Bridging The Chasm Between Fundamental, Momentum, and Quantitative Investing

Jeff Reed, CFA1, Allen Hoskins, MBA1, Robert Slater, PhD2

1 Master of Science in Data Science, Southern Methodist University,

Dallas, TX 75275 USA

2 SMU Adjunct Lecturer,

Southern Methodist University, Dallas, TX 75275 USA

{jeffr, ahoskins}@smu.edu

rslater@mail.smu.edu

**Abstract.** A chasm exists between the fundamental, momentum, and quantitative sides of the active public equity investment management industry. 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 develop effective tools and strategies which are tested in the volatile stock market of 2020 and 2021.

1 Introduction

The investment management industry is a highly competitive industry in which the participants are battling daily to earn excess returns for their clients while outperformance can be attained by any number of methods, 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 a likely explanation as to why data science tools are not currently being embraced by many fundamental investment managers. A 2019 study by the CFA Institute [4] surveyed portfolio managers and confirmed that as most continue to rely on Excel and desktop market data tools with only 10% of respondents having used 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 delving deeper into the fundamentals, and given the industry pressures and trends, would not be a well-received proposition. Momentum managers would need to step back from technical analysis and short-term trends to evaluate and understand 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 take advantage of their expertise in a collaborative manner 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 need to have 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 prove to be detrimental to performance. The incorporation of more disciplined steps in an investment process can result in an increased likelihood of challenging consensus views when such are not aligned with the current data. A related characteristic, repeatablility, is an important element in investment management that is generally attainable with a disciplined, systematic process.

Understandability is another necessary component of success in this industry for investment managers and their clients. It is important for an investment manager to have a deep understanding first and foremost of both the data and tools being used to 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 adequately adapt to changes taking place in the market. It is not feasible for humans to be able to process the amount of information that computers can, thus leaning on the latter is ideal when it comes to 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 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 changes, which often turn out to be the exact 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 tools that are efficient enough to adequately cover the entire selected universe, enabling one to see not only the overall picture but also sufficient details. An important aspect of such efficiency is the ability to identify key data sources and use 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 as well as a significant challenge, as one must have the capability to determine which sources of information are value-additive.

Related to the aforementioned efficiency 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 the execution ability. Tapping into the power of crowdsourcing and data science methods are two examples of ways to 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 to be 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, which in turn requires 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, but they are slow to embrace it in their own work.

The investment management industry is primarily, if not entirely, about generating excess returns for clients which for this study is focused on investment managers seeking to outperform a U.S. large-cap benchmark. As such, developing valued additive tools to aid in the decision-making process for active long-only investment managers is the end goal of this research. The effectiveness of these tools 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, due to the global pandemic and resulting factors.

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 in some cases 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. As noted by Subramanian (2022)[[1]](#footnote-1), quantitative investing has become more competitive, complicated, and crowded, as industry participants are being forced to adapt their strategies to remain competitive and viable. Simple factor investing strategies that are now well-known and researched have been broadly exploited by market participants. 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 the use of traditional fundamental investing [1]. With this trend, new data is being collected, as industry participants have learned that without differentiated data, outperformance is more difficult to be achieved. Often this data is being gathered and dispersed by third parties that are not managing clients’ funds. While third-party data may display historical efficacy, it can be difficult to incorporate into an existing investment process and philosophy. Also, if the third-party data is proven to be exploitable, it is likely that others will capitalize on this as well, given the financial incentives in place for the data provider.

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 [1]. 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 has been and is likely going to 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 [2] and UBS Quantitative Research [3]. 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 an attempt at a balance between assuming knowledge of how things work and observing what is occurring. Also noted is how machine learning can help especially when the reality differs from its precedents. Jorgensen et al. (2021) researched and proposed the use of 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 not only 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 to be minimal in the context of the size of the industry.

Despite the evidence of growth in quantitative investing and technological transformation taking place in the investment industry, there remains a cloud of skepticism toward such methods. According to research published by the CFA Institute [4], relatively few investment professionals are currently exploiting artificial intelligence (AI) and big data applications in their investment processes. Identified in this research are 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 that has been 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 size of the industry. 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 PMs. Let us hire 50 PhDs and demand that each of them produce an investment strategy within six months. This approach tends to backfire 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.4). This research serves to highlight several of the shortcomings 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, the lack of widespread utilization, evidence of broad skepticism, and slow speed of adoption can be viewed as an opportunity to be in a first-mover advantage position for those willing and able to exploit it.

