Literature Review

THE CURRENT STATE OF QUANTITATIVE EQUITY INVESTING

Ying L. Becker and Marc R. Reinganum

CFA Institute Research Foundation

Research
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Review

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The Current State of Quantitative Equity Investing

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Introduction: Risk and Return

The current approaches and products of quantitative equity investing stand on the shoulders of major theoretical and empirical contributions in financial economics. At the root of disciplined, modern investment processes are two intuitive concepts: risk and return. The notion of total return is obvious—price appreciation plus any dividend payments. Risk is not so straightforward. Indeed, in *Risk, Uncertainty, and Profit*, Knight (1921) distinguished between risk and uncertainty. In essence, uncertainty involves environments in which investors cannot articulate potential outcomes or the likelihood of those outcomes. In contrast, risk is much more precise, like a roulette wheel. The possible outcomes are well specified and the likelihood of each outcome is known, but in advance, an investor does not know which outcome will be realized. Quantitative methods rely on this view of risk, although in the literature, risk and uncertainty are often used interchangeably. In the early 20th century, however, links between risk and asset pricing were not established. Economic analysis dealt with the concept of expected utility. For example, in "The Utility Analysis of Choices Involving Risk," Friedman and Savage (1948) offered an explanation of why an individual may both gamble and buy insurance based on the shape of her utility curve.

Models explicitly linking risk and return began to blossom in the 1950s. Markowitz (1952) famously wrote about portfolio selection in a mean–variance framework. He defined an efficient portfolio as one that minimizes variance for a given level of expected return and maximizes expected return for a given level of variance. Investors should consider only portfolios along the efficient boundary, although the precise portfolio of choice depended on an investor's utility preferences. Markowitz established relationships between risk and return at a portfolio level but not at the level of individual assets. In a somewhat different context, Tobin (1958) used similar thinking to analyze liquidity preferences. Another major theoretical development occurred shortly afterward when Arrow and Debreu (1954) proved the existence of a unique general equilibrium. Their work allowed for state pricing, in which case a security would pay one unit in that state and zero otherwise, a paradigm that led to much theoretical work in financial economics. Viewed from the vantage point of a company, Modigliani and Miller (1958) modeled a partial equilibrium world in which the cost of capital of a company with risky projects was independent of capital structure, although the equity component of return may contain an additional premium related to financial risk arising from leverage. In more aggregate macro models, risk and return were being explicitly linked. The importance of these contributions can be gleaned by looking at the list of Nobel Prize in Economic Sciences winners from this period.

Modern Portfolio Theory and Asset Pricing

After Markowitz (1952) developed portfolio theory, it took more than a decade for his insights to be used in creating asset pricing models at the level of individual risky securities. Sharpe (1964), Lintner (1965), Mossin (1966), and Treynor (1962) developed what came to be called the "capital asset pricing model" (CAPM). This model had alluring simplicity and powerful insights. For individual securities, it demonstrated that there is a cross-sectional relationship between expected returns and security risk as measured by beta, the covariance between the security return and the market return scaled by the variance of the market return. More formally,

$$E\left(R_i\right) = R_f + \beta_i\left[E\left(R_M\right) - R_f\right], \tag{1}$$

where $E(R_i)$ is the expected return of risky asset i; $E(R_M)$ is the return of the market portfolio, the cap-weighted portfolio of all risky assets; R_f is the risk-free rate of interest; β_i is the relative risk of security i in the market portfolio (beta), which is equal to $[\mathrm{cov}(R_i, R_M)/\mathrm{var}(R_M)]$; and $E(R_M) - R_f$ is often called the "market risk premium."

Although the modeling required much heavy lifting, the end result linked risk and return in a straightforward way: The expected return of a risky asset equals the risk-free rate of interest plus a risk premium, where the risk premium is proportional to the asset's beta. In this framework, there may be many risky events that could affect the realized returns of securities, but only beta risk is systematically priced. Stated differently, the cross section of security expected returns should depend on only betas and nothing else. No risks except for beta, a covariance measure of risk, are meaningful in the pricing of risky securities because other risks can be "diversified away."

The market portfolio also plays a pivotal role in the CAPM. Indeed, according to the CAPM theory, the risky portfolio each and every investor holds is the market portfolio. The market portfolio is efficient in terms of how Markowitz described efficiency. Furthermore, it can be shown to be the portfolio that maximizes the Sharpe ratio, where

$$\text{Sharpe ratio} = \frac{\mathrm{E}\left(R_p\right) - R_f}{\sigma\left(R_p\right)}. \tag{2}$$

That is, the Sharpe ratio is a portfolio's expected return in excess of the risk-free rate, scaled by the standard deviation of the portfolio return. The market portfolio in the CAPM is the unique portfolio that attains the maximum value of the Sharpe ratio and offers investors the best possible risk–return trade-off. It is the only portfolio of risky assets that all investors need and want.

The theoretical advances of the 1960s in asset pricing were accompanied by similar advances in computer technology and "big data." For example, the IBM System/360 mainframe computer was introduced in 1964 and began delivery in 1965. Concurrently, the first big dataset in finance was created at the University of Chicago. As Fisher and Lorie (1964) explained, the Center for Research in Security Prices (CRSP) was created to transcribe into computer-readable form monthly data on individual NYSE companies dating back to 1926. These data included security prices, capital changes, and dividends—all the data required to compute total return. With large-scale data, computing power, and a theoretical model in hand, academic research empirically tackled the question of whether the CAPM is a good quantitative approximation to the observed behavior of stock prices. This early period of testing the CAPM perhaps culminated with the seminal study of Fama and MacBeth (1973) that both set an enduring standard for methods to test cross-sectional relationships in equity markets with time-series data and concluded that the null hypothesis of the CAPM could not be rejected.

Although most empirical interest in the CAPM focused on the cross-sectional relationship described in Equation 1, the model was in fact tested with time-series data. Apart from potential econometric estimation complications, understanding the time-series properties of security returns became important too. Earlier statistical work by Working (1934), Kendall (1953), and Roberts (1959) suggested that security and commodity prices behaved like cumulative series of random numbers, a concept popularized by Malkiel (1973) in his book *A Random Walk down Wall Street*. The serial independence of price changes over time led to another key quantitative insight: the efficient market hypothesis (EMH). According to the EMH, price changes over time are uncorrelated because current prices "fully" reflect all relevant information. Fama (1970) clearly articulated this hypothesis and refined the notion of "fully" by classifying tests as weak form, semi-strong form, or strong form based on the type of information used to test the hypothesis.

The necessary introduction of time-series data into cross-sectional tests of relationships in asset pricing models leads to an unavoidable ambiguity in interpreting and using the empirical results. The reason is that empirical research actually tests a joint hypothesis—that the cross-sectional model is correct and that markets are informationally efficient. For example, if empirical tests reject the cross-sectional relationship between expected returns and betas in Equation 1, is it because the CAPM is misspecified? Or is it because markets are informationally inefficient?[1] Similar questions can be and are asked of even the most contemporary research. Trying to discern between the two is often a matter of examining the reaction of stock prices to certain events, such as earnings releases (for an early study in this vein, see Ball and Brown 1968).

Anomalies: The Precursors to Factors

By the late 1970s and early 1980s, cracks in the CAPM and the efficient market hypothesis were beginning to surface in academic research. Basu (1977) reported that portfolios of low-P/E stocks earned on average about 7% more annually than portfolios of high-P/E stocks even after adjusting for estimates of CAPM betas, at least during the 14-year period from 1957 to 1971. Basu interpreted his results as a rejection of the semi-strong form of the efficient market hypothesis, insofar as the information contained in P/Es did not appear to be "fully reflected" in prices. Interestingly, Basu chose not to attribute his results to any shortcoming in the CAPM, a reflection perhaps of how deeply ingrained the CAPM had become as perceived truth in the academic community.

[1]Roll (1977) questioned whether tests of asset pricing models were ever empirically possible.

Banz (1981) and Reinganum (1981a) changed the tenor of the discussions regarding the CAPM. Both researchers reported that differences in the average returns of portfolios grouped by company size (as measured by stock market capitalization) could not be explained by differences in estimated betas. In particular, portfolios of small-cap stocks outperformed portfolios of large-cap stocks on a beta risk-adjusted basis—the so-called size effect. Reinganum further reported that P/Es could not explain the size effect, because the size effect was present even after controlling for P/Es. Perhaps the enduring contribution of Banz and Reinganum was that both attributed their research results to a misspecification of the CAPM rather than a market inefficiency. A misspecified CAPM meant that size proxied for some missing risk factor(s) and that the cross-sectional relationship between expected returns and market betas was incomplete; other risk factors seemed to be needed. At the time of publication, Banz's and Reinganum's results were viewed as anomalous, tentative, and not necessarily correct. In retrospect, the course of modern quantitative equity investments had been altered.

Other anomalous evidence began appearing in the literature. For example, Keim (1983) found that the size effect had a strong seasonal component concentrated in the month of January. This result certainly challenged the belief that stock returns were independently and identically distributed and suggested that a simple seasonal dummy variable could help predict stock returns. Latané and Jones (1977) reported that quarterly standardized unexpected earnings (based on reported earnings) were reflected in stock prices only with a lag. Unlike Banz's and Reinganum's results, this result was centered on a specific event—the reporting of quarterly earnings—and eventually dissipated, a pattern more likely to be market inefficiency. In a somewhat similar vein, Givoly and Lakonishok (1979) concluded that revisions in analysts' forecasts of earnings could be used to earn abnormal returns in the two months following the release—a violation of the semi-strong form of the efficient market hypothesis. Rosenberg, Reid, and Lanstein (1985) reported that book-to-price ratios could help investors exploit pricing errors after controlling for several "risk indexes." Although the authors considered this finding a market inefficiency, the book-to-price ratios are not events like earnings releases or revisions in analysts' forecasts. The initial foundations of the CAPM and the efficient market hypothesis were showing cracks that might be exploited by investors.

The Age of Factor Investing

The era of factor investing might be traced back to Ross (1976), who developed a theory of security pricing with multiple factors. Ross's arbitrage pricing theory (APT) was purely theoretical and did not specify how many factors were appropriate, nor did it label what the factors might be.[2] The effective era of equity factor investing, however, might more appropriately be attributed to the empirically based three-factor model explicated by Fama and French (1993). Fama and French essentially combined previous research on the size effect, the value effect, and the overall market factor into one cross-sectional equation. Unlike the CAPM, this model was not explicitly anchored in a theory but did have much empirical evidence to support it. Fama and French suggested that, at least empirically, a three-factor model better fits the cross section of average equity returns than does the CAPM. The three factors are MKT (the difference in return between the cap-weighted market portfolio and the risk-free rate of interest); SML (the difference in returns between a portfolio of small-cap stocks and a portfolio of large-cap stocks); and HML (the difference in returns between a portfolio with high book values of equity relative to market values of equity [BE/ME] and a portfolio with low BE/ME). This paradigm became the baseline standard for much quantitative equity work that followed it.[3]

Following Fama and French (1993), the floodgates for factor investing seemed to open. For example, Jegadeesh and Titman (1993) reported that over 3- to 12-month time horizons, an investor who purchased stocks that had performed well in the past and sold past poor performers would earn significant abnormal returns. Stated differently, over short and intermediate time horizons, stock returns exhibit momentum. More recently, Geczy and Samonov (2016) documented momentum in more than two centuries of price data. Carhart (1997) suggested that momentum should be considered a common factor, and indeed, later studies often spoke of a four-factor model—one with the three Fama–French factors plus momentum. De Bondt and Thaler (1985) reported the opposite of short- to intermediate-term momentum at longer (three- to five-year) investment horizons; specifically, prior stock market losers tend to become subsequent winners relative to prior winners De Bondt and Thaler strongly suggested that the stock market overreacts to unexpected and dramatic news events and that this overreaction can account for a return differential between winners and losers of 25% over three years.

Momentum and reversal are often characterized as expressions of investor sentiment. De Bondt and Thaler (1985) may very well be considered the seminal study in "behavioral finance," because the authors rooted their work in

[2]Connor and Korajczyk (1988) suggested that an asymptotic principal components technique for estimating and testing the APT yields better results than the CAPM does.

[3]Jacobs and Levy (1988) looked at a variety of anomalies within a multiple regression analysis to disentangle the various effects but did not explicitly link their results to asset pricing.

the psychology of investor decision making.[4] Understanding investor sentiment became a key aspect to model empirical asset pricing, regardless of whether sentiment represented behavioral biases.[5] For example, Lakonishok, Shleifer, and Vishny (1994) argued that the value effect arose because these strategies exploited suboptimal choices of the typical investor; in essence, investors overpay for "glamour" stocks, perhaps overestimating their future growth prospects. In subsequent research, this expectational "error" was attributed in part to the finding that value stocks tended to have earnings surprises that were systematically more positive than those of glamour stocks (see La Porta, Lakonishok, Shleifer, and Vishny 1997). But this explanation could not be a complete one, because the return differences between value and glamour stocks persisted much longer than did the magnitude of differences in the earnings surprises.

Apart from the market, size, value, and momentum factors, other credible factors muscled their way into the empirical equity asset pricing world. Amihud and Mendelson (1991) argued that liquidity—as measured by, say, the bid–ask spread—is not only an issue for market microstructure. Rather, they saw illiquidity premiums as a significant influence on expected returns because even seemingly small differences in transaction costs could make a meaningful difference in asset values. Pástor and Stambaugh (2003) reported that expected returns are cross-sectionally related to sensitivities of stock returns to fluctuations in aggregate liquidity; the difference in annual returns between high-sensitivity stocks and low-sensitivity stocks was about 7.5% after controlling for the market, size, value, and momentum factors. Taking a different tack, Sloan (1996) made a convincing case that investors pay too much attention to bottom-line earnings numbers and not enough attention to the quality of those earnings, as reflected in accruals, a noncash component of earnings. Sloan found that accruals and subsequent stock returns were negatively related: High-accrual companies underperformed low-accrual companies over the course of at least a year, and about half of the annual outperformance was concentrated around the four quarterly earnings announcements.

The search for better factors continues in quantitative equity investing. Fama and French (2015) revisited their three-factor pricing model from the early 1990s.[6] In this more recent work, they proposed a five-factor model that includes the market premium (MKT), size (SML), and value (HML), plus

[4]Kahneman and Tversky wrote extensively about potential biases and heuristics used in the psychology of decision making under risk (for example, see Tversky and Kahneman 1974; Kahneman and Tversky 1979, 1984).

[5]Barberis, Schleifer, and Vishny (1998) developed a model that attempted to explain both investor overreaction and investor underreaction.

[6]Grover and Kizer (2016) estimated the cost of these factor exposures in well-known mutual funds and exchange-traded funds.

RMW (the difference in returns between portfolios with robust versus weak operating profitability) and CMA (the difference in returns between portfolios with low [conservative] and high [aggressive] investment, where investment is measured by the change in total assets). In part, Fama and French (2015) was a reaction to new research findings. For example, Novy-Marx (2013) found a gross profitability premium in the cross section of average returns, where gross profitability is simply defined as revenues minus cost of goods sold, all scaled by total assets. Novy-Marx reported that the gross profitability premium is equally strong as the book-to-market premium; further, gross profitability is complementary to value and diversifies the risk of value.[7] In addition, research has documented that substantial increases in capital investments tend to be associated with subsequent negative abnormal returns (see Titman, Wei, and Xie 2004); empire building might be hazardous to shareholder wealth! This general sentiment is echoed in work by Cooper, Gulen, and Schill (2008), who reported an inverse relationship between asset growth and subsequent stock returns. Thus, as a result of research since the early 1990s, the venerable three-factor Fama–French model has now been modulated to a five-factor version.

Perhaps the most puzzling cross-sectional anomaly is risk itself. Intuition and theory certainly suggest that average returns and systematic risk should be positively correlated: Higher systematic risk should be associated with higher average returns, but all other risks should not be priced. Ang, Hodrick, Xing, and Zhang (2006) reported that companies with high idiosyncratic risk relative to the Fama–French (1993) model had abysmally low average returns. This finding survived after the authors controlled for size, book-to-market ratio, leverage, liquidity, volume, turnover, bid–ask spreads, co-skewness, and dispersion in analysts' forecasts. In theory, this risk should not be priced at all. An equally startling result was published by Clarke, de Silva, and Thorley (2006), who found that, on the basis of optimizations from 1968, the minimum-variance portfolios had about three-fourths the risk of the cap-weighted market portfolio but higher average returns. In other words, the low-volatility portfolio had a better Sharpe ratio than the market portfolio had. Li, Sullivan, and Garcia-Feijóo (2016) and Baker (2016) concluded that this empirical regularity is a systematic mispricing of risk.

