Financial Analysts Journal

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/ufaj20

Long-Term Shareholder Returns: Evidence from 64,000 Global Stocks

Hendrik Bessembinder, Te-Feng Chen, Goeun Choi & K. C. John Wei

To cite this article: Hendrik Bessembinder, Te-Feng Chen, Goeun Choi & K. C. John Wei (2023) Long-Term Shareholder Returns: Evidence from 64,000 Global Stocks, Financial Analysts Journal, 79:3, 33-63, DOI: 10.1080/0015198X.2023.2188870

To link to this article: https://doi.org/10.1080/0015198X.2023.2188870

Financial Analysts Journal | A Publication of **CFA Institute**
https://doi.org/10.1080/0015198X.2023.2188870

Research

Long-Term Shareholder Returns: Evidence from 64,000 Global Stocks

Hendrik Bessembinder, Te-Feng Chen, Goeun Choi, and K. C. John Wei

Hendrik Bessembinder is at the W. P. Carey School of Business, Arizona State University, Tempe, Arizona. Te-Feng Chen is at the School of Accounting and Finance, Hong Kong Polytechnic University, Hong Kong Special Administrative Region (SAR), China. Goeun Choi is at the A. B. Freeman School of Business, Tulane University, New Orleans, Louisiana. K. C. John Wei is a distinguished research professor in the School of Accounting and Finance at the Hong Kong Polytechnic University, Hong Kong Special Administrative Region (SAR), China. Send correspondence to Hendrik Bessembinder at hb@asu.edu.

We study long-run shareholder outcomes for more than 64,000 global common stocks during the January 1990 to December 2020 period. The majority, 55.2% of U.S. stocks and 57.4% of non-U.S. stocks, underperform one-month U.S. Treasury bills in terms of compound returns over the full sample. Focusing on aggregate shareholder outcomes, we find that the top-performing 2.4% of firms account for all of the $US 75.7 trillion in net global stock market wealth creation from 1990 to December 2020. Outside the United States, 1.41% of firms account for the $US 30.7 trillion in net wealth creation.

Keywords: compound returns; long-term returns; return skewness; stock investing and shareholder wealth

Disclosure: No potential conflict of interest was reported by the author(s).

PL Credits: 2.0

Introduction

The literature includes hundreds of empirical studies that report on rates of return to equity investors. These studies typically focus on returns measured over relatively short horizons, such as monthly or quarterly, and often describe long-term outcomes based on arithmetic means of shorter-term returns.[1] In this study, we aim to provide broader insights into the nature of the returns realized by shareholders in the long run. To do so, we consider a broad global sample consisting of more than 64,000 individual common stocks and measure long-term shareholder outcomes in terms of both compound returns and enhancements to shareholders' wealth.

Many of the empirical outcomes documented here are attributable to the fact that the distribution of compound returns is positively skewed. Such skewness arises even if the distribution of short-horizon returns is symmetric, as first pointed out by Arditti and Levy (1975) and explored further by Bessembinder (2018) and Farago and Hjalmarsson (2023). Indeed, the assumption often employed for modeling purposes that stock returns conform to the log-normal distribution implies positive skewness at any horizon except instantaneous, with greater skewness at longer horizons. The results we present illustrate the practical implications of such positive skewness. To the extent that the findings here are surprising, the cause may be that the empirical literature tends to focus on parameter estimates that describe the short-horizon return distribution, where the effects of skewness are modest.

We document that the majority of compound (buy-and-hold) long-term returns measured for our January 1990 to December 2020

The authors thank William Goetzmann (executive editor), Daniel Giamouridis (co-editor), and two anonymous referees for constructive and insightful comments and suggestions that have significantly improved the article. Bessembinder acknowledges financial support from Baillie Gifford & Company. Wei acknowledges financial support from the Research Grants Council of the Hong Kong SAR, China (GRF15505518).

sample, including 55.2% of U.S. stocks and 57.4% of non-U.S. stocks, fall short of returns to one-month U.S. Treasury bills over matched time horizons.[2] This finding does not contradict the evidence (see, for example, Dimson, Marsh, and Staunton, 2002) that returns to broad stock *markets* handily outperform the returns earned on Treasury instruments in the long run. Indeed, the mean buy-and-hold return across stocks in our sample greatly exceeds the U.S. Treasury bill return at each horizon we study. Rather, the distinction between the positive return premium for the broad stock markets and the negative premium for most individual stock returns is a manifestation of the strong positive skewness in the distribution of returns to individual stocks, particularly at longer horizons.[3] This skewness in turn implies that the positive mean excess long-run returns observed for stock portfolios are driven by very large returns to a relative few stocks.

We measure for each sample firm the dollar amount by which the wealth of shareholders in aggregate was enhanced by their decision to take on the risk of stock investing rather than low-risk U.S. Treasury bills. Summing across the 63,785 firms that issued common stock contained in the January 1990 to December 2020 sample, we calculate net global stock market wealth creation of $US 75.7 trillion, measured as of December 2020. Wealth creation is highly concentrated. The five firms (0.008% of the total) with the largest wealth creation during the January 1990 to December 2020 period (Apple, Microsoft, Amazon, Alphabet, and Tencent) accounted for 10.3% of global net wealth creation. The best-performing 159 firms (0.25% of total) accounted for half of global net wealth creation. The best-performing 1,526 firms (2.39% of total) can account for all net global wealth creation.

Bessembinder (2018) previously studied long-term shareholder outcomes for U.S. stocks.[4] Here, we show that the practical implications of skewness in compound returns are even stronger outside the United States. The present sample includes 46,723 non-U.S. stocks. Of these, 42.6% generated buy-and-hold returns measured in U.S. dollars that exceed one-month U.S. Treasury bill returns over matched horizons. By comparison, 44.8% of the 17,776 U.S. stocks in the present sample outperformed Treasury bills.

The positive skewness in distribution of compound returns is of substantial practical importance. While, as noted, most empirical analyses of stock markets focus on arithmetic means and other parameters of returns measured over short (e.g., monthly) horizons, the investment and decision horizons of individuals or fund managers can stretch to decades and can differ across investors. The strong positive skewness in the distribution of long-horizon stock returns implies a cautionary lesson that is particularly relevant for financial planning. The assessment of whether pension funds are adequately capitalized, for example, is often based on assumptions regarding mean returns and the mean of the distribution of possible future outcomes. Distinct from the ongoing debate as to whether the assumed means are appropriate, the (potentially large) majority of individual future outcomes in a positively skewed distribution can be less than the mean. Our results highlight that it is important for financial planners to explicitly consider the skewed distribution of compound long-horizon returns.

Utility-maximizing investors may also rationally prefer to seek out or to avoid the strong positive skewness that is present in long-horizon returns. This can be accomplished by selecting portfolios with greater or less short-horizon return volatility, which Farago and Hjalmarsson (2023) show is a main determinant of long horizons skewness. A useful benchmark is provided by Samuelson (1969), who shows that long-horizon investors will optimally select portfolio weights based on the parameters of the short-horizon return distribution and then rebalance each period to the same constant weights. For the investors on which he focuses, the skewness induced by compounding is not relevant. Samuelson obtains these implications while assuming that successive returns are independently and identically distributed (iid) and that investors maximize the expectation of a power utility function. Investors with skewness preference that differs as compared to that implied by power utility will generally not be indifferent to the skewness induced by compounding.[5] It is also important to note that Samuelson's prescription cannot apply all to investors. If some investors sell (buy) stocks that have appreciated (depreciated) in relative terms in order to return to constant portfolio weights, then other investors necessarily trade in the opposite direction. These investors, as well as the market as a whole, will be subject to more return skewness over multiple periods as compared to the rebalancing investors they focus on and hence will indeed be concerned with the skewness implicit in the multi-period investing.

The results obtained here are also relevant to the debate regarding the selection of relatively narrow portfolios vs. the passive holding of broadly diversified portfolios. The results here confirm in a global sample that the wealth created by stock market investing is largely attributable to extreme positive outcomes of a relatively few stocks. We report that the modal long-horizon return to individual stocks involves a complete or near-complete loss of capital. However, the prospect of some −100% returns may not be as daunting in light of the documented frequency with which longer-term returns to individual stocks exceed benchmarks such as 1,000%.[6] That is, the results here highlight the magnitude of the potential gains to a long-horizon investor with a comparative advantage in identifying *ex ante* those stocks that will generate large long-run returns, even while they also illustrate how the odds of underperformance loom large for an investor who selects a narrow portfolio in the absence of such a comparative advantage. Of course, our study does not clarify which, if any, investors possess the requisite comparative advantage.

While the results reported here verify that positive skewness characterizes the distribution of compound global stock returns, we also compare the observed outcomes to a simple benchmark. In particular, we use simulation methods to estimate the degree of skewness (and related statistics) implied by the widely used lognormal distribution, when assuming iid monthly returns that are calibrated to the observed mean and variance of actual monthly returns as well as to observed distribution of stock lives. The simulation actually implies *more* skewness and *lower* rates of outperformance relative to benchmarks as compared to outcomes observed in the actual data. An intriguing question for future research is to assess what features of the actual data lead to less skewness in the empirical distribution of compound long-run returns as compared to that implied by this simple benchmark.

Sample and Measures Employed

Data Sources and Sample Overview. We identify securities as common stocks using methods described in detail in the Internet Data Appendix. The data required to compute monthly returns, market capitalization, and trading volume for U.S. stocks are obtained from CRSP and for non-U.S. stocks from the Compustat Global and Compustat North America databases.[7] Our study includes 42 markets. These are the markets with the largest average GDP during the sample interval, except that we exclude Iran (because return data are available for only 10 years) and include Singapore and New Zealand due to their relative economic prominence. Many common stocks are listed and traded in more than one market. To avoid double counting, we assign each common stock to a single market, as described more fully in the Internet Data Appendix.

Our sample includes 26 developed and 16 developing economies. In addition, we compute outcomes for 239 firms that are traded in the United States as American Depository Receipts (ADRs), but are not listed on any other exchange during the sample period.[8] We categorize these "homeless" ADRs as a separate market and hence refer to outcomes across 43 markets. The markets included in the sample represent approximately 88% of global stock market capitalization as of the end of 2020.

We begin our study as of January 1990 (as Compustat coverage is thin prior to this date) or at the first date when monthly return data for each stock are available and end the study as of December 2020. The CRSP and Compustat data pertain to publicly listed stocks. Our study should therefore be viewed as summarizing return outcomes and wealth creation in the publicly accessible stock markets. We do not capture the pre-IPO experience of private (e.g., venture capital, private equity, and founder) investors or returns from the IPO price to the first end-of-month price contained in the databases. We exclude stocks listed on minor stock exchanges, where an exchange is deemed to be minor if its share of own-market trading volume (measured in U.S. dollars) during the sample period is less than 2%.

In our view, a meaningful comparison of investment outcomes across stocks that are traded in multiple markets requires that all results be measured in a common currency. The alternative of comparing local currency returns across currencies could be misleading, particularly if inflation rates differ across markets. Further, the reliance on local currency returns necessitates comparisons to benchmark interest rates denominated in the same currency, which can vary substantively across markets in terms of default risk. To ensure a common yardstick for firms traded in multiple currencies, returns, market capitalizations, and trading volumes for non-U.S. stocks are all converted to U.S. dollars. In untabulated results, we verify that our conclusions are uniformly unaltered when outcomes are measured in British pounds instead.

Stocks are tracked through time based on the CRSP PERMNO variable (for U.S. stocks) and the Compustat GVKEY and IID variables (for non-U.S.

stocks). We compute returns separately by share class for firms with multiple classes. We also compute separate return series for Chinese stocks that are traded in Hong Kong SAR as H-shares and in China as A-shares. However, we aggregate dollar wealth creation to the firm level by summing across share classes, based on the PERMCO variable for firms contained in the CRSP database and the Compustat GVKEY variable for other firms.

Visual examination indicates that the data for non-U.S. stocks contain occasional but substantial data errors. Prior authors have addressed this problem by either excluding or winsorizing extreme observations.[9] While these methods may be adequate for studies that consider returns to value-weighted portfolios, our focus is on the distribution of long-horizon returns to individual stocks. While we also eliminate from the sample some observations that are likely to reflect potentially influential errors, we attempt to retain large but accurate observations and to repair some data errors, for example, those that result from an erroneous temporary shift of the decimal. Our filtering and correction algorithms are described in the Internet Data Appendix. After implementing these filters, the sample contains 8.37 million monthly observations on 64,738 stocks issued by 63,785 firms.

Table 1 lists the markets included in the study, along with descriptive statistics. Data are available from January 1990 for most markets, but the earliest data pertain to 1991 for China; 1993 for Brazil, Nigeria, and Poland; 1994 for Israel; 1995 for Russia; 2000 for Saudi Arabia; and 2001 for the United Arab Emirates. End-of-period market capitalization for sample stocks ranges from $US 42 billion for Greece to $US 41.0 trillion for the United States. The ratio of average market capitalization to GDP provides an indication of the importance of stock markets in each sample market and ranges from 0.08 for Nigeria to 5.51 for Hong Kong SAR.[10]

Table 2 provides information regarding the stock exchanges studied in each market. In each case, the count refers to the Exchange where a stock first appeared in our sample. The U.S. sample includes 3,224 New York Stock Exchange stocks, 1,556 American Stock Exchange Stocks, and 12,996 NASDAQ stocks, while the China sample includes 1,719 stocks listed on the Shanghai Stock Exchange and 2,333 listed on the Shenzhen Stock Exchange. Table 2 also reports the percentage of dollar trading volume that occurs on each exchange within each sample market.[11]

Measuring Long-Term Shareholder Outcomes. A common method of assessing shareholder outcomes over multiple time periods is to focus on the arithmetic mean of short-horizon (e.g., monthly) returns. In particular, many studies form portfolios of stocks based on observable characteristics and then compare arithmetic mean returns across portfolios. Other studies estimate linear regressions where the dependent variable is a series of returns to stocks or portfolios of interest.[12] Fitted values from such regressions estimate arithmetic mean returns conditional on specific explanatory variable outcomes. However, it is well known (and discussed in most corporate finance and investment textbooks) that arithmetic mean returns are potentially misleading, in the sense that compounding the arithmetic mean return will, in any sample with a non-zero standard deviation, overstate the actual compound return earned by a passive, that is, "buy-and-hold" investor. We therefore focus on investor's buy-and-hold returns, inclusive of reinvested dividends. If R_t is the time t return to shareholders inclusive of capital gains and reinvested dividends, then the buy-and-hold return from time 0 to T is simply $BHR_t = (1 + R_1) \times (1 + R_2) \ldots \times (1 + R_T) - 1$.

