Building on Finance Theory to Forge the Future of Investment Practice

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KEY FINDINGS

- Academic asset pricing theories are parsimonious and rely on unrealistic, neoclassical assumptions. Real-world financial markets are too complex, dynamic, and subject to behavioral biases to fit into such narrow confines.
- Successful implementation of theory in practice requires a thorough understanding of the assumptions and limitations of each theory and an effort to adapt and enhance research methodologies to better explain the real world.
- We discuss several cases that highlight our efforts to bridge the gap between theory and application: adopting smart alpha—an active, dynamic, multifactor approach to overcome the limitations of smart beta imposed by the standard factor models; incorporating investor aversion to leverage risk into modern portfolio theory; embracing enhanced active equity long–short strategies to improve portfolio efficiency; and simulating financial markets to better reflect market realities.

ABSTRACT

Academic asset pricing research has served as a foundational element in quantitative investing over the past several decades. However, its neoclassical assumptions and preference for parsimony have made academic research less useful when applied directly to complex, dynamic, and behavioral real-world markets. Successful investment practice requires a thorough grasp of the assumptions and limitations of each theory and involves adapting and enhancing research methodologies to better explain the real world. This article presents several examples of the authors' research that highlight efforts to bridge the gap between theory and application. An active, dynamic, multifactor approach called smart alpha will help overcome the limitations of smart beta imposed by the standard factor models by accounting for a wider range of factors and changing market conditions. Mean–variance analysis will not yield optimal portfolios for leverage-averse investors but mean–variance–leverage analysis will by accounting for investor aversion to leverage risk. Enhanced active equity long–short strategies provide improved efficient frontiers by relaxing the long-only constraint while maintaining full benchmark index exposure. Hence, these strategies improve portfolio efficiency compared to long-only portfolios. Continuous-time finance models are not useful for explaining the behavior of financial markets; asynchronous, discrete-time, dynamic simulations are. Despite the many challenges, building on finance theory to forge the future of investment practice continues to be an exciting and rewarding endeavor.

The prime time of modern finance theory is generally considered to be the period from the 1950s to the 1970s. During this prodigious era, several seminal theories and asset pricing models were developed that have had a lasting impact on the field. Key milestones include modern portfolio theory (MPT) (Markowitz 1952); the capital asset pricing model (CAPM) (Sharpe 1964); the efficient market hypothesis (EMH) (Fama 1970); option pricing models (Black and Scholes 1973; Merton 1973); and the arbitrage pricing theory (APT) (Ross 1976). In the neoclassical school of finance (Ross 2005), the pricing models generally assume that markets are informationally efficient, prices are rational, and they are at or near equilibrium. This is facilitated by the absence of restrictions on borrowing or lending, buying long or selling short, and by unlimited liquidity. The models are elegant and parsimonious. Investor behavior is not considered, and market anomalies are assumed not to exist.

While these theories are widely appreciated for their intellectual merit, they are idealized market paradigms that are not directly applicable to the imperfect world, influenced by investors' behavioral traits and biases. The theories represent, however, a formidable edifice to surmount. Nonetheless, investors must question their assumptions and limitations. Otherwise, it is not possible to adapt and enhance these groundbreaking ideas to bridge the gap between theory and practice. Successful investing requires grappling with complex, dynamic, real-world markets in which human behavioral traits and biases matter. We offer four examples of our research that emphasize the necessity of thoroughly understanding financial theories before putting them into practice: factor modeling in the debate on smart beta versus smart alpha, incorporating leverage risk into MPT, improved efficient frontiers of enhanced active equity long–short strategies, and simulating financial markets to better represent real-world markets.

FACTOR MODELS: SMART BETA VERSUS SMART ALPHA

Since the introduction of Markowitz's portfolio theory (1952), academic research has had a great impact on quantitative investment practice. A prominent and relatively recent example is research on asset-pricing factor models, including Fama and French's three- and five-factor models (1993, 2015), Carhart's four-factor model (1997), Hou, Xue, and Zhang's q-factor model (2015), and Daniel, Hirshleifer, and Sun's behavioral factor model (2020). The development of such factor models has greatly contributed to the emergence and growth of so-called factor investing and investment products like smart beta.[1]

Although smart beta's underlying factors were expected to deliver positive average excess returns relative to the aggregate market, many smart beta strategies, notably those based on the value factor, underperformed the market over the past 15 years.[2] This should not be surprising because factor models do not rule out the possibility that factors may perform poorly for extended periods, which calls for caution when applying academic research to investment practice (Jacobs, Levy, and Lee 2025). While academia provides theoretical and empirical foundations, successful investment practice involves adapting and enhancing research methodologies to explain the complex and dynamic real-world market. Naively relying on static academic factor models to outperform the market can be harmful to investors

[1] Smart beta has been one of the fastest-growing investment products over the last decade. According to data from ETFGI (2024), an independent research and consultancy firm, global assets invested in smart beta exchange-traded funds (ETFs) and exchange-traded products (ETPs) reached $1.67 trillion with a five-year annual growth rate of 22.5% by the end of June 2024.

[2] See, e.g., Riding (2019a, 2019b), Johnson (2020a, 2020b), McCann (2020), and Jacobs, Levy, and Lee (2025). For the performance over earlier periods, see Malkiel (2014), Jacobs (2015), and Glushkov (2016).

because of the models' parsimonious nature and the time-varying performance of factors, which we discuss below.

Parsimony versus Complexity

First, academic factor models, exemplified by the Fama–French three- and five-factor models, are parsimonious. They include only a limited number of factors (typically five or fewer) to explain and predict stock returns. While parsimony may be a virtue of a good academic model, the stock market is far too complex a system to understand with just a handful of factors (Jacobs and Levy 1989a).[3] The choice between parsimonious and complex models is closely tied to the bias-variance trade-off, which demonstrates that increasing model complexity can lead to higher predictive accuracy, but only up to a point (Hastie, Tibshirani, and Friedman 2001).[4] Beyond that, further complexity may decrease accuracy due to overfitting.[5] Achieving the optimal level of model complexity implies reaching a point at which a more complex model starts to capture from data more noise than signal (Gauch 2002). In essence, it means finding a balance between underfitting and overfitting the data.

