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The capital asset pricing model (CAPM) predicts that the relation between beta and return is linearly positive, but the initial empirical tests of the capital asset pricing model (CAPM) done by Black, Jensen, and Scholes [1972], Fama and MacBeth [1973] and Haugen and Heins [1975] observed that the risk–return relation is flatter than the model predicts. Twenty years later, the seminal Fama and French [1992] paper found that, after adjusting for size effects, the relation between CAPM beta and return is flat over the period from 1963 to 1990. Various subsequent studies have confirmed this flat empirical relation between beta and return, or even found that the relation is negative; see, e.g., Black [1993], Haugen and Baker [1991, 1996, 2010], Falkenstein [1994], Clarke, de Silva, and Thorley [2010], and Baker, Bradley and Wurgler [2011].

Blitz and van Vliet [2007], Frazzini and Pedersen [2014], Baker and Haugen [2012] and Blitz, Pang, and van Vliet [2013] provide international evidence, finding that the anomaly is also present in international developed and emerging equity markets. In addition, both Blitz and van Vliet [2007] and Baker, Bradley, and Wurgler [2011] find that the anomaly is even stronger, by using simple volatilities instead of more sophisticated CAPM betas.[1] Other studies have observed that the low-volatility anomaly is robust within equity markets[2] and also present in other asset classes.[3] Throughout the remainder of this article, we refer to the anomalous relation between risk and return as the volatility effect.

Numerous studies argue that the CAPM might still be saved. Examples include the zero-beta CAPM (Black [1972]), models which add macro-economic factors (Chen, Roll, and Ross [1986]), human capital (Jagannathan and Wang [1996]), the consumption-wealth ratio (Lettau and Ludvigson [2001]), consumption risk (Jacobs and Wang [2004]) or consumption growth (Jagannathan and Wang [2007]), conditional asset-pricing models (Ferson and Schadt [1996]), and models that consider stochastic volatility (Campbell, Giglio, Polk, and Turley [2012]). Although these studies are also motivated by the observation that the basic CAPM does not work, they argue that this can be resolved by extending the model, without the need to abandon the fundamental notion of a positive risk–return relation.

The volatility effect is just one of multiple anomalies that have been identified in the asset-pricing literature. For example, Fama and French [1993] propose a three-factor model in which the CAPM is augmented with priced size and value factors, in order to explain those anomalies.[4] These debates on CAPM extensions and other asset-pricing anomalies are beyond the scope of our article, which focuses on providing an overview of explanations for the possibility that the fundamental risk–return relation is not positive, but flat or even negative.

As the CAPM can be mathematically derived from a set of assumptions, it follows that an empirical CAPM failure must be attributable to a violation of one or more of these assumptions in practice. The specific assumptions necessary to derive the CAPM can be found in standard finance textbooks. For the purposes of this article, we categorize them as follows:

(I) There are no constraints (e.g., on leverage and short-selling).
(II) Investors are risk averse, maximize the expected utility of absolute wealth, and care only about the mean and variance of return.[5]
(III) There is only one period.
(IV) Information is complete and rationally processed.
(V) Markets are perfect (i.e., all assets are perfectly divisible and perfectly liquid, there are no transaction costs, there are no taxes, and all investors are price takers).

Although the literature provides a lot of empirical evidence for the existence of a volatility effect, there appears to be no consensus on the reason(s) that the effect exists, although a wide range of explanations have been proposed in various streams of literature. The main objective of our article is to organize this fragmented literature by providing a broad overview of the various explanations for the volatility effect and by categorizing each explanation according to the CAPM assumption to which it relates.

Our article's insights can be summarized as follows. First, by taking the CAPM assumptions as a starting point, we provide a consistent structure for the various explanations for the volatility effect, and we take into account Fama's [1998] main critique on the field of behavioral finance, that often inconsistent and non-falsifiable explanations are proposed to explain market anomalies (e.g., overreaction versus underreaction). One of our findings is that not just one or two, but at least four of the five CAPM assumptions are involved with the various explanations. Second, our overview may help develop tests for discriminating between different explanations. Third, a key takeaway of our analysis is that, contrary to the popular notion that anomalies in financial markets are driven by irrational investor behavior, various explanations for the volatility effect are actually rooted in rational investor behavior, especially when considered in the context of institutional constraints. Finally, we argue that although the CAPM may be bad at explaining reality, addressing some of the reasons for its failure might well be a normative arbitrage opportunity.

CAPM ASSUMPTION (I): NO CONSTRAINTS

In this section, we discuss various explanations for the volatility effect that can be linked to the CAPM assumption of no constraints. Specifically, we discuss explanations based on leverage constraints, regulatory constraints, and short-selling constraints.

Leverage Constraints

In the early days of the CAPM, Brennan [1971] and Black [1972] had already showed that leverage (or borrowing) constraints may lower the slope of the security market line, causing low-beta stocks to have higher returns than predicted by the model. Examples of leverage restrictions include margin rules, bankruptcy laws that limit lender access to a borrower's future income, and tax rules that limit deductions for interest expenses. Two decades later, Black [1993] revisits this subject, arguing that leverage restrictions have tightened rather than weakened over time.

The general intuition is as follows. In the world of the CAPM there is only one efficient portfolio, and investors simply lever or de-lever this portfolio based on their degree of risk aversion. However, when borrowing constraints prevent leverage, investors looking to increase their return have no option other than to tilt their portfolios towards high-beta securities, in order to garner more of the equity risk premium. This extra demand for high-beta securities and reduced demand for low-beta securities may explain a less steeply upward-sloping security market line than the CAPM predicts. Some have argued that this mechanism can also explain a flat or even an inverted security-market line, as long as investors believe that the slope is positive when making their investment decisions. Obviously, however, the latter reasoning violates the CAPM assumption of rational investor behavior.

More recently, Frazzini and Pedersen [2014] also attribute the volatility effect to leverage constraints. In addition to examining the cross-sectional risk–return relation, they also provide time-series evidence by showing that when funding constraints tighten, betas tend to be compressed toward one and the risk–return relation becomes flatter. One of the predictions of their model is that less leverage-constrained investors (e.g., private equity) will hold low-beta stocks, while more leverage-constrained investors (e.g., mutual funds) prefer high-beta stocks.

It is important to note that many explanations discussed in the remainder of this article also (implicitly) assume constraints on leverage, as these arguments no longer apply if a levered position in low-risk stocks were to constitute a feasible alternative to high-risk stocks. As such, the leverage-constraints explanation is not just important on its own but also as an important auxiliary to many other explanations for the volatility effect.

Regulatory Constraints

Although equity fund managers may find it difficult to take a levered position in low-risk stocks, asset allocators should have no such problems, as they can simply create leverage by changing the asset mix. In fact, Black [1993] suggested an increased allocation to low-beta stocks as an alternative to a given allocation to the market portfolio. Instead of investing 60% in a conventional capitalization-weighted stock portfolio and 40% in bonds, for example, an investor might decide to invest 80% in low-beta stocks and 20% in bonds instead. In practice, we rarely see such a large strategic allocation to low-beta stocks. In fact, practitioners don't even consider it, because investors do not tend to identify low-risk stocks as a separate asset class when determining a strategic asset mix.

