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IT'S EASY TO BEAT THE MARKET

Moshe Levy[a]

The perception that it's hard to beat the market portfolio is widespread. Indeed, passive investment has more than doubled in the last decade. While various different strategies have been suggested to outperform passive indexing, the market is still considered by many as the relevant benchmark to beat. The evidence in this paper suggests that this perception requires a fundamental re-examination. We compare the market with a large number of randomly constructed and passively held portfolios. We find that 69% of these random portfolios yield higher Sharpe ratios than the market. Practical implications and theoretical consequences for market equilibrium are discussed.

The market index is widely perceived as a benchmark portfolio that is hard to beat. This perception has both theoretical and empirical foundations. Theoretically, the cornerstone Capital Asset Pricing Model (CAPM) implies that the market portfolio is the optimal mean–variance portfolio of risky assets. In addition, the market portfolio reflects the average portfolio holdings of all investors (weighted by wealth), and thus resonates with the notion of the "wisdom of the crowds"—the idea that the average estimate is better than the individual estimate of a single person.[1] Empirically, it is well-established that active portfolio managers typically underperform passive index investing.[2] This is typically interpreted as evidence suggesting that the market index is, at least, close to optimal.

The optimality of the market portfolio has important theoretical and practical implications. Theoretically, it is at the core of the CAPM.[3] From a practical perspective, an optimal market portfolio implies that passive indexing dominates active management. Most academics view the market as being hard to beat, and advocate passive investment in the market index. For example, Samuelson opens his article about the possibility of finding managers who are able to beat the market with the following statement:

> "*Forsake search for needles that are so very small in haystacks that are so very large*".

[a]School of Business Administration, the Hebrew University. E-mail: mslm@huji.ac.il.

He then continues to write:

> "*The security analyst industry does not on the average perform quite as well over time as an indexed portfolio that passively holds stocks in proportions approximating their respective market capitalizations*". (Samuelson, 1989, p. 4)

In their classic textbook, Bodie *et al.* (2009) write:

> "*...a passive investor may view the market index as a reasonable first approximation to an efficient risky portfolio*". (p. 283)

Levy and Post (2005) concur, stating that:

> "*The empirical evidence finds consistently that mutual fund managers on average lag behind the market if we correct for risk and costs*". (p. 797)

These are just a few examples illustrating the widely accepted notion that the market is close to optimal, and therefore hard to beat. Indeed, the proportion of funds invested passively in the market has grown persistently and significantly. In 2003 the proportion of assets held passively by U.S. equity funds was approximately 17%. A decade later, this figure has more than doubled, reaching 35%.[4]

Various different strategies have been suggested for outperforming the market, most notably strategies based on the small-firm effect, the value effect, momentum, calendar effects, fundamental indexing, event-based strategies, and sentiment-based strategies. While there is a varying degree of agreement about the past and present success of each of these strategies in beating the market in practice, the market portfolio is still considered the consensus benchmark to beat. The purpose of this paper is not to suggest yet another strategy for beating the market, but rather, to argue that the market is a bad benchmark. Our goal is to convince the reader that the market is a benchmark that is actually very easy to beat. This can be achieved without employing any sophisticated trading strategies. In fact, it is embarrassingly simple.

Rather than comparing the market with a specific alternative strategy, this paper takes a different methodological approach. Our goal is to sketch a wide-angle picture of the performance of the market portfolio relative to the performance landscape of a very large number of randomly constructed buy-and-hold portfolios. We consider the most general form of random portfolios—the initial weights in each portfolio are randomly drawn at the beginning of the period from a uniform distribution on the segment [0, 1],[5] and from that time onwards the portfolio is held passively with no rebalancing.

We employ all 5-year time windows spanning the entire 1927–2014 timeframe, with 1-month increments between windows (i.e. the first window is January 1, 1927 to December 31, 1931; the second window is February 1, 1927 to January 31, 1932, etc.). For each 5-year sub-period we draw 10 random passive portfolios and compare their performance with that of the value-weighted market index over the same period. We find that the random portfolios yield a higher Sharpe ratio than the market in 69% of the cases. They yield a higher terminal value in 67% of the cases. The difference in performance is very significant both statistically and economically.

