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A Smart Beta Approach to Fama-French and Profitability

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Table of Contents

1. Introduction:

Ever since the Capital Asset Pricing Model (CAPM) proposed by Sharpe (1964), investors and academics alike have sought after anomalies that cannot be explained by the model. Studies such as Fama and French (1993) and Fama and French (2006) contributed to this pursuit by introducing the role of factors. As the understanding of factors progressed, smart beta emerged as an increasingly popular approach to beating the CAPM by using factors. Smart beta can be explained as follows.

Traditionally, investing in the stock market is done either actively or passively. Active investing generally entails selecting certain companies with the hopes that they will beat the market. Passive investing invests in the broad market by choosing a security, such as the S&P 500, that tracks the market. These market mimicking indices are generally weighted based on market cap. Smart beta, on the other hand, lies somewhere between active and passive investing by weighting the market index differently. Many strategies, therefore, seek out exposure to factors other than the market. Since these factors have positive risk premia, a factor based strategy that heavily weights securities with exposures to these factors ought to beat a market index. This study focuses on the profitability factor.

Fama and French (2013) introduce the profitability factor to their seminal factor model and are able to use that factor to capture some of the patterns in average returns. This profitability factor can, in practice, be turned into a smart beta investment strategy. This task is approached by applying the methodology that the Fama and French model uses. The purpose of this paper is to incorporate the landmark model of Fama and French into the exciting new financial strategy that is smart beta in order to create a novel strategy that beats the market.

This process starts with the S&P 500 index. The S&P 500 is a market-cap weighted index representative of the market as a whole. Therefore, an investment strategy that alternatively weights the companies within it by profitability would be considered a smart beta strategy. I construct two portfolios, both of which are heavily weighted on profitability. First, I take the 50 S&P 500 companies with the highest sensitivity to the Fama and French profitability factor. Such stocks should outperform if the profitability risk premium is positive. Second, I take the 50 S&P 500 companies with the highest ratio of gross profit to assets and construct a second portfolio. Then, I compare the performance of these portfolios against each other and against the traditionally-weighted S&P 500 index, or, the market.

Figure 1 shows the findings. The gross profit portfolio delivers the strongest overall returns over the 15-year period while both portfolios significantly outperform the market. The reason for this outperformance pertains to the manner in which they are constructed. The factor sensitivity portfolio is constructed by loading up on sensitivity to the profitability factor. This, however, does not disentangle the portfolio from the other Fama and French factors. Each factor is somehow correlated with the others, and strangely enough, the portfolio returns are negatively correlated with the same profitability factor that they are supposed to be sensitive to. This is because the portfolio returns are still strongly exposed to the market, and the market is negatively correlated with the profitability factor. Thus, the market exposure overpowers the profitability exposure and appears to be more responsible than profitability for the outperformance found in this study.

Section 2 discusses the existing literature. Section 3 presents the data and methodology. The empirical strategy and results are presented in section 4 and section 5 concludes.

2. Literature Review:

Sharpe (1964) began the discussion by asserting a capital asset pricing model (CAPM) in which expected returns were linearly related to the market risk of a given security. This model served as the foundation for much research that followed. Fama (1970) popularized the idea of efficient markets and their ability to “fully reflect” public information. Fama-MacBeth (1973) essentially reaffirms this idea with its failure to reject the CAPM. Many investors have since attempted to exploit ‘anomalies’ in order to disprove the efficient market hypothesis. If they can prove skillful and consistent outperformance, then they can essentially disprove the idea that markets are efficient. Not long after Sharpe, researchers started to find factors with explanatory power that threaten the reign of the CAPM.

Banz (1981) offers one of the first counters to the CAPM. It asserts the existence of a size factor by which smaller firms prove to have higher risk-adjusted returns than their larger counterparts. This throws a wrench in the linear model of the CAPM which shows returns to be strictly dependent on market risk. It also gives life to other previously inconclusive literature that propose additional factors. It opens the floodgates. In the same year, Reinganum (1981) confirms the findings of Basu (1977): that a value factor can explain returns beyond that which the CAPM is able to explain.

Fama and French (1992) affirms Banz (1981) and Reinganum (1981) by sorting through various factors to show that size and value offer significant explanatory power. The tests place increasing pressure on the CAPM and even provide evidence against the market beta and stock return relationship. Fama and French (1993) take the first try at their five factor model, incorporating the size and value factors as well as additional bond market related factors in order to explain the cross-section of average returns. The study provides strong support in favor of the idea that market beta is insufficient and that models superior to the CAPM can, and are, being constructed. These factor models have factor risk premia. If these premia are not incorporated in a market benchmark, one can overweight securities with high sensitivities to these factors and beat the market benchmark on average. That is the premise of this study.

Because smart beta is somewhat new, many approaches and weighting strategies have not yet been investigated. There are, however, various studies that I can use to inform my decisions and methodology. I begin by discussing previous works related to profitability, followed by those pertaining to Fama-French, and finally those in the newer space of smart beta.

Profitability has long been a measure of quality used to seek alpha. Sloan (1996) shows an imbalance in the components of profitability calculations and therefore a chance to profit off of mispricing. Fama and French (2006) put into action the Fama-French factor model. With respect to profitability, they believe that profitable firms should outperform less profitable firms, consistent with Haugen and Baker (1996). While Fama and French (2006) find this to be true in general, they find that profitability has little to no predictive power on top of size and value when it comes to explaining future returns. The efficacy of the study lies in how it stacks each factor on top of the others in order to discover the marginal explanatory power that each factor has beyond that which the others have already explained. By doing so, Fama and French are able to better isolate and identify the drivers of returns as they add more factors into the model. My approach adopts their methodology in order to identify what factors are influencing my portfolio returns.