One reason for this reluctance may be that regulators do not particularly encourage investors to replace a conventional equity allocation with an increased position in low-volatility stocks. In several countries, for instance, regulators have imposed hard limits on the weight of equities allowed in institutional portfolios.[6] In addition, regulators typically do not distinguish between different stock types, but merely consider the total amount invested in stocks for determining required solvency buffers. Examples include the standard models in the Basel II and III frameworks (which set a fixed capital charge of 23.2% for equity holdings[7]), Solvency II (which sets a fixed capital charge of 32% for equity holdings), and the FTK for pension funds in the Netherlands (which prescribes a fixed capital buffer of 25% for equity holdings). Investors who wish to maximize equity exposure but minimize the associated capital charge under such regulations are drawn to the high-volatility segment of the equity market, as it effectively gives most equity exposure per unit of capital charge.

Constraints on Short Selling

Whereas leverage constraints may explain why low-risk stocks are underpriced, short-selling constraints may explain why, at the same time, high-risk stocks can be overpriced. The theoretical foundation for this was laid by Miller [1977], who argued that in a market with little or no short selling, the demand for a particular security comes from the minority who hold the most optimistic expectations about it. This phenomenon is also referred to as the winner's curse. As divergence of opinion is likely to increase with risk, high-risk stocks are more likely to be overpriced than are low-risk stocks, because their owners have the greatest bias. This explanation needs not merely constraints, but also heterogeneous beliefs and irrationality, because rational investors should anticipate this effect and adjust their demand accordingly.

More recently, De Giorgi and Post [2011] argue that short-selling constraints cause a concave risk–return relation, while Hong and Sraer [2012] show that even if investors only disagree about the common factor of cash flows, high-beta assets are more sensitive to this macro-disagreement and experience a greater divergence of opinion about their payoffs. As a result of this, their model also predicts that high-beta assets are more prone to speculative overpricing than are low-beta assets. In addition, their model predicts that high-beta assets have greater shorting from unconstrained arbitrageurs and more share turnover; their empirical analysis seems to confirm these predictions.

In short, restrictions on short selling help to distort the risk–return relation, as such constraints prevent arbitrageurs from correcting the inflated prices of high-volatility stocks.

CAPM ASSUMPTION (II): INVESTOR UTILITY

CAPM assumption (II) states that investors are risk averse, maximize the expected utility of their absolute wealth, and care only about the mean and variance of return. Combined, this implies that investors aim to maximize the following objective function:

$$\mathrm{E}(R_p) - \lambda \mathrm{E}\left(R_p - \mathrm{E}(R_p)\right)^2 \qquad (1)$$

where R_p represents the absolute portfolio return and λ represents a risk-aversion parameter that is greater than zero. In this section, we discuss explanations for the volatility effect that assume an alternative utility function. The first explanation is based on literature arguing that the volatility effect arises because people consider wealth relative to others more important than absolute wealth. The second explanation is based on literature arguing that investment professionals do not necessarily behave in a risk-averse manner for their clients, as these agents seek to maximize the value of their own option-like incentive contracts. The remaining explanations are based on the recognition that investors may care about more than just the mean and variance of return.

Relative Utility

The CAPM assumes that investors maximize the expected utility of their own personal wealth, thereby not recognizing the possibility that people may, in fact, care more about their wealth and consumption relative to others. The difference between absolute wealth preferences (greed) and relative wealth preferences (envy) is often subtle, as an increase in absolute wealth usually goes hand in hand with an increase in relative wealth. For asset-pricing purposes, however, the implications of this distinction can be far reaching, as relative preferences can explain a flatter security market line than predicted by the CAPM, or even an entirely flat relation between risk and return.

Many streams of literature provide evidence for the assertion that humans are primarily relatively oriented, not absolutely oriented. From a biological perspective, Rayo and Becker [2007] argue that species designed with relative preferences are more robust over several generations than are species with absolute preferences. Various social studies also conclude that human beings are driven by envy and a concern for relative status.[8] Additional evidence is provided by fMRI studies, such as Fliessbach et al. [2007], who conclude that people's pleasure centers respond more forcefully to relative rather than absolute rewards. Various economists studying happiness have found relative income more significant than absolute income. For examples, see Ferrer-i-Carbonell [2005], Luttmer [2005], Clark and Oswald [1996], and Knight, Song, and Gunatilaka [2009]. This is related to the famous Easterlin paradox, in which reported happiness seems unaffected by wealth over time in various countries. Frank [2011] provides a simple example of the prevalence of relative utility, finding that an overwhelming majority of people would rather earn \$100,000 when others earn \$90,000, than earn \$110,000 when others earn \$200,000. People prefer higher relative wealth over lower absolute wealth.

Formal relative utility models that incorporate "keeping up with the Joneses" behavior have been proposed in studies such as Abel [1990], Gali [1994], DeMarzo, Kaniel, and Kremer [2004], and Roussanov [2010], where utility is relative to others. Although these are general equilibrium models, they are only applied to explain specific issues, such as the Internet bubble or the low return to undiversified entrepreneurial investments documented by Heaton and Lucas [2000]. Lettau and Ludwigson [2001] and Campbell and Cochrane [1999] incorporate some relative utility by assuming a habit formation in time, but this generally does not decrease the equity risk premium and never removes it cross-sectionally.

Others have applied relative utility to asset pricing by starting from Sharpe [1981] and Roll [1992]'s observation that professional portfolio managers are typically evaluated on their return relative to some pre-specified benchmark index. For delegated portfolio managers, the focus therefore shifts from absolute return and absolute risk to benchmark-relative return (outperformance) and benchmark-relative risk (e.g., tracking error). In other words, relative utility has effectively been institutionalized in the money management industry. We can obtain the objective function for benchmark-relative investors simply by replacing absolute portfolio returns in the CAPM objective function (Equation (1)) with benchmark-relative portfolio returns, as in:

$$\mathrm{E}\left(R_p - R_b\right) - \lambda \mathrm{E}\left((R_p - R_b) - \mathrm{E}(R_p - R_b)\right)^2 \qquad (2)$$

where R_b represents the return on the relevant benchmark index.

Falkenstein [2009] argues that if the risk–return relation were positive, as the CAPM predicts, portfolio managers would strictly prefer the higher-returning, high-beta securities over the lower-returning, low-beta securities, as both represent similar risk from a benchmark-relative perspective (e.g., beta of 1.5 versus beta of 0.5). This results in upward price pressure for high-beta securities and downward price pressure for low-beta securities. The study formally shows that this gives rise to an equilibrium in which every security has the same expected return. The argument is essentially that with utility based on relative wealth, risk taking becomes deviating from the consensus or market portfolio, and in such an environment all risk becomes like idiosyncratic risk in the standard model, avoidable and therefore unpriced.[9] Others, such as Brennan [1993] and Brennan, Cheng, and Li [2012] assume the simultaneous presence of absolute and relative return-oriented investors and show that this implies a partial flattening of the security market line, with the degree of flattening depending on the number of relative-return investors, versus the number of absolute-return investors.