In CAPM theory, no portfolio has a better Sharpe ratio than the market portfolio. The anticipated link between risk and return seemed to be broken: Low-volatility portfolios were earning higher returns relative to high-volatility portfolios. Baker, Bradley, and Wurgler (2011) analyzed the low-risk

[7]Ball, Gerakos, Linnainmaa, and Nikolaev (2016) found that cash-based operating profitability, which excludes accruals, outperforms gross profitability that includes accruals.

anomaly, where risk is defined as both total volatility and beta. That is, unexpectedly large returns are seen in the data with respect to low-volatility stocks (versus high-volatility ones) and with respect to low-beta stocks (versus high-beta ones). Sometimes the inverted relationship between betas and returns is called "betting against beta" (BAB; see Frazzini and Pedersen 2014). This reversal in the relationship between risk and return is puzzling. Indeed, Baker et al. (2011) believe that this may be the greatest anomaly in finance.[8]

Investor interest in low volatility and betting against beta seems to have increased since the dot-com bubble crash in the early 2000s and the global financial crisis of 2008. Investors seem to be acutely attuned to "downside protection," which low-volatility and low-beta strategies tend to offer, especially in long-only portfolios. Yet the supposedly unusual relationship between risk and return was noted many years earlier. Black, Jensen, and Scholes (1972) reported that the cross-sectional relationship between CAPM betas and average returns was flatter than the theory would predict; contrary to the CAPM, high-beta securities had significantly more-negative returns and low-beta securities had significantly more-positive returns than the theory would predict. Haugen and Heins (1975) found little support for the notion that risk premiums had manifested themselves in realized rates of return over long periods; the authors also reported that portfolios with low-variance stocks had earned greater average returns than portfolios with higher-variance stocks. Reinganum (1981b) reported that estimated betas were not systematically related to average returns across securities and that high-beta securities and portfolios with widely different estimated betas possessed statistically indistinguishable average returns. He cautioned that the CAPM may lack significant empirical content. Even a close look at the evidence in Fama and MacBeth (1973) suggests that the cross-sectional relationship between average returns and security variance may not have been completely extinguished by beta. Whatever the reason, after a nearly 30-year hiatus, low risk seems to be back on the table as a bona fide investment tool and strategy, supported by more empirical work.

If your head is spinning with the proliferation of factors beyond market, size, and value, you are not alone. In his American Finance Association Presidential Address, Cochrane (2011) described the situation as a "zoo of new factors." Indeed, Harvey, Liu, and Zhu (2016) analyzed 313 published papers that studied cross-sectional return patterns. The backlash against the proliferation of potential factors emerged well before their exponential growth in the literature. Lo and MacKinlay (1990) raised the issue of data snooping in tests of asset pricing models. Lo and MacKinlay argued that

[8]Auer and Schuhmacher (2015) confirmed the BAB phenomenon even among the 30 large, liquid stocks in the Dow Jones Industrial Average from 1926 through 2013.

newly discovered relations must be weighed in view of past inferences; the conditions underlying standard statistical tests may be violated. This concern about overfitting and potential solutions to it has only grown over time. Hsu, Kalesnik, and Viswanathan (2015) proposed a three-step heuristic framework to assess factors: (1) Does a factor persist across time and geographies? (2) Does a factor persist with respect to sensible perturbations in its definition and construction? (3) Is a factor validated and vetted numerous times in top-tier journals? More formally, Harvey and Liu (2015) developed a measure called the "haircut Sharpe ratio" that takes into account multiple testing and data mining. Harvey et al. (2016) provided a nice discussion and analysis of the issue of multiple testing and suggested that a *t*-statistic of 3.0 is a good cutoff value for testing factors; they argued that a *t*-statistic of 2.0 is no longer appropriate. Suhonen, Lennkh, and Perez (2017), using a sample of 213 "alternative beta" index funds, found that performance deteriorated substantially after a strategy went live, compared with performance during its backtest period.

In short, there is a potpourri of potential and reasonable risk factors that investors may consider. The frustration arises, perhaps, because there is currently no one right answer as with the CAPM, in which the cap-weighted market portfolio is the optimal and right choice for each and every investor. But the lack of a single right answer may be an insight in itself. Perhaps the answer is that there is no one right choice for each and every investor, and perhaps the future of factor investing lies in illuminating different investor-appropriate paths.

The Prime Factor and Smart Factors

In the beginning, there was one factor and it was the market factor. A cap-weighted return of all risky securities, the market factor was reasonably easy to calculate, and it was buttressed by an elegant theory that asserted no other factor need be worshipped. The final 25 years of the 20th century was a golden era for this factor, in terms of both performance and industry adoption (see Reinganum 2014). Indeed, the market factor anchored quantitative equity in terms of performance attribution, compensation schemes, and terminology. The cap-weighted market portfolio became synonymous with "passive" investing; "active" portfolios were defined as portfolios whose security weights differed from those of cap weights. In many institutions, the view of risk also shifted subtly from the total risk of the market portfolio to tracking error risk—the variability in differential returns between an investor's portfolio and the market portfolio. Such metrics as the information ratio were developed to assess whether deviations from the benchmark return were worth the tracking error risk (for example, see the classic book *Active Portfolio Management* by Grinold and Kahn 2000).

Investor appetite for factor investing seems to have increased so far in the 21st century. Invesco PowerShares Capital Management LLC (2015) reported that factor-based investing is gaining traction in the institutional community and that institutions plan to increase their use of smart-beta exchange-traded funds (ETFs) more than any other category. Morningstar (2014) also reported that factor investing is a fast-growing segment in the marketplace and offered its analysis of what it termed "strategic beta." Hill (2016) argued that these new products are the next evolutionary step in "the triumph of indexing."

In part, the increasing acceptance of factor-based quantitative equity investing may be driven by the relatively low economic returns that the prime factor (the market return) has delivered relative to investor and actuarial expectations. Part of the allure of factor investing is its potential to improve returns at lower cost. In a well-publicized study for the Norwegian Government Pension Fund, Ang, Goetzmann, and Schaefer (2009) recommended that this very large sovereign fund adopt a factor risk premium approach to gain exposures that were otherwise attained by its group of active managers. The report suggested that appropriate factor exposures could be achieved by moving assets out of many actively managed strategies without detriment and with lower costs (for example, see Kidd 2014). In a similar vein, Bender, Briand, Nielsen, and Stefek (2010) suggested that strategy and style risk premiums could be used as the building blocks of a diversified portfolio. Kahn and Lemmon (2015) suggested that asset owners may be disappointed by their aggregate active performance because they may be overpaying by 43% on average for their active risk, given that this part of risk could be obtained through low-cost factor solutions.

The discussion about factors in the previous section was a bit vague in some respects. Any portfolio manager knows that, in the final analysis, implementation of a strategy and its performance are about portfolio weights. The same group of securities can be combined into two portfolios with very different risk and return characteristics by weighting the same securities differently. For example, consider a portfolio formed on the basis of, say, sensitivities to the Fama–French HML factor. What does this exactly mean? One can rank securities from high to low using this metric, but this ranking does not create a portfolio. The portfolio is a set of weights, and so one needs to devise an approach to construct the portfolio weights. Thus, factor investing, whether for one factor or multiple factors, involves portfolio construction, and in the end, portfolio construction ends up with one set of security weights.

With the prime factor—the market—portfolio construction was straightforward: Just cap-weight the securities. We term the other factors "smart factors" to correspond to the current industry practice of referring to "smart beta." The smart factors can be implemented in a variety of weighting schemes. But the smart factors and the strategies based on them all scream out at least one common chorus: "I am not cap-weighted!"

If not cap-weighted, then what? Arnott, Hsu, and Moore (2005) developed indexes that explicitly avoid price and market-cap metrics in the weighting scheme. Instead, the authors used such items as gross revenue, equity book value, and total employment to calculate security weights. Arnott et al. (2005) called these "Fundamental Indexes" and argued that they deliver superior mean–variance performance relative to cap-weighted indexes; that is, they have higher Sharpe ratios.[9] Perold (2007) argued that cap-weighting is not an intrinsic drag on performance and that fundamental indexing is actually a form of value investing. In a similar vein, Chow, Hsu, Kalesnik, and Little (2011) argued that the outperformance (relative to a cap-weighted index) of most alternative equity strategy indexes can be attributed to their value and size factor exposures, a view basically corroborated by Dubil (2015). Van Gelderen and Huij (2014) found that mutual funds that tilted toward low-volatility, value, and small-cap factors outperformed mutual funds that did not implement the factor approach.[10]

Qian (2005) suggested another approach for portfolio construction and coined it "risk parity." Qian noted that market-cap allocations are not equivalent to risk allocations. For example, a stock/bond portfolio weighted 60/40 in terms of capital allocation had a risk allocation of 93/7. Qian suggested allocating weights such that each risky asset has the same risk allocation. He proposed that doing so would lead to better diversification and more portfolio efficiency, a conclusion later buttressed by his colleagues Sorensen and Alonso (2015). Like Arnott et al.'s Fundamental Indexes, Qian's risk parity approach yields weights that differ from market-cap weights. Fisher, Maymin, and Maymin (2015) argued that although risk parity is a fast and frugal heuristic, it tends to outperform both knowledge-intensive mean–variance approaches and knowledge-independent equal-weighted approaches.[11]

[9]In a couple of clever articles, Arnott and coauthors suggested that almost any weighting scheme of securities that differs from weighting by current market cap will outperform cap-weighted benchmarks (see Arnott, Hsu, Kalesnik, and Tindall 2013; Arnott, Beck, and Kalesnik 2015).

[10]Simon, Omar, Lazam, and Amin (2015) studied Shariah-compliant factors based on the Musharakah principle and reported superior results relative to cap-weighted indexes for securities in Malaysia from 2009 through 2013.

[11]Another line of research explored whether genetic programming algorithms might better articulate security weights (for example, see Becker, Fei, and Lester 2006).

Amenc, Goltz, Lodh, and Martellini (2014) nicely articulated a more nuanced approach to smart factor construction. They suggested that smart factor construction needs to balance exposures to desired and rewarded risks while mitigating and diversifying away as much unrewarded risk as possible. The result will, of course, be a non-cap-weighted portfolio. Not surprisingly, Amenc, Ducoulombier, Goltz, Lodh, and Sivasubramanian (2016) suggested that smart factor tilts be well diversified rather than highly concentrated among a limited number of securities. Of course, as Clarke, de Silva, and Thorley (2002) demonstrated much earlier, the impact of factors in realized returns will diminish as more constraints are placed on the portfolio construction process. Sorensen, Hua, Qian, and Schoen (2004) suggested some simple criteria that might assist factor construction in a sensible way. Bender and Wang (2016) as well as Clarke, de Silva, and Thorley (2016) pointed out that combining factor subportfolios is not an efficient way to capture the information content of multiple factors; bottom-up approaches using individual securities capture factor exposure more efficiently than top-down approaches do because bottom-up approaches better capture nonlinear cross-sectional interaction effects between factors.

The term "smart beta" was probably introduced into the quantitative equity management lexicon by Towers Watson, a global consulting firm, in 2013. In its 2013 report, Towers Watson suggested that exposures to different return drivers could be achieved without hedge-fund-like fees. This conclusion was echoed by Mladina (2015), who concluded that the risk and return profile of hedge funds could be explained by a mix of systematic risk factors. These factor exposures could be achieved simply and with transparency. The term "smart beta" itself has engendered some spicy comments. For example, Malkiel (2014) argued that smart beta is more about marketing than investing. He cautioned that the realizations of these smart factor premiums are not always positive. In "Beta as an Oxymoron," Anson (2015) argued smart beta isn't smart; it's dumb. If it were smart, providers would charge much higher fees. Qian, Alonso, and Barnes (2015) echoed the view that smart beta is surely a misnomer and can't be that smart *now* because quantitative and fundamental managers have been using these factors for years. Bogle (2016) remained unconvinced that smart beta has slain traditional cap-weighted indexing.

With all due respect to criticisms of the term "smart beta," smart-beta and smart factor investing are probably here to stay, as evidenced by the attention focused on them by large asset managers and advisory firms.[12] For example, Morningstar published its "A Global Guide to Strategic-Beta

[12]Vadlamudi and Bouchey (2014) questioned whether smart-beta solutions are actually smart for taxable investors on an after-tax basis.

Exchange-Traded Products" in 2014; the firm noted that "strategic beta" is its term for smart beta. Kahn and Lemmon (2016), both with BlackRock, discussed how smart-beta products are disrupting the investment management industry by providing an important component of active strategies in a low-cost, transparent, and rule-based way. Philips, Bennyhoff, Kinniry, Schlanger, and Chin (2015) of Vanguard published "An Evaluation of Smart Beta and Other Rules-Based Active Strategies," in which they concluded that an index should be constructed using market-capitalization weights. State Street Global Advisors (2016) published a piece titled "The Factor Revolution: Moving beyond Traditional Investment Models" to address the issue of investors' realizations that their desired outcomes are likely to be difficult to achieve with current approaches. Melas (2016) of MSCI asserted that factor investing will have a profound effect on long-term portfolio management. In short, from its humble and outcast beginning nearly 40 years ago, factor investing has now gone mainstream.

The Second Coming of Big Data and Technology in Quantitative Equity

The first era of big data in finance occurred in the 1960s with the creation of CRSP and Standard & Poor's Compustat tapes and mainframe computers. The data in this era were predominantly well structured, numeric, standardized, and curated, primarily consisting of company-specific information on stock prices, dividends, and capital changes, as well as officially filed financial and accounting information conforming to proscribed standards. Time-stamping information release, a necessary input for understanding the incorporation of information into stock prices, was not an easy or trivial matter and often required hand-collected datasets. Eventually, time stamping and event identification became easier as newswire services began to put press releases in computer-searchable databases.

Perhaps with the widespread acceptance of momentum as a factor, researchers and investors tried to better understand the drivers of sentiment. An early indicator of sentiment came from earnings forecasts made by financial analysts, although the early focus of this research was whether financial analysts made better earnings forecasts than did econometric models of actual earnings (for example, see Brown, Richardson, and Schwager 1987). Often this research used data supplied by I/B/E/S that aggregated the forecasts of individual financial analysts. The data were generally believed to be trustworthy because they came from bona fide financial firms, although they were not standardized because the earnings that analysts were forecasting were not necessarily consistent with GAAP. Since these early measures of sentiment, the range of investor sentiment metrics has expanded greatly.

Big data is often discussed in terms of the four Vs: volume, variety, velocity, and (more recently) veracity. With advances in technology, the different types of information that quantitative equity might find useful has exploded. In practice, most "big data" analyses to date in quantitative equity have focused on unstructured data emanating from text-based sources, with various degrees of credibility and curation. Some of the early research in this area dates to the so-called dot-com era. For example, Tumarkin and Whitelaw (2001) studied the relationship between postings on a specific internet bulletin board (RagingBull.com) and stock prices during the period from April 1999 to February 2000 for a group of stocks classified in the internet service sector. The authors concluded that message board activity could not predict stock returns, consistent with the efficient market hypothesis. But they also noted that strong positive returns preceded days with unusual message board activity and strong positive opinions. Dewally (2003) examined the stock recommendations on two newsgroup sites in April 1999 and February 2001 and concluded that newsgroups provided no value to their readers in terms of predicting subsequent returns. A slightly more positive spin on the information content of internet stock message boards was reported by Antweiler and Frank (2004). These authors analyzed about 1.5 million messages posted on Yahoo! Finance and RagingBull.com during 2000 for 45 firms using computational linguistic algorithms (naive Bayes and support vector machine) to assign buy, hold, and sell tags for each message. The authors concluded that internet chatter is pertinent for predicting trading volume and volatility. Clarkson, Joyce, and Tutticci (2006) studied the market reaction to takeover rumors posted on the Australian internet discussion site HotCopper between May 1999 and March 2000. From this very narrowly defined event in a sample of 189 firms, the authors found intraday abnormal returns and trading volume in the 10-minute intervals around the posting of the rumors, driven mostly by firms not identified in the press in the preceding year. Das and Chen (2007) proposed a method using statistical and natural language processing techniques to classify opinions from internet stock message boards. The authors used their method to extract views on 24 high-tech stocks from messages in July and August 2001 and found some contemporaneous (but not predictive) relationships between message board activity and market variables.

