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Quality-at-Reasonable-Price: Developing a UK Equity Portfolio

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Abstract

Equity investing has evolved significantly since its formalisation during the early twentieth century. Two major recent evolutions are Quality investing and Value investing. Asness et al. (2019) demonstrate fundamentally strong stocks have higher expected returns. Solt and Statman (1989) show that strong companies can be bad investments. Therefore, it is important that investors do not overpay for quality. In this research, I demonstrate that a quality-at-reasonable-price equity portfolio outperforms on an absolute and risk-adjusted basis.

Using the non-financial FTSE 350 constituents at the end of December of each year from 2000 to 2016, I develop a multidimensional approach using Quality and Value variables that generate a significant outperformance. Before risk adjustment, the portfolio produces an average monthly return of 0.99% with an annualised Sharpe ratio of 0.73. This compares with an average monthly return of 0.46% and an annualised Sharpe ratio of 0.30 for the remaining stocks in the benchmark.

Regression analysis demonstrates that the investment approach produces statistically significant Alpha. Adjusting for risk using the Fama and French (1993) and Carhart (1997) four-factor model, the portfolio earns a statistically highly significant ($t = 4.4$) abnormal return of 0.56% per month. This compares with a weakly significant ($t = 1.5$) abnormal return of 0.16% per month for the remaining stocks in the benchmark.

In this project, I propose an optimised approach to equity investing relative to passive indexing and traditional active stock selection. Unlike most academic research which works with all stocks including small and micro stocks (e.g. Fama and French (1992, 1993, 1996), Piotroski (2000) and Bartram and Grinblatt (2018)), I consider only the larger stocks in the UK by restricting my sample to the non-financial members of the FTSE 350 index. Since I use only large and more liquid stocks, my strategy can be easily implemented by investors.

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1. Introduction

1.1 History of Equity Investing

Equity investing as a science has evolved considerably since common shares and stock exchanges were created. The earliest structured equity investor is commonly recognised as Graham (1949) who established the initial approach to stock selection and investment. His investment approach was taken to an industrial scale by his former student, Warren Buffett, firstly through the setup of the Buffett Partnership in 1956 and subsequently through Berkshire Hathaway, which became one of the world's most successful investment holding firms.

The first stream of literature relevant to my study deals with the idea that the risk of single stock selection is diversified away by passively holding all the securities held in a given stock index (Markowitz, 1952). This approach endorses probability theory's Central Limit Theorem. Under the Efficient Markets Hypothesis, since stock prices reflect all available information, it is better to hold the largest possible number of securities rather than select individual stocks and be faced with idiosyncratic risk that can be diversified away (Fama, 1970). Index funds are based on the assumption that the Efficient Markets Hypothesis holds and it is not possible to identify mis-valued securities.

The first index fund was created in 1971 by Wells Fargo for Samsonite Corporation's pension programme (Ancell, 2012). The first index fund to be offered to the public was effectively launched in 1972 by Qualidex Fund (Marks, 2018). John Bogle, through the setup of the Vanguard Group in 1975, was instrumental in making this investment approach mainstream by replicating the S&P 500 index into investable funds.

However, a large number of active investors also operate in the markets. They usually seek to acquire equities at a price deemed lower than the value of the assets held by the companies (see e.g. Graham and Dodd (1934) and Graham (1949)). This investment approach was enhanced by Charles Munger who introduced quality considerations at Berkshire Hathaway. Such quality considerations include high returns on equity, earnings stability, goodwill, brands, and other elements that provide companies with "moats" that enable them to ward off competition (see e.g. Greenwald (2004) and Asness, Frazzini and Pederson (2019)). An economic moat is any element that enables a business to preserve its competitive advantages and maintain market share and profits. Examples of such economic moats include patents, franchises, brands, and economies of scale (Dorsey, 2004).

Numerous portfolio managers, such as Fundsmith's Smith (Smith, 2016), have since utilised such an approach to outperform peers and benchmarks. This approach can also assist in avoiding "value traps", a situation where a low valuation is caused by significant distress in the business rather than from a mispriced bargain.

Smart Beta is the second stream of literature relevant to my study. Traditional indexing relies on market capitalisation-weighted investing whereby the largest companies by the market value of equity are the most represented in the portfolio. Banz (1981) shows smaller firms earn higher returns, thus improvements and enhancements to the traditional market capitalisation-weighted approach gradually emerged. Arnott, Hsu and Moore (2005) introduce the idea of indexing based on the economic footprint of companies rather than on market capitalisation. As such, companies with higher sales or those with more assets would be more represented in a fundamentals-weighted index. Greenblatt (2011) proposes a variation of value-weighted indexing whereby equities are represented relative to their valuation discount. Lastly, other historical alternatives include equally-weighted indexes in which every member of an equity index has the same representation and is not weighted by any other factor or variable (DeMiguel, Garlappi and Uppal, 2009).

The third stream of literature relevant to my study relates to replicable patterns in equity returns that seem to violate the Efficient Market Hypothesis. A vast body of empirical literature has identified many anomalies that can be exploited to produce higher expected returns. An overview of the most robust of these anomalies is presented in this study. These anomalies are Beta and Volatility, Size, Value, Prior Stock Returns, Accruals, Profitability, Growth, Asset Turnover, Organisational Capital, and Stock Issuances. A final strand of relevant literature synthesises financial statement information into composite multivariate measures that are related to future stock returns. The seminal works in that strand of literature, such as Piotroski (2000), are presented in this study.

1.2 Objectives

The 2013 Nobel Memorial Prize in Economic Sciences was awarded to three Laureates: Eugene Fama, Lars Peter Hansen, and Robert J. Shiller. That year, the award focused on the analysis of the predictability of asset price movement over the long-term. Fama and Hansen argue that markets are inherently efficient thus favouring passive management whereas Shiller believes that markets are inherently inefficient thus favouring active management. This highlights the ongoing debate regarding active and passive management in the industry.

Though just over a fifth of the estimated USD 64 trillion of equity assets under management are passively invested (Willis Towers Watson, 2017), the shift from actively managed investment products (such as managed accounts) to passively managed products (such as index funds) is accelerating. The assets in passive funds have grown four times faster than those in active funds since 2007 (Ellis, 2017). Malkiel (2007) demonstrates that in the long-run, passive indexing will consistently outperform most active investors. In other words, most active investors will likely underperform their benchmarks in the long-run. Additionally, most active managers charge substantially higher fees compared to passive indexers further compounding their underperformance. This is causing the emergence of new fee structures by active managers such as charging only performance fees or capping management fees to the rate of comparable passive indexing funds.

Blanchette (2010) uncovers that the outperformance of most investment managers does not persist. Similarly, Carhart (1997) demonstrates that the current outperformance of an investment manager is not predictive of future outperformance. However, there is a small minority of investment managers that are able to outperform consistently (Buffett, 1984) though it is difficult to select them on an ex-ante basis (Barras, Scaillet and Wermers, 2010).

Using elements from Quality investing and Value investing, I demonstrate in this research that a quality-at-reasonable-price equity portfolio outperforms on an absolute and risk-adjusted basis. There is a vast body of literature in finance demonstrating that there are predictable returns that can be exploited by active management.¹ However, with a few exceptions (see e.g. Ou and Penman (1989), Holthausen and Larcker (1992) and Piotroski (2000)), the literature looks at only one variable at a time while I consider several variables. Closest to my research is Piotroski (2000), which defines the F_SCORE framework. In this framework, he combines nine variables that indicate strength for a firm through a single fundamental score.² He shows that a high book-to-market investor can increase returns by at least 7.5% per annum by selecting high F_SCORE firms. I use a system similar to Piotroski's (2000) F_SCORE for the Quality scoring of stocks.

Guay (2000), in his discussion in the same issue, raises four fundamental questions about the validity of the results of Piotroski (2000). Firstly, he questions whether there is any reason to believe the strategy would not work on the general population. Secondly, he questions the implementability of the

¹ Examples of such literature include Banz (1981) for the Size effect, Rosenberg et al. (1985) for the Value effect, and Jegadeesh and Titman (1993) for the Momentum effect.

² The nine variables are: ROA, Δ ROA, CFO, ACCRUAL, Δ MARGIN, Δ TURN, Δ LEVER, Δ LIQUID, and EQ_OFFER

strategy if it is driven by small stocks as these stocks may be costly and difficult to trade. Thirdly, Piotroski (2000) uses simply the market-adjusted model to adjust for risk and Guay (2000) argues the results might be different if more appropriate risk adjustment is made using the Fama and French (1993) and Carhart (1997) four-factor model. Finally, Guay (2000) raises the prospect of sample selection bias and whether the results are robust to small changes in the sample.

While I use many of the factors identified by Piotroski (2000) for scoring firms on the Quality dimension, my work is significantly different to Piotroski's in several ways and also addresses the criticisms of Guay (2000). Firstly, Piotroski uses the F_SCORE framework on a subset of the US all-stocks universe (highest 20% book-to-market ratio stocks) and argues his results are driven by firms that are neglected by analysts and have low level of investor interest. I address these criticism by working with all non-financial firms in the UK's FTSE 350, thus expanding the sample to the general population. In addition, the universe that I use is more relevant to institutional investors as it consists solely of larger-capitalisation stocks and is investible due to higher liquidity and lower transaction costs. Secondly, I enhance the Quality-score framework with a multidimensional Value-score. I focus on two dimensions, Quality and Value, and establish their complementarity to generate outperformance. This enables the approach to resemble the investment philosophy of Buffett (1990) who also focuses on these two dimensions. Thirdly, I address the criticism regarding Piotroski's (2000) use of the market-adjusted model by implementing the four-factor model for risk adjustment as well as using the Sharpe ratio for calculating the reward-risk pay-off. To address the data snooping bias highlighted by Guay (2000), I use a more recent (2001 to 2017) time period in the UK as compared to the 1976 to 1996 period in the US of Piotroski (2000). Using a different time period and a different country alleviates the data snooping bias (Lo and MacKinlay, 1990). My analysis thus further contributes by providing an out-of-sample test of Piotroski (2000).

1.3 Data and Method

The data consists of all non-financial members of the FTSE 350 index at the end of December of each year from 2000 to 2016. This gives a total of 17 years of observations on the non-financial members of the FTSE 350. The FTSE 350 index is used as the benchmark for this study due to the broad universe of companies and sectors that it provides. It also alleviates the issues raised by Guay (2000) about the Piotroski (2000) dataset.

For the risk-adjusted performance, regression analysis is performed using data for the three Fama and French (1993) factors and the Carhart (1997) Momentum factor obtained from the University of Exeter Business School's website (Gregory, Tharyan and Christidis, 2013). This model was used rather than alternatives such as the Fama and French (2015) five-factor model or the Hou, Xue and Zhang (2015) q-factor model as the full relevant history of factor values for the UK market is only available for the four-factor model. Using regression analysis, it can be determined whether any outperformance can be attributed to existing factors (Beta, Value, Size, and Momentum) and if significant Alpha is consequently created.

1.4 Results

Over the tested time period, the developed multidimensional approach using Quality and Value succeeds in generating a significant outperformance. The portfolio that overlays the Quality dimension with Value generates 0.99% per month before risk adjustment and an annualised Sharpe ratio of 0.73. It also generates a monthly Alpha of 0.56% which is significantly different to zero ($t = 4.4$).

I thus successfully demonstrate that my strategy is capable of generating significant absolute and risk-adjusted outperformance. Nevertheless, practical implications such as algorithm aversion (Dietvorst, Simmons and Massey, 2015) and the requirement of a live track record for acceptance by the practitioner community are major impediments that are further elaborated upon subsequently in this thesis.

1.5 Structure of the Research

The rest of the thesis is structured as follows: the second chapter provides a review of the relevant literature, and chapter three describes the data and the research design. The fourth chapter presents the results. An impact assessment is then included in chapter five, and chapter six concludes.

2. Literature Review

This chapter presents the detailed review of the literature in four related areas of equity investing. The first section presents the role of the Efficient Markets Hypothesis in shaping our thinking about equity returns. It then briefly discusses the debate in the literature about whether active managers have the ability to generate abnormal returns. The second section discusses the Smart Beta indexing approach. The third section (Replicable Patterns in Stock Returns) presents an overview of some of the more well-established patterns in stock returns that have been identified over the years. Section four discusses the literature that has employed multivariate fundamental analysis using information from published financial statements in an attempt to devise strategies that generate abnormal stock returns. The final section brings together the elements from the prior four sections to establish the framework of the proposed investment approach.

2.1 The Efficient Market Hypothesis and Capital Asset Pricing Model

The Efficient Market Hypothesis (EMH) broadly stipulates that it is not possible to consistently outperform the aggregate market portfolio as current security prices incorporate all publicly available information. As such, active security selection cannot provide any investment advantage over holding the market portfolio (Fama, 1991).

Under the Modern Portfolio Theory (MPT) framework of Markowitz (1952), risk is a pure function of variance. The more the price of a selected security fluctuates, the higher the perceived risk of investment in that security. CAPM introduces a portfolio approach in which risk is calculated as Beta, the sensitivity of an investment or portfolio relative to the market portfolio (Fama and French, 2003). In the CAPM, it is thus the covariance at a portfolio level that matters as single position idiosyncratic risk can be diversified away (Fama and French, 2003). As such, outperforming the market portfolio is a function of additional risk taken in the form of higher Beta.

Malkiel (2007) argues that since it is not possible to predict the price behaviour of a single stock, it is more appropriate and safer to randomly select a large number of stocks to benefit from the Central Limit Theorem and diversify away idiosyncratic risk. The EMH thus naturally favours passive indexing of broad benchmarks as the most efficient investment approach and there is a large body of literature that seems to support the EMH. For example, Gruber (1996) looks at the performance of a sample of 270 open-ended funds over 1985 to 1994 and finds that on average, they underperform by 0.65% per year on a risk-adjusted basis using a four-factor model. Given that the average

fees in his sample is 1.13% per year, it suggests that while active managers have the ability to earn abnormal returns, the fees they charge is more than the value they add.

Carhart (1997) studies a larger sample of 1,892 funds over 1962 to 1993 and finds that differences in exposure to small stocks and to past winners explain most of the return predictability of active funds. He also finds that most of the funds underperform by the amount of their investment costs. Barras, Scaillet and Wermers (2010) find that in their sample of over 2,000 actively managed open-ended funds between 1975 and 2006, 75% failed to generate any Alpha (after costs) while almost 24% generate negative Alpha. They also find that only 0.6% of the funds in their sample generate a positive Alpha in 2006. Similarly, Fama and French (2010) find that the few funds that do generate Alpha rarely produce it in sufficient amounts to cover their costs.