We also measure outcomes to shareholders in aggregate in dollar terms, which following Bessembinder (2018), we refer to as the amount of wealth creation. This figure can be interpreted as the premium, in terms of end-of-sample wealth, earned by the shareholders who exposed themselves to the risk of investing in company stock, as compared to the wealth they would have attained if they had invested in one-month Treasury bills. Aside from the distinction that wealth creation is measured in dollars while the buy-and-hold return is a percentage, wealth creation differs conceptually. In particular, the wealth creation calculation (i) explicitly allows for the fact that shareholders in aggregate do not reinvest dividends (while the buy-and-hold return calculation assumes dividend reinvestment) and (ii) incorporates the fact that shareholders in aggregate fund new equity issuances and receive the proceeds of share repurchases, while the buy-and-hold return excludes the effects of net equity issuances. When summed across firms, wealth creation is similar to a value-weighted return in the sense that it captures the reality that large companies are more important than small ones in determining aggregate investor outcomes. Bessembinder (2018) shows that the enhancement in aggregate shareholder wealth from investing in a given stock as opposed to Treasury bills, measured as of the

Table 1. Summary Statistics by Market

Market	Number of Stocks	First Month	Last Month	GDP per Capita (US$, 2020)	Avg. GDP Growth Rate (%)	GDP Creation ($US billions)	Total Market Cap ($US billions, 2020)	Avg. Market Cap ($US billions)	Avg. Market Cap to GDP
United States	17,776	199001	202012	63,416	2.28	14,970	41,038	15,104	1.01
Canada	2,041	199001	202012	43,278	1.98	1,047	1,876	940	0.90
Austria	177	199001	202012	48,154	1.71	262	123	73	0.28
Belgium	298	199001	202012	44,529	1.59	313	386	215	0.69
Denmark	365	199001	202012	60,494	1.63	214	606	179	0.84
Finland	275	199001	202012	48,981	1.57	129	308	160	1.24
France	1,722	199001	202012	39,907	1.30	1,326	2,744	1,384	1.04
Germany	1,516	199001	202012	45,733	1.43	2,204	2,416	1,237	0.56
Greece	411	199001	202012	17,670	0.64	92	42	59	0.64
Ireland	86	199001	202012	83,850	5.55	371	155	63	0.17
Italy	725	199001	202012	31,288	0.44	716	663	501	0.70
Netherlands	332	199001	202012	52,248	1.93	588	1,036	489	0.83
Norway	578	199001	202012	67,176	2.19	242	269	141	0.58
Portugal	122	199001	202012	22,489	1.44	152	84	58	0.38
Spain	379	199001	202012	27,132	1.74	743	688	485	0.65
Sweden	1,056	199001	202012	51,796	1.98	278	1,013	381	1.37
Switzerland	408	199001	202012	86,849	1.58	481	1,824	791	1.64
United Kingdom	4,192	199001	202012	40,406	1.59	1,517	2,672	2,226	1.47
Australia	2,962	199001	202012	52,825	2.82	1,036	1,499	712	0.69
Hong Kong SAR	2,626	199001	202012	46,753	3.28	273	5,453	1,502	5.51
Israel	641	199411	202012	43,689	3.83	318	193	105	0.33
Japan	3,983	199001	202012	40,146	0.88	1,852	6,740	3,811	2.06
New Zealand	271	199001	202012	41,127	2.62	164	131	39	0.24
Singapore	1,043	199001	202012	58,902	5.49	301	406	280	0.93
South Korea	3,060	199001	202012	31,497	4.98	1,348	1,909	606	0.45
Taiwan	2,440	199001	202012	28,306	4.65	502	1,730	562	1.12
Argentina	118	199001	202012	8,555	2.34	230	49	44	0.19
Brazil	395	199308	202012	6,783	2.33	1,005	692	365	0.36
China	4,052	199101	202012	10,484	9.27	14,310	11,160	2,544	0.18
Colombia	66	199001	202012	5,336	3.17	215	90	65	0.30
India	3,967	199001	202012	1,965	6.08	2,382	2,517	755	0.32
Indonesia	782	199001	202012	3,922	4.94	921	425	151	0.16
Malaysia	1,364	199001	202012	10,270	5.41	291	418	246	0.85
Mexico	251	199001	202012	8,421	2.23	786	362	219	0.28
Nigeria	202	199311	202012	2,083	4.76	373	46	30	0.08

continued

Table 1. Summary Statistics by Market (continued)

Market	Number of Stocks	First Month	Last Month	GDP per Capita (US$, 2020)	Avg. GDP Growth Rate (%)	GDP Creation ($US billions)	Total Market Cap ($US billions, 2020)	Avg. Market Cap ($US billions)	Avg. Market Cap to GDP
Poland	994	199306	202012	15,654	4.00	504	153	98	0.19
Russia	279	199508	202012	10,037	2.60	1,138	590	298	0.26
Saudi Arabia	201	200001	202012	20,178	3.13	512	2,607	439	0.86
South Africa	853	199001	202012	5,067	1.93	187	380	277	1.48
Thailand	923	199001	202012	7,190	4.11	413	486	186	0.45
Turkey	441	199002	202012	8,548	4.55	512	158	99	0.19
United Arab Emirates	126	200105	202012	31,982	3.40	251	242	140	0.56

Notes: This table reports summary statistics by market, including the number of stocks included in the sample, the beginning month and the ending month of the sample in each market, GDP per capita in U.S. dollars in 2020, the average GDP growth rate, GDP creation in U.S. dollars during the sample period in each market, the total market capitalization in billion U.S. dollars at the end of December 2020, the average market capitalization in U.S. dollars at the end of December 2020, and the average market cap to GDP over the sample period. There are 42 markets included in the sample. Source of GDP: International Monetary Fund World (IMF) World Economic Outlook Database April 2021.

end sample (time T) and denoted WC_T can be obtained as:

$$WC_T = I_0(R_1 - R_{f1})FV_{1,T} + I_1(R_2 - R_{f2})FV_{2,T} + \ldots + I_{T-2}(R_{T-1} - R_{fT-1})FV_{T-1,T} + I_{T-1}(R_T - R_{fT}), \tag{1}$$

where I_t is the value of shareholders' common stock investment at time t, R_{ft} is the time t return on a one-month Treasury bill, and $FV_{t,T} = (1 + R_{ft+1})(1 + R_{ft+2}) \ldots (1 + R_{fT})$ is a compounding factor. Because it seems natural to measure aggregate investor experience at the firm level, we sum wealth creation outcomes across classes for those firms that issued more than one class of common stock. We implement expression (1) using the firm's market capitalization (the product of shares outstanding and price per share) to measure aggregate I_t at each time t.

Returns to Investing in Individual Global Common Stocks

In this section, we report on the distribution of returns in the sample of 64,738 individual global common stocks over the period January 1990 to December 2020.

Monthly Returns. The sample includes 8.37 million monthly returns on the 64,738 sample stocks, as stocks are included in the database for an average of 129 months each. Figure 1 displays the frequency distribution of monthly returns (rounded to 1%, to a maximum of 200%), separately for U.S. and non-U.S. stocks.[13] Panel A of Table 3 shows that the mean monthly return for the pooled sample is 1.05%. In contrast to the anticipated positively monthly means, the median monthly return is zero (to four digits) for the full sample as well as the developed economies and North American subsamples. The median monthly return ranges from −0.18% per month for the Asia Pacific region to 0.05% for the Europe region. The percentage of monthly returns that exceed zero is 49.4% for the full sample and ranges in subsamples from 48.9% in emerging markets to 50.3% in Europe.

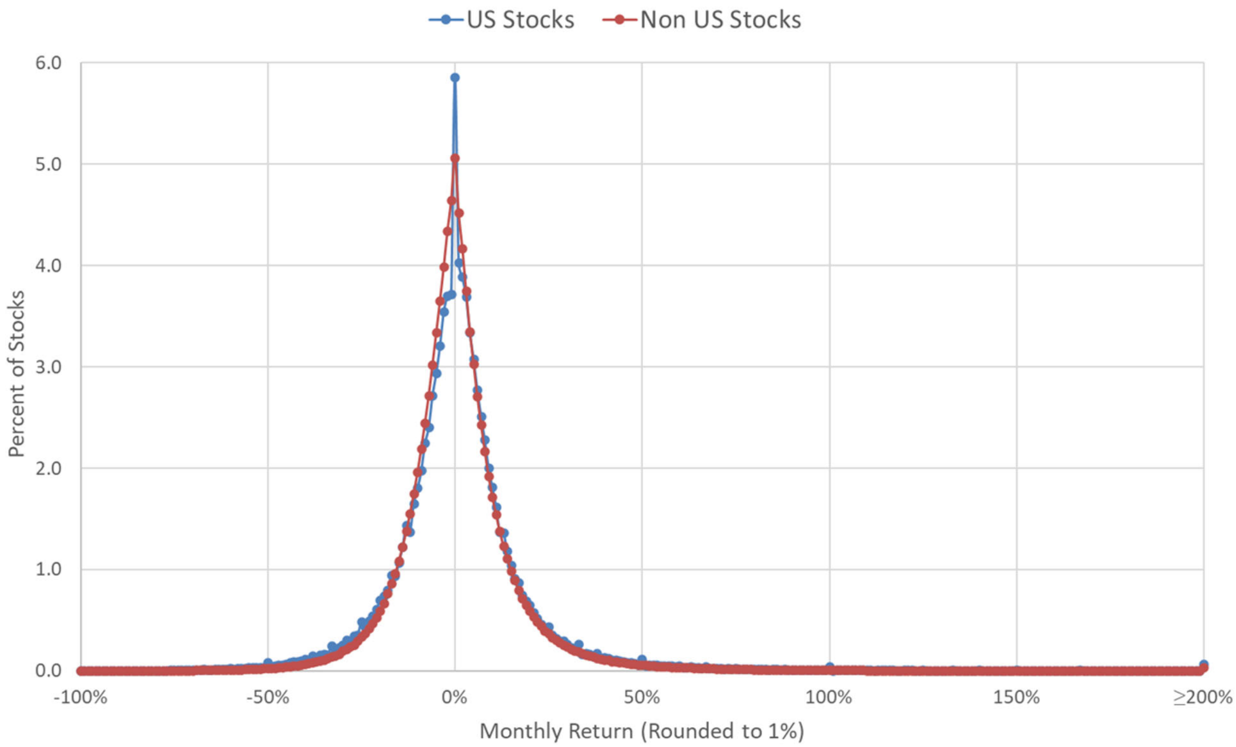
The facts that (i) the median monthly return is approximately zero even while the mean monthly return is positive and (ii) only a minority of monthly returns are positive are attributable to positive skewness in the pooled distribution of monthly returns. The standardized skewness coefficient is 8.71 for the full sample and in subsamples ranges from 6.52 for the Europe region to 9.50 for the North American region. By comparison, Bessembinder (2018) reports

Table 2. Summary Statistics by Exchange

Market	Exchange	Number of Stocks	Average % of Trading Volume (%)
United States	New York Stock Exchange	3,224	58.64
United States	Amex	1,556	2.75
United States	NASDAQ	12,996	38.61
Homeless Firms (U.S. ADRs)	New York Stock Exchange	99	74.11
Homeless Firms (U.S. ADRs)	Amex	6	0.02
Homeless Firms (U.S. ADRs)	NASDAQ	134	25.57
Canada	Toronto Stock Exchange	2,041	98.31
Austria	Wiener Boerse AG	177	98.44
Belgium	NYSE Euronext Brussels	298	99.76
Denmark	OMX Nordic Exchange Copenhagen AS	365	100.00
Finland	NASDAQ OMX Helsinki Ltd	275	100.00
France	NYSE Euronext Paris	1,722	99.93
Germany	Deutsche Boerse AG	929	11.85
Germany	XETRA	587	87.08
Greece	Athens Exchange SA Cash Market	411	100.00
Ireland	Irish Stock Exchange All Market	86	100.00
Italy	Borsa Italiana Electronic Share Market	725	100.00
Netherlands	NYSE Euronext Amsterdam	332	100.00
Norway	Oslo Bors ASA	578	100.00
Portugal	NYSE Euronext Lisbon	122	100.00
Spain	Bolsa De Madrid	379	99.98
Sweden	NASDAQ OMX Nordic	1,056	99.69
Switzerland	Swiss Exchange	408	99.97
United Kingdom	London Stock Exchange	4,192	97.47
Australia	ASX All Markets	2,962	100.00
Hong Kong SAR	Hong Kong Exchanges and Clearing Ltd	2,626	93.98
Israel	Tel Aviv Stock Exchange	641	99.87
Japan	Tokyo Stock Exchange	3,983	98.11
New Zealand	New Zealand Exchange Ltd	271	99.35
Singapore	Singapore Exchange	1,043	100.00
South Korea	Korea Exchange KOSDAQ	1,666	20.09
South Korea	Korea Exchange Stock Market	1,394	79.91
Taiwan	Taipei Exchange	1,345	16.39
Taiwan	Taiwan Stock Exchange	1,095	82.94
Argentina	Bolsa De Comercio De Buenos Aires	118	100.00
Brazil	BM and F Bovespa SA Bolsa De Valores Mercadorias E Futuros	395	100.00
China	Shanghai Stock Exchange	1,719	53.83
China	Shenzhen Stock Exchange	2,333	38.36
Colombia	Bolsa De Valores De Colombia	66	100.00
India	BSE Ltd	2,205	11.47
India	National Stock Exchange of India	1,762	88.53
Indonesia	Indonesia Stock Exchange	782	100.00
Malaysia	Bursa Malaysia	1,364	100.00
Mexico	Bolsa Mexicana De Valores Mexican Stock Exchange	251	100.00
Nigeria	Nigerian Stock Exchange	202	100.00
Poland	Warsaw Stock Exchange	994	100.00
Russia	MICEX Stock Exchange	279	91.61
Saudi Arabia	Saudi Stock Exchange	201	100.00
South Africa	Johannesburg Stock Exchange	853	100.00
Thailand	Stock Exchange of Thailand	923	99.99
Turkey	Istanbul Stock Exchange	441	100.00
United Arab Emirates	Abu Dhabi Securities Exchange	70	37.42
United Arab Emirates	Dubai Financial Market	56	59.72

Note: This table reports the summary statistics by exchange from 42 markets, including the number of stocks and the average percentage of dollar trading volume in each exchange to the total dollar trading volume in a market.

Figure 1. Percentage of Stock-Months with Indicated Return



a skewness coefficient of 6.96 for monthly U.S. stock returns during the 1926 to 2016 period. The data therefore indicate somewhat greater skewness in the monthly returns to international stocks in the recent January 1990 to December 2020 sample as compared to the sample of U.S. stocks he studied. For the global sample, 48.7% of monthly common stock returns exceed the U.S. Treasury interest rate. The percentage of stocks that outperform Treasury bills ranges from 48.2% in emerging markets and the Asia Pacific region to 49.2% in Europe and North America.

The positive skewness in compound returns also manifests itself in the observation that most individual stocks' returns are lower than the mean return computed across all stocks. For each month we compute the cross-sectional average stock return, weighted by firm values (market capitalization in dollars) as of the end of the prior month. The right column of Table 3, Panel A reports on the percentage of individual stock returns that exceed the value-weighted average stock return in the same month. For the full sample, 45.9% of monthly stock returns exceed the value-weighed mean return in the same month. This percentage ranges from 44.9% for the Asia Pacific region to 47.5% for North America.

Annual and Decade Buy-and-Hold Returns.

Panels B and C of Table 3 report on buy-and-hold returns computed over annual and decade horizons, respectively.[14] Each buy-and-hold return is obtained by simply compounding the individual monthly returns inclusive of reinvested dividends. In those cases where a stock enters or departs the dataset within a calendar year or decade, the return is computed based on the partial year or partial decade when data are available, thereby avoiding survivorship bias. Farago and Hjalmarsson (2023) show that empirical estimates of the stock return skewness coefficient (the standardized third central moment) can be severely downward biased when returns are compounded over long horizons. Thus, while positive skewness remains the driving feature, we focus this discussion more on the observable implications of such skewness rather than the estimated skewness coefficients themselves.

