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Syntax

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This article introduces a novel index methodology, functional information system (FIS)—based stratification, underpinned by the identification of a new risk category, *related business risk* (RBR); a new business risk classification technology called an FIS; and a statistical methodology called stratification to effectively diversify RBRs. When two or more companies' earnings are affected by the same economic drivers, such as similar suppliers, customers, or product types, they share an RBR.

Although traditional finance divides risk into systematic and idiosyncratic, we believe that an important third category of risks exists: those shared by companies engaged in related businesses. RBRs are different from single-company idiosyncratic risks such as management or product failures. RBRs also differ from systematic risk (e.g., market, sector, and style) because they relate to underlying operating risks and not those directly reflected by market prices.

RBRs can affect many companies at the same time due to regulatory change, customer trends, or commodity shocks, for example. If these related businesses are an inadvertently large proportion of a portfolio, an event associated with these businesses can have a disproportionately large performance impact relative to the performance of the market as a whole. This can be especially problematic when, for example, the event

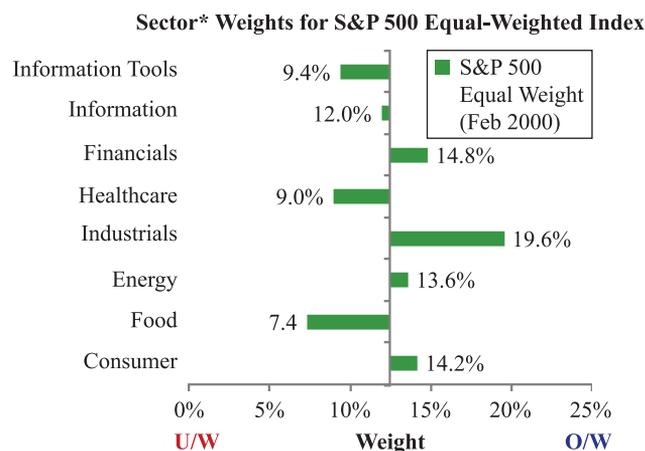
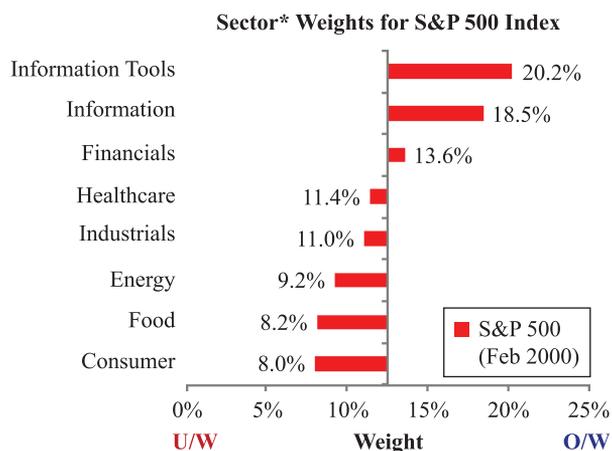
causes a large permanent decline in valuation, such as the related-business bankruptcies of the tech companies following the Internet bubble. If related businesses that have a large permanent decline in value are a disproportionate share of a portfolio, these declines can result in negative portfolio performance that is not representative of the aggregate constituents of the portfolio.

Such risks are not explicitly controlled in either capitalization-weighted or equal-weighted indexes, and their impact on the index performance can be significant. This article proposes that this risk is diversifiable by hierarchically allocating portfolio exposure to groups of companies that share RBRs using the FIS-based classification of business risk and a process called stratification. By allocating risk in this way, absolute and risk-adjusted portfolio performance is enhanced relative to other weighting methodologies.

A key component of FIS-based stratification is the introduction of a new type of business risk classification system called an FIS. Unlike traditional industry classification systems like North American Industry Classification System (NAICS; www.census.gov/eos/www/naics) or Global Industry Classification Standard (GICS; <https://www.msci.com/gics>), in which businesses are assigned to a single category at each level in a static hierarchy, FIS defines a set of universal functional attributes that encode the nature

EXHIBIT 1

Sector Weights of S&P 500 Indexes



*Based on level 1 FIS sector classifications as of February 29, 2000. Over/underweight relative to an equal (12.5%) allocation to each sector.

of any company’s business. These functional attributes are derived from systems economics, a field that models the structure of an economy by decomposing it into component parts and studying the interactions between these parts. FIS attributes capture the functional identity of a company’s products, customers, suppliers, and other economic and operating facets. These attributes are the underlying drivers of business performance, including changing product demand, supply chain shifts, or new regulations. FIS provides a precise, systematic approach to the identification of RBRs. By grouping together companies that share particular FIS attributes, we can more effectively navigate, compare, and study their economic drivers and RBRs.

Stratification is a statistical method for obtaining an unbiased, representative sample of a heterogeneous population. This article uses stratification to reduce biases in indexes of investment securities. As first formally described by Neyman [1934], stratification divides a population into homogeneous groups and subgroups and performs separate measurements on each group, thus controlling the impact of each group on the overall population measure. This approach is fundamental to most clinical trials.

FIS-based stratification, then, is the stratification of a population of investment securities using FIS attributes to define the relevant subsets. The goals are to effectively identify, group, and diversify index exposure to related economic activities. Stratified indexes accomplish this

by sorting companies into FIS-coded industries, which are groups of businesses that share specific functional attributes. These groups are then further refined and divided into FIS-coded subgroups, sub-subgroups, and beyond based on more granular attributes within the parent FIS-based economic activity. Weights are then distributed across these many groups to achieve effective diversification. The objective of FIS-based stratification is to maintain an index whose performance is most representative of the underlying economics of a universe of constituents, such as large-cap U.S. equities.

This article argues that stratifying based on business activity in this manner is an effective way to reduce the portfolio risk associated with inadvertent overconcentration of specific, related economic activity. Moreover, this article suggests that this concentration of RBRs is a structural flaw of both capitalization-weighted and equal-weighted methodologies, exposing investors to the risk that the performance of one portion of an index can drive the performance of the entire index (i.e., the index is not properly diversified). This is highlighted in Exhibit 1, where at the height of the dotcom bubble, capitalization-weighted and equal-weighted versions of the S&P 500 had significant over- and underexposure to many of the eight FIS-based top-level sectors.

Stratified indexes have a different performance target from their capitalization-weighted and equal-weighted counterparts. Whereas capitalization-weighted indexes provide the investor with an aggregate equity

risk premium for the market as a whole (the more investable market cap listed, the greater the index weight) and equal-weighted indexes provide the investor with an average company equity risk premium (the dollar holdings of each position are equal at rebalance), FIS-based stratified-weight indexes provide exposure to the diversified equity risk premium (a type of economic risk parity). Each weighting methodology provides a different but complementary performance measure.

The diversification this article proposes is not based on market factors. Rather, it is focused on diversifying RBRs and, in so doing, reducing the impact of a group of related companies all simultaneously missing their earnings targets because of the same economic shock. In this sense, the FIS-based stratified approach is quite distinct from smart beta approaches, which are largely based on quantitative market or fundamental factors. FIS, instead, provides a tool to identify, group, and weight companies based on the underlying functional attributes that drive such factors; companies that share functional attributes should respond similarly to economic shocks. By assigning fixed weights to each functional category, FIS-based stratification diversifies exposure to RBRs, thus reducing the risk of being overexposed to a large economic shock.

Compared to capitalization weighting and equal weighting methodologies, the benefit of stratifying RBRs is evident across a wide array of performance metrics over different periods of time and in different markets. This article compares over 25 years of back tested performance data for the constituents of the S&P 500 and S&P MidCap 400 Indexes using three different weighting methodologies: capitalization weighting, equal weighting, and FIS-based stratified weighting. The article also gives stratified results for eight FIS-based stratified sector indexes based on the constituents of the S&P 900 Index (the union of the S&P 500 and S&P MidCap 400). The performance of all 11 stratified indexes is calculated by S&P Dow Jones Indices.

This article argues that FIS-based indexes achieve the following:

1. Consistent and superior returns relative to a capitalization-weight methodology;
2. Consistent and superior returns relative to an equal-weight methodology;
3. A consistent premium to long-term treasury bonds;
4. Consistent results across FIS-based sector indexes and composite broad-based indexes.

The indexes compared in this article use an identical constituents and index calculation methodology, including corporate action treatment, dividend reinvestments, security additions and deletions, and rebalancing schedule. The only difference among the capitalization-weighted, equal-weighted, and stratified-weighted indexes is their specific weighting methodology. Given this, the superior results of stratified indexes can be attributed to both the FIS-based method used to identify, segment, and diversify the underlying RBR in an index and the stratification methodology used to determine portfolio weights.

In summary, the comparative performance of a stratified-weight methodology versus a capitalization-weight or equal-weight methodology suggests that effectively controlling for RBRs positively affects returns after periods of downward earnings surprises in related businesses and does not appear on average to have an adverse performance impact during periods of expanding earnings.