2.2 Machine Learning Research in Investments

Li and Tam (2018) sought to analyze the momentum and reversal phenomenon in stock markets by using ML. In the study, various machine learning techniques, including the Decision Tree (DT), Support Vector Machine (SVM), Multilayer Perceptron Neural Network (MLP), and Long Short-Term Memory Neural Network (LSTM) were explored and compared. The experimental results demonstrated that these ML approaches, especially the SVM, are potentially beneficial for capturing relevant momentum and reversal effects, and may aid in trading strategies.

Though research and the primary industry application have generally focused on utilizing ML for short-term trading strategies, there has been some research completed on applying ML to fundamental analysis. Researchers Cao and You (2020) examined the efficacy of ML to forecast 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 on 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 the topic of 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, how and if such academic research has been applied in real-world situations remains relatively unknown or at least not widely publicized.

Attempting to address the aforementioned application topic was research performed by Rasekhschaffe and Jones (n.d.). In this research, the authors describe some of the 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 the ways this can lead to unfavorable results. One of their recommendations is to carefully structure the ML problem so that the inputs are guided by a reasonable hypothesis. 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 that offer 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. The valuation and growth aspects of this analysis 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.

Lee (2014) explored the background of what is known as value investing. Value investing can be described as the process of analyzing stocks based on a perceived gap between their current market price and their fundamental value, which is 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 take into account numerous financial statement outputs and current price levels, such as the forward price-to-earnings ratio. Such multiples can be compared relative to the overall market, the company's 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 elements of this effect have been confirmed and rediscovered by a host of academic studies in the ensuing 80 years [13]. Typically value investors also consider the quality characteristics of companies to avoid that 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 based on how the market is valuing their growth potential, rather than on existing investments. These types of investors believe that their competitive edge is in assessing the value of growth and assume they are more likely to find bargains in growth investments [14]. There are various means by which this type of analysis is performed which includes: Analyzing historical growth levels. Forecasting growth in the years to come and comparing growth to current consensus estimates. Looking at numerous financial metrics that capture growth attributes on a trailing and forward-looking basis, as well as 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 been in decline 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 either value or growth, an investor may lack the ability to adjust to secular or cyclical changes taking place in the market.

While the headwinds facing fundamental analysis are well-known and largely understandable, the researchers in this study still believe there are valuable insights that 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 manner that is unique and value-additive.

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 issues with communication, understanding, and interaction, allowing for potential disagreements on foundational principles. For example, there may be quantitative models used on the front end of a stock screening process, then 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 sources of data are often sought out, which may or may not align with the foundational principles of the process. This challenge is especially prevalent when unstructured data is incorporated into one’s process. This data search is often led by the quantitative team members. Such efforts can result in data mining, when the data chosen to be incorporated is primarily due to the historical backtests 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 commentary regarding the companies that 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' forecasts of earnings 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 the changes in forecasts may be relatively slow and may provide return opportunities for investors. Another historical perspective on this topic comes from one of the same authors. Fried and Givoly (1982) assessed the quality of analysts' forecasts as a representation of the market expectation of earnings and compared it with other prediction models. These researchers suggested that analysts' forecasts provide a better surrogate for market expectations than forecasts generated by time-series models. The study identified factors that might contribute to the performance of financial analysts' forecasts. It also provides a historical perspective on the concept of crowdsourcing for information, as they assessed the use of analyst forecasts as surrogates for the market's expectation of future earnings. Not only are the revisions of analysts potentially powerful, but the consistency and stability of such metrics may be informative as well. 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 analyst 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, as well as 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 as well as 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. Broadly speaking, momentum is based on the theory that stocks that have been performing well during a certain time period 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, which 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, which 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 indicators of momentum. The researchers suggest that the ability to identify under or over-valued stocks by analysts as information intermediaries is important in the price-continuation momentum effect. This paper supports the notion of momentum in the markets as well as 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 to be untrue and actually found the long side to 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, momentum is too volatile to rely on, one should be particularly worried about momentum’s returns disappearing, and momentum is best used with screens rather than as a direct factor. By providing evidence against these myths and thus for using price momentum as part of one’s stock selection process, this 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. An inherent efficiency and competition within the market is seen by the decay in simple factor investing, thus a differentiated perspective must be taken. It is the researchers’ opinion 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. The researchers intend to develop a binary classification price momentum (PMO) model to aid in timing to be used as an overlay tool.