This paper supports and expands the findings of Arnott *et al.* (2013) and Clare *et al.* (2013). Arnott *et al.* show that many strategies, including strategies based on optimization, fundamental analysis, and risk weighting, beat the market. Surprisingly, the "upside-down" version of the same strategies, i.e. weighting based on the inverse of the strategies' logic, also beat the market. They also show that "Malkiel's monkey"—a portfolio composed of 30 stocks randomly selected at the beginning of each year—also on average beats the market in terms of the Sharpe ratio. Clare *et al.* analyze portfolios constructed by randomly selecting (with replacement) one of the 1,000 largest stocks, adding 0.1% to its portfolio weight, and repeating this procedure 1,000 times until the entire portfolio weight of 100% is assigned. The portfolio is constructed at the beginning of each year. They find that for the 1968–2011 period the vast majority of random portfolios yield higher Sharpe ratios than the market portfolio.

Our analysis supports these results and extends them in several important ways. First, our study covers the entire 1927–2014 period. Second, we introduce a different kind of random weighting: rather than equally weighting the 30 randomly chosen stocks, or employing the additive weight approach by Clare *et al.*, we attempt to consider the most general form of random weighting, i.e. portfolios spread all over the space of possible portfolio weights. Third, we employ only the 500 largest stocks, in order to avoid potential liquidity issues that may affect smaller stocks. Finally and most importantly, we consider pure buy-and-hold portfolios that are not rebalanced for the entire 5-year period over which they are held. This avoids both transaction cost issues, and the extra "mixing" of weights that is obtained when the portfolio weights are re-drawn every year.

How can these results be reconciled with the prevailing widespread perception of optimality, or near-optimality, of the market portfolio? When comparing a specific portfolio or strategy with the market, it is typically difficult to make inference about the *ex-ante* relative performance, because the estimation errors involved are usually very large. For example, Levy and Roll (2010) show that given the empirical parameter estimates, one cannot reject the mean–variance optimality of the market index. While the market does not seem optimal with the observed parameters, a small adjustment to these parameters, well within their estimation error bounds, makes the market portfolio optimal. The approach we take here is somewhat different: rather than comparing the market with a specific alternative portfolio or strategy, we compare it with a very large number of random portfolios. Even if the estimation errors are large, if the market is close to optimal, we would expect it to beat *at least* 50% of these random portfolios. We would certainly not expect most of the random portfolios to beat the market... But this is exactly what we find.

Still, one may ask, what about the fact that the market outperforms most active managers? We argue that this observation is less of a tribute to the market, than it is a bleak indication about most active management funds.

1 The market versus random portfolios

To evaluate how hard, or easy, it is to beat the market index, we compare it with a large number of buy-and-hold portfolios with random initial weights. In order to avoid small stocks with potential illiquidity issues, which have been argued to drive various anomalies (Avramov *et al.*, 2006; Avramov *et al.*, 2013), we restrict the analysis to only the 500 largest-cap stocks. Thus, we should stress that the results reported below are not driven by the well-known small-firm effect, which is primarily focused on the decile of smallest stocks in the market, because the 500 largest stocks are all in the *largest*-stock decile.

The performance of the market portfolio relative to other portfolios may obviously depend on the sample period employed. As we are interested in making a general statement about the performance of the market, we report results for all 5-year periods spanning the January 1, 1927–December 31, 2014 timeframe, with a 1-month increment between windows. For each sample period, our stock universe is the set 500 stocks with largest market capitalization at the beginning of the period (in keeping with previous work in this area, ETFs and ADRs are excluded). As we consider completely passive buy-and-hold portfolios we stick to these stocks, and do not change the stock set through the 5-year period. A random portfolio is a portfolio with randomly assigned initial portfolio weights for each of these stocks. The initial weights of random portfolio p are drawn in the following way: for each stock i we draw a random variable $\tilde{x}_i^p$ from a uniform distribution over the segment [0, 1]. To obtain a pure stock portfolio with weights adding up to 1, we then normalize the random weights. Thus, the initial weight of stock i is set as: $\tilde{w}_i^p = \tilde{x}_i^p / \sum_{i=1}^{500} \tilde{x}_i^p$.

After the portfolio is formed, it is held passively with no further trading.[6] We calculate the evolution of portfolio weights, and the portfolio return for each month in the sample, employing the CRSP monthly stock file. We then record the monthly returns for each portfolio, and calculate the monthly Sharpe ratio by using the average 30-day T-Bill rate in the sample period as the risk-free rate.

As will be shown in what follows, the results reported below are robust to the performance measure employed, the holding period over which returns are calculated, the number of stocks in the random portfolios, and the distribution from which the random weights are drawn.