Fama and French use a factor model to try and attribute returns to each of the factors in order to explain the movements in stocks. They do so by using cross-section regressions to allocate stocks to high or low expected return portfolios based on a variety of factors including asset growth, accruals, and profitability.

My approach differs in that I apply a smart beta approach to what they do. Rather than just a high and low expected return portfolio comprised of various factors, I use a more concentrated selection of stocks by cutting it down to 50 stocks whose expected returns is determined solely by their profitability factor sensitivities. This should take advantage of the profitability factor risk premium. Rather than explanatory power, I seek market outperformance adjusted accordingly for risk.

Lastly, Fama and French test the lag of profitability by evaluating its ability to explain returns one, two, or three years into the future and they find decaying persistence each year after the first. The test in this study goes beyond three years to evaluate the predictive power or performance of profitability over a subsequent five-year period.

Novy-Marx (2012) offers improvements to the Fama and French methodology by adding two things. First, that more profitable firms deliver stronger returns even despite higher valuation ratios. Second, that gross profits to assets is much more powerful than earnings in predicting returns. This means that tilting a value strategy towards gross profitability will offer improved equity performance. Celis and Kalra (2016) also use gross profitability and an asset based metric in the denominator to calculate a profitability factor that performs well during times of strong volatility or market declines. Fama and French rely on earnings, but, in accordance with Novy-Marx and Celris and Kalra, I use gross profit to assets in an alternative approach to portfolio selection. This is because profitability metrics that are higher up on the income statement are cleaner measures of raw profitability. Furthermore, Novy-Marx (2012) uses a value-weighted portfolio sorted by profitability which dilutes the isolation of the profitability factor and therefore detracts from the approach as a profitability-centric investment strategy. I use equal-weighting, which, while it may introduce a size bias, will better concentrate my stock selections around profitability. I also consider the various other factors driving returns to account for the extent of this potential size bias.

Fama and French (2013) introduce the five-factor model, adding profitability and investment to value, size, and the market return. I use this model to discover the factor sensitivities that construct my portfolio. The study finds that HML, the value factor, is redundant in that the returns it explains are already entirely captured by the other four factors. Perhaps this is due to the value factor's exposure to market expectations of profitability and investment. This is noteworthy given that one argument in favor of smart beta disapproves of market cap weighting schemes because they overweight overvalued firms and underweight undervalued firms. An alternative factor weighting scheme may be able to eliminate this problem. The study also finds that with over 600 monthly observations, the profitability factor is actually negatively correlated with the market and size factors. This information and factor correlation in general are considered in the analysis of my results.

While the aforementioned works all pertain to profitability, it is also important to understand smart beta as a strategy and as a method by which profitability can be isolated. Factor investing evolves largely from the landmark study of Sharpe (1964) which establishes the Capital Asset Pricing Model (CAPM) and asserts the optimality of a market cap weighting scheme.

My approach tests the efficacy of CAPM as well as uses it to risk adjust returns. As mentioned, this study essentially serves as the basis from which countless studies have since tried to beat the CAPM and is, in theory, what prompts the area of smart beta. Both Haugen and

Baker (1991) and Grinold (1992) counter Sharpe's conclusion of optimality. They show that various other factors, value in the case of Grinold (1992), can be used to construct weighting strategies that can match Sharpe's returns, and can do so with less volatility.

As mentioned, smart beta lies somewhere between active and passive investing. Cremers and Petajisto (2009) develops a methodology to evaluate how active a given fund is relative to benchmarks by using metrics other than tracking error. It could be used to evaluate how active a given smart beta strategy really is. Philips et al. (2015) argues it is little more than an active strategy since smart beta strategies generally have large tracking errors. This is attributed to inconsistent factors and the difficulty of capturing them due to their ever-changing nature and the issue of rebalancing, an issue also addressed by Rowley, Bennyhoff, and Choa (2014).

Kahn and Lemmon (2016) state that market, size, value, quality, momentum, and volatility are the most common smart beta factors referenced in literature. That said, smart beta can define any alternative weighting strategy. The study uses regressions to find what percent of various funds' active variance can be explained by the smart beta factors listed above. It shows what fees should be associated with each level of smart beta exposure compared to that of pure alpha, and that in practice this differs drastically from the fees that are actually charged. Hallerbach (2012) reintroduces the idea of a lag by weighting an index based on one-month of volatility. Rather than reweighting monthly based on this lag, I observe the persistence of factor sensitivity over time.

Amenc, Goltz, Martellini (2013) details the various approaches to smart beta including equally weighted portfolios, maximum diversification portfolios, maximum Sharpe ratio portfolios, and fundamentally-weighted portfolios. Fundamentally-weighted indices replace market cap with a different measure. Schwartz and Siracusano (2007) use earnings whereas Arnott et al. (2004) use measures like sales and cash flow.

Brightman, Clements, and Kalesnick (2017) attempt to incorporate the Fama and French profitability and investment factors into a smart beta strategy but do so by using raw metrics rather than sensitivities. They attribute future returns to the factors' identification of sustainable EPS growth companies. This, however, does not use factor sensitivities, the basis of the Fama and French methodology, nor does it account for the explanatory power of the other variables. It merely invests more heavily in companies with stronger measures of the Fama and French model's last two factors. My approach introduces factor sensitivity to the equation by evaluating its persistence and its direct influence on future results. In other words, my model turns Fama and French into a smart beta strategy.

