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Active vs. Passive: Old Wine in New Wine Skins

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Introduction

Active portfolio management is one of few professions for which worth is defined by a single phrase: *risk-adjusted excess return*. "Active" in professional equity investing does not mean merely ex-ante hard work against heady competition.[1] Active also means that ex-post victory is expected and demands measurement.

In this paper, we perform an empirical examination of a dominant, decades-old victory metric: the capitalization-weighted index portfolio. We model the cycles of index dominance (inferiority) compared to alternative portfolios that differ by non-cap weighting schemes and by simulated active stock picking skills. We find that macroeconomic influences through monetary expansion/contraction and market interest rates correlate closely with the concentration of large constituents within the index. These cycles of concentration have major implications for the debate about active versus passive equity investing. One conclusion is that correct investor decisions to move into (or out of) benchmark alternatives to the cap-weighted benchmark are largely conditional on macro influences. Moving to (from) passive should be an active decision. Moreover, currently the current environment favors the choice of moving away from cap-weighted passive to alternatives.

Concentration Cycles

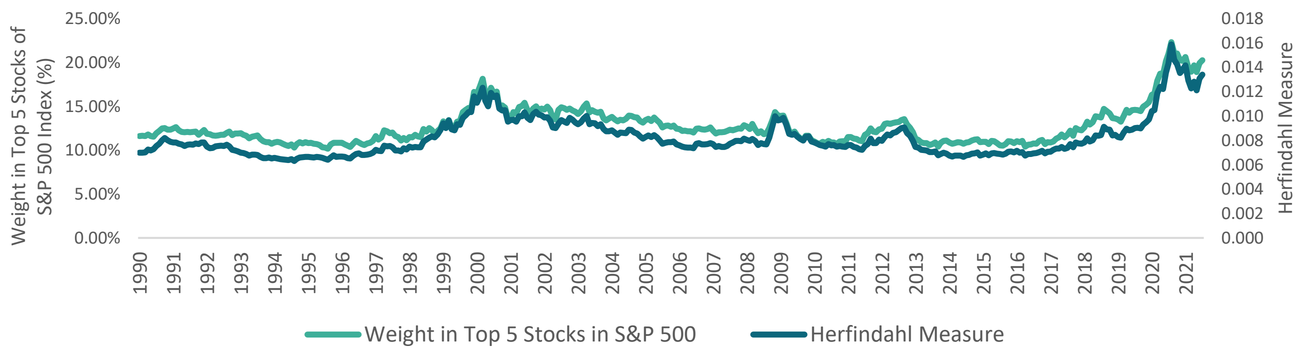
Critical to this paper is the notion of concentration. Index concentration is the magnitude that a specific few number of constituents have on the index return. During the recent 2017–2020 period, passive benchmark indexing appears to be a winner. During these years, the five largest cap stocks in the S&P accounted for 25% of the index.[2] By contrast, in 2016, the influence of the largest five stocks contributed only 10% of the index return, which is more comparable to historical levels. Exhibit 1 graphs a history of S&P 500 Index's five largest stocks' market cap as a percentage of the total index market cap, plus a measure of the Herfindahl Index.[3] Given the rise in indexing and the extreme concentration of “the market,” some in the press have recently characterized the market environment with provocative titles: "Could Index Funds Be ‘Worse than Marxism'?” (Lowrey, 2021) and "Wall Street Rebels Warn of ‘Disastrous' $11 Trillion Index Boom'" (Lee and Peterseil, 2021).

[1]Competitive success in the money management business in reality depends on deliverables beyond return performance, such as client service, corporate structure, and the like.

[2]These five stocks were: Apple (NASDAQ: AAPL), Microsoft (NASDAQ: MSFT), Amazon (NASDAQ:AMZN), Alphabet (NASDAQ:GOOG, GOOGL), and Facebook (NASDAQ:FB).

[3]The Herfindahl Index was introduced by economist Orris C. Herfindahl. It measures the market concentration of each firm in an industry. It has been applied often across industries to measure organizational and participant profiles.

Exhibit 1: S&P 500 Index Measures of Concentration Over Time



Source: PanAgora. Past performance does not guarantee future results. For illustrative purposes only. An explanation of the Herfindahl Measure can be found in the third footnote.

We can see in Exhibit 1 that the index was characterized by an increasingly narrow set of securities in the runup to the dot-com ebullience around 2000. This was followed by a general dissipation of index crowding that was interrupted by brief escalations in 2007 and 2012. It is intuitive (if not tautological) that an increasingly narrow set of stocks driving the index is likely problematic for active investing, which often deploys portfolio weighing approaches to 'bet against' the index constituents and/or index weights.

Why the Passive Index

Prior to the 1970s, there was a dearth of formal theory and metrics in the study of financial markets.[4] However, beginning in the late 1960s, financial economists and academicians introduced significant advancements that modernized the world of asset management, much like scientists' contributions have improved the quality of their respective disciplines, be it medicine, communication, digital technology, or travel.

In the early days (pre-1970s) of professional management, the measures of victory were elusive. For example, "stock managers" would sometimes own assets that were very different from common stock, such as cash, bonds, and gold. Using a term of recent times, all investing could be "alternative." Relative performance was hard to pin down. Indeed, all strategies were some sort of "alternative."