Agents Maximize Option Value

Investing relative to a benchmark, as discussed in the previous section, can explain a flat relation between risk and return. However, this is not the only agency issue involved in delegated portfolio management. In this section, we discuss other agency effects, which can explain why the relation between risk and return may even turn negative. An inverse risk–return relation means that investors are willing to accept a below-average expected return on high-risk stocks. The reason agents may be willing to pay for volatility is because their incentive structures resemble a call option, as in the following payoff function:

$$c + \max(R_p - X, 0) \tag{3}$$

where c represents a fixed constant (such as a base salary or fee), and X a hurdle level above which the agent receives a bonus.[10] We stress that here one does not need to assume risk-seeking behavior, as with a strong skewness preference, but rather assume that risk-averse agents will maximize the expected value of their own call options, instead of the expected utility of their clients' money. In the next section, we discuss what happens if we assume skewness preference. Next, we discuss optionality in payoffs for three types of agents: portfolio managers, their analysts, and the owners of money management firms.

First, Baker and Haugen [2012] observe a portfolio manager is typically paid a base salary, plus a bonus if performance is sufficiently high. They argue that this compensation arrangement resembles a call option on the portfolio return, the value of which can be increased by creating a more volatile portfolio. In other words, there is a conflict of interest between professional investors, who have an incentive to engage in risk-seeking behavior, and their clients, who are more likely to be risk-averse, as assumed by the CAPM.

Falkenstein [2009] takes the optionality argument one step further by arguing that the rewards of being recognized as a top manager are much larger than the rewards for second quintile managers, for instance. For example, top managers receive a disproportionate share of attention from outside investors, such as making it to the front cover of *Bloomberg Markets* magazine. In order to become a top investment manager, one must generate an extreme, outsized return. This has the additional benefit of signaling to potential future investors and employers that one is truly skilled, as it is virtually impossible to distinguish between skill and luck in a modest outperformance. Delegated portfolio managers focused on realizing an extreme return in the short run may be willing to accept a lower long-term expected return on the high-risk stocks that enable such returns.

Second, Baker and Haugen [2012] argue that the way in which investment processes are typically organized also gives analysts an incentive to focus on high-risk stocks. During periodic investment committee meetings, analysts can make a case for stocks they believe the lead portfolio manager should select. To advance their career, these analysts must impress the lead portfolio manager and their fellow analysts with their ability to select the highest-performing stocks. This naturally attracts them to hot stocks, which tend to be associated with above-average media attention, but typically also with above-average volatility. The interesting nature of these stocks also makes it easier for professional money managers to explain their buy decisions to their clients. Hsu, Kudoh, and Yamada [2012] make a similar argument, arguing that analysts inflate earnings forecasts more aggressively for volatile stocks, in part because the inflation is more difficult for investors to detect. Falkenstein [2009]'s previously mentioned argument—that portfolio managers have an incentive to clearly stand out from the rest—applies just as well to analysts.[11]

Third, not only portfolio managers and their analysts, but also the owners of fund management firms have an incentive to generate volatile fund performance. Chevalier and Ellison [1997] and Sirri and Tufano [1998] document that flows into mutual funds are highly skewed, with a small proportion of funds receiving the largest share of new money. These funds are the ones that show the very highest performance compared to their peers, following periods when the market itself has also done well. This flow–performance relation suggests that, in order to maximize expected profits, fund management firms should offer high-beta funds. Karceski [2002] develops an agency model that predicts a flattening of the relation between CAPM beta and expected stock returns as a result of this so-called tournament behavior, that is, as a result of fund managers adapting their behavior towards the empirical flow–performance relationship. Intuitively, if flows are linearly related to relative performance, but inflows amount to two units of new funds in up years and outflows amount to one unit of lost funds in down years, a higher beta tends to generate higher assets under management after a couple of bull and bear cycles. The study does not discuss to what extent the empirical risk–return relation may be distorted as a result of this conflict of interest, but we argue that if the payoffs to a strong performance in good times are sufficiently attractive, tournament behavior might even cause the risk–return relation to turn negative. In other words, if fund flows are sufficiently skewed, delegated portfolio managers may even be willing to bid up the price of high-beta stocks to such an extent that the long-term expected return on these stocks drops below the benchmark level.

Baker and Haugen [2012] provide empirical evidence for professional money managers' risk-seeking behavior. They document that mutual funds and institutional portfolios contain a disproportionate number of highly volatile securities. Falkenstein [1996] documents that, controlling for size and price, mutual funds hold disproportionately larger positions in higher-volatility stocks.

Preference for Skewness

In the previous section, we discussed how the volatility effect may arise from agents maximizing the expected value of their option-like incentive structures, rather than their clients' expected utility. These agents may still have mean–variance preferences, but because of their option-like payoffs, they also have a preference for high-volatility stocks when investing their clients' money. In this section, we discuss how the skewness preferences of investors themselves might explain the volatility effect.

Barberis and Huang [2008] use Tversky and Kahneman's [1992] cumulative prospect theory to argue that a security's skewness can be a price factor. In their behavioral framework, a positively skewed security may appear to be overpriced and earn a negative average excess return. This phenomenon may also explain the popularity of lotteries, as the small chance of a large gain, combined with the large chance of a small loss is a typical example of a payoff profile with positive skewness. Blitz and van Vliet [2007], Falkenstein [2009], Kumar [2009], Baker, Bradley, and Wurgler [2011], and Ilmanen [2012] link skewness preference to the volatility effect by arguing that low-priced, volatile stocks also offer positive skewness and bear a strong resemblance to lottery tickets. If investors care not only about the first and second moments of the return distribution, as the CAPM assumes, but also about the third moment (or, more generally, about lottery-like characteristics), this may explain why the CAPM appears to fail empirically in explaining the most risky stocks' returns.

One way to address this concern is by replacing the objective function that the CAPM assumes, as in Equation (1), with a cubic objective function, as in:

$$\mathrm{E}\left(R_p\right) - \lambda\, \mathrm{E}\left(R_p - \mathrm{E}(R_p)\right)^2 + \gamma\, \mathrm{E}\left(R_p - \mathrm{E}(R_p)\right)^3 \quad (4)$$

where γ is a parameter greater than zero reflecting skewness preference. Such an objective function recognizes a preference for positive skewness and the human desire to seek upside potential, as in Friedman and Savage [1948].

For asset-pricing tests under the assumption of a cubic objective function, however, it is important to understand that a strong skewness preference implies risk-seeking behavior. Therefore Levy and Markowitz [1979] argue that, for all concave (i.e., global risk aversion) utility functions, the mean–variance assumption is a good approximation. Investors with a strong preference for skewness will not hold the market portfolio, because upside potential is diversified away. Instead, they will prefer to invest in only a small number of stocks. Although this is in line with empirical observations, this kind of risk-seeking behavior does not result in an equilibrium outcome (market efficiency). Thus the three-moment CAPM proposed and tested by Kraus and Litzenberger [1976], Friend and Westerfield [1980], and Harvey and Siddique [1999] only holds for concave (globally risk-averse) cubic utility functions. Post, van Vliet, and Levy [2008] find that under the assumption of such utility functions, co-skewness has little explanatory power. The key is that if a skewness preference resides within a globally risk-averse investor, the skewness effect is an order of magnitude lower than the first-order risk premium if the investor is to remain risk averse as well. That is, if the equity risk premium is 5%, the skewness premium can only be 0.5%, and generally these articles assert a much stronger skewness effect.