2 Results

We have 996 five-year sample periods. For each sample period initial date we construct 10 random portfolios, to be held passively for 5 years with no updating. For each period we compare the performance of the random portfolios with that of the value-weighted market portfolio over the same period.[7] The random portfolios have an average monthly return of 0.99% and an average standard deviation of 5.06% (both averaged across all 9,960 random portfolios: 996 sample periods $\times$ 10 random portfolios). The average Sharpe ratio is 0.163. For the market portfolio the average return and average standard deviation (averaged across the same 996 sub-periods) is 0.90% and 5.01%, respectively, and the average Sharpe ratio is 0.153. This difference in Sharpe ratios translates to a difference of 1.1% in the risk-adjusted annual returns.[8] In 66% of the cases the random portfolio has a higher average monthly return than the market portfolio over the same period. In 53% of the cases the random portfolio has a lower standard deviation, and in 29% of the cases the random portfolio has *both* higher average return and lower standard deviation relative to the market portfolio.

For each random portfolio we record the difference between its Sharpe ratio and the Sharpe ratio of the value-weighted index in the corresponding period:

$$\Delta_{\text{Sharpe}} \equiv SR_{\text{random}} - SR_{\text{market}}.$$

We have 9,960 observations of the above Δ_{Sharpe} values. Figure 1 provides the distributions of these deltas. Δ_{Sharpe} is positive in 69% of the cases. The difference between the Sharpe ratios is statistically very significant. The average Δ_{Sharpe} is 0.010 with a standard error of 0.0018 and a t-value of 5.6.

These results imply that 69% of the completely random buy-and-hold portfolios beat the market. This is the central result and main take-away message of the paper. It is a result that calls for a fundamental revision in the way most of us perceive the optimality of the market portfolio.

Do the random portfolios yield more extreme Sharpe ratios than the market portfolio? Figure 2 depicts the cumulative distribution of Sharpe ratios for the random portfolios and for the market portfolio (for all sub-periods). The figure reveals

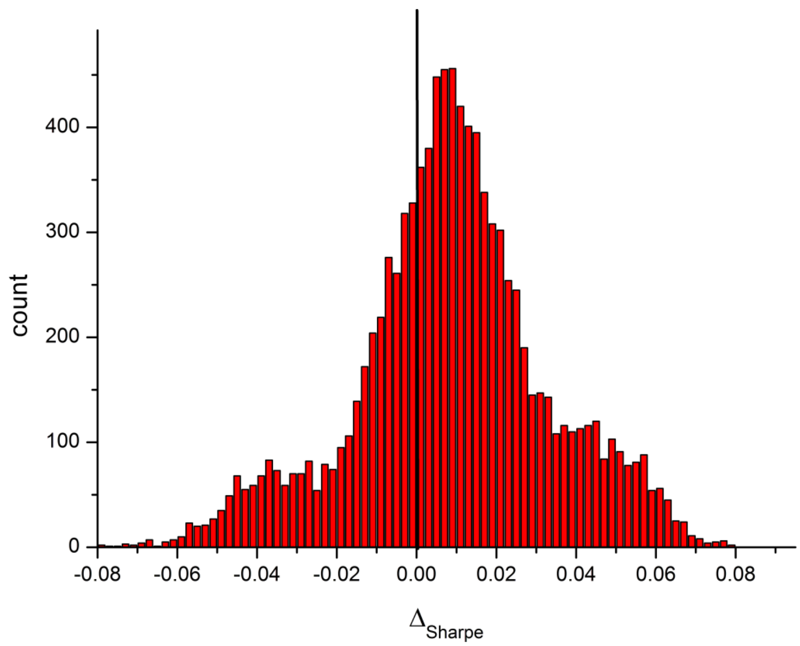

Figure 1 The distribution of Δ_{Sharpe}.