METHODOLOGY

Theory of FIS-Based Stratification: Normalizing Outcomes by Controlling for RBR Concentrations

The need to group common risks and control exposure to these risks to reduce bias in a population is not unique to finance but, in fact, exists in many types of population statistics and risk management. It is common practice in any population study to conduct a population weighting analysis to test for the existence of subpopulations that can be expected to behave differently from one another (see Addelman [1970] or David [2008]). A common test of population bias is whether the behavior of an average population differs from an aggregate population. If certain subpopulations are given too much weight in the study, the outcome of the study may be biased toward that subpopulation. This bias can be mitigated by population stratification, either by limiting the number of participants selected from the subpopulations or by controlling the weight of the data measured from each group.

Different fields use defined categories, specific to their domain, to control for risks in population studies. In each case, the process of identifying and controlling for population bias is identical, even if the categories

are different. Researchers may not know how various subpopulations will perform, but they can anticipate which are likely to exhibit similar results because of shared underlying attributes. In healthcare, for example, Kernan et al. [1999] described how clinicians cannot predict the effectiveness of a new drug for individual patients before the first human drug trial, but they can use established demographic categories corresponding to groups of patients with similar responses to existing treatments as a method for controlling for possible patient responses to the trial drug. Each group can (and often does) have different biases, so the clinician must control the study to ensure its overall results are consistent and representative. In other words, they must make sure that the results are not biased by a trial's inadvertent overexposure to a particular demographic subpopulation.

Insurance is another field that controls risk in this manner. In disaster insurance, the location and timing of future disasters is unknown, but specific geographic zones based on geographic information system (GIS) coordinates (i.e., longitude, latitude, and elevation) can effectively define risk groups likely to have associated outcomes (Porrini [2016]). In life insurance, the same can be done with subpopulations defined by common genetic attributes (Joly et al. [2014]). In both cases, premiums are set to manage the weights of diversified pools of common risk groups defined using domain-specific multi-attribute risk identification systems.

In portfolio management, FIS can be used like the other multi-attribute risk identification systems referenced to accomplish the same objective: controlling risk caused by inadvertent overweighting of subpopulations. Like GIS, FIS provides tags based on a coordinate-based multi-attribute system that provides a standardized method of capturing the business risk attributes that affect a company's differential performance. These tags can be used to define customized risk groups for collections of investable securities.

Stratification assigns preset weights to subpopulations with associated attributes to maintain a statistically controlled population-wide risk profile. If two companies share the same customer group or supply chain, they likely have RBRs. Companies that share multiple RBRs should, in turn, share strong performance associations, especially in times when one or more of these RBRs experience stress.

If these relationships are not directly considered when constructing a portfolio, overexposure to

constituents' RBRs can result in significant underperformance. For example, telecommunication switches and routers companies are an RBR group identifiable by the FIS model. In 2000, companies in this group suffered widespread, unanticipated declines in their financial health and, subsequently, their market values. A similar shock affected money center banks, another RBR group, in 2008. Neither of these declines was a transient fluctuation resulting from market efficiencies and the general ebb and flow of markets; instead, these groups of related companies had significant, unexpected reversals of fortune. In each case, after the market became aware of the earnings impediments, the valuation of the companies sharply declined, with some losing virtually all of their value. These devaluations are often black swan events that take place when the market becomes aware of materially negative unexpected business performance information, resulting in permanent devaluation of equity securities analogous to realized principal losses in debt securities. Inadvertent overweighting of companies or groups of companies can leave investors overexposed to these catastrophic losses, resulting in a negative performance bias through economic cycles.

Similar to idiosyncratic risk, shocks affecting RBRs can be thought of as following a statistical distribution, in which each independent RBR is equally likely to be shocked at any point in time. Given this assumption, to achieve proper diversification, equal exposure should be allocated to each RBR. FIS-based stratification achieves this exposure and hence reduces the severity of RBR shocks.

FIS-Based Classification and Stratification

Stratification is performed using the following methodology. First, a universe of constituents is selected, whether by adopting the constituents of an existing index, such as the S&P 500 Index, or by using a series of filters to pare a broad universe down to a desired one. The larger and more functionally heterogeneous the population, the more potential exists for effective stratification. Second, a hierarchical structure consisting of a parent group and nested RBR groups associated with the parent is created. The population is subdivided until no additional meaningful subdivisions are available—that is, when the bottom-level groups are functionally homogeneous.

The way in which the parent groups are subdivided can differ depending on the concentration of different business risks within the given universe. These differences vary by both geography and size: The United States, Europe, Asia, and the emerging markets have very different mixes of constituent groups, as do large cap, mid cap, and small cap. Moreover, appropriate groupings may change over time as the underlying structure of the economy evolves. In a stratified structure, the related business groupings are designed to comprehensively reflect the underlying business risks of the universe at any point in time.

In FIS-based stratification, the hierarchical structure is formed using FIS attribute-value pairs to define groups. FIS attributes are assigned based on careful consideration of each company's qualitative and quantitative operating characteristics, in particular, the functional nature of each company's reporting segments. For each constituent, FIS tags are assigned to each product line detailing the nature of that product (e.g., what the product is, how it is used, who its customers are). These product line tags are revenue weighted and aggregated to create a set of FIS tags for the constituent. Constituents are then allocated to groups based on their FIS tags. In the United States, the eight top-level FIS-defined sectors are financials, energy, industrials, information tools, information products and services, consumer products and services, food, and healthcare. Each of these sectors is associated with specific FIS-based business risks that are differentiated from the other sectors. For the indexes discussed in this article, FIS attributes are assigned to all current and historical constituents of the S&P 500 and S&P MidCap 400 Indexes from December 20, 1991, to December 31, 2016.

In a stratified index, constituent target weights are determined first by assigning an equal weight to each top-level group in the hierarchy. The weight of each of these groups is then equally divided across its child groups, and this process is repeated until each bottom-level leaf group has been assigned a target weight. Finally, each bottom-level group's weight is divided equally across its constituent companies. Because each group may have a different number of children and each bottom-level group may have a different number of securities, the resulting constituent weights differ significantly from a pure equal-weight index.

Exhibit 2 provides an illustration of this process. In the industrial sector presented, the parent group

"Related Industrials Risk" is defined. This group is then divided into a series of hierarchical subdivisions starting with four groups that share RBRs based on their specific products. The industrial sector is subdivided into raw materials, components, finished equipment, and services RBR groups. These groups are further subdivided according to their RBRs; for example, the raw materials group is subdivided into three subgroups: plastics, metals, and natural resources. This process continues to the most granular grouping (the fifth level in the case of U.S. LargeCap). Constituents are assigned to groups based on their FIS attributes, and each bottom-level group's weight is equally divided among its constituent stocks.

This process of identifying and hierarchically grouping the associated RBRs is applied to all eight sectors. The Appendix lists the RBRs controlled for in each of the eight FIS-based sectors used in this study. These RBRs, which represent granular business risks in the large- and mid-cap U.S. equity market, are used to stratify the Syntax Stratified Core Index. Each quarter, sector weight is apportioned following this methodology; constituent weights are then allowed to drift until the following rebalance.

IMPLEMENTATION AND RESULTS

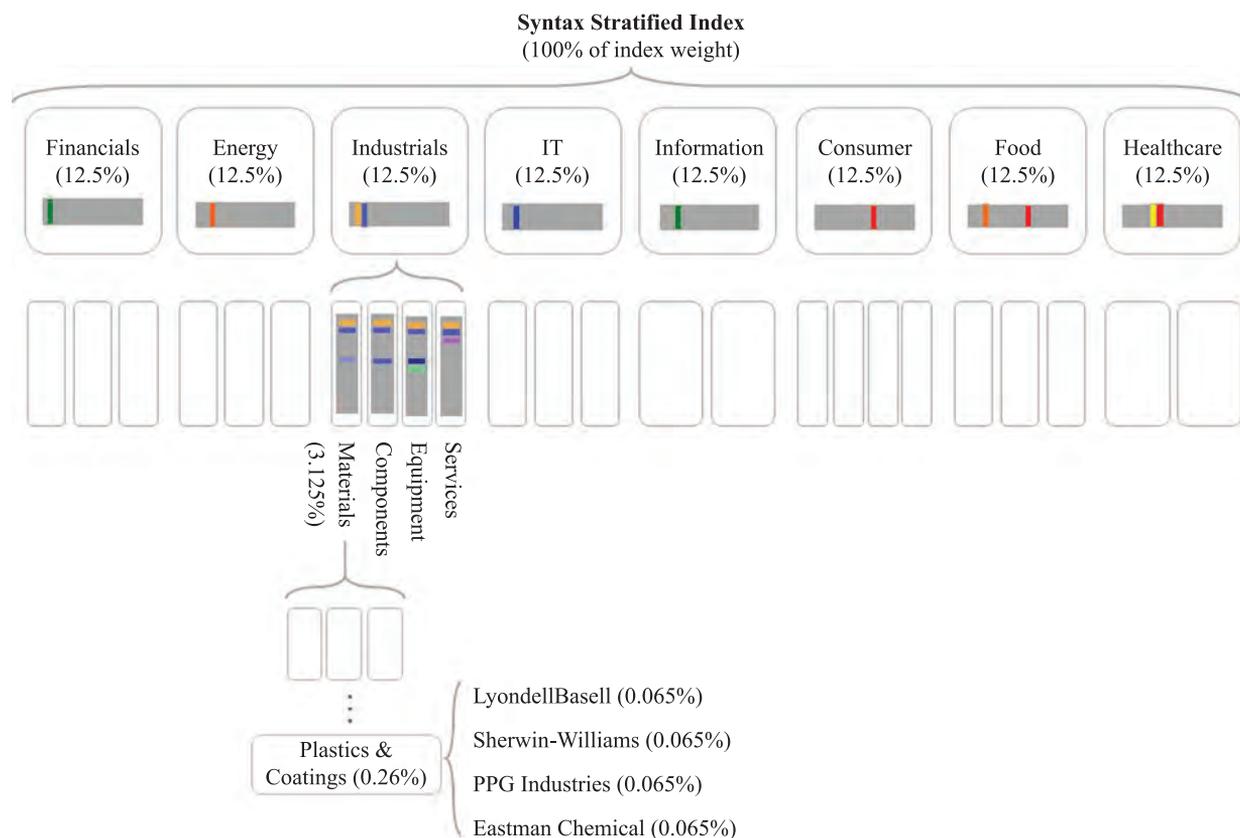
Evaluating Stratified-, Capitalization-, and Equal-Weighting Methodologies