However, even the literature cited above finds some evidence that managers do have the ability to generate Alpha, it is just that they do not seem to be able to generate enough Alpha to cover their fees (Berk and Green, 2004). Berk and Van Binsbergen (2015) argue that gross Alpha is a better measure of skill than net Alpha because fees depend on the competition between investors for scarce managerial skills.

There is plenty of other evidence that shows managers do have the ability to identify mispriced stocks. For example, Chen et al. (2000) find that the stocks that are bought by active managers significantly outperform those that are sold by 4.7% over the next year (2.0% on a risk-adjusted basis). Similarly, Jiang et al. (2014) find that stocks in which active managers are overweight outperform those that are underweight by a risk-adjusted 7.6% per annum on an equally-weighted basis (4.6% value-weighted). Kacperczyk et al. (2014) find that managers are able to time the market on the downside and select stocks on the upside. This suggest markets may not be efficient and actively managed funds can earn significant risk-adjusted returns.

2.2 Smart Beta

Smart beta indexing further challenges the most important implication of the EMH: it is not possible to consistently beat the market. The starting point for this approach is the fact that while most traditional indexes are market capitalisation-weighted, there is no reason to *a-priori* believe that larger firms will provide higher stock returns. In fact, there is extensive evidence (starting with Banz (1981)) that smaller firms tend to outperform larger firms.

The Smart Beta approach is broadly defined as any index construction method that deviates from market capitalisation-weighted indexing (Hsu et al., 2012). For instance, a Smart Beta index using valuation would tilt the weights

in a traditional index like the S&P 500 such that stocks with favourable valuations are overweighted and those with unfavourable valuations are underweighted. The iShares Edge MSCI USA Value Factor ETF (exchange traded fund) is a live example of this approach. The tracked index of this ETF “captures large and mid-cap representation across the US equity markets exhibiting overall value style characteristics. The index is designed to represent the performance of securities that exhibit higher value characteristics relative to their peers” (MSCI, 2019).

Arnott, Hsu and Moore (2005) follow this approach and construct several portfolios where the weight of the stocks is based on their “fundamentals”: the trailing five-year average of revenue, dividends, cash flows, book value of equity, and total employment. They identify the largest 1000 stocks on Compustat for each of these characteristics at the end of each year from 1962 to 2004 and show that their “fundamental indexes” outperform the value-weighted S&P 500 in terms of returns, information ratios, and Sharpe ratios. Similarly, Hand and Green (2011) show that portfolios constructed by weighting on accruals, change in earnings, and asset growth generate an annual information ratio of 1.9, much higher than the 1.5 generated by portfolios weighted on size, book-to-market, and momentum. Bender and Wang (2016) find that combining factors to generate portfolio weights can lead to higher outperformance.

DeMiguel, Garlappi and Uppal (2009) use the simplest variation on traditional market capitalisation-weighted indexing: invest equal amounts in all the stocks in the index. They find this simple approach has a significantly higher Sharpe ratio than that of the traditional market capitalisation-weighted index in five of the seven datasets they use (equally-weighted index has better Sharpe ratio in the other two as well, though statistically not significant).³ However, unlike the value-weighted indexes, these equally-weighted portfolios require frequent rebalancing that can reduce the potential gains.

However, there seems to be considerable doubt about the performance of these strategies once risk is properly taken into account. For example, Amenc, Goltz and Le Sourd (2009) compare the performance of seven Smart Beta indexes against the value-weighted S&P 500 as well as an equally-weighted index. They find that though Smart Beta strategies deliver higher absolute performance relative to the S&P 500, they underperform the equally-weighted index. They further show that most of the outperformance of Smart Beta indexes can be attributed to higher exposure to the Size, Value, and

³ In fact, they find the “naïve 1/N” approach generally does better than thirteen other “mean-variance optimized” portfolios.

Momentum factors of the Fama and French (1993) and Carhart (1997) four-factor model. Similarly, Bennyhoff et al. (2015) argue that since Smart Beta strategies generally have higher volatility than the corresponding market capitalisation-weighted indexes, it is a form of active management whereby higher returns are simply a reward for higher risk. Further, Kaplan (2008) argues that such characteristics based weights (e.g. Revenue, Net Income) will, in general, not be independent of the market value weights.

2.3 Replicable Patterns in Stock Returns

The EMH implies that the aggregate market portfolio cannot be consistently outperformed without taking more risk. However, there is now a vast body of empirical literature that has identified replicable patterns in equity returns that seem to violate the EMH (or the CAPM, depending on the reader's point of view). In this section I present the overview of the most robust of these anomalies.

2.3.1 Beta and Volatility

The basic assumption of CAPM that Beta is positively related to returns has been questioned almost from the time it was formulated. As early as 1967, Pratt fails to find a positive relationship between Beta and returns for the 1928 to 1960 period in the US while Friend and Blume (1970) find a negative correlation between Beta and subsequent stock returns during 1960 to 1968.

Black (1993) supports the view that Beta and stock returns are positively correlated. He uncovers a data mining bias in research that find a negative relationship between Beta and returns. He shows that many of the historical portfolios were constructed using information on covariances which were historically unavailable to investors. Similarly to Black (1993), Kothari and Shanken (1995) also find a positive relationship between Beta and returns for the stock market. They demonstrate that the relationship only turns negative when a shorter monthly time-scale is used in historical portfolios.

In a seminal paper, Fama and French (1992) demonstrate that Beta has no explanatory power over the period 1963 to 1990 in the US. Similarly, Poon and Taylor (1992) find a negative relationship between volatility and returns for the UK stock market. The uncovering of this weak relationship could explain why investment portfolios exploiting Beta and volatility have produced inconsistent results. This inconsistency was also previously identified by Pratt (1967) and Friend and Blume (1970).

In another influential paper⁴, Frazzini and Pedersen (2014) construct a betting against Beta (BAB) factor by going long on a portfolio of below median Beta stocks and short on a portfolio of above median Beta stocks.⁵ They find that in the US over 1926 to 2012, the BAB factor earns 0.70% per month before risk adjustment and 0.55% per month after risk adjustment using the Fama and French (1993) and Carhart (1997) four-factor model, both returns being statistically highly significant. They also report a Sharpe ratio of 0.78, which is twice that of the value strategy and 40% larger than for the Momentum factor. They also report the BAB factor returns 0.64% before risk adjustment and a 0.30% four-factor Alpha for portfolios formed using stocks from nineteen other developed market countries (though the Alpha for the UK is insignificant).

The core tenet of the CAPM is that it is not the total variance of security returns but only the covariance of a security with the market portfolio (as measured through its Beta) that is positively correlated with expected returns. Fama and MacBeth (1973) provide early evidence that it is the systematic risk (measured by Beta) and not the idiosyncratic risk (measured by variance of CAPM residual) that is correlated with stock returns.

More recent work finds conflicting evidence on the relation between returns and volatility. Ang et al. (2006) demonstrate that stocks with higher volatility have lower returns even after accounting for exposure to Fama-French factors, liquidity, and Momentum. Similarly, Clarke, De Silva and Thorley (2010), through their volatile-minus-stable stocks measure of volatility, also find that more volatile stocks tend to underperform. Finally, Chow et al. (2014) show that the Sharpe ratios of low volatility portfolios are generally more than double those of value-weighted indexes in the US (1967-2012), emerging markets (2002-2012), and globally (1987-2012).

However, other studies find that volatility does not impact future returns. For example, Guo and Whitelaw (2006) conclude that there is a weak or negative relationship between conditional variance and expected aggregate stock market returns.

These anomalously low returns on high risk stocks have not gone unnoticed by the market participants. While, to the best of my knowledge, there is no commercial product that exploits the low returns on high Beta stocks, MSCI has a Europe Minimum Volatility index that is tracked by the iShares Edge MSCI Min Vol Europe ETF. The performance of this index,

⁴ With 235 citations, it is currently the second most cited paper (among those published since 2014) as per the Journal of Financial Economics website.

⁵ The high Beta portfolio is weighted such that higher Beta stocks have higher weights while the low Beta portfolio is weighted such that low Beta stocks have higher weight.

however, is mixed. As of 28 February 2019, while it has produced higher returns than the MSCI Europe index over the past 5 years (3.95% versus 1.80% annualised) with a higher Sharpe ratio (0.46 versus 0.23), it has underperformed over three-year and ten-year measurement periods (MSCI, 2019).

2.3.2 Size Effect in Stock Returns

Banz (1981) finds that stocks of smaller firms tend to outperform those of larger firms. For the period 1936 to 1975, he finds that a portfolio of smallest firms outperforms the portfolio of largest firms by 1.5% per month. The existence of this “Size effect” has been confirmed by later studies in the US (for example Fama and French (1992)) as well as the UK (for example Levis (1989)). The usual concerns of data snooping seem to be allayed as there is substantial evidence of Size effect in markets around the world. Van Dijk (2011) looks at studies for 19 different markets and finds (with some caveats about risk adjustment) that the Size effect is reported to be strong in 18 of these countries.

The reason for the existence of the Size effect is not clear even after decades of research (Fama and French (1992 and 1993)). It is well established that smaller stocks are more likely to go bankrupt (see e.g. Dichev (1998), Agarwal and Taffler (2008) and Campbell et al. (2008)). The reduced balance sheet of smaller firms diminishes their refinancing ability creating a higher probability of distress if business conditions deteriorate. Chan and Chen (1991) find that almost 2/3rd of the smallest size quintile firms are “fallen angels” that started life as larger firms but have fallen on bad times. Hence, Fama and French (1992, 1993) argue that higher returns on small firms are simply a compensation for bearing higher distress risk, which for some reason, is missed by the Market factor. Fama and French (1993) find that a default risk factor is priced and helps explain returns on small stocks. Ferguson and Shockley (2003) develop a theoretical model that shows why the Beta of distressed firms is more likely to be underestimated and argue that the seemingly high returns on small stocks are simply because their systematic risk is underestimated.

However, recent empirical evidence is inconsistent with this explanation. For example, Dichev (1998) finds that stocks with higher bankruptcy risk produce lower returns than average and Campbell et al. (2008) find that distressed stocks have delivered lower returns (both with and without risk adjustment using the four-factor model) with higher standard deviations, resulting in substantially poorer Sharpe ratios. Further, Agarwal and Taffler (2008) and Agarwal and Poshakwale (2010) find that while distressed stocks do

indeed have higher exposures to the Size factor of Fama and French (1993), they earn lower returns than non-distressed stocks. The evidence thus shows that higher returns on small stocks are unlikely to be compensation for higher default risk since stocks with higher bankruptcy risk earn lower returns.

The other explanations for the Size effect that have been put forward in the literature are the “neglected stocks” effect and the liquidity effect. Fama and French (1992) acknowledge that it is possible that small stocks are neglected by institutional investors because of lack of liquidity⁶ and hence become undervalued due to the reduced pool of potential investors.

It is well-established in the literature that less liquid stocks earn higher returns (see e.g. Amihud and Mendelson (1986), Brennan et al. (1998), and Fiori (2000)). Pastor and Stambaugh (2003) find that over the period 1966 to 1999, stocks with lower liquidity have significantly higher loadings on SMB (Small-Minus-Big), thus demonstrating that less liquid stocks tend to be smaller. This is to be expected as securities with lower liquidity require more time to be sold exposing investors to higher risks. Additionally, they may need to be sold at a discount and the transaction costs are also likely to be higher relative to more liquid securities. Consistent with the small firm effect being driven by liquidity, Liu (2006) presents an empirical model where his liquidity-based factor drives out both the Size and Value factors from the pricing equation.

The Size anomaly has been actively exploited within the practitioner community for many years. For example, for the five-year period ending December 2018, the iShares FTSE 100 ETF reports a cumulative return of 28.98% while the iShares MSCI UK Small Cap ETF returned 34.09%.

Funds created to invest directly in stocks with lower measured liquidity have not been able to raise significant assets. However, products focused on smaller market capitalisation stocks and would provide exposure to less liquid securities (Vanguard, 2018).

2.3.3 Value Effect in Stock Returns

Equity valuation is usually measured as the ratio of the market value of a stock (its market capitalisation) relative to an accounting measure, such as net income or the book value of equity. As early as the period 1956 to 1971, Basu (1977) finds that a portfolio of stocks with high Price-to-Earnings (P/E) ratios underperforms a low P/E portfolio by approximately 7% per annum even though it has higher Beta. Rosenberg et al. (1985) find that stocks with higher book-to-market (B/M) ratio stocks earn higher future returns. Over a period of 141 months from 1973 to 1984, they find their high B/M portfolio beats their

⁶ Liquidity refers to the ease with which an asset can be bought or sold without moving the price.

low B/M portfolio by 0.36% per month ($t = 5.7$), and in 102 months (over 70%).⁷ Fama and French (1998) extend the analysis and report that high B/M stocks consistently outperform in 12 out of 13 major international markets. Lakonishok et al. (1994) extend this research and find that between 1963 and 1990, stocks with a low price relative to multiple measures of fundamental value (book value of equity, cash flows, and earnings), as well as those with low past revenue growth provide higher future returns. Loughran and Wellman (2011) show that between 1963 and 2009, their Enterprise Value-to-EBITDA factor (EM factor) produces a statistically significant four-factor Alpha of 0.16% per month ($t = 2.4$). Asness et al. (2015) demonstrate that the Value effect is still strong.

While the existence of Value effects in stock returns is widely accepted, there is still considerable debate in the literature as to whether the higher returns on value stocks represent risk or mispricing. For instance, Lakonishok et al. (1994) argue that value stocks are typically those that have poor past performance and the growth stocks typically have strong past performance. Investors naively project the continuation of poor (and good) past performance and do not fully appreciate the mean reversal. This results in growth stocks being overvalued while value stocks are undervalued. Subsequently, growth firms earn lower returns because the investors are disappointed by their lower than expected performance. Similarly, value stocks outperform as the investors are pleasantly surprised by their better than expected results. Asness and Frazzini (2013) also conclude that the higher returns on value stocks are due to mispricing. They demonstrate that the standard method of using lagged data to calculate the B/P ratio results in inaccurate valuations. They propose using more timely data for the B/P calculation and form portfolios that produce better returns.

On the other hand, Zhang (2005) argues that value stocks are riskier than growth stocks because these are the firms that are less productive. During recessions, they would benefit by scaling down their operations but scaling down is far more expensive than scaling up. Petkova and Zhang (2005) provide empirical evidence that value firm Betas are higher during bad times and lower during good times. However, they also find that the time-variation in the Betas are too small to explain the magnitude of the observed value premium. More recently, Penman et al. (2015) also conclude that value stocks have higher risk. They argue that the higher expected returns of high B/P

⁷ Their portfolios were constructed such that they had similar weights by industry, P/E, size, Beta, past growth, etc.

stocks is a compensation for the higher risk of earnings growth not being realized.

