Multi-Dimensional Quality Among the S&P500

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Main Idea

Traditional factor-based asset pricing models, like the Fama-French three-factor model, use metrics such as firm size and book-to-market ratio to explain deviations from beta-predicted returns (Fama and French, 1992). We propose an enhancement of these models by implementing a trading threshold based on a quality factor that accounts for a company's relative measures of profitability, stability, and growth within its sector. Using this quality factor as a means to elevate the returns of the SMB portfolio, we are able to generate outsized risk-adjusted returns and achieve a higher Sharpe ratio than traditional benchmarks. In designing our quality factor, we drew inspiration from academic literature on the existence of unexplained returns for "quality companies," but reconstitute this research to create a novel strategy that is applicable to constituents of the S&P500 where it is typically much harder to generate outsized returns. Our strategy also deploys an integrated rolling block-list that shields our returns from the unpredicted performance of equities that deviate from our model. This feature helps avoid continual investment in stocks whose price movement is not explained by traditional measures of financial quality, and thus limits losses.

Specifically, our strategy initiates long positions in stocks that are both in the 80$^{\text{th}}$ universal percentile in size (where a higher percentile indicates lower market capitalization) and the 70$^{\text{th}}$ sectorized percentile in quality and initiates short positions in stocks that rank both below the 20$^{\text{th}}$ percentile in size and the 30$^{\text{th}}$ percentile in quality. Profit is generated when stocks with high expected returns are identified and bought and stocks with low expected returns are identified and sold, leading to above market excess returns and Sharpe ratios. Importantly, the strategy generates alpha at a statistically significant level when compared to the traditional three-factor model and performs opposite the market portfolio during periods of recession.

Economic Hypothesis

We base the economic theory driving our strategy on the Gordon Growth hypothesis that future cash flows are the key determinant of a security's price. Therefore, a company with positive, growing, and continuous cash flows should demand a price premium. We synthesize the key metrics driving the achievement of attractive cash flows into a quality factor, which accounts for both the magnitude and the riskiness of a company's future cash flow generation ability. The premium that investors should be willing to pay for the stocks we classify as high-quality means we can predict and capture higher expected returns when trading within our defined universe. Furthermore, our quality factor supplants the traditional value factor used by Fama-French (HML). Simply put, a quality factor captures the future earnings potential of a firm and thus the true future value of its shares regardless of its current share price (or its book-to-market ratio).

Trading on quality alone, however, is not sufficient, as smaller firms tend to have substantially lower quality ratings while still producing higher returns. Rather than trade counter to the size premium, we seek to enlarge the often excessively *small* size premium in expected returns that is frequently cited by academics as a symptom of the increased operational riskiness of smaller firms (Bloomfield and Michaely, 2004). By adjusting security selection to account for both size and quality, we can filter out the lower quality small firms while retaining the highest quality ones, allowing us to capture higher expected returns. Additionally, during recessionary periods where uncertainty increases in the market, we expect to see a "flight to quality" that will insulate our portfolio from economic downturns.

Implementation

We first decompose the abstract concept of "quality" into concrete financial metrics. Leaning on industry literature, we view "stocks that [are] profitable, stable, [and] growing" as high-quality. (Frazzini, Kabiller, Pederson, 2018). Thus, we rate securities on their profitability, stability, and ability to grow and average these components to draw a final valuation. To avoid data mining, we build our factor using only metrics that are publicly available and widely used in financial analysis. We also select a variety of metrics for the creation of each component of quality to prevent model overdependence on any single metric (Appendix A).

- **Profitability**: The value of profitability cannot be understated as a key driver of stock price appreciation. We use several metrics to construct the profitability component, including various profit margin ratios, return on invested capital, cash conversion cycle, etc.

- **Stability**: Investors should value a company's ability to remain a going concern. Without this assurance, the ability to expect, and thus pay for, future cash flows is severely diminished. Therefore, we evaluate a company's ability to remain afloat using metrics such as debt and capitalization ratios.
- **Growth**: Given that stock prices are based on expectations of future cash flows, investors cannot expect outsized returns if a company's future cash flows stagnate. Growth is a major component of traditional valuation models, like the dividend discount model and discounted cash flow model, where increasing cash flows drive stock price appreciation. To measure the growth component of quality, we consider quarterly changes in metrics including current revenue, EPS, R&D/sales, etc.

We find the percentile ranking of each equity in the S&P500 from 1990 to 2017 for each identified metric. Metrics are standardized for scale through conversion to percentile rank basis and combined through averaging to arrive at our final quality score. Rankings account for the presence of metrics that are preferable when lower rather than higher (such as the debt ratios) by converting these metrics into negative numbers before calculating percentiles. Specifically, we evaluate two separate types of percentile ranking: universal percentile ranking and sectorized percentile ranking (ranking within the company's GICS sector). This differentiation proves useful as we rely on universal percentile ranking for size (market capitalization) and value (book-to-market) since these factors are comparable across sectors. On the other hand, we evaluate quality on a sectorized percentile ranking basis. Since what is deemed high-quality is dependent on sector-specific characteristics, it is more reasonable to compute quality percentile rankings against comparable peers rather than the wider market. Using these percentiles, we are able to test the efficacy of considering quality in factor strategies in enhancing risk-adjusted returns.