3. Data and Methodology:

The data used in my model comes both from the Ken French website[1] and the Wharton Research Data Services (WRDS). The Ken French website lists factor returns for the five factors of the Fama and French five factor model. I discuss each factor individually in more detail below. The WRDS provides various datasets via Compustat, one of which is a list of all S&P 500 firms at any given point in time. These companies are referred to as 'constituents'. It also provides the returns of all these companies at the monthly level. Lastly, it provides financial fundamental numbers including gross profit and total asset numbers on an annual basis at the firm level.

[1] Ken French website can be found at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

The WRDS return data exists at the firm level over the time period queried rather than strictly for when the security existed within the S&P 500 index. The data, therefore, requires formatting so as to achieve a list of monthly returns by security for only the months during which those securities are constituents of the S&P 500 index. The data covers 20 years from January of 1996 through December of 2015. This enables three test periods of five years each: 2001-2005, 2006-2010, and 2011-2015. The 1996-2000 period serves strictly as a base formation period from which the subsequent period's portfolio is established.

Fama and French (2006) use up to three years of return information to evaluate the predictive power of factors, so using five should provide additional insight into the longevity of the efficacy of the strategy year by year. By testing for three different five-year periods, the performance of the strategy can be evaluated over a relatively long period of time and under different market conditions. Rebalancing occurs at the beginning of each five-year period.

The selection of stocks at the beginning of each five-year return period is a selection of the most factor sensitive stocks. For example, the period of 1996-2000, the formation period, is used to calculate factor sensitivities that determine which stocks are selected in the subsequent five-year period, 2001-2005, the return period. In this example, for a company to be selected into the portfolio it must exist within the S&P 500 for the entirety of 1997 through 2005. The reason it must exist from 1997 through 2000 is so that there is sufficient return data, 48 months at least, from which a regression can yield factor sensitivity information. Less than four years would risk an insufficient sample size and greater than four would unnecessarily eliminate more companies from the list. Since companies that exist for five years in the portfolio must also exist for those same five years in the S&P 500, the performance comparison is apples to apples in the sense that smart beta is being accurately established. The profitability weighted portfolio is compared to the market-cap weighted S&P 500 index with companies that exist in both simultaneously over the entire period. Thus, the five-year restriction helps create a more accurate smart beta strategy by excluding any companies that cease to exist in the benchmark index.

Another reason why companies must also exist in the index from 2001-2005 is to hold beta constant. The intent is to observe the risk adjusted returns of the portfolio in this period and if companies are falling out of the index during these five years, beta changes and this corrupts the risk adjusted return results.

Once companies have met this nine-year constituent requirement, their factor sensitivities must be calculated. This is achieved by regressing each of the stocks' returns against each of the five Fama and French factor returns in the five-year formation period. In the example above, the formation period is 1996-2000. In particular, I estimate a model of the following form:

$$R_{it} - R_f = a_i + B_i(R_{mt} - R_f) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it} \qquad (1)$$

where R_{it} is the portfolios expected rate of return and R_f is the risk-free rate. R_{mt}-R_f is the return on the market minus the risk-free rate. SMB (small minus big) is the size factor. It represents firm size and is used by Fama and French to explain returns. For example, if a company's stock goes up, that movement may be partially attributable to the fact that the company is relatively small. Thus, its size is one of the factors explaining its returns. HML (high minus low) is the value factor, and CMA (conservative minus aggressive) is the investment factor.

RMW (robust minus weak) is the profitability factor and the most important factor for the sake of this study. Fama and French (2013) constructs RMW by using accounting data such that RMW equals annual revenue minus cost of goods sold, selling, general, and administrative expenses, and interest expense all over book equity as of the fiscal year t-1. It is essentially an operating profitability measure that also considers costs associated with interest.

The coefficient on the profitability factor is used to create a portfolio consisting of 50 companies at a time. DeMiguel et al. (2007) and Statman (1987) support the idea that 50 stocks in a portfolio is generally accepted as reasonable and commonplace in both theory and practice. The portfolio represents the top 50 companies of a list of approximately 300 in a given formation period in terms of sensitivity to profitability returns.

It is generally about 300 rather than 500 or greater because of the nine-year constituent requirement mentioned above. This drop-off is a downside to the nine-year requirement, since many companies which enter or leave the S&P 500 index during that nine-year period are excluded from being selected into the portfolio, thereby shrinking the list of investment candidates and also incorporating a look ahead component to a strategy that is being back-tested. This should not introduce any sort of selection bias though it does introduce an element that is not entirely replicable today.

That said, there should be no reason why this requirement would help or hurt actual returns except for the fact that it might introduce a component of survivorship bias. The companies that remain in the portfolio will maintain a stronger level of diversification and will also be the companies sufficiently successful to remain fortune 500 companies during the return period. Despite that, the strategy can otherwise be replicated without requiring that stocks remain in the S&P index for at least five years of returns.

The 50 chosen companies are equally weighted. Plyakha et al. (2012) finds that the equal-weighted portfolio outperforms other weighting strategies. It is the most straightforward approach and is universally applied. An equally-weighted approach will, however, face exposure to market, size, and value factors. This can be addressed by calculating the portfolio's sensitivity to these other factors to show what all may be driving returns. The weighting strategy is therefore 1/50 for each of the 50 most sensitive stocks and 0 for the remaining stocks. In theory, assuming sensitivities remain somewhat constant over years going forward, this portfolio should be affected directly by the return on the profitability factor throughout the return period.