While overfitting has been a major focus of debate in the era of big data and machine learning, underfitting has often been overlooked. Nonetheless, ample evidence on proliferation of factors (e.g., Jacobs and Levy 1988; Harvey, Liu, and Zhu 2016; and Green, Hand, and Zhang 2017) suggests that well-known factor models will underfit and have a large bias. In other words, factor models are not complex enough, so they will result in an oversimplification of the drivers of stock returns. Smart beta strategies are susceptible to the challenges of parsimonious factor models because they are typically built upon standard factor models with a limited number of factors. Smart beta strategies disregard many potential factors that could provide additional return opportunities while also allowing for greater diversification. As a result, they are prone to periods of poor performance by the chosen factor or factors.

In contrast, an active, dynamic, multifactor approach, known as smart alpha, can take fuller advantage of the market's multidimensionality by exploiting numerous fundamental and behavioral factors (Jacobs and Levy 2014b, 2014d). Smart alpha strategies can do so because they adopt a cross-sectional approach to factor modeling that disentangles the unique contributions of each of numerous factors to the pricing of individual stocks (Jacobs and Levy 1988), which we discuss later in comparison to the standard academic time-series approach to factor modeling.

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[3] See Chapter 8 of Gauch (2002) for further discussion of the principle of parsimony, which prefers the simplest model among those that fit data equally well.

[4] Bias refers to the difference between the average model prediction and the true value of the output. If a model has high bias, it is too simple to capture the relationship between the inputs and the output, resulting in underfitting. Variance refers to the variability of model prediction. If a model has high variance, it is too complex and fits too closely to in-sample data, and thus is not able to fit accurately to out-of-sample data, resulting in overfitting.

[5] Contrary to the principle of parsimony, Kelly, Malamud, and Zhou (2024) document that in a regime where the number of predictors exceeds the number of data observations, the accuracy of market-return prediction can continue to improve with more complex, nonlinear, machine learning models. Research suggests caution, however, when applying machine learning to investment management practice. For example, Israel, Kelly, and Moskowitz (2020) point out that stock return prediction is a less-than-ideal environment for machine learning. Although machine learning thrives in a big-data and high-signal-to-noise-ratio environment, stock return prediction has relatively limited data and low signal-to-noise ratio, which is further challenged by the adaptive and dynamic nature of the stock market. Another fundamental concern among investment managers is the lack of interpretability of machine learning models. Because machine learning models often operate as black boxes, we do not know how they make inferences. Bartram, Branke, and Motahari (2020) suggest that their lack of interpretability presents challenges for performance attribution systems, which are typically based on intuitive linear factor models, because the success of machine learning models mainly comes from less-intuitive nonlinearity.

Although striking a balance between parsimonious and complex models is easier said than done, evidence suggests the presence of many more factors than the limited number endorsed by well-known academic factor models.

Second, although factors proposed in academic factor models, such as small size and value, have historically delivered a positive return, on average, their return performance has varied over time. Some factors have underperformed for extended periods as market conditions changed (Jacobs, Levy, and Lee 2025).[6] Blitz (2020) showed that for the decade from 2010 to 2019, when each of the four Fama–French nonmarket factors had realized returns that were well below their long-term averages or negative, many factors that were not part of the Fama–French five-factor model delivered a positive return. These findings suggest that passively relying on a limited set of factors that performed well historically may disappoint investors for extended periods; instead, investors need to explore new factors and ones that may behave differently in changing market conditions to achieve greater consistency of performance.

Static versus Dynamic Design

Smart beta is typically a static strategy by design, regardless of whether it seeks exposure to a single factor or a few factors. It offers rules-based portfolio construction designed to provide exposure to targeted factors, with rebalancing at predetermined intervals. The rules are typically set out during the design phase of smart beta, rather than as part of the ongoing investment process. As a result, smart beta performance tends to be vulnerable to changing market conditions. Smart beta providers who claim that their strategies can beat the broad market with some consistency are overlooking the potential prolonged underperformance inherent in standard factor models. If investors mistakenly expect smart beta to deliver consistent returns over time, it could be because smart beta providers have not properly educated them about the strategy's inherent variability and risks.

In contrast, smart alpha is dynamic. It derives the time series of disentangled factor returns from a cross-sectional approach to factor modeling using regression. It then uses time-series analysis to forecast pure returns to each factor, while considering market and economic conditions (Jacobs and Levy 1989b). Smart alpha actively monitors factor performance as conditions change and makes adjustments to factor selection and factor exposures based on ongoing proprietary research.

Time-Series versus Cross-Sectional Methods

To highlight the edge of smart alpha over smart beta, we compare time-series versus cross-sectional methods of factor construction.[7] The time-series approach has been the popular method for constructing factor models (e.g., Fama and French 1993, 2015) and hence the factors underlying smart beta strategies. A time-series factor is constructed using a sorting routine based essentially on a single corresponding

[6] This evidence is consistent with the adaptive market hypothesis (Lo 2004, 2005), which, unlike the efficient market hypothesis, suggests that factor performance will vary with the market environment. Lo reasons that factor performance will depend on the cross-sectional distribution of preferences of investors at a given point in time. For example, if a significant fraction of investors prefers growth over value, value will underperform the broad market. To the contrary, as the number of growth-oriented investors decreases, say, due to retirements, the performance of value may improve. He suggests that investment managers need to adapt to changing market conditions to achieve a consistent level of expected returns.