Specifically relevant to professional money management of equities, the early pricing research was descriptive. The work of Treynor, Sharpe, Lintner, and Mossin gave rise to the Capital Asset Pricing Model (CAPM), which describes the way the world of return and risk should look (linear, in fact). Then, almost-overnight, description became normative. MacKenzie (2006) provides an excellent social science perspective of this change in purpose: how a camera became an engine. Descriptive morphed into normative. The market of common stocks had to make room for a new entrant that was biased toward large cap—the "aggregate market." The market as measured by a market capitalization–weighted index gradually

[4]*Condensing, we would summarize this rich academic legacy:*
1. You should earn returns consistent with risk taken, i.e., asset pricing equilibria;
2. You should earn no more than expected returns, i.e., asset pricing competition;
3. But, should you beat the historic long-run 9.3% Lorie and Fisher finding, it must be an anomaly, i.e., asset pricing behavior;
4. You should use modern techniques to model future price behavior, i.e., asset pricing econometrics (Quant).

became the metric for assessing victory of alternative and/or active processes for professional equity investing.

The Crowd Gets Larger

There is extensive literature on the wisdom of crowds, dating back 250 years with Condorset.[5] Much of this work centers on probabilities of accuracy as the number of active participants increases versus an individual opinion or guess. On average, when uncertainty increases and participants increase, crowd wisdom dominates individuals. This work is largely modeled in a "single period" framework. For example, Condorset applies his theory to the work of a jury in which decision makers have a single vote at a specific time.

Literature on the stock market also invokes the concept of a crowd or crowding, beginning in 1841 with Charles Mackay's "Extraordinary Popular Delusions and the Madness of Crowds". Mackay's writing was not mathematical but rather a somewhat entertaining story telling of crowding (bubble) episodes in the markets. As opposed to the early Condorset-like crowding literature, his notions were figuratively framed in a "multi-period" setting. One hundred- and thirty-years post-Mackay, the professional academicians referenced above formalized the model of markets and, specifically, the centricity of the crowd —"the market model."

Index concentration correlates with crowding. What are the aggregate investor actions that produce crowding into larger names? We can easily envision two types of active decisions contributing to the most recent escalation of concentration in the market. One typifies a macro manager actively moving tactically and expeditiously into the stock market exposure as monetary liquidity increases. For example, macro-oriented hedge funds and tactical allocators forecasting monetary ease will rebalance allocations that create momentum in liquid large cap names and/or industries. Others follow. Momentum begets momentum. This represents an "index momentum trade."

A second active decision is a fiduciary firing an active portfolio manager and reallocating to the cap weight passive index. The cycle of concentration will not arise simply by cash assets going into index funds, per se. However, concentration will increase, ceteris paribus, if in aggregate funds come out of active portfolios and go passive. Effectively, the active aggregate market is funding increased percentage demand for large index names by increasing supply (selling) of other names.[6] The simple Illustration in footnote 6 is stylistic by design. Its message becomes real, however, when we consider the degree that such bulk of actively managed portfolios (approximating equal weightings) were moved to passive over the last several years at an accelerated pace.

We will demonstrate in the next section that monetary ease begets concentration. The dynamics of concentration attracts a crowd. Active large cap stock allocators and others reallocating equity to passive feed on themselves. Metaphorically, the decisions to go large and the decisions to go "passive" represent a

[5] *See Marquis de Condorcet (1785).* Essai sur l'application de l'analyse à la probabilité des décisions rendues à la pluralité des voix *(PNG) (in French). Retrieved 2008-03-10; Landemore, Hélène (2012).* "Collective Wisdom—Old and New" *(PDF). In Landemore, Hélène; Elster, Jon (eds.).* Collective wisdom: principles and mechanisms. *Cambridge: Cambridge University Press. ISBN 9781107010338. OCLC 752249923*

[6] *Consider a simple economy with two equity portfolios of equal AUM and 100 stocks. One portfolio is concentrated, with the top 10 names accounting for half the wealth, say 50 pesos. The other half (50 pesos) is equally allocated to the remaining 90 names. For example, it is a 100-peso portfolio with 5 pesos in each of the top 10 names and .56 pesos in each of the remaining 90. The second portfolio of 100- peso AUM is equal weighted, 1 peso each. Thus, the aggregate market has 10 stocks with market cap of 6 pesos and 90 with cap of 1.56. The largest 10 stocks are 30% of the aggregate market. Now suppose that forces motivate liquidation (rebalancing) of the second portfolio into the weighting scheme of the first. The resulting aggregate market remains 200 pesos. Ten stocks now have aggregate cap of 5 + 50 /10, or 10 pesos. The other 90 have 1.116 pesos cap. Prior to the trade, the top 10 aggregate comprises 30% of the market. After the trade, It comprises 50%. That's an increase in concentration.*

symbiotic relationship between those who actively time the large index names and those who actively allocate to them via moving to the passive cap-weighted index. This was the most powerful dynamic catalyst of increased concentration in the 2016–2020 period, when trillions of dollars moved across the border from traditional differentiation in management to the "group think" of the crowd mentality. [7]

Various Alternatives vs. Passive

The basic CAPM presumes that corporate valuations are fairly (correctly) assessed in equilibrium. The price is right, so to speak, meaning that a company's market capitalization is dynamically moved to equilibrium by forces of supply and demand. Myriad investors who may or may not bear costs for implementing portfolios and who may or may not possess homogeneous expectations create these dynamics.

Researchers have taken various approaches to examining active alternatives. These substitutes center on any number of systematic approaches, such as skilled stock picking, factor exposures in "smart beta" weighting alternatives, and so on. With regard to skill, Grinold and Kahn (2000) model the importance of superior skill vis-à-vis the breadth of choices. Their work is a widely accepted framework, the "fundamental law of active management." Researchers have conducted empirical tests to validate this framework. For example, Sorensen and Miller (1998) analyze the performance associated with various degrees of skill in various equity styles for the 1985–1997 period. Here, skill is defined as hypothetically having some positive forecasting ability to discern future winners from losers. Interestingly, they find (like others) that a modest amount of stock picking skill goes a long way and that the optimal amount of allocation to indexing declines as skill increases.

