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Claremont McKenna College

**Does Fundamental Analysis Lead to a Rudimentary Momentum Strategy for the
Inexperienced Investor?
Evidence from a Student Investment Fund**

submitted to
Professor Eric Hughson
and
Dean Peter Uvin

by
Nicholas Lillie

for
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Author

Nicholas Lillie

Abstract

Using the Student Investment Fund at Claremont McKenna College as a proxy for inexperienced investors, I demonstrate that inexperienced investors using fundamental analysis produce momentum-like buying patterns. The results show that the Student Investment Fund is on average buying stocks that outperform Carhart's four-factor asset pricing model in the year before purchase. As a result, the Student Investment Fund has, on average, underperformed the S&P500 by .48% per year since 1996. My thesis explores why the Student Investment Fund may have adopted momentum-like purchasing patterns and what steps can be taken to remedy it.

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I. Introduction

Investing icons such as Benjamin Graham and his disciple, Warren Buffett, are two of the most influential figures in finance. Their success makes them legendary, but their simple investment approach makes them relatable. Both Graham and Buffett are major proponents of an investment strategy called fundamental analysis. The relative ease and accessibility of the strategy cause waves of new investors to try their hand at investing like Graham,¹ employing fundamental analysis to ascertain the intrinsic value of securities.²

Broadly speaking, fundamental analysis is the process of delving into the financial statements of a company, determining basic financial ratios, and identifying trends of key financial metrics to discover undervalued investments. The apparent simplicity of the strategy attracts newcomers interested in replicating their approach. Ignoring the vicissitudes of the market, Graham uses fundamental analysis to invest in heavily discounted assets, which often have severely depressed stock prices. Finding companies that are trading at significant discounts by scrutinizing public financial filings is the spirit of fundamental analysis.

If it is as simple as analyzing financial filings and calculating basic accounting ratios, why can't inexperienced investors make money like Graham? The answer to this

¹ ---. Amazon: Editorial Reviews. Accessed November 17, 2016. https://en.wikipedia.org/wiki/Benjamin_Graham. Benjamin Graham's book, *The Intelligent Investor: The Definitive Book on Value Investing*, is often referred to as the value investor's bible and has sold over a million copies.

² Myers, Daniel. "The 3 Most Timeless Investment Principles." Investopedia. 2007. Accessed November 30, 2016. <http://www.investopedia.com/articles/basics/07/grahamprinciples.asp>.

question, and the foundation of my thesis, is inexperienced investors, although applying the same investment methods, are not buying the same types of stocks that Graham selects for his investments.

To examine what stocks they are buying, I analyze the buying patterns of a student-run investment fund that exclusively invests using fundamental analysis. My findings show that the buying patterns of the fund resemble a basic momentum strategy. Instead of investing in clearly undervalued stocks like Graham, those with large differences between the stock price and its intrinsic value, the fund buys stocks that have performed well in recent past, betting they will perform better in the future. While it may be true that a stock with rising prices may still be undervalued, the likelihood of that occurrence is less compelling because the margin of error for the analysis is much smaller.

Momentum is an investment strategy that seeks to capitalize on weak-form market inefficiency³ by using past prices to predict future prices. Pure momentum traders⁴ buy stocks that do well and sell stocks that do poorly over various periods of time. The idea behind this strategy is that each stock has inertia and thus high performers will continue to outperform (for a while) and losers continue to underperform (for a

³ Weak-form market efficiency claims that the current price of a stock reflects all past prices and thus technical analysis cannot be used to predict, and subsequently beat the market. Some argue that because momentum exists and generates profits, the weak-form market efficiency hypothesis is incorrect.

⁴ I use the term “pure” to distinguish between investors who knowingly invest using momentum strategies and those that accidentally produce a rudimentary momentum result, such as the subjects of this study.

while). Thus, if I distill momentum investing into a simple idea, it is that investors buy winners (Jageedesh and Titman 1993).⁵

The purpose of my thesis is twofold. First, I seek to fill the current gap in the literature. While many studies have examined fundamental analysis (see for example, Ou and Penman),⁶ momentum (see for example, Lo and MacKinlay 1989),⁷ and behavior of the inexperienced investor (see for example Greenwood and Nagel 2006),⁸ to the best of my knowledge no study exists that has examined the causal relationship between all three. Second, I posit why this relationship occurs and the implications that it has. It takes focused strategies that carry high amounts of risk to produce abnormal returns utilizing momentum.⁹ Even when professional traders explicitly use momentum, it is difficult

⁵ Jegadeesh, Narasimhan, and Sheridan Titman. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *The Journal of Finance* 48, no. 1 (1993): 65. doi:10.2307/2328882. Per Jageedesh and Titman (1993), winners are stocks that had returns in the top decile. However, the classification of winners varies by strategy.

⁶ Ou, Jane A., and Stephen H. Penman. "Financial Statement Analysis and the Prediction of Stock Returns." *Journal of Accounting and Economics* 11, no. 4 (1989): 295-329. doi:10.1016/0165-4101(89)90017-7.

⁷ Lo, Andrew, and A. Craig MacKinlay. "When Are Contrarian Profits Due to Stock Market Overreaction?" *Review of Financial Studies*, 1989. doi:10.3386/w2977.

⁸ Greenwood, Robin, and Stefan Nagel. "Inexperienced Investors and Bubbles." *Journal of Financial Economics* 93, no. 2, 239-58. Accessed December 2, 2016. <http://dx.doi.org/10.1016/j.jfineco.2008.08.004>.