We first test the hypothesis that our quality factor supplants the traditional value factor and counteracts the size factor. The correlations in *Table 1* summarize our findings. First, a highly significant correlation of 0.49 between quality and value signals the use of both variables may be redundant; in fact, we actually account for book-to-market in our calculation of stability. Second, the correlation between quality and size is highly negative, affirming our belief that the size premium comes at the cost of quality in traditional models and supporting our strategy of trading on size in combination with quality.

Correlation Matrix			
	Quality Percentile	Book-To-Market Percentile	Market Cap Percentile
Quality Percentile	1		
Book-To-Market Percentile	0.498	1	
Market Cap Percentile	-0.078	-0.183	1

Table 1*:* The table presents the correlation calculations between the different percentile rankings of quality (highest to lowest), book-to-market (highest to lowest), and market capitalization (smallest to biggest) against each other.

Having affirmed the conceptual underpinnings of our strategy, we then move to determine optimal limits for size and quality for initiation of long/short positions by analyzing the resulting CAPM alphas, Sharpe ratios, and cumulative returns for portfolios generated on varying threshold levels. To avoid data-mining, we limit our analysis to commonly traded size portfolios (long smallest 10/15/20% and short largest 10/15/20% of stocks) and evaluate only the relative improvement in portfolio attributes when adding a quality factor that limits trades based on standard industry threshold levels ranging from 50% to 90% for longs and 10% to 50% for shorts. For each size and quality limit pair, we evaluate S&P500 constituents on the trading days from January 1990 to December 2017 and take a long position in equities that have a universal percentile size ranking above our size limit and a sectorized percentile ranking above our quality limit. We take a short position in equities that are below one minus these set limits.

Our analysis makes several key assumptions:

I. **Equal Weighting.** Each position is equally weighted. However, the portfolio is not zero-cost basis since equities that meet the long criteria may outnumber those that meet the short criteria and vice versa. Additionally, for back-testing purposes, we assume 100% margin on shorts. Therefore, the sum of the absolute dollar value of all positions equals total AUM for each day.

II. **Partial Shares.** Partial shares are allowed in order to enable the creation of perfectly equal weighted positions. This assumption means that for the purposes of our analysis, we do not hold any cash positions.

III. **Daily Reweighting.** The positions are determined daily. We adjust held positions for weighting purposes, close positions that no longer meet threshold levels, and initiate new positions. All positions hold an updated amount of capital based on capital gains of the previous trading day.

IV. **Information Lag.** The portfolio assumes lagged use of information; therefore, trades are initiated at the open of the next trading day rather than the day of percentile analysis. We also assume quarterly financial information is unavailable until earnings announcement. This reflects the reality of financial information dissemination, which is often a drawn-out process.

From the results visualized in *Figure 1*, we can see that a quality threshold limit of 0.7 produces the best combination of three-factor model alpha and Sharpe ratio across the three size thresholds.

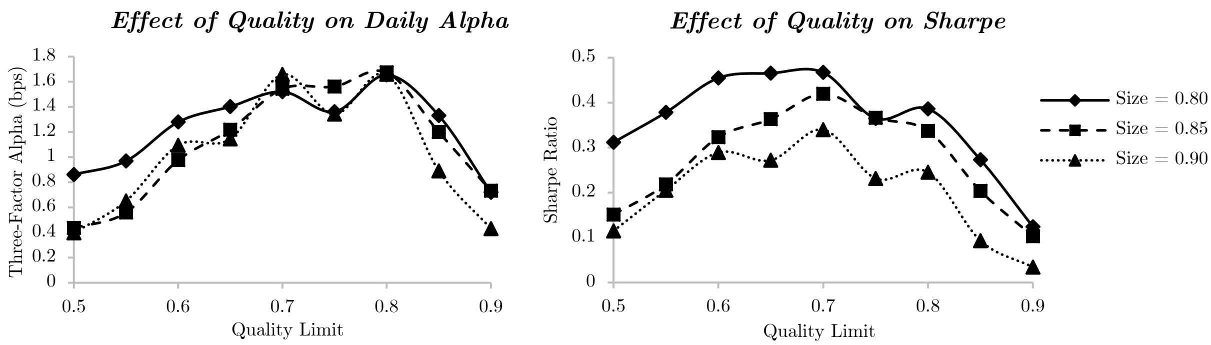

Figure 1: The figure shows the resulting average daily alpha and Sharpe ratio from portfolios constructed using the S&P500. Daily alphas and Sharpe ratios were calculated for each Quality and Size percentile cut-off and were tested over a 28-year period from 1990 to 2017. *This set of portfolios does not assume the use of a later implemented block-list, which further improves results.*

On average, when comparing the portfolios created using a 0.7 quality threshold limit versus baseline portfolios of no quality threshold limit, we find that the 0.7 threshold portfolio produces a 25.59% higher CAPM alpha, 25.85% higher three-factor model alpha, and 6.18% higher Sharpe ratio. Additionally, we find that while a size threshold of 0.9 produced the portfolio with the highest alpha, the portfolio with the highest Sharpe ratio is produced using a size threshold of 0.8. We opt for a size threshold of 0.8 over 0.9, favoring a portfolio that will hold a larger and more diverse range of stocks over the comparatively limited contents of a more stringently selected stock portfolio. It is not unlikely that investors will choose different thresholds than those proposed here based on their portfolio construction considerations.

