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Active versus Passive:
Old Wine in New Wine Skins

Eric Sorensen, Nicholas Alonso, Sebastian Lancetti, and Daniel Belanger

PanAgora

PanAgora Asset Management is a quantitative investment manager whose proprietary approach is designed to capitalize on inefficiencies across market cycles and to deliver relative and absolute returns through distinct and innovative Equity, Multi Asset and Risk Premia strategies. PanAgora's approach combines the firm's fundamental investment philosophy and original research with an advanced quantitative framework. These elements come together in an open, collaborative environment that builds upon the intellectual versatility of its team and leverages their complementary strengths — essential to serving the evolving objectives of institutional investors worldwide.

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Eric Sorensen, PhD

President & Chief Executive Officer

Dr. Sorensen is the President and Chief Executive Officer of PanAgora, and a member of the firm's Board of Directors, Investment, Operating, Risk, Code of Conduct & Ethics, and Directors' Committees. He is responsible for PanAgora's business and investment activities.

He took over leadership of PanAgora in 2004 and established a new research and investment direction for the firm. Prior to joining PanAgora, Dr. Sorensen was Director of Quantitative Research at Putnam Investments, overseeing the activities of several quantitative teams including equity, fixed income, asset allocation and financial engineering. He was also Chief Investment Officer of Structured Equity, which managed institutional portfolios using advanced quantitative approaches.

Between 1986 and 2000 Dr. Sorensen was the Global Head of Quantitative Research at Salomon Brothers (now Citigroup). At the end of his 14 years on Wall Street, he led a group of 55 quantitative analysts comprising teams in New York, London, Singapore, Tokyo and Australia. During that time, he published extensively, and consulted with institutional investor clients around the world. His honors include many years on the Institutional Investor All American Research Team, and several Graham and Dodd awards for excellence in financial writing.

Prior to Wall Street, he was a professor with a productive academic career from 1974 to 1986. For a decade he was Professor of Finance and Department Head at the University of Arizona. He has published over 50 journal articles and served on the editorial boards of several academic Finance journals. He is also co-author of the recent book, Quantitative Equity Portfolio Management.

Between 1969 and 1974 he served the country as a United States Air Force Officer and jet pilot. His primary mission was instructor pilot in high-performance jet aircraft.

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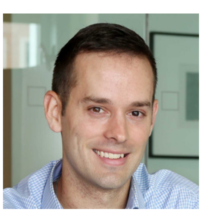

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Active versus Passive: Old Wine in New Wine Skins

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KEY FINDINGS

- A time-series model of real M2 and long-term bond rates explains S&P 500 index concentration behavior. The index spreads versus equal weight, risk weight, and skill weight are highly correlated with monetary policy and associated index concentration.
- A skilled manager who beats the S&P 500 by 4% annually over 30 years will underperform the index during short periods of excessive monetary expansion. The active manager will then win—by several percent annually—during periods of normal liquidity 80% of the time (because of changes in Fed policy and not changes in skill by the active manager).
- Even alternative stock weights weigh heavily. The two most extreme concentration periods of the last 30 years only lasted for 2.5 years. At concentration extremes, cap weights win by 5% annually versus equal weighting, and alternately lose by 10%. As of 2020, markets began a 10-year dominance period of active and alternative strategies.

ABSTRACT

Creators of the 1970s' capital asset pricing model could not have imagined how their descriptive theory of risk and return would come to dominate as a normative benchmark and reach extreme cycles of concentration. The cap-weighted index is central to the topic of active versus passive equity management. The authors study the 30-year history of S&P concentration cycles (when, on a few occasions, a handful of stocks dominates the metric). Excessive, policy-induced monetary expansion (M2) plus long-term bond rates predict index concentration and explain the return spreads between the S&P 500 index and alternatives (portfolio-weighting schemes or manager skill). The periodic comparisons between active skill investing and passive indexing have more to do with index concentration behavior and less to do with skill variability. As of 2020, a shift toward a new 10-year period of dominance for active and alternative strategies appears to have emerged. The authors expect stock selection and thoughtful risk management to retake their prominence as key drivers of success in global equity markets.

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.

[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.

In this article, we perform an empirical examination of a dominant, decades-old victory metric: the capitalization-weighted (CW) 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 CW 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 CW passive to alternatives.

CONCENTRATION CYCLES

Critical to this article is the notion of concentration. Index concentration is the magnitude of effect that a specific few 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 the 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).