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 model that is effective and reliable and is 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 study 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 which 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 U.S. large capitalization active investment managers. Companies in the real estate sector were removed given they typically are valued and analyzed based on different metrics and involve funds from operations instead of earnings per share like 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 rerun 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 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 representative 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 over time regardless of the environment.

Valuation Metrics: 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 the financial statements and their related financial 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.

After 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 included in this research, which are predicted during the modeling analysis.

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 the three-month growth-related percentage rank for both analyst EPS estimates and analyst revenue estimates.

Price: The researchers created a three-month binary classification model which 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, and 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 U.S. 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

Hypothesis: 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, and they then perform some form of fundamental analysis. 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 ***if*** a stock will mean revert and outperform, though most struggle in determining ***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 numerous 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.

Strategy: 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 relative percentage rank. The initial model assessment is based on a five-year lookback from the end of 2014 to the end of 2019.

Details: Upon loading the data, initial preprocessing steps were taken such as imputing 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. All models used K-fold cross-validation with five splits during the construction process. Then these five tuned models were stacked together using Scikit Learn’s StackingRegressor algorithm with XGBoost regressor as the final meta learner. Five-fold cross-validation was also used during the training process.

Applications: The use cases for these types of models include but are not limited to selecting stock by deciphering between stock opportunities as to which is more or less likely to rerate based on a specified valuation metric, avoiding value traps in which 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 models to better determine fundamental and statistical attractiveness.

Results: Table 1 below details the average mean absolute error (MAE) for each of the valuation models developed. The best performance for each metric varied across the models, and the stacked ensemble did not show improvement relative to other individual models. Despite the lack of superior performance, the researchers utilized the stacked model for the scenario analysis based on the aforementioned theoretical foundation. As seen in the results below, the DY and PB metrics resulted in the lowest average MAE. This was expected by the researchers, given the perceived higher relative stability in the underlying metrics, as the dividends paid and book value for these respective models are more stable than the earnings and revenue components incorporated into the other models. Also, the EVS modeling scores were lower than the FPE models, which also was not surprising, given in most cases the revenues of a given company are more stable than the EPS and thus is better able to be modeled.

**Table 1.** Machine learning value model results – average MAE

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | DY | FPE | EVS | PB |
| Extra Trees | 9.5 | 17.3 | 13.3 | 20.2 |
| Random Forest | 10.9 | 13.9 | 13.3 | 13.1 |
| KNN | 11.2 | 11.5 | 12.3 | 11.8 |
| XGBoost | 9.8 | 11.8 | 9.9 | 10.6 |
| CatBoost | 9.3 | 11.6 | 10.6 | 9.9 |
| Stacking Regressor | 11.1 | 14.6 | 11.1 | 10.4 |

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.

Strategy: The three-month growth relative percentage rank is to be modeled for both analyst median EPS and revenue estimates. The same time period and lookback were used on these models as the valuation models.

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 selecting stock by identifying the relative attractiveness of near-term growth trends, avoiding growth traps in which 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 models to better determine fundamental and statistical attractiveness.

Results: Table 2 below details the average MAE for each of the growth models developed. Similar to the valuation models, the best performance for each metric varied across the models, and the stacked ensemble did not always show improvement relative to other individual models. Again, despite the lack of superior performance, the researchers utilized the stacked model for the scenario analysis based on the aforementioned theoretical premises. Interestingly, the models' outputs evidenced a greater ability to model the revision of both the EPS and revenues rankings relative to the growth ranking counterparts as evidenced by lower average MAE metrics.

**Table 2.** Machine learning growth model results – average MAE

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | DY | FPE | EVS | PB |
| Extra Trees | 11.4 | 10.7 | 11.5 | 11.0 |
| Random Forest | 10.7 | 8.3 | 10.8 | 8.1 |
| KNN | 5.7 | 6.4 | 5.8 | 6.7 |
| XGBoost | 8.1 | 5.5 | 7.7 | 5.5 |
| CatBoost | 8.6 | 6.5 | 8.6 | 6.7 |
| Stacking Regressor | 7.0 | 5.5 | 7.1 | 5.4 |

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 binary classification price momentum (PMO) model to aid in timing and primarily as an overlay tool.

Strategy: A price momentum binary classification model is to be developed which predicts whether or not a given stock will outperform the defined universe during the next three-month time period.