Figure 2 displays the frequency distribution of annual buy-and-hold returns, rounded to the nearest 1% and

Table 3. Buy-and-Hold Returns, with Dividends Reinvested in Stock

Sample	*N*	Mean	Median	*SD*	Skewness	% > 0 (%)	% > *T*-bill (%)	% > VW Market (%)
A. Monthly Horizon								
Global	8,370,770	0.0105	0.0000	0.179	8.714	49.4	48.7	45.9
Global (Excl. U.S.)	6,372,336	0.0101	−0.0010	0.172	8.992	49.3	48.5	45.3
By Development								
Developed	6,431,891	0.0102	0.0000	0.179	8.490	49.6	48.8	46.2
Developed (Excl. U.S.)	4,433,457	0.0094	−0.0008	0.168	8.729	49.5	48.6	45.5
Emerging	1,938,879	0.0116	−0.0017	0.180	9.440	48.9	48.2	45.0
By Region								
North America	2,265,906	0.0123	0.0000	0.202	9.497	49.7	49.2	47.5
Europe	1,585,358	0.0076	0.0005	0.158	6.521	50.3	49.2	46.2
Asia Pacific	2,580,627	0.0099	−0.0018	0.169	7.559	49.0	48.2	44.9
B. Annual Horizon								
Global	749,430	0.1477	0.0174	0.898	18.541	51.9	50.0	43.2
Global (Excl. U.S.)	569,840	0.1451	0.0107	0.877	17.072	51.2	49.4	42.3
By Development								
Developed	575,818	0.1402	0.0244	0.889	19.922	52.8	50.6	44.0
Developed (Excl. U.S.)	396,228	0.1332	0.0181	0.853	18.475	52.1	50.0	42.9
Emerging	173,612	0.1724	−0.0087	0.927	14.480	49.1	47.9	40.8
By Region								
North America	203,463	0.1647	0.0415	1.007	21.766	54.2	51.9	46.4
Europe	145,016	0.1123	0.0291	0.738	16.399	53.5	51.0	44.5
Asia Pacific	227,339	0.1361	0.0084	0.864	17.596	51.0	49.1	41.4
C. Decade Horizon								
Global	110,964	1.1667	0.0147	8.443	68.270	50.6	46.5	35.4
Global (Excl. U.S.)	81,479	1.1114	−0.0014	6.976	66.959	49.9	45.8	33.5
By Development								
Developed	86,559	1.1571	0.0377	8.933	71.964	51.4	47.1	36.7
Developed (Excl. U.S.)	57,074	1.0732	0.0230	7.205	81.217	50.9	46.6	34.8
Emerging	24,405	1.2008	−0.0572	6.409	18.482	47.6	44.1	30.7
By Region								
North America	33,277	1.3568	0.0796	11.077	59.987	52.7	48.5	40.7
Europe	22,325	0.9432	0.0338	3.999	14.840	51.5	46.5	36.1
Asia Pacific	30,957	1.0968	0.0003	8.924	77.496	50.0	46.1	32.9
D. Lifetime Horizon								
Global	64,738	3.6683	−0.0678	36.763	51.169	48.2	43.2	29.3
Global (Excl. U.S.)	46,723	3.2211	−0.0763	34.225	62.739	47.7	42.6	26.6
By Development								
Developed	49,724	3.7766	−0.0439	38.555	50.458	48.9	43.6	31.0
Developed (Excl. U.S.)	31,709	3.1791	−0.0494	36.024	65.253	48.7	43.0	28.0
Emerging	15,014	3.3098	−0.1209	30.073	50.904	45.8	41.6	23.5
By Region								
North America	20,056	4.8059	−0.0208	40.808	34.603	49.5	44.9	36.6
Europe	12,642	2.9703	−0.0311	17.381	21.587	49.2	43.5	30.7
Asia Pacific	17,026	3.1629	−0.0707	46.404	55.945	48.0	42.2	24.7
By Market								
Developed								
United States	17,776	4.8797	−0.0215	42.906	33.499	49.5	44.8	36.6
Homeless (U.S. ADRs)	239	1.0109	−0.3854	5.753	7.368	35.6	35.1	24.7
Canada	2,041	4.6072	0.0643	18.046	10.200	51.2	47.1	38.1
Austria	177	1.7747	0.0410	5.025	4.358	51.4	42.4	26.0

continued

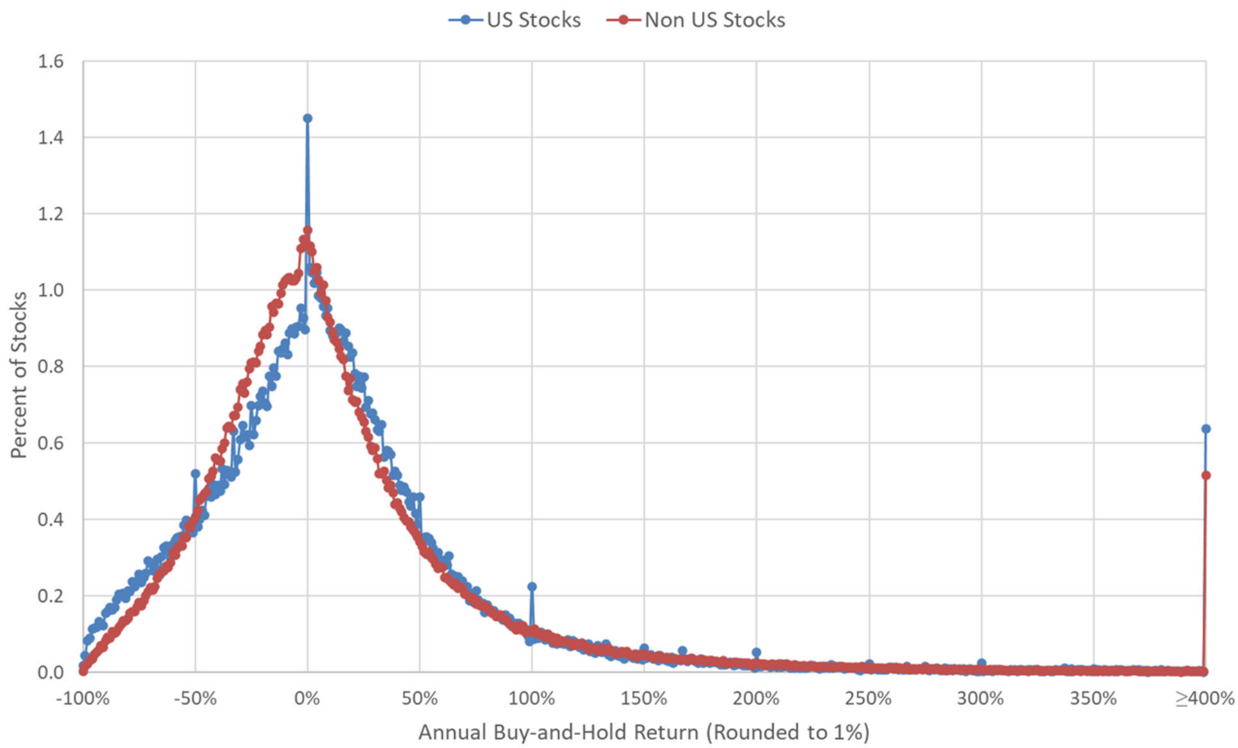
Table 3. Buy-and-Hold Returns, with Dividends Reinvested in Stock (continued)

Sample	*N*	Mean	Median	*SD*	Skewness	% > 0 (%)	% > *T*-bill (%)	% > VW Market (%)
Belgium	298	3.5552	0.5663	9.928	5.669	62.4	56.0	43.3
Denmark	365	5.0296	0.2786	20.140	8.111	57.0	51.0	37.3
Finland	275	5.7199	1.1649	16.066	7.968	70.2	65.8	52.4
France	1,722	2.7274	0.1248	12.447	14.144	53.7	47.7	32.9
Germany	1,516	3.0184	−0.3192	29.400	23.309	42.9	38.2	25.5
Greece	411	0.4072	−0.7002	2.977	4.271	30.7	25.5	16.8
Ireland	86	10.5514	−0.0583	58.727	8.221	48.8	44.2	34.9
Italy	725	0.9444	−0.1975	5.315	10.312	41.2	32.4	21.7
Netherlands	332	3.9776	0.4087	14.784	11.117	63.9	54.2	39.2
Norway	578	2.4515	0.0419	12.715	10.941	51.9	46.2	33.4
Portugal	122	0.9818	0.0243	3.542	4.849	51.6	42.6	29.5
Spain	379	3.0977	0.1143	13.498	9.751	55.7	49.1	35.1
Sweden	1,056	5.3019	0.2989	21.368	7.890	56.5	53.5	42.0
Switzerland	408	7.5638	0.9715	23.253	8.323	72.5	67.6	45.8
United Kingdom	4,192	2.1517	−0.2743	12.948	15.554	43.4	37.8	26.2
Australia	2,962	6.0432	−0.4321	96.983	29.318	39.1	36.1	27.0
Hong Kong SAR	2,626	3.7262	−0.2747	53.150	39.371	40.4	37.2	21.1
Israel	641	3.5208	0.5943	8.761	4.272	62.4	60.1	47.6
Japan	3,983	1.8411	0.0202	10.297	21.756	50.6	38.0	17.7
New Zealand	271	7.2575	0.3967	28.984	6.518	62.0	56.1	42.4
Singapore	1,043	1.8815	−0.1508	8.629	16.498	45.9	41.0	24.6
South Korea	3,060	2.0558	−0.0675	9.546	11.690	48.0	44.2	24.1
Taiwan	2,440	2.6050	0.3059	11.044	14.732	58.2	53.6	30.5
Emerging								
Argentina	118	5.0315	−0.0955	24.669	8.617	47.5	39.0	26.3
Brazil	395	3.7745	0.0380	12.191	5.389	51.4	49.1	34.7
China	4,052	2.1288	0.1879	11.372	21.613	58.1	52.2	23.9
Colombia	66	9.6914	1.2206	25.723	4.594	65.2	65.2	51.5
India	3,967	5.0099	−0.3358	47.858	40.666	38.4	36.3	24.2
Indonesia	782	2.9943	−0.3877	18.274	9.213	34.9	31.3	18.7
Malaysia	1,364	2.8065	−0.2358	22.815	22.627	44.5	37.2	18.3
Mexico	251	3.5772	0.2293	10.698	5.708	55.4	49.8	33.5
Nigeria	202	1.2250	−0.7057	10.888	9.875	26.2	25.2	17.3
Poland	994	0.8510	−0.4127	5.183	8.501	35.6	33.5	19.0
Russia	279	1.6770	−0.3163	16.192	14.705	37.3	35.5	20.8
Saudi Arabia	201	2.0018	0.4798	4.106	2.569	63.2	60.2	30.3
South Africa	853	4.4781	−0.3342	52.423	19.878	36.6	31.4	24.2
Thailand	923	3.7199	−0.1103	14.603	8.041	47.1	42.8	23.7
Turkey	441	4.6507	0.0325	15.120	5.498	51.2	46.0	30.6
UAE	126	1.0594	−0.0837	3.622	3.217	46.0	43.7	18.3

Notes: This table reports the cross-sectional mean, median, standard deviation, and standardized skewness of buy-and-hold returns as well as the percentage of stock outcomes greater than zero, the U.S. Treasury bill rate, and the corresponding value-weighted market return. The sample period is from January 1990 to December 2020 and includes 43 markets (including homeless U.S. ADRs) and 64,738 stocks.

to a maximum of 400% (i.e., to a maximum gross return of five times the initial investment). Figure 3 displays the frequency distribution of decade buy-and-hold returns, rounded to the nearest 5% and to a maximum of 900% (i.e., to a maximum gross return of 10 times the initial investment). The contrast between Figures 2 and 3 is notable. The most frequently observed annual returns are clustered in the vicinity of zero. In contrast, on Figure 3 the most frequently observed returns for both U.S. and non-U.S. stocks at the decade horizon (rounded to 5%) are −95% and −100%, and frequencies of decade horizon returns decline almost monotonically for higher returns.[15]

Figure 2. Percentage of Stock-Years with Indicated Buy-and-Hold Return

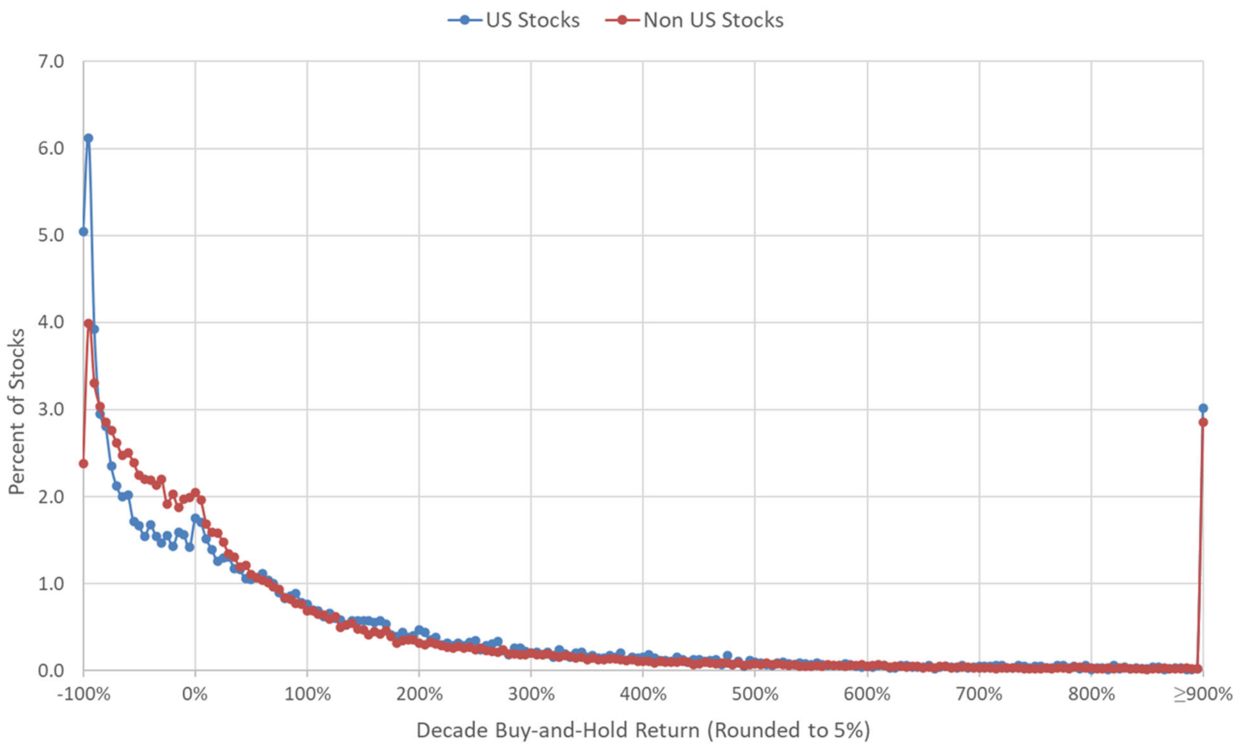


The data on Table 3 verify the simple intuition that the mean buy-and-hold return across all global stocks naturally increases with return horizon, from 1.05% at the monthly horizon to 14.77% at the annual horizon and 116.67% at the decade horizon. However, reflecting the positive skewness, full-sample median returns are far lower: zero at the monthly horizon, 1.74% at the annual horizon, and 1.47% at the decade horizon. The percentage of stocks in the full sample that generate a buy-and-hold return that exceeds the compound return to the one-month U.S. Treasury bill over the same period is 48.7% in monthly returns, 50.0% in annual returns, and 46.5% in decade returns. Within the decade-horizon results, the percentage of stocks with returns that outperform Treasury bills ranges from 44.1% for the emerging economy subsample to 48.5% for the North America subsample. The percentage of stocks in the full sample that generate buy-and-hold returns that exceed the value-weighted average stock return over the matched time period is 45.9% in monthly returns, 43.2% in annual returns, and 35.4% in decade returns.

Full Sample Buy-and-Hold Returns. Panel D of Table 3 reports on buy-and-hold returns to global common stocks, based on the full January 1990 to December 2020 sample period. Figure 4 displays the frequency distribution of full-sample buy-and-hold returns (rounded to the nearest 5%, to a maximum of 900% or a gross return of 10 times the initial investment). The mean full-sample buy-and-hold return across all 64,738 sample stocks is 366.83%. However, the median buy-and-hold return for the full sample is −6.8%, and only 48.2% of sample stocks have a positive full-sample buy-and-hold return. Only 43.2% of global common stocks have a full-sample buy-and-hold return that exceeds the return to one-month U.S. Treasury bills over the matched time horizons. Across subsamples, the percentage of individual stocks with buy-and-hold returns that exceed the time-matched one-month U.S. Treasury bill return ranges from 41.6% for emerging markets to 44.9% for North American stocks.