Fama and French (1992, 1993, 1996) conjecture that the excess returns produced by high B/M and smaller size stocks are because such stocks are at a higher risk of financial distress. They argue that the market value of the stocks with poor prospects will drop immediately while the effects will only appear in the book value with a lag. Hence, relatively distressed firms will have higher B/M ratio and consequently will be expected to earn higher returns to compensate investors for the higher risk. Consistent with this argument, Fama and French (1995) find that higher book-to-market ratio stocks have persistently lower earnings while lower book-to-market ratio stocks have persistently higher earnings. Fama and French (1996) show their three-factor model is able to capture the anomalies identified by Lakonishok et al. (1994) and argue the results are due to incorrect risk measurement by CAPM rather than market inefficiency.

Vassalou and Xing (2004) find that both smaller market capitalisation and lower valuation are predictive of higher returns only if the stocks also have higher default risk. The Fama-French Size and Value factors can thus act as a proxy for expected returns due to default risk and distress. However, Da and Gao (2010) find that Vassalou and Xing's results are driven by first month returns. Chava and Purnanandam (2010) also find a positive relationship between expected returns (estimated using analysts' forecasts) and default risk. However, there are question marks about their sample as analyst coverage of distressed firms is typically quite poor. Campbell, Hilscher and Szilagyi (2011) also contradict the distress risk explanation for the Value effect as they find that distressed stocks earn lower returns even when they have high B/M ratios.

Given the vast body of literature, the Value effect has also become well accepted in the practice as is evident in the proliferation of value indexes (e.g. MSCI value indexes) and ETFs. Since their inception in May 2005 until 30 November 2018, the iShares Russell 1000 Value Index ETF has outperformed the iShares Russell 1000 Index ETF on an absolute basis (6.70% versus 5.64% per annum respectively) with a higher Sharpe ratio (iShares, 2018). This demonstrates that the stocks with better valuation were able to provide higher returns beyond any contribution from additional volatility when compared with the broader index.

2.3.4 Prior Stock Returns

There are two separate documented relationships between past and future returns: the long-term reversal of returns (contrarian) and the medium-term

continuation of returns (momentum). On contrarian investing, De Bondt and Thaler (1985) find that portfolios of firms with low returns over the last 3 to 5 years outperform the portfolio of firms with high past returns. In particular, they show that between 1930 and 1982, an arbitrage portfolio that buys the poorest 35 (50) performers and sells the best 35 (50) performers over the last 36 (60) months earns 24.6% (31.9%) over the next 36 (60) months ($t = 2.20$ and 3.28 respectively). They attribute this to market overreaction: the poor performers have become undervalued and strong performers have become overvalued.

Ball et al. (1995) raise several questions about the validity of the profitability of contrarian strategies. First, they find that the returns are largely driven by very low priced (average price \$1.04) loser stocks and even a \$1/8 price change reduces the profits by 25%. Second, trading in such stocks would incur significant transaction costs. Third, the profits are sensitive to the portfolio formation month. The profits vanish if the portfolios are formed at the end of June or August instead of December. Additionally, Fama and French (1996) show their three-factor model is able to explain long-term return reversal.

Further, using data from 1946 to 2013 on non-micro-cap stocks⁸, Goyal and Jegadeesh (2018) find the 36X36 and 60X60 month strategies used by De Bondt and Thaler (1985) generate statistically significant annualised excess returns of 5.44% and 7.71% respectively. However, using the Fama and French (1993) three-factor model, the Alpha is an insignificant 0.22% and -0.20% respectively. It thus appears that the long-term reversal of stock returns does not exist outside of micro-cap stocks or is captured by the Fama and French (1993) three-factor model. Hence, I do not control for it as micro-cap stocks are excluded in the approach that I propose.

To test momentum investing, Jegadeesh and Titman (1993) show that portfolios that are long outperforming stocks and short underperforming stocks over the past 3 to 12 months earn significantly positive performance over 3 and 12-month holding periods. In particular, over 1965 to 1989, they find that the portfolio of stocks in the top 10% in terms of returns over the last 6 months outperform those in the bottom 10% by 0.95% per month over the next 6 months and the difference is statistically significant.

Fama and French (1996) find that this is the only tested anomaly that their three-factor model is unable to explain. Rouwenhorst (1998) documents the medium-term continuation of returns in all the 12 developed markets he covers and Rouwenhorst (1999) finds similar results across 20 emerging markets. Lesmond et al. (2004) show that the costs of trading the “loser” and

⁸ They define micro-cap as the smallest 20% of the stocks.

“winner” stocks are higher than the trading costs for average stocks and, when taking transaction costs into account, the profitability of the Momentum strategy. Fama (2008) calls this the “mother of all anomalies”. Geczy and Samonov (2017) confirm the existence of this phenomena in data covering 47 country indexes, 48 currencies, 43 government bond indexes, and 76 commodities using a vast dataset going back to 1800. Given the pervasiveness of the medium-term continuation of returns, it is important to control for it using the Carhart (1997) Momentum factor.

The practitioner community widely exploits the Momentum anomaly. The MSCI US Momentum index filters the broader MSCI US index to select stocks exhibiting high price momentum (MSCI, 2018). As of November 2018, the Momentum index has provided higher absolute returns with a higher Sharpe ratio on a five-year and ten-year basis than the broader index (MSCI, 2018). The higher Momentum stocks were thus able to produce higher returns above the contribution from additional volatility. The MSCI USA Momentum index is investible using the iShares Edge MSCI USA Momentum Factor ETF.

2.3.5 Accruals

Accruals are generally defined as the difference between operating cash flow and net income (i.e. the non-cash portion of earnings). For a period spanning 30 years from 1962 to 1991, Sloan (1996) finds that a hedge portfolio long on low accrual stocks and short on high accrual stocks earns a statistically highly significant ($t = 4.4\%$) CAPM Alpha of 10.4% per annum. He also shows that low accrual stocks earn higher returns than high accrual stocks in the cross-section even after controlling for Beta, Size, book-to-market, and Earnings-to-Price. He concludes that investors do not rationally differentiate between the cash and non-cash components of earnings even though earnings attributable to accruals also tend to be less persistent than the cash component of earnings.

Bradshaw et al. (2001) further reason that firms with high accruals are more likely to encounter problems in future earnings that are unanticipated by investors. In a similar vein, Hirshleifer et al. (2004) define “balance sheet bloat” as the difference between cumulative operating income and cumulative free cash flow. Over a period covering 1965 to 2002, they find that the hedge portfolio long on firms with lowest and short on those with highest ratio of net operating assets to total assets (their proxy for balance sheet bloat) earns statistically highly significant ($t = 10.1$) four-factor Alpha of 1.26% per month on equally-weighted and 0.61% per month ($t = 4.7$) on value-weighted basis. They attribute this to, *inter alia*, the inability of the investors to understand the importance of free cash flow in the persistence of future earnings.

An exploitable Accrual anomaly thus exists as future returns can be expected to increase as the non-cash portion of earnings diminishes. Lev and Nissim (2004) confirm the persistence of the Accrual anomaly as identified by Sloan (1996) and find that it is enduring due to the difficulty of implementing strategies to exploit it. LaFond (2005) investigates the presence of this anomaly in international equity markets between 1989 and 2003 and finds that it occurs in 17 developed markets globally. Dechow et al. (2011) reinvestigate the initial research of Sloan (1996) and provide practical implications for exploiting the Accrual anomaly such as shorting and trading in thinly traded stocks.

Chan et al. (2006) conclude that accruals (non-cash earnings) can impact future returns. They demonstrate that ignoring the composition of earnings can be detrimental for investors as increasing accruals are followed by declining stock returns. Fama and French (2008) similarly uncover that extreme positive (negative) accruals tend to be followed by negative (positive) returns. Ball et al. (2016) also identify that levels of accruals can be indicative of future returns. They conclude that higher levels of cash flow from operations are predictive of higher stock returns while higher levels of accruals indicate lower stock returns.

Pincus, Rajgopal and Venkatachalam (2007) investigate the international evidence on the Accrual anomaly and uncover that it does occur in developed markets such as the US, Australia, Canada, and the UK. They conclude that the Accrual anomaly is generally present in countries with common law regimes, countries with low concentration of shareholder ownership, and countries that allow broad use of accrual accounting. However, the Accrual anomaly does not seem to occur in countries that do not possess these characteristics.

Avramov et al. (2013) find that the Accrual anomaly is stable regardless of the credit condition of firms. As such, in contrast to many other anomalies, the Accrual anomaly can be exploited without the need to short stocks. This is a valuable characteristic as the stock of distressed firms can be illiquid and thus difficult to short sell (Avramov et al., 2013).

The Accrual anomaly is included in the methodology for creating Quality equity indexes (MSCI, 2017) and investible through products such as the iShares Edge MSCI World Quality Factor ETF. Since their inception, these products have generally outperformed their broader indexes. However, since accruals is only one of the several components of Quality, it is difficult to attribute the outperformance of the ETF to the firms with low accruals.

2.3.6 Profitability

Gross profit scaled by total assets was included in the Ou and Penman (1989) model for predicting higher equity returns. Holthausen and Larcker (1992) also use gross profit scaled to total assets ratio within their predictive model.

Profitability as a source of abnormal returns was then formalised by Haugen and Baker (1996). Covering a time period from 1979 to 1993, their research presents 41 characteristics that determine future returns. These characteristics include risk, liquidity, price level, growth potential, technical factors, and sectors. They show that US stocks scoring in the top decile of their characteristics model outperform the stocks in the lowest decile by 35.4% (30.9% versus -4.5%). They also report similar results in Japan, France, Germany, and the UK.

Further, Haugen and Baker (1996) find that better performing stocks tend to exhibit greater profitability in five markets they study. Fama and French (2006), Chen, Novy-Marx and Zhang (2011), Novy-Marx (2013a), and Novy-Marx (2013b) also find that more profitable firms have higher expected returns.

Hou, Xue and Zhang (2015), include a profitability measure (return on equity) within their q-factor model. Using data from 1967 to 2013, they develop a model consisting of market capitalisation, annual change in total assets scaled to total assets, and return on equity. The explanatory power of this model outperforms the Fama-French five-factor model (Hou, Xue and Zhang, 2015) thus confirming the robustness of the Profitability anomaly.

Similarly, using data from 1963 to 2014, Ball et al. (2016) demonstrate that accruals, cash flows, and operating profitability are predictive of future returns. This follows on Ball et al. (2014) uncovering an operating profitability measure that predicts higher expected returns. They find that “deflating” gross profit or net income by the book value of total assets improves that measure’s predictability of future returns.

Operating profitability is subsequently included as an additional factor (Profitability factor) in the Fama and French (2015) five-factor model. Recently, DeMiguel et al. (2017) identify gross profitability as one of only 15 significant characteristics (from an initial list of 51 characteristics tested) that investors should consider for improving risk, returns, and transaction costs. When the impact of transaction costs is considered, gross profitability remains within the selection of significant characteristics that are relevant for investors. Additionally, Huguen and Strauss (2017) show that portfolios of top-quintile stocks on EBITDA, gross profit or operating profit outperform those in the bottom-quintile by between 10% and 14% per annum on a risk-adjusted basis.

Within the Piotroski (2000) F_SCORE framework, several measures of profitability are included. These include measures of cash flow from

operations, return on assets, and change in gross margin. The Profitability anomaly is one of several elements within the methodology for creating Quality equity indexes (MSCI, 2017). These Quality indexes have generally outperformed their corresponding broader indexes since inception. An example of an investible Quality index product is the Vanguard US Quality Factor ETF.

2.3.7 Growth

Asset growth is defined as the increase in the book value of assets on a firm's balance sheet. Though unexplained by the Fama-French three-factor model, firms with higher asset growth rates are found to subsequently underperform (Fama and French, 1993). This effect was initially observed only in small and micro-cap firms. This asset growth effect is thus attributed to the small firm Size effect by Fama and French (2008). This differs from the discount effect that Lakonishok et al. (1994) propose as it rations that the additional risk, due to the Size anomaly, provides higher expected returns with these stocks.

In their study on accruals, Fairfield, Whisenant and Yohn (2003) find that the stock of firms engaging in asset growth tends to underperform. They uncover that similarly to accruals, markets tend to misprice the impact of growth in assets on future returns. As such, they argue that the Accrual anomaly identified by Sloan (1996) can be categorised as a subset of a more general Asset Growth anomaly.

Aggressive asset growth can be indicative of management that lacks prudence thus increasing the likelihood of mistakes and lower future returns. Titman, Wei and Xie (2004) find that the “empire building tendencies of managers” is detrimental to future returns and that the impact of this phenomenon tends to be underestimated by investors. Fama and French (2015) also find that the asset growth effect is sufficiently robust for inclusion as the Investment factor in their Fama-French five-factor model.

Lakonishok et al. (1994) argue that when compared to value stocks, the higher price multiple assigned to growth stocks tends to overestimate future potential growth rates. Contrarily to the traditional view that value stocks provide higher expected returns due to their greater investment risk, Lakonishok et al. (1994) propose that value stocks benefit from a discount due to the investor preference for growth stocks and their subsequent higher valuation. As they are expected to provide less growth, the future growth rate of value stocks is thus relatively under-priced and provides higher future returns.

Thus, rather than being a function of higher investment risk, value stocks provide higher expected returns due to the under-pricing of potential

sales growth. As this contradicts the notion that higher returns are a function of greater investment risk, investors are more likely to have ignored this anomaly and preserved its persistence.

The Asset Growth anomaly is part of the methodology for Quality equity index construction (MSCI, 2017). As demonstrated by the iShares Edge MSCI World Quality Factor ETF, Quality indexes have overall outperformed their broader indexes. As the Asset Growth anomaly is a single element in its composition methodology, the outperformance of Quality cannot be attributed only to Asset Growth.

Similarly to the Size and Value anomalies, this Sales Growth anomaly has been exploited by the practitioner community for many years. Identifying and investing in stocks exhibiting above average sales growth is the primary means through which this anomaly has been exploited. On a five-year and ten-year basis, the iShares Russell 1000 Growth Index ETF has outperformed the iShares Russell 1000 Index ETF on an absolute basis with a lower Sharpe ratio (iShares, 2018). The higher growth stocks are thus able to provide higher returns beyond any contribution from additional volatility.