Risks

The biggest dimension of risk associated with implementing a quality driven trading strategy is accuracy, or framework/model risk. We cannot expect our model to accurately reflect the pricing mechanisms of all equities. For example, quality may not account for economic bubble situations, wherein short sale restrictions and lockup periods may make it difficult for all available information to be incorporated into asset pricing (Ofek and Richardson, 2003). Moreover, in the case of many tech companies with negative earnings, quality may not be reflective of how the broader investment community values these companies using multiples that will yield a positive value regardless of cash flow (Damodaran, 2000). Like the aphorism states: the market can remain irrational longer than you can remain solvent. Rather than continuously lose money on failed positions due to model inaccuracy, we implement a fail-safe mechanism in the form of a rolling block-list, which is also a major differentiating characteristic of our strategy. The block-list evaluates the trades executed in the trailing two-year period and identifies equities that have been included in the portfolio for more than a quarter. For equities that meet this criterion, those where the average return of all past positions is negative are added to the block-list. No positions are initiated on constituents of the block-list regardless of whether they meet the model's threshold for size and quality.

The implementation of a rolling block-list also helps mitigate the risk that the efficacy of the model shifts over time. Certain stocks may deviate from traditional measures of financial quality due to externalities. For example, the late 2017 addition of Chipotle Mexican Grill, a company with a high quality score within its sector, to the block-list is representative of the need for such a list to remove stocks that may not be trading based on fundamentals, but rather on idiosyncratic non-financial factors (in this case, investor sentiment towards food safety issues). Put simply, the predictive power of quality (and size) on price may vary depending on the particular security and idiosyncratic events over time. The block-list ensures that outsized, long-term losses due to these factors are limited. We find that the implementation of this block-list *significantly improves* both the alpha and Sharpe ratio we identified earlier when testing portfolios of various threshold values. We summarize our final results and explore more examples of the loss mitigating effect of the block-list as case studies in the "Analysis of Strategic Prospects" section of this paper.

Analysis of Strategy Prospects

To evaluate the effectiveness of our strategy, we simulate trades for the time period 1990-2017. The historical data used for the simulation is retrieved from Wharton Research Data Services.

The annual alphas produced by our final simulated strategy, which enhances the traditional SMB portfolio using a quality threshold and a two-year rolling block-list, are shown in *Table 2*. Our strategy generates positive alpha against both the Capital Asset Pricing Model and the Fama-French three-factor model. On average, between the years 1990 and 2017, we produce a 26.85% average yearly alpha against CAPM and a 28.24% average yearly alpha against the Fama-French Model. Notably, we generate a positive annual Fama-French alpha for all years of the test period with the exception of 1990.

Annual CAPM, SMB, and Three-Factor Alphas

Year	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**
CAPM	7.50%	21.79	26.07	18.95	8.33	3.05	2.05	24.59	11.87	30.21	36.66	60.03	47.88	22.88
SMB	7.19%	25.39	26.78	25.79	5.64	26.32	8.90	30.73	13.71	31.57	37.89	57.72	52.79	13.53
Three-Factor	-0.99%	23.77	33.19	20.68	7.27	9.68	8.25	47.49	13.57	43.14	22.50	52.91	48.48	9.68
Year	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
CAPM	18.24%	17.59	22.76	37.19	88.64	98.32	25.02	23.51	17.89	2.08	19.94	11.71	27.94	19.08
SMB	23.23%	19.16	24.47	39.94	88.85	86.34	27.56	22.78	17.01	24.97	30.36	12.14	28.75	29.32
Three-Factor	16.53%	20.02	23.39	37.69	96.44	101.51	24.90	22.57	21.90	2.35	23.28	11.20	25.83	23.54

Table 2*:* The table shows the annual alphas of our portfolio when compared against the Capital Asset Pricing Model, Small Minus Big portfolio, and Fama-French three-factor model. Daily alphas are calculated using standard linear regressions and annualized to produce the results found in the table. All regressions are performed using excess portfolio returns.

On a risk-adjusted basis, we find that, on average, this portfolio offers a superior Sharpe ratio of 2.376 versus the average market Sharpe ratio of 0.797 over the 28-year period from 1990 until the end of 2017. We also analyze the Sortino ratio to see how excess returns compare in terms of negative volatility and find an average annual Sortino Ratio of 4.068 versus the market's average annual Sortino Ratio of only 1.132. From this perspective, even to the risk-averse investor, our strategy offers attractive returns. In terms of market beta, our portfolio beta against daily positive S&P500 returns is 0.131 and our portfolio beta against daily negative S&P500 returns is -0.243, both at statistically significant levels. This result implies that regardless of the movement of the S&P500, our portfolio is generally expected to have positive returns.

Then, turning to an absolute annual return perspective in *Table 3*, we find that the annual excess returns generated by our portfolio vastly exceed those generated by the market portfolio. In fact, during our 28-year test period, our portfolio only underperforms the market four times. Our maximum loss occurs in 1998 where we underperform the market about 9.6%. However, our gains during the years we outperform the market drastically surpass our losses. For example, in 2008, one of our best performing years, we produce returns 125.8% higher than the market's.

