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Bridging The Chasm Between Fundamental, Momentum, and Quantitative Investing

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Abstract. A chasm exists between the active public equity investment management industry's fundamental, momentum, and quantitative styles. In this study, the researchers explore ways to bridge this gap by leveraging domain knowledge, fundamental analysis, momentum, crowdsourcing, and data science methods. This research also seeks to test the developed tools and strategies during the volatile time period of 2020 and 2021.

1 Introduction

The investment management industry is highly competitive as the participants contend daily to earn excess returns for their clients. While many methods can attain outperformance, the ability to capitalize on the strength of multiple investment styles is rarely achieved. The researchers in this study hypothesize that there is a gap between fundamental, momentum, and quantitative investing and seek to bridge it by utilizing aspects of each. This divide is likely to explain why many fundamental investment managers are not currently embracing data science tools. A 2019 study by the CFA Institute [1] surveyed portfolio managers confirmed that most continue to rely on Excel and desktop market data tools, with only 10% of respondents using artificial intelligence (AI) or machine learning (ML) techniques in the past 12 months. For quantitative managers to embrace more of the fundamental side of the equation would likely require changing the way they approach problems and delving deeper into company fundamentals. Most often, quantitative investors use computing power to capture alpha signals versus applying technology to flesh out previously attained knowledge. Given the industry trends and the amount of time needed to hone fundamental analysis skills and insight, this would not be a well-received proposition by quants. Momentum managers would need to step back from technical analysis and short-term trends to evaluate and understand better both fundamental and data science-driven methods. Additionally, while ML and crowdsourcing in the form of analyst estimates and price momentum are well-documented, the combination of these alongside the now less-utilized methods related to fundamental analysis methods is lacking in the academic realm and likely in the active management industry as well. Rarely do fundamental, momentum, and quantitative managers collaboratively take advantage of their expertise as they are often entrenched in their respective camps. Therefore, the researchers believe that a value-additive opportunity exists.

The tools necessary to accomplish this task are believed to need to address the following characteristics: systematic, understandable, adaptable, complementary, efficient, scalable, multidimensional, innovative, and effective.

Systematic tools enable the minimization of biases during the investment process, many of which are driven by emotions and often prove detrimental to performance. Incorporating more disciplined steps in an investment process can increase the likelihood of challenging consensus views when such are not aligned with the current data. A related characteristic, repeatability, is an important element in investment management that is generally attainable with a disciplined, systematic process.

Understandability is another necessary component of success for investment managers and their clients. It is important for an investment manager to have a deep understanding of the data and tools used in order to comprehend the outputs and then communicate effectively with clients.

Though the human psyche is not prone to change, the world is constantly doing so. As such, investment managers must be able to adapt to changes taking place in the market. It is not possible for humans to process the amount of information that computers can. Thus leaning on the latter is ideal for developing adaptability in an investment process. As Mark Twain said, "History doesn't repeat itself, but it often rhymes," and so it is deemed beneficial to have the capability to adapt to and identify changes in the markets by taking into account timely information that computers are proficient at processing.

In the active investment management industry, the word "change" often has a negative connotation. This is understandable given the many examples of managers being pressured to change their decision-making process in the heat of market volatility, which often is the wrong time to do so. Managers need tools capable of complementing one's historical process that do not uproot the core tenets and foundation.

Being able to sufficiently cover all the stocks in a given universe, which can equate to a few thousand and up to greater than ten thousand, is daunting. Some may segment the universe and focus only on those with predetermined criteria, while others use screening tools to narrow down the universe without going into much detail or depth. Ideally, an investment manager will have efficient enough tools to adequately cover the entire selected universe, enabling one to see the overall picture and sufficient details. An important aspect of such efficiency is identifying key data sources and using various tools to draw out information that reduces the information noise intake and isolates the important elements. This type of crowdsourcing represents both a benefit and a significant challenge, as one must be able to determine which information sources are consistently value-additive.

Related to the efficiency mentioned above is the concept of scalability. Fees are being compressed in the investment management industry and are likely to remain to be, so reducing costs without sacrificing the quality of service provided is essential. By having scalable tools, one can expand the scope of their process without losing execution ability. Tapping into the power of crowdsourcing and data science methods would enhance scalability within an investment process.

Multidimensionality is a complex concept in principle and practice. In the investment management industry, breaking down silos between roles and individuals' expertise is deemed favorable. By gathering pertinent information from varied sources and utilizing data science tools, such multidimensionality can be achieved and can tap into the strengths of the various parties. Costs are reduced when people, tools, models, etc., interact with each other and cover more bases, requiring less overhead.

Innovation is at the heart of technological change. To thrive in the future, investment managers must not resist technological change but rather embrace it. There is a dichotomy prevalent in the industry in that investment managers often invest in innovative companies because of such innovation. Still, they are slow to embrace it in their work.

The investment management industry is primarily, if not entirely, about generating excess returns for clients. This study focuses on long-only investment managers seeking to outperform a US large-cap benchmark. The effectiveness of the tools developed by the researchers is tested in a scenario analysis for the years 2020 and 2021, which are well-known to be challenging times for the entire world, the stock market included.

2 Literature Review

2.1 Quantitative Investing

The utilization of data science tools is not a new concept in the investment industry. Numerous tools and methods have been available for many years and sometimes decades. However, the dynamics have been changing in recent years. With the increased computational power and growing sources and amounts of data, the opportunity to utilize data science techniques has grown proportionally. Subramanian (2022) noted that quantitative investing has become more competitive, complicated, and crowded, as industry participants are forced to adapt their strategies to remain competitive and viable. Market participants have broadly exploited simple factor investing strategies that are now well-known and researched. As such, the number of factors being used by such investors has grown threefold. All the while, this increased focus has been at the expense of traditional fundamental investing [2]. With this trend, alternative data is being collected, as industry participants have learned that outperformance is more difficult to achieve without differentiated data. Often this data is being gathered and dispersed by third parties that are not managing clients' funds. While third-party alternative data may display historical efficacy, it can be difficult to incorporate it into an existing investment process and philosophy seamlessly. Also, if the third-party alternative data is proven to be powerful, other market participants will likely exploit it, which in turn will likely reduce the future efficacy.

This focus on quantitative aspects at the expense of fundamental analysis is further evidenced by the number of job postings for data scientists and quantitative analysts outnumbering those for fundamental analysts by a factor of eight [2]. Not only is the trend toward less fundamentally driven investing, but also toward a shorter-term investing horizon, as there is a growing proliferation of strategies attempting to profit from insights garnered from short-term data. Clearly, the trend will continue to be toward the growing field of quantitative investing, though how to create value in such an increasingly crowded space remains a debated topic.

A few examples of how machine learning is being used or proposed to be used in the investment industry are detailed by research provided by Empirical Research Partners [3] and UBS Quantitative Research [4]. Empirical Research Partners (ERP) is an independent research boutique that provides research on portfolio strategy and quantitative topics. With decades of experience in quantitatively driven analytical research, ERP began incorporating machine learning into its analytical processes in 2021. Goldstein et al. (2021) discussed the advantages of machine learning models as they are agnostic to the way things are "supposed" to work. Also noted was a weakness of the machines: they tend to be opaque in their decision-making and can be slow to adapt when things change. Jorgensen et al. (2021) researched and proposed using a machine learning algorithm, XGBoost, to predict future earnings growth. Their model sought to identify stocks with strong growth at low risk based on the view that higher growth is often perceived to imply higher risk. These two examples of machine learning applications in the investment industry not only evidence ways to leverage machine learning tools, but they do so in a manner that aligns with foundational views of one's process and philosophy. However, applications of tools similar to these two examples are deemed minimal in the context of the industry's size.