Lastly, Compustat through WRDS enables a data pull of fundamental financial information on the firm level by year. In order to compare performance with my initial factor sensitivity portfolio, I construct an additional portfolio for the same time periods with the same list of S&P 500 constituents, however this one equally weights 50 companies by selecting the 50 most profitable in terms of gross profit divided by total assets. This financial metric uses the numbers reported by each company in the year immediately prior to the return period. For example, the portfolio constructed for the years 2001-2005 is determined by selecting the 50 companies with the highest gross profit over total assets reported in the fiscal year 2000. In theory, these larger established companies ought to have relatively constant measures of profitability over the span of the return period.

In order to combat deteriorating persistence of both profitability and exposure to it, I could rebalance the portfolios more frequently than once every five years. This would better maintain the intent of the strategy. It is, however, costly to rebalance more frequently given transaction fees associated with making the trades as well as tax expenses associated with realizing gains so frequently. These two expenses are omitted in this study for the sake of simplicity as well as the difficulty and variability in determining how costly trades and tax liabilities may in fact be. Furthermore, if an investor were to hold the S&P 500, it would have similar such transaction fees and tax implications. If the index were held via fund or ETF such

that it was rebalanced on behalf of the investor, then there would be management fees. Therefore, the omission of these costs from this study ought to maintain a nearly apples to apples comparison between the performance of the S&P 500 and these profitability strategies.
Thus, rebalancing every five years enables a similar tactic with fewer expenses and offers the opportunity to evaluate how the strategy does over time. It also shows how its intended concentration of profitability deteriorates over time via mean regression.

Novy-Marx (2012) argues that gross profit to assets is a stronger measure than earnings for identifying profitable firms namely because it is higher up on the income statement thus accounting for a given company's raw cash generating profitability and not accounting for expenses lower on the income statement that concern management and various other operational decisions. This is why I use the Novy-Marx measure rather than the Fama and French measure.

The factor sensitivity portfolio, by definition, is loaded heavily on the sensitivity to the profitability factor in the formation period. The average sensitivities of the portfolio for each formation period are shown in Table 1. The portfolio has an average sensitivity to the profitability factor, RMW, of 1.2, outdone only by the market factor. Given that the portfolio is constructed with 50 companies from an index that represents the market, the portfolio will almost inevitably be strongly exposed to market movements. I discuss this issue at more length in the data section. Naturally, these sensitivities will change during the return periods and the RMW sensitivity will likely shrink. I also discuss this in the data section.

4. Empirical Strategy and Results:

In order to discover how a profitability based smart beta strategy performs over time relative to the market, I take two approaches. I discuss each in turn.

First is the strategy I refer to as the factor sensitivity portfolio. This portfolio consists of the 50 S&P 500 stocks that are most sensitive to the Fama and French profitability factor over a five-year formation period. This portfolio exists for the subsequent 15 years with rebalancing performed every five years.

The second strategy I refer to as the gross profit portfolio. This one selects the 50 S&P 500 stocks with the highest gross profit to total assets ratios in the year immediately prior to the return period. This portfolio also exists for 15 years with rebalancing performed every five years.

The factor sensitivity approach makes the assumption that factor sensitivities will remain somewhat constant over the duration of the return period. The second approach assumes the same but that profitability as measured by gross profit over assets will persist. Deterioration of this persistence will with it deteriorate the intent of the strategy and therefore the expected returns. Both strategies are controlled such that beta is consistent for the entire return period and ultimately can be used to risk-adjust the returns. Since the portfolios are equally weighted, the returns are simply the average of the returns of the 50 stocks as achieved via the empirical approach discussed in section 3.

Once the returns are discovered, they must be risk adjusted. This is because the beta of the returns differs from the market beta of 1. Thus, if a portfolio achieved outperformance, it could simply be due to taking on more risk. The risk adjustment evaluates returns against the market on a level playing field. This risk adjustment occurs by incorporating the following model:

$$R_t - R_f = a_t + B_t(R_{mt} - R_f) + e_t \qquad (2)$$

where $R_t - R_f$ represents the portfolio's returns minus the risk free rate over the five year return period. This serves as the y variable while the Fama and French market return minus the risk free rate is the x variable. a_t is the intercept and represents the risk adjusted monthly outperformance or the alpha of the portfolio over the market. The epsilon is an error term with normal white noise properties.

Once returns are risk adjusted, they can be properly evaluated. Figure 1 shows the returns from 2001-2015, the entire period during which the portfolios exist. It shows what one dollar invested would turn into by the end of the 15 years. The returns of both strategies and of the Fama and French factors are shown. The figure shows the S&P 500 return instead of the Fama and French market return factor. This is because the Fama and French factor subtracts out the risk free rate which makes it less comparable to the strategy returns. Thus, the S&P return is simply the market factor plus the risk free rate.

As shown in Figure 1, both strategies generate very strong alphas with the gross profit approach outperforming the factor sensitivity approach. One dollar invested in the gross profit approach in 2001 would 15 years later yield nearly three times that which the same dollar invested in the S&P 500 index would have yielded.

The annualized risk adjusted returns of both strategies are shown in Table 2. The returns are separated into the three five year return periods each immediately subsequent to rebalancing. The table shows statistically significant outperformance in the first two five-year periods for the factor sensitivity approach, 7.2% and 5.2%, with statistically significant underperformance in the final five years, -5.1%. Despite underperforming the market in the final five years, the portfolio is still up over that period.