The internet stock bulletin boards of the late 1990s and early 2000s certainly represented some elements of big data in terms of volume, variety, and velocity, but the sources were not typically verified or vetted in terms of expertise. Tetlock (2007) took a different approach by analyzing the relationship between content in the *Wall Street Journal*'s "Abreast of the Market" column and stock market returns. Unlike stock market bulletin boards, the source of this content is easily identifiable and presumably a bit higher in veracity. Tetlock used the General Inquirer linguistic content program to quantify daily changes in the column over the 1984–1999 period. He reported that pessimism in the column's content did predict short-run downward price movements in the market, especially for smaller-cap companies. It was unclear, however, whether trading on this information would yield economic profits after accounting for transaction costs.

Tetlock, Saar-Tsechansky, and Macskassy (2008) extended the work of Tetlock (2007) by assessing the impact of negative words in all *Wall Street Journal* and Dow Jones News Service stories from 1980 to 2004 for S&P 500 Index companies.[13] This study reported the following: (1) The fraction of negative words can forecast low company earnings; (2) statistically, negative words predict negative abnormal returns on the next day (although transaction costs may wipe out the economic profit of a trading strategy); and (3) the predictability of earnings and returns from negative words is greatest for stories that focus on fundamentals (as measured by stories containing the word stem "earn"). In a study of 2.2 million news articles between 1989 and 2010, Hillert, Jacobs, and Muller (2014) suggested that the momentum effect is exacerbated by news coverage. That is, prior stock market winners with excessively high media coverage experience returns substantially greater than the returns of prior losers with excessive media coverage over about nine months. Most importantly for this study, the return differential between winners and losers is much smaller for companies with excessively low media coverage compared with high-media-coverage companies. The interest in news stories, sentiment, and stock returns has remained. For example, using a proprietary Thomson Reuters neural network measure of sentiment, Heston and Sinha (2017) found that daily news predicts stock returns for perhaps only one or two days, confirming previous research; news aggregated over a week has longer-lasting effects.[14] Unlike much of the previous research cited, however, this research offers no transparency into how tone or sentiment were actually constructed.

Moving from media to corporate-released information, Li (2008) analyzed the relationship between the readability of a company's annual report and its subsequent performance and earnings persistence. On the basis of the

[13]Tetlock (2010) studied an even larger dataset of news stories from 1979 to 2007 and focused on how news stories might resolve asymmetric information. Tetlock (2011) also analyzed investor reactions to stale information in news stories, where "stale" was defined as textual similarity in the previous 10 stories for a company.

[14]Using sentiment data from Thomson Reuters' News Analytics, Uhl, Pedersen, and Malitius (2015) claimed that filtered sentiment data could be used to perform tactical asset allocation.

Fog Index from computational linguistics and the length of reports for the period from 1994 to 2004, Li concluded that companies with easier-to-read annual reports tend to have more-persistent profits and that poor-performing companies have more-difficult-to-read annual reports. The *tone* of how companies voluntarily communicate with investors through press releases was studied by Henry (2008), who reported that abnormal returns increase as the tone of the earnings press release becomes more positive. Feldman, Govindaraj, Livnat, and Segal (2010) focused specifically on tone changes in the management discussion and analysis (MD&A) section of Forms 10-Q and 10-K. The authors concluded that tone changes do convey information not embedded in the regular financial statements. In particular, they concluded that tone changes are significantly correlated with short-window contemporaneous returns around SEC filing dates and with drift returns. Li (2010) isolated the forward-looking statements (FLSs) in the MD&A sections of 10-Q and 10-K reports to measure tone. This research found that FLS tone is correlated with several variables, including current performance, accruals, company size, return volatility, and company age. The author concluded that the Bayesian tone measure of FLSs is positively associated with future earnings.

In an analysis of 10-K filings, Loughran and McDonald (2011) developed a list of negative words that they considered more appropriate for financial analysis. According to the authors, the revised list, along with term weighting, should yield more informative measures of tone in financial documents. Jegadeesh and Wu (2013) used term weighting based on market reactions to 10-K filings from 1995 through 2010 downloaded from the SEC's EDGAR database. The authors reported that their measure of tone is significantly related to companies' market returns around their SEC filing dates; there is some initial underreaction to tone, but it quickly corrects within two weeks. The authors extended their method to IPO prospectuses and found a negative relation between tone and IPO underpricing.[15]

An interesting offshoot of corporate-released information is the management conference call. On these calls, company managers present prepared remarks, which are typically followed by a question and answer session with financial analysts. Brockman, Li, and Price (2015) extracted the linguistic tones of both managers and analysts during earnings conference calls. Perhaps not surprisingly, the authors found that manager tones are more optimistic than analyst tones; in addition, the market reacts much more attentively to analyst tones than to manager tones.

[15]Hanley and Hoberg (2010) examined the implications of the information content of IPO prospectuses using textual analysis on various aspects of the underwriting process.

This section began with a review of big data as gleaned from internet stock bulletin boards around 2000 and will come full circle by concluding with opinions expressed on social media. Bollen, Mao, and Zeng (2011) analyzed daily Twitter feeds using two mood-tracking tools (OpinionFinder and Google Profile of Mood States) and concluded that at least one metric of mood—calmness—improves the predictability of changes in the Dow Jones Industrial Average level. Using textual analysis, Chen, De, Hu, and Hwang (2014) extracted the tone of all opinion pieces between 2005 and 2012 from Seeking Alpha (SA), one of the biggest investment-related social media websites. Opinion content on SA is curated by a panel. The authors observed that the fraction of negative words in SA opinions and commentaries seems to have predictive power for individual stock returns over the ensuing three months. Azar and Lo (2016) measured Twitter sentiment around Federal Open Market Committee (FOMC) meetings between 2007 and 2014. Their evidence suggests that the information content of Twitter sentiment is predictive of market returns around FOMC meetings. In another Twitter-based study, Liew and Wang (2016) studied the cross-sectional relationship between sentiment in tweets and first-day IPO performance, from opening price to closing price. The authors did not calculate the sentiment measure themselves in a transparent way but, rather, used a proprietary metric provided by iSENTIUM, LLC. Based on this source, the study reports that prior-day sentiment can predict an IPO's first-day return and that there is a contemporaneous relationship between sentiment and IPO first-day returns. Liew and Budavari (2017) used a bullish–bearish sentiment bar indicator, filled in by users, from StockTwits. The authors found that for 15 stocks with a high volume of sentiment data, the "percent bullish" measure can add explanatory power to time series of daily returns beyond the five factors of Fama–French (2015). Karagozoglu and Fabozzi (2017) analyzed minute-by-minute, proprietarily calculated sentiment data from the commercial company PsychSignal in its Trader Mood product. The authors reported that this product and associated algorithms contain useful information about future stock market volatility.

Firms can employ, but also must contend with reactions on, social media.[16] For example, Lee, Hutton, and Shu (2015) explored crises caused by product recalls. Based on a sample of 405 recalls between 2000 and 2012, the evidence suggests that companies with social media messaging can attenuate the negative price consequences of the recall relative to companies with no social media presence. The attenuation benefits of social media declined as social media became more interactive. Indeed, the frequency of tweets by

[16]In April 2013, the SEC decided to allow companies to use social media to disclose key information.

disgruntled individuals exacerbates the negative price reaction, which can be offset somewhat by more-frequent tweeting by companies. Companies might also use Twitter to improve market liquidity for their publicly traded equity. Blankespoor, Miller, and White (2014), using a final sample of 85 technology companies, found that corporate tweets with links to their press releases lowered bid–ask spreads and increased market depth, presumably because the tweets reduced informational asymmetry.

The growing interest in big data in finance is perhaps illustrated by the fact that large financial firms have found it necessary to offer clients their views on this issue. These firms include Citi ("Big Data & Investment Management: The Potential to Quantify Traditionally Qualitative Factors," 2015), BNY Mellon ("Big Data and Investment Management: The Application of Data to Product Management and Client Satisfaction," 2015), Deutsche Bank ("Big Data Investment Management," 2016), and Goldman Sachs Asset Management ("The Role of Big Data in Investing," 2016).

To date, most published work on big data in equity management has focused on investor sentiment extracted from natural language processing algorithms applied to social media, official 10-Q and 10-K documents, press releases, and company conference calls.[17] The preponderance of published evidence indicates that to the extent that big data does contain useful sentiment information, it is for the most part short-lived in terms of profitable stock trading. Although these data may be quite relevant for market makers and trade desks, they do not seem to contain hidden, easy-to-exploit gems of information. Indeed, for long-term investors, it is not yet clear that big data per se is a big deal for their investment processes. As of this writing, we have yet to see refereed journal articles suggesting that big data and software can create long-term, persistent insights about quantitative equity management. Nonetheless, with so much digital data untagged and unexplored, this question remains open.[18]

Getting Dynamic

Although unstructured big data is one focus of current quantitative equity research, another focus may very well be dynamic factor models. In some ways, even with the explosion in potential factors, standard cross-sectional research

[17]Other suggested uses of big data include satellite imagery and microtransaction data. Conceptually, these potential uses might be considered as similar extensions to the work on economic links (Cohen and Frazzini 2008) and supply chains (Shahrur, Becker, and Rosenfeld 2010).

[18]Deutsche Bank (2016) reported that Google has indexed only about 0.01% of the accessible data on the internet.

between security returns and factors may be approaching a point with limited additional insights. Indeed, McLean and Pontiff (2016) even questioned whether academic research destroys stock return predictability and found evidence that it does, particularly after publication. But future quantitative equity insights may turn out to be centered much more on what factors are rewarded at given points in time than on what factors are rewarded on average over time. Some might label this approach "factor timing." As the search to outperform standard, passive benchmarks intensifies, some might view dynamic factor models as a reasonable investment approach. Of course, dynamic factor models and factor timing are not without critics and skeptics. For example, Asness (2016) opined that factor timing just might be a siren song.

The academic underpinnings for dynamic factor models can arguably be traced back to at least the 1980s. Ferson, Kandel, and Stambaugh (1987) reported evidence of a time-varying risk premium over the period 1963 through 1982 in common stock portfolios formed on the basis of market capitalization. The notion of time-varying risk premiums is also supported by Fama and French (1989), who found a risk premium in expected returns that varies with business conditions. Keim and Stambaugh (1986) also detected evidence of changing expected risk premiums. Ferson and Harvey (1991) concluded that time variation in risk premiums, as contrasted with time variation in betas, accounted for most of the return predictability. This list of early articles is not exhaustive but merely indicative that time-varying risk premiums were reported in the literature about 30 years ago. That they should be considered controversial now is somewhat puzzling. Perhaps the controversy is attributable partially to the observation that investors tend to implement timing decisions poorly, which causes realized returns to fall well short of proven strategy returns (see Hsu, Myers, and Whitby 2016).

Connor (1995) suggested classifying factors into three types: macroeconomic, fundamental, and statistical. For example, Boguth and Kuehn (2013) claimed that macroeconomic uncertainty affects asset pricing and that exposure to consumption volatility predicts future returns. Feldman, Jung, and Klein (2015) claimed that the Conference Board's Leading Economic Indicators could be used to create a time strategy that beats a simple buy-and-hold strategy.[19] The cyclically adjusted price-to-earnings ratio (CAPE; see Campbell and Shiller 1998), a fundamental-type factor with long-horizon predictability, continues to receive attention. For example, Siegel (2016) suggested ways to improve the predictive power of this approach by substituting NIPA (national income and product account) after-tax corporate profit data

[19]Bali, Brown, and Tang (2017) found that exposure to an economic uncertainty index is reflected in cross-sectional returns and labeled this risk an "uncertainty premium."

for GAAP earnings. Philips and Ural (2016) also investigated the CAPE and developed a list of recommendations to improve its efficacy. Hull and Qiao (2017) argued that the CAPE can be used to reduce sequencing risk in the decumulation phase of investing. Momentum, a statistical factor, continues to be a bedrock of factor investing, yet it doesn't always work and sometimes crashes dramatically, such as in 2009. Daniel and Moskowitz (2016) demonstrated that a dynamic momentum strategy can double the alpha and the Sharpe ratio of a static momentum strategy. Garcia-Feijóo, Kochard, Sullivan, and Wang (2015) concluded that there are cycles in low-volatility investing and that the performance of low volatility is time varying and influenced by the economic environment. Miller, Li, Zhou, and Giamouridis (2015) suggested a dynamic factor-weighting framework to respond to changes in factor predictability. Incorporating classification tree analysis, these authors concluded that their multifactor dynamic approach generated reward-to-risk ratios nearly four times greater than those generated by static approaches. Using more-conventional regression analysis, Reinganum, Becker, and He (2011) presented a dynamic multifactor model, conditioned on macroeconomic, fundamental, and statistical variables, that also significantly outperformed its fixed-weight, static counterpart.

Dynamic modeling is a current, promising area of quantitative research, with roots dating back to the 1980s and models of time-varying expected returns. Evidence of predictable returns can be found in very recent research as well (for example, see Hull and Qiao 2017). Closely related to dynamic models in quantitative equity investing are regime-shifting models. In an analysis of both developed and emerging markets, Pereiro and González-Rozada (2015) reported that regime-shifting models outperformed single-regime models. Using a different methodological toolbox, Nystrup, Hansen, Madsen, and Lindström (2015) also suggested that a simple regime-shifting approach will outperform a static allocation approach. Mulvey and Liu (2016) used a machine learning algorithm, trend filtering, to categorize regimes. They found these approaches most useful for long-term planning, and they suggested that such methods might help reduce the downside risks for university endowments and foundations. Xiong, Idzorek, and Ibbotson (2016) demonstrated the value of forecasting left-tail risk—though not the same as a regime—because it provided better downside protection while maintaining Sharpe ratios.

Ang, Madhavan, and Sobczyk (2017) developed a methodology to separate the effects of static factor exposures from dynamic timing from security selection. They reported that in a sample of mutual funds, each component tends to be distinct. But perhaps more important than this specific empirical result itself is that mainstream investment practitioners are recognizing the importance of being able to attribute performance to dynamic factor-timing skills. In part, this trend is undoubtedly a reflection of the explosion in smart-beta products and ETFs that tend to deliver static factor exposures in a very low-cost approach. Perhaps this is why Jacobs (2015) questioned whether smart beta is really state of the art. Indeed, the author argued that dynamic, multifactor approaches can lead to better outcomes than those of static, smart-beta approaches.

The surge in interest on dynamic factor timing may very well alter what is meant by the term “factor.” For decades, factors have been associated with exposures that are priced on average over time. But as conditional models become better understood, this definition may evolve. Whereas forecasting factors that are priced on average will always remain of keen interest, factors that are not priced on average (at least in a statistical sense) may garner interest. For example, oil prices may not be a priced factor in the standard long-term sense but may very well speak loudly in certain economic environments and conditions. One can imagine that the search for dynamic factors that condition expected returns will continue and perhaps expand. Separating the wheat from the chaff will be a continuing challenge for quantitative dynamic factor investing. But dynamic factor-timing models appear to be here to stay and are likely to grow in importance.

Conclusion

Quantitative equity management is alive and well—and intellectually active—as investors seek to better manage risk and return. Factor investing has taken off commercially in the form of smart-beta products and strategies, vetted by decades of prior and current research. Dynamic factor-timing approaches are probably still in the early stages, especially from a commercial perspective. However, one might reasonably forecast this to be a growth area for the quantitative equity field. A new generation of big data approaches is developing in the field and will likely grow as technology becomes more capable and more data are digitally available. Quantitative equity management techniques are helping investors achieve more-efficient and appropriate investment outcomes.

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References

Amenc, N., F. Ducoulombier, F. Goltz, A. Lodh, and S. Sivasubramanian. 2016. "Diversified or Concentrated Factor Tilts?" *Journal of Portfolio Management* 42 (2): 64–76.

The authors conduct a detailed comparison of the performance and risks of concentrated and diversified factor-tilted indexes for six factor tilts in both the long and short terms. The authors argue that concentrated portfolios expose investors to too much unrewarded risk and suggest diversified factor-tilted portfolios. Empirical evidence is presented to support this view.

Amenc, N., F. Goltz, A. Lodh, and L. Martellini. 2014. "Towards Smart Equity Factor Indices: Harvesting Risk Premia without Taking Unrewarded Risks." *Journal of Portfolio Management* 40 (4): 106–22.

Smart factor indexes are meant to be the outcome of a process that carefully distinguishes the security selection stage from the portfolio construction process. The security selection stage is meant to ensure that the right factor tilt is attained. The portfolio construction phase is meant to diversify away unrewarded risk as much as possible by using some naive or scientific approach to diversification. Thus, the factor index is made "smart"—that is, better diversified—and an investor can hope to gain a larger fraction of the reward (Sharpe ratio) associated with the factor.