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

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

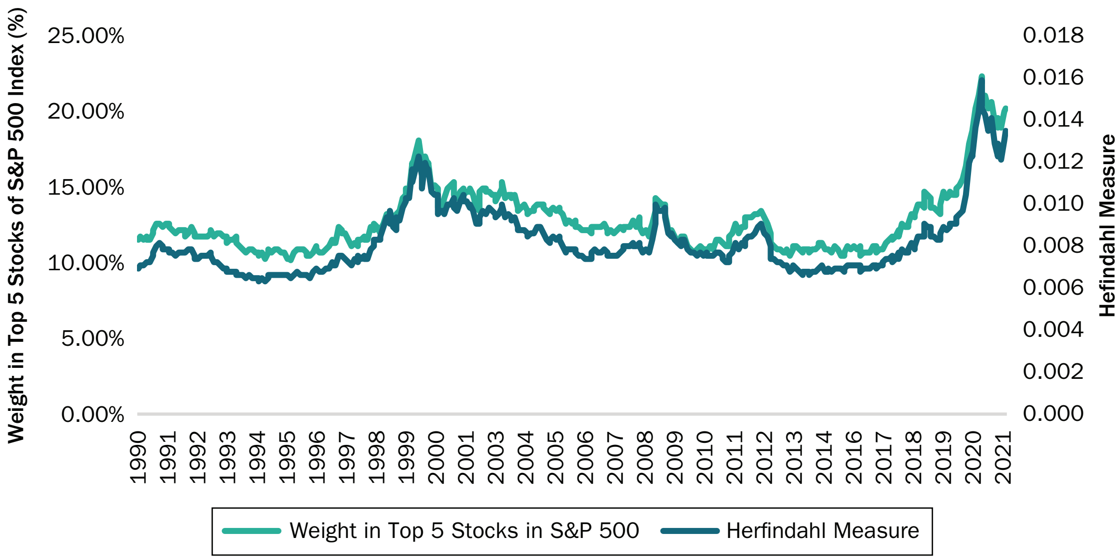
[3]The Herfindahl index was introduced by economist Orris C. Herfindahl. It measures the market concentration of each firm in an industry. It has been applied often across industries to measure organizational and participant profiles.

[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. Should you beat the historic long-run 9.3% Lorie and Fisher finding, however, it must be an anomaly (i.e., asset pricing behavior).
4. You should use modern techniques to model future price behavior—that is, asset pricing econometrics (quant).

EXHIBIT 1

S&P 500 Index Measures of Concentration over Time



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

SOURCE: PanAgora.

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) has provided an excellent social science perspective of this change in purpose: how a camera became an engine. Thus, 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 became the metric for assessing the 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 de Condorcet (1785).[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 individual wisdom. This work is largely modeled in a single-period framework. For example, de Condorcet applied his theory to the work of a jury, in which decision makers have a single vote at a specific time.

[5] See also Landemore (2012).

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 de Condorcet-like crowding literature, his notions were figuratively framed in a multiperiod setting. One hundred thirty years post-Mackay, the professional academicians referenced earlier 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 of 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 funds in aggregate come out of active portfolios and go passive. Effectively, the active aggregate market is funding an 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 magnitude of actively managed portfolios (approximating equal weighting [EW]) that were moved to passive at an accelerated pace over the last several years.

We will demonstrate in the next section that monetary ease begets concentration. The dynamics of concentration attract a crowd. Active large-cap stock allocators and others reallocating equity to passive feed on themselves. Metaphorically, decisions to go large and decisions to go passive represent a symbiotic relationship between those who actively time the large index names and those who actively allocate to them via moving to the passive CW 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 VERSUS 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

[6] Consider a simple economy with two equity portfolios of equal assets under management 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 (e.g., a 100-peso portfolio with 5 pesos in each of the top 10 names and 0.56 pesos in each of the remaining 90). The second portfolio of 100-peso assets under management is equal weighted, 1 peso each. Thus, the aggregate market has 10 stocks with market cap of 6 pesos and 90 with a cap of 1.56. The largest 10 stocks are 30% of the aggregate market. Now suppose that the situation motivates liquidation (rebalancing) of the second portfolio into the weighting scheme of the first. The resulting aggregate market remains 200 pesos. Ten stocks now have an aggregate cap of 5 + 50 /10, or 10 pesos. The other 90 have a 1.116-peso cap. Prior to the trade, the top 10 aggregate comprises 30% of the market. After the trade, it comprises 50%. That is an increase in concentration.