Researchers have tested imposing factor exposures in lieu of superior forecasting skill. Most notably, the strategy now known as "low vol" emerged from the pioneering work of Haugen and Baker (1991,1996). Portfolios tilted away from the index in favor of lower volatility stocks have higher than index risk-adjusted returns.

In another direction, researchers have studied alternative weighting schemes for the same constituents in the S&P 500. For example, an equal weighting (EW) of the S&P names may at times be superior to the cap-weighted (CW) choice. S&P has produced an EW version of the index for decades. In recent years, practitioners have implemented a variety of so-called smart beta portfolios that deviate from CW.

One example of a recent type of alternative weighting is risk weighting (RW). This approach weights each stock so that it has parity in the contribution to portfolio risk. Qian (2005, 2006) first introduced the term "risk parity" in research devoted to alternative multi-asset allocation applications. There is now considerable empirical evidence that multi-asset risk parity applications offer return distributions that are superior to traditional allocation schemes. However, there are many approaches to estimating and implementing risk weights in actual portfolios.

Once specific approach was used by Sorensen and Alonso (2015) to study the choice of the S&P 500 (market-cap-weighted) in contrast to an RW portfolio of the same stocks over time. They find that risk weighting provides a superior wealth creation profile over almost all reasonable holding periods of 5 years and beyond. During the period between January 1995

[7] *Again, those titles referenced earlier:* "Could Index Funds Be 'Worse Than Marxism'?" *(Lowrey, 2021) and* "Wall Street Rebels Warn of 'Disastrous' $11 Trillion Index Boom" (*Lee and Peterseil, 2021).*

and April 2014, RW is dominant for 75% of the historical periods over any two-year horizon and is dominant in all cases over six-year horizons. They then go on to test for conditionality. RW achieves dominance over capitalization-weighted indices over shorter horizons during periods of higher market volatility, periods of higher inflation, and periods with steep yield curves.

Conditionality Counts

Our objective is to expand the conditionality tests surrounding the CW comparisons with alternatives such as EW, RW, and simulated skill portfolios. Regardless of the chosen comparative technique, is the CW benchmark relative to performance dependent on dynamic forces as they cycle over time? That is, do alternative beta processes, stock picking skill, and the like suffer (or excel) depending on specific macroeconomic environments? What causes the benchmark dominance versus deficiency to vary? We begin with a closer look at the CW dominance as a function of the cycle of concentration. We highlight the close association between index concentration and monetary cycles.

Monetary Conditions

Monetary expansion is often found to be causal in economic cycles. The direct relationship between monetary expansion and contraction with real economic activity is well documented. Similarly, the interplay between monetary aggregates and stock market moves has also intrigued researchers. Sorensen (1982) finds that, based on the rational expectations theory, the unanticipated component of monetary activity has a significantly positive relationship with returns in the broad market.[8]

The unprecedented monetary expansion in the US over the last two decades is a positive for overall market performance.

Just as excessive monetary policy can create inflation in goods and services, it can also create excess demand for risky financial assets (namely stocks). It now appears that this monetary liquidity, as opposed to creating inflation in real goods and services, has created financial asset inflation.

Here we are primarily interested in the "way" in which aggressive monetary activity impacts markets, namely a disproportionate demand for equities in general, and large index names in particular. Above, we discussed the two types of active decisions leading to crowding. One of these is when active market timers buy large names. Our hypothesis holds that the abnormal inducement of monetary liquidity motivates flow into stocks. That flow is quickly and easily implemented into buying the index itself through use of futures on the S&P 500 index, index ETFs, and the like. This flow lifts the overall market. Larger names offer the capacity to absorb excess risk-seeking liquidity induced by loose monetary policy. This is because large cap names, by definition, would have a greater impact on the index when their prices change. The anticipation of expansion and contraction of money flow creates a “momentum index trade” opportunity for macroeconomically oriented investors.[9] The second type of active decision occurs during periods of rising concentration. Fiduciaries may see to active to passive index allocations as superior and fund these allocations with the termination of active managers.

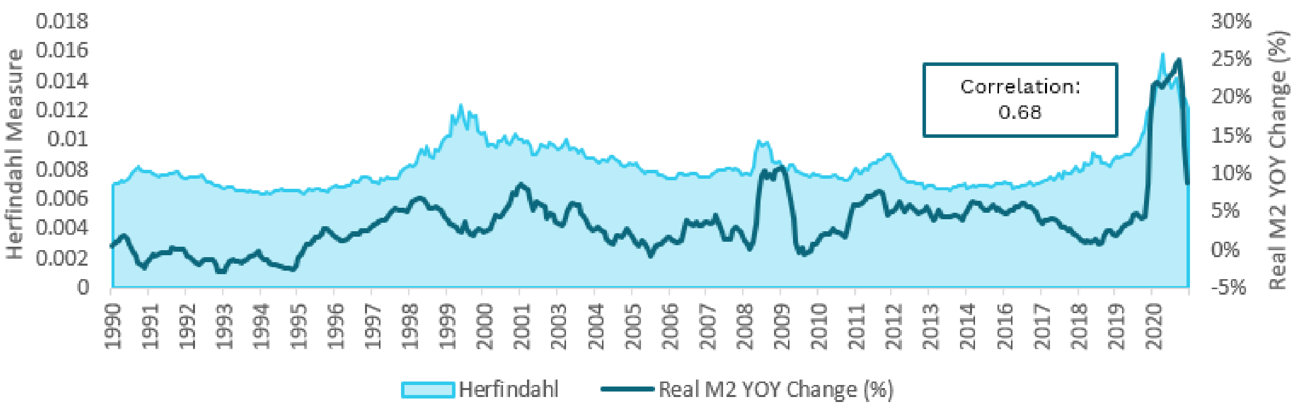
We use the monetary aggregate M2 to relate system liquidity to index concentration. In theory, normalized monetary aggregate growth created by the Federal