Despite the evidence of growth in quantitative investing and technological transformation in the investment industry, there remains a cloud of skepticism toward such methods. According to research published by the CFA Institute [1], relatively few investment professionals are currently exploiting artificial intelligence (AI) and big data applications in their investment processes. This research identifies five major hurdles to the successful adoption of AI and big data in investment processes: cost, talent, technology, leadership vision, and time. Other published research has detailed potential use cases for ML in equity analysis [5] but from a highly skeptical perspective. Despite the sizable amount of academic research devoted to this topic and the favorable results presented by many, Buczynski et al. (2021) outlined the ambiguity and lack of high-profile real-world success cases in the investment industry. Supporting this is the low number of AI funds and their assets under management (AUM) currently standing at low levels relative to the industry's size. Some reasons discussed for this include ambiguous definitions of investing strategies, trading vs. investing (i.e., mainly short-term trading focus), and paper profits that do not factor in potential trading costs.

Additional research from Prado (2018) notes the high rate of failure in quantitative finance, particularly so in the use of machine learning. A few are successful, but this is a rare outcome for reasons that the researchers detail in their report. One of the noted reasons for failure is related to the "Sisyphus Paradigm" [6]. This is premised on portfolio managers making investment decisions that do not follow a particular disciplined process, so improvement by consistent adaptation and execution is rarely achieved. These portfolio managers often do not naturally work well as a team. Wherever this formula is overlaid with more quantitative talent, it has not produced favorable results:

> The boardroom's mentality is, let us do with quants what has worked with discretionary PMs. Let us hire 50 PhDs and demand that each of them produce an investment strategy within six months. This approach always backfires, because each PhD will frantically search

> for investment opportunities and eventually settle for (1) a false positive that looks great in an overfit backtest or (2) standard factor investing, which is an overcrowded strategy with a low Sharpe ratio, but at least has academic support (Prado, 2018, p.5).

This research highlights several of the issues of quantitative finance, in particular, many of the shortcomings previously addressed in the overview related to biases, emotions, discipline, and repeatability.

Opportunity and risk lie ahead, though which outweighs the other is highly debatable. Though there are numerous challenges to implementing AI and ML in investment management, such as the lack of widespread utilization, evidence of broad skepticism, and slow speed of adoption, these can be viewed as opportunities to be in a first-mover advantage position for those willing and able to exploit them.

2.2 Machine Learning Research in Investments

Li and Tam (2018) used ML, including Decision Tree (DT), Support Vector Machine (SVM), Multilayer Perceptron Neural Network (MLP), and Long Short-Term Memory Neural Network (LSTM) in their study. Their results indicated that ML, particularly SVM, is useful in analyzing momentum and reversal effects and can be used to assist with trading decisions.

Though research and the primary industry application have generally focused on utilizing ML for short-term trading strategies, some research has been completed on applying ML to fundamental analysis. Researchers Cao and You (2020) examined the efficacy of ML in forecasting corporate earnings. The researchers concluded that such models, especially those that accommodate nonlinearities, are powerful. Similarly, researchers Amel-Zadeh et al. (2020) explored the use of ML in forecasting various metrics and concluded that non-linear models, such as random forest models and neural-network-based models, have the potential to produce forecasting efficacy. Anand et al. (2019) researched utilizing random forest models to predict directional changes in five profitability measures. The results from this study aligned with the others regarding non-linear models and suggested that machine learning methods offer better predictive performance than traditional regression-based methods. Despite this intriguing research, the application of such academic research in real-world situations remains relatively unknown or at least not widely publicized.

Rasekhschaffe and Jones (n.d.) performed research that attempted to address the application of the above-mentioned topic. In this research, the authors describe some basic concepts surrounding ML and provide a simple example of how investors can use such techniques to forecast the cross-section of stock returns while limiting the risk of overfitting. Such overfitting is argued to be predicated by the inclusion of only individual equity characteristics and not any macro variables.

Researchers Arnott et al. (2018) address risks associated with misapplying ML techniques and how this can lead to unfavorable results. One of their recommendations is to carefully structure the ML problem so that a reasonable hypothesis guides the inputs. Another is to refrain from tweaking one's model. This research supports the notion that the human element is important in leveraging the power of ML models by starting with an underlying hypothesis and knowledge and then using data supporting this hypothesis to be fed into models. As previously discussed regarding discipline, there may be times when temptations exist to tweak a model, likely due to poor performance, and this research would argue against doing so.

2.3 Fundamental Investing

Fundamental analysis attempts to identify stocks with attractive valuation and/or growth characteristics. There is no standardized method of applying such analysis, but the process generally involves the assessment of the financial statements of a company and various other factors. This analysis's valuation and growth aspects are often segregated by industry clients, even though investors are typically looking at similar metrics but with differing priorities and preferences. This segregation typically results in classifying investment managers as either value or growth. Fundamental analysis is considered a skill honed over many years of real-world experience, but it is very time-consuming and difficult to scale.

Lee (2014) explored the background of what is known as value investing. Value investing can be described as analyzing stocks based on a perceived gap between their current market price and their fundamental value, commonly defined as the present value of the expected future payoffs to shareholders [13]. Value investors mainly focus their efforts on buying stocks that appear to be inexpensive relative to their intrinsic value and selling stocks that seem expensive. Other methods used to determine value involve calculating valuation multiples that consider numerous financial statement outputs and current price levels, such as the forward price-to-earnings ratio. Such multiples can be compared to the overall market, company history, and relevant company peers. The "value effect" was first recognized by Columbia University professor Benjamin Graham, who served as a mentor to the famed Warren Buffett, and has been documented as early as 1934. Various academic studies have confirmed and rediscovered various elements of this effect in the ensuing 80 years [13]. Typically value investors also consider the quality characteristics of companies to avoid what are called "value traps," whereby a stock has an attractive valuation but continues to underperform due to fundamental deterioration.

Growth investing is described by researcher Damodaran (2012) as investing in companies using growth potential instead of investments. The method involves an attempt to create and advantage by identifying stocks that have significant potential to grow [14]. There are various means by which this type of analysis is performed, including analyzing historical growth levels; forecasting growth in the coming years and comparing growth to current consensus estimates; and looking at numerous financial metrics that not only capture growth attributes on a trailing and forward-looking basis but also seek to exploit opportunities related to small-cap companies, initial public offerings, and macroeconomic trends that can drive growth trajectories. Valuation considerations may or may not be considered, though growth characteristics often drive the decision-making process.

Both value and growth investing offer potentially value-additive attributes to one's investment philosophy and process. However, these forms of traditional fundamental analysis have declined in recent years. There are several potential reasons for this decline: They are not scalable, as it is difficult and extremely costly to fundamentally analyze all stocks in a given universe. Due to being less systematic than other types of investing, fundamental analysis can be more subjective and prone to being influenced by biases and emotions. By focusing on value or growth, an investor may not be able to adjust to secular or cyclical changes in the market.

While the headwinds facing fundamental analysis are well-known and largely understandable, the researchers in this study still believe valuable insights can be gleaned. This comes not from incorporating simple metrics and ratios into a strategy or model, but rather from being able to systematically and broadly quantify domain knowledge and financial acumen in a unique and value-additive manner.

