THREE ESSAYS ON THE VALUE PREMIUM: CAN INVESTORS CAPTURE THE PROMISED REWARDS?

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ABSTRACT

A consensus exists in the body of academic literature that stocks with high BE/ME characteristics outperform stocks with low BE/ME characteristics. Researchers disagree, however, as to the cause of the phenomenon. Two competing theories have emerged. The value premium originates either from the relative riskiness of high BE/ME value and low BE/ME growth stocks or from the persistent irrational pricing of those stocks. Market participants question whether the long lineage of academic research showing the existence of the value premium can actually be applied to their portfolio decision-making. The lack of a pervasive value premium across stock size strata suggests the return phenomenon may result from information asymmetry or trading noise, and not from the pricing of greater risk. The value premium appears to be exclusively available to market participants who can effectively navigate the smallest, most illiquid segment of the stock market. In other words, the value premium does not appear to be available to large institutional investors.

DECLARATIONS

I, Kenneth E. Scislaw, hereby certify that this thesis, which is approximately 65,000 words in length, has been written by me, that it is the record of work carried out by me and that it has not been submitted in any previous application for a higher degree.

Date_____ Signature of Candidate_____

I was admitted as a research student in September 2007 and as a candidate for the degree of Doctor in Philosophy in May 2008; the higher study for which this is a record was carried out in the University of St Andrews between 2007 and 2009.

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I hereby certify that the candidate has fulfilled the conditions of the Resolution and Regulations appropriate for the degree of PhD in the University of St Andrews and that the candidate is qualified to submit this thesis in application for that degree.

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PREFACE

By the late 1980s, the need for separate value and growth performance benchmarks had become clear - at least to value investment managers who invested globally. Value investment managers were finding that their low P/E and low B/M portfolios significantly underweighted a surging Japanese equity sector that represented virtually half of the MSCI EAFE benchmark index. Value managers defended their poor relative performance to EAFE by arguing that results were not a function of poor investment decisions, but instead a function of a fundamental methodological difference between value investing and growth investing. In short, value managers would never own what they viewed as wildly overvalued Japanese stocks; thus their effective universe of investable securities was not properly represented in current index benchmarks. In 1988, I specifically asked an investment consultant employed by SEI why a series of equity style benchmark indexes had not been constructed.

The nature of my question ultimately found its way into the academic literature, first with the publication of value and growth indexes in Sharpe (1991) and then with the seminal work on value and growth stocks in Fama and French (1992). Over the next ten to fifteen years, the lineage of research on value and growth stocks primarily concentrated on conclusions that value stocks actually outperformed growth stocks. Research attempted to determine whether the return premium occurred as a function of risk-pricing or rather as a function of an un-arbitraged return anomaly. Curiously, while the issue of value and growth had been well known to industry participants, a *value premium* was largely unknown to fund managers around the world. Of course, it would seem odd to think that thousands of value managers who operate in a highly competitive global environment could fail to recognize such an obvious competitive return advantage that appeared in numerous academic research. But, market-based value and growth portfolio returns did not show a premium for value portfolios. Instead, portfolio return statistics showed that value performance virtually equaled growth performance over time, contrary to implied promises in the academic literature.

After more than a decade of exhaustive research by academics confirming the existence of the value premium in stock returns, market participants are still left with two key unanswered questions: 1) If the premium is statistically valid, then how can value investment managers earn the promised rewards that have clearly eluded them, or 2) If the premium is statistically valid, then do trading and market barriers exist to prevent the premium's capture? The latter question is important. If barriers exist to prevent the premium's capture (and without remedy), then the long lineage of academic research is likely to have limited relevance to the portfolio management community over time.

The first of three essays presented in this thesis, "The value premium within and across GICS industry sectors", attempts to identify the time varying characteristics of the value premium in industry returns. The purpose is to assist managers in capturing the premium - the first of the two key questions itemized above. Several prior academic papers specifically address the issue of value and growth returns within and across industry groups, most notably Fama and French (1997) and more recently, Banko and Conover (2006). However, neither study investigates the question from an applied perspective. Results in the first essay are as follows: Findings of Banko and Conover (2006) that industry groups exhibit large differences in BE/ME characteristics are indeed confirmed in this work. In an applied context, this finding may offer opportunities for investors to capture the value premium in average returns by strategically allocating funds to targeted industry groups. Further, this essay adds to the findings of Banko and Conover by showing that the annual ranking of industry BE/ME appears to be relatively stable and potentially predictable for investors. Results also suggest that relatively poor returns generated by low BE/ME growth stocks may largely originate in a few persistently poor performing growth-oriented industry groups. Conceptually, if growth industries (or sectors) consistently underperform value industries, then investors can use these temporal characteristics to allocate away from these industries. However, further tests show that the relationship is more complex.

Next, the first essay contributes to the academic debate by helping to establish whether the value premium is pervasive across all size strata of stocks. Answering this important question can help determine whether the value premium is a function of risk or whether the premium is an un-arbitraged return anomaly – a question at the core of the research conversation on the subject. Tests in this essay show that the value premium disappears in large cap stocks both within and across industry sectors - consistent with results in Loughran (1997) and problematic for the explanatory power of the 3-factor model and a risk-based book-to-market effect. This essay also contributes specifically to ideas surrounding the risk-pricing argument. Unique sample period characteristics allow for tests of the risk-pricing thesis of Chen and Zhang (1998) within and across industry sectors as well as a confirmation of similar tests in Banko and Conover (2006). During this unique return sample period covering the dotcom boom/bust/recovery period, the value premium is stronger in low BE/ME growth sectors, contrary to a risk-pricing thesis. However, growth industry sectors are found to simultaneously experience unusual distress conditions during the sample period, a result preventing the rejection of arguments by Banko and Conover that the value premium is a function of investor risk-pricing of distress.

Next, the first essay advances the academic discussion of seasonality in stock returns by confirming results in Haug and Herschey (2006) that a strong January anomaly exists in more recent

time periods. However, the average value premium computed across GICS industry sectors does not appear to be impacted by January returns. Results also show the value premium is not stronger in the eleven months, January excluded, as argued by Dhatt, Kim and Mukherji (1999). In fact, the average across-sector value premium is virtually identical when computed with, or without, January returns, contrary to findings in Loughran (1997). From an applied perspective, if the January anomaly is found to subsume the value premium, then investors would be better served to ignore the value premium and concentrate their strategies on capturing the seasonal anomaly.

The second of the three essays presented in this thesis, "The search for an exploitable value premium in market indexes", attempts to add clarity to both the first and second of the two key questions itemized above, by asking whether the value premium exists in passive investment vehicles. The thesis is straightforward. If the value return premium is compensation for the assumption of greater risk, as argued by Fama and French (1993), then stocks observed within a market index that exhibit relatively higher BE/ME characteristics should still produce superior returns to stocks (within that same index) that exhibit relatively lower BE/ME characteristics. Results in this essay are inconsistent with this argument and consistent with those in Houge and Loughran (2006) who observe that the value premium is absent at the index return level. Similarly, observations of a statistically significant value premium by Dhatt, Kim, and Mukherji (1999) in the Russell 2000 index constituents are not confirmed through tests of another set of competitive indexes. Moreover, unlike findings in Dhatt et. al., no statistically significant value premium is observed when index constituents are sorted on ME/BE or when value is redefined using P/S or P/E.

If the value premium does not exist in passive index returns or in returns of index constituencies themselves, then it is unlikely that investment managers - who use index benchmarks as effective investment universes – will easily capture the return premium identified in the academic literature. The absence of a value premium in relatively more liquid, widely traded stocks typically found in market indexes seems to hint that the statistical value premium is found in areas difficult to reach for institutional investors. At minimum, results in this essay suggest that a passive route to capturing the premium appears to be unavailable to market participants.

The third of the three essays presented in this thesis, "Can any mutual fund capture the value premium", is a direct attempt to answer the key question of whether value investment managers can capture the premium in stock returns. This essay adds considerable support to findings in Phalippou (2008) who finds no statistical value premium in stocks held by institutional investors. Phalippou suggests that the premium exists only in small relatively illiquid stocks held by individual investors and

that institutional funds would find it quite difficult (if not impossible) to capture it. While the DFA Small Cap Value Fund, a unique fund specifically designed to capture the value premium, operates with a philosophy and investment strategy consistent with academic research evidence, the fund is shown in this essay to fail in its attempt to capture the premium. The fund apparently suffers from many of Phalippou's predicted maladies when trading small, relatively illiquid stocks.

DFA returns are analyzed in the third essay using the decomposition method in Keim (1999) to determine to what extent the fund's portfolio constituent rules and trading strategies impact its ability to capture the premium. Results show that portfolio constituent restrictions provide very little if any benefit to DFA in their small cap value-oriented investment space. Conversely, a very large, statistically significant negative return impact can be attributed to trading strategies of the company. However, tests for a trading impact in this essay include the existence of seasonality in DFA returns. Fund returns are indeed shown to exhibit seasonal variation, but this type of seasonality is potentially driven by year-end trading activities and possibly the costs associated with it.

Curiously, results in the third essay also imply that growth-oriented small cap stock investors can improve results by as much as 10.2% per annum by implementing similar portfolio constituency restrictions employed by DFA. Attributing the value premium in stock returns in part to poor growth stock performance is consistent with findings by Loughran (1997) who finds that poor performance of recent growth stock IPOs materially contributes to the relative value/growth performance difference. From an applied perspective, this result hints that the absence of a value premium in managed portfolio returns may originate from wise decision-making by growth managers rather than poor decision-making by value managers.

INTRODUCTION

Eugene Fama and Kenneth French, pioneer researchers in the area now known as the value premium, did not initially seek to determine whether a value investment strategy was superior to a growth investment strategy. Instead, their research sought to preserve the foundational theory of efficiency in financial markets – a theory that had suffered considerable damage to that point. The target of their research had its origins not in industry where the labels *value* and *growth* were long known and understood[1], but in prior academic work where the overarching research questions extended back to theoretical studies of stock price behaviour.

Prior to the publication of the seminal work, Fama and French (1992), various researchers had exposed fundamental weaknesses in the theory of market efficiency and the Capital Asset Pricing Model (CAPM). For example, Basu (1977) contradicted the predictions of CAPM by showing that stocks with high E/P ratios generate higher returns than stocks with low E/P ratios. Banz (1981) showed that stocks with small market capitalizations generate higher returns than stocks with large market capitalizations. Bhandari (1988) showed that stocks with high leverage (D/BE) generate greater returns than stocks with low leverage. Finally, Rosenberg, Reid, and Lanstein (1985) showed that stocks with high BE/ME ratios generate greater returns than stocks with low BE/ME ratios. The latter result is now commonly known as the *value premium* in stock returns.

Figure 1 presents an updated illustration of the findings in Rosenberg et al. of the historical value premium. The chart shows the compound growth of a dollar invested each in a diversified portfolio of stocks with high and low BE/ME characteristics – again, the difference in returns being the value premium.[2] Returns for a sample period subsequent to that used in Rosenberg et al (1985) indicate the value premium is still economically very strong in aggregate stock returns. A dollar invested in a portfolio of high BE/ME value stocks in July 1963 rose to $742 by December 2006 while the same dollar invested in low BE/ME growth stocks rose only to $37.

Despite extensive research on the subject of the existence of the premium in financial markets, it remains to be determined whether the information is useful to market participants. To determine

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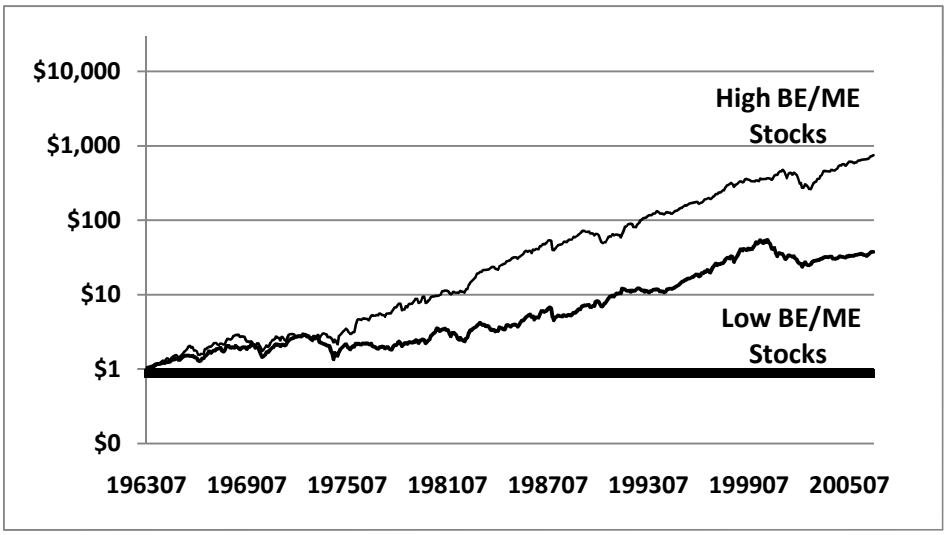
[1] The most notable early mass-market treatise on the subject can be found in various editions of Security Analysis, Principles and Technique, by Graham, Dodd, and Cottle, McGraw-Hill. For example, in the 1962 edition: a discussion on value analysis begins p. 30 and the growth stock approach p. 424.

[2] High and low portfolios represent the extreme first and tenth deciles of portfolios one-dimensionally sorted annually on BE/ME. Portfolios are formed from NYSE, AMEX, and NASDAQ stocks. Monthly returns are obtained from the website of Kenneth French. The sample begins in July 1963 to coincide with that in Fama and French (1992). Extended results are observed for 16 years to December 2006.

FIGURE 1: The monthly compound growth of $1 invested in a portfolio of high and low BE/ME stocks. July 1963 to December 2006. (n = 522)



whether investors can capture the value premium observed in academic literature, several questions need to be answered: 1) Are research and data used to observe the value premium in prior academic research comprehensive? 2) Are econometric tests properly constructed and results free from sample dependence? 3) What is the nature of the historical variation in the premium and can investors use that historical information to anticipate future shifts? Finally, 4) if academic findings of a value premium are robust, then are investors still prevented from capturing it due to structural market barriers?

This research will address many of these questions over the course of five chapters. Chapter one presents a literature review and update of the most relevant empirical findings from research published on the value premium over the last two decades. Chapter two presents the first of three pieces of original research asking why investors have failed to capture the value premium promised in prior academic research. The second chapter asks whether prior observations of the value premium across and within industry sectors are dependent upon the classification method employed to assign various stocks to each sector. The chapter also asks whether value-oriented investors can construct their portfolios to strategically profit from this information. Chapter three extends the work of Houge and Loughran (2006) and Dhatt, Kim, and Mukherji (1999) who attempt to observe the value premium in managed portfolios and market indexes, the latter being the effective universe of investment opportunities for various investment styles. This research explores whether the value premium exists in a larger sample of market indexes than that used by Houge and Loughran, and also attempts to confirm

results by Dhatt et al using a different index vehicle. Chapter four explores whether one particular mutual fund that has been specifically designed to capture the value premium has been successful in its effort. Finally, chapter five provides a closing summary review of the literature specifically investigating whether investors can capture the value premium and offers several unexplored opportunities for future research.

CHAPTER ONE:

Research review and update of empirical findings

Section 1: The beginning - Fama and French (1992, 1993)

Fama and French (1992) test the explanatory power of beta, ME, E/P, D/BE, and BE/ME on average stock returns - using the foundation of return anomalies observed by Basu (1977), Banz (1981), Bhandari (1988) and Rosenberg et al. (1985) - to demonstrate that recently exposed violations of market efficiency would simply mean CAPM is mis-specified, not that market efficiency is untrue. The authors find that if stocks are priced rationally, then risk is proxied by only two dimensions, the size of a stock and its book-to-market characteristics. Fama and French argue that small stocks are riskier than large stocks and value stocks are riskier than growth stocks. The value premium observed in Rosenberg et al. (1985), therefore, acts as compensation for the assumption of greater risks associated with stocks exhibiting high BE/ME characteristics.

The Fama and French study, as well as their follow-on work in Fama and French (1993), resulted in a flurry of publications designed to refute or confirm the authors' results. Early concerns about data mining and survivorship bias were effectively dismissed by successfully extending the data out of sample and observing the value premium in earlier time periods, as in Davis (1994) and Davis, Fama and French (2000), and by successfully observing the value premium in non-US markets, as was done in Chan, Hamao and Lakonishok (1991), Fama and French (1998), and Chen and Zhang (1998).

Curiously, Chen and Zhang find the value premium virtually nonexistent in certain developing markets such as Taiwan and Thailand. While still arguing a risk-based thesis to the driver of the value premium within each of the markets, Chen and Zhang explain the unexpected results by showing that the economies of Taiwan and Thailand were growing at much faster rates during the observation period. They argue that under high growth conditions, marginal firms that typically exhibit the greatest value effect are at less risk for default. This argument is clearly important to investors in larger, more developed markets who are required to navigate changing economic conditions. However, if the explanation of Chen and Zhang holds, then the value effect in places like Turkey, a slower growth economy, might be expected to appear relatively strong. Gonenc and Karan (2003) actually find the reverse. Growth stocks outperform value stocks in that particular market. Of course, research methodological differences or differences in the economic conditions could explain the conflict. Still, the issue remains unclear and unresolved.

In their follow-on work, Fama and French (1993) adjust their methodological approach to explain the cross sectional variation of stock returns by switching from the cross-section regressions of Fama and MacBeth (1973) to the time series regressions of Black, Jensen, and Scholes (1972). This change is made in large part to expand the set of model variables to explain bond returns as well as stocks. However, the most interesting aspect of methodological changes in Fama and French (1993) for the purpose of this research is the authors' construction of new book-to-market (HML) and size (SMB) factors for their explanatory model. The HML factor, a zero-investment factor mimicking portfolio, is a mathematical construction of the value premium itself, representing the average return on value portfolios minus the average return on growth portfolios.[3] In other words, the return time series of the HML factor is similar in concept to the value premium results shown in Figure 1 of the introduction. A comprehensive discussion of the Fama and French 3-factor model, including an analysis of its failings, is provided in the Appendix to this chapter.

1.1 The value premium in average monthly stock returns – updated results

Table 1 shows average monthly returns for portfolios comprised of NYSE, AMEX, and NASDAQ stocks formed through annual sorts on BE/ME for the period July 1963 to December 1990. Portfolios are constructed using the data from the website of Kenneth French and the methodology in Fama and French (1992, 1993). Results for the earlier time period in Table 1 replicate the findings in Fama and French (1992) for average monthly equal-weighted returns of ten portfolios.[4] For comparison, the behaviour of high and low BE/ME stocks are further observed for an updated sample period.[5] Results in Table 1 show that the average returns for portfolios sorted only on BE/ME between January 1991 and December 2006 are consistent with those in the earlier period observed in Fama and French (1992). Returns rise monotonically and are positively related to BE/ME portfolio characteristics. The difference in returns between the highest BE/ME portfolio and the lowest BE/ME portfolio is remarkably stable between both the 17 year period observed in Fama and French (1992) and the subsequent 15 year period extended for this research. The highest BE/ME portfolio outperforms the lowest BE/ME portfolio by 1.53% per month in the Fama and French study and by 1.61% in the more recent 15 year period.

Since high BE/ME (value) stocks tend to be smaller than low BE/ME (growth) stocks, a legitimate question arises as to the impact size plays on the results shown in Table 1. To address this question,

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[3] HML = 1/2 (Small Value + Big Value) - 1/2 (Small Growth + Big Growth).

[4] Fama and French (1992), Table IV page 442.

[5] Portfolios for the updated period include financial and utility stocks which were previously excluded in the Fama and French data. Barber and Lyon (1997) argue financials, and by extension utilities, are not likely to alter results.

TABLE 1: Average equal-weighted monthly returns of portfolios formed on BE/ME. (n = 192)

Returns for July 1963 to Dec 1990 are replicated from Fama and French (1992). Otherwise, data for portfolios formed on book-to-market equity were sourced from the website of Kenneth French and represent stocks from the NYSE, AMEX and NASDAQ. The updated sample excludes stocks with negative book value similar to the presentation in Fama and French (1992), but unlike the presentation in Fama and French (1992), the sample for the present computations includes stocks from the financial and utility sectors. As in FF, average monthly returns are computed as the 1991 to 2006 average of the equal-weighted monthly portfolio returns.

	Book-to-market Portfolios											
	Low BE/ME											High BE/ME
	1a	1b	2	3	4	5	6	7	8	9	10a	10b
July 1963 to Dec 1990	0.30	0.67	0.87	0.97	1.04	0.06	1.30	1.44	1.50	1.59	1.92	1.83
Jan 1991 to Dec 2006	0.81		1.15	1.39	1.52	1.67	1.72	1.78	1.77	2.04	2.42	

Fama and French construct one hundred portfolios sorted independently 10x10 on size and book-to-market equity and observe their average monthly returns.[6] Table 2 updates the portfolio matrix presentation in Fama and French (1992) used to control for the effects of size on average returns.

Surprisingly, extended return results between January 1991 and December 2006 are quite different than those in Fama and French (1992). A positive relationship continues to exist between average monthly returns and book-to-market ratios. However, this relationship is confined only to the smallest companies. The value premium (H-L) is large and statistically different from zero in only the smallest size deciles, 1 through 3 (and 6). With one exception, the value premium is small and statistically insignificant in size deciles 4 through 10. Results for the more recent sample period seem to confirm findings in Loughran (1997) that the book-to-market effect "simply does not exist" in large companies - stocks that represent an overwhelming majority of the capitalization of the US market.

However, results in Table 2 continue to show that value stocks continue to *economically* outperform growth stocks across all but one size decile. The average spread of returns between the highest BE/ME portfolio and the lowest BE/ME portfolio across each size grouping is 0.99% per month for the earlier sample tested in Fama and French (1992) and 0.77% for the current test shown in Table 2. On average, small stocks continue to outperform large stocks. The spread of average returns across size within each book-to-market grouping (Small-ME minus Large-ME) expands from 0.58% per month for the earlier sample to 0.81% per month for the current period.

[6] Fama and French (1992), Table V page 446.

TABLE 2: Average equal-weighted monthly returns on portfolios formed on size and book-to-market equity. January 1991 to December 2006 (n = 192).

Data for portfolios formed on size and book-to-market equity were found on the website of Kenneth French and represent stocks from the NYSE, AMEX and NASDAQ that met requirements of the authors as in Fama and French (1992). The sample excludes stocks with negative book value similar to the presentation in Fama and French (1992), but unlike the presentation in Fama and French (1992), the sample for the present computations includes stocks from the financial and utility sectors. As in FF, average monthly returns are computed as the 1991 to 2006 average of the equal-weighted monthly portfolio returns.

	Book to Market Portfolios											
	GROWTH									VALUE		
	Low	2	3	4	5	6	7	8	9	High	H - L	*t-stat*
Small-ME	1.00	1.11	1.77	1.79	2.09	1.93	1.94	1.97	2.28	2.62	1.62	*3.75*
ME-2	0.49	1.27	1.25	1.58	1.46	1.56	2.04	1.64	1.83	1.65	1.16	*2.12*
ME-3	0.60	1.15	1.25	1.26	1.45	1.89	1.48	1.56	1.63	1.93	1.33	*2.47*
ME-4	0.85	1.12	0.97	1.27	1.35	1.73	1.43	1.72	1.52	1.24	0.39	*0.72*
ME-5	0.84	1.33	1.15	1.56	1.46	1.37	1.52	1.48	1.59	1.81	0.97	*1.92*
ME-6	0.84	1.21	1.06	1.37	1.29	1.36	1.33	1.41	1.51	2.21	1.37	*2.29*
ME-7	1.22	1.25	1.43	1.31	1.32	1.67	1.59	1.50	1.23	1.21	-0.01	*-0.02*
ME-8	1.08	1.05	1.18	1.26	1.44	1.46	1.31	1.55	1.04	1.67	0.60	*1.05*
ME-9	1.16	1.18	1.11	1.08	1.51	1.05	1.80	1.33	1.29	1.25	0.09	*0.17*
Large-ME	0.93	1.05	1.17	1.28	0.98	1.27	1.01	0.60	1.02	1.14	0.22	*0.48*

1.2 Portfolio construction methods - rebalancing

Fama and French (1992, 1993) rebalance and reorder stocks annually when employing an independent 5x5 and 10x10 sort on ME and BE/ME. Following each formation period, portfolio returns are observed over each of the subsequent twelve month periods. This method is comparable to a portfolio manager (in the extreme) turning over 100% of her portfolio each year, or a 1-year holding period for each portfolio constituent. In reality, not all stocks in each theoretical Fama and French portfolio are replaced each year. At formation date, the weight of stocks that do not change BE/ME characteristics is simply rebalanced, either due to changes in market value (value weight) or changes in the number of stocks observed in each portfolio (equal weight). If practitioners are ultimately able to capture the value premium identified in academic research, they will need to understand whether they too need to rebalance their portfolios in the manner of Fama and French. A pure replication would likely generate considerable transaction costs from re-weighting portfolio holdings each year.

The question of rebalancing was tested fairly quickly following the publication of Fama and French (1993). Lakonishok, Shleifer and Vishny (1994) test returns for portfolios over a 5-year post-

formation holding period rather than over a 1-year period and find no reduction in value stock superiority. Stocks representing the highest BE/ME characteristics generate a 10% per annum average return premium to stocks representing the lowest BE/ME characteristics.[7] In a related study, Dennis, Perfect, Snow, and Wiles (1995) suggest that the optimal rebalancing period for portfolios formed on BE/ME and size for the sample period 1963 to 1988 is 2 years.

1.3 Portfolio construction methods - ME, sample size, and volatility

Several returns shown earlier in Table 2 suffer from considerable noise associated with small portfolio sample sizes. Fama and French (1992) use a 10x10 market segmentation on size and book-to-market in their initial work, but shift to more aggregated portfolio segments in later studies, 5x5 in Fama and French (1993, 2006) and 3x3 matrices in Davis, Fama, and French (2000). In Fama and French (2006), the authors change the method of computing the value premium itself, using the lowest and highest *two* BE/ME quintiles rather than computing the difference in monthly returns between only the first and fifth quintiles as had been the custom. Fama and French lament "the paucity of firms that are both large and in the extreme value group" and claim the computational change is necessary because "some extreme portfolios are undiversified". In the same paper, the authors perform regressions on portfolios sorted 2x3 on size and book-to-market characteristics. This more highly aggregated portfolio construction is used again in Fama and French (2007).

Table 3 illustrates the problem of small sample sizes when using less aggregated portfolio constructs. The table shows the average market capitalisation and average number of stocks for portfolios independently sorted 10x10 on size and book-to-market. While it is clear that the 10x10 matrix successfully controls for size across each book-to-market decile shown in Panel A – the median market capitalisation of portfolios across BE/ME deciles are relatively similar – the method does a poor job in constructing portfolios with enough stocks to make proper statistical inferences. Six portfolios shown in Panel B, representing stocks with large ME and high BE/ME characteristics, contain less than ten stocks over the sample period. Thirty percent of the one hundred portfolios, mostly bearing large ME, value-oriented characteristics, contain less than twenty stocks on average each year. Clearly, many of the underlying portfolio returns shown earlier in Table 2 in the large ME and high BE/ME area of the matrix are unavoidably impacted by specific company risks due to the small number of stocks generating the time series.

[7] July 1963 to December 1990. Portfolio returns were equally weighted as in Fama and French (1992) but unlike Fama and French (1993).

TABLE 3: Median Market Equity (in millions) and Average Number of Stocks of Portfolios Formed on Size and Book-to-Market Equity: January 1991 to December 2006. (n = 192)

Data for portfolios formed on size and book-to-market equity were found on the website of Kenneth French and represent stocks from the NYSE, AMEX and NASDAQ that met requirements of the authors as in Fama and French (1992). The sample excludes stocks with negative book value similar to the presentation in Fama and French (1992), but unlike the presentation in Fama and French (1992), the sample for the present computations includes stocks from the financial and utility sectors.

Panel A: Median market equity

	Book-to-Market Portfolios									
	GROWTH									VALUE
	Low	2	3	4	5	6	7	8	9	High
Small-ME	42	40	42	42	45	43	43	39	36	27
ME-2	141	150	153	150	157	159	162	153	154	149
ME-3	273	283	304	296	287	305	299	298	301	287
ME-4	464	463	467	479	483	494	463	489	464	458
ME-5	691	719	721	773	721	746	722	723	726	690
ME-6	1044	1045	1112	1133	1072	1095	1093	1045	1095	1123
ME-7	1746	1664	1765	1753	1749	1840	1776	1786	1712	1609
ME-8	2912	3058	3052	2874	3134	3030	2845	2967	3177	2942
ME-9	6272	6573	6475	5973	5922	6055	6477	6582	6066	5139
Large-ME	49018	36178	30398	31705	22945	22171	16925	14022	18664	19947

Panel B: Average number of stocks

	Book-to-Market Portfolios									
	GROWTH									VALUE
	Low	2	3	4	5	6	7	8	9	High
Small-ME	322	194	162	165	174	190	225	274	329	484
ME-2	124	82	73	69	71	69	70	68	69	58
ME-3	80	58	49	47	50	47	46	41	35	25
ME-4	61	43	40	36	35	38	32	27	23	15
ME-5	53	39	35	31	30	26	24	22	17	12
ME-6	47	36	27	28	26	23	19	17	16	10
ME-7	40	29	28	23	22	21	17	16	14	9
ME-8	39	30	26	23	21	16	16	14	12	8
ME-9	42	26	22	18	17	14	15	16	13	6
Large-ME	51	29	21	19	16	12	12	8	7	4

Section 2: Are value stocks riskier than growth stocks?

The question of whether value stocks are riskier than growth stocks divides academic researchers into two distinct camps. Each advocates a different theoretical explanation for the difference in returns between the two categories of stocks. Fama and French argue that value stocks have higher average returns because they are riskier. In Fama and French (1993, 1995, 1998), the authors suggest that stocks with low BE/ME (growth) characteristics operate under conditions of strength and reflect lower risk to investors, while stocks with high BE/ME (value) characteristics exhibit conditions of distress and are, therefore, higher risk to investors. Having empirically shown that the difference in returns is not by chance, Fama and French argue that investors have simply been compensated for assuming greater risk.

Conversely, a behavioural explanation of the statistical value premium argues that investors assign irrationally low values to distressed (value) stocks and irrationally high values to glamour (growth) stocks. The resulting superior performance by the former is a function of a market-correcting mechanism, not risk. Research shows that growth stocks tend to outperform value stocks in earnings, sales, and cash flow prior to portfolio formation. Behaviouralists believe that investors extrapolate past performance into the future – believing that growth stocks will continue to generate superior operating performance and value stocks will continue to perform poorly. Behaviouralists also argue that institutional investors might find it psychologically difficult to justify buying poor performing value stocks for their pension or university endowment clients. As a result, investors continue to bid up the price of growth stocks and bid down the price of value stocks until growth stocks become overpriced and value stocks become underpriced.

Firmly in the behavioural camp, La Porta, Lakonishok, and Vishny (1997) argue that investors indeed irrationally overprice growth stocks based on extrapolated expectations and are subsequently disappointed in their performance. Investors underprice value stocks and are pleasantly surprised to see that the operating performance of these stocks reverts. The authors find that growth stocks generate negative post-earnings announcement returns (-0.5%) in the first year after portfolio formation while value stocks generate positive post earnings announcement returns (+3.5%).

Addressing the risk-pricing thesis of Fama and French directly, Chan and Lakonishok (2002) are incredulous in wondering how dotcom growth stocks that possessed virtually no book equity and extraordinarily high market values in the late 1990s could somehow be less risky than value-oriented utility stocks that possessed high levels of book equity and relatively lower market values.

2.1 Traditional risk measures – standard deviation of returns

Lakonishok, Schliefer and Vishny (1994) and Chan and Lakonishok (2002) argue that value stocks are not riskier than growth stocks when using traditional definitions of risk. The authors find that between May 1968 and April 1989 average annual standard deviation of size-adjusted returns of low BE/ME portfolios are indistinguishable from that of high BE/ME portfolios. Lakonishok et al. suggest that investors could generate extra returns by investing in value stocks without bearing commensurate volatility in those returns.

Table 4 updates the evaluation of volatility by Lakonishok et al. to include the sample of returns for a more recent period, January 1991 to December 2006. Monthly standard deviation of returns are presented for 10x10 portfolios formed on size and BE/ME, as in Fama and French (1992). Again, this finer, less aggregated cut in size and book-to-market helps to delineate volatility of portfolios between various strata. Results using this methodology show that monthly volatility of average portfolio returns increase monotonically from the largest ME portfolio to the smallest ME portfolio only for low BE/ME growth stocks portfolios. Generally small value stocks are no more volatile than large value stocks. On a risk/reward basis, investors do not pay in increased volatility for capturing the increased returns of small stocks. Moreover, growth stocks exhibit considerably higher monthly volatility relative to value stocks in all but one of the ME size strata during the updated sample period. The difference in relative volatility from that shown by Lakonishok et al. is likely a function of the unusual bubble condition during the late 1990s when growth stocks were distinctly in favour and then subsequently distinctly out of favour. Not unexpectedly, several of the largest ME, value-oriented portfolios exhibit greater monthly return volatility than the smallest value portfolios. The small average number of stocks constituting the portfolios in that portion of the matrix discussed in the prior section is likely the culprit for this unconventional small/big stock relationship. Results for the extended period sample shown in Table 4 continue to support behavioural arguments that value stocks are not riskier than growth stocks using traditional definitions of risk.

2.2 Value and growth equity market betas

Lakonishok et al. find that average pre-formation market betas for the extreme value portfolio ($\beta = 1.443$) are indeed greater than the extreme growth portfolio ($\beta = 1.248$) for the period 1963 to 1990 suggesting the extra return in value stocks might be explained by greater systematic risk. However, the

TABLE 4: Monthly standard deviation of returns of portfolios formed on size and BE/ME for the period January 1991 to December 2006 (n = 192).

Data for portfolios formed on size and book-to-market equity were found on the website of Kenneth French and represent stocks from the NYSE, AMEX and NASDAQ that met requirements of the authors as in Fama and French (1992). The sample excludes stocks with negative book value similar to the presentation in Fama and French (1992), but unlike the presentation in Fama and French (1992), the sample for the present computations includes stocks from the financial and utility sectors. As in FF (1993), average monthly returns are computed as the 1991 to 2006 average of the value-weighted monthly portfolio returns. Standard deviations are computed from monthly portfolio returns.

	Book-to-market									
	GROWTH									VALUE
	Low	2	3	4	5	6	7	8	9	High
Small-ME	10.37	8.84	8.10	7.05	6.32	5.55	4.86	4.96	5.27	6.05
ME-2	10.19	8.51	7.00	6.36	5.59	4.99	5.53	5.04	5.41	5.98
ME-3	9.10	7.66	6.71	5.64	4.76	4.72	4.62	4.79	5.24	6.21
ME-4	8.98	6.52	6.01	5.19	5.28	4.52	5.03	5.23	5.27	7.40
ME-5	9.16	6.39	5.97	5.07	4.74	5.03	5.04	5.15	4.63	6.84
ME-6	8.32	5.88	5.28	5.07	4.57	4.68	4.72	4.65	5.41	6.15
ME-7	7.30	5.75	4.74	4.89	4.98	4.59	4.75	4.59	4.69	6.45
ME-8	7.89	5.15	4.71	5.19	4.56	5.09	5.32	4.55	4.74	6.48
ME-9	6.40	4.89	4.37	4.67	4.78	4.33	4.52	4.06	4.69	5.99
Large-ME	5.15	4.34	4.62	4.42	4.79	4.86	4.43	5.44	6.49	6.56

authors argue that the difference in risk cannot fully explain the larger difference in returns. Ang and Chen (2007) argue that a static view of value and growth betas over time is not necessarily informative. The authors show that betas for high book-to-market value stocks have fallen dramatically over time ($\beta = 2.2$ in 1940, to about $\beta = 0.5$ in 2001). Prior to the 1960s, extreme value stock betas are persistently well above those for extreme growth stocks. Between the early 1960s and early 1980s the rolling 5-year betas of the two extreme equity styles are approximately the same, experiencing mild variation around the mean beta of about 1.1. However, after the 1980s, value stock betas fall below those for growth stocks and have remained in that condition to the present. Spyrou and Kassimatis (2006) observe the same considerable variation in value and growth portfolio market betas in non-US markets.[8]

Figure 1 replicates the time varying characteristics of value and growth stock betas observed in Ang and Chen (2007) and extends results from the end of their sample in 2001 through December 2006.

[8] Spryou and Kassimatis conclude, "OLS regressions may be an inappropriate tool to assess whether HML returns contradict the CAPM.....and [results] indicate that the profitability of value vs. growth investment strategies may have been overstated in previous studies."

Interestingly, Figure 1 shows the rolling 5-year value stock beta rising dramatically after 2001, a period when the value premium is observed to be very strong. To test whether the value premium is associated with the changing levels of systematic market risk, the 5-year rolling market betas of value stocks are ranked from high to low and then divided into quintiles. Next, the corresponding rolling 5-year average monthly value premium return is observed for each of these quintiles. Table 5 shows that the value premium is relatively stronger during periods when value stocks exhibit their highest levels of market risk. An average portfolio beta of 1.88 is associated with an average value premium of 1.05% per month, while an average portfolio beta of 0.78 is associated with an average premium of only 0.55% per month. Although the correlation coefficient between market beta and the value premium is positive and quite high (ρ =0.74, t = 1.91), not much change is observed in the value premium between the first four beta

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FIGURE 1: Time varying systematic risk of extreme high and low BE/ME portfolios. Rolling five-year single factor model market betas updated to the present period. July 1926 to December 2006 (n = 966).

Data for portfolios formed on size and book-to-market equity were obtained from the website of Kenneth French and represent stocks from the NYSE, AMEX and NASDAQ that met requirements of the authors as in Fama and French (1992). The sample excludes stocks as discussed earlier in Table 3. Five-year rolling portfolio betas of the two extreme high BE/ME and low BE/ME portfolios are computed by regressing value-weighted portfolio returns against aggregate market returns also obtained from the website of Kenneth French.

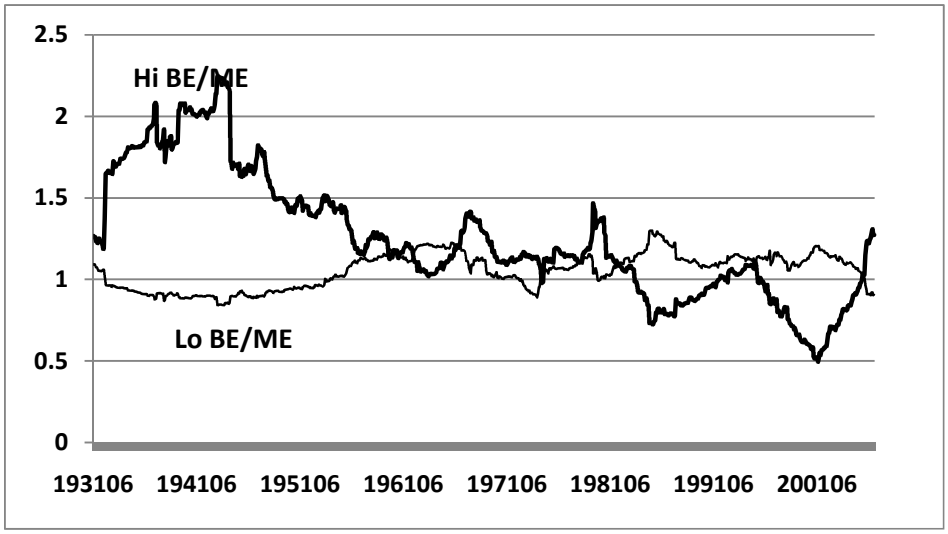

TABLE 5: Average monthly Hi minus Lo returns observed in periods ordered by rankings of Hi BE/ME betas. Rolling 5-year betas and average value premiums observed from July 1926 to December 2006. (n = 966)

Portfolio data are observed as discussed in the notes to Figure 1. Portfolios are annually ranked from high to low betas using the rolling 5-year betas observed in Figure 1. Results are then divided into quintiles. Next, the corresponding rolling 5-year average monthly value premium return is observed for each beta quintile.

	Lo Beta	2	3	4	Hi Beta
Avg. Beta	0.78	1.05	1.17	1.40	1.88
Avg. value premium return	0.55	0.43	0.31	0.50	1.05

quintiles. This seems to suggest that the value premium is not related to market risk except when risk in these stocks is extreme.

However, the story is likely a bit murkier. When using a finer cut of beta deciles rather than quintiles, it emerges that the majority of the strength in the value premium shown in the Hi Beta quintile in Table 5 is largely the function of the size of the premium in only one decile, the ninth. The Pearson correlation coefficient between decile betas and decile value premium returns falls to 0.51 and is statistically indistinguishable from zero at the 5% level of significance (t = 1.61). While the time varying nature of the value stock betas may have implications for the choice of explanatory models, it is unclear whether they add much information to the relative strength of the value premium in average stock returns.

2.3 The value premium in up and down markets

The evidence of a value premium in stocks is substantial. Value stocks have been shown to outperform growth stocks across multiple sample periods and in multiple countries. However, according to behavioural arguments in Lakonishok, Shleifler and Vishny (1994), if the premium is a function of risk as advocated by Fama and French, then value stocks should underperform growth stocks during negative market conditions and outperform growth stocks during positive market conditions. Lakonishok et al. observe average monthly returns for 10 portfolios formed on BE/ME (adjusted for size) during differing stock market conditions and differing periods of real GNP growth. Both tests generate similar results. As should be expected for riskier stocks, value-oriented portfolios generate a 2.6% higher monthly return on average than growth-oriented portfolios during periods sorted for the 25 best performing months. However, contrary to a risk-based thesis, value stocks lose on average 1.1% *less*

than growth stocks during months registering the 25 worst monthly performance, May 1968 to April 1989.

Updated results for best and worst period returns between January 1991 to December 2006 are shown in Table 6. In this test, size is controlled using the matrix methodology in Fama and French (1993). This method, in contrast to that used by Lakonishok et al., allows for an observation of the various size strata to further distinguish where a value premium is being generated during the sample period. Panel A presents the average returns for portfolios sorted 5x5 on size and book-to-market during the ranked 25% worst monthly market conditions and for the ranked 25% best monthly market conditions (n = 48 months each). Panel B presents the computed High minus Low value premium and level of statistical significance for each size strata. Again, portfolios are formed using the methodology in Fama and French (1993).

Results in Panel B show that during the worst market periods, value stocks perform better than growth stocks, consistent with findings for an earlier sample period by Lakonishok et al. However, growth stocks generally outperform value stocks during months when the market achieves its best returns, contrary to findings for the earlier sample period. At a minimum, tests of updated down-market results continue to support arguments in Lakonshok, Shliefer and Vishny (1994) that the value premium is not likely a function of risk. Once again, value stocks outperform growth stocks. From a contrarian view, value managers who fill their portfolios with low BE/ME stocks are likely to expect their out-of-favour stocks to lose relatively less money during down markets. In other words, at the point of portfolio formation, distressed value stocks may already be priced at or near liquidation value and have less room to fall than their growth stock counterparts if the market tumbles.

It is interesting to note in Panel B that the value premium falls from 4.75% to 1.09% with increasing market capitalisation during the worst market conditions. The premium is fairly stable across size quintiles (albeit economically negative) during the best conditions. This suggests that the size of the long term value premium between large and small company stocks, the subject of criticism in Loughran (1997), may be largely determined during down market periods. Panel B of Table 6 shows that a statistically significant return difference (at the 5% level) is observed for only the smallest stocks during the worst market conditions (4.74%, t = 2.15). Otherwise, all of the other H-L mean returns are not statistically different from zero. In any event, results in Panel B suggest that the bulk of the value premium might be best captured by investors during the poorest stock market conditions and only by investing in the smallest stocks.

TABLE 6: Average monthly returns of portfolios formed on size and BE/ME during varying stock market conditions January 1991 to December 2006.

Data for portfolios formed on size and book-to-market equity were found on the website of Kenneth French and represent stocks from the NYSE, AMEX and NASDAQ that met requirements of the authors as in Fama and French (1993). The sample excludes stocks as discussed earlier in Table 3. Panel A presents average returns for portfolios sorted 5x5 on size and book-to-market during the ranked 25% worst monthly market conditions and for the ranked 25% best monthly market conditions (n = 48 months each). Panel B presents the computed High minus Low value premium and level of statistical significance for each size strata.