⁹ Lowenstein, Roger. *When Genius Failed: The Rise and Fall of Long-Term Capital Management*. New York: Random House, 2000. As is the problem with all technically based investment strategies, they work when the statistical relationships between market forces hold. In the case of momentum, investors depend on past price patterns to predict future prices. The spectacular failures of such strategies are well-documented. For instance, a hedge fund utilizing mostly technical strategies called Long-Term Capital Management lost \$4.6 billion in four months.

enough to produce abnormal returns.¹⁰ Doing so unwittingly makes it nearly impossible. Unsurprisingly, the SIF has underperformed the S&P500 index since 1996 (average annual return for the SPX was 7.60% compared to 7.12% for the SIF¹¹). My thesis will expose, and explain why, rudimentary momentum masquerades as fundamental analysis among inexperienced investors.

In this case study, I use the Student Investment Fund (SIF) at Claremont McKenna College (CMC)¹² as a proxy for the inexperienced investor employing fundamental analysis. The SIF is a good choice for my analysis for the following reasons. First, according to the SIF's website:

The student investment fund practices 'bottom-up' investing, using fundamental analysis of financial and economic information to identify mispriced securities. Students evaluate vital information including financial reports, industry comparisons, new regulations, demographic trends, earnings statements, and economy-wide trends to build discounted cash flow models and relative valuations to identify potentially mispriced securities.¹³

¹⁰ Kinnel, Russel. "Why Momentum Funds Don't Have Any." Morningstar. November 29, 2010. Accessed December 2, 2016. <http://news.morningstar.com/articlenet/article.aspx?id=361034>.

¹¹ Returns are from the SIF's trading data and Bloomberg. The difference between the SIF and SPX returns are insignificant at conventional levels.

¹² Henceforth referred to as "the SIF."

¹³ ---. "Our Investment Strategy." CMC Student Investment Fund. Accessed November 28, 2016. <http://www.cmcsif.org/index.php/about-us/our-investment-strategy>.

Secondly, even though the SIF is one of the largest student-run investment organizations in the country,¹⁴ its investors are students with very limited investing experience. The average age of an SIF member is 19 and average years of investing experience are less than two.

I examine whether the SIF is buying winners based on Carhart's four-factor model (Carhart 1997)¹⁵ by using data from the SIF in conjunction with data from the Wharton Research Data Services (CRSP) database of stock returns,¹⁶ and Ken French's database.¹⁷ If the SIF is buying winners, I then determine how they win – are they loading up on the momentum factor or are they generating pure alpha, abnormal returns above Carhart's four-factor model? I find that the SIF has indeed invested in winners, but the momentum factor does not load. The average monthly alpha in the year before the SIF purchased a stock was 1%, amounting to annual abnormal returns of 12%, which is significant at the 1% level.

¹⁴ The following information can be found within CMC SIF's recent presentation called *CMC SIF Advisory Board Presentation (9/30/2016)*. The SIF at CMC is one of the largest run student investment funds in the country, managing over \$1.7 million in endowment assets. It is composed of over 45 students and overseen by 15 industry professionals, a faculty advisor, and the Chief Investment Officer (CIO) of CMC.

¹⁵ Carhart, Mark M. "On Persistence in Mutual Fund Performance." *The Journal of Finance* 52, no. 1 (1997): 57. doi:10.2307/2329556.

¹⁶ ---. "Wharton Research Data Services." Wharton Research Data Services. Accessed November 28, 2016. <https://wrds-web.wharton.upenn.edu/wrds/>.

¹⁷ French, Ken R. "Kenneth R. French - Data Library." Kenneth R. French - Data Library. Accessed November 28, 2016. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

I organize the remainder of the paper as follows. Section 2 discusses the existing literature on fundamental analysis, momentum, and behavior of inexperienced investors. Sections 3 and 4 examine the data and my strategy and results, respectively. I present my conclusions in the final section.

II. Literature Review

While there is a significant amount of literature on momentum, fundamental analysis, and the inexperienced investor, to the best of my knowledge there are no studies that seek to find a causal relationship between fundamental analysis and momentum for the inexperienced investor. As previously noted, the first purpose of my paper is to address the missing intersection between the three strands of literature. Before I attempt to do this, I will discuss each strand of literature in turn.

The first strand of literature focuses on momentum. Momentum is a trading strategy that capitalizes on the momentum of stocks that are performing well and those that are performing poorly, offering, as Eugene Fama put it, the “biggest embarrassment to the [efficiency market hypothesis].”¹⁸ Although investment professionals accept momentum strategies as legitimate,¹⁹ there is still debate regarding the source of the momentum profits.

A popular view in academia, to the despair of Fama, is that momentum profits are a result of weak-form market inefficiency. Lo and MacKinlay (1989)²⁰ investigate a

¹⁸ Asness, Clifford S. "AQR - Fama on Momentum." AQR - Fama on Momentum. February 5, 2016. Accessed November 29, 2016. <https://www.aqr.com/cliffs-perspective/fama-on-momentum>. Eugene Fama conceived of the efficient market hypothesis.

¹⁹ See footnote five above. Jegadeesh and Titman (1993) find that by buying certain stocks that had performed well in the past and selling stocks that had not performed well in the past, one could generate abnormal excess returns over 3-12 month periods. They argue that employing such strategies has become a distinct and popular trading strategy in the United States.

²⁰ See footnote seven above.

contrarian strategy of selling winners and buying losers. They find that weekly portfolio returns are positively autocorrelated and that returns of large capitalization stocks lead the returns of small capitalization stocks. As such, they argue that overreaction in the markets is the sole source of contrarian profits. Overreaction by investors would imply markets are inefficient since stock prices are either inflated or depressed based on sentiments, not based on facts about the stock. One could take advantage of this by merely analyzing past stock prices.