The gross profit over total assets (GP/TA) approach produces consistent outperformance, with an average annualized alpha of about 5.7% and alphas of at least 5% in each of the three periods. The first and third period are statistically significant while the second period falls just short of the mark for statistical significance with a T-Stat of 1.53. This approach proves more consistent and more often produces a positive alpha relative to the factor sensitivity strategy.

Interestingly enough, the two portfolios have relatively small overlap with respect to stocks held. In the first five years, just 12 companies exist in both of the profitability-based strategies. In the second period that number is down to just 11 and in the third period only five companies overlap. Despite strong outperformance on the part of both strategies, it appears that this outperformance was driven by a largely different group of companies. The limited overlap, however, is not completely unsurprising as the factor sensitivity approach is not seeking out profitable companies, but rather companies most sensitive to the profitability factor. The gross profit approach is strictly holding the most profitable companies. There is, however, far more overlap between the most profitable companies and the most factor sensitive companies than there is between the most profitable companies and the least factor sensitive ones. This goes to show that the most profitable companies are generally more sensitive to the profitability factor.

As mentioned, persistence of the strategy is pivotal in determining its efficacy over time. Figure 2 shows the average annualized risk adjusted returns for each year subsequent to rebalancing. For example, year one is the average of the annualized risk adjusted returns of years 2001, 2006, and 2011. These are the three years during which the portfolio had been balanced one year prior. Although a sample size of just three observations for each of the five years is not statistically sufficient, it provides a sense for how returns change as the foundation of the rebalancing deteriorates.

The trend lines show deteriorating performance over time for both strategies to a similar degree. The gross profit strategy loses just over 2% in returns each year post rebalancing while the factor sensitivity strategy loses about 1.5% on average. This implies that the strategies indeed lose efficacy over time as they fall out of their intended exposures and regress to the mean. The takeaway from this is that more frequent rebalancing, perhaps annually, would likely improve returns.

Figure 3 sheds some light on how the five Fama and French factor returns performed on average in each of the five years after rebalancing. Naturally, the sensitivity of the portfolio to the profitability factor is loaded up large and positive over the formation period and in the early years of the return period, however it falls off as time goes on after rebalancing. Thus, the sensitivity to the profitability factor return as it is shown in Figure 2 weakens over time. The strong overall performance in the first year makes intuitive sense because that is also the year, in Figure 3, where the profitability factor return is highest and where the portfolio is generally most sensitive to profitability.

Table 3 shows how sensitive the portfolio returns are to the Fama and French factors over the 15-year period. Considering only the factor sensitivity portfolio at this point, it follows that the market equity beta is over one for the period, showing that the portfolio is highly sensitive to market movements. The portfolio is constructed directly from an index representative of the market, so it is no surprise that this is true. The portfolio is second most sensitive to the profitability factor. This makes sense given that it was constructed by selecting companies based on this factor. Next is investments, then size, then value. The strong profitability sensitivity at the very least shows that there is some degree of persistence in sensitivity.

In theory, a portfolio could be constructed by shorting various stocks so as to zero out sensitivities to factors besides profitability. In practice, however, this would likely not be feasible and would require rebalancing at an unrealistic frequency.

The strong sensitivity to the market, however, is tough to remove and cannot be ignored. While the market exposure proves helpful in achieving outperformance, it is an unintentional outcome. In order to evaluate how it might affect the portfolio returns, correlation between both factors and returns ought to be considered.

Table 4 shows this correlation matrix for returns over the 15 years. Despite high factor sensitivity to the profitability factor, RMW, the portfolio is actually strongly negatively correlated with RMW. This seems counterintuitive at first. It means that although the portfolio is exposed to RMW in the sense that returns should go up when RMW increases, in practice the returns are operating inversely to the RMW returns.

The reason behind this lies in the correlations between Fama-French factors. As briefly mentioned in Fama and French (2013), profitability is found to be negatively correlated with the market factor in every test ran, however little to no explanation is given for why this might be. The 15 years over which this study evaluates returns finds an extremely strong negative correlation of -.61 between RMW and the market factor. For whatever reason, returns on profitability are decreasing when market returns are moving up.

According to Table 4, the portfolio returns have a .91 correlation with the market factor. They move practically hand in hand. Thus, the reason why the portfolio returns are strongly negatively correlated with RMW (-.43) is because RMW is strongly negatively correlated with the market.

The portfolio is far and away most sensitive to market movements as seen in Table 3, and therefore is more powerfully influenced by and strongly correlated with market returns. Thus, while an increase in RMW will provide the portfolio with a small boost in its returns, this marginal increase will be completely overshadowed by the probable decrease in market returns to which the portfolio is far more sensitive.

The role of inter-factor correlation ultimately plays an enormous role in determining the returns of an investment strategy based on Fama and French factor sensitivities. The interconnectedness of the factors makes it practically impossible to successfully isolate the returns of just one factor. However, given the success of the factor sensitivity portfolio over the returns on RMW, it appears that complete factor isolation mirroring those RMW returns may in fact be an inferior approach as well as a far more difficult one to achieve.

My strategy proves successful, but not necessarily for the reason hypothesized. Returns are highly sensitive and correlated with the market, far more so than they are with profitability. They are also sensitive and very correlated with the size factor (.375), however the size factor’s strong correlation with the market (.295) could explain that. In all, returns seems to be driven by the market but with enough exposure to other factors such that returns are boosted to outperformance.