Annual Excess Returns for Different Strategies

Year	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**
Portfolio	7.81%	22.61	27.32	24.25	5.49	28.92	9.57	33.03	8.86	29.11	36.42	58.42	53.65	23.00
Market	14.15%	27.75	5.98	8.00	-3.86	29.48	15.26	24.58	18.50	20.03	-16.79	-14.45	-22.45	30.38
SMB	-8.30%	18.16	9.82	8.03	2.51	-1.62	1.46	-1.71	-17.38	17.24	2.50	23.02	5.88	20.73
HML	-4.13%	-5.02	26.61	20.90	3.04	9.33	10.06	19.83	-3.65	-20.66	50.80	21.73	10.46	4.22
Year	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Portfolio	26.20%	18.42	24.11	37.02	88.14	86.56	33.72	21.74	16.41	28.43	26.14	11.78	29.34	27.76
Market	10.62%	2.94	10.14	1.05	-37.63	28.13	17.26	0.45	16.24	35.16	11.72	0.11	13.22	21.54
SMB	5.99%	1.40	5.34	-2.48	4.61	6.94	12.96	-4.16	-0.58	5.44	-7.00	-4.13	5.89	-2.96
HML	8.15%	11.05	17.90	-9.56	6.20	-2.82	-3.25	-8.02	8.48	1.25	-1.99	-9.87	21.07	-10.27

Table 3*:* The table shows the annual excess returns of our portfolio, the market, the SMB portfolio, and the HML portfolio on an annual basis. Annual excess returns for the portfolio and the market were found using annual returns net of the risk-free rate.

We further our conclusions by comparing the cumulative excess returns on a dollar-invested basis of our portfolio versus the S&P500's. For the test period from 1990-2017, the results are as follows: market +663%, our portfolio +120,376%. On an annualized basis, the performance is: market +7.0%, our portfolio +28.8%. This outperformance is displayed graphically in *Figure 2*. Of course, this assumes the ability to purchase partial shares. In a more realistic trading situation, our overall portfolio returns would be lower due to some of the portfolio being held in cash. Therefore, if we do not allow the purchase of partial shares, it is best to think of these returns as an ROIC-based performance metric rather than the increase in the total value of the portfolio (which would include a cash position).

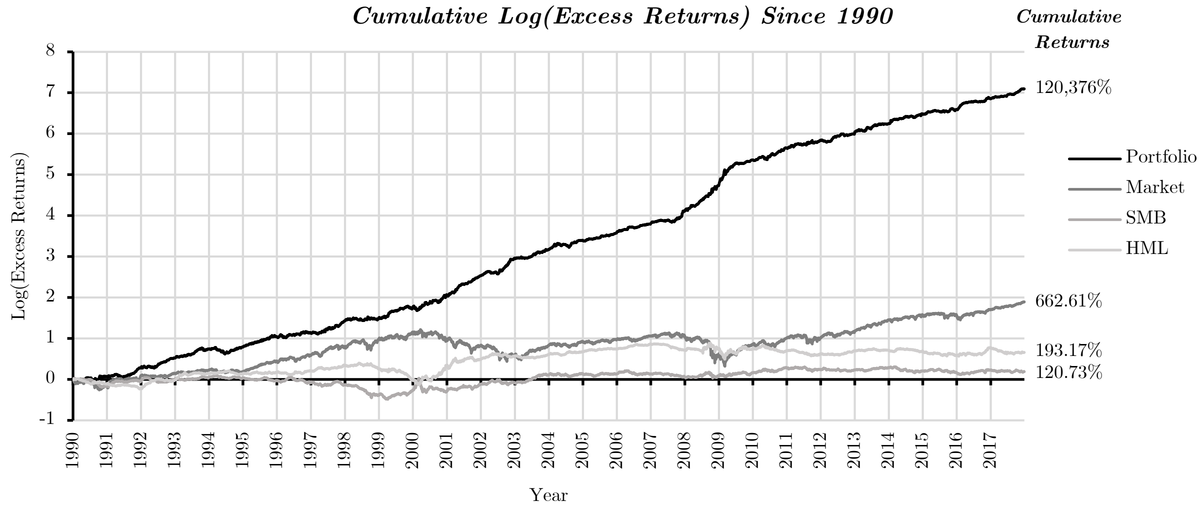

Figure 2: The figure shows the log value of the excess returns of our portfolio, the market portfolio, the SMB portfolio, and the HML portfolio over a 28-year period from 1990-2017. Our portfolio's cumulative returns were calculated from 28 years of S&P500 constituent data. The absolute cumulative returns over the time period are noted on the right side of the graph.

Finally, we analyze the downside risk of our strategy using daily and monthly VaR metrics. Our daily VaR(95) is -0.9%, and our daily VaR(99.5) is -2.0%. On our worst trading day, we suffer a limited -5.96% loss. In terms of monthly metrics, our VaR(95) is -2.61%, and our VaR(99.5) is -5.0%. The worst trading month produces a similarly limited -5.2% loss. Of the 335 months we analyze, only 72 (21.5%) produce negative returns, exemplifying the limited downside risk of our strategy.

Significant Historical Case Studies

To validate our hypothesis on "flight to quality," we analyze our performance during the two major bubbles that popped during our testing period. During both the 2000s dot-com bubble and the 2008 housing bubble, our strategy performs remarkably well.

The year 2000 is an excellent year for our portfolio as well as for the HML portfolio. On an excess return basis, the S&P500 index ends the year at -16.79%, while Fama and French's HML portfolio ends up +50.8%. Our strategy returns +36.4% for the year. We attribute this outsized return to the portfolio doing exactly what it is designed to do – invest in stocks with sound financial quality, short stocks with low financial quality, and avoid stocks that appear not to trade on any fundamental basis of quality. Lucent Technologies, IBM, and HP are all blocked by our strategy going into 2000, where exorbitant increases in prices are unjustified under our model. Then, during the latter half of 2000, our strategy initiates short positions in all three equities, making +397.2%, +22.9%, and 62.6% respectively.