Another study that sought to prove momentum was an indicator of market inefficiency was Bondt and Thaler (1985),²¹ who find that over long time horizons (three to five years), stocks that had performed poorly in the past outperformed those that had done well. Their main finding was that the market was weak-form inefficient; and, similar to Lo and MacKinlay's (1989)²² conclusion, investors tend to overreact to bad news in a way that makes predicting future stock prices based on past stock prices possible. The procedure in Further, Grundy, and Martin (2001)²³ illustrates that since 1926, using momentum strategies-- buying recent winners and selling recent losers-- guarantees returns that are more profitable than those based on total returns. Chan,

²¹ Bondt, Werner F. M. De, and Richard Thaler. "Does the Stock Market Overreact?" *The Journal of Finance* 40, no. 3 (1985): 793-805. doi:10.1111/j.1540-6261.1985.tb05004.x.

²² See footnote seven above.

²³ Further, Grundy, and J. Spencer Martin. "Understanding the Nature of the Risks and the Source of the Rewards to Momentum Investing." *SSRN Electronic Journal SSRN Journal*, 2001. doi:10.2139/ssrn.94049.

Jegadeesh, and Lakonishok (1995)²⁴ try to explain the success of momentum strategies as a function of the market underreacting to current information. The results suggest that investors could generate significant returns using the stock's prior six-month performance and most recent earning surprise over the next six months. Additionally, studies such as Barberis, Schleifer and Vishny (1997),²⁵ Daniel, Hirshliefer, and Subrahmanyam (1998),²⁶ and Hong and Stein (1999)²⁷ find momentum profits are generated because of inherent biases in how investors process information.

Despite the papers seeking to prove momentum profits are a result of capitalizing on market inefficiency, others try to prove momentum returns are simply compensation for hidden risk. Conrad and Kaul (1998),²⁸ Lo and MacKinlay (1989),²⁹ and Jegadeesh and Titman (1993)³⁰ all argue that when controlling for certain risks, excess returns from

²⁴ Chan, Louis K., Narasimhan Jegadeesh, and Josef Lakonishok. "Momentum Strategies." *The Journal of Finance*, 1995. doi:10.3386/w5375.

²⁵ Barberis, Nicholas, Andrei Shleifer, and Robert Vishny. "A Model of Investor Sentiment." *Journal of Financial Economics*, 1997. doi:10.3386/w5926.

²⁶ Daniel, Kent, David Hirshliefer, and Avanidhar Subrahmanyam. "Investor Psychology and Security Market Under- and Overreactions." *The Journal of Finance* 53, no. 6 (1998): 1839-885. doi:10.1111/0022-1082.00077.

²⁷ Hong, Harrison, and Jeremy C. Stein. "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets." *The Journal of Finance* 54, no. 6 (1999): 2143-184. doi:10.1111/0022-1082.00184.

²⁸ Conrad, Jennifer, and Gautam Kaul. "An Anatomy of Trading Strategies." *Rev. Financ. Stud. Review of Financial Studies* 11, no. 3 (1998): 489-519. doi:10.1093/rfs/11.3.489.

²⁹ See footnote seven above.

³⁰ See footnote five above.

momentum are explainable. Additionally, some thought momentum was not an anomaly or reward for risk-taking but a result of data mining. For instance, Levy (1967)³¹ finds that buying stocks at prices greater than their 27-week average lead to excess abnormal returns. However, a study by Jensen and Bennington (1970)³² questioned the results, arguing data mining³³ was responsible for producing the result. Nevertheless, if momentum profits are simply a result of taking on additional risk, then its returns can be controlled for in an asset pricing model. Carhart (1997)³⁴ creates a four-factor model that attempts to do just that, controlling for price momentum by using a momentum factor. Thus, Carhart's four-factor model is the benchmark I use in my analysis.

Although the literature regarding momentum is well-developed, none posit that momentum can be achieved unwittingly through fundamental analysis. In other words, the literature has focused on its viability as a strategy and source of its profits. Although the purpose of the paper is to not explicitly take a side in this debate, because of my usage of Carhart's four-factor model, I implicitly assume it is a risk factor. My paper

³¹ Levy, Robert A. "Relative Strength As A Criterion For Investment Selection." *The Journal of Finance* 22, no. 4 (1967): 595-610. doi:10.1111/j.1540-6261.1967.tb00295.x.

³² Jensen, Michael C., and George A. Bennington. "Random Walks and Technical Theories: Some Additional Evidence." *The Journal of Finance* 25, no. 2 (1970): 469. doi:10.2307/2325495.

³³ Fama, Eugene F. "Efficient Capital Markets: II." *The Journal of Finance* 46, no. 5 (1991): 1575. doi:10.2307/2328565. Data mining as described by Fama (1991): "With clever researchers on both sides of the efficiency fence, rummaging for forecasting variables, we are sure to find instances of 'reliable' return predictability that are in fact spurious." Essentially, data mining finds returns by comparing pseudo-anomaly portfolios with real anomaly portfolios, finding false correlations.

³⁴ See footnote 15 above.

explores how an investor, attempting to utilize fundamental analysis to invest in undervalued companies, could produce a momentum-like result.