Crash Aversion

Markowitz [1959] acknowledged that investors are mainly concerned about downside risk and that semi-variance is a more appropriate risk measure than variance. In addition, many psychological studies show that people perceive risk differently than simple variance aversion; see, for example, Kahneman and Tversky [1979], Tversky and Kahneman [1992], and Starmer [2000]. Bawa and Lindenberg [1977] developed a lower-partial-moment CAPM, where variance is replaced by downside risk measures. Empirically, Bernartzi and Thaler [1995] find that downside risk aversion helps explain the equity premium puzzle, while Ang, Chen, and Xing [2006] and Bali, Demirtas, and Levy [2009] find that stocks with higher downside risk have higher returns. With downside risk aversion, the objective function becomes:

$$E(R_p) - \lambda \, \mathrm{LPM}(R_p, \theta, n) \tag{5}$$

where LPM denotes the lower partial moment, with θ representing a threshold parameter and n the number of moments, often assumed to be two, as in Hogan and Warren [1974].

The threshold parameter θ is often set at zero (or the mean), in which case it models the human aversion to losses. In the extreme case, where investors equate risk with crash-beta (or, in terms of Equation (5), θ is close to –100%) and the market may drop by –100% due to some catastrophe, such as war or confiscation, all stocks have equal expected risk and thus must have the same expected return. In equilibrium, a completely flat risk–return relation would result. Because empirical research tends to focus on markets that still exist, that is, markets that have been successful (e.g., the U.S. equity market over the 20th century), such extreme data points tend to be absent from the sample. However, this might be a "peso problem," because a different picture would likely emerge if data for non-surviving markets were also considered (e.g., the "black swan" events of Russia in 1917 and Germany in 1945). Empirically, Post and van Vliet [2006] find that correlations tend to go up during market crashes for the U.S. equity market from 1933 to 2002, but not nearly to the extent that they go to one. As a result, assuming crash aversion and taking empirically observed correlation patterns into account, the risk–return relation will be flatter than the mean–variance CAPM suggests.

CAPM ASSUMPTION (III): ONE-PERIOD MODEL

The CAPM one-period assumption raises at least two questions: 1) how long is this single period and 2) what are the implications of multiple periods instead of a single period? Merton [1973] addressed the latter question, proposing a continuous-time generalization of the CAPM called the intertemporal CAPM (ICAPM). Although uncertainty in future investment opportunities enters the equation in this model, it retains the essential CAPM feature of a positive risk–return relation.

The first question has received much less attention. Our focus in this section is on the ambiguity introduced by using a single period, without specifying the period's length.

Most likely due to practical data availability, empirical studies often assume a one-month investment horizon, without making this implicit choice explicit. In practice, however, investors have heterogeneous investment horizons, ranging from shorter than one day to a lifetime. For example, Blume and Stambaugh [1983] discuss the effect of the investment horizon with an application to the size effect, where a 0.1% daily premium would translate into a 30% annualized size premium. The average investor probably has a horizon well beyond a single month, for example, three to five years or even longer. It might therefore be more appropriate to look at five-year returns, for example. However, this would leave only a small number of independent observations, and empirical tests would lack statistical power.

Another way to address the investment horizon issue is by considering geometric (compounded) instead of arithmetic (simple) average returns. Geometric average returns take into account that an investor in low-volatility stocks who experiences a return of +20% followed by a return of –20% will have a much higher terminal wealth (–4%) than an investor in high-volatility stocks who experiences a return of +50% followed by a return of −50% (−25%). Theoretically, the correct approach is to first compound returns to the appropriate investment horizon and then take the arithmetic average of these returns, as this represents the sample equivalent of expected return. For instance, the one-month horizon that the empirical asset-pricing literature typically assumes means that, implicitly, daily returns are first transformed to monthly returns with compounding, after which these monthly returns are averaged without compounding.

Empirically, compounding effects cause the long-term return spread between low-risk stocks and high-risk stocks to widen by around 3% annually compared with a one-month perspective, as evidenced, for example, by the geometric versus arithmetic average returns that Baker, Bradley, and Wurgler [2011] report. In other words, the CAPM may paradoxically hold and fail at the same time, depending only on the assumed investment horizon. With geometric average returns, one implicitly assumes an evaluation horizon equal to the sample period, which typically spans several decades. As this is likely to be longer than the average investor's investment horizon, the truth is probably somewhere in between the arithmetic and geometric return figures.

CAPM ASSUMPTION (IV): INFORMATION IS COMPLETE AND RATIONALLY PROCESSED

In this section, we discuss various explanations that are based on the CAPM assumption that investors have complete information. Perhaps even more important than having complete information is that investors rationally process the available information, which the CAPM theory also (implicitly) assumes. Most of the explanations for the volatility effect discussed in this section relate to the latter assumption, as investors seem to be plagued by various systematic behavioral biases that thwart their efforts at making rational investment decisions.

Attention-Grabbing Stocks

Falkenstein [1996] documents that mutual funds hold firms that are more in the news. Barber and Odean [2008] also find that individual investors are net buyers of attention-grabbing stocks, such as stocks in the news, stocks experiencing high abnormal-trading volume, and stocks with extreme recent returns. The idea is that attention-driven buying may result from investors' difficulty in searching the thousands of stocks they could potentially buy, that is, from a violation of the CAPM assumption that investors have complete information. They also argue that many investors' attention-based purchases can temporarily inflate a stock's price, leading to disappointing subsequent returns. Attention-grabbing stocks are typically found in the high-volatility segment of the market. Boring low-volatility stocks are the flip side of the coin, suffering from investor neglect. The attention-grabbing phenomenon is therefore another argument supporting the volatility effect's existence.

Representativeness Bias

Falkenstein [2009] argues that representativeness bias may also explain the volatility effect. This bias also conflicts with the assumption that investors have correct information and rationally act on this information. The idea behind representativeness bias, as established by Tversky and Kahneman [1983] and Kahneman, Slovic, and Tversky [1982], is that people rely more on appealing anecdotes than on dull statistics. New listings, for example, are regarded as potential Microsofts or Googles in spite of IPOs' documented poor average performance, because most investors are either unaware or choose to ignore such statistics, preferring to rely on anecdotes instead. Highly volatile stocks generate a lot of favorable anecdotes. This bias is a classic logical error: Stocks that had the highest returns were risky, therefore risky stocks should have high expected returns. The widespread heuristic that risk creates a return premium can lead investors seeking return premium to overweight risky stocks, and thus actually negate the effect through their collective action.

Mental Accounting

Shefrin and Statman [2000] argue that investors apply a two-pronged approach to investing that, while rationally inconsistent, is still descriptive (i.e., behavioral finance). The first approach is like that of a standard rational mean–variance optimizing investor. The second approach occurs when investors allocate a secondary amount for aspirational purposes, buying lottery-like investments that offer the possibility of not just more and higher return, but a new lifestyle. Such investments have the potential to double or go even higher, and these clearly have higher volatility than average. They argue this is consistent with major brokerage marketing strategies that present investments to take "a lot" of risk with some of one's wealth and the commonality of underdiversified, highly volatile individual equity choices; see Statman [2004]. Note that risk-seeking behavior in the high-aspiration layer also relates to the previously discussed preference for skewness explanation.