This section compares the performance of the FIS-based stratified-weight methodology to that of capitalization-weight and equal-weight methodologies across 11 different universes: the S&P 500 universe; the S&P MidCap 400 universe; and eight mutually exclusive, FIS-based sector subsets of the S&P 900 universe, comprising financials, energy, industrials, information tools, information, consumer products, food, and healthcare. Index levels for the FIS-based stratified-weighted variants of these universes are calculated by S&P Dow Jones Indices, and all data are presented gross of transaction costs and fees.

The only difference between the FIS-based stratified-weight variant and the capitalization-weight and equal-weight variants of each of these universes is the weighting methodology. Each methodology assigns strictly positive weights to all securities in the universe. The FIS-based stratified-weight indexes discussed in this

EXHIBIT 2

Example of the Stratification Process



Notes: Barcodes are a visual representation of FIS attribute tags. Constituents of each group share common FIS attributes. Groups at each level of the hierarchy represent RBRs. For example, Industrials is a broad group of companies that share RBRs when producing tools for business customers. Materials is a narrower group comprising those Industrials companies that share risks related to the production of raw materials used in industrial applications. Plastics & Coatings is a very specific RBR group comprising those Materials companies that produce plastics, coatings, and other bulk commodity chemicals, which share material risks relating to the nature of this business. Details of the hierarchy, including a representation of the fourth level, are omitted from this visualization due to space constraints.

article follow the S&P Dow Jones Indices methodology for treatment of corporate actions, dividend reinvestments, security additions and deletions, and rebalances.

Prior to the inception of Syntax Stratified Indices on December 27, 2016, data presented herein are back tested. It is worth noting that this backtest methodology does not involve security selection because the universes used are contemporaneously defined by S&P Dow Jones Indices. Additionally, FIS-based stratified weights are selected independent of historical fundamental or market data, and they are not determined by optimizing any objective function.

Exhibit 3 compares the performance of the FIS-based stratified-weight, capitalization-weight, and equal-weight variants of the S&P 500 universe from

December 20, 1991, to December 31, 2016. The Syntax Stratified LargeCap, which stratifies the constituents of the S&P 500, exhibits substantially higher returns than the capitalization-weight and equal-weight variants, outperforming by 3.89% and 1.75% per year, respectively. These results have significant *t*-statistics.

The stratified index has only slightly greater volatility than the capitalization-weight S&P 500 and comparable volatility to the equal-weight variant, resulting in a significantly higher Sharpe ratio for the stratified-weight index. Downside volatility, Sortino ratio, tracking error, and information ratio further demonstrate the diversification benefits of stratification. The MidCap 400 universe exhibits the same trends as LargeCap stratification: higher return, similar volatility,

EXHIBIT 3

Performance of Different Weighting Methodologies for LargeCap and MidCap Indexes

| | Ann. Return (%) | Excess Return (%) | t-Stat | Vol. | Sharpe Ratio | Down Vol. | Sortino Ratio | Track. Error | Inf. Ratio |
|-----------------------------|-----------------------|-------------------------|--------|-------|-----------------|--------------|------------------|-----------------|---------------|
| Syntax Stratified LargeCap | 13.38 | 3.89 | 13.37 | 15.44 | 0.69 | 8.90 | 1.19 | 5.04 | 0.77 |
| S&P 500 | 9.50 | – | – | 14.24 | 0.47 | 8.47 | 0.79 | – | – |
| S&P 500 Equal Weight | 11.64 | 2.14 | 6.99 | 15.85 | 0.56 | 9.17 | 0.96 | 5.31 | 0.40 |
| Syntax Stratified MidCap | 14.90 | 2.70 | 12.09 | 16.98 | 0.71 | 9.62 | 1.26 | 3.88 | 0.70 |
| S&P MidCap 400 | 12.20 | – | – | 16.56 | 0.57 | 9.81 | 0.96 | – | – |
| S&P MidCap 400 Equal Weight | 12.40 | 0.20 | 0.85 | 17.22 | 0.56 | 9.95 | 0.96 | 4.05 | 0.05 |

Notes: Annualized return is the geometric average of monthly returns. Excess return is the difference in annualized return of each index against its capitalization-weighted analog; t-statistic shows the statistical significance of the excess return. Volatility is the annualized standard deviation of monthly returns. Downside volatility is the annualized standard deviation of returns less than 0%. Sharpe and Sortino ratios (Sortino and Price [1994]) show the excess return of each index relative to the risk-free rate, as measured by the Barclays U.S. Treasury Bills Index, divided by the volatility or downside volatility of the index, respectively. Tracking error is the annualized standard deviation of excess returns against the capitalization-weighted analog, and the information ratio shows excess return divided by tracking error. All calculations use monthly returns from December 20, 1991, (the start of the backtest sample for Syntax Stratified Indices) to December 31, 2016.

EXHIBIT 4

CAPM Performance Comparison

| | Corr. | Beta | Alpha | t-Stat |
|----------------------------|-------|------|-------|--------|
| Syntax Stratified LargeCap | 0.95 | 1.03 | 0.29 | 3.44 |
| S&P 500 Equal Weight | 0.94 | 1.05 | 0.15 | 1.71 |
| Syntax Stratified MidCap | 0.97 | 1.00 | 0.21 | 3.15 |
| S&P 400 Equal Weight | 0.97 | 1.01 | 0.01 | 0.20 |

Notes: Correlation shows the degree of comovement between each index and its capitalization-weighted analog. Beta and alpha are the slope and intercept of a linear regression of excess returns over the risk-free rate, as measured by the Barclays U.S. Treasury Bills Index, against the excess returns of the capitalization-weighted analog. The t-statistic shows the statistical significance of alpha. All calculations use monthly returns from December 20, 1991, to December 31, 2016.

and lower downside volatility and, hence, improved Sharpe, Sortino, and information ratios, with a statistically significant excess return over its respective capitalization-weighted index.

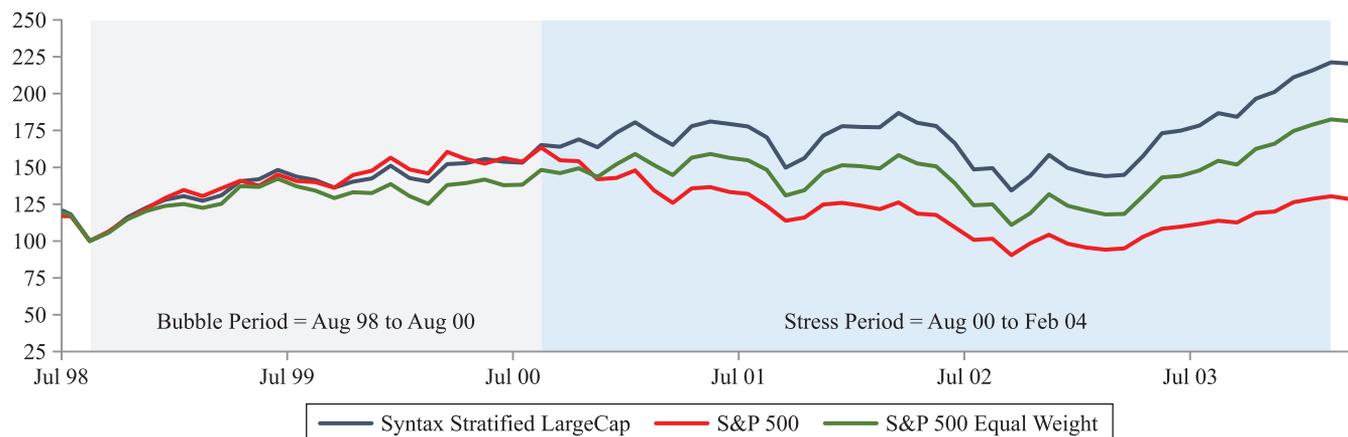
Exhibit 4 details the capital asset pricing model (CAPM) (as described by Sharpe [1964]) performance attributes of these same indexes. Relative to the capitalization-weighted S&P 500, the FIS-based stratified-weight variant exhibits slightly higher beta and a statistically significant positive alpha of 29 bps per month. This alpha is 14 bps higher than the S&P 500 Equal Weight, which does not exhibit statistical significance at the 5% level.