2.4 Quantamental Investing

In recent years there have been efforts to combine computer-driven and human-driven research, which has been labeled as "quantamental investing." Tadoori and Guguloth (2020) researched this topic and provided a background of both sides of the equation. They discussed that most often the signals used in the quantitative models include value, momentum, growth, volatility, leverage, size, and profitability. Advantages noted from this type of strategy included increased discipline, decision-making speed, anomaly exploitation, scalability, and risk control. Issues noted with implementing this type of strategy included large upfront costs, scarcity of talent pool with needed expertise, elimination of fund manager authority, and generally being developed for a short duration only and therefore struggling in changing market conditions. While this type of investing is believed to be a step in the right direction, the researchers of this study identify shortcomings that make this suboptimal. The description implies that there are still challenges related to different people with different skills, preferences, and biases trying to work together. Often different teams are leveraged at different steps, creating communication, understanding, and interaction issues, allowing for potential disagreements on foundational principles. For example, quantitative models may be used on the front end of a stock screening process. Then the fundamental analysis is performed. This may seem reasonable, but the quantitative screens are often based on simple factors and are not premised on deep analytical insights; thus, the likelihood of differentiated results due to the quantitative tools is minimal.

Additionally, other data sources are often sought out, which may or may not align with the foundational principles of the process. This challenge is especially prevalent when unstructured and/or alternative data is incorporated into one's process. The quantitative team members often lead this data search. Such efforts can result in data mining when the data is chosen to be incorporated primarily due to the historical backtest rather than financial acumen gained over time via experiential knowledge. With this being more of a siloed process rather than a full integration of people with various expertise, it not only lacks the ability to optimize collective wisdom in an aligned manner, but also lacks clarity in the execution of decision-making when conflicting opinions exist. For example, a quantitative model may recommend a stock, but the fundamental analysis may not, and it is unclear how this is settled systematically and optimally.

2.5 Financial Analyst Estimates

Scale in an investment process can be garnered by crowdsourcing, which involves obtaining data and insights from a large group of people. One means of applying such crowdsourcing is via data provided by sell-side financial analysts that provide estimates, ratings, target prices, and general comments regarding the companies each is assigned to cover. The topic of financial analysts' forecasts providing and containing valuable information to the marketplace has been well documented. In the late 1970s, researchers Givoly and Lakonishok (1979) assessed the information content of revisions in analysts' earnings forecasts by assessing the relationship between the direction of these revisions and stock price movement. This research serves as one of the foundational research reports for this topic. The results support the notion that market reaction to forecast changes may be relatively slow and provide investors with return opportunities. Another historical perspective on this topic comes from one of the same authors. Fried and Givoly (1982) studied analysts' forecasts and compared this method to other models in accurately predicting earnings. They found that the forecasts were more accurate than time-series models in market expectations. They also found factors that might affect the accuracy of financial analysts' forecasts. It also provided a historical perspective on crowdsourcing for information, as they assessed the use of analyst forecasts as surrogates for the market's expectation of future earnings. Not only are analysts' revisions potentially powerful, but the consistency and stability of such metrics may also be informative. Li (2021) also studied this topic and suggested the consistency of estimates and revisions contains informational value to investors when comparing stocks to each other.

The underlying premise as to why analysts' forecasts provide potential value to investors is a debated matter. Possibilities include the fact that they get much of their information from company management, which has deep insights, and social behaviors in the form of herding. Raafat et al. (2009) addressed the social behavior of herding and how its application can be generally applied. The authors also address the mechanisms of transmission and the patterns of connection between herding agents and their effects on the revision patterns of analysts. On this topic, Welch (2000) further expounded as he sought to show that the buy or sell recommendations of security analysts have positive effects on the recommendations of the next two analysts. This influence can be linked to short-term information in the most recent revisions. This research indicates the potential for consensus herding consistent with models in which analysts herd based on little information.

Additionally, Durand et al. (2014) analyzed the potential for behavioral bias among analysts as they tend to move away from the prevailing consensus as their confidence increases over time. The researchers suggest that sell-side analysts perform an economically useful service by providing information to the market, which is not believed to be perfectly informationally efficient. Herding is also economically rational, given analysts' career concerns, as being wrong when everyone else is wrong is preferable to being wrong on one's own. This research supports the notion that sell-side analysts should be studied as a group rather than as specific individuals. Also, this research is premised on analyzing sell-side analyst estimates rather than their buy and sell recommendations and ratings, which are believed to be more influenced by the aforementioned herding mechanisms, pressures, and biases.

2.6 Momentum Investing

Price momentum in the stock market is a phenomenon that has been discussed and studied for many decades. Momentum is based on the theory that stocks that have been performing well during a certain time will continue to do so. This phenomenon can be viewed as another form of crowdsourcing, as such trends can be described to represent the collective opinion of marketplace participants. Though many investors utilize such metrics and tools, their underlying calculation and application are far from standardized nor agreed upon by many. This supports the notion that they may still be exploitable depending on how one defines and utilizes such information. Chan et al. (1995) researched the topic of relating the predictability of future returns from past returns to the market's underreaction to information. They used a particular focus on past earnings news. The researchers concluded that past returns and past earnings surprises each have predictive power on future returns after controlling for the other. This supports the inclusion of momentum and price trend information in this analysis.

Additionally, research was conducted by Low and Tan (2016) to assess the extent to which sell-side equity analysts can facilitate market efficiency. Their study finds that analysts can provide value-relevant signals to investors by identifying momentum indicators. The researchers suggest that analysts' ability to identify under or over-valued stocks as information intermediaries is important in the price-continuation momentum effect. This paper supports the notion of momentum in the markets and the value-relevant signals provided to the marketplace by the actions of sell-side analysts.

Not only is the topic of momentum not standardized, but it also is often misunderstood. Asness et al. (2014) addressed this in their research titled "Fact, Fiction and Momentum Investing." One myth addressed in this study was that momentum cannot be captured by long-only investors because momentum can be exploited only on the short side [24]. On a risk-adjusted return basis, this study found such claims untrue and found the long side to actually have higher returns. Another myth addressed was that momentum is much stronger among small-cap stocks than large-cap stocks. Again, this study found such claims to be false based on risk-adjusted returns of varied time periods. Other myths this study sought to debunk included that there is no theory behind momentum as it is too volatile to rely on, its returns are likely to disappear, and it is best used with screens rather than as a direct factor. Providing evidence against these myths and thus for using price momentum as part of one's stock selection process supports the researchers' hypothesis regarding the use of price momentum metrics in the ML modeling efforts.

Using ML, this research seeks to create tools and strategies that leverage a combination of domain knowledge, fundamental analysis, momentum, crowdsourcing, and data science methods. Inherent efficiency and competition within the market are seen by the decay in simple factor investing. Thus a differentiated perspective must be taken. The researchers believe that humans should determine the inputs to the models to leverage financial acumen and mitigate risks associated with data mining, in which a strategy is derived mainly based on past results.

This review supports the following aspects for approaching the problem at hand: Given the lack of widespread adoption of AI and ML tools by investment managers, there are perceived advantages to be gained related to early adoption, but current quantitative-driven models focus primarily on the short-term, supporting the need to develop tools for medium-term horizons. Analyst estimates and revisions are informative and potentially value-additive. Quantamental investing has potential but remains difficult to exploit given the lack of collaboration and foundational overlap of people with varied expertise. Lastly, momentum is prevalent and exploitable given skepticism and the wide range of application methods in the stock market, and sell-side analysts play a role in such phenomena, thus linking the two together. Combining machine learning and data science with the positive aspects of these methods creates a framework that seeks to be effective and supported by the results of testing on historical data.