The results described in the previous paragraph show that the positive mean buy-and-hold return for the full sample of stocks is attributable to large returns to a relatively few stocks, while the majority of stocks generate buy-and-hold returns that fall short of returns to one-month Treasury bills. The skewness of returns also manifests itself in the fact that less

Figure 3. Percentage of Stock-Decades with Indicated Buy-and-Hold Return



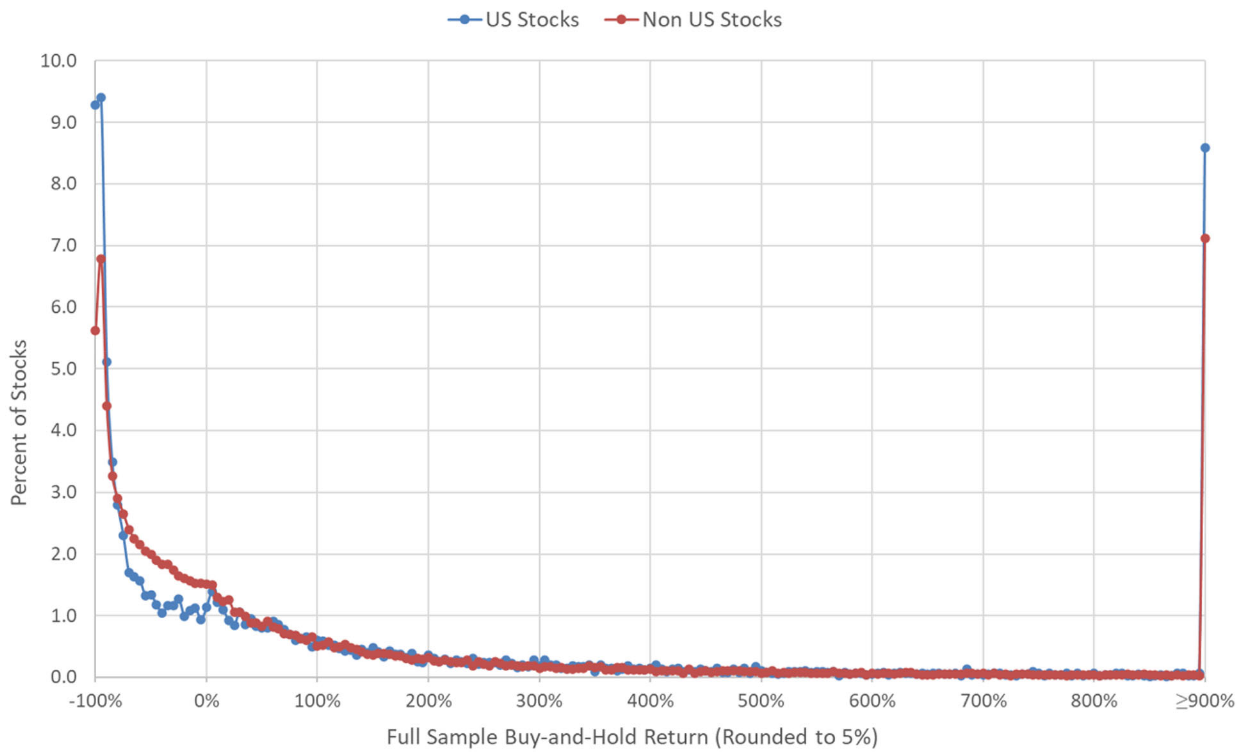
than one-third (29.3%) of individual common stocks have a full-sample buy-and-hold return that exceeds the value-weighted average stock return over the matched time horizon. That is, most stocks underperform their own cross-sectional (value-weighted) average.

The data reported in Table 3 verify (i) that the positive skewness in the distribution of individual common stock returns is a global, not a U.S.-specific, phenomenon and (ii) that the effects of skewness are actually stronger for non-U.S. than for U.S. stocks. Focusing on the 46,723 non-U.S. stocks in the sample, the mean across stocks of the full-sample buy-and-hold return is 322.1%, while the median is −7.6%. Only 47.7% of non-U.S. stocks have positive buy-and-hold returns over the full sample, and only 42.6% have buy-and-hold returns that exceed returns to one-month U.S. Treasury bills. On balance, the evidence supports the conclusion that the positive skewness in long-run returns for non-U.S. common stocks is even more pronounced than for U.S. stocks. Positive skewness is empirically important for common stocks in both developed and emerging economies. Slightly fewer than three of every seven (41.6%) emerging economy stocks have full-sample buy-and-hold returns that exceed returns to one-month U.S. Treasury bills, while 43.0% of non-U.S. developed economy stocks have full sample buy-and-hold returns better than one-month U.S. Treasury bills.

Turning to individual markets, the cross-sectional mean buy-and-hold return for the full January 1990 to December 2020 sample period is positive in all 43 markets, ranging from 40.7% for Greek stocks to 1055.1% for Irish stocks. In contrast, the cross-sectional median buy-and-hold return is negative, implying negative outcomes for more than half of the individual stocks, in 21 of the 43 markets. The median buy-and-hold return is notably small (i.e., less than −30%) in Nigeria (−70.6%), Greece (−70.0%), Australia (−43.2%), Poland (−41.3%), Indonesia (−38.8%), India (−33.6%), South Africa (−33.4%), Germany (−31.9%), and Russia (−31.6%). The divergences between mean and median buy-and-hold returns reflect positive skewness in the return distribution in every market. The standardized skewness coefficient for full-sample buy-and-hold returns ranges from 2.57 in Saudi Arabia to 39.37 in Hong Kong SAR and 40.67 in India.

The effects of positive skewness can also be observed in the fact that less than half of individual

Figure 4. Percentage of Stocks with Indicated Full-Sample Period Buy-and-Hold Return



stocks outperform the value-weighted market over their full lifetimes in 41 of the 43 markets (the only exceptions are Columbia, where 51.5% of the 66 firms outperformed the value-weighted market, and Finland, where 52.4% of the 275 stocks outperform the value-weighted market), including 16.8% in Greece, 17.3% in Nigeria, 17.7% in Japan, 18.3% in Malaysia and the United Arab Emirates, 18.7% in Indonesia, 19.0% in Poland, 21.1% in Hong Kong SAR, 23.9% in China, 25.5% in Germany, and 26.2% in the United Kingdom.

While the majority of global common stocks have full-sample buy-and-hold returns that fail to match one-month U.S. Treasury returns, this finding does not extend to each individual market. In 12 sample markets, more than half of individual common stocks outperformed U.S. Treasury returns, and in 4 markets—Saudi Arabia, Israel, Switzerland, and Finland—more than 60% of stocks outperformed U.S. Treasury returns. In contrast, less than 25% of stocks outperformed U.S. Treasury returns in 16 markets, including 10 of the 16 emerging markets in the sample. We assess later the extent to which differences in outperformance rates across markets are random or have systematic explanations.

While the global stock market performed strongly during the full 1990 to 2020 sample, market returns were negative over some shorter time periods. Some sample stocks may have low returns simply because the months they were included in the database were characterized by disappointing returns globally. We compile results separately for the 57,850 sample stocks where the overall market return exceeded the U.S. Treasury bill return during the period the stocks were contained in the database and for the 6,888 stocks where the overall market return fell short of the U.S. Treasury bill return during the period the stocks were contained in the database. Not surprisingly, stocks in the latter group performed poorly, with mean and median lifetime returns of −22.0% and −72.2%, respectively. Results for the former group are more informative. Even though the overall market outperformed Treasury bills during the periods that these stocks are included in the sample, the median return is barely positive (equal to 3.26%), only 45.7% delivered lifetime returns that exceeded those to Treasury bills, and less than one-third (29.7%) outperformed the value-weighted average returns. We conclude that positive skewness is an empirically important feature of long-run stock returns, even during periods when the ex-post market return is favorable, and that only a minority of stocks outperform Treasury bills at these times as well.

A Comparison of Observed Outcomes to a Simple Benchmark.

The data reported in Table 3 verify that the effects of positive skewness in compound individual stock returns exist as a global phenomenon and indeed are slightly stronger for non-U.S. stocks. Of course, models of compound stock returns generally imply that such positive skewness should be observed. As noted, to the extent that the results reported here are surprising the cause may be the fact that most studies focus on short-horizon returns, not on the compound long-horizon returns that can be computed from the short-horizon return data or that are implied by existing models.

In particular, many models assume that stock returns conform to the log-normal distribution, which displays positively skewness at all horizons except the instantaneous. The positive skewness of log-normally distributed returns depends only on, and is strictly increasing in, the variance of the log returns. This variance is, assuming iid return increments, proportional to the return horizon, so the implication that the positive skewness of log normal returns increase with return horizon immediately follows. We next assess how the indications of skewness observed in the sample data, as reported in Table 3, compare to what would be observed in a simple setting where each monthly return is a draw from a log-normal distribution with time-invariant parameters.

To do so, we create simulated log returns for a number of stocks equal to our sample size. Parameters are selected so that the mean and standard deviation of simulated monthly log returns are matched to the actual data.[16] We incorporate a block diagonal covariance structure that accommodates observed average correlations of stocks within each of 10 industries (based on stock SIC codes and industry definitions on Ken French's website) as well as the dependence of all stock returns on common market outcomes.

The skewness of compound returns depends in part on the number of months over which returns are compounded. While our sample spans 31 years, individual stocks are present in the data for a widely varying number of months (or "lives"). To accommodate this feature of the actual data in our simulation, we assign a lifetime to each simulated stock as a random draw from the distribution of lifetimes for sample stocks in the same industry. We generate simulated log returns for each sample stock for each month of its assigned life, convert the log returns to simple returns, and compound over the indicated horizons. The entire simulation is repeated 1,000 times to obtain a distribution of simulated compound returns at various horizons. Additional details regarding this simulation are contained in the Internet Data Appendix.

Table 4 reports average outcomes by horizon, when the simulation includes stocks calibrated to the full sample of 64,738 stocks, as well as to the subsamples of U.S. and non-U.S. stocks. The main implication of this exercise is that the iid log-normal benchmark implies *more* skewness in compound returns as compared to that observed in the data. Focusing, for example, on the global sample, the percentage of simulated stocks with compound returns that exceed matched-period returns to U.S. Treasury bills is 46.1% at the annual horizon, 40.4% at the decade horizon, and 38.0% at the lifetime horizon. By comparison, a higher proportion of sample stocks outperform U.S. Treasury bills: 50.0% at the annual horizon, 46.5% at the decade horizon, and 43.2% at the lifetime horizon (from Table 3). Similar results are observed when focusing on benchmarks of zero or the value-weighted market and for the U.S. and non-U.S. subsamples.

These results pose an intriguing challenge for future research. Is the more modest effect of skewness in the actual compound return data attributable to the fact that actual returns deviate from the log-normal assumption, because actual returns deviate from the iid assumption in terms of non-zero serial dependence and non-constant volatility, or for other reasons?

Outcomes across All Sample Years for Stocks and Portfolios of Stocks.

We study returns more than 31 calendar years: 1990 to 2020. However, for most stocks the lifetime return pertains to a much shorter period. The median period that stock is included in our sample is 102 months, or 8.5 years.

To obtain evidence regarding the long-term performance of individual stock positions that spans the full sample, we follow Bessembinder (2018) and implement a bootstrap procedure. In particular, for each month from January 1990 to December 2020, we select one stock at random from those available in the sample that month and then compound the

Table 4. Simulation Outcomes, Assuming Lognormal Monthly Returns

Horizon	Mean	Median	*SD*	Skewness	% > 0 (%)	% > *T*-bill (%)	% > VW Market (%)
Global							
Monthly	0.0105	−0.0025	0.165	0.514	49.4	48.8	47.7
Annual	0.1259	−0.0261	0.669	2.221	47.9	46.1	42.4
Decade	1.4906	−0.1225	11.810	58.974	44.8	40.4	31.8
Lifetime	6.8492	−0.1759	251.345	120.540	43.3	38.0	27.8
Global (Excl. U.S.)							
Monthly	0.0100	−0.0022	0.159	0.484	49.4	48.9	48.0
Annual	0.1191	−0.0225	0.635	2.027	48.1	46.3	43.5
Decade	1.3897	−0.1080	9.390	42.843	45.2	40.6	34.0
Lifetime	5.7967	−0.1528	151.815	97.990	43.8	38.0	30.1
United States							
Monthly	0.0122	−0.0038	0.185	0.606	49.1	48.6	47.0
Annual	0.1460	−0.0385	0.780	2.917	47.2	45.5	40.2
Decade	1.6750	−0.1616	19.309	56.375	43.3	39.7	28.6
Lifetime	10.4875	−0.2259	518.476	76.811	41.8	37.4	24.9

Notes: This table reports regarding simulated compound returns, when simulated stocks are assigned to 10 industries that correspond to SIC codes and industry definitions provided by Kenneth French. The simulated log return for stock j in each month depends on the simulated market and industry return according to $r_j = a_I + b_{I,M} r_{Mkt} + b_{I,Ind} r_{I,Ind} + \epsilon_I$, where r_j is the log return for the stock j, r_{Mkt} is the log market return, and $r_{I,Ind}$ is the log return for the industry I. We select parameter estimates to match the average observed mean log return as well as the average correlation and return variance by industry. The number of monthly observations for each stock is a random draw from the distribution of the actual number of sample observations by industry. Each simulated log return is restated as the equivalent simple return, $r_j = \log(1 + R_j)$, and the simple returns are then compounded across months for each stock. The figures in the table are mean outcomes across 1,000 repetitions of the simulation.

resulting returns across months. The result is one possible outcome from a strategy of holding a random stock in each month of the sample, ignoring any transaction costs. We conduct the bootstrap simulation when stocks are drawn from the full global sample, from U.S. stocks only, and from non-U.S. stocks only. We compare compound returns from the single-stock strategy realized over five-year, decade, and full-sample horizons to the benchmarks of zero, the accumulated return to holding one-month U.S. Treasury bills over the same interval, and the accumulated return on the value-weighted portfolio of all common stocks in the sample over the same interval. We repeat the procedure 1,000 times to obtain a bootstrap distribution of possible returns to single-stock strategies at each horizon.

The results, reported in the first three rows of Table 5, indicate that the effects of return skewness are stronger when considering individual stocks over the full 31-year sample as compared to those in the actual sample data, where individual stock lives are shorter. Focusing, for example, on global stocks and the full sample period, only 37.2% of single-stock strategies have a positive return, as compared (Table 3, Panel D) to positive lifetime returns for 48.2% of sample stocks. In the same sample, 28.4% of single-stock strategies have returns greater than those to U.S. Treasury bills over the full 31 years, compared to 43.2% of sample stocks, and just 15.2% of single-stock strategies produce returns that exceed the value-weighted market, compared to 29.3% of sample stocks. That is, the full-sample results reported in Table 3 actually understate the effects of skewness over a three-decade horizon, because the available return series for most individual stocks pertain to shorter periods.

Also following Bessembinder (2018), we repeat the bootstrap simulations to assess the effects of portfolio diversification. In particular, for each month from January 1990 to December 2020 we select sets of 5, 25, 50, and 100 stocks at random from the set of stock with available return data. Within each month, we compute the value-weighted return to the selected portfolio, and we then link these monthly returns over horizons of 5 years, 10 years, and the full 31 sample years. The procedure is repeated 1,000 times.

Farago and Hjalmarsson (2023) show that the skewness in long-horizon returns depends mainly on the

Table 5. Bootstrap Simulations

	5-Year Horizon			10-Year Horizon			31-Year Horizon		
	Global (%)	Global (Excl. U.S.) (%)	United States (%)	Global (%)	Global (Excl. U.S.) (%)	United States (%)	Global (%)	Global (Excl. U.S.) (%)	United States (%)
Single-stock positions									
% > 0	45.6	46.2	43.0	42.0	43.6	36.9	37.2	36.8	30.0
% > T-bill	41.8	42.3	39.3	36.9	38.4	32.3	28.4	26.8	21.1
% > VW Market	33.5	35.8	28.1	27.7	30.6	21.5	15.2	17.3	7.8
5-stock portfolios, value-weighted									
% > 0	62.7	60.2	68.0	66.2	65.4	69.3	76.1	73.0	88.0
% > T-bill	56.1	53.4	61.9	56.5	55.3	60.5	59.5	53.3	73.8
% > VW Market	41.3	43.3	39.1	38.0	40.8	35.8	27.1	30.5	23.4
25-stock portfolios, value-weighted									
% > 0	76.3	70.8	81.1	85.1	80.7	87.5	97.5	94.2	99.7
% > T-bill	67.7	60.8	74.7	73.2	67.2	78.2	86.9	75.9	98.1
% > VW Market	45.8	47.0	45.3	45.3	46.3	44.8	36.7	40.1	36.4
50-stock portfolios, value-weighted									
% > 0	80.0	75.4	83.7	89.6	86.0	91.4	99.3	97.6	100.0
% > T-bill	71.4	64.0	77.3	77.6	72.0	82.7	93.9	83.2	99.7
% > VW Market	46.6	48.2	47.8	46.5	48.9	47.9	40.7	43.6	42.9
100-stock portfolios, value-weighted									
% > 0	83.5	78.3	84.4	93.4	90.2	92.8	100.0	99.7	100.0
% > T-bill	74.9	66.1	77.6	82.2	75.2	84.7	97.6	89.0	99.9
% > VW Market	47.6	49.2	47.6	48.8	49.6	47.1	42.4	45.4	39.6

Notes: This table reports the results of bootstrap simulations to assess the long-term performance of global individual stocks and portfolios following Bessembinder (2018). For each month from January 1990 to December 2020, 1, 5, 25, 50, and 100 stocks are randomly selected from each subsample (global, non-U.S., and U.S. stocks), and value-weighted portfolio returns for the selected stocks are calculated. These returns are computed over 5-, 10-, and 31-year horizons, and the procedure is repeated 1,000 times. Each of these returns is compared to three benchmarks: zero, the U.S. Treasury bill rate, and the corresponding value-weighted market return, over the same horizon. The numbers refer to the mean across the 1,000 outcomes.

volatility of short-horizon returns. Because diversification reduces portfolio return volatility, it can be anticipated that compound portfolio returns will be less positively skewed than single-stock returns. The data in Table 5 illustrate the extent to which this is true.