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 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 or valuation reasoning, and use of a front-end stock selection or overlay tool in a quantitatively-driven investment process.

Results: Table 3 below details the average F1 score for the price momentum model developed. Once again, despite the lack of superior performance, the researchers utilized the stacked model for the scenario analysis.

**Table 3.** Machine learning price momentum model results – average F1 score

|  |  |
| --- | --- |
| Model | PMO |
| Extra Trees | 0.89 |
| Random Forest | 0.89 |
| KNN | 0.77 |
| XGBoost | 0.88 |
| CatBoost | 0.89 |
| Stacking Regressor | 0.87 |

4.6 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 adjust to changes taking place in the market in a timely manner.

The researchers assessed the models’ performance by comparing the stocks in the top and bottom 100 of each model’s predictions, which approximates the top and bottom quintile of rankings, based on the median relative return and hit rates. The top 100 and bottom 100 strategies are considered recommended buys and sells, respectively. A combination portfolio (Combo) was built to assess the models’ collective efficacy at the approximate top 5% level. This consisted of including the top 25 ranked stocks for the four value models and two growth models, with the weights for each stock being 0.5% and 1.0%, respectively, so that there is a 50/50 balance between value and growth models. 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 100 holdings unless it was predicted to outperform. The opposite was applied to the bottom 100 holdings, as no stock was included unless it was predicted to underperform.

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 most recent data has a greater overall weight and thus impact in the model’s predicted outputs.

4.7 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 stopped three months prior to the test date. Table 4 below details the hit rates for each of the model portfolios at this point in time. The left side of the table represents the standalone models, while the right side includes the models with the PMO overlay. 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. For the bottom 100 predictions, the hit rate was calculated in reverse, with a positive hit implying the model’s ability to correctly predict underperformance.

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 PMO overlay tool did not prove to be additive to performance based on this assessment.

**Table 4.** Q1 2020 model portfolio hit rates

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Top 100  w/ PMO | Bottom 100  w/ PMO |
| FPE | 56% | 51% | 55% | 52% |
| EVS | 67% | 48% | 66% | 54% |
| DY | 57% | 65% | 59% | 68% |
| PB | 65% | 51% | 64% | 55% |
| EPS Growth | 56% | 63% | 64% | 60% |
| Revenue Growth | 64% | 66% | 62% | 62% |
| PMO | 57% | 60% | N/A | N/A |
| Combo | 63% | N/A | 63% | N/A |

Table 5 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 model generated alpha on the buy and sell side of the equation. The PMO overlay strategy again did not prove to be value additive.

**Table 5.** Q1 2020 model portfolio 3-month median relative out- / (under-) performance

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Difference | Top 100  w/ PMO | Bottom 100  w/ PMO | Difference  w/ PMO |
| FPE | 2.1% | (0.9%) | 2.9% | 1.7% | (1.0%) | 2.8% |
| EVS | 4.3% | 1.8% | 2.4% | 3.4% | (1.7%) | 5.2% |
| DY | 2.2% | (10.1%) | 12.4% | 3.2% | (9.5%) | 12.7% |
| PB | 5.4% | (0.7%) | 6.1% | 4.1% | (2.8%) | 6.9% |
| EPS Growth | 3.3% | (8.2%) | 11.5% | 5.0% | (6.9%) | 11.9% |
| Revenue Growth | 8.2% | (10.7%) | 18.9% | 5.8% | (5.7)% | 11.5% |
| PMO | 3.6% | (4.7%) | 8.3% | N/A | N/A | N/A |
| Combo | 6.3% | N/A | N/A | 3.3% | 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 at or above 60%. The growth models’ hit rates fell during this time period, with the EPS Growth model in particular. The PMO overlay evidenced being additive mainly on the bottom 100 side of the equation.

**Table 6.** Q2 2020 model portfolio hit rates

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Top 100  w/ PMO | Bottom 100  w/ PMO |
| FPE | 66% | 61% | 58% | 66% |
| EVS | 61% | 59% | 51% | 63% |
| DY | 60% | 62% | 52% | 67% |
| PB | 64% | 64% | 60% | 70% |
| EPS Growth | 33% | 43% | 42% | 48% |
| Revenue Growth | 49% | 37% | 51% | 48% |
| PMO | 53% | 60% | N/A | N/A |
| Combo | 63% | N/A | 61% | N/A |

During this time period, the market recovered in excess of 20%. The results in Table 7 evidence the models being able to adjust quickly to the changes in the market and company metrics in a timely manner, such that most of the strategies were able to outperform on the market rebound during this quarter. The growth models struggled, which aligns with the weaker hit rates above, though the value models all generated significant levels of alpha on the buy and sell side.