3 Methods

3.1 Analytical Foundation

There are many ways to estimate the value of a publicly traded stock, though for this research, the following formula and its underlying components serve as the basis.

$$Price = Valuation\ Metric * Financial\ Output$$

This formula states that a given stock price value can be estimated based on a chosen valuation metric multiplied by a financial output that aligns with such valuation metric. One example of this is the formula that states that the stock price is estimated to be the forward price-to-earnings ratio multiplied by the forward earnings per share estimate.

It is undeniable that all of the aforementioned components are important when determining the attractiveness of a given stock, though how one goes about taking them into account can differ greatly. Some choose to focus on the growth potential and primarily on the forecasted financial output, which as discussed above are typically labeled as growth investors. Value investors often focus first and foremost on the valuation component and its attractiveness when analyzing a given stock. Momentum investors generally use technical and trend analysis using the price movement of a given stock to determine its appeal. This study is premised on the belief that each component is valuable and worthy of analysis, but all have different underlying attributes. More specifically, it is believed that valuation is a measure that oscillates over time and is likely to gravitate toward the mean. Alternately, financial outputs, such as earnings and revenues, may oscillate for some companies more than others but are less likely to gravitate toward the mean and instead trend over time. The price then takes both into account but is a fallout of the two rather than the driver. Based on these foundational differences and opinions, these components are modeled separately.

3.2 Data

The data for this study was sourced from FactSet, a financial data and analytics company. The researchers downloaded data via FactSet's Excel add-in and then compiled the data into CSV files. The starting universe chosen was the constituents of the Russell 1000 Index, which serves as a benchmark for many US large capitalization active investment managers. Companies in the real estate sector were removed given they typically are valued and analyzed based on different metrics that involve funds from operations instead of earnings per share as are other sectors. The universe was then reduced to 652 by only including those companies that have financial data extending back to 2009. Weekly data was collected spanning from the end of 2009 to the end of June 2022. The decision to use weekly data was premised on the idea that the developed tools could be updated by users weekly.

The market cap range for this universe of stocks at the end of June 2022 was from approximately $2.7 billion to $2.3 trillion. The universe is diverse in terms of sector exposure, as all Global Industry Classification Standard (GICS) economic sectors except Real Estate were included. The highest number of stocks in any sector was 102 in Industrials, and the Communication Services sector had the least at 18. From an industry perspective, the greatest number of stocks came from Regional Banks at 25.

Multicollinearity was evidenced in the dataset but was not sought to be addressed. Given the researchers were focused on performance over interpretability, it was deemed to be outside the scope of this project.

3.3 Machine Learning Modeling Overview

The data downloaded can be categorized into valuation metrics, analyst revisions, analyst EPS estimates, analyst revenue estimates, and price. The explanatory variables seek to capture the researchers' domain knowledge and experience, as many of the calculated metrics are not believed to be widely utilized nor discussed in the marketplace. Given the factor decay caused by simple factor investing that has been prevalent in the industry in recent years, the need for more granular yet foundational variables has grown. The researchers thus lean on experiential wisdom rooted in the study of underlying characteristics, trends, and volatility for company fundamentals, analyst estimates and revisions, valuation multiples, and momentum. Given there is often a low signal-to-noise ratio for investment-related datasets, the researchers sought to quantify specific domain knowledge in a manner that can be utilized for machine learning modeling, which the researchers believe is a critically important aspect of bridging the aforementioned gap. Also, machine learning in investments can be challenged by small data sets, thus the researchers chose metrics that are applicable to all companies in this universe regardless of industry classification and business model. The difficulty of evolution and cyclicality in the markets was addressed by choosing metrics that are comparable and exhibit stability over time regardless of the environment.

<u>Valuation Metrics</u>: To garner an encompassing assessment of each company's valuation, the researchers included the following valuation metrics: Price to Forward 12M EPS (FPE), Dividend Yield (DY), Price to Book (PB), Enterprise Value to Sales (EVS), Price to Trailing 12M EPS (TPE), Enterprise Value to EBITDA (EVEBITDA), Enterprise Value to Free Cash Flow (EVFCF), Price to Cash Flow (PCF), and Price to Sales (PS). By factoring in several valuation metrics, the researchers believe that the

analysis sufficiently accounts for all financial statements and their related outputs and underlying information. The researchers included absolute and relative value metrics that capture levels, trends, and volatility of these metrics at various time periods.

Analyst Revisions: As discussed in the literature review, there is presumed to be informational value in the sell-side analyst revisions. In this category, the direction of revisions is accounted for as well as the second-derivative changes of such revisions over various time periods.

Analyst EPS Estimates: Sourced from the same analysts as above, these estimates are for the earnings per share (EPS) estimates for a given company during the next 12-month period. With these estimates, the researchers calculated numerous metrics, which account for the growth, second-derivative changes, and volatility.

Analyst Revenue Estimates: These estimates are similar to the EPS estimates and the associated calculated metrics; however they represent the revenue estimates instead.

Price: The price for each stock was gathered, and then several metrics assessing the trend of each stock over various time periods were calculated.

Upon gathering and calculating the aforementioned metrics, the researchers then calculated the percentile (0-100) of each metric relative to this universe at that specific point in time. This was premised on being able to compare one stock to the entire universe based on every metric to determine its relative attractiveness. In total there were 370 explanatory variables.

There were seven different response variables in this research that included the following:

Valuation: The four valuation metrics modeled included: FPE, DY, PB and EVS. For each of these metrics, the researchers sought to predict the following three-month revision relative percentage rank.

Analyst EPS / Revenue Estimates: The two growth metrics modeled included: Analyst EPS estimates' and analyst revenue estimates' three-month growth relative percentage rank.

Price: The researchers created a three-month binary classification model that measures the predicted probability that a stock in this universe will outperform the universe median during this time period. The equal-weighted Russell 1000 Index was considered instead of the median universe return, but given the superior returns for the latter in the years 2020 through 2021, the researchers deemed this to be more conservative. Also, though the Russell 1000 Index is the predominant index used by US large capitalization managers, which is the primary target audience for this study, this research's use of the median removes the different individual weightings within the index.

4 Results

4.1 Machine Learning Modeling Analysis Introduction

Before creating any ML models, the researchers first utilized PyCaret to determine the potential efficacy of various algorithms on the dataset. PyCaret is an open-source, low-code machine learning in Python that automates machine learning workflows. This package provided evidence that across the selected response variables the following five models had the most potential explanatory power: Extra Trees, Random Forest, K-Nearest Neighbor (KNN), XGBoost, and CatBoost. With this in mind, the researchers sought to develop and tune each of these models and then stack them to develop a final prediction model for each of the chosen explanatory variables, which are detailed below. The researchers decided to use stacked models as the final models to make predictions on the data based on the theory that stacking can harness the capabilities of a range of models to make predictions that have better performance, more stability, and better generalization capabilities on new data.