Fama and French (2013) attempts to disentangle characteristics by sorting groups on several criteria. If two factors are negatively correlated, they perform two distinct sorts so as to remain diversified rather than allowing that negative correlation to essentially cancel out returns. However, if this study filtered out companies so as to load up on those with low factor sensitivity to the market in addition to high profitability sensitivity, the resulting portfolio would hardly be isolating RMW. Disentangling proves impractical and extremely difficult when the intent is isolation of a single factor. Thus, a true smart beta approach to Fama and French proves extremely difficult to implement.

The more straightforward financial metric based gross profit smart beta strategy proves far easier to implement and significantly more successful. The gross profitability over total assets portfolio approach performs better overall in this study and there are several reasons why this may be.

Fama and French (2008) shows that with controls for size and value, there is insufficient evidence that profitability shares any positive relation with returns. Novy-Marx (2012) argues that this is because the Fama and French study uses earnings, and that gross profitability proves a far more powerful predictor of returns than earnings does. Therefore, it makes sense that the gross profit to total assets portfolio outperforms the factor sensitivity portfolio which relies on the Fama and French version of a profitability factor.

The factor sensitivity portfolio also selects companies based on sensitivity to RMW whereas the gross profit strategy selects based on straight profitability. This leads to two portfolios with limited overlap. These alternative approaches to portfolio construction in turn lead to different levels of “profitability” persistence and different time frames with respect to formation, where the first is built with five years of information and the stronger performer is constructed off just one year of financial information.

5. Conclusion:

With the recent emergence and growing popularity of smart beta as an investment strategy, many potential versions of smart beta have been left untested or otherwise unconsidered. The purpose of this study is to add to the work performed on smart beta by evaluating the efficacy of two profitability focused strategies. This is done by attempting both a simplistic approach to smart beta as well as a strategy that builds off the well documented factor model of Fama and French. Fama and French built a model for explaining returns, and I see this as an opportunity to mold their approach into an investment strategy that incorporates the central concept behind smart beta: the idea that alternative weighting schemes centered around factors other than traditional market-cap can capture excess returns. Extremely limited work has explored a profitability focused smart beta strategy and none has adapted Fama and French in the manner that this study does.

I construct two portfolios, both consisting of 50 S&P 500 companies, equally weighted, that exist for the 15 years from 2001-2015, and are rebalanced every five years. The first portfolio consists of the 50 most sensitive to the Fama and French profitability factor and the second consists of the 50 with the highest ratio of gross profit to total assets.

I find that both portfolios significantly outperform the market, as shown in Figure 1, and that the gross profit to total assets approach provides the strongest returns. While the factor sensitivity approach proves successful as well, its success cannot be entirely attributed to the profitability factor given its large exposure to the market factor and the negative correlation between market and profitability returns. Thus, while isolating the profitability factor proves extremely difficult as an investment strategy in practice, outperformance is still generated and is driven by a combination of the various other factors.

Both strategies could be replicated today and if back testing is any indication, they prove to be viable options for beating the market. The gross profit to total assets approach, however, produces stronger returns for various reasons and is a far more straightforward strategy to implement. Its outperformance is likely attributable to the fact that it consists of companies that are profitable and not just sensitive to profitability. These companies ultimately prove more successful and less subject to drops in the market. This goes to prove that profitability at the firm level enables companies to offer excess returns and to better withstand adversity in the market.

Additional research could be performed to test what the optimal number of holdings is in a portfolio with factor entanglement, what the optimal weighting strategy is, as well as what the optimal frequency for rebalancing is, perhaps considering the tax implications and transaction fees that this strategy would incur. A similar approach could be applied to the other Fama and French factors and controls could be incorporated to try and better isolate an individual factor. Additionally, a model for analyzing what exactly drives returns in a portfolio with varying sensitivities and also entangled correlations could help provide much clarity into what exactly produces such strong outperformance in this study.

Table 1.
This table shows the average factor sensitivity of the 50 companies in the portfolio during the formation years. The formation period consists of the five years preceding each return period over which the S&P 500 constituents were regressed against the Fama-French factor returns. Naturally, on average the sensitivity to RMW, the profitability factor, is highest since these are the 50 companies with the highest sensitivities to that factor. This data pertains only to the factor sensitivity portfolio.

Formation Period Portfolio Factor Sensitivities					
	Rm-Rf	SMB	HML	RMW	CMA
1996-2000	1.082	0.298	-0.153	1.211	0.303
2001-2005	1.267	0.320	-0.013	0.984	0.296
2006-2010	1.575	0.342	0.289	1.405	-0.123
Average	**1.308**	**0.320**	**0.041**	**1.200**	**0.159**

Figure 1.