Panel A: Average Monthly Portfolio Returns During Varying Market Conditions

	25% Worst Market Returns (n = 48)					25% Best Market Returns (n = 48)				
	Low	2	3	4	High	Low	2	3	4	High
SMALL	-8.07	-5.31	-3.79	-3.03	-3.32	6.49	6.10	5.23	5.16	5.11
2	-7.37	-4.76	-3.44	-3.44	-3.89	6.99	5.54	5.00	4.87	5.16
3	-4.48	-3.50	-3.10	-3.10	-3.24	5.76	5.10	4.80	4.80	4.98
4	-5.95	-3.96	-3.46	-3.27	-3.36	6.83	5.48	5.06	4.87	4.75
BIG	-4.67	-3.72	-3.34	-2.77	-3.58	5.71	4.98	4.57	4.30	4.39

Panel B: Average Monthly Returns for High BE/ME minus Low BE/ME Portfolios (H-L) by Size

	25% Worst Market Returns			25% Best Market Returns	
	H-L Returns	t-statistic		H-L Returns	t-statistic
SMALL	4.75	(2.15)	SMALL	-1.38	(-0.62)
2	3.49	(1.57)	2	-1.83	(-0.85)
3	3.59	(1.42)	3	-1.54	(-0.63)
4	2.59	(1.10)	4	-2.08	(-0.93)
BIG	1.09	(0.48)	BIG	-1.32	(-0.64)

Fama and French (1995) rebut claims by Lakonishok et al. that the risk thesis is damaged because value stocks do not generate returns according to expectations during down markets when the marginal utility of wealth is high. The authors claim that a distress premium proxied by BE/ME is separate from influences of a market factor and should not be related to market volatility. They add that in a multi-factor framework, "variance is not a sufficient statistic for a portfolio's risk." This argument may be true in describing the nature of explanatory variables using a traditional multi-factor model framework; however, the HML factor used in the 3-factor model is, by construction, the value premium itself. If the value premium is observed to be consistently positive in the worst market conditions and consistently negative in the best conditions - as is observed in Table 6 - and statistically correlated with these events, then the HML factor coefficients are indeed related to market volatility - and the 3-factor model potentially mis-specified, at least during extreme conditions.[9]

[9] Any statistical association between the HML factor and market volatility may only apply to down markets since Lakonishok et al. find the value premium to be positive in the 25 best monthly conditions between 1968 and 1989.

However, another explanation for results in Table 6 might be found in a research conversation about growth options and assets in place. Gomes, Kogan, and Zhang (2003) argue that growth stock valuations are driven by a relatively larger set of expected growth opportunities, or options. Growth options carry greater future cash flow uncertainty and that these opportunities carry implicit leverage, thus increasing their levels of systematic risk, especially during good economic conditions when these options are best exploited. By this reasoning, growth stocks must be riskier and should generate superior returns to stocks with higher levels of assets in place. In contrast, Zhang (2005) argues that assets in place are riskier than growth options during bad periods when the marginal utility of wealth is high. Zhang reasons that during bad economic conditions, high BE/ME value companies, while operating under considerable distress, carry greater levels of unproductive assets. During bad times, these firms cannot offload this burden as easily as growth firms might. The difference in risk between value firms and growth firms is therefore high. However, during a recovery and boom period, the unproductive assets of high BE/ME value firms are once again fully utilised. But since boom periods allow growth firms to take advantage of leveraged growth options with relative ease, the risk disparity between growth and value companies during this period is small, even negative. Zhang argues that under a rational expectations thesis, the value premium is a function of risk dispersion between value and growth stocks and the market risk premium. Results in Panel B of Table 6 are consistent with this argument. The value premium is seen to be larger during bad market conditions when, according to Zhang, the dispersion of risk between value and growth companies is higher. The value premium is economically smaller (even negative) during good market conditions when Zhang argues that the dispersion of risk is lower.

2.4 Is persistence of the value premium due to the high cost of arbitrage?

Chan and Lakonishok (2002) observe that large stocks generate a lower value premium than small stocks. Arguing a behavioural explanation, they suggest that since the financial media provide limited coverage of small stocks and that research analysts provide only sporadic coverage, then much of the value premium could result from mis-pricing as a function of asymmetry of publicly available information. Persistence of the value premium in these size strata could result from the high cost of arbitrage associated with buying and selling small illiquid stocks. Indeed, a snapshot of analyst coverage taken at year end 2007 supports this view. Results in Table 7 show that median analyst coverage for stocks sorted independently for size and then book-to-market characteristics varies considerably from small company stocks to large company stocks. At the end of 2007, small company stocks average only three research analysts covering their performance while big company stocks average over fourteen

TABLE 7: Median analyst coverage for a portfolio of stocks independently sorted on size and book-to-market characteristics. At 31 December 2007.

Average analyst coverage is documented in I/B/E/S for 4583 stocks sorted 5x5 on size and book-to-market characteristics at December 2007. Stocks without BE/ME, ME, or I/B/E/S data as well as stocks exhibiting negative BE/ME characteristics at 31 December 2007 are omitted.

	Book-to-market					
	Low	2	3	4	High	Avg.
SMALL	3	3	3	3	3	3
2	7	7	6	6	6	6
3	8	7	7	7	7	7
4	10	9	9	10	11	10
BIG	15	14	14	14	17	15
Average	9	8	8	8	9	

analysts each. However, little variation in analyst coverage is observed across BE/ME quintiles suggesting that asymmetrical information generated by professional research analysts is not likely associated with the difference in returns between growth and value stocks when controlled for size.

Lakonishok, Schliefler, and Visney (1994) argue that monthly returns for the Fama and French HML factor are almost always positive (two-thirds of the time) and therefore should be subject to arbitrage. Fama and French (1996) respond by arguing that if arbitrage opportunities exist, then the standard deviations of HML factor returns would need to be fairly small. The authors show that the historical standard deviations of annual returns for their HML factor is in fact not small for the 30 years ending 1993 (σ = 13.1), and relatively similar to that of the market's volatility (σ = 16.3) and to the volatility of the SMB factor (σ = 15.4).

Updating the data to the current date shows little change in either the frequency of value stock domination or the volatility in monthly HML returns. Annual HML returns for the 30 years ending December 2008 are again negative (growth outperforms value) only 33% of the time. The standard deviation of annual HML returns increases from 13.1 in the earlier period to 15.6; thus continuing to support the argument by Fama and French that high volatility of HML returns negate any opportunities for arbitrage to exist. Finally, Lakonishok et al. speculates that the value premium might disappear once investors become aware of the statistical work found in academic literature. The mean annual HML (value premium) return has indeed fallen in the period subsequent to the publication of the original work by Fama and French (1992, 1993) – from 6.33% to 4.74%. But the size of the economic decline

does not suggest investors are now exploiting the difference in HML returns and capturing the premium – thus causing its ultimate disappearance.[10]

2.5 Implications for investment management

A risk-based explanation of the value premium in average stock returns states that value stocks are inherently riskier than growth stocks. Therefore, it follows that portfolios containing value stocks would be riskier than portfolios containing growth stocks. If value stocks are riskier than growth stocks, then an industry consultant might recommend that clients allocate a smaller portion of their portfolios to relatively riskier value stocks, similar to the strategy employed in the marketplace today for small company stocks. Consultants might further recommend a correspondingly higher weight to growth for a risk-averse institutional client.[11] However, growth fund managers may find certain aspects of the academic discussion extremely problematic for their long term survival. If risk does not prevail as an explanation for the value premium and if the difference between value and growth stock returns is not arbitraged away, then a lower-performing, growth strategy, of comparable risk to a value strategy, might be considered irrational and not survive in the marketplace. Growth fund managers must either advocate a risk-based explanation of the value premium, thus allowing clients to allocate funds to a lower risk growth style strategy, or advocate that regardless of its existence, the value premium cannot be captured in large institutional portfolios due to some market barrier such as illiquidity. Lakonishok et al. argue that Fama and French have abandoned the traditional definitions of risk in order to be consistent with their empirical outcomes. The key to a growth fund manager's future may lie in the ultimate consensus definition of risk.

Section 3: Is the value premium a function of financial or operating distress?

3.1 Relative profitability

There is no basis in finance theory to justify the power of an accounting ratio to explain the cross section of average stock returns. There is only the possibility, if the phenomenon is risk-based, that BE/ME

[10] Mean annual HML returns for the sample period observed in Fama and French (1992) compared to HML returns for the subsequent fifteen years, 1994 to 2008. The t-statistic testing the hypothesis that the mean annual return is different from zero is 2.60 for the 30 year period tested by Fama and French, but only 1.11 for the shorter, more recent 15 year period. The standard deviation of annual HML returns, however, increases to 15.6 for the 15 year period likely reflecting the increased volatility associated with the dotcom boom and bust period.

[11] This example hints at the problem faced by risk-based explanations of the statistical value premium. Industry participants are likely to find the logic in the example bewildering based on commonly held beliefs about relative risks.

proxies for an underlying economic fundamental and that it has somehow successfully captured this risk in econometric tests across the statistical spectrum of low to high BE/ME company fundamentals.

Fama and French (1993) conjecture that relative profitability might be the economic fundamental that explains the common risk factor driving the relationship between book-to-market and average returns. The authors find that HML regression slopes for portfolios formed on E/P follow the pattern of average monthly returns and are similar to slopes of portfolios formed on size and BE/ME, thus indicating that average returns are a function of loadings on the HML factor.

Fama and French (1995) observe that portfolios formed on high BE/ME signal persistent low earnings. Indeed, high BE/ME value stocks are associated with persistently low returns on assets while low BE/ME growth stocks are associated with persistently high returns on assets. Consistent with these findings, Chen and Zhang (1998) find that stocks with high BE/ME characteristics typically exhibit persistent low returns on equity while stocks with low BE/ME characteristics typically exhibit high ROE.

3.2 The value premium and the risk of bankruptcy

Distress factors in Chen and Zhang (1998) representing dividends, earnings, and debt are clearly more informative descriptors of risk than the relationship between the market and book valuation of a company's equity. Common distress factors such as earnings and debt provide investors a better intuitive understanding of the conditions under which they may use their stock screens - to include or exclude stocks that could generate premium returns. It would thus be ideal for investors to use a statistical rating index to find these distressed stocks rather than pouring over piles of income and balance sheet statements. One such easily accessible tool is the Z-score, a characteristics-based business failure classification model developed in Altman (1968), designed to indicate the risk of company bankruptcy within the next 2 years.[12] A company's Z-score is a weighted sum of several accounting ratios: working capital to total assets, retained earnings to total assets, EBIT to total assets, market value of equity to book value of liabilities and sales to total assets.[13] Since BE/ME is a related construction to the accounting items in the Z-score, it would not be unexpected to see a relationship between the two data series, and thus operationally useful to investors.

Griffin and Lemmon (2002) briefly evaluate the Z-score as a proxy for distress. They find that high BE/ME stocks that exhibit the highest distress (lowest Z-score) generate a superior average return of almost 12% per annum over low BE/ME stocks. Using the O-score, a similar bankruptcy prediction

[12] Not to be confused with a standard score, or Z-score, in the field of statistics.

[13] The S&P Research Insight concept for Z-Score is 1.2*(WCAP/AT)+1.4*(RE/AT)+ 3.3*(EBIT/AT)+ .6*(@VALUE(PRCCF*CSHO,CEQ)+ PSTK)/(AT-CEQ-PSTK)+.999*(SALE/AT)

tool, the authors successfully show the value effect to be associated with high distress. The authors suggest, however, that the superior returns of these stocks are not a function of risk as suggested by Fama and French but of mispricing. Griffin and Lemmon observe that the returns between high and low BE/ME stocks in the most distressed quintiles are unusually high when compared to other quintiles and could not, in their opinion, be fully explained by the Fama and French 3-factor model or by other fundamental characteristics such as leverage.

Table 8 shows the median Z-Score for the smallest ME quintile of stocks trading on the NYSE, AMEX, and NASDAQ markets between June 2001 and June 2006. The sample of small stocks is used in this instance because prior research has indicated that the value premium – potentially generated as a function of distress – is statistically larger in the lowest size deciles. It is expected, therefore, that distress could be better differentiated within this size strata.

If the value premium is a function of risks associated with distress, then value stocks would be expected to systematically reflect a lower Z-Score than growth stocks. Results in Table 8 clearly show that BE/ME is indeed inversely related to a company's Z-Score, indicating a positive relationship between value stock returns and the risk of bankruptcy over the next two years. High BE/ME value stocks exhibit the lowest average Z-Score ($Z = 1.85$). The low Z-score for the most extreme portfolio of value stocks indicates considerable financial and operating distress – and high probability of bankruptcy over the next two years. Conversely, growth stock portfolios with the lowest median BE/ME characteristic exhibit the highest average Z-Score ($Z = 5.82$). A high Z-score suggests that stocks are experiencing low operating and financial distress and have a low probability of bankruptcy over the next two years. The correlation between the Z-score and portfolio BE/ME characteristics is negative, very high, and statistically significant ($\rho = -0.89$, $t = -5.52$). Therefore, results show a strong positive relationship between book-to-market and the risk of bankruptcy during the observation period, consistent with findings for the O-Score by Griffin and Lemmon.

Contrary to arguments by Fama and French, both Dichev (1998) and Agarwal and Taffler (2003) find that distressed stocks earn lower post-formation returns than non-distressed firms. Dichev argues this outcome is contrary to conditions of market efficiency but Agarwal and Taffler disagree saying pricing of bankruptcy risk is rational when the nature of the risk is evaluated under varying economic conditions. Hwang and George (2008) find that the counter-intuitive negative relationship between high company distress and low returns observed in the two earlier studies evaporates when controlled for leverage.

TABLE 8: Median Z-score for portfolios of small cap stocks sorted on BE/ME. June 2001 to June 2006

Z-scores, BE/ME and ME for all NYSE, AMEX and NASDAQ stocks are sourced from Standard and Poor's Research Insight and observed at June of each year beginning 2001 and ending June 2006. Stocks without computed Z-scores, primarily banks and financials, were eliminated from the sample. Stocks are sorted for each year to form 10 portfolio s on BE/ME. Medians are computed from the aggregated annual data for each decile. Since the sample in this exercise is screened to include only those stocks up to the smallest 20% Fama-French ME breakpoint for December 2006, $754 million in market value, it is therefore only necessary to sort the data for BE/ME. The BE/ME deciles are fixed over time and represent the average of the breakpoints for each 10th percentile over the six years as found at the website of Kenneth French. Results for Z-score, BE/ME and ME are expressed as medians of each portfolio.

	Small cap portfolios sorted on BEME			
	Z-SCORE*	BE/ME	ME	Stocks
GROWTH	5.82	0.12	82.10	1593
2	4.41	0.26	105.00	964
3	4.40	0.36	126.48	811
4	4.04	0.44	121.36	703
5	3.53	0.53	120.23	764
6	3.32	0.62	100.24	675
7	3.24	0.73	74.01	718
8	3.06	0.89	61.01	864
9	2.63	1.17	42.23	991
VALUE	1.85	2.03	18.03	1243

* Z-Score less than 1.81 indicates a high probability of bankruptcy over the next two years; a Z-Score greater than 3.00 indicates a low probability of bankruptcy over the next two years.

More interesting to the question here, Agarwal and Taffler determine that SMB and HML are not influenced by a bankruptcy factor, thus suggesting SMB and HML are not proxies for bankruptcy or financial distress. Penman, Richardson and Tuna (2007) and Hwang and George (2008) may have formulated a resolution to the conflict. Consistent with what is hinted at by Argawal and Taffler, both Penman et al. and Hwang and George argue that *financial* distress and *operating* distress are separately priced by the market and that they are captured separately by leverage and BE/ME respectively. Therefore, the book-to-market effect (and the value premium) may be a function of operating distress and not financial distress.

Section 4: Evaluating the stability of the value premium

4.1 Style rotation and stability

Investors seeking to capture the value premium want to know whether the phenomenon is substantial enough to warrant an attempt to capture it and whether it is stable enough for their portfolios to survive normal periods of growth stock supremacy. Moreover, if changes in the historical value premium are predictable, then investors may have an opportunity to achieve abnormal returns through timing or tactical asset allocation strategies. Bauer and Molenaar (2002) and Swinkels (2007) claim to successfully forecast the time-varying value premium while Kumar (2009) and Liodakis and Levis (1999) find no ability to do so. Interestingly, Kumar (2009) identifies key links between style rotation and various macroeconomic variables. Similarly, Black (2002) evaluates the volatility of value stock returns in several countries under various monetary policy regimes and finds that in most countries, a restrictive monetary regime (proxied by US monetary policy) lowers value stock returns relative to growth stock returns. Black and McMillan (2005) find that book-to-market portfolios exhibit an "asymmetric response to changes in economic conditions over the business cycle." In fact, they find that when adjusted for risks associated with macroeconomic influences, excess high BE/ME minus low BE/ME returns essentially disappear over the sample period.

4.2 Persistence of the value premium

The average monthly value premium does indeed persist when observing returns over long periods. The average difference between returns of the first and tenth BE/ME decile portfolios of NYSE, AMEX, and NASDAQ stocks is 0.55% per month, or 6.6% per year, between July 1926 and December 2006 (t = 2.54).[14] However, investors should view this premium with some caution. Over the same 80 year period of 966 monthly return observations, value stocks outperform growth stocks only 51% of the time. When value stocks dominate, they do so with greater superiority. The average monthly return premium for periods of value dominance is 4.64%, well above the 3.75% average monthly premium for periods when growth stocks dominate. This suggests that minor timing errors while using an equity style switching strategy could eliminate any profits compared to those using a simple buy and hold value strategy.

Figure 2 illustrates the return volatility of the Fama and French HML factor - again the factor being a mathematical representation of the value premium itself. The historical time series of HML

[14] Average monthly returns of the 1st and 10th BE/ME decile portfolios are obtained from the website of Kenneth French.

returns shows several unusual periods of shock notably during the 1930s, 1970s, and 1990s. These shocks are further illustrated in the frequency distribution of HML return observations shown in Chart B. Since 1926, a large portion of the premium has been earned during rare (or outlier) monthly return periods. Value stocks dominate growth stocks at return levels greater than 10% in thirteen of the 975 months from July 1926 to September 2007. Interestingly, when the thirteen extreme monthly returns are removed from the sample, the average monthly HML premium is more than halved from 0.41% to 0.19%.

Periods of extreme volatility in the value premium illustrate serious problems facing investors who try to tactically capture the value premium. Investment managers who construct high BE/ME portfolios for their clients must survive any extended period when value stocks underperform their growth counterparts. Even a buy and hold strategy may not prevent value managers from being fired by their clients in the short term. As an illustration, Figure 3 demonstrates that value strategies do not always dominate growth strategies over a reasonable portfolio evaluation period. Chart A shows that investors who constructed a portfolio to capture the value premium beginning in the mid-1990s

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FIGURE 2: The stability of High BE/ME stock returns minus Low BE/ME stock returns. July 1926 to Sept 2007. (n = 975)

HML factor data sourced from the website of Kenneth French. HML (High minus Low) is the "average return on the two value portfolios minus the average return on the two growth portfolios." HML = 1/2(SV +BV) – 1/2(SG +BG).

Chart A: Fama and French HML factor return stability.

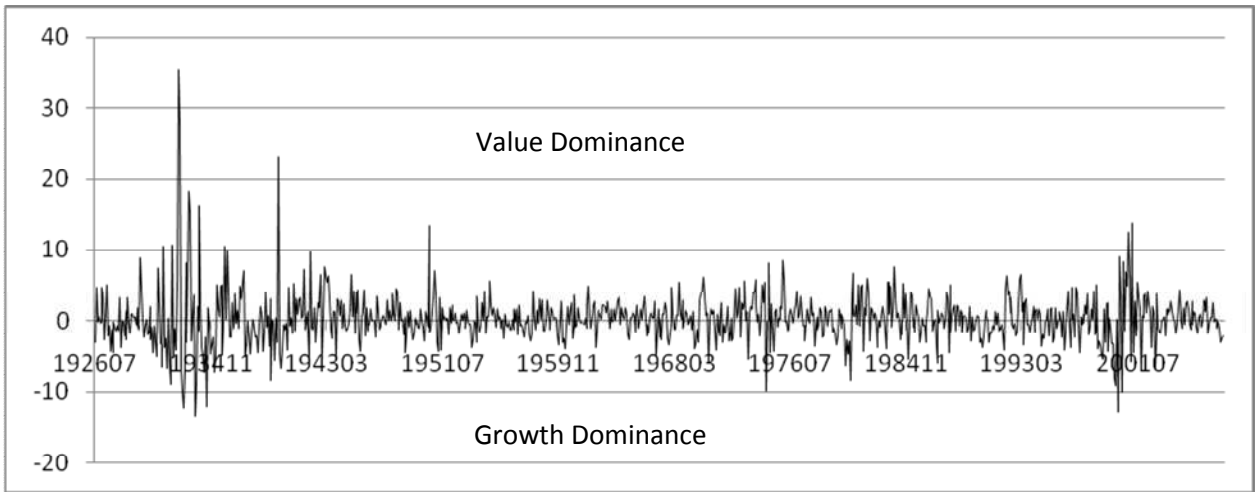
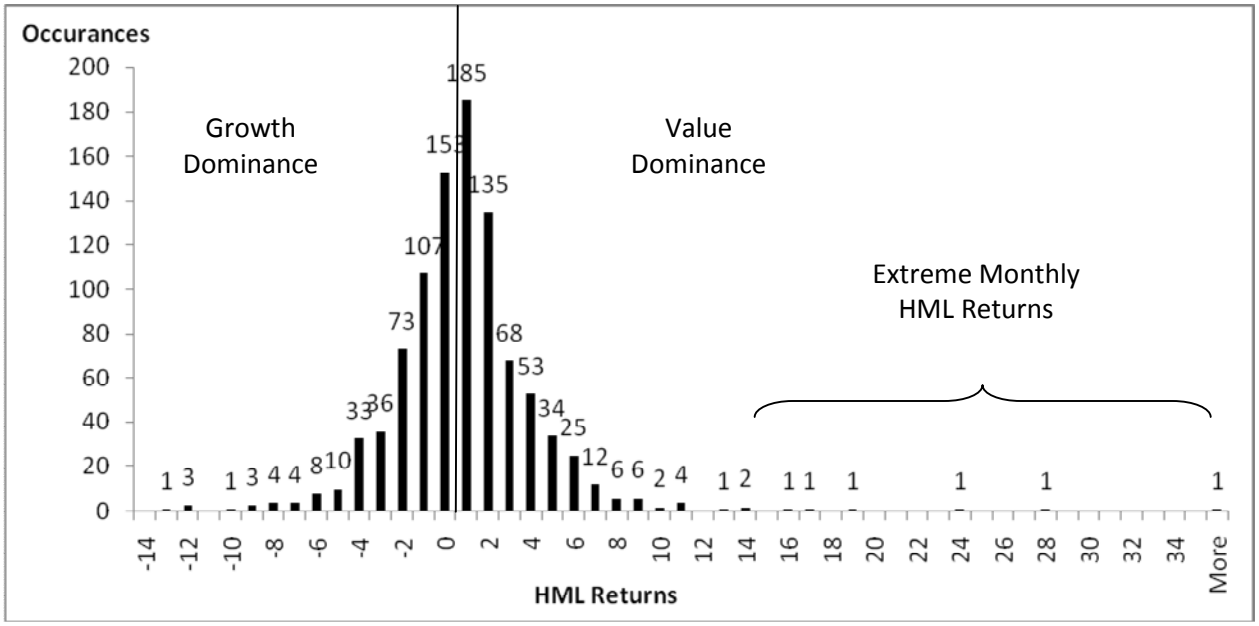


FIGURE 2: continued

Chart B: Distribution of monthly HML factor returns



would have been disappointed. Growth stocks outperformed value stocks during the five year period ending December 1999. This results contrasts with those in Chart B for the subsequent market period five years ending December 2006. Although research findings have indicated the latter period to be more typical of outcomes over time, this is not likely to comfort investment managers who are fired by their clients for poor relative performance during a market period similar to that in Chart A.

Section 5: Recent research

5.1 The value premium, risk, and the dispersion of earnings forecasts

Doukas, Kim, and Pantzalis (2004) use a novel approach to determine whether the difference in value and growth returns compensates for risk. The authors working under the assumption that investors' heterogeneous beliefs have implications in asset prices employ the dispersion of analyst forecasted earnings of companies as a proxy for risk. Chen and Zhang (1995) had previously used the standard deviation of the earnings yield (E/P) as a risk proxy for the same reason. However, it can be

FIGURE 3: Geometrically linked cumulative monthly returns of portfolios formed on BE/ME. Returns are those of the highest 30% BE/ME stocks (value) minus the lowest 30% BE/ME stocks (growth).

Chart A: 5-Year growth stock dominance: January 1995 to December 1999

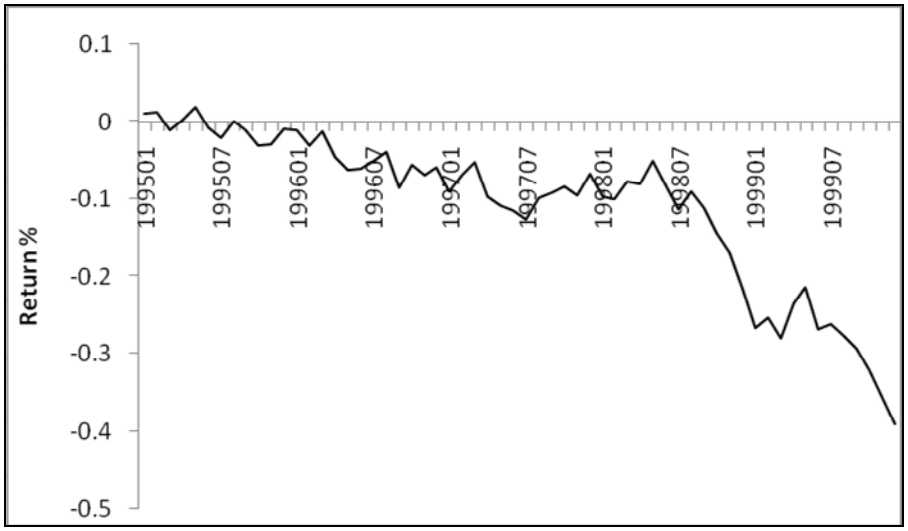
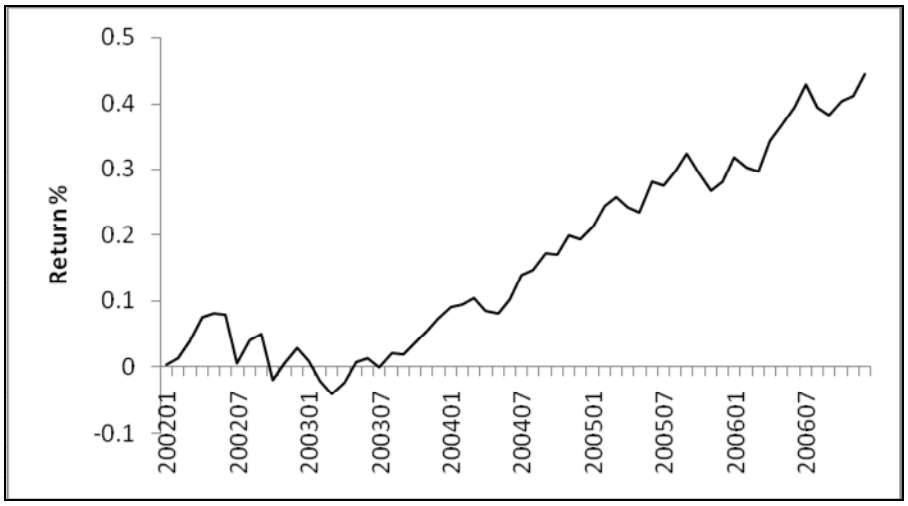


Chart B: 5-Year value stock dominance: January 2002 to December 2006



Value-weighted monthly return data sourced from the website of Kenneth French.

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argued that the variation in the historical yield does a poorer job than analyst forecasts when proxying for *future* uncertainty, or risk, in earnings.

Deither, Malloy, and Sherbina (2002) find that stocks with high dispersion of earnings forecasts perform poorly compared to stocks with low dispersions. However, when the sample of all stocks is

segmented by BE/ME characteristics, Doukas, Kim, and Pantzalis (2004) find that higher value stock returns are indeed associated with greater investor disagreement about forecasted earnings. The authors observe the dispersion of analyst earnings for portfolios independently sorted by size and then by BE/ME and find that portfolios of high BE/ME value stocks exhibit greater investor disagreement than portfolios of low BE/ME growth stocks.[15] They argue their results are consistent with a risk-based explanation - that future earnings streams for value stocks are viewed with lower levels of certainty and necessitate higher compensation for holding them.

5.2 Intangible assets and the value premium

Nelson (2006) suggests that if the market discounts intangible assets at a higher rate than tangible assets, then the level and type of a firm's intangible assets could impact the book-to-market valuation. Nelson uses R&D and advertising spending sourced from the income statement (rather than the balance sheet) as proxies for intangible asset risk factors. While Nelson's model improves upon the explanatory power of the 3-factor model and eliminates two mis-specification anomalies, the lack of a direct decomposition of R&D and advertising from accounting book equity potentially casts a shadow on the relevance of intangible assets to explain the true origin of the book-to-market effect found in prior research.[16]

However, another research lineage may provide the link between balance sheet intangibles and the book-to-market effect, and by extension to the value premium. As mentioned in the previous section, Doukas et al. find that higher performing value stocks exhibit a greater variation in earnings expectations than lower performing growth stocks. Moreover, Barron, Byard, Kile and Riedl (2002) find that investor disagreement – as defined by the correlation in individual analyst forecast errors – is associated with stocks with low levels of intangible assets and that high disagreement is associated with high levels of intangible assets. In a risk framework, these results suggest that high levels of intangible assets create greater uncertainty and greater risk in pricing expected future cash flows. With some caveat in making any claim of transitivity from disjointed lineages of research, the findings mentioned above suggest that if value stocks are associated with high investor disagreement, and if high investor

[15] For robustness, the authors perform a second test triple sorting earnings dispersion on size, BE/ME, and the number of analysts forecasts to ensure higher earnings dispersion in value stocks was not due to a smaller number of analysts covering these stocks vis a vis growth stocks. Shown in the prior section in this research, Table 7 confirms the monotonic relationship between size and analyst coverage. But consistent with Doukas et al, results also do not show any relationship between value or growth stocks and analyst coverage when controlled for size.

[16] Results suggest that book-to-market equity and income statement 'intangibles' both proxy for the same unknown common risk factor.

disagreement is associated with high levels of firm intangible assets, then it potentially follows that value stocks should be associated with high levels of firm intangible assets. In this line of thinking, it might be theorized that the BE/ME premium is a reward for assuming greater risks associated with uncertainty in pricing intangible assets.

Unfortunately, such a proposed research lineage that improves upon the use of intangibles from the income statement in Nelson (2006) is probably more complex. In fact, it is clear that the above transitive condition is not true. Low BE/ME growth stocks, such as those in the healthcare and computer technology sectors are more commonly associated with high levels of balance sheet intangible assets as a percent of total assets. Patents, software and so forth, as well as income statement expenditures such as R&D, are less likely to be found in high BE/ME value stocks. Intangible assets found in high BE/ME value stocks are more likely to involve accounting for goodwill rather than an investment into the company's future prospects.

However, if the type of intangible assets in value stocks – despite their smaller relative size in proportion to total assets – are found to be riskier than the type of intangibles found in growth stocks, then the transitive lineage of research from value stocks to intangible assets could hold. If tangible assets are indeed discounted at a lower rate than intangible assets, then it is expected that the value premium should appear relatively stronger in a sort on the intangible component of BE/ME, and diminish or disappear in an independent sort on the residual book-to-market computation (BE/ME minus the intangible assets).

As a cursory test of this thesis, portfolios of NYSE, AMEX, and NASDAQ stocks, shown in prior research to exhibit a strong value premium, are re-tested by decomposing book value of equity into the intangible component of BE and its residual, i.e. a company's book equity minus its intangible assets. Results in Panel A of Table 9 show that the value premium (H-L) in portfolios sorted on the residual (tangible) portion of BE/ME remarkably disappear. Low t-statistics indicate that none of the H-L value premium returns are different from zero, although economically the value premium continues to exist in the tangible component of BE/ME.

Like those for the residual book value, average value-weighted portfolio returns sorted for the ratio of intangible assets divided by ME shown in Panel B show no statistically significant value premium. In fact, three of the five H-L returns economically reflect a growth premium rather than a value premium. If the value premium disappears when intangible assets are removed from BE/ME computations, then it should be surprising to find it also absent when stocks are sorted for INTAN/ME. Results in Panel B are disappointing and cast doubt as to the meaning of initial results in Panel A. A

Table 9: Average monthly value-weighted returns of portfolios sorted 5x5 on size and then on two disaggregated components of the book-to-market characteristic. July 1989 to June 2007 (n = 216).

To construct homogeneous portfolios, stocks are first sorted independently on size and then on either the ratio of Intangible assets divided by market equity (ME) or the ratio of the aforementioned residual, BE/ME – INTAN/ME. Both market equity and Intangible assets (defined in Research Insight using the mnemonic INTAN) are observed for stocks at year end December of year t-1. Deferred taxes and investment tax credits, observed at December of year t-1, are added each year to intangibles in order to facilitate a direct comparison to aggregate book equity computed in Fama and French (1993). Stocks with negative intangible book value or the tangible residual are omitted, as is the custom in prior research. Market equity used to control for size is observed at June of each year t. Portfolios are formed annually at July of year t between July 1989 and June 2007. Portfolio returns are observed from July of year t through June of t+1.

Panel A: Sorts on size and residual book-to-market (intangibles removed)

	Book-to-market*						
	Low	2	3	4	High	H-L	t-stat
SMALL	1.65	1.91	1.57	1.63	1.94	0.29	0.87
2	1.25	1.23	1.42	1.51	1.55	0.30	1.03
3	1.23	1.39	1.27	1.38	1.58	0.35	1.09
4	1.39	1.13	1.43	1.37	1.47	0.08	0.25
LARGE	1.04	1.20	1.25	1.15	1.43	0.38	1.22

Panel B: Sorts on size and intangible book-to-market

	INTAN/ME						
	Low	2	3	4	High	H-L	t-stat
SMALL	1.66	1.62	1.60	1.85	2.02	0.36	1.38
2	1.46	1.45	1.43	1.39	1.51	0.05	0.20
3	1.68	1.25	1.29	1.33	1.36	-0.32	-0.98
4	1.52	1.28	1.24	1.22	1.13	-0.39	-1.14
LARGE	1.11	1.15	1.06	1.02	0.98	-0.13	-0.46

result showing the value premium absent from both disaggregated components of BE/ME appears to provide further evidence that BE/ME acts as a proxy (in aggregate form only) for some other common risk factor in explaining the variation in stock returns. For robustness, average portfolio returns were computed using equal weights, but results were not meaningfully different from those in Table 9.

5.3 Migration

Researchers have tried to understand the origins of the value premium since the publication of Rosenberg, Reid, and Lanstein (1985). The driver of the premium, however, cannot be understood theoretically until there is a definitive mapping of exactly where the premium originates statistically in

the various BE/ME and size portfolios. Fama and French (2007) once again lead the community in addressing that question and provide a nice illumination of the changing size and BE/ME characteristics of individual stocks when viewed across annual periods of portfolio formation. This type of portfolio movement is described by Fama and French as *migration*.

According to the authors, the migration of value stocks provides the largest economic impact on the value premium. While some of the impact on returns is generated by a few extremely distressed high BE/ME firms that are ultimately removed from the computation of portfolio returns, and by a few value companies that are acquired by other companies, most of the difference in returns is generated when value stocks subsequently earn high operating returns and are rewarded with higher market values. Mechanically, these successful value stocks migrate from high BE/ME portfolios toward larger size, lower BE/ME quintiles at the time of annual portfolio formation.

Next, Fama and French find that the value premium is also a function of poorer performance by the lowest BE/ME growth stocks that migrate to core size and BE/ME portfolios at the time of annual portfolio formation. However, the impact from growth stock migration is smaller than that from value stock migration. Value stocks that migrate contribute approximately 3.5% more per year to overall returns than growth stocks that migrate. However, migratory growth stocks that suffer deteriorating fundamentals generate a relative return disadvantage to similarly suffering value stocks by 5.1% per year for small cap stocks and a return disadvantage by 1.2% for large cap stocks.

Finally, Fama and French suggest that the value premium is also generated by growth and value stocks that do not change characteristics over time and thus do not migrate. However, the difference in performance is small for this group of non-migratory stocks. Small cap stocks that do not migrate contribute 1% per year to the value premium, while large stocks contribute 1.7%. The authors describe this contribution to the value premium as *modest*.

Figure 4 provides a graphical illustration of data presented in Fama and French (2007).[17] The two charts represent two ends of the size and valuation spectrum, i.e. big growth stocks and small value stocks. In Chart A, Fama and French observe returns for stocks that begin in the Big/Growth portfolio and then observe their average annual migration to various size and BE/ME portfolios. Results show that stocks migrating away from the Big/Growth portfolio to smaller ME characteristics typically generate large negative returns - as would be expected. Big/Growth stocks that do not migrate (87% of stocks) generate small, albeit positive, returns. The total average portfolio return for Big/Growth stocks over the entire sample period is a loss of almost 1% per year.

[17] Fama and French (2007), Tables 1 and 2.

Chart B shows that approximately 31% of surviving Small/Value stocks (not defunct or acquired) migrate and change characteristics, a percentage significantly greater than their Big/Growth counterparts. While average annual returns for non-migrating Small/Value portfolio are also fractionally positive (0.40%), one-step migration as a function of changes to BE/ME from Small/Value to Small/Neutral is large (16% of stocks) and generates large positive annual returns (+19%). One-step migration as a function of changes to size from Small/Value to Big/Value is relatively small, only 5% of stocks in the original portfolio. However, this migration generates very large average annual returns (+53%). It is important for investment managers who analyse these results for potential exploitation to remember that Fama and French rebalance portfolios yearly; therefore, the same stocks are not likely responsible for generating returns of 166% per year for the few stocks (0.3%) migrating from the Small/Value to the Big/Growth portfolio.

Fama and French explain stock migration by saying that extreme portfolio size and BE/ME quintiles are simply bounded by operational reality. Again, higher distressed value companies, identified at the beginning of each statistical year, become defunct, acquired for a premium, or restructure and

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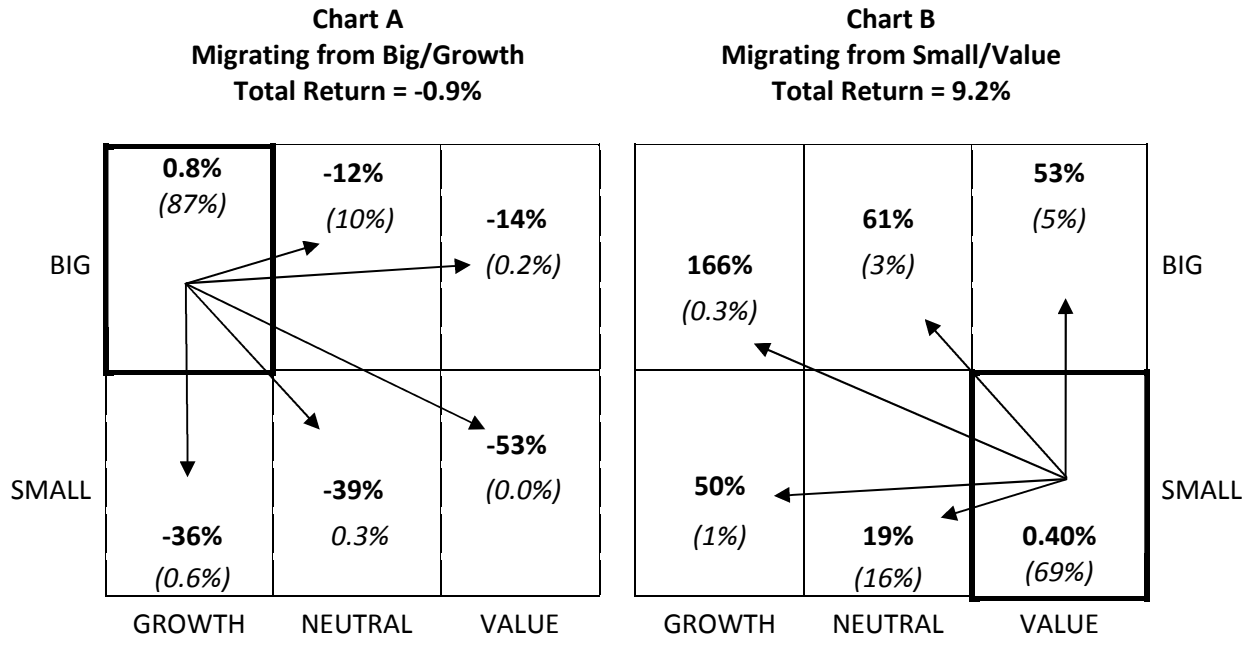
FIGURE 4: Average annual returns of stocks migrating from Big/Growth and Small/Value portfolios. (percent market cap of migrating stocks in parenthesis)



Data source: Fama and French (2007), Tables 1 and 2

improve in type during subsequent annual observation periods. The status quo distress condition is largely untenable for such companies. Results are consistent with observations in Fama and French (1995) that growth stock earnings, relatively strong at portfolio formation, tend to migrate in the subsequent period to lower levels. Poor value stock earnings, observed at portfolio formation, tend to rebound in the subsequent return observation period. Again, behaviouralists would suggest investor surprise is responsible for the return premium and not risk differences.

Fama and French (2007) somewhat logically observe that negative migration of value stocks is (and would be) rare. There is simply nowhere to go for these stocks but up or out. Similarly, the least distressed growth companies that are identified at the beginning of each portfolio formation period have little room to improve; therefore, positive migration for these stocks is rare. There is nowhere to go for growth stocks but down or out.

Figure 5 illustrates what should be the typical bounded characteristics for the accounting book value statistic. The chart plots the relationship between all NYSE, AMEX, and NASDAQ stock returns and their price-to-book characteristics observed at January 2007. The usual BE/ME ratio has been flipped to ME/BE (or price-to-book) to better reflect the migratory relationship for conditions of negative book value. The distressed value condition (in this instance low P/B) is clearly bounded by zero since stocks rarely experience negative book values for any meaningful period of time.[18] Growth stocks also have a statistical P/B ceiling. For the month ending January 2007, few stocks trade at more than 10 times its fundamental value – a condition not likely to vary greatly over time.

Since 1992, the academic and investment community have debated the existence and origins of the value premium in US and global stock returns. The lineage of almost two decades of academic research has been dominated largely by two authors, Eugene Fama and Kenneth French. The research conversation over this period can best be characterised by a repeating cycle of three phases. First, Fama and French offer periodic advances in assessing the validity of the 3-factor model and its ability to successfully explain the cross section of average stock returns. Next, other researchers test potential problems with the model or attempt to advance the identification of the underlying risk (or behavioural condition) for which the individual factors proxy; and finally, Fama and French produce research rebuttals to successful challenges to their work. Unfortunately, the repeating cycle of the three phases has yet to conclusively identify why the value premium exists, whether it is a function of some

[18] Negative book value stocks represent less than 1% of the sample used in Fama and French (2007).

underlying common risk factor, or whether it is simply a un-arbitraged persistent return premium originating from investor over-reaction.