[8] *See the references in Sorensen (1982) for the pioneering studies of money supply and the stock market.*

[9] *The knife cuts both ways. Liquidity events also drain the larger stocks relatively. For example, on October 19, 1987, when the US market fell more than 20%, small and mid-size stocks did not move much due to a perceived lack of liquidity. Again, cap-weighted indexes are more volatile during both “meltdowns” and "melt-ups.”*

Reserve Board should correlate with economic growth. However, when we measure M2 growth in real terms (adjusted for CPI inflation), we have a measure of abnormal monetary growth. Exhibit 2 graphs the year-over-year growth rate in M2 deflated by the contemporaneous CPI level. The exhibit overlays this on our Exhibit 1 graph of S&P concentration. Graphically, there appears to be a strong positive relationship between M2 growth rates and index concentration. Indeed, a linear correlation analysis of M2 and concentration reveals a correlation coefficient of .68, with a t-statistic of 18.

Exhibit 2: Monetary Liquidity and Concentration



Source: PanAgora, FRED®, Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/). Time period: June 1990 - March 2021. For illustrative purposes only.

Interest Rate Conditions

We also posit a relationship between long-term Treasury rates and concentration in the large cap stock constituents. Equities have a duration component, which varies greatly from stock to stock.[10]

Large cap stocks are typically longer in duration in a bond sense. Sorensen and Gould (1986) observe that companies with more predictable and stable earnings growth rates react more predictably as the yield curve shifts. In addition, Liebowitz and Sorensen (1989) argue that companies with stronger franchise earnings are better able to sustain profit margins as inflation-induced rates shift the yield curve upward. In both instances, we expect that large cap companies are priced more precisely as rates vary, with PE ratios rising (falling) as long rates are falling (rising).

As shown in Appendix A, we present the multiple regression results using our M2 measure (described above) and a 10-year Treasury rate variable as explanatory variables for S&P concentration measured with the Herfindahl index. The Treasury rate is the monthly change in the 10-year rate. This measure of long rates serves to link current rate information month by month as opposed to the yearly moving change in monetary liquidity. The summary tables show an absence of multicollinearity and significant t-statistics for the independent variables. Both variables have the expected signs, with monetary expansion directly related to concentration of the index and long rate moves indirectly

[10] *See Sorensen and Gould (1986) for an early discussion of equity duration. In addition, see Liebowitz and Sorensen (1989).*

related. The explanatory power is high, with an R^2 statistic of 47%. The dominant variable is M2 expansion and contraction.

For a graphic illustration, Exhibits 3 and 4 highlight the interplay between index concentration with monetary liquidity and long-term rates, respectively. In Exhibit 3, we chart the quarterly change in real M2 by decile and view commensurate level of the concentration index. As the level of monetary expansion rises, so does the Herfindahl concentration. Interestingly, Exhibit 4 shows that the negative interplay between long rates represented by the 10-year Treasury rate is rather nonlinear. (In the regression this is suspected with a lower t-statistic.) The major sensitivity with rates and concentration is in the decile of more extreme rate declines. This is perhaps where the duration of large stocks is most dramatically expressed. Large rate declines boost the valuation of the large stocks to extremes in bond market rallies.

Exhibit 3: Herfindahl vs. Real M2 Money Supply

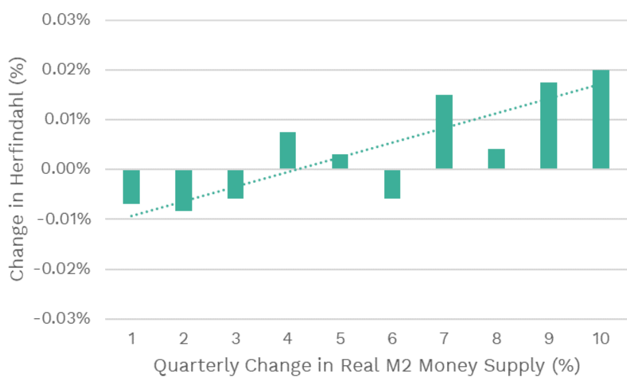
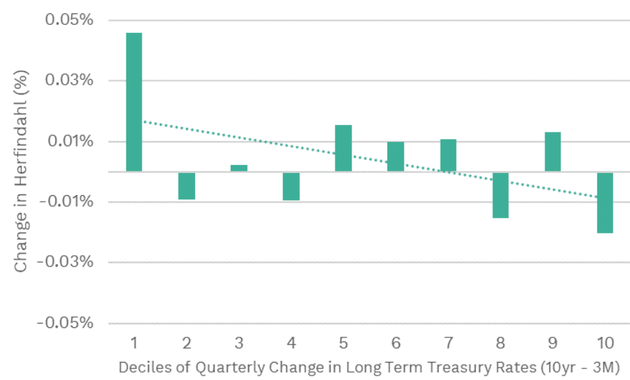