Amihud, Y., and H. Mendelson. 1991. "Liquidity, Asset Prices and Financial Policy." *Financial Analysts Journal* 47 (6): 56–66.

When designing an investment portfolio, a portfolio manager should consider not only the client's risk aversion but also the investment horizon. A long investment horizon enables the investor to earn higher net returns by investing in illiquid assets. Illiquidity costs can be separated into a number of distinct components: (1) bid–ask spreads, (2) market impact, (3) delay and search costs, and (4) direct transaction costs, including transaction taxes.

Ang, A., W. N. Goetzmann, and S. M. Schaefer. 2009. "Evaluation of Active Management of the Norwegian Government Pension Fund—Global" (14 December). https://www0.gsb.columbia.edu/faculty/aang/papers/report%20Norway.pdf.

This commissioned report aims to evaluate the role of active management in the Norwegian Government Pension Fund—Global. Analysis of the active management style indicates that a significant component of performance is explained by exposure to systematic factors that fared very poorly during the global financial crisis. In light of the relative importance that factor exposures play in the fund's returns, the report suggests that the fund consider a framework that more explicitly recognizes the structure of its return-generating process via investment in factor benchmark portfolios—and that both the way the fund is monitored and the way it is organized on a day-to-day basis be adapted to this new framework.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang. 2006. "The Cross-Section of Volatility and Expected Returns." *Journal of Finance* 61 (1): 259–99.

Stocks with high idiosyncratic volatility relative to the Fama and French (1993) model have abysmally low average returns. This phenomenon cannot be explained by exposure to aggregate volatility risk. Size, book-to-market ratio, momentum, and liquidity effects cannot account for either the low average returns earned by stocks with high exposure to systematic volatility risk or the low average returns of stocks with high idiosyncratic volatility.

Ang, A., A. Madhavan, and A. Sobczyk. 2017. "Estimating Time-Varying Factor Exposures (Corrected October 2017)." *Financial Analysts Journal* 73 (4): 41–54.

The authors present a methodology to estimate dynamic factor loadings using cross-sectional risk characteristics. Applying it to a dataset of US-domiciled mutual funds, the authors distinguish the components of active returns attributable to (1) constant factor exposures (e.g., a tilt to value stocks), (2) time-varying factor exposures, and (3) security selection. Large-cap growth funds tend to be concentrated in two factors (momentum and quality), whereas large-cap blend funds have the most factor diversity.

Anson, M. 2015. "Beta as an Oxymoron." *Journal of Portfolio Management* 41 (2): 1–2.

In this invited editorial, the author argues that smart beta is dumb. Beta is the capture of a systematic risk premium associated with an asset class that has minimal cost and high efficiency. Want proof that beta is dumb? If beta were smart, asset managers would find a way to charge higher fees for it.

Antweiler, W., and M. Z. Frank. 2004. "Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards." *Journal of Finance* 59 (3): 1259–94.

The authors study the effect of more than 1.5 million messages posted on Yahoo! Finance and RagingBull.com for 45 companies in the Dow Jones Industrial Average and the Dow Jones Internet Index. Bullishness is measured using computational linguistics methods. Stock messages help predict market volatility, but their predictive effect on stock returns is economically small. Disagreement among the posted messages is associated with increased trading volume.

Arnott, R., N. Beck, and V. Kalesnik. 2015. "Rip Van Winkle Indexing." *Journal of Portfolio Management* 41 (4): 50–67.

The authors use 20-year-old market capitalization weights, leaving out stocks that no longer exist in their original form, as the basis for a current investment portfolio and rebalance this portfolio annually, maintaining the 20-year gap. In testing over 67 years, this approach produces a risk-adjusted alpha of about 180 bps per year. Twenty-year-old cap weights perform better than current cap weights.

Arnott, R. D., J. Hsu, V. Kalesnik, and P. Tindall. 2013. "The Surprising Alpha from Malkiel's Monkey and Upside-Down Strategies." *Journal of Portfolio Management* 39 (4): 91–105.

The authors invert the weighting algorithms of sensible investment heuristics, effectively turning them upside down, and find that these upside-down strategies also beat the cap-weighted benchmark. The findings suggest that the investment beliefs on which many investment strategies are ostensibly based play little or no role in the strategies' outperformance. Rather, these beliefs introduce, often unintentionally, value and small-cap tilts into the portfolio. When these strategies are inverted, the resulting portfolios continue to display value and small-cap bias.

Arnott, R. D., J. C. Hsu, and P. Moore. 2005. "Fundamental Indexation." *Financial Analysts Journal* 61 (2): 83–99.

This study investigates whether stock market indexes based on an array of cap-indifferent measures of company size are more mean–variance efficient than those based on market cap. The measures of company size used include book value, trailing five-year average cash flow, trailing five-year average revenue, trailing five-year average gross sales, trailing five-year average gross dividends, and total employment. "Fundamental" indexes were found to deliver consistent, significant benefits relative to standard cap-weighted indexes.

Arrow, K. J., and G. Debreu. 1954. "Existence of an Equilibrium for a Competitive Economy." *Econometrica* 22 (3): 265–90.

In a highly theoretical paper, proofs of the existence of an equilibrium are given for an *integrated* model of production, exchange, and consumption, unlike the work of Wald, who offered proofs of the existence of an equilibrium for each of them. In addition, the assumptions made on the technologies of producers and the tastes of consumers are significantly weaker than Wald's.

Asness, C. S. 2016. "The Siren Song of Factor Timing aka 'Smart Beta Timing' aka 'Style Timing'." *Journal of Portfolio Management* 42 (5): 1–6.

In this invited editorial, the AQR Capital Management cofounder argues that factor timing is highly analogous to timing the stock market, is difficult, and should be done in very small doses, if at all (only "sin a little"). Good factors and diversification, in his view, easily trump the potential of factor timing. The implication is to maintain passive exposures to good factors with small, if any, variation over time.

Auer, B. R., and F. Schuhmacher. 2015. "Liquid Betting against Beta in Dow Jones Industrial Average Stocks." *Financial Analysts Journal* 71 (6): 30–43.

Liquidity and transaction costs are considered in an implementation of betting against beta strategies using the 30 highly liquid stocks of the Dow Jones Industrial Average from 1926 through 2013. The authors report strong evidence that pure BAB trading portfolios generate significant abnormal returns that cannot be explained by standard asset pricing factors, both before and after transaction costs.

Azar, P. D., and A. W. Lo. 2016. "The Wisdom of Twitter Crowds: Predicting Stock Market Reactions to FOMC Meetings via Twitter Feeds." *Journal of Portfolio Management* 42 (5): 123–34.

The study investigates investor sentiment on social media around FOMC meeting dates and creates a dataset of tweets that cite the Federal Reserve. Based on natural language processing techniques, a polarity score is assigned to each Twitter message, identifying the emotion in the text. This polarity score can be used to predict the returns of a broad stock market index, even when limiting the data to articles and tweets published at least 24 hours *before* the FOMC meeting.

Baker, M. 2016. "Risk Neglect in Equity Markets." *Journal of Portfolio Management* 42 (3): 12–25.

Examining 47 years of data, the authors find that investors have demanded high compensation for bearing market risk across asset classes but have neglected market risk within the equity market entirely. The author's view is that the flat relationship between beta and returns within equities represents the systematic mispricing of risk and is not a fluke of the data or a mismeasurement of risk.

Baker, M., B. Bradley, and J. Wurgler. 2011. "Benchmarks as Limits to Arbitrage: Understanding the Low-Volatility Anomaly." *Financial Analysts Journal* 67 (1): 40–54.

Noting that high-beta and high-volatility stocks have long underperformed low-beta and low-volatility stocks, the authors argue that this anomaly may be partly explained by mandates required to beat a fixed benchmark. Institutional impediments (such as leverage restrictions and tracking error constraints) discourage arbitrage activity in both high-alpha, low-beta stocks and low-alpha, high-beta stocks. Investors who want to maximize returns subject to total risk must incentivize their managers to do just that—by focusing on the benchmark-free Sharpe ratio, not the commonly used information ratio.

Bali, T. G., S. J. Brown, and Y. Tang. 2017. "Is Economic Uncertainty Priced in the Cross-Section of Stock Returns?" *Journal of Financial Economics* 126 (3): 471–89.

This study investigates the role of economic uncertainty in the cross-sectional pricing of stocks. The authors estimate each stock's exposure to an economic uncertainty index. From July 1977 to December 2014, stocks in the lowest-uncertainty-beta decile generated about 6% more annual returns compared with stocks in the highest-uncertainty-beta decile. After controlling for the well-known market, size, book-to-market ratio, momentum, liquidity, investment, and profitability factors, the authors find that the difference between the returns on the portfolios with the highest and lowest uncertainty beta remains negative and highly significant. The uncertainty premium appears to be driven by the outperformance (underperformance) of stocks with negative (positive) uncertainty beta.

Ball, R., and P. Brown. 1968. "An Empirical Evaluation of Accounting Income Numbers." *Journal of Accounting Research* 6 (2): 159–78.

This pioneering study explores the information content and timeliness of accounting income numbers. The authors find the annual income report does not rate highly as a timely medium, because most of its content (about

85%–90%) is captured by more-prompt media, which perhaps include interim accounting reports.

Ball, R., J. Gerakos, J. T. Linnainmaa, and V. Nikolaev. 2016. "Accruals, Cash Flows, and Operating Profitability in the Cross Section of Stock Returns." *Journal of Financial Economics* 121 (1): 28–45.

Accruals, the noncash component of earnings, generate a profit measure largely unaffected by the timing of receipts and payments of cash. Cash-based operating profitability (a measure that excludes accruals) outperforms measures of profitability that include accruals and subsumes accruals in predicting the cross section of average returns. Higher Sharpe ratios can be attained by adding just a cash-based operating profitability factor rather than by adding both an accruals factor and a profitability factor that includes accruals.

Banz, R. W. 1981. "The Relationship between Return and Market Value." *Journal of Financial Economics* 9 (1): 3–18.

This classic study examines the empirical relationship between the return and the total market value of NYSE common stocks using monthly data between 1926 and 1975. Smaller companies had higher risk-adjusted returns, on average, than did larger companies. This "size effect" suggests that the capital asset pricing model is misspecified. The author is unable to determine whether size per se is responsible for the effect or whether size is just a proxy for one or more true unknown factors correlated with size.

Barberis, N., A. Schleifer, and R. Vishny. 1998. "A Model of Investor Sentiment." *Journal of Financial Economics* 49 (3): 307–43.

The authors develop a theoretical model to explain two documented empirical regularities: (1) the tendency of stocks to underreact to news, such as that contained in earnings announcements, and (2) the tendency of stocks to overreact to a series of good or bad news. The models shows how investors can form beliefs in such a way that is consistent with both empirical observations.

Basu, S. 1977. "Investment Performance of Common Stocks in Relation to Their Price–Earnings Ratios: A Test of the Efficient Market Hypothesis." *Journal of Finance* 32 (3): 663–82.

Based on a sample of 753 industrial companies with December fiscal year-ends and listed on the NYSE from 1956 to 1971, this study examines the relationship between P/Es and subsequent stock returns. Annual earnings are used to rank stocks once a year based on their P/Es. Low-P/E portfolios on average earned higher absolute and risk-adjusted returns than did high-P/E portfolios. The author concludes that the information in P/Es was not fully reflected in security prices, a violation of the semi-strong efficient market hypothesis.

Becker, Y. L., P. Fei, and A. M. Lester. 2006. "Stock Selection — An Innovative Application of Genetic Programming Methodology." In *Genetic Programming Theory and Practice IV*, edited by Rick Riolo, Terence Soule, and Bill Worzel, 315–334. New York: Springer.

Genetic programming processes can explore both linear and nonlinear combinations of factors. Using 191 months of data for stocks in the S&P 500, the authors report that genetic programming greatly enhances the factor selection process relative to traditional linear factor models and leads to better predictions of future stock returns.

Bender, J., R. Briand, F. Nielsen, and D. Stefek. 2010. "Portfolio of Risk Premia: A New Approach to Diversification." *Journal of Portfolio Management* 36 (2): 17–25.

This article explores risk premiums as basic units in investment management as opposed to asset classes. The results suggest that combinations of risk premiums could prove to be an attractive alternative to a traditional asset allocation approach.

Bender, J., and T. Wang. 2016. "Can the Whole Be More Than the Sum of the Parts? Bottom-Up versus Top-Down Multifactor Portfolio Construction." *Journal of Portfolio Management* 42 (5): 39–50.

Multifactor portfolios can be constructed either by combining individual single-factor portfolios or by creating bottom-up portfolios in which security weights are a function of multiple factors simultaneously. The authors suggest the bottom-up approach will generally produce superior results than will a combination of individual single-factor portfolios because bottom-up approaches capture nonlinear, cross-sectional interaction effects between factors that simple combination approaches do not.

Black, F., M. Jensen, and M. Scholes. 1972. "The Capital Asset Pricing Model: Some Empirical Tests." *Studies in the Theory of Capital Markets*, edited by Michael C. Jensen. New York: Praeger.

The evidence presented indicates the expected excess return on an asset is not strictly proportional to its beta. The authors believe that the evidence is sufficiently strong to warrant rejection of the traditional form of the CAPM over the 1926–1966 period using all NYSE-listed stocks. To mitigate errors in beta estimation, the authors group securities into portfolios.

Blankespoor, E., G. S. Miller, and H. D. White. 2014. "The Role of Dissemination in Market Liquidity: Evidence from Firms' Use of Twitter." *Accounting Review* 89 (1): 79–112.

This study examines whether companies can reduce information asymmetry by broadly disseminating their news. In particular, using a sample of 102 technology companies, the authors examine the impact of using Twitter to send market participants links to press releases that are provided via traditional disclosure methods. The additional dissemination of company-initiated news via Twitter is associated with lower abnormal bid–ask spreads and greater abnormal depths. The results hold mainly for companies that are not highly visible.

BNY Mellon. 2015. "Big Data and Investment Management: Application to Product Development and Client Satisfaction" (May).

Volume, variety, veracity, and velocity are all characteristics of big data. The quantity, speed, and diversity of information flows continue to expand at a geometric rate, further swelling the pools of available data to be analyzed and acted on. This report articulates potential applications of big data in investment management and identifies some sources of these data pools (e.g., custodian banks, transactional data, and personal and community data).

Bogle, J. C. 2016. "David and Goliath: Who Wins the Quantitative Battle?" *Journal of Portfolio Management* 43 (1): 127–37.

The founder of the Vanguard Group examines who wins the investment battle: arithmetic quants (such as simple index funds) or algorithmic quants (such as hedge funds). Arithmetic investing has a huge cost advantage over algorithmic investing, and the volatility of algorithmic strategies can be large. The author conjectures that over the long run, simple arithmetic investing will win out.

Boguth, O., and L. Kuehn. 2013. "Consumption Volatility Risk." *Journal of Finance* 68 (6): 2589–615.

Time variation in macroeconomic uncertainty affects asset prices. Consumption volatility is a negatively priced source of risk. At the company level, exposure to consumption volatility risk predicts future returns, generating a spread across quintile portfolios in excess of 7% annually.

This premium is explained by cross-sectional differences in the sensitivity of dividend volatility to consumption volatility. Stocks with volatile cash flows in uncertain aggregate times require higher expected returns.

Bollen, J., H. Mao, and X. Zeng. 2011. "Twitter Mood Predicts the Stock Market." *Journal of Computational Science* 2 (1): 1–8.

The authors investigate whether measurements of collective mood states derived from large-scale Twitter feeds correlate with the value of the DJIA over time. They analyze the text content of daily Twitter feeds using two mood tracking tools—OpinionFinder, which measures positive versus negative mood, and Google Profile of Mood States (GPOMS), which measures mood in terms of six dimensions (calm, alert, sure, vital, kind, and happy). The calmness of the public (as measured by GPOMS), rather than general levels of positive sentiment (as measured by OpinionFinder), is found to be predictive of the DJIA.

Brockman, P., X. Li, and S. M. Price. 2015. "Differences in Conference Call Tones: Managers vs. Analysts." *Financial Analysts Journal* 71 (4): 24–42.

The authors extract the linguistic tones of managers and analysts during earnings conference calls and examine the differences between them. Manager tones convey much more optimism (less pessimism) than do analyst tones. Institutional investors react more strongly to analyst tones than to manager tones. The most optimistic tone during a conference call occurs during the prepared introduction. Once the session is opened up for questions, the tone becomes significantly more pessimistic. Managers are simply unable to maintain their rosy outlook after analysts weigh in with questions and comments.

Brown, L. D., G. D. Richardson, and S. J. Schwager. 1987. "An Information Interpretation of Financial Analyst Superiority in Forecasting Earnings." *Journal of Accounting Research* 25 (1): 49–67.