A similar phenomenon occurs during the 2008 collapse of the real estate bubble. As shown previously in *Table 2*, our portfolio dramatically outperforms, generating +88.1% excess return compared to the market's -37.6%, HML's +4.6%, and SMB's +6.2%. Again, we see the block-list swelling from only 13 stocks to almost 25 near the end of 2007. Blocked names include AIG, Bank of America, and Lehman Brothers.

Liquidity and Capital Considerations

Since our strategy uses the constituents of the S&P500 index as its universe of investable securities, there is very little liquidity risk. The requirements for a stock to be added to the S&P500 include two important measures focused on liquidity: 1) annual dollar value traded to float-adjusted market capitalization greater than 1.0, and 2) minimum monthly trading volume of 250,000 shares in each of the six months leading up to the evaluation date (S&P Global, 2019). However, trading solely within the S&P500 produces two additional concerns: shorting ability and diversification ability.

Shorting. Our analysis assumes the ability to short any stock in the S&P500. That said, we realize that in certain situations, there may be restrictions on our ability to execute on shorts, such as prohibitively high cost to borrow or stocks that have no available shares to short sell. Fortunately, because this strategy is not predicated on zero-cost basis, not initiating these short positions is not necessarily harmful to portfolio construction. While there may be slight decreases in return due to this limitation, the overall prospects of the strategy are unharmed. Furthermore, with S&P500 companies as the investable universe, there is a decreased risk of short restrictions versus much smaller market capitalization companies.

Diversification. Being restricted to the universe of S&P500 stocks also means our strategy occasionally produces a limited number of securities that meet our investment criteria. However, during our 28-year historical test, our strategy was able to find 10 or more positions to initiate on 97.9% of trading days (Appendix B). To illustrate the implications of this on capital deployment, we perform a quick exercise:

> Given the S&P's restriction of constituents to firms with market capitalizations above $6 billion and annual dollar value traded to market capitalization above 1.0, the smallest firm in the index is trading roughly $24 million per day (S&P Global, 2019). If we wish to trade less than 5% of volume in any one stock on any particular day, our strategy will still be able to deploy at least $12 million ($24 million * 5% * 10 positions) on 97.9% of trading days. Depending on how much relative volume the fund is comfortable trading, deployment can be scaled up dramatically. Twelve million dollars simply serves as a ceiling for funds that do not wish to pass the 5% of volume mark.

Expanding on our discussion of capital limitations, we believe capital deployed has material impacts on performance. Because our strategy assumes the ability to purchase partial shares, if actually implemented, produced returns will prove lower than estimated due to the initiation of inevitable cash positions. However, this limitation becomes less significant as more capital is invested. The tradeoff, however, is the accumulation of higher trading fees when initiating and closing larger positions. Thankfully, because the size and quality of companies change gradually rather than suddenly, most of our positions are relatively long-term at an average holding period of 35 days and trading costs incurred would be limited compared to those suffered in high-frequency strategies (Appendix C). Additionally, to counteract higher trading fees, the implementing firm can consider a looser definition of "equal-weight" to limit costs of rebalancing.

We perform some cursory tests to quantify the hypothesized effects of partial shares absence and trading fees and find that while our strategy can accommodate portfolios of varying sizes, deploying more capital, as predicted, results in the accumulation of higher trading costs and reduces cumulative returns (Appendix E). However, we predict the true return of larger portfolios will fall somewhere in between the results of our first test run (that assumes the stringent fee structure in Appendix D and no fee reduction algorithms), and the results of our second test run in Appendix F (that assumes the absence of fees). Depending on how the fund chooses to handle equal weighting, cash positions, and trading fees, the strategy can easily deploy capital amounts ranging from $10,000 to several hundred million dollars.

Conclusion

In conclusion, our strategy enhances the performance of traditional factor models and generates outsized returns by trading on the S&P500 through the intelligent application of a quality threshold and rolling block-list. First, our automated, wide-ranging, and holistic quantification of quality allows us to effectively capture the future earnings potential of a large number of firms based on their current financial profiles. This automated analysis enables us to trade on our fundamental economic hypothesis – that securities should be priced according to their potential to generate growing, stable future cash flows – after evaluating a large basket of liquid stocks and take advantage of situations where quality is incorrectly priced. Second, our rolling block-list enables our algorithm to avoid making repetitive mistakes trading on stocks that are not valued by the market based on fundamentals. This tool acts as a "circuit breaker" that recognizes when our economic hypothesis is invalid for a particular security so that we can avoid trading it. Together these two innovations allow our model to systematically identify and exploit opportunities to invest in securities that are trading at a discount relative to their future earnings potential. The outperformance of our investment strategy relative to the two most common pricing models (CAPM and Fama-French) over a long test period (1990-2017) indicates that the quality factor we construct and the block-list we use to reinforce and de-risk our strategy represent a source of return that is currently not priced into the market.