Although the capitalization-weight and equal-weight S&P 400 outperform the S&P 500 in absolute and risk-adjusted returns, neither exhibits a statistically significant alpha, whereas the same constituents indexed on a stratified-weighted basis have a significant alpha of 21 bps. All indexes exhibit betas near unity. This risk-adjusted performance aligns with the theory behind FIS-based stratification. Capitalization-weighted indexes amplify exposure to particular RBRs because a capitalization-weighted methodology allocates more weight to the outperforming companies or industries. This momentum bias has led capitalization-weighted indexes to experience sharp corrections, leaving investors exposed to long periods of underperformance.

The decade spanning 2000 to 2010 provides an excellent example. The capitalization-weighted S&P 500 not only failed to beat 10-year Treasury bonds, but it closed the decade lower than it started, even including dividend reinvestment. During this period, both financials and IT had periods of supernormal growth followed by a collapse that included significant permanent devaluations and bankruptcies. However, in many parts of the market and the economy, it was not a lost decade. Although the S&P 500 returned –8.7% cumulatively over this decade, returns improved to over 29.1% by excluding the IT, telecommunications, and financial GICS sectors. The severity of the capitalization-weighting biases toward IT, telecommunications, and financials was sufficient to completely negate the positive performance of the other

EXHIBIT 5

Before and after the Bursting of the Tech Bubble



Notes: Cumulative returns of the Syntax Stratified LargeCap, S&P 500, and Barclays U.S. Aggregate Investment Grade Corporate Debt Indexes. Index levels are normalized to a starting value of 100 on July 1, 1998.

EXHIBIT 6

Monthly Returns Distribution Statistics

| | Mean Monthly Return | Median Monthly Return | Skew. | Excess Kurt. |
|----------------------------|---------------------------|-----------------------------|-------|-----------------|
| Syntax Stratified LargeCap | 1.15 | 1.50 | -0.63 | -0.34 |
| S&P 500 | 0.84 | 1.28 | -0.66 | -1.62 |
| S&P 500 Equal Weight | 1.03 | 1.31 | -0.50 | -0.39 |
| Syntax Stratified MidCap | 1.29 | 1.68 | -0.52 | -0.85 |
| S&P MidCap 400 | 1.08 | 1.40 | -0.62 | -0.78 |
| S&P MidCap 400 Eq. Wgt. | 1.10 | 1.43 | -0.39 | -0.29 |

Note: Mean, median, skew, and kurtosis of the monthly returns of each index, December 20, 1991, to December 31, 2016.

sectors. This is a prime example of the need for population stratification of RBR in passive index management.

Over this same decade, the Syntax Stratified LargeCap Index more than doubled in value, returning 102.9%, rising to 156.9% after excluding those same sectors. Exhibit 5 shows the performance of the Syntax Stratified LargeCap Index against the S&P 500 Index during this bubble's growth and crash.

Studying the distribution of monthly returns, the Syntax Stratified LargeCap Index also exhibits more positive skew and higher excess kurtosis than the other weighting strategies applied to the same constituents. In the MidCap 400 universe, equal-weight exhibits a less negative skew than both stratified weight and

capitalization weight but, as mentioned earlier, has lower returns than and risk comparable to the stratified-weight index (Exhibit 6).

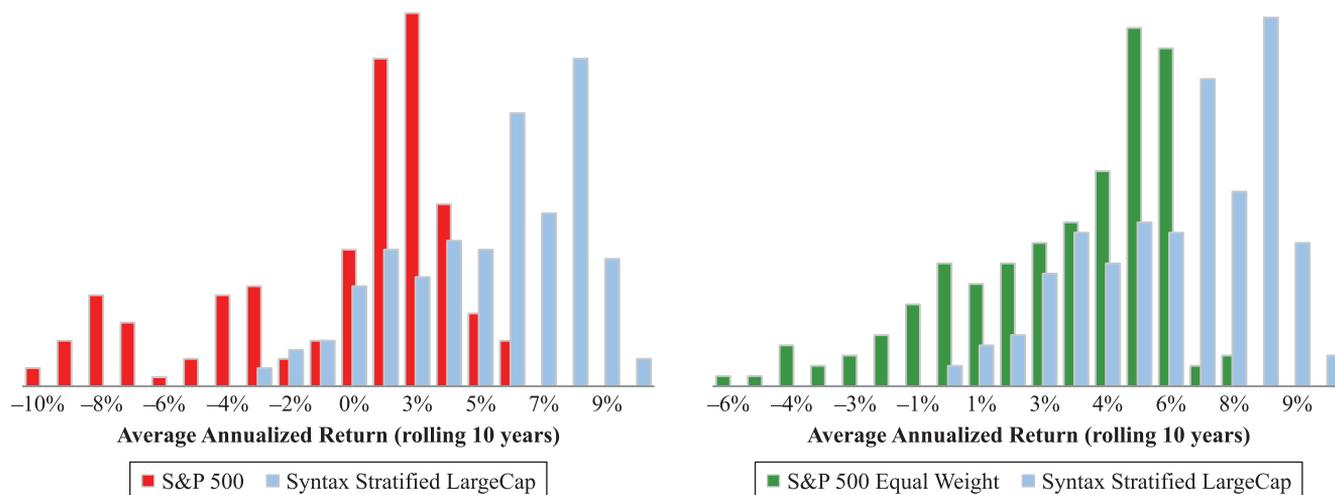
Exhibit 7 shows histograms of the distribution of annualized 10-year rolling monthly excess returns relative to U.S. Treasury bills for capitalization-weighted and equal-weighted indexes relative to the stratified indexes for the S&P 500 universe. Taken together with Exhibit 6, these data indicate that FIS-based stratified weighting yields a superior return profile, outperforming capitalization weighting by 4.9% and equal weighting by 2.1% per year in the average 10-year holding period. The left tail of the stratified indexes is reduced, and the mean of the distribution is significantly higher relative to both capitalization-weighted and equal-weighted alternatives. A similar pattern is seen in the distribution of returns in the MidCap 400 universe (Exhibit A1).

This performance is also consistent with theory: If capitalization-weighted indexes are biased toward the performance of particular types of companies and shocks are randomly distributed across different RBRs, then the effect of a negative RBR shock will eventually hit the larger market cap companies in the index, negatively affecting a significant proportion of the index weight. Stratified-weight indexes are designed to correct for such biases, thereby reducing the impact of the RBR shock and diminishing the size of the left tail.

In addition to reduced left tail event occurrence, stratified indexes also do not decline as much

EXHIBIT 7

Histograms of Excess Returns (vs. 10-year Treasuries) for Different Weighting Methodologies



as cap-weighted indexes during weak market periods. Exhibit 8 shows the performance of the S&P 500 capitalization- and equal-weighted index versus the Syntax Stratified LargeCap for rolling 1-year and 10-year periods. The relative performance of the stratified index during bull markets (defined as S&P 500 annualized rolling returns $> 10\%$), bear markets ($S\&P\ 500 < 0\%$), and stable markets ($0\% < S\&P\ 500 < 10\%$) are shown in different colors. Points above the 45° line denote periods when stratified indexes outperform, and points below the line denote periods of underperformance. On a one-year rolling basis, the Syntax Stratified LargeCap Index outperforms 83% of the time during bear markets, and although the relative performance is not as strong during bull markets, the stratified index outperforms 58% of the time, suggesting that the upside is not sacrificed in lieu of downside protection (see Exhibit A2 for additional rolling periods).

Remarkably, over the lowest returning 10-year period of absolute total returns for the Syntax Stratified LargeCap Index, March 1999 to February 2009, the stratified index cumulatively returned 39%. In that same decade, the S&P 500 and S&P 500 Equal Weight had cumulative returns of -29% and 4% , respectively.

Moreover, although equity investments should exhibit more risk than debt, well-diversified equity indexes should not expect to experience long periods of underperforming debt. Yet, with capitalization-weighted indexes, this does occur. Exhibit 9 shows that, following a month when the equity index underperforms

U.S. Treasuries, the stratified-weight S&P 500 takes an average of eight months to generate a cumulative return above debt, and the capitalization-weighted variant takes almost three times as long.