4.2 Machine Learning Value Modeling Analysis

<u>Hypothesis</u>: The researchers hypothesize that value managers generally follow a process whereby they first seek to find attractive valuation candidates that are likely to mean revert and outperform. Then some form of fundamental analysis is performed. Lastly, a catalyst is identified, which is expected to be the impetus for the stock's valuation rerating and outperforming in the near term. The researchers believe that successful value managers are adept at discerning the question of "***if*** a stock will mean revert and outperform," though where most struggle is answering the question of "***when*** a stock will mean revert and outperform." The "when" factor is often sought to be answered by determining the aforementioned catalyst. Achieving this with precision and scale is considered to be extremely difficult and often adversely affected by biases. With this in mind, the researchers built models that predict near-term relative valuation rerating. As such, these models seek to replace the value manager catalyst identification process with statistically driven calculations that are more scalable and powerful. There are numerous valuation multiples used by investors though, for this research, the following four were modeled given their prevalence in the industry: FPE, DY, PB, and EVS. Each is to be modeled in an effort to predict the three-month revision percentage relative rank.

<u>Details</u>: Upon loading the data and initial preprocessing steps were taken such as filling in missing values with the median and transforming the explanatory variables with Scikit Learn's PowerTransformer function to make the data more Gaussian-like. Then for each model, hyperparameter tuning was performed using various randomized search algorithms with mean absolute error set as the evaluation metric of choice. Then these five tuned models were stacked together using Scikit Learn's StackingRegressor algorithm with XGBoost regressor as the final meta learner.

Applications: The use cases for these types of models include but are not limited to the following: stock selection by deciphering between stock opportunities as to which is more or less likely to rerate based on a specified valuation metric, avoiding value traps whereby the valuation is deemed attractive but the stock continues to underperform in the near term aiding in the timing of exit and rebalancing of current holdings, and combining with other investment processes and/or models to better determine fundamental and statistical attractiveness.

Assessment: In order to assess efficacy, each model and associated strategy will be tested quarterly on new data during the years 2020 and 2021.

4.3 Machine Learning Growth Modeling Analysis

Hypothesis: The researchers hypothesize that companies with superior future EPS and revenue growth within a given universe are rewarded by the market. Though there are numerous metrics to quantify growth, these two are commonly used in the industry. Determining which companies are currently growing the fastest is a relatively simple task, as the main challenge comes in the form of determining the growth trajectory into the future. As such, the models built attempt to predict growth relative to the defined universe. The three-month growth percentage relative rank is to be modeled for both analyst median EPS and revenue estimates.

Details: The same modeling techniques were applied for these two growth models as were used to build the aforementioned valuation models.

Applications: The use cases for these types of models include but are not limited to the following: stock selection by identifying the relative attractiveness of near-term growth trends, avoiding growth traps whereby the current growth trajectory is deemed attractive but the outlook is less favorable, aiding in the timing of exit and rebalancing of current holdings, and combining with other investment processes and/or models to better determine fundamental and statistical attractiveness.

Assessment: Similar to the value models, each model and associated strategy will be tested quarterly on new data during the years 2020 and 2021.

4.4 Machine Learning Price Momentum Modeling Analysis

Hypothesis: The researchers consider valuation and growth metrics as the primary driver of the stock selection with the price trend as something that is to be respected. As such, the hypothesis is to develop a three-month binary classification price momentum (PMO) model to aid in timing and to function primarily as an overlay tool.

Details: A similar modeling framework was used for the classification model, except the F1 score was the chosen evaluation metric and stratified K-fold cross-validation was used. The F1 score was deemed to be an appropriate evaluation metric given it is useful when seeking to correctly identify positive outcomes in the model (i.e. choose the stocks that will outperform).

Applications: The use cases for this type of model include but are not limited to the following: aid in the timing of the purchase as a stock may be deemed attractive but the current timing is not deemed to be statistically advantageous, help with timing the exit of a stock that is no longer deemed attractive for some fundamental and/or valuation reasoning, and using as a front-end stock selection or overlay tool in a quantitatively driven investment process.

Assessment: Similar to the other models, this model will be tested quarterly on new data during the years 2020 and 2021.

4.5 Scenario Analysis Background

Upon completion of the modeling analysis, the researchers then tested the models during the years 2020 and 2021. These years were chosen given the volatility experienced as a result of the global COVID pandemic and the ensuing recovery. With market dynamics changing in a short amount of time, the researchers were interested in assessing the ability of the developed tools to not only generate relative outperformance but also to capture dislocations and adjust to changes taking place in the market in a timely manner.

The researchers utilized two metrics to assess model and strategy performance, hit rate and relative return. The hit rate equates to the number of holdings in a given strategy model that produced alpha, which means outperformed the universe median during this time period. The relative return quantifies the amount of out- or (under-) performance compared to the universe median. Given factors related to noisy data, high competition, market efficiency, and the time-sensitive nature of decision-making, hit rates above 50% are often viewed as a benchmark that needs to be exceeded to be considered value-additive.

This study followed common industry practices whereby model efficacy was assessed primarily based on comparing top and bottom quintiles or deciles. Often the top predictions are considered to be the most attractive buy candidates, and the opposite is true for the bottom candidates. To assess the PMO model as an overlay tool, the researchers then repeated the steps above except used the PMO model such that no stock was included in the top and bottom quintile unless it was predicted to outperform or underperform, respectively.

The initial model training and predictions for the portfolio construction process for each of these portfolio strategies had a five-year lookback in the data. Due to the volatility seen in the market after the first fiscal quarter, the researchers then changed the lookback period to three years for the ensuing quarters. This is premised on the hypothesis that during heightened volatility and market conditions that are perceived to involve greater change, by lessening the data lookback period, the underlying models are better able to adapt to such conditions, given the more recent data has a greater overall weight and thus impact in the model's predicted outputs.

4.6 Scenario Analysis Results

Q1 2020: As mentioned above, the initial models were trained based on a five-year lookback that spanned from 12/26/2014 to 9/27/2019. Given the researchers predicted three months into the future, the training data was ended three months prior to the test date. Table 1 below details the hit rates for each of the model's top and bottom quintile predictions. The left side of the table represents the standalone models, while the right side includes the models with the PMO overlay. Note that the hit rate for the bottom quintile was calculated in reverse, as a high hit rate represents the model better predicting underperforming stocks.

The overall hit rates were favorable, as all models except one had hit rates in excess of 50%, which is considered a minimum benchmark, with several approaching the 70% level. The results from overlaying the models with the PMO model were mixed.

Table 1. Q1 2020 model portfolio hit rates

Model Portfolio	Top Quintile	Bottom Quintile	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO
FPE	58%	49%	58%	48%
EVS	67%	50%	65%	53%
DY	58%	65%	64%	65%
PB	64%	51%	66%	53%
EPS Growth	56%	60%	57%	67%
Revenue Growth	61%	63%	64%	66%
PMO	55%	62%	N/A	N/A

Table 2 below details the relative return figures for the model strategies, which quantifies the amount of out- or (under-) performance during this time period. During the first quarter of 2020, the overall market dropped over 20% due to concerns about the global pandemic. As such, these models were able to hold up relatively well in a challenging market environment. All but one standalone model generated alpha on the buy (i.e. top quintile) and sell (i.e. bottom quintile) side of the equation.