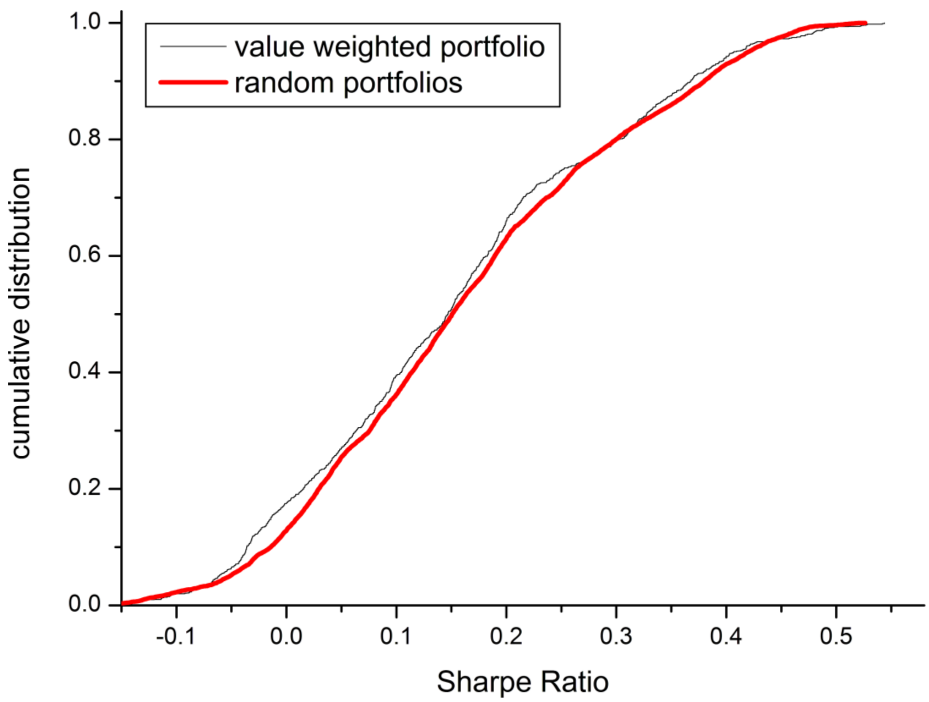

Figure 2 The cumulative distribution of Sharpe ratios.

that the distribution of Sharpe ratios is not more extreme for the random portfolios. In fact, there is almost a First-degree Stochastic Dominance type of dominance of the random portfolios over the market: for almost any given value, the probability of having a Sharpe ratio *higher* than this value is greater for the random portfolios than for the market portfolio.

3 Robustness

We examine the robustness of the results to various alternative specifications: employing a different performance measure, quarterly instead of monthly returns, a different number of stocks, a normal rather than uniform distribution of random portfolio weights, and focusing on only the last two decades. As detailed below, the random portfolios beat the market under all of these specifications in 63–88% of the cases. The difference is statistically very significant under all specifications.

3.1 Alternative performance measure

As an alternative to the Sharpe ratio one can look at the terminal portfolio value. For each random portfolio we calculate the terminal portfolio value obtained from a \$1 initial investment at the beginning of the sample period, and we compare it with the terminal value obtained from a \$1 initial investment in the market portfolio over the same period. The random portfolios yield an average terminal value of \$1.77, with a standard deviation of \$0.66. The market portfolio yields an average terminal value of \$1.69, with the same standard deviation of \$0.60. For each random portfolio we record the difference between its terminal value and the terminal value of the market portfolio held over the same period:

$$\Delta_{\text{Ter. Value}} \equiv V_{\text{random}} - V_{\text{market}}.$$

Figure 3 shows the distribution of these differences in terminal values. We find that $\Delta_{\text{Ter. Value}}$ is positive in 67% of the cases with an average value of 0.077 and a standard error of 0.017. The t-value is 4.5.

3.2 Quarterly returns

When we calculate the Sharpe ratio with quarterly instead of monthly returns we find that Δ_{Sharpe} is positive in 63% of the cases, with an average value of 0.0110, a standard error of 0.0036, and a t-value of 3.1.