2.3.8 Asset Turnover

Ou and Penman (1989) include asset turnover and the change in asset turnover in the initial 68 accounting descriptors that they use in their model to predict subsequent earning changes. Additionally, the change in asset turnover remains in their final predictive model for higher equity returns which contained only 16 (or 18, depending on the tested time period) accounting descriptors. The change in asset turnover also remains significant within Holthausen and Larcker's (1992) revised predictive model of Ou and Penman (1989) highlighting the robustness of this anomaly.

Since this ratio is a measure of asset use efficiency, Novy-Marx's (2013a) Asset Turnover anomaly is thus not a function of higher investment risk. Ou and Penman (1989) and Holthausen and Larcker (1992) both include the change in the current ratio as a predictive indicator of future equity returns in their models; this is also not an indicator of higher investment risk. This view can also be applied to Piotroski (2000) as the F_SCORE framework seeks to rank the quality of a stock rather than its level of investment risk.

The Asset Turnover anomaly, similarly to the Asset Growth anomaly, is also included in the methodology for constructing Quality equity indexes (MSCI, 2017). As demonstrated by the Vanguard US Quality Factor ETF, these Quality indexes have overall outperformed. However, as the Asset Turnover anomaly is a single element within the broader composition methodology of Quality indexes, outperformance cannot be solely attributed to its presence.

2.3.9 Organisational Capital

Organisational capital is the value to an enterprise that is derived by its systems and philosophies. This concept was first defined by Prescott and Visscher (1980) and formalised into a source of value to the enterprise. A contemporary example of organisational capital would be Apple's expertise in creating a fluid user experience.

Eisfeldt and Papanikolaou (2009) demonstrate that the stock of firms with relatively higher amounts of organisational capital tend to outperform. In their study, organisational capital was measured by accumulating the reported Selling, General, and Administrative (SG&A) expense of companies. Those with higher SG&A expenses were considered to have higher organisational capital. Similarly, Chan, Lakonishok and Sougiannis (2001) uncover that growth stocks with higher intensity R&D (research and development) or higher advertising expenditures tend to have higher future returns.

Lev and Thiagarajan (1993) uncover that when a firm increases R&D at a lower rate than its industry average, its stock tends to underperform. Similarly, Ou and Penman (1989) include the change in R&D as part of their initial 68 accounting descriptors that are predictive of subsequent changes in earnings. The change in R&D scaled to sales is also included within the initial 68 accounting descriptors of this study.

The organisational capital anomaly deviates from the traditional view of excess returns to compensate for additional investment risk and is thus likely to persist. Additionally, as the global economy evolves increasingly towards pursuing intellectual property and innovation, firms with high organisational capital are likely to benefit from this trend.

For the practitioner community, assessing stocks with high organisational capital has largely been a qualitative task. This would be achieved by attempting to ascertain the sustainability of the structural advantages identified within firms. A high degree of subjective human judgement is thus introduced in this process. However, as described hereabove, Eisfeldt and Papanikolaou (2009) and Chan, Lakonishok and Sougiannis (2001) demonstrate that organisational capital can be quantified using more direct measures relating to R&D and SG&A.

Funds, such as the iShares Exponential Technologies ETF or the iShares Healthcare Innovations ETF, attempt to provide investors with exposure to firms with high organisational capital. However, the difficulty in identifying such firms results in portfolios that are characterised by high volatility or Beta (iShares, 2018).

2.3.10 Stock Issuance

Loughran and Ritter (1995) find that net stock issuances are indicative of subsequent underperformance. In a time period covering 1970 to 1990, they find that firms issuing stock, whether through a seasoned or initial public offering, tend to underperform firms not issuing stock for five years. Daniel and Titman (2006), in their study covering the 1968 to 2003 time period, also conclude that stock issuances are predictive of future returns. They find that growth that is financed using stock issuances tends to produce negative subsequent returns.

Similarly, Pontiff and Woodgate (2008) find that stock issuances are predictive of lower future returns. They uncover that stock issuances do not exhibit predictive power prior to 1970 and are only useful as an indicator post-1970. They conclude that this could be explained by the lower frequency of stock issuances prior to 1970. The Fama-French three-factor model fails to account for this effect. It is nevertheless stable across many different markets, particularly if the size of the issue or repurchase is large (Fama and French, 2008).

An example of a fund exploiting this anomaly is the SPDR S&P 500 Buyback ETF. This fund invests in the index of stocks with the highest buyback ratios from the S&P 500.⁹ On a ten-year basis from 30 November 2018, this index has outperformed the S&P 500 on an absolute and risk-adjusted basis (Standard and Poor's, 2018).

2.4 Multivariate Fundamental Analysis

In addition to the “anomalies” literature that typically focuses on identifying single variables that have a relationship with stock returns, there is another strand of literature that synthesises the multifaceted information in published financial statements into composite measures that are related to future stock returns. The seminal paper in this area is Ou and Penman (1989) who propose trading strategies based on the accounting information for NYSE and AMEX firms over 1973 to 1983. They start with 68 accounting ratios and end up with a final model with 16 (or 18, depending on the tested time period) accounting descriptors that predict the subsequent change in earnings. They find that a portfolio that is long on stocks predicted to have an earnings increase and short on stocks predicted to have an earnings decrease earns a statistically significant 14.5% (9.1% on size-adjusted basis) over a 24-month holding period. It also generates positive returns in 10 out of 11 years (9 years on size-

⁹ Stock repurchases are equivalent to negative stock issuances.

adjusted basis) in their sample period. They conclude that market prices do not seem to fully reflect the information in financial statements.

Holthausen and Larcker (1992) replicate Ou and Penman's strategy over the 1978 to 1988 period and fail to find abnormal returns, primarily because the strategy performs poorly in the 1983-88 period which was not covered by Ou and Penman (1989). However, they find that a similar model that directly predicts subsequent stock returns (rather than change in earnings) is able to generate statistically significant size-adjusted returns of 7.9% (9.5% CAPM-adjusted) over a 12-month holding period.

Lev and Thiagarajan (1993) provide further evidence that financial statement information can be used to predict subsequent earnings. They also demonstrate that the role of different variables in predicting earnings and returns also depends on macroeconomic regimes. In a similar vein, Abarbanell and Bushee (1998) demonstrate that an equity investment portfolio built using fundamental analysis signals can produce abnormal returns of around 13.2% per annum.

Setiono and Strong (1998) replicate Ou and Penman (1989) and Holthausen and Larcker (1992) for the UK from 1980 to 1988. They find the strategy of predicting earning changes (as in Ou and Penman (1989)) earns a statistically significant 17.38% over a 24-month holding period while that of predicting excess returns (as in Holthausen and Larcker (1992)) fails to generate abnormal returns.

The Piotroski (2000) F_SCORE model uses nine fundamental descriptors of profitability, financial leverage, liquidity, and operating efficiency. He uses a sample of firms listed on the NYSE, AMEX and NASDAQ between 1976 and 1996. He restricts his sample to only those in the quintile with the highest book-to-market ratio, resulting in a sample of 14,043 firms. He demonstrates that stocks with a High F_SCORE (8 or 9 out of 9) outperform stocks with a Low F_SCORE (0 or 1 out of 9) by 23% on average per annum ($t = 3.14$). Stocks with a High F_SCORE are also shown to outperform the entire universe of top quintile book-to-market stocks by 7.5% annually on average ($t = 5.59$). Nevertheless, Piotroski (2000) acknowledges that this outperformance is provided by an overweight in stocks in the lower 2/3rd of market capitalisations. Due to their smaller size, these stocks are thus also impacted by the higher expected returns resulting from reduced liquidity.

Using this model, Piotroski increases the returns of a high book-to-market equity portfolio by at least 7.5% annually. However, Guay (2000) has four criticisms on Piotroski (2000); 1, the returns may not be achievable because they are driven by small firms with low turnover and no analyst following. 2, there is poor control for risk as only the market-adjusted model

(Beta) is used. 3, there is no reason to restrict the sample to the highest book-to-market quintile. 4, a data snooping bias is highlighted in the study. Using a similar approach to Piotroski's (2000) for the Quality scoring of stocks, I address the criticisms of Guay (2000) regarding F_SCORE.

Bartram and Grinblatt (2018) take a different approach to fundamental analysis. They generate mispricing signals using all the information in financial statements, thus avoiding the data snooping bias (since they do not "select" the variables). They show that over 1987 to 2012, their hedge portfolio long on "undervalued" firms and short on "overvalued" firms earns statistically significant returns of between 4% and 10% per annum depending on the method of risk adjustment.

2.5 Summary of the Literature and Research Hypothesis

Though the EMH states that it is not possible to consistently outperform the aggregate market portfolio on a risk-adjusted basis, the review of the literature in this chapter shows extensive evidence of anomalies that seem to contradict the EMH. Nevertheless, there are several conditions that need to be fulfilled to adequately exploit these anomalies.

For example, the Smart Beta approaches that create portfolios where stocks are weighted by some fundamental characteristic (e.g. Sales, Profit, etc.) do not seem to outperform once risk is appropriately accounted for using the four-factor model (Amenc, Goltz and Le Sourd, 2009). In addition to producing higher volatility portfolios (Bennyhoff et al., 2015), the evidence suggests that Smart Beta returns are explained by greater exposure to small firms, high book-to-market firms, prior-year winners, and high volatility stocks.

The review of the literature shows quite robust evidence regarding the relationship between certain firm-specific variables and subsequent returns. The main issue with this literature is that it uses all the stocks and hence the sample contains many smaller and less liquid stocks. Such stocks are not readily investible raising doubts about whether many (or indeed any) of these strategies can actually be implemented. Strategies that seek to exploit the mean reversion of stocks with high valuation require short positions to benefit from the drop in prices, which is difficult to implement by non-institutional investors.

The proposed investment approach focuses on Quality and Value, two factors successfully used by Buffett and Munger to produce substantial outperformance (see e.g. Buffett (1990) and Frazzini, Kabiller and Pedersen (2018)). Bender and Wang (2016) advocate using such a multifactor approach to investing. Additionally, using a simple equal-weighting of multiple factors tends to outperform or produce similar results to more complex models of

factor exposure (DeMiguel, Garlappi and Uppal, 2009). Finally, by focusing on larger cap stocks, issues relating to the cost and difficulty of trading micro-cap stocks (Guay, 2000) are addressed.

In this study, I demonstrate that a portfolio of high Quality stocks outperforms a portfolio of low Quality stocks just as a portfolio of attractively valued stocks outperforms a portfolio of stocks with excessive valuation. Additionally, I demonstrate that a portfolio of high Quality stocks with an attractive valuation outperforms any of the other single dimension portfolios (i.e. Value or Quality).

The three hypotheses to be tested are as follows:

- H1₀: There is no difference in the returns on low Quality and high Quality stocks
- H2₀: There is no difference in the returns on low Value and high Value stocks
- H3₀: There is no difference in the returns on high Quality and high Value stocks, and the rest

These three hypothesis are used to test Piotroski's (2000) F_SCORE and address the criticisms of Guay (2000). H1₀ ensures that Quality is tested for large cap stocks as Piotroski (2000) only used small stocks. Similarly, H2₀ tests the Value dimension for large cap stocks. Finally, H3₀ tests if the overlay of both Quality and Value produces any outperformance.

3. Research Design and Methodology

Similar to Piotroski (2000), the core principle behind the investment approach in this research is the development of Quality and Value scores: QScore and VScore, respectively. These two are then overlaid to construct the quality-at-reasonable-price portfolio using non-financial FTSE 350 constituents. Performance measurement is through risk-adjusted returns using the Fama and French (1993) and Carhart (1997) four-factor model.

3.1 QScore

The review of the literature shows that there are several firm specific characteristics that are related to future stock returns. Similar to Piotroski's F_SCORE framework (Piotroski, 2000), I construct a QScore framework that proxies for the financial strength of a firm. This QScore is a single number that captures several attributes that have been shown in the existing literature to be related to subsequent stock returns. The variable definitions are in Table 1 panel A.

Table 1. Panel A. Definition of Quality Variables

Name	Variable	Formula
QScore	Q	Sum of all Q1 to Q8 scores [0 to 8]
Q1	ROA	(Net Income / Total Assets)
Q2	Δ ROA	(Annual change in ROA)
Q3	CFO	(Cash Flow from Operations / Total Assets)
Q4	ACCRUAL	(Cash Flow from Operations / Total Assets) - (Net Income / Total Assets)
Q5	Δ MARGIN	(Annual change in EBITDA / Revenues)
Q6	Δ TURN	(Annual change in Sales / Total Assets)
Q7	Δ LEVER	(Annual change in Long-Term Debt / Average Total Assets)
Q8	Δ LIQUID	(Annual change in Current Assets / Current Liabilities)

The investment approach adopted in this study addresses the identified abnormal return patterns to varying degrees. It uses a universe consisting of larger market capitalisation stocks (members of the FTSE 350) and does not require shorting. The strategy uses an annual holding period with equally-weighted positions to reduce the impact of trading costs. These measures ensure that a broad realistic exploitation is possible with minimal constraints or costs.

Beta is not explicitly addressed by the investment approach though controlled through performance decomposition to the Beta factor of the four-

factor model. Volatility is also not explicitly addressed by the investment approach but controlled for by risk-adjusting all returns using the Sharpe ratio.

The Size anomaly is explicitly addressed as only large firms are included (FTSE 350 members) and exposure is controlled through performance decomposition to the Size factor of the four-factor model. Consequently, the lack of liquidity is not a concern in the proposed approach as only large stocks are considered. Unlike Size, Momentum is not explicitly addressed by the investment approach however it is controlled through performance decomposition to the Momentum factor of the four-factor model.

Distress risk can be defined using the Altman's (1968) Z-score framework. In addition to Gearing (Market Value of Equity scaled by Book Value of Debt), it uses four other variables that are scaled by Total Assets: Working Capital, Retained Earnings, Profitability (EBIT), and Sales. Within the proposed investment approach, only the Retained Earnings and the Working Capital variables are not directly addressed. However, it can be argued that the Q8 variable of the approach does use both the Current Assets and Current Liabilities components of Working Capital and thus addresses it indirectly. The remaining variables in the Z-score framework, Gearing, EBIT, and Sales, are explicitly addressed by the Q7, Q1, and Q6 variables, respectively.

The Accruals, Profitability, and Asset Turnover anomalies are directly addressed respectively by the Q4, Q1, and Q6 variables of the proposed approach. However, other anomalies such as Stock Issuance, Asset Growth, and Organisational Capital are not adequately addressed or controlled for in the investment approach. The Sales Growth anomaly is not a concern as Fama and French (1996) demonstrate it is captured by their three-factor model.