The second strand of existing literature focuses on fundamental analysis and whether it can yield excess returns. It seems that no paper has investigated a causal relationship between fundamental analysis and momentum. Abarbanell and Bushee (1998)³⁵ find that fundamental analysis of inventories, effective tax rates, audit qualifications, accounts receivable, gross margins, selling expenses, and other fundamental metrics yield an average 12-month cumulative size-adjusted abnormal return. Dechow, Hutton, Meulbroek and Sloan (2001)³⁶ show that fundamental analysis can be used by short-sellers to identify firms likely to exhibit lower expected future returns. Finally, Ou and Penman (1989)³⁷ argue that fundamental analysis successfully identifies equity values that are not currently valued in the stock price. However in response, Greig (1992)³⁸ re-examined Ou and Penman (1989)³⁹ and found that once an investor controls for certain risk factors, there is no incremental predictive ability in an

³⁵ Abarbanell, Jeffery S., and Brian J. Bushee. "Abnormal Returns to a Fundamental Analysis Strategy." *SSRN Electronic Journal SSRN Journal*, 1998. doi:10.2139/ssrn.40740.

³⁶ Dechow, Patricia M., Amy P. Hutton, Lisa K. Meulbroek, and Richard G. Sloan. "Short Interests, Fundamental Analysis, and Stock Returns." *SSRN Electronic Journal SSRN Journal*, 2001. doi:10.2139/ssrn.167154.

³⁷ See footnote six above.

³⁸ Greig, Anthony C. "Fundamental Analysis and Subsequent Stock Returns." *Journal of Accounting and Economics* 15, no. 2-3 (1992): 413-42. doi:10.1016/0165-4101(92)90026-x.

³⁹ See footnote six above.

earnings increase. In total, research regarding fundamental analysis as an investment strategy is well-developed, but its connection to momentum is left unanalyzed.

Although relatively underdeveloped compared to the other two strands, the third strand of literature dissects various behavioral patterns of inexperienced investors. Greenwood and Nagel (2006)⁴⁰ found younger investors were more likely to buy stocks at the peak of the Internet bubble as compared to older investors. They posit inexperienced investors are more influenced by sentiment. Further, Peterson (2002)⁴¹ argues that inexperienced investors are more likely to succumb to behavioral impulses than experienced investors. Finally, Sorensen (2007)⁴² says experienced venture capitalists, investors that subsidize the creation and growth of start-up companies, are 82% more likely to succeed on an investment than inexperienced investors. Overall, the body of literature on inexperienced investors suggests they are susceptible to market sentiments and their performance is worse than those with more experience.

By arguing that momentum is an unintended consequence of fundamental analysis, my thesis seeks to marry the three strands of literature together in a novel way. My thesis will provide the opportunity for numerous other studies that explore questions including, but not limited to: does the type of fundamental analysis materially impact buying patterns? Does momentum, generated by fundamental analysis, actually produce

⁴⁰ See footnote eight above.

⁴¹ Peterson, Richard L. "Buy on the Rumor and Sell on the News." *Risk Management*, 2006. doi:10.1016/b978-012088438-4.50030-7.

⁴² Sorensen, Morten. "How Smart is Smart Money? A Two-Sided Matching Model of Venture Capital." 2007. <http://dx.doi.org/10.1111/j.1540-6261.2007.01291.x>.

abnormal returns? What type of momentum is generated by fundamental analysis? Does fundamental analysis-generated momentum outperform technical analysis-generated momentum? Does the relationship between fundamental analysis and momentum exist for experienced investors? My thesis will provide the starting point for a new area of investigation in financial literature.

III. Data

I divided the data section into four parts: an overview of my data set, the structure of the data that makes my estimation possible, definitions of variables, and limitations of the data.

I. Data set construction

I form a custom data set from three different sources to do my analysis: CRSP database on stock returns, SIF's trading records, and Ken French's database. By combining the essential pieces from each data set, I create a custom data set that provides all the data needed to perform my analysis. Each independent data set is formed from reputable sources, and I did not construct any of the factors myself. The final custom data set includes 82 stocks. For each stock, the data, where available, extends 72 months before the buy date (see section III.II for more information).

Table 1
Complete data set

Variable	Obs	Mean	Std. Dev.	Min	Max
Ticker	82				
Buydate	82				
date	4,705				
stock_Ret	4,705	0.0229	0.1450	-0.6203	1.8273
rf	4,705	0.0020	0.0018	0.0	0.0056
hml	4,705	0.0022	0.0327	-0.1125	0.1291
smb	4,705	0.0025	0.0333	-0.1717	0.2208
mktrf	4,705	0.0051	0.0472	-0.1723	0.1135
mom	4,705	0.0033	0.0566	-0.3458	0.1838

The complete data set is formed by combining SIF's trading data, CRSP data, and Ken French's data. All data is monthly besides Ticker and Buydate.

The statistic that stands out from a summary of the complete data set is the `stock_Return` variable, which is the raw monthly return of a stock (see section III.III for more information). The average raw return per month was 2.29%. On an annualized basis, that is equal to a 27.48% return. In comparison, the excess return of the market was 6.12% on an annualized basis. So, in raw returns, without controlling for risks, the SIF is buying stocks that have done exceedingly well in the past.

II. Data set structure for estimation

My estimation process requires two distinct, data intensive steps. First, calculation of the factor betas in the pre-event period and second, calculation of the alphas in the pre-purchase period (see section IV for more information). To facilitate easier estimation, I broke up the complete data set into two data sets, one for the pre-event period and one for the pre-purchase period. The pre-event period data is a subset of the complete data set (see Table 1) and includes data from 72 months before a stock was purchased (or the earliest available data) up until 12 months before the buy date. It spans five years before the pre-purchase period.