**Table 7.** Q2 2020 model portfolio 3-month median relative out- / (under-) performance

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Difference | Top 100  w/ PMO | Bottom 100  w/ PMO | Difference  w/ PMO |
| FPE | 6.3% | (7.3%) | 13.5% | 3.1% | (7.5%) | 10.7% |
| EVS | 4.3% | (3.8%) | 8.1% | 0.2% | (9.4%) | 9.6% |
| DY | 4.4% | (6.9%) | 11.4 | 1.6% | (7.5%) | 9.2% |
| PB | 8.9% | (6.7%) | 15.7% | 6.7% | (8.8%) | 15.6% |
| EPS Growth | (7.5%) | 4.3% | (11.9%) | (3.0%) | 0.9% | (3.9%) |
| Revenue Growth | (1.1%) | 7.7% | (8.8%) | 0.3% | 2.7% | (2.4%) |
| PMO | 0.9% | (6.5%) | 7.4% | N/A | N/A | N/A |
| Combo | 5.5% | N/A | N/A | 1.2% | 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, as they were at acceptable levels at or above 50%, and the growth models struggled again mainly on the buy side.

**Table 8.** Q3 2020 model portfolio hit rates

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Top 100  w/ PMO | Bottom 100  w/ PMO |
| FPE | 59% | 51% | 51% | 53% |
| EVS | 55% | 47% | 54% | 43% |
| DY | 48% | 51% | 50% | 55% |
| PB | 50% | 39% | 51% | 47% |
| EPS Growth | 36% | 54% | 39% | 44% |
| Revenue Growth | 29% | 56% | 44% | 44% |
| PMO | 46% | 46% | N/A | N/A |
| Combo | 49% | N/A | 46% | 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 a few generated alpha on the buy and sell side, with the FPE value model and the combo model performing best.

**Table 9.** Q3 2020 model portfolio 3-month median relative out- / (under-) performance

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Difference | Top 100  w/ PMO | Bottom 100  w/ PMO | Difference  w/ PMO |
| FPE | 3.3% | (0.3%) | 3.6% | 0.8% | (0.5%) | 1.3% |
| EVS | 1.3% | 0.9% | 0.4% | 0.7% | 2.6% | (1.9%) |
| DY | (1.6%) | (0.3%) | (1.3%) | 0.1% | (1.0%) | 1.0% |
| PB | 0.0% | 3.8% | (3.8%) | 0.6% | 0.8% | (0.3%) |
| EPS Growth | (3.4%) | (1.1%) | (2.3%) | (2.8%) | 1.7% | (4.5%) |
| Revenue Growth | (4.5%) | (3.4%) | (1.1%) | (2.2%) | 1.4% | (3.7%) |
| PMO | (1.3%) | 1.7% | (3.0%) | N/A | N/A | N/A |
| Combo | 5.5% | N/A | N/A | 1.2% | N/A | N/A |

Q4 2020: During the final three month period of 2020, the hit rate improved for the standalone value models, with the exception of the PB model. Such models outperformed the growth models and those with the PMO overlay.

**Table 10.** Q4 2020 model portfolio hit rates

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Top 100  w/ PMO | Bottom 100  w/ PMO |
| FPE | 54% | 56% | 42% | 49% |
| EVS | 55% | 58% | 49% | 51% |
| DY | 53% | 38% | 41% | 41% |
| PB | 42% | 62% | 36% | 51% |
| EPS Growth | 40% | 39% | 33% | 37% |
| Revenue Growth | 30% | 30% | 28% | 37% |
| PMO | 41% | 45% | N/A | N/A |
| Combo | 55% | N/A | 47% | 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 prediction data preceded the vaccine news, it was not surprising that performance generally was weaker during this time. The standalone value models generated respectable relative returns though, as they continued to exhibit superior performance compared to the growth models and PMO overlay models. Interestingly, the combo model performed best, as the model was able to select winning stocks within that top 25 threshold among the individual models.