[7] See Jacobs and Levy (2021) for a detailed comparison of factor models using cross-sectional factors and those using time-series factors.

characteristic.[8] In contrast, cross-sectional factors are estimated from cross-sectional analysis in which security returns for each period are regressed on multiple firm characteristics (e.g., Jacobs and Levy 1988; Lewellen 2015). The cross-sectional approach has not been widely adopted in academic factor models, as academia has favored parsimonious time-series models. But cross-sectional models can address one of the most fundamental issues in investment management—explaining and predicting returns for individual stocks.

Prior to the advent of the earliest Fama–French model, Jacobs and Levy (1988) developed a cross-sectional model that uses numerous factors to explain stock returns, taking into account their interrelationships. We used cross-sectional regressions at the individual stock level to disentangle multiple firm and stock characteristics, or factors, to estimate the pure returns to each factor. Disentangling can reveal which factors really matter; it provides the pure return to each factor, uncontaminated by the effects of other factors. By contrast, when a single firm characteristic is used in a sort or a univariate regression (i.e., a regression with a single independent variable), there is no disentangling across related characteristics; returns estimated from simple regressions are what we call naive returns. Jacobs and Levy (1988, 1989a) pioneered these insights and introduced the terms “disentangling” as well as “pure” and “naive” returns.

The cross-sectional approach to factor modeling overcomes the parsimonious and static nature of academic factor models. First, cross-sectional models can be extended to encompass a large number of characteristics associated with stock returns (Jacobs and Levy 1988, 2014d). This allows for the formation of a single multidimensional portfolio with simultaneous exposures to a large number of factors that can exploit more opportunities than a portfolio based on only one or a few targeted factors. Furthermore, a multidimensional portfolio can benefit from diversification across numerous factors.

Second, the use of cross-sectional factor returns allows for the construction of dynamic portfolios (Jacobs and Levy 2014b, 2021). As mentioned earlier, factor forecasts derived from cross-sectional regression can be conditioned on the market environment (Jacobs and Levy 1989b). These factor forecasts can be combined with the observed values of each firm’s characteristics to obtain the predicted return for each stock. Portfolios constructed from these return forecasts can adapt to varying market and economic conditions. In contrast, portfolios constructed using return forecasts from naive factors will ignore time-varying correlations among factors. Markowitz (2000) noted that the disentangling of multiple equity attributes improves estimates of expected return.[9] Lewellen (2015) reported that expected returns derived from cross-sectional regressions have strong predictive power for actual returns.

[8] For example, Fama and French (1993, 2015) sort stocks on the corresponding characteristic and firm size when constructing their value, profitability, and investment factors. For the size factor, they sort on size and book-to-market ratio. However, their two-way portfolio sorting controls for only one characteristic and does not optimally isolate one characteristic from another.

[9] Editor’s note: Nobel laureate Harry M. Markowitz referred to Jacobs and Levy (1988) as “seminal” in his forewords to two editions of their book *Equity Management* (Markowitz 2000, 2017). He also acknowledged the methodology, terminology, and insights of the article in other work (Markowitz and van Dijk 2006):

> “Before Jacobs and Levy (1988) anomaly studies considered small numbers of variables, usually one to three at a time. Observing that some apparent anomalies may be surrogates for others, Jacobs and Levy fit a series of monthly cross-sectional regressions of security excess returns against 25 anomaly and 38 industry variables. This allowed them to ‘disentangle’ what they called the ‘pure’ (i.e., underlying) anomalous effects from what they called the ‘naive’ effects observed from simple regressions against anomalous variables one at a time. The Jacobs and Levy methodology may be used for expected return estimation as well as for explaining observed anomalies.”

Additional Advantages of the Cross-Sectional Method

Cross-sectional factors have several additional advantages over time-series factors for investment management. First, Fama and French (2020) acknowledged that models using cross-sectional factors have higher explanatory power for the average returns of various anomaly portfolios than do models using time-series factors. This supports Jacobs and Levy's (1988) much earlier insight of disentangling returns cross-sectionally across factors.

Second, while time-series factors are constructed ad hoc, cross-sectional factors are optimally constructed. Consider the four nonmarket factors of the Fama–French five-factor model (2015).[10] Each of these time-series factors is constructed from sorts of stocks into portfolios based on the corresponding characteristic. As acknowledged by Fama and French (1993), the number of portfolio groups and the breakpoints chosen are arbitrary and ad hoc. Because Fama–French regressions use ad hoc factors as explanatory variables, the resulting time-series estimates of factor loadings are not optimal. In contrast, cross-sectional factors resulting from the regressions of returns on prespecified characteristics are optimal.

Third, each time-series factor sort unavoidably captures return effects from other factors, while the cross-sectional regression disentangles other return effects. For example, Fama and French (1993) constructed SMB and HML based on double sorts on size and value to control the correlation between the two characteristics. Unlike the regression method of least squares, however, portfolio sorts do not optimally disentangle the return effects from each factor. Jacobs and Levy (1988, 1989b) provided pure returns to each factor, avoiding the confounding influence of the other factors by disentangling returns across 25 factors, as well as 38 industry classifications, in a cross-sectional model.

Fourth, the cross-sectional approach is readily applicable to individual stocks, while the time-series approach is more widely used for portfolios. Investment practitioners are generally concerned with understanding and predicting the cross-sectional difference in expected returns of individual stocks. This feature of the cross-sectional approach also allows for time-varying firm characteristics. Firm characteristics evolve as a firm moves through the various stages of its life cycle. For example, a small company grows into a large company by becoming more profitable and successful; a growth stock turns into a value stock by transitioning to a low-growth stage. Cross-sectional models can capture the evolution of these characteristics for each individual firm with time-varying factor exposures, while factor exposures in standard factor models, which are estimated in a time-series regression, are stationary over a fixed period.