[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).

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) modeled 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) analyzed 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 found (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 are tilted away from the index in favor of lower-volatility stocks that 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 EW of the S&P names may at times be superior to the 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.

One 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 found that RW provides a superior wealth creation profile over almost all reasonable holding periods of five years and beyond. During the period between January 1995 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 went on to test for conditionality. RW achieves dominance over CW indexes 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 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 and real economic activity is well documented. Similarly, the interplay between monetary aggregates and stock market moves has also intrigued researchers. Sorensen (1982) found 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 United States 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 affects markets, namely a disproportionate demand for equities in general and large index names in particular. Earlier, we discussed the two types of active decisions leading to crowding. One 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 exchange-traded funds, 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 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 Reserve Board should correlate with economic growth. However, when we measure M2 growth in real terms (adjusted for Consumer Price Index inflation), we have a measure of abnormal monetary growth. Exhibit 2 graphs the year-over-year growth rate in M2 deflated by the contemporaneous Consumer Price Index 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 0.68, with a *t*-statistic of 18.

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]

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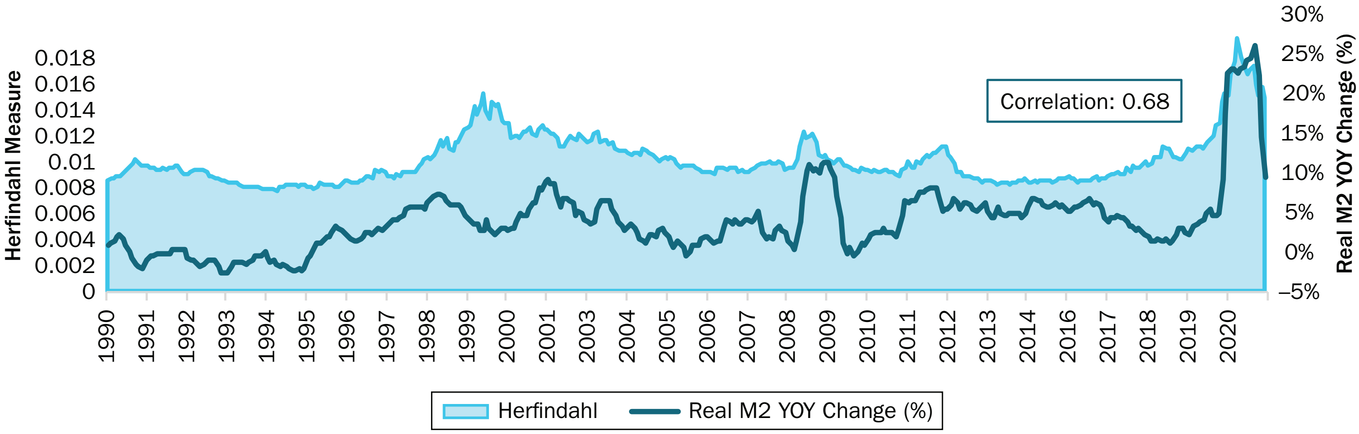
[8] See the references from Sorensen (1982) for pioneering studies of money supply and the stock market.

[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 owing to a perceived lack of liquidity. Again, CW indexes are more volatile during both meltdowns and melt-ups.

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

EXHIBIT 2

Monetary Liquidity and Concentration

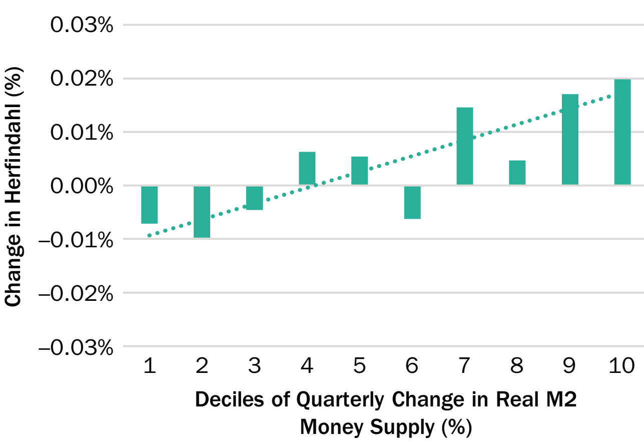


NOTES: Time period: June 1990–March 2021. For illustrative purposes only.