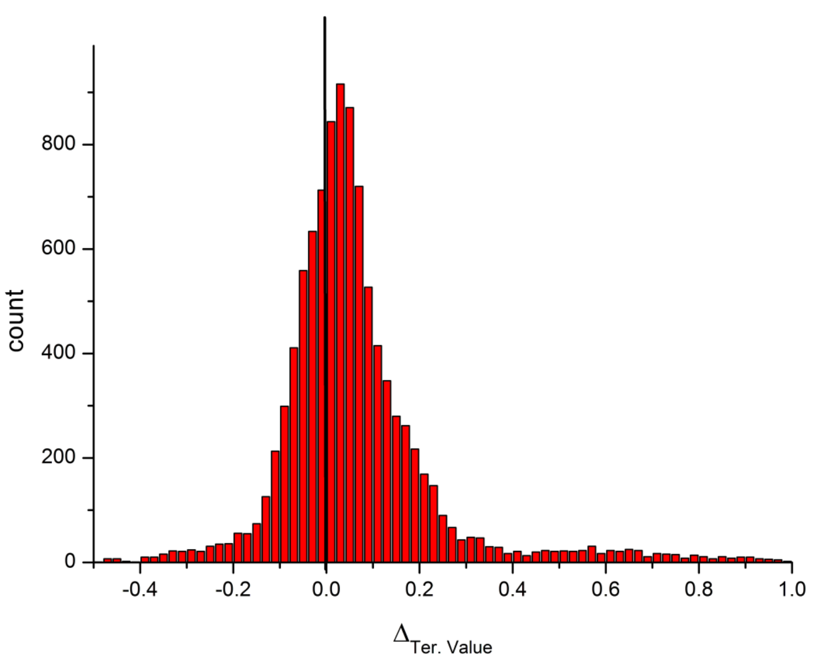

Figure 3 The distribution of $\Delta_{\text{Ter. Value}}$.

3.3 Number of stocks

When the number of stocks included in the random portfolios is 1,000 instead of 500 (the 1,000 stocks with largest market value at the beginning of the sample period), we obtain an average Δ_{Sharpe} value of 0.0111, with a standard error 0.0029 of and a t-value of 3.8. Δ_{Sharpe} is positive in 63% of the cases.

With 1,000 stocks the average value of $\Delta_{\text{Ter. Value}}$ is 0.1412 with a standard error of 0.0310 and a t-value of 4.5. $\Delta_{\text{Ter. Value}}$ is positive in 64% of the cases.

3.4 Only the last two decades

In order to examine whether the results reported above are driven by market conditions in the distant past, that may no longer be relevant today, we repeat the analysis where the 5-year sub-periods are drawn from the January 1, 1995–December 31, 2014 timeframe. We obtain an average Δ_{Sharpe} value of 0.0259 with a standard error of 0.0038 and a t-value of 6.8. Δ_{Sharpe} is positive in 88% of the cases. The average value of $\Delta_{\text{Ter. Value}}$ is 0.0820 with a standard error of 0.0228 and a t-value of 3.6. $\Delta_{\text{Ter. Value}}$ is also positive in 88% of the cases.

3.5 Normally distributed random weights

We consider the case where the random portfolio weights are drawn from a normal, rather than a uniform, distribution. We take a normal distribution with parameters that are similar to those of the uniform distribution—a mean of 0.5 and a standard deviation of 0.3 (the corresponding parameters for the uniform distribution on the segment [0,1] are 0.5 and 0.287, respectively). As before, the weights are normalized to add up to 1. The normal weight distribution is similar to the random additive weight approach employed by Clare *et al.* (2013). The main differences are that the portfolios considered here are bought and held for the entire period, with no annual "reshuffling" of the weights, and that the entire 1927–2014 period is employed. We obtain an average Δ_{Sharpe} value of 0.0087 with a standard error of 0.0019 and a t-value of 4.6. Δ_{Sharpe} is positive in 68% of the cases. The average value of $\Delta_{\text{Ter. Value}}$ is 0.0740 with a standard error of 0.0174 and a t-value of 4.3. $\Delta_{\text{Ter. Value}}$ is positive in 66% of the cases.

The random portfolios do not generate significant four-factor alphas. Table 1 provides statistics on the random portfolios' exposure to the Fama–French–Carhart four factors. As expected, the random portfolios on average have positive exposure to the size factor. Value and momentum exposures are also positive. Consistent with the findings of Arnott *et al.* (2013), the alphas are not statistically different than zero. From this perspective, the random portfolios do not seem superior to the market portfolio. However, for an investor who is concerned with his portfolio's Sharpe ratio, or with his terminal wealth, the random portfolios clearly outperform the market.

Table 1 Exposure to the four factors and alpha.