Smart Beta Has Often Failed to Live Up to Its Hype

The development of academic factor models based on the time-series approach has made a substantial contribution to the emergence and growth of smart beta products. Despite its rising popularity, smart beta investing has often failed to live up to its hype, suggesting that an investor needs to exercise caution when applying such academic research to the real-world stock market (Jacobs and Levy 2015). We have discussed two major features of academic factor models that may contribute to the potential underperformance of factor investing when such models are naively applied to investment practice. First, academic factor models lack sufficient complexity to explain and predict stock returns and, as a result, will underfit the data. Second, factors proposed in academic factor models may underperform for extended periods. Overcoming these

[10] Those four factors are: SMB, HML, RMW, and CMA. They represent differences between returns on diversified portfolios of small and big stocks, stocks with high and low book-to-market ratios, stocks with robust and weak operating profitability, and stocks with conservative and aggressive investments, respectively.

limitations requires steps toward an active, dynamic, multifactor, smart alpha approach. A cross-sectional approach to factor modeling facilitates smart alpha strategies by including numerous factors and allowing for the construction of dynamic portfolios.

INCORPORATING LEVERAGE RISK INTO MODERN PORTFOLIO THEORY

Our work on long–short portfolios led us to consider how leverage affects portfolio risk and investor preferences. To the extent that leverage increases a portfolio's volatility, mean–variance (MV) optimization, which is the formulation of Markowitz's MPT, captures increased risk associated with leverage. However, it fails to capture components of risk that are unique to using leverage. A portfolio with leverage differs in a fundamental way from one without leverage. A leveraged investor must take into account the risks and costs of margin calls, which can force borrowers to liquidate securities at adverse prices due to illiquidity, the possibility of losses exceeding the capital invested, and even bankruptcy.[11]

Kroll, Levy, and Markowitz (1984) assumed a proportional, or linear, increase in portfolio volatility with portfolio leverage. In the section "The Effect of Leverage," they state: "Leverage increases the risk of the portfolio. If the investor borrows part of the funds invested in the risky portfolio, then the fluctuations of the return on these leveraged portfolios will be proportionately greater."[12]

There was precedence in the literature for the linearity assumption. Hester (1967) simplified his efficient frontier calculations by assuming "investors believe that they will incur a margin call with probability zero," or alternatively, "the investor retains other assets which he may use to offset margin calls." Hester acknowledged this was the least palatable of his assumptions. He concluded that the "Markowitz efficient frontier portfolio locus is dominated by a locus which allows short sales and margin positions" (Hester 1967). Later, Pogue (1970) had the same finding regarding the efficient frontier in an extended Markowitz model that includes shorts and leverage as well as transaction costs and taxes. He, too, recognized the possibility of margin calls (Pogue 1970) in which the "borrower [has to] increase the equity status of his account." He also recognized that the provision of credit will depend on the creditor's risk aversion. In both articles, however, investor aversion to leverage risk was not modeled.

Implications of Leverage Risk

MV analysis will result in optimal unleveraged (long-only) portfolios for investors not able to tolerate any leverage. But, for investors who use leverage, MV analysis can result in "optimal" portfolios that are highly leveraged. This is because MV optimization implicitly assumes the investor has an infinite tolerance for the unique risks of leverage. In practice, however, investors *are* leverage averse. If offered a choice, they would prefer a portfolio having a particular expected return and variance *without* leverage to one that offers the same expected return and variance *with* leverage. The conventional MV utility function cannot distinguish between these two portfolios because it does not account for an important aspect of investors' behavior, namely, investors' aversion to the unique risks of leverage.

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[11] In extreme cases, the adverse consequences of leverage can impact the stability of markets, as in 2008, when the highly leveraged housing sector collapsed, taking down the debt instruments that supported it and precipitating a global financial crisis (Jacobs 2009).

[12] Note that linearity may hold under certain unrealistic conditions, such as unlimited capital availability, frictionless markets with continuous pricing, and costless liquidity which, in theory, could render margin calls of practical irrelevance.

Because investors are typically leverage averse, those who use leverage usually limit it. They often do so in a largely ad hoc manner, choosing a leverage level (often dependent on the risk of the underlying securities) and imposing it on the portfolio by means of a leverage constraint in the optimization process.[13] However, for an investor who is averse to leverage, using the conventional MV utility function and optimizing with a leverage constraint is unlikely to lead to the portfolio offering the highest utility. An investor can determine the portfolio that is optimal for a given level of constraint, but which level of constraint is optimal? Imposing a leverage constraint denies the investor the ability to balance the economic trade-offs between expected portfolio return, portfolio volatility risk, and portfolio leverage risk.

Adding a Third Dimension

In a series of articles (Jacobs and Levy 2012, 2013a, 2013b, 2014a, 2014c), we proposed adding to the MPT utility function a term that captures aversion to the unique risks of leverage.[14] Just as an investor averse to volatility risk will give up some expected return in exchange for a lower volatility, an investor averse to leverage risk will give up some expected return in exchange for less exposure to the unique risks of leverage.

In Markowitz's foreword (Markowitz 2000) to the first edition of our *Equity Management* (2000) book, he wrote: "By and large, I still believe, as I did in 1952, that mean–variance analysis can provide the 'right kind' of diversification for the 'right reason.' Diversification makes sense, and proper diversification depends on a consideration of covariances."

The mean–variance–leverage (MVL) model is an approach that allows investors to determine the "right amount" of portfolio leverage with the "right kind" of diversification, taking into account an investor's volatility aversion and aversion to the unique risks of leverage.[15] Further, use of an MVL model will provide optimal portfolios with more modest leverage levels than those based on the mean-variance model.

MVL Model versus MV Model

The MV model is a special case of the MVL model in two cases. As the investor's tolerance for the unique risks of leverage approaches zero, the investor has an infinite aversion to leverage, and the optimizer forces the portfolio's leverage level to zero. In this case, the MVL model reduces to the traditional long-only MV model. At the other extreme, as the investor's tolerance for the unique risks of leverage approaches infinity, the investor has no aversion to leverage. The leverage term in the MVL model is multiplied by zero leverage aversion, and that term drops out of the MVL utility function. Again, the MVL model reduces to the MV model; however, in this case, leverage is used.

