CHAPTER 1

Introduction

An economy can be regarded as a *machine* that takes in input labor and natural resources and outputs products and services. Studying this machine from a physical point of view would be very difficult because we should study the characteristics and the interrelationships among all modern engineering and production processes. Economics takes a bird's-eye view of these processes and attempts to study the dynamics of the economic value associated with the structure of the economy and its inputs and outputs. Economics is by nature a quantitative science, though it is difficult to find simple rules that link economic quantities.

In most economies value is presently obtained through a market process where supply meets demand. Here is where finance and financial markets come into play. They provide the tools to optimize the allocation of resources through time and space and to manage risk. Finance is by nature quantitative like economics but it is subject to a large level of risk. It is the measurement of risk and the implementation of decision-making processes based on risk that makes finance a quantitative science and not simply accounting.

Equity investing is one of the most fundamental processes of finance. Equity investing allows allocating the savings of the households to investments in the productive activities of an economy. This investment process is a fundamental economic enabler: without equity investment it would be very difficult for an economy to properly function and grow. With the diffusion of affordable fast computers and with progress made in understanding financial processes, financial modeling has become a determinant of investment decision-making processes. Despite the growing diffusion of financial modeling, objections to its use are often raised.

In the second half of the 1990s, there was so much skepticism about quantitative equity investing that David Leinweber, a pioneer in applying advanced techniques borrowed from the world of physics to fund management, and author of *Nerds on Wall Street*,[1] wrote an article entitled: "Is

[1]David Leinweber, *Nerds on Wall Street: Math, Machines, and Wired Markets* (Hoboken, NJ: John Wiley & Sons, 2009).

quantitative investment dead?"[2] In the article, Leinweber defended quantitative fund management and maintained that in an era of ever faster computers and ever larger databases, quantitative investment was here to stay. The skepticism toward quantitative fund management, provoked by the failure of some high-profile quantitative funds at that time, was related to the fact that investment professionals felt that capturing market inefficiencies could best be done by exercising human judgment.

Despite mainstream academic opinion that held that markets are efficient and unpredictable, the asset managers' job is to capture market inefficiencies and translate them into enhanced returns for their clients. At the academic level, the notion of efficient markets has been progressively relaxed. Empirical evidence led to the acceptance of the notion that financial markets are somewhat predictable and that systematic market inefficiencies can be detected. There has been a growing body of evidence that there are market anomalies that can be systematically exploited to earn excess profits after considering risk and transaction costs.[3] In the face of this evidence, Andrew Lo proposed replacing the efficient market hypothesis with the *adaptive market hypothesis* as market inefficiencies appear as the market adapts to changes in a competitive environment.

In this scenario, a quantitative equity investment management process is characterized by the use of computerized rules as the primary source of decisions. In a quantitative process, human intervention is limited to a control function that intervenes only exceptionally to modify decisions made by computers. We can say that a quantitative process is a process that quantifies things. The notion of quantifying things is central to any modern science, including the dismal science of economics. Note that everything related to accounting—balance sheet/income statement data, and even accounting at the national level—is by nature quantitative. So, in a narrow sense, finance has always been quantitative. The novelty is that we are now quantifying things that are not directly observed, such as risk, or things that are not quantitative per se, such as market sentiment and that we seek simple rules to link these quantities

In this book we explain techniques for quantitative equity investing. Our purpose in this chapter is threefold. First, we discuss the relationship between mathematics and equity investing and look at the objections raised. We attempt to show that most objections are misplaced. Second, we discuss the results of three studies based on surveys and interviews of major market

[2]David Leinweber, "Is Quantitative Investing Dead?" *Pensions & Investments*, February 8, 1999.

[3]For a modern presentation of the status of market efficiency, see M. Hashem Pesaran, "Market Efficiency Today," Working Paper 05.41, 2005 (Institute of Economic Policy Research).

participants whose objective was to quantitative equity portfolio management and their implications for equity portfolio managers. The results of these three studies are helpful in understanding the current state of quantitative equity investing, trends, challenges, and implementation issues. Third, we discuss the challenges ahead for quantitative equity investing.

IN PRAISE OF MATHEMATICAL FINANCE

Is the use of mathematics to describe and predict financial and economic phenomena appropriate? The question was first raised at the end of the nineteenth century when Vilfredo Pareto and Leon Walras made an initial attempt to formalize economics. Since then, financial economic theorists have been divided into two camps: those who believe that economics is a science and can thus be described by mathematics and those who believe that economic phenomena are intrinsically different from physical phenomena which can be described by mathematics.

In a tribute to Paul Samuelson, Robert Merton wrote:

> Although most would agree that finance, micro investment theory and much of the economics of uncertainty are within the sphere of modern financial economics, the boundaries of this sphere, like those of other specialties, are both permeable and flexible. It is enough to say here that the core of the subject is the study of the individual behavior of households in the intertemporal allocation of their resources in an environment of uncertainty and of the role of economic organizations in facilitating these allocations. It is the complexity of the interaction of time and uncertainty that provides intrinsic excitement to study of the subject, and, indeed, the mathematics of financial economics contains some of the most interesting applications of probability and optimization theory. Yet, for all its seemingly obtrusive mathematical complexity, the research has had a direct and significant influence on practice[4]

The three principal objections to treating finance economic theory as a mathematical science we will discuss are that (1) financial markets are driven by unpredictable unique events and, consequently, attempts to use mathematics to describe and predict financial phenomena are futile, (2) financial phenomena are driven by forces and events that cannot be quantified, though we can use intuition and judgment to form a meaningful finan-

[4] Robert C. Merton, "Paul Samuelson and Financial Economics," *American Economist* 50, no. 2 (Fall 2006), pp. 262–300.

cial discourse, and (3) although we can indeed quantify financial phenomena, we cannot predict or even describe financial phenomena with realistic mathematical expressions and/or computational procedures because the laws themselves change continuously.

A key criticism to the application of mathematics to financial economics is the role of uncertainty. As there are unpredictable events with a potentially major impact on the economy, it is claimed that financial economics cannot be formalized as a mathematical methodology with predictive power. In a nutshell, the answer is that black swans exist not only in financial markets but also in the physical sciences. But no one questions the use of mathematics in the physical sciences because there are major events that we cannot predict. The same should hold true for finance. Mathematics can be used to understand financial markets and help to avoid catastrophic events.[5] However, it is not necessarily true that science and mathematics will enable unlimited profitable speculation. Science will allow one to discriminate between rational predictable systems and highly risky unpredictable systems.

There are reasons to believe that financial economic laws must include some fundamental uncertainty. The argument is, on a more general level, the same used to show that there cannot be arbitrage opportunities in financial markets. Consider that economic agents are intelligent agents who can use scientific knowledge to make forecasts.

Were financial economic laws deterministic, agents could make (and act on) deterministic forecasts. But this would imply a perfect consensus between agents to ensure that there is no contradiction between forecasts and the actions determined by the same forecasts. For example, all investment opportunities should have exactly identical payoffs. Only a perfectly and completely planned economy can be deterministic; any other economy must include an element of uncertainty.

In finance, the mathematical handling of uncertainty is based on probabilities learned from data. In finance, we have only one sample of small size and cannot run tests. Having only one sample, the only rigorous way to apply statistical models is to invoke ergodicity. An ergodic process is a stationary process where the limit of time averages is equal to time-invariant ensemble averages. Note that in financial modeling it is not necessary that economic quantities themselves form ergodic processes, only that residuals after modeling form an ergodic process. In practice, we would like the models to extract all meaningful information and leave a sequence of white noise residuals.

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[5]This is what Nassim Taleb refers to as "black swans" in his critique of financial models in his book *The Black Swan: The Impact of the Highly Improbable* (New York: Random House, 2007).

If we could produce models that generate white noise residuals over extended periods of time, we would interpret uncertainty as probability and probability as relative frequency. However, we cannot produce such models because we do not have a firm theory known a priori. Our models are a combination of theoretical considerations, estimation, and learning; they are adaptive structures that need to be continuously updated and modified.

Uncertainty in forecasts is due not only to the probabilistic uncertainty inherent in stochastic models but also to the possibility that the models themselves are misspecified. Model uncertainty cannot be measured with the usual concept of probability because this uncertainty itself is due to unpredictable changes. Ultimately, the case for mathematical financial economics hinges on our ability to create models that maintain their descriptive and predictive power even if there are sudden unpredictable changes in financial markets. It is not the large unpredictable events that are the challenge to mathematical financial economics, but our ability to create models able to recognize these events.

This situation is not confined to financial economics. It is now recognized that there are physical systems that are totally unpredictable. These systems can be human artifacts or natural systems. With the development of nonlinear dynamics, it has been demonstrated that we can build artifacts whose behavior is unpredictable. There are examples of unpredictable artifacts of practical importance. Turbulence, for example, is a chaotic phenomenon. The behavior of an airplane can become unpredictable under turbulence. There are many natural phenomena from genetic mutations to tsunami and earthquakes whose development is highly nonlinear and cannot be individually predicted. But we do not reject mathematics in the physical sciences because there are events that cannot be predicted. On the contrary, we use mathematics to understand where we can find regions of dangerous unpredictability. We do not knowingly fly an airplane in extreme turbulence and we refrain from building dangerous structures that exhibit catastrophic behavior. Principles of safe design are part of sound engineering.

Financial markets are no exception. Financial markets are designed artifacts: we can make them more or less unpredictable. We can use mathematics to understand the conditions that make financial markets subject to nonlinear behavior with possibly catastrophic consequences. We can improve our knowledge of what variables we need to control in order to avoid entering chaotic regions.

It is therefore not reasonable to object that mathematics cannot be used in finance because there are unpredictable events with major consequences. It is true that there are unpredictable financial markets where we cannot use mathematics except to recognize that these markets are unpredictable. But we can use mathematics to make financial markets safer and more stable.[6]

Let us now turn to the objection that we cannot use mathematics in finance because the financial discourse is inherently qualitative and cannot be formalized in mathematical expressions. For example, it is objected that qualitative elements such as the quality of management or the culture of a firm are important considerations that cannot be formalized in mathematical expressions.

A partial acceptance of this point of view has led to the development of techniques to combine human judgment with models. These techniques range from simply counting analysts' opinions to sophisticated Bayesian methods that incorporate qualitative judgment into mathematical models. These hybrid methodologies link models based on data with human overlays.

Is there any irreducibly judgmental process in finance? Consider that in finance, all data important for decision-making are quantitative or can be expressed in terms of logical relationships. Prices, profits, and losses are quantitative, as are corporate balance-sheet data. Links between companies and markets can be described through logical structures. Starting from these data we can construct theoretical terms such as volatility. Are there hidden elements that cannot be quantified or described logically?