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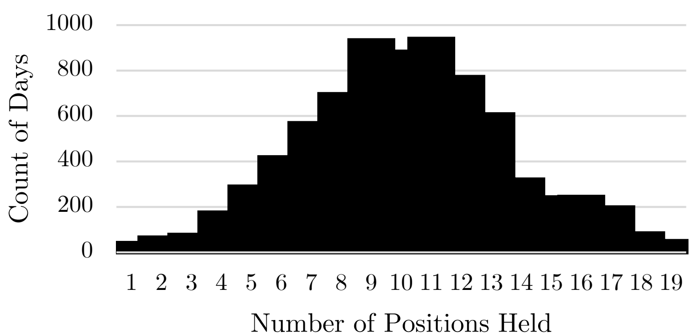
Appendices

Appendix A: Metrics Utilized for Each Component of Quality

Profitability	Stability	Growth
Net Profit Margin	Long-term Debt/Invested Capital	ΔNet Profit Margin
Operating Profit Margin Before Depreciation	Total Debt/Invested Capital	ΔOperating Profit Margin Before Depreciation
Gross Profit Margin	Capitalization Ratio	ΔGross Profit Margin
Pre-Tax Profit Margin	Interest/Average Long-Term Debt	ΔPre-Tax Profit Margin
Cash Flow Margin	Interest/Average Total Debt	ΔCash Flow Margin
Return on Assets	Cash Balance/Total Liabilities	ΔReturn on Assets
Return on Equity	Total Debt/Total Assets	ΔReturn on Equity
Return on Capital Employed	Total Debt/EBITDA	ΔReturn on Capital Employed
After-tax Return on Average Common Equity	Profit Before Depreciation/Current Liabilities	ΔAfter-tax Return on Average Common Equity
After-tax Return on Invested Capital	Operating CF/Current Liabilities	ΔAfter-tax Return on Invested Capital
After-tax Return on Total Stockholders Equity	Cash Flow/Total Debt	ΔAfter-tax Return on Total Stockholders Equity
Pre-tax Return on Net Operating Assets	Total Liabilities/Total Tangible Assets	ΔPre-tax Return on Net Operating Assets
Pre-tax Return on Total Earning Assets	Long-term Debt/Book Equity	ΔPre-tax Return on Total Earning Assets
Gross Profit/Total Assets	Total Debt/Total Assets	ΔGross Profit/Total Assets
Free Cash Flow/Operating Cash Flow	Total Debt/Capital	ΔFree Cash Flow/Operating Cash Flow
Cash Conversion Cycle (Days)	Total Debt/Equity	ΔCash Conversion Cycle (Days)
	After-tax Interest Coverage	
	Interest Coverage Ratio	
	Cash Ratio	
	Quick Ratio	
	Current Ratio	
	Dividend Yield	
	Book-to-Market Value	

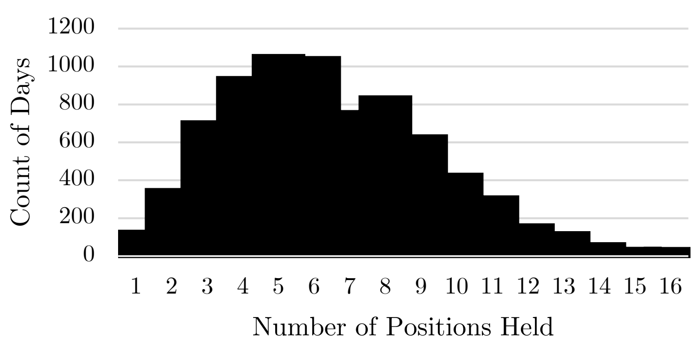
Appendix B: Daily Long and Short Positions Summary Statistics

Long Positions Histogram



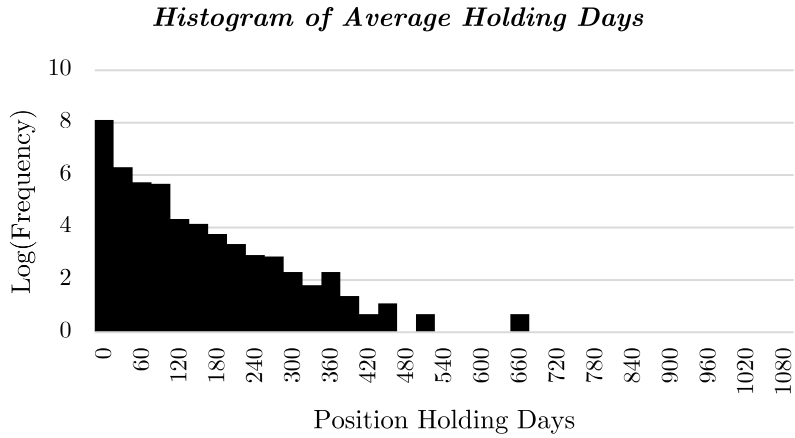
Average	10.16
Standard Deviation	3.19
Minimum	1.00
Median	10.00
Maximum	19.00
Quartile 1	8.00
Quartile 3	12.00

Short Positions Histogram



Average	6.30
Standard Deviation	2.68
Minimum	1.00
Median	6.00
Maximum	16.00
Quartile 1	4.00
Quartile 3	8.00

Appendix C: Position Holding Days Summary Statistics



Average	35.03
Standard Deviation	66.12
Minimum	1.00
Median	9.00
Maximum	1093.00
Quartile 1	2.00
Quartile 3	43.00

Appendix D: Trading Cost Fee Structure

Roundtrip Fee	% of Average Daily Volume ($)
0.10%	<0.1%
0.25%	0.1-0.5%
0.50%	0.5-2%
1.00%	2-5%
2.00%	5-10%

Appendix E: Strategy Portfolio with Stringent Fee Structure for Trading Costs (1990-2017)