The MV model, used with a portfolio constraint enforcing zero leverage, therefore implies that the investor has an infinite aversion to the unique risks of leverage, or zero leverage tolerance. The MV model, used without a leverage constraint, implies that the investor has zero aversion to the unique risks of leverage, or infinite leverage tolerance. Although we observe zero leverage tolerance in practice—some investors are averse to any borrowing—infinite leverage tolerance seems contrary to investor behavior because it can give rise to extreme levels of leverage in the absence of upper bounds on individual security holdings (Jacobs and Levy 2013a, 2014a).

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[13] Markowitz (1959) showed how to use individual security and portfolio constraints in MV optimization.

[14] Augmenting the MV paradigm is robust given its universality. See Benveniste, Kolm, and Ritter (2024).

[15] Edirisinghe, Chen, and Jeong (2023) extended MVL to include liquidity costs in their MVLL model.

Markowitz responded to our proposal for an MVL model, and, in particular, to our article "Leverage Aversion, Efficient Frontiers, and the Efficient Region" (Jacobs and Levy 2013a), with his own solution for optimization with leverage risk. In Markowitz (2013), he suggested extending the general MV portfolio selection model by including a measure of short-run volatility, as determined by a stochastic margin call model. We responded (Jacobs and Levy 2013b) that a stochastic margin call model has yet to be developed, whereas the MVL model is available for immediate use.[16]

Markowitz always believed that theories, including his own, are improved by incorporating the innovations of others. He provided a new foreword (Markowitz 2017) for the second edition of our *Equity Management* (2017) book, in which he wrote: "Some of the new sections include works on which Jacobs, Levy, and I collaborated—or, in the case of leverage aversion, debated—so, we have continued to build upon each other's research."

ENHANCED ACTIVE EQUITY LONG–SHORT STRATEGIES: IMPROVED EFFICIENT FRONTIERS

We applied the MVL utility function to a leveraged long–short portfolio, which allowed us to examine the effects of different levels of leverage tolerance on portfolio choice. We had previously examined the optimality of long–short strategies. In Jacobs, Levy, and Starer (1998), we said, "The important question is not how one should allocate capital between a long-only portfolio and a long–short portfolio, but rather how one should blend active positions (long and short) with a benchmark security in an integrated optimization." Jacobs, Levy, and Starer (1999) showed that a theoretically optimal portfolio would be constructed in a single, integrated optimization that considers the expected returns, risks, and correlations of all securities and any benchmark simultaneously. Our research also examined the conditions under which an optimal long–short portfolio would be naturally dollar or beta neutral.

Optimization with Short Positions

We also considered efficient ways to compute optimal portfolios that included short positions. We developed theorems regarding the conditions under which standard optimization algorithms could be applied to the long–short problem (Jacobs, Levy, and Markowitz 2005) and the concept of "trimability" (Jacobs, Levy, and Markowitz 2006). Trimability is a sufficient condition under which a fast portfolio optimization algorithm designed for long-only portfolios will find the correct long–short portfolio, even if the algorithm's use would violate certain assumptions made in the formulation of the long-only problem.[17]

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[16] Jason Zweig (2012) of the *Wall Street Journal* quotes Jacobs and Markowitz:

> "Conventional portfolio theory says not to hold all your eggs in one basket," says Mr. Jacobs. What that misses, he adds, is that "using leverage is like piling baskets of eggs on top of one another until the pile becomes unsteady." Borrowed money can make an optimally diversified—and theoretically "safe"—portfolio risky.
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> Prof. Markowitz agrees. If you're a diversified investor who can afford to be patient, you should worry primarily about how you'll do on average in the long run, he says.
>
> "But if you're leveraged, then you can get wiped out before the long run comes," he says. "Keeping that in mind as you diversify," he adds, is "very important."

[17] The mathematical specifics of this condition are described in detail in Jacobs, Levy, and Markowitz (2005).

Conceptually, if we are able to transform a feasible portfolio that is untrim (i.e., one that has at least one security in which it has simultaneous long and short positions) into a feasible portfolio that is trim in a way that does not reduce the portfolio's expected return, the "trimability condition" is satisfied. Such a portfolio is called "trimable." Importantly, we can apply existing fast portfolio optimization algorithms to trimable long–short portfolio models.

Optimization with Investor Leverage Aversion

We applied the MVL utility function to an enhanced active equity (EAE) long–short portfolio structure. Jacobs, Levy, and Starer (1998) provided the theoretical underpinnings for EAE portfolios. In these types of portfolios, the long-only constraint is relaxed so that the manager can sell stocks short up to some prespecified percentage of capital (e.g., 30%) and use the proceeds of the short sales to buy additional long positions.[18] The overall portfolio thus has 130% of its capital long and 30% short. Overall, it maintains a 100% net exposure to the chosen benchmark index. This is a 130–30 long–short portfolio.[19]

For expository purposes, we assume the 130–30 portfolio is self-financing and entails no financing costs. While MV optimization is a quadratic mathematical problem, MVL optimization is a quartic problem. Our solution method to maximize the MVL utility function was to use fixed-point iteration that applied a quadratic solver iteratively (Jacobs and Levy 2013b).

Using data for stocks in the S&P 100 Index over the two years ending September 30, 2011, and the estimation procedures described in Jacobs and Levy (2012), we derived optimal portfolios given a range of leverage and volatility tolerances.[20] Exhibit 1 illustrates, with familiar two-dimensional efficient frontiers, how consideration of leverage aversion can affect the investor's choice of the optimal portfolio. The frontier portfolios are constrained by a 10% active security weight constraint.[21] The zero-leverage-tolerance curve represents an investor unwilling to use leverage, that is, an investor who prefers long-only portfolios. As Exhibit 1 shows, increasing leverage tolerance allows higher efficient frontiers; hence, improved portfolio efficiency compared to long-only portfolios.