Ultimately, in finance, the belief in hidden elements that cannot be either quantified or logically described is related to the fact that economic agents are human agents with a decision-making process. The operational point of view of Samuelson has been replaced by the neoclassical economics view that, apparently, places the accent on agents' decision-making. It is curious that the agent of neoclassical economics is not a realistic human agent but a mathematical optimizer described by a utility function.

Do we need anything that cannot be quantified or expressed in logical terms? At this stage of science, we can say the answer is a qualified no, if we consider markets in the aggregate. Human behavior is predictable in the aggregate and with statistical methods. Interaction between individuals, at least at the level of economic exchange, can be described with logical tools. We have developed many mathematical tools that allow us to describe critical points of aggregation that might lead to those situations of unpredictability described by complex systems theory.

We can conclude that the objection of hidden qualitative variables should be rejected. If we work at the aggregate level and admit uncertainty,

[6]A complex system theorist could object that there is a fundamental uncertainty as regards the decisions that we will make: Will we take the path of building safer financial systems or we will build increasingly risky financial systems in the hope of realizing a gain?

there is no reason why we have to admit inherently qualitative judgment. In practice, we integrate qualitative judgment with models because (presently) it would be impractical or too costly to model all variables. If we consider modeling individual decision-making at the present stage of science, we have no definitive answer. Whenever financial markets depend on single decisions of single individuals we are in the presence of uncertainty that cannot be quantified. However, we have situations of this type in the physical sciences and we do not consider them an obstacle to the development of a mathematical science.

Let us now address a third objection to the use of mathematics in finance. It is sometimes argued that we cannot arrive at mathematical laws in finance because the laws themselves keep on changing. This objection is somehow true. Addressing it has led to the development of methods specific to financial economics. First observe that many physical systems are characterized by changing laws. For example, if we monitor the behavior of complex artifacts such as nuclear reactors we find that their behavior changes with aging. We can consider these changes as structural breaks. Obviously one could object that if we had more information we could establish a precise time-invariant law. Still, if the artifact is complex and especially if we cannot access all its parts, we might experience true structural breaks. For example, if we are monitoring the behavior of a nuclear reactor we might not be able to inspect it properly. Many natural systems such as volcanoes cannot be properly inspected and structurally described. We can only monitor their behavior, trying to find predictive laws. We might find that our laws change abruptly or continuously. We assume that we could identify more complex laws if we had all the requisite information, though, in practice, we do not have this information.

These remarks show that the objection of changing laws is less strong than we might intuitively believe. The real problem is not that the laws of finance change continuously. The real problem is that they are too complex. We do not have enough theoretical knowledge to determine finance laws and, if we try to estimate statistical models, we do not have enough data to estimate complex models. Stated differently, the question is not whether we can use mathematics in financial economic theory. The real question is: How much information we can obtain in studying financial markets? Laws and models in finance are highly uncertain. One partial solution is to use adaptive models. Adaptive models are formed by simple models plus rules to change the parameters of the simple models. A typical example is nonlinear state-space models. Nonlinear state-space models are formed by a simple regression plus another process that adapts continuously the model parameters. Other examples are hidden Markov models that might represent prices as formed by sequences of random walks with different parameters.

We can therefore conclude that the objection that there is no fixed law in financial economics cannot be solved a priori. Empirically we find that simple models cannot describe financial markets over long periods of time: if we turn to adaptive modeling, we are left with a residual high level of uncertainty.

Our overall conclusion is twofold. First, we can and indeed should regard mathematical finance as a discipline with methods and mathematics specific to the type of empirical data available in the discipline. Given the state of continuous change in our economies, we cannot force mathematical finance into the same paradigm of classical mathematical physics based on differential equations. Mathematical finance needs adaptive, nonlinear models that are able to adapt in a timely fashion to a changing empirical environment.

This is not to say that mathematical finance is equivalent to data-mining. On the contrary, we have to use all available knowledge and theoretical reasoning on financial economics. However, models cannot be crystallized in time-invariant models. In the future, it might be possible to achieve the goal of stable time-invariant models but, for the moment, we have to admit that mathematical finance needs adaptation and must make use of computer simulations. Even with the resources of modern adaptive computational methods, there will continue to be a large amount of uncertainty in mathematical finance, not only as probability distributions embedded in models but also as residual model uncertainty. When changes occur, there will be disruption of model performance and the need to adapt models to new situations. But this does not justify rejecting mathematical finance. Mathematical finance can indeed tell us what situations are more dangerous and might lead to disruptions. Through simulations and models of complex structure, we can achieve an understanding of those situations that are most critical.

Economies and financial markets are engineered artifacts. We can use our science to engineer economic and financial systems that are safer or we can decide, in the end, to prefer risk-taking and its highly skewed rewards. Of course we might object that uncertainty about the path our societies will take is part of the global problem of uncertainty. This objection is the objection of complex system theorists to reductionism. We can study a system with our fundamental laws once we know the initial and boundary conditions but we cannot explain how initial and boundary conditions were formed. These speculations are theoretically important but we should avoid a sense of passive fatality. In practice, it is important that we are aware that we have the tools to design safer financial systems and do not regard the path towards unpredictability as inevitable.

STUDIES OF THE USE OF QUANTITATIVE EQUITY MANAGEMENT

There are three recent studies on the use of quantitative equity management conducted by Intertek Partners. The studies are based on surveys and interviews of market participants. We will refer to these studies as the 2003 Intertek European study,[7] 2006 Intertek study,[8] and 2007 Intertek study.[9]

2003 Intertek European Study

The 2003 Intertek European study deals with the use of financial modeling at European asset management firms. It is based on studies conducted by The Intertek Group to evaluate model performance following the fall of the markets from their peak in March 2000, and explores changes that have occurred since then. In total, 61 managers at European asset management firms in the Benelux countries, France, Germany, Italy, Scandinavia, Switzerland, and the U.K. were interviewed. (The study does not cover alternative investment firms such as hedge funds.) At least half of the firms interviewed are among the major players in their respective markets, with assets under management ranging from €50 to €300 billion.

The major findings are summarized next.[10]

Greater Role for Models

In the two years following the March 2000 market highs, quantitative methods in the investment decision-making process began to play a greater role.

[7]The results of this study are reported in Frank J. Fabozzi, Sergio M. Focardi, and Caroline L. Jonas, "Trends in Quantitative Asset Management in Europe," *Journal of Portfolio Management* 31, no. 4 (2004), pp. 125–132 (Special European Section).

[8]The results of this study are reported in Frank J. Fabozzi, Sergio M. Focardi, and Caroline Jonas, "Trends in Quantitative Equity Management: Survey Results," *Quantitative Finance* 7, no. 2 (2007), pp. 115–122.

[9]The results of this study are reported in Frank J. Fabozzi, Sergio M. Focardi, and Caroline Jonas, *Challenges in Quantitative Equity Management* (CFA Institute Research Foundation, 2008) and Frank J. Fabozzi, Sergio M. Focardi, and Caroline L. Jonas, "On the Challenges in Quantitative Equity Management." *Quantitative Finance* 8, no. 7 (2008), pp. 649–655.

[10]In the quotes from sources in these studies, we omit the usual practice of identifying the reference and page number. The study where the quote is obtained will be clear.

Almost 75% of the firms interviewed reported this to be the case, while roughly 15% reported that the role of models had remained stable. The remaining 10% noted that their processes were already essentially quantitative. The role of models had also grown in another sense; a higher percentage of assets were being managed by funds run quantitatively. One firm reported that over the past two years assets in funds managed quantitatively grew by 50%.

Large European firms had been steadily catching up with their U.S. counterparts in terms of the breadth and depth of use of models. As the price of computers and computer software dropped, even small firms reported that they were beginning to adopt quantitative models. There were still differences between American and European firms, though. American firms tended to use relatively simple technology but on a large scale; Europeans tended to adopt sophisticated statistical methods but on a smaller scale.

Demand pull and management push were among the reasons cited for the growing role of models. On the demand side, asset managers were under pressure to produce returns while controlling risk; they were beginning to explore the potential of quantitative methods. On the push side, several sources remarked that, after tracking performance for several years, their management has made a positive evaluation of a model-driven approach against a judgment-driven decision-making process. In some cases, this led to a corporate switch to a quantitative decision-making process; in other instances, it led to shifting more assets into quantitatively managed funds.

Modeling was reported to have been extended over an ever greater universe of assets under management. Besides bringing greater structure and discipline to the process, participants in the study remarked that models helped contain costs. Unable to increase revenues in the period immediately following the March 2000 market decline, many firms were cutting costs. Modeling budgets, however, were reported as being largely spared. About 68% of the participants said that their investment in modeling had grown over the prior two years, while 50% expected their investments in modeling to continue to grow over the next year.

Client demand for risk control was another factor that drove the increased use of modeling. Pressure from institutional investors and consultants in particular continued to work in favor of modeling.

More generally, risk management was widely believed to be the key driving force behind the use of models.

Some firms mentioned they had recast the role of models in portfolio management. Rather than using models to screen and rank assets—which has been a typical application in Europe—they applied them after the asset manager had acted in order to measure the pertinence of fundamental analysis, characterize the portfolio style, eventually transform products through derivatives, optimize the portfolio, and track risk and performance.

Performance of Models Improves

Over one-half of the study's participants responded that models performed better in 2002 than two years before. Some 20% evaluated 2002 model performance as stable with respect to two years ago, while another 20% considered that performance had worsened. Participants often noted that it was not models in general but specific models that had performed better or more poorly.

There are several explanations for the improved performance of models. Every model is, ultimately, a statistical device trained and estimated on past data. When markets began to fall from their peak in March 2000, models had not been trained on data that would have allowed them to capture the downturn—hence, the temporary poor performance of some models. Even risk estimates, more stable than expected return estimates, were problematic. In many cases, it was difficult to distinguish between volatility and model risk. Models have since been trained on new sets of data and are reportedly performing better.

From a strictly scientific and economic theory point of view, the question of model performance overall is not easy to address. The basic question is how well a theory describes reality, with the additional complication that in economics uncertainty is part of the theory. As we observed in the previous section, we cannot object to financial modeling but we cannot pretend a priori that model performance be good. Modeling should reflect the objective amount of uncertainty present in a financial process. The statement that "models perform better" implies that the level of uncertainty has changed. To make this discussion meaningful, clearly somehow we have to restrict the universe of models under consideration. In general, the uncertainty associated with forecasting within a given class of models is equated to market volatility. And as market volatility is not an observable quantity but a hidden one, it is model-dependent.[11] In other words, the amount of uncertainty in financial markets depends on the accuracy of models. For instance, an ARCH-GARCH model will give an estimate of volatility different from that of a model based on constant volatility. On top of volatility, however, there is another source of uncertainty, which is the risk that the model is misspecified. The latter uncertainty is generally referred to as *model risk*.