3.2 VScore

For the Value dimension, Piotroski (2000) uses Price-to-Book as it is recognised as the most reliable indicator for valuation (Fama and French, 1992). The review of the literature uncovers two additional variables that possess demonstrable predictive power: Price-to-Earnings (Basu, 1977) and Enterprise Value-to-EBITDA (Loughran and Wellman, 2011).

To produce a more robust approach than Piotroski's (2000) univariate use of Price-to-Book for the Value dimension, I produce a VScore framework that proxies for the Value dimension. This VScore is a single number that combines three Value proxies. Table 1 panel B provides the formal definitions of these Value proxies.

Table 1. Panel B. Definition of Value Variables

Name	Variable	Formula
VScore	V	Sum of all V1 to V3 scores [0 to 3]
V1	P/B	(Market Value of Equity / Book Value of Equity)
V2	P/E	(Market Value of Equity / Net Income)
V3	EV/EBITDA	((Market Value of Equity + Total Debt - Cash) / Earnings before Interest, Tax, Depreciation and Amortisation)

Regarding the abnormal return patterns identified in this study, VScore explicitly addresses the Value anomaly as only better value stocks are selected. Additionally, exposure to Value is controlled through performance decomposition to the four-factor model.

3.3 Data

The FTSE 350 index is selected as the benchmark for this study as it provides a broad universe of companies of various sizes from various sectors. As such, using the FTSE 350 as benchmark addresses the issues highlighted by Guay (2000) concerning the Piotroski (2000) dataset. The non-financial constituents of the FTSE 350 index are extracted from Datastream on 31st December of each year from 2000 to 2016 (inclusive). This provides a 17-year track record of backtested performance.

Monthly Total Returns Index values (RI variable in Datastream) are downloaded for the sample stocks to calculate monthly stock returns (including dividends). Using this data, I calculate monthly returns on each stock using the following equation:

Equation 1. Monthly Total Return Calculation

$$S_{Pt} = S_{RIt} / S_{RIt-1}$$

Where:

S_{Pt} is the total percentage return for stock S in month t,

S_{RIt} is the RI value for stock S in month t,

S_{RIt-1} is the RI value for stock S in month t-1.

Since the study uses accounting variables and the accounting statements of financial firms are fundamentally different to those of industrial firms (e.g. Leverage, Current Assets, and Liabilities), in line with most of the literature on anomalies, financial stocks (Industry Classification Benchmark code 8) are excluded.

The data covers 17 years consisting of 3,324 firm years and an average of 196 firms per year. The number of firms in a year range from a minimum of

175 (in 2003) to a maximum of 225 (in 2001) firms. On average, every year 108 firms are excluded from the sample because they are financials (Industry Classification Benchmark code 8) and 50 firms are excluded due to incomplete data. The sample contains a total of 358 unique firms.

The following data is collected from Datastream for each stock in the sample every year: Net Income, EBIT, EBITDA, Cash Flow from Operations, Total Assets, Total Liabilities, Total Debt, Sales, Long-Term Debt, Current Assets, Current Liabilities, and Market Capitalisation. A validation test is performed whereby if one of these data items is missing for a stock in a given year, the stock is excluded from consideration that year.

A problem occurs when valuation ratios produce negative numbers. For example, a company with negative earnings will produce a negative P/E ratio. This would incorrectly be interpreted as a low valuation and consequently skew the dataset and medians. By ensuring that the Market Value and Enterprise Value variables are always placed in the denominator of valuation ratios, this non-linearity is adequately addressed. It causes negative values to correctly indicate a high valuation rather than the opposite. This correction was applied to the three valuation ratios used in VScore: P/B, P/E, and EV/EBITDA. For all performed calculations, reciprocals are thus used: B/P, E/P, EBITDA/EV.

Stocks that get delisted (e.g. from bankruptcy or acquisition) during the 12-month holding period are assumed to earn portfolio returns for the rest of the holding period. For example, if a stock in HQ gets delisted in July of 2017, that stock is assumed to earn the same return as the HQ portfolio from August to December 2017.

To avoid using historical balance sheet data that would not yet be available at the time of portfolio formation (hindsight bias), a three-month lag is assumed between the fiscal year-end and the availability of the accounting data.¹⁰

3.4 Construction of the Test Portfolios

To test the proposed hypotheses and main research questions, scoring is performed on the non-financial firms in the FTSE 350 index with sufficient data each year from 2001 to 2017. For the profitability and cash flow variables in F_SCORE, Piotroski (2000) uses a scoring system whereby a negative value is given a score of 0 and a positive value is given a score of 1. Doing this for the FTSE 350 would create uneven portfolios with insufficient variation as most firms are profitable and produce positive cash flows. Additionally, the smaller

¹⁰ For the portfolio formed on 31st December of year t , the accounting data comes from the latest year-end on or before 30th September of year t .

number of firms in the FTSE 350 relative to Piotroski's (2000) sample would create unbalanced portfolios if they are constructed using the same approach.

To address these issues, median values are calculated for each of the eight Quality and three Value variables using all eligible stocks. Then, for each stock, each of the eleven variables is compared with its median and assigned a score of zero if below the median and one if above the median. The Quality scores and Value scores are summed up for each stock to provide a total score out of eight for QScore and out of three for VScore, respectively.

The stocks are then sorted into two portfolios based on their QScore and VScore values. To obtain a similar number of stocks across portfolios, stocks with a QScore of three or lower are classified as low Quality (LQ) while those with four or higher score are high Quality (HQ). Similarly, low Value (LV) stocks are those with a VScore of 0 and 1, while high Value (HV) stocks have a VScore of 2 and 3. All the portfolios are built with equally-weighted positions and rebalanced on an annual basis.

In addition, in order to test for H3₀, I construct three further portfolios by overlaying QScore with VScore. HQHV is the portfolio of stocks in both HQ and HV while portfolio NonHQHV consists of all other stocks not in HQHV. Similarly, portfolio LQLV is the portfolio of stocks in both LQ and LV. All portfolios are built with equally-weighted positions and annual rebalancing.

In addition to testing the hypotheses that were established in the Literature Review, the HQHV portfolio needs to demonstrate excess returns on a risk-adjusted basis. The regression analysis is performed using the Fama and French (1993) and Carhart (1997) four-factor model (Equation 2). From the regression analysis, it is determined whether this outperformance can be attributed to existing factors (Beta, Value, Size, and Momentum) or if significant Alpha is created.

Comparative analysis using the remaining stocks provides further confirmation of the investment approach. The LQLV needs to produce lower returns and Alpha than the HQHV portfolio. An arbitrage portfolio consisting of the difference in performance between the HQHV and LQLV portfolios is constructed and similarly analysed. Another arbitrage portfolio consisting of the difference in performance between the HQHV and NonHQHV portfolios is constructed and analysed.

3.5 Performance Evaluation

Performance of any strategy needs to be evaluated relative to an appropriate benchmark. CAPM used to be the standard model for assessing portfolio performance given the risk the investors are exposed to. However, as shown in chapter 2, there is a vast body of literature that finds CAPM to be an

inadequate risk measurement tool. Fama and French (1993, 1996) show that their three-factor model that consists of, in addition to the Market factor, a factor that mimics Size effect and a factor that mimics Value effect in stock returns, fares much better at explaining the cross-section of stock returns. Carhart (1997) adds a fourth factor that mimics the medium-term continuation of returns as the three-factor model is unable to capture this effect.

Given the substantial evidence on the relationship between profitability and stock returns as well as asset growth and stock returns, Fama and French (2015) add a profitability factor and a growth factor to their original three-factor model. However, it is not clear whether or why these factors capture risk. Profitability is part of the Quality dimensions sought after by modern active investors such as Novy-Marx (2013b). It is therefore more of an attribute of Quality companies that is indicative of future higher returns (Novy-Marx, 2013a) rather than being a “risk” factor like Beta, Size, or Value. With regards to the Investment factor, conservative asset growth is indicative of prudent management and can qualify as a qualitative Quality factor targeted by quality investors.

I, therefore, use the Fama and French (1993) and Carhart (1997) four-factor model to evaluate the risk-adjusted performance of the portfolios and run the following regression using 204 months of returns:

Equation 2. Four-Factor Model Regression

$$R_{Pt} - R_{Ft} = \alpha_P + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t$$

Where:

R_{Pt} is the return on portfolio P in month t,

R_{Ft} is the risk-free rate in month t,

$RMRF_t$ is the return on the Market factor in month t,

SMB_t is the return on the factor mimicking the Size effect in month t,

HML_t is the return on the factor mimicking the Value effect in month t,

and

UMD_t is the return on the factor mimicking the Momentum effect in month t.

α_P is the abnormal return on the portfolio, β_s are the factor loadings, and ε is the mean-zero residual.

The data on the three Fama and French (1993) factors (Market factor, Size factor, and Value factor) and the Carhart (1997) Momentum factor for the UK market from 2001 to 2017 is obtained from the data library on the

University of Exeter Business School's website (see Gregory, Tharyan and Christidis (2013) for details on factor construction).

Sharpe ratios are also used to compare the various portfolios. This is calculated using this formula:

Equation 3. Sharpe Ratio

$$S_P = (\mu_P - R_F) / \sigma_P$$

Where:

S_P is the Sharpe ratio for portfolio P,

μ_P is the mean return of portfolio P,

R_F is the risk-free rate,

σ_P is the standard deviation of returns in the portfolio.

To test if Sharpe ratios are significantly different, a z-score is calculated as per Memmel (2003) using the following formula:

Equation 4. Test Statistic for Equality of Sharpe Ratios

$$z = (\sigma_1 \mu_1 + \sigma_2 \mu_2) / \sqrt{\theta}$$

Where:

$$\theta = (1 / n) (2\sigma_1^2\sigma_2^2 - 2\sigma_1\sigma_2\text{cov}_{1,2} + 0.5\mu_2^2\sigma_1^2 + 0.5\mu_1^2\sigma_2^2 - (\mu_1\mu_2\text{cov}_{1,2} / \sigma_1\sigma_2))$$

Where:

n is the number of observations,

σ_1 is the standard deviation of returns in the first portfolio,

σ_2 is the standard deviation of returns in the second portfolio,

μ_1 is the mean return of the first portfolio,

μ_2 is the mean return of the second portfolio,

$\text{cov}_{1,2}$ is the covariance between the two portfolios.

The data produced by the various backtests and regressions is thoroughly analysed to enable the establishment of robust conclusions on the characteristics of this investment approach.

4. Results

4.1 Quality, Value, and Stock Returns

From the collected data, the initial premise of whether a quality-at-reasonable-price portfolio can produce a significant difference in performance is tested. The number of stocks (average, minimum, and maximum) for each produced portfolio are provided in Appendix A.

To identify the source of any potential outperformance, it is necessary to breakdown the analysis into single dimensions of Quality and Value. The performance difference between the high Quality (Hi QScore) scoring portfolio and low Quality (Lo QScore) scoring portfolio as well as the high Value (Hi VScore) scoring portfolio and low Value (Lo VScore) scoring portfolio are tested for significance. Table 2 presents the results of this analysis on each of the eight Quality and three Value variables, as well as for the portfolios formed on VScore and QScore. As advocated by DeMiguel, Garlappi and Uppal (2009), the difference in Sharpe ratios between the Hi and Lo portfolios is tested using the z-score as per Memmel (2003).

Table 2. Performance Comparison of Single Dimension Portfolios on Quality and Value

The sample consists of all non-financial firms in the FTSE350 on the 31st of December of each year from 2000 to 2017. The firms are sorted into two portfolios (Hi and Lo) based on each of the eight Quality and three Value characteristics independently, using median as the breakpoint. The stocks are also grouped into two portfolios (Hi and Lo) based on QScore and two based on VScore as described in section 4.1. For each portfolio, the table presents the average monthly returns in excess of the risk-free rate, and the Sharpe ratio. For the arbitrage portfolio (Hi – Lo), the figures in parenthesis are the t-statistics for the difference in returns between the Hi and Lo portfolio. The last column provides a z-score for the test of equality between the Hi and Lo Sharpe ratios calculated as per Memmel (2003). All the portfolios are equally-weighted. The variables are as defined in Table 1.

	Monthly excess return (%)				Sharpe ratio		
	Hi	Lo	Hi - Lo	t-stat	Hi	Lo	z-score
Panel A. Quality variables							
QScore	0.78	0.43	0.34	(2.61)	0.58	0.27	3.60
ROA	0.84	0.43	0.41	(2.69)	0.65	0.27	4.18
ΔROA	0.73	0.54	0.19	(1.56)	0.53	0.36	1.94
CFO	0.77	0.51	0.26	(1.92)	0.59	0.32	3.24
ACCRUAL	0.70	0.58	0.11	(1.11)	0.49	0.40	1.15
ΔMARGIN	0.74	0.54	0.21	(1.94)	0.53	0.36	2.23
ΔTURN	0.77	0.51	0.26	(1.85)	0.56	0.33	2.35
ΔLEVER	0.67	0.61	0.05	(0.58)	0.45	0.43	0.35
ΔLIQUID	0.65	0.63	0.02	(0.20)	0.46	0.43	0.34

Panel B. Value variables							
VScore	0.89	0.39	0.51	(2.30)	0.62	0.25	2.49
P/B	0.87	0.40	0.47	(2.05)	0.63	0.25	2.51
P/E	0.74	0.55	0.19	(0.96)	0.48	0.39	0.68
EV/EBITDA	0.94	0.34	0.60	(2.92)	0.66	0.22	3.16

The results in Table 2 panel A show that the Hi QScore portfolio earns, on average, an excess return of 0.78 % per month and outperforms the Lo QScore portfolio by 0.34% per month (significant at the 5% level). The annualised Sharpe ratio of the Hi QScore portfolio is 0.58 and is significantly higher than 0.27 for the Lo QScore portfolio (z-score for difference = 3.6). This shows that the Hi QScore portfolio has a much better return-to-risk ratio.

Table 2 panel A also presents the performance of the high Quality portfolios formed on individual Quality variables. It shows that though all the high Quality portfolios formed on individual variables outperform their low Quality counterparts, the difference is significant at the 5% level for only one variable (ROA).¹¹ The ROA portfolio generates the greatest difference in mean (0.41% per month) and the highest Sharpe ratio (0.65). It also shows that the Sharpe ratios for “Hi” portfolios on all the Quality variables except Accruals, Δ LEVER, and Δ LIQUID are significantly higher than for corresponding “Lo” portfolios.

The significant outperformance of the Hi ROA portfolio is in line with the existing literature (e.g. Novy-Marx (2013a) and Ball et al. (2014)). However, the Hi Δ ROA portfolio did not produce a significant outperformance. This is not surprising as Δ ROA is rarely used in the literature and was only included here following Piotroski (2000). In fact, Ou and Penman (1989) also did not include Δ ROA in their set of predictor variables.