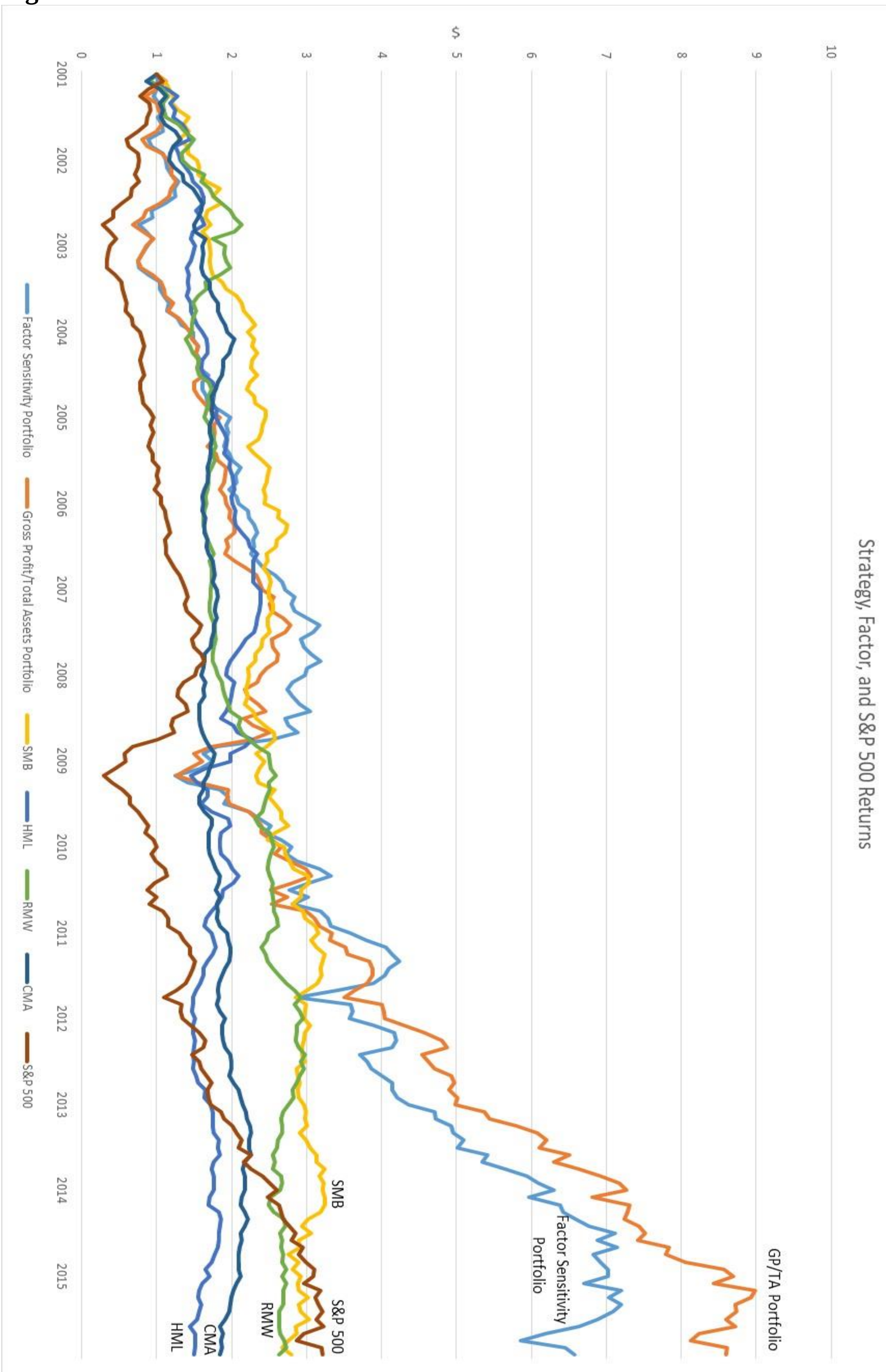
Strategy, Factor, and S&P 500 Returns
$
0
1
2
3
4
5
6
7
8
9
10
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
GP/TA Portfolio
Factor Sensitivity Portfolio
SMB
S&P 500
RMW
CMA
HML
Factor Sensitivity Portfolio
Gross Profit/Total Assets Portfolio
SMB
HML
RMW
CMA
S&P 500

Table 2.
This table shows the risk adjusted returns for both the factor sensitivity portfolio and the gross profit over total assets (GP/TA) portfolio. This is achieved by using the CAPM to risk adjust the monthly return data for each portfolio such that the portfolio beta equals the market beta in order to account for the additional risk taken on by the portfolio approach. Statistical significance (T>2) is achieved in all but one period. Underperformance occurs in just one five-year period for the factor sensitivity portfolio.

	Factor Sensitivity Portfolio		**GP/TA Portfolio**	
	Risk Adj. Alpha	T-Stat	Risk Adj. Alpha	T-Stat
2001-2005	7.18%	2.18	6.05%	2.44
2006-2010	5.19%	2.08	5.14%	1.53
2011-2015	-5.06%	-2.01	6.06%	2.57

Figure 2.