Focusing on the 5-year horizon and the global sample excluding U.S. stocks, the percentage of portfolio returns that exceed returns to one-month U.S. Treasury bills increases from 42.3% for single-stock portfolios to 53.4% for 5-stock portfolios, 60.8% for 25-stock portfolios, 64.0% for 50-stock portfolios, and 66.1% for 100-stock portfolios. Corresponding outcomes at the full-sample (31-year) horizon, still focusing on the non-U.S. sample, outperformance rates relative to U.S. Treasury bills are 26.8% for single-stock portfolios, 53.3% for 5-stock portfolios, 75.9% for 25-stock portfolios, 83.2% for 50-stock portfolios, and 89.0% for 100-stock portfolios. The effects of skewness are stronger for portfolios formed from non-U.S. stocks. For example, at the full-sample horizon, 99.7% of the U.S. portfolios containing 50 stocks outperform U.S. Treasury bills, compared to 83.2% of the non-U.S. stock portfolios.

Despite that diversification reduces the degree of skewness and the attendant effects in long-horizon returns, the effects of skewness remain noticeable even at the full-sample horizon and in the 100-stock portfolios. The percentages of bootstrapped 100-stock portfolios that outperform the value-weighted portfolio at the 31-year horizon are 39.6% in U.S. stocks and 45.4% in non-U.S. stocks. Long-term financial planning, for example, at pension funds, often incorporates assumptions regarding mean returns that are based on evidence for overall market proxies. Positive skewness implies that the majority of possible future outcomes, even to a diversified portfolio, are less than outcome to the fully diversified portfolio.

Table 6. Full-Sample Wealth Creation, Top 50 Global Firms

Firm Name	Market	PERMCO/ GVKEY*	Wealth Created ($Millions)	Accumulated % of Global Gross Wealth Creation (%)	Accumulated % of Global Net Wealth Creation (%)	Annualized Dollar Weighted Return (%)	First Month	Last Month
APPLE INC	United States	7	2,674,231	2.74	3.53	23.51	199002	202012
MICROSOFT CORP	United States	8048	1,910,158	4.69	6.06	19.16	199002	202012
AMAZON COM INC	United States	15473	1,569,085	6.30	8.13	31.09	199706	202012
ALPHABET INC	United States	45483	979,133	7.30	9.43	19.34	200409	202012
TENCENT HOLDINGS LTD	Hong Kong SAR	270615*	691,671	8.00	10.34	48.11	200407	202012
TESLA INC	United States	53453	639,266	8.66	11.19	65.44	201007	202012
WALMART INC	United States	21880	568,713	9.24	11.94	13.51	199002	202012
FACEBOOK INC	United States	54084	553,675	9.81	12.67	30.39	201206	202012
SAMSUNG ELECTRONICS CO LTD	South Korea	104604*	540,605	10.36	13.38	20.17	199002	202012
JOHNSON & JOHNSON	United States	21018	535,317	10.91	14.09	13.86	199002	202012
TAIWAN SEMICONDUCTOR MFG CO	Taiwan	201395*	525,515	11.44	14.79	18.30	199502	202012
BERKSHIRE HATHAWAY INC DEL	United States	540	504,079	11.96	15.45	11.68	199002	202012
NESTLE SA/AG	Switzerland	016603*	478,110	12.45	16.08	13.21	199002	202012
PROCTER & GAMBLE CO	United States	21446	451,109	12.91	16.68	13.05	199002	202012
EXXON MOBIL CORP	United States	20678	437,083	13.36	17.26	10.65	199002	202012
JPMORGAN CHASE & CO	United States	20436	414,080	13.78	17.81	9.76	199002	202012
HOME DEPOT INC	United States	5085	399,790	14.19	18.33	16.55	199002	202012
KWEICHOW MOUTAI CO LTD	China	251321*	395,870	14.60	18.86	38.98	200205	202012
VISA INC	United States	52983	384,977	14.99	19.37	23.77	200804	202012
ROCHE HOLDING AG	Switzerland	025648*	377,253	15.38	19.86	14.09	199002	202012
MASTERCARD INC	United States	50700	374,932	15.76	20.36	32.98	200606	202012
ALIBABA GROUP HLDG	Hong Kong SAR	020530*	374,085	16.14	20.85	17.17	201410	202012
UNITEDHEALTH GROUP INC	United States	7267	370,220	16.52	21.34	21.23	199002	202012
ALTRIA GROUP INC	United States	21398	364,636	16.89	21.83	17.03	199002	202012
INTEL CORP	United States	2367	340,219	17.24	22.28	15.95	199002	202012
COCA COLA CO	United States	20468	329,515	17.58	22.71	12.93	199002	202012
LVMH MOET HENNESSY LOUIS V	France	014447*	327,264	17.91	23.14	12.36	199002	202012
ORACLE CORP	United States	8045	318,543	18.24	23.56	19.50	199002	202012
DISNEY WALT CO	United States	20587	311,559	18.56	23.98	10.56	199002	202012

continued

Table 6. Full-Sample Wealth Creation, Top 50 Global Firms (continued)

Firm Name	Market	PERMCO/ GVKEY*	Wealth Created ($Millions)	Accumulated % of Global Gross Wealth Creation (%)	Accumulated % of Global Net Wealth Creation (%)	Annualized Dollar Weighted Return (%)	First Month	Last Month
NVIDIA CORP	United States	16382	309,415	18.87	24.39	27.51	199902	202012
NOVARTIS AG	Switzerland	101310*	308,868	19.19	24.79	10.16	199002	202012
MERCK & CO INC NEW	United States	21188	294,504	19.49	25.18	11.80	199002	202012
ABBOTT LABORATORIES	United States	20017	278,012	19.78	25.55	14.42	199002	202012
PEPSICO INC	United States	21384	274,708	20.06	25.91	12.68	199002	202012
INTERNATIONAL BUSINESS MACHS COR	United States	20990	251,798	20.32	26.25	9.72	199002	202012
GENERAL ELECTRIC CO	United States	20792	249,413	20.57	26.58	9.90	199002	202012
TOYOTA MOTOR CORP	Japan	019661*	248,904	20.82	26.90	7.37	199002	202012
CHEVRON CORP NEW	United States	20440	246,044	21.08	27.23	10.37	199002	202012
L'OREAL SA	France	100581*	245,549	21.33	27.55	15.43	199002	202012
COMCAST CORP NEW	United States	43613	243,004	21.58	27.88	11.81	200212	202012
MCDONALDS CORP	United States	21177	242,631	21.82	28.20	13.00	199002	202012
ADOBE INC	United States	8476	240,417	22.07	28.51	19.52	199002	202012
NETFLIX INC	United States	43145	232,391	22.31	28.82	38.71	200206	202012
SAUDI ARABIAN OIL CO	Saudi Arabia	334426*	231,228	22.54	29.13	12.91	202001	202012
CISCO SYSTEMS INC	United States	10486	229,556	22.78	29.43	9.37	199003	202012
PAYPAL HOLDINGS INC	United States	55341	227,990	23.01	29.73	39.18	201508	202012
PFIZER INC	United States	21394	219,723	23.24	30.02	6.50	199002	202012
CHINA CONSTR BANK CORP	China & Hong Kong SAR	274364*	216,922	23.46	30.31	11.63	200512	202012
INDUSTRIAL & COMM BANKCHINA	China & Hong Kong SAR	279378*	213,988	23.68	30.59	7.87	200612	202012
ASML HOLDING NV	Netherlands	061214*	209,298	23.89	30.87	22.13	199504	202012

Notes: This table shows the wealth creation for the 50 global firms that created the most wealth during our sample period from January 1990 to December 2020. It also shows the market from which the firm comes, the wealth creation in million USD, accumulated percentage of global gross wealth creation, accumulated percentage of global net wealth creation, the annualized dollar-weighted return, and the beginning and ending months that the firm appears in the sample.

Stock Market Wealth Creation

We measure stock market wealth creation by implementing expression (1) for each of the 63,785 companies in the sample, using all available data during the January 1990 to December 2020 sample period. As noted, expression (1) can be viewed as quantifying the increase in end-of-period wealth to shareholders because they earned on their invested capital the stock's actual returns rather than one-month Treasury bill returns. Wealth creation is distinguished from a simple examination of firms' end-of-sample market capitalization by the fact that it considers all prior cash flows to or from shareholders. In particular, share repurchases and dividends reduce market capitalization, while these transactions do not similarly decrease calculated shareholder wealth creation. For many firms that made substantive shareholders distributions in the form of dividends or share repurchases wealth creation outcomes exceed the firm's end-of-sample market value.

The Top Wealth-Creating Companies. We compute that sample companies collectively created $US 75.66 trillion in shareholder wealth between January 1990 and December 2020 (Table 8). The sample includes 26,967 firms (42.28% of total) with positive wealth creation and 36,818 (57.72% of total) with negative wealth creation. Focusing only on those firms for which wealth creation was positive, the sum is $US 97.75 trillion in wealth creation (Table 8). This total was offset by $US 22.09 trillion in wealth reduction by the remaining sample firms. We will refer to the sum of wealth creation across firms with positive outcomes as "gross wealth" created and to the sum across all firms as "net wealth" created.

Table 6 reports on the 50 firms that created the most wealth during the sample period. The table also reports the first month and the last month that the firm appears in the database and the annualized internal (or dollar-weighed) rate of return to shareholders in aggregate.[17] The firm ranked first in terms of wealth creation during the January 1990 to December 2020 period is Apple, with wealth creation of $US 2.67 trillion. The rest of the top-five firms are Microsoft ($US 1.91 trillion in wealth creation), Amazon ($US 1.57 trillion), Alphabet ($US 979 billion), and Tencent ($US 692 billion). Amazon entered the sample in 1997, while Alphabet and Tencent both entered 2004. In contrast, Apple and Microsoft were present since the beginning of the sample in January 1990. The youngest firms among the top 50 wealth creators include Facebook, which entered the sample in 2012, Alibaba, which entered in 2014, Tesla, which entered in 2010, and remarkably, the Saudi Arabian Oil Company, which was present in the sample only during the year 2020.

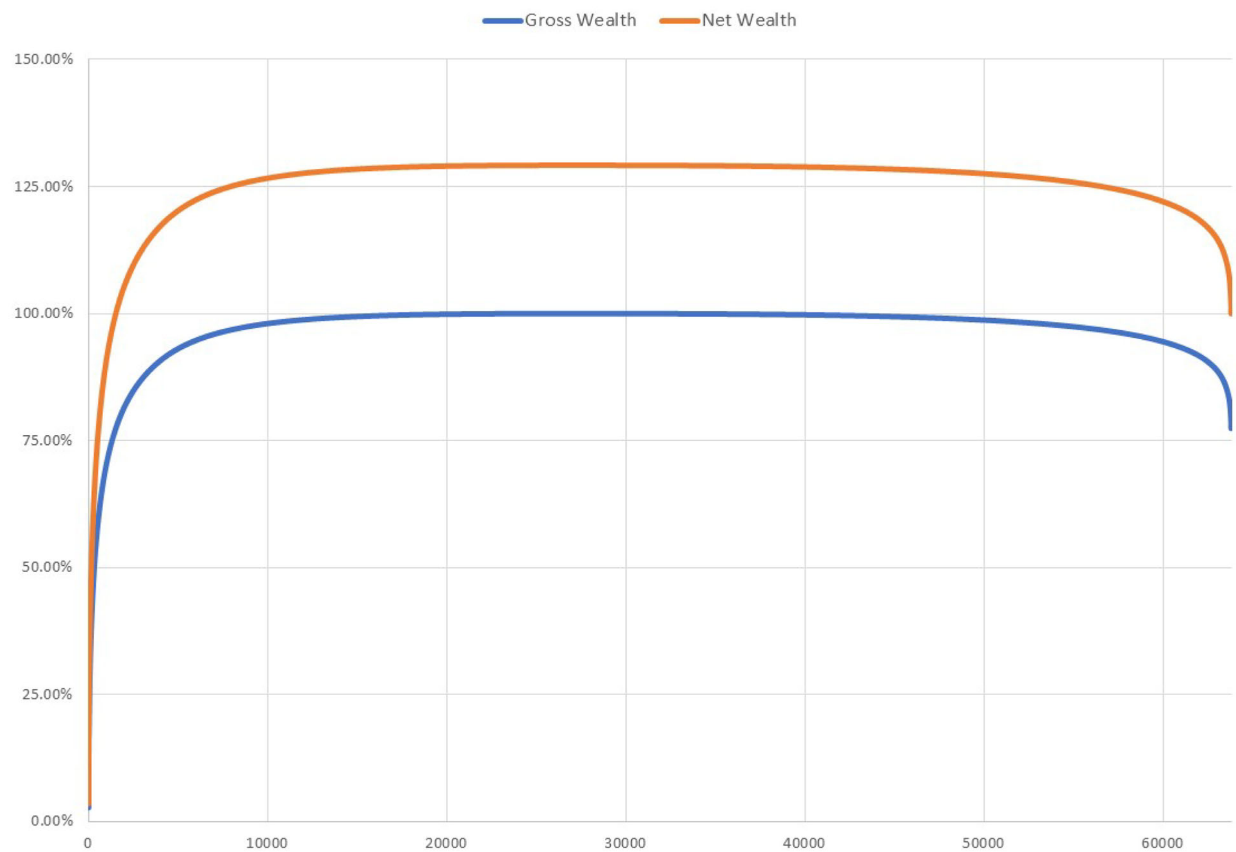
Thirty-five of the top fifty wealth creating firms listed on Table 6 are American. The non-U.S. firms include Tencent, Samsung, Taiwan Semiconductor, Nestle, Kweichow Moutai, Roche Holding, Alibaba, LVMH Moet Hennessy Louis Vuitton, Novartis, Toyota, L'Oréal, the Saudi Arabian Oil Company, China Construction Bank, Industrial and Commercial Bank of China, and ASML Holding.

The dollar-weighted return to Tesla shareholders during the sample period was 65.4%, which was the highest among the top 50 wealth-creating firms listed in Table 6. Other firms that generated shareholder returns that exceed 30% per year include Tencent (48.1%), PayPal (39.2%), Kweichow Moutai (39.0%), Netflix (38.7%), Mastercard (33.0%), Amazon.com (31.1%), and Facebook (30.4%).

As noted, Apple created $US 2.67 trillion in stock market wealth during the January 1990 to December 2020 sample. Thus, Apple alone accounted for 3.53% of the $US 75.66 trillion in net global wealth creation and 2.74% of the $US 97.75 trillion in gross global wealth creation. Table 6 also reports the percentage of global net (across all firms) and gross (across firms with positive outcomes) wealth creation during the January 1990 to December 2020 sample period accounted for by the indicated firm and those listed above it. The top five firms (Apple, Microsoft, Alphabet, Amazon, and Tencent), which represent 0.008% of the 63,785 firms in the sample, accounted for 10.34% of global net wealth creation and 8.00% of global gross wealth creation. The top 20 firms (0.031% of the firms in the sample) accounted for 19.86% of global net wealth creation and 15.38% of global gross wealth creation. The top 50 firms (0.078% of the firms in the sample) accounted for 30.87% of global net wealth creation and 23.89% of global gross wealth creation.