	Market exposure	Size exposure	Value exposure	Momentum exposure	Alpha (%)	Alpha (t-value)
Mean	0.98	0.15	0.08	0.01	−0.01	−0.12
25th percentile	0.94	0.01	0.05	−0.02	−0.06	−0.71
Median	0.97	0.12	0.08	0.01	−0.02	−0.19
75th percentile	1.02	0.30	0.12	0.03	0.04	0.45

4 The reason for the market's inefficiency

There are two main candidate explanations for the market's underperformance. First, it is a portfolio with a very skewed distribution of weights. The weight of the largest market capitalization S&P 500 stock (Apple, market cap of $571.5B, as of July 2014) is more than 100 times larger than the weight of the smallest cap S&P 500 stock (U.S. Steel, market cap of $3.9B, as of July 2014). The 10 largest stocks in the S&P 500 index account for 17.3% of the total S&P 500 market capitalization, and the 20 largest stocks account for 27.6% of the total S&P 500 market capitalization.[9] The largest firm is on average 68.1 times larger than the median S&P 500 firm. In contrast, in the random portfolios the largest portfolio weight is only twice the median portfolio weight. The very skewed distribution of weights in the market portfolio makes the diversification in this portfolio less effective, because most of the portfolio is concentrated in a very small number of stocks. One could obtain a higher diversification benefit with a more evenly weighted portfolio (such as the random portfolios considered here).

A second possible explanation for the market portfolio's inefficiency is that it is tilted toward large company stocks that tend to be, according to some researchers, overvalued. This is the main argument for fundamental indexing (see, for example, Arnott *et al.*, 2005; Treynor, 2005). Indeed, Table 2 reveals that the largest stocks tend to have lower average returns. The table reports the average returns and standard deviations of the 500 largest stocks by size deciles, which are updated annually. The table shows an almost monotonic relationship between size, average return, and volatility: the larger stocks tend to have both lower average returns and lower standard deviations.[10] The market portfolio is heavily tilted toward the largest stocks, which induce its lower average return. However, the largest stocks also have lower volatilities (see Table 2), so it is not obvious that the large-stock tilt necessarily hinders performance. Indeed, despite of the fact that the market portfolio is not very well diversified, its volatility is not very high, because it is concentrated in the largest stocks, which tend to have low standard deviations.

Table 2 Return parameters by size decile.

Decile	Average monthly return (%)	Average monthly standard deviation (%)
(Smallest) 1	1.06	9.95
2	1.07	9.50
3	1.03	9.29
4	1.04	9.09
5	1.06	8.78
6	0.95	8.46
7	0.93	8.27
8	0.91	7.90
9	0.86	7.62
(Largest) 10	0.84	6.89

The performance of the market portfolio is affected by both the skewed weight distribution and the large-cap tilt. In order to disentangle these two effects, we analyze two additional portfolios: one without any of these two effects, and one with only the skewed weight effect. For the portfolio without any of the effects we take the equal-weighted portfolio. This portfolio has no large-cap tilt and no skewness of the weight distribution. For consistency, we take buy-and-hold portfolios with initial equal weighting of the 500 largest stocks, and no rebalancing. For portfolios that have the skewed weight effect but no large-cap tilt, we take a portfolio that has the exact same distribution of weights as the market portfolio in the beginning of the period, but the weights are randomly permuted among assets. In other words, we randomly shuffle the initial weights across the stocks. Then we just hold the portfolio passively for the entire sub-period. We repeat this for 100 different portfolios with random permutations of the initial weights, and record the average return parameters of these portfolios. The permuted portfolios have the same skewed weight distribution as the market portfolio, but no tilt toward large stocks. A comparison of the performance of the market portfolio with the equal-weighted portfolio and the permuted portfolios is provided in Table 3. All results are averages of all 5-year periods in the 1927–2014 sample. A comparison of the equal-weighted portfolio with the permuted-weight portfolios reveals the effect of the skewed weights, in isolation of the large-cap tilt. As expected, these two portfolios have almost identical expected returns, because none of these portfolios has a size tilt. The difference in standard deviations, due to the skewed weights of the permuted portfolios is not large. The permuted portfolios have an average monthly standard deviation of 5.14%, compared with the average standard deviation of the equal-weighted portfolio, which is only 5.07%. This increase in standard deviation is the result of the skewed portfolio weights. The market portfolio has not only skewed weights, but it is also systematically tilted toward the large-cap stocks, which have lower returns and lower standard deviations. As the table reveals, the large-cap tilt has two effects: it reduces both the portfolio mean return and its standard deviation. Overall, the tilt decreases the Sharpe ratio relative to the permuted portfolios, because the reduction in expected returns is more dramatic than the reduction in volatility. This analysis suggests that the main reason for the market portfolio's inefficiency is its large cap tilt.