The Hi CFO portfolio did not produce significant outperformance which confirms the conclusion of Brochet, Nam and Ronen (2008) that portfolios formed on CFO alone fail to produce significantly positive returns. The lack of outperformance of the Hi ACCRUAL portfolio could be because my sample consists only of larger stocks. Dechow et al. (2011) argue that exploiting the Accrual anomaly may be difficult as it requires trading in illiquid stocks. The Hi Δ MARGIN portfolio failing to produce a significant outperformance also confirms the results of Ou and Penman (1989) whereby Δ MARGIN is removed in their reduced set of predictor variables. The Hi Δ TURN portfolio does not produce a significant outperformance consistent with the evidence of Fairfield and Yohn (2001) who disaggregate ROA into profit margin and asset turnover

¹¹ The difference between Hi and Lo Quality portfolios is also significant at the 10% level for CFO, Δ MARGIN, and Δ TURN.

and find that the latter is not useful in a forecasting context. The lack of outperformance by the Hi Δ LEVER portfolio is consistent with the findings of Fama and French (1992, 1993) that the leverage effect in stock returns is captured by the B/M factor. Finally, the Hi Δ LIQUID portfolio failing to produce significant outperformance confirms Shumway (2001) who states that the current ratio is not significantly related to bankruptcy.

Table 2 panel B shows that the Hi VScore portfolio earns 0.89% per month in excess of the risk-free rate and outperforms the Lo VScore portfolio by 0.51% per month, a difference that is statistically significant at the 5% level. It also has much better return-to-risk characteristics as evidenced by its Sharpe ratio of 0.62 as against that of 0.25 for the Lo VScore portfolio. Table 2 panel B also shows that while all the Hi portfolios formed on individual Value variables earn higher returns than their corresponding Lo portfolios, the outperformance is not statistically significant for P/E and EV/EBITDA generates the greatest difference in mean (0.60% per month) and the highest Sharpe ratio (0.66). It also shows that the Sharpe ratios for Hi portfolios formed on P/B and EV/EBITDA are statistically significantly higher than the corresponding Lo portfolios though the difference is not significant for P/E based portfolios.

The Hi P/B portfolio producing significant outperformance is in line with Fama and French (1995) who use this ratio to identify higher expected returns. The Hi P/E portfolio failing to produce significant outperformance confirms Kane, Marcus and Noh (1996) who find that higher volatility reduces the usefulness of the P/E ratio. Their finding is particularly relevant for the dataset used as the time period is impacted by many volatility causing events (e.g. bear market in 2002, financial crisis in 2007, Brexit referendum in 2016). Finally, the Hi EV/EBITDA portfolio producing significant outperformance confirms Loughran and Wellman (2011) who show that this variable is predictive of significant higher returns.

To summarise, results in Table 2 panel A provide compelling evidence leading to the rejection of null hypothesis $H1_0$ that there is no difference between the returns of high and low Quality stocks, at least for the QScore and ROA. This result is in line with the literature on the Quality anomalies (e.g. Chen, Novy-Marx and Zhang (2011), DeMiguel et al. (2017), and Novy-Marx (2013a)) that contradict the EMH and CAPM. Comparable results in panel B strongly reject the second null hypotheses $H2_0$ that the returns on high Value stocks are higher than those on low Value stocks, except in the case of the P/E ratio. This is in line with the discussed literature addressing the Value effect whereby stocks with better valuation provide higher expected returns (e.g. Lakonishok et al. (1994) and Zhang (2005)).

Table 3 presents the results when both the Quality and the Value criteria are used to identify high Quality stocks that have low valuations. Specifically, each year, the stocks are sorted into two portfolios based on their QScore (stocks with QScore of 4 and above are HQ, rest are LQ). The stocks are independently sorted into two portfolios based on their VScore (HV have VScore of 2 and above, rest are LV). Portfolios are then formed at the intersection of Quality and Value.

Table 3. Performance Comparison of Multiple Dimension Portfolios on Quality and Value

The sample consists of all non-financial firms in the FTSE350 on the 31st of December of each year from 2000 to 2017. The firms are sorted into two portfolios (Hi and Lo) based on QScore and two based on VScore as described in section 4.1. HQHV is the portfolio of stocks that are in both Hi QScore and Hi VScore, LQLV is the portfolio of stocks that are in both Lo QScore and Lo VScore, and NonHQHV is the portfolio of all stocks that are not in HQHV. For each portfolio, the table presents the average monthly returns in excess of the risk-free rate, and the annualised Sharpe ratio. For the arbitrage portfolios (HQHV-LQLV and HQHV-NonHQHV), the figures in parenthesis are the t-statistics for the difference in returns between the HQHV and LQLV, and HQHV and NonHQHV, respectively. The Sharpe ratio figure in parenthesis for each arbitrage portfolio is the z-score for the test of equality between the two Sharpe ratios calculated as per Memmel (2003). All the portfolios are equally-weighted.

	Monthly excess return (%)	Sharpe ratio
HQHV	0.99	0.73
LQLV	0.28	0.17
HQHV-LQLV	0.71, (2.82)	(3.47)
NonHQHV	0.46	0.30
HQHV-NonHQHV	0.53, (3.09)	(3.50)

Table 3 shows that the HQHV portfolio produces an average monthly excess return of 0.99% and an annualised Sharpe ratio of 0.73. It also shows that the HQHV portfolio outperforms the LQLV portfolio by an economically large 0.71% per month, and the difference is statistically highly significant ($t = 2.8$). The results also show that the HQHV portfolio earns significantly higher returns than the rest of the stocks (0.53% per month, $t = 3.1$). Further, the HQHV portfolio also benefits from a higher Sharpe ratio than both the Hi QScore (0.58) and Hi VScore (0.62) portfolios. On a raw returns basis, it outperforms both the Hi QScore portfolio (0.78% per month) and the Hi VScore portfolio (0.89% per month). The difference in Sharpe ratios in both arbitrage portfolios is statistically highly significant (z-score for difference = 3.5 in both cases). Thus, combining quality and low valuation does seem to produce

portfolios with more desirable risk-returns characteristics than either characteristic taken on its own. The results in Table 3 clearly reject the third null hypothesis $H3_0$ that there is no difference in the returns of HQHV stocks and the rest.

4.2 Quality, Value, and Risk-Adjusted Returns

The results so far have looked at the performance of Quality and Value portfolios on raw returns basis and risk-return profiles using Sharpe ratio. This sub-section extends the analysis by using the Fama and French (1993) and Carhart (1997) four-factor model for risk adjustment. Table 4 panel A reports the four-factor Alpha with individual factor loadings and the corresponding t-statistics for the QScore portfolio and the portfolios formed on individual quality variables. Table 4 panel B reports the same data for the VScore portfolio and the portfolios formed on individual Value variables.

Table 4 panel A shows that all the Hi portfolios have significantly positive Alphas.¹² The Hi QScore portfolio outperforms the Lo QScore portfolio by 0.29% per month on a risk-adjusted basis, and this is statistically significant ($t = 2.4$). Among the individual quality variables, only the Hi ROA portfolio produces a statistically significant outperformance relative to its Lo portfolio at the 5% level ($t = 2.8$). These outcomes are similar to those in section 4.1 and reconfirm the findings of Novy-Marx (2013a) on ROA as predictive of significant outperformance. Panel A also shows that compared to the low quality portfolios, most high quality portfolios (both on QScore and on an individual variable basis) have a lower exposure to the Market factor, signifying their lower market risk. The two portfolios on QScore have similar exposure to the Size factor though the picture is mixed with individual quality variables. There is also minimal difference in the exposure to the Value factor for the high and low quality portfolios. Finally, high quality portfolios tend to have a greater exposure to the Momentum factor. The adjusted R^2 s for all the portfolios are 90% or above demonstrating that the four-factor model is doing a particularly good job of explaining the variation in portfolio returns.

Table 4 panel B shows comparable results with the Hi VScore portfolio and all the Hi portfolios on individual Value variables having significantly positive Alphas. For the individual variables, only the high EV/EBITDA portfolio

¹² The table also shows that five of the eight individual Lo quality portfolios also have significant intercepts. The fact that both Lo and Hi portfolios on some characteristics earn significant abnormal returns suggests a portfolio of all stocks in the sample would also have a positive Alpha. This could indicate model mis-specification or indeed that during this period, larger stocks (FTSE 350) earned higher returns than other London Stock Exchange listed stocks.

Table 4. Regression Analysis of Single Dimension Portfolios on Quality and Value

The sample consists of all non-financial firms in the FTSE350 on the 31st of December of each year from 2000 to 2017. The firms are sorted into two portfolios (Hi and Lo) based on each of the eight Quality and three Value characteristics independently, using median as the breakpoint. The stocks are also grouped into two portfolios (Hi and Lo) based on QScore and two based on VScore as described in section 4.1. For each portfolio, the table presents the intercepts, parameter estimates, and adjusted R²s from the following regression (Equation 2) using monthly data:

$$R_{Pt} - R_{Ft} = \alpha_P + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t$$

All the portfolios are equally-weighted. The variables are as defined in Table 1.

A. Regression Analysis of the Quality Portfolios

	Alpha	Beta	SMB	HML	UMD	Adj R ²
Hi QScore	0.41%, (4.63)	1.00, (43.89)	0.47, (17.91)	-0.10, (-3.03)	-0.07, (-3.37)	0.93
Lo QScore	0.12%, (0.94)	1.15, (35.05)	0.45, (11.90)	-0.07, (-1.38)	-0.17, (-5.84)	0.90
QScore (Hi - Lo)	0.29%, (2.35)	-0.15, (-4.54)	0.02, (0.61)	-0.04, (-0.76)	0.10, (3.58)	0.20
Hi ROA	0.48%, (4.78)	0.97, (37.61)	0.41, (13.73)	-0.11, (-3.00)	-0.04, (-1.86)	0.91
Lo ROA	0.11%, (0.97)	1.16, (38.62)	0.51, (14.72)	-0.06, (-1.44)	-0.18, (-6.79)	0.92
ROA (Hi - Lo)	0.36%, (2.84)	-0.19, (-5.62)	-0.10, (-2.61)	-0.05, (-1.04)	0.13, (4.69)	0.35
Hi ΔROA	0.36%, (3.87)	1.03, (42.97)	0.52, (18.92)	-0.14, (-3.89)	-0.07, (-3.28)	0.93
Lo ΔROA	0.23%, (2.00)	1.10, (36.59)	0.40, (11.58)	-0.04, (-0.85)	-0.15, (-5.71)	0.91
ΔROA (Hi - Lo)	0.13%, (1.06)	-0.07, (-2.38)	0.12, (3.40)	-0.10, (-2.19)	0.08, (3.04)	0.15
Hi CFO	0.41%, (4.45)	1.00, (41.76)	0.39, (13.99)	-0.09, (-2.73)	-0.06, (-2.73)	0.92
Lo CFO	0.18%, (1.58)	1.13, (38.06)	0.54, (15.61)	-0.08, (-1.88)	-0.16, (-6.28)	0.92
CFO (Hi - Lo)	0.23%, (1.99)	-0.14, (-4.53)	-0.15, (-4.37)	-0.01, (-0.31)	0.11, (4.07)	0.32
Hi ACCRUAL	0.35%, (3.40)	1.07, (40.30)	0.42, (13.65)	-0.06, (-1.60)	-0.10, (-4.37)	0.92
Lo ACCRUAL	0.24%, (2.40)	1.06, (40.39)	0.50, (16.56)	-0.11, (-2.92)	-0.11, (-5.02)	0.93
ACCRUAL (Hi - Lo)	0.10%, (0.97)	0.01, (0.31)	-0.08, (-2.63)	0.05, (1.23)	0.01, (0.57)	0.03
Hi ΔMARGIN	0.38%, (4.04)	1.04, (43.02)	0.50, (17.74)	-0.13, (-3.80)	-0.08, (-3.62)	0.93

Lo ΔMARGIN	0.22%, (1.99)	1.09, (38.42)	0.43, (13.04)	-0.04, (-1.02)	-0.14, (-5.75)	0.92
ΔMARGIN (Hi - Lo)	0.16%, (1.50)	-0.05, (-1.68)	0.07, (2.20)	-0.09, (-2.31)	0.07, (2.74)	0.10
Hi ΔTURN	0.38%, (3.81)	0.99, (37.98)	0.51, (16.96)	-0.04, (-0.95)	-0.07, (-3.17)	0.92
Lo ΔTURN	0.20%, (1.66)	1.14, (36.50)	0.41, (11.50)	-0.14, (-3.03)	-0.14, (-5.31)	0.91
ΔTURN (Hi - Lo)	0.18%, (1.33)	-0.15, (-4.14)	0.10, (2.32)	0.10, (1.95)	0.07, (2.31)	0.12
Hi ΔLEVER	0.31%, (3.13)	1.07, (41.22)	0.51, (17.04)	-0.11, (-2.85)	-0.11, (-4.79)	0.93
Lo ΔLEVER	0.36%, (3.87)	1.03, (42.97)	0.52, (18.92)	-0.14, (-3.89)	-0.07, (-3.28)	0.93
ΔLEVER (Hi - Lo)	0.04%, (0.38)	0.01, (0.34)	0.10, (3.37)	-0.04, (-1.11)	0.00, (0.05)	0.04
Hi ΔLIQUID	0.34%, (3.39)	1.04, (40.70)	0.45, (15.31)	-0.08, (-2.23)	-0.13, (-5.70)	0.93
Lo ΔLIQUID	0.26%, (2.68)	1.09, (43.31)	0.47, (16.19)	-0.09, (-2.47)	-0.09, (-4.17)	0.93
ΔLIQUID (Hi - Lo)	0.07%, (0.82)	-0.05, (-2.12)	-0.02, (-0.68)	0.01, (0.22)	-0.04, (-1.73)	0.01

B. Regression Analysis of the Value Portfolios

	Alpha	Beta	SMB	HML	UMD	Adj R ²
Hi VScore	0.47%, (3.64)	0.97, (28.96)	0.52, (13.50)	0.14, (2.89)	-0.07, (-2.54)	0.88
Lo VScore	0.11%, (0.77)	1.16, (30.79)	0.40, (9.16)	-0.33, (-6.09)	-0.13, (-3.98)	0.87
VScore (Hi - Lo)	0.36%, (1.69)	-0.19, (-3.41)	0.12, (1.95)	0.47, (5.92)	0.06, (1.17)	0.16
Hi P/B	0.46%, (3.66)	0.94, (28.83)	0.50, (13.23)	0.11, (2.38)	-0.07, (-2.35)	0.87
Lo P/B	0.12%, (0.75)	1.19, (29.80)	0.42, (9.05)	-0.30, (-5.24)	-0.14, (-4.08)	0.86
P/B (Hi - Lo)	0.35%, (1.56)	-0.25, (-4.37)	0.08, (1.22)	0.42, (5.02)	0.07, (1.51)	0.15
Hi P/E	0.34%, (2.90)	1.06, (34.58)	0.50, (14.15)	0.17, (3.83)	-0.13, (-4.95)	0.91
Lo P/E	0.25%, (1.98)	1.07, (32.38)	0.42, (10.99)	-0.36, (-7.40)	-0.08, (-2.84)	0.88
P/E (Hi - Lo)	0.09%, (0.51)	-0.01, (-0.30)	0.08, (1.53)	0.53, (8.04)	-0.05, (-1.28)	0.28
Hi EV/EBITDA	0.52%, (4.20)	0.96, (29.77)	0.52, (13.98)	0.13, (2.68)	-0.07, (-2.67)	0.88
Lo EV/EBITDA	0.06%, (0.44)	1.17, (32.88)	0.40, (9.75)	-0.31, (-6.07)	-0.13, (-4.37)	0.88
EV/EBITDA (Hi - Lo)	0.46%, (2.36)	-0.21, (-4.10)	0.12, (2.06)	0.44, (5.95)	0.06, (1.37)	0.18

produces a significant outperformance and the Hi P/E portfolio does not. However, the outcome differs for the Hi P/B portfolio in that a significant outperformance ($t = 2.1$) is produced but without any significant Alpha when compared with the Lo P/B portfolio ($t = 1.6$). This divergence can be explained by the fact that the P/B portfolios use the same ratio as the Value factor of the Fama and French (1993) model. As such, any outperformance produced by the difference between the Hi and Lo P/B portfolios would be attributed to the Value factor and not to Alpha when regressed against the Fama and French (1993) and Carhart (1997) four-factor model.