Table 2
Pre-event period data

Variable	Obs	Mean	Std. Dev.	Min	Max
Ticker	82				
Buydate	82				
date	3,787				
stock_Ret	3,787	0.0233	0.1435	-0.6203	1.8273
rf	3,787	0.0021	0.0018	0.0	0.0056
hml	3,787	0.0026	0.0330	-0.1125	0.1291
smb	3,787	0.0027	0.0341	-0.1717	0.2208
mktrf	3,787	0.0049	0.0474	-0.1723	0.1135
mom	3,787	0.0032	0.0571	-0.3458	0.1838

Note: Average length of pre-event period was only 46 months (3,787 / 82) for each stock.

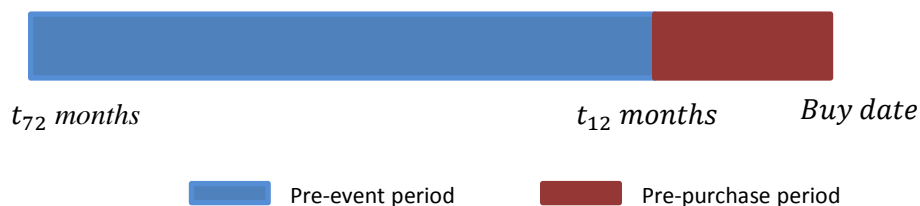
The pre-purchase period data is also a subset of the complete data set (see Table 1) and includes data from 12 months before a stock was purchased up until the buy date. It spans one year before a stock was purchased.

Table 3
Pre-purchase period data

Variable	Obs	Mean	Std. Dev.	Min	Max
Ticker	82				
Buydate	82				
date	918				
stock_Ret	918	0.0215	0.1511	-0.6129	1.0533
rf	918	0.0016	0.0018	0.0	0.0056
hml	918	0.0007	0.0312	-0.1125	0.1291
smb	918	0.0018	0.0297	-0.1717	0.2208
mktrf	918	0.0061	0.0460	-0.1723	0.1135
mom	918	0.0036	0.0543	-0.3458	0.1838

Note: Average pre-purchase period was 11.2 months. However, when the regressions were run to estimate alpha, stocks without a complete pre-purchase period were dropped.

Figure 1
Visualization of complete data set



This is a graphical representation of the complete data set. It shows the complete data as a sum of its two component sub data sets, the pre-event period and the pre-purchase period.

III. Variable definitions

Buydate

I pulled this variable from SIF's trading data. It is the date at which the SIF asked the Chief Investment Officer (CIO) of CMC to purchase a stock. Usually, the stock was bought a few days later because SIF does not do the physical trading of securities themselves. Because they must wait for the CIO to approve and execute the transaction, there is a short delay between when the SIF ordered the stock and when the CIO bought it. For my analysis, the difference of a few days is insignificant. I chose to use the ordered date instead of the transacted date because that is the day the SIF would theoretically have bought if they were executing trades themselves.

stock_Ret

I pulled this variable from CRSP for each stock. It is defined as the change in the total value of an investment in a common stock over some period per dollar of initial

investment.⁴³ For my purposes, it is a monthly return.⁴⁴ Excess security return subtracts the risk-free rate from the stock_Return ($stock_Ret - r_f$).

Benchmark variables

The benchmark I use to evaluate whether certain stocks are generating abnormal returns is Carhart's four-factor model. Carhart (1997)⁴⁵ created his model when he extended the Fama-French three-factor model, an asset pricing model that sought to explain the variability in stock prices based on three factors, to include a momentum factor.

hml:

Pulled from Ken French's database, hml is the first of four factors used to calculate Carhart's four-factor benchmark. It measures the value factor, the company's price-to-book ratio. Over the long run, value stocks tend to outperform growth stocks. The hml factor seeks to explain if and how much of a stock's returns are attributable to a loading on value. See below for its construction.⁴⁶

$$hml = \frac{1}{2}(Small\ value + Big\ value) - \frac{1}{2}(Small\ growth + Big\ growth) \quad (1)$$

⁴³ See footnote 16 above.

⁴⁴ For instance, if the return of a stock in nominal dollars in month n was \$10, and in month $n + 1$ the return was \$11, the CRSP database would display a stock_Return in month $n + 1$ of 10%.

⁴⁵ See footnote 15 above.

⁴⁶ See footnote 17 above.

smb:

Pulled from Ken French's website, the smb variable is the second factor in Carhart's four-factor model and seeks to explain security returns as a function of market capitalization. It measures the historical excess returns of small capitalization stocks over large capitalization stocks.⁴⁷

$$smb = \frac{1}{3}(Small\ value + Small\ neutral + Small\ growth) - \frac{1}{3}(Big\ value + Big\ neutral + Big\ growth) \quad (2)$$

mktrf:

Also pulled from Ken French's website, mktrf is the market risk premium, which is the difference in the market return and the risk-free rate ($r_m - r_f$), and the third factor in Carhart's four-factor model. Ken French utilizes a multitude of US stock index returns found within CRSP to form the overall market return.⁴⁸ As for the risk-free rate, French utilizes the one-month US Treasury bill rate, sourced from Ibbotson Associates, a private company that provides research and services to financial services companies. By taking the difference in the market returns and the risk-free

⁴⁷ See footnote 17 above.