Portfolios consisting of only 30 randomly selected stocks also beat the market on average (see Arnott *et al.*, 2013). After all, these portfolios are also not "well diversified". This is consistent with the above results, as these portfolios have no size tilt. In addition, while these portfolios are composed of only 30 stocks, these stocks are equally weighted. In contrast, in the market portfolio the weights are very different, even within the largest stocks: the weight of the largest firm in the S&P 500 index is typically more than five times larger than the weight of the 30th largest firm. Also, the random portfolios in Arnott *et al.* are randomly re-drawn every year. This implies an advantage of a "time diversification" effect (see, for example, Samuelson, 1989), which is absent in the market portfolio. It is interesting to note that if the 30 randomly selected stocks are

Table 3 Decomposing the skewed-weight effect and the large-cap tilt effect.

	Average monthly return (%)	Standard deviation of monthly returns (%)	Sharpe ratio
Equal-weighted portfolio (no skewed weights, no size tilt)	0.98	5.07	0.161
Permuted portfolios (skewed weights, no size tilt)	0.97	5.14	0.159
Value-weighted portfolio (skewed weights and large-cap tilt)	0.90	5.01	0.153
Buy-and-Hold, 30 random stocks (equal weights, no size tilt)	0.98	5.28	0.154

bought and passively held for the entire 5-year period (i.e. the time diversification effect is neutralized), the average Sharpe ratio of these random 30-stock portfolios is similar to that of the market portfolio, as shown in Table 3. A comparison of the average standard deviation of the random 30-stock portfolios (5.28%) with the average standard deviation of the permuted-weight portfolios (5.14%) suggests that the diversification disadvantage implied by the skewed portfolio weights is less severe than the disadvantage of holding only 30 equally weighted stocks (note that both portfolios have no size tilt).

5 Discussion

The evidence presented here suggests that the value-weighted market index is very far from being mean–variance optimal. It is easy to beat even without any sophisticated investment strategy. This is in sharp contrast to the widely accepted perception of the market being hard to beat, and thus being the relevant benchmark. The non-orthodox perspective advocated in this paper is based on a non-standard methodology: rather than comparing the market to a single alternative portfolio, or strategy, a comparison which may be *ex-ante* inconclusive due to the large estimation errors involved, here we compare the market with a large number of buy-and-hold portfolios with initial weights that are completely random. While we would expect the market to beat most of these portfolios (or at least 50% of them) if it is efficient, even if the estimation errors are large, in fact, we find that 63–88% of the random portfolios beat the market.

Our findings suggest that the main reason for the market portfolio's inefficiency is the fact that it is tilted toward large stocks, that tend to have lower returns.

It is well-documented that most active managers are unable to beat the market. Indeed, this is viewed as some of the evidence supporting the optimality of the market. Our results put this observation into a different perspective: rather than indicating the efficiency of the market, they make active management seem even worse than previously believed. This is in line with the literature pointing to the drawbacks of active management (see, for example, Barber and Odean, 2000, 2001; French, 2008).

Our results have several key implications. First, one should be very doubtful of investing in the market index. The evidence suggests that one could do much better. While we have no pretense of determining which strategy is best, we show that even most "dumb" buy-and-hold portfolios with arbitrary initial weights beat the market. Thus, it is possible to invest passively and still considerably outperform the market.

What are the implications for the empirical validity of the CAPM? The CAPM has two fundamental results: (1) that the market portfolio is the optimal mean–variance equity portfolio, and (2) the Security Market Line (SML) linear risk–return relationship. Our findings cast serious doubt about the empirical validity of (1). However, this does not necessarily mean that the SML risk–return relationship does not approximately hold. As Roll and Ross (1994) have shown, the market portfolio may be very mean–variance inefficient, while at the same time the SML approximately holds. Thus, the implications of the CAPM for the cost of capital and the valuation of risky projects may still be approximately valid.