SOURCE: PanAgora, FRED, Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/).

EXHIBIT 3

Herfindahl vs. Real M2 Money Supply



NOTES: For illustrative purposes only. The horizontal axis represents the decile groupings of each measure. Deciles were computed in ascending order. Time period: June 1990–March 2021, quarterly observations.

SOURCE: PanAgora, FRED, Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/).

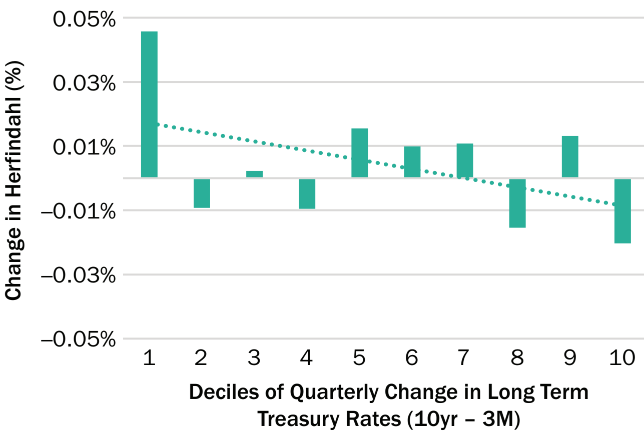
Large-cap stocks are typically longer in duration in a bond sense. Sorensen and Gould (1986) observed that companies with more predictable and stable earnings growth rates react more predictably as the yield curve shifts. In addition, Liebowitz et al. (1989) argued that companies with stronger franchise 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 price/earnings ratios rising (falling) as long rates are falling (rising).

As shown in the Appendix, we present the multiple regression results using our M2 measure (described earlier) 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 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 of 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 the 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

EXHIBIT 4

Herfindahl vs. Change in Long-Term Treasury



NOTES: For illustrative purposes only. The horizontal axis represents the decile groupings of each measure. Deciles were computed in ascending order. Time period: June 1990–March 2021, quarterly observations.

SOURCE: PanAgora, FRED, Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/).

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.

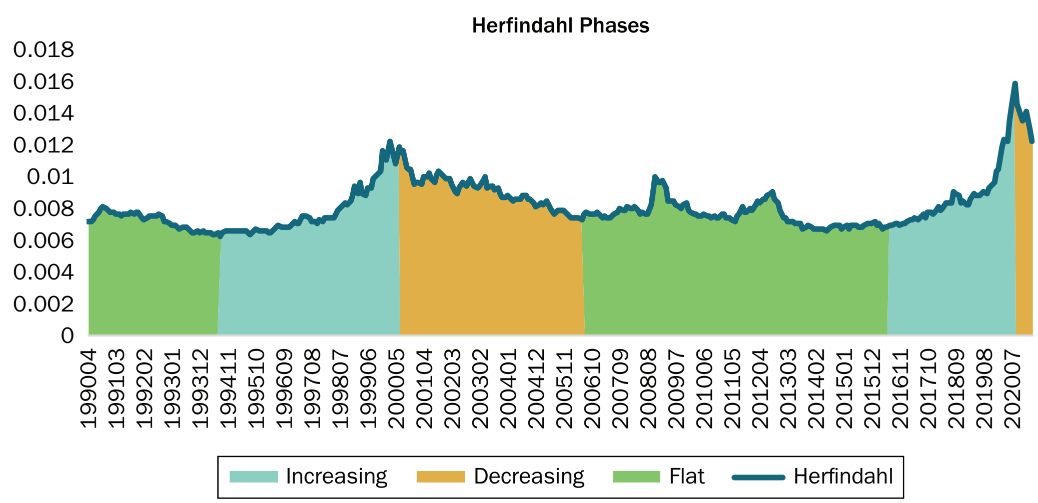
HISTORICAL PHASES OF CONCENTRATION AND WEIGHTING STRATEGIES

Exhibit 5 shows the history of the Herfindahl for the S&P 500 partitioned by three phases. One phase is the 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).

We would expect periods of methodically rising (falling) concentration shown here to benefit (hamper) CW 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 an approximately 2% annualized edge over CW.

EXHIBIT 5

Phases of Concentration



NOTE: For illustrative purposes only.

SOURCE: PanAgora.