⁴⁸ Includes NYSE, NASDAQ, and AMEX.

rate, the mktf factor seeks to explain the sensitivity of a stock to the market.⁴⁹

mom:

The fourth and final factor, called mom, is the momentum factor. By attempting to control for price momentum, the asset pricing model switches from a Fama French three-factor model to a Carhart four-factor model. The momentum factor simulates a strategy wherein the highest performing stocks over the past 12 months are bought and the worst performing stocks over the past 12 months are sold short.⁵⁰ The momentum factor is constructed by taking the average returns from the prior month of high performing small and large capitalization portfolios and subtracting the average returns from the prior month of low-performing small and large capitalization portfolios. A significant loading, or a significant regression coefficient on the mom factor, would indicate a price momentum stock, or that price momentum can partially explain a stock's returns.⁵¹

⁴⁹ See footnote 17 above.

⁵⁰ Lee, Samuel. "Understanding Factor Models." Morningstar. February 26, 2014. Accessed November 13, 2016. <http://ibd.morningstar.com/article/article.asp?id=636847&CN=brf295>, <http://ibd.morningstar.com/archive/archive.asp?inputs=days=14;frmtId=12,brf295>.

⁵¹ See footnote 17 above.

$$mom = \frac{1}{2}(Small\ high + Big\ high) - \frac{1}{2}(Small\ low + Big\ low)$$

(3)

IV. *Data set limitations*

Despite the advantages of the complete data set (see section III.I), there are several limitations worth discussing. First, because of various issues with the data, I had to reduce the sample size. There were originally 276 buy orders in SIF's trading data since 1996 when CMC began to track trades. 85 of the 276 buy orders were purchases of exchange-traded funds (ETFs). Historically, the SIF has not purchased ETFs directly. Instead, it uses them to invest excess cash from the selling of positions in other stocks. Since buying these ETFs was not a decision that was a result of fundamental analysis but rather an organizational decision, I removed them from the sample. Additionally, of the total 276 buy orders, 71 companies were bought multiple times. I removed the additional purchases of these stocks from my sample, considering only first-time purchases to avoid corrupting the pre-event period beta estimation. Therefore, by only looking at company stocks purchased once and removing ETF purchases, the sample size was reduced to 120 stocks.⁵² Next, I removed 38 stocks because there was no data for them in CRSP. After a company is either bought by another company (due to an acquisition or merger), taken private (bought by a financial sponsor), or gone bankrupt, CRSP removes them from the database. The final complete data set has 82 stocks.

⁵² 15 of the 120 stocks had multiple sell dates, meaning the SIF sold them off in increments. I kept them in the sample because I am only analyzing the buying patterns of the fund.

In addition to being required to work with a smaller sample size, there are not 72 observations for each stock. The average was only 58 months' worth of observations per stock. The reason for CRSP not having 72 observations for each stock is that some companies did not exist a full 72 months before the purchase date. Unfortunately, this means that the pre-event period was not a full 60 months for every stock (see Table 2 for more information), which reduces the precision of the beta estimates. In turn, this could negatively impact the precision of the alpha calculations in the pre-purchase period.

Thirdly, for 80 individual monthly observations, CRSP gave two different returns. Because there are 4,705 total observations, the duplicates made up only 1.7% of the data set. Since the duplicate observations were not concentrated within any one stock, and to err on the conservative side, I dropped the higher of the duplicate observations.

Finally, by using Ken French's data, I did not create the factor returns myself. In the next section, I will use the data described to test my hypothesis.

IV. Estimation and Results

To ascertain whether the stocks that the SIF buys outperform Carhart's four-factor benchmark in the pre-purchase period and, if so, whether they are price momentum stocks, I first calculate the difference between an individual stock's return in the pre-purchase period and the benchmark return in the pre-purchase period. The difference is abnormal return, or alpha, because it is not explained by an asset pricing model or benchmark. The existence of cumulative alpha over the course of the fund's buying history determines if the fund is buying of winners.

The first step in calculating alpha is determining the factor loadings, or benchmark regression coefficients, in the pre-event period. Using a span of five years provides a large enough sample to determine what each stock's beta, or regression coefficient, should be. To calculate the betas for each factor, I run a linear regression of the excess returns of each stock onto the four-factor returns during the pre-event period.

$$ESR_t = a_t + B_{hml}hml_t + B_{smb}smb_t + B_{mktrf}mktrf_t + B_{mom}mom_t + \varepsilon_t \quad (4)$$

where ESR_t is excess security return and $mktrf_t$, smb_t , hml_t , mom_t are the respective factor returns for month t .

Table 4
Summary of regression coefficients

Coefficient	Mean	Std. Dev.	Min	Max
Ticker				
hml	-0.2620	1.4149	-2.5790	7.6354
smb**	0.5752	1.2344	-3.8350	3.3841
mktrf**	1.1809	1.0389	-3.0920	4.8463
mom	-0.1060	1.1870	-2.4170	7.5184
Obs.	73			

** p < .001

This table represents the summary statistics for the results of 73 regressions. For instance, for any given stock in the pre-event period, on average the beta for the size factor is .57.

Note: Due to a lack of data, betas could not be calculated for nine stocks. Thus, I dropped the nine stocks and ran 73 regressions.

Overall, only β_{mktrf} and β_{smb} , on average, are statistically significant at conventional levels. The regression coefficient results demonstrate that the stocks the SIF invested in loaded on $mktrf$ and smb . In monthly terms, a significant positive loading on smb means that for each percentage point a small capitalization stock beat a large capitalization stock, the predicted return for an SIF stock rose by .57%, all other factors remaining constant. Similarly, a positive loading on the $mktrf$ factor shows that SIF tended to invest in high market beta stocks. On average, if the market rose one percentage point, the predicted return for an SIF stock rose by about 1.2%.