**Table 11.** Q3 2020 model portfolio 3-month median relative out- / (under-) performance

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Difference | Top 100  w/ PMO | Bottom 100  w/ PMO | Difference  w/ PMO |
| FPE | 1.3% | (1.5%) | 2.7% | (2.5%) | 0.5% | (3.1%) |
| EVS | 1.6% | (1.5%) | 3.1% | (0.2%) | (0.1%) | (0.1%) |
| DY | 2.0% | 5.8% | (3.8%) | (2.5%) | 4.9% | (7.5%) |
| PB | (2.6%) | (4.3%) | 1.7% | (4.5%) | (0.1%) | (4.4%) |
| EPS Growth | (4.1%) | 7.1% | (11.2%) | (5.8%) | 7.8% | (13.6%) |
| Revenue Growth | (5.7%) | 14.0% | (19.7%) | (7.4%) | 6.3% | (13.7%) |
| PMO | (2.4%) | 3.6% | (6.0%) | N/A | N/A | N/A |
| Combo | 7.9% | N/A | N/A | 6.1% | 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 other models. The PMO model as an overlay tool did not prove to be additive yet generated alpha on a standalone basis. The strongest efficacy was evidenced by the standalone value models, as they generated significant alpha on the buy and sell side of the equation. The combo model also generated solid levels of alpha during the year.

**Table 12.** 2020 model portfolio cumulative median relative out- / (under-) performance

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Difference | Top 100  w/ PMO | Bottom 100  w/ PMO | Difference  w/ PMO |
| FPE | 12.9% | (9.9%) | 22.8% | 3.2% | (8.6%) | 11.7% |
| EVS | 11.4% | (2.6%) | 14.0% | 4.2% | (8.6%) | 12.8% |
| DY | 7.0% | (11.6%) | 18.6% | 2.4% | (13.1%) | 15.4% |
| PB | 11.7% | (7.9%) | 19.7% | 6.9% | (10.9%) | 17.8% |
| EPS Growth | (11.8%) | 2.1% | (13.9%) | (6.6%) | 3.4% | (10.0%) |
| Revenue Growth | (3.1%) | 7.7% | (10.7%) | (3.5%) | 4.7% | (8.2%) |
| PMO | 0.9% | (6.0%) | 6.8% | N/A | N/A | N/A |
| Combo | 19.4% | N/A | N/A | 11.1% | 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 and PB performed best within the value models, while EPS growth outperformed revenue growth, which was not the case during the preceding year.

**Table 13.** Q1 2021 model portfolio hit rates

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Top 100  w/ PMO | Bottom 100  w/ PMO |
| FPE | 30% | 39% | 30% | 36% |
| EVS | 45% | 58% | 53% | 50% |
| DY | 53% | 45% | 58% | 39% |
| PB | 53% | 64% | 48% | 46% |
| EPS Growth | 56% | 62% | 45% | 56% |
| Revenue Growth | 40% | 40% | 31% | 48% |
| PMO | 47% | 51% | N/A | N/A |
| Combo | 49% | N/A | 47% | N/A |

The stock market continued to march higher during this time period, as the post-COVID recovery was well underway. The first quarter of 2021 was considered by some market commentators to be a low-quality rally. The models generally struggled to generate alpha during the first quarter, though the deeper value metrics / models represented by DY and PB outperformed the other value models, which is not unexpected given the environment.

**Table 14.** Q1 2021 model portfolio 3-month median relative out- / (under-) performance

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Difference | Top 100  w/ PMO | Bottom 100  w/ PMO | Difference  w/ PMO |
| FPE | (6.4%) | 5.5% | (11.9%) | (5.6%) | 8.1% | (13.7%) |
| EVS | (1.7%) | (4.3%) | 2.6% | 2.1% | 0.2% | 1.9% |
| DY | 3.0% | 2.6% | 0.4% | 3.0% | 4.5% | (1.6%) |
| PB | 1.6% | (5.1%) | 6.7% | (0.9%) | 2.3% | (3.2%) |
| EPS Growth | 4.1% | (5.2%) | 9.3% | (4.2%) | (2.5%) | (1.7%) |
| Revenue Growth | (5.3%) | 5.7% | (11.0%) | (6.6%) | 2.8% | (9.3%) |
| PMO | (1.2%) | (0.6%) | (0.6%) | N/A | N/A | N/A |
| Combo | 2.6% | N/A | N/A | 0.7% | 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, as all but two of the standalone models generated hit rates above the 50% threshold.