Figure 5 displays the cumulative percentages of gross and net wealth creation when firms are ranked from highest to lowest wealth creation, for all 63,785 firms in the sample. The net wealth creation curve ends at 100% by construction and reaches a maximum of 129%, which reflects that gross wealth creation (summed across only firms with positive wealth creation) was 29% larger than net wealth creation (which includes the effects of wealth reduction at

Figure 5. Cumulative Percentage of Global Dollar Wealth Creation, All Sample Firms



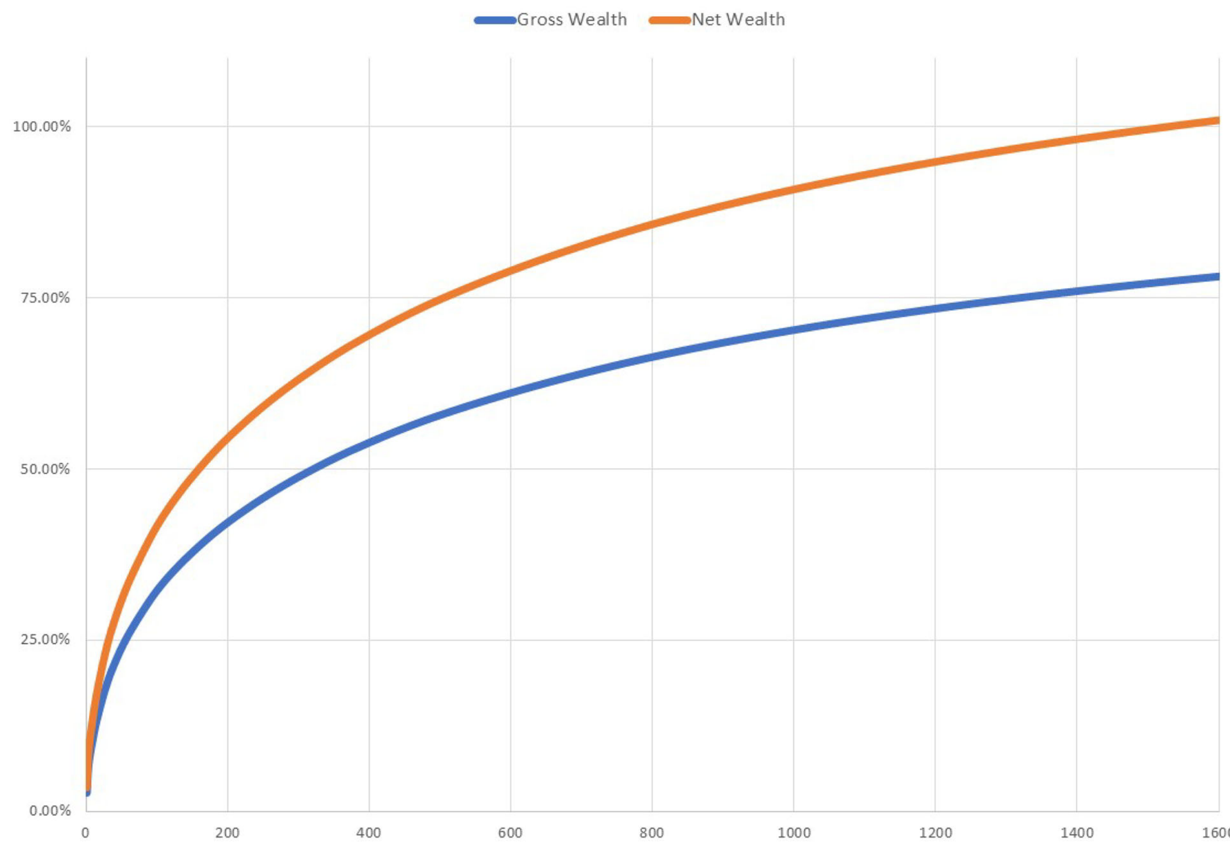
the majority of firms). The gross wealth creation curve reaches a maximum of 100% by construction.

Figure 6 displays the same data as Figure 5, but only for the 1,600 firms with the greatest wealth creation. The net wealth creation curve reaches 25% at 32 firms (0.05% of the total), 50% at 159 firms (0.25% of the total), 75% at 505 firms (0.79% of the total), and 100% at 1,526 firms (2.39% of the total). That is, the top-performing 2.4% of firms in the sample created net wealth of $US 75.66 trillion, equivalent to the wealth creation of the entire sample of global firms, while the remaining 97.6% of firms collectively matched the returns to one-month U.S. Treasury bills. By comparison, Bessembinder (2018) reports that 4.1% of stocks contained in the CRSP (U.S.) database account for all net dollar wealth creation during the 1926 to 2016 sample period.

In addition to the 1,526 firms that created wealth equivalent to the full sample, another 25,441 firms (39.9% of the total) generated positive wealth for their shareholders. However, the wealth creation of these firms just offset the wealth reduction of the remaining 36,818 (57.7% of firms), such that the 62,259 firms (97.6% of total) not included among the top 1,526 best performers collectively generated returns on invested capital that just matched one-month Treasury bills. The finding that just 2.4% of firms generated wealth (measured in dollars) equivalent to total global stock market wealth creation can be attributed to several interrelated factors, including dispersion in firm sizes and in the length of time that firms are included in the sample, and purely random outcomes. It also reflects the practical importance of positive skewness in the distribution of long-horizon stock returns.

We report in Tables 1 through 43 of the Internet Global Appendix the top 20 firms in terms of full-sample wealth creation for each of the individual markets included in this study. The data in these tables indicate that the single top-performing firm often explains a substantial portion of gross wealth

Figure 6. Cumulative Percentage of Global Dollar Wealth Creation, Top 1,600 Firms



creation in each market. Prominent examples include Anheuser-Busch Inbev (28.5% of gross wealth creation in Belgium), Novo Nordisk (26.5% in Denmark), Samsung Electronics (33.5% in South Korea), Taiwan Semiconductor (36.6% in Taiwan), Nestle (21.4% in Switzerland), and Saudi Arabian Oil Company (33.4% in Saudi Arabia). By comparison, Apple, with the largest wealth creation of any individual firm in the sample, accounts for 5.3% of gross wealth creation among U.S. firms.

Table 7 reports on the 20 firms with the most negative wealth creation in the global sample. We calculate that Petro China was responsible for the largest wealth reduction, $US 553 billion. Nine of the bottom eleven firms are Japanese, including six banks (Industrial Bank of Japan, Bank Tokyo-Mitsubishi, Fuji Bank, Dai-Ichi Kangyo Bank, Sakura Bank, and Sanwa Bank) as well as Sumitomo-Mitsui Financial Group, Nippon Telegraph and Telephone, and Tokyo Electric Power Company.[18] The worst-performing American firms were WorldCom, Viavi Solutions, Lucent Technologies, and Wachovia.

How Concentrated Is Wealth Creation?

We show in the prior section that five firms account for more than 10% of the net shareholder wealth created by the 63,785 firms in our 1990 to 2020 sample. We next report additional information on the degree to which wealth creation is concentrated for subsamples and individual markets. In Table 8, we report on the percentage of net wealth creation (summed across all firms) and gross wealth creation (summed across firms with positive wealth creation) accounted for by the best-performing 0.25%, 0.5%, 1.0%, and 5.0% of firms in each subsample.

The data in Table 8 show that net wealth creation is more concentrated among non-U.S. firms than among U.S. firms. The top-performing 0.25% of U.S. firms accounted for 44.3% of net wealth creation for all U.S. firms, while the top-performing 0.25% of non-U.S. firms accounted for 51.2% of net wealth creation in the non-U.S. sample. The top-performing 1% of U.S. firms accounted for 70.2% of U.S. net wealth creation, while the top-performing 1% of non-U.S.

Table 7. Full-Sample Wealth Reduction, Bottom 20 Global Firms

Firm Name	Market	PERMCO/ GVKEY*	Wealth Created ($Millions)	% of Global Gross Wealth Reduction (%)	Accumulated % of Global Gross Wealth Reduction (%)	Annualized Dollar Weighted Return (%)	First Month	Last Month
PETROCHINA CO LTD	China & Hong Kong SAR	133870*	−552,527	2.50	2.50	−11.23	200006	202012
INDUSTRIAL BANK OF JAPAN LTD	Japan	015685*	−177,456	0.80	3.30	−13.36	199002	200009
SUMITOMO MITSUI FINANCIAL GR	Japan	010137*	−156,954	0.71	4.02	−3.09	199002	202012
NIPPON TELEGRAPH & TELEPHONE	Japan	007908*	−144,330	0.65	4.67	0.67	199002	202012
BANK TOKYO-MITSUBISHI	Japan	015627*	−128,566	0.58	5.25	−8.91	199002	200103
CHINA SHENHUA ENERGY CO LTD	China & Hong Kong SAR	273153*	−115,090	0.52	5.77	−6.64	200608	202012
FUJI BANK LTD	Japan	015556*	−112,527	0.51	6.28	−8.55	199002	200009
DAI-ICHI KANGYO BANK LTD	Japan	015550*	−101,150	0.46	6.74	−8.04	199002	200009
TOKYO ELECTRIC POWER CO HOLD	Japan	100688*	−97,850	0.44	7.18	−7.35	199002	202012
SAKURA BANK LTD	Japan	015624*	−97,377	0.44	7.62	−9.63	199002	200103
SANWA BANK LTD	Japan	006775*	−97,096	0.44	8.06	−9.86	199002	200103
WORLDCOM INC GA NEW	United States	61	−94,472	0.43	8.49	−50.47	199002	200205
VIAVI SOLUTIONS INC	United States	12583	−84,482	0.38	8.87	−13.15	199312	202012
LUCENT TECHNOLOGIES INC	United States	31614	−84,196	0.38	9.25	−19.45	199605	200611
UNICREDIT SPA	Italy	015549*	−80,173	0.36	9.62	−11.37	199002	202012
NATWEST GROUP PLC	United Kingdom	015634*	−77,522	0.35	9.97	−10.08	199002	202012
NOMURA HOLDINGS INC	Japan	015613*	−75,762	0.34	10.31	−2.45	199002	202012
MITSUBISHI UFJ FINANCIAL GRP	Japan	252940*	−65,993	0.30	10.61	−2.37	200105	202012
MIZUHO FINANCIAL GROUP INC	Japan	248136*	−65,445	0.30	10.91	−3.80	200011	202012
WACHOVIA CORP 2ND NEW	United States	1869	−65,404	0.30	11.20	−25.39	199002	200812

Notes: This table shows the wealth reduction for the 20 global firms with the most negative wealth creation outcomes during our sample period from January 1990 to December 2020. It also shows the market from which the firm comes, the wealth creation in million USD, percentage of global gross wealth reduction, accumulated percentage of global gross wealth reduction, the annualized dollar-weighted return, and the beginning and ending months that the firm appears in the sample.

Table 8. Concentration of Gross and Net Wealth Creation

	Total Firms			Top 0.25% of Firms			Top 0.5% of Firms			Top 1% of Firms			Top 5% of Firms		
Sample	# Firms	Gross Wealth ($Bil.)	Net Wealth ($Bil.)	# Firms	% of Gross Wealth	% of Net Wealth	# Firms	% of Gross Wealth	% of Net Wealth	# Firms	% of Gross Wealth	% of Net Wealth	# Firms	% of Gross Wealth	% of Net Wealth
Global	63,785	97,750	75,661	160	38.81%	50.14%	319	49.91%	64.48%	638	62.26%	80.44%	3,190	88.00%	113.69%
Global (Excl. U.S.)	46,221	47,193	30,733	116	33.32%	51.17%	232	45.34%	69.62%	463	58.68%	90.10%	2,312	86.36%	132.62%
By Development															
Developed	49,044	84,931	67,290	123	39.30%	49.61%	246	50.43%	63.66%	491	62.71%	79.16%	2,453	88.52%	111.73%
Developed (Excl. U.S.)	31,480	34,374	22,362	79	34.03%	52.31%	158	46.20%	71.01%	315	59.82%	91.95%	1,574	87.35%	134.27%
Emerging	14,860	12,863	8,371	38	29.60%	45.49%	75	41.25%	63.39%	149	53.82%	82.71%	743	83.14%	127.77%
By Region															
North America	19,568	52,948	46,874	49	38.84%	43.87%	98	50.07%	56.56%	196	62.06%	70.11%	979	87.74%	99.11%
Europe	12,479	17,838	14,457	32	28.67%	35.37%	63	40.44%	49.90%	125	54.14%	66.80%	624	84.80%	104.63%
Asian Pacific	17,002	14,144	5,958	43	40.81%	96.88%	86	52.69%	125.07%	171	65.05%	154.41%	851	89.12%	211.56%
By Market															
Developed															
United States	17,330	50,096	44,558	44	39.36%	44.25%	87	50.55%	56.84%	174	62.43%	70.19%	867	87.87%	98.79%
Homeless (U.S. ADRs)	239	461	370	1	24.53%	30.58%	2	36.98%	46.10%	3	48.43%	60.36%	12	81.56%	101.67%
Canada	2,001	2,392	1,946	6	29.16%	35.83%	11	40.17%	49.37%	21	53.13%	65.29%	101	83.04%	102.05%
Austria	177	97	38	1	15.29%	39.08%	1	15.29%	39.08%	2	30.47%	77.86%	9	66.94%	171.07%
Belgium	297	423	346	1	28.54%	34.91%	2	35.75%	43.72%	3	40.03%	48.96%	15	69.61%	85.13%
Denmark	346	692	660	1	26.48%	27.76%	2	36.73%	38.51%	4	49.54%	51.94%	18	82.72%	86.72%
Finland	249	413	376	1	12.87%	14.12%	2	23.99%	26.33%	3	34.22%	37.56%	13	74.00%	81.24%
France	1,721	2,942	2,481	5	33.20%	39.38%	9	47.35%	56.16%	18	63.34%	75.12%	87	88.34%	104.78%
Germany	1,492	2,426	1,924	4	21.07%	26.57%	8	34.10%	43.00%	15	49.21%	62.05%	75	84.72%	106.81%
Greece	411	60	−53	2	41.86%	NA	3	46.40%	NA	5	54.31%	NA	21	80.46%	NA
Ireland	85	135	101	1	24.08%	32.11%	1	24.08%	32.11%	1	24.08%	32.11%	5	84.45%	112.65%
Italy	725	800	349	2	23.48%	53.75%	4	33.61%	76.96%	8	48.32%	110.63%	37	81.43%	186.43%
Netherlands	329	1,143	1,035	1	18.31%	20.22%	2	31.10%	34.36%	4	43.80%	48.38%	17	85.28%	94.21%
Norway	564	364	275	2	28.38%	37.49%	3	39.38%	52.02%	6	51.61%	68.16%	29	78.14%	103.22%
Portugal	122	82	30	1	25.21%	67.93%	1	25.21%	67.93%	2	43.47%	117.11%	7	76.89%	207.14%
Spain	376	839	649	1	13.31%	17.22%	2	24.63%	31.86%	4	41.76%	54.00%	19	77.37%	100.06%
Sweden	993	1,228	1,176	3	18.39%	19.21%	5	26.64%	27.83%	10	40.17%	41.96%	50	77.68%	81.14%
Switzerland	405	2,235	2,158	2	38.27%	39.63%	3	52.08%	53.94%	5	57.41%	59.45%	21	79.67%	82.51%
United Kingdom	4,188	3,958	2,911	11	30.51%	41.48%	21	42.94%	58.39%	42	56.68%	77.07%	210	85.77%	116.62%
Australia	2,962	1,831	1,594	8	41.55%	47.72%	15	52.71%	60.55%	30	63.48%	72.92%	149	89.75%	103.09%

continued

Table 8. Concentration of Gross and Net Wealth Creation (continued)