Table 2. Q1 2020 model portfolio 3-month median relative out- / (under-) performance

Model Portfolio	Top Quintile	Bottom Quintile	Difference	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO	Difference w/ PMO
FPE	2.3%	(0.2%)	2.5%	2.1%	1.4%	3.5%
EVS	3.7%	0.7%	3.0%	4.1%	(1.0%)	5.1%
DY	1.7%	(9.4%)	11.1%	2.6%	(9.8%)	12.4%
PB	4.9%	(0.7%)	5.6%	5.9%	(1.2%)	7.1%
EPS Growth	3.0%	(4.7%)	7.7%	3.5%	(7.6%)	11.1%
Revenue Growth	5.4%	(7.0%)	12.4%	5.2%	(6.5%)	11.7%
PMO	2.8%	(5.8%)	8.6%	N/A	N/A	N/A

Q2 2020: As mentioned above, the ensuing models for the remaining quarters of 2020 were trained based on a three-year lookback. During the second quarter, the hit rates for the value models on a standalone basis were all near 60% or above. The growth models' hit rates fell during this time period, in particular the EPS growth model. The PMO overlay evidenced being additive mainly on the bottom quintile holdings.

Table 3. Q2 2020 model portfolio hit rates

Model Portfolio	Top Quintile	Bottom Quintile	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO
FPE	64%	58%	59%	64%
EVS	57%	58%	53%	63%
DY	60%	62%	58%	67%
PB	62%	64%	59%	73%
EPS Growth	36%	43%	35%	44%
Revenue Growth	45%	41%	52%	47%
PMO	51%	59%	N/A	N/A

During this time the market recovered strongly in excess of 20%. The results in Table 4 evidence the value models being able to generate alpha in the top and bottom quintiles during the market reversion. The growth models struggled, which aligns with the weaker hit rates above. The PMO overlay tool added value on the bottom quintile holdings in the value models, but did not contribute to performance in the top quintile.

Table 4. Q2 2020 model portfolio 3-month median relative out- / (under-) performance

Model Portfolio	Top Quintile	Bottom Quintile	Difference	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO	Difference w/ PMO
FPE	6.0%	(6.4%)	12.4%	3.2%	(7.2%)	10.4%
EVS	3.1%	(3.6%)	6.7%	1.1%	(9.1%)	10.2%
DY	4.4%	(7.2%)	11.6%	1.2%	(9.8%)	11.0%
PB	7.3%	(7.8%)	15.1%	5.3%	(10.0%)	15.3%
EPS Growth	(7.0%)	3.7%	(10.7%)	(7.9%)	3.0%	(10.9%)
Revenue Growth	(3.1%)	7.1%	(10.1%)	(0.9%)	4.2%	(5.1%)
PMO	0.6%	(6.4%)	7.0%	N/A	N/A	N/A

Q3 2020: In the third quarter of 2020, the hit rates dropped across the strategies. The valuation models again produced better hit rates on a standalone basis, though only two models were above the 50% threshold on the top quintile holdings.

Table 5. Q3 2020 model portfolio hit rates

Model Portfolio	Top Quintile	Bottom Quintile	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO
FPE	56%	52%	51%	52%
EVS	55%	46%	55%	41%
DY	48%	51%	47%	51%
PB	49%	42%	49%	43%
EPS Growth	39%	53%	31%	51%
Revenue Growth	36%	53%	32%	48%
PMO	45%	45%	N/A	N/A

During this time period, the stock market slightly increased as the initial volatility experienced from the pandemic impact dampened. The value models continued to outperform the growth models, though only the FPE model generated alpha on the buy and sell side.

Table 6. Q3 2020 model portfolio 3-month median relative out- / (under-) performance

Model Portfolio	Top Quintile	Bottom Quintile	Difference	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO	Difference w/ PMO
FPE	1.7%	(0.1%)	1.8%	1.3%	0.3%	1.0%
EVS	1.7%	1.8%	(0.1%)	1.6%	3.0%	(1.4%)
DY	(1.2%)	0.2%	(1.4%)	(2.4%)	0.4%	(2.8%)
PB	(0.9%)	3.1%	(4.0%)	(1.2%)	2.8%	(4.0%)
EPS Growth	(2.3%)	(1.2%)	(1.1%)	(5.0%)	(0.7%)	(4.3%)
Revenue Growth	(3.9%)	(2.0%)	(5.9%)	(4.5%)	0.6%	(5.1%)
PMO	(1.3%)	2.6%	(3.9%)	N/A	N/A	N/A

Q4 2020: During the final three-month period of 2020, the hit rate improved for the standalone value models with such models outperforming the growth models and those with the PMO overlay.

Table 7. Q4 2020 model portfolio hit rates

Model Portfolio	Top Quintile	Bottom Quintile	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO
FPE	51%	57%	43%	55%
EVS	53%	57%	49%	54%
DY	53%	38%	49%	43%
PB	40%	58%	36%	57%
EPS Growth	37%	37%	30%	32%
Revenue Growth	30%	33%	28%	35%
PMO	42%	43%	N/A	N/A

During the last quarter of 2020, the stock market was choppy but then rallied hard in early November on the back of positive vaccine news and ended up over 10%. Given the predictions were made preceding the vaccine news, it was not surprising that performance generally was weaker during this time. The standalone value models generated respectable relative returns as they continued to exhibit superior performance compared to the growth models and PMO overlay models.

Table 8. Q4 2020 model portfolio 3-month median relative out- / (under-) performance

Model Portfolio	Top Quintile	Bottom Quintile	Difference	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO	Difference w/ PMO
FPE	1.2%	(2.8%)	4.0%	(1.3%)	(1.3%)	0.0%
EVS	1.1%	(1.7%)	2.8%	0.1%	(0.5%)	0.6%
DY	3.0%	6.1%	(2.9%)	3.7%	5.4%	(1.7%)
PB	(3.3%)	(3.0%)	(0.3%)	(4.0%)	(2.2%)	(1.8%)
EPS Growth	(4.7%)	6.9%	(11.6%)	(5.8%)	9.4%	(15.2%)
Revenue Growth	(6.4%)	11.3%	17.7%	(6.2%)	9.8%	15.0%
PMO	(1.8%)	4.1%	(5.9%)	N/A	N/A	N/A

2020: To summarize 2020, though there was a high amount of volatility, the overall market as measured by this study's universe median and the Russell 1000 Index generated strong absolute returns in excess of 24% and 20%, respectively. While the growth models struggled to generate alpha, that was not the case for the value models. The PMO model as an overlay tool did not prove to be additive. The strongest efficacy was evidenced by the standalone value models, as they generated significant alpha on the buy and sell side of the equation.

Table 9. 2020 model portfolio 12-month median relative out- / (under-) performance

Model Portfolio	Top Quintile	Bottom Quintile	Difference	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO	Difference w/ PMO
FPE	11.3%	(9.6%)	20.9%	5.4%	(6.8%)	12.2%
EVS	9.5%	(2.9%)	12.4%	6.9%	(7.6%)	14.5%
DY	8.0%	(10.3%)	18.3%	5.1%	(13.7%)	18.8%
PB	7.9%	(8.3%)	16.2%	6.0%	(10.7%)	16.7%
EPS Growth	(11.0%)	4.7%	(15.7%)	(15.1%)	4.2%	(19.3%)
Revenue Growth	(7.9%)	9.4%	(17.1%)	(6.5%)	8.1%	(14.6%)
PMO	0.2%	(5.5%)	(5.3%)	N/A	N/A	N/A

Q1 2021: Moving forward into the next year, the hit rates generally dropped across the strategies during the first quarter. DY, EVS and PB slightly exceeded the 50% threshold within the value models, while EPS growth outperformed revenue.