Does a mean–variance very inefficient market portfolio imply that drastic changes in market values are required in order to make the market efficient and restore the CAPM equilibrium? The answer is no. In fact, it is quite clear that the optimal mean–variance portfolio cannot have weights which are very different than the current market portfolio weights. After all, the market portfolio weights, as well as the optimal portfolio weights, are primarily driven by the fundamental operations of firms. Apple has a large market cap primarily because it has annual earnings of billions of dollars. The distribution of fundamental firm values, measured by sales, earnings, or book values, is very skewed—there are a few firms that make up a sizeable portion of the total firm value (Axtell, 2001; Gabaix, 2011). This drives the very unequal weights in the market portfolio. The weights in the CAPM equilibrium optimal mean–variance portfolio are also tightly linked with the firms' fundamental values, as modeled, for example, by Lintner (1965). Thus, the optimal portfolio weights cannot be too different from the market weights. However, a relatively small difference in portfolio weights can have a big difference on expected returns and on the performance of the portfolios. For example, suppose that a firm has an expected end-of-period liquidation value of $100, and that its CAPM equilibrium value à-la Lintner (1965) is $90, implying an equilibrium CAPM expected return of 11.1%. Now, suppose that the market deviates from the CAPM equilibrium, and that this firm's market value is only $80. With this lower market value, the stock's expected return is 25%, more than twice the equilibrium expected return. Thus, small changes in market values can lead to large changes in expected returns, and in turn, to large changes in the *non-equilibrium* optimal portfolio weights and performance. In the above out-of-equilibrium example, the mean–variance optimal portfolio weight in this stock may be much higher than both its actual market weight and its theoretical CAPM equilibrium weight. The performance of the mean–variance optimal portfolio may be much better than that of the market portfolio in this non-equilibrium setting.

Our results imply that portfolios that are more evenly weighted than the very skewed value-weighted portfolio perform much better. A rather modest increase in the market value of smaller stocks, and a modest decrease in the market value of larger stocks, may suffice to bring the market to the CAPM equilibrium. These are exactly the changes in values that will occur if investors shift their portfolios toward more equally weighted portfolios. If this happens, the market will be driven closer to the mean–variance frontier. Until this happens, though, the market portfolio will continue to perform poorly, and investors will have much to gain by deserting the value-weighted index, and adopting portfolios which are more evenly balanced across stocks.

Tremendous amounts of wealth are invested in the market index, a portfolio which is shown here to be clearly inefficient. The implication is a great loss of welfare. This loss is partly due to the wrong belief of many investors and fund managers that it is hard to beat the market. However, this is not the entire story. Even if a fund manager thinks that she can beat the market, she knows that she will be evaluated relative to the market benchmark. Thus, deviations from the market are risky from the career perspective of the fund manager (Chevalier and Ellison, 1999). The goal of this paper is to change this situation, and to challenge the perception that the market is the relevant benchmark to beat.

Notes

1 Perhaps the first to express this idea was Francis Galton (1907), who reported that the average guess of a crowd at a county fair about the weight of an ox was closer to the ox's true weight than the estimates of most crowd members, and also closer than any of the separate estimates made by cattle experts. Surowiecki (2005) provides a comprehensive review of the idea of the wisdom of crowds. Levy *et al.* (2006) make an argument along these lines for the efficiency of the market portfolio.

2 See, for example, Sharpe (1966, 1992), Jensen (1968), Samuelson (1989), Gruber (1996), Carhart (1997), French (2008), and Fama and French (2008). For a

different view, see, for example, Grinblatt and Titman (1992).

[3] We should note that we are referring to the "market portfolio" as the value-weighted index of stocks. This is a limited (but practical) version of the theoretical market portfolio which encompasses *all* assets, including real-estate, human capital, etc., as pointed out by Roll (1977). See Markowitz (2005) for a discussion of the limitations of the CAPM.

[4] http://finance.yahoo.com/news/bull-market-passive-investing-120000260.html. Reinganum (2014) suggests that this trend can be viewed as chasing past performance, as launches of new S&P funds tend to follow years of higher returns on the S&P index.

[5] The weights are then normalized by their sum, so that they add up to 1.

[6] Dividends are assumed to be reinvested. If a firm is delisted during the sample period, the delisting return is employed.

[7] We take the market portfolio as the CRSP value-weighted portfolio. Similar results are obtained when instead we take the value-weighted portfolio of only the 500 largest stocks.

[8] For a monthly standard deviation of 5%, the random portfolios yield an average monthly return of 0.98%. Translating the difference in average monthly returns to a difference in average annual returns we have: $1.0098^{12} - 1.009^{12} = 0.011$.

[9] See, for example, https://www.cboe.com/products/snp500.aspx.

[10] Note that this is not a documentation of the famous small-firm effect for two reasons: first, we do not document excess returns relative to betas, just the average returns. More importantly, these are the 500 largest firms, and thus they are all rather large, while the small-firm effect is typically driven by the smallest firms in the market.

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