The authors report that financial analysts' forecasts of earnings are superior to time-series modeled forecasts. The authors explore the reasons for this superiority—in particular, the dimensionality of information. The superiority of financial analysts' forecasts is positively related to company size and the extent to which there is agreement among analysts regarding the companies' future earnings numbers.

Campbell, J. Y., and R. J. Shiller. 1998. "Valuation Ratios and the Long-Run Stock Market Outlook." *Journal of Portfolio Management* 24 (2): 11–26.

Dividend-to-price and price-smoothed-earnings valuation ratios, with more than a hundred years of data, relate stock prices to careful evaluations of the fundamental value of corporations. Based on statistical analysis, the results forecast substantial declines in real stock prices, as well as real stock returns close to zero, over the 10-year period after 1997.

Carhart, M. M. 1997. "On Persistence in Mutual Fund Performance." *Journal of Finance* 52 (1): 57–82.

Common factors in stock returns and investment expenses almost completely explain persistence in equity mutual funds' mean and risk-adjusted returns. Mutual funds that earn higher one-year returns do so not because fund managers successfully follow momentum strategies but because some mutual funds just happen by chance to hold relatively larger positions in last year's winning stocks. Hot-hands funds infrequently repeat their abnormal performance.

Chen, H., P. De, Y. (J.) Hu, and B.-H. Hwang. 2014. "Wisdom of Crowds: The Value of Stock Opinions Transmitted through Social Media." *Review of Financial Studies* 27 (5): 1367–403.

This study investigates the extent to which investor opinions transmitted through social media predict future stock returns and earnings surprises. To examine the role of peer-based advice, user-generated opinions are extracted from Seeking Alpha, one of the biggest investment-related social media websites in the United States, using the frequency of negative words to capture the tone. The authors report that peer-based opinions expressed on Seeking Alpha can predict future stock returns and earnings surprises.

Chow, T., J. Hsu, V. Kalesnik, and B. Little. 2011. "A Survey of Alternative Equity Index Strategies." *Financial Analysts Journal* 67 (5): 37–57.

Using both heuristic-based and optimization-based index strategies, the authors found that the outperformance of these strategies relative to their cap-weighted counterparts is largely owing to their exposures to value and size factors. Almost entirely spanned by market, value, and size factors, any one of these strategies can be mimicked by combinations of the others. Implementation cost is a better evaluation criterion than returns.

Citi. 2015. "Big Data & Investment Management: The Potential to Quantify Traditionally Qualitative Factors." Citi Business Advisory Services.

Big data principles are being adopted in many industries and in many varieties. Adoption by investment managers, however, has so far been limited.

A wave of innovation could begin in the quantitative investment space as the differences between what used to represent quantitative and qualitative research disappear. This paper outlines potential paths and uses of big data in investment management, as well as some of the tools in this field.

Clarke, R., H. de Silva, and S. Thorley. 2002. "Portfolio Constraints and the Fundamental Law of Active Management." *Financial Analysts Journal* 58 (5): 48–66.

A portfolio manager's success is driven in large part by the ability to forecast returns, but constraints placed on the portfolio construction process may attenuate these insights and limit a manager's ability to transfer valuable information into portfolio positions. The authors derive the relationships between the information ratio, the transfer coefficient, the information coefficient, and the number of securities. They give examples in which up to two-thirds of the information is not transferred because of constraints.

Clarke, R., H. de Silva, and S. Thorley. 2016. "Fundamentals of Efficient Factor Investing." *Financial Analysts Journal* 72 (6): 9–26.

Combining long-only-constrained factor subportfolios is generally not a mean–variance-efficient way to capture expected factor returns. Even when the investor has no views on security alphas, a well-constructed portfolio of individual securities has the flexibility needed for a nearly optimal simultaneous exposure to the underlying factors. The additional layer of constraints in combining factor-replicating subportfolios materially reduces mean–variance efficiency.

Clarke, R. G., H. de Silva, and S. Thorley. 2006. "Minimum-Variance Portfolios in the U.S. Equity Market." *Journal of Portfolio Management* 33 (1): 10–24.

The authors construct global minimum-variance portfolios using a large set of US equity securities and examine the realized risk and return statistics from 1968 through 2005. Empirically over the entire sample, the alpha of this portfolio relative to a cap-weighted benchmark is about 2.8% per year, the realized standard deviation is lowered by about one-fourth, and risk as measured by market beta is lowered by about one-third.

Clarkson, P., D. Joyce, and I. Tutticci. 2006. "Market Reaction to Takeover Rumour in Internet Discussion Sites." *Accounting and Finance* 46 (1): 31–52.

This study examines the market reaction to 189 takeover rumor postings between May 1999 and March 2000 on HotCopper, an Australian internet discussion site. Results from the analysis show abnormal returns and trading volumes on the day of the posting and the day before. Intraday analysis documents significant returns and trading volume during the 10-minute posting interval and abnormal trading volume during the 10-minute interval immediately preceding it. The subsample of companies that had not been identified as likely takeover targets in the press during the year preceding the posting largely drove the results.

Cochrane, J. 2011. "Presidential Address: Discount Rates." *Journal of Finance* 66 (4): 1047–108.

Discount rate variation is the central organizing question of current asset pricing research. The author surveys facts, theories, and applications. Previously, it was believed that returns were unpredictable, with variation in price-to-dividend ratios resulting from variation in expected cash flows. Now it seems that all price-to-dividend ratio variation corresponds to discount rate variation. Also, the cross section of expected returns was once believed to come from the CAPM, but now there is a zoo of new factors.

Cohen, L., and A. Frazzini. 2008. "Economic Links and Predictable Returns." *Journal of Finance* 63 (4): 1977–2011.

The authors find evidence of return predictability across economically linked companies. Using a dataset of companies' principal customers to identify a set of economically related companies from 1980 to 2004, the authors find that stock prices do not incorporate news involving related companies, generating predictable subsequent price moves. A long–short equity strategy based on this effect yields monthly alphas of more than 150 bps.

Connor, G. 1995. "The Three Types of Factor Models: A Comparison of Their Explanatory Power." *Financial Analysts Journal* 51 (3): 42–46.

Multifactor models of security market returns can be divided into three types: macroeconomic, fundamental, and statistical factor models. Based on the particular specification of each of the three types of models chosen by the author, the statistical and fundamental factor models substantially outperformed the macroeconomic factor model. The fundamental factor model slightly outperformed the statistical factor model.

Connor, G., and R. A. Korajczyk. 1988. "Risk and Return in an Equilibrium APT." *Journal of Financial Economics* 21 (2): 255–89.

An asymptotic principal components model is used to estimate the pervasive factors influencing asset returns. The empirical techniques allow for time variation in risk premiums. The arbitrage pricing theory provided a better description of expected returns than did the capital asset pricing model.

Cooper, M. J., H. Gulen, and M. J. Schill. 2008. "Asset Growth and the Cross-Section of Stock Returns." *Journal of Finance* 63 (4): 1609–51.

The authors test for company-level asset investment effects in returns by examining the cross-sectional relation between companies' annual asset growth and subsequent stock returns from 1963 through 2003. Asset growth rates are strong predictors of future abnormal returns, even among large-capitalization stocks. A company's annual asset growth rate emerges as an economically and statistically significant predictor of the cross section of US stock returns even after controlling for book-to-market ratios, company capitalization, lagged returns, accruals, and other growth measures.

Daniel, K., and T. J. Moskowitz. 2016. "Momentum Crashes." *Journal of Financial Economics* 122 (2): 221–47.

Momentum strategies can experience infrequent and persistent strings of negative returns. Momentum crashes are partly forecastable, occurring in panic states following market declines. An implementable dynamic momentum strategy based on forecasts of momentum's mean and variance approximately doubles the alpha and Sharpe ratio of a static momentum strategy and is not explained by other factors.

Das, S., and M. Chen. 2007. "Yahoo! for Amazon: Sentiment Extraction from Small Talk on the Web." *Management Science* 53 (9): 1375–88.

The authors develop a methodology for extracting small investor sentiment for 24 stocks in the Morgan Stanley High-Tech Index in July and August 2001 based on stock market message boards. Sentiment is the net of positive and negative opinions expressed about a stock on message boards using statistical and natural language processing techniques. Five distinct classifier algorithms, coupled with a voting scheme, are evaluated with a range of metrics. Empirical results suggest small investor sentiment may be useful in evaluating market activity.

De Bondt, W., and R. Thaler. 1985. "Does the Stock Market Overreact?" *Journal of Finance* 40 (3): 793–805.

This is a classic paper in the field of behavioral finance. The authors report evidence consistent with the overreaction hypothesis. Portfolios of prior "losers" outperform portfolios of prior "winners." Thirty-six months after the formation date, the losing stocks had earned about 25% more than the prior winners, even though the latter are significantly riskier.

Deutsche Bank. 2016. "Big Data Investment Management." Deutsche Bank Market Research (February).

This report discusses the opportunities and challenges of adopting big data in investment management and analyzes a wide spectrum of large datasets from satellite imagery, web mining, social media, textual data, and crowdsourcing to accounting data, macroeconomic data, and even IRS tax filings. In addition, various analytical frameworks for analyzing big data, such as machine learning, deep learning, and graph theory, are discussed. Also, key infrastructure elements needed to integrate big data, such as programming languages (e.g., R and Python), cloud computing (e.g., Amazon Web Services), and distributed file systems (e.g., Hadoop), are outlined.

Dewally, M. 2003. "Internet Investment Advice: Investing with a Rock of Salt." *Financial Analysts Journal* 59 (4): 65–77.

The author examines stocks recommended on two newsgroup sites (misc.invest.stocks and alt.invest.pennystocks) in April 1999 and February 2001 and reports that the newsgroups provided little value to their readers. Unusual performance relative to benchmarks is not detected in either the short term or the long term. Stock recommendations in aggregate tended to follow a momentum strategy.

Dubil, R. 2015. "How Dumb Is Smart Beta? Analyzing the Growth of Fundamental Indexing." *Journal of Financial Planning* 28 (3): 49–54.

Based on a set of popular "smart beta" ETFs, the author's results suggest that outperformance (relative to cap-weighted benchmarks) can be largely explained by overweighting in systematic risk factors.

Fama, E. F. 1970. "Efficient Capital Markets: A Review of Theory and Empirical Work." *Journal of Finance* 25 (2): 383–419.

This is a foundational paper in the efficient market hypothesis literature. The hypothesis is that market prices fully reflect all available information—that is, prices respond quickly to new information. The author classifies empirical tests of this hypothesis into three forms: weak form, semi-strong form, and strong form. The classification is based on the information set used to test the hypothesis. A survey of results indicates that the evidence in support of the efficient market hypothesis is extensive and the contradictory evidence is sparse.

Fama, E. F., and K. R. French. 1989. "Business Conditions and Expected Returns on Stocks and Bonds." *Journal of Financial Economics* 25 (1): 23–49.

Expected returns on common stocks and long-term bonds contain a risk premium that is related to longer-term aspects of business conditions. The variation over time in this premium is stronger for low-grade bonds than for high-grade bonds and stronger for stocks than for bonds. The general message is that expected returns are lower when economic conditions are strong and higher when conditions are weak. The empirical evidence is that long- and short-term economic conditions produce a rich mix of variation in expected asset returns.

Fama, E. F., and K. French. 1993. "Common Risk Factors in Stock and Bond Returns." *Journal of Financial Economics* 33 (1): 3–56.

The authors propose that there are three common factors that can empirically explain the cross-sectional relationships between stock returns: an overall market factor and factors related to company size and book-to-market equity. In many subsequent studies, this is referred to as the Fama–French three-factor model. The authors also link maturity and default risk factors to bonds and conclude that these five factors can explain average returns on stocks and bonds.

Fama, E. F., and K. R. French. 2015. "A Five-Factor Asset Pricing Model." *Journal of Financial Economics* 116 (1): 1–22.

A five-factor model directed at capturing the size, value, profitability, and investment patterns in average stock returns performs better than the three-factor model of Fama and French. The five-factor model's main problem is its failure to capture the low average returns on small stocks whose returns behave like those of companies that invest a lot despite low profitability. The model's performance is not sensitive to the way its factors are defined. With the addition of profitability and investment factors, the value factor of the Fama–French three-factor model becomes redundant for describing average returns in the sample they examine.

Fama, E. F., and J. D. MacBeth. 1973. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy* 81 (3): 607–36.

The authors test the cross-sectional relationship between average returns and CAPM beta risk using NYSE stock monthly returns from 1926 through 1968. The authors claim that their result is consistent with the CAPM in that there seems to be a positive trade-off between average returns and beta. In addition, they cannot reject the hypothesis that other measures of risk were systematically related to averaged returns. Perhaps equally important to the specific empirical results, the authors establish a way to test cross-sectional relationships for stocks using time-series data, the so-called Fama–MacBeth methodology, which is still widely used.

Feldman, R., S. Govindaraj, J. Livnat, and B. Segal. 2010. "Management's Tone Change, Post Earnings Announcement Drift and Accruals." *Review of Accounting Studies* 15 (4): 915–53.

The authors report that the management discussion and analysis section of Forms 10-Q and 10-K has incremental information content beyond financial measures, such as earnings surprises and accruals. They use a scheme to classify words into positive and negative categories to measure the tone change in the MD&A section relative to prior periodic SEC filings. Short-window market reactions around the SEC filing are significantly associated with the tone change of the MD&A section, and there is some drift afterward.

Feldman, T., A. Jung, and J. Klein. 2015. "Buy and Hold versus Timing Strategies: The Winner Is . . .." *Journal of Portfolio Management* 42 (1): 110–18.

The authors investigate a market-timing strategy that switches from fully invested in the S&P 500 to fully invested in three-month T-bills whenever the conference board leading economic indicator (LEI) declines three months in a row and switches back into the S&P 500 when the LEI increases three months in a row. This strategy modestly outperforms the S&P 500 by 1.66% annually over the 1970–2012 period; statistical significance is at the 10% level.

Ferson, W. E., and C. R. Harvey. 1991. "The Variation of Economic Risk Premiums." *Journal of Political Economy* 99 (2): 385–415.

Predictable components of monthly common stock and bond portfolio returns are analyzed. Most of the predictability is associated with sensitivity to economic variables in a rational asset pricing model with multiple betas. The stock market risk premium is the most important for capturing predictable variation of the stock portfolios, whereas premiums associated with interest rate risks capture predictability of the bond returns. Time variation in the premium for beta risk is more important than changes in the betas.

Ferson, W. E., S. Kandel, and R. F. Stambaugh. 1987. "Tests of Asset Pricing with Time-Varying Expected Risk Premiums and Market Betas." *Journal of Finance* 42 (2): 201–20.

The authors develop tests of asset pricing models that allow expected risk premiums and market betas to vary over time. Using weekly data for 1963 through 1982 on 10 common stock portfolios formed according to equity capitalization, a single risk premium model is not rejected if the expected premium is time varying and not constrained to correspond to a market factor. Conditional mean–variance efficiency of a value-weighted stock index is rejected.

Fisher, G. S., P. Z. Maymin, and Z. G. Maymin. 2015. "Risk Parity Optimality." *Journal of Portfolio Management* 41 (2): 42–56.

Risk parity allocates capital to each asset in inverse proportion to its future expected volatility. Risk parity, as a fast and frugal heuristic, tends to outperform the more complex and knowledge-intensive mean–variance approach. It also tends to outperform the overly simple and nearly entirely knowledge-independent equally weighted approach. The authors offer some theoretical conjectures as to why this might be the case.

Fisher, L., and J. H. Lorie. 1964. "Rates of Return on Investments in Common Stocks." *Journal of Business* 37 (1): 1–21.

Data for rates of return for all common stocks on the NYSE from 1926 through 1960 are presented. This work is the first to emerge from the Center for Research in Security Prices (CRSP) at the University of Chicago's Booth School of Business (sponsored by Merrill Lynch, Pierce, Fenner & Smith).

Frazzini, A., and L. H. Pedersen. 2014. "Betting against Beta." *Journal of Financial Economics* 111 (1): 1–25.

In a model with leverage and margin constraints, constrained investors bid up high-beta assets. Thus, high-beta assets are associated with low alpha, as is empirically found for US equities, 20 international equity markets, Treasury bonds, corporate bonds, and futures. A "betting against beta" factor that is long leveraged low-beta assets and short high-beta assets produces significant positive risk-adjusted returns.

Friedman, M., and L. J. Savage. 1948. "The Utility Analysis of Choices Involving Risk." *Journal of Political Economy* 56 (4): 279–304.