Start Amount	End Amount	Cumulative Returns	Daily Alpha (bps)	Daily Three-Factor Alpha (bps)	Sharpe Ratio	Sortino Ratio	Percent Cash
$ 100	$ 1,929	1929%	2.925	2.851	1.396	1.645	75.263%
1,000	1,247,465	124746%	9.111	9.105	2.190	3.463	6.783%
5,000	6,162,591	123252%	9.090	9.105	2.092	3.280	1.349%
10,000	11,040,250	110402%	8.934	8.952	2.045	3.206	0.667%
50,000	32,923,473	65847%	8.202	8.221	1.871	2.931	0.138%
100,000	46,009,790	46010%	7.695	7.714	1.756	2.747	0.071%
1,000,000	94,820,782	9482%	5.458	5.478	1.252	1.948	0.008%
5,000,000	136,657,542	2733%	3.696	3.716	0.857	1.326	0.002%
10,000,000	160,833,780	1608%	2.944	2.965	0.690	1.065	0.001%

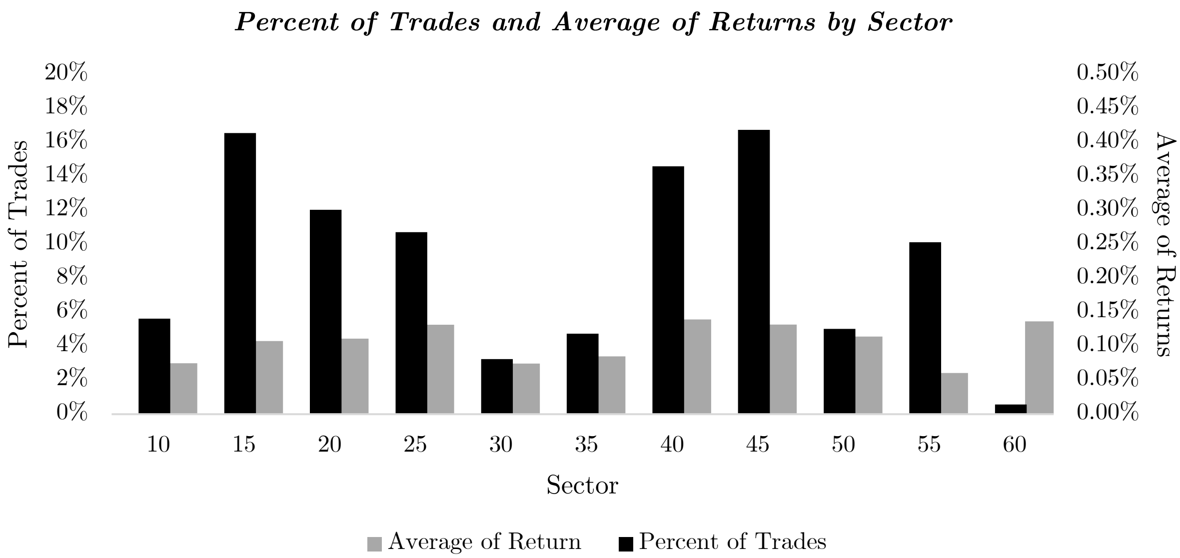
Appendix F: Strategy Portfolio with No Trading Costs (1990-2017)

Start Amount	End Amount	Cumulative Returns	Daily Alpha (bps)	Daily Three-Factor Alpha (bps)	Sharpe Ratio	Sortino Ratio	Percent Cash
$ 100	$ 3,240	3240%	3.652	3.580	1.612	1.932	70.193%
1,000	1,825,722	182572%	9.652	9.648	2.310	3.616	6.631%
5,000	11,381,577	227632%	9.960	9.976	2.288	3.597	1.278%
10,000	23,125,055	231251%	9.983	10.000	2.280	3.582	0.632%
50,000	117,551,251	235103%	10.007	10.026	2.275	3.569	0.128%
100,000	235,668,535	235669%	10.010	10.029	2.274	3.567	0.064%
1,000,000	2,360,930,064	236093%	10.013	10.032	2.274	3.566	0.006%
5,000,000	11,806,768,599	236135%	10.013	10.032	2.274	3.566	0.001%
10,000,000	23,613,764,151	236138%	10.013	10.032	2.274	3.566	0.001%

Appendix G: GICS Sector Codes

Code	Sector Name
10	Energy
15	Materials
20	Industrials
25	Consumer Discretionary
30	Consumer Staples
35	Health Care
40	Financials
45	Information Technology
50	Communication Services
55	Utilities
60	Real Estate

Appendix H: Breakdown of Trades by Sector and Average Daily Returns by Sector



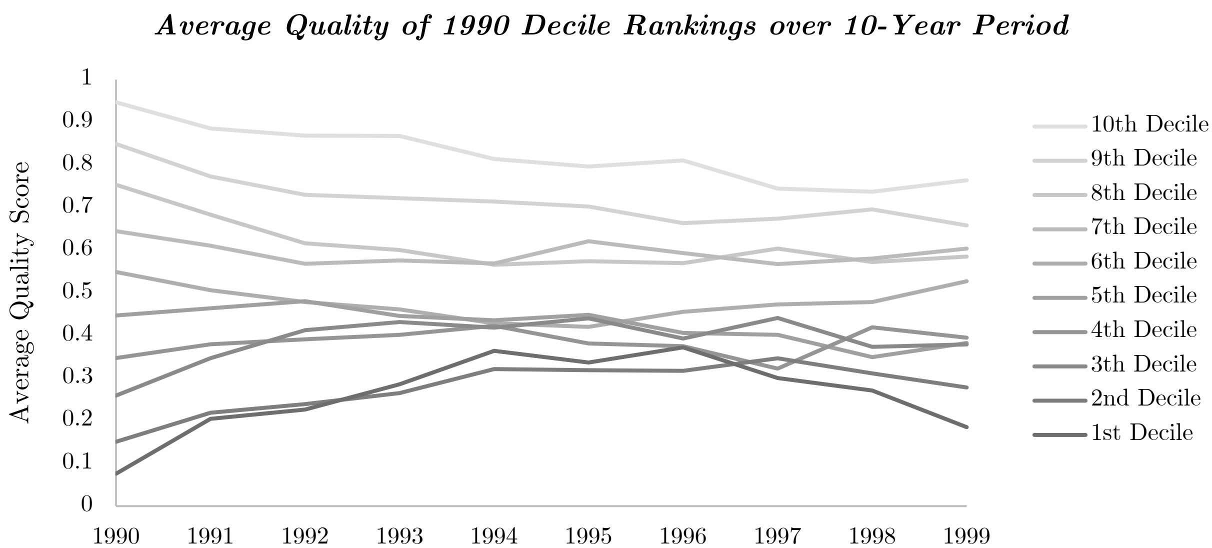
Appendix I: Best Performing Trades from Our Strategy