Blitz and van Vliet [2007] give a related mental-accounting explanation for the volatility effect, arguing that investors may make rational risk-averse choices when making their asset allocation decisions (driven by their low-aspiration layer, designed to avoid poverty), but can then become risk-neutral or even risk-seeking within a specific asset class (driven by their high-aspiration layer, designed for a shot at riches). Mental accounting also provides another explanation for why investors do not simply arbitrage away the volatility effect by investing in a low-volatility equity portfolio at the expense of a combination of their risk-free and conventional equity holdings, in the spirit of Black [1993], because an obstacle to that solution is the fact that it involves two mentally separated accounts.

Overconfidence

Overconfidence is probably one of the most pervasive behavioral biases. Haidt [2006] shows that most people see themselves as better than average on nearly any quality that is both subjective and socially desirable. The most celebrated overconfidence anecdote is Svenson's [1981] finding that 93 percent of American drivers rate themselves as better than the median. There are plenty of other such findings, and they do not relate only to the uneducated: 94 percent of college professors think they are above-average teachers, and 90 percent of entrepreneurs think that their new business will be a success. Paradoxically, overconfidence is rational meta-disposition. Overconfident people have lower rates of mortality and a variety of health benefits. People who are confident about the future do not get discouraged as easily, making them more successful. Other people like optimistic people because they tend to be less defensive, and are more likely to assume the good faith of others. Kahneman, in his popular book *Thinking, Fast and Slow* [2011], states this is the one bias he most wants his children to have, because of its myriad benefits. But overconfidence may also be linked to the volatility effect.

As Sharpe [1991] pointed out, active management is a zero-sum game before costs and a negative-sum game after costs. This notion has been confirmed by a large number of studies that have empirically evaluated mutual funds performance; see Carhart [1997], for example. As each active manager individually believes that he or she is capable of beating the market, or at least acts in concordance with this belief, it follows that active managers exhibit collective overconfidence. The collective overconfidence of active managers violates the CAPM assumption of rational information processing and can be another factor contributing to the volatility effect, because if an active manager is skilled, it makes sense to be particularly active in the high-volatility segment of the market, as that segment offers the largest rewards to skill. However, this reasoning results in excess demand for high-volatility securities when active managers are collectively overconfident about their ability to add value and are all drawn towards the high-volatility segment of the market (Kozhemiakin [2007]).

Falkenstein [2009] provides a related explanation based on investor overconfidence. He argues that many people believe they are capable of successful stock picking but need to prove this in order to convince others, or just themselves. Actual trading generates valuable information about the trader's skills, and trades in more volatile assets are more informative. Thus investors may be biased towards more-volatile assets for alpha discovery purposes, which are rooted in overconfidence.

Yet another related explanation for the volatility effect is based on implicit overconfidence with regard to market timing. For an investor who believes that the market will go up, it makes sense to invest in stocks, particularly high-beta stocks, as these are likely to benefit most from a rising market. An investor who believes that the market will go down, on the other hand, should not invest in low-beta stocks, but is best off staying out of equities altogether. According to this reasoning, an overconfident market-timer will never be invested in low-risk stocks. Kozhemiakin [2007] relates credit investors' overconfidence to high-yield bonds' relatively weak long-term performance.

IMPLICATIONS

In this final section, we first reflect on the various explanations for the volatility effect discussed in this article and on how tests might be developed to distinguish between the various explanations. We next discuss implications for investors, arguing in particular that, although the CAPM may be an empirical failure, it still represents a valuable normative framework and also helps us understand how various factors contribute to shaping the risk–return relation.

Reflecting on the Various Explanations

Discussions of the existence of anomalies, once one can refute simple measurement error, typically focus on the broad theme of whether these are the result of irrational investor behavior or misspecified models where the anomaly is really a proxy for risk. For example, Lakonishok, Shleifer, and Vishny [1994] attribute the value effect to investors' systematic biases with regard to firms' future expected growth rates, while Fama and French [1996] argue that the same variable proxies risk. Various explanations for the volatility effect fall in a hybrid category, as they relate to behavior that is rational, given exogenous incentive structures or constraints that are themselves irrational.

It is important to note which explanations are profoundly irrational, such as the winner's curse, because these are presumably more ephemeral, like a trading rule that exists until people see the profit opportunities it generates. If, on the other hand, the irrationality comes from constraints or agency issues that drive managers towards higher-volatility stocks, the effect is not likely to disappear unless some major industry-wide changes are implemented. Examples of such organizational reforms would be a fundamentally different way to structure incentive contracts for delegated portfolio managers, or a drastic and effective alleviation of constraints on leverage, short-selling, and regulatory distortions.

The large number of potential explanations for the volatility effect discussed in this article raises the question of which explanation(s) are the effect's actual key drivers. An interesting direction for follow-up research would involve developing and applying tests that let one distinguish between the various competing explanations. This is not a straightforward exercise, as it may be hard to disentangle the various explanations. A complicating issue is that most explanations imply a combination of factors, such as the winner's curse, which needs not just heterogeneous expectations or overconfidence, but also a short-sales constraint. Another example occurs when investors are faced with leverage constraints and, at the same time, do not have standard absolute utility preferences. For instance, the empirical evidence that Frazzini and Pedersen [2014] provide on mutual-fund betas being above one is not only consistent with their leverage-constraints hypothesis but might also reflect relative utility, agents maximizing option value, or skewness preference. One way to discriminate between various explanations is to consider their predictions. For example, some explanations are only consistent with a flatter (but still positive) risk–return relation, while other explanations allow for an entirely flat or even inverted risk–return relation.[12]

Another way to empirically evaluate a given explanation is to construct two different samples: one for which the explanation should clearly apply and one for which it should clearly not apply. Based on the explanations that attribute the volatility effect to agency issues involved with delegated portfolio management, for instance, one would expect the effect to be smaller or even absent in markets that are less institutionalized, or in periods during which markets were less institutionalized than they are now. Next, we offer more concrete examples of tests that may help distinguish between different explanations.

Consider, for example, the explanation based on benchmark-relative incentive contracts. According to this explanation, one would expect the volatility effect to be present in all situations where benchmarking is prevalent, but absent in situations where absolute risk–return considerations still prevail. Corporate bonds are an example of an asset class in which fund managers are typically benchmarked to some broad market index, similar to the way in which equity fund managers are evaluated. Consistent with the benchmarking explanation, recent research on the risk–return relation in the corporate bond market finds that the volatility effect appears to be clearly present there as well.[13] The asset allocation decision, on the other hand—i.e., the decision of how much to invest in high-risk equities versus lower-risk bonds or risk-free assets—is an example of a decision where absolute risk–return considerations probably still prevail, as the asset allocation decision is typically driven by risk tolerance considerations or, in the case of institutional investors, an asset liability management (ALM) study, rather than some pre-specified benchmark asset allocation. The existence of a positive equity risk premium suggests that a volatility effect does not exist at the level of asset classes, which is again consistent with the predictions of the benchmark-relative incentive contracts explanation.