[11]This statement is not strictly true. With the availability of high-frequency data, there is a new strain of financial econometrics that considers volatility as an observable realized volatility.

The problem experienced when markets began to fall was that models could not forecast volatility simply because they were grossly misspecified. A common belief is that markets are now highly volatile, which is another way of saying that models do not do a good job of predicting returns. Yet models are now more coherent; fluctuations of returns are synchronized with expectations regarding volatility. Model risk has been reduced substantially.

Overall, the global perception of European market participants who participated in the study was that models are now more dependable. This meant that model risk had been reduced; although their ability to predict returns had not substantially improved, models were better at predicting risk. Practitioners' evaluation of model performance can be summarized as follows: (1) models will bring more and more insight in risk management, (2) in stock selection, we will see some improvement due essentially to better data, not better models, and (3) in asset allocation, the use of models will remain difficult as markets remain difficult to predict.

Despite the improved performance of models, the perception European market participants shared was one of uncertainty as regards the macroeconomic trends of the markets. Volatility, structural change, and unforecastable events continue to challenge models. In addition to facing uncertainty related to a stream of unpleasant surprises as regards corporate accounting at large public firms, participants voiced the concern that there is considerable fundamental uncertainty on the direction of financial flows.

A widely shared evaluation was that, independent of models themselves, the understanding of models and their limits had improved. Most traders and portfolio managers had at least some training in statistics and finance theory; computer literacy was greatly increased. As a consequence, the majority of market participants understand at least elementary statistical analyses of markets.

Use of Multiple Models on the Rise

According to the 2003 study's findings, three major trends had emerged in Europe over the prior few years: (1) a greater use of multiple models, (2) the modeling of additional new factors, and (3) an increased use of value-based models.

Let's first comment on the use of multiple models from the point of view of modern financial econometrics, and in particular from the point of view of the mitigation of model risk. The present landscape of financial modeling applied to investment management is vast and well articulated.[12]

[12]For a discussion of the different families of financial models and modeling issues, see Sergio M. Focardi and Frank J. Fabozzi, *The Mathematics of Financial Modeling and Investment Management* (Hoboken, NJ: John Wiley & Sons, 2004).

Financial models are typically econometric models, they do not follow laws of nature but are approximate models with limited validity. Every model has an associated model risk, which can be roughly defined as the probability that the model does not forecast correctly. Note that it does not make sense to consider model risk in abstract, against every possible assumption; model risk can be meaningfully defined only by restricting the set of alternative assumptions. For instance, we might compute measures of the errors made by an option pricing model if the underlying follows a distribution different from the one on which the model is based. Clearly it must be specified what families of alternative distributions we are considering.

Essentially every model is based on some assumption about the functional form of dependencies between variables and on the distribution of noise. Given the assumptions, models are estimated, and decisions made. The idea of estimating model risk is to estimate the distribution of errors that will be made if the model assumptions are violated. For instance: Are there correlations or autocorrelations when it is assumed there are none? Are innovations fat-tailed when it is assumed that noise is white and normal? From an econometric point of view, combining different models in this way means constructing a mixture of distributions. The result of this process is one single model that weights the individual models.

Some managers interviewed for the 2003 study reported they were using judgment on top of statistical analysis. This entails that models be reviewed when they begin to produce results that are below expectations. In practice, quantitative teams constantly evaluate the performance of different families of models and adopt those that perform better. Criteria for switching from one family of models to another are called for, though. This, in turn, requires large data samples.

Despite these difficulties, application of multiple models has gained wide acceptance in finance. In asset management, the main driver is the uncertainty related to estimating returns.

Focus on Factors, Correlation, Sentiment, and Momentum

Participants in the 2003 study also reported efforts to determine new factors that might help predict expected returns. Momentum and sentiment were the two most cited phenomena modeled in equities. Market sentiment, in particular, was receiving more attention.

The use of factor models is in itself a well-established practice in financial modeling. Many different families of models are available, from the widely used classic static return factor analysis models to dynamic factor models, both of which are described later in Chapter 5. What remains a challenge is determination of the factors. Considerable resources have been devoted to studying market correlations. Advanced techniques for the robust estimation of correlations are being applied at large firms as well as at boutiques.

According to study respondents, over the three years prior to 2001, quantitative teams at many asset management firms were working on determining which factors are the best indicators of price movements. Sentiment was often cited as a major innovation in terms of modeling strategies. Asset management firms typically modeled stock-specific sentiment, while sentiment as measured by business or consumer confidence was often the responsibility of the macroeconomic teams at the mother bank, at least in continental Europe. Market sentiment is generally defined by the distribution of analyst revisions in earnings estimates. Other indicators of market confidence are flows, volume, turnover, and trading by corporate officers.

Factors that represent market momentum were also increasingly adopted according to the study. *Momentum* means that the entire market is moving in one direction with relatively little uncertainty. There are different ways to represent momentum phenomena. One might identify a specific factor that defines momentum, that is, a variable that gauges the state of the market in terms of momentum. This momentum variable then changes the form of models. There are models for trending markets and models for uncertain markets.

Momentum can also be represented as a specific feature of models. A random walk model does not have any momentum, but an autoregressive model might have an intrinsic momentum feature.

Some participants also reported using market-timing models and style rotation for the active management of funds. Producing accurate timing signals is complex, given that financial markets are difficult to predict. One source of predictability is the presence of mean reversion and cointegration phenomena.

Back to Value-Based Models

At the time of the 2003 study, there was a widespread perception that value-based models were performing better in post-2000 markets. It was believed that markets were doing a better job valuing companies as a function of the value of the firm rather than price trends, notwithstanding our remarks on the growing use of factors such as market sentiment. From a methodological point of view, methodologies based on cash analysis had increased in popularity in Europe. A robust positive operating cash flow is considered to be a better indication of the health of a firm than earnings estimates, which can be more easily massaged.

Fundamental analysis was becoming highly quantitative and automated. Several firms mentioned they were developing proprietary methodologies for the automatic analysis of balance sheets. For these firms, with the information available on the World Wide Web, fundamental analysis could be performed without actually going to visit firms. Some participants remarked that caution might be called for in attributing the good performance of value-tilted models to markets. One of the assumptions of value-based models is that there is no mechanism that conveys a large flow of funds through preferred channels, but this was the case in the telecommunications, media, and technology (TMT) bubble, when value-based models performed so poorly. In the last bull run prior to the study, the major preoccupation was to not miss out on rising markets; investors who continued to focus on value suffered poor performance. European market participants reported that they are now watching both trend and value.

Risk Management

Much of the attention paid to quantitative methods in asset management prior to the study had been focused on risk management. According to 83% of the participants, the role of risk management had evolved significantly over the prior two years to extend across portfolios and across processes.

One topic that has received a lot of attention, both in academia and at financial institutions, is the application of *extreme value theory* (EVT) to financial risk management.[13] The RiskLab in Zurich, headed by Paul Embrechts, advanced the use of EVT and copula functions in risk management. At the corporate level, universal banks such as HSBC CCF have produced theoretical and empirical work on the applicability of EVT to risk management.[14] European firms were also paying considerable attention to risk measures.

For participants in the Intertek study, risk management was the area where quantitative methods had made their biggest contribution. Since the pioneering work of Harry Markowitz in the 1950s, the objective of investment management has been defined as determining the optimal risk-return trade-off in an investor's profile. Prior to the diffusion of modeling techniques, though, evaluation of the risk-return trade-off was left to the judgment of individual asset managers. Modeling brought to the forefront the question of ex ante risk-return optimization. An asset management firm that uses quantitative methods and optimization techniques manages risk at the

[13]See Sergio M. Focardi and Frank J. Fabozzi, "Fat Tails, Scaling, and Stable Laws: A Critical Look at Modeling Extremal Events in Financial Phenomena," *Journal of Risk Finance* 5, no. 1 (Fall 2003), pp. 5–26.

[14]François Longin, "Stock Market Crashes: Some Quantitative Results Based on Extreme Value Theory." *Derivatives Use, Trading and Regulation* 7 (2001), pp. 197–205.

source. In this case, the only risk that needs to be monitored and managed is model risk.[15]

Purely quantitative managers with a fully automated management process were still rare according to the study. Most managers, although quantitatively oriented, used a hybrid approach calling for models to give evaluations that managers translate into decisions. In such situations, risk is not completely controlled at the origin.

Most firms interviewed for the study had created a separate risk management unit as a supervisory entity that controls the risk of different portfolios and eventually—although still only rarely—aggregated risk at the firm-wide level. In most cases, the tools of choice for controlling risk were multifactor models. Models of this type have become standard when it comes to making risk evaluations for institutional investors. For internal use, however, many firms reported that they made risk evaluations based on proprietary models, EVT, and scenario analysis.

Integrating Qualitative and Quantitative Information

More than 60% of the firms interviewed for the 2003 Intertek study reported they had formalized procedures for integrating quantitative and qualitative input, although half of these mentioned that the process had not gone very far; 30% of the participants reported no formalization at all. Some firms mentioned they had developed a theoretical framework to integrate results from quantitative models and fundamental views. Assigning weights to the various inputs was handled differently from firm to firm; some firms reported establishing a weight limit in the range of 50%–80% for quantitative input.

A few quantitative-oriented firms reported that they completely formalized the integration of qualitative and quantitative information. In these cases, everything relevant was built into the system. Firms that both quantitatively managed and traditionally managed funds typically reported that formalization was implemented in the former but not in the latter.

Virtually all firms reported at least a partial automation in the handling of qualitative information. For the most part, a first level of automation—including automatic screening and delivery, classification, and search—is provided by suppliers of sell-side research, consensus data, and news. These suppliers are automating the delivery of news, research reports, and other information.

[15]Asset management firms are subject to other risks, namely, the risk of not fulfilling a client mandate or operational risk. Although important, these risks were outside the scope of the survey.

About 30% of the respondents note they have added functionality over and above that provided by third-party information suppliers, typically starting with areas easy to quantify such as earnings announcements or analysts' recommendations. Some have coupled this with quantitative signals that alert recipients to changes or programs that automatically perform an initial analysis.