Section 6: The value premium in managed portfolios

Evidence from Houge and Loughran (2006), Chan, Chen, and Lakonishok (2002), and Phalippou (2008) suggests that institutional investment consultants should not rush to alter the methods by which they have traditionally hired and fired fund managers – despite academic findings of a statistical value

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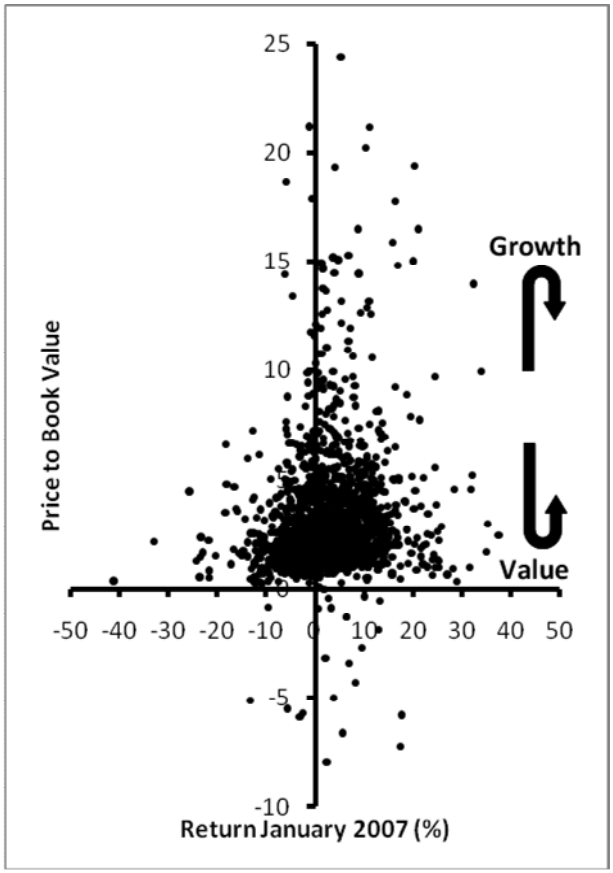
FIGURE 5: Single period observation of the relationship between NYSE, AMEX, NASDAQ stock returns for the month of January 2007 and price-to-book value characteristics captured at year end December 2006. The sample is winsorized at 1%. (n = 1932)

Data for all NYSE, AMEX, and NASDAQ stock returns and their price-to-book characteristics observed at January 2007 from Compustat via Market Research. The usual BE/ME ratio has been flipped to ME/BE (or price-to-book) to better reflect the migratory relationship for conditions of negative book value.



equity premium. Chan et al. (2002) find that US growth mutual fund managers actually contradict what would be expected by the body of research and outperform value managers by about 1.2% per year. However, that difference is largely found in the small-cap fund subset – a condition problematic for managers with billions of dollars to invest. Due to trading difficulties, large Institutional funds are able to purchase only the largest and most liquid securities.

Is illiquidity the reason managers have yet to capture the elusive value premium promised in the body of academic literature? Argawal and Wang (2007) recently argue that if high transaction costs prevent the arbitrage of the premium, then "value stocks will appear to have higher returns than growth stocks when in fact the transaction-cost-adjusted returns of these two types of stocks are similar." The authors find that value stocks have higher costs associated with trading and that once returns are adjusted for these costs, the value premium disappears. Similarly, Brown, Crocker, and Foerster (2009) find that three measures of stock trading liquidity are negatively related to BE/ME. Testing a sample of large cap S&P 500 index constituents and a sample mimicking the Russell 1000 large cap index constituents, the authors find that low BE/ME growth stocks are associated with higher liquidity and high BE/ME value stocks are associated with lower liquidity. However, the authors observe that low liquidity of value stocks are not associated with higher returns in two of the three liquidity measures, namely dollar volume of trading, daily trading volume, and percentage turnover. This result is likely due to the use of a sample of large cap S&P 500 index constituents in their research. Large cap value stocks are relatively more illiquid than large cap growth stocks, but the size strata used in the research was apparently too large to provide a further association between illiquidity and relative returns. Houge and Loughran do not find a statistically significant value return premium in the large cap S&P 500/BARRA style indexes and Loughran (1997) observes that the value premium disappears in a sample of large cap NYSE, AMEX, and NASDAQ stocks. The authors also find that mutual fund expense ratios cannot account for the failure of value funds to capture the value premium. Houge and Loughran observe that growth funds typically charge much higher fees to investors than do value funds – and as such, the fees should accentuate rather than mitigate the return spread to investors.

Phalippou (2008) finds that portfolios constructed of stocks with high concentrations of institutional ownership, representing 93% of total market capitalization of US equities, do not exhibit a value premium. Conversely, portfolios constructed of stocks held by individual investors exhibit a substantial value premium. Phalippou finds that the book-to-market effect, explaining the cross sectional variation in average returns, is strong in stocks with low institutional ownership and not statistically significant in stocks with high institutional ownership. Similarly, Nagel (2005) uses the level

of institutional ownership as a proxy for stock loan levels and finds that the book-to-market effect is strongest in stocks that are the most difficult for which to execute short sales (i.e. small illiquid stocks).

Both Phalippou and Nagel conclude that the value premium is indeed due to mis-pricing of small stocks or hard-to-short stocks, and that any attempt by the investment industry to capture the premium would be cost prohibitive. Nagel observes that the value premium is driven mostly by growth stocks with low institutional ownership rather than the consistently superior performance of value stocks (regardless of institutional ownership). Nagel suggests that although optimistic investors overvalue growth stocks, arbitrageurs are prevented from shorting them due to market constraints - such as high transactions costs relating to low stock loan supply. Therefore, these (typically small) overvalued growth stocks subsequently generate low returns relative to value stocks. Each author rejects the thesis of Fama and French that the value premium is a function of risk pricing.[19]

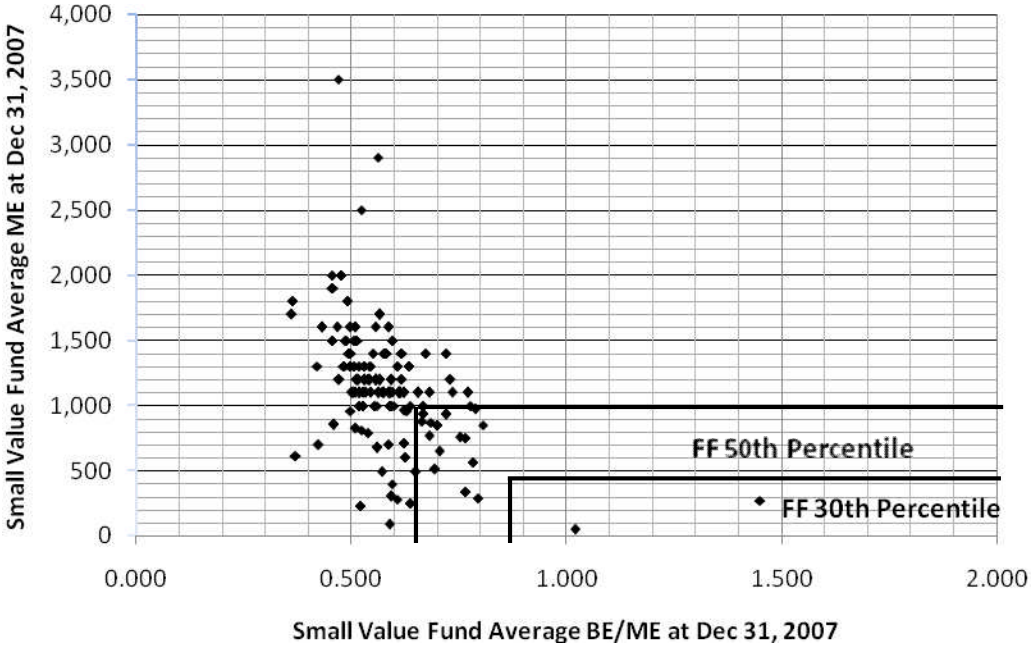
According to Chan et al., value managers have yet to seize upon their natural superior market position. Figure 1, a snapshot of size and BE/ME characteristics of all US small cap value funds at 31 December 2007, provides a good illustration of the problems addressed by Chan et al. Average fund BE/ME and ME characteristics for 371 funds are captured and plotted against Fama-French BE/ME and ME portfolio formation breakpoints averaged for the period January 1991 to December 2006.[20] The marketplace's definition of small is clearly inconsistent with that defined in Fama and French (1993) and is likely to prevent investors in those actively managed funds from capturing effects suggested in research. Of course, mutual fund BE/ME and ME characteristics can and do migrate somewhat over time. However, the snapshot of size and BE/ME characteristics shown in Figure 6 hints at the difficulty investors will face in capturing the value premium using actively managed US mutual funds. Results show only two of the 371 small value mutual funds reflect ME characteristics smaller than the Fama-French 30th percentile size breakpoint and BE/ME characteristics higher than the 30th percentile book-to-market breakpoint – areas shown to exhibit the strongest value premium.

[19] Phalippou's findings were extensively publicized and reported by the New York Times, the Wall Street Journal, The Economist, and the Financial Times.

[20] Small cap value funds are identified using the readily available Morningstar online screening tool. Detzel (2006) finds that discrete factor loadings generally perform better than the Morningstar characteristics-based methodology in determining a fund's equity style. However, the author finds that the readily available Morningstar screen performs better than DFL after 2003 when Morningstar altered its methodology.

FIGURE 6: Characteristics of US Small Value Funds at 31 December 2007 Compared to the Fama-French BE/ME and ME Breakpoint Percentiles (all stocks)

Funds were identified using the readily available Morningstar fund screening tool and sorted for the small value style. Average BE/ME and ME characteristics for 371 small value funds were captured at December 31, 2007 and plotted against Fama-French BE/ME and ME breakpoints. Breakpoints were found at the website of Kenneth French and are averaged for the period January 1991 to December 2006. The FF 30th percentile in this presentation describes the highest BE/ME percentiles and the lowest ME percentiles.



Appendix A: An updated analysis of the Fama and French 3-factor model

A.1: Updated 3-factor model results

Fama and French (1993) argue that the regression slopes (factor loadings) and R^2 of the factor mimicking portfolios, SMB and HML, can provide "evidence of shared and un-diversifiable risk factors" and thus indicate whether stocks are priced rationally. They further argue that their 3-factor model should not only capture the variation in returns, but that it should also explain the cross-section of average returns. As in Merton (1973), this means that the estimated intercepts of the regressed explanatory variables should be zero. Fama and French observe that when excess returns of twenty-five portfolios of NYSE, AMEX, and NASDAQ stocks formed on size and BE/ME are regressed on a single factor model of excess market returns, a majority of the intercepts are large and statistically greater than zero. When only the SMB and HML factors are used, the intercepts for the twenty-five portfolios are again almost all statistically significant. According to the authors, while the two factors alone may explain the difference in average returns, they do not explain excess returns over one-month treasury bills. When the excess returns of 25 portfolios are regressed on all three factors, the intercepts are almost all statistically zero. Fama and French argue that a 3-factor model is thus properly specified leaving no residual size and BE/ME effect in average returns. Contrary to their earlier tests, Fama and French observe that the market factor is indeed needed to perform the task of explaining the cross section of average stock returns successfully.[21]

Panel A of Table A1 shows 3-factor model regression intercepts for 25 portfolios independently sorted on size and BE/ME as replicated from Fama and French (1993).[22] For the sample 1963 to 1992, three of 25 intercepts are statistically different from zero – each from the low BE/ME growth stock segment of the matrix. Later, Davis, Fama, and French (2000) use a longer observational period beginning in 1929 and observe mixed results for the 3-factor model in explaining average returns of low BE/ME growth portfolios. While only one of their nine intercepts is significant in the longer sample period, the offending portfolio once again represents a portfolio of the smallest ME and lowest BE/ME

[21] Carhart (1997) adds a fourth factor to explain the effects of short term momentum in stock prices. Jagadeesh and Titman (1993) show that stocks with poor recent performance continue to exhibit poor future performance over the short term. Davis (2001) accepts that the 3-factor model performs poorly in explaining stock price momentum but argues that the issue is largely inconsequential due to high transaction costs implicit in any attempt to earn abnormal returns from the strategy. The subject of momentum is largely ignored in this research because, unlike the issue of size, it has greater implications for the proper specification of explanatory models rather than implications for whether investors can capture the difference between value and growth stock returns.

[22] Fama and French (1993), Table 9a, page 36.

TABLE A1: Regression intercepts of 25 portfolios formed on ME and BE/ME for various sample sets: FF 3-Factor Model. Value weighted excess returns.

Regression intercepts for July 1963 to Dec 1992 are replicated from Fama and French (1993). As in FF (1993), average monthly excess portfolio returns are computed as the Jan 1992 to Dec 2006 average of the value-weighted monthly portfolio returns. This data as well as three-factor model returns are obtained from the website of Kenneth French. The updated sample excludes stocks with negative book value similar to the presentation in Fama and French (1992), but unlike the presentation in Fama and French (1993), the sample for the present computations includes stocks from the financial and utility sectors.

$$Rpt - Rft = a + b[\mathrm{R}mt - \mathrm{R}ft] + s\mathrm{SMB}t + h\mathrm{HML}t + et$$

Panel A: Fama and French (1993) Results July 1963 to December 1992 (n = 354)

	a					t(a)				
	LOW	2	3	4	HIGH	LOW	2	3	4	HIGH
SMALL	-0.34	0.12	-0.05	0.01	0.00	-3.16	-1.47	-0.73	0.22	0.14
2	-0.11	-0.01	0.08	0.03	0.02	-1.24	-0.20	1.04	0.51	0.34
3	-0.11	0.04	-0.04	0.05	0.05	-1.42	0.47	-0.47	0.71	0.56
4	0.09	-0.22	-0.08	0.03	0.13	1.07	-2.65	-0.99	0.33	1.24
BIG	0.21	-0.05	-0.13	-0.05	-0.16	3.27	-0.67	-1.46	-0.69	-1.41

Panel B: Updated Sample Results January 1992 to December 2006 (n = 180)

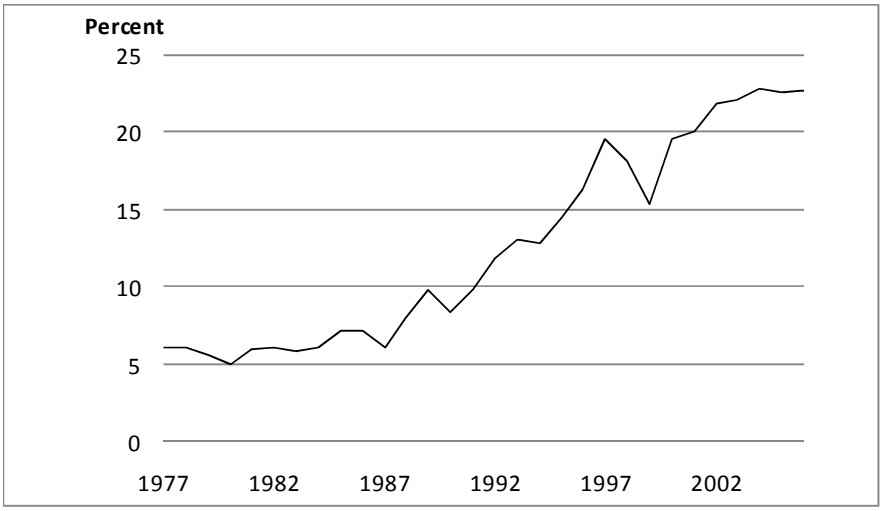
	a					t(a)				
	LOW	2	3	4	HIGH	LOW	2	3	4	HIGH
SMALL	-0.68	0.20	0.32	0.47	0.35	-3.00	1.19	2.64	3.63	2.68
2	-0.38	-0.25	0.00	-0.09	-0.24	-2.69	-1.96	-0.01	-0.81	-2.04
3	-0.11	-0.20	-0.21	-0.36	-0.05	-0.81	-1.26	-1.51	-2.57	-0.32
4	0.11	-0.14	-0.13	-0.12	-0.29	0.84	-1.02	-0.92	-0.84	-1.75
BIG	0.21	0.01	-0.10	-0.21	-0.31	2.56	0.12	-0.74	-1.59	-1.56

growth stocks. Moreover, when Davis et al, test a sub-sample, 1963 to 1997, one third of their nine portfolio intercepts are statistically different from zero. Two of the three offending portfolios have low BE/ME growth characteristics. Panel B of Table A1 presents an updated sample of returns from January 1992 to December 2006. In this sample (albeit taken from a shorter, more volatile observation period), eight of 25 intercepts statistically differ from zero and economically range in value from -0.68% per month to as much as 0.47%. The 3-factor model continues to have difficulty explaining growth stock returns in this extended time period.

A.2: Omission of financial stocks

In Fama and French (1993), the authors argue that "the high leverage that is normal for [financial] firms probably does not have the same meaning as for nonfinancial firms, where high

FIGURE A1: Financial services sector as a percent of total market capitalization of the S&P 500 Index.[23]



leverage more likely indicates distress." Therefore, the authors omit financials from their sample of NYSE, AMEX, and NASDAQ stocks used to construct homogeneous portfolios. This omission is problematic conceptually for a number of reasons, one of which is simply the circular nature of their thesis assigning distress as the origin of higher risk in value securities. Fama and French omit securities on the basis of differing implications of distress and then explain that distress is a likely proxy for their research findings. However, more problematic for the stability of the 3-factor regression slopes is that financials as a percent of the total market capitalization has grown dramatically over time. As an illustration, the chart in Figure A1 shows that financials have steadily risen from a market capitalisation weight of 6% of the S&P 500 index in 1977 to 23% at year-end 2006. The mean weight for financials over 15 years ending 1991, the end date of data in Fama and French (1992), was only 6.9% of the S&P 500 Index at the time of their omission. It is clearly more difficult for researchers to claim that a pricing model successfully captures the cross section of average stock returns while omitting whole sectors of the economy from their examination. Ironically, the omission of financial stocks may have successfully silenced nagging data mining criticisms of the early work of Fama and French. Barber and Lyon (1997) test the hold-out sample of US financial stocks and compare their characteristics to those stocks used in the prior Fama and French studies. The authors find few material differences between the two samples.

[23] Data sourced from the website of Morgan Stanley Capital International subsidiary, Barra, on January 11,2008; http://www.barra.com/Research/SectorWeights.aspx

Since value fund managers typically hold financials in large proportion to other sectors, any reconciliation between academic research testing individual securities and observations of the performance of managed investment portfolios must deal with this very large data omission. Table A2 shows a new estimation of 3-factor model regression coefficients for 25 portfolios formed on size and BE/ME covering the same sample period as in Fama and French (1993). Consistent with what Barber and Lyon predict, results show that omitting financials and utilities have no material impact on the explanatory power of the model during this sample period. Twenty of twenty-five intercepts remain near zero and insignificant and not materially unlike those shown earlier in Panel A of Table A1. Market betas are all close to one while the slopes for size and value are, with few exceptions, significant at the5% level. Most importantly, the economic size and value effects remain intact. In every quintile, average portfolio returns [not shown] rise monotonically from large stocks to small stocks and rise monotonically from low BE/ME stocks to high BE/ME stocks. It is clear that criticism of early Fama and French studies over the omission of financial stocks has little merit.

A.3: The HML factor introduces a downward bias in the intercept

Nelson (2006) addresses two long-recognized problems with the 3-factor model, namely the failure of the model to successfully explain portfolio returns sorted by industry and the failure of the model to explain NASDAQ stock returns. Fama and French (1997) acknowledge the problem when observing that ten of their forty-eight industry regression intercepts are significantly different from zero.[24] Addressing a more worrisome problem, the authors observe that the Pearson correlation between the intercept and the HML slope coefficient is negative (ρ = -0.67) and significant at the 1% level. Fama and French speculate that the 3-factor model could be exaggerating what they theorize as the distress premium proxied by the HML factor or that the significant negative correlation is simply a result of time varying risk loadings.

To answer the question of factor bias posed in Fama and French (1997), Nelson constructs one thousand random portfolios from NYSE, AMEX, and NASDAQ stocks and observes simulated returns for these portfolios from 1973 to 2001. From this data, the author computes mean coefficients on one thousand regressions for four basic models: the market model of Jensen (1968), a second model adding the Fama and French SMB factor to the single factor market model, a third model adding the Fama and French HML factor, and a fourth model constructed from all three factors. Regression results on

[24] Fama and French (1997), Table 2 pp. 157-158.

TABLE A2: Reformulated 3- factor model regression intercepts and slopes of 25 portfolios formed on ME and BE/ME. Data includes Financial and Utility stocks omitted in Fama and French (1993). July 1963 to December 1992. (n = 354)

Results in Table A2 are directly comparable to those in Panel A of Table A1. Excess portfolio return data as well as three-factor model returns are obtained from the website of Kenneth French. The sample excludes stocks with negative book value similar to the presentation in Fama and French (1992), but unlike the presentation in Fama and French (1993), the sample for the present computations includes stocks from the financial and utility sectors.

$$Rpt - Rft = a + b[\mathrm{R}mt - \mathrm{R}ft] + s\mathrm{SMB}t + h\mathrm{HML}t + et$$

	a					t(a)				
	LOW	2	3	4	HIGH	LOW	2	3	4	HIGH
SMALL	-0.41	-0.09	-0.09	0.09	0.06	-3.93	-1.09	-1.47	1.43	0.91
2	-0.12	-0.01	0.18	0.15	0.09	-1.46	-0.18	2.73	2.36	1.36
3	-0.02	0.13	0.00	0.16	0.06	-0.23	1.73	0.04	2.42	0.68
4	0.14	-0.15	0.04	0.09	0.04	1.86	-1.85	0.43	1.16	0.41
BIG	0.22	0.00	-0.04	-0.08	-0.18	3.29	0.03	-0.48	-1.07	-1.57

	b					t(b)				
	LOW	2	3	4	HIGH	LOW	2	3	4	HIGH
SMALL	1.04	0.97	0.94	0.90	0.96	39.97	50.06	59.73	59.06	58.20
2	1.11	1.03	0.97	0.97	1.07	53.69	59.10	60.43	62.92	64.00
3	1.11	1.03	0.97	0.97	1.07	59.59	56.72	53.70	58.64	51.49
4	1.07	1.08	1.05	1.04	1.15	57.58	53.08	51.58	51.04	46.30
BIG	0.96	1.03	0.97	1.01	1.04	57.19	57.40	44.25	55.54	36.98

	s					t(s)				
	LOW	2	3	4	HIGH	LOW	2	3	4	HIGH
SMALL	1.42	1.29	1.15	1.11	1.20	37.53	45.58	50.05	50.00	50.08
2	1.00	0.91	0.83	0.71	0.84	33.33	36.18	35.77	31.52	34.54
3	0.70	0.61	0.54	0.44	0.64	25.62	23.25	20.37	18.09	21.23
4	0.29	0.26	0.23	0.20	0.35	10.89	8.75	7.84	6.69	9.58
BIG	-0.20	-0.20	-0.27	-0.19	-0.04	-8.23	-7.75	-8.56	-7.28	-1.01

	h					t(h)				
	LOW	2	3	4	HIGH	LOW	2	3	4	HIGH
SMALL	-0.28	0.10	0.25	0.38	0.64	-6.68	3.19	9.81	15.33	23.63
2	-0.48	0.02	0.23	0.46	0.69	-14.13	0.76	8.63	18.26	25.27
3	-0.44	0.04	0.31	0.49	0.72	-14.27	1.32	10.41	18.01	21.02
4	-0.45	0.03	0.31	0.54	0.72	-14.95	0.90	9.17	16.34	17.62
BIG	-0.44	-0.01	0.20	0.55	0.79	-16.14	-0.47	5.57	18.39	17.21

simulated portfolio returns show the intercepts for both the Jensen and the Jensen+SMB models are not different from zero. However, when the HML factor is introduced to create Jensen+HML and Jensen+SMB+HML, the alpha becomes significant at the 10% and 1% level respectively.[25] Nelson's simulated results show that the HML factor generates a downward bias on the portfolio regression intercept by 70 basis points. Nelson suggests this downward bias potentially explains the persistent strong negative correlation between the alpha and HML coefficient in 3-factor regressions addressed in Fama and French (1997).

Since Fama and French (1997) define and allocate stocks to various industry portfolios using their own classification methodology, it should be interesting to determine whether classifying stocks with a different industry coding system provides a simpler solution to the 3-factor model's weakness in explaining industry returns. To evaluate this question, stocks are allocated to one of twenty-three industry groups using the Global Industry Classification Standard (GICS) rather than using SIC codes of Fama and French.[26] Average industry returns are observed from June 1999 to May 2007. Industry returns computed using equal weights are shown in Table A3 while those computed using value weights are shown in Table A4.

Three factor model regression results for equal-weighted excess industry returns show that intercepts are similarly problematic to those in Fama and French (1997). Four of the twenty-three intercepts, or 17%, are statistically greater than zero. This compares to 21% of intercepts in Fama and French (1997). However, when using value weights to compute returns, comparable to the method used in Fama and French (1997), none of the intercepts are statistically different from zero. Moreover, value-weighted GICS classified portfolios improves the explanatory performance of the model by reducing the average absolute regression alpha across the twenty-three industries from 0.59 for equal-weighted industry returns shown in Table A3 to 0.30 for the value-weighted returns shown in Table A4. By comparison, the average absolute regression intercept across the forty-eight value-weighted industry portfolios in Fama and French (1997) is 0.28, a condition almost identical to that for the value-weighted GICS defined industry portfolios.

Successful results for value-weighted returns presented in Table A4 seem to initially suggest that problems with model mis-specification in explaining average industry returns observed in Fama and French (1997) might be related to the choice of industry classification coding and to the choice of return

[25] Results also showed that adding SMB to the Jensen+HML model increases the HML coefficient by 60%. Nelson suggests this result is consistent with arguments in Loughran (1997) that the BE/ME effect is impacted by size.
[26] See Bhojraj, Lee, and Oler (2003) for a thorough analysis of the differences between GICS, SIC, NAICS, and Fama-French industry coding systems.

weights. However, the larger problem of negative correlation between the intercepts and the HML slope coefficient is not resolved using a different coding system. The Pearson correlation coefficient remains negative and statistically significant between intercepts and HML slopes in Table A3 (ρ = -0.53, t = -2.87) and also negative and significant in Table A4 (ρ = -0.52, t = -2.77).[27] Apparently using a different industry classification system does nothing to address any downward bias in the alpha caused by the HML factor as argued in Nelson (2006).

A.4: Recent time variation in 3-factor model coefficients

To illustrate the problem of any time variation in the power of the 3-factor model to explain more recent stock returns, the updated sample presented in Table A1 is split into two 5 year sub-periods. The choice of the split is deliberate to observe whether certain market conditions impact the performance of the 3-factor model. The first sub-period shown in Panel A of Table A5 reflects a period when growth stocks outperform value stocks. Results of this test show very little change in model specification from the overall sample in Panel B of Table A1. Once again, eight of the 25 intercepts differ statistically from zero ranging economically from 0.40% per month to -0.62%.

Results for the second sub-period shown in Panel B of Table A5 hint at a potential problem in 3-factor model construction. During the 5 year sub-period ending December 2004, the model performs extremely well, and certainly much better than the overall updated sample time series and the prior series sample in Fama and French (1993), both shown in Table A1. Interestingly, the model achieves this superior explanatory power during a period when value stocks outperform growth stocks, thus hinting that the Fama and French 3-factor model may be better specified for periods of value dominance or for portfolios containing value equities. Of course, higher volatility during the growth dominant sub-period could explain the loss of statistical significance. However, the absolute average intercept for the 25 portfolios during growth dominance was 0.18% while the average intercept during value dominance was virtually zero at 0.03%. Therefore volatility cannot account for the entire difference in explanatory power.

[27] An interesting research question might be to determine whether the apparent solution in Nelson (2006) replacing HML with two intangible factors is confirmed using the GICS industry definitions.

TABLE A3: Equal-weighted excess monthly returns of GICS sorted industry groups regressed on the Fama-French 3-factor model. June 1999 to May 2007 (n= 96)

The sample is collected from all active and inactive US firms trading on the NYSE, AMEX, NASDAQ exchanges and all other over-the-counter stocks (OTCBB, Pink Sheets, and "Other-OTC") sourced from the Research Insight database. Securities not representing the primary trading equity of the company are omitted. GICS history in Research Insight is available only from June 1999 to May 2007. Stock GICS are observed at May of year t except for the initial year 1999 when data history limitations require GICS for 1999 to be observed in June rather than in May. Prior to 2003, the GICS industry group code 4530 representing the semiconductors industry is included in code 4520. The two industry groups are re-combined for the purpose of this research because no data for code 4530 is available prior to 2003. Book-to-market equity (BE/ME) is observed in Research Insight at month end December t-1. Market equity (ME) is observed at May of year t. Stocks with negative BE/ME, stocks without data reporting for ME, GICS, BE/ME and stocks within the GICS unassigned industry group '0' data are removed from the sample. Stocks with a ME less than $1 million are removed to mitigate problems associated with non-synchronous trading, bid-ask noise and error pricing. Three-factor model returns obtained from the website of Kenneth French.

$$Rpt - Rft = a + b[\mathrm{R}mt - \mathrm{R}ft] + s\mathrm{SMB}t + h\mathrm{HML}t + et$$

	GICS Industry Group	Code	Median BE/ME	a	b	s	h	t(a)	t(b)	t(s)	t(h)	R2
1	Pharmaceuticals, Biotech & Life Sciences	3520	0.25	1.59	0.92	1.55	-0.68	2.49	3.80	4.51	-2.96	0.69
2	Health Care Equipment & Services	3510	0.41	0.82	0.84	0.94	0.25	1.86	6.61	6.62	1.92	0.62
3	Software & Services	4510	0.42	1.22	1.49	0.90	-0.84	1.72	10.21	4.45	-3.49	0.72
4	Household & Personal Products	3030	0.44	0.64	0.66	0.55	0.25	1.26	5.04	4.30	1.33	0.35
5	Telecommunication Srvs	5010	0.50	0.62	1.27	0.71	-0.37	1.03	7.00	4.39	-1.92	0.63
6	Technology Hardware & Equipment	4520	0.50	1.03	1.55	1.17	-0.47	1.93	9.10	6.32	-2.94	0.80
7	Media	2540	0.51	-0.11	1.12	0.48	-0.05	-0.22	9.59	3.50	-0.36	0.62
8	Energy	1010	0.52	1.49	0.97	0.48	0.80	2.55	5.50	2.86	4.41	0.32
9	Food, Beverage & Tobacco	3020	0.56	0.56	0.50	0.45	0.53	1.79	7.25	5.43	5.16	0.37
10	Commercial Services & Supplies	2020	0.58	0.40	0.93	0.61	0.34	0.93	10.96	5.62	2.66	0.55
11	Utilities	5510	0.59	0.18	0.60	0.22	0.75	0.67	7.02	3.43	8.61	0.51
12	Capital Goods	2010	0.62	0.85	0.99	0.58	0.37	2.26	11.56	5.57	2.96	0.65
13	Food & Staples Retailing	3010	0.62	-0.08	0.78	0.44	0.59	-0.24	8.52	4.75	4.80	0.50
14	Banks	4010	0.65	0.45	0.38	0.22	0.48	1.98	7.59	2.95	6.31	0.38
15	Materials	1510	0.65	0.30	1.08	0.53	0.72	0.89	14.17	5.30	6.50	0.66
16	Retailing	2550	0.66	0.21	1.07	0.60	0.42	0.40	9.63	3.55	2.15	0.48
17	Diversified Financials	4020	0.67	1.05	0.98	0.53	0.19	2.48	9.98	4.96	1.44	0.59
18	Consumer Services	2530	0.67	0.55	0.78	0.62	0.53	1.39	8.71	5.59	3.55	0.50
19	Transportation	2030	0.69	0.31	1.12	0.45	0.66	0.63	8.95	3.34	4.34	0.52
20	Real Estate	4040	0.74	0.52	0.42	0.37	0.50	1.86	7.32	5.11	5.83	0.42
21	Automobiles & Components	2510	0.74	-0.37	1.09	0.55	0.67	-0.69	8.98	3.89	3.82	0.46
22	Consumer Durables & Apparel	2520	0.79	0.05	0.99	0.54	0.57	0.12	11.45	4.70	4.27	0.59
23	Insurance	4030	0.83	0.28	0.77	0.18	0.63	1.14	11.84	2.63	7.83	0.62

t-stats use heteroskedasticity-consistent errors

TABLE A4: Value-weighted excess monthly returns of GICS sorted industry groups regressed on the Fama-French 3-factor model. June 1999 to May 2007 (n= 96)

The sample is collected from all active and inactive US firms trading on the NYSE, AMEX, NASDAQ exchanges and all other over-the-counter stocks (OTCBB, Pink Sheets, and "Other-OTC") sourced from the Research Insight database. Securities not representing the primary trading equity of the company are omitted. GICS history in Research Insight is available only from June 1999 to May 2007. Stock GICS are observed at May of year t except for the initial year 1999 when data history limitations require GICS for 1999 to be observed in June rather than in May. Prior to 2003, the GICS industry group code 4530 representing the semiconductors industry is included in code 4520. The two industry groups are re-combined for the purpose of this research because no data for code 4530 is available prior to 2003. Book-to-market equity (BE/ME) is observed in Research Insight at month end December t-1. Market equity (ME) is observed at May of year t. Stocks with negative BE/ME, stocks without data reporting for ME, GICS, BE/ME and stocks within the GICS unassigned industry group '0' data are removed from the sample. Stocks with a ME less than $1 million are removed to mitigate problems associated with non-synchronous trading, bid-ask noise and error pricing. Three-factor model returns obtained from the website of Kenneth French.

$$Rpt - Rft = a + b[\mathrm{R}mt - \mathrm{R}ft] + s\mathrm{SMB}t + h\mathrm{HML}t + et$$

	GICS Industry Group	Code	Median BE/ME	a	b	s	h	t(a)	t(b)	t(s)	t(h)	R2
1	Pharmaceuticals, Biotech & Life Sciences	3520	0.25	0.46	0.49	-0.47	-0.12	1.08	5.20	-3.56	-0.82	0.29
2	Health Care Equipment & Services	3510	0.41	0.15	0.58	0.20	0.51	0.43	6.69	2.10	4.60	0.34
3	Software & Services	4510	0.42	0.55	1.45	-0.16	-1.01	1.16	10.98	-0.92	-5.75	0.81
4	Household & Personal Products	3030	0.44	0.27	0.27	-0.16	0.22	0.54	1.84	-0.72	1.56	0.07
5	Telecommunication Srvs	5010	0.50	0.01	1.06	-0.49	-0.20	0.01	7.65	-2.59	-0.81	0.49
6	Technology Hardware & Equipment	4520	0.50	0.17	1.71	0.11	-0.66	0.32	12.36	0.72	-3.52	0.79
7	Media	2540	0.51	-0.23	1.21	0.03	0.01	-0.56	9.60	0.34	0.08	0.68
8	Energy	1010	0.52	0.39	0.84	0.04	0.66	0.89	6.57	0.38	4.60	0.36
9	Food, Beverage & Tobacco	3020	0.56	0.21	0.45	-0.16	0.42	0.52	4.14	-1.50	3.59	0.25
10	Commercial Services & Supplies	2020	0.58	-0.24	1.09	0.20	0.55	-0.78	16.25	2.19	5.77	0.71
11	Utilities	5510	0.59	-0.36	0.79	0.10	0.85	-0.84	5.48	1.02	6.69	0.35
12	Capital Goods	2010	0.62	0.30	1.00	-0.23	0.20	0.88	11.04	-2.47	1.53	0.66
13	Food & Staples Retailing	3010	0.62	-0.50	0.59	0.02	0.56	-1.27	6.43	0.29	4.59	0.28
14	Banks	4010	0.65	0.11	0.84	-0.30	0.58	0.29	10.17	-2.78	4.27	0.54
15	Materials	1510	0.65	-0.15	1.23	0.05	0.75	-0.49	15.80	0.57	6.94	0.68
16	Retailing	2550	0.66	0.12	1.15	0.01	0.21	0.29	9.42	0.09	1.66	0.55
17	Diversified Financials	4020	0.67	0.47	1.35	-0.30	0.17	1.52	18.01	-3.55	1.28	0.77
18	Consumer Services	2530	0.67	-0.05	0.94	0.19	0.75	-0.14	9.89	1.75	6.31	0.53
19	Transportation	2030	0.69	0.19	0.99	0.03	0.62	0.46	8.83	0.35	4.49	0.47
20	Real Estate	4040	0.74	0.35	0.50	0.31	0.61	0.89	6.39	3.39	5.19	0.30
21	Automobiles & Components	2510	0.74	-1.15	1.44	0.11	0.94	-1.84	9.83	0.66	4.50	0.48
22	Consumer Durables & Apparel	2520	0.79	-0.38	1.15	0.21	0.76	-1.02	12.78	1.93	6.46	0.62
23	Insurance	4030	0.83	0.16	0.88	-0.45	0.55	0.43	9.68	-3.81	5.04	0.61

t-stats use heteroskedasticity-consistent errors

TABLE A5: Regression intercepts of 25 portfolios formed on ME and BE/ME for various sample sets: FF 3-Factor Model. Value weighted excess returns. (n = 60)[28]

$$Rpt - Rft = a + b[\mathrm{R}mt - \mathrm{R}ft] + s\mathrm{SMB}t + h\mathrm{HML}t + et$$

Panel A: Updated Sample Results January 1995 to December 1999 (L > H)

	a					t(a)				
	LOW	2	3	4	HIGH	LOW	2	3	4	HIGH
SMALL	-0.34	0.17	0.31	0.37	0.40	-1.13	0.60	1.53	2.21	2.04
2	-0.47	-0.45	-0.17	-0.03	-0.37	-1.99	-2.67	-0.81	-0.15	-1.35
3	-0.55	-0.51	-0.62	-0.10	-0.04	-2.17	-2.26	-3.34	-0.54	-0.14
4	-0.58	-0.32	-0.19	-0.05	0.34	-2.26	-1.67	-1.16	-0.18	2.15
BIG	-0.12	-0.33	-0.22	-0.32	-0.32	-0.58	-1.54	-1.18	-1.56	-1.56

TABLE A5: continued

Panel B: Updated Sample Results January 2000 to December 2004 (H > L)

	a					t(a)				
	LOW	2	3	4	HIGH	LOW	2	3	4	HIGH
SMALL	-0.38	0.21	0.52	0.90	0.43	-0.63	0.57	1.98	2.96	1.36
2	-0.41	-0.40	0.01	-0.15	-0.41	-1.27	-1.30	0.03	-0.63	-1.58
3	-0.11	0.19	0.09	-0.10	0.29	-0.37	0.58	0.34	-0.34	0.76
4	0.19	0.30	0.34	0.15	-0.28	0.63	1.19	1.06	0.44	-0.80
BIG	0.17	-0.01	-0.15	-0.19	-0.52	1.48	-0.04	-0.50	-0.67	-1.04

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[28] Explanatory notes for this table are the same as those for Table A1.

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CHAPTER TWO:
The value premium within and across GICS industry sectors

Value investment management techniques described many years ago by Graham and Dodd and employed over the years by such notable practitioners as Warren Buffett and Sir John Templeton are not homogeneous. Two general methods are observed in constructing a value-oriented portfolio. First, a manager utilizing what is known as a bottom-up approach typically ignores macroeconomic and industry-specific data, and targets a value stock defined and preferred by that manager; for example, stocks exhibiting low price-to-earnings (P/E) or high book-to-market ratios (BE/ME). A portfolio's industry allocation using this method is generated not from active consideration by the investment manager but from passive outcomes resulting from individual stock selection within the portfolio. An allocation to banking stocks, for example, results from the weighting of individual stocks the manager happens to purchase from that industry or sector group.[29] The second method used to construct a value-oriented portfolio involves employing a combined top-down/bottom-up approach. The manager first makes an industry or sector allocation from the top down, and then fills those sector allocations from the bottom up with stocks deemed to be appropriate to the value manager.[30]

Top-down/bottom-up value investment managers seeking to capture the value premium promised in academic literature would want to first determine whether the premium exists across industries and not just in firm-specific BE/ME relationships. Next, the investor would want to know if BE/ME characteristics are stable across these defined homogeneous groups or whether there is considerable variation. If BE/ME observed across industry groups is stable and temporal variations small, then the value manager could strategically allocate funds away from industry groups that historically exhibit a weak premium, and then away from individual stocks that exhibit low BE/ME characteristics found within the remaining industry groups. The resulting portfolio should allow a manager the best opportunity to capture the value premium promised originally in the work of Rosenberg, Reid, and

[29] In practice, institutional clients of the bottom-up investment manager may place maximum industry sector allocation restrictions on the portfolio. Professional Investment managers are usually mindful of risk management through prudent diversification not only of individual securities within a portfolio but also across industry sectors. Managers will often place a final industry allocation overlay at the end of the security selection process.

[30] Fabozzi, Frank J., 1999, Investment Management, 2nd ed. Prentice-Hall, pp 172-174. A manager utilizing what is known as a top-down method makes a forecast of relevant macroeconomic variables and constructs a portfolio across various economic sectors to capitalize on these forecasts. However, this method is not likely to accommodate a traditional value orientation to portfolio management.

Lanstein (1985) and later most notably in Fama and French (1992, 1993).[31] Of course, the difficulty in assessing an industry impact on the BE/ME effect is made extremely difficult because BE/ME is by nature an accounting construction with considerable differences in meaning and interpretation across industry groupings.

Historically, an industry effect in explaining average stock returns has been evaluated in the context of the relative power of industry-versus-country influences. This global perspective asks whether investors can achieve risk reduction by diversifying global equity portfolios across industries as well as across national stock markets. Early papers such as Roll (1992) observe the industrial structure and the comparative behaviour of international stock market indices. More recently, Cavaglia, Brightman and Aked (2000) conclude that industry factors now dominate country factors - a dramatic shift in factor dominance from prior research. Cavaglia et al. argue that investors can now gain a larger risk reduction from global industry diversification than from global country diversification [See also Xia and Phylaktis, 2006, Steliaros and Thomas, 2006, and Isakov and Sonney, 2004].

Banko and Conover (2006) conclude that the analysis of an industry effect is also critical in determining the origin of the value effect, and thus critical for the proper specification of pricing models. The authors argue that if industry affiliation influences a company's factor model loading on BE/ME, then a properly specified pricing model should be estimated to include some factor that can capture this influence. Fama and French (1997) observe HML factor loadings for forty-eight industries groupings and find them to vary considerably across industries as well as to vary considerably across time. The authors find the results "distressing" with negative implications for any precise computation of a company's cost of equity capital. Cohen and Polk (1998) and Nelson (2006) both attempt with some success to resolve the 3-factor model's difficulty in explaining returns when stocks are sorted by industry. Results from Banko and Conover are consistent with those from Cohen and Polk that the value effect is indeed found across industry groupings but at a much lower level of power than at the firm level.

Section 1: Objectives and Results

The first goal of this essay is to begin the body of literature evaluating within-industry and across-industry value premium characteristics using the Global Industry Classification Standard (GICS), a proprietary coding system jointly produced by Standard & Poor's and Morgan Stanley Capital International. The choice to use GICS rather than other schemes to allocate stocks to a particular

[31] See Davis (2001), and Chan and Lakonishok (2004) for two extensive academic literature reviews on the subject of the value premium.

industry grouping is substantiated in the research of Bhojraj, Lee, and Oler (2003) who find GICS to be materially different (and better) than other classification systems.

The second objective of this essay is to provide further information about BE/ME characteristics, both within and across industry sectors. Banko and Conover (2006) find the value effect related to both firm and industry risk characteristics - albeit the latter with less power to explain returns. However, if industry group BE/ME characteristics are not stable and predictable, then investors would have a difficult time strategically capturing the promised value premium when allocating funds *ex ante* across industry groups. Results in this essay confirm observations by Banko and Conover that BE/ME characteristics vary considerably across industry groupings. However, the annual ordering of industry BE/ME appears to be relatively stable and potentially predictable for investors. Certain industries appear to have a natural or structural tendency to reflect either a high or low BE/ME characteristic. This essay also shows that growth industry BE/ME characteristics appear to be more stable than value industries over time. Moreover, stocks from growth-oriented industries tend to cluster at high rates in the lowest BE/ME quintile while stocks from value-oriented industries appear more evenly distributed across middle BE/ME quintiles over time.