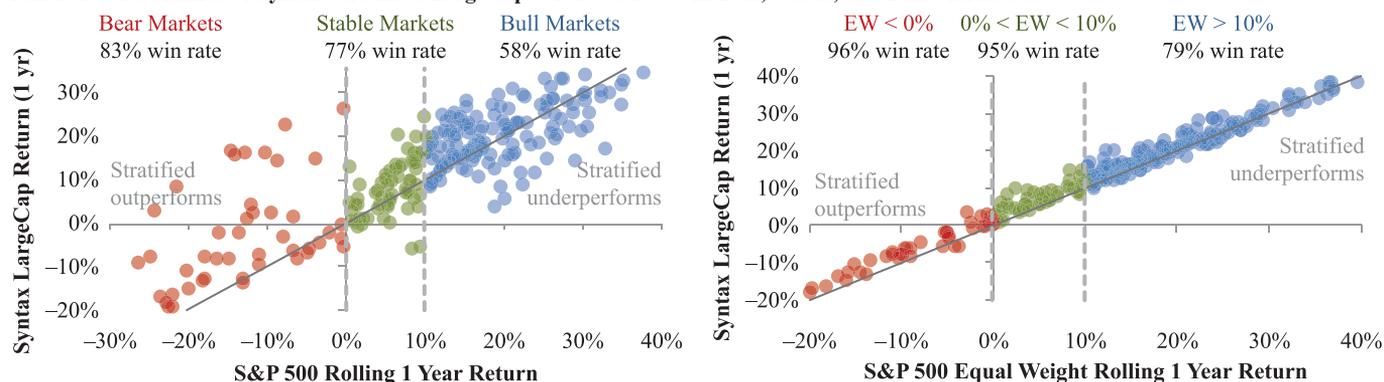
The longest such period experienced by the Syntax Stratified LargeCap Index was just over six years, whereas an investment made in the capitalization-weight S&P 500 at the start of 2000 is still underwater relative to U.S. Treasuries 17 years later and counting (as of December 31, 2016). In the MidCap 400 universe, the average time underwater is a less severe problem, but stratification exhibits a large advantage over both capitalization- and equal-weight strategies in terms of the longest amount of time spent underperforming debt. By controlling for RBRs, stratified-weight indexes achieve a more consistent equity risk premium, better fitting theoretical expectations that equity indexes should outperform debt over the long term.

One reason why capitalization-weighted sector indexes have significant RBR exposures is that they often allocate as much as half of their weight to the 10 largest constituents. Exhibit 10 compares the aggregate weight of the 10 largest constituents in each sector by weighting methodology. Note that stratification can correct for concentrations in particular RBRs even in smaller, more homogeneous populations. The performance of each sector is summarized in Exhibit 11. In addition to equally weighting stratified sectors to form the stratified composite index, these

EXHIBIT 8

Performance of Syntax Stratified LargeCap Index

Panel A: Performance of Syntax Stratified LargeCap versus S&P 500 in Bear, Stable, and Bull Markets



Panel B: Performance of Syntax Stratified LargeCap versus S&P 500 Equal Weight Index

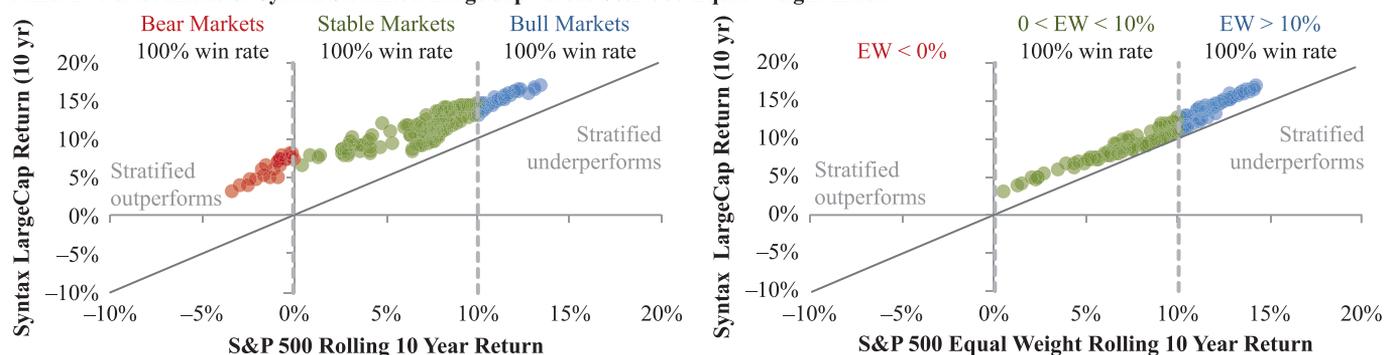


EXHIBIT 9

Recovery Durations

| | Average Time Underwater | Longest Time Underwater |
|----------------------------|-------------------------|-------------------------|
| Syntax Stratified LargeCap | 8 | 74 |
| S&P 500 | 22 | 205* |
| S&P 500 Equal Weight | 9 | 77 |
| Syntax Stratified MidCap | 7 | 45 |
| S&P 400 | 10 | 76 |
| S&P 400 Equal Weight | 8 | 72 |

Note: Average time underwater indicates the number of months the index underperforms the cumulative performance of the Citigroup 10-year Treasury Benchmark.

*Active streak.

indexes may have value in a wide range of strategies because they provide diversified exposure and superior performance versus comparative cap-weighted sector indexes (Exhibit 12).

EXHIBIT 10

Total Weight of Largest 10 Stocks

| | Strat.-Weight | Cap-Weight | Equal-Weight |
|-------------|---------------|------------|--------------|
| IT | 31.5 | 75.1 | 13.0 |
| Food | 30.8 | 65.9 | 16.4 |
| Information | 18.9 | 55.8 | 7.7 |
| Financials | 19.5 | 50.5 | 6.5 |
| Consumer | 21.0 | 49.5 | 6.1 |
| Healthcare | 24.6 | 48.9 | 10.5 |
| Energy | 29.2 | 48.7 | 9.3 |
| Industrials | 11.6 | 35.4 | 5.6 |

CONCLUSION

This article discusses a new risk category called RBR. Unlike systematic risk factors, such as market, sector, or style, RBR is associated with the tail risk that a shock will affect the business factors common to a group

EXHIBIT 11

Performance of Different Weighting Methodologies for Sector Indexes

| | Ann. Return (%) | Excess Return (%) | t-Stat | Vol. | Sharpe Ratio | Down Vol. | Sortino Ratio | Track. Error | Inf. Ratio |
|-------------------------------|-----------------------|-------------------------|--------|-------|-----------------|--------------|------------------|-----------------|---------------|
| Syntax Stratified Financials | 12.78 | 3.50 | 9.62 | 19.72 | 0.51 | 12.26 | 0.81 | 6.31 | 0.55 |
| Cap-Weight Financials | 9.28 | – | – | 20.83 | 0.31 | 13.45 | 0.48 | – | – |
| Equal-Weight Financials | 12.89 | 3.61 | 11.51 | 20.14 | 0.50 | 12.63 | 0.80 | 5.43 | 0.66 |
| Syntax Stratified Energy | 12.14 | 2.58 | 7.63 | 18.83 | 0.50 | 10.87 | 0.86 | 5.86 | 0.44 |
| Cap-Weight Energy | 9.57 | – | – | 16.00 | 0.42 | 9.51 | 0.71 | – | – |
| Equal-Weight Energy | 11.13 | 1.56 | 5.00 | 17.26 | 0.48 | 10.07 | 0.83 | 5.43 | 0.29 |
| Syntax Stratified Industrials | 12.30 | 2.87 | 7.55 | 19.06 | 0.50 | 11.07 | 0.86 | 6.59 | 0.43 |
| Cap-Weight Industrials | 9.44 | – | – | 17.27 | 0.38 | 10.25 | 0.65 | – | – |
| Equal-Weight Industrials | 11.19 | 1.75 | 4.59 | 19.26 | 0.44 | 11.23 | 0.75 | 6.63 | 0.26 |
| Syntax Stratified IT | 16.31 | 4.02 | 6.36 | 29.99 | 0.45 | 17.58 | 0.77 | 10.97 | 0.37 |
| Cap-Weight IT | 12.29 | – | – | 26.25 | 0.36 | 15.79 | 0.60 | – | – |
| Equal-Weight IT | 14.75 | 2.46 | 3.88 | 30.23 | 0.40 | 17.98 | 0.66 | 10.99 | 0.22 |
| Syntax Stratified Information | 12.35 | 2.96 | 6.52 | 17.93 | 0.53 | 10.58 | 0.90 | 7.86 | 0.38 |
| Cap-Weight Information | 9.39 | – | – | 16.53 | 0.40 | 9.69 | 0.68 | – | – |
| Equal-Weight Information | 11.82 | 2.42 | 5.76 | 16.97 | 0.53 | 9.99 | 0.90 | 7.30 | 0.33 |
| Syntax Stratified Consumer | 11.69 | 1.73 | 4.90 | 18.31 | 0.49 | 10.79 | 0.83 | 6.13 | 0.28 |
| Cap-Weight Consumer | 9.96 | – | – | 15.53 | 0.46 | 9.21 | 0.78 | – | – |
| Equal-Weight Consumer | 11.09 | 1.13 | 2.61 | 19.63 | 0.42 | 11.45 | 0.72 | 7.52 | 0.15 |
| Syntax Stratified Food | 12.83 | 2.07 | 5.37 | 12.24 | 0.82 | 7.27 | 1.38 | 6.67 | 0.31 |
| Cap-Weight Food | 10.77 | – | – | 12.33 | 0.65 | 7.70 | 1.04 | – | – |
| Equal-Weight Food | 12.58 | 1.81 | 4.49 | 12.48 | 0.78 | 7.42 | 1.32 | 6.99 | 0.26 |
| Syntax Stratified Healthcare | 14.80 | 4.49 | 9.01 | 14.59 | 0.82 | 8.52 | 1.41 | 8.64 | 0.52 |
| Cap-Weight Healthcare | 10.32 | – | – | 14.33 | 0.52 | 8.58 | 0.88 | – | – |
| Equal-Weight Healthcare | 14.26 | 3.95 | 7.87 | 14.91 | 0.77 | 8.91 | 1.29 | 8.70 | 0.45 |

Notes: Annualized return is the geometric average of monthly returns. Excess return is the difference in the annualized return of each index against its capitalization-weighted analog; t-statistics show the statistical significance of the excess return. Volatility is the annualized standard deviation of monthly returns. Downside volatility is the annualized standard deviation of returns less than 0%. Sharpe and Sortino ratios show the excess return of each index relative to the risk-free rate, as measured by the Barclays U.S. Treasury Bills Index, divided by the volatility or downside volatility of the index, respectively. Tracking error is the annualized standard deviation of excess returns against the capitalization-weighted analog, and the information ratio shows excess return divided by tracking error. All calculations use monthly returns from December 20, 1991, to December 31, 2016.

of companies (e.g., a supply chain or customer shock) and as such will significantly affect their share prices.