The authors extend orthodox utility theory to explain the empirical observation that an economic agent will buy insurance and participate in lotteries (gamble). Over some ranges of wealth, the utility curve displays a risk-averse shape, but at other ranges, the curve might be risk loving. This type of utility curve can explain both insurance and gambling behaviors.

Garcia-Feijóo, L., L. Kochard, R. N. Sullivan, and P. Wang. 2015. "Low-Volatility Cycles: The Influence of Valuation and Momentum on Low-Volatility Portfolios." *Financial Analysts Journal* 71 (3): 47–60.

The historical performance of low-risk investing, like that of any quantitative investment strategy, is time varying. Low-risk strategies exhibit dynamic exposure to the well-known value, size, and momentum factors and appear to be influenced by the overall economic environment. Time variation in the performance of low-risk strategies is influenced by the market environment and associated valuation premiums.

Geczy, C. C., and M. Samonov. 2016. "Two Centuries of Price-Return Momentum." *Financial Analysts Journal* 72 (5): 32–56.

The authors create a dataset of US security prices between 1801 and 1926 and test a traditional equity price-return momentum strategy using the data. In these pre-1927 data, the mean return of the basic price-return momentum effect was statistically significant and about half that from the post-1926 period. A dynamically hedged momentum strategy significantly outperformed the unhedged strategy.

Givoly, D., and J. Lakonishok. 1979. "The Information Content of Financial Analysts' Forecasts of Earnings: Some Evidence on Semi-Strong Inefficiency." *Journal of Accounting and Economics* 1 (3): 165–85.

The information content of revisions in financial analysts' forecasts of earnings is assessed. The relation between the direction of these revisions and stock price behavior is analyzed. Based on abnormal returns during the months surrounding the revisions, the results indicate that information on revisions in forecasts of earnings per share is valuable to investors. The market reaction to the disclosure of analysts' forecasts was relatively slow during the years 1967–1974.

Goldman Sachs Asset Management. 2016. "The Role of Big Data in Investing." GSAM Perspectives (July).

This is a very brief question and answer piece in which the respondents are three quantitative portfolios managers who each focus on their own approach.

Grinold, R. C., and R. N. Kahn. 2000. *Active Portfolio Management: A Quantitative Approach for Producing Superior Returns and Controlling Risk*, 2nd ed. New York: McGraw-Hill.

This book thoroughly explains many concepts and practices in the investment management industry, such as the information ratio (IR). Perhaps most famously, it articulates the fundamental law of active management: $IR = IC\sqrt{\text{Breadth}}$, where IC is the information coefficient.

Grover, S., and J. Kizer. 2016. "An Analysis of the Expense Ratio Pricing of SMB, HML, and UMD Exposure in U.S. Equity Mutual Funds." *Journal of Portfolio Management* 43 (1): 138–43.

Although the expense ratio price of US market equity exposure is near zero, the expense ratio price of exposure to other factors, such as size (SMB), value (HML), and momentum (UMD), is less clear. For a sample of long-only US equity funds with 60 months of return history ending January 2015, results indicate that investors are paying 11.9 bps, 27.0 bps, and 72.5 bps for unit exposure to SMB, HML, and UMD, respectively. In addition, the expense ratio price of factor exposure appears to vary widely across the four fund companies in the sample.

Hanley, K. W., and G. Hoberg. 2010. "The Information Content of IPO Prospectuses." *Review of Financial Studies* 23 (7): 2821–64.

Using word content analysis, information in the initial public offering prospectus is decomposed into standard and informative components. Greater informative content, as a proxy for premarket due diligence, results in more-accurate offer prices and less underpricing because it decreases the issuing company's reliance on book building to price the issue. Greater content from high-reputation underwriters and issuing company managers, through management discussion and analysis, contributes to the informativeness of the prospectus.

Harvey, C. R., and Y. Liu. 2015. "Backtesting." *Journal of Portfolio Management* 42 (1): 13–28.

There are many considerations involved in evaluating a trading strategy, including the strategy's economic foundation, Sharpe ratio, significance level, drawdown, consistency, diversification, and recent performance. A real-time evaluation method for determining the significance of a candidate trading strategy is proposed. The method explicitly takes into account that hundreds, if not thousands, of strategies have been proposed and tested in the past. Given these multiple tests, inference must be recalibrated.

Harvey, C. R., Y. Liu, and H. Zhu. 2016. ". . . and the Cross-Section of Expected Returns." *Review of Financial Studies* 29 (1): 5–68.

Hundreds of papers and factors attempt to explain the cross section of expected returns. Given this extensive data mining, it does not make sense to use the usual criteria for establishing significance. This paper introduces a multiple testing framework and provides historical cutoffs from the first empirical tests from 1967 to 2014; threshold cutoffs increase over time as more factors are data mined. The authors argue that a new factor needs to clear a much higher hurdle, with a *t*-statistic greater than 3.0, and that most claimed research findings in financial economics are likely false.

Haugen, R. A., and A. J. Heins. 1975. "Risk and the Rate of Return on Financial Assets: Some Old Wine in New Bottles." *Journal of Financial and Quantitative Analysis* 10 (5): 775–84.

After observing the performance of an extremely large number of NYSE issues from 1926 to 1971, the authors find little support for the notion that risk premiums have, in fact, manifested themselves in realized rates of return. In addition, over the long run, stock portfolios with less variance in monthly returns have experienced greater average returns than their "riskier" counterparts.

Henry, E. 2008. "Are Investors Influenced by the Way Earnings Press Releases Are Written?" *Journal of Business Communication* 45 (4): 363–407.

This study examines the market impact of tone and other stylistic attributes of earnings press releases using 1,366 company-year observations of annual press releases issued by companies in the telecommunications and computer industries between 1998 and 2002. The results suggest that the tone of earnings press releases, even controlling for financial performance, influences investors, as indicated by market reaction. Specifically, abnormal market returns are higher as the tone of the press release becomes more positive, up to a point. The results also indicate that longer press releases diminish the market impact of unexpected earnings.

Heston, S. L., and N. R. Sinha. 2017. "News vs. Sentiment: Predicting Stock Returns from News Stories." *Financial Analysts Journal* 73 (3): 67–83.

The authors used a dataset of more than 900,000 news stories from 2003 to 2010 and measured sentiment with a proprietary Thomson Reuters neural network. Results indicate that daily news predicts stock returns for only one to two days. When news is aggregated over a week, the predictability lasts up to a quarter. However, positive news stories increase stock returns quickly, but negative stories receive a relatively long delayed reaction.

Hill, J. M. 2016. "The Evolution and Success of Index Strategies in ETFs." *Financial Analysts Journal* 72 (5): 8–13.

The author outlines the drivers of growth of the ETF market. The author argues that investors should celebrate ETF development as the next step in the evolution of the "triumph of indexing" and seek opportunities to increase the use of ETFs in portfolio management and adapt exchange structures and regulatory frameworks to accommodate this growth.

Hillert, A., H. Jacobs, and S. Muller. 2014. "Media Makes Momentum." *Review of Financial Studies* 27 (12): 3467–501.

Relying on 2.2 million articles from 45 national and local US newspapers between 1989 and 2010, this study reports that companies with "excess media coverage" exhibit, ceteris paribus, significantly stronger momentum. The effect depends in part on article tone and is more pronounced for stocks with high uncertainty. The findings suggest that media coverage can exacerbate investor biases, leading return predictability to be strongest for companies in the spotlight of public attention.

Hsu, J., V. Kalesnik, and V. Viswanathan. 2015. "A Framework for Assessing Factors and Implementing Smart Beta Strategies." *Journal of Index Investing* 6 (1): 89–97.

The authors suggest a simple, three-step heuristic for establishing the robustness of a factor premium: (1) Economic underpinnings and persistence have been debated and validated in numerous research papers published in top-tier journals, (2) the effect persists across time periods and regions, and (3) the effect should survive reasonable perturbations in the definition of the factor strategy.

Hsu, J., B. W. Myers, and R. Whitby. 2016. "Timing Poorly: A Guide to Generating Poor Returns While Investing in Successful Strategies." *Journal of Portfolio Management* 42 (2): 90–98.

Investors in value mutual funds have produced an average internal rate of return that is meaningfully lower than the average buy-and-hold returns reported by the corresponding value mutual funds. Average investors do not time their allocations well and actually underperform their buy-and-hold benchmark by almost 2% per year by directing money to value mutual funds when value stocks are expensive. Mutual fund investors, through their poor timing decisions, may provide alpha to other investors.

Hull, B., and X. Qiao. 2017. "A Practitioner's Defense of Return Predictability." *Journal of Portfolio Management* 43 (3): 60–76.

The study examines 20 prominent return predictors proposed in the literature and combines them using correlation screening. The results indicate that one can forecast market returns six months into the future. The authors suggest that it will be considered irresponsible not to engage in informed market timing 30 years from now.

Invesco PowerShares Capital Management LLC. 2015. "The Evolution of Smart Beta ETFs: Gaining Traction in the Institutional Community." Market Strategies International (January).

This paper presents a marketing analysis of smart-beta ETFs as of January 2015. Smart-beta ETFs accounted for over 17% of US ETF net inflows in 2014. As of 2014, there were more than 350 smart-beta ETFs available in the United States, representing over $230 billion in assets under management, up from just 212 products and $64.8 billion in 2010. ETFs saw the highest year-over-year increase in institutional usage—from 24% in 2013 to 36% in 2014. Continued growth is anticipated.

Jacobs, B. I. 2015. "Is Smart Beta State of the Art?" *Journal of Portfolio Management* 41 (4): 1–3.

In this invited editorial, the author argues that smart beta is really not state of the art compared with dynamic active management. A dynamic portfolio responds to changes in stock fundamentals and underlying market and economic conditions and takes advantage of shorter-term market events, earnings announcements, and other company news. In contrast, a smart-beta portfolio follows static rules, tends to maintain constant factor exposures, and rebalances infrequently.

Jacobs, B., and K. Levy. 1988. "Disentangling Equity Return Regularities: New Insights and Investment Opportunities." *Financial Analysts Journal* 44 (3): 18–43.

This article represents an effort to disentangle prominent stock market anomalies identified in the 1980s. The authors refer to the multivariate return attributions as "pure" returns and to the univariate attributions as "naive" returns. Some anomalies appear to be true pockets of stock market inefficiency. Other anomalies might represent empirical return regularities that can be explained only in a broader macroeconomic framework.

Jegadeesh, N., and S. Titman. 1993. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance* 48 (1): 65–91.

Strategies that buy stocks that have performed well in the past and sell stocks that have performed poorly in the past generate significant positive returns over 3- to 12-month holding periods. The profitability of these strategies does not result from their systematic risk or from delayed stock price reactions to common factors. Part of the abnormal returns generated in the first year after portfolio formation dissipate in the following two years.

Jegadeesh, N., and D. Wu. 2013. "Word Power: A New Approach for Content Analysis." *Journal of Financial Economics* 110 (3): 712–29.

This study suggests a new approach for content analysis to quantify document tone. A significant relation between the authors' measure of the tone of 10-Ks and the market reaction for both negative and positive words is reported. The appropriate choice of term weighting in content analysis is at least as important as, and perhaps more important than, a complete and accurate compilation of the word list. This approach circumvents the need to subjectively partition words into positive and negative word lists.

Kahn, R., and M. Lemmon. 2015. "Smart Beta: The Owner's Manual." *Journal of Portfolio Management* 41 (2): 76–83.

The authors suggest decomposing returns into returns due to a cap-weighted index and active returns, where active returns can be broken down into smart-beta factors; security selection (beyond smart beta); and macro, industry, country, and asset-class bets beyond smart-beta factors. Active returns over time can also be broken down into static smart-beta exposures and smart-beta timing.

Kahn, R., and M. Lemmon. 2016. "The Asset Manager's Dilemma: How Smart Beta Is Disrupting the Investment Management Industry." *Financial Analysts Journal* 72 (1): 15–20.

Smart-beta products are a disruptive financial innovation with the potential to significantly affect the business of traditional active management. They provide an important component of active management via simple, transparent, rule-based portfolios delivered at lower fees. They clarify that what investors need from their active managers is pure alpha—returns beyond those from static exposures to smart-beta factors.

Kahneman, D., and A. Tversky. 1979. "Prospect Theory: An Analysis of Decision under Risk." *Econometrica* 47 (2): 263–91.

Risky prospects exhibit pervasive effects that are inconsistent with classic utility theory. The certainty effect is the tendency to underweight outcomes that are merely probably relative to those that are obtained with certainty. In addition, people discard components that are shared by all prospects (the isolation effect). The authors suggest that decision weights are more relevant than probability weights.

Kahneman, D., and A. Tversky. 1984. "Choices, Values, and Frames." *American Psychologist* 39 (4): 341–50.

The psychophysics of value induce risk aversion in the domain of gains and risk seeking in the domain of losses. The psychophysics of chance induce overweighting of sure things and improbable events relative to events of moderate probability. Decision problems can be described or framed in multiple ways that give rise to different preferences, contrary to the invariance criterion of rational choice. The process of mental accounting explains some anomalies of consumer behavior.

Karagozoglu, A. K., and F. J. Fabozzi. 2017. "Volatility Wisdom of Social Media Crowds." *Journal of Portfolio Management* 43 (2): 136–51.

Information contained in the volatility sentiment extracted from social media data sources can be used to create profitable investment strategies for stock market volatility instruments. In this study, over the period July 2012–August 2016, the social media data are provided by PsychSignal and are derived from the firehose of raw tweets from both StockTwits and Twitter. PsychSignal's proprietary natural language processing algorithm generates a minute-by-minute social media sentiment measure.

Keim, D. B. 1983. "Size-Realized Anomalies and Stock Return Seasonality." *Journal of Financial Economics* 12 (1): 13–32.

In NYSE and AMEX common stocks, the "size effect" in January is large relative to the remaining 11 months, and the relation between abnormal returns and size is always negative and more pronounced in January than in any other month. Nearly 50% of the average magnitude of the size effect over the 1963–1979 period results from January abnormal returns. More than 50% of the January premium is attributable to large abnormal returns during the first week of trading in the year, particularly on the first trading day.

Keim, D. B., and R. F. Stambaugh. 1986. "Predicting Returns in the Stock and Bond Markets." *Journal of Financial Economics* 17 (2): 357–90.

Several predetermined variables that reflect levels of bond and stock prices (such as the difference in yields between long-term low-grade corporate bonds and one-month T-bills) appear to predict returns on common stocks of companies of various sizes, long-term bonds of various default risks, and default-free bonds of various maturities. The returns on small-company stocks and low-grade bonds are more highly correlated in January than during the rest of the year. Seasonality is found in several conditional risk measures and must be a consideration of any study dealing with changing expectations.

Kendall, M. G. 1953. "The Analysis of Economic Time-Series—Part I: Prices." *Journal of the Royal Statistical Society. Series A (General)* 116 (1): 11–34.

The pattern of events in 22 price series is much less systematic than is generally believed. In series of prices, which are observed at fairly close intervals, the random changes from one term to the next are so large as to swamp any systematic effect that may be present. The data behave almost like wandering series. An analysis of stock exchange movements reveals little serial correlation within series and little lag correlation between series. Unless individual stocks behave differently from the average of similar stocks, there is no hope of being able to predict movements on the exchange for a week ahead without extraneous information.

Kidd, D. 2014. "Factor Investing: When Alpha Becomes Beta." CFA Institute.

The identification of beta strategies that masquerade as alpha has significant implications for investors in terms of risk control, diversification, and fees. The ability to isolate and understand a greater number of systematic risk factors enables investors to structure more-defined risk profiles for fees that are closer to those of beta strategies than to those of alpha strategies. Hedge fund investors have been slower than equity investors to reap the benefits from factor investing because hedge fund managers are not generally motivated to offer their products at low fees.

Knight, F. H. 1921. *Risk, Uncertainty, and Profit*. Hart, Schaffner, and Marx Prize Essays, no. 31. Boston and New York: Houghton Mifflin.

This book, which stems from the author's PhD dissertation, observes that the sacrifice of present for future necessarily means sacrifice of a fairly immediate, definite, predictable, and secure future for one that is opposite in all these respects. Risk is associated with a future with known outcomes and probabilities. Uncertainty has even less clarity and cannot be characterized with probabilities.

La Porta, R., J. Lakonishok, A. Shleifer, and R. Vishny. 1997. "Good News for Value Stocks: Further Evidence on Market Efficiency." *Journal of Finance* 52 (2): 859–74.