Only the braver will be tackling difficult tasks such as automated news summary and analysis. For the most part, news analysis was still considered the domain of judgment. A few firms interviewed for this study reported that they attempted to tackle the problem of automatic news analysis, but abandoned their efforts. The difficulty of forecasting price movements related to new information was cited as a motivation.

2006 Intertek Study

The next study that we will discuss is based on survey responses and conversations with industry representatives in 2006. Although this predates the subprime mortgage crisis and the resulting impact on the performance of quantitative asset managers, the insights provided by this study are still useful. In all, managers at 38 asset management firms managing a total of $4.3 trillion in equities participated in the study. Participants included individuals responsible for quantitative equity management and quantitative equity research at large- and medium-sized firms in North America and Europe.[16] Sixty-three percent of the participating firms were among the largest asset managers in their respective countries; they clearly represented the way a large part of the industry was going with respect to the use of quantitative methods in equity portfolio management.[17]

The findings of the 2006 study suggested that the skepticism relative to the future of quantitative management at the end of the 1990s had given way by 2006 and quantitative methods were playing a large role in equity portfolio management. Of the 38 survey participants, 11 (29%) reported that more than 75% of their equity assets were being managed quantitatively. This includes a wide spectrum of firms, with from $6.5 billion to over $650 billion in equity assets under management. Another 22 firms (58%) reported that they have some equities under quantitative management, though for 15 of these 22 firms the percentage of equities under quantitative management was less than 25%—often under 5%—of total equities under

[16]The home market of participating firms was a follows: 15 from North America (14 from the United States, 1 from Canada) and 23 from Europe (United Kingdom 7, Germany 5, Switzerland 4, Benelux 3, France 2, and Italy 2).

[17]Of the 38 participants in this survey, two responded only partially to the questionnaire. Therefore, for some questions, there are 36 (not 38) responses.

management. Five of the 38 participants in the survey (13%) reported no equities under quantitative management.

Relative to the period 2004–2005, the amount of equities under quantitative management was reported to have grown at most firms participating in the survey (84%). One reason given by respondents to explain the growth in equity assets under quantitative management was the flows into existing quantitative funds. A source at a large U.S. asset management firm with more than half of its equities under quantitative management said in 2006 "The firm has three distinct equity products: value, growth, and quant. Quant is the biggest and is growing the fastest."

According to survey respondents, the most important factor contributing to a wider use of quantitative methods in equity portfolio management was the positive result obtained with these methods. Half of the participants rated positive results as the single most important factor contributing to the widespread use of quantitative methods. Other factors contributing to a wider use of quantitative methods in equity portfolio management were, in order of importance attributed to them by participants, (1) the computational power now available on the desk top, (2) more and better data, and (3) the availability of third-party analytical software and visualization tools.

Survey participants identified the prevailing in-house culture as the most important factor holding back a wider use of quantitative methods (this evaluation obviously does not hold for firms that can be described as quantitative): more than one third (10/27) of the respondents at other than quant-oriented firms considered this the major blocking factor. This positive evaluation of models in equity portfolio management in 2006 was in contrast with the skepticism of some 10 years early. A number of changes have occurred. First, expectations at the time of the study had become more realistic. In the 1980s and 1990s, traders were experimenting with methodologies from advanced science in the hope of making huge excess returns. Experience of the prior 10 years has shown that models were capable of delivering but that their performance must be compatible with a well-functioning market.

More realistic expectations have brought more perseverance in model testing and design and have favored the adoption of intrinsically safer models. Funds that were using hundred fold leverage had become unpalatable following the collapse of LTCM (Long Term Capital Management). This, per se, has reduced the number of headline failures and had a beneficial impact on the perception of performance results. We can say that models worked better in 2006 because model risk had been reduced: simpler, more robust models delivered what was expected. Other technical reasons that explained improved model performance included a manifold increase in computing power and more and better data. Modelers by 2006 had available on their desk top computing power that, at the end of the 1980s, could be got only from multimillion-dollar supercomputers. Cleaner, more complete data, including intraday data and data on corporate actions/dividends, could be obtained. In addition, investment firms (and institutional clients) have learned how to use models throughout the investment management process. Models had become part of an articulated process that, especially in the case of institutional investors, involved satisfying a number of different objectives, such as superior information ratios.

Changing Role for Models in Equity Portfolio

The 2006 study revealed that quantitative models were now used in active management to find sources of excess returns (i.e., alphas), either relative to a benchmark or absolute. This was a considerable change with respect to the 2003 Intertek European study where quantitative models were reported as being used primarily to manage risk and to select parsimonious portfolios for passive management.

Another finding of the study was the growing amount of funds managed automatically by computer programs. The once futuristic vision of machines running funds automatically without the intervention of a portfolio manager was becoming a reality on a large scale: 55% (21/38) of the respondents reported that at least part of their equity assets were being managed automatically with quantitative methods; another three planned to automate at least a portion of their equity portfolios within the next 12 months. The growing automation of the equity investment process suggests that there was no missing link in the technology chain that leads to automatic quantitative management. From return forecasting to portfolio formation and optimization, all the needed elements were in place. Until recently, optimization represented the missing technology link in the automation of portfolio engineering. Considered too brittle to be safely deployed, many firms eschewed optimization, limiting the use of modeling to stock ranking or risk control functions. Advances in robust estimation methodologies (see Chapter 2) and in optimization (see Chapter 8) now allow an asset manager to construct portfolios of hundreds of stocks chosen in universes of thousands of stocks with little or no human intervention outside of supervising the models.

Modeling Methodologies and the Industry's Evaluation

At the end of the 1980s, academics and researchers at specialized quant boutiques experimented with many sophisticated modeling methodologies including chaos theory, fractals and multifractals, adaptive programming, learning theory, complexity theory, complex nonlinear stochastic models, data mining, and artificial intelligence. Most of these efforts failed to live up to expectations. Perhaps expectations were too high. Or perhaps the resources or commitment required were lacking. Emanuel Derman provides a lucid analysis of the difficulties that a quantitative analyst has to overcome. As he observed, though modern quantitative finance uses some of the techniques of physics, a wide gap remains between the two disciplines.[18]

The modeling landscape revealed by the 2006 study is simpler and more uniform. Regression analysis and momentum modeling are the most widely used techniques: respectively, 100% and 78% of the survey respondents said that these techniques were being used at their firms. With respect to regression models used today, the survey suggests that they have undergone a substantial change since the first multifactor models such as Arbitrage Pricing Theory (APT) were introduced. Classical multifactor models such as APT are static models embodied in linear regression between returns and factors at the same time. Static models are forecasting models insofar as the factors at time t are predictors of returns at time behavior $t + 1$. In these static models, individual return processes might exhibit zero autocorrelation but still be forecastable from other variables. Predictors might include financial and macroeconomic factors as well as company specific parameters such as financial ratios. Predictors might also include human judgment, for example, analyst estimates, or technical factors that capture phenomena such as momentum. A source at a quant shop using regression to forecast returns said,

> Regression on factors is the foundation of our model building. Ratios derived from financial statements serve as one of the most important components for predicting future stock returns. We use these ratios extensively in our bottom-up equity model and categorize them into five general categories: operating efficiency, financial strength, earnings quality (accruals), capital expenditures, and external financing activities.

Momentum and reversals were the second most widely diffused modeling technique among survey participants. In general, momentum and reversals were being used as a strategy, not as a model of asset returns. Momentum strategies are based on forming portfolios choosing the highest/lowest returns, where returns are estimated on specific time windows. Survey participants gave these strategies overall good marks but noted that (1) they do not always perform so well, (2) they can result in high turnover (though

[18]Emanuel Derman, "A Guide for the Perplexed Quant," *Quantitative Finance* 1, no. 5 (2001), pp. 476–480.

some were using constraints/penalties to deal with this problem), and (3) identifying the timing of reversals was tricky.

Momentum was first reported in 1993 by Jegadeesh and Titman in the U.S. market.[19] Nine years later, they confirmed that momentum continued to exist in the 1990s in the U.S. market.[20] Two years later, Karolyi and Kho examined different models for explaining momentum and concluded that no random walk or autoregressive model is able to explain the magnitude of momentum empirically found;[21] they suggested that models with time varying expected returns come closer to explaining empirical magnitude of momentum. Momentum and reversals are presently explained in the context of local models updated in real time. For example, momentum as described in the original Jegadeesh and Titman study is based on the fact that stock prices can be represented as independent random walks when considering periods of the length of one year. However, it is fair to say that there is no complete agreement on the econometrics of asset returns that justifies momentum and reversals and stylized facts on a global scale, and not as local models. It would be beneficial to know more about the econometrics of asset returns that sustain momentum and reversals.

Other modeling methods that were widely used by participants in the 2006 study included cash flow analysis and behavioral modeling. Seventeen of the 36 participating firms said that they modeled cash flows; behavioral modeling was reported as being used by 16 of the 36 participating firms.[22] Considered to play an important role in asset predictability, 44% of the survey respondents said that they use behavioral modeling to try to capture phenomena such as departures from rationality on the part of investors (e.g., belief persistence), patterns in analyst estimates, and corporate

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[19]Narasimhan Jegadeesh and Sheridan Titman, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *Journal of Finance* 48, no. 1 (1993), pp. 65–92.

[20]Narasimhan Jegadeesh and Sheridan Titman, "Cross-Sectional and Time-Series Determinants of Momentum Returns," *Review of Financial Studies* 15, no. 1 (2002), pp. 143–158.

[21]George A. Karolyi and Bong-Chan Kho, "Momentum Strategies: Some Bootstrap Tests," *Journal of Empirical Finance* 11 (2004), pp. 509–536.

[22]The term behavioral modeling is often used rather loosely. Full-fledged behavioral modeling exploits a knowledge of human psychology to identify situations where investors are prone to show behavior that leads to market inefficiencies. The tendency now is to call any model *behavioral* that exploits market inefficiency. However, implementing true behavioral modeling is a serious challenge; even firms with very large, powerful quant teams who participated in the survey reported that there is considerable work needed to translate departures from rationality into a set of rules for identifying stocks as well as entry and exit points for a quantitative stock selection process.

executive investment/disinvestment behavior. Behavioral finance is related to momentum in that the latter is often attributed to various phenomena of persistence in analyst estimates and investor perceptions. A source at a large investment firm that has incorporated behavioral modeling into its active equity strategies commented,

> The attraction of behavioral finance is now much stronger than it was just five years ago. Everyone now acknowledges that markets are not efficient, that there are behavioral anomalies. In the past, there was the theory that was saying that markets are efficient while market participants such as the proprietary trading desks ignored the theory and tried to profit from the anomalies. We are now seeing a fusion of theory and practice.