Enter Date	Exit Date	Ticker	Position	Return	Market	RF	SMB	HML	Sector
07/20/00	04/04/01	LU	SHORT	397.23%	-27.89%	4.24%	-6.79%	71.12%	45
10/16/92	06/15/95	CA	LONG	325.95	42.55	10.30	5.74	19.66	45
03/03/08	09/15/08	AIG	SHORT	312.17	-8.45	1.05	11.18	5.92	40
03/01/90	12/11/90	LCE	SHORT	164.23	-1.65	6.18	-15.26	-11.08	15
07/02/10	05/05/11	ANF	LONG	129.65	33.42	0.15	6.12	-6.53	25
10/26/92	08/31/93	AMD	LONG	119.13	17.41	2.52	6.13	20.00	45
01/17/14	06/30/14	MA	SHORT	110.89	6.06	0.00	-4.87	4.67	45
01/21/09	05/08/09	FITB	LONG	101.18	17.32	0.06	-2.24	10.27	40
10/01/03	04/30/04	ADSK	LONG	96.89	13.07	0.53	2.73	5.84	45
05/21/01	08/14/02	F	SHORT	95.36	-26.42	2.90	13.05	14.36	25

Appendix J: Worst Performing Trades from Our Strategy

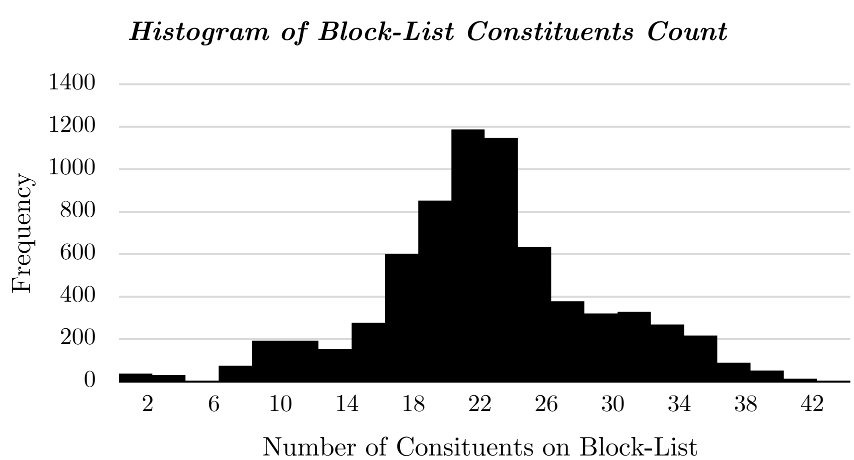
Enter Date	Exit Date	Ticker	Position	Return	Market	RF	SMB	HML	Sector
09/05/08	12/10/08	AKS	LONG	-75.89%	-27.62%	0.24%	-9.89%	-3.45%	15
10/16/08	01/23/09	ACAS	LONG	-71.12	-7.40	0.07	-0.09	-17.86	40
06/01/94	09/06/94	CPQ.2	LONG	-70.08	3.89	1.01	-0.61	-0.07	45
09/03/08	11/24/08	ATI	LONG	-59.25	-34.17	0.25	-10.06	-7.71	15
09/04/08	11/11/08	ANF	LONG	-57.50	-29.85	0.23	-8.37	-2.97	25
02/23/09	03/17/09	BAC	SHORT	-55.45	1.20	0.02	-3.43	5.71	40
06/18/90	07/26/90	CPQ.2	LONG	-54.79	-2.15	0.88	-1.19	-2.40	45
07/01/98	10/06/98	CR	LONG	-52.90	-15.70	1.35	-15.41	1.84	20
08/05/08	10/08/08	JNS	LONG	-49.91	-21.28	0.29	-0.67	5.17	40
07/20/98	10/15/98	ANV.1	LONG	-49.84	-14.59	1.23	-18.69	2.06	20

Appendix K: Average Quality of 1990 Quality Ranking Deciles over 10-Year Period



Note: The constituents of each of the 1990 deciles were tracked over a 10-year period. Every year, we took the average quality score of all the constituents in the original 1990 deciles to determine the average quality score of the original decile in later years. Tracking the average scores for each of these deciles over a 10-year period is important in determining persistence of the quality score over time.

Appendix L: Block-List Constituents Summary Statistics



Average	21.68
Standard Deviation	6.73
Minimum	0.00
Median	21.00
Maximum	42.00
Quartile 1	18.00
Quartile 3	25.00