Consider the three portfolios labeled A, B, and C. Portfolio A is optimal for an investor with a leverage tolerance of 1 and a volatility tolerance of 0.24. This is a 125–25 long–short portfolio with a standard deviation of active return of 5% and

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[18] Long-only portfolios are constrained in their ability to underweight securities by more than the securities' benchmark weights. See Jacobs and Levy (2006, 2007b).

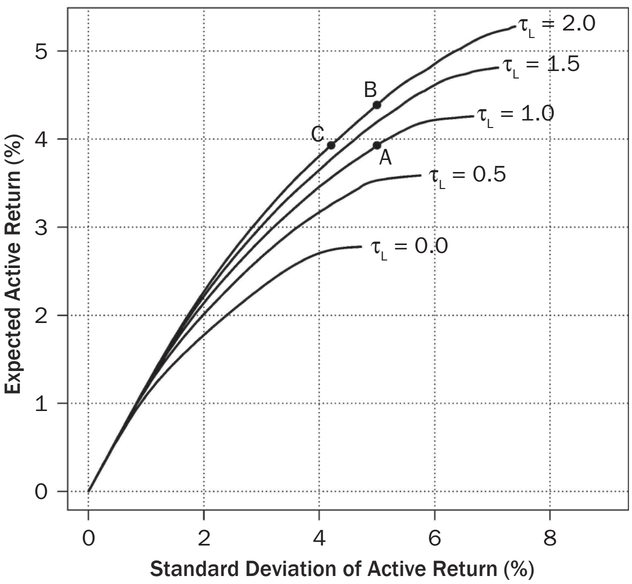
[19] Jacobs and Levy (2007a) applied the concept of trimability to illustrate the relationship between equitized market neutral long–short (ELS) portfolios and enhanced active equity (EAE) portfolios, such as 130-30 portfolios, and to show specifically that every ELS portfolio has an equivalent EAE portfolio, and vice versa. An ELS portfolio also has a 100% exposure to the market, achieved with stock index futures or exchange-traded funds (ETFs), and it has a long–short component that may have 100% of capital long and 100% of capital short. The EAE portfolio is essentially a compact form of the ELS portfolio. If the ELS portfolio contains short positions in stocks that are held in the equitizing instrument (i.e., in the underlying index of the stock index future, or in the ETF), then the ELS portfolio is untrim. While the ELS portfolio may not be trimable in practice because individual securities in the equitizing instrument cannot be sold to remove overlaps, there is a unique EAE portfolio that is functionally identical to, but more compact than, the untrimmed ELS portfolio. For transaction cost differences between ELS and EAE portfolios, see Jacobs and Levy (2007a).

[20] We estimated the variance of the portfolio's total return based on historical data in the same way that we estimated the variance of the portfolio's active return. The investor, in practice, could estimate these variances on a forward-looking basis, taking into account security position sizes relative to the market and the expected market impact upon liquidation. Note that leverage increases portfolio illiquidity. Leverage and illiquidity are different, however, because illiquid portfolios without any leverage are not exposed to margin calls and cannot lose more than the capital invested.

[21] Because different security active weight constraints become binding as one moves along each of the constant leverage-tolerance frontiers, a curve connecting the endpoints would not be smooth.

EXHIBIT 1

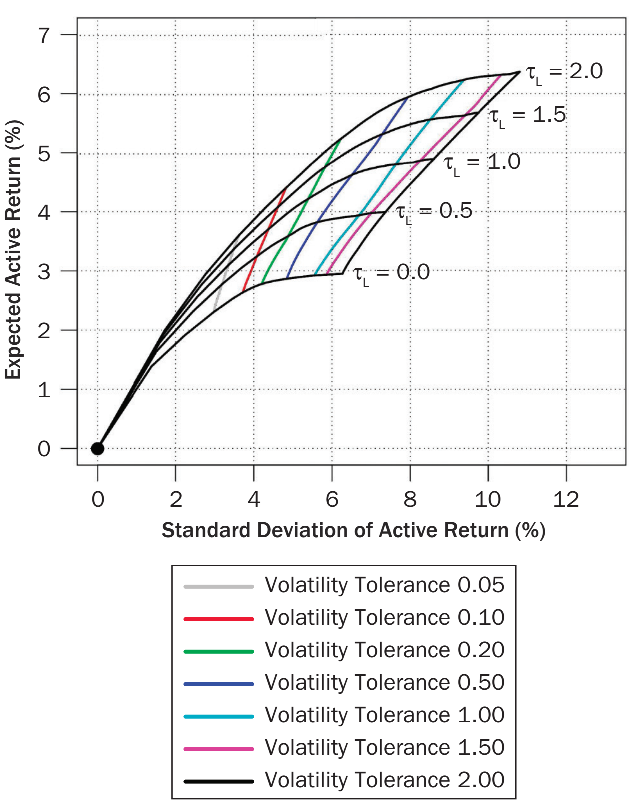
Efficient Frontiers for Various Leverage Tolerance (τ_L) Cases



SOURCE: Jacobs and Levy (2013a).

EXHIBIT 2

Efficient Frontiers for Various Leverage (τ_L) and Volatility (τ_V) Tolerance Cases with No Security Active Weight Constraint



SOURCE: Jacobs and Levy (2013a).

an expected active return of 3.93%. Of note, this investor prefers Portfolio A to Portfolio B, which has a higher expected return and the same volatility, and also to Portfolio C, which has a lower volatility and the same expected return. Portfolios B and C are preferred by investors having a leverage tolerance of 2. Both Portfolio B (139-39) and Portfolio C (135-35) have too much leverage risk for the investor with a leverage tolerance of 1 who prefers Portfolio A.

Exhibit 2 illustrates the efficient frontiers without the active weight constraints for various levels of investor leverage tolerance and for various levels of investor volatility tolerance. Every leverage-tolerance level has a corresponding two-dimensional MV efficient frontier. Similarly, for a particular level of volatility tolerance, there is a corresponding two-dimensional MV efficient frontier. Because Exhibit 2 assumes no constraint on the security active weights, the curves linking the optimal portfolios at each level of leverage tolerance are smooth (unlike in Exhibit 1).