As for other methodologies used in return forecasting, sources cited nonlinear methods and cointegration. Nonlinear methods are being used to model return processes at 19% (7/36) of the responding firms. The nonlinear method most widely used among survey participants is classification and regression trees (CART). The advantage of CART is its simplicity and the ability of CART methods to be cast in an intuitive framework. A source in the survey that reported using CART as a central part of the portfolio construction process in enhanced index and longer-term value-based portfolios said,

> CART compresses a large volume of data into a form which identifies its essential characteristics, so the output is easy to understand. CART is non-parametric—which means that it can handle an infinitely wide range of statistical distributions—and nonlinear—so as a variable selection technique it is particularly good at handling higher-order interactions between variables.

Only 11% (4/36) of the respondents reported using nonlinear regime-shifting models; at most firms, judgment was being used to assess regime change. Participants identified the difficulty in detecting the precise timing of a regime switch and the very long time series required to estimate shifts as obstacles to modeling regime shifts. A survey participant at a firm where regime-shifting models have been experimented with commented,

> Everyone knows that returns are conditioned by market regimes, but the potential for overfitting when implementing regime-switching models is great. If you could go back with fifty years of data—but

> we have only some ten years of data and this is not enough to build a decent model.

Cointegration was being used by 19% (7/36) of the respondents. As explained in Chapter 3, cointegration models the short-term dynamics (direction) and long-run equilibrium (fair value). A perceived plus of cointegration is the transparency that it provides: the models are based on economic and finance theory and calculated from economic data.

Optimization

Another area where much change was revealed by the 2006 study was optimization. According to sources, optimization was being performed at 92% (33/36) of the participating firms, albeit in some cases only rarely. Mean variance was the most widely used technique among survey participants: it was being used by 83% (30/36) of the respondents. It was followed by utility optimization (42% or 15/36) and, robust optimization (25% or 9/36). Only one firm mentioned that it is using stochastic optimization.

The wider use of optimization was a significant development compared to the 2003 study when many sources had reported that they eschewed optimization: the difficulty of identifying the forecasting error was behind the then widely held opinion that optimization techniques were too brittle and prone to error maximization. The greater use of optimization was attributed to advances in large-scale optimization coupled with the ability to include constraints and robust methods for both estimation and optimization. This result is significant as portfolio formation strategies rely on optimization. With optimization feasible, the door was open to a fully automated investment process. In this context, it is noteworthy that 55% of the survey respondents in the 2006 study reported that at least a portion of their equity assets is being managed by a fully automated process.

Optimization is the engineering part of portfolio construction and for this reason is discussed in Chapters 6, 7, and 8. Most portfolio construction problems can be cast in an optimization framework, where optimization is applied to obtain the desired optimal risk-return profile. Optimization is the technology behind the current offering of products with specially engineered returns, such as guaranteed returns. However, the offering of products with particular risk-return profiles requires optimization methodologies that go well beyond classical mean-variance optimization. In particular one must be able to (1) work with real-world utility functions and (2) apply constraints to the optimization process.

Challenges

The growing diffusion of models is not without challenges. The 2006 survey participants noted three: (1) increasing difficulty in differentiating products; (2) difficulty in marketing quant funds, especially to non-institutional investors; and (3) performance decay.

Quantitative equity management has now become so wide spread that a source at a long-established quantitative investment firm remarked,

> There is now a lot of competition from new firms entering the space [of quantitative investment management]. The challenge is to continue to distinguish ourselves from competition in the minds of clients.

With quantitative funds based on the same methodologies and using the same data, the risk is to construct products with the same risk-return profile. The head of active equities at a large quantitative firm with more than a decade of experience in quantitative management remarked in the survey, "Everyone is using the same data and reading the same articles: it's tough to differentiate."

While sources in the survey reported that client demand was behind the growth of (new) pure quantitative funds, some mentioned that quantitative funds might be something of a hard sell. A source at a medium-sized asset management firm servicing both institutional clients and high-net worth individuals said,

> Though clearly the trend towards quantitative funds is up, quant approaches remain difficult to sell to private clients: they remain too complex to explain, there are too few stories to tell, and they often have low alpha. Private clients do not care about high information ratios.

Markets are also affecting the performance of quantitative strategies. A report by the Bank for International Settlements (2006) noted that this is a period of historically low volatility. What is exceptional about this period, observes the report, is the simultaneous drop in volatility in all variables: stock returns, bond spreads, rates, and so on. While the role of models in reducing volatility is unclear, what is clear is that models immediately translate this situation into a rather uniform behavior. Quantitative funds try to differentiate themselves either finding new unexploited sources of return forecastability, for example, novel ways of looking at financial statements, or using optimization creatively to engineer special risk-return profiles.

A potentially more serious problem is performance decay. Survey participants remarked that model performance was not so stable. Firms are tackling these problems in two ways. First, they are protecting themselves from model breakdown with model risk mitigation techniques, namely by averaging results obtained with different models. It is unlikely that all models break down in the same way in the same moment, so that averaging with different models allows asset managers to diversify risk. Second, there is an ongoing quest for new factors, new predictors, and new aggregations of factors and predictors. In the long run, however, something more substantial might be required: this is the subject of the chapters ahead.

2007 Intertek Study

The 2007 Intertek study, sponsored by the Research Foundation of the CFA Institute, is based on conversations with asset managers, investment consultants, and fund-rating agencies as well as survey responses from 31 asset managers in the United States and Europe. In total, 12 asset managers and eight consultants and fund-rating agencies were interviewed and 31 managers with a total of $2.2 trillion in equities under management participated in the survey. Half of the participating firms were based in the United States; half of the participating firms were among the largest asset managers in their countries. Survey participants included chief investment officers of equities and heads of quantitative management and/or quantitative research.

A major question in asset management that this study focused on was if the diffusion of quantitative strategies was making markets more efficient, thereby reducing profit opportunities. The events of the summer of 2007 which saw many quantitatively managed funds realize large losses brought an immediacy to the question. The classical view of financial markets holds that market speculators make markets efficient, hence the absence of profit opportunities after compensating for risk. This view had formed the basis of academic thinking for several decades starting from the 1960s. However, practitioners had long held the more pragmatic view that a market formed by fallible human agents (as market speculators also are) offers profit opportunities due to the many small residual imperfections that ultimately result in delayed or distorted responses to news.

A summary of the findings of this study are provided next.

Are Model-Driven Investment Strategies Impacting Market Efficiency and Price Processes?

The empirical question of the changing nature of markets is now receiving much academic attention. For example, using empirical data from 1927 to

2005, Hwang and Rubesam[23] argued that momentum phenomena disappeared during the period 2000–2005, while Figelman,[24] analyzing the S&P 500 over the period 1970–2004, found new evidence of momentum and reversal phenomena previously not described. Khandani and Lo[25] show how a mean-reversion strategy that they used to analyze market behavior lost profitability in the 12-year period from 1995 to 2007.

Intuition suggests that models will have an impact on price processes but whether models will make markets more efficient or less efficient will depend on the type of models widely adopted. Consider that there are two categories of models, those based on fundamentals and those based on the analysis of time series of past prices and returns. Models based on fundamentals make forecasts based on fundamental characteristics of firms and, at least in principle, tend to make markets more efficient. Models based on time series of prices and returns are subject to self-referentiality and might actually lead to mispricings. A source at a large financial firm that has both fundamental and quant processes said,

> The impact of models on markets and price processes is asymmetrical. [Technical] model-driven strategies have a less good impact than fundamental-driven strategies as the former are often based on trend following.

Another source commented,

> Overall quants have brought greater efficiency to the market, but there are poor models out there that people get sucked into. Take momentum. I believe in earnings momentum, not in price momentum: it is a fool buying under the assumption that a bigger fool will buy in the future. Anyone who uses price momentum assumes that there will always be someone to take the asset off your hands—a fool's theory. Studies have shown how it is possible to get into a momentum-type market in which asset prices get bid up, with everyone on the collective belief wagon.

The question of how models impact the markets—making them more or less efficient—depends on the population of specific models. As long as

[23]Soosung Hwang and Alexandre Rubesam, "The Disappearance of Momentum" (November 7, 2008). Available at SSRN: http://ssrn.com/abstract=968176.

[24]Ilya Figelman, "Stock Return Momentum and Reversal," *Journal of Portfolio Management* 34 (2007), pp. 51–69.

[25]Amir E. Khandani and Andrew W. Lo, "What Happened to the Quants in August 2007," *Journal of Investment Management* 5 (2007), pp. 29–78.

models based on past time series of prices and returns (i.e., models that are trend followers) are being used, it will not be possible to assume that models make markets more efficient. Consider that it is not only a question of how models compete with each other but also how models react to exogenous events and how models themselves evolve. For example, a prolonged period of growth will produce a breed of models different from models used in low-growth periods.

Performance Issues

When the 2006 Intertek study was conducted on equity portfolio modeling in early 2006, quantitative managers were very heady about performance. By mid-2007, much of that headiness was gone. By July–August 2007, there was much perplexity.

Many participants in the 2007 Intertek study attributed the recent poor performance of many quant equity funds to structural changes in the market. A source at a large financial firm with both fundamental and quantitative processes said,

> The problem with the performance of quant funds [since 2006] is that there was rotation in the marketplace. Most quants have a strong value bias so they do better in a value market. The period 1998–1999 was not so good for quants as it was a growth market; in 2001–2005 we had a value market so value-tilted styles such as the quants were doing very well. In 2006 we were back to a growth market. In addition, in 2007, spreads compressed. The edge quants had has eroded.

One might conclude that if markets are cyclical, quant outperformance will also be cyclical. A leading investment consultant who participated in the survey remarked,

> What is most successful in terms of producing returns—quant or fundamental—is highly contextual: there is no best process, quant or fundamental. Quants are looking for an earnings-quality component that has dissipated in time. I hate to say it but any manager has to have the wind behind its strategies, favoring the factors.

Speaking in August 2007, the head of active quantitative research at a large international firm said,

> It has been challenging since the beginning of the year. The problem is that fundamental quants are stressing some quality—be it value or growth—but at the beginning of the year there was a lot of activity of hedge funds, much junk value, much froth. In addition there was a lot of value-growth style rotation, which is typical when there is macro insecurity and interest rates go up and down. The growth factor is better when rates are down, the value factor better when rates are up. Fundamental quants could not get a consistent exposure to factors they wanted to be exposed to.

Another source said, "We tried to be balanced value-growth but the biggest danger is rotation risk. One needs a longer-term view to get through market cycles." The CIO of equities at a large asset management firm added, "Growth and value markets are cyclical and it is hard to get the timing right."