This article also introduces an FIS, which identifies RBR, and FIS-based stratification, which hierarchically distributes constituent weights to groups of companies that share RBRs. The article shows how these tools can be used to effectively diversify index exposure to RBR. RBR can significantly affect a portfolio's performance when uncontrolled because unintentional exposure to supply and demand shocks can propagate through a large proportion of the portfolio's holdings. Diversifying exposure to RBR dampens the effects of related-business shocks.

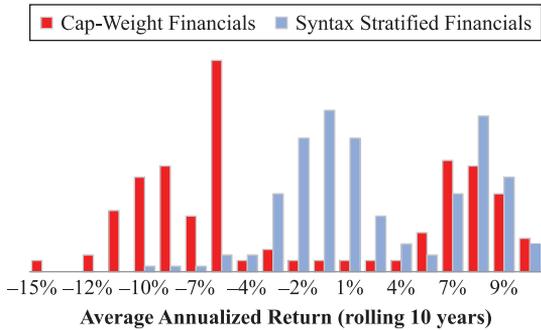
The empirical evidence in this article suggests that 1) there is a real risk associated with the inadvertent overweighting of RBRs that regularly occurs in both capitalization-weighted and equal-weighted indexes, and 2) this risk is diversifiable using a new weighting methodology called FIS-based stratification. The performance benefit of this new stratified methodology versus capitalization-weighting and equal-weighting methodologies is shown over 25 years in 11 constituent groups, including the S&P 500, the S&P 400, and sectors.

The Syntax Stratified LargeCap Index exhibited higher returns (13.38% annualized) than its cap-weighted (9.50%) and equal-weighted counterparts (11.64%).

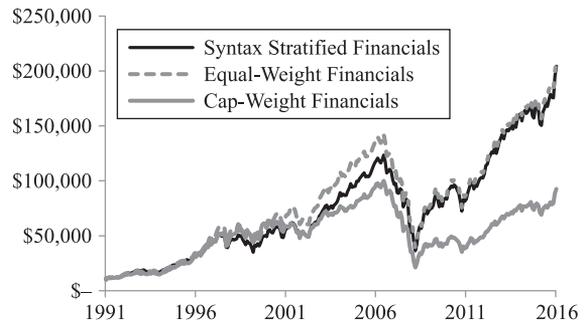
EXHIBIT 12

Sector Returns Comparison

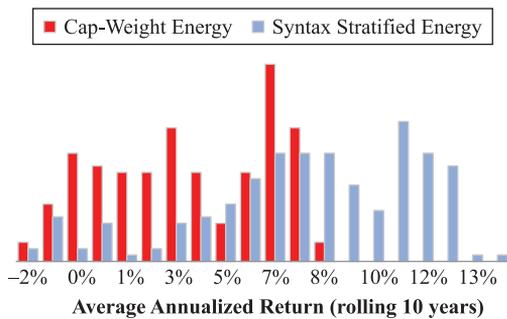
Financials Returns Distributions



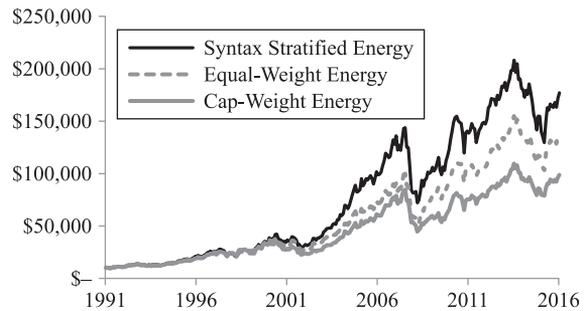
Financials Indexes



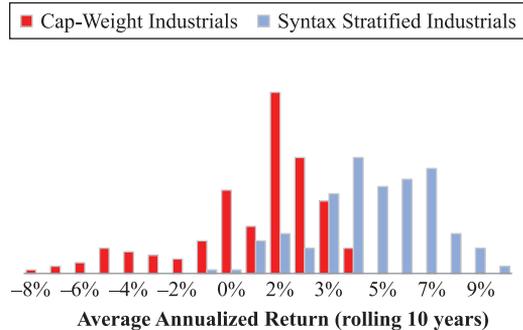
Energy Returns Distributions



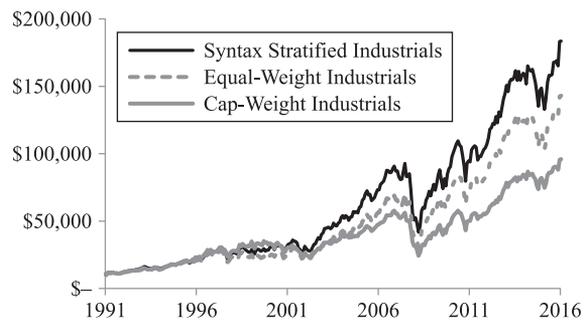
Energy Indexes



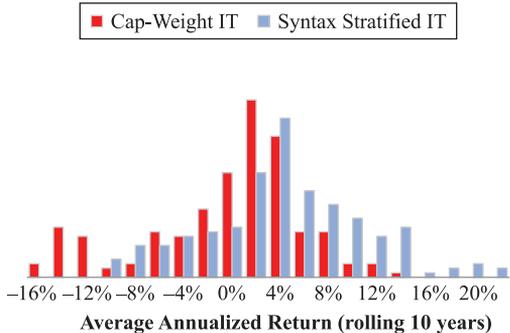
Industrials Returns Distributions



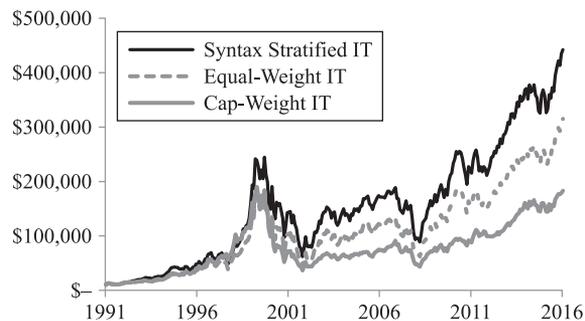
Industrials Indexes



IT Returns Distributions



IT Indexes

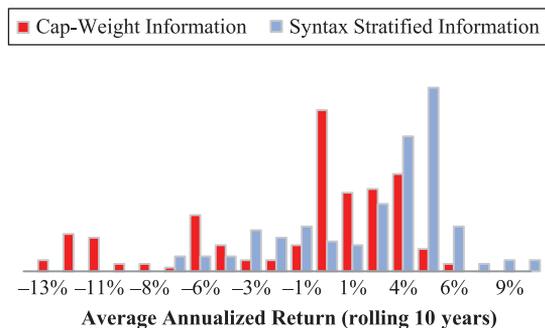


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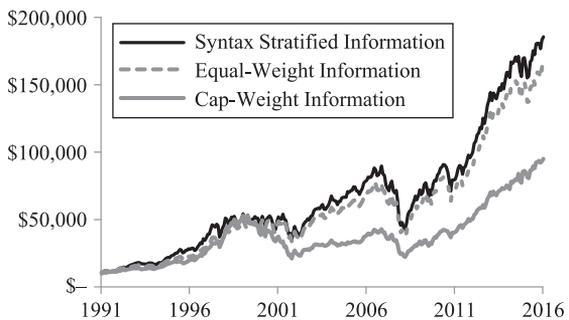
EXHIBIT 12 (continued)