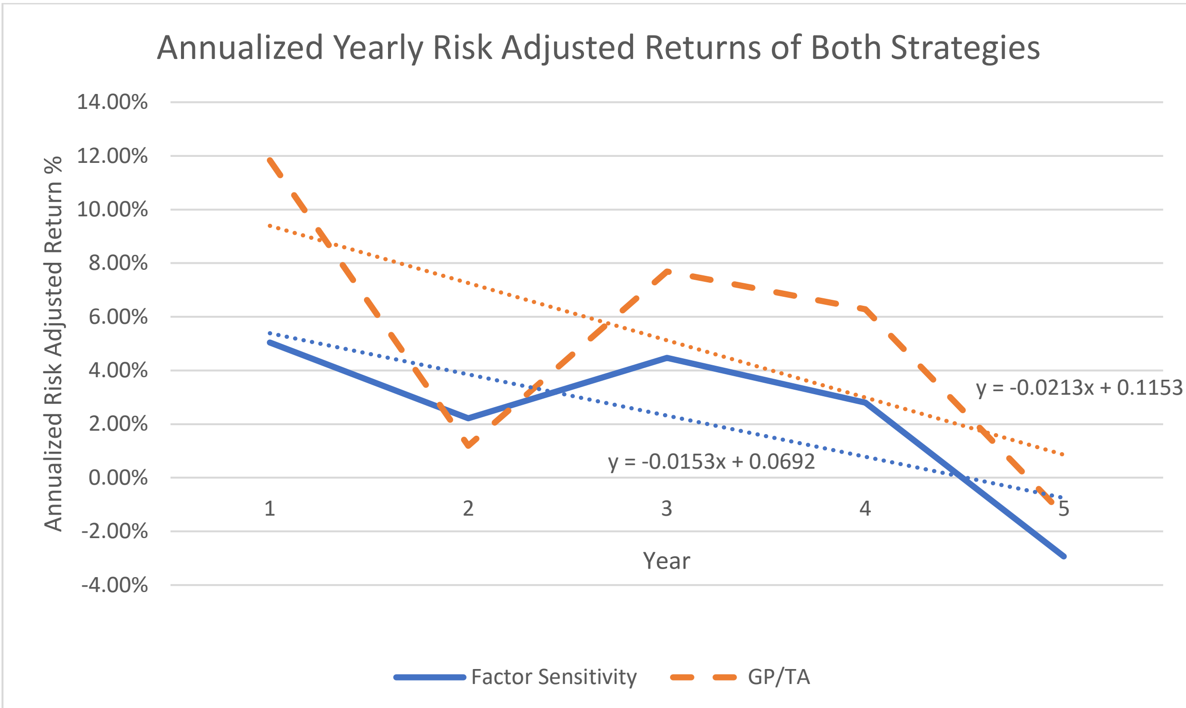

Figure 3.

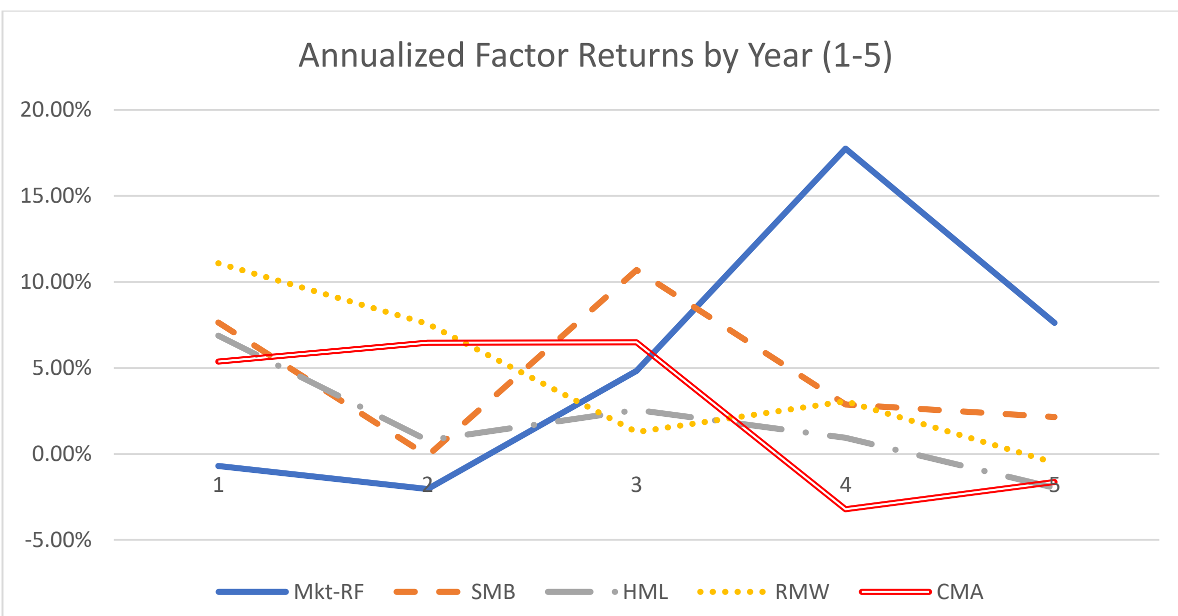

Table 3.
This table shows the average factor sensitivity of each portfolio over the entire 15 year return period (2001-2015). The gross profit over total assets portfolio (GP/TA) was not constructed with any consideration to factor sensitivities. Therefore, it follows that GP/TA sensitivity to RMW is positive (.178) but much smaller than the factor sensitivity portfolio's sensitivity (.343). This data shows how persistent sensitivities can be over the return period once the portfolios are constructed, particularly when analyzed with consideration to Table 1.

	Factor Sensitivities Over the 15 Years	
	Factor Sensitivity Portfolio	GP/TA Portfolio
Mkt-RF	1.080	0.956
SMB	0.204	0.201
HML	0.176	-0.036
RMW	0.343	0.178
CMA	0.204	0.073

Table 4.
This table shows the correlations between the returns of each Fama-French factor over the 15 year return period (2001-2015). This shows how factors are entangled with one another by means of correlation. It can help explain what drives portfolio returns by considering how sensitive a portfolio is to the various factors (Table 3) as well as how correlated the various factors are to each other. The correlations of the factor sensitivity portfolio returns with the Fama-French factor returns are shown in the bottom row.

Factor Sensitivity and Portfolio Return Correlation Matrix

	Mkt-RF	SMB	HML	RMW	CMA
Mkt-RF	1	0.295	0.054	-0.608	-0.141
SMB		1	0.200	-0.306	0.083
HML			1	0.184	0.557
RMW				1	0.192
CMA					1
Returns	0.912	0.375	0.251	-0.432	0.038

6. Acknowledgments

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