The problem of style rotation (e.g., value versus growth) is part of the global problem of adapting models to changing market conditions. Value and growth represent two sets of factors, both of which are captured, for example, in the Fama–French three-factor model.[26] But arguably there are many more factors. So factor rotation is more than just a question of value and growth markets. Other factors such as momentum are subject to the same problem; that is to say, one factor prevails in one market situation and loses importance in another and is replaced by yet another factor(s).

Other reasons were cited to explain why the performance of quantitative products as a group has been down since 2006. Among these is the fact that there were now more quantitative managers using the same data, similar models, and implementing similar strategies. A source at a firm that has both quant and fundamental processes said,

> Why is performance down? One reason is because many more people are using quant today than three, five years ago. Ten years ago the obstacles to entry were higher: data were more difficult to obtain, models were proprietary. Now we have third-party suppliers of data feeds, analytics, and back-testing capability.

A consultant concurred,

> The next 12 to 24 months will be tough for quants for several reasons. One problem is … the ease with which people can now buy and manipulate data. The problem is too many people are running

[26]Eugene F. Fama and Kenneth R. French, "Common Risk Factors and the Returns on Stocks and Bonds," *Journal of Financial Economics*, 47 (1993), pp. 427–465.

similar models so performance decays and it becomes hard to stay ahead. Performance is a genuine concern.

Still another source said,

Quant performance depends on cycles and the secular trend but success breeds its own problems. By some estimates there are $4 trillion in quantitative equity management if we include passive, active, hedge funds, and proprietary desks. There is a downside to the success of quants. Because quants have been so successful, if a proprietary desk or a hedge fund needs to get out of a risk, they can't. Then you get trampled on as others have more to sell than you have to buy. The business is more erratic because of the sheer size and needs of proprietary desks and hedge funds whose clients hold 6 to 12 months against six years for asset managers.

However, not all sources agreed that the fact that quantitative managers are using the same data and/or similar models entails a loss of performance. One source said,

Though all quants use the same data sources, I believe that there is a difference in models and in signals. There are details behind the signals and in how you put them together. Portfolio construction is one very big thing.

Another source added,

All quants use similar data but even minor differences can lead to nontrivial changes in valuation. If you have 15 pieces of information, different sums are not trivial. Plus if you combine small differences in analytics and optimization, the end result can be large differences. There is not one metric but many metrics and all are noisy.

Investment consultants identified risk management as among the biggest pluses for a quantitative process. According to one source,

Quantitative managers have a much greater awareness of risk. They are attuned to risk in relation to the benchmark as well as to systemic risk. Fundamental managers are often not aware of concentration in, for example, factors or exposure.

In view of the performance issues, survey participants were asked if they believed that quantitative managers were finding it increasingly difficult to generate excess returns as market inefficiencies were exploited. Just over half agreed while 32% disagreed and 16% expressed no opinion. When the question was turned around, 73% of the survey participants agreed that, though profit opportunities would not disappear, quantitative managers would find it increasingly hard to exploit them. One source remarked,

> Performance is getting harder to wring out not because everyone is using the same data and similar models, but because markets are more efficient. So we will see Sharpe ratios shrink for active returns. Managers will have to use more leverage to get returns. The problem is more acute for quant managers as all quant positions are highly correlated as they all use book to price; fundamental managers, on the other hand, differ on the evaluation of future returns'.

When asked what market conditions were posing the most serious challenge to a quantitative approach in equity portfolio management, survey respondents ranked in order of importance on a scale from one to five the rising correlation level, style rotation, and insufficient liquidity. Other market conditions rated important were a fundamental market shift, high (cross sector) volatility and low (cross) volatility. Felt less important were the impact of the dissipation of earnings and non-trending markets.

In their paper on the likely causes of the summer 2007 events, Khandani and Lo[27] note the sharp rise in correlations over the period 1998–2007. They observe that this rise in correlations reflects a much higher level of interdependence in financial markets. This interdependence is one of the factors responsible for the contagion from the subprime mortgage crisis to the equity markets in July–August 2007. When problems began to affect equity markets, the liquidity crisis started. Note that liquidity is a word that assumes different meanings in different contexts. In the study, liquidity refers to the possibility of finding buyers and thus to the possibility of deleveraging without sustaining heavy losses. One CIO commented,

> Everyone in the quant industry is using the same factors [thus creating highly correlated portfolios prone to severe contagion effects]. When you need to unwind, there is no one there to take the trade: Quants are all children of Fama and French. Lots of people are using earnings revision models.

[27]Khandani and Lo, "What Happened to the Quants in August 2007?"

Another source remarked, "Because quants have been so successful, if you need to get out of a risk for whatever reason, you can't get out. This leads to a liquidity sell-off."

Specific to recent market turmoil, participants identified the unwinding of long–short positions by hedge funds as by far the most important factor contributing to the losses incurred by some quant equity finds in the summer of 2007. One source said wryly, "Everyone is blaming the quants; they should be blaming the leverage."

Improving Performance

As it was becoming increasingly difficult to deliver excess returns, many quant managers had turned to using leverage in an attempt to boost performance—a strategy most sources agreed was quite risky. The events of the summer of 2007 were to prove them right. Given the performance issues, survey participants were asked what they were likely to do to try to improve performance.

The search to identify new and/or unique factors was the most frequently cited strategy and complementary to it, the intention to employ new models. A CIO of equities said,

> Through the crisis of July–August 2007, quant managers have learned which of their factors are unique and will be focusing on what is unique. There will be a drive towards using more proprietary models, doing more unique conceptual work. But it will be hard to get away from fundamental concepts: you want to hold companies that are doing well and do not want to pay too much for them.

As for the need to employ new models, the global head of quantitative strategies at a large financial group remarked,

> Regression is the art of today's tool kit. To get better performance, we will have to enlarge the tool kit and add information and dynamic and static models. People are always changing things; maybe we will be changing things just a bit quicker.

Other strategies to improve performance given by the 2007 survey participants included attempts to diversify sources of business information and data. As one investment consultant said,

> All quant managers rely on the same set of data but one cannot rely on the same data and have an analytical edge; it is a tough sell. Quant managers need an informational edge, information no one else has or uses. It might be coming out of academia or might be information in the footnotes of balance sheet data or other information in the marketplace that no one else is using.

Just over 60% of the survey participants agreed that, given that everyone is using the same data and similar models, quantitative managers need a proprietary informational edge to outperform. Sources mentioned that some hedge fund managers now have people in-house on the phone, doing proprietary market research on firms.

Opinions among survey respondents diverged as to the benefits to be derived from using high-frequency (up to tick-by-tick) data. Thirty-eight percent of the participants believed that high-frequency data can give an informational edge in equity portfolio management while 27% disagreed and 35% expressed no opinion. It is true that there was still only limited experience with using high-frequency data in equity portfolio management at the time of the survey. One source remarked, "Asset managers now have more frequent updates, what was once monthly is now daily with services such as WorldScope, Compustat, Market QA, Bloomberg, or Factset. But the use of intraday data is still limited to the trading desk."

Fund Flows

Estimates of how much was under management in active quant strategies in 2007 vary from a few hundred million dollars to over $1 trillion. In a study that compared cumulative net flows in U.S. large cap quantitative and "other" products as a percentage of total assets during the 36-month period which coincided with the 2001–2005 value market, Casey, Quirk and Associates[28] found that assets grew 25% at quantitative funds and remained almost flat for other funds. A co-author of that study commented,

> What we have seen in our studies, which looked at U.S. large cap funds, is that since 2004 investors have withdrawn money from the U.S. large cap segment under fundamental managers but active quants have held on to their assets or seen them go up slightly.

[28]Casey, Quirk and Associates, "The Geeks Shall Inherit the Earth?" November 2005.

Addressing the question of net flows into quantitatively managed equity funds before July–August 2007, a source at a leading investment consultancy said,

> There has been secular growth for quant equity funds over the past 20 or so years, first into passive quant and, over the past 12–36 months, into active quant given their success in the past value market. Right now there is about an 80/20 market split between fundamental and active quant management. If active quants can continue their strong performance in a growth market which I think we are now in, I can see the percentage shift over the next three years to 75/25 with active quant gaining a few points every year.

Despite the high-profile problems at some long–short quantitative managed funds during the summer of 2007, 63% of the respondents indicated that they were optimistic that, overall, quantitatively managed equity funds will continue to increase their market share relative to traditionally managed funds, as more firms introduce quantitative products and exchange-traded funds (ETFs) give the retail investor access to active quant products. However, when the question was reformulated, that optimism was somewhat dampened. Thirty-nine percent of the survey participants agreed that overall quantitatively managed funds would not be able to increase their market share relative to traditionally managed funds for the year 2007 while 42% disagreed.

Many consultants who were interviewed for the study just before the July–August 2007 market turmoil were skeptical that quantitative managers could continue their strong performance. These sources cited performance problems dating back to the year 2006.

Lipper tracks flows of quantitative and non-quantitative funds in four equity universes: large cap, enhanced index funds, market neutral, and long-short funds. The Lipper data covering the performance of quantitatively and nonquantitatively driven funds in the three-year period 2005-2007 showed that quant funds underperformed in 2007 in all categories except large cap—a reversal of performance from 2005 and 2006 when quant managers were outperforming nonquantitative managers in all four categories. However, Lipper data are neither risk adjusted nor fee adjusted and the sampling of quant funds in some categories is small. For the period January 2005–June 2008, according to the Lipper data, long-only funds—both quant and nonquant—experienced a net outflow while all other categories experienced net inflows—albeit at different rates—with the exception of nonquant market neutral funds. The differences (as percentages) between quant and non-quant funds were not very large but quant funds exhibited more negative results.

In view of the preceding, the survey participants were asked if, given the poor performance of some quant funds in the year 2007, they thought that traditional asset management firms that have diversified into quantitative management would be reexamining their commitment. Nearly one third agreed while 52% disagreed (16% expressed no opinion). Those that agreed tended to come from firms at which equity assets under management represent less than 5% of all equities under management or where there is a substantial fundamental overlay to the quantitative process.

The head of quantitative equity at a large traditional manager said,

> When the firm decided back in the year 2000 to build a quant business as a diversifier, quant was not seen as a competitor to fundamental analysis. The initial role of quant managers was one of being a problem solver, for 130/30-like strategies or whereever there is complexity in portfolio construction. If quant performance is down, the firm might reconsider its quant products. Should they do so, I would expect that the firm would keep on board some quants as a support to their fundamental business.