Exhibit 4: Herfindahl vs. Change in Long-Term Treasury

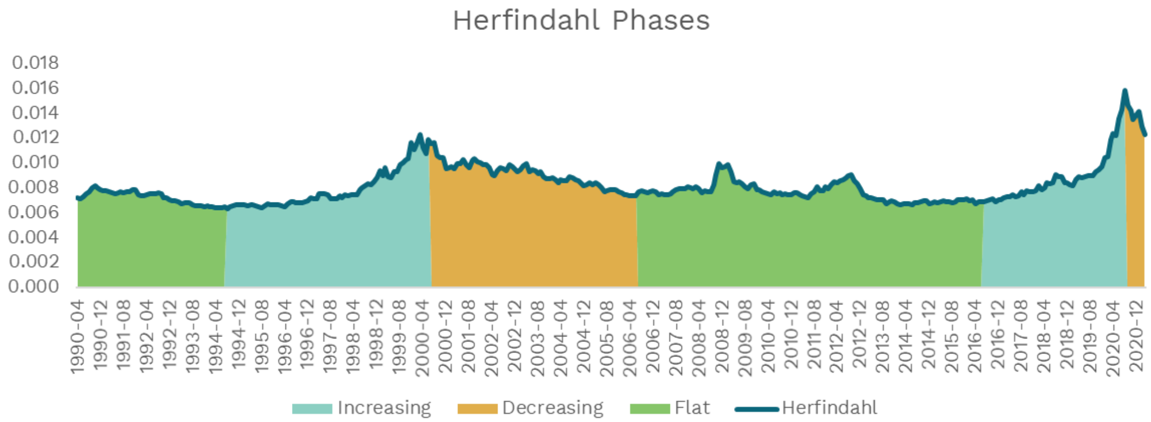


Source: PanAgora, FRED®, Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/). For illustrative purposes only. The horizontal axis on both charts represents the decile groupings of each measure. Deciles were computed in ascending order. Time period: June 1990-March 2021, quarterly observations.

Historical Phases of Concentration and Weighting Strategies

Exhibit 5 below shows the history of the Herfindahl for the S&P 500 partitioned by three phases. One phase is steadily rising concentration of reasonable duration (blue). These were most dramatic going into the dot-com peak and the 2016-2020 mega cap leadership. These phases are followed by steadily declining concentration (orange). A third period Is relatively sideways/flat (with some volatility, shown in green) between 2007 and 2016 (and 1990 to 1994).

Exhibit 5: Phases of Concentration



Source: PanAgora. For illustrative purposes only.

We would expect periods of methodically rising (falling) concentration shown here to benefit (hamper) capitalization weighted strategies versus alternative weighting strategies. This expectation is borne out in Exhibit 6. The Exhibit presents the annualized returns for CW, EW, and RW for each of the six partitions (two rising concentration, two falling, and two more or less flat with a bit of a downward bias). The periods of rising concentration have significantly higher monthly returns for CW, and the periods of declining concentration have significantly lower returns for CW. The 10-year period of July 2006-June 2016 (absent a persistent rising or falling Herfindahl measure) has a slightly higher return profile for EW and RW, with approximately a 2% annualized edge over CW.

Exhibit 6: Annualized Returns vs. Concentration Regimes (S&P 500, Equally Weighted, and Risk Weighted)

Herfindahl Phases	S&P 500 Index (Market Cap Weighted)	Equally-Weighted	Risk Weighted*	Market Cap Weighted less Equally-Weighted (t-stat)	Market Cap Weighted less Risk Weighted* (t-stat)
Flat 1st Phase	10.48	12.28	--	-1.96	--
(1990/04 - 1994/07)				(0.95)	--
Increasing 1st Phase	23.64	17.54	16.79	5.00	5.54
(1994/08 - 2000/06)				2.06	2.12
Decreasing 1st Phase	-0.40	9.95	10.50	-9.98	-9.94
(2000/7 - 2006/06)				(4.27)	(4.17)
Flat 2nd Phase	7.41	8.84	9.74	-1.91	-2.11
(2006/07 - 2016/06)				(1.20)	(2.00)
Increasing 2nd Phase	15.47	10.18	8.31	4.27	6.46
(2016/07 - 2020/08)				1.94	3.30
Decreasing 2nd Phase	26.03	55.32	41.87	-19.92	-11.44
2020/09 - 2021/03				(3.52)	(2.73)

*Source: PanAgora. Annualized returns are computed for periods longer than a year in each phase, as shown in the table. Past performance does not guarantee future results. *The Risk Weighted backtest starts in 1995 as a result of data availability., hence the backtest did not have returns available in the "Flat 1st Phase" segment.*

Simulating Active Stock Selection with Skill

The results above suggest that the relative performance of alternative weighting methodologies is highly dependent on the cycle. What about alternative selection methodologies? In other work, we demonstrate that selection of small cap stocks versus large cap stocks is cycle dependent—see Sorensen, Mezrich, and Miller (1998) and Sorensen and Lancetti (2020). Whereas these small cap versus large cap studies highlight results that can potentially assist active asset class decisions, our focus here is active stock selection versus passive cap weighting within the large cap universe.

Researchers have studied this in the past using simulations that superimpose a measure of stock picking skill in the portfolio process.[11]

In a similar spirit, we seek to study simulated portfolio experiments in contrast to passive (i.e., CW) investing by 1) applying a positive skill quotient and 2) conditioning on the index concentration cycles studied above. Skill is simply the ability to, *ex ante*, identify and hold winners over some future period. The overall data period is mid-1990 to mid-2021 represented by quarterly returns for the S&P 500 constituents. Our process of creating simulated portfolios first designs stock selection processes that have either zero-stock picking skill or some positive amount of skill. Then we form optimized portfolios each quarter. Each quarter in the experiment aggregates the performance characteristics of hundreds of simulations. Critical to the experiment are 1) how we impose a variable skill quotient and 2) how we optimally weight the selected holdings in each simulated portfolio.

First, imagine that a manager picks among the S&P 500 stocks at random. Each stock is assigned a random probability that generates a "naïve" set. It is like drawing out of a bag with a blindfold on, with the holdings having random probabilities of being chosen. Then, to simulate a degree of skill, the random probabilities are altered so that the probability of a stock being selected correlates with the future return. A perfect clairvoyant process enables all the draws to be clear choices of the best-performing stocks. This is perfect foresight knowledge of the *ex-post* one quarter's return on each stock. We use a metric analogous to "correlation" that allows the draws to vary from zero knowledge (zero correlation) and perfect foresight (correlation of 1). With a correlation of 0, there is no skill. A correlation of .05 renders a small positive bias of selections coming from a perfect knowledge procedure.