The third objective of this essay is to determine whether the event shocks and uncertainty that occurred during the sample period impact relationships observed between growth and value stocks in earlier research. Specifically, this essay tests the thesis of Chen and Zhang (1998) that the value premium, as a function of investor pricing of risk, should be weaker during high growth, less distressed economic conditions. Banko and Conover (2006) use industry analysis to confirm this thesis, and find that value stocks in (distressed) value industries perform better than value stocks in (less distressed) growth industries. Arguments by Chen and Zhang and Banko and Conover should be robust to the use of a different industry classification system. Results in this essay show that returns for the more recent sample period are materially different from those observed by Banko and Conover. Value stocks found in growth sectors actually outperform value stocks in value sectors. However, the period tested is not normal. Growth sectors experience negative ROA, a reversal of what Banko and Conover observe in earlier sample periods. Therefore, results here are not inconsistent with arguments by Banko and Conover that the value premium results from investor risk-pricing of distress.

Finally, this essay provides a check on the strength of the value premium within and across GICS industry sectors by controlling for the January anomaly. Curiously, the well-documented January effect possesses characteristics similar to the value effect. Loughran (1997) suggests the value effect is in fact partially driven by the January effect, among other factors. Conversely, Dhatt, Kim and Mukherji (1999)

observe that most of the value premium in small cap stocks occurs outside the month of January. Results in this essay show that the January premium exists both within and across GICS industry sectors, but the value premium is not subsumed by the January effect in either analysis. The strength of the value premium within sectors survives even after removing January returns, consistent with findings in Daniel and Titman (1997). Further, the average value premium computed across GICS industry sectors is virtually identical to the premium computed when January returns are omitted. Results do not suggest the value premium is stronger in the eleven months, February to December, as observed by Dhatt, Kim and Mukherji (1999). Nor are results consistent with findings in Loughran (1997) that the value premium is boosted in part by January returns.

Section 2: The Global Industry Classification Standard (GICS)

The decision to use the Global Industry Classification Standard (GICS) in this essay rather than the North American Industry Classification System (NAICS), the Standardized Industry Classification System (SIC) or the Fama and French industry codes (FF) is justified by Bhojraj, Lee, and Oler (2003) who find GICS to be a superior industry classification system. The authors find GICS to be superior at explaining co-movement in stock prices and cross-sectional variations in forecasted growth rates, financial ratios and valuation metrics – issues critical to academic research findings.[32] Additionally, Bhojraj et al. find that sorting stocks by GICS creates materially different industry samples than when sorting by the other three classification systems. NAICS samples map to SIC at a rate of 80% and FF map at 84% to SIC. GICS, however, map to SIC-defined samples at a rate of only 56% of the time. The authors find that NAICS, SIC and FF "differ little from each other in most applications." In other words, researchers who perform industry analyses utilizing GICS rather than the more common SIC and FF classification systems might experience results that are different from those in prior research. These differences, if any, could be very informative in re-interpreting observed outcomes.

Another important reason to use GICS rather than FF codes is that any research attempting to reconcile academic research with market-based portfolios should use definitions and methods common and available to investors. Several important financial products are now constructed based on GICS.[33]

[32] Chan, Lakonishok and Swaminathan (2007) find that both GICS and FF yield "sets of economically related stocks." They compared GICS and FF systems with a mechanical industry clustering method and find GICS and FF performs well in capturing out of sample return covariance as well as co-movement in fundamental characteristics such as sales growth.

[33] Yet another popular classification system in wide use by practitioners is the Industry Classification Benchmark (ICB) by Dow Jones Indexes and FTSE. The popular Dow Jones I-Shares utilize the ICB classification system.

The Standard & Poor's Company uses GICS for its highly popular SPDR® exchange traded funds. S&P converted its ETF funds to the GICS system in June 2002. The giant Vanguard investment firm also uses GICS to classify stocks to their various sector ETFs. Internationally, several stock exchanges such as the Toronto, ASX in Australia, and Nordic exchanges use GICS for stock listing classifications. According to the sales literature produced by S&P, eight of the top ten sell-side investment firms and nine of the top ten buy-side investment firms utilize the GICS system. The fact that Standard &Poor's and Morgan Stanley own and manage the dominant S&P and MSCI global index products ensures that GICS will be heavily used by the practitioner community to construct any index-related industry sub-classifications.[34]

Section 3 Characteristics of the sample

The length of the GICS history for this research is not optimal. However, the sample period, June 1999 to May 2007, experienced several unique events that may shed further light on prior research questions such as whether the BE/ME effect is a proxy for distress risk as advocated in Fama and French (1996) and later in Chen and Zhang (1998). The beginning of the sample period reflects approximately six months of the tail-end of the dotcom price exuberance, then followed by a serious and lengthy return reversion by the same growth-oriented companies. The first half of the sample period includes a slowing of the US economy resulting from the dotcom collapse and the economic shock from the attacks on 11 September 2001. The second half of the sample period through May 2007 consists of a steady economic recovery and expansion, despite the uncertainty created by the US war in Iraq which began in March of 2003.

In order to make inferential claims that are linked to findings in prior research, it is critical for the abbreviated sample period to reflect return and volatility characteristics observed in, for example, Fama and French (1993) and Davis, Fama, and French (2000). Indeed, despite unique event shocks incurred during the period, the eight year sample represents a period typical of monthly return samples found in prior research. Value stock returns continue to dominate growth stock returns. For example, the Dow Jones Wilshire US Large Cap Value index outperformed the Dow Jones Wilshire US Large Cap Growth index by an average of 0.50% per month. Also during this period, the Fama and French zero investment HML factor mimicking portfolio generated a positive average monthly return of 0.69%, thus similarly indicating a superior performance by value stocks over growth stocks. By comparison, returns for the HML factor over eighty-one years, July 1926 and May 2007 (n = 971 months) average 0.42% - the

[34] S&P announced that the conversion of their popular S&P/Citicorp equity growth and value indexes to GICS was completed in July 2005.

same positive sign and approximate size to the current sample. Comparisons to prior observations using shorter observation periods raise the spectre of data mining depending upon the question being answered. Market conditions experienced during the late 1990s through the mid-to-late 2000s are indeed unique. However, this period could potentially provide out-of-period confirmation of results observed over longer, possibly less eventful periods.

3.1 Tests of the value premium in the sample

All returns used in testing research questions in this essay are accessed from COMPUSTAT in the Research Insight database. Unfortunately, COMPUSTAT pricing and return data appear to be riddled with suspicious reports and possible errors for stocks trading outside the NYSE, AMEX and the NASDAQ National Market System. An analysis of eight years of monthly return data for 20,745 NYSE, AMEX, NASDAQ, and OTC stocks shows an alarming number of pricing outliers for a small subset of companies. Sixty-nine stocks reported at least one monthly return greater than +100,000%. Ten stocks had monthly return reports of exactly +99,900%. Thirty-one stocks had a return report of +19,900%, and 136 stocks had a monthly return report of exactly +9900%, and so forth. However, identifying problematic pricing was not as simple as observing returns expressed as whole numbers. For example, ten stocks suspiciously reported monthly returns of +328.571%, possibly a function of similarly priced bid/ask noise before the introduction of decimalisation of prices in early 2001. The largest monthly return in the COMPUSTAT data sample was reported at an astonishing +3,999,900%, an extreme illustration of the possible damage these stocks might do to econometric inferences when using equal-weighted returns. Not surprising, the overwhelming majority of the problematic pricing is found in the smallest size and lowest book-to-market, or growth, quintile of stocks – segments of the market that traditionally experience considerably greater return volatility, bid-ask noise, and problems with non-synchronous trading.

Traditional screening criteria used in tests on the value premium, such as the removal of stocks with negative book value (as in Fama and French, 1993) clean most of the offending return series.[35] For

[35] Even after using various stock screens to construct a final sample of stocks appropriate for the research question under consideration, approximately fifty stocks with suspicious monthly return reports remain. To mitigate the impact of the fifty remaining price reports on later equal-weighted portfolio return analysis, the returns from COMPUSTAT were compared to reports from the Thomson Datastream database. If the individual stock return from Datastream was observed to be different from reports in COMPUSTAT for any of the fifty surviving stocks, then the COMPUSTAT number was replaced. However, if the report in Datastream was consistent with the suspicious COMPUSTAT number, then the return was eliminated altogether from the sample. In the rare event a stock was removed, only the twelve months of the portfolio formation period surrounding the offending monthly return were eliminated leaving the remaining returns for the stock.

confirmation, annual returns for the surviving COMPUSTAT dataset were compared to an identical sample of returns and identical time horizon in Thomson Datastream. Returns from both sets were found to be positively correlated at levels above 90% for each of the years in the time series. This high level of comparability, while not perfect, provides some confidence that the pricing noise is mitigated, and most importantly, that the resulting sample is a valid representation of US stock returns during the period.[36] In the end, empirical work in this essay tested 536,622 monthly return observations over the eight year sample period.

To begin the process of validating the sample for comparability to prior research, returns are computed and observed for twenty-five portfolios constructed by independent sorts first on size (ME) and then on book-to-market (BE/ME) characteristics. Average excess value weighted monthly returns of portfolios formed on size and book-to-market are computed as in Fama and French (1993) for the eight years of available GICS historical classification data. The sample was collected from all active and inactive US firms trading on the NYSE, AMEX, NASDAQ exchanges and all other over-the-counter stocks (OTCBB, Pink Sheets, and 'Other-OTC') sourced from the Research Insight database. Time series of securities not representing the primary trading equity of the company are omitted. Book to market equity (BE/ME) is observed in Research Insight at month end December (t-1) of the portfolio formation year. Market equity (ME) is observed at May of year t. A portfolio formation date of June is used and monthly total returns are observed from June 1999, representing the earliest date available for historical GICS series in Research Insight, and extend to May 2007. Portfolios are re-formed annually. Stocks with negative BE/ME, stocks without data reporting for ME and BE are all removed from the original sample. Stocks with a ME less than $1 million are removed to mitigate problems associated with non-synchronous trading, bid-ask noise and error pricing. The risk free rate is defined as the 90 day Treasury bill.

3.2 Portfolio return characteristics

Portfolio returns shown in Panel A of Table 1 confirm that the value and size premium exist in the GICS-limited sample period. Value oriented portfolios generally outperform growth portfolios monotonically across all size (ME) quintiles, consistent with similar tests in Fama and French (1993), Lakonishok, Shleifer and Vishny (1994), and others. Small size portfolios outperform large size portfolios

[36] Datastream is not used for this research because it is deemed preferable to use the same source for returns as used to capture related fundamental characteristics such as book-to-market equity and others. See also Ince and Porter (2006) for a thorough discussion of return reporting problems in Datastream.

TABLE 1: Excess value-weighted monthly returns of stocks sorted independently on ME and BE/ME June 1999 to May 2007 (n = 96)

The sample is collected from all active and inactive US firms trading on the NYSE, AMEX, NASDAQ exchanges and all other over-the-counter stocks (OTCBB, Pink Sheets, and 'Other-OTC') sourced from the Research Insight database. Securities not representing the primary trading equity of the company are omitted. Book to market equity (BE/ME) is observed in Research Insight at month end December (t-1) of the portfolio formation year. Market equity (ME) is observed at May of year t. A portfolio formation date of June is used and monthly total returns are observed from June 1999 representing the earliest date available for historical GICS series in Research Insight and extend to May 2007. Portfolios are re-formed annually. Stocks with negative BE/ME, stocks without data reporting for ME and BE are removed from the original sample. Stocks with a ME less than $1 million are removed to mitigate problems associated with non-synchronous trading, bid-ask noise and error pricing. The risk free rate, defined as the 90 day treasury bill, is obtained from the website of Kenneth French.

Panel A: Monthly Portfolio Returns

.		BE/ME				
		Growth				Value
		LO	2	3	4	HI
	SMALL	1.38	1.80	1.54	1.73	2.35
	2	0.78	1.11	1.17	1.28	1.21
ME	3	0.59	1.04	1.16	1.18	1.20
	4	0.84	0.99	1.04	1.17	1.29
	LARGE	0.32	0.69	0.74	0.90	0.92

Panel B: Standard Deviation

		BE/ME				
		Growth				Value
		LO	2	3	4	HI
	SMALL	10.90	7.85	5.92	5.12	6.51
	2	9.20	5.48	4.43	4.74	6.29
ME	3	7.73	4.68	4.14	4.59	5.91
	4	7.10	4.67	4.49	4.30	6.11
	LARGE	5.33	4.12	4.50	4.91	6.13

across all BE/ME quintiles, again consistent with prior findings.[37] A noticeable difference in this period is reflected in volatility of monthly returns. Lakonishok et al. find that once adjusted for size, return volatility differs little between value stocks and growth stocks. Using the method of Fama and French (1993) to control for size, Panel B of Table 1 shows a large difference in volatility of returns between value and growth stocks. Growth stocks experience greater volatility than value stocks – a result not wholly unexpected considering the nature of event shocks that occurred during the sample period. The standard deviation of monthly returns for the Small/LO growth portfolio is 10.90% while Small/HI value portfolio is 6.51%. Daniel and Titman (1997), who analyse volatility during pre- and post-portfolio formation periods, also find small growth portfolios to be more volatile than small value portfolios. It is

[37] Fama and French (1993) use value-weighted returns; however, the authors provide data for equal-weighted returns computed from the same sample. For robustness, returns in Table 1 are recomputed using equal-weighted returns and then compared to those constructed using the data of Fama and French. The data was sourced from the website of Kenneth French and represent a longer sample period, 1992 to 2006. Results show that the value and size premium observed during the GICS-limited sample period is similar to that found in prior data for equal-weighted returns using an extended sample period.

important to note that the difference in volatility shown in Panel B is only observed in the smallest size quintiles. Very little difference in volatility is observed between growth and value in the large ME quintiles. As expected, small stock portfolios experience greater volatility than large stock portfolios across all BE/ME quintiles, although the difference virtually disappears as BE/ME rises. Small value portfolios shown in Panel B experience no material increase in volatility (6.51%) than large value portfolios (6.13%). Volatility across BE/ME quintiles was U-shaped for all size quintiles, a result consistent with findings in Lakonishok, Shleifer and Vishny (1994) and in the data of Fama and French for a sample period 1992 to 2006.[38]

3.3 Three-Factor model regression results

For further confirmation that the current sample exhibits similar characteristics to samples used in prior research, excess average monthly portfolio returns are regressed on the Fama and French 3-factor model. The model has been shown to do a very good job in explaining the cross sectional variation in average returns of stocks over long sample periods. Therefore, any meaningful deviation in outcomes from 3-factor model results observed in prior research could preclude certain inferences from econometric tests presented later in this work.

Table 2 shows the Fama and French 3-factor regression coefficients for value-weighted excess returns of 25 portfolios formed on size (ME) and book-to-market (BE/ME) constructed exactly as before in Table 1 and mirroring the methodology in Fama and French (1993). Results show alphas are mostly small and insignificant, thus indicating the model is properly specified for this particular sample with the exception of small-size portfolios – a well known problem for the 3-factor model as observed in Davis, Fama, and French (2000) who use a sample period, 1929 to 1997 - a date ending just prior to the sample used in this essay. [39] Observed regression coefficients for each of the three independent variables of the 3-factor model; *viz.* excess market returns, the SMB size factor, and the HML factor, are consistent with tests of other sample periods.

[38] Daniel and Titman (1997) do not observe a volatility 'free lunch' between large and small value stocks for all pre- and post-portfolio formation years.

[39] By comparison, only three of the 25 intercepts are significant in value weighted portfolio returns presented in Fama and French (1993). Regressing excess returns of 25 portfolios on the 3-factor model for a more recent sample, January 1992 to December 2006 [not shown] exposes considerable temporal inconsistency in the statistical significance of the intercept. During this period, nine of the 25 alphas are large and significant at the 5% level. See Nelson (2006) for a discussion of the poor performance of the 3-factor model in explaining returns of relatively smaller sized NASDAQ stocks.

TABLE 2: Fama and French 3-factor regression coefficients of 25 portfolios formed on ME and BE/ME. Excess value-weighted monthly portfolio returns averaged over the sample period June 1999 to May 2007 (n = 96)

The sample is collected from all active and inactive US firms trading on the NYSE, AMEX, NASDAQ exchanges and all other over-the-counter stocks (OTCBB, Pink Sheets, and 'Other-OTC') sourced from the Research Insight database. See notes to Table 1 for additional comments on the method of computation.

$$Rpt - Rft = a + b[\mathrm{R}mt - \mathrm{R}ft] + s\mathrm{SMB}t + h\mathrm{HML}t + et$$

	a					t(a)				
	LO	2	3	4	Hi	LO	2	3	4	Hi
Small	0.72	0.91	0.70	0.88	1.37	1.04	2.13	2.06	2.65	2.97
2	0.18	0.07	0.05	-0.02	-0.52	0.54	0.31	0.25	-0.11	-1.58
3	0.20	0.18	0.15	0.02	-0.09	0.60	0.81	0.70	0.08	-0.25
4	0.67	0.18	0.11	0.19	-0.18	2.33	0.74	0.52	0.84	-0.52
Large	0.22	0.10	-0.05	0.07	0.45	1.14	0.56	-0.22	0.28	1.00
	b					t(b)				
	LO	2	3	4	Hi	LO	2	3	4	Hi
Small	1.09	0.95	0.86	0.70	0.78	6.19	7.74	9.59	8.24	6.54
2	1.33	1.08	0.95	1.00	1.25	19.94	20.79	19.12	21.62	14.75
3	1.23	1.06	0.97	1.09	1.33	18.25	21.04	17.16	20.18	15.33
4	1.28	1.14	1.11	1.01	1.33	14.80	15.74	17.30	15.83	10.18
Large	1.14	1.02	1.05	1.07	1.19	22.19	25.53	18.24	17.82	11.47
	s					t(s)				
	LO	2	3	4	Hi	LO	2	3	4	Hi
Small	1.04	0.95	0.72	0.72	0.83	5.00	7.16	6.79	8.49	6.12
2	0.80	0.69	0.60	0.71	0.95	7.38	10.42	7.80	10.24	7.85
3	0.47	0.37	0.36	0.43	0.40	4.41	6.44	5.66	6.71	4.55
4	0.15	0.08	0.15	0.24	0.38	1.75	0.87	2.35	3.54	5.11
Large	-0.14	-0.08	-0.08	-0.15	-0.30	-2.38	-1.55	-1.33	-2.35	-2.49
	h					t(h)				
	LO	2	3	4	Hi	LO	2	3	4	Hi
Small	-0.44	0.02	0.21	0.28	0.33	-1.88	0.12	1.74	2.69	2.15
2	-0.40	0.44	0.69	0.83	1.12	-3.71	7.21	11.63	13.76	11.02
3	-0.35	0.49	0.76	0.86	0.98	-3.23	5.83	8.70	13.60	8.18
4	-0.38	0.67	0.79	0.80	1.27	-4.50	7.22	12.83	7.59	11.70
Large	-0.15	0.55	0.82	0.94	0.52	-2.53	9.64	11.45	14.17	3.28
	adj-R2									
	LO	2	3	4	Hi					
Small	0.63	0.68	0.68	0.66	0.52					
2	0.88	0.87	0.84	0.85	0.79					
3	0.86	0.82	0.79	0.83	0.71					
4	0.89	0.79	0.81	0.75	0.69					
Large	0.91	0.84	0.80	0.79	0.54					

As expected, Table 2 shows that with rare exception, coefficients are generally large and significant. Factor loadings for both size and book-to-market are consistent with expectations. Large stocks load negatively on the SMB factor while growth stocks load negatively on the HML factor. Adjusted R-squares are lower than expected but this is likely a function of the increased volatility associated with event shocks experienced during the period.

Overall, aggregated sample results in Tables 1 and 2 show that the sample constricted by the limited GICS history is a not unlike results of tests of the value premium and the 3-factor model using much longer sample periods. This provides some comfort that outcomes and statistical inferences shown in later sections are not simply a function of data mining.

Section 4: BE/ME characteristics using GICS industry sorts

Fundamental characteristics and monthly returns are collected for a sample of all active and inactive US NYSE, AMEX, NASDAQ, and all other over-the-counter stocks (OTCBB, Pink Sheets, and Other-OTC) sourced from the Research Insight database. Securities not representing the primary trading equity of the company are omitted. To create homogeneous industry groupings, 4-digit GICS codes for individual securities are observed at May of year t, except for the initial year 1999 when data history limitations require GICS for 1999 to be observed in June rather than in May.[40] GICS history in Research Insight is available only from June 1999 to May 2007. Prior to 2003, the GICS industry group code 4530 representing the semiconductors industry is included in code 4520. The two industry groups are re-combined for the purpose of this research because no data for code 4530 is available prior to 2003. Book-to-market equity (BE/ME) is observed in Research Insight at month end December t-1 of the portfolio formation year. Market equity (ME) is observed at May of year t. Stocks with negative BE/ME, stocks without data reporting for ME, GICS, BE and stocks within the GICS unassigned industry group '0' data are removed from the sample. Stocks with a ME less than $1 million are removed to mitigate problems associated with non-synchronous trading, bid-ask noise, and error pricing.

Industry and sector returns and characteristics in this essay are generally observed using equal weights as in Fama and French (1992) rather than value weights as used subsequently in Fama and French (1993) and many others. The choice of equal weights is driven by the desire for comparability to equal weighted return observations in Banko and Conover (2006), a paper that asks similar questions to those here. While it is worth mentioning that Banko and Conover state their results are robust to the choice of equal or value weights it is well known that equal weighted average monthly returns are generally higher and more volatile than those calculated using value weights.[41]

General industry characteristics for market equity and book-to-market using the GICS classification system are presented in Table 3. Unsurprisingly, biotechnology, health care, software,

[40] Short term migration in GICS classifications for individual stocks appears rare, so this single timing adjustment is not expected to materially impact results

[41] See Chiang (2002) for a comprehensive literature survey and analysis of the effect of statistical return weighting methods on the value effect.

telecommunications, and technology industry groups – those typically found in growth mutual fund portfolios - are found in the growth end of the BE/ME ranking when ordered by median BE/ME across the sample period. As a quick illustration, at 30 September 2008, the growth-oriented Janus Twenty mutual fund ($ 9 billion in net assets) held 23% and 20% of its portfolio in technology and health care stocks respectively. Moreover, industries exhibiting high BE/ME characteristics shown in Table 3 are the same as those found in the value-oriented Franklin Templeton Mutual Shares fund ($8 billion in net assets). At 30 September 2008, the fund held 19% and 23% of its portfolio in financial and consumer goods stocks respectively.[42]

Cohen and Polk (1998) suggest that an industry group or sector may exhibit consistently high BE/ME characteristics over time. The authors argue that a persistently high BE/ME characteristic may result from a unique accounting standard or the industry may simply be a riskier industry than others. Conversely, an industry whose BE/ME characteristic migrates from low to high may simply be under temporary distress. Insurance, transportation, financials and consumer durables are observed in the high end of the median BE/ME ordering in Table 3. However, variation in the median BE/ME, computed as the standard deviation of the observed eight year time series and presented in the last column of Table 3, is large enough to warrant caution by value investors in allocating funds based on the historical median BE/ME of these industry groups.

Table 4 shows the temporal consistency of the annual median BE/ME ranking of GICS industry groupings, similar to the presentation in Banko and Conover (2006) for SIC sorted groupings. Although periodic migration does occur, specifically the energy and telecommunications industries, the overall temporal consistency in BE/ME ranking is fairly high. Pharmaceuticals exhibit the lowest median BE/ME characteristic for all but one of the eight years in the sample period while the insurance industry exhibits the highest median BE/ME characteristic in five of the eight years of the sample. The Pearson correlation coefficient evaluating the degree of association between the annual BE/ME ranking and the aggregate median ranking over the entire sample period is greater than 0.66 for each of the eight years, and most of the annual coefficients are above 0.80. High positive correlations for the annual BE/ME rankings with the eight year median for that industry are, of course, somewhat predictable given that the rankings are subsets of the aggregate data used to compute the median. However, the consistency of the resulting high correlations across time suggest that some predictability in observing industry ordering of BE/ME

[42] Mutual fund portfolio holding data source: Thomson Reuters, accessed 12 December 2008 from Morningstar.com.

TABLE 3: Industry group BE/ME characteristics ordered by Median BE/ME. June 1999 to May 2007, (n = 96)

The sample is collected from all active and inactive US firms trading on the NYSE, AMEX, NASDAQ exchanges and all other over-the-counter stocks (OTCBB, Pink Sheets, and "Other-OTC") sourced from the Research Insight database. Securities not representing the primary trading equity of the company are omitted. GICS history in Research Insight is available only from June 1999 to May 2007. Stock GICS are observed at May of year t except for the initial year 1999 when data history limitations require GICS for 1999 to be observed in June rather than in May. Prior to 2003, the GICS industry group code 4530 representing the semiconductors industry is included in code 4520. The two industry groups are re-combined for the purpose of this research because no data for code 4530 is available prior to 2003. Book-to-market equity (BE/ME) is observed in Research Insight at month end December t-1. Market equity (ME) is observed at May of year t. Stocks with negative BE/ME, stocks without data reporting for ME, GICS, BE/ME and stocks within the GICS unassigned industry group '0' data are removed from the sample. Stocks with a ME less than $1 million are removed to mitigate problems associated with non-synchronous trading, bid-ask noise and error pricing.

		Industry Group	Sample	Median ME	Mean BE/ME	Median BE/ME	Std Dev. BE/ME
1	Pharmaceuticals, Biotech & Life Sci.	3520	324	149.84	0.38	0.25	0.08
2	Health Care Equipment & Services	3510	458	106.31	0.94	0.41	0.10
3	Software & Services	4510	587	88.72	0.49	0.42	0.21
4	Household & Personal Products	3030	54	53.07	0.87	0.44	0.13
5	Telecommunication Srvs	5010	93	209.47	0.77	0.50	0.20
6	Technology Hardware & Equipment	4520	651	130.05	0.65	0.50	0.17
7	Media	2540	161	279.53	0.68	0.51	0.13
8	Energy	1010	274	239.99	0.96	0.52	0.15
9	Food, Beverage & Tobacco	3020	134	159.95	0.86	0.56	0.08
10	Commercial Services & Supplies	2020	300	103.59	0.96	0.58	0.13
11	Utilities	5510	134	1344.05	0.80	0.59	0.05
12	Capital Goods	2010	430	150.54	1.06	0.62	0.15
13	Food & Staples Retailing	3010	44	436.43	0.86	0.62	0.13
14	Banks	4010	723	106.69	0.74	0.65	0.13
15	Materials	1510	264	206.88	1.28	0.65	0.16
16	Retailing	2550	280	238.71	1.38	0.66	0.26
17	Diversified Financials	4020	165	190.73	1.39	0.67	0.21
18	Consumer Services	2530	196	116.67	1.36	0.67	0.23
19	Transportation	2030	94	314.27	0.88	0.69	0.20
20	Real Estate	4040	251	363.25	1.09	0.74	0.17
21	Automobiles & Components	2510	75	177.28	0.97	0.74	0.23
22	Consumer Durables & Apparel	2520	288	99.77	1.50	0.79	0.23
23	Insurance	4030	143	538.78	1.02	0.83	0.12

TABLE 4: Annual ranking of GICS industry BE/ME characteristics. June 1999 to May 2007, (n=96).

The sample is collected from all active and inactive US firms trading on the NYSE, AMEX, NASDAQ exchanges and all other over-the-counter stocks (OTCBB, Pink Sheets, and "Other-OTC") sourced from the Research Insight database. Results are formulated as in Table 3.

		Industry Group	2000	2001	2002	2003	2004	2005	2006	2007	Median BEME Rank	Min. BEME Rank	Max. BEME Rank	Range BEME Rank
1	Pharm., Biotech. & Life Sci.	3520	1	2	1	1	1	1	1	1	1	1	2	1
2	Software & Serv.	4510	2	1	10	3	6	3	2	4	3	1	10	9
3	Health Care Equip. & Serv.	3510	8	6	3	2	3	4	4	2	4	2	8	6
4	Household & Personal Prod.	3030	5	7	7	4	2	2	3	5	5	2	7	5
5	Techn. Hardware & Equip.	4520	11	4	4	5	20	5	7	10	6	4	20	16
6	Energy	1010	20	8	2	6	4	13	8	3	7	2	20	18
7	Telecom. Serv.	5010	3	3	6	11	21	9	6	17	8	3	21	18
8	Media	2540	4	5	9	8	9	6	14	15	9	4	15	11
9	Food, Beverage & Tobacco	3020	6	11	8	9	5	14	16	12	10	5	16	11
10	Comm. Serv. & Supplies	2020	7	9	12	12	10	7	10	13	10	7	13	6
11	Utilities	5510	10	13	5	10	7	22	22	18	12	5	22	17
12	Capital Goods	2010	15	16	11	13	14	12	11	8	13	8	16	8
13	Retailing	2550	12	10	22	14	18	10	9	7	11	7	22	15
14	Diversified Financials	4020	18	14	19	18	13	8	12	11	14	8	19	11
15	Food & Staples Retailing	3010	9	12	13	7	15	19	21	16	14	7	21	14
16	Consumer Services	2530	22	20	18	17	12	11	5	6	15	5	22	17
17	Banks	4010	13	17	14	15	8	15	17	21	15	8	21	13
18	Materials	1510	17	15	15	19	16	16	13	14	16	13	19	6
19	Transportation	2030	14	18	20	20	17	18	15	9	18	9	20	11
20	Automobiles & Components	2510	16	19	23	21	19	17	19	22	19	16	23	7
21	Real Estate	4040	23	22	17	16	11	21	20	19	20	11	23	12
22	Consumer Durables & Apparel	2520	21	21	21	22	22	20	18	20	21	18	22	4
23	Insurance	4030	19	23	16	23	23	23	23	23	23	16	23	7
	Pearson Correlation: Annual median BE/ME ranking with the overall sample period median BE/ME Ranking		0.76	0.94	0.80	0.93	0.66	0.86	0.81	0.75		Average Rank Range		11

characteristics may be possible. Banko and Conover perform similar temporal consistency tests for 21 industries defined by SIC. The average range of BE/ME rank migration for each of their 21 industries is 14 places. This compares to an average annual range of BE/ME rank migration shown in the last column of Table 4 of only 11 places for the 23 industries defined by GICS (albeit for a shorter time period). The four lowest BE/ME ranked industries migrate on average only 5 places, suggesting that extreme growth-oriented industries exhibit some level of temporal BE/ME stability.

Figure 1 provides further information on the consistency of BE/ME characteristics that may be beneficial for investment professionals seeking to allocate funds across industry groups. For this presentation, all NYSE, AMEX, NASDAQ, and all "other" OTC stocks are annually sorted into BE/ME quintiles. GICS industry codes are next observed for stocks within each quintile for each year in the sample and then averaged across time for each industry. Chart A shows that on average approximately 60% of pharmaceutical stocks are found in the lowest BE/ME quintile across the entire sample period. This compares to less than 10% of insurance stocks found in that same growth-oriented quintile. Industry allocations across the middle 2nd, 3rd and 4th quintiles are fairly evenly distributed with two exceptions. The largest portion of utility and bank stocks are found in the middle quintile in Chart C. This is somewhat surprising given the tendency of value investment managers to allocate large portions of their portfolios to these industry groups. This observation may hint to a reason why Houge and Loughran (2006) find that value managers have generally failed to capture the statistical rewards of the value premium as promised in the academic literature.

Chart E, reflecting the highest BE/ME value-oriented stocks, again show predictable contents. On average, over 30% of insurance, consumer durables, and automobile stocks are found in this extreme BE/ME quintile over the sample period. Results from Figure 1 show that stocks from growth-oriented industries tend to cluster at high rates in the lowest BE/ME quintile while stocks from value-oriented industries are more evenly distributed across the middle quintiles. This hints that the computed value premium in returns for stocks occupying the highest BE/ME quintile is driven from a more equitable distribution of industry groups.

FIGURE 1: Average annual percentage of GICS industry group stocks appearing in various BE/ME quintiles, June 1999 to May 2007 (n = 96)

All NYSE, AMEX, NASDAQ, and all "other" OTC stocks are annually sorted into BE/ME quintiles. GICS industry codes are next observed for stocks within each quintile for each year in the sample and then averaged across time for each industry. Industry portfolios are computed as described previously in Table 3.

Chart A: Lowest BE/ME Quintile

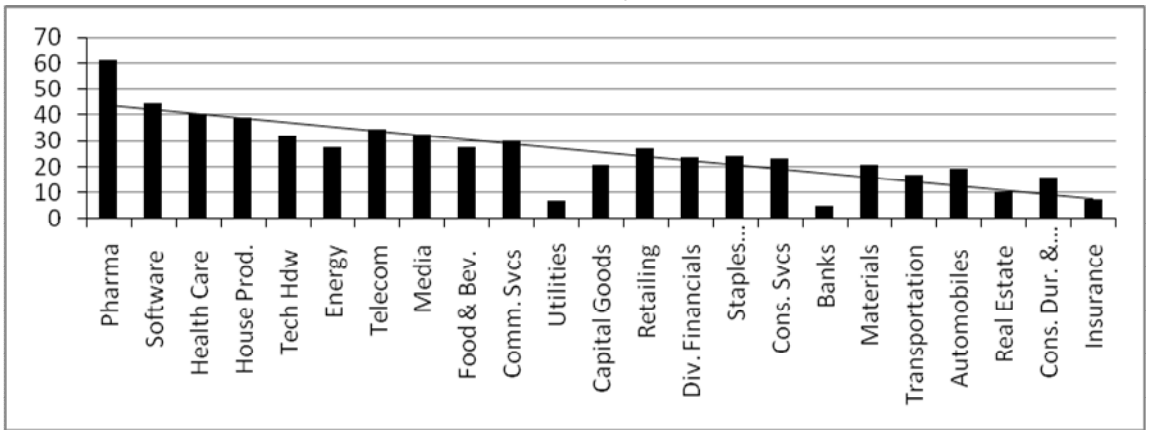


Chart B: 2nd BE/ME Quintile

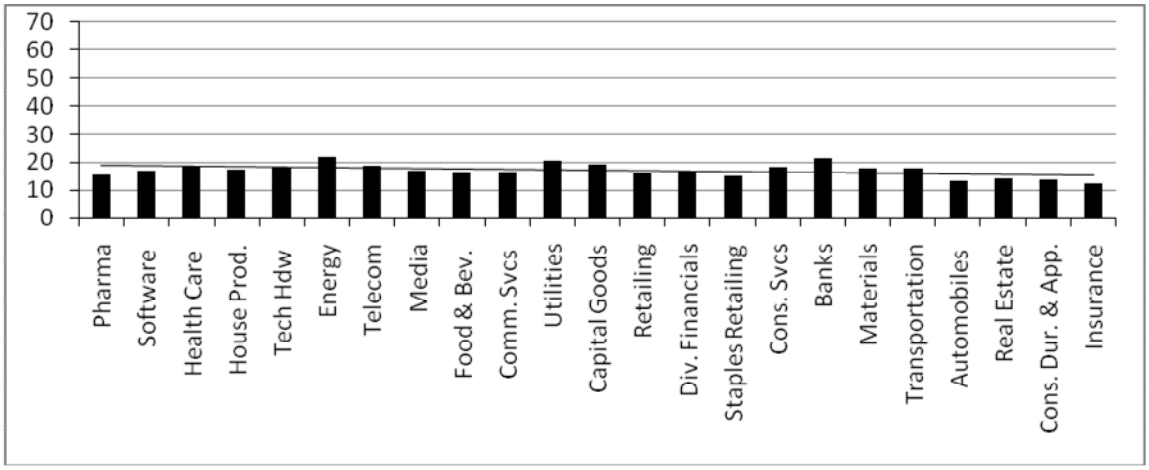


Chart C: 3rd BE/ME Quintile

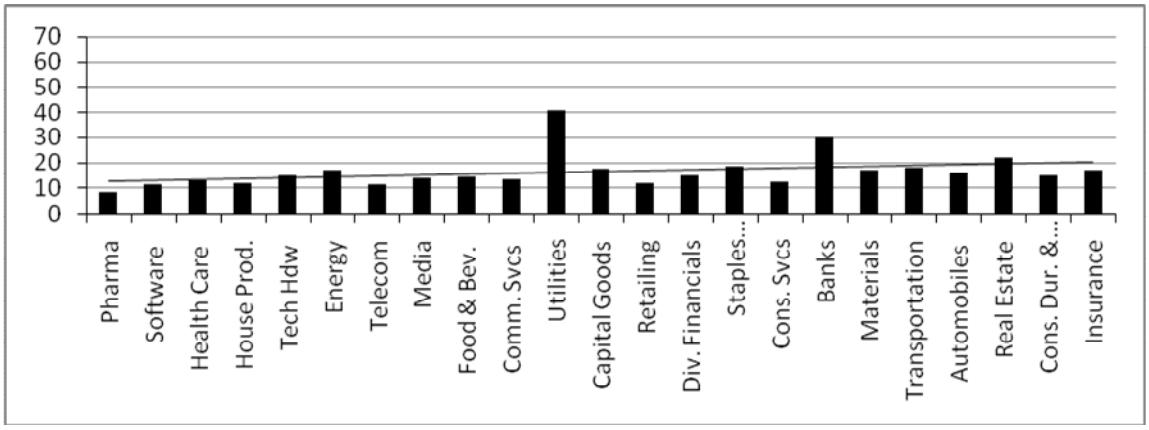


FIGURE 1: ***continued***

Chart D: 4th BE/ME Quintile

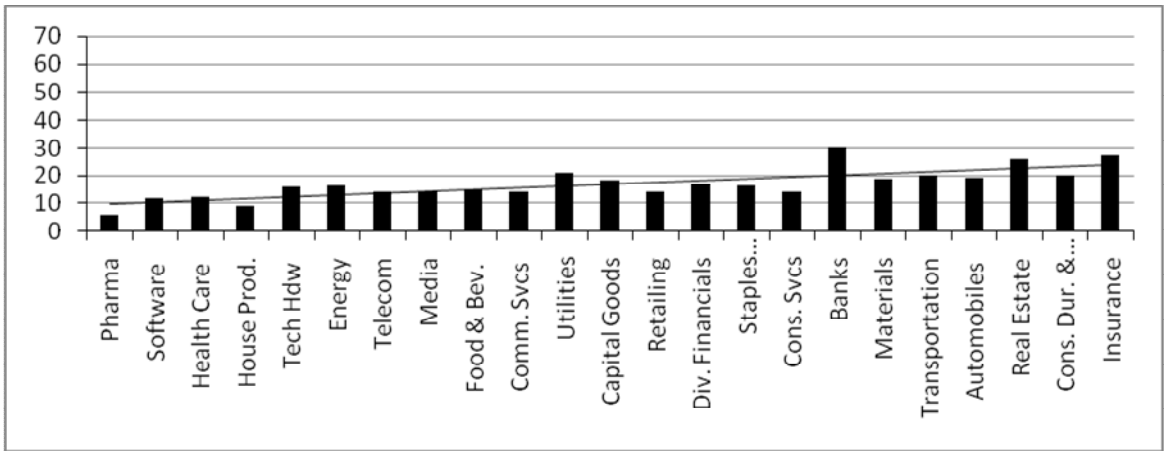
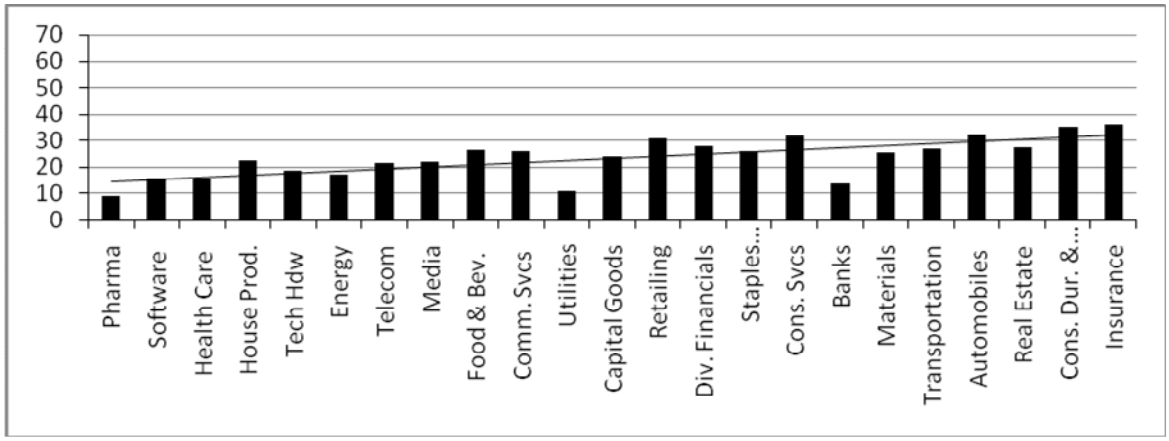


Chart E: Highest BE/ME Quintile



Results from Tables 3 and 4 as well as Figure 1 suggest that value investors using a top-down/bottom-up method may be able to avoid the relatively inferior returns of low BE/ME firms by avoiding certain industry groups, but investors may not be able to capture the superior returns of high BE/ME stocks by exclusively allocating to industry groups historically exhibiting a high BE/ME characteristic. Results showing the temporal stability of growth industry BE/ME and relative temporal instability of value industry BE/ME are consistent with findings in Banko and Conover (2006) of the relatively weaker power of an across-industry effect.

Results in both Table 4 and from the various quintile charts in Figure 1 suggest that certain industries have a natural or structural tendency with respect to BE/ME characteristics. Technology stocks appear to generally exhibit low BE/ME fundamental characteristics while Insurance stocks appear to generally exhibit high BE/ME fundamental characteristics. Growth managers who exclusively screen

companies based on low BE/ME characteristics may find their portfolios disproportionately weighted with technology industry stocks over time. Conversely, value managers who exclusively screen companies based on high BE/ME characteristics may find their portfolios disproportionately weighted with insurance stocks.

Section 5: The value premium across industry sectors

Chen and Zhang (1998) find that stocks in certain developing economies like Thailand and Taiwan do not exhibit a value premium. They argue this is due to high economic growth conditions and therefore a lack of overall market distress. If Chen and Zhang are correct, then high BE/ME value stocks found within (distressed) value industries should exhibit superior performance to high BE/ME value stocks found within (less distressed) growth industries. Banko and Conover (2006) test this thesis in a cross-industry analysis and find that value firms in value industries do indeed generate superior returns to value firms in growth industries, consistent with predictions of Chen and Zhang.

The performance of value and growth stocks within each GICS industry group are next examined to determine whether value stocks in value industries indeed generate premium returns. Portfolios are formed by first sorting stocks by GICS industry sector and then independently sorting NYSE, AMEX, NASDAQ and all other OTC stocks 2x5 by size and BE/ME, using the method in Fama and French (1993). In this examination, sample size restrictions force the use of broader 2-digit GICS industry classifications, a more macro combination of the various 23 GICS industry groupings (See Appendix A for a map of the GICS classification system). Ideally, within-industry performance of the entire set of 23 GICS industry groups would be evaluated to create a finer cut of performance differentiation. However, the use of industry (or economic) sectors rather than industry groups allows for tests of larger samples through time and therefore better statistical inferences from those samples. Larger sample sizes also allow for the use of controls for size and greater differentiation within BE/ME characteristics.[43]

Following standards established in Banko and Conover to ensure proper statistical inferences, all econometric tests using industry sectors in this essay require a fifteen stock minimum portfolio sample, when controlling for size. This restriction results in the exclusion of two sectors, telecom (GICS code 50) and utilities (GICS code 55), which average portfolio sample sizes over the eight year period of only eight stocks and thirteen stocks respectively. Since the nature of questions in this essay is to evaluate within-

[43] Chan, Lakonishok, and Swaminathan (2007) find that 2-digit GICS codes provide lower differences between return correlations for stocks in a particular sector and correlations for all other stocks outside that sector when compared to the four, six, and eight digit codes. While not optimal, 2-digit GICS sorted sectors still reflect a considerable range of BE/ME characteristics.

sector and across-sector returns and risk characteristics, the only requirement for such analysis is that remaining sectors reflect substantial variation across BE/ME characteristics. Such variation in the BE/ME characteristic will allow a proper delineation between value-oriented sectors and growth-oriented sectors. Indeed, average BE/ME characteristics across the eight remaining sectors do range considerably. BE/ME characteristics for financials average 0.72, more than double the average BE/ME characteristic 0.33 for healthcare. Banko and Conover apparently experience similar problems with industry sample sizes. Their solution is to create generic groups of low BE/ME growth industry portfolios and generic groups of high BE/ME value portfolios – thus eliminating industry and sector identities altogether.