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)

NOTES: Annualized returns are computed for periods longer than a year in each phase, as shown in the exhibit. Past performance does not guarantee future results. *The RW backtest starts in 1995 as a result of data availability; hence, the backtest did not have returns available in the "flat 1st phase" segment.

SOURCE: PanAgora.

SIMULATING ACTIVE STOCK SELECTION WITH SKILL

The results suggest that the relative performance of alternative weighting methodologies is highly dependent on the cycle. What about alternative selection methodologies? In other work, we have demonstrated 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 earlier. 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. We then 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 draws to be clear choices of the best-performing stocks.

[11] See Sorensen and Miller (1998).

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 (1.0% future information)	Simulated Portfolio (1.5% future information)
56%	57%	62%	64%

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

SOURCE: PanAgora.

This is perfect foresight knowledge of the ex post one-quarter return on each stock. We use a metric analogous to "correlation" that allows the draws to vary from zero knowledge (correlation of 0) to perfect foresight (correlation of 1). With a correlation of 0, there is no skill. A correlation of 0.05 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% is sufficiently strong to ensure 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%), 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-CW versus CW portfolios owing 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%.

As is the case with the alternative weightings (EW and RW) discussed earlier, 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 of 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 of 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 0 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 than of 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

EXHIBIT 8

Returns of Different Strategies (June 1990–March 2021)

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)
				Annualized Returns (%)			
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

NOTES: 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 RW backtest starts in 1995 as a result of data availability.

SOURCE: PanAgora.

EXHIBIT 9

Table of Average Returns during Different Herfindahl Regimes

Herfindahl Phases	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)
Annualized Returns (%)							
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

NOTES: 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 RW backtest starts in 1995 as a result of data availability; hence, the backtest did not have returns available in the “flat 1st phase” segment.

SOURCE: PanAgora.

of cap weighting on relative performance are 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 work). 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]

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

EXHIBIT 10

Annualized Returns vs. Concentration Regimes for Simulated Portfolios

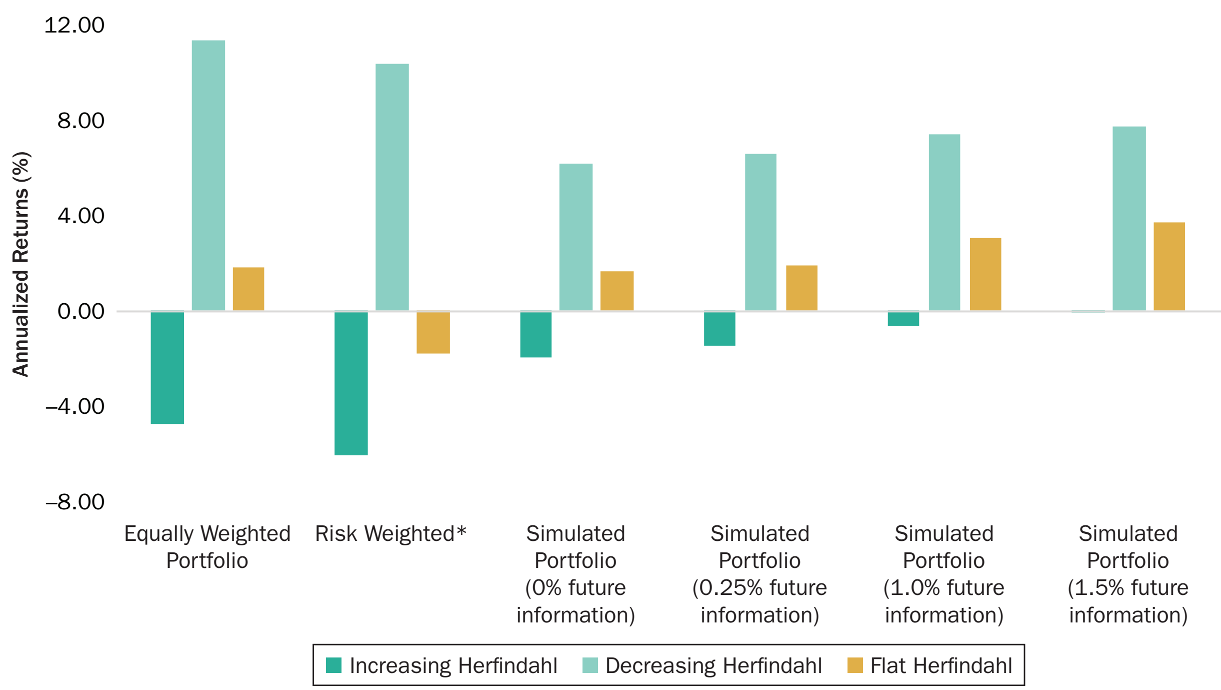
Herfindahl Phases	S&P 500 Index (market cap weighted)	Simulated Portfolio (0% future information)	Simulated Portfolio (1.5% future information)	Market Cap Weighted less Sim. Portfolio (0%) (*t*-Stat)	Market Cap Weighted less Sim. Portfolio (1.5%) (*t*-Stat)
Flat 1st Phase	10.48	13.32	15.43	–2.66	–4.47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