The Hi VScore portfolio does not significantly outperform the Lo VScore portfolio on a risk-adjusted basis at the 5% level ($t = 1.7$). This occurs even though the outcome in section 4.1 demonstrates that the Hi VScore portfolio produces significant outperformance ($t = 2.3$). This result is to be expected as two out of three components of VScore (P/B and P/E) fail to produce significant Alpha when their respective Hi and Lo portfolios are compared.

Further, the results show that the Hi portfolios have lower exposure to the Market factor (except for P/E), and as expected, a higher exposure to the Value factor. High VScore and high EV/EBITDA portfolios have higher exposure to the Size factor indicating these portfolios are tilted towards relatively smaller stocks. Finally, there is minimal difference in the exposure to the Momentum factor for any of the variables. High adjusted R^2 s (lowest is 0.86) show the success of the model in explaining variation in stock returns.

The results in Table 4 reinforce those in Table 2, and lead to the rejection of null hypothesis $H1_0$; investing in high Quality stocks as well as high Value stocks (for EV/EBITDA) generates statistically significant outperformance, both without and with risk adjustment.

Table 5 presents analysis parallel to that in Table 3 but with risk-adjusted returns using the four-factor model as in Table 4. It shows that the HGHV portfolio generates an Alpha of 0.56% per month that is significant at the 5% level with an adjusted R^2 of 0.87. Further, the abnormal returns of this portfolio are significantly greater than that of the LQLV portfolio ($t = 2.3$). A portfolio of all other stocks (NonHGHV) earns a statistically insignificant 0.16% per month and significantly underperforms the HGHV portfolio by 0.40% per month after adjusting for risk ($t = 2.4$). The table also shows that the HGHV portfolio has significantly lower exposure to market risk than either of the two comparators. Further, the HGHV portfolio has a slight tilt towards smaller stocks (the loading on SMB is higher at the 10% level), and as expected, has a higher exposure to the Value factor. It also consists of more past winners as evidenced by higher exposure to the Momentum factor.

Table 5. Regression Analysis of Multiple Dimension Portfolios on Quality and Value

The sample consists of all non-financial firms in the FTSE350 on the 31st of December of each year from 2000 to 2017. The firms are sorted into two portfolios (Hi and Lo) based on QScore and two based on VScore as described in section 4.1. HQHV is the portfolio of stocks that are in both Hi QScore and Hi VScore, LQLV is the portfolio of stocks that are in both Lo QScore and Lo VScore, and NonHQHV is the portfolio of all stocks that are not in HQHV. For each portfolio, the table presents the intercepts, parameter estimates, and adjusted R²s from the following regression (Equation 2) using monthly data:

$$R_{Pt} - R_{Ft} = \alpha_P + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t$$

All the portfolios are equally-weighted.

	Alpha	Beta	SMB	HML	UMD	Adj R ²
HQHV	0.56%, (4.39)	0.93, (28.41)	0.52, (13.65)	0.10, (2.18)	-0.04, (-1.32)	0.87
LQLV	0.00%, (-0.01)	1.22, (25.37)	0.39, (6.95)	-0.26, (-3.75)	-0.15, (-3.71)	0.82
HQHV-LQLV	0.56%, (2.27)	-0.29, (-4.49)	0.13, (1.80)	0.37, (3.95)	0.12, (2.12)	0.14
NonHQHV	0.16%, (1.46)	1.13, (39.44)	0.44, (13.17)	-0.19, (-4.53)	-0.14, (-5.69)	0.92
HQHV-NonHQHV	0.40%, (2.40)	-0.20, (-4.66)	0.08, (1.65)	0.29, (4.72)	0.10, (2.81)	0.18

The evidence in Table 5 strongly rejects null hypothesis $H3_0$ that the portfolio that combines Quality and Value scores does not earn returns different to other stocks. The results also show that combining the Quality and Value dimensions leads to enhanced performance. It confirms that the documented Value effect (Fama and French, 1993) applies in this case and provides higher expected returns when combined with stocks exhibiting high quality features (e.g. Ball et al. (2014) and Hou, Xue and Zhang (2015)).

Additionally, the abnormal monthly return of 0.56% generated by the portfolio that overlays Value on Quality is higher than both, the portfolio on Quality alone (0.41% per month) and Value alone (0.47% per month).

4.3 Portfolio Returns using ROA and EV/EBITDA

Results in Tables 2 and 4 show that while high Quality and high Value portfolios based on QScore and VScore respectively outperform corresponding low Quality and low Value portfolios, the performance of portfolios based on ROA was better than that of QScore while EV/EBITDA outperformed VScore. This section therefore repeats the analysis of the previous section replacing QScore with ROA and VScore with EV/EBITDA.

Table 6. Performance Comparison of Adjusted Multiple Dimension Portfolios on Quality and Value

The sample consists of all non-financial firms in the FTSE350 on the 31st of December of each year from 2000 to 2017. The firms are sorted into two portfolios (Hi and Lo) based on ROA and two based on EV/EBITDA as described in section 4.3. HGHV is the portfolio of stocks that are in both Hi ROA and Hi EV/EBITDA, LQLV is the portfolio of stocks that are in both Lo ROA and Lo EV/EBITDA, and NonHGHV is the portfolio of all stocks that are not in HGHV. For each portfolio, the table presents the average monthly returns in excess of the risk-free rate, and the annualised Sharpe ratio. For the arbitrage portfolios (HGHV-LQLV and HGHV-NonHGHV), the figures in parenthesis are the t-statistics for the difference in returns between the HGHV and LQLV, and HGHV and NonHGHV, respectively. The Sharpe ratio figure in parenthesis for each arbitrage portfolio is the z-score for the test of equality between the two Sharpe ratios calculated as per Memmel (2003). All the portfolios are equally-weighted.

	Monthly excess return (%)	Sharpe ratio
HGHV	1.01	0.76
LQLV	0.15	0.09
HGHV-LQLV	0.86, (3.55)	(4.39)
NonHGHV	0.48	0.31
HGHV-NonHGHV	0.53, (2.99)	(3.53)

Table 6 demonstrates that the adjusted HQHV portfolio produces the highest average monthly return (1.01%) and the highest Sharpe ratio (0.76) amongst all the portfolios in this study.¹³ It outperforms the corresponding LQLV portfolio by 0.86% per month compared to the 0.71% outperformance in Table 3. The outperformance relative to all other stocks is 0.53% per month, the same as in Table 3.

This HQHV portfolio has a higher Sharpe ratio than both the Hi QScore (0.58) and Hi VScore (0.62) portfolios. On a raw returns basis, it also outperforms the Hi QScore portfolio (0.78% per month in Table 2 panel A) and the Hi VScore portfolio (0.89% per month in Table 2 panel B). The difference in Sharpe ratios in both arbitrage portfolios is also statistically highly significant ($z = 4.4$ and $z = 3.5$). This further confirms that combining quality and low valuation does seem to produce portfolios with more desirable risk-returns characteristics than either characteristic taken on its own.

Table 7 presents the Alpha, factor loadings, and t-statistic for the different portfolios on ROA and EV/EBITDA using the Fama and French (1993) and Carhart (1997) four-factor model for risk adjustment. It shows that the Alpha of the HQHV portfolio is 0.58% per month and statistically highly significant ($t = 4.2$).¹⁴ It outperforms the corresponding LQLV portfolio by 0.74%, and all other stocks by 0.40%, both the differences are significant at the 5% level. The table also shows that the HQHV portfolio has a market Beta of only 0.92 which is significantly lower than both the LQLV portfolio and the portfolio of all other stocks.¹⁵ The HQHV portfolio has similar exposure to the Size factor as other comparators while as expected, it has a higher exposure to the Value factor. Finally, this portfolio also has a higher exposure to the Momentum factor suggesting it has more past winners than the other two portfolios.

¹³ For comparison, the average monthly excess return on the original HQHV portfolio is 0.99% with an annualised Sharpe ratio of 0.73 (Table 3)

¹⁴ The corresponding abnormal return in Table 5 is 0.56% ($t = 4.4$)

¹⁵ In fact, its Beta of 0.92 is the lowest among all the portfolios in this study.

Table 7. Regression Analysis of Adjusted Multiple Dimension Portfolios on Quality and Value

The sample consists of all non-financial firms in FTSE350 on the 31st of December of each year from 2000 to 2017. The firms are sorted into two portfolios (Hi and Lo) based on ROA and two based on EV/EBITDA as described in section 4.3. HQHV is the portfolio of stocks that are in both Hi ROA and Hi EV/EBITDA, LQLV is the portfolio of stocks that are in both Lo ROA and Lo EV/EBITDA, and NonHQHV is the portfolio of all stocks that are not in HQHV. For each portfolio, the table presents the intercepts, parameter estimates, and adjusted R²s from the following regression (Equation 2) using monthly data:

$$R_{Pt} - R_{Ft} = \alpha_P + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t$$

All the portfolios are equally-weighted.

	Alpha	Beta	SMB	HML	UMD	Adj R ²
HQHV	0.58%, (4.18)	0.92, (25.69)	0.48, (11.64)	0.09, (1.81)	-0.02, (-0.73)	0.84
LQLV	-0.16%, (-0.98)	1.25, (29.71)	0.46, (9.39)	-0.22, (-3.59)	-0.17, (-4.67)	0.87
HQHV-LQLV	0.74%, (3.21)	-0.33, (-5.63)	0.02, (0.34)	0.31, (3.64)	0.15, (2.87)	0.20
NonHQHV	0.18%, (1.66)	1.13, (41.25)	0.46, (14.48)	-0.17, (-4.21)	-0.15, (-6.17)	0.93
HQHV-NonHQHV	0.40%, (2.37)	-0.21, (-4.87)	0.02, (0.43)	0.26, (4.12)	0.12, (3.27)	0.19

5. Impact Assessment

Though backtesting can help determine whether an equity investment approach can deliver risk-adjusted outperformance, any proposed model is unlikely to solicit significant engagement from the business community solely based on a pro-forma track record. The results produced in this study demonstrate that the proposed investment approach is valid and produces significant outperformance. However, a real-world multiyear track record with invested money is often necessary for meaningful traction to be gained in the business community.

Dissemination of the concept within the academic community would primarily be achieved through publication in a leading journal. For the practitioner community, engagement and exploitation would be accomplished through the launch of a fund or other investable vehicle.

Subsequent evaluation of the impact can be performed around one year after the publication of findings and the launch of an investible vehicle. This will provide sufficient time for the academic community to evaluate published findings. It will also enable the production of a one-year live track record for the practitioner community.

5.1 Engagement

Fundamentally, this project proposes an optimised approach to equity investing relatively to passive indexing and traditional single security selection methods. Potential users can be broadly partitioned into two groups: asset managers and the academic community.

The asset managers group consists of financial institutions, investment firms, and other end-users that purchase equity securities. Banks (such as Barclays Bank) and brokerage firms (such as Interactive Brokers) can purchase securities for their clients through managed account or advisory services. Wealth managers (such as Killik & Co) and institutional investment firms (such as Standard Life Investments) provide similar services to the banks and brokerage firms but focus on more liquid private and institutional investors such as pension providers, insurance companies, and corporate treasuries. All these asset managers and their end-users can also use products such as ETFs and open-ended funds from fund managers (such as Blackrock) to fulfil their equity investment needs.

Members of the academic community are best engaged by disseminating knowledge through journals. The academic community focused on asset management, particularly factor-based equity investing, are likely to have the most interest in this research. Even prior to real-world implementation

of the strategy, backtesting already provides useful data such as exposure to Fama-French factors and whether significant Alpha is generated. These elements are all relevant to the academic community and enable evolution of the body of knowledge in this field.

The best means to attain engagement with the practitioner community is through the launch of an investment fund. Initially, a segregated portfolio fund (such as an open-ended investment company or an investment trust) would be setup and maintained by a regulated Investment Manager such as State Street Global Advisors or Schroders. If not fulfilled directly by the Investment Manager, implementation of the investment strategy could be delegated to an Investment Advisor. The Investment Advisor would provide investment recommendations to the Investment Manager in accordance with the investment strategy.

Discussions held with some members of the investment community have indicated that there is interest in the proposed investment approach. Testimonials regarding the project are provided hereunder:

“The work Ali is doing is very interesting. I look forward to seeing his results and how we could use them for our mandates.”

Cyrille Flichy, Head of Investment Advisory, Arab Bank Switzerland *

“Ali’s research could provide us with a list of safe stocks that we can use. This will let us invest more comfortably in equities.”

Mark Demirjian, CEO, Dem Capital *

“I’m curious to see how the portfolio would perform compared to hedged equity funds. Those that use long-short or market-neutral strategies.”