Quantitative Processes, Oversight, and Overlay

Let's define what we mean by a quantitative process. Many traditionally managed asset management firms now use some computer-based, statistical decision-support tool and do some risk modeling. The study referred to an investment process as fundamental (or traditional) if it is performed by a human asset manager using information and judgment, and quantitative if the value-added decisions are made primarily in terms of quantitative outputs generated by computer-driven models following fixed rules. The study referred to a process as being *hybrid* if it uses a combination of the two. An example of the latter is a fundamental manager using a computer-driven stock-screening system to narrow his or her portfolio choices.

Among participants in the study, two-thirds had model-driven processes allowing only minimum (5%–10%) discretion or oversight, typically to make sure that numbers made sense and that buy orders were not issued for firms that were the subject of news or rumors not accounted for by the models. Model oversight was considered a control function. This oversight was typically exercised when large positions were involved. A head of quantitative equity said, "Decision-making is 95% model-driven, but we will look at a trader's list and do a sanity check to pull a trade if necessary."

Some firms indicated that they had automated the process of checking if there are exogenous events that might affect the investment decisions. One source said,

> Our process is model driven with about 5% oversight. We ask ourselves: "Do the numbers make sense?" and do news scanning and flagging using in-house software as well as software from a provider of business information.

This comment underlines one of the key functions of judgmental overlays: the consideration of information with a bearing on forecasts that does not appear yet in the predictors. This information might include, for example, rumors about important events that are not yet confirmed, or facts hidden in reporting or news releases that escape the attention of most investors.

Fundamental analysts and managers might have sources of information that can add to the information that is publicly available. However, there are drawbacks to a judgmental approach to information gathering. As one source said, "An analyst might fall in love with the Chief Financial Officer of a firm, and lose his objectivity."

Other sources mentioned using oversight in the case of rare events such as those of July–August 2007. The head of quantitative management at a large firm said,

> In situations of extreme market events, portfolio managers talk more to traders. We use Bayesian learning to learn from past events but, in general, dislocations in the market are hard to model."

Bayesian priors are a disciplined way to integrate historical data and a manager's judgment in the model.

Another instance of exercising oversight is in the area of risk. One source said, "The only overlay we exercise is on risk, where we allow ourselves a small degree of freedom, not on the model."

The key question is: Is there a best way to comingle judgment and models? Each of these presents pitfalls. Opinions among participants in the 2007 Intertek study differed as to the advantage of commingling models and judgment and ways that it might be done. More than two-thirds of the survey participants (68%) disagreed with the statement that the most effective equity portfolio management process combines quantitative tools and a fundamental overlay; only 26% considered that a fundamental overlay adds value. Interestingly, most investment consultants and fund-rating firms interviewed for the study shared the appraisal that adding a fundamental overlay to a quantitative investment process did not add value.

A source at a large consultancy said,

> Once you believe that a model is stable, effective over a long time, it is preferable not to use human overlay as it introduces emotion, judgment. The better alternative to human intervention is to arrive at an understanding of how to improve model performance and implement changes to the model.

Some sources believed that a fundamental overlay had value in extreme situations, but not everyone agreed. One source said,

> Overlay is additive and can be detrimental, oversight is neither. It does not alter the quantitative forecast but implements a reality check. In market situations such as of July–August 2007, overlay would have been disastrous. The market goes too fast and takes on a crisis aspect. It is a question of intervals.

Among the 26% who believed that a fundamental overlay does add value, sources cited the difficulty of putting all information in the models. A source that used models for asset managers said,

> In using quant models, there can be data issues. With a fundamental overlay, you get more information. It is difficult to convert all fundamental data, especially macro information such as the yen/dollar exchange rate, into quant models.

A source at a firm that is using a fundamental overlay systematically said,

> The question is how you interpret quantitative outputs. We do a fundamental overlay, reading the 10-Qs and the 10-Ks and the footnotes, plus looking at, for example, increases in daily sales invoices. I expect that we will continue to use a fundamental overlay: it provides a common-sense check. You cannot ignore real-world situations.

In summary, overlays and human oversight in model-driven strategies can be implemented in different ways. First, as a control function, oversight allows managers to exercise judgment in specific situations. Second, human judgment might be commingled with a model's forecasts.

Implementing a Quant Process

The 2007 survey participants were asked how they managed the model building and back-testing process. One-fourth of the participants said that their firms admitted several processes. For example, at 65% of the sources, quantitative models are built and back-tested by the asset manager him/herself; at 39% quantitative models are built and back-tested by the firm's central research center. More rarely, at 23% models might also be built by the corporate research center to the specifications of the asset manager, while at 16% models might also be built by the asset manager but are back-tested by the research center.[29]

Some sources also cited a coming together of quantitative research and portfolio management. Certainly this is already the case at some of the largest quantitative players that began in the passive quantitative arena, where, as one source put it, "the portfolio manager has Unix programming skills as a second nature."

The need to continuously update models was identified by sources as one of the major challenges to a quantitative investment process. A consultant to the industry remarked,

> The specifics of which model each manager uses is not so important as long as management has a process to ensure that the model is always current, that as a prism for looking at the universe the model is relevant, that it is not missing anything. One problem in the U.S. in the 1980s–90s was that models produced spectacular results for a short period of time and then results decayed. The math behind the models was static, simplistic, able to capture only one trend. Today, quants have learned their lesson; they are paranoid about the need to do a constant evaluation to understand what's working this year and might not work next year. The problem is one of capturing the right signals and correctly weighting them when things are constantly changing.

The need to sustain an on-going effort in research was cited by investment consultants as determinant in manager choices. One consultant said,

> When quant performance decays it is often because the manager has grown complacent and then things stop working. When we look at a quant manager, we ask: can they continue to keep doing research?

[29]The percentages do not add to 100 because events overlap.

One way to ensure that models adapt to the changing environment is to use adaptive modeling techniques. One quantitative manager said,

> You cannot use one situation, one data set in perpetuity. For consistently good performance, you need new strategies, new factors. We use various processes in our organization, including regime-shifting adaptive models. The adaptive model draws factors from a pool and selects variables that change over time.

The use of adaptive models and of strategies that can self-adapt to changing market conditions is an important research topic. From a mathematical point of view, there are many tools that can be used to adapt models. Among these is a class of well-known models with hidden variables, including state-space models, hidden Markov models, or regime-shifting models. These models have one or more variables that represent different market conditions. The key challenge is estimation: the ability to identify regime shifts sufficiently early calls for a rich regime structure, but estimating a rich regime shifting model calls for a very large data sample—something we rarely have in finance.

The survey participants were asked if they thought that quantitative-driven equity investment processes were moving towards full automation. By a fully automated quant investment process we intend a process where investment decisions are made by computers with little or no human intervention. An automated process includes the input of data, production of forecasts, optimization/portfolio formation, oversight, and trading. Among those expressing an opinion, as many believed that quantitative managers are moving toward full automation (38%) as not (38%). Industry observers and consultants also had difficulty identifying a trend. One source remarked, "There are all degrees of automation among quants and we see no obvious trend either towards or away from automation." It would appear that we will continue to see a diversity in management models. This diversity is due to the fact that there is no hard science behind quantitative equity investment management; business models reflect the personalities and skill sets inside an organization.

Obstacles to full automation are not due to technical shortcomings. As noted earlier, there are presently no missing links in the automation chain going from forecasting to optimization. Full automation is doable but successful implementation depends on the ability to link seamlessly a return forecasting tool with a portfolio formation strategy. Portfolio formation strategies can take the form of full optimization or might be based on some heuristics with constraints.

The progress of full automation will ultimately depend on performance and investor acceptance. Consultants that interviewed for this study were divided in their evaluation of the advisability of full automation. One source said, "All things being equal, I actually prefer a fully automated process once you believe that a model is stable, effective over a long time." However, in a divergent view, another consultant said, "I am not keen on fully automated processes. I like to see human intervention, interaction before and after optimization, and especially before trading."

Risk Management

The events of July–August 2007 highlighted once more that quantitatively managed funds can be exposed to the risk of extreme events (i.e., rare large—often adverse—events). Fundamentally managed funds are also exposed to the risk of extreme events, typically of a more familiar nature such as a market crash or a large drop in value of single firms or sectors. A head of quantitative management remarked, "There are idiosyncratic risks and systemic risks. Fundamental managers take idiosyncratic risk while the quants look at the marginal moves, sometimes adding leverage."

There seems to be a gap between state-of-the-art risk management and the practice of finance. At least, this is what appears in a number of statements made after the summer of 2007 that attributed losses to multi-sigma events in a Gaussian world. It is now well known that financial phenomena do not follow normal distributions and that the likelihood of extreme events is much larger than if they were normally distributed. Financial phenomena are governed by fat-tailed distributions. The fat-tailed nature of financial phenomena has been at the forefront of research in financial econometrics since the 1990s. Empirical research has shown that returns are not normal and most likely can be represented as fat-tailed processes.

Facts like this have an important bearing on the distribution of returns of dynamic portfolios. Consequently, the 2007 study asked survey participants if they believed that the current generation of risk models had pitfalls that do not allow one to properly anticipate risks such as those of July–August 2007. Just over two-thirds of the survey respondents evaluated agreed that, because today's risk models do not take into consideration global systemic risk factors, they cannot predict events such as those of July–August 2007. One source commented,

> Risk management models work only under benign conditions and are useless when needed. We use two risk methods, principal component analysis and rare (six-sigma) events, and risk models from

> MSCI Barra and Northfield. But the risk models are mis-specified: most pairs of stocks have high correlations.

Another source added,

> There are estimation errors in everything, including in risk models. You know that they will fail, so we add heuristics to our models. Risk models do not cover downside risk but they do help control it. Studies have shown that risk models do improve the information ratio.

The growing use of derivatives in equity portfolio management is adding a new type of risk. One source commented,

> The derivatives markets are susceptible to chaos; they overheat compared to normal markets. Derivatives contracts are complex and no one knows how they will behave in various scenarios. In addition, there is credit risk/counterparty risk dealing with entities such as Sentinel—not a Wall Street firm—that can go with a puff of smoke. Their going under was blamed on the subprime crisis but it was fraud.

Sixty-three percent of the survey participants agreed that the derivative market is a market driven by its own supply and demand schedule and might present risk that is not entirely explained in terms of the underlying.

Why Implement a Quant Process?

According to survey respondents, three main objectives were behind the decision to adopt (at least partially) a quantitative-based equity investment process: tighter risk control, more stable returns, and better overall performance. The profile of a firm's founder(s) and/or the prevailing in-house culture were correlated in that they provided the requisite environment.