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

SOURCE: PanAgora.

EXHIBIT 11

Relative Returns of Strategies vs. S&P 500 Index



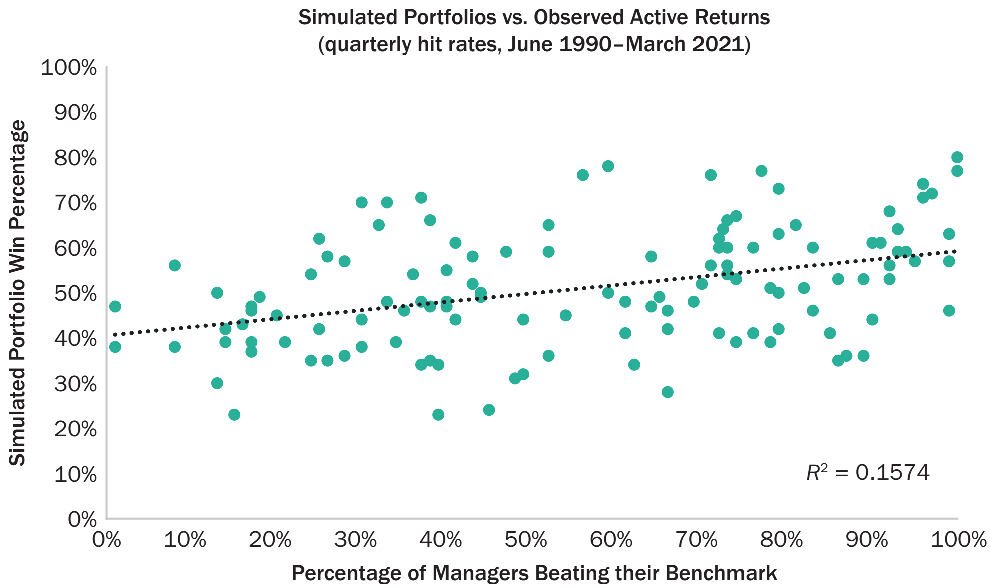
NOTES: Time period is June 1990–March 2021. Each bar represents the active annualized return of the strategy versus the S&P 500 index during each Herfindahl phase. Returns for phases longer than one year are annualized. *The RW backtest starts in 1995 as a result of data availability.

SOURCE: PanAgora.

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%



NOTES: eVestment methodology: Investment universe as specified in eVestment is the US 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).

SOURCE: PanAgora, eVestment.

CORROBORATION FROM REAL PORTFOLIOS USING EVESTMENT DATA

The simulation results seem to capture the real-world experience of active managers. In Exhibit 12, we present a comparison between active returns for all US 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.

SUMMARY

We believe that our work here brings insight into the age-old debate of active versus passive management of institutional equity portfolios. On one hand, we have identified a strong correlation between monetary regimes and benchmark index concentration that drives (or deprives) the dominance of the price-weighted behemoth performance. We have identified cyclical effects of CW portfolios through the transmission of monetary action affecting market concentration, for good and bad. On the other hand, we have not explicitly directly and econometrically correlated the return spread between active and passive. We have done so in earlier work on small-cap and large-cap returns (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 CW indexes 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 owing 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 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.

APPENDIX

EXHIBIT A1

Descriptive 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%

SOURCE: PanAgora.

EXHIBIT A2

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**

SOURCE: PanAgora.

[13] See Sorensen and Alonso (2015).

EXHIBIT A3

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

SOURCE: PanAgora.

EXHIBIT A4

Herfindahl Regression—Analysis of Variance

Source	Degrees 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			

SOURCE: PanAgora.

EXHIBIT A5

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

SOURCE: PanAgora.

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