Nadim Haidar, Director, FFA Private Bank *

** The expressed opinion is personal and does not necessarily reflect the official position of the employer/company*

5.2 Dissemination

Fundamentally, this research project demonstrates that the construction of equity portfolios can be systematically produced in a manner that provides higher risk-adjusted returns and Alpha. As a real-world track record is not yet available, the first stage of dissemination would focus on academic and practitioner publications. This would enable the presentation of backtested results and demonstrate that the investment approach would function in a live invested context.

For this research project, the best journal to target is the CFA Institute’s Financial Analysts Journal (FAJ). This journal benefits from credibility within

both the academic and practitioner communities. This project will be rewritten in line with the FAJ's Author Guidelines (Brown and Petitt, 2017). This will enable its submission to the FAJ as a stand-alone article detailing the strategy and its performance characteristics. Other journals will be considered should the article be declined by the FAJ.

Practitioner events can act as a conduit between the academic and practitioner communities as both audiences can be targeted through this medium. Additionally, through consulting services provided to portfolio managers, positive results from given advice could generate credibility and enable traction to be gained for the investment approach.

To deal with the anticipated algorithm aversion in the practitioner community (Dietvorst, Simmons and Massey, 2015), a live track record of at least one year is required. This will validate the investment approach and demonstrate a realised outperformance rather than one which is only theoretically backtested.

Adherence to good practice and transparency would also ensure that such fears are diminished. Beyond regulatory solutions, clear explanations on the portfolio structure would also alleviate fears. The proposed portfolio consists entirely of a long-only selection of single line securities that are part of broad equity benchmarks. There would also be no asymmetric risks present in the portfolio as no leverage or derivatives are used in the investment strategy.

If sufficient seed investment cannot be secured to launch a fund, an Investment Bank (such as Morgan Stanley) can be solicited to issue a one-year structured note tracking the stocks selected using the investment approach. This would enable the establishment of a one-year track record with minimal assets prior to the launch of a fund.

5.3 Exploitation

As this research project focuses on equity investing, it can be exploited in any investment process or portfolio that uses equities. The business community is naturally the primary beneficiary of such research. Overall, the best manner to exploit this research is through the provision of a fund or ETF. Investable indexes based on the strategy could also be provided that would be replicated by investors or used as benchmarks for stock pickers. Additionally, the research can be used by traditional equity funds to develop cost effective stock screeners.

As the industry has evolved, particularly due to recent leaps in data processing capabilities, this research can also be exploited in more novel contexts such as automated products where human intervention and fees are

minimised. This trend can be observed both by the growth of the robo-advisory business and increasing volumes in Smart Beta funds and ETFs.

Robo-advisory services provide portfolios where allocations are calculated algorithmically based on the data collected on the investor. For example, a forty-year-old person with a ten-year investment horizon and low tolerance for volatility would probably obtain a 60/40 fixed income and equity portfolio that would be rebalanced annually. Robo-advisory services are experiencing considerable growth. One-third of new investors are selecting robo-advisory services rather than traditional fund platforms such as Hargreaves Lansdown (Beioley, 2018).

Robo-advisory services would normally use index funds or ETFs to implement these asset allocations as they provide the simplest and lowest cost means for investing. A fund based on this research would provide an ideal equity product used by robo-advisors if they can provide higher risk-adjusted returns. Further, the rule-based approach of this research is aligned with the philosophy of robo-advisory as it requires minimal human intervention. In addition to potentially substituting traditional indexing products, a fund based on this investment approach could also substitute Smart Beta funds as Chow et al. (2011), Bennyhoff et al. (2015), and Amenc, Goltz and Le Sourd (2009) demonstrate that such funds have not produced consistent risk-adjusted outperformance.

The key issue when launching a fund is the selection of either an onshore domicile (such as Luxembourg or Ireland) or an offshore domicile (such as Guernsey or the British Virgin Islands). There are numerous advantages and disadvantages for each type of domicile.

Onshore domiciliation enables the fund to be fully regulated within its local market. Under the European Undertakings for Collective Investment in Transferable Securities (UCITS) directive (European Union, 2009), onshore funds complying with set standards can obtain European passporting and be marketable to the retail market across the European Union. Nevertheless, substantial seed investment would need to be secured to adequately cover the operating costs of a regulated onshore fund. Contacted service providers suggested that a minimum of at least USD 50 million would be needed to cover the operating costs of a UCITS-compliant fund. It was also suggested that many top-tier banks and financial institutions would be unwilling to provide custody services for a fund having less than USD 100 million of assets under management.

Discussions held also clarified that operating costs at offshore-domiciled funds are substantially lower than those of onshore-domiciled funds. Service providers suggested that costs for running a fund domiciled in Jersey

or the British Virgin Islands would be less than USD 100,000 annually. Thus, to target a Total Expense Ratio (TER) of less than 1%, seed investment of at least USD 10 million would need to be secured before the fund can operate without excessive performance attrition from fees.

A major disadvantage of offshore domiciliation is the restrictions on marketability. Active marketing (such as through advertisements or roadshows) of offshore funds is restricted or prohibited in almost all markets. They also cannot be sold to retail and non-professional investors. These funds can only be proposed to professional investors such as financial institutions, registered family offices, and high-net-worth individuals with sufficient market experience. Additionally, such funds can only be proposed based upon enquiries received and often after registration with a local sales representative. Even if an offshore structure is used to reduce operating costs, adherence to the AIFMD (Alternative Investment Fund Managers Directive) guidelines could help ensure that any doubts investor may have about the offshore domiciliation are best addressed.

Due to the benefits and drawbacks of either domiciliation, the ideal strategy would be to initially launch as an offshore fund and subsequently migrate to an onshore vehicle. The offshore fund would enable the construction of a track record with substantially less seed investment required. Once a successful live track record is established, the fund would then be migrated to a fully regulated onshore fund that could target a much broader investor base.

An alternative to the fund route would be through the use of an Alpha Capture System from providers such as Squarepoint. These enable the testing of trading and investment ideas in a live electronic format. The providers of these platforms execute the trades of a proposed investment strategy. The proceeds of any generated performance would then be shared with the user as per an initially set contractual agreement. However, unlike a fund, the disadvantage of using such platforms is that they are unlikely to tolerate underperformance for more than around six months before shutting down a strategy. Nevertheless, should launching through a fund structure be problematic or too costly, an Alpha Capture System can be a reasonable initial short-term solution before more assets can be raised.

5.4 Evaluation of Impact

The impact of this research project on the academic community and the practitioner community differs considerably. Successful publication of the research in a high quality journal such as the FAJ can be a catalyst for considerable impact on the academic community. The broad readership of that

journal would ensure that the research is widely disseminated and contemplated within the community.

In addition to the backtests, a live track record is required to maximise impact on the practitioner community. When live outperformance can be demonstrated for at least one year, interest would likely start to develop within the practitioner community. As suggested by a service provider, once a live outperformance is available on a fund that is provided on platforms such as Hargreaves Lansdown, the fund would sell itself with minimal additional marketing.

The core determinant of impact will be whether users are willing to constructively shift from traditional equity investment approaches towards the approach proposed by this research project. As previously stated, achieving a consequential shift will be a challenge prior to the availability of a multiyear real world track record.

For the first few years after its implementation, the only actual beneficiaries of this project are likely to be the seed and early-stage investors of a hypothetical fund employing the proposed investment approach. Nevertheless, before such a fund can be implemented, the academic community would probably be the greatest beneficiary of this project as rigorous backtested results are sufficient to provide acceptance and utility.

Companies such as AQR and Arnott's Research Affiliates use an approach that could be adequate to maximise impact. These firms publish research that is used by both the academic and practitioner communities. This is achieved by focusing their published research on actual products they manage or on strategies for which products will be launched.

The fact that these managers have earned credibility in both the academic and practitioner communities enables them to benefit from such a position of privilege. Such a configuration would be optimal for maximising impact though a real-world track record is nevertheless required before sufficient credibility can be attained within the practitioner community.

6. Conclusions

The EMH broadly stipulates that it not possible to consistently outperform the market on a risk-adjusted basis as all publicly available information is already reflected in the current price of securities. Therefore, relative to the market portfolio, active security selection does not provide any investment advantage after costs (Fama, 1991).

Research over the past five decades has identified patterns in stock returns that seem to be in conflict with the EMH. Smart Beta indexing is one such approach, broadly defined as the construction of indexes that deviate from traditional market capitalisation-weighting (Hsu et al., 2012). There is also a broad body of empirical literature that identifies individual stock characteristics that are linked to future stock returns.

Asset pricing literature has responded to these anomalies in four ways: (1) by arguing that these excess returns are due to risks that are missed by the single factor CAPM and consequently expanding the model to multiple factors (e.g. Fama and French (1993 and 2015)), (2) these anomalies are driven by smaller stocks and hence not tradeable due to transaction costs (e.g. Lesmond et al. (2004)), (3) these are artefacts of the data due to data snooping (e.g. Lo and MacKinlay (1992)), (4) these are evidence of market mispricing due to cognitive biases of investors (e.g. Asness et al. (2015)).

In this study, I use an approach that is very close to that of Piotroski (2000). In particular, using the non-financial constituents of FTSE 350, I develop a quality-at-reasonable-price approach by overlaying Quality and Value dimensions to address Guay's (2000) criticisms of Piotroski (2000). Foremost, my strategy does not rely on small-capitalisation stocks or short positions and succeeds in generating significant absolute and risk-adjusted outperformance. Additionally, the time period I use (2001 to 2017) is more recent, longer, and tests a broader range of macroeconomic environments. Risk is also better controlled through the use of Sharpe ratios and the Fama and French (1993) and Carhart (1997) four-factor model. A stable strategy is thus produced that outperforms in 14 out of 17 tested years.

Existing multivariate approaches suffer from drawbacks that are addressed by the model I propose. For instance, to produce abnormal returns, the approach in Ou and Penman (1989) requires both long and short positions. Abarbanell and Bushee (1998) recognise that that the price impact of trading in small-capitalisation stocks and the inability to short would have substantial impact on the outperformance produced by their model. Finally, Lev and Thiagarajan (1993) conclude that the persistence of the abnormal return produced by their approach is dependent on the prevailing macroeconomic

environment. Over the period 2001 to 2017, the HGHV portfolio produces 0.99% of average monthly returns, and a statistically significant ($t = 4.2$) four-factor Alpha of 0.56% per month. It outperforms the equally-weighted portfolio of all other stocks by 0.53% per month ($t = 3.1$) before risk adjustment and by 0.40% per month ($t = 2.4$) on a four-factor Alpha basis.

Though they are usually very reliable, the factors used in the performed regressions are often criticised. For example, Bartholdy and Peare (2005) state that both the CAPM and Fama-French three-factors models poorly estimate expected returns. Novak and Petr (2010) further claim that since Beta, the three Fama-French factors, and Momentum failed to explain returns on the Stockholm Stock Exchange, the overall validity of the model is questionable.

Despite this criticism, research has shown that the Fama-French model is an adequate enhancement to the CAPM (Lettau and Wachter, 2007). Its identified shortcomings could be time-varying and caused by cycles favouring the Value or Size factors (Wang et al., 2014). Murguia, Phil and Umemoto (2002) also demonstrate that the original Fama-French three-factor model can be used to explain approximately 95% of stock return variability. The inclusion of the Momentum factor in the performed regressions thus further improves this model's predictive power.

In addition to validation of the investment approach, a thorough assessment of the impact of this result needs to be considered. The academic and practitioner communities are both impacted by this research and require different means of engagement. For the academic community, publication of the backtested and empirical results in a high quality journal would produce adequate dissemination of knowledge. The CFA Institute's Financial Analysts Journal is identified as the most suitable journal for this research as it is highly esteemed in both the academic and practitioner communities.

The practitioner community is best engaged through the production of a live track record of outperformance. This outperformance needs to be consistent for at least one year before sufficient credibility can be attained. The best means to produce this track record would be through the launch of a fund implementing the proposed investment approach. Successful outperformance will generate the credibility required by the practitioner community.

If a fund is launched and as its track record is gradually constructed over time, the focus of this research project's engagement can be shifted to progressively include more of the practitioner community. Consequently, the approach used by AQR and Research Affiliates is an ideal means for dissemination. These firms are able to successfully capture both the academic and practitioner communities by focusing their published research on actual products they manage.

Algorithm aversion (Dietvorst, Simmons and Massey, 2015) is a major practical issue that may dissuade many potential investors. A live track record demonstrating stable returns would also help to dissipate any algorithm aversion that may affect the strategy and permit its successful exploitation.

With regards to public policy implications, the proposed approach could be used by pension funds and endowment funds as a better means to invest in equities. Essentially, substantial live proof (over several years) of higher risk-adjusted returns is required to persuade such entities due to the strict risk-reduction mandates that they tend to carry.

Appendix A. Additional Data Tables

For each portfolio, the tables present the average number of stocks, the minimum number of stocks, and the maximum number of stocks that are present throughout the backtested period from 2001 to 2017 (inclusive).

Table A1. Number of Stocks in Single Dimension Portfolios on Quality and Value

A. Quality Dimension			B. Value Dimension		
	Hi	Lo		Hi	Lo
QScore	115.88	79.65	VScore	101.53	94.00
	103	72		86	83
	131	94		116	109
ROA	98.53	97.00	P/B	102.71	92.82
	84	91		116	84
	116	109		90	109
Δ ROA	96.53	99.00	P/E	100.53	95.00
	81	92		88	84
	111	114		116	109
CFO	99.00	96.53	EV/EBITDA	100.88	94.65
	89	86		85	86
	116	109		116	109
ACCRUAL	95.76	99.76			
	88	87			
	111	114			
Δ MARGIN	96.88	98.65			
	88	87			
	114	111			
Δ TURN	97.88	97.65			
	85	90			
	112	113			
Δ LEVER	95.59	99.94			
	85	90			
	103	122			
Δ LIQUID	97.24	98.29			
	88	83			
	113	112			

Table A2. Number of Stocks in Multiple Dimension Portfolios on Quality and Value

		Quality		NonHQHV
		Hi	Lo	
Value	Hi	65.06	36.47	
		56	27	
		77	49	
	Lo	50.82	43.18	
		39	29	
		56	55	
	NonHQHV			130.47
				116
				148

Table A3. Number of Stocks in Adjusted Multiple Dimension Portfolios on Quality and Value

		Quality		NonHQHV
		Hi	Lo	
Value	Hi	56.12	44.41	
		47	37	
		71	52	
	Lo	42.00	53.00	
		32	43	
		48	65	
	NonHQHV			139.41
				126
				154

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