Table 10. Q1 2021 model portfolio hit rates

Model Portfolio	Top Quintile	Bottom Quintile	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO
FPE	32%	39%	31%	39%
EVS	51%	58%	52%	52%
DY	54%	46%	57%	41%
PB	51%	61%	52%	48%
EPS Growth	55%	59%	40%	60%
Revenue Growth	41%	43%	30%	43%
PMO	45%	46%	N/A	N/A

The stock market continued to march higher during this time period as the post-COVID recovery was well underway due to positive vaccine news and massive relief stimulus. From the vaccine announcement in November 2020 through the first quarter of 2021 was considered by some market commentators to be a low-quality rally. Model performance was generally mixed without any standout performance on the positive side.

Table 11. Q1 2021 model portfolio 3-month median relative out- / (under-) performance

Model Portfolio	Top Quintile	Bottom Quintile	Difference	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO	Difference w/ PMO
FPE	(6.5%)	6.1%	(12.6%)	(6.0%)	6.9%	(12.9%)
EVS	0.5%	(4.6%)	5.1%	4.9%	0.5%	4.4%
DY	1.6%	2.4%	(0.8%)	2.7%	4.7%	2.0%
PB	(0.5%)	(4.4%)	3.9%	(0.2%)	0.9%	(1.1%)
EPS Growth	2.5%	(3.0%)	5.5%	(5.6%)	(3.6%)	(2.0%)
Revenue Growth	(5.1%)	4.6%	(9.7%)	(8.8%)	4.5%	(13.3%)
PMO	(1.9%)	1.6%	(3.5%)	N/A	N/A	N/A

Q2 2021: The hit rates improved for the FPE and EVS value models but fell for the other models during the second quarter of 2021. Better results were found across many of the bottom 100 holdings, which predicts the stocks to avoid, as all but two of the standalone models generated hit rates above the 50% threshold.

Table 12. Q2 2021 model portfolio hit rates

Model Portfolio	Top Quintile	Bottom Quintile	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO
FPE	56%	55%	57%	56%
EVS	54%	46%	54%	45%
DY	48%	54%	48%	52%
PB	47%	52%	48%	49%
EPS Growth	43%	58%	47%	62%
Revenue Growth	46%	59%	46%	62%
PMO	50%	58%	N/A	N/A

Stocks climbed a wall of worry in the second quarter as concerns ranged from higher inflation and future interest rate hikes to further COVID restrictions amid rising cases overseas. As has been the case in most quarters, the value models generally performed better, and the PMO overlay tool was not broadly additive to relative performance.

Table 13. Q2 2021 model portfolio 3-month median relative out- / (under-) performance

Model Portfolio	Top Quintile	Bottom Quintile	Difference	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO	Difference w/ PMO
FPE	1.9%	(0.2%)	2.1%	1.3%	(0.1%)	1.4%
EVS	1.0%	0.2%	0.8%	1.6%	0.4%	1.2%
DY	0.4%	(1.3%)	1.7%	0.1%	(0.9%)	1.0%
PB	(1.4%)	(0.2%)	(1.2%)	(1.2%)	0.2%	(1.4%)
EPS Growth	(2.0%)	(0.6%)	(1.4%)	(0.4%)	(0.8%)	0.4%
Revenue Growth	(1.1%)	(1.1%)	0.0%	(1.2%)	(1.3%)	0.1%
PMO	0.0%	(1.1%)	1.1%	N/A	N/A	N/A

Q3 2021: The third quarter of 2021 saw a reversal of trends seen during much of 2020. The hit rates were relatively unfavorable for the value models, while the growth models performed well as they exceeded the 50% threshold on both sides.

Table 14. Q3 2021 model portfolio hit rates

Model Portfolio	Top Quintile	Bottom Quintile	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO
FPE	41%	39%	39%	41%
EVS	43%	48%	40%	47%
DY	39%	45%	34%	44%
PB	48%	36%	44%	40%
EPS Growth	62%	58%	60%	52%
Revenue Growth	58%	55%	57%	51%
PMO	47%	42%	N/A	N/A

During the third quarter the market was relatively flat, which seems to have favored the growth models. The value models struggled to generate alpha during this environment, though the growth models evidenced relative outperformance on the buy and sell side.

Table 15. Q3 2021 model portfolio 3-month median relative out- / (under-) performance

Model Portfolio	Top Quintile	Bottom Quintile	Difference	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO	Difference w/ PMO
FPE	(1.5%)	2.3%	(3.8%)	(1.6%)	2.1%	(3.7%)
EVS	(0.4%)	0.8%	(1.2%)	(0.9%)	0.3%	(1.2%)
DY	(1.7%)	1.4%	(3.1%)	(2.1%)	1.1%	(3.2%)
PB	(1.8%)	3.1%	(4.9%)	(1.9%)	2.1%	(4.0%)
EPS Growth	3.8%	(1.6%)	5.4%	1.9%	(0.7%)	2.6%
Revenue Growth	2.0%	(1.3%)	3.3%	1.8%	(0.7%)	2.5%
PMO	(0.4%)	1.7%	(2.1%)	N/A	N/A	N/A

Q4 2021: The hit rates during the fourth quarter of 2021 reverted to the predominant trends seen during this two year-period as the value models outperformed the growth models. All of the value models performed well with hit rates for the top quintile all above 60%.

Table 16. Q4 2021 model portfolio hit rates

Model Portfolio	Top Quintile	Bottom Quintile	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO
FPE	68%	65%	68%	69%
EVS	63%	55%	64%	54%
DY	69%	61%	76%	63%
PB	63%	51%	68%	58%
EPS Growth	43%	64%	52%	42%
Revenue Growth	48%	40%	54%	58%
PMO	68%	50%	N/A	N/A

During the third quarter, the market continued to climb higher as the Russell 1000 Index rose another 10%. Though supply chain bottlenecks, labor shortages, and soaring commodity prices led to the highest inflation levels in four decades, robust corporate earnings supported rising stock prices. Aligning with the commentary on hit rates, the value models outperformed the growth models and generated alpha on the buy and sell side. This was the one quarter where the PMO model added value for all the models as an overlay.

Table 17. Q4 2021 model portfolio 3-month median relative out- / (under-) performance

Model Portfolio	Top Quintile	Bottom Quintile	Difference	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO	Difference w/ PMO
FPE	3.5%	(4.3%)	7.8%	3.6%	(4.9%)	8.5%
EVS	2.6%	(2.0%)	4.6%	2.6%	(2.2%)	4.8%
DY	4.2%	(3.5%)	7.7%	6.2%	(4.0%)	10.2%
PB	3.3%	(0.7%)	4.0%	3.5%	(2.2%)	5.7%
EPS Growth	(1.8%)	1.9%	(3.7%)	2.7%	1.0%	1.7%
Revenue Growth	0.0%	(0.2%)	0.2%	0.9%	(2.5%)	3.4%
PMO	3.4%	(4.4%)	7.8%	N/A	N/A	N/A

2021: During 2021, results were more mixed for the models. The EVS and DY value models continued to add alpha on the buy and sell side, while the opposite was true for the FPE model. Among the growth models, the EPS growth model beat the revenue growth model on both the buy and sell side. In terms of spread between the top and bottom quintile, the EVS value model proved to be the most value additive during the year.