Table 5 shows the average equal-weighted monthly return of GICS sector portfolios sorted independently 2x5 on size and BE/ME. Stocks are first sorted into one of the eight GICS sectors. Then, within each sector, stocks are sorted by size at a breakpoint above and below $491 million. The breakpoint is derived using the average of the Fama and French ME breakpoints for the 25th percentile over the eight year period, June 1999 to May 2007. A fixed breakpoint over time is preferred rather than a floating or relative annual ME or BE/ME breakpoint because it establishes fixed characteristics for specific levels of ME and BE/ME. Testing stocks below and above the 25th percentile helps in three ways. First, small stocks dominate the sample; therefore, skewing the size breakpoint to 25%/75% creates samples big enough to test large cap stocks within each economic sector. Second, the value premium has been shown to predominate in the small cap stratum of stocks. If the value premium is present within and across economic sectors, it is more likely to be found below a portfolio market capitalization of $491 million and less likely above it. Third, because of liquidity constraints and other trading difficulties, $491 million in individual stock market capitalization represents a level below which most institutional investors rarely invest. Therefore, results for stocks above the $491 million market cap would be informative regarding the question of institutional investors' ability to capture the value premium.[44] Following the sort for size, stocks are further sorted into quintiles using the Fama and French20th, 40th, 60th, and 80th percentile BE/ME breakpoints averaged over the sample period. Stocks are sorted and rebalanced annually to form ten portfolios for each sector. The traditional portfolio formation date in prior research occurs in July of year t capturing returns from that date through June of year t+1. However, in order to maximize the length of the historical GICS time series available, a portfolio formation date of June is used. Monthly total portfolio returns are observed June to May and

[44] For robustness, a check was also performed using the Fama and French average 50th percentile ME breakpoint on size, and results [not shown] are not materially different.

TABLE 5: Average portfolio returns for stocks sorted by GICS industry sector and then 2x5 on size and BE/ME. June 1999 to May 2007, (n = 96).

Average equal-weighted monthly return of GICS sector portfolios sorted independently 2x5 on size and BE/ME. Stocks are first sorted into one of the eight GICS sectors. Then, within each sector, stocks are sorted by size at a breakpoint above and below $491 million. The breakpoint is derived using the average of the Fama and French ME breakpoints for the 25th percentile over the eight year period, June 1999 to May 2007. Returns and industry composition are described earlier in Table 3.

Panel A: Monthly time series of portfolio returns

			Below ME Breakpoint of $491 million Book to Market Equity							Above ME Breakpoint of $491 million Book to Market Equity						
Sector	GICS	BE/ME	LO	2	3	4	HI	HI-LO	t-stat	LO	2	3	4	HI	HI-LO	t-stat
HEALTH CARE	35	0.33	2.09	2.49	2.37	3.06	4.05	**1.96**	**3.45**	1.26	1.72	1.70	1.36	1.03	**-0.24**	**-0.20**
INFORM TECH	45	0.46	1.60	2.19	3.00	2.28	3.07	**1.48**	**2.41**	1.10	1.43	1.64	1.76	0.78	**-0.31**	**-0.39**
ENERGY	10	0.52	2.65	2.25	2.87	3.28	4.72	**2.07**	**2.23**	2.17	2.05	2.38	2.05	1.41	**-0.76**	**-0.82**
CONS. STAPLES	30	0.54	1.09	1.69	1.54	1.39	2.79	**1.69**	**2.35**	1.02	0.94	0.91	1.70	1.43	**0.41**	**0.17**
INDUSTRIALS	20	0.63	1.24	1.62	1.76	1.92	2.44	**1.20**	**2.27**	1.01	1.35	1.24	1.23	0.61	**-0.40**	**-0.63**
MATERIALS	15	0.65	0.93	1.73	0.62	1.62	2.55	**1.62**	**2.06**	1.10	1.49	1.24	1.89	2.38	**1.27**	**1.54**
CONS. DISCR.	25	0.67	0.80	1.49	1.28	1.36	1.95	**1.15**	**2.62**	0.91	0.94	0.91	1.11	1.36	**0.45**	**0.93**
FINANCIALS	40	0.72	1.23	1.32	1.20	1.39	1.73	**0.50**	**1.00**	1.03	1.21	1.13	1.40	1.16	**0.13**	**0.34**
		AVERAGE	**1.45**	**1.85**	**1.83**	**2.04**	**2.91**	**1.46**		**1.20**	**1.39**	**1.39**	**1.56**	**1.27**	**0.07**	
Pearson correlation: BE/ME with HI-LO Returns								-0.74	-2.69						0.46	1.26

Panel B: Portfolio returns averaged across time

			Below ME Breakpoint of $491 million Book to Market Equity							Above ME Breakpoint of $491 million Book to Market Equity						
Sector	GICS	BE/ME	LO	2	3	4	HI	HI-LO	t-stat	LO	2	3	4	HI	HI-LO	t-stat
HEALTH CARE	35	0.33	1.92	2.56	2.54	3.58	4.58	**2.66**	**4.51**	1.09	1.63	1.63	1.93	1.62	**0.53**	**0.64**
INFORM TECH	45	0.46	1.20	2.27	3.13	2.66	3.84	**2.65**	**2.32**	0.69	1.27	1.31	1.72	0.87	**0.18**	**0.12**
ENERGY	10	0.52	2.45	2.23	2.82	3.21	4.69	**2.24**	**2.29**	1.64	2.11	2.48	2.44	2.47	**0.84**	**0.86**
CONS. STAPLES	30	0.54	0.92	1.46	1.61	1.14	2.76	**1.84**	**2.88**	0.89	0.85	1.09	1.96	2.60	**1.71**	**1.29**
INDUSTRIALS	20	0.63	1.28	1.45	1.73	1.84	2.29	**1.01**	**1.82**	1.01	1.41	1.31	1.46	1.14	**0.13**	**0.18**
MATERIALS	15	0.65	1.08	1.76	0.69	1.37	2.39	**1.31**	**1.87**	1.22	1.56	1.26	1.18	2.44	**1.21**	**1.07**
CONS. DISCR.	25	0.67	0.60	1.30	1.16	1.28	2.00	**1.40**	**2.52**	0.84	0.90	0.86	1.31	1.67	**0.83**	**1.30**
FINANCIALS	40	0.72	1.27	1.12	1.10	1.50	2.07	**0.80**	**1.85**	1.05	1.14	1.10	1.43	1.45	**0.40**	**1.24**
		AVERAGE	**1.18**	**1.70**	**1.72**	**1.98**	**3.01**	**1.83**		**0.61**	**1.05**	**1.25**	**1.60**	**1.95**	**1.34**	
Pearson correlation: BE/ME with HI-LO Returns								-0.94	-6.90						0.08	0.21

accessed in Research Insight. Portfolio returns in Panel A of Table 5 are computed as equal-weighted arithmetic averages of monthly returns across stocks in the sample. Returns reflect the average of monthly returns for each quintile over the eight year sample period (n = 96). Returns in Panel A can be defined as the average monthly return for various size and BE/ME portfolios over the eight year sample period.

Certain portfolio returns shown in Panel A, namely returns for stocks larger than the ME breakpoint, suffer some degree of noise due to relatively small number of stocks in the portfolio. For further confidence in results, returns are computed using a different method. Panel B shows returns for stocks sorted by sector and then 2x3 on size and BE/ME as before. However, returns in this presentation are averaged across time rather than creating a 96 month time series of portfolio returns. Data presented in Panel B can be defined as average monthly returns for the average stock in a specific size and BE/ME strata in a specific sector. For example, it can be said that on average, each stock in the small cap LO BE/ME healthcare portfolio returned 1.92% per month between June 1999 and May 2007.

Results are summarised as follows: The HI-LO value premium shown in Panel A of Table 5 is statistically significant within all sectors below the size breakpoint, with the exception of financials.[45] In Panel B, five of the HI-LO quintile sector returns below the 25th size percentile are statistically significant at the 5% level and the remaining 3 at the 10% level. Results in Panels A and B demonstrate that the value premium is clearly related to size. The premium is statistically non-existent (often negative) within each sector above the size breakpoint of both panels. Observing the value premium in only small cap stocks is consistent with findings in Loughran (1997) and problematic for the explanatory power of the 3-factor model. Fama and French (2006), in an attempt to remedy the challenge from Loughran, argue that the weakness of the value premium in large stocks is unique to Loughran's sample period 1963 to 1995 and unique to US stocks. Results in Table 5, using a sample subsequent to the period tested by Loughran, certainly undermines the argument that the weakness is sample specific- although possibly still a function of more recent market conditions.

Banko and Conover observe that growth stocks in value industries have superior returns to growth stocks in growth industries. Further, value stocks in value industries have superior returns to value stocks in growth industries. Both observations are inconsistent with results in Table 5. For small cap stocks, low BE/ME growth stocks in growth industries have superior returns to low BE/ME growth stocks in value industries. High BE/ME value stocks in growth industries outperform high BE/ME value

[45] The Hi-LO value premium was statistically significant at the 5% level for all sectors using the 50/50 ME breakpoint and once again not statistically different from zero for all sectors above the size breakpoint.

stocks in value industries. Table 5 shows that, while the within-industry value premium is apparently not subsumed by industry-specific influences, industry distinctions do remain. During this sample period, the value premium is remarkably stronger in growth sectors such as health care (1.96% per month) and information technology (1.48% per month) and weaker in value sectors such as financials (0.50% per month) and consumer discretionary (1.15% per month). Pearson correlation coefficients for HI-LO returns and median BE/ME characteristics across the eight economic sectors confirm the association between a higher value premium and a lower BE/ME characteristic. Coefficients shown in Table 5 are strong and negative for stocks below the 25th size percentile (ρ = -0.74, t = 2.69). However, no statistically significant association between the value premium and a sector's BE/ME ranking is observed in large cap stocks above the 25th size percentile (ρ = 0.46, t = 1.26).

Section 6: Relative sector distress

The question of whether distress risk is a driver of the value premium is important not only to researchers creating pricing models, but also important to investment practitioners. Value money managers, with the exception of some extreme contrarian investors, tend to exclude stocks bearing characteristics of high financial or operating distress from their portfolios. Lakonishok, Shleifer, and Vishny (1994) suggest that institutional investors are likely to believe that excluding stocks exhibiting extreme distress works to mitigate portfolio risk. However, if characteristics of financial or operating distress can provide a different opportunity to capture the value premium (possibly at the cost of higher risk) where BE/ME alone has not yet yielded promised results for managed portfolios, then a rational investment manager would want to include rather than omit such distressed stocks.

Distress is a fundamental operating and balance sheet condition of numerous definitions. Chen and Zhang (1998) extend the analysis of fundamental characteristics of earnings distress in Fama and French (1995) to include definitions of financial distress measuring three characteristics; namely, a company's reduction in dividends, earnings uncertainty measured by the volatility of the earnings yield (E/P), and financial leverage distress measured by the traditional debt-to-equity ratio. The authors find that value stocks observed across several international markets consistently provide investors with low returns prior to portfolio formation periods and also exhibit low return-on-equity ratios. Banko and Conover (2006) confirm the distress/risk thesis of Chen and Zhang in their evaluation of the value premium and effect across and within industry groupings. The authors specifically find that value

portfolios exhibit lower returns on assets (ROA) than growth portfolios within each industry grouping, and that ROA is lower for value industries when observed across industry results.[46]

At first glance, across-sector portfolio return results presented earlier in Table 5 are not consistent with expectations that the value premium is compensation for the assumption of higher firm risk. When viewed across-sector, the value premium (HI-LO) in Table 5 is monotonically stronger within low BE/ME growth sectors than within high BE/ME value sectors - contrary to expectations and results in Banko and Conover. However, if growth sector return characteristics are shown during this unique sample period to be associated with greater relative distress than value sector characteristics, then across-sector returns shown in Table 5 would, at minimum, not be inconsistent with the pricing of distress risk of various definitions.

Results for one measure of distress shown next in Table 6 confirm that this particular sample period is different than that tested by Banko and Conover.[47] Low BE/ME growth sectors exhibit relatively greater operating stress, as defined by ROA, than high BE/ME value sectors. Average returns on assets for the lowest BE/ME sectors such as healthcare (ROA = -4.6%) and information technology (ROA = -4.0%) are generally negative for the sample period, while returns for the highest BE/ME value sectors such as consumer discretionary (ROA = 4.3%) and materials (ROA = 2.2%) are positive. Across-sector results in Table 6 are unusual and in direct contradiction to ROA observations for value and growth industry groups in Banko and Conover (2006). The average across-sector correlation coefficient for all BE/ME quintiles is 0.72 (t = 2.35). Individual across-sector, within-quintile coefficients are somewhat stronger after omitting ROA characteristics for the financial sector [See note in the body of Table 6].

Since value stocks are shown in Table 5 to have outperformed growth stocks within each sector, within-sector ROA characteristics for value portfolios should be worse (more distressed) than ROA characteristics for growth portfolios. The within-sector (across BE/ME quintile) ROA pattern is consistent with these expectations. With the exception of three sectors where the pattern is an inverted U-shape (healthcare, technology, and materials), within-sector ROA generally falls monotonically as BE/ME rises

[46] Loughran (1997) also observe superior ROA for growth-oriented portfolios sorted 5x5 on size and BE/ME for a sample of all stocks, 1963 to 1995.

[47] Banko and Conover compute ROA across and within industry groups but do not differentiate the characteristic by size. Table 6 does not control for size to facilitate meaningful comparability of ROA results. For robustness, ROA is observed for stocks sorted first by GICS and then 2x5 on size and BE/ME using the same averaging method used in Panel B of Table 5 for both the 25/75 size sort and the 50/50 size sort. Average ROA for small stocks [not shown] suggest considerably greater ROA distress than large stocks during the period. Correlation coefficients, testing associations between across-sector ROA and ranked median BE/ME (and t-stats), are not materially different than results shown in Table 4 for small company portfolios. However, coefficients for large company portfolios are small and indistinguishable from zero.

across BE/ME quintiles. High BE/ME value portfolios exhibit relatively lower ROA than low BE/ME growth portfolios – a result consistent with Banko and Conover's risk thesis for tests of within-industry ROA. Although the pattern of value/growth returns is different than that observed in prior sample periods across industry sectors, the pattern of distress underlying these returns changes commensurately. Despite the unique event shocks experienced during the GICS-limited sample period, patterns of within-sector and across-sector operating distress as defined by returns on assets are not inconsistent with the argument that the value premium reflects compensation for the assumption of greater risk – in this instance, distress is measured by a company's return on assets.

TABLE 6: Average annual ROA for sector portfolios sorted by BE/ME only. June 1999 to May 2007, (n = 96).

All NYSE, AMEX, NASDAQ and "other" OTC stocks are independently sorted first into GICS sectors as discussed earlier in Table 3 and then into book-to-market quintiles using breakpoints obtained from the website of Kenneth French. Industry sector ROA characteristics are observed annually at May of year t, the point of portfolio formation, and then averaged across time for each book-to-market quintile portfolio.

Industry		Median	BE/ME Portfolio						
Sector	GICS	BE/ME	LO	2	3	4	HI	HI-LO	AVG.
Healthcare	35	0.33	-16.4	0.1	0.7	-1.1	-6.5	9.9	-4.6
Info Tech	45	0.46	-1.2	1.5	-1.2	-3.3	-16.0	-14.8	-4.0
Energy	10	0.52	5.1	4.9	3.8	2.6	-2.3	-7.5	2.8
Cons. Stap.	30	0.54	7.8	5.7	4.4	2.6	0.6	-7.2	4.2
Industrials	20	0.63	5.8	5.2	4.3	3.0	0.6	-5.2	3.8
Materials	15	0.65	0.5	4.7	3.4	2.7	-0.1	-0.6	2.2
Cons. Discr.	25	0.67	6.9	5.9	4.8	3.4	0.6	-6.3	4.3
Financials*	40	0.72	1.7	1.3	1.1	0.9	0.6	-1.1	1.1
Correlation ROA with BE/ME			0.71	0.48	0.47	0.63	0.66		0.72
t-stat			2.44	1.35	1.30	1.99	2.14		2.57

*ROA for Financials is not directly comparable to ROA in other sectors. Commercial banks, the largest industry component in the financial sector, are heavily leveraged as a function of their core business. Therefore, a small ROA will generate very large profits compared to similar ROA in other sectors. Results for correlation coefficients and t-stats adjusted to exclude ROA for financials are shown below.

Correlation ROA with BE/ME			0.80	0.87	0.73	0.77	0.64		0.84
t-stat			2.95	3.91	2.38	2.66	1.86		3.41

To test the risk thesis of Chen and Zhang further, another distress characteristic is observed for portfolios formed as before. The Altman Z-score, an algorithmic construction of various accounting ratios was shown in Altman (1968) to successfully capture the probability of bankruptcy. When applied here, results using the Z-score to determine the relative distress of value and growth sector portfolios are inconclusive. While a positive association is found between the risk of bankruptcy and higher return within each industry sector, the association is not confirmed when viewing risk across industry sectors. Results for the within-sector analysis are not without criticism and may not, upon further consideration, be reflective of risk pricing. See Appendix B for a full discussion of the Altman Z-Score and analysis of the within and across sector results.

In a final examination of the issue, the BE/ME characteristic is decomposed into two parts following the method of Penman, Richardson, and Tuna (2007). Penman et al. showed that BE/ME has two parts - an unlevered operating component and a levered financial component. If BE/ME is decomposed into its levered and unlevered components, finance theory tells us to expect the levered component to be positively related to superior returns. Moreover, if financial distress is driving the value premium, then the debt component of book value should be the driver of the return differential. Results for the analysis of the levered component of BE/ME within and across industry sector are presented in detail in Appendix C and are inconclusive. Results in Appendix C show that adding leverage does not generate lower returns, contrary to findings by Penman et al. However, results also show that adding leverage does not appear to result in higher returns either. The latter findings are in clear contradiction to Banko and Conover (2006) and Chen and Zhang (1998), and also inconsistent with a financial distress thesis in explaining the value premium in average returns.

Section 7: The impact of a January anomaly on the value premium within and across industry sectors

The January anomaly in returns is a well-documented challenge to the theory of efficient markets. Rozeff and Kinney (1976) initially observe the anomaly in equal-weighted NYSE returns, and the phenomenon is confirmed in Reinganum (1983) and Roll (1983) showing the effect to predominate in small stocks. Lakonishok and Smidt (1988) find the January anomaly to persist over their ninety year sample period of daily data. Explanations for the effect have ranged from end-of-year window dressing by institutional investors to individual tax loss selling.[48] Haug and Herschey (2006) recently update

[48] The January premium may simply be the result of data snooping as generally suggested by Lo and MacKinlay (1990) and Fama (1998). Fama argues that most market anomalies disappear after certain tweaks in statistical methods.

research on the January effect to test its existence subsequent to the enactment of the Tax Reform Act of 1986, a US tax law that materially impacted mutual fund capital gain distributions. The authors find a persistent January effect in equal-weighted returns in small cap stocks despite the change in tax law.

The question for this research is whether the January anomaly in returns subsumes or impacts the value premium in industry sectors shown previously in Table 5. In addition to documenting the January premium across and within GICS industry groupings, this research seeks to shed further light on Loughran (1997) who argues that the book-to-market premium is driven in large part, first by low returns of growth stocks in the eleven months excluding January and second by returns associated with the January anomaly.

This section asks, 1) Does the January premium in returns exist within each industry sector using a sample period subsequent to the US Tax Reform Act of 1986, and more importantly, 2) If a January anomaly exists in this data, do value premium characteristics in equal-weighted returns observed earlier in Table 5 survive after re-testing only the 11 months excluding January? If the value premium is subsumed by the January anomaly within and across industry sectors, then investors who make industry allocations within their portfolios need only to concentrate on the January premium rather than the BE/ME premium in their attempt to capture superior returns over time.

Results shown in Table 7 confirm findings in Haug and Herschey (2006) that the January anomaly exists in equal-weighted returns observed subsequent to the enactment of the US Tax Reform Act of 1986. The January premium in small stock returns, shown in Panel A as the difference between average January returns and the returns for the other eleven months, is large and statistically significant across industry sectors for all BE/ME quintiles. For example the average difference between returns for January and the average monthly returns for the other eleven months for the LO BE/ME quintile is very large at 11.70% (t = 8.28). However, the January premium generally disappears or appears relatively weaker in large cap stocks shown in Panel B.[49] These findings are consistent with prior research that isolated the January anomaly as a small cap stock phenomenon. Curiously, the January return premium in small cap stocks is more pronounced in both the lowest (11.70%) and highest (10.69%) BE/ME quintiles, approximately double the premium in the middle three quintiles (6.11%, 5.59%, 5.59%). Surprisingly, returns for the month of January, as well as differences between returns within each industry sector shown in Panel A of Table 7, appear larger for growth industry sectors than for value industry sectors.

[49] Results shown in Table 5 represent stocks above and below the Fama and French 25th percentile average size breakpoint for the sample period. The January premium completely disappears in large stocks in sorts using a 50th (below 50th/above 50th) size breakpoint.

TABLE 7: Average January returns and average monthly returns excluding January for sector portfolios sorted 2x5 for size and BE/ME. June 1999 to May 2007.

Average equal-weighted monthly return of GICS sector portfolios sorted independently 2x5 on size and BE/ME. Stocks are first sorted into one of the eight GICS sectors. Then, within each sector, stocks are sorted by size at a breakpoint above and below $491 million. The breakpoint is derived using the average of the Fama and French ME breakpoints for the 25th percentile over the eight year period, June 1999 to May 2007. Returns and industry composition are described earlier in Table 3.

Panel A: Small Stocks

	Book to Market Quintiles (BE/ME)														
	LO			2			3			4			HI		
Sector	January	11 Mos.	Difference	January	11 Mos.	Difference	January	11 Mos.	Difference	January	11 Mos.	Difference	January	11 Mos.	Difference
HEALTH CARE	11.56	1.04	10.51	12.48	1.66	10.82	11.80	1.69	10.11	13.47	2.68	10.79	16.51	3.50	13.02
INFORM TECH	19.04	-0.43	19.47	12.94	1.29	11.65	11.27	2.39	8.88	11.53	1.86	9.67	16.51	2.69	13.82
ENERGY	7.92	1.96	5.96	5.82	1.90	3.92	4.98	2.62	2.36	4.89	3.06	1.83	15.36	3.72	11.64
CONS. STAPLES	12.41	-0.12	12.52	4.76	1.16	3.60	7.75	1.05	6.70	4.69	0.82	3.87	11.62	1.96	9.67
INDUSTRIALS	12.27	0.28	11.99	5.75	1.06	4.69	6.40	1.31	5.09	6.65	1.40	5.25	12.00	1.41	10.59
MATERIALS	12.25	0.06	12.19	6.63	1.32	5.31	5.41	0.27	5.14	5.38	1.00	4.38	12.27	1.49	10.79
CONS. DISCR.	12.54	-0.48	13.02	8.14	0.68	7.46	6.28	0.70	5.58	7.95	0.67	7.28	12.27	1.07	11.20
FINANCIALS	8.52	0.61	7.92	2.46	1.00	1.46	1.90	1.03	0.86	3.01	1.36	1.65	6.44	1.67	4.77
Average	**12.06**	**0.36**	**11.70**	**7.37**	**1.26**	**6.11**	**6.97**	**1.38**	**5.59**	**7.20**	**1.61**	**5.59**	**12.87**	**2.19**	**10.69**
		t-stat	**8.28**		**t-stat**	**4.82**		**t-stat**	**5.16**		**t-stat**	**4.65**		**t-stat**	**11.04**

Panel B: Large Stocks

	Book to Market Quintiles (BE/ME)														
	LO			2			3			4			HI		
Sector	January	11 Mos.	Difference	January	11 Mos.	Difference	January	11 Mos.	Difference	January	11 Mos.	Difference	January	11 Mos.	Difference
HEALTH CARE	0.39	1.15	-0.76	0.98	1.69	-0.72	0.77	1.71	-0.93	2.68	1.86	0.82	2.05	1.58	0.47
INFORM TECH	6.64	0.15	6.49	1.25	1.28	-0.03	2.68	1.19	1.49	8.00	1.15	6.84	6.44	0.37	6.07
ENERGY	1.82	1.62	0.19	1.50	2.17	-0.67	2.89	2.44	0.45	0.16	2.65	-2.49	4.86	2.26	2.60
CONS. STAPLES	0.64	0.92	-0.28	-1.48	1.06	-2.55	0.19	1.17	-0.98	1.03	2.05	-1.02	10.30	1.90	8.40
INDUSTRIALS	-0.17	1.12	-1.30	0.20	1.51	-1.31	0.06	1.42	-1.36	-0.33	1.63	-1.96	1.34	1.12	0.22
MATERIALS	0.61	1.28	-0.67	1.30	1.58	-0.28	-0.12	1.39	-1.51	-1.41	1.42	-2.83	5.05	2.20	2.86
CONS. DISCR.	1.30	0.80	0.50	0.92	0.90	0.01	1.00	0.85	0.16	1.01	1.33	-0.32	2.23	1.62	0.61
FINANCIALS	0.87	1.06	-0.19	-0.47	1.29	-1.76	-0.34	1.23	-1.57	-0.02	1.56	-1.58	0.27	1.55	-1.28
Average	**1.51**	**1.01**	**0.50**	**0.52**	**1.44**	**-0.91**	**0.89**	**1.42**	**-0.53**	**1.39**	**1.71**	**-0.32**	**4.07**	**1.58**	**2.49**
		t-stat	**0.57**		**t-stat**	**-2.86**		**t-stat**	**-1.35**		**t-stat**	**-0.29**		**t-stat**	**2.16**

For example, the difference in returns across all BE/ME quintiles for the health care sector averages over 10% while the difference across BE/ME quintiles for the financial sector averages just over 3%. The relationship is considerably more monotonic when viewing across-sector differences in quintiles 2 through 4.

A critical question remains whether the value premium as shown previously in Table 5 continues to survive once the January premium is removed from the sample. If the value premium is independent of the January anomaly, then superior returns for high BE/ME stocks should still persist in average portfolio returns when testing only the other 11 months of the calendar year. To examine this question, stocks are once again sorted 2x5 on size and BE/ME as before. Returns are again captured over the eight year period June 1999 to May 2007 and computed in the manner presented in Panel B of Table 5. Return observations for the month of January are excluded for each size and BE/ME portfolio and outcomes presented in Table 8. Results show that the value premium is robust even after removing the superior returns generated during the month of January - consistent with findings in Daniel and Titman (1997) who find the value effect to be independent of the January anomaly. [50] Removing returns for the month of January does not materially impact the relative HI-LO value premium relationship. The key across-sector value premium characteristics shown previously in Table 5, critical to inferences related to risk made in earlier sections of this essay, survive. The value premium is larger within growth sectors than within value sectors during this sample period even when returns for the month of January are omitted. Sector HI-LO premiums continue to be highly negatively correlated with the average sector BE/ME characteristics for small stocks (ρ = -0.81, t = -3.40). The premium is statistically significant for small cap stocks at the 5% level within five of eight industry sectors and significant at the 10% level within the remaining three – a result similar to within sector premiums observed earlier in Table 5. After omitting returns for the month of January, the value premium continues to be non-existent in large cap stocks. None of the HI-LO computations are statistically different from zero. Moreover, correlations between sector HI-LO premiums and sector BE/ME characteristics in large cap stocks are indistinguishable from zero (ρ = 0.22, t = 0.55) reflecting no association between the computed premia and the ordering of sector book-to-market characteristics.

Average monthly returns in Table 8, computed after excluding superior January returns, are by definition smaller than those shown earlier in Panel B of Table 5. However, the average monthly value

[50] Daniel and Titman (1997) document a large January effect in portfolio returns sorted on size and BE/ME. They observe that average pre-formation portfolio returns for the month of January are positive while returns for the other 11 months are negative.

TABLE 8: Average monthly GICS industry sector portfolio returns for stocks sorted 2x5 on size and BE/ME, excluding returns for the month of January. June 1999 to May 2007, (n = 88).

Average equal-weighted monthly return of GICS sector portfolios sorted independently 2x5 on size and BE/ME. Stocks are first sorted into one of the eight GICS sectors. Then, within each sector, stocks are sorted by size at a breakpoint above and below $491 million. The breakpoint is derived using the average of the Fama and French ME breakpoints for the 25th percentile over the eight year period, June 1999 to May 2007. Returns and industry composition are described earlier in Table 3.

			Below ME Breakpoint of $491 million Book to Market Equity							Above ME Breakpoint of $491 million Book to Market Equity						
Sector	GICS	BE/ME	LO	2	3	4	HI	HI-LO	t-stat	LO	2	3	4	HI	HI-LO	t-stat
HEALTH CARE	35	0.33	1.04	1.66	1.69	2.68	3.50	**2.45**	**4.06**	1.15	1.69	1.71	1.86	1.58	**0.43**	**0.47**
INFORM TECH	45	0.46	-0.43	1.29	2.39	1.86	2.69	**3.12**	**2.74**	0.15	1.28	1.19	1.15	0.37	**0.22**	**0.13**
ENERGY	10	0.52	1.96	1.90	2.62	3.06	3.72	**1.76**	**1.89**	1.62	2.17	2.44	2.65	2.26	**0.64**	**0.61**
CONS. STAPLES	30	0.54	-0.12	1.16	1.05	0.82	1.96	**2.08**	**3.20**	0.92	1.06	1.17	2.05	1.90	**0.99**	**0.81**
INDUSTRIALS	20	0.63	0.28	1.06	1.31	1.40	1.41	**1.13**	**1.89**	1.12	1.51	1.42	1.63	1.12	**0.00**	**0.00**
MATERIALS	15	0.65	0.06	1.32	0.27	1.00	1.49	**1.43**	**1.89**	1.28	1.58	1.39	1.42	2.20	**0.92**	**0.76**
CONS. DISCR.	25	0.67	-0.48	0.68	0.70	0.67	1.07	**1.55**	**2.65**	0.80	0.90	0.85	1.33	1.62	**0.82**	**1.17**
FINANCIALS	40	0.72	0.61	1.00	1.03	1.36	1.67	**1.06**	**2.81**	1.06	1.29	1.23	1.56	1.55	**0.49**	**1.44**
		AVERAGE	**0.37**	**1.26**	**1.38**	**1.61**	**2.19**	**1.82**		**1.01**	**1.44**	**1.42**	**1.71**	**1.58**	**0.56**	
Pearson correlation: BE/ME with HI-LO Returns								-0.81	-3.40						0.22	0.55

premium in sector returns for small cap stocks in Table 5 (1.83%) is virtually identical to the premium for small stocks in Table 8 (1.82%). Results show that the average value premium computed across GICS industry sectors is not impacted by January returns – although slight variations in individual sector premia are observed. Results, however, do not suggest the value premium is stronger in the eleven months excluding the month of January as observed by Dhatt, Kim and Mukherji (1999). Nor are results consistent with findings in Loughran (1997) that the value premium is boosted in part by January returns.

Section 8: Conclusion

This essay provides numerous contributions to the body of academic literature that currently exists on the value premium. First, results confirm findings of Banko and Conover (2006) that industry groups exhibit large differences in BE/ME characteristics. In an applied context, this finding may offer opportunities for investors to capture the value premium in average returns by strategically allocating funds to targeted industry groups. Further, this essay adds to the findings of Banko and Conover by showing that the annual ranking of industry BE/ME appears to be relatively stable and potentially predictable for investors. The four lowest BE/ME ranked industries migrate to higher BE/ME characteristics on average only 5 places, suggesting that extreme growth-oriented industries have considerable temporal BE/ME stability. Value-oriented industry groupings are less stable over the sample period. Stocks from growth-oriented industries tend to cluster at high rates in the lowest BE/ME quintile while stocks from value-oriented industries appear more evenly distributed across the middle BE/ME quintiles over time. This means that the relatively poor returns generated by low BE/ME growth stocks may largely originate in a few persistently poor performing growth-oriented industry groups. If growth industries (or sectors) consistently underperform value industries, then investors can use these temporal characteristics to allocate away from these industries. However, Table 5 shows the relationship to be more complex. During the sample period, high BE/ME value stocks residing in low BE/ME growth sectors actually outperform value stocks in value sectors.

Next, this essay contributes to the academic debate by helping to establish whether the value premium is pervasive across all size strata of stocks. Answering this important question can help determine whether the value premium is a function of risk or whether the premium is an un-arbitraged return anomaly – a question at the core of the research conversation on the subject. Tests in this essay show that the value premium disappears in large cap stocks both within and across industry sectors - consistent with results in Loughran (1997) and problematic for the explanatory power of the 3-factor

model and a risk-based book-to-market effect. Results in Table 5, using a sample period subsequent to that in Loughran (1997), appear to undermine the argument in Fama and French (2006) that Loughran's observation of a weak value premium in large stocks is sample specific. This essay shows that the value premium is found to be statistically significant in all but one sector containing small cap stocks and not statistically different from zero in all sectors containing large cap stocks.

This essay also contributes specifically to ideas surrounding the risk-pricing argument. Unique sample period characteristics allow for tests of the risk-pricing thesis of Chen and Zhang (1998) within and across industry sectors as well as a confirmation of findings in Banko and Conover (2006). During this unique period, the value premium is stronger in low BE/ME growth sectors. At first glance, this outcome is counter to an investor risk-pricing thesis. A risk-based explanation for the value premium says that growth sectors would need to show distress during a period when they outperform value sectors. Indeed, growth sectors are shown during this unique period to experience negative ROA, a reversal of what researchers observe in earlier sample periods. Therefore, results from this examination are not inconsistent with arguments by Banko and Conover that the value premium results from investor risk-pricing of distress.

Next, this essay advances the academic discussion of seasonality in stock returns by confirming results in Haug and Herschey (2006) that a strong January anomaly exists in more recent time periods. Findings in this essay also show that a seasonal impact on the value premium is more complex (or possibly more time varying) than argued by Loughran (1997). Results are not consistent with findings by Loughran that the value premium is boosted in part by January returns. Table 8 shows that the average value premium computed across GICS industry sectors is not impacted by January returns – although slight variation in sector premia is observed. Interestingly, results from within-sector tests of the value premium in Table 5 still survive once returns from the month of January are removed. In fact, the average across-sector value premium is virtually identical with, or without, January returns. This result shows the value premium is not stronger in the eleven months, January excluded, as argued by Dhatt, Kim and Mukherji (1999). Equally important, the across-sector association between sector BE/ME and the value premium in small cap stocks remains unchanged and statistically significant.

Finally, this essay helps to establish the body of research literature using the Global Industry Classification Standard (GICS), a system that Bhojraj et al. argue is superior for testing many industry-related research questions. Moreover, several important financial products are now constructed based on the GICS industry classification system; therefore, any research attempting to reconcile academic

research with market-based portfolios should use definitions and methods common and available to investors.

Appendix A: The Global Industry Classification Standard (GICS) sector and industry group sub-classifications.

Source: MSCI Barra (classifications effective through 29 August 2008)

Code	Sector	Subcode	Industry Groups
10	Energy	1010	Energy
15	Materials	1510	Materials
20	Industrials	2010	Capital Goods
		2020	Commercial Services & Supplies
		2030	Transportation
25	Consumer Discretionary	2510	Automobiles and Components
		2520	Consumer Durables and Apparel
		2530	Consumer Services
		2540	Media
		2550	Retailing
30	Consumer Staples	3010	Food & Staples Retailing
		3020	Food, Beverage & Tobacco
		3030	Household & Personal Products
35	Health Care	3510	Health Care Equipment & Services
		3520	Pharmaceuticals, Biotechnology & Life Sciences
40	Financials	4010	Banks
		4020	Diversified Financials
		4030	Insurance
		4040	Real Estate
45	Information Technology	4510	Software & Services
		4520	Technology Hardware & Equipment
		4530	Semiconductors & Semiconductor Equipment
50	Telecommunication Services	5010	Telecommunication Services
55	Utilities	5510	Utilities

Appendix B: The value premium and the risk of bankruptcy

Distress factors in Chen and Zhang (1998) relating to dividends, earnings and debt levels are clearly more informative descriptors of risk than book value of equity. Dividends, earnings and debt levels provide investors a better intuitive understanding of the conditions under which they may use their portfolio screens to include or exclude stocks that could generate premium returns promised in earlier research. Investors ideally could use a compact rating or index to identify distressed stocks that may generate the value premium, rather than pouring over piles of financial statements. One such accessible tool developed in Altman (1968) is the Z-score, a characteristics-based business failure classification model designed to indicate the risk of bankruptcy within the next two years.[51]

A company's Z-score is a weighted sum of working capital to total assets, retained earnings to total assets, EBIT to total assets, market value of equity to book value of liabilities, and lastly, sales to total assets.[52] Mathematically, a higher Z-score indicates lower risk of bankruptcy while a lower Z-score indicates a higher risk. A company Z-score less than 1.81 indicates a high probability of bankruptcy over the next two years and a Z-score greater than 3.00 indicates a low probability of bankruptcy over the next two years. Previous research testing the relationship between the Z-score and returns includes Ng (2005) who find that high default risk is positively associated with high returns once returns are controlled for size and BE/ME. Dichev (1998) and Griffin and Lemmon (2002) find the relationship between risk of bankruptcy and returns to be mixed. Dichev observes a positive association between the risk of bankruptcy (low Z-score) and returns but that relationship is reversed when testing a similar bankruptcy scoring tool, the O-score. Griffin and Lemmon observe a negative correlation between risk of bankruptcy and returns in low BE/ME growth stock quintiles but a positive correlation in high BE/ME value stock quintiles.

Table B1 shows the average Z-score for portfolios formed by sorting stocks trading on the NYSE, AMEX, NASDAQ and over-the-counter first by GICS industry sector and then 2x5 by size and then BE/ME. The GICS financial sector is removed from the original test of sectors presented earlier in Table 5 because no Z-score is computed and available in Research Insight for banks, thus leaving a sample of non-bank financial companies too small to use. Portfolios are rebalanced annually and annual Z-scores are observed at month end December of year t-1 prior to portfolio formation. Data represent averages

[51] Not to be confused with a standard score or Z-score in the field of statistics.

[52] The S&P Research Insight concept for Z-score is 1.2*(WCAP/AT)+1.4*(RE/AT)+ 3.3*(EBIT/AT)+ .6*(@VALUE(PRCCF*CSHO,CEQ)+ PSTK)/(AT-CEQ-PSTK)+.999*(SALE/AT)

of the annual portfolio median Z-scores between 1999 and 2007. Once again, the 25th percentile breakpoint is used in this instance because prior research has indicated that the value premium is strongest in the lowest size deciles. It is expected, therefore, that distress could be better differentiated within this size strata.[53] If the value premium is a function of distress, then value stocks would be expected to systematically reflect a lower Z-score than growth stocks.

Results in Table B1 clearly show in average data computed across sector and within sector (across BE/ME quintiles), that average portfolio returns are inversely associated with a company's Z-score within six of the seven GICS sectors. Pearson correlation coefficients for portfolios between Z-scores and portfolio returns within each sector BE/ME quintile are negative, very high, and almost all statistically significant for both small stocks and large size stocks. For example, the Pearson correlation coefficient for across-quintile returns and Z-scores within the small stock health care sector is -0.92 ($t = -4.14$). As average quintile returns rise monotonically from growth to value (refer to results from Table 5), average Z-scores fall monotonically from growth to value. This result is consistent with findings in Ng (2005) and Dichev (1998) that the risk of bankruptcy is positively associated with average stock returns. Results in Table B1 also show bankruptcy to be positively associated with the value premium.

However, across-sector Z-scores (from heath care to consumer discretionary) are apparently not positively related to returns. Pearson correlation coefficients between average sector returns and average sector Z-scores (across sectors) for each of the five quintiles are generally low and statistically not distinguishable from zero for both small and large stocks. The two exceptions are the extreme value quintile in small stocks ($\rho = -0.84$, $t = -3.49$) and the extreme growth quintile in large stocks ($\rho = -0.70$, $t = -2.18$). Although correlation coefficients for small cap stocks are not statistically significant for the first four quintiles, and caution is advised in making inferences, the signs are consistent with Z-score findings in Griffin and Lemmon (2002) that bankruptcy risk is positively correlated with returns in high BE/ME value quintiles (a negative ρ) and negatively correlated with returns in low BE/ME growth quintiles (a positive ρ). However, results for small stocks in Table B1 are not consistent with those for large stocks. Low BE/ME quintiles appear to exhibit higher negative correlation than high BE/ME quintiles.

Comparing within-sector Z-scores with across-sector returns also provides mixed results. Results observed within each sector are consistent with a risk-based explanation to returns. Value stocks in each sector exhibit higher risk of bankruptcy (lower Z-score) than growth stocks in the same sector. The relationship weakens, however, when viewing results across sectors. In small cap stocks where the value

[53] Results were unaffected in robustness tests using the size breakpoint above and below the Fama and French 50th percentile.

TABLE B1: Average Altman Z Scores for portfolios sorted by industry sector and then 2x5 on size and BE/ME. Statistics across quintiles and across sectors. June 1999 to May 2007. (n = 88)

Portfolio returns and industry sector allocations are described earlier in Table 3. Z-scores, BE/ME and ME for all NYSE, AMEX and NASDAQ stocks are sourced from Standard and Poor's Research Insight and observed at June of each year beginning 1999 and ending May 2007. Stocks without computed Z-scores, primarily banks and financials, were eliminated from the sample. Stocks are sorted annually independently 2x5 on size and then on BE/ME. Returns are computed as in Table 5. Average Z-scores are expressed as the average of median Z-scores of stocks within each portfolio.

			Below $491 million ME									Above $491 million ME								
Industry		Median	BE/ME Portfolio					Average	Average	Sector		BE/ME Portfolio					Average	Average	Sector	
Sector	GICS	BE/ME	LO	2	3	4	HI	Z-Score	Return	ρ	t-stat	LO	2	3	4	HI	Z-Score	Return	ρ	t-stat
Healthcare	35	0.33	5.19	4.60	3.19	2.89	1.60	3.49	3.04	-0.92	-4.14	7.36	4.27	3.21	2.17	1.44	-5.92	1.58	-0.86	-2.87
Info Tech	45	0.46	4.49	3.98	3.35	2.91	1.88	3.32	2.62	-0.92	-4.08	9.51	4.62	4.03	3.29	2.09	-7.42	1.18	-0.53	-1.07
Energy	10	0.52	3.53	2.67	1.90	1.58	0.95	2.13	3.08	-0.84	-2.63	3.43	2.64	2.14	1.89	1.54	-1.90	2.23	-0.95	-5.57
Cons. Stap.	30	0.54	3.24	4.42	4.09	2.94	2.52	3.44	1.58	-0.37	-0.69	4.77	3.84	3.87	2.89	2.15	-2.61	1.48	-0.94	-4.62
Industrials	20	0.63	3.74	3.64	3.50	3.05	2.19	3.22	1.72	-0.96	-5.59	5.25	3.57	3.00	2.29	2.12	-3.13	1.27	-0.55	-1.14
Materials	15	0.65	3.28	2.85	3.01	2.59	1.93	2.73	1.46	-0.84	-2.63	2.94	2.64	2.36	2.02	1.28	-1.66	1.53	-0.76	-2.05
Cons. Discr.	25	0.67	3.86	3.69	3.51	3.20	2.50	3.35	1.27	-0.91	-3.83	5.74	4.02	3.23	2.39	1.92	-3.82	1.12	-0.80	-2.27
		Across Sector Quintile ρ	0.27	0.09	-0.36	-0.47	-0.84					-0.70	-0.57	-0.59	-0.04	-0.43				
		t-stat	0.63	0.20	-0.88	-1.18	-3.49					-2.18	-1.54	-1.63	-0.09	-1.08				

premium has been shown to exist, value stocks in growth sectors outperform value stocks in value sectors and growth stocks in growth sectors outperform growth stocks in value sectors (as shown previously in Table 5). While the relationship for value stock returns and Z-scores is as expected (a lower Z-score associated with higher returns), growth stocks in growth sectors in the lowest BE/ME exhibit less risk of bankruptcy (a higher Z-score) than growth stocks in value sectors. This result is contrary to a distress risk-based explanation of returns. One possible explanation for this reversal may be found in Griffin and Lemmon (2002). The authors find that the Z-score relationship to returns is "U" shaped. The authors argue that returns are more impacted by the risk of bankruptcy in the critical zone around the score of 2. As the Z-score increases above this zone and companies are considered relatively safe, returns are less and less impacted by the risk of bankruptcy and are largely driven by other factors. The authors argue the same explanation for scores below the critical zone. As the Z-score falls and the probability of bankruptcy rises to near certainty, the Z-score has less and less power to explain returns. It could be argued that at that low level of Z-score, a risk of bankruptcy has already been priced into the stock. While this would explain why only HI-quintile returns across all sectors in small cap stocks in Table B1 are positively associated with bankruptcy risk (a negative ρ), it would not explain why only LO-quintile returns across all sectors in large cap stocks are likewise associated with bankruptcy risk.

