,97 %	29,52 %	1984-03	2000-06	196
27	8045	ORACLE CORP	214244,1717	0,64 %	30,94 %	1986-04	2016-12	369
28	21734	TEXACO INC	207468,622	1,36 %	29,81 %	1926-07	2001-10	904
29	21205	3M CO	200357,0234	0,60 %	31,54 %	1946-02	2016-12	851
30	20587	DISNEY WALT CO	188385,1084	0,56 %	32,09 %	1957-12	2016-12	709
31	20191	AMOCO CORP	186067,6219	0,95 %	37,55 %	1934-09	1998-12	772
32	54084	FACEBOOK INC	181243,057	0,54 %	32,63 %	2012-06	2016-12	55
33	20017	ABBOTT LABORATORIES	181151,4782	0,54 %	33,17 %	1937-04	2016-12	957
34	21394	PFIZER INC	179893,3919	0,53 %	33,71 %	1944-02	2016-12	875
35	21177	MCDONALDS CORP	178326,5457	0,53 %	34,24 %	1966-08	2016-12	605
36	21886	WARNER LAMBERT CO	172259,9273	0,77 %	38,71 %	1951-07	2000-06	588
37	7267	UNITEDHEALTH GROUP INC	172168,0769	0,51 %	34,75 %	1984-11	2016-12	386
38	21645	A T & T INC	169525,3459	0,50 %	35,25 %	1984-03	2016-12	394
39	20288	VERIZON COMMUNICATIONS INC	165102,0169	0,49 %	35,74 %	1984-03	2016-12	394
40	20331	BRISTOL MYERS SQUIBB CO	161918,1216	0,48 %	36,22 %	1929-08	2016-12	1049
41	20088	AMERITECH CORP	155381,896	0,74 %	41,47 %	1984-03	1999-10	188
42	20290	BELLSOUTH CORP	147288,3581	0,69 %	27,19 %	1984-03	2006-12	274
43	1928	GENENTECH INC	145405,3149	1,08 %	32,62 %	1980-11	2009-03	341
44	21592	SEARS ROEBUCK & CO	145349,543	0,79 %	28,87 %	1926-07	2005-03	945
45	20086	WYETH	144841,6208	0,86 %	28,19 %	1926-07	2009-10	1000
46	21401	CONOCOPHILLIPS	143860,714	0,43 %	36,65 %	1926-07	2016-12	1086
47	20315	BOEING CO	139354,5716	0,41 %	37,06 %	1934-10	2016-12	987
48	216	AMGEN INC	137876,9924	0,41 %	37,47 %	1983-07	2016-12	402
49	21576	SCHLUMBERGER LTD	134183,0349	0,40 %	37,87 %	1926-07	2016-12	1086
50	10486	CISCO SYSTEMS INC	131294,8783	0,39 %	38,26 %	1990-03	2016-12	322

Table 11: Aggregate Wealth creation, replication of Bessembinder's results