**Table 15.** Q2 2021 model portfolio hit rates

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Top 100  w/ PMO | Bottom 100  w/ PMO |
| FPE | 58% | 59% | 53% | 51% |
| EVS | 53% | 47% | 54% | 47% |
| DY | 48% | 53% | 49% | 47% |
| PB | 47% | 49% | 48% | 53% |
| EPS Growth | 42% | 61% | 46% | 54% |
| Revenue Growth | 45% | 60% | 49% | 58% |
| PMO | 46% | 58% | N/A | N/A |
| Combo | 45% | N/A | 42% | N/A |

The stock market continued to move higher during this period, and the model performance was mixed. The FPE and EVS once again reasserted their strength by outperforming the other standalone models on the buy side of the equation. As has been the case in most quarters, the value models performed better, and the PMO overlay tool was not broadly additive to relative performance.

**Table 16.** Q2 2021 model portfolio 3-month median relative out- / (under-) performance

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Difference | Top 100  w/ PMO | Bottom 100  w/ PMO | Difference  w/ PMO |
| FPE | 1.8% | (1.8%) | 3.6% | 0.7% | (0.3%) | 1.1% |
| EVS | 0.7% | 0.4% | 0.3% | 0.9% | 0.7% | 0.3% |
| DY | 0.0% | (0.7%) | 0.6% | 0.0% | 0.8% | (0.9%) |
| PB | (0.8%) | 0.4% | (1.2%) | (1.6%) | (0.5%) | (1.0%) |
| EPS Growth | (1.9%) | (0.8%) | (1.1%) | (0.9%) | (0.4%) | (0.5%) |
| Revenue Growth | (1.9%) | (0.9%) | (1.0%) | (0.2%) | (0.7%) | 0.5% |
| PMO | (1.5%) | (0.9%) | (0.6%) | N/A | N/A | N/A |
| Combo | 0.2% | N/A | N/A | (0.9%) | N/A | N/A |

**STOP HERE…..still working on these results and the final commentary**

Q3 2021:

**Table 17.** Q3 2021 model portfolio hit rates

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Top 100  w/ PMO | Bottom 100  w/ PMO |
| FPE |  |  |  |  |
| EVS |  |  |  |  |
| DY |  |  |  |  |
| PB |  |  |  |  |
| EPS Growth |  |  |  |  |
| Revenue Growth |  |  |  |  |
| PMO |  |  | N/A | N/A |
| Combo |  | N/A |  | N/A |

**Table 18.** Q3 2021 model portfolio 3-month median relative out- / (under-) performance

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Difference | Top 100  w/ PMO | Bottom 100  w/ PMO | Difference  w/ PMO |
| FPE |  |  |  |  |  |  |
| EVS |  |  |  |  |  |  |
| DY |  |  |  |  |  |  |
| PB |  |  |  |  |  |  |
| EPS Growth |  |  |  |  |  |  |
| Revenue Growth |  |  |  |  |  |  |
| PMO |  |  |  | N/A | N/A | N/A |
| Combo |  | N/A | N/A |  | N/A | N/A |

Q4 2021:

**Table 19.** Q4 2021 model portfolio hit rates

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Top 100  w/ PMO | Bottom 100  w/ PMO |
| FPE |  |  |  |  |
| EVS |  |  |  |  |
| DY |  |  |  |  |
| PB |  |  |  |  |
| EPS Growth |  |  |  |  |
| Revenue Growth |  |  |  |  |
| PMO |  |  | N/A | N/A |
| Combo |  | N/A |  | N/A |

**Table 20.** Q4 2021 model portfolio 3-month median relative out- / (under-) performance

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Difference | Top 100  w/ PMO | Bottom 100  w/ PMO | Difference  w/ PMO |
| FPE |  |  |  |  |  |  |
| EVS |  |  |  |  |  |  |
| DY |  |  |  |  |  |  |
| PB |  |  |  |  |  |  |
| EPS Growth |  |  |  |  |  |  |
| Revenue Growth |  |  |  |  |  |  |
| PMO |  |  |  | N/A | N/A | N/A |
| Combo |  | N/A | N/A |  | N/A | N/A |