Second, the manager constructs the portfolio with realistic risk controls. The risk constraints are those from typical active versus CW benchmark criteria. An optimization controls the overall portfolio parameters to not exceed an estimated tracking error of 5%. In addition, positive or negative active weights per stock are not to exceed 2%. These weighting controls typically produced simulated holdings in the range of 50 to 100 stocks.

Exhibit 7 shows the percentage of winning (beating CW) on average quarterly as we increase the skill quotient. For example, a skill quotient of 1.5% correlation is sufficiently strong to insure that of the thousands of quarterly portfolios, 64% are outperforming over the quarters in the entire sample period. The zero-skill simulations reveal an aggregate winning percentage of 56%. Even with no skill, the disciplined portfolio construction used here adds value over time, on average.

Exhibit 8 presents the return characteristics of the simulated portfolios over the entire sample period. As with winning percentage, the zero-skill simulations render a slightly higher annualized return than the S&P (12.10% versus 10.56%),

[11]See Sorensen and Miller (1998).

with only slightly higher risk. The higher return-to-risk ratio over longer horizons is consistent with the Sorensen and Alonso (2015) finding that the longer the holding period, the better the advantage for non-cap weighted versus cap weighted portfolios due to the larger drawdowns of the latter. Further from Exhibit 8, as expected when we increase the correlation skill quotient above zero, the mean return- and reward-to-risk metrics improve. For example, given a 1.5% skill quotient, the simulated annualized return across hundreds of runs is 14.21%.

Exhibit 7: Simulation Win Percentages

Simulation Quarterly Win Percentage vs. S&P 500 Index (June 1990 - March 2021)			
Simulated Portfolio (0% Future Information)	Simulated Portfolio (0.25% Future Information)	Simulated Portfolio (10% Future Information)	Simulated Portfolio (15% Future Information)
56%	57%	62%	64%

Source: PanAgora. Values are the arithmetic average of the win percentage of simulation portfolios on a quarterly basis from June 1990 to March 2021.

Exhibit 8: Returns of Different Strategies (June 1990-March 2021)

Annualized Returns (%)							
June 1990 to March 2021	S&P 500 Index	Equally Weighted	Risk Weighted* (starts in 1995)	Simulated Portfolio (0% Future Information)	Simulated Portfolio (0.25% Future Information)	Simulated Portfolio (1.0% Future Information)	Simulated Portfolio (1.5% Future Information)
Return (annualized)	10.56	12.08	10.11	12.10	12.47	13.58	14.21
Risk (annualized)	14.51	16.58	14.21	14.93	14.92	14.93	14.92
Ratio	0.73	0.73	0.71	0.81	0.84	0.91	0.95

*Source: PanAgora. Returns are annualized. Time period is June 1990 - March 2021. Risk is defined as the annualized standard deviation of returns. Ratio is the annualized return divided by the annualized standard deviation. Past performance does not guarantee future results. *The Risk Weighted backtest starts in 1995 as a result of data availability.*

As is the case with alternative weightings (EW and RW) above, the long-term skill-based averages of Exhibit 8 dramatically change when we partition the study on subperiods of rising, falling, and flat index concentration using the Herfindahl Index. These subperiods are shown in Exhibits 9 through 11. For example, during periods of falling concentrations, even zero skill has, on average, more than twice the return as the CW index. In contrast, during periods of rising concentration, an increased skill degree of 1.5% does not outperform the CW index. During periods of declining concentration, the 1.5% skill simulations deliver more than three times the return to the CW index.

Exhibit 10 is analogous to Exhibit 6 in showing annualized return differentials. The first two columns are identical (phase and S&P returns). The next two columns show the annualized returns for skill quotients of zero and 1.5. We can see that the relative performance differentials for skill in columns 5 and 6 confirm the idea that active management performance is cycle-dependent. Exhibit 11 shows this graphically.

An examination of Exhibit 10 column by column shows the differential returns for rising and declining concentration, which is driven a bit more by the CW performance than by the skill contributions. One conclusion is that, over time, the risk-adjusted performance of active investing may be more a result of the *cycle-dependent behavior* of the index rather than the skill quotient. We can also see this in the bar charts of Exhibit 11. Note that the alternative weighting (EW and RW) on the left have more cycle-dependent variability than the skill-based bars. This confirms that the effects of cap weighting on relative performance is likely a factor in the fortunes of active managers—as is skill.

These results are very telling. Over the long haul, active skill stands to outperform passive CW, according to our work here (and prior). However, during the two major historical periods of momentum-inducing rising monetary liquidity that leads to index concentration, all bets may be off for active stock pickers—even those with reasonable skill. A bet against cap weight is lethal even for the gifted in markets with escalating narrowness.

In sum, we have evidence that the more concentrated the index, the larger the impact on the active versus passive debate. The momentum in large cap names associated with concentration adds fuel to the fire. The accelerating pace of this "index momentum" phenomenon over the past few years clearly stretched valuations between large and small companies, reaching a peak in the fall of 2020.[12]