Sector Returns Comparison

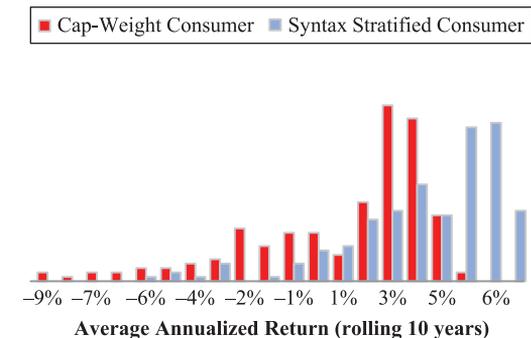
Information Returns Distributions



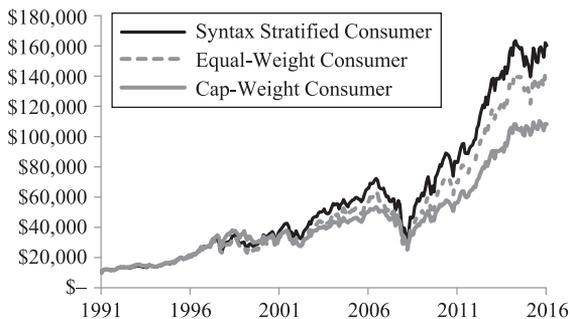
Information Indexes



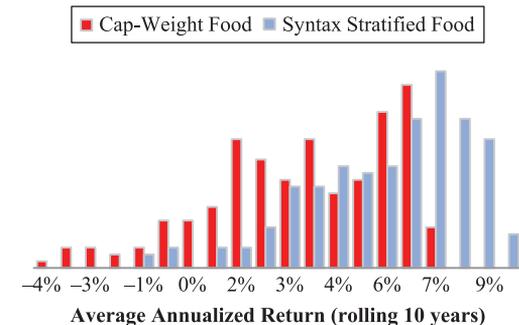
Consumer Returns Distributions



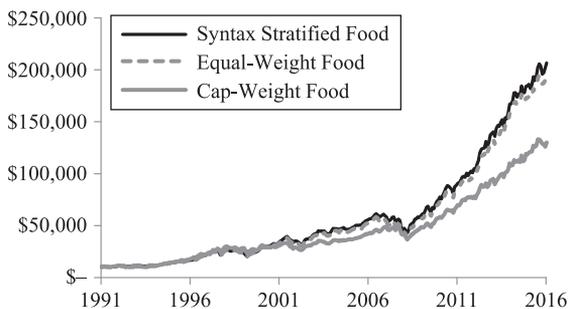
Consumer Indexes



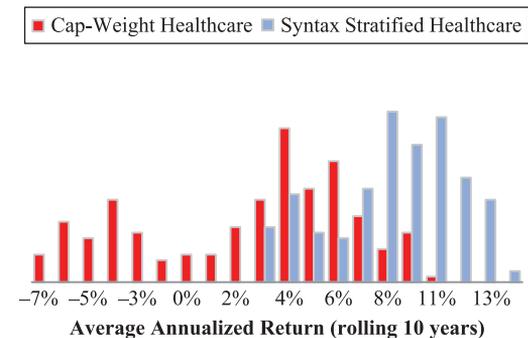
Food Returns Distributions



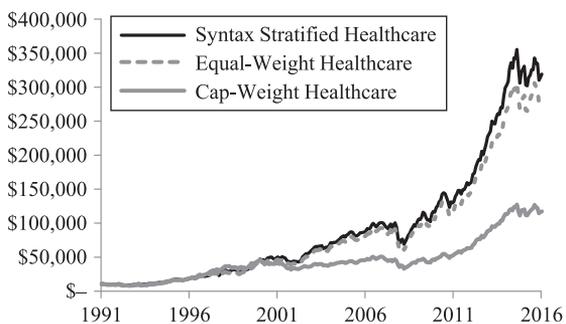
Food Indexes



Healthcare Returns Distributions



Healthcare Indexes



This trend is seen in each of the 11 universes. Furthermore, when equities underperform debt after a broad equity market shock, the stratified-weighted portfolio recovers faster (on average) than both its cap- and equal-weighted variants. This suggests that FIS-based stratified indexes better capture the broad equity risk premium than other methodologies.

The performance comparisons between capitalization-weighted, equal-weighted, and stratified-weighted methodologies for a wide range of universes suggests that the results are robust and that the outperformance of stratified indexes represents a class difference over cap- or equal-weighted methodologies. This is an important argument for using capitalization-weighted, equal-weighted, and stratified-weighted methodologies together as a suite of performance measures of the underlying market at any given point in time. The biases that exist in capitalization-weighted indexes may be desirable to investors because they offer higher exposure to momentum and large cap factors than the other weighting methodologies discussed in this article. However, as shown, these biases come at the cost of underperformance following periods when RBR shocks are prevalent.

Additional work is needed to validate the notion of class differences in portfolio performance associated with different weighting methodologies. The evidence of a class difference between a capitalization-weighted and stratified-weighted index is an important implication of this article, and we look to extend this research to international universes (e.g., FIS-based stratified MSCI EAFE Index) and other asset classes (e.g., FIS-based stratified debt index) in subsequent research.

A P P E N D I X

U.S. CORE UNIVERSE: BOTTOM-LEVEL RBR GROUPS

This appendix presents a complete list of bottom-level RBR groups used to determine the rebalance weights of the Syntax Stratified Core Index as of December 31, 2016, organized by top-level RBR group.

Financials

Consumer Mortgage Banking, Diversified Consumer Banking, Credit and Charge Cards, Commercial Mortgage

Banking, Commercial Banking, Diversified Commercial Banking, Regional Capital Markets Banking, Global Capital Markets Banking, Security Dealers, Life Insurance, Supplemental Insurance, Consumer P&C Insurance, Diversified Consumer Insurance, Commercial Insurance, Reinsurance, Insurance Conglomerates, Residential REITs, Office REITs, Retail and Industrial REITs, Hotels, Specialty Real Estate Operators, Home Developers.

Energy

Drilling Services, Energy Facilities Engineering, Onshore Equipment, Offshore Equipment, Gas Extraction, Oil Extraction, Refining and Retail, Integrated Oil and Gas, Midstream Gas, Gas Distributors, Electric Deregulated Utilities, Electric Diversified Utilities, Electric Regulated Utilities.

Industrials

Gases, Specialty Chemicals, Plastics and Coatings, Agricultural Chemicals, Diversified Chemicals, Industrial Metals, Precious Metals, Lumber, Construction Aggregates, Packaging, Structural Components, Fluid Processing Components, Mechanical Power Components, Electrical and Optical Components, Information Systems for Defense, Construction and Mining Equipment, Manufacturing Equipment, Agriculture Equipment, Testing and Monitoring Equipment Commercial Transport and Aerospace Equipment, Diversified Transportation and Aerospace Equipment, Defense Equipment, Industrial Conglomerates, Logistics and Support Services, Direct Delivery, Railroads and Shipping, Trucking, Electronics Distribution, Diversified Equipment Wholesale, Equipment Leasing, Waste and Environmental Services, Security and Cleaning Services, and General Contractors.

Information Tools

Semiconductors, Communication Processors, Central Processors, Storage Processors, Semiconductor Services and Equipment, Enterprise Software, Operating Systems and Middleware, Design and Engineering Software, Telecommunication Switches and Routers, Commercial Network Hardware, Servers and Storage, Transaction Equipment, End User Hardware.

Information

Staffing Services, Marketing Services, Advisory Services, IT Services, HR and Payroll Solutions, Specialty Payables Processing, Credit Card Networks, Specialty Receivables Processing, Financial Exchanges, Transactions