**Table 21.** 2021 model portfolio 12-month median relative out- / (under-) performance

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Difference | Top 100  w/ PMO | Bottom 100  w/ PMO | Difference  w/ PMO |
| FPE |  |  |  |  |  |  |
| EVS |  |  |  |  |  |  |
| DY |  |  |  |  |  |  |
| PB |  |  |  |  |  |  |
| EPS Growth |  |  |  |  |  |  |
| Revenue Growth |  |  |  |  |  |  |
| PMO |  |  |  | N/A | N/A | N/A |
| Combo |  | N/A | N/A |  | N/A | N/A |

**Table 22.** 2020 through 2021 model portfolio cumulative median relative out- / (under-) performance

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Model Portfolio | Top 100 | Bottom 100 | Difference | Top 100  w/ PMO | Bottom 100  w/ PMO | Difference  w/ PMO |
| FPE |  |  |  |  |  |  |
| EVS |  |  |  |  |  |  |
| DY |  |  |  |  |  |  |
| PB |  |  |  |  |  |  |
| EPS Growth |  |  |  |  |  |  |
| Revenue Growth |  |  |  |  |  |  |
| PMO |  |  |  | N/A | N/A | N/A |
| Combo |  | N/A | N/A |  | N/A | N/A |

There were no adjustments made for trading costs or market liquidity impact. Given the high liquidity of mid- and large-cap US stocks, such impacts would be minimal. Even if one were to conservatively deduct a few percentage points of the absolute returns, the overall results would only see a minimal impact given the amount of outperformance of these portfolios.

5 Discussion

The researchers view the overall results of this study as highly favorable and supportive of the aforementioned hypotheses. The initial model-building efforts gave evidence of potential model efficacy, but the scenario analysis provided more quantifiable and objective measurements of the results.

The model portfolios were premised on a broad range of metrics and produced varied returns, though every single one generated outperformance over the benchmark during the collective analyzed time periods. Not only was the amount of alpha deemed strong, but so was the consistency, as there was only one quarter where the strategies underperformed.

This level of outperformance may be skeptically viewed by some, given the high level of competition and factor decay prevalent in the industry. In response to such doubt, the researchers propose the possibility of unique insights providing the foundation for unique results. One cannot do what everyone else is doing and expect to have vastly different results. Rather, one must think differently, and the researchers believe that this study serves as an example of attempting to test and analyze a different method.

The stock market is known to go through cycles with various processes, strategies, and tools going in and out of favor. Though the strategies developed in this study are likely to be similarly affected, the consistency of performance achieved in this study is notable. The researchers are of the opinion that such consistency may be the result of gathering and creating variables that are mainly premised on comparing stocks to each other within a given universe. While the overall market and macroeconomic environment can change, if one’s measurements are more stable and less affected by such forces in a direct manner but rather seek to find the statistically most favorable opportunity within a universe at any given time, the results may prove to be more consistent. Not only may this help to dampen the forces behind the cyclical volatility but may be able to capture such changes in a value-additive manner if there is built-in flexibility and capability of doing so which this study sought to achieve.

In the investment industry the phrase, “Past results are no guarantee of future performance,” is used for legal and client expectation reasons. While the future cannot be known nor guaranteed, 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.

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 deep understanding and rationale for every variable input fed into a given model, then the researchers believe that confidence can and should be present regarding a model’s output, regardless of the knowledge of feature importances. Additionally, the process that is most often utilized by humans with regard to stock investments could arguably be described as 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 unbiased decision-making capabilities.

Numerous options exist for the method by which an investment manager could utilize the developed tools from this study. 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. In this case, the use of a model such as the PMO overlay tool could aid in the timing of entry of potential candidates and exit of existing holdings. As is often the case, investment managers are prone to buying and selling too early. With a PMO overlay tool, one would be assisted in being more patient in both situations. Additionally, an entire investment strategy could also be built out based on this type of data and modeling framework.

Future research that could be explored to build upon this study could include the following: Analyzing the valuation components in more depth whereby the stocks are compared to relevant peers would be beneficial, as this study mainly accounts for stocks valuation relative to the overall universe and the stock’s 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. For those with macroeconomic proficiency, such variables could also be included in the dataset. Additionally, exploring different time periods for the study and prediction periods would be intriguing, not only to assess efficacy, but as a way to potentially reduce the turnover of 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 are supportive of being effective but more importantly demonstrate application 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 and unique data, then applying powerful 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 many other outstanding problems that seek to be solved.

Acknowledgments. The heading should be treated as a 3rd level heading and should not be assigned a number.

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Appendix

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