Results from the Z-score analysis shown in Table B1 are mixed and may not be reliable. Within-sector scores appear to confirm a positive association between returns and financial risk, or the risk of bankruptcy, also observed in Ng (2005) and Dichev (1998). Caution should be warranted in viewing within-sector results in Table B1. All things equal, Z-scores rise with size. While Table B1 controls for size by sorting stocks above and below the Fama and French 25th percentile size breakpoint, considerable variation still exists between company size observed in growth portfolios and in value portfolios within the same industry sector. For example, the median size for stocks in the health care 'LO' BE/ME small cap portfolio is $90 million, while the median size in the same sector's 'HI" portfolio is only $15 million.

Across-sector scores do not reflect a positive association between returns and bankruptcy risk, as defined by the Z-Score. It is possible that sector-specific influences (e.g. cash flows in support of leverage) are not fully captured by variations in Z-scores. It is also possible that the Z-score relationship to returns is simply nonlinear above and below a critical area of the score as Griffin and Lemmon argue. Another explanation not related to the idiosyncratic construction of the Z-score is found in Loughran (1997). The author, examining non-merger market de-listings in a sample of all stocks, concludes that the premium of returns in value stocks simply could not be explained by bankruptcy at all.

Appendix C: Financial distress and the leveraged component of BE/ME

To examine the relationship between financial distress and the value premium both within and across industry sectors, the BE/ME characteristic is decomposed into 2 parts following the method of Penman, Richardson, and Tuna (2007). Penman et al. show that BE/ME has two parts - an unlevered operating component and a levered financial component. If BE/ME is decomposed into its levered and unlevered components, finance theory tells us to expect the levered component to be positively related to superior returns. Moreover, if financial distress is driving the value premium, then the debt component of book value should be the driver of the return differential. Penman et al. find the opposite to be true. The authors observe that the levered component actually reduced returns, contrary to finance theory and contrary to arguments by Chen and Zhang (1998) and to findings by Banko and Conover (2006). Certain industries group constituents normally carry high debt because, among many reasons, they generate high cash flows to cover interest costs. The question is whether high debt companies, regardless of sector, outperform those with low debt - as is found in Banko and Conover (2006).

Replicating Penman, Richardson, and Tuna (2007), the balance sheet is restated into two components, 1) operations: defined as operating assets minus operating liabilities (often known as NOA or net operating assets), and 2) financing: defined as financial liabilities minus financial assets. This latter computation is known as Net Debt (ND). Completing the reconfigured balance sheet identity:

$$\text{NOA} = \text{ND} + \text{Book value of equity (BE)} \qquad (1)$$

And therefore:

$$\text{BE/ME} = \text{NOA/ME} - \text{ND/ME} \qquad (2)$$

Where:

1. *NOA is defined as assets used by management to generate earnings, commonly known as "Enterprise Book Value"*
2. *Operating liabilities = borrowing originating from vendor trade such as A/P, etc.*
3. *Financial liabilities = liabilities from financial borrowing*
4. *Financial assets = cash, short term securities etc.*

According to finance theory, returns of high BE/ME portfolios should be positively associated with higher priced leverage ND/ME ratios if BE/ME is acting as a proxy for financial distress. Table C1

shows mixed results for average ND/ME characteristics observed for portfolios sorted by GICS industry sector and then 2x3 on ND/ME and BE/ME as computed before. Portfolios sorted to include stocks with relatively high levels of financial leverage (high ND/ME) exhibit characteristics consistent with those found by Banko and Conover as was expected. For example, the HI minus LO result for portfolios exhibiting the highest ND/ME characteristics in the health care sector is 0.52. Mathematically, this means that either high BE/ME value stocks also have higher levels of priced financial leverage than low BE/ME growth stocks (numerator) or they have lower ME valuations relative to the same level of leverage (denominator). Results are consistent across book-to-market terciles for all industry groups.[54]

Stocks with low ND/ME financial leverage characteristics show surprising results. Within low BE/ME growth sectors, growth stock portfolios are observed to be relatively riskier than value stock portfolios. For example, the HI minus LO results for portfolios sorted for the lowest levels of ND/ME in the health care sector was -0.21, a negative number signifying growth portfolios reflect smaller relative net cash positions and larger ND/ME characteristics than value portfolios. Again, similar results are observed within each GICS economic sector.

The thesis that a premium in value stock returns is a function of investors pricing of risk requires in this instance that growth stocks with a relatively smaller net cash position generate higher returns than value stocks - all other things equal. Average portfolio returns for stocks sorted by GICS industry sector and then 2x3 on ND/ME and BE/ME shown in Table C2 show this not to be the case. Value stocks continue to dominate growth stocks within each industry group sorted for stocks with low net debt characteristics. The portfolio return for the Hi BE/ME value tercile in the health care sector averages 3.03% per month larger than the LO BE/ME tercile in the same sector. Across-quintile HI minus LO returns are large and statistically significant at the 5% level for both levels of priced financial leverage within most sectors. For robustness, returns in Table C2 are further adjusted for size, but results are unaffected.[55]

[54] Results for Table C1 are similar to tests of another leverage ratio, total liabilities/market equity (TL/ME). Characteristics [not shown] were observed for portfolios sorted by GICS sector and then 2x5 for size and BE/ME as above. Correlation coefficients testing the association between sector BE/ME and TL/ME were large and positive indicating value sector portfolios carried larger levels of liabilities than growth sector portfolios. Across-sector coefficients were significant at the 5% level for all small cap BE/ME quintiles with the exception of the extreme growth quintile. None of the large cap coefficients were statistically significant indicating no difference in the level of liabilities when viewed across sectors.

[55] The method used to adjust returns for size follows the method in Penman, Richardson, and Tuna (2007).

TABLE C1: Average net debt statistics for portfolios sorted by GICS industry sector and then 2x3 on net debt (ND/ME) and book-to-market (BE/ME). June 1999 to May 2007

The sample, stock allocations and book-to-market portfolios are defined earlier in Tables 3 and 5 except with a 2x3 sort on ND/ME and book-to-market rather than using a 2x5 sort. Average portfolio net debt characteristics, defined in equation 2, are observed annually at month-end May of year t, the point of portfolio formation, and then averaged across time.

Industry Sector	GICS			Book to Market Portfolios			
				LO	2	HI	HI-LO
HEALTH CARE	35	ND/ME	LO	-0.05	-0.10	-0.26	-0.21
			HI	0.12	0.21	0.65	0.52
INFORM TECH	45	ND/ME	LO	-0.05	-0.14	-0.32	-0.27
			HI	0.12	0.21	0.44	0.32
FINANCIALS	40	ND/ME	LO	-0.04	-0.08	-0.16	-0.12
			HI	0.59	0.75	1.15	0.55
ENERGY	10	ND/ME	LO	-0.02	-0.04	-0.15	-0.13
			HI	0.20	0.29	0.68	0.47
CONS. STAPLES	30	ND/ME	LO	-0.04	-0.09	-0.19	-0.14
			HI	0.22	0.33	0.84	0.63
INDUSTRIALS	20	ND/ME	LO	-0.04	-0.08	-0.21	-0.17
			HI	0.17	0.28	0.74	0.57
MATERIALS	15	ND/ME	LO	-0.03	-0.06	-0.19	-0.17
			HI	0.24	0.35	0.84	0.60
CONS. DISCR.	25	ND/ME	LO	-0.04	-0.10	-0.24	-0.20
			HI	0.21	0.31	0.83	0.62

Results shown in Table C2 are consistent with findings by Penman et al. who observe that lower financial leverage is associated with higher returns regardless of BE/ME characteristic.[56] Value stocks with high financial leverage underperform value stocks with low financial leverage within all sectors. Caution should be made reading results in Table C2 since almost none of the differences are statistically significant - again likely due to the volatility of returns during the short evaluation period. Interestingly, the signs are identical to those observed by Penman et al for value quintiles. However, Table C2 shows no pattern of superior performance across sectors, economic or statistical, between growth stocks with low financial leverage and growth stocks with high financial leverage, a result similar to the weakness found by Penman et al.

[56] Although several of their BE/ME decile results, primarily those of growth stocks, were not statistically significant.

TABLE C2: Average returns for portfolios sorted by GICS industry sector and then 2x3 on net debt (ND/ME) and book-to-market (BE/ME). June 1999 to May 2007

The sample, stock allocations and book-to-market portfolios and portfolio returns are defined earlier in Tables 3 and 5 except with a 2x3 sort on ND/ME and book-to-market rather than 2x5. Average portfolio net debt characteristics, defined in equation 2, are observed annually at month-end May of year t, the point of portfolio formation, and then averaged across time.

Industry Sector	GICS			Book to Market Portfolios				
				LO	2	HI	HI-LO	*t-stat*
HEALTH CARE	35		LO	1.43	2.82	4.47	3.03	*3.34*
		ND/ME	HI	1.84	1.44	3.50	1.65	*2.22*
			HI-LO	0.41	-1.38	-0.97		
			t-stat	*1.17*	*-2.43*	*-1.24*		
				LO	2	HI	HI-LO	*t-stat*
INFO TECH	45		LO	0.98	2.21	3.20	2.22	*1.91*
		ND/ME	HI	1.11	2.67	2.84	1.73	*2.54*
			HI-LO	0.13	0.46	-0.36		
			t-stat	*0.20*	*0.60*	*-0.46*		
				LO	2	HI	HI-LO	*t-stat*
ENERGY	10		LO	2.00	2.31	3.98	1.99	*2.79*
		ND/ME	HI	1.61	2.43	3.82	2.21	*2.06*
			HI-LO	-0.39	0.12	-0.17		
			t-stat	*-0.62*	*0.25*	*-0.21*		
				LO	2	HI	HI-LO	*t-stat*
CONS. STAPLES	30		LO	0.95	1.42	2.47	1.52	*2.23*
		ND/ME	HI	0.60	1.51	1.82	1.22	*2.09*
			HI-LO	-0.36	0.08	-0.66		
			t-stat	*-0.82*	*0.18*	*-0.92*		
				LO	2	HI	HI-LO	*t-stat*
INDUSTRIALS	20		LO	1.38	1.92	2.51	1.14	*3.20*
		ND/ME	HI	0.86	1.57	1.74	0.88	*2.13*
			HI-LO	-0.51	-0.35	-0.78		
			t-stat	*-1.15*	*-1.01*	*-2.76*		
				LO	2	HI	HI-LO	*t-stat*
MATERIALS	15		LO	1.86	1.89	2.05	0.20	*0.41*
		ND/ME	HI	1.65	1.38	1.72	0.07	*0.12*
			HI-LO	-0.21	-0.51	-0.34		
			t-stat	*-0.34*	*-1.04*	*-0.77*		
				LO	2	HI	HI-LO	*t-stat*
CONS. DISCR.	25		LO	0.74	1.30	2.00	1.26	*2.96*
		ND/ME	HI	0.96	0.85	1.45	0.49	*0.85*
			HI-LO	0.22	-0.45	-0.55		
			t-stat	*0.63*	*-1.18*	*-1.25*		

It cannot be argued from findings in Tables C1 and C2 that adding leverage generates lower returns because results are neither statistically significant within industry sectors nor economically apparent across industry sectors. However, it can be argued that adding leverage does not appear to

result in higher returns as advocated in prior research. This argument is contrary to findings in Banko and Conover (2006) and Chen and Zhang (1998) and inconsistent with a risk thesis in explaining the BE/ME effect in average returns. Results suggest that investors need not abandon their screens that exclude financially distressed companies in their quest to capture the elusive value premium. Moreover, the opposing ROA and ND/ME results suggest that the pricing of operating risk – as argued by Penman et al. – might be a better driver of the BE/ME effect (and the value premium) than the pricing of leverage, or financial distress as has been suggested in Fama (1998).

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CHAPTER THREE:
The Search for an Exploitable Value Premium in Market Indexes

Since academic research has shown value stocks to persistently outperform growth stocks, should industry consultants not expect value investment managers to outperform their growth counterparts over time? Houge and Loughran (2006) actually find that value-oriented US large-cap and small-cap mutual fund managers fail to outperform their growth counterparts. Chan, Chen, and Lakonishok (2002) find that US growth mutual fund managers surprisingly outperform value managers; however, that difference is largely found in the small-cap fund subset. Small-cap growth funds generate an alpha of 2.82% more per year than similarly size-oriented value funds. One should also be able to argue that if the value premium is compensation for the assumption of greater risk, then stocks that exhibit relatively higher BE/ME characteristics within a market index should still produce superior returns to stocks within that exhibit relatively lower BE/ME characteristics. But Houge and Loughran also find that the value premium at the index return level, defined as the average difference in monthly returns between value and growth sub-indexes, is absent in two major market index products, thus suggesting a passive route to capturing the premium may also be unavailable to market participants.[57]

This research extends the research of Houge and Loughran and examines the value premium in a large array of US small cap, large cap, and broad market indexes. Results can be stated briefly: statistically weak premiums observed in a broader survey of indexes indicate that results in Houge and Loughran are not special to their two index series. No statistically significant value premium is apparent in any US index series examined in this essay regardless of average market cap or breadth of index coverage. However, a similar examination using the Fama and French benchmark portfolios hints that the value premium at the index level is potentially time varying and may have existed in large cap and small cap index returns prior to 1979 - had a pre-1979 market index return history been available for analysis. Weak results for US index returns may coincide with an era when the value premium was considerably reduced in all stocks.

According to Loughran (1997) active investors can structure their portfolios to reflect a relatively smaller, higher book-to-market characteristic, and in theory, outperform the index benchmark – especially if that index exhibits a growth tilt. Results in this essay regressing returns of various Wilshire, S&P, and Russell index series on the Fama and French 3-factor model show that most indexes exhibit a

[57] Similarly, Faff (2003) used style portfolios constructed by consultant firm Frank Russell and did not find a positive risk premium for the BE/ME factor in these managed portfolios.

strong value tilt in returns, not a growth tilt. Indeed, the S&P 500 index is the only series to reflect a neutral stance between the two styles. Results in this essay do not suggest that any opportunities exist for managers to capitalise on any structural tilt in index returns. A strong value tilt observed in index returns may actually pose a significant threat to managers in their attempt to outperform these benchmarks.

Dhatt, Kim, and Mukherji (1999) conclude that a meaningful value premium does indeed exist in relatively larger investable constituents of the small cap Russell 2000 index, a finding likely in conflict with those by Houge and Loughran for the S&P 500/BARRA and Russell 3000 indexes and in conflict with results for a larger survey of index returns in this essay as described above. The difference might be explained methodologically. Dhatt et al. construct relative value and growth portfolios by sorting index constituents for low ME/BE and high ME/BE characteristics (and for P/S and P/E). This method has the advantage of being a better test of opportunities available to market participants since it mimics how portfolio managers may or may not tilt their own portfolios to outperform an index benchmark. If findings of a value premium by Dhatt et al. can be confirmed in the constituency of other passive index vehicles, then investors may indeed begin to comprehend how to capture the elusive value premium promised in a long lineage of research literature. Therefore, an interesting question remains whether the findings by Dhatt et al. are special to the Russell 2000 index. But unfortunately, results in this essay show that success does not apparently extend beyond the Russell 2000 – at least not to the S&P 1500 and S&P 600 index constituencies. No statistically significant value premium is observed when S&P index constituents are sorted independently first on size and then on ME/BE, P/S or P/E. Contrary to results observed by Dhatt et al., the price-to-sales ratio does not appear to be a stronger driver of the value premium than market-to-book value in the constituencies of the two S&P indexes examined in this study.

Kao and Shumaker (1999) show that considerable monthly and quarterly seasonality occurs in the value premium of the Russell 2000 indexes. This essay attempts to determine whether seasonality is special to the Russell 2000 equity style index series and/or special to the observation period considered in the study. Curiously, the existence of quarterly seasonality of the value premium is indeed confirmed in the Russell 2000, but also in the Wilshire Target Large and S&P 500/Citigroup style indexes. Seasonality of the value premium around the turn of the year is not inconsistent with arguments related to portfolio window dressing.

This essay is organised as follows: The first section provides descriptive information on the construction of several major market equity style index series. The second section asks whether the lack

of a value premium at the index return level is unique to the specific index algorithms used in the Houge and Loughran study. The third section provides context and academic linkage to index returns by evaluating returns for the Fama and French benchmark portfolios. The fourth section attempts to substantiate whether various index series have a statistical growth-oriented tilt. The fifth section is used to confirm the findings in Dhatt, Kim, and Mukherji (1999) that an exploitable value premium does indeed exist in constituents of a major market passive index vehicle other than the Russell 2000. The last section tests the value premium in various major market indexes for quarterly seasonal variation.

Section 1: Index and benchmark portfolio construction

Table 1 provides information about index constituency and exclusion rules, weighting method, style definitions, and the allocation and rebalancing rules for each of the four index series evaluated in the next section. The Fama and French (FF) benchmark portfolio series is also evaluated to provide a critical comparative link to empirical work in academic research. The FF benchmark portfolio construction method presented in Table 1 is noticeably simpler than the S&P/Citigroup, the Wilshire Target, and the Russell index series. Each of the three market-based index products makes considerable adjustments for float and other unique circumstances. The FF benchmarks do not make adjustments for float. Equally noticeable is the complex definition of growth and value in the S&P and in the Wilshire Target index series. Each style is independently defined by four factors in the S&P and by three factors in the Wilshire. None of the three market index series mimic the traditional academic definition of value and growth, e.g. a simple ranking on book-to-market characteristics. Index allocation methods also differ considerably. The FF benchmarks allow for stocks to be excluded from either the growth or value sets. Only the methodologies of the pure style indexes of the S&P and the Wilshire allow for a similar buffer (or neutral set) between the two styles. The non-pure S&P style indexes as well as the Russell series force all stocks to fit into one of the two growth or value bins. Finally, only Wilshire performs index rebalancing at the same periodic frequency (quarterly) as FF. The other two series perform the task annually as is done in Fama and French (1993). And finally, all four series use value weights to compute performance. What do all of these differences potentially mean? If the FF portfolios as described in Table 1 reflect a value premium and the others do not, then it may mean that growth and value characteristics observed in market index constituents are poorly defined for this purpose.

TABLE 1: Index constituent definitions and construction methodology of various major market equity style index series and the Fama and French benchmark portfolios.

	Market Index Series			
	S&P/Citigroup	**Wilshire Target**	**Russell**	**Fama and French**
Index Constituency	A select sample of US stocks that reflect "the US economy." NYSE (including NYSE Arca and NYSE Alternext), the NASDAQ Global Select Market, the NASDAQ Select Market or the NASDAQ Capital Market. Subsets of the S&P 1500 Composite index	NYSE, AMEX and NASDAQ Subsets of the Wilshire 5000 Index	NYSE, AMEX, NASDAQ Largest 3000 or 2000 depending on the index series.	NYSE, AMEX, NASDAQ
Exclusions	OTCBB and Pink Sheet stocks. Foreign shares and ADRs. Some REITs and units of beneficial interest.	OTCBB and Pink Sheet stocks. Foreign shares and ADRs. REITs and limited partnerships are NOT excluded.	Stocks below $1.00, foreign shares and ADRs, OTCCBB and Pink Sheet stocks, units of beneficial interest.	OTCBB and Pink Sheet stocks (not in CRSP) Stocks with negative BE/ME, ADRs REITs and units of beneficial interest.
Weighting	Value weighted Pure style indexes utilize a "style attractiveness" weighting method.	Value weighted Uses both full and float-adjusted market caps.	Value weighted Adjusted for large private holdings	Value weighted No adjustments
Style Definition	Growth Factors: 5-Year Earnings per Share Growth Rate, 5-Year Sales per Share Growth, 5-Year Internal Growth Rate (IGR) (IGR = ROE x Earnings Retention Rate) Value Factors: Book Value to Price Ratio Rate, Cash Flow to Price Ratio, Sales to Price Ratio Dividend Yield	Ranked by price-to-earnings ratio, projected earnings growth, price-to-book ratio, dividend yield, trailing revenue growth and trailing earnings growth.	Stocks ranked by book-to-market and the I/B/E/S forecast long-term growth mean	Ranked by independent sorts on size and book-to-market.
Style Allocation	Ranked using a proprietary scoring algorithm. Stocks are divided into two equally weighted value and growth indexes by market cap. Pure style indexes represent the top and bottom third of the parent style index	Stocks are ranked highest to lowest style score and allocated to either growth or value using a buffer of stocks that are not allocated to either set.	70% allocated to growth or value based on membership rank criteria. Remaining 30% allocated using a proprietary non-linear probability algorithm.	Growth and value are allocated using the resulting style membership 30th and 70th percentiles
Rebalance	Annual rebalance. Other adjustments made "as needed".	Quarterly rebalance. Monthly additions and deletions	Annual rebalance. Monthly additions and deletions.	Quarterly rebalance.

Section 2: The value premium in equity index returns - a survey of market indexes

Houge and Loughran (2006) test the existence of a value premium in the monthly return time series of two major market indexes, the S&P 500/BARRA and the Russell 3000. The authors find that while the S&P 500/BARRA value index subset outperforms the growth index during the observation period - as would be predicted by the academic literature - the difference of 11 basis points per month, or 1.32%

per year, is not statistically different from zero.[58] Houge and Loughran also find the value premium statistically absent in returns for the relatively smaller cap Russell 3000 equity style indexes. The return for the hedged portfolio, the Russell 3000 value index minus the Russell 3000 growth index is once again statistically insignificant at only 11 basis points per month. The latter findings are especially problematic for investors since research evidence suggests that the value premium predominates in smaller stocks (See Loughran, 1997, and Phalippou, 2008).

This essay extends the survey of market indexes in Houge and Loughran (2006) to help determine whether the authors' results are special to the S&P or to the Russell index algorithm or to the average size of their constituencies. Monthly returns of a broad array of US equity style and pure style indexes are evaluated and results presented in Table 2. The survey includes numerous S&P/Citigroup value and growth indexes as well as an examination of the Wilshire Target and the Russell 2000 equity style indexes - the latter to facilitate a comparison to results by Dhatt et al. Index return premia are observed by constructing a portfolio consistent with the method in Houge and Loughran (2006) - buying long the value index and selling short the growth index. Tests of mean difference are used to determine whether average monthly returns of the market risk hedging portfolio are statistically different from zero.

Average monthly returns are observed over two overlapping time periods, 330 months from February 1979 to July 2006 (Panel A) and 133 months from July 1995 to July 2006 (Panel B). The choice of the two time periods is necessitated by a need to harmonize the various base dates for index return data. For example, the S&P 500 index has a base price date in Datastream of February 1975 while the Russell 2000 index has a base price date of January 1979 [see notes to Table 2 for the base dates of each index used in the analysis].[59]

Results in both Panel A and in Panel B are consistent with findings in Houge and Loughran (2006). No statistically significant value premium (v-g) is observed in any of the index return series surveyed in Table 2 regardless of size characteristic. While the value equity style economically outperforms the growth style in all index series in both time periods, the difference in returns in each

[58] Scislaw and Evans (2004) find the S&P/BARRA style index series and those of similar construction to be poor statistical benchmarks for differentiating between styles. The index series was subsequently discontinued, replaced by the S&P/Citigroup equity style series.

[59] The ending date of July 2006 is a function of the last available data of the Wilshire Target index series before their replacement by the Dow Jones Wilshire index series. The Dow Jones Wilshire indexes only have reconstructed return histories available from January 1992.

TABLE 2: The value premium in equity index returns

S&P and Russell index series returns are obtained from Datastream. Wilshire Target index series returns are sourced from Wilshire Associates. The beginning date for available Wilshire Target index return data from the source is February 1979; Russell index data: from January 1979; S&P 500: February 1975; S&P pure style indexes, S&P 600 style indexes, and all S&P 1500 data: July 1995; Index abbreviations are as follows: S&P 500 (sp500) value (sp500v) and growth (sp500g), pure value (sp500pv) and pure growth (sp500pg); Similar treatment for the S&P 600 and 1500 series; Russell 2000 (R2) value (R2v) and growth (R2g); Wilshire Target Large (WTL) value (WTLv) and growth (WTLg) and Wilshire Target Small (WTS) value (WTSv) and growth (WTSg).

Panel A: February 1979 to July 2006 (n = 330)

Large Cap Style Indexes			Small Cap Style Indexes		
Index Series	Avg Return %	t-stat	Index Series	Avg Return %	t-stat
WTLg	1.15	4.24	WTSg	1.19	3.56
WTLv	1.19	5.46	WTSv	1.4	6.38
v-g	0.04	0.21	v-g	0.21	0.98
sp500g	1.08	4.14	R2g	1.01	2.71
sp500v	1.15	4.99	R2v	1.31	5.06
v-g	0.08	0.59	v-g	0.29	1.52

Panel B: July 1995 to July 2006 (n = 133)

Large Cap Style Indexes			Small Cap Style Indexes			Broad Market Style Indexes		
Index Series	Avg. Return %	t-stat	Index Series	Avg. Return %	t-stat	Index Series	Avg. Return %	t-stat
sp500g	0.81	1.96	WTSg	0.89	1.78	sp1500g	0.89	2.2
sp500v	0.93	2.47	WTSv	1.11	3.01	sp1500v	0.92	3.00
v-g	0.12	0.47	v-g	0.22	0.64	v-g	0.03	0.11
sp500pg	1.17	1.92	sp600pg	1.22	2.19	sp1500pg	1.21	2.45
sp500pv	1.18	2.91	sp600pv	1.28	3.00	sp1500pv	1.1	3.15
v-g	0.01	0.01	v-g	0.06	0.18	v-g	-0.11	-0.31
WTLg	0.89	2.05	R2g	0.71	1.12			
WTLv	0.97	2.74	R2v	1.17	3.07			
v-g	0.08	0.24	v-g	0.46	1.13			

instance is not statistically distinguishable from zero. As expected, the small cap value premium is relatively stronger than the large cap premium during both time periods. For example, The Wilshire Target Small Cap (WTS) value premium in Panel A is 0.21% per month (2.52% per year) while its Wilshire Target Large Cap (WTL) counterpart generates only a 0.04% premium (0.48% per year). The relationship

is in the same direction and of similar size for the Wilshire small and large cap indexes for the shorter, more recent time period shown in Panel B of Table 3 (0.22% and 0.08% respectively).[60]

The pure style index series offered by S&P/Citigroup might be expected to produce a larger value premium than a traditional, less focused index product. The pure style index series, analogous to the more extreme high and low book-to-market quintiles in Fama and French (1993), is strategically constructed to represent the more focused style definitions used by S&P. However, results in Panel B for large cap style indexes show no meaningful value premium for either the normal S&P 500/Citigroup series (sp500g and sp500v) or its purer style product (sp500pg and sp500pv). Average monthly returns for the value and growth series are higher for the pure product, but the value premium is not improved. In fact, the value premium is actually weaker, averaging 0.01% per month for the S&P 500/Citigroup large cap pure style (sp500pv-g) compared to 0.12% for the traditional large cap S&P 500/Citigroup index series (sp500v-g). Again, both premiums are statistically indistinguishable from zero. The complexity of the style definitions shown previously in Table 1 may be the culprit.

Dhatt et al. find a statistically significant value premium in the small cap Russell 2000 index constituency. The choice of the Russell 2000 index by the authors may not have been accidental. Compared to other indexes in Table 2 , the value premium in the Russell 2000 index (R2v-g) is the strongest of any examined during both the longer observation period in Panel A (0.29%, t = 1.52) and the shorter period shown in Panel B (0.46%, t = 1.13). Economically, the small cap Russell 2000 value index provides a 5.52% per year premium over its growth counterpart during the more volatile short sample period.

Section 3: The value premium in Fama and French benchmark portfolios

Returns for a series of benchmark portfolios, similarly constructed to portfolios found in Fama and French (1993), are next examined to provide a link between empirical results in academic literature and market-based index results presented in Table 2.[61] Table 3 shows the average monthly difference in

[60] The Wilshire Target index series was replaced by the Dow Jones Wilshire equity style indexes in July 2006. A reconstructed return history for the DJW indexes is available from 1992. Results for the large cap and small cap DJW v-g [not shown] are not meaningfully different from the Wilshire Target series shown in Table 3. The large cap v-g return was 0.18% per month (t = 0.54) and 0.28% per month (t = 0.67) for the small cap v-g return.

[61] The Fama and French benchmark portfolio returns (FF) are offered separately on the website of Kenneth French from the traditional 2x3 'research' portfolios formed from stocks that have been independently sorted on size and book-to-market. However, the difference in the average returns for the six portfolios (S/L, S/N, S/H, B/L, B/N, B/H) between the research portfolios and the benchmark portfolios averages less than 0.05% per month from July 1926 to August 2008. The only computational difference revealed on the website relates to the frequency of portfolio

returns between both the FF large cap and small cap value and growth benchmark portfolios. Return differences are computed for a sample period, July 1926 to July 2006, as well as for three sub-periods coinciding with sub-periods in Table 2.

The value premium in the FF benchmarks in Table 3 is clearly evident in the overall sample period in both the large cap portfolio shown in Panel A where the mean monthly premium is 0.31% (t = 2.26) and also the small cap portfolio in Panel B where the premium is 0.42% per month (t = 3.47). However, the value premium disappears statistically in the FF large cap portfolio for two sub-periods subsequent to January 1979 (t = 0.68 and t = 0.22 respectively). The economic premium has generally weakened in recent years, from 0.41% per month to 0.12%. The value premium for the small cap portfolio shown in Panel B also statistically disappears after July 1995, (t = 1.08).[62] However, unlike large cap stocks, the economic premium between the two FF small cap portfolios has strengthened in recent years. The average monthly value premium return rises from 0.39% for the period July 1926 to 1979 to 0.51% in the most recent sub-period.

Results in Tables 2 and 3, as well as results for the S&P 500/BARRA and Russell 3000 indexes found in Houge and Loughran (2006), seem to demonstrate that the value premium - defined as returns generated by buying the value index series long and selling the growth series short - is not available to investors in large cap or small cap major market equity style indexes in the period after February 1979. A possible explanation for the conflicting results can be found in the dramatically different definitions of value and growth outlined in Table 1. The S&P/Citigroup and the Dow Jones Wilshire indexes have a complex definition of growth and value and none of the three market index series mimic the traditional academic definition of value and growth, e.g. a simple ranking on book-to-market characteristics. Index allocation methods also differ considerably.

However, results in Table 3 for the Fama and French benchmark portfolios show that the value premium is potentially time varying and may have existed in large cap and small cap index returns prior to 1979 - had a pre-1979 market index return history been available for analysis. It may be possible to conjecture that weak results for US index returns in Table 2 are associated in some part with an era

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rebalancing. The research portfolios rebalance annually at June 30, while the benchmark portfolios rebalance at the end of each calendar quarter.

[62] 3-factor regression tests of the FF benchmark portfolios [not shown] indicate the explanatory power of the book-to-market effect seems to weaken in the period following January 1979. HML coefficients for the FF large cap portfolios fall monotonically from 1.08 in the pre-1979 sub-period to 0.84 in the most recent sub-period, 1995 to 2006. T-statistics for the coefficients also fall commensurately but all coefficients remain strongly significant. HML coefficients for the FF small cap portfolios remain fairly stable (0.89, 0.94, 0.94) over the three sub-periods.

TABLE 3: The value premium in average monthly returns of the Fama and French benchmark portfolios. July 1926 to July 2006 (n = 961)

Fama and French benchmark portfolio returns are obtained from the website of Kenneth French. The beginning date for available Fama and French benchmark portfolios: July 1926. Sub-sample periods are constructed to coincide with those in Table 2.

Panel A: ***Large Cap Portfolios***	**Mo. Return**	**t-stat**
July 1926 to July 2006 (n = 961)		
FF Benchmark Portfolio B/H (value)	1.22	5.14
FF Benchmark Portfolio B/L (growth)	0.91	5.19
Value - Growth	0.31	2.26
July 1926 to January 1979 (n = 631)		
FF Benchmark Portfolio B/H (value)	1.23	3.63
FF Benchmark Portfolio B/L (growth)	0.82	3.59
Value - Growth	0.41	2.19
February 1979 to July 2006 (n = 330)		
FF Benchmark Portfolio B/H (value)	1.19	4.96
FF Benchmark Portfolio B/L (growth)	1.07	4.09
Value - Growth	0.12	0.68
July 1995 to July 2006 (n = 133)		
FF Benchmark Portfolio B/H (value)	0.86	2.08
FF Benchmark Portfolio B/L (growth)	0.78	1.95
Value - Growth	0.08	0.22

Panel B: ***Small Cap Portfolios***	**Mo. Return**	**t-stat**
July 1926 to July 2006 (n = 961)		
FF Benchmark Portfolio S/H (value)	1.49	5.52
FF Benchmark Portfolio S/L (growth)	1.07	4.23
Value - Growth	0.42	3.47
July 1926 to January 1979 (n = 631)		
FF Benchmark Portfolio S/H (value)	1.46	3.83
FF Benchmark Portfolio S/L (growth)	1.07	3.25
Value - Growth	0.39	2.74
February 1979 to July 2006 (n = 330)		
FF Benchmark Portfolio S/H (value)	1.54	5.28
FF Benchmark Portfolio S/L (growth)	1.06	2.79
Value - Growth	0.48	2.12
July 1995 to July 2006 (n = 133)		
FF Benchmark Portfolio S/H (value)	1.43	2.70
FF Benchmark Portfolio S/L (growth)	0.92	1.36
Value - Growth	0.51	1.08

when the value premium was considerably reduced in all stocks, as reflected in results in Table 3. Table 3 also hints that an index (or benchmark) of simple construction, such as that employed in the FF benchmark portfolios, may offer investors an opportunity to capture the value premium in a passive small cap investment vehicle. However, it is important to note that each of the FF benchmark portfolios may periodically reflect returns of hundreds of stocks, and that a portfolio manager who desires to replicate results in the FF portfolios would need to rebalance each of these stocks quarterly and thus incur significant transactions costs. Therefore, it may be very difficult to profitably mimic the value premium results of FF in an investable portfolio. Moreover, results in Loughran (1997), Fama and French (2006), and Phalippou (2008), who each observe the value premium in tests of all stocks trading on the

NYSE, AMEX, and NASDAQ, cast doubt as to whether most of that premium in small cap stocks exists in companies large enough and liquid enough to facilitate its capture.

Section 4: Tests for an exploitable style tilt in index returns

Loughran (1997) suggests that if the value premium exists in large cap stocks, then logically it should be relatively easy to outperform the S&P 500 index by simply constructing a portfolio of index constituents with relatively smaller size and higher book-to-market characteristics. Dhatt, Kim, and Mukherji (1999) successfully demonstrate that investors may be able to persistently outperform the Russell 2000 index by tilting a portfolio of stocks comprised of index constituents toward companies with relatively lower market-to-book characteristics. Of course in both instances, industry consultants would simply change the manager's performance benchmark to the S&P 500/Citigroup value and the Russell 2000 value indexes respectively - each a better reflection of the manager's effective investment universe. Moreover, neither strategy could be successful if the target benchmark index exhibits a natural style tilt itself.

Three-factor model regression results in Table 4 suggest that the S&P 500 index (sp500) does not exhibit a perceptible tilt toward growth or value. The HML coefficient for the index shown in Panel A (1) is 0.02 and statistically indistinguishable from zero (t = 1.14). In recent tests, Houge and Loughran (2006) also fail to observe a statistical tilt in the S&P 500 index when excess monthly index returns are regressed on the Carhart 4-factor (momentum) model. Also in that study, regression coefficients for the now defunct S&P 500/BARRA value and growth style index series, representing two equal halves by market cap of the S&P 500 Index, load virtually identically (but opposite sign) on the HML book-to-market factor (value = 0.32, growth = -0.30). Results in Panel A (3) confirm the balanced loading for the new S&P 500/Citigroup series that replaced the defunct style indexes. The HML coefficients for the two S&P 500 equity style subset indexes, sp500g and sp500v, are -0.35 and 0.41 respectively during the period July 1995 to July 2006. Coefficients are not materially different in the longer sample, February 1979 to July 2006 shown in Panel B. Also in Panel A (1), the two small cap indexes, the Wilshire Target Small (WTS) and the Russell 2000 (R2), both exhibit relatively large positive and statistically significant HML coefficients (WTS = 0.30, t = 9.11; R2 = 0.33, t = 10.19) thus indicating a value tilt in returns during the sample period.

The S&P 500/Citigroup style series (sp500v and sp500g) appear to be the only pair of equity style indexes with a neutral v-g loading on the HML book-to-market factor. While none of the eight pairs

TABLE 4: Book-to-market style tilt in excess average monthly returns of various large and small cap major market equity style indexes. July 1995 to July 2006 (n = 133).

Excess average monthly index returns are regressed against the Fama and French 3-factor model. Data for 3-factor model returns are obtained from the website of Kenneth French. S&P and Russell index series returns are obtained from Datastream. Wilshire Target index series returns are sourced from Wilshire Associates. The beginning date for available Wilshire Target index return data from the source is February 1979; Russell index data: from January 1979; S&P 500: February 1975; S&P pure style indexes, S&P 600 style indexes, and all S&P 1500 data: July 1995; Index abbreviations are as follows: S&P 500 (sp500) value (sp500v) and growth (sp500g), pure value (sp500pv) and pure growth (sp500pg); Similar treatment for the S&P 600 and 1500 series; Russell 2000 (R2) value (R2v) and growth (R2g); Wilshire Target Large (WTL) value (WTLv) and growth (WTLg) and Wilshire Target Small (WTS) value (WTSv) and growth (WTSg).

$$Rpt - Rft = a + b[\mathrm{R}mt - \mathrm{R}ft] + s\mathrm{SMB}t + h\mathrm{HML}t + et$$

Panel A: July 1995 to July 2006 (n = 133)

(1) US Parent Indexes			(2) US Broad Market Style Indexes		
Index	***h***	**t(h)**	**Index**	***h***	**t(h)**
sp500	0.02	1.14	sp1500g	-0.31	-11.41
WTL	-0.01	-1.18	sp1500v	0.43	16.21
WTS	0.30	9.11	v-g	0.73	16.25
R2	0.33	10.19			
sp1500	0.06	4.41	sp1500pg	0.04	0.75
			sp1500pv	0.97	21.08
			v-g	0.93	15.69

(3) US Large Cap Style Indexes			(4) US Small Cap Style Indexes		
Index	***h***	**t(h)**	**Index**	***h***	**t(h)**
sp500g	-0.35	-9.83	WTSg	0.18	2.89
sp500v	0.41	12.30	WTSv	0.93	17.45
v-g	0.75	12.31	v-g	0.75	12.63
sp500pg	-0.40	-5.93	sp600pg	0.31	4.41
sp500pv	1.01	18.00	sp600pv	0.99	16.05
v-g	1.41	16.52	v-g	0.68	8.75
WTLg	-0.36	-11.53	R2g	-0.09	-1.99
WTLv	0.61	13.94	R2v	0.80	20.53
v-g	0.97	14.79	v-g	0.88	18.13

Panel B: February 1979 to July 2006 (n = 330)

(1) US Large Cap Style Indexes			(2) US Small Cap Style Indexes		
Index	***h***	**t(h)**	**Index**	***h***	**t(h)**
WTLg	-0.32	-16.45	WTSg	-0.01	-0.27
WTLv	0.52	19.72	WTSv	0.72	20.58
v-g	0.84	21.88	v-g	0.73	17.30
sp500g	-0.31	-16.27	R2g	-0.19	-7.33
sp500v	0.35	20.04	R2v	0.62	21.70
v-g	0.70	20.76	v-g	0.81	25.80

of equity style indexes shown in Panel A (2), (3), and (4) exhibits a growth tilt in returns, each pair when viewed together exhibits without exception a strong tilt toward value. In each case, HML factor sensitivities for the value index is much farther from a zero loading than for the respective growth index. Curiously, the Wilshire Target Small growth series (WTSg), the small cap S&P 600/Citigroup pure growth (sp600pg) shown in Panel A (4), and the broader S&P 1500/Citigroup pure growth series (sp1500pg) shown in Panel A (2) each load positively on the HML factor. This result indicates a value orientation in returns despite a growth construction. If value stocks are riskier than growth stocks and are systematically rewarded with higher returns, then growth managers would likely find it extremely difficult to outperform these growth benchmarks if the condition persists over a long period. The value tilt observed in the WTSg index is minimised when tested over an extended sample, but the HML factor loading shown in Panel B (1) still does not exhibit an appropriate growth orientation (h = -0.01, t = -0.27).[63] Style tilt is not just a problem for growth managers. Value managers might find comparisons to the value-oriented indexes shown in Table 4 also difficult to overcome. If a value index has a dramatic tilt in its HML loading, then an investor with a relatively more moderate book-to-market stance would likely underperform the index over time.[64]

Results across the survey of equity style indexes show that the HML factor does a very good job explaining returns of value indexes. However, growth index HML factor loadings appear problematic. HML loadings are weaker for growth indexes than for their value index counterparts. HML coefficients for two indexes, the Russell 2000 growth style (R2g) in Panel A (4) and the S&P 1500 pure growth style (sp1500pg) in Panel A (2), are not statistically different from zero at the 5% level of significance. Weak HML t-stats for growth indexes suggest that consultants should be cautious when using the Fama and French 3-factor model for tests of performance alpha for actively managed growth portfolios.

Section 5: The value premium in S&P/Citigroup index constituents

Davis (2001) conjectures that investment managers have failed as yet to capture the value premium because they have not properly concentrated their portfolios in the small cap, high book-to-market

[63] No earlier return history is available for the S&P 600 and 1500 style indexes.

[64] As a point of explanation, the large coefficients and t-stats for the HML factor for each of the v-g monthly return estimations are primarily a function of the v-g computation itself. In this treatment, the difference in value and growth index returns is expected to be largely explained by the value (or book-to-market) effect since the two equity style indexes are primarily differentiated by that characteristic (with the average market cap in each style index being roughly the same). Conversely, if returns of a large value index was subtracted from a small value index, s-l rather than v-g, then SMB coefficients would be large and the HML coefficients very small.

segment of the market. Despite research showing the value premium to be more pronounced in the small cap space, Davis argues that fund managers are simply not investing in the right small cap stocks, and thus suggests that opportunities to capture the value premium in the small cap space remain. However, Chan et al. (2002) compute the average factor loadings on size (3-factor SMB coefficient) for a large sample of fund manager returns between 1978 and 1997 and observe that 94% of fund managers had size factor sensitivities above that of the S&P 500 index. Managers held smaller stocks on average than the index, and were therefore at a competitive advantage to that benchmark with respect to the size effect in stock market returns.

If mainstream small cap index series are not reflecting value premia in returns, then the superior returns promised by research are not likely to be achieved passively using conventional index products and may not be achieved through active management techniques. Results in Dhatt, Kim, and Mukherji (1999) that the value premium is statistically significant in Russell 2000 index constituents are inconsistent with growing evidence that the premium is out of reach for professional investment managers.[65] However, if findings by Dhatt et al. can be confirmed in the constituency of other passive index vehicles, then investors may indeed begin to comprehend how to capture the elusive value premium promised in a long lineage of research literature. Therefore, an interesting question remains whether the findings by Dhatt et al. are special to the Russell 2000 index, special to the authors' methodology, and/or special to the 1979-1997 time period used in their analysis.