The regression coefficients reveal that SIF's investment portfolio in the pre-event period tilts towards small capitalization, high market beta stocks, with little exposure to growth or price momentum stocks. In fact, only six stocks had positive and significant momentum factors. Although the stocks do not load on price momentum in the pre-event period, the first part of my hypothesis is unaffected. Rather, the insignificant loading

indicates the SIF is not buying stocks sensitive to price momentum. Put another way, price momentum does not explain the abnormal returns. This means the SIF is not buying price momentum stocks but still could be buying winners overall.

Next, using the estimated betas, I calculate the monthly \hat{a}_i for each stock in the pre-purchase period as follows:

$$\hat{a}_i = ESR_t - (mktrf_t * \beta_{mktrf}) - (smb_t * \beta_{smb}) - (hml_t * \beta_{hml}) - (mom_t * \beta_{mom}) \quad (5)$$

where B_{hml} , B_{smb} , B_{mktrf} , and B_{mom} are the value, size, market premium, and momentum regression coefficients and all other variables are as previously defined.

Next, I calculate the cumulative abnormal return for each stock (CAR_{stock}) by adding up each monthly \hat{a}_i for each stock.

$$CAR_{stock} = \sum_{i=1}^{12} \hat{a}_i \quad (6)$$

Table 5
Summary of CAR_{stock}

CAR_{stock}	
Mean	0.1197
Standard Error	0.0961
Median	0.1209
Standard Deviation	0.8208
Minimum	-4.578
Maximum	2.6653
Count	73

Note: The standard error in this chart is not the one used in the t-statistic test. See below for more information.

Table 5 reveals that by taking an average of all the CAR_{stock} , I find the \overline{CAR} is equal to ~12%. In other words, on average, any stock that SIF purchased outperformed Carhart's four-factor benchmark by 12% over the previous 12 months. To prove the \overline{CAR} is significant, I also calculate the standard error. To do so, I calculate the σ_i for each stock using stock returns during the pre-event period, σ_{CAR} , and $\sigma_{\overline{CAR}}$ as follows:

$$\sigma_{CAR} = \sqrt{12} \times \sigma_i \quad (7)$$

$$\sigma_{\overline{CAR}} = \left(\frac{\sqrt{12}}{73}\right) \sqrt{\sum_{i=1}^{73} \sigma_i^2} \quad (8)$$

Once I calculate the $\sigma_{\overline{CAR}}$, I perform a t-test to ascertain the statistical likelihood that the \overline{CAR} is significantly different from zero. In particular, I calculate the t-statistic using the following equation:

$$t - statistic = \frac{\bar{x} - u_0}{s / \sqrt{n}} \quad (9)$$

where \bar{x} is \overline{CAR} , u_0 is zero, s is $\sigma_{\overline{CAR}}$, and \sqrt{n} is the square root of the number of observations.

The \overline{CAR} for all the stocks in the sample is .1197 or ~12%. The $\sigma_{\overline{CAR}}$ is .2177 or 21.8%. The null hypothesis of the statistical hypothesis is that the \overline{CAR} is equal to zero. To reject the null hypothesis, I run the t-test below.

$$t - statistic = \frac{(\overline{CAR} - 0)}{\sigma_{\overline{CAR}} / \sqrt{73}} = \frac{(.1197 - 0)}{.2177 / \sqrt{73}} = 4.7 \quad (10)$$

The t-statistic is equal to 4.7, which is significant at the .01% level.⁵³ As such, I reject the null hypothesis; the \overline{CAR} is statistically different from zero, which means that the SIF is buying winners.

⁵³ Gerstman, Burt B. "StatPrimer (Version 7.0)." StatPrimer (Version 7.0). Accessed November 15, 2016. <http://www.sjsu.edu/faculty/gerstman/StatPrimer>.

V. Conclusion

Fundamental analysis is a particularly attractive investing strategy for investors. Its relative simplicity makes it accessible by allowing even inexperienced investors to employ it. However, when inexperienced investors do so, they produce an unintended momentum-like pattern, often leaving money on the table.

The primary purpose of my thesis is to demonstrate that the fundamental analysis inexperienced investors use may, in fact, produce a momentum-based trading pattern that fails to capture undervalued stocks with the potential to generate excess returns over the long term. I use the Student Investment Fund (SIF) at Claremont McKenna College (CMC) as a proxy for inexperienced investors, analyze the buying patterns of the fund, and determine if they roughly follow a rudimentary momentum strategy of buying winners.⁵⁴ My findings show that this is precisely what occurs. On average from 1996 to 2015, the stocks the SIF purchased had statistically significant annual abnormal returns of 12%. Although the insignificance of the momentum factor in the pre-event period means that the abnormal returns are not attributable to price momentum, it does prove for the SIF that their fundamental analysis investing results in buying winners.⁵⁵

The secondary purpose of my thesis is to explain why this relationship exists. Fundamental analysis relies on making intrinsic value calculations based on a deep understanding of the firm's current and expected future condition through critical analysis

⁵⁴ Winners were defined as stocks with abnormal returns above Carhart's four factor model in the year before purchase.