Another example concerns the explanation based on short-selling constraints. If these constraints are the volatility effect's key drivers, we would expect to find no evidence for a volatility effect in markets where these constraints do not apply. The commodity market may be an example of such a market, because commodities are traded by means of futures, and taking a short position in futures is about as easy as taking a long position. Several studies, including Miffre, Fuertes, and Fernández-Pérez [2012] and Frazzini and Pedersen [2014], have tested for the existence of a volatility effect in commodities markets. Their results show that the effect is also clearly present in these markets, so it seems unlikely that short-selling constraints are the volatility effect's key driver.

The CAPM Is Dead, Long Live the CAPM!

From the large amount of empirical evidence for the existence of the volatility effect, and the large number of plausible explanations that explain the effect, one might be tempted to conclude that the CAPM is now truly obsolete and only deserves a place in history books. As a descriptive model for reality, the CAPM may indeed be considered a failure, given that the shape of the risk–return relation in practice appears to be so fundamentally different from the model's predictions. But this should not be a reason to simply discard the CAPM.

For example, if agency issues involved with delegated portfolio management distort the risk–return relation, should the main conclusion be that our theory is wrong, or that perhaps something is seriously wrong with current incentive structures in the asset management industry? A major step forward could be achieved if, instead of making straightforward return comparisons, funds were evaluated on their risk-adjusted performance. For example, Jensen's alpha is a metric that can be directly linked to the client's utility function. In other words, the volatility effect's existence may help us understand the importance of designing strategies that appeal to those thoughtful enough to see the emergent implications of their parochial incentives and find something better.

Similarly, if leverage and short-selling constraints distort the theoretical CAPM risk–return relation, then perhaps we should take this as an important signal to devise effective mechanisms to alleviate these constraints. If regulatory requirements contribute to the volatility effect, then perhaps we need capital charges that are not uniform across all stocks, but that explicitly distinguish between low- and high-risk stocks.

Finally, if behavioral biases play a major role in causing the volatility effect, we should perhaps think about how we might overcome the influence of our irrational behavioral tendencies. This probably starts with creating more awareness that we should invest in a more modest (less overconfident), better informed (less anecdotal), more systematic (not only stocks in the news), and more holistic (no mental accounts) way. Investors should realize that these biases are costly. Although they create portfolio choices that may make investors more comfortable, they come with an implicit tax. As such, the CAPM may be even more relevant if it does not work than if it does, because of the normative implications that follow from its failure as a descriptive model of reality.

ENDNOTES

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[1]Ang, Hodrick, Xing, and Zhang [2006, 2009] also identify a negative relation between very short-term (past one month) idiosyncratic volatility and subsequent stock returns, but it is unclear whether this is the same or a separate anomaly. Several studies show that short-term idiosyncratic volatility is not very robust and involves significant trading costs in illiquid stocks; see Bali and Cakici [2008] and Li, Sullivan, and Garcia-Feijóo [2012], for instance.

[2]Baker, Bradley, and Wurgler [2012] show that the volatility effect is not confined to the small-cap segment of the equity market but is also clearly present among large caps. Blitz and van Vliet [2007] find that the effect is robust to controlling for value and momentum effects, and Asness, Frazzini, and Pedersen [2013] find robust results when controlling for industry effects.

[3]For example, Derwall, Huij, and de Zwart [2009] report the existence of a beta anomaly for U.S. corporate bonds (sorted by maturity) and Frazzini and Pedersen [2014] document beta anomalies for U.S. Treasuries, U.S. corporate bonds (sorted on maturity or on rating), and futures markets (considering equity index, bond index, and commodity futures). Falkenstein [2009] provides more than twenty empirical examples of higher volatility not being associated with higher returns in all major asset classes, as well as some more-exotic ones.

[4]This three-factor model has become very popular, despite the fact that Fama and French [1993] themselves statistically reject it based on a test on the size- and value-sorted portfolios it was designed to explain. Their analysis does not even consider tests on beta- or volatility-sorted portfolios, despite Fama and French's [1992] conclusion that CAPM beta does not appear to be a priced risk factor.

[5]The latter condition can also be replaced by the assumption that returns are normally distributed.

[6]For instance, in Germany and Switzerland pension funds are not allowed to invest more than 30% of their portfolio in listed equities.

[7]Calculated as 8% times a risk weight of 290%.

[8]There is a lot of evidence that social context is key in evaluating reality. Specialized neural mechanisms process social information and empathy, ensuring that normal humans cannot make themselves blind to context. Mirror neurons tie others to us in a deep way, as we are constantly empathizing and imitating, a dominant strategy given the wealth of acquired knowledge in modern society; see Pagel [2011], Insel, and Fernald [2004], and Rizzolatti and Craighero [2004], for example. At a much simpler level, envy and concern for status is in anthropologist Dan Brown's book *Human Universals* [1991], which lists preferences found across all cultures. Interestingly, greed is not on that list.

[9]Falkenstein's model [2009] not only implies a flat relation between risk and return in the cross-section, but also a zero equity-risk premium. The model does not require the assumption of leverage constraints. Blitz [2012] provides an alternative model, assuming a two-stage hierarchical investment process in which investors first determine their desired allocation to risky assets based on absolute risk–return considerations, and next delegate the management of these risky portfolios to leverage-constrained managers who are evaluated on their relative performances. This model can explain a flat relation between risk and return in the cross-section, in combination with an equity risk premium that is still positive.

[10]A more sophisticated payoff function would recognize that in reality the fixed reward, c, is not entirely fixed, but also at risk. (For example, a portfolio manager may be fired after a very bad performance). Such considerations probably explain why portfolio managers typically do not create extremely volatile portfolios (e.g., ten times levered), even though this would further increase the expected payoff, according to Equation (3).

[11]A good example is analyst Henry Blodget, who in October 1998 predicted that Amazon.com's stock price would double to $400, which it did a month later. He instantly became well known and took a new job where he earned more than a million dollars a year. Such audacious predictions greatly increase the chance that an analyst will be noticed among many analysts.

[12]Note, however, that one should be careful with rejecting explanations. For example, although the benchmark-driven investing explanation can only explain a flat risk–return relation, empirical evidence for an inverse relation merely implies that this explanation cannot be the entire story, not that this explanation can be dismissed altogether.

[13]See, for example, Ilmanen, Byrne, Gunasekera, and Minikin [2004], Derwall, Huij, and de Zwart [2009], and Frazzini and Pedersen [2014], who consider U.S. corporate bonds sorted on maturity and rating.

REFERENCES

Abel, A. "Asset Prices under Habit Formation and Catching up with the Joneses." *American Economic Review*, 80 (1990), pp. 38-42.

Ang, A., J. Chen, and Y. Xing. "Downside Risk." *Review of Financial Studies*, 19 (2006), pp. 1191-1239.

Ang, A., R. Hodrick, Y. Xing, and X. Zhang. "The Cross-Section of Volatility and Expected Returns." *Journal of Finance*, 61 (2006), pp. 259-299.