Stock price reactions around earnings announcements are studied for value and glamour stocks over a five-year period after portfolio formation. The announcement returns suggest that a significant portion of the return difference between value and glamour stocks is attributable to earnings surprises that are systematically more positive for value stocks. The evidence is inconsistent with a risk-based explanation for the return differential and is more consistent with errors in expectations about future earnings prospects.

Lakonishok, J., A. Shleifer, and R. Vishny. 1994. "Contrarian Investment, Exploration, and Risk." *Journal of Finance* 49 (5): 1541–78.

The authors argue and present evidence that value strategies outperform the market because these strategies exploit the suboptimal behavior of the typical investor and not because these strategies are fundamentally riskier. Historically, glamour stocks have grown faster in sales, earnings, and cash flows relative to value stocks. However, forecasted growth rates tied to historical growth rates were too optimistic for glamour stocks, in contrast to those for value stocks.

Latané, H. A., and C. P. Jones. 1977. "Standardized Unexpected Earnings—A Progress Report." *Journal of Finance* 32 (5): 1457–65.

The data presented in this paper suggest that excess holding-period returns are very significantly related to standardized unexpected quarterly earnings and that the adjustment to the unexpected quarterly earnings is relatively slow, probably because the unexpected earnings themselves are significantly serially correlated. Unexpected earnings are estimated on the basis of the seasonally adjusted trend of earnings in the preceding 20 quarters.

Lee, L. F., A. P. Hutton, and S. Shu. 2015. "The Role of Social Media in the Capital Market: Evidence from Consumer Product Recalls." *Journal of Accounting Research* 53 (2): 367–404.

The effect of corporate social media on the capital market consequences of companies' disclosures in the context of consumer product recalls is examined. Product recalls constitute a crisis that exposes a company to reputational damage, loss of future sales, and legal liability. Corporate social media, on average, attenuates the negative price reaction to recall announcements. With the arrival of Facebook and Twitter, however, companies relinquished complete control over their social media content, and the attenuation benefits of corporate social media, although still significant, lessened. The negative price reaction to a recall is weakened by the frequency of tweets by the company and exacerbated by the frequency of tweets by other users.

Li, F. 2008. "Annual Report Readability, Current Earnings, and Earnings Persistence." *Journal of Accounting and Economics* 45 (2–3): 221–47.

This study examines the relation between annual report readability and company performance and earnings persistence between 1994 and 2004. The readability of public company annual reports is measured using the Fog Index from the computational linguistics literature and the length of the document. The findings are as follows: (1) Annual reports of companies with lower earnings are harder to read (i.e., they have a higher Fog Index and are longer), and (2) companies with annual reports that are easier to read have more-persistent positive earnings.

Li, F. 2010. "The Information Content of Forward-Looking Statements in Corporate Filings—A Naïve Bayesian Machine Learning Approach." *Journal of Accounting Research* 48 (5): 1049–102.

This study examines the information content of the FLSs in the MD&A of 10-K and 10-Q filings using a naive Bayesian machine learning algorithm. Companies with better current performance, lower accruals, smaller size, a lower market-to-book ratio, less return volatility, a lower MD&A Fog Index, and a longer history tend to have more positive FLSs. The average tone of the FLS is positively associated with future earnings even after controlling for other determinants of future performance. The tone measures based on three commonly used dictionaries (Diction, General Inquirer, and the Linguistic Inquiry and Word Count) do not positively predict future performance; these dictionaries might not work well for analyzing corporate filings.

Li, X., R. N. Sullivan, and L. Garcia-Feijóo. 2016. "The Low-Volatility Anomaly: Market Evidence on Systematic Risk vs. Mispricing." *Financial Analysts Journal* 72 (1): 36–47.

Covering a 46-year period (1966–2011), the results suggest that the relatively high returns of low-volatility portfolios cannot be viewed solely as compensation for systematic factor risks. The results from the cross-sectional analyses indicate that average returns to low-volatility portfolios are determined by common variations associated with the idiosyncratic volatility characteristic rather than factor loadings. Thus, excess returns are more likely driven by market mispricing connected with volatility as a stock characteristic.

Liew, J., and T. Budavari. 2017. "The "Sixth" Factor—A Social Media Factor Derived Directly from Tweet Sentiments." *Journal of Portfolio Management* 43 (3): 102–11.

This study indicates that tweet sentiment for 15 individual stocks helps explain the time-series variation of security returns beyond the variation explained by the Fama–French five-factor model. User-defined tweet sentiment aggregated at the daily level provides significant characteristic information.

Liew, J. K., and G. Z. Wang. 2016. "Twitter Sentiment and IPO Performance: A Cross-Sectional Examination." *Journal of Portfolio Management* 42 (4): 129–35.

This article examines the cross-sectional relationships between sentiment extracted from tweets and IPO first-day performance, from opening price to closing price. All sentiment data extracted from tweets are provided by iSENTIUM LLC, which takes all real-time tweets mentioning targeted stock tickers and uses natural language processing algorithms to interpret each tweet and assign it with a number. There is a contemporaneous relationship between an IPO's tweet sentiment and returns on the first trading day, and the prior day's IPO sentiment can signal and predict the IPO's first-day returns from opening price to closing price.

Lintner, J. 1965. "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets." *Review of Economics and Statistics* 47 (1): 13–37.

This study theoretically models the problem of selecting optimal security portfolios for risk-averse investors who have the alternative of borrowing or lending a risk-free asset. The paper also develops equilibrium properties within the risk asset portfolio, including expected returns for a given security.

Lo, A. W., and A. C. MacKinlay. 1990. "Data Snooping Biases in Tests of Financial Asset Pricing Models." *Review of Financial Studies* 3 (3): 431–67.

Tests of financial asset pricing models may yield misleading inferences when properties of the data are used to construct the test statistics. Such tests are often based on returns to portfolios of common stocks, where portfolios are constructed on the basis of some empirically motivated characteristic, such as market value of equity. Analytic calculations, Monte Carlo simulations, and two empirical examples indicate that the effects of this type of data snooping can be substantial.

Loughran, T., and B. McDonald. 2011. "When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks." *Journal of Finance* 66 (1): 35–65.

Previous accounting and financial research often uses negative word counts to measure the tone of text. Word lists developed for other disciplines misclassify common words in financial text. In a large sample of 10-Ks from 1994 to 2008, almost three-fourths of the words identified as negative by the widely used Harvard Dictionary are words typically not considered negative in financial contexts. The authors develop an alternative negative word list, along with five other word lists, that better reflects tone in financial text. They link the word lists to 10-K filing returns, trading volume, return volatility, fraud, material weakness, and unexpected earnings.

Malkiel, B. G. 1973. *A Random Walk down Wall Street*. New York: W.W. Norton and Company.

This book popularized the view that stock prices are random walks and that investors would likely be best served by low-cost, passive index funds rather than higher-cost, actively managed funds.

Malkiel, B. G. 2014. "Is Smart Beta Really Smart?" *Journal of Portfolio Management* 40 (5): 127–34.

Smart beta is much more about smart marketing than smart investing. The author argues that any excess returns from smart-beta strategies are achieved by assuming greater risk, and he believes market-cap-weighted index funds are the way to go for most investors, institutional or retail, over the long term.

Markowitz, H. 1952. "Portfolio Selection." *Journal of Finance* 7 (1): 77–91.

This foundational article shows how relevant beliefs about future performance affect portfolio choice. The rule that an investor should maximize discounted expected, or anticipated, returns is rejected both as a hypothesis to explain and a maxim to guide investment behavior. Instead, the rule that the investor should consider expected return a desirable thing and variance of return an undesirable thing has many sound points, both as a maxim for and hypothesis about investment behavior.

McLean, R. D., and J. Pontiff. 2016. "Does Academic Research Destroy Stock Return Predictability?" *Journal of Finance* 71 (1): 5-32.

The authors investigate the out-of-sample and post-publication predictions of 97 variables previously claimed to have cross-sectional stock return predictability. The authors report portfolio returns are 26% lower out-of-sample and 58% lower post-publication. Post-publication declines are greater for predictors with higher in-sample returns.

Melas, D. 2016. "Power to the People: The Profound Impact of Factor Investing on Long-Term Portfolio Management." *Journal of Portfolio Management* 42 (2): 6–8.

In this invited editorial, the author argues that factor investing, also known as smart beta, is having a profound and lasting impact on the way long-term investors construct and manage their portfolios by providing a transparent and cost-effective method to seek systematic exposure to factors. It bridges the gap and seeks to combine some of the benefits of traditional passive investing and active portfolio management.

Miller, K. L., H. Li, T. G. Zhou, and D. Giamouridis. 2015. "A Risk-Oriented Model for Factor Timing Decisions." *Journal of Portfolio Management* 41 (3): 46–58.

This article develops a framework for dynamic factor weighting that is designed to accommodate sudden changes in factor predictability. To quantify the effect of risk and other factor portfolio characteristics on factor predictability, the authors use a classification tree analysis. A simple dynamic factor weighting approach results in an increase in the reward-to-risk ratio relative to a passive multifactor portfolio from 0.12 to 0.33, whereas a more sophisticated model generates a reward-to-risk ratio of 0.52.

Mladina, P. 2015. "Illuminating Hedge Fund Returns to Improve Portfolio Construction." *Journal of Portfolio Management* 41 (3): 127–39.

Many investors own hedge funds because of their high Sharpe ratios and low volatility profile. But the risk and return profile of hedge funds as a group is almost totally explained by the mix of systematic risk premiums. Knowing this, hedge fund manager selection and broader portfolio construction can focus on identifying and capturing diversifying sources of return in the form of alternative risk premiums, exotic risk premiums, and skill-based returns.

Modigliani, F., and M. H. Miller. 1958. "The Cost of Capital Corporation Finance and the Theory of Investment." *American Economic Review* 48 (3): 261–97.

In the presence of uncertainty, profit maximization no longer has operational meaning. However, market value maximization can provide an operational definition of the cost of capital and a workable theory of investment. This article develops a theory of the effect of financial structure on market valuation and its implication for the cost-of-capital problem. The theory shows that the cutoff point for investment in the company will be completely unaffected by the type of security used to finance the investment.

Morningstar. 2014. "A Global Guide to Strategic-Beta Exchange-Traded Products" (September).

As of 30 June 2014, there were 673 strategic-beta (or smart-beta) exchange-traded products, with collective assets under management of approximately $396 billion worldwide. The common thread among them is that they seek to either improve their return profile or alter their risk profile relative to more-traditional market benchmarks. In the case of equity products, which account for the overwhelming majority of assets in this area, the result is typically one or more factor tilts relative to standard market indexes. A stock portfolio's exposure to a handful of factors can usually explain most of its performance. These factors include the market risk premium, size, value, momentum, and quality factors. Fixed-income portfolios typically rely on credit and duration factors instead.

Mossin, J. 1966. "Equilibrium in a Capital Asset Market." *Econometrica* 34 (4): 768–83.

This paper investigates the properties of a market for risky assets on the basis of a simple model of general equilibrium of exchange, where individual investors seek to maximize preference functions over expected yield and variance of yield on their portfolios. The author outlines a theory of market risk premiums and shows that general equilibrium implies the existence of a so-called market line, relating per dollar expected yield and the standard deviation of yield. The concept of the price of risk is discussed in terms of the slope of this line.

Mulvey, J. M., and H. Liu. 2016. "Identifying Economic Regimes: Reducing Downside Risks for University Endowments and Foundations." *Journal of Portfolio Management* 43 (1): 100–08.

Trend filtering is one of the nonparametric approaches that has become common in the machine learning domain. The authors use this algorithm to identify and categorize economic regimes, which in turn helps in the modeling of downside risk. To improve the worst-case outcomes, institutions may wish to adjust spending rules during drawdown periods. The long-term benefits of return-contingent spending rates indicate that institutions may wish to plan for such contingencies, despite how rarely they occur.

Novy-Marx, R. 2013. "The Other Side of Value: The Gross Profitability Premium." *Journal of Financial Economics* 108 (1): 1–28.

Profitability, measured by gross profits to assets, has roughly the same power as the book-to-market ratio in predicting the cross section of average returns. Profitable companies generate significantly higher returns than unprofitable companies, despite having significantly higher valuation ratios. Controlling for profitability also dramatically increases the performance of value strategies, especially among the largest, most liquid stocks. Controlling for gross profitability explains most earnings-related anomalies and a wide range of seemingly unrelated profitable trading strategies.

Nystrup, P., B. W. Hansen, H. Madsen, and E. Lindström. 2015. "Regime-Based versus Static Asset Allocation: Letting the Data Speak." *Journal of Portfolio Management* 42 (1): 103–09.

The authors assert that regime-based investing is distinct from tactical asset allocation: The latter is shorter term, and the former targets a longer time horizon (i.e., a year or more) and is driven by changing economic fundamentals. A regime-based approach straddles a middle ground between strategic and tactical. Even without any level of forecasting skill, holding a static portfolio may not be optimal. With some level of forecasting skill, an RBAA (regime-based asset allocation) strategy's potential outperformance could be substantial.

Pástor, L., and R. F. Stambaugh. 2003. "Liquidity Risk and Expected Stock Returns." *Journal of Political Economy* 111 (3): 642–85.

This study reports that expected stock returns are cross-sectionally related to the sensitivities of returns to fluctuations in aggregate liquidity. The monthly liquidity measure is an average of individual stock measures estimated with daily data. From 1966 through 1999, the average return on stocks with high sensitivities to liquidity exceeds that for stocks with low sensitivities by 7.5% annually, adjusted for exposures to the market return as well as the size, value, and momentum factors. A liquidity risk factor accounts for half of the profits to a momentum strategy over the same period.

Pereiro, L. E., and M. González-Rozada. 2015. "Forecasting Prices in Regime-Switching Markets." *Journal of Portfolio Management* 41 (4): 133–39.

This study uses the self-exciting threshold autoregressive model, or SETAR, to identify regime shifts. Regimes are not subjectively defined by the analyst but are instead patterned after the observed data. SETAR decomposes the nonlinear behavior of a stock price index into two or more linear regimes separated by thresholds. In a sample of emerging and developed markets, the potential value of SETAR is illustrated.

Perold, A. 2007. "Fundamentally Flawed Indexing." *Financial Analysts Journal* 63 (6): 31–37.

The author argues that holding a stock in proportion to its capitalization weight does not change the likelihood that the stock is overvalued or undervalued. Thus, the notion that capitalization weighting imposes an intrinsic drag on performance is false. Fundamental indexing is a strategy of active security selection through investing in value stocks.

Philips, C. B., D. G. Bennyhoff, F. M. Kinniry, T. Schlanger, and P. Chin. 2015. "An Evaluation of Smart Beta and Other Rules-Based Active Strategies." Vanguard Research (August).

The authors strongly believe that smart-beta indexes should be considered rule-based active strategies because their methodologies tend to generate meaningful security-level deviations, or tracking error, versus a broad market-cap index. The "excess return" of such strategies can be partly (and in some cases largely) explained by time-varying exposures to certain risk factors, such as size and style. The authors find little evidence that smart-beta strategies have been able to capture any security-level mispricings in a systematic or meaningful way.

Philips, T., and C. Ural. 2016. "Uncloaking Campbell and Shiller's CAPE: A Comprehensive Guide to Its Construction and Use." *Journal of Portfolio Management* 43 (1): 109–25.

Using data from 1925 to 2015, the authors make 10 specific recommendations to enhance the implementation of the cyclically adjusted P/E.

Among the recommendations are to use CAPE to forecast nominal, not real, returns; weight past earnings by revenues; and be cautious when using CAPE or its variants as a market-timing tool, because markets can rise or fall to unusually high or low levels of valuation for extended periods.

Qian, E. 2005. "Risk Parity Portfolios." Research paper, PanAgora.

Risk parity portfolios are a family of portfolios that allocate market risk equally across asset classes, including stocks, bonds, and commodities. With risk parity portfolios, investors can reap the benefits of true diversification: Their eggs are placed evenly and safely in many baskets. The empirical outcomes of risk parity portfolios also seem to be efficient.

Qian, E., N. Alonso, and M. Barnes. 2015. "The Triumph of Mediocrity: A Case Study of Naïve Beta." *Journal of Portfolio Management* 41 (4): 19–34.

The authors study diversification-based sector portfolios within the S&P 500 universe using four different portfolio construction principles: equal weight, minimum variance, maximum diversification, and risk parity. Expected returns, expected Sharpe ratios, and risk contribution all outperformed the traditional beta of the S&P 500 in terms of risk-adjusted returns.

Reinganum, M. R. 1981a. "Misspecification of Capital Asset Pricing: Empirical Anomalies Based on Earnings' Yields and Market Values." *Journal of Financial Economics* 9 (1): 19–46.