	Total Firms			Top 0.25% of Firms			Top 0.5% of Firms			Top 1% of Firms			Top 5% of Firms		
Sample	# Firms	Gross Wealth ($Bil.)	Net Wealth ($Bil.)	# Firms	% of Gross Wealth	% of Net Wealth	# Firms	% of Gross Wealth	% of Net Wealth	# Firms	% of Gross Wealth	% of Net Wealth	# Firms	% of Gross Wealth	% of Net Wealth
Hong Kong SAR	2,609	4,610	4,026	7	39.43%	45.15%	14	50.31%	57.61%	27	61.51%	70.43%	131	89.83%	102.85%
Israel	636	201	175	2	14.67%	16.85%	4	24.26%	27.86%	7	34.00%	39.05%	32	61.90%	71.10%
Japan	3,983	3,828	−2,219	10	28.71%	NA	20	43.50%	NA	40	58.99%	NA	200	88.21%	NA
New Zealand	271	152	138	1	12.06%	13.28%	2	21.65%	23.84%	3	29.94%	32.97%	14	66.08%	72.76%
Singapore	1,042	469	350	3	27.34%	36.62%	6	43.58%	58.36%	11	55.83%	74.77%	53	85.45%	114.43%
South Korea	3,060	1,616	1,149	8	52.41%	73.70%	16	62.15%	87.39%	31	71.68%	100.80%	153	89.08%	125.27%
Taiwan	2,439	1,436	745	7	50.68%	97.76%	13	57.83%	111.55%	25	66.37%	128.03%	122	86.24%	166.36%
Emerging															
Argentina	114	52	22	1	40.08%	96.02%	1	40.08%	96.02%	2	58.96%	141.27%	6	82.95%	198.75%
Brazil	390	600	424	1	15.23%	21.55%	2	22.40%	31.69%	4	32.29%	45.67%	20	69.34%	98.07%
China	3,962	6,214	3,822	10	23.44%	38.12%	20	33.44%	54.37%	40	46.79%	76.07%	199	74.78%	121.58%
Colombia	66	107	99	1	22.46%	24.20%	1	22.46%	24.20%	1	22.46%	24.20%	4	46.10%	49.68%
India	3,967	2,102	1,630	10	38.26%	49.34%	20	52.08%	67.16%	40	65.46%	84.43%	199	92.08%	118.75%
Indonesia	781	354	213	2	30.37%	50.57%	4	43.72%	72.81%	8	61.51%	102.43%	40	88.80%	147.88%
Malaysia	1,364	383	188	4	20.70%	42.23%	7	29.08%	59.34%	14	44.03%	89.83%	69	81.47%	166.22%
Mexico	205	445	340	1	14.29%	18.67%	2	25.79%	33.71%	3	36.41%	47.59%	11	72.03%	94.15%
Nigeria	202	23	−24	1	17.95%	NA	2	35.72%	NA	3	51.02%	NA	11	92.03%	NA
Poland	994	142	72	3	35.01%	69.00%	5	44.58%	87.87%	10	61.86%	121.93%	50	89.44%	176.28%
Russia	276	462	263	1	19.60%	34.50%	2	37.13%	65.36%	3	46.11%	81.16%	14	87.53%	154.08%
Saudi Arabia	201	691	614	1	33.44%	37.68%	2	53.08%	59.80%	3	61.22%	68.97%	11	79.81%	89.91%
South Africa	852	513	259	3	31.99%	63.34%	5	39.54%	78.28%	9	51.12%	101.22%	43	88.24%	174.71%
Thailand	923	445	279	3	26.03%	41.57%	5	35.23%	56.27%	10	50.50%	80.65%	47	83.90%	133.99%
Turkey	437	148	92	2	14.68%	23.65%	3	21.28%	34.29%	5	32.99%	53.15%	22	74.79%	120.49%
UAE	126	181	79	1	32.13%	74.12%	1	32.13%	74.12%	2	45.92%	105.93%	7	80.01%	184.57%

Notes: This table reports the number of firms, percentage of gross wealth creation (summed across firms with positive wealth creation), and net wealth creation (summed across all firms) accounted for by the best-performing 0.25%, 0.5%, 1.0%, and 5.0% of firms in each subsample during our sample period from January 1990 to December 2020.

firms accounted for 90.1% of net wealth creation among all non-U.S. firms in the sample.

Stock market wealth creation, as well as the degree to which wealth creation is concentrated, varies considerably across markets. Net wealth creation at the national level (obtained by summing firm-level wealth creation across all firms in a market) is *negative* during the sample period for Greece and Japan in the developed markets and Nigeria in the emerging markets. In Japan, wealth creation aggregated across all 3,983 sample firms was −$US 2.22 trillion.

For markets with negative net wealth creation, the calculated percentage contribution would be negative for all firms that created positive wealth. Further, a focus on the concentration of net wealth creation (obtained as the sum of both positive and negative wealth firm-by-firm wealth creation outcomes) can be misleading in those cases where net wealth creation is a modest positive number.[19] While this is a minor consideration at the global level, where net wealth creation for the current sample exceeds $75 trillion, it can be an issue for specific markets. These considerations support the desirability of also studying the concentration of gross wealth creation, obtained by summing wealth creation for those firms with positive outcomes only.

Focusing on the top-performing 1% of firms in each market, the least concentration is observed in Columbia, where the best-performing firms accounted for 22.5% of gross wealth creation. In contrast, the percentage of gross wealth creation accounted for by the top-performing 1% of firms exceeded 60% in the United States, France, Australia, Hong Kong SAR, South Korea, Taiwan, India, Indonesia, Poland, and Saudi Arabia. Focusing on the top-performing 5% of firms in each market, the percentage of gross wealth creation explained ranges from 46.1% in Columbia to 92.1% in India. Wealth creation is more concentrated in the Asia Pacific region (1% of firms account for 65.1% of gross wealth creation) as compared to North America and, particularly, Europe, where the top 1% of firms account for 62.1% and 54.1%, respectively, of gross wealth creation.

As noted, we measure shareholder wealth creation by implementing expression (1). The term I_t in Equation (1) denotes the time t value of shareholders' investment in the firm, which we measure as the firm's market capitalization. However, in those cases where one sample firm owns shares in another sample firm, the sum of market capitalizations across firms exceeds the actual investment by external shareholders. As a consequence, our calculations may double count wealth creation to some degree. Duchin, Gilbert, Harford, and Hrdlicka (2017) document that S&P 500 firms in aggregate hold equity investments amounting to only 0.30% of the market value of their own equity. However, the degree of double counting could be greater in some markets and for some specific firms.[20]

To address the double counting issue, we obtain from Refinitiv ownership data on the number of shares in sample firms held by firms that also appear in our sample and compute wealth creation outcomes that are adjusted to avoid double counting. Because we are concerned with cross-holdings *within* our sample, we exclude from consideration holdings by non-sample entities such as mutual funds, hedge funds, and individual investors.[21] We are able to obtain data regarding the shareholdings of 55,966 firms. These firms account for 96% of the market valuation of the sample, and they hold positions in 29,692 stocks that are also included in the sample. For each pair of such firms, we compute on a quarterly basis the percentage of shares held by each other firm contained in the sample.[22] As examples, the Refinitiv ownership data indicate that Berkshire Hathaway held positions in Apple stock ranging from 0.18% of Apple's outstanding shares in the first quarter of 2016 to 5.67% of Apple's outstanding shares in the first quarter of 2020 and that Nippon Steel held positions in Kobe Steel stock ranging from 1.80% to 6.89% of Kobe's outstanding shares at various times from 2003 to 2020. We then sum this percentage across all investing firms to obtain the portion of the shares in each sample firm that are held by other sample firms. Let Pc_t denote this percentage as of time t. The pooled value-weighted average Pc_t for the full sample is 4.9.[23] We compute wealth creation adjusted for in-sample cross-holdings by modifying expression (1) to replace I_t with $I_t(1 - Pc_t)$ in each period. Note that the adjusted wealth creation calculation credits each firm in each period only for portion of the enhancement in market value that accrues to shareholders that are not also sample firms.

Table 44 in the Internet Global Appendix contains wealth creation outcomes after allowing for cross-holdings, in a format identical to Table 8, which contains unadjusted wealth creation outcomes. The results on balance indicate that cross-holdings have a relatively minor effect on wealth creation totals. Gross wealth creation for the global sample is $US 93.49 trillion with adjustment for cross-holdings as compared to $US 97.75 trillion without the adjustment (Table 8). The adjustment for cross-holdings reduces net wealth creation for the global sample from $US 75.66 trillion (Table 8) to $US 72.44 trillion. Similarly, the effect of cross-holdings on the degree to which wealth creation is concentrated is also minor.[24] The top-performing 0.25% of firms account for 50.14% of global net wealth creation without the adjustment for cross-holdings (Table 8), compared to 50.64% of global net wealth creation with the adjustment for cross-holdings. Similarly, the top-performing 1% of firms account for 80.44% of global net wealth creation without the adjustment for cross-holdings (Table 8), compared to 80.80% of global net wealth creation with the adjustment for cross-holdings. Thus, the adjustment for cross-holdings indicates slightly more concentration in wealth creation as compared to the unadjusted figures.

Assessing Cross-Market Variation in Underperformance Rates and Concentration of Wealth Creation

The results reported in the preceding sections show that long-run returns to the majority of global common stocks are less than matched-horizon returns to one-month U.S. Treasury bills and the net wealth creation revealed by stock market prices is attributable to a relatively few stocks. However, the degree to which these results hold varies across markets. For example, the percentage of stocks with long-run returns that exceed those of U.S. Treasury bills varies from 25.5% in Greece and 36.1% in Australia to 67.6% in Switzerland and 65.2% in Columbia. We next assess the empirical determinants of cross-market variation in outcomes.

The key findings in this paper are attributable to the empirical fact that the distribution of long-horizon return outcomes is positively skewed across stocks. Farago and Hjalmarsson (2023) show theoretically that long-horizon returns will be positively skewed, even if short-horizon returns are distributed symmetrically and returns are independent across time, and that the skewness in long horizon resulting from compounding is greater if the volatility of short-horizon returns is higher. We therefore include in our cross-sectional analysis the average, across stocks within each market, of the standard deviation of the time series of monthly returns to each stock.

It is intuitive that, other things equal, positive skewness in the distribution of short-horizon returns will lead to greater skewness in long-horizon outcomes. We therefore also include in our cross-sectional analysis the average, across stocks within each market, of the skewness of the time series of monthly returns to each stock. We also include the cross-sectional average of the time series mean return to the individual stocks in each market. While it is somewhat self-evident that a higher mean return across stocks will be associated with a greater rate of outperformance relative to Treasury bills, this inclusion allows for the assessment of robustness of outcomes regarding volatility and skewness.

In addition, we control for the potential effects of macroeconomic performance by including in the cross-sectional analysis 2020 GDP per capita in U.S. dollars as well as the annual growth rate from beginning to end of sample in real GDP. Further, we follow Chui, Titman, and Wei (2010), who report that the measures of individualism provided by Hofstede (2001) have explanatory power across markets for the degree of momentum in stock returns, and we propose that investor risk-taking behavior may also be associated with our outcome variables. We obtain the Global Preference Survey (GPS) risk-taking preference from Falk, Becker, Dohmen, Enke, Huffman, and Sunde (2018).

We consider the possibility that individualism is associated with overconfidence and that markets with more overconfident and risk-taking individuals would be willing to invest to a greater extent in uncertain projects with the potential for high payoffs. If so, we expect individualism and risk taking to be associated with fewer stocks outperforming Treasury bills and greater concentration of wealth creation. The Hofstede individualism measure is available for 38 sample markets, while the GPS risk-taking measure is available for 33 sample markets. We use an indicator variable set equal to one in the multiple regressions in those cases where a Hofstede variable or the GPS risk-taking measure is missing.

In Table 9, we report the results of cross-sectional regressions estimated across the 42 sample markets ("homeless ADRs" are excluded). We focus on explaining the proportion of stocks in each market whose long-term returns exceed matched-horizon returns to U.S. Treasury bills (Panel A) and the proportion of total gross wealth created in each market by the 0.5% best-performing firms (Panel B). Because we seek in each case to explain a proportion that is necessarily bounded by zero and one, the dependent variable in each case is the logistic transformation of the original variable (X), $ln(X/(1-X))$.

Table 9. Market-Level Cross-Sectional Analysis

	Panel A					Panel B				
	Buy-and-Hold Returns > T-bill (%)					Gross Wealth Creation by the Top 0.5% (%)				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Standard Deviation	−4.727**	−5.538***			−6.522***	5.504*	5.928**			7.858**
	(−2.28)	(−3.95)			(−3.73)	(1.87)	(2.07)			(2.19)
Skewness	−0.614**	−0.773***			−0.743***	−0.096	−0.013			−0.390
	(−2.56)	(−4.74)			(−3.31)	(−0.28)	(−0.04)			(−0.85)
Mean		58.112***			56.336***		−30.374*			−32.695*
		(6.92)			(6.31)		(−1.77)			(−1.78)
Real GDP Growth %			0.024		0.044			0.048		−0.019
			(0.58)		(1.54)			(0.93)		(−0.33)
GDP Per Capita ($US)			0.010**		0.007			0.005		0.006
			(2.17)		(1.51)			(0.84)		(0.70)
Individualism				−0.077	−0.324				−0.471	−1.207*
				(−0.19)	(−1.12)				(−1.03)	(−2.04)
Risk Taking				0.127	0.182				0.498	0.339
				(0.40)	(1.08)				(1.35)	(0.98)
I_{Missing Individualism}				−0.068	−0.474**				−0.113	−0.092
				(−0.18)	(−2.05)				(−0.26)	(−0.19)
I_{Missing RiskTaking}				0.034	−0.068				−0.058	0.027
				(0.18)	(−0.65)				(−0.27)	(0.13)
I_{Developed}				0.192	0.004				0.276	0.158
				(0.99)	(0.03)				(1.23)	(0.54)
Number of Stocks					0.012					0.058*
					(0.79)					(1.94)
Constant	1.212***	1.067***	−0.527**	−0.291	1.087***	−1.349***	−1.273***	−0.836***	−0.485**	−0.860
	(3.90)	(5.07)	(−2.38)	(−1.49)	(3.28)	(−3.07)	(−2.96)	(−3.05)	(−2.14)	(−1.27)
Adj. R^2	0.34	0.70	0.07	−0.09	0.72	0.05	0.10	−0.02	−0.05	0.16
N	42	42	42	42	42	42	42	42	42	42

Notes: This table reports on cross-sectional regressions of the determinants of (i) the proportion of stocks in each market whose buy-and-hold returns greater than the matched U.S. Treasury bill rates (Panel A) and (ii) the percentage of total gross wealth created in each market by the 0.5% best-performing firms (Panel B) for 42 markets. The original dependent variable (Y) is logistic transformed to $\ln(Y/(1-Y)$. Standard deviation, skewness, and mean are the time-series averages of the cross-sectional standard deviation, skewness, and mean of monthly stock return by market. Number of stocks is the time-series average of the number of stocks for each market. Real GDP growth % is the real GDP growth rate (in %) during the sample period for each market. GDP per capita ($US) is the 2020 GDP per capita in U.S. dollars. Individualism is the Hofstede (2001) individualism index for the markets with the index value and zero for markets with missing value. I_{Missing Individualism} equals one for markets with missing value of Individualism and zero otherwise. Risk taking is the Global Preference Survey (GPS) risk taking preference index from Falk et al. (2018) for markets with the index value and zero for markets with missing value. I_{Missing Risk taking} equals one for markets with the missing value of Risk taking and zero otherwise. I_{Developed} equals one if a market belongs to IMF developed markets and zero otherwise. The *t* statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

In column (1) of Panels A and B, we report results obtained when the only explanatory variables are the average standard deviation and average skewness of monthly returns. The resulting coefficient estimates support the implication of Farago and Hjalmarsson (2023) that the volatility of short-horizon returns is a determinant of the degree of positive skewness in long-horizon returns. In particular, the average standard deviation of monthly returns is negatively associated (t statistic = −2.28) with the proportion of stocks that outperform U.S. Treasury bills in the long run. The results also indicate that fewer stocks outperform U.S. Treasury bills at long horizons in markets where short-horizon returns are more highly skewed (t statistic = −2.56).

In column (2) of Panels A and B, we report results obtained when the cross-sectional regression also includes the average across stocks of the time-series mean monthly return to each stock in the market. As would be anticipated, a higher average stock return in a given market is associated (column 2 of Panel A) with more stocks outperforming the U.S. Treasury bill benchmark (t statistic = 6.92). The mean stock return in a market is only a marginally significant predictor (t statistic = −1.77) of the degree of concentration in wealth creation. More informative, inclusion of the average stock return in the regression only strengthens the result that the average standard deviation and skewness of stock returns have significant explanatory power for the percentage of stocks that outperform Treasury bills.

Column (3) of Panels A and B on Table 9 reports estimates obtained when we use the two macroeconomic variables as explanatory variables. We find that national GDP per capita has significant explanatory power (t statistic = 2.17) for the proportion of stocks in a market with cumulative returns that exceed U.S. Treasury bills but that neither variable has significant explanatory power for the degree of concentration in wealth creation.