Table 18. 2021 model portfolio 12-month median relative out- / (under-) performance

Model Portfolio	Top Quintile	Bottom Quintile	Difference	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO	Difference w/ PMO
FPE	(2.7%)	3.9%	(6.6%)	(2.7%)	4.0%	(6.7%)
EVS	3.6%	(5.6%)	9.2%	8.2%	(0.9%)	9.1%
DY	4.4%	(1.1%)	5.5%	7.0%	0.9%	7.9%
PB	(0.3%)	(2.2%)	1.9%	0.2%	1.0%	(0.8%)
EPS Growth	2.5%	(3.4%)	5.9%	(1.3%)	(4.1%)	2.9%
Revenue Growth	(4.1%)	1.9%	(6.0%)	(7.2%)	0.0%	(7.2%)
PMO	1.0%	(2.2%)	3.2%	N/A	N/A	N/A

Summary: In terms of hit rates over the entire two-year period, each of the value models on a standalone basis exceeded the 50% threshold on the buy and sell side. That was not the case for the growth models as only the sell side of the EPS growth model exceeded the threshold.

Table 19. 2020-2021 model portfolio hit rates

Model Portfolio	Top Quintile	Bottom Quintile	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO
FPE	53%	52%	51%	53%
EVS	55%	52%	54%	51%
DY	53%	53%	54%	54%
PB	53%	52%	53%	53%
EPS Growth	46%	51%	44%	51%
Revenue Growth	46%	50%	45%	51%
PMO	50%	52%	N/A	N/A

The amount of alpha generated by the value models on a standalone basis and with the PMO overlay was additive during this two-year time period. The EVS generated the most alpha on the buy side, but the DY model produced the greatest spread between the top and bottom quintiles.

Table 20. 2020-2021 model portfolio 12-month median relative out- / (under-) performance

Model Portfolio	Top Quintile	Bottom Quintile	Difference	Top Q-tile w/ PMO	Bottom Q-tile w/ PMO	Difference w/ PMO
FPE	8.6%	(5.6%)	14.2%	2.6%	(2.8%)	5.4%
EVS	13.1%	(8.5%)	21.6%	15.1%	(8.6%)	23.7%
DY	12.5%	(11.4%)	23.9%	12.0%	(12.8%)	24.8%
PB	7.6%	(10.6%)	18.2%	6.2%	0.1%	6.1%
EPS Growth	(8.6%)	1.4%	(10.0%)	(16.5%)	8.1%	(24.6%)
Revenue Growth	(12.0%)	11.3%	(23.3%)	(13.7%)	(9.7%)	(4.0%)
PMO	1.3%	(7.7%)	9.0%	N/A	N/A	N/A

There were no adjustments made for trading costs or market liquidity impact in the results above. Given the high liquidity of mid- and large-cap US stocks, such impacts are deemed to be minimal. Even if one were to conservatively deduct 0.25% of total cost on a quarterly basis, which sums to 2% overall, the cumulative results and resulting conclusion would be minimally altered.

5 Discussion

The researchers view the overall results of this study as generally favorable and supportive of the aforementioned hypotheses. The standalone value model portfolios generated strong levels of outperformance on the buy and sell side. The performance of these models was not surprising to the researchers and aligns with the aforementioned hypotheses. The researchers believe that value and growth characteristics should be modeled separately given different underlying attributes and drivers of performance. During the two-year period from 2020 through 2021, the market experienced high levels of volatility and reversion forces as sharp falls were then followed by moves back to previous levels. The researchers believe that value attributes are mean reverting in nature, thus are better able to outperform during such types of markets. This proved to be the case during this time period, as the value models were able to generate alpha with some of the strongest relative returns captured during the times of greatest dislocation, such as the second quarter of 2020.

The individual performance of each of the value models also aligned with the researchers' views. The denominator of the FPE multiple is the least stable of group, thus modeling this metric proved to be the most difficult. In terms of consistency, the EVS and DY models were best, as they outperformed during seven and six of the eight quarters, respectively.

The standalone growth models did not generate value-additive performance during this scenario analysis. As previously discussed, the researchers view these types of attributes as driven more so by trends rather than by reversion forces. This two-year period was marked more so by the latter of the two, which is believed to be a main driver of the underperformance, as the models were challenged to identify and capitalize on trends. This was most evident during 2020, which drove high levels of volatility in both EPS and revenues of companies.

The PMO model was additive on a standalone basis but detracted from performance as an overlay tool. The latter results were surprising to the researchers and led them to ponder the possibility of the overlay model dampening the ability of the other models to take on risk when it was actually advantageous to do so. Similar to the growth models, it is presumed that the PMO models struggled to outperform as they are also more premised on trend behavior, which was difficult to identify during this two-year period.

In the investment industry the phrase, "Past results don't guarantee future performance" is used for legal and client expectation purposes. While the future cannot be known nor guaranteed as this statement makes clear, the researchers structured the chosen variables to have a distribution that is likely to remain relatively stable into the future, given it is mainly predicated on rankings within the selected universe. For this reason, the researchers are optimistic that the developed tools and strategies can be value-additive into the future. Additionally, it is believed that being able to discern between reversion and trending markets would prove to be helpful in timing one's emphasis on the predictions from this study's value and growth models.

As previously discussed, the investment management industry has not embraced AI and ML tools broadly yet, likely due to lack of knowledge and an overall skeptical view. While it can be difficult to put one's trust in a black box model that is not fully understood in terms of decision-making processes and steps, the researchers are of a different perspective on this topic. If one utilizes a fully supervised learning model and has a deep understanding and rationale for every variable input devoid from data mining, then the researchers believe that confidence can and should be present regarding a model's output, regardless of whether importance is known or not. Additionally, the process that is most often utilized by humans with regard to stock investments could arguably be described as somewhat of a black box process within a human mind. As such, though the processing by models and humans cannot always be fully understood, the researchers would lend support for the former of the two given the superior computing power and more unbiased decision-making capabilities.

In terms of how an investment manager could utilize the developed tools from this study into an investment process, there are numerous options. One could fully embrace the tools for front-end screening and/or stock selection efforts. Others may prefer to apply the tools to an existing process and philosophy. Additionally, an entire investment strategy could be built out based upon this type of data and modeling framework.

Future research that could be explored to build upon this study could include the following: Using clustering on the stock universe before creating ML models in efforts to better group stocks with similar underlying characteristics, which could improve model efficacy. Incorporating interaction features whereby one's domain knowledge can be more deeply quantified in efforts to draw out more value additive insights from the models. Analyzing the valuation components in more depth whereby the stocks are compared to relevant peers as this study mainly accounted for stocks' valuation relative to the overall universe and its own trading history. Exploring other crowdsourcing avenues, such as additional technical analysis variables and notable transactions made by key insiders of companies such as C-suite managers and board members. Including different growth characteristics to help the models identify such trends, especially in light of the weaker performance with such models. For those with macroeconomic proficiency, such variables could also be included as inputs into the models.

6 Conclusion

The goal of this study was to develop tools for active investment managers to effectively compete in the current industry landscape. The researchers provided reasonable evidence of achieving this goal and being able to bridge the aforementioned chasm between fundamental, momentum, and quantitative investing. The tools developed and tested are believed to align with the needs of investment firms, which include being systematic, understandable, adaptable, complementary, efficient, scalable, multidimensional, innovative, and effective. Initial model results were supportive of being effective but more importantly were shown how to be applied in value additive ways to actual market situations.

A key takeaway from this study is the power of leveraging the strengths of various sources in a collaborative and integrated manner. The power of data science methods was evidenced in this study by gathering insightful data, then applying tools and methods to draw out the underlying potential of the data. This was the foundation applied for the hypotheses explored in this study and is believed to be applicable to many other industries and outstanding problems.

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