——. "High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence." *Journal of Financial Economics*, 91 (2009), pp. 1-23.

Asness, C., A. Frazzini, and L. Pedersen. "Low-Risk Investing without Industry Bets." SSRN Working Paper No. 2259244, 2013.

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

Baker, N., and R. Haugen. "Low Risk Stocks Outperform within All Observable Markets of the World." SSRN Working Paper No. 2055431, 2012.

Bali, T., and N. Cakici. "Idiosyncratic Volatility and the Cross Section of Expected Returns." *Journal of Financial and Quantitative Analysis*, 43 (2008), pp. 29-58.

Bali, T., K. Demirtas, and H. Levy. "Is There an Intertemporal Relation between Downside Risk and Expected Returns?" *Journal of Financial and Quantitative Analysis*, 44 (2009), pp. 883-909.

Barber, B., and T. Odean. "All That Glitters: The Effect of Attention on the Buying Behavior of Individual and Institutional Investors." *Review of Financial Studies*, 21 (2008), pp. 785-818.

Barberis, N., and M. Huang. "Stocks as Lotteries: The Implications of Probability Weighting for Security Prices." *American Economic Review*, 98 (2008), pp. 2066-2100.

Bawa, V., and E. Lindenberg. "Capital Market Equilibrium in a Mean-Lower Partial Moment Framework." *Journal of Financial Economics*, 5 (1977), pp. 189-200.

Black, F. "Capital Market Equilibrium with Restricted Borrowing." *Journal of Business*, 45 (1972), pp. 444-455.

——. "Beta and Return: Announcements of the 'Death of Beta' Seem Premature." *The Journal of Portfolio Management*, 20 (1993), pp. 8-18.

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

Blitz, D. "Agency-Based Asset Pricing and the Beta Anomaly." SSRN Working Paper No. 2068535, 2012. (Forthcoming *European Financial Management*.)

Blitz, D., and P. van Vliet. "The Volatility Effect." *The Journal of Portfolio Management*, 34 (2007), pp. 102-113.

Blitz, D., J. Pang, and P. van Vliet. "The Volatility Effect in Emerging Markets." *Emerging Markets Review*, 16 (2013), pp. 31-45.

Blume, M., and R. Stambaugh. "Biases in Computed Returns: An Application to the Size Effect." *Journal of Financial Economics*, 12 (1983), pp. 387-404.

Brennan, M. "Capital Market Equilibrium with Divergent Borrowing and Lending Rates." *Journal of Financial and Quantitative Analysis*, 6 (1971), pp. 1197-1205.

——. "Agency and Asset Pricing." Working paper, University of California, 1993.

Brennan, M., X. Cheng, and F. Li. "Agency and Institutional Investment." *European Financial Management*, 18 (2012), pp. 1-27.

Campbell, J., and J. Cochrane. "By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior." *Journal of Political Economy*, 107 (1999), pp. 205-251.

Campbell, J., S. Giglio, C. Polk, and R. Turley. "An Intertemporal CAPM with Stochastic Volatility." SSRN Working Paper No. 2021846, 2012.

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

Chen, N., R. Roll, and S. Ross. "Economic Forces and the Stock Market." *Journal of Business*, 59 (1986), pp. 383-403.

Chevalier, J., and G. Ellison. "Risk Taking by Mutual Funds as a Response to Incentives." *Journal of Political Economy*, 105 (1997), pp. 1167-1200.

Clark, A., and A. Oswald. "Satisfaction and Comparison Income." *Journal of Public Economics*, 61 (1996), pp. 359-381.

Clarke, R., H. de Silva, and S. Thorley. "Know Your VMS Exposure." *The Journal of Portfolio Management*, 36 (2010), pp. 52-59.

De Giorgi, E., and T. Post. "Capital Market Equilibrium with Binding Portfolio Restrictions." SSRN Working Paper No. 1800229, 2011.

DeMarzo, P., R. Kaniel, and I. Kremer. "Diversification as a Public Good: Community Effects in Portfolio Choice." *Journal of Finance*, 59 (2004), pp. 1677-1715.

Derwall, J., J. Huij, and G. de Zwart. "The Short-Term Corporate Bond Anomaly." SSRN Working Paper No. 1101070, 2009.

Falkenstein, E. *Mutual Funds, Idiosyncratic Variance, and Asset Returns*. PhD thesis, Northwestern University, 1994.

——. "Preferences for Stock Characteristics as Revealed by Mutual Fund Portfolio Holdings." *Journal of Finance*, 51 (1996), pp. 111-135.

——. "Risk and Return in General: Theory and Evidence." SSRN Working Paper No. 1420356, 2009.

Fama, E., "Market Efficiency, Long-Term Returns, and Behavioral Finance." *Journal of Financial Economics*, 49 (1998), pp. 283-306.

Fama, E., and K. French. "The Cross-Section of Expected Stock Returns." *Journal of Finance*, 47 (1992), pp. 427-465.

——. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics*, 33 (1993), pp. 3-56.

——. "Multifactor Explanations of Asset Pricing Anomalies." *Journal of Finance*, 51 (1996), pp. 55-84.

Fama, E., and J. MacBeth. "Risk, Return and Equilibrium: Empirical Tests." *Journal of Political Economy*, 81 (1973), pp. 607-636.

Ferrer-i-Carbonell, A. "Income and Well-Being: An Empirical Analysis of the Comparison Income Effect." *Journal of Public Economics*, 89 (2005), pp. 997-1019.

Ferson, W., and R. Schadt. "Measuring Fund Strategy and Performance in Changing Economic Conditions." *Journal of Finance*, 51 (1996), pp. 425-461.

Fliessbach, K., B. Weber, P. Trautner, T. Dohmen, U. Sunde, C.E. Elger, and A. Falk. "Social Comparison Affects Reward-Related Brain Activity in the Human Ventral Striatum." *Science*, 318 (2007), pp. 1305-1308.

Frank, R. *The Darwin Economy: Liberty, Competition, and the Common Good*. Princeton, NJ: Princeton University Press, 2011.

Frazzini, A., and L.H. Pedersen. "Betting Against Beta." *Journal of Financial Economics*, 111 (2014), pp. 1-25.

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

Friend, L., and R. Westerfield. "Co-Skewness and Capital Asset Pricing." *Journal of Finance*, 35 (1980), pp. 897-913.

Gali, J. "Keeping Up with the Joneses: Consumption Externalities, Portfolio Choice, and Asset Prices." *Journal of Money, Credit and Banking*, 26 (1994), pp. 1-8.

Haidt, J. *The Happiness Hypothesis: Finding Modern Truth in Ancient Wisdom*. New York: Basic Books, 2006.

Harvey, C., and A. Siddique. "Autoregressive Conditional Skewness." *Journal of Financial and Quantitative Analysis*, 34 (1999), pp. 465-488.

Haugen, R., and N. Baker. "The Efficient Market Inefficiency of Capitalization-Weighted Stock Portfolios." *The Journal of Portfolio Management*, 17 (1991), pp. 35-40.

——. "Commonality in the Determinants of Expected Stock Returns." *Journal of Financial Economics*, 41 (1996), pp. 401-439.