Exhibit 9: Table of Average Returns During Different Herfindahl Regimes

Herfindahl Phases	Annualized Returns (%)						
	S&P 500 Index	Equally Weighted Portfolio	Risk Weighted*	Simulated Portfolio (0% Future Information)	Simulated Portfolio (0.25% Future Information)	Simulated Portfolio (1.0% Future Information)	Simulated Portfolio (1.5% Future Information)
Increasing Herfindahl	19.59	14.85	13.50	17.64	18.09	18.94	19.55
Decreasing Herfindahl	2.75	14.07	13.16	8.96	9.33	10.15	10.52
Flat Herfindahl	9.06	10.89	7.25	10.73	10.95	12.12	12.73
	Breakdown of Herfindahl Phases						
Flat 1st Phase (1990/04 - 1994/07)	10.48	12.28	--	13.32	13.74	15.05	15.43
Increasing 1st Phase (1994/08 - 2000/06)	23.64	17.55	16.79	21.39	22.23	23.04	23.74
Decreasing 1st Phase (2000/07 - 2006/06)	-0.40	9.95	10.50	5.28	5.66	6.46	6.80
Flat 2nd Phase (2006/07 - 2016/06)	7.41	8.84	9.74	8.63	8.81	10.08	10.89
Increasing 2nd Phase (2016/07 - 2020/08)	15.47	10.18	8.31	12.99	13.12	14.36	15.12
Decreasing 2nd Phase (2020/09 - 2021/03)	26.03	55.32	41.87	42.52	43.22	45.07	46.10

*Source: PanAgora. For the time period of June 1990 to March 2021. Returns for phases longer than one year are annualized. Past performance does not guarantee future results. *The Risk Weighted backtest starts in 1995 as a result of data availability, hence the backtest did not have returns available in the "Flat 1st Phase" segment.*

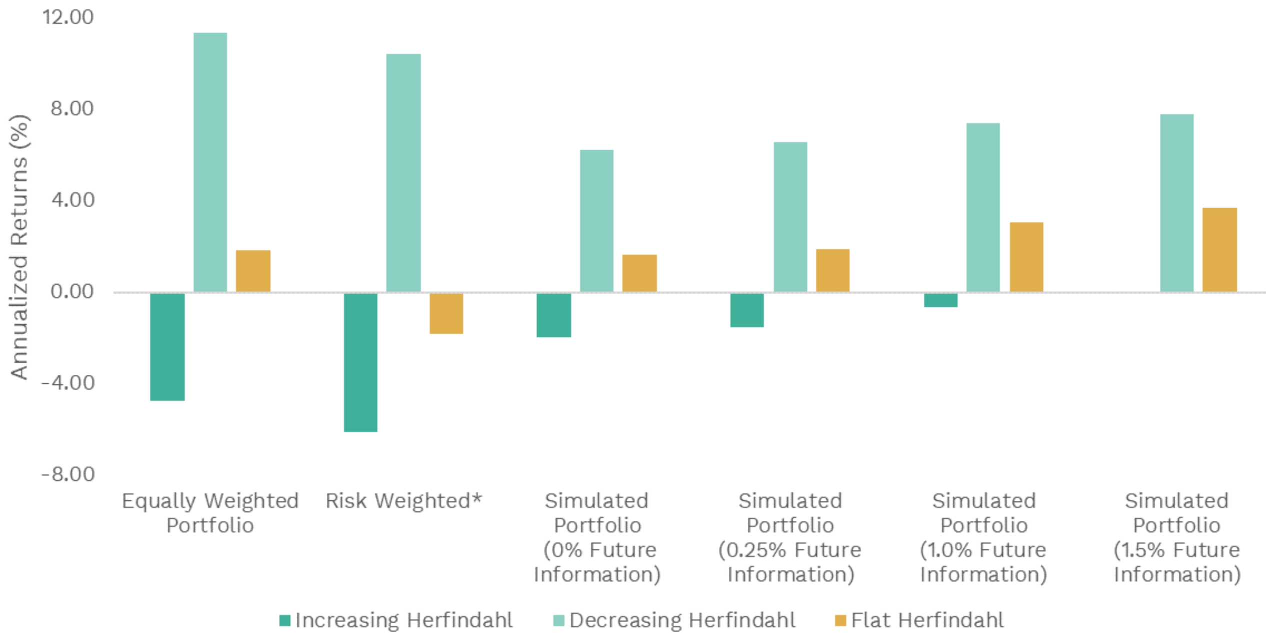
Exhibit 10: Annualized Returns vs. Concentration Regimes for Simulated Portfolios

Herfindahl Phases	S&P 500 Index (Market Cap Weighted)	Simulated Portfolio (0% Future Information)	Simulated Portfolio (1.5% Future Information)	Market Cap Weighted less Sim. Portfolio (0%) (t-stat)	Market Cap Weighted less Sim. Portfolio (1.5%) (t-stat)
Flat 1st Phase (1990/04 - 1994/07)	10.48	13.32	15.43	-2.66 (2.24)	-4.47 (3.90)
Increasing 1st Phase (1994/08 - 2000/06)	23.64	21.39	23.74	1.89 1.34	-0.06 (0.00)
Decreasing 1st Phase (2000/7 - 2006/06)	-0.40	5.28	6.80	-5.46 (5.39)	-6.83 (6.76)
Flat 2nd Phase (2006/07 - 2016/06)	7.41	8.63	10.89	-1.27 (1.62)	-3.28 (4.25)
Increasing 2nd Phase (2016/07 - 2020/08)	15.47	12.99	15.12	1.96 1.44	0.07 0.08
Decreasing 2nd Phase 2020/09 - 2021/03	26.03	42.52	46.10	-11.99 (4.65)	-14.38 (4.31)

Source: PanAgora. Annualized returns are computed for periods longer than a year in each phase, as shown in the table. Past performance does not guarantee future results.