Portfolios based on company size or earnings-to-price ratios (E/Ps) experience average returns that are systematically different from those predicted by the CAPM. The "abnormal" returns persist for at least two years; this persistence reduces the likelihood that the results are generated by a market inefficiency. The data also reveal that an E/P effect does not emerge after returns are controlled for the size effect; the size effect largely subsumes the E/P effect.

Reinganum, M. R. 1981b. "A New Empirical Perspective on the CAPM." *Journal of Financial and Quantitative Analysis* 16 (4): 439–62.

The author empirically investigates whether securities with different estimated betas systematically experience different average rates of return. The tests indicate that estimated betas are not systematically related to average returns across securities. The average returns of high-beta stocks are not reliably different from the average returns of low-beta stocks. Estimated betas, based on standard market indexes, do not appear to reliably measure a risk that is priced in the market, suggesting that the CAPM may lack significant empirical content.

Reinganum, M. R. 2014. "Anchored in Reality or Blinded by a Paradigm: The Role of Cap-Weighted Indices in the Future." *Journal of Portfolio Management* 40 (5): 119–25.

Cap-weighted indexes anchored the investment world of practitioners since the 1990s. One might argue that the skyrocketing interest in, and acceptance of, cap-weighted market indexes in the 1990s was not so much an intellectual embrace of Sharpe's elegant economic theory by practitioners but, rather, was driven by marketing and product analysis of stock market performance in the 1980s and 1990s, a golden era for large-cap stocks. The performance of cap-weighted indexes has most likely disappointed investors since the 1990s, and new factor-based indexes are challenging cap-weighted ones and will likely be incorporated into investor solutions in the future.

Reinganum, M. R., Y. L. Becker, and C. He. 2011. "Active Equity Portfolio Strategies: Dynamic Quantitative Models." In *Institutional Money Management: An Inside Look at Strategies, Players, and Practices*, edited by David M. Smith and Hany A. Shawky, 161–179. Hoboken, NJ: John Wiley & Sons.

The authors argue that the weakness observed in many standard quantitative models during the global financial crisis could be attributed to their static or all-season nature. In turbulent and extreme periods, a static fixed-weight factor approach struggles to provide superior performance. The study empirically investigates dynamic models that vary factor weights as the macroeconomic environment and investment conditions change. For Russell 1000 Index stocks from 1996 to 2010, the dynamic model outperformed the static model by about 750 bps on an annualized basis.

Roberts, H. V. 1959. "Stock-Market 'Patterns' and Financial Analysis: Methodological Suggestions." *Journal of Finance* 14 (1): 1–10.

The patterns of technical analysis may be little more than statistical artifacts. Looking at changes in stock market index levels rather than the levels themselves suggests that a "chance" model is a better descriptor of the data.

Roll, R. 1977. "A Critique of the Asset Pricing Theory's Tests Part I: On Past and Potential Testability of the Theory." *Journal of Financial Economics* 4 (2): 129–76.

Testing the two-parameter asset pricing theory is difficult and currently infeasible. Owing to a mathematical equivalence between the individual return/ beta linearity relation and the market portfolio's mean–variance efficiency, any valid test presupposes complete knowledge of the true market portfolio's composition. This implies, among other things, that every individual asset must be included in a correct test.

Rosenberg, B., K. Reid, and R. Lanstein. 1985. "Persuasive Evidence of Market Inefficiency." *Journal of Portfolio Management* 11 (3): 9–16.

Using a sample of 1,400 stocks of the largest companies in the Computstat database from 1980 to 1984, the authors investigate two strategies: (1) a book/price strategy (buy high book/price and sell low book/price) and (2) a "specific-return-reversal" strategy. The strategy returns are constructed to be orthogonal to 11 prespecified "risk indexes." Both strategies independently achieved highly significant results.

Ross, S. A. 1976. "The Arbitrage Theory of Capital Asset Pricing." *Journal of Economic Theory* 13 (3): 341–60.

The arbitrage pricing theory was proposed as an alternative to the mean–variance CAPM. Employing a proof with no-arbitrage conditions, the model yields a cross-sectional relationship between expected returns and the betas of multiple factors. Unlike the CAPM, the number of factors is not specified by the theory and the identity of the factors is not explicit.

Shahrur, H., Y. L. Becker, and D. Rosenfeld. 2010. "Return Predictability along the Supply Chain: The International Evidence." *Financial Analysts Journal* 66 (3): 60–77.

In a sample of equities listed on the exchanges of 22 developed countries, equity returns of customer industries led the returns of supplier industries. This customer–supplier lead–lag effect exhibits characteristics consistent with the view that the effect results from a slow diffusion of value-relevant information.

Sharpe, W. F. 1964. "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk." *Journal of Finance* 19 (3): 425–42.

The author develops a theory of capital asset pricing building on the work of Markowitz and others. He develops a capital market line that combines the risk-free asset with an optimal portfolio of risky assets (the market portfolio). A linear relationship between expected returns and market betas is implied. Only systematic risk is compensated.

Shiller, R. J. 1981. "Do Stock Prices Move Too Much to Be Justified by Subsequent Changes in Dividends?" *American Economic Review* 71 (3): 421–36.

Measures of stock price volatility over a century seem 5 to 13 times too high to be attributable to new information about future dividends if uncertainty about future dividends is measured by sample standard deviations of real dividends. The author strongly suggests that this is a failure of the efficient market model.

Siegel, J. 2016. "The Shiller CAPE Ratio: A New Look." *Financial Analysts Journal* 72 (3): 41–50.

Forecasts of future equity returns using the CAPE may be overly pessimistic because of changes in the computation of GAAP earnings (e.g., "mark-to-market" accounting) that are used in the Shiller CAPE model. When consistent earnings data, such as NIPA (national income and product account) after-tax corporate profits, are substituted for GAAP earnings, the CAPE model's forecasting ability improves and forecasts of US equity returns increase significantly.

Simon, S., M. Omar, N. M. Lazam, and M. N. M. Amin. 2015. "Factor Investing Based on Musharakah Principle." *AIP Conference Proceedings* 1682 (1).

This paper discusses the rationale for factor investing based on the Musharakah principle. Indexes consisting of Shariah-compliant stocks are created. Based on Malaysian stocks from January 2009 to December 2013, these factor indexes earned excess returns over market-capitalization-weighted indexes and experienced higher Sharpe ratios.

Sloan, R. G. 1996. "Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings?" *Accounting Review* 71 (3): 289–315.

This study investigates the extent to which stock prices reflect information about future earnings contained in the accrual and cash flow components of current earnings. The author finds that stock prices act as if investors "fixate" on earnings, failing to fully reflect information contained in the accrual and cash flow components of current earnings until that information affects future earnings. The difference in annual returns between the lowest- and highest-accrual portfolios was about 11%, on average.

Sorensen, E. H., and N. F. Alonso. 2015. "The Resale Value of Risk-Parity Equity Portfolios." *Journal of Portfolio Management* 41 (2): 23–32.

The authors empirically compare a risk parity (equal contribution to risk) weighting approach to equity portfolios as an alternative to holding capitalization-weighted portfolios and pay particular attention to "investor horizon." The risk parity approach dominates the cap-weighting approach in S&P 500 constituents over the period 1995–2014.

Sorensen, E. H., R. Hua, E. Qian, and R. Schoen. 2004. "Multiple Alpha Sources and Active Management." *Journal of Portfolio Management* 30 (2): 39–45.

The authors discuss ways to improve active management through a combination of multiple alpha signals. Optimality is defined in terms of *ex ante* information ratios. The authors offer several simple criteria to decide which alpha signals should be included: average information coefficient (IC), standard deviation of IC, breadth, tracking error, dispersion, and transmission drain.

State Street Global Advisors. 2016. "The Factor Revolution." Investment Roundtable: Moving beyond Traditional Investment Models (March).

Factor investing is disrupting traditional active management, raising the bar for managers to show their skill-based returns beyond replicable factor-based returns. The next frontier is beginning to challenge the alternatives investment space.

Suhonen, A., M. Lennkh, and F. Perez. 2017. "Quantifying Backtest Overfitting in Alternative Beta Strategies." *Journal of Portfolio Management* 43 (2): 90–104.

The authors investigate backtest bias in a proprietary dataset composed of the daily returns of 215 alternative beta strategies across five asset classes, 11 identifiable strategy groups, and 15 sponsor investment banks. The authors report a median Sharpe ratio of 1.20 for the strategies during their respective backtest periods, compared with 0.31 during live performance. The results support the recent warnings in the finance literature regarding "factor fishing," multiple testing, overfitting, and selection and reporting biases in financial research and product development.

Tetlock, P. C. 2007. "Giving Content to Investor Sentiment: The Role of Media in the Stock Market." *Journal of Finance* 62 (3): 1139–68.

The author measures the interactions between the daily content from the "Abreast of the Market" *Wall Street Journal* column and the stock market. Using the General Inquirer language processing program, the author finds that high media pessimism predicts downward pressure on market prices followed by a reversion to fundamentals. Also, unusually high or low pessimism predicts high market trading volume. The author claims that the results are inconsistent with theories of media content as a proxy for new information about fundamental asset values, as a proxy for market volatility, or as a sideshow with no relationship with asset markets.

Tetlock, P. C. 2010. "Does Public Financial News Resolve Asymmetric Information?" *Review of Financial Studies* 23 (9): 3520–57.

Using all Dow Jones Newswire and all *Wall Street Journal* stories about publicly traded US companies from 1979 to 2007, the author tests four predictions from an asymmetric information model of a company's stock price. Public news predicts substantially lower 10-day reversals of daily stock returns and higher 10-day volume-induced momentum in daily returns. News resolves more asymmetric information in illiquid stocks. The number of newswire messages subsumes much of the predictive power of news day trading volume.

Tetlock, P. C. 2011. "All the News That's Fit to Reprint: Do Investors React to Stale Information?" *Review of Financial Studies* 24 (5): 1481–512.

The staleness of a news story is defined as its textual similarity to the previous 10 stories about the same company. Based on publicly traded US companies in the Dow Jones Newswires archive from 1996 to 2008, companies' stock returns respond less to stale news. Even so, a company's return on the day of stale news negatively predicts its return in the following week. Individual investors seem to overreact to stale information.

Tetlock, P. C., M. Saar-Tsechansky, and S. Macskassy. 2008. "More Than Words: Quantifying Language to Measure Firms' Fundamentals." *Journal of Finance* 63 (3):1437–67.

Based on all *Wall Street Journal* and Dow Jones News Service stories about individual S&P 500 companies from 1980 to 2004, a simple quantitative measure of language can be used to predict individual companies' accounting earnings and stock returns. The fraction of negative words in company-specific news stories forecasts low company earnings, and companies' stock prices briefly underreact to the information embedded in negative words. Predictability from negative words is largest for the stories that focus on fundamentals, suggesting that linguistic media content captures otherwise hard-to-quantify aspects of companies' fundamentals.

Titman, S., K. C. J. Wei, and F. Xie. 2004. "Capital Investment and Stock Returns." *Journal of Financial and Quantitative Analysis* 39 (4): 677–700.

Companies that substantially increase capital investments subsequently achieve negative benchmark-adjusted returns, even though they tend to have past high returns. The negative abnormal capital investment/return relation is shown to be stronger for companies that have greater investment discretion (i.e., companies with higher cash flows and lower debt ratios) and is shown to be significant only during periods when hostile takeovers were less prevalent. This relation is independent of the previously documented long-term return reversal and secondary equity issue anomalies.

Tobin, J. 1958. "Liquidity Preference as Behavior towards Risk." *Review of Economic Studies* 25 (2): 65–86.

The author attempts to explain the liquidity preference function of individuals when the yield on cash is less than the yield on alternative assets. The research does not focus on the alternative risky assets per se but, rather, on the choice between risky assets and cash, and it derives a separation theorem.

Towers Watson. 2013. "*Understanding Smart Beta*" (July).

Smart beta is simply about trying to identify good investment ideas that can be structured better, whether that means improving existing beta opportunities or creating exposures or themes that are implementable in a low-cost, systematic way. This paper discusses the spectrum of investment approaches from bulk beta to smart beta to alpha. Smart-beta strategies should be implemented over a broad universe and are not relative return products.

Treynor, J. L. 1962. "Toward a Theory of Market Value of Risky Assets." Unpublished manuscript. Final version in *Asset Pricing and Portfolio Performance* (1999), edited by Robert A. Korajczyk, 15–22. London: Risk Books.

This paper develops a theory of market value that incorporates risk. The author presents a highly idealized model of a capital market in which it is relatively easy to see how risk premiums implicit in present share prices relate to individual investors' portfolio decisions. In a real market, institutional complexities, frictions, taxes, and certain other complications that are absent in the model may have a significant effect on share prices.

Tumarkin, R., and R. Whitelaw. 2001. "News or Noise? Internet Posting and Stock Prices." *Financial Analysts Journal* 57 (3): 41–51.

The authors examine the relationships between internet message board activity and abnormal stock returns and trading volume for a sample of companies in the internet service sector from mid-April 1999 to mid-February 2000. The study focuses on the RagingBull.com discussion forum and reports that on days with abnormally high message activity, changes in investor opinion correlated with abnormal industry-adjusted returns. These event days also coincided with abnormally high trading volume that persisted for a second day. However, message board activity did not predict industry-adjusted returns or abnormal trading volume.

Tversky, A., and D. Kahneman. 1974. "Judgment under Uncertainty: Heuristics and Biases." *Science* 185 (4157): 1124–31.

Biases are found in the intuitive judgment of probabilities. This article describes three heuristics used to assess probabilities and predict values: (1) representativeness (if A is perceived to be similar to B, the probability that A originated from B is judged to be high); (2) availability—the probability of the event is assessed by the ease with which occurrences can be brought to mind—and (3) adjustment from an anchor, such as a numerical value. These three heuristics can lead to systematic and predictable errors.

Uhl, M. W., M. Pedersen, and O. Malitius. 2015. "What's in the News? Using News Sentiment Momentum for Tactical Asset Allocation." *Journal of Portfolio Management* 41 (2): 100–12.

The news sentiment data are from Thomson Reuters' News Analytics. The sentiment scores (+1, 0, –1) are obtained from a linguistic algorithm that uses a bag-of-words approach (i.e., it looks at positive and negative words according to a dictionary). The study combines company- and macro-specific news sentiment from around 100,000 news pieces per week and uses the CUSUM (cumulative sum) filter method to calculate momentum in news sentiment. The results suggest that longer-term news sentiment cycles exist and that news sentiment momentum can be exploited by investment strategies.

Vadlamudi, H., and P. Bouchey. 2015. "Is Smart Beta Still Smart after Taxes?" *Journal of Portfolio Management* 40 (4): 123–34.

Smart-beta strategies have higher turnover than a capitalization-weighted index that results in a greater tax burden on the returns of these strategies. The authors report that despite this tax drag, smart-beta strategies still earn long-term excess returns. However, they suggest that tax-managed versions of these strategies may serve some investors better.

Van Gelderen, E., and J. Huij. 2014. "Academic Knowledge Dissemination in the Mutual Fund Industry: Can Mutual Funds Successfully Adopt Factor Investing Strategies?" *Journal of Portfolio Management* 40 (4): 157–67.

Based on a large sample of US equity mutual funds from 1990 to 2010, the evidence supports added value for investors who adopt factor investing strategies documented in the academic literature. In particular, low-beta, small-cap, and value funds earn significant excess returns. The results indicate that these excess returns are sustainable and did not disappear after the public dissemination of the anomalies.

Working, H. 1934. "A Random-Difference Series for Use in the Analysis of Time Series." *Journal of the American Statistical Association* 29 (185): 11–24.

Time series commonly possess in many respects the characteristics of series of cumulated random numbers. The separate items in such time series are by no means random in character, but the changes between successive items tend to be largely random. In a series composed of purely random changes, conspicuous trends will be found. Such "trends," however, must be regarded merely as generalized descriptions of the course of the series over a certain period, not as norms nor as bases for predicting the future course of the series over even the briefest subsequent period.

Xiong, J. X., T. M. Idzorek, and R. G. Ibbotson. 2016. "The Economic Value of Forecasting Left-Tail Risk." *Journal of Portfolio Management* 42 (3): 114–23.

The authors show that it is possible to reduce tail risk without giving up much return. The key is to forecast *forward*-looking skewness. Forecasting skewness can help the popular low-volatility strategy reduce tail risk without lowering the Sharpe ratio. For a lottery-type investor, the best timing for market entry is when forecasted skewness is very positive or after the market has suffered a huge loss.

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