Furthermore, without the security active weight constraints, both the standard deviation of active return and the expected active return ranges are higher than in Exhibit 1. As either volatility tolerance or leverage tolerance declines from 2, the frontiers shift to the left and downward. When volatility tolerance is zero, the optimal portfolio—an index fund—lies at the origin. Depending on an investor's leverage and volatility tolerances, the optimal portfolio will lie somewhere in the MVL *efficient region* shown. The critical roles of both leverage and volatility tolerance in portfolio selection are apparent.

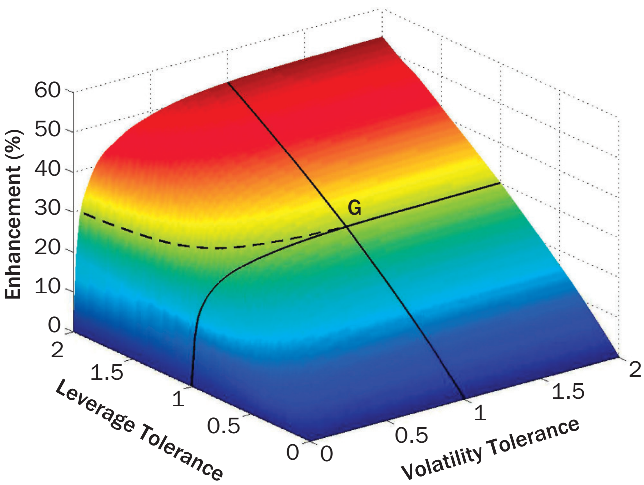
Exhibit 3 shows the optimal amount of leverage, called here the "enhancement." It shows that MVL optimization provides a three-dimensional "efficient surface" as a function of the investor's volatility tolerance and leverage tolerance. Here, for an investor with a volatility tolerance of 1 and a leverage tolerance of 1, the optimal portfolio enhancement, at point G, is about 30% for a 130–30 long–short portfolio. For investors with greater (lesser) tolerances, the optimal portfolio enhancement will be greater (lesser).

SIMULATING FINANCIAL MARKETS TO REPRESENT REAL-WORLD MARKETS

With Markowitz, we designed and built a simulator that could explain the behavior of financial markets better than existing models. Many market models use continuous-time methods, such as those used in the Black–Scholes–Merton option pricing model. These models rely on certain simplifying assumptions—for

EXHIBIT 3

MVL Efficient Surface



SOURCE: Jacobs and Levy (2014a).

example, that the underlying security price process is fixed and that prices change randomly and continuously over time. The models may be useful because they can often be solved analytically. They are not useful, however, when investment actions or changes in the underlying environment alter the price process. Nor can they tell us whether theories about the behavior of investors explain the observed phenomena of the market.

Dynamic Market Simulation

We developed a market simulator, the Jacobs–Levy–Markowitz market simulator (JLMSim), which has the potential to address these problems. JLMSim is an asynchronous, discrete-time, dynamic market simulator whose objective is to model the evolution of market prices and trading volumes over time. It assumes that price changes reflect events, which can unfold in an irregular fashion. The price process of securities is not fixed, but rather is the result of simulated market participants trading with one another to maximize their individual utility functions as conditions change and as random money flows occur into or out of the market. JLMSim allows users to model financial markets using their own inputs about the numbers and types of investors, traders, securities, and other entities that would have a bearing on markets in the real world.

Asynchronous models such as that used in JLMSim may also be better than continuous-time models for analyzing whether micro theories about investor behavior can explain market macrophenomena. From time to time, the market manifests liquidity black holes, which seem to defy rational investor behavior. One extreme case was the stock market crash on October 19, 1987, when option-replication portfolio insurers engaged in an avalanche of selling (Jacobs 1998, 1999, 2004, 2018). When prices fell precipitously and discontinuously on that day, rational value investors could have stepped in to pick up bargain stocks, but few did. Asynchronous models could explain both the abundance of sellers and the dearth of buyers. Our experiments with JLMSim showed that a relatively small proportion of momentum investors can destabilize markets, overwhelming value investors. Similarly explosive behavior, such as flash crashes that have occurred in real markets, can result when traders do not anchor their bid or offer prices to existing market prices. Our belief is that an asynchronous-time market simulator—such as JLMSim, capable of modeling the agents and market mechanisms behind observed prices—is much better than continuous-time models at representing the reality of markets.

We have described JLMSim running in its dynamic analysis (DA) mode to simulate market behavior. More details about JLMSim running in the DA mode are given in Jacobs, Levy, and Markowitz (2004, 2010). Now we turn to capital markets equilibrium simulation.

Capital Market Equilibrium Simulation

JLMSim can also operate in what we call capital market equilibrium (CME) mode to seek equilibrium expected returns. Black and Litterman (1992) suggested a “reverse optimization” procedure to find equilibrium expected security returns that are consistent with a given covariance matrix and a specified market portfolio.

The Black–Litterman (BL) procedure operates under the CAPM assumptions that investors can borrow all they want at the risk-free rate and that portfolios are constrained only by budget.

The BL procedure for estimating expected returns has the following inputs: a covariance matrix; the market weights of each security; views about expected returns for some, all, or none of the securities; and a parameter that serves to anchor the general level of expected returns. If the user supplies no views, the BL procedure produces CME expected return estimates that would clear the market.

Under the BL procedure, investors are essentially unconstrained and can borrow without limit at the risk-free rate. Under these assumptions, the Tobin (1958) separation theorem applies, and all investor portfolios lie on the straight capital market line (CML). Portfolios on the CML consist of various combinations of the riskless security and the *same* market portfolio of risky securities.

In reality, contrary to the assumptions of the BL procedure, investors are constrained and cannot borrow without limit at the risk-free rate. Thus, investor portfolios do not all lie on the CML. Instead, they lie on the curved efficient frontier at positions determined by investor risk tolerances, and the compositions of the portfolios of risky securities differ from investor to investor. In such cases, the market portfolio may not even be efficient (see Markowitz 2005).