Column (4) of Panels A and B on Table 9 reports results obtained when the Hofstede (2001) individualism variable and the risk-taking measure are included, along with an indicator variable for developed economies. In contrast to our conjectures, none of these variables have significant explanatory power for either the proportion of stocks that outperform the U.S. Treasury bill benchmark or the concentration of wealth creation.

Finally, to assess robustness, we report in column (5) of Panels A and B results obtained when all explanatory variables are simultaneously included in the regressions. The results confirm that the average standard deviation of monthly returns continues to have significant explanatory power for both dependent variables and that the average monthly return and the skewness of monthly returns continue to have significant explanatory power for the proportion of stocks that outperform the U.S. Treasury bill benchmark. Other variables, including measures of macroeconomic performance, and the cultural variables are largely insignificant.[25] That is, the results confirm that, aside from the somewhat self-evident result that higher mean returns in a given market are associated with greater rates of outperformance for stocks in that market, the main determinants of the percentage of stocks with long-run returns that exceed U.S. Treasury bills are the volatility and skewness of short-horizon returns and the degree to which wealth creation is concentrated is mainly driven by the volatility of short-horizon returns.

Conclusions

We rely on a broad sample consisting of more than 64,000 global common stocks to assess long-term outcomes to shareholders. We focus in particular on compound buy-and-hold returns and on the enhancement in shareholder wealth as a result of investing in the public stock markets, as compared to a U.S. Treasury bill benchmark. We obtain several insights. First, we document that the majority of compound long-term returns measured for our January 1990 to December 2020 sample, including 55.2% of U.S. stocks and 57.4% of non-U.S. stocks, fall short of returns to one-month U.S. Treasury bills over matched time horizons. The fact that the majority of publicly traded stocks underperform Treasury bills even while the stock markets in aggregate enhanced shareholder wealth by many trillions of dollars is attributable to the strong positive skewness in compound stock returns. This positive skewness is attributable, in turn, to both skewness in the distribution of monthly stock returns and to the effects of compounding.

Second, we show that stock market wealth creation is highly concentrated: Just five firms (Apple, Microsoft, Amazon, Alphabet, and Tencent) account for 10.3% of the $US 75.66 trillion in global public stock market net wealth creation in our sample. The best-performing 0.25% of firms accounted for half of global net wealth creation, and the best-performing 2.39% of firms accounted for all net global wealth creation. The concentration of wealth creation in a relatively few firms is attributable to several, potentially interacting, explanations, including cross-sectional variation in firm size, variation in the number of months that stocks are present in the database, the aforementioned positive skewness in compound returns, as well as purely random outcomes.

The results reported here are important from a number of perspectives. While most empirical analyses of stock markets focus on arithmetic means of returns measured over short (e.g., monthly) horizons, the investment and decision horizons of individuals or fund managers (particularly pension funds) can stretch to decades and no doubt differ across investors. The results here show that the properties of stock returns compounded over long horizons differ substantially from those of short-horizon returns. These results are somewhat more pronounced for non-U.S. as compared to U.S. stocks.

The results are also relevant to the debate regarding active vs. passive investing. The results here show that the wealth created by stock market investing is largely attributable to large positive outcomes to a relatively few stocks. For those investors without a comparative advantage in identifying the few stocks that will create the most wealth (or in selecting a manager with the ability to do so) and without a substantial preference for positive skewness, the results reinforce the desirability of investing in a broad passive index. On the other hand, for investors with a sufficiently strong preference for positive skewness or for the (presumably few) investors with the appropriate comparative advantage in identifying stocks poised to deliver outsized long-run returns, the results highlight the degree to which successful stock selection can enhance wealth.

The strong positive skewness in the distribution of long-horizon stock returns is particularly important for financial planning. For example, the assessment of whether pension funds are adequately capitalized is typically based on assumptions regarding mean returns and the mean of the distribution of possible future portfolio values. Distinct from the ongoing debate as to whether the assumed means are appropriate, the (potentially large) majority of individual future outcomes in a positively skewed distribution will be less than the mean. It is therefore important that financial planning explicitly accounts for the skewness nature of the distribution of long-horizon returns.

Editor's Note

Submitted 4 May 2022

Accepted 6 March 2023 by William N. Goetzmann

Notes

1. Many studies report unconditional arithmetic mean returns to characteristic-sorted portfolios, while many others estimate conditional arithmetic mean returns by implementing regression analyses with short-horizon returns as the dependent variables.

2. We focus on returns and wealth measured in U.S. dollars to provide a common yardstick that can be compared across stocks traded in currencies with differing inflation rates. The comparison to the short-term U.S. Treasury rate reflects that this rate is often viewed as the best available proxy for the "risk-free" interest rate envisioned by theory.

3. The positive skewness arises in part because the distribution of monthly individual stock returns is positively skewed, but mainly due to the effects of compounding. See, for example, Simkowitz and Beedles (1978), Albuquerque (2012), Heaton, Poulson, and Witte (2017), Bessembinder (2018), Fama and French (2018), and Farago and Hjalmarsson (2023), all of which focus on the U.S. markets.

4. Fang et al. (2021) document that the majority of *monthly* local-currency stock returns in a global sample are less than *local-currency* short-term interest rates in the same months. However, they do not study compound returns, nor do they study wealth creation outcomes. Further, their "Treasury bill" proxies are local currency interest rates as diverse as the Luxembourg 10-year Government Bond Yield, the Peru Time Deposit Rate, and the Zimbabwe 3-month Time Deposit Rate. We convert all returns to U.S. dollars to allow comparisons of returns across stocks from different markets and to the common U.S. Treasury bill interest rate, which arguably comprises the best global proxy for the risk-free interest rate envisioned in theory.

5. Indeed, Samuelson (1969) acknowledges (his footnote #1) that his results hold *only* under the assumption of power utility. For other utility functions outcomes will depend on the preference for skewness relative to other moments of the return distribution (e.g., kurtosis), which also depend on horizon, as Farago and Hjalmarsson (2023) show.

6. In addition, while the issue is not skewness per se, Bessembinder, Cooper, and Zhang (2022) show that alpha and beta parameters (and estimates thereof) differ when returns are measured over long vs. short horizons.

7. The Compustat data upon which we rely for non-U.S. stock returns does not include information regarding post-delisting share values or post-delisting payments to shareholders. Following Shumway (1997), we set the final return on non-U.S. stocks with an incomplete return series, as well as stocks indicated to be delisted for reasons of bankruptcy or liquidation, to −30%. For U.S. stocks, we incorporate CRSP delisting returns where available, while setting the final return to −30% in the few cases where the delisting return is missing and the CRSP delisting code is 500, 520, 551–573, 580, 574, or 584.

8. Examples of "homeless ADRs" include Baidu, Inc. and BioNTech, SE. Firms that were formerly listed only as ADRs but also listed on a local market before the end of the sample (e.g., Alibaba Group) are included with the relevant local market.

9. See, for example, Chui, Titman, and Wei (2010), Hou, Karolyi, and Kho (2011), and Fama and French (2017).

10. Hong Kong SAR and Singapore are exceptional in terms of market capitalization relative to GDP, with many large firms listed on their exchanges. A number of large Chinese firms in particular are listed in Hong Kong SAR, and five members of the Jardine Group, which is headquartered in Hong Kong SAR, shifted from Hong Kong SAR to Singapore in 1994 (Chan, Hameed, and Lau, 2003). Prior to the change in listing, Jardine composed about 10% of the total market capitalization in Hong Kong SAR.

11. Percentages can sum to less than 100% because minor exchanges are excluded from the study.

12. As three examples among many, Fama and French (2017), Jacobs and Muller (2020), and Bartram and Grinblatt (2021) study arithmetic mean portfolio returns and estimates regressions with returns as dependent variables in their international stock market studies.

13. A notable feature of the distribution of monthly returns to U.S. stocks is the peak at zero, which is presumably attributable to non-trading and price rounding. For non-U.S. stocks the peak at zero is less notable, which reflects that a zero return in local currency may not equate, even with rounding, to a zero return in U.S. dollars.

14. We define decades as January 1990 to December 1999, January 2000 to December 2009, and January 2010 to December 2020.

15. The data on Figures 3 and 4 indicate that returns very close to −100% are more frequently observed for U.S. as compared to non-U.S. stocks. However, this observation is likely an artifact of the fact that CRSP provides actual delisting returns for the United States, while in the absence of accurate delisting returns we follow the prior literature in imputing a −30% return when non-U.S. firms exit the database.

16. The match of simulated and actual monthly log returns is almost perfect in terms of these parameters. In particular, the monthly mean log return across all stocks is −0.3% and the standard deviation of monthly log returns is 16.2%, in both the simulated and the actual data. However, skewness is not as well matched. The average skewness in simulated monthly log returns is zero by construction, while the average skewness of monthly log returns in the sample is −0.78. This discrepancy reflects that the sample monthly returns do not conform to the log-normal assumption.

17. The dollar-weighted return corresponds to the calculated wealth creation figure more cleanly than the buy-and-hold return, as it also allows for net equity issuances and the fact that dividends are not, in aggregate, reinvested in stock. See Dichev (2007) and Dichev and Zheng (2020) for discussion the computation of dollar-weighted returns.

18. The Japanese stock market performed very well in the years preceding 1990 (the Nikkei Index reached its all-time high on December 29, 1989), so the result that the worst-performing firms were predominantly Japanese would differ over a longer sample period.

19. The issue, described for example by Ellenberg (2014), is that a few observations can explain far more than 100% of a figure that is obtained by summing across positive and negative observational outcomes, particularly when the sum is itself modest in magnitude. Ellenberg goes so far as to suggest that one should not report percentages when studying the sum of positive and negative outcomes. It is, however, unclear how far this reasoning should be pushed when studying stock market outcomes, where the natural object of interest is the gain to the investor as defined by the net of many individual up and down price movements. For example, focusing on accumulated outcomes from only those days with positive price changes would be of little or no practical interest.

20. Note that the double counting issue arises only due to the ownership of equity in sample stocks by other companies also included in the sample. The fact that a given non-corporate shareholder may hold positions in multiple companies does not lead to double counting in our setting.

21. More specifically, we focus on the holdings of firms with owner type codes equal to Bank and Trust (101), Finance company (103), Investment advisor (107), Insurance company (108), Brokerage firms (200), Research firm (201), Independent research firm (202), Corporation (301), and Holding company (302).

22. The Refinitiv ownership data begins in the first quarter of 1997. We backfill the initial data to earlier quarters.

23. Perhaps the most striking observation in the cross-holding data concerns Naspers' holdings of Tencent, which averaged over 30% of outstanding shares. Tencent's full sample wealth creation for non-sample shareholders was $463 billion, as compared to $692 billion for all shareholders (including Naspers).

24. Despite that Berkshire Hathaway obtained a substantive position in Apple just before the end of the sample, outcomes for Apple are also little affected. Apple's wealth

creation outcome was reduced to $US 2.57 trillion (from $US 2.67 trillion) and its share of global net wealth creation was reduced to 3.40% (from 3.53%).

25. We note that the individualism variable is marginally significant when explaining the concentration of wealth creation (t statistic $= -2.04$) and that the dummy variable indicating the individualism variable to be missing is marginally significant when explaining the percentage of stocks that outperform Treasury bills, but it is unlikely that either of these results would survive an adjustment for multiple testing of the set of Hofstede variables.

References

Albuquerque, R. 2012. "Skewness in Stock Returns: Reconciling the Evidence on Firm versus Aggregate Returns." *Review of Financial Studies* 25 (5): 1630–1673. doi:10.1093/rfs/hhr144.

Arditti, Fred D., and Haim Levy. 1975. "Portfolio Efficiency Analysis in Three Moments: The Multiperiod Case." *The Journal of Finance* 30 (3): 797–809. doi:10.2307/2326859.

Bartram, S. M., and M. Grinblatt. 2021. "Global Market Inefficiencies." *Journal of Financial Economics* 139 (1): 234–259. doi:10.1016/j.jfineco.2020.07.011.

Bessembinder, H. 2018. "Do Stocks Outperform Treasury Bills?" *Journal of Financial Economics* 129 (3): 440–457. doi:10.1016/j.jfineco.2018.06.004.

Bessembinder, H., M. Cooper, and F. Zhang. 2022. What You See May Not Be What You Get: Return Horizon and Investment Alpha, Working paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4096412.

Chan, K., A. Hameed, and S. T. Lau. 2003. "What If Trading Location is Different from Business Location? Evidence from the Jardine Group." *The Journal of Finance* 58 (3): 1221–1246. doi:10.1111/1540-6261.00564.

Chui, A. C., S. Titman, and K. J. Wei. 2010. "Individualism and Momentum around the World." *The Journal of Finance* 65 (1): 361–392. doi:10.1111/j.1540-6261.2009.01532.x.

Dichev, I. D. 2007. "What Are Stock Investors' Actual Historical Returns? Evidence from Dollar-Weighted Returns." *American Economic Review* 97 (1): 386–401. doi:10.1257/aer.97.1.386.

Dichev, I. D., and X. Zheng. 2020. *The Volatility of Stock Investor Returns, Working paper*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3663350.

Dimson, E., P. Marsh, and M. Staunton. 2002. *Triumph of the Optimists: 101 Years of Global Investment Returns*. Princeton, NJ: Princeton University Press.

Duchin, R., T. Gilbert, J. Harford, and C. Hrdlicka. 2017. "Precautionary Savings with Risky Assets: When Cash is Not Cash." *The Journal of Finance* 72 (2): 793–852. doi:10.1111/jofi.12490.

Ellenberg, J. 2014. *How Not to Be Wrong, the Power of Mathematical Thinking*. New York: Penguin Books.

Falk, A., A. Becker, T. Dohmen, B. Enke, D. Huffman, and U. Sunde. 2018. "Global Evidence on Economic Preferences." *The Quarterly Journal of Economics* 133 (4): 1645–1692. doi:10.1093/qje/qjy013.

Fama, E. F., and K. R. French. 2017. "International Tests of a Five-Factor Asset Pricing Model." *Journal of Financial Economics* 123 (3): 441–463. doi:10.1016/j.jfineco.2016.11.004.

Fama, E. F., and K. R. French. 2018. "Long Horizon Returns." *The Review of Asset Pricing Studies* 8 (2): 232–252. doi:10.1093/rapstu/ray001.

Fang, J., B. R. Marshall, N. H. Nguyen, and N. Visaltanachoti. 2021. "Do Stocks Outperform Treasury Bills in International Markets?" *Finance Research Letters* 40: 101710. doi:10.1016/j.frl.2020.101710.

Farago, A., and E. Hjalmarsson. 2023. "Compound Returns Are Positively Skewed." *Review of Finance* 27 (2): 495–538. doi:10.1093/rof/rfac021.

Heaton, J. B., N. G. Polson, and J. H. Witte. 2017. "Why Indexing Works." *Applied Stochastic Models in Business and Industry* 33:690–693.

Hofstede, G. 2001. *Culture's Consequences: Comparing Values, Behaviors, Institutions, and Organizations across Nations*. 2nd ed. Beverly Hills, CA: Sage Publications.

Hou, K., G. A. Karolyi, and B. C. Kho. 2011. "What Factors Drive Global Stock Returns?" *Review of Financial Studies* 24 (8): 2527–2574. doi:10.1093/rfs/hhr013.

Jacobs, H., and S. Muller. 2020. "Anomalies across the Globe: Once Public, No Longer Existent?" *Journal of Financial Economics* 135 (1): 213–230. doi:10.1016/j.jfineco.2019.06.004.

Samuelson, P. A. 1969. "Lifetime Portfolio Selection by Dynamic Stochastic Programming." *The Review of Economics and Statistics* 51 (3): 239–246. doi:10.2307/1926559.

Shumway, T. 1997. "The Delisting Bias in CRSP Returns." *The Journal of Finance* 52 (1): 327–340. doi:10.1111/j.1540-6261.1997.tb03818.x.

Simkowitz, M. A., and W. L. Beedles. 1978. "Diversification in a Three-Moment World." *The Journal of Financial and Quantitative Analysis* 13 (5): 927–941. doi:10.2307/2330635.