EXHIBIT A1

Stratified LargeCap vs. EW and S&P 500 in Bull, Stable, and Bear Markets

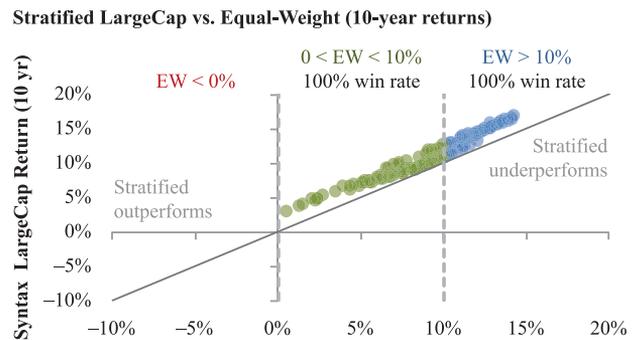
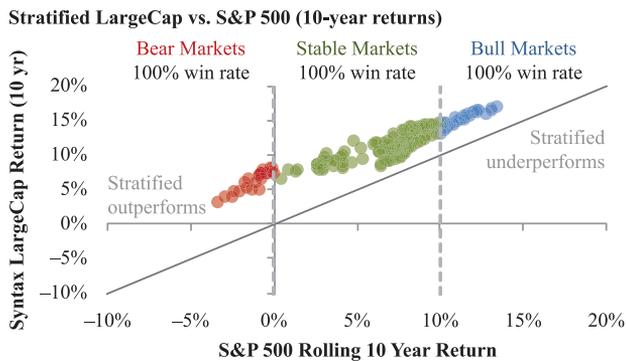
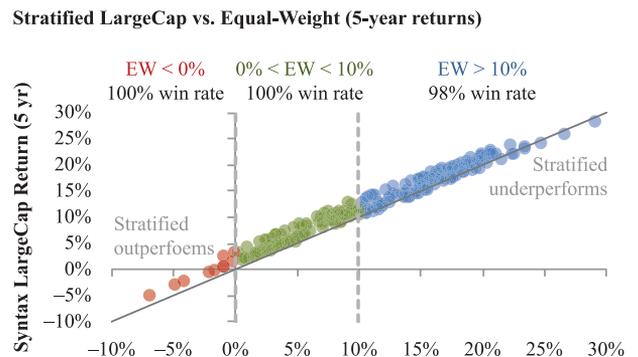
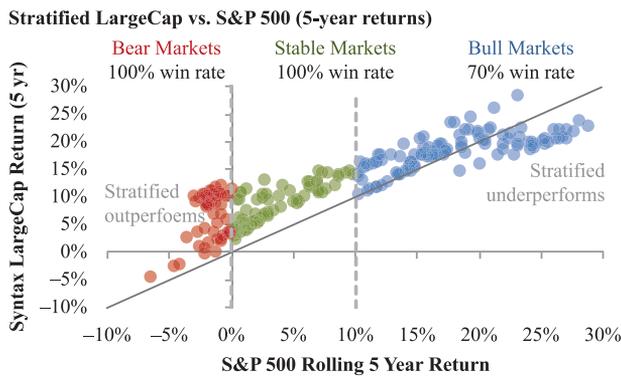
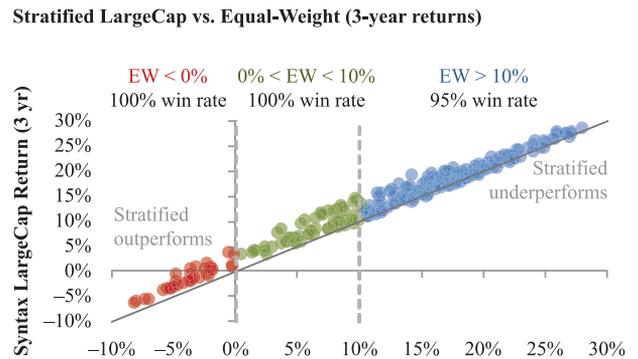
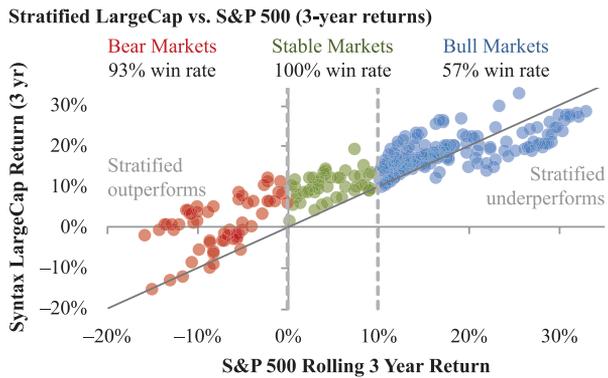
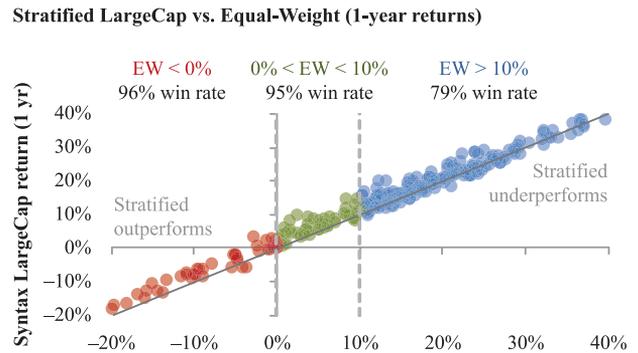
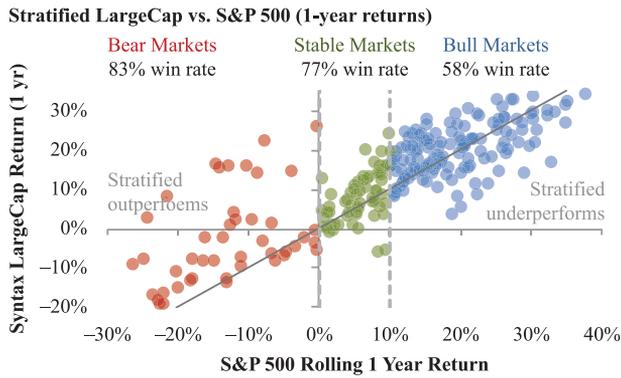
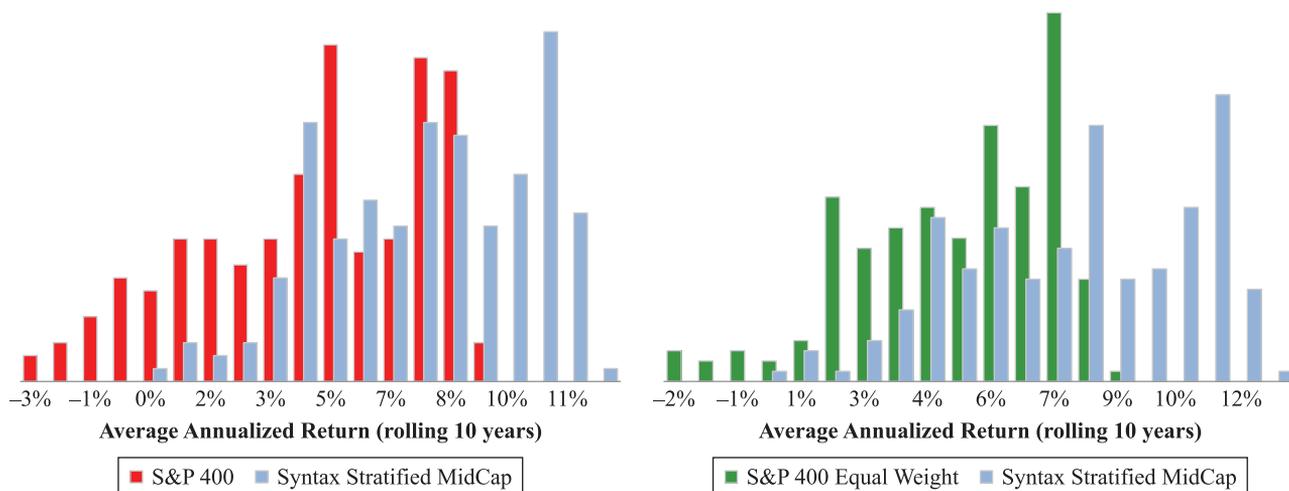


EXHIBIT A 2

Histograms of Excess Returns (vs. 10-year Treasuries) for MidCap Methodologies



Brokers, Financial Databases, Asset Management, Asset Servicing, Consumer Knowledge Products, Consumer Knowledge Services, Movies and Games, Media Networks, Diversified Media, Landline Networks, Wireless Networks, Connecting Networks, Search Networks, Specialty Retail Networks, Diversified Retail Networks.

Consumer Products and Services

Personal Products, Household Products, Integrated Branded Apparel, Branded Apparel, Accessories and Footwear, Apparel Retailers, Home Fixtures, Furniture, Tableware, Power Tools, Toys, Electronics and Office Products Retail, Home Improvement Retail, Specialty Home Product Retail, Diversified Consumer Retail, Automobile Components, Automobiles, Automobile Services, Airlines.

Food

Agriculture, Meat and Dairy, Food Additives, Processed Foods, Snacks, Beverages, Alcohol, Tobacco, Food Wholesalers, Supermarkets, Hypermarkets, Limited Service Restaurants, Full Service Restaurants.

Healthcare

Small Portfolio Biologics, Large Portfolio Biologics, Small Portfolio Branded Pharmaceuticals, Large Portfolio Branded Pharmaceuticals, Generic Pharmaceuticals, Implantable Medical Devices, Non-Implantable Medical Devices,

Diversified Drugs and Devices, Research Services and Equipment, Diagnostic Equipment, Operation Equipment, Healthcare Equipment Distribution, Pharmaceutical Distribution, Medical Facility Rental, Acute Care Facilities, Outpatient Facilities, Health Insurance, Drugstores.

REFERENCES

- Addelman, S. "Variability of Treatments and Experimental Units in the Design and Analysis of Experiments." *Journal of the American Statistical Association*, Vol. 65, No. 331 (1970), pp. 1095-1108.
- David, H.A. "The Beginnings of Randomization Tests." *The American Statistician*, Vol. 62, No. 1 (2008), pp. 70-72.
- Joly, Y., H. Burton, B.M. Knoppers, I.N. Feze, T. Dent, N. Pashayan, S. Chowdhury, W. Foulkes, A. Hall, P. Hamet, N. Kirwan, A. Macdonald, J. Simard, and I.V. Hoyweghen. "Life Insurance: Genomic Stratification and Risk Classification." *European Journal of Human Genetics*, Vol. 22, No. 5 (2014), pp. 575-579.
- Kernan, W.N., C. Viscoli, R. Makuch, L. Brass, R. Horwitz. "Stratified Randomization for Clinical Trials." *Journal of Clinical Epidemiology*, Vol. 52, No. 1 (1999), pp. 19-26.
- Neyman, J. "On the Two Different Aspects of the Representative Method: The Method of Stratified Sampling and the Method of Purposive Selection." *Journal of the Royal Statistical Society*, Vol. 97, No. 4 (1934), pp. 558-625.

Porrini, D. "Risk Classification in Natural Catastrophe Insurance: The Case of Italy." *International Journal of Financial Research*, Vol. 7, No. 1 (2016), pp. 39-49.

Sharpe, W. "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk." *The Journal of Finance*, Vol. 19, No. 3 (1964), pp. 425-442.

Sortino, F.A., and L.N. Price. "Performance Measurement in a Downside Risk Framework." *The Journal of Investing*, Vol. 3, No. 3 (1994), pp. 59-64.

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