The first task is to confirm whether the findings by Dhatt et al. are special to the Russell 2000 index. This is accomplished by re-testing the constituents of a different major market index series, the S&P 1500 and its small cap subset, the S&P 600, in the same manner to facilitate comparability to the authors' earlier results. The second task is to alter the examination methodology to control for size.[66] Dhatt et al. use univariate sorts on three fundamental characteristics to form portfolios. Today, we know that market-to-book has a considerable size effect inherent in the ratio (see Loughran, 1997, and Nelson, 2006). Therefore, it is entirely possible that the superior portfolio performance disappears once results are controlled for size. Dhatt et al. argue that because relatively larger stocks in the small cap Russell 2000 index perform better than smaller stocks, then no size effect was apparent in the value premium. A quick 3-factor model regression of excess Russell 2000 index returns shows a strong size effect during the authors' sample period for both the growth index (SMB coefficient = 1.01, t = 37.50)

[65] See additionally Phalippou (2008) for an analysis about the value premium and liquidity; Bogle and Malkiel (2006) for a criticism about fundamental indexing and style tilt strategies

[66] Unfortunately, the time series of Russell 2000 index constituents is not accessible from available resources. Ideally, a re-test of the work of Dhatt et al. would be presented for comparison using the altered methodology.

and the value index (SMB coefficient = 0.82, t = 32.84). However, t-stats are primarily a reflection of the small cap orientation of the two Russell 2000 indexes. Specific to the question, the size effect is also statistically significant in explaining the difference between the Russell 2000 value and growth v-g returns (SMB coefficient = -0.19, t = -5.23) despite the assumption the two style indexes should be stylistically identical by market cap.

The constituents of the S&P 1500 and 600 indexes are each sorted on three variables, price-to-earnings (P/E), price-to-sales (P/S), and price-to-book value (ME/BE) as was performed by Dhatt et. al. Price-to-earnings is defined as the month end closing price at June of portfolio formation year t divided by the 12 month trailing earnings per share, where earnings is computed as the reported EPS figure including extraordinary items and discontinued operations. Price-to-sales reflect trailing 12 month sales per share observed at June of year t. Price-to-book value of equity is defined as the total market value of the stock (shares outstanding multiplied by month end price at December of year t-1) divided by total common equity at liquidation. Common equity is defined as total common stock outstanding (adjusted for treasury stock) plus capital surplus and retained earnings. Adjustments are made for preferred stockholders' legal claims against the company as well as for deferred taxes and investment tax credits. ME/BE is observed at December of year t-1 to allow for information relating to a company's balance sheet to be fully available to the market at the time of portfolio formation June of year t, as is the custom in most research. In independent bivariate sorts, size (ME) is computed as above and observed at June of year t.

Samples are observed for index constituents between July 1998 and April 2008 (n = 118).[67] Annual 30th and 70th percentile breakpoints used to sort stocks (Low, Middle, and High) on ME and then on either ME/BE, P/E, or P/S are constructed by independently ranking the S&P 1500 constituents by each variable to be sorted.[68] Stocks with negative ME/BE at month-end December of year t-1 are omitted from the breakpoint ranking as well as stocks with negative P/E and all other stocks with no P/E, P/S or ME value at month-end June of year t.

Average monthly returns for portfolios constructed from univariate sorts on ME/BE, P/S, and P/E for the constituents of the S&P 1500 and 600 indexes are shown in Table 5. Again, the methodology for this test

[67] The sample period is unfortunately restricted by three conditions: first, the historical time series of S&P 1500 index constituents (inclusive of S&P 600 stocks) are only identified in Research Insight (Compustat) from 1994 to the present. Second, sales figures in Research Insight are only available for the ten years beginning 1998. Third, at the time of this research, monthly return data is only available through April of 2008.

[68] In 2x3 sorts on size and then either ME/BE, P/E, or P/S the annual median ME is observed for S&P 600 index constituents to identify the size breakpoints rather than using the median for the overall S&P 1500 index as was discussed before.

is intentionally comparable to that by Dhatt et al. who test constituents of the Russell 2000 index. However, results in Table 5 differ considerably from those produced by the authors. While the value premium is economically observed in sorts on ME/BE, P/S, and P/E, none of the premiums are statistically different from zero even at the 10% level of confidence. Dhatt et al. provide only a summarized presentation of annual t-stats rather than results for the overall sample period. For comparison, Table 5 provides a similar presentation of annual statistical significance. Confidence in results for the S&P 1500 and 600 index constituent premia are materially weaker than those for the Russell 2000 observed by Dhatt et al. Value stock returns (defined as Low ME/BE) observed in the constituency of the S&P 1500 index do not statistically differ from growth stock returns (High ME/BE) in any of the ten annual periods nor in 80% of the periods testing constituents of the small cap S&P 600 index. Similar results are observed for value and growth stocks defined from sorts on P/S and P/E.

TABLE 5: Equal weighted average monthly returns of the broad market S&P 1500 and small cap S&P 600 index constituents. Portfolios constructed from sorts on ME/BE, P/S, and P/E. July 1998 to April 2008 (n = 118)

S&P 1500 and 600 Index constituents are obtained from the Research Insight database. Annual 30th and 70th percentile breakpoints are used when independently sorting index constituents (Low, Middle, and High) on ME and then on either ME/BE, P/E, or P/S. Stocks with negative ME/BE at month-end December of year t-1 are omitted from the breakpoint ranking as well as stocks with negative P/E and all other stocks with no P/E, P/S or ME value at month-end June of year t. See the text in this section for the specific definition of ME/BE, P/E and P/S.

	Value		Growth			# Years Significant (of 10)	
Index Constituents	**Low**	**Middle**	**High**	**Low - High**	**t-stat**	**Value Dominance**	**Growth Dominance**
		Panel A: ME/BE					
S&P 1500	1.22	1.07	0.86	0.36	1.31	0	1
S&P 600	1.43	1.35	0.95	0.47	1.40	2	0
		Panel B: P/S					
S&P 1500	1.25	1.03	0.93	0.32	0.97	1	1
S&P 600	1.34	1.19	1.26	0.08	0.18	3	2
		Panel C: P/E					
S&P 1500	1.13	0.93	0.91	0.22	0.76	1	0
S&P 600	1.23	1.10	1.15	0.09	0.26	1	1

Dhatt et al. find that P/S is actually a stronger source for the value premium than ME/BE. Results in Table 5 do not confirm the authors' findings in the S&P 1500 or 600 index constituents.[69] The value premium (Low – High) in sorts for price-to-sales is not observed to be materially different than those observed for ME/BE or P/E. This suggests that univariate results in Dhatt et al. (1999) are unique to the Russell 2000 constituency and/or the sample period used in the study.

A change in methodology from that by Dhatt et al. to adjust for size does not alter results. Constituents for the S&P 600 and 1500 indexes are independently sorted 2x3 first on size and then on their book-to-market, price-to-sales, or price-to-earnings characteristics. Portfolios are formed as before. Results for average equal weighted monthly portfolio returns are shown in Table 6. The value premia (Low - High) in S&P 1500 and small cap S&P 600 index constituent returns continue to be statistically non-existent after adjusting for size. Again, none of alternative definitions of the value premium, price-to-sales and price-to-earnings, presented in Panels B and C show any meaningful improvement over market-to-book, contrary to assertions by Dhatt et al. for the Russell 2000.[70] Surprisingly, Dhatt et al. observe that large cap stocks in the Russell 2000 constituency actually outperform those of small cap stocks during their observation period. This curious relationship does not exist in the S&P 1500 index. As expected, small cap S&P 1500 stocks outperform those of large cap S&P 1500 stocks across each of the three market-to-book strata and for each of the three definitions of value. However, results for the S&P 600 index are consistent with findings by Dhatt et al. Large cap stocks in the S&P 600 index do indeed outperform small cap stocks across the strata of two of the three definitions of value, ME/BE and P/E.

Section 6: Seasonality

Houge and Loughran (2006) observe that value and growth equity styles rotate in performance dominance over time. Thus, investment managers who maintain a strict value style strategy can suffer periods of relative underperformance to growth managers who pursue a different style of investing. For observations of short term rotation, Kao and Shumaker (1999) show that a seasonal effect exists in the

[69] Constituents of the large cap S&P 500 were also examined in the manner of Panels A, B, and C in Table 5. No meaningful difference in results [not shown] is observed from those presented for the S&P 1500 and 600 indexes.

[70] A second methodological issue in Dhatt et al. (1999) is the authors' use of equal weights rather than market weights when testing portfolio returns ranked by fundamental characteristics. Equal weights subject large market samples to considerable small-cap noise related to illiquidity, non-synchronous trading among other maladies. However, using equal weights in the small but relatively liquid universe of the Russell 2000 or S&P 600 index is not likely problematic for the above reason. The question of whether the superior returns observed by Dhatt et al. for the Russell 2000 constituents are magnified as a function of the weighting scheme employed is not re-examined here since no statistically significant value premium is observed in Table 5.

TABLE 6: Equal weighted average monthly returns of the broad market S&P 1500 and small cap S&P 600 index constituents. Portfolios constructed from independent sorts on size and then on each ME/BE, P/S, and P/E. July 1998 to April 2008 (n = 118)

S&P 1500 and 600 Index constituents are obtained from the Research Insight database. Annual 30th and 70th percentile breakpoints are used when independently sorting index constituents (Low, Middle, and High) on ME and then on ME/BE. Stocks with negative ME/BE at month-end December of year t-1 are omitted from the breakpoint ranking as well as stocks with no ME value at month-end June of year t. See the text in this section for the specific definition of ME/BE.

		Value		Growth			# Years Significant (of 10)	
Index Constituents		**Low**	**Middle**	**High**	**Low - High**	**t-stat**	**Value Dominance**	**Growth Dominance**
			Panel A: ME/BE					
S&P 1500	Large	0.99	0.96	0.83	0.16	0.53	1	1
	Small	1.30	1.19	0.97	0.33	1.12	2	0
S&P 600	Large	1.43	1.50	1.29	0.14	0.33	0	1
	Small	0.97	1.16	0.99	-0.02	-0.05	1	0
			Panel B: P/S					
S&P 1500	Large	1.07	0.93	0.82	0.25	0.83	2	1
	Small	1.30	1.15	1.28	0.02	0.05	3	1
S&P 600	Large	1.13	0.92	1.14	-0.01	-0.04	1	1
	Small	1.43	1.45	1.57	-0.15	-0.21	1	0
			Panel C: P/E					
S&P 1500	Large	1.12	0.82	0.79	0.33	1.01	1	0
	Small	1.13	1.05	1.18	-0.05	-0.17	0	1
S&P 600	Large	1.34	1.02	1.66	-0.33	-0.89	0	0
	Small	1.08	1.13	0.91	0.18	0.46	1	1

Russell 2000 equity style indexes. The value premium is noticeably stronger in the first quarter of the calendar year (January through March) while the reverse is observed to be true in the fourth quarter. If results in the latter study are confirmed in a longer sample and in additional index products, then investors might be able to capture additional returns by overweighting growth stocks in calendar Q4 and overweighting value stocks in Q1.

A Q1/Q4 seasonality in the Russell 2000 value premiums are retested in this research using a longer sample period than in Kao and Shumaker, from Q4 1979 through Q1 2006. Average quarterly value premium returns are computed by subtracting the average of the three monthly value-minus-growth returns, October, November, and December of year t from the average of the three monthly value-minus-growth returns, January, February, and March, of year t + 1. The process is extended to the Wilshire Target Small as well as to two large cap index series, the Wilshire Target Large and S&P 500 previously surveyed in Panel A of Table 2. Results in Table 7 confirm the continued existence of quarterly value premium seasonality in the Russell 2000 style indexes. Between 1979 and 2006, the average monthly value premium observed during Q1 between the two Russell 2000 equity style indexes is larger than the average monthly premium during the prior Q4 by 1.21% (t = 2.17) over the 27 year sample. Results in Table 7 for the other three major market index series confirm that seasonality in the value premium is not exclusive to the Russell index product. While no quarterly seasonality is observed for the Wilshire Target Small series due to a low v-g return difference between Q1 and the prior year's Q4 (0.41%, t = 0.72), the average monthly difference is large and statistically significant in the Wilshire Target Large (1.00%, t = 2.29) and the S&P 500 indexes (0.85%, t = 2.43). Interestingly, the power of seasonality is weakened when the calendar is shifted. When Q4 returns of year t are subtracted from Q1 returns occurring six months prior also in year t, return differences are reduced and statistical significance lost. Therefore, value premium seasonality in index returns appears to be a turn of the year effect.

Despite the lack of statistical significance in their results, Kao and Shumaker conjecture that seasonality in the value premium between Q4 and Q1 is consistent with arguments in Ritter and Chopra (1989) and Lakonishok, Shleifer, Thaler, and Vishny (1991) who surmise that portfolio managers are under considerable performance pressures during the fourth quarter of each year and seek to 'window dress' their portfolios. During Q4, previous period winners (growth stocks) are purchased while prior period losers (value stocks) are sold. At the turn of the year, portfolio managers are once again able to seek bargains and purchase undervalued value stocks, thus driving up the value premium in the first quarter of each calendar year. These individual stock returns are then captured at the index level. Results in Table 7 are not inconsistent with the behavioural explanation of Ritter and Chopra and others. Researchers advocating market efficiency would find a persistent and predictable seasonal pattern in the value premium problematic.

TABLE 7: Seasonality in average quarterly return differences between value and growth indexes , i.e. value premia. Results are expressed as average monthly return differences. Q4 1979 to Q1 2006. (n = 27)

Average quarterly value premium returns are computed by subtracting the average of the three monthly value-minus-growth returns, October, November, and December of year t from the average of the three monthly value-minus-growth returns, January, February, and March, of year t + 1.

	Q1 minus Q4 Returns (monthly average)			
	Small Cap Indexes		Large Cap Indexes	
	Russell 2000	Wilshire Target Small	Wilshire Target Large	S&P 500
1979/80	3.27	3.34	2.08	0.66
1980/81	5.85	6.04	6.20	4.20
1981/82	3.54	4.68	2.88	2.11
1982/83	2.63	2.19	2.44	1.59
1983/84	0.81	0.89	1.49	1.16
1984/85	-2.62	-4.66	-1.33	-0.05
1985/86	0.16	0.77	1.32	2.26
1986/87	-1.34	-1.90	-0.77	-0.63
1987/88	0.11	-4.54	-1.15	1.57
1988/89	0.08	-1.10	-0.28	0.24
1989/90	1.14	-1.90	0.20	1.43
1990/91	1.48	-1.76	-1.65	-0.44
1991/92	4.64	2.23	3.78	4.69
1992/93	4.88	5.05	3.86	3.97
1993/94	0.96	1.16	2.08	1.70
1994/95	0.15	-0.10	0.89	0.42
1995/96	-0.92	-2.21	-1.24	0.35
1996/97	0.34	1.65	-1.60	-1.36
1997/98	-4.50	-5.58	-2.57	-0.95
1998/99	1.46	2.13	0.74	0.69
1999/00	7.10	3.40	5.55	2.03
2000/01	-4.26	-0.02	-0.54	-2.63
2001/02	6.35	3.14	3.24	2.34
2002/03	0.54	-1.20	0.76	-2.45
2003/04	-0.68	-0.94	-1.43	-0.33
2004/05	1.53	0.06	1.32	-0.65
2005/06	0.06	0.22	0.65	0.98
Mean	**1.21**	**0.41**	**1.00**	**0.85**
Std Dev.	**2.90**	**2.94**	**2.26**	**1.81**
t-stat.	**2.17**	**0.72**	**2.29**	**2.43**

Section 7: Conclusion

Results in this essay advance the emerging body of literature that asks whether the value return premium observed in academic studies can be captured by institutional investors. Palippou (2008), for example, suggests that the premium is unavailable to large institutional investors. But, if the value premium is compensation for the assumption of greater risk, as argued by Fama and French (1993), then stocks observed within a market index that exhibit relatively higher BE/ME characteristics should still produce superior returns to stocks within that same index that exhibit relatively lower BE/ME characteristics. Results in this essay are consistent with those in Houge and Loughran (2006) who observe that the value premium is absent at the index return level. A passive route to capturing the premium may indeed be unavailable to market participants.

The absence of the value premium is robust to an extended survey of both large cap equity style indexes as well as small cap indexes. Moreover, results are similar for both a recent observation period as well as for an extended sample. Contrary to expectations, the value premium in the Fama and French benchmark portfolios is also found to be relatively weaker during the same time period as that tested for index returns. However, strong value premium results for the Fama and French benchmark portfolios prior to 1979 suggest that the premium may also be time varying at the index level. It may have been the case that a value premium – buying long a value style index and selling short a growth style index – was observable in the S&P 500/Citigroup, Russell 2000, or the Wilshire Target index series prior to 1979, had a reconstructed return history for those indexes been available to test.

Three-factor model regression results fail to expose any meaningful style tilt in the S&P 500 index series, although a considerable value tilt is observed in the S&P small cap and pure style indexes as well as the other equity style index series surveyed in Table 2. Contrary to comments in Loughran (1997) a structural opportunity does not appear to exist for investors to outperform any of the various market indexes surveyed in Table 2 by systematically buying relatively smaller, more value-oriented index constituents.

The choice of testing the value premium in constituents of the Russell 2000 index in Dhatt et al. (1999) may not have been a coincidence. The value premium at the index time series level in the Russell 2000 series is observed to be the strongest of those surveyed in this essay. However, tests by Dhatt et al. for the value premium in index constituents are not robust to another set of competitive indexes, the S&P 1500 and 600 indexes. No statistically significant value premium is observed when index constituents are sorted on ME/BE, P/S, or P/E. Sorts to control for size weaken results further. However, it is still possible that a value premium could exist in Russell 2000 constituents in the same sample

period tested here. Moreover, further research might be warranted testing the constituency of the Wilshire Target small cap index since that series exhibits a similar value tilt in returns to that observed in the Russell 2000. At minimum, results in this essay indicate that investors who are seeking to actively tilt a portfolio of index constituents to capture the value premium would need to be very careful in selecting the underlying benchmark index. Contrary to results by Dhatt et al. the price-to-sales ratio does not appear to be a stronger driver of the value premium than market-to-book value in an alternative style index constituency to the Russell 2000.

This essay also contributes to the literature that suggests that seasonality continues to impact returns in more recent time periods. Results confirm the existence of quarterly seasonality in the Russell 2000 index returns. A stronger value premium is generated in the first quarter of each calendar year compared to the premium in the fourth quarter of the prior calendar year. This pattern is robust for tests of two other index series, the Wilshire Target Large and the S&P 500/Citigroup. Turn-of-the-year seasonality of the value premium suggests an opportunity exists for investment managers to tactically allocate funds between value and growth index constituents and potentially achieve abnormal returns to that index.

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CHAPTER FOUR:
Can any mutual fund capture the value premium?

The value premium in stock returns has been documented in a long lineage of research. Rosenberg, Reid and Lanstein (1985) began the conversation by showing that value stocks with high book-to-market characteristics outperform growth stocks with low book-to-market characteristics. The discussion accelerated upon the publication of Fama and French (1992 and 1993) who argue that the difference between value and growth stock returns could be explained by risk. Lakonishok, Shleifer, and Vishny (1994), among others, disagree. The conversation continued over the years with challenges and counter-challenges to the Fama and French thesis of risk with alternative explanations of the book-to-market phenomena, as in the characteristics-based argument in Daniel and Titman (1994). After many years, several researchers began to investigate the next logical question, whether the so-called value premium could be captured in traditional investment vehicles.

Houge and Loughran (2006) find that small-cap value funds actually generate slightly smaller returns (14.10%) than small-cap growth funds (14.52%) between 1965 and 2001. The authors' results are of course contrary to implied promises in prior research. Houge and Loughran conclude that a value premium does not exist in managed mutual funds or in passive indexes. Davis (2001) similarly finds that value funds fail to capture the value premium when operating even in the most extreme size deciles. Davis ironically observes that funds exhibiting even a slight positive statistical sensitivity to the BE/ME factor are the poorest performers during the period 1965 to 1998. Phalippou (2008) tests the existence of the value premium in stocks held by institutional investors and finds no significant superior returns for high book-to-market stocks. The author does, however, find a large 2% per month premium in value stocks typically held by individual investors. Phalippou suggests that illiquidity and mis-pricing are at the root of the value premium and that institutional investors such as mutual funds are not likely to capture or arbitrage it away due to tremendous costs involved. However, Phalippou does not say it is impossible for a fund to operate successfully in this size and BE/ME investment space, only that it would be difficult.

One particular mutual fund launched in 1994 by Dimensional Fund Advisors is specifically designed to operate successfully in the illiquid space described by Phalippou. Moreover, the DFA Small Cap Value Fund is created as a passive (not active) vehicle to be invested in the manner consistent with tests of the value premium in academic literature. Due to its unique design, the DFA fund is an ideal target to determine whether it is indeed possible for institutional portfolios to capture the value

premium beyond the work of Davis (2001), Houge and Loughran (2006), and Phallipou (2008). This essay attempts to answer that question.

Results evaluating the performance of the DFA fund can be summarized fairly succinctly. When returns are computed similarly to that found in academic research, the DFA fund underperforms three benchmark portfolios, each of which have been shown to exhibit a return premium when compared to their growth-oriented counterparts. Indeed, tests show that the DFA fund fails to capture the value premium implicitly promised in academic research. Seasonality in manager trading strategies appears to be the culprit. In fact, when returns for the months of December and January are removed from the sample, the DFA Small Cap Value Fund statistically outperforms the growth portfolio benchmarks, thus indicating its successful capture of the value premium. Results suggest that actively managed value funds may still have a chance to systematically outperform their growth fund counterparts. The path to that premia, however, is yet to be determined.

Section 1: DFA and academia

To understand the importance of the DFA Small Cap Value Fund to the question of whether any institutional fund can capture the value premium, one must first gain an understanding of the company that created the fund. Dimensional Fund Advisors (DFA) is unique among its peers in the mutual fund marketplace. The company was born in the halls of academia and its investment products firmly rooted in the body of research literature. DFA was founded in 1981 by David Booth and Rex Sinquefield, two former graduate students of Eugene Fama at the University of Chicago.[71] The two disciples of Fama's market efficiency thesis were so convinced that passive investment vehicles would outperform actively managed funds that they founded DFA to financially capitalize on their beliefs. DFA was one of the first companies, along with Wells Fargo, to launch a series of passive investment funds that so dominate the marketplace today. DFA launched its Small Cap Value Fund in 1994, the year after the publication of Fama and French (1992) and Fama and French (1993), two seminal papers exploring the existence of a risk-based return premium between low and high BE/ME stocks. The Small Cap Value Fund was uniquely designed to passively capture the value premium in direct response to the work of their former academic mentor. One might argue that if the DFA Small Cap Value Fund fails to capture the value premium, then surely, it would seem incredibly difficult for others to do so.

[71] Co-authors with Eugene Fama and Kenneth French on the paper, "Differences in the Risks and Rewards to NYSE and NASD Stocks," Financial Analysts Journal, 1993.

Section 2: How to capture the value premium

A quick review of the relevant literature is necessary at this point. Research evidence suggests that the value premium, whether derived as a function of risk or investor mis-pricing, is found in three distinct, but clearly related areas of the universe of stocks: 1) small-cap stocks [see Kothari, Shanken and Sloan, 1995, Loughran, 1997, among many others[72]], 2) stocks experiencing some type of distress or poor prior performance [see Fama and French, 1995, Dichev, 1998, Griffin and Lemmon, 2002, and Penman, Richardson and Tuna, 2007], and 3) stocks suffering from illiquidity issues [see Pastor and Stambaugh, 2003 and Dimson, Nagel and Quigley, 2003]. This means that an institutional investor constructing a separate account or mutual fund portfolio specifically designed to capture the value premium would need to alter her stock screens to include small-cap stocks perceived to reflect considerable distress-related risks and trading noise. Moreover, based on problems relating to liquidity, funds would need to hold large numbers of these stocks to minimize any market impact from their purchase. The fund would need to minimize portfolio turnover to again lessen its market footprint.

Fama and French (2007) provide further evidence about optimal portfolio turnover in the quest for the value premium. The authors observe the value premium to be a function of changing fortunes, originating as a function of 3 events: value stocks are either 1) acquired or become defunct during the observation period, or 2) improve operating returns, thus leaving the high BE/ME value category. Growth stocks simultaneously experience diminishing returns, thus leaving the low BE/ME category. The authors observe only a slight performance premium in value stocks *vis a vis* growth stocks in portfolios where no migration occurs and a consistent BE/ME characteristic is maintained. Evidence from this research suggests that a fund manager is not likely to capture a large premium by purchasing high BE/ME stocks and utilizing a buy and hold method. According to Fama and French, value stocks that generate superior performance in one period migrate to become stocks that in future periods fail to generate the same relative superior performance. By implication, it would be wise for fund managers to rebalance their portfolios by size and BE/ME characteristics frequently to capture the superior performance of value stocks prior to their ultimate migration (or acquisition). Consistent with this view, Dennis, Perfect, Snow and Wiles (1995) suggest that the optimal rebalancing period for portfolios formed on BE/ME and size for the sample period 1963 to 1988 is 2 years.

However, it is important to make a distinction between rebalancing in the context of the Fama and French portfolio construction method and turnover occurring in actively managed or passive

[72] Davis, Fama and French (2000) find that large cap stocks produced a larger value premium than small cap stocks between July 1929 to June 1963.

investment portfolios. For portfolio returns constructed as in Fama and French (1993), Lakonishok, Shleifer and Vishny (1994), Banko and Conover (2002) among many others, stocks may or may not be effectively 'sold' at each annual rebalancing or portfolio formation period if their relative size and BE/ME characteristics do not change, or the relative size and BE/ME characteristic for the entire sample shifts proportionately to the shift in characteristics of the stock. Therefore, while rebalancing occurs annually using these methods, some stocks may be held in the same Fama and French-style portfolios (size and BE/ME deciles) for many years across many rebalancing periods.

The DFA Small Cap Value Fund investment philosophy and strategy are consistent with research evidence in academic literature on where and how to capture the value premium. The fund begins with a universe of all stocks traded on the NYSE, AMEX and NASDAQ markets and then eliminates certain stocks to capture the rewards within the small-cap investment space. The fund then excludes or screens stocks for cause before reaching its final portfolio. DFA currently defines small-cap for the Small Cap Value Fund as those residing in the last decile of stocks ranked by market capitalization, or stocks ranking smaller than the 1,000th largest US company, whichever results in the largest market capitalization boundary. Detzel (2008) observes that the average annual market cap of the DFA Small Cap Value Fund is only $312 million between January 1994 and December 2005. That size characteristic is somewhat larger than the $269 million average size for the small value mutual fund category and $309 million for the small growth fund category observed by Detzel. The DFA prospectus adds that the fund typically buys stocks in the lowest 8th percentile of market capitalization and may from time to time buy stocks with larger market caps. Characteristics of stock purchases are only part of the story. A portfolio is clearly influenced by the market cap of stocks that continue to be held long after purchase. Morningstar reports that the average market cap of the DFA Small Cap Value Fund is $673 million at 31 March 2008, nearly double its 12 year average reported in Detzel (2008).

The DFA Small Cap Value Fund undoubtedly operates in the size area shown by research to generate the largest value premium. However, trading rules imposed by the company exclude many of the most illiquid stocks traded on the exchanges. The fund is restricted from buying any of the thousands of OTC stocks not traded on the National Market System (NMS) of NASDAQ. Moreover, the fund eschews NMS stocks with fewer than four market makers, as well as stocks defined as REITs, limited partnerships, closed-end funds, ADRs and foreign stocks, stocks currently in bankruptcy, those stocks valued under $10 million, or stocks priced under $2.00 per share. DFA also tends to wait six

months before purchasing IPOs.[73] While the above trading restrictions do not violate the concept of investment *passivity*, they do create potential return differences between the DFA small-cap portfolio and the universe of small cap value stocks traded on those three markets. However, since portfolio constituency restrictions of similar definition are also found in academic research (e.g. Fama and French, 1993), such rule restrictions may have little impact on the process of capturing the value premium.

The DFA Small Cap Value Fund officially defines a value stock quite vaguely.[74] The company states in their fund prospectus that, "Securities are considered value stocks primarily because a company's shares have a high book value in relation to their market value." They broaden the definition stating that "cash flow or price-to-earnings ratios may be considered, as well as economic conditions and developments in the issuer's industry." DFA says that the criteria for "assessing value are subject to change from time to time."[75] However, as a practical matter, DFA defines value as the highest 30% of stocks ordered by book-to-market value and defines growth as the bottom 30% prior to portfolio formation, a definition also used in Fama and French (2007). Similarly, DFA trading rules restrict portfolios to stocks exhibiting positive BE/ME characteristics, again similar to most academic research restrictions. Morningstar reports that the average BE/ME of the DFA Small Cap Value Fund observed at 31 March 2008 is 1.10, considerably higher than the 0.70 average for the Morningstar small cap value fund category and 0.50 average for the S&P 500 Index, and virtually identical to the breakpoint value (1.17) for the highest BE/ME decile portfolio at year end December 2007 computed by Fama and French. This suggests that DFA is populating the value portfolio with stocks possessing high BE/ME characteristics consistent with findings of the value premium in academic literature.

Finally, Detzel (2008) observes that the average annual microcap value-oriented mutual fund portfolio turnover is 61% between January 1994 and December 2005, but only 21% for the DFA Small Cap Value Fund. In other words, the DFA fund holds stocks on average about 5 years, a rate apparently at odds with capturing the pattern of migration observed in Fama and French (2007). As discussed earlier, portfolio turnover rates observed in market-based funds, and rebalancing rates observed for

[73] Source: Keim (1999) and the DFA funds prospectus dated 29 March 2008.

[74] It is not unusual for fund prospectuses submitted as a legally binding document to the Securities and Exchange Commission to be intentionally vague. The threat of investor lawsuits as well as the dynamics of the competitive marketplace often preclude the presentation of a more specific set of rules and definitions

[75] DFA funds prospectus dated 29 March 2008.

hypothetical portfolios in academic research, are not necessarily comparable.[76] A low turnover rate does, however, allow DFA to tread lightly in the market for illiquid stocks.

The question of whether the DFA Small Cap Value Fund captures the value premium will be evaluated in the next four sections. Section three discusses the choice of return computation used in this essay. Section four defines the investable universe for the DFA fund and provides a return comparison and discussion of the performance tracking error. Section four also tests the question of whether the DFA fund captures the value premium. DFA excess returns are also regressed against the Fama and French 3-factor model to observe the fund's sensitivities to the size and BE/ME factors. This begins the process of evaluating the drivers of performance and determining why the fund either does or does not capture the value premium. Following the method of Keim (1999), section five decomposes fund returns identifying the return impact from DFA portfolio constituency rules as well as the impact from the company's unique trading strategies. Section six further tests returns for periodic changes and time varying characteristics while the seventh section tests for seasonality in DFA returns. An appendix to the essay further investigates the drivers of performance using Sharpe's return based style analysis (RBSA). These tests help to illuminate market-segment influences on DFA returns over the entire sample period, as well as observing any changes in these influences by using a rolling sixty month RBSA computation.

Section 3: The choice of DFA return data

Stock returns reported in academic research are typically computed as period arithmetic averages, using an ending value, plus any distributions, less its beginning value, then divided by the beginning value. Once computed, stock returns are either equal weighted or value weighted when forming portfolios (see Fama and French 1993, among many others). Conversely, returns for mutual funds, as prescribed by the Association of Investment Management and Research (AIMR), are typically time-weighted.[77] Unlike returns in academic research, US mutual fund monthly returns reported in datasets offered by Morningstar and others are usually computed by geometrically linking these daily fund cash flows.

Time-weighted returns are indeed preferable when comparing fund performance against the performance of benchmarks, indexes, or fund competitors. However, this essay is not interested in the

[76] However, it is worth noting that Lakonshok, Shliefer and Vishny (1994) indeed observe a value premium in average (and average size-adjusted) returns for portfolios held for rolling 5 year periods, 9.3% for the extreme growth portfolio compared to 19.8% for the extreme value portfolio using a 27 year sample ending 1990.
[77] The *Global Investment Standards* (GIPS) which prescribe similar rules are scheduled to be applied on a voluntary basis around the world beginning 2010.

question of the relative superior performance of the DFA Small Cap Value fund versus any off-the-shelf benchmark or whether investor behaviour impacts returns - a question better tested using dollar weights. Rather, the focus of this essay is to determine whether the DFA Small Cap Value Fund is capturing the same value premium as promised by academic research. For that question, it is necessary to compute the performance of the DFA Small Cap Value fund similarly to the performance represented in academic literature, not the time-weighted returns found in the marketplace. See Clarfield (1998) for a short treatment of the various return computations used in the marketplace.

Monthly returns for the DFA Small Cap Value Fund are obtained from Datastream computing the periodic relative change from their Return Index (RI) datatype time series. The Datastream return index measure is preferable in this treatment because the time series, adjusted for dividends and capital change, is more closely aligned with returns calculated from adjusted daily price relatives, a method used by the academic researchers whose findings are evaluated in this essay. Most importantly, neither method adjusts for the impact of time. The return index in Datastream is computed first as a function of adjusted daily prices expressed simply as a percentage (PI) of its index base date. The total return index (RI) is then computed thusly: [78]

$$RI_t = RI_{t-1} * \frac{P_t}{P_{t-1}}$$

except when t = ex-date of the dividend payment D_t then:

$$RI_t = RI_{t-1} * \frac{P_t + D_t}{P_{t-1}}$$

Where:

RI_t = return index on day t

RI_{t-1} = return index on previous day

P_t = price on ex-date

P_{t-1} = price on previous day

D_t = dividend payment associated with ex-date t

[78] Source: Thomson Financial. Gross dividends are used where available and Ignores tax and re-investment charges.

Section 4: DFA returns compared to its investable universe

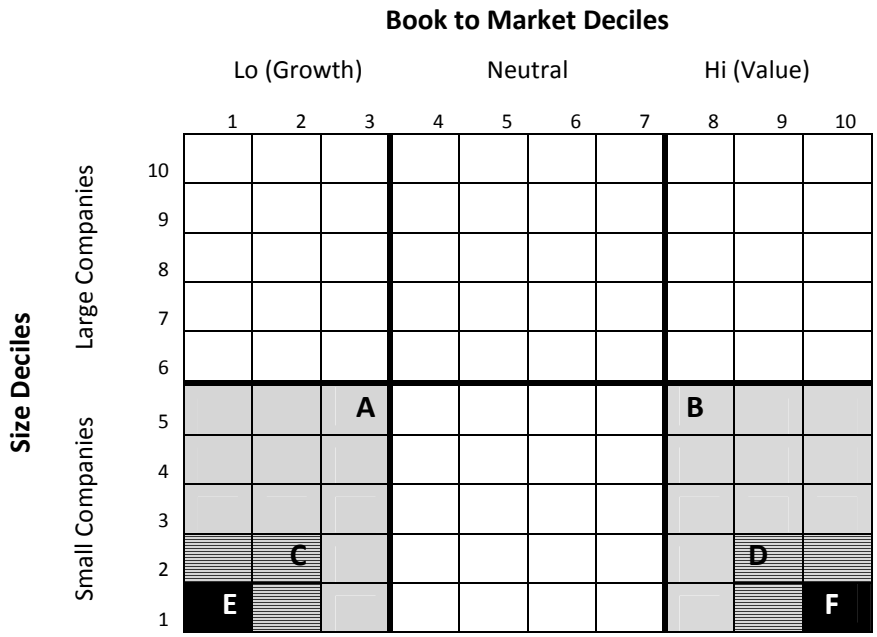
The choice of the fund's investable universe is quite straight forward. Given the fund's origin and design and the nature of the questions in this research, the investable universe can be said to be represented by the various small cap value portfolios constructed in Fama and French (1993). First, stocks in the hypothetical Fama and French small cap value portfolios have been shown to possess the value premium. Second, they are passive and constructed using many of the same portfolio constituent rules as the DFA portfolio. For example, both the Fama and French portfolios and the DFA Small Cap Value Fund portfolio consist of stocks from the NYSE, AMEX, and NASDAQ. Each excludes ADRs, foreign shares, REITs and other shares of beneficial interest. Most importantly, neither the DFA, nor the Fama and French portfolios contain stocks with negative book-to-equity characteristics. While the portfolios are quite similar in construction, there are enough differences to allow tests as in Keim (1999) isolating rule-based and trading-based similarities and differences.

4.1 The investable universe

Three overlapping Fama and French portfolios are chosen to define DFA's investable universe. Each is presented graphically in Figure 1. Fama and French portfolio A represents stocks in the smallest half and the lowest 30th BE/ME percentile. Portfolio B represents the value portfolio counterpart for A. Portfolio C represents stocks in the smallest 20% size and lowest 20% BE/ME percentile, and D - its value portfolio counterpart. Fama and French portfolio E represents stocks in the smallest 10% size and lowest 10% BE/ME percentile, and F - its value portfolio counterpart.

To be precise, DFA's size and BE/ME trading universe is arguably more closely compared to a Fama and French portfolio constructed from stocks in the smallest size decile and the 4th highest BE/ME quartile space, or 10/75 portfolio. However, a portfolio with that sort is not readily available at the same data source used in this analysis. Constructing a 10/75 portfolio by replicating the methodology in Fama and French (1993) is indeed possible. However, the lack of access to the precise universe of stocks used by authors could introduce noise in comparisons to the other Fama and French portfolios. Plus, the precise time varying characteristics of the DFA fund would be difficult to benchmark even with a 10/75 portfolio. In any event, the three value-oriented Fama and French portfolios, B, D, and F, representing a range from the first to the fifth decile of small cap stocks, as well as a range from the eighth to the tenth BE/ME decile surrounds the 10/75 investment space. Moreover, using a series of portfolios for

FIGURE 1: Map of book-to-market and size percentile coverage of the six Fama and French growth and value portfolios



comparison rather than defining a sole benchmark provides an interesting context to DFA returns across the two dimensions of size and book-to-market.

4.2 Regression results

The first task in analysing DFA returns is to identify sensitivities to the market, size, and BE/ME risk factors as defined in the Fama and French 3-factor model. Table 1 shows the regression coefficients and t-statistics for DFA as well as the regression coefficients and t-statistics for each of the three Fama and French small cap size and BE/ME value portfolios (B, D, F) and growth portfolios (A, C, E) mapped in Figure 1. Excess monthly returns of each of the Fama and French portfolios are accessed from the website of Kenneth French.

Results in Table 1 show that excess DFA fund returns differ considerably in factor sensitivities to the three non-investable Fama and French small cap value-oriented benchmark portfolios. The fund's alpha -0.56 is negative, significant (t= -2.58), and unexpectedly similar to results of the three small cap

growth portfolios, rather than to the three value portfolios.[79] The return underperformance is large and approximately 6.72% per year.[80] DFA return sensitivity to market risk is also more similar to the small cap growth portfolios than to the value portfolios. DFA loads larger in size than any of the three value portfolios, B, D and F. However, DFA loadings on the HML book-to-market factor as well as adjusted R-square and volatility are virtually identical to the loadings of the FF Portfolio (F), the smallest, most value-oriented portfolio. These results hint that DFA bought stocks with the correct BE/ME characteristics. Other performance drivers, possibly relating to trading issues, appear to generate a significant influence on market exposure, growth orientation, and size, thus generating a negative impact on returns. This question will be investigated in later sections.

TABLE 1: Three-factor regression analysis of excess monthly returns of the DFA Small Cap Value Fund and various hypothetical Fama and French small cap value and growth portfolios. May 1994 to December 2007 (n = 164)

Monthly DFA returns are obtained from Datastream. All other data including excess monthly returns of the six Fama and French portfolios, 3-factor model returns, as well as the risk free rate are obtained from the website of Kenneth French.

$$Rpt - Rft = a + b[\mathrm{R}mt - \mathrm{R}ft] + s\mathrm{SMB}t + h\mathrm{HML}t + et$$

Portfolio	a	b	s	h	t(a)	t(b)	t(s)	t(h)	Adj. R^2	σ
DFA	-0.56	1.02	0.76	0.65	-2.58	17.26	12.30	8.32	0.74	5.27
Small Value										
FF Portfolio (B)	0.06	1.00	0.84	0.77	1.14	73.41	58.72	42.52	0.98	4.62
FF Portfolio (D)	0.29	0.96	0.95	0.67	2.15	26.61	25.10	13.90	0.90	5.12
FF Portfolio (F)	0.47	0.89	0.92	0.64	2.26	15.62	15.59	8.54	0.76	5.25
Small Growth										
FF Portfolio (A)	-0.32	1.12	1.01	-0.20	-3.35	43.43	37.65	-5.94	0.97	7.29
FF Portfolio (C)	-0.54	1.13	1.29	-0.41	-2.29	17.81	19.37	-4.90	0.90	9.07
FF Portfolio (E)	-0.64	1.01	1.33	-0.52	-1.71	9.88	12.49	-3.86	0.78	9.77

[79] For robustness, DFA returns are regressed on the series known as the "Fama and French Benchmark Factors". Results are consistent with regression results from Table 1 with one curious difference. The regression intercept, factor coefficients, and t-statistics are each reduced. In this test, DFA's negative alpha became statistically insignificant at the 5% level. However, the R-square remains the same. On his faculty website, Kenneth French states that the benchmark factor returns are "designed for investors seeking benchmarks for asset class portfolio returns" and not for academic use.

[80] Results in Table 1 contrast to alpha results of +0.11 for the DFA Small Cap Value Fund returns in Detzel (2008). DFA returns are regressed on Carhart's 4-factor model and observed over a similar sample period as in this study. However, unlike in this study, the author uses time-weighted returns accessed from the Morningstar database.

4.3 Tracking Error

Most research on the issue of portfolio tracking error concentrates on methods to minimize the difference in returns, or volatility of returns, between a chosen benchmark index and the target portfolio (see the literature survey in Beasley, Meade and Chang, 2000, and Corelli and Massolino, 2006). Unlike most papers on the topic, this essay is interested in evaluating the impact of any tracking trade-off on the ability of the DFA managers to capture the value premium. The DFA Small Cap Value Fund is not a 100% replication of the smallest, most value-oriented portfolio previously constructed and evaluated in Fama and French (1993), although the fund makes a bold attempt to get close to a full replication within the confines of its composition rules and trading restrictions. Unlike many passive or index funds, DFA does not attempt to replicate the benchmark universe by sampling or by hedging in the futures markets, therefore its returns may vary considerably. Keim (1999) observes considerable return variability for the DFA 9-10 Small Cap Fund . In theory, any variation in returns or tracking error between the DFA Small Cap Fund and the Fama and French portfolios identified in Figure 1 should indicate that stocks omitted from the portfolio by policy or trading constraint are on average generating returns not consistent with the stocks that survived the constraints.

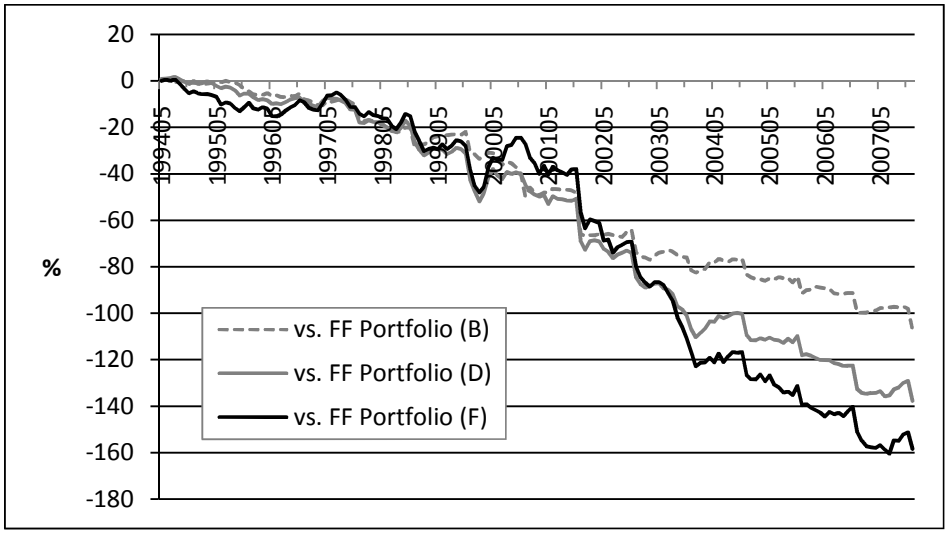
Figure 2 shows the cumulative sum of excess return differences between the DFA Small Cap Value Fund and the three Fama and French small cap portfolios. As expected from regression results in Table 2, the DFA fund appears to systematically underperform all three small cap Fama and French value portfolios. The underperformance becomes relatively worse as the size and BE/ME space becomes progressively smaller and more value-oriented. These results provide visual evidence to regression results in Table 1 indicating returns inconsistent with a traditional Fama and French small cap value portfolio - previously shown to generate superior returns to its growth counterpart.