In CME mode, JLMSim seeks CME expected returns for markets in which the CAPM assumptions do not necessarily hold. It allows users to solve for expected returns for markets in which investors cannot borrow, or have restricted borrowing, and in which investors can or cannot short. In other words, it can be used to seek CME returns for any of the large variety of markets that can be simulated by JLMSim. Naturally, not all such markets are consistent with equilibrium solutions.

CME returns are found by adjusting securities' expected returns, thereby causing investors to change their portfolios in such a way that the aggregate of all investors' portfolios converges to given (or target) market portfolio weights. Generally, if the weight of a security in the current market portfolio is above a given target weight, the simulator lowers the security's estimated expected return. If the current market weight is below the target weight, the simulator raises the security's estimated return.

To create a realistic representation of market participants' holdings when running JLMSim in CME mode, the user can provide several investor templates that would place representative portfolios on various parts of the efficient frontier and not just on the CML. With such placement, the BL assumptions are no longer satisfied. Therefore, the BL procedure would not provide correct equilibrium expected returns.

In contrast, JLMSim does provide correct results under these circumstances. The estimated equilibrium expected returns at the end of a CME run are the returns that are consistent with the given market portfolio and given covariance matrix. Furthermore, they are consistent with realistic assumptions regarding limits on investors' ability to borrow. Specific examples are provided in Jacobs, Levy, and Markowitz (2010).

Asynchronous Discrete Event Simulation

Markowitz, in his foreword to Guerard (2010), distinguished between the Jacobs–Levy–Markowitz asynchronous discrete event simulation, the Sharpe single-period model, and the Merton continuous-time models:

> Sharpe (1964) and Lintner (1965) present an "equilibrium" model. They say that, given certain assumptions, "in equilibrium" such-and-such will be true. Their model may be interpreted as a single-period or a static steady-state model. On the other hand, Merton (1990) and his many follow-

> ers present continuous-time models in which price is assumed to follow one or another stochastic process, assumed a priori. In contrast to both these types of models—the static and the continuous-time dynamic—the model presented by Jacobs, Levy, and Markowitz (2004, 2010) is an asynchronous discrete event simulation in which time advances, usually in irregular jumps, to the next most imminent event. Prices are endogenous, resulting from the interaction of thousands of investors and their traders following various investment and trading rules. (p. E1)

We hope that over time and with input from the finance community, JLMSim will develop into a simulator that researchers can use to create realistic dynamic models of the market. Potentially, these models could help to test the effects on securities' prices of real-world events such as changes in investment strategy or regulatory policy. Other examples may include examining the effects on markets of various levels of passive portfolio management or leverage, investigating the impact of institutional structures (such as minimum tick sizes or the use of crossing networks), or statutory and regulatory policies (including, e.g., capital gains taxation and circuit breakers). JLMSim can already be used to compute CME under fairly realistic constraints that would make the same problem analytically intractable.[22]

CONCLUSION

Academic research on asset pricing has often been reliant on a neoclassical view of financial markets and asset prices. Asset pricing theories and models typically ignore much of reality; they are usually developed based on a set of unrealistic assumptions (e.g., rational investors and no market frictions), resulting in rational prices. Models tend to be overly simplistic with few factors. Real-world markets are far too complex to fit neatly into such narrow confines. Successful implementations of investment practice require a thorough understanding of the assumptions and limitations of each theory and an ability to bridge the gap between theory and application.

We presented several examples of our research that demonstrate the challenges of applying finance theory to investment practice. First, academic factor models are parsimonious, while markets are complex and behavioral. Since smart beta originates from standard factor models with a few, generic, well-known factors, it was inevitable that it would produce poor returns for extended periods. Smart alpha, with its active, dynamic, multifactor approach, is an alternative that accounts for a wider range of factors and changing market conditions. Second, leverage entails a unique set of risks, including margin calls and bankruptcy. MPT fails to account for these unique risks, thus traditional MV analysis will not result in optimal portfolios for leverage-averse investors. Our MVL model extended MPT to account for investor aversion to leverage risk. Third, enhanced active equity long–short strategies provide improved efficient frontiers by relaxing the long-only constraint, while maintaining full benchmark index exposure. Hence, these strategies improve portfolio efficiency compared to long-only portfolios. Fourth, continuous-time finance has been a widely adopted method for asset pricing because of its analytical tractability. But continuous-time models are not equipped to represent markets in which investor behavior plays a large role in pricing securities. Asynchronous, discrete-time, dynamic simulation is a viable alternative.

[22] Those interested in finding out more about JLMSim, or experimenting with it, can download it from https://jlem.com/research#/market-simulation/5,/selection/1. Since we made it available, the simulator has been used by researchers in more than 70 countries.

The field of investment management has benefited from ties between academia and industry over the past several decades, fostering collaboration and innovation. MPT laid the foundation for portfolio optimization and has significantly influenced the rise of quantitative investing. The Black–Scholes–Merton option pricing model led to the dramatic growth of options trading. Factor models provided the foundations for the creation and growth of smart beta products. Research in anomalies using a cross-sectional approach has demonstrated promise and has led to the development of strategies that focus on firm and stock characteristics and investor behavior.

These collaborations show that academic research can be a building block. However, when faced with the imperfections of the real world, following academic research blindly can do more harm than good, as demonstrated by the role of portfolio insurance in the crash of 1987 and the underperformance of many smart beta strategies. Investment managers utilizing academic research need to clearly understand its underlying limitations, modify models to strike the right balance between simplicity and complexity, and adapt strategies to changing economic and market conditions.

As we celebrate the 50th anniversary of *The Journal of Portfolio Management*, we recognize the Journal for fostering the academic–industry dialogue and thereby promoting useful research that directly addresses problems faced by practitioners. Despite the many challenges, building on finance theory to forge the future will continue to be an exciting and rewarding endeavor.

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