[12] *September 2020, we showed this graphically in Sorensen and Lancetti (2020). Small valuations relative to large cap had reached a point not seen since 2000.*

Exhibit 11: Relative Returns of Strategies vs. S&P 500 Index



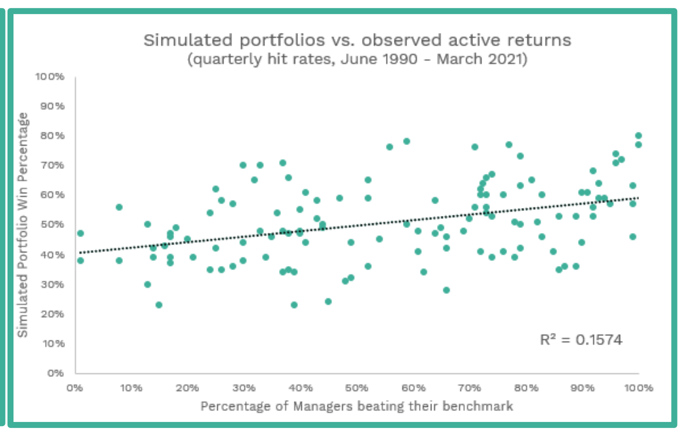
*Source: PanAgora. Time period is June 1990 - March 2021. Each bar represents the active annualized return of the strategy vs. the S&P 500 index during each Herfindahl phase. Returns for phases longer than one year are annualized. *The Risk Weighted backtest starts in 1995 as a result of data availability.*

Corroboration from Real Portfolios Using eVestment Data

The simulation results seem to capture the real-world experience of active managers. In Exhibit 12 below, we present a comparison between active returns for all U.S. large cap active portfolios using eVestment data and our simulations. Using quarterly data, we can see that the correlation between the percentage of simulated portfolios winning and the percentage of active managers beating their benchmarks is positive and statistically significant. This is particularly true at the extreme periods of positive simulated returns. During the periods of top decile simulated relative returns, 65% of active large cap managers beat their benchmarks.

Exhibit 12: Simulated Portfolios vs. eVestment Active Returns

Decile of Simulated Portfolio Win Percentage	Average Win Simulated	Average Win Active Manager
1	12.2%	41.9%
2	24.1%	46.8%
3	33.7%	51.4%
4	40.6%	48.3%
5	50.4%	47.2%
6	63.5%	47.7%
7	72.5%	57.1%
8	79.2%	55.8%
9	89.1%	49.6%
10	96.8%	64.7%



Source: PanAgora, eVestment. eVestment methodology: Investment universe as specified in eVestment is the "U.S. Large Cap Core Universe." Returns were computed on a quarterly basis from January 1990 – March 2021. The percentage of managers who beat their benchmarks was determined by dividing the number of managers with a positive excess return on their preferred benchmarks by the total number of managers in the universe (quarterly frequency).

Summary

We believe that our work here brings insight into the age-old debate of active versus passive management of institutional equity portfolios. On the one hand, we have identified a strong correlation between monetary regimes and benchmark index concentration that drives (or deprives) dominance of the price-weighted behemoth performance. We have identified cyclical effects of cap-weighted portfolios through the transmission of monetary action affecting market concentration, for good and bad. On the other hand, we have not explicitly directly correlated econometrically the return spread between active and passive. We have done such in earlier work of small cap and large cap returns, in Sorensen and Lancetti (2020). Earlier work indicates that active versus passive relates to 1) the slope of the yield curve; 2) long-term interest rates; and 3) market volatility.[13]

Simulated skill-based results conditioned on the phase of the cycle of concentration are consistent with our expectations. Skill and alternative weighting approaches win over time and during phases of the cycle. Skill, or lack of it, is one driver of benchmark relative performance. Actively motivated flow into large stocks and cap-weighted indices leading to concentration is another. When critiques of active management surface, we suspect the latter is dominating the former.

Our findings here should present useful guidance for the timing of "going passive" by fiduciaries. Given the current trend of a fall-off in concentration, which could last for years due to less aggressive monetary liquidity and rising long-rates, current moves into passive may be ill-timed. Moreover, historical evidence suggests that a concentration peak leads to years of concentration dissipation and the potential dominance for all kinds of alternative strategies. The last episode like this lasted 10 years and generated value-added opportunities for myriad active strategies.

[13] *See Sorensen and Alonso (2015).*

Appendix A:

Description Statistics:

Variable	Observations	Minimum	Maximum	Mean	Standard Deviation
Herfindahl	377	0.006	0.016	0.008	0.002
Real M2 Money Supply (Yearly change)	377	-2.8%	24.9%	3.6%	4.4%
10-year Treasury Rate (Monthly change)	377	-42.0%	27.8%	-0.2%	6.8%

Correlation Matrix:

	Real M2 Money Supply (Yearly change)	10-year Treasury Rate (Monthly change)	Herfindahl
Real M2 Money Supply (Yearly change)	**1**	0.144	0.682
10-year Treasury Rate (Monthly change)	0.144	**1**	0.027
Herfindahl	0.682	0.027	**1**

Herfindahl Regression - Goodness of Fit Statistics:

Observations	Sum of weights	DF	R^2	Adjusted R^2	MSE	RMSE	MAPE	DW	Cp	AIC	SBC	PC
377	377	374	0.47	0.467	0	0.001	10.837	0.114	3	-5102.054	-5090.257	0.538

Herfindahl Regression - Analysis of Variance:

Source	Degress of Freedom	Sum of squares	Mean squares	F-Statistic	Pr > F
Model	2	0	0	165.836	**<0.0001**
Error	374	0	0		
Corrected Total	376	0.001			

Computed against model Y=Mean(Y)

Herfindahl Regression - Model Parameters:

Source	Value	Standard error	T-Statistic	Pr > |t|	Lower bound (95%)	Upper bound (95%)
Intercept	0.007	0	95.143	**<0.0001**	0.007	0.007
Real M2 Money Supply (Yearly change)	0.025	0.001	18.198	**<0.0001**	0.022	0.027
10-year Treasury Rate (Monthly change)	-0.002	0.001	-1.899	0.058	-0.003	0

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