4.4 The value premium

Mean difference in returns between the DFA fund and each of the three hypothetical Fama and French small value portfolios are shown in Panel A of Table 2. This statistic, also defined as the average monthly tracking error, is large, negative, and significant at the 5% level for each decile space. For example, monthly return tracking error between the fund and the smallest/most value-oriented FF Portfolio (F) averages -0.97% per month (t = -3.59). Periodic tracking error variation is approximately +/- 3% per month for each of the three 'DFA minus Value' comparisons in Panel A, a result probably not

FIGURE 2: Cumulative sum of excess return differences between the DFA Small Cap Value fund and 3 Fama and French value portfolios. May 1994 to December 2007.

Monthly DFA returns are obtained from Datastream. All other data including excess monthly returns of the three Fama and French value portfolios as well as the risk free rate are obtained from the website of Kenneth French.



fully explained by an average 0.50% per annum management fee or by periodic trading costs. These results are consistent with general observations in Keim (1999) that DFA fund managers allow the passive DFA small cap 9-10 portfolio to vary significantly from its underlying benchmark in order to manage liquidity and to protect returns which would otherwise be negatively impacted by trading.[81] Results in Panel B of Table 2 reflect monthly mean difference performance between the DFA fund and the three Fama and French small cap growth portfolios. This is the test of the value premium. Difference in returns between DFA and the Fama and French portfolio, constructed using the smallest 10% and lowest 10% of BE/ME stocks is economically 0.39% per month. However, the result is not statistically different from zero (t = 0.67). Results in Panel B clearly show that the DFA fund performance is not statistically different from any of the three small cap growth portfolios and therefore has not captured the value premium during this sample period. Difference returns in Panel C of Table 2 are shown to illustrate the opportunity set of returns between the Fama and French value and growth portfolios for each of the three size and BE/ME spaces. During this sample period, the value premium is large and

[81] Note: The same return comparisons are performed against the time series known as the "Fama and French Benchmark Portfolios", a set of portfolio returns available on the website of Kenneth French representing the same space as the two FFSm50Hi80 and FFSm50Lo30 series. Results showed no material change in size or statistical significance of the results.

TABLE 2: Mean monthly return difference between the DFA Small Cap Value Fund and the various Fama and French size and BE/ME portfolios

Monthly DFA returns are obtained from Datastream. All other data including excess monthly returns of the six Fama and French portfolios as well as the risk free rate are obtained from the website of Kenneth French

Return Differences

Panel A: DFA minus Value				Panel B: DFA minus Growth				Panel C: Opportunity Returns			
Decile Space	Mean	t-stat	σ	Decile Space	Mean	t-stat	σ	Decile Space	Mean	t-stat	σ
DFA – FF (B)	-0.65	-3.24	3.20	DFA – FF (A)	-0.07	-0.18	4.74	FF (B) – FF (A)	0.59	1.76	4.26
DFA – FF (D)	-0.84	-3.66	2.94	DFA – FF (C)	0.17	0.34	6.58	FF (D) – FF (C)	1.01	2.31	5.61
DFA – FF (F)	-0.97	-3.59	3.45	DFA – FF (E)	0.39	0.67	7.48	FF (F) – FF (E)	1.42	2.83	6.44

significant at the 5% level for the two smallest/most value-oriented Fama and French portfolios and significant at the 10% level for the Fama and French portfolio occupying the largest/least value-oriented investment space (mean = 0.59%, t = 1.76). Results in Panel C are consistent with prior research findings of the value premium being monotonically more pronounced toward the most extreme small size and high BE/ME portfolios.

Section 5: Decomposition of the DFA value premium

To further investigate the nature of DFA performance, fund returns are decomposed in a manner similar to the method used in Keim (1999) who examined the performance of another DFA fund, the Small Cap 9-10 mutual fund. This research will evaluate the contribution to returns from two components: returns from the fund's unique trading strategies and returns from portfolio constituent rules.[82] This treatment alters Keim's work in an attempt to identify the drivers of DFA's inability to capture the value premium. Any deviation in portfolio construction by the DFA Small Cap Fund from a sample of small cap value stocks shown to generate superior performance to small cap growth stocks originating either by trading strategy or portfolio rule restriction represents a potential cause for not capturing the premium.

Keim finds that the DFA 9-10 fund captures extra returns resulting from a unique trading strategy that supplies liquidity to the market. Most importantly to this research, Keim observes that fund strategic investment rules create a large cap and growth tilt to return characteristics when compared to the CRSP 9-10 benchmark. Despite evidence of a tilt away from an extreme small size

[82] Donald Keim, a member of faculty at the University of Pennsylvania, is also a DFA board member. This position provided unusual access to inside trading strategies, decisions and mechanisms of fund activities. This research does not benefit from such access and company cooperation.

orientation, Keim's results still suggest that the DFA 9-10 fund provides value-added returns to investors who might otherwise suffer from the effects of illiquidity when purchasing micro-cap stocks.

This research attempts to determine whether similar trading strategies and/or portfolio constituent rules that appear to tilt the DFA 9-10 fund away from small cap stocks and toward larger growth-oriented stocks have impacted returns of the DFA Small Cap Value Fund in a similar manner. A tilt toward larger and more growth-oriented stocks could materially limit the ability of the DFA Small Cap Value Fund from capturing the value premium.

5.1 Equations

Decomposition of returns tested in this section begins with the computation of the value premium (VP) for the overall small cap size space using Fama and French portfolios (FF) identified in Table 1. VP is defined in equation (1) as the difference between the returns of a portfolio of small value stocks (FF_{value}) of a determined size and BE/ME characteristic and returns of a portfolio of small growth stocks (FF_{growth}) of the same size, but opposite BE/ME characteristic:

$$VP = FF_{value} - FF_{growth} \tag{1}$$

The construction and characteristics of the two portfolios used in equation (1) are detailed later in column A of Table 3. As in Keim (1999), equation (1) can be further defined to include any changes from the original FF_{value} portfolio imposed by rule on portfolio constituency (Rule), plus any changes from the impact of trading decisions and methods (Trading). For example, if the value portfolio under consideration is an exact replica of the FF_{value} portfolio in the size and BE/ME space, then the outcomes for both Rule and Trading impact will naturally be zero. If the impact from constituency rules and/or trading strategies has a positive (negative) impact on FF_{value} returns, then the value premium return is increased (decreased):

$$VP = (FF_{value} + Rule + Trading) - FF_{growth} \tag{2}$$

Changes imposed by rule on portfolio constituency are further defined as in Keim (1999) where Rule equals the return differences between FF_{value} and some value portfolio which mimics the portfolio rule constraints of the DFA Small Value Fund as closely as possible. This DFA rule mimicking portfolio is denoted in equation (3) as RM_{value} and defined in column B of Table 3. Changes resulting from trading decisions are defined as being the difference in returns between the DFA Small Cap Value Fund (DFA)

and the portfolio that mimics the rule constraints of the DFA fund as closely as possible, once again denoted as the value-oriented RM_{value} portfolio. Equation (2) is restated as:

$$VP = [FF_{value} + (RM_{value} - FF_{value}) + (DFA - RM_{value})] - FF_{growth} \quad (3)$$

and then arithmetically reduced to its final form in equation (4) as:

$$VP = DFA - FF_{growth} \quad (4)$$

The question of whether the DFA Small Value Fund provides investors with an off-the-shelf vehicle to capture the value premium as defined by equation (4) has already been tested, and results shown in Panel B of Table 2. It must be said that the value premium computation in equation (4) is somewhat theoretical and unrealistic for market participants. The more realistic comparison, one that excludes tiny illiquid stocks that mass-market investment funds simply have no ability to select for their portfolios, might be better made by observing differences in returns between the DFA fund and its growth-oriented rule mimicking portfolio:

$$VP^* = DFA - RM_{\text{growth}} \quad (5)$$

The latter represents a more pragmatic investable universe for comparison and places the entire blame for any failure to capture the value premium squarely on trading issues. However, results provided by equation (4) are more informative in determining whether the value premium does in fact exist in the space in which the DFA fund operates.

5.2 Rule and trading strategies impact on DFA returns

To determine the impact of constituent rules on DFA returns, the fund's value premium is evaluated to see if it is more pronounced in stocks DFA omitted by rule, such as stocks smaller than $10 million, stocks priced below $2 per share, and non-NMS stocks.[83] Rule mimicking portfolios shown in Table 3 are constructed using a sample of stocks trading on the NYSE, AMEX and NASDAQ NMS, thus omitting non-NMS and *other* OTC stocks. These rules are consistent with the portfolio constituent rules used by DFA. All data for the rule mimicking portfolio are sourced from the Research Insight database.

[83] Keim finds that returns for the similar DFA 9-10 fund are almost perfectly positively correlated (0.98) with the CRSP 9-10 index, a benchmark reflecting all stocks within the two 9-10 size deciles. The author also concludes that the performance of the DFA 9-10 small cap fund is not materially impacted by the omissions by rule of small and illiquid stocks. In fact, the DFA 9-10 small cap fund generates a 2.2% superior average annual value-weighted return to the CRSP 9-10 benchmark index over the entire sample period 1982 to 1995. However, Keim observes considerable tracking error and volatility in the error between the DFA fund and the CRSP index over the duration of the sample.

TABLE 3: Portfolio description, constituency rules and trading strategies

Portfolios	A. Fama and French Portfolios[1] (FF)		B. DFA Rule Mimicking Portfolios (RM)		C. DFA Small Cap Value Fund (DFA)
Description	**Value** FFSm1-5/Hi8-10 FFSm1-2/Hi9-10 FFSm1/Hi10	**Growth** FFSm1-5/Lo1-3 FFSm1-2/Lo1-2 FFSm1/Lo1	**Value** RMSm1-5/Hi8-10 RMSm1-2/Hi9-10 RMSm1/Hi10	**Growth** RMSm1-5/Lo1-3 RMSm1-2/Lo1-2 RMSm1Lo1	**DFA**
1. Hypothetical or real portfolio	Hypothetical		Hypothetical		Real
Shared Portfolio Constituency Rules					
2. ADRs and Foreign Shares	Excluded		Excluded		Excluded[2]
3. REITs and units of beneficial interest	Excluded		Excluded		Excluded[3]
4. Stocks with Negative or Zero Book-to-market	Excluded		Excluded		Excluded[4]
5. Size	Restricted to the 1st, 2nd, or 5th size decile of stocks at each portfolio formation period, (depending upon the portfolio being used above)		Restricted to the 1st, 2nd, or 5th size decile of stocks at each portfolio formation period, (depending upon the portfolio being used above)		Restricted to the smallest 10% of stocks or investments below the smallest 1000th stock whichever is larger[4]
6. Book-to-market	Restricted to the 8th, 9th, or 10th highest BE/ME decile of stocks observed at each portfolio formation period, (depending upon the portfolio being used above)		Restricted to the 8th, 9th, or 10th highest BE/ME decile of stocks observed at each portfolio formation period, (depending upon the portfolio being used above)		Restricted to the highest 25th percentile by BE/ME rank[4]
Unique Portfolio Constituency Rules					
7. Portfolios constructed from NYSE, AMEX, NASDAQ stocks	All		NYSE, AMEX, Restricted to NASDAQ NMS stocks; Non-NMS stocks excluded.		NYSE, AMEX, Restricted to NASDAQ NMS stocks; Non-NMS stocks excluded[2]
8. Stocks in bankruptcy	Included		Excluded		Excluded[5]
9. Stocks priced below $2	Included		Excluded		Excluded[6]
10. Stocks with market values below $10 million	Included		Excluded		Excluded[6]
Trading Strategies					
11. Buy with discretion	None		None		May exclude stocks involved in mergers; stocks with a portion closely held; and "other"[3]
12. Rebalancing/Sell with discretion	Annually Without exception, stocks are theoretically sold at the end of each portfolio formation period and re-purchased based on size and book-to-market criteria		Annually Without exception, stocks are theoretically sold at the end of each portfolio formation period and re-purchased based on size and book-to-market criteria		"Not less than semi-annually"[7] Stocks are sold when: Market caps rise significantly above stocks that are candidates for inclusion[7]; BE/ME falls significantly below stocks that are candidates for inclusion[7]
13. Selling Microcap Stocks	Same rule as above		Same rule as above		Microcaps are generally held for longer periods despite BE/ME changes[7]
14. Calculation of portfolio stock weightings	Observed at month end prior to portfolio formation. No adjustments		Observed at month end prior to portfolio formation No adjustments		Computed at the time of purchase/rebalancing Adjustments allowed for free float, stock momentum, round lots, liquidity management and "other given market conditions"[8]
15. Other	None		None		Any unknown/undisclosed variation from policy during the course of daily operation

Notes to TABLE 3: sources for Fama and French and DFA portfolio constituency and trading rules:

1. Fama and French (1993), pp 8-9.
2. *Dimensional Fund Advisors, US Small Cap Value Portfolio Class I* 'Fact Sheet' dated June 30, 2008, p 1-2.
3. DFA Investment Dimensions Group, Inc. Prospectus dated 29 March 2008, p 56.
4. *Dimensional Fund Advisors, US Small Cap Value Porfolio Class I* 'Fact Sheet' dated June 30, 2008, p 1-2.
5. DFA Investment Dimensions Group, Inc. Prospectus dated 28 March 2008, p 56. "stocks in extreme financial difficulty", Also implied in Keim (1999) p 176 using the term "bankrupt firms" while citing actual rules for the DFA small cap master fund
6. Implied for the DFA small cap value portfolio in Keim (1999), p 176-177 citing actual rules for the DFA small cap master fund
7. DFA Investment Dimensions Group, Inc. Prospectus dated 29 March 2008, p 39.
8. DFA Investment Dimensions Group, Inc. Prospectus dated 29 March 2008, p 76.

The sample excludes foreign shares, ADRs, and stocks not representing the primary common equity of a particular firm. The latter restriction further mimics the DFA Small Cap Value Fund's constituency rules as well as rules in Fama and French (1993). Stocks are excluded if no computed book equity (BE) exists at calendar year end t-1 or market equity (ME) at April of year t prior to each annual portfolio formation. Portfolios are formed each May of year t by independently sorting first by size and then by the firm's book-to-market equity ratio (BE/ME). For the sort on size, a firm's market equity is observed at the end of April in year t just prior to portfolio formation. BE and ME are each observed at calendar year end t-1 for the sort on book-to-market equity. As in Fama and French (1993), BE is defined as the book value of shareholder's equity minus the book value of any preferred shares computed at liquidation value, plus any deferred taxes and investment tax credits.[84] Twelve months of total returns are then observed for each stock beginning in year t through t+1 from May 1994 through December 2007. A portfolio formation date of May is dictated by the first full month of returns available for the DFA fund. Annual BE/ME and ME sorts performed each April are structured using the Fama and French NYSE breakpoints from the CRSP database. The BE used in the construction of breakpoints represents the non-negative book equity observed at year end t-1 while the ME breakpoints are observed at April of year t just prior to portfolio formation.

For clarity, empirical results evaluating the value premium characteristics of the various DFA rule mimicking (RM) portfolios are shown in Table 4. As expected, RM portfolios restricted to the smallest stocks (e.g. RMSm1) exhibit a larger value premium than portfolios that include larger stocks (e.g. RMSm1-5) regardless of BE/ME sorts in Panels A-C. This is consistent with the lack of uniformity of the

[84] Fama and French (1992) find little impact on results from using calendar year end ME vs. fiscal year end ME.

value premium across size strata known to exist in the Fama and French portfolios. Value-oriented RM portfolios outperform growth portfolios for every BE/ME sort and regardless of size restriction. While none of the return differences between value and growth are statistically significant, the economic

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TABLE 4: Observation of the value premium for DFA rule mimicking portfolios for various sorts on size and BE/ME. Average monthly returns between May 1994 to December 2007.

Rule mimicking portfolios are constructed using a sample of stocks trading on the NYSE, AMEX and NASDAQ NMS, thus omitting non-NMS and *other* OTC stocks. All data for the rule mimicking portfolio are sourced from the Research Insight database. The sample excludes foreign shares, ADRs, and stocks not representing the primary common equity of a particular firm. Stocks are excluded if no computed book equity (BE) exists at calendar year end t-1 or market equity (ME) at April of year t prior to each annual portfolio formation. Portfolios are formed each May of year t by independently sorting first by size and then by the firm's book-to-market equity ratio (BE/ME). For the sort on size, a firm's market equity is observed at the end of April in year t just prior to portfolio formation. BE and ME are each observed at calendar year end t-1 for the sort on book-to-market equity. As in Fama and French (1993), BE is defined as the book value of shareholder's equity minus the book value of any preferred shares computed at liquidation value, plus any deferred taxes and investment tax credits. Twelve months of total returns are then observed for each stock beginning in year t through t+1 from May 1994 through December 2007. A portfolio formation date of May is dictated by the first full month of returns available for the DFA fund. Annual BE/ME and ME sorts performed each April are structured using the Fama and French NYSE breakpoints from the CRSP database. The BE used in the construction of breakpoints represents the non-negative book equity observed at year end t-1 while the ME breakpoints are observed at April of year t just prior to portfolio formation.

Panel A:

		BE/ME Decile			
		Growth Lo1-3	Value Hi8-10	Val. – Gr. Difference	t-stat
Size Decile	RMSm1	1.59	1.82	0.23	0.56
	RMSm1-2	1.35	1.69	0.35	0.86
	RMSm1-5	1.19	1.52	0.33	1.06

Panel B:

		Growth Lo1-3	Value Hi9-10	Val. – Gr. Difference	t-stat
Size Decile	RMSm1	1.43	2.00	0.57	1.34
	RMSm1-2	1.18	1.78	0.60	1.39
	RMSm1-5	1.15	1.54	0.40	1.12

Panel C:

		Growth Lo1	Value Hi10	Val. – Gr. Difference	t-stat
Size Decile	RMSm1	1.44	1.96	0.52	1.16
	RMSm1-2	1.14	1.90	0.76	1.54
	RMSm1-5	1.16	1.66	0.50	1.20

return differences Increase, with minor exception, in portfolios sorted further toward the extreme percentiles of BE/ME. For example, the return difference for the RMSm1-2 portfolio rises from 0.35 in the BE/ME sort shown in Panel A to 0.60 in Panel B, to 0.76 in Panel C, a characteristic consistent with the BE/ME return premium across the various Fama and French portfolios.

Table 4 shows that no statistically significant value premium exists between the value and growth RM portfolios of any combination size or any BE/ME sort presented in Panels A-C. This suggests that the value premium which is observed in all comparable Fama and French small cap portfolios in Panel C of Table 2 may be more pronounced in stocks omitted from both the value and growth RM portfolios such as non-NMS stocks, stocks below $10 million and stocks priced below $2 per share. It remains to be determined whether the value-oriented and/or growth-oriented subset of these omitted stocks is uniquely driving the value premium in the FF portfolios. This question is explored next.

Table 5 shows the computed value premium for the DFA fund as defined earlier in both equations (3) and (4). The value premium is decomposed to reflect the impact from portfolio constituency rules imposed by DFA, computed as the difference between the rule mimicking portfolio and the corresponding Fama and French value portfolio, B, D, and F ($RM_{value} – FF_{value}$). The premium is further decomposed to reflect the impact from unique trading strategies employed by DFA, computed as the difference in returns between DFA and the value rule mimicking portfolio (DFA – RM_{value}). Interestingly, results in Table 5 show no statistically significant impact to the value premium caused by portfolio constituency rules employed by DFA. For example, the net impact of these rules for the FF (E) size and BE/ME investment space are slightly negative (*Rule* = -0.05, t = -0.26). Results for each of the three investment spaces under evaluation are statistically indistinguishable from zero. It seems stocks that are omitted by DFA rule from the rule mimicking portfolios such as non-NMS NASDAQ stocks, stocks trading below $2 per share and stocks below $10 million in market cap do not contribute to the value premium on a relative basis. Since the value premium is statistically significant in the Fama and French portfolios but not in the rule mimicking portfolios as shown in Table 4, it is apparent that growth stocks omitted from the Fama and French portfolios, when constructing the growth-oriented rule mimicking portfolios, perform worse than the growth stocks that are not omitted. In other words, the value premium in the Fama and French portfolios is generated by poor growth stock performance not superior value stock performance when compared to the value and growth rule mimicking portfolios. Return differences between the Fama and French growth portfolios and the corresponding RM growth portfolios [shown in the footnote to Table 5] are large and statistically significant, contrary to results for the value side of the equation shown in Table 5. Constituent restrictions provide very little, if any,

TABLE 5: Decomposition of the DFA Value Premium. Average monthly returns[85]

Eq (3): $VP = [FF_{value} + (RM_{value} - FF_{value}) + (DFA - RM_{value})] - FF_{growth}$

Eq (4): $VP = DFA - FF_{growth}$

Size/BEME Decile	DFA VP	FF value Portfolio	Rule Impact	Trading Impact	FF growth Portfolio
DFA-FF (A)	-0.07	1.05	0.15	-0.80	0.46
	(-0.18)		*(1.35)*	*(-3.73)*	
DFA-FF (C)	0.17	1.23	0.22	-1.06	0.22
	(0.34)		*(1.67)*	*(-4.63)*	
DFA-FF (E)	0.13	1.69	-0.05	-1.24	0.26
	(0.19)		*(-0.26)*	*(-4.82)*	

benefit to DFA in the value-oriented investment space. However, results for $RM_{growth} - FF_{growth}$ suggest that growth-oriented small cap stock investors can improve results by as much as 10.2% per annum by implementing similar portfolio constituency restrictions.

As in Keim (1999), any observed return difference, while holding the impact from constituent rules constant, can be said to result from trading restrictions and decisions. In this research, the definition of a trading strategies impact will also include return differences caused by periodic portfolio rebalancing issues.[86] Results in Table 5 show that DFA trading rules negatively impact the performance of the fund by as much as 14.9% per annum. Monthly returns for the fund trail the RM (B) portfolio by 0.80% per month, the RM (D) portfolio by 1.06% per month, and the RM (F) portfolio by 1.24% per month. All results are significant at the 5% level. It is clear that unique trading-related characteristics defined earlier in Table 3 prevent the DFA fund from capturing the value premium.[87] The value premium, computing performance against a more liquid growth-oriented portfolio as per equation (5), show no statistical difference between the performance of the DFA fund and the more liquid growth-

[85] Performance difference for constituency rules between the Fama and French growth portfolios and the corresponding RM portfolios are as follows ($RM_{growth} - FF_{growth}$): Decile space (A) = 0.40, t = 2.43; (C) = 0.63, t = 3.14; (E) = 1.37, t = 2.17.

[86] As a reminder, the formula for computing the trading rule impact is $DFA - RM_{value}$

[87] Sorting stocks in the rule mimicking portfolio for the smallest 10% and highest 75th BE/ME percentile, the static sort arguably the most closely aligned with the DFA portfolio constituency, does not alter results.

oriented rule mimicking portfolio. The relative performance between the two funds is economically weak with DFA trailing the growth portfolio by 0.72% per month.

5.3 Three-Factor regression of return differences

DFA's exposure to various risk factors is next explored to determine whether returns exhibit a perceptible tilt. The time series of monthly returns differences previously computed in equation (3) to define the rule and trading component of returns are regressed against the Fama and French 3-factor model. Coefficients represent the sensitivities to market risk and the risks associated with size and the BE/ME effect. Table 6 shows the sensitivity of the performance differences between DFA and each of the three FF size and BE/ME portfolios, as well as sensitivities for the overall performance difference.

Regression coefficients for portfolio rules and coefficients for trading strategies represent the two components of overall sensitivity between the DFA fund and the portfolios representing the three investment spaces (size and BE/ME sorts). Results in Table 6 show that portfolio constituency rules (Rule Impact) contribute, in the margin, to lower market sensitivity. Coefficients (*b*) are negative and significant for the smaller and more value-oriented portfolios, C and E. However, this effect is more than offset by the company's trading strategies (Trading Impact) which had the impact of increasing the fund's sensitivity to market risk. The value premium loads more characteristically toward larger stocks than the three Fama and French growth portfolios, A, C, and E. All of the 'Return Difference' size coefficients (*s*) are negative. However most of the difference in sensitivities to size appears to be generated from portfolio constituency rules. Rule impact coefficients are negative and statistically significant while none of the trading impact coefficients are large or significantly different from zero. This result is undoubtedly caused by the elimination of stocks priced under $2 per share, stocks less than $10 million in market cap as well as the elimination of any stock not traded on NASDAQ NMS, a set of stocks typically smaller than those not traded on the NMS. Keim (1999) observes contrasting trading sensitivities for the DFA 9-10 mutual fund, a fund similar in size (although not BE/ME) to the DFA Small Cap Value Fund. Keim observes that the company's trading activities contribute to a greater sensitivity toward small cap stocks and speculates that the company's active block trading programme might be the driver.

Results in Table 6 show that portfolio rules tend to increase the exposure of the DFA Small Cap Value fund to the BE/ME effect. However, only the exposure representing the comparison to the smallest, most extreme BE/ME space, FF (E), is statistically different from zero (h = 0.16, t = 2.02). DFA trading strategies tend to reduce the value premium, although results are only significant for the

TABLE 6: Three-Factor model sensitivities of performance differences between the DFA Small Cap Value Fund and three FF growth portfolios representing various size and BE/ME investment spaces. May 1994 to December 2007 (n = 164)

Monthly DFA returns are obtained from Datastream. All other data including excess monthly returns of the six Fama and French portfolios, 3-factor model returns, as well as the risk free rate are obtained from the website of Kenneth French

3-Factor Model Coefficient	Investment Space	Return Difference (Value Prem.)	Rule Impact	Trading Impact	t-statistics Difference	t-statistics Rule	t-statistics Trading
	DFA-FF (A)	-0.62	0.16	-0.78	-3.31	1.75	-4.15
a	DFA-FF (C)	-0.85	0.27	-1.11	-3.84	2.38	-5.11
	DFA-FF (E)	-1.46	-0.02	-1.43	-4.58	-0.12	-5.85
	DFA-FF (A)	0.02	-0.02	0.04	0.35	-0.87	0.86
b	DFA-FF (C)	0.05	-0.07	0.12	1.07	-2.96	2.54
	DFA-FF (E)	0.17	-0.10	0.27	2.10	-2.01	3.98
	DFA-FF (A)	-0.08	-0.17	0.09	-1.28	-4.01	1.34
s	DFA-FF (C)	-0.19	-0.17	-0.02	-3.11	-5.28	-0.31
	DFA-FF (E)	-0.16	-0.15	-0.02	-1.88	-2.36	-0.21
	DFA-FF (A)	-0.12	0.06	-0.18	-1.43	1.48	-2.14
h	DFA-FF (C)	-0.02	0.07	-0.09	-0.22	1.79	-1.18
	DFA-FF (E)	0.22	0.16	0.06	2.20	2.02	0.75

*Heteroskedasticity-consistent standard errors

broadest size and broadest BE/ME investment space. R-squares [not shown] are similar to those observed in Keim (1999) when testing for each impact.

Section 6: Time variation and sub-period analysis

Research into the value premium's relationship with macroeconomic risks and the business cycle provides additional insight into the volatility of the premium. The critical question for investors seeking to capture the value premium is whether the phenomenon is substantial enough to warrant an attempt to capture it and whether it is stable enough for their portfolios to survive normal periods of growth stock supremacy. As a passive portfolio, the DFA Small Cap Value Fund is not designed to provide investors with a vehicle to capture returns via style shift. However, Investors in the DFA fund (and any others like it) need to determine whether funds designed to capture the value premium exhibit a level of

constancy in their fund characteristics and fund returns to navigate and survive any time varying characteristics of the value premium.

Keim (1999) test the time varying nature of the decomposed performance of the DFA Small Cap 9-10 Fund by dividing the sample into two subsets. The author defines those subsets as the *growing/learning* phase and the *mature* phase of the fund. In this treatment, the time varying nature of the fund's value premium is evaluated using three distinctly objective criteria. The first test evaluates the value premium during each of two equal time periods constructed through a simple division of the sample. The second evaluates the DFA value premium during bull and bear market periods. The third evaluates the premium during periods representing the greatest value stock superiority, greatest growth stock superiority, greatest large cap stock superiority and the greatest small cap stock superiority.

The sample is first divided into two equal halves, May 1994 to February 2001 and March 2001 to December 2007. Since both sub-periods capture periods of considerable economic expansion and stock market rewards as well as slices of the dotcom recession and market contraction, it would be surprising to observe performance differences between the two sub-periods. It would also be surprising to observe differences to outcomes shown previously in Table 5. Indeed, VP results for the equally divided sample shown in Table 7 computed using the smallest size and most extreme value, FF (F), and growth, FF (E) decile portfolios, are not meaningfully different from each other and different from the VP computed for the entire 164 month sample shown previously in Table 5. Results for the two equal halves show once again that DFA fails to capture the value premium in either sample period. Moreover, the impact on average monthly VP returns from portfolio constituency rules is unchanged from Table 5 (t = -0.26) and not statistically significant for either segmented period (t = -0.60 and 0.41 respectively). Similarly, the impact on returns from trading strategies is once again large, negative, and statistically significant in both sample periods (-0.81%, t = -2.72; -1.67%, t = -4.01). Trading strategies reduces the DFA value premium on average by over 20% per annum in the period March 2001 to December 2007. Results are not meaningfully different for tests of the other two size and book-to-market sorted portfolios, FF (A, B) and the FF (C, D) investment spaces [not shown].

Next, the sample is divided into periods of market expansion and market contraction. Results in Table 5 have previously shown that trading strategies generate a large, negative impact on DFA performance. A bull/bear evaluation may help determine whether the company's trading strategies are rewarded during one type of market condition and punished in another type of market condition. Results in Panel B of Table 7 show that the DFA fund consistently generates an economically negative, but statistically insignificant, monthly value premium return during both trough-to-peak bull market sub-

TABLE 7: Time variation of the DFA value premium (VP) using the smallest size and lowest 10th growth and highest 10th value BE/ME portfolios. Average monthly returns May 1994 to December 2007.

Monthly DFA returns are obtained from Datastream. All other data including excess monthly returns of the six Fama and French portfolios as well as the risk free rate are obtained from the website of Kenneth French.

Eq (3): $VP = [FF_{value} + (RM_{value} - FF_{value}) + (DFA - RM_{value})] - FF_{growth}$

Which is reduced to Eq (4): $VP = DFA - FF_{growth}$

DFA Entire Period		VP	FF value	Rule Impact	Trading Impact	FF growth
(from Table 5)		0.13	1.69	-0.05	-1.24	0.26
		(0.19)		*(-0.26)*	*(-4.82)*	
Panel A: Equal Halves	DFA	VP	FF value	Rule Impact	Trading Impact	FF growth
First Half *(n = 82)*	0.50	0.39	1.52	-0.20	-0.81	0.11
May 1994 - Feb 2001		*(0.33)*		*(-0.60)*	*(-2.72)*	
Second Half *(n = 82)*	0.29	-0.13	1.86	0.10	-1.67	0.42
Mar 2001 - Dec 2007		*(0.00)*		*(0.41)*	*(-4.01)*	
Panel B: Bull and Bear Cycles	DFA	VP	FF value	Rule Impact	Trading Impact	FF growth
Trough to Peak *(n = 63)*	0.78	-0.66	2.14	-0.58	-0.78	1.43
Jan 1995 - Mar 2000		*(-0.66)*		*(-1.68)*	*(-2.22)*	
Peak to Trough *(n = 30)*	-0.73	2.93	-0.26	1.43	-1.90	-3.65
Apr 2000 - Sep 2002		*(1.06)*		*(2.41)*	*(-2.45)*	
Trough to Peak *(n = 61)*	1.00	-0.69	2.67	-0.29	-1.38	1.69
Oct 2002 - Oct 2007		*(-1.12)*		*(-1.13)*	*(-3.27)*	
Panel C: Periods of Style Supremacy*	DFA	VP	FF value	Rule Impact	Trading Impact	FF growth
Value Supremacy	-1.10	4.43	-0.01	0.72	-1.81	-5.53
		(5.49)		*(2.12)*	*(-4.86)*	
Large Supremacy	-2.42	3.32	-1.80	0.61	-1.23	-5.74
		(4.17)		*(2.04)*	*(-3.41)*	
Small Supremacy	3.91	-2.66	5.75	-0.92	-0.91	6.57
		(-1.82)		*(-2.50)*	*(-1.98)*	
Growth Supremacy	1.19	-3.38	2.37	-0.58	-0.60	4.56
		(-2.59)		*(-1.60)*	*(-1.58)*	

**n = 60*

periods (-0.66% and -0.69%). Again, results are robust for similar tests of the other two size and book-to-market sorted portfolios, FF (A, B) and the FF (C, D) investment spaces [not shown]. As in Table 5, the impact from portfolio constituency rules is negligible during bull markets.

The most interesting result in Table 7 is observed in the bear market condition shown in Panel B. Unlike for all previously examined time periods, the fund's average monthly value premium is economically large and positive (2.96%, t = 1.06). Better performance does not result from a reduction in the impact of the fund's trading strategies. The negative impact from trading strategies is actually greater (-1.90%, t = -2.45) than in the two bull market periods (-0.78% and -1.38%). Instead, the positive change in the VP originates in the boost from portfolio constituency rules (1.43%, t = 2.41). Screening out stocks such as those trading below $2 per share and omitting stocks with less than $10 million in market value appear to have a very large positive impact on performance during a bear market. This clearly suggests that the performance of less-liquid microcap stocks suffers relative to larger, more-liquid stocks during periods of distress. Moreover, the value premium during the bear market is also driven in large part due to the demonstrably poorer performance of growth stocks. The overall opportunity set value premium (FF_{value} - FF_{growth}) is much larger during the bear period and weaker during bull markets. The relative superior performance of value stocks during bear market periods is consistent with findings in Lakonishok, Shleifer and Vishny (1994). Value stocks perform better than growth stocks during poor economic and market periods.

Finally, DFA returns are evaluated for asset class influences by sorting 164 monthly returns in the overall sample for periods reflecting the greatest relative performance by value stocks over growth stocks and the greatest relative performance by growth stocks over value stocks. A size influence is observed by sorting monthly returns for relative superior small cap stock performance and then for relative superior large cap stock performance. The top sixty months of superior performance are observed for samples independently ranked for each of the four value/growth and small/large asset classes. Periods of superior small cap (large cap) stock performance are defined by ranking the largest (smallest) positive monthly performance of the Fama and French SMB factor. Similarly, periods for superior value (growth) stock returns are identified by ranking the largest (smallest) Fama and French HML factor returns. DFA returns are observed for the dates corresponding with the ranked performance of each asset class. Value premium results are computed and presented in Panel C of Table 7.

The value premium, or the return difference between the DFA fund and the FF (E) growth portfolio, is large and positive during periods of value stock supremacy (VP = 4.43%, t = 5.49) and large

stock supremacy (VP = 3.32%, t = 4.17%). However, during both value and large stock supremacy, monthly returns of the fund itself are highly negative, thus suggesting that the combination of constituency and trading rules are not relatively important for the production of large VP returns during these market subperiods. Indeed, it is clear from Panel C that during both sub-periods, poor average monthly returns of the FF growth portfolio (-5.53% and -5.74%) drive the large relative superior performance of the DFA fund. Internally, the positive change in impact from the constituency rules during the sub-period are somewhat offest by a negative change in the impact from trading strategies – a condition quite stable when compared to the impact observed for the overall sample period. Outcomes are reversed for periods of growth supremacy and small cap supremacy. The DFA value premium is large and negative during periods of small cap supremacy (VP = -2.66%, t = -1.82) and during growth stock supremacy (VP = -3.38%, t = -2.59).

The net impact from constituency rule and trading strategies are not as benign in these two sub-periods. Results for the overall sample period shown earlier in Table 5 suggest portfolio constituency rules contribute little to the DFA value premium. It is clear from results in Panel C of Table 7 that the impact shown earlier is not constant over the entire sample period, but varies with market rewards to size and BE/ME. The omission by constituency rule of stocks trading below $2, stocks less than $10 million in market value , and non-NMS stocks from the DFA portfolio appears to boost VP returns during periods when large cap stocks or value stocks generate superior relative returns, but reduce returns during periods when small cap stocks or growth stocks generate superior relative returns. During the former sub-periods, constituency rules increase VP monthly returns on average 0.75% and 0.66% from results observed over the entire sample period, but reduces VP returns on average -0.87% and -0.53% during the latter sub-periods. Explanation of results for periods of large cap and small cap supremacy is probably self explanatory. However, results suggest that omitted stocks by rule exhibit less value-oriented characteristics and more growth-oriented characteristics than stocks that remain. 3-factor regression results shown earlier in Table 6 are consistent with this view. Constituency rules are shown to have a net value stock impact on DFA portfolio returns.

The negative impact from trading strategies, consistently observed in prior sub-period analysis, is materially unchanged during periods of value stock supremacy. Although, during periods of growth stock supremacy, the negative trading impact that plagues the DFA fund is reduced and statistically indistinguishable from zero (-0.60%, t = -1.58). Overall, results suggest that discretionary buying, selling, holding periods, portfolio weights, and any residual impact the category captures are not generally

sensitive to up and down market conditions, nor sensitive to changing market conditions when the rewards to growth, value, large cap, or small cap stocks are rotated.

DFA actually claim their trading strategies add liquidity to the purchase and sale of stocks that normaly suffer from illiquidity, and that this active market intervention boosts returns. Keim (1999) describes the benefit in some detail for the DFA 9-10 fund. However, the company's beneficial trading impact are clearly non-existent in this section. There are two possible explanations: The first explanation allows that DFA's claims are simply incorrect for this particular fund. The company employs a consistent and disciplined trading strategy, but contrary to company claims, that strategy results in large statistically significant negative returns that are largely impervious to changes in market conditions. The second explanation allows for an unknown *other* factor (Row #15 in Table 3) that dominates the residual catch-all items isolated and captured by comparing returns of the DFA fund with the performance of the DFA rule mimicking portfolio. This explanation suggests that the *other* factor is large and negates any benefit to returns from the company's proprietary trading strategies that are documented by Keim. This *other* explanation is hinted at in a brief note in Keim (1999) and is explored next.

Section 7: Seasonality in DFA returns

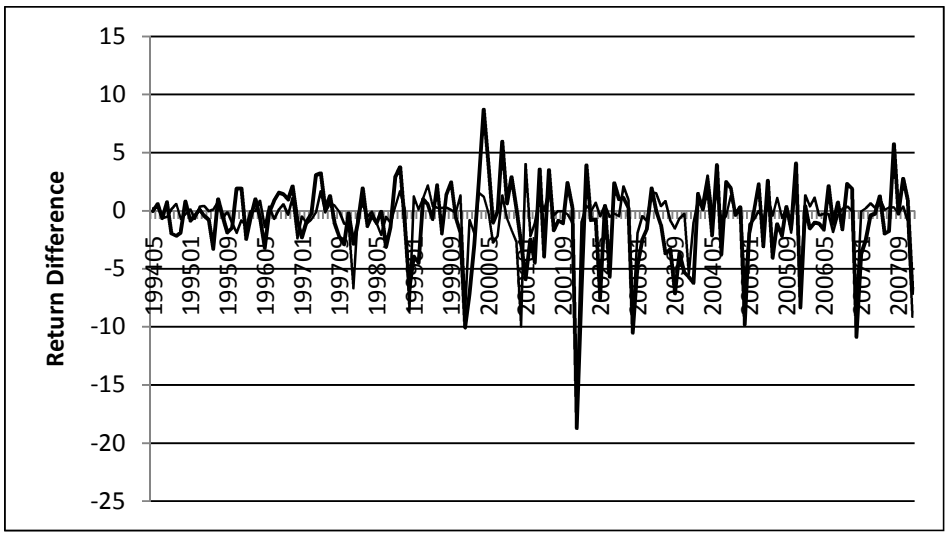
Keim (1999) observes a very large underperformance by the DFA small cap 9-10 Fund relative to the CRSP 9-10 benchmark index during the month of January (1.26% per month, t = 3.38). As a result of Keim's findings, further analysis of the DFA Small Cap Value Fund's return tracking error is warranted to determine if seasonality is the source for negative trading strategy returns observed earlier in Table 5.

Observing the time series of monthly return tracking error between the DFA Small Cap Value Fund and FF (F), the smallest size, highest BE/ME portfolio, reveals a more complex picture than the systemic underperformance by the DFA fund shown earlier in Figure 2. Shown next, Figure 3 clearly shows that the DFA fund is riddled with regularly occurring negative performance shocks. The DFA fund generates poor relative performance compared to the FF (F) small value portfolio every year around the two months of December and January. Not unexpectedly, when compared to returns of the Fama and French growth portfolio [not shown], the fund's tracking error is especially pronounced around the time of the dotcom boom and bust period. However, upon closer observation, seasonal negative shocks, similar that those shown in Figure 3 for the value portfolio, are still apparent in comparisons to the Fama and French growth portfolio time series. The monthly data suggests that seasonal issues are pervasive throughout the small cap value and small cap growth stock investment space, or that seasonal issues have their origins in DFA returns – or possibly a combination of both.

The January effect is well documented in academic literature beginning with Rozeff and Kinney (1976) and extending with Reinganum (1983) and Roll (1983) who showed the anomaly predominates in

FIGURE 3: Time series of monthly excess return differences between the DFA Small Cap Value Fund and the FF (F) small value portfolio. May 1994 to December 2007.

Monthly DFA returns are obtained from Datastream. Monthly return data of the Fama and French small value portfolios as well as the risk free rate are obtained from the website of Kenneth French.



small cap stocks. The work of Ritter (1988) and later D'Mello, Ferris, and Hwang (2003) suggest that seasonality in returns is the function of buying and selling habits of small investors. This view is particularly interesting in the context of findings by Phallipou (2008) who find the value premium only existing in stocks bought and sold by individual investors. Loughran (1997) among others argue that the book-to-market effect and by extension, the value premium is largely a function of seasonal issues.[88]

The pattern of DFA returns show that negative seasonality may possibly exist in both January *and* December returns during the sample period. This is an interesting twist to the prevailing literature surrounding the month of January alone. However, Grinblatt and Moskowitz (2004) recently observe a pronounced December effect in returns of losing firms. To begin the analysis, the Fama and French 3-factor model is re-estimated by adding two dummy variables to determine whether calendar anomalies

[88] Eugene Fama concedes Loughran's findings and the existence of a January anomaly in the book-to-market effect stating it is bigger in small and large value stocks than in small and large growth stocks. "Professor Fama Answers the Critics Interview by Gene Fama Jr." 1 Dec. 1999, URL: http://www.indexfunds.com/PFarticles/19991201_famaint_iss_int_GF.htm

during the months of December and January can help explain the variation in DFA's excess returns. The new regression model shown in equation (6) is estimated to measure the sensitivity of DFA returns to the market, to the size effect and to the BE/ME effect as before. The January dummy variable is denoted as D1 and the December dummy variable as D2.

$$Rpt - Rft = a + b[\mathrm{R}mt - \mathrm{R}ft] + s\mathrm{SMB}t + h\mathrm{HML}t + j\mathrm{D1}t + d\mathrm{D2}t + et \tag{6}$$

Results shown in Table 8 from the re-modeled regression equation continue to reflect the statistically significant importance of the excess market returns, size and the BE/ME factors in explaining excess DFA fund returns. Curiously, a statistically significant January effect is not observed in fund returns (*j* = 0.12%, t = 0.28). However, returns exhibit a very strong negative December effect (*d* = -7.59%, t = -6.89). Interestingly, the estimated adjusted R-square increases dramatically from 0.74 shown earlier in Table 2 to 0.90 when the 3-factor model is adjusted to include seasonal factors. Clearly, a model that includes a December seasonal factor performs much better than the standard 3-factor model in explaining the variation in average DFA returns. Indeed, the alpha of the re-estimated equation is virtually zero (*a* = 0.02, t = 0.18). For comparison, excess returns of the three Fama and French portfolios that were identified earlier in Figure 1