Other major objectives reported behind the decision to implement a quantitative equity investment process include diversification in general or in terms of new products such as 130/30-type strategies and scalability, including the ability to scale to different universes. Relative to the diversification in a global sense, a source at a large asset management firm with a small quant group said,

> An important motivating factor is diversification of the overall product lineup performance. Management believes that quant and fundamental products will not move in synch.

As for the ability to offer new products such as the long–short strategies, a source at a sell-side firm modeling for the buy side remarked,

> We are seeing a lot of interest by firms known for being fundamental and that now want to introduce quant processes in the form of screens or other. These firms are trying to get into the quant space and it is the 130/30-type product that is pushing into this direction.

It was generally believed that quantitatively managed funds outperform fundamental managers in the 130/30-type arena. The ability to back-test the strategy was cited as giving quantitatively managed funds the edge. A manager at a firm that offers both fundamental and quantitative products said, "Potential clients have told us that new products such as the 130/30 strategies are more believable with extensive quant processes and testing behind them."

More generally, sources believed that quantitative processes give an edge whenever there is a complex problem to solve. An investment consultant remarked,

> Quant has an advantage when there is an element of financial engineering. The investment process is the same but quant adds value when it comes to picking components and coming up with products such as the 130/30.

Another source added,

> A quant process brings the ability to create structured products. In the U.S., institutional investors are using structured products in especially fixed income and hedge funds. Given the problem of aging, I would expect more demand in the future from private investors who want a product that will give them an income plus act as an investment vehicle, such as a combination of an insurance-type payout and the ability to decompose and build up.

As for scalability, a consultant to the industry remarked,

> One benefit a quantitative process brings to the management firms is the ability to apply a model quickly to a different set of stocks. For example, a firm that had been applying quant models to U.S. large cap also tested these models on 12–15 other major markets in the backroom. Once they saw that the models had a successful in-house track record in different universes, they began to commercialize these funds.

Among survey participants, the desire to stabilize costs, revenues, and performance or to improve the cost/revenues ratio were rated relatively low as motivating factors to introduce quantitative processes. But one source at a large asset management firm said that stabilizing costs, revenues, and performance was an important factor in the firm's decision to embrace a quantitative process. According to this source, "Over the years, the firm has seen great consistency in a quant process: fees, revenues, and costs are all more stable, more consistent than with a fundamental process."

Bringing management costs down was rated by participants as the weakest factor behind the drive to implement a quantitative-driven equity investment process. A source at a large asset management firm with a small quantitative group said,

> Has management done a cost/benefit analysis of quant versus fundamental equity investment management process? Not to my knowledge. I was hired a few years ago to start up a quant process. But even if management had done a cost/benefit analysis and found quant attractive, it would not have been able to move into a quant process quickly. The average institutional investor has a seven-man team on the fund. If you were to switch to a two-man quant team, 80% of the clients would go away. Management has to be very careful; clients do not like to see change.

Barriers to Entry

The 2007 study concluded with an investigation of the barriers to entry in the business. Seventy-seven percent of the survey respondents believed that the active quantitative arena will continue to be characterized by the dominance of a few large players and a large number of small quant boutiques. Only 10% disagreed.

Participants were asked to rate a number of factors as barriers to new entrants into the quant equity investment space. The most important barrier remained the prevailing in-house culture. While one source at a fundamental-oriented firm said that very few firms are seriously opposed to trying to add discipline and improve performance by applying some quant techniques, the problem is that it is not so easy to change an organization.

A source at a large international investment consultancy commented,

> For a firm that is not quant-endowed, it is difficult to make the shift from individual judgment to a quant process. Those that have been most successful in terms of size in the active quant arena are those that began in passive quant. They chose passive because they understood it would be easier for a quantitative process to perform well in passive as opposed to active management. Most of these firms have been successful in their move to active quant management.

A source at a large firm with fundamental and quant management styles said,

> Can a firm with a fundamental culture go quant? It is doable but the odds of success are slim. Fundamental managers have a different outlook and these are difficult times for quants.

Difficulty in recruiting qualified persons was rated the second most important barrier while the cost of qualified persons was considered less of a barrier. Next was the difficulty in gaining investor confidence and the entrenched position of market leaders. An industry observer remarked,

> What matters most is the investment culture and market credibility. If an investor does not believe that the manager has quant as a core skill, the manager will not be credible in the arena of quant products. There is the risk that the effort is perceived by the investor as a backroom effort with three persons, understaffed, and undercommitted.

Among the selling points, participants (unsurprisingly) identified alpha generation as the strongest selling point for quant funds, followed by the disciplined approach and better risk management. Lower management and trading costs and a statistics-based stock selection process were rated lowest among the suggested selling points.

Survey participants were also asked to rate factors holding back investment in active quant equity products. A lack of understanding of quant processes by investors and consultants was perceived to be the most important factor holding back investments in active quant products. As one quantitative manager at an essentially fundamental firm noted, "Quant products are unglamorous. There are no 'story' stocks to tell, so it makes it a hard sell for consultants to their clients."

The need to educate consultants and investors alike, in an effort to gain their confidence, was cited by several sources as a major challenge going forward. Educating investors might require more disclosure about quant processes. At least that was what just under half of the survey participants believed, while one-fourth disagree and one-fourth have no opinion.

One CIO of equities who believes that greater disclosure will be required remarked,

> Following events of this summer [i.e., July–August 2007], quants will need to be better on explaining what they do and why it ought to work. They will need to come up with a rationale for what they are doing. They will have to provide more proof-of-concept statements.

However, among the sources that disagreed, the CIO of equities at another firm said,

> One lesson from the events of July–August 2007 is that we will be more circumspect when describing what we are doing. Disclosing what one is doing can lead to others replicating the process and thus a reduction of profit opportunities.

Lack of stellar performance was rated a moderately important factor in holding back investments in quantitative funds. Lack of stellar performance is balanced by a greater consistency in performance. A source at a fund rating service said, "Because quant funds are broadly diversified, returns are watered down. Quants do not hit the ball out of the park, but they deliver stable performance." The ability to deliver stable if not stellar performance can, of course, be turned into a major selling point.

Quantitative managers cite how Oakland Athletics' manager Billy Beane improved his team's performance using sabermetrics, the analysis of baseball through objective (i.e., statistical) evidence. Beane's analysis led him to shifting the accent from acquiring players who hit the most home runs to acquiring players with the most consistent records of getting on base.[30] Interestingly, Beane is credited with having made the Oakland Athletics the most cost-effective team in baseball though winning the American League Championship Series has proved more elusive.

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[30]As reported in Michael Lewis, *Moneyball: The Art of Winning an Unfair Game* (New York: Norton, 2003).

LOOKING AHEAD FOR QUANTITATIVE EQUITY INVESTING

The studies we have just discussed suggested challenges that participants see in implementing quantitative strategies. We can see a number of additional challenges. Robust optimization, robust estimation, and the integration of the two are probably on the research agenda of many firms. As asset management firms strive to propose innovative products, robust and flexible optimization methods will be high on the R&D agenda. In addition, as asset management firms try to offer investment strategies to meet a stream of liabilities (i.e., measured against liability benchmarking), multistage stochastic optimization methods will become a priority for firms wanting to compete in this arena. Pan, Sornette, and Kortanek call "Intelligent Finance" the new field of theoretical finance at the confluence of different scientific disciplines.[31] According to them, the theoretical framework of intelligent finance consists of four major components: (1) financial information fusion, (2) multilevel stochastic dynamic process models, (3) active portfolio and total risk management, and (4) financial strategic analysis.

Modelers are facing the problem of performance decay that is the consequence of a wider use of models. Classical financial theory assumes that agents are perfect forecasters in the sense that they know the stochastic processes of prices and returns. Agents do not make systematic predictable mistakes: their action keeps the market efficient. This is the basic idea underlying rational expectations and the intertemporal models of Merton.[32]

Practitioners (and now also academics) have relaxed the hypothesis of the universal validity of market efficiency; indeed, practitioners have always being looking for asset mispricings that could produce alpha. As we have seen, it is widely believed that mispricings are due to behavioral phenomena, such as belief persistence. This behavior creates biases in agent evaluations—biases that models attempt to exploit in applications such as momentum strategies. However, the action of models tends to destroy the same sources of profit that they are trying to exploit. This fact receives specific attention in applications such as measuring the impact of trades. In almost all current implementations, measuring the impact of trades means measuring the speed at which models constrain markets to return to an unprofitable efficiency. To our knowledge, no market impact model attempts to measure the opposite effect, that is, the eventual momentum induced by a trade.

It is reasonable to assume that the diffusion of models will reduce the mispricings due to behavioral phenomena. However, one might reasonably

[31]Heping Pan, Dider Sornette, and Kenneth Kortanek, "Intelligent Finance—An Emerging Direction." *Quantitative Finance* 6, no. 4 (2006), pp. 273–277.

[32]Robert C. Merton, "An Intertemporal Capital Asset Pricing Model," *Econometrica*, 41, no. 5 (1973), pp. 867–887.

ask whether the action of models will ultimately make markets more efficient, destroying any residual profitability in excess of market returns, or if the action of models will create new opportunities that can be exploited by other models, eventually by a new generation of models based on an accurate analysis of model biases. It is far from being obvious that markets populated by agents embodied in mathematical models tend to be efficient. In fact, models might create biases of their own. For example, momentum strategies (buy winners, sell losers) are a catalyst for increased momentum, further increasing the price of winners and depressing the price of losers.

This subject has received much attention in the past as researchers studied the behavior of markets populated by boundedly rational agents. While it is basically impossible, or at least impractical, to code the behavior of human agents, models belong to a number of well-defined categories that process past data to form forecasts. Several studies, based either on theory or on simulation, have attempted to analyze the behavior of markets populated by agents that have bounded rationality, that is, filter past data to form forecasts.[33] One challenge going forward is to study what type of inefficiencies are produced by markets populated by automatic decision-makers whose decisions are based on past data. It is foreseeable that simulation and artificial markets will play a greater role as discovery devices.

[33]For the theoretical underpinning of bounded rationality from the statistical point of view, see Thomas J. Sargent, Bounded Rationality in Macroeconomics (New York: Oxford University Press, 1994). For the theoretical underpinning of bounded rationality from the behavioral finance perspective, see Daniel Kahneman, "Maps of Bounded Rationality: Psychology for Behavioral Economics," *American Economic Review* 93, no. 5 (2003), pp. 1449–1475. For a survey of research on computational finance with boundedly rational agents see Blake LeBaron, "Agent-Based Computational Finance," in Leigh Tesfatsion and Kenneth L. Judd (eds.) *Handbook of Computational Economics* (Amsterdam: North-Holland: 2006).