⁵⁵ Reminder: winners are defined as stocks that have produced abnormal returns in the pre-event period. They are not necessarily stocks that continue to outperform past the buy date.

of a company's financial statements. The valuation is linked directly to its accounting numbers and other financials. A firm with good accounting numbers or trends has a high projected intrinsic value and is the type of firm likely to be invested in by an inexperienced investor employing fundamental analysis. Since stock prices are leading indicators, stock prices will increase in anticipation of good accounting numbers, which makes it difficult for fundamental analysis to get in front of the market. When a fundamental analysis investor views the numbers, he or she will be viewing old data. The stock will have already reacted to any good numbers or trends by the time of the investment. Thus, by investing using fundamental analysis, inexperienced investors may unwittingly be buying stocks that have done well in the recent past, reflecting rudimentary momentum. While it may be true that a stock with a rising price could still be undervalued, the likelihood of that occurrence is less compelling because the margin for error in that circumstance is much smaller. Investors like Graham and Buffett differ from traditional investors because they add another condition to focus their analyses. They invest according to a margin of safety, requiring at least a 50% discount on the stock price to its intrinsic value.⁵⁶ This significant margin sensitizes their assumptions and assures, even with inaccurate intrinsic value calculations, that the investment will make money. In contrast to the SIF, the significant margin of safety will ensure that most of the time investments are not in stocks that have significantly outperformed in the recent past. The SIF, despite their inexperience and consequently inaccurate intrinsic value calculations, has a much smaller margin of safety than Graham.

⁵⁶ See footnote one above.

Aside from lagging the stock price, the time constraints students face could amplify the relationship between fundamental analysis and selecting winners. A student participates in the SIF as an extra-curricular activity and thus does not have the time to research enough companies to evaluate which stocks are trading at significant discounts. They instead choose to analyze companies they know about or find a company that has been in the news. For instance, recent evidence suggests that stocks in the news are more likely to be traded. Engelberg and Parsons (2011)⁵⁷ argue that an increase in press coverage strongly predicts an increase in trading volume and Fang, Peress, and Zheng (2014)⁵⁸ find that stocks receiving media coverage are bought more heavily by mutual funds. Using the news as a screening tool, students in the SIF narrow the universe of stocks to invest in, applying fundamental analysis to already well-known stocks. Lin (2011)⁵⁹ finds that the more media coverage a stock receives, the more it outperforms its peers that do not receive media attention. If the SIF does utilize the news as a screen to which they apply fundamental analysis, it could explain why the SIF buys winners and not Graham's margin of safety stocks.

⁵⁷ Engelberg, Joseph E., and Christopher A. Parsons. "The Causal Impact of Media in Financial Markets." *The Journal of Finance* 66, no. 1 (2011): 67-97. doi:10.1111/j.1540-6261.2010.01626.x.

⁵⁸ Fang, Lily H., Joel Peress, and Lu Zheng. "Does Media Coverage of Stocks Affect Mutual Funds' Trading and Performance?" *Review of Financial Studies* 27, no. 12 (2014): 3441-466. doi:10.1093/rfs/hhu056.

⁵⁹ Lin, Shengle. "Stock Return and Financial Media Coverage Bias." October 2011. Accessed November 30, 2016. http://www.haas.berkeley.edu/groups/finance/Lin_JobMktPaper.pdf.

The implications of my findings are important to understanding the shortcomings of fundamental analysis. Although tempting to use stocks in the news, it is likely that they have already performed well, and thus the upside of investing in them as undervalued assets is diminished. Achieving the same level of success as Graham and Buffet is difficult, but it is nearly impossible if you ignore a central and often overlooked tenet of fundamental analysis: it is harder to find a good deal if the price has already risen. My advice to the aspiring investor based on the results of this thesis would be to use fundamental analysis like Graham and not like the SIF: employ fundamental analysis to find stocks with severely depressed stock prices and a large margin of safety. The more inexperienced one is, the larger the margin of safety should be to compensate for the inaccuracy of the valuation. Indeed, the SIF has failed to duplicate Graham's 17% average annual return from 1934 to 1956⁶⁰ and Buffet's 20% average annual over the past 50 years.⁶¹ Its average annual return since 1996 is 7.12%, underperforming the market by .48%. By buying winners, the SIF is probably buying fully valued firms, and thus it exposes itself to a random walk. Finding such severely undervalued companies like Graham is tough, or else everyone would do it. So, in the future, the SIF should consider remaining more passively invested and spending more time on due diligence for each individual investment idea. Assuming students do not wait until the last minute to find a

⁶⁰ Loth, Richard. "The Greatest Investors: Benjamin Graham." Investopedia. Accessed December 4, 2016. <http://www.investopedia.com/university/greatest/benjaminraham.asp>.

⁶¹ Sommer, Jeff. "Warren Buffett's Awesome Feat at Berkshire Hathaway, Revisited." New York Times. March 2015. http://www.nytimes.com/2015/03/08/your-money/warren-buffetts-awesome-feat-at-berkshire-hathaway-revisited.html?_r=0.

company to pitch, a more passively managed fund would alleviate the time constraint problem students have and increase the chances of finding a company Graham might invest in.

There is much potential future research on the topic. For instance, a similar analysis on the SIF or an equivalent organization should be completed and include a detailed audit of how students sourced each investment idea to further distinguish the difference between Graham's and the inexperienced investor's fundamental analysis. Additionally, the analysis should be performed on professional funds that use fundamental analysis to see if the effect persists. Third, given what we now know about the SIF, its investment strategy, and its resulting trading pattern, investigating the specific conditions of the SIF that could amplify the momentum effect could yield interesting insights. While time constraints certainly limit a student's ability to performed detailed due diligence, other factors could also influence a student's success with employing fundamental analysis. For instance, do students feel pressure to pitch stocks that have recently performed well because people do not like pitching losers? Is risk-aversion preventing students from investing in beaten down securities?

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