——. "Case Closed." Chapter 23 in *The Handbook of Portfolio Construction: Contemporary Applications of Markowitz Techniques*, edited by John Guerard, Jr. New York: Springer, 2010.

Haugen, R., and A. Heins. "Risk and the Rate of Return on Financial Assets: Some Old Wine in New Bottles." *Journal of Financial and Quantitative Analysis*, 10 (1975), pp. 775-784.

Heaton, J., and D. Lucas. "Portfolio Choice and Asset Prices: The Importance of Entrepreneurial Risk." *Journal of Finance*, 55 (2000), pp. 1163-1198.

Hogan, W., and J. Warren. "Toward the Development of an Equilibrium Capital-Market Model Based on Semivariance." *Journal of Financial and Quantitative Analysis*, 9 (1974), pp. 1-11.

Hong, H., and D. Sraer. "Speculative Betas." NBER Working Paper No. 18548, 2012.

Hsu, J., H. Kudoh, and T. Yamada. "When Sell-Side Analysts Meet High-Volatility Stocks: An Alternative Explanation for the Low-Volatility Puzzle." SSRN Working Paper No. 2061824, 2012.

Ilmanen, A. "Do Financial Markets Reward Buying or Selling Insurance and Lottery Tickets?" *Financial Analysts Journal*, 68 (2012), pp. 26-36.

Ilmanen, A., R. Byrne, H. Gunasekera, and R. Minikin. "Which Risks Have Been Best Rewarded?" *The Journal of Portfolio Management*, 30 (2004), pp. 53-57.

Insel, T., and R. Fernald. "How the Brain Processes Social Information: Searching for the Social Brain." *Annual Review of Neuroscience*, 27 (2004), pp. 697-722.

Jacobs, K., and K. Wang. "Idiosyncratic Consumption Risk and the Cross Section of Asset Returns." *Journal of Finance*, 59 (2004), pp. 2211-2252.

Jagannathan, R., and Z. Wang. "The Conditional CAPM and the Cross-Section of Expected Returns." *Journal of Finance*, 51 (1996), pp. 3-53.

Jagannathan, R., and Y. Wang. "Lazy Investors, Discretionary Consumption, and the Cross-Section of Stock Returns." *The Journal of Finance*, 62 (2007), pp. 1623-1661.

Kahneman, D., and A. Tversky. "Prospect Theory: An Analysis of Decision under Risk." *Econometrica*, 47 (1979), pp. 263-291.

Kahneman, D., P. Slovic, and A. Tversky. *Judgment under Uncertainty: Heuristics and Biases.* New York: Cambridge University Press, 1982.

Karceski, J. "Returns-Chasing Behavior, Mutual Funds, and Beta's Death." *Journal of Financial and Quantitative Analysis*, 37 (2002), pp. 559-594.

Knight, J., L. Song, and R. Gunatilaka. "Subjective Well-Being and Its Determinants in Rural China." *China Economic Review*, 20 (2009), pp. 635-649.

Kozhemiakin, A. "The Risk Premium of Corporate Bonds." *The Journal of Portfolio Management*, 33 (2007), pp. 101-109.

Kraus, A., and R. Litzenberger. "Skewness Preference and the Valuation of Risk Assets." *Journal of Finance*, 31 (1976), pp. 1085-1099.

Kumar, A. "Who Gambles in the Stock Market?" *Journal of Finance*, 64 (2009), pp. 1889-1933.

Lakonishok, J., A. Shleifer, and R. Vishny. "Contrarian Investment, Extrapolation and Risk." *Journal of Finance*, 49 (1994), pp. 1541-1578.

Lettau, M., and S. Ludvigson. "Consumption, Aggregate Wealth, and Expected Stock Returns." *Journal of Finance*, 56 (2001), pp. 815-849.

Levy, H., and H. Markowitz. "Approximating Expected Utility by a Function of Mean and Variance." *American Economic Review*, 69 (1979), pp. 308-317.

Li, X., R. Sullivan, and L. Garcia-Feijóo. "The Limits to Arbitrage Revisited: The Low-Risk Anomaly." SSRN Working Paper No. 1738316, (2012). (Forthcoming in *Financial Analysts Journal*.)

Luttmer, E. "Neighbors as Negatives: Relative Earnings and Well-Being." *Quarterly Journal of Economics*, 120 (2005), pp. 963-1002.

Markowitz, H. *Portfolio Selection: Efficient Diversification of Investments.* New York: John R. Wiley and Sons, 1959.

Miffre, J. A. Fuertes, and A. Fernández-Pérez. "Commodity Futures Returns and Idiosyncratic Volatility." SSRN Working Paper No. 2120587, 2012.

Miller, E. "Risk, Uncertainty, and Divergence of Opinion." *Journal of Finance*, 32 (1977), pp. 1151-1168.

Pagel, M. *Wired for Culture: Origins of the Social Mind.* New York: W.W. Norton & Company, 2011.

Post, T., and P. van Vliet. "Downside Risk and Asset Pricing." *Journal of Banking and Finance*, 30 (2006), pp. 823-849.

Post, T., P. van Vliet, and H. Levy. "Risk Aversion and Skewness Preference." *Journal of Banking and Finance*, 32 (2008), pp. 1178-1187.

Rayo, L., and G. Becker. "Evolutionary Efficiency and Happiness." *Journal of Political Economy*, 115 (2007), pp. 302-337.

Rizzolatti, G., and L. Craighero. "The Mirror-Neuron System." *Annual Review of Neuroscience*, 27 (2004), pp. 169-192.

Roll, R. "A Mean/Variance Analysis of Tracking Error." *The Journal of Portfolio Management*, 18 (1992), pp. 13-22.

Roussanov, N. "Diversification and Its Discontents: Idiosyncratic and Entrepreneurial Risk in the Quest for Social Status." *Journal of Finance*, 65 (2010), pp. 1755-1788.

Sharpe, W. "Decentralized Investment Management." *Journal of Finance*, 36 (1981), pp. 217-234.

——. "The Arithmetic of Active Management." *Financial Analysts Journal*, 47 (1991), pp. 7-9.

Shefrin, H., and M. Statman. "Behavioral Portfolio Theory." *Journal of Financial and Quantitative Analysis*, 35 (2000), pp. 127-151.

Sirri, E., and P. Tufano. "Costly Search and Mutual Fund Flows." *Journal of Finance*, 53 (1998), pp. 1589-1622.

Starmer, C. "Developments in Non-Expected Utility Theory: The Hunt for a Descriptive Theory of Choice under Risk." *The Journal of Economic Literature*, 38 (2000), pp. 332-382.

Statman, M. "What Do Investors Want?" *The Journal of Portfolio Management*, 30 (2004), pp. 153-161.

Svenson, O. "Are We All Less Risky and More Skillful Than Our Fellow Drivers?" *Acta Psychologica*, 47 (1981), pp. 143-148.

Tversky, A., and D. Kahneman. "Extension versus Intuitive Reasoning: The Conjunction Fallacy in Probability Judgment." *Psychological Review*, 90 (1983), pp. 293-315.

——. "Advances in Prospect Theory: Cumulative Representation of Uncertainty." *Journal of Risk and Uncertainty*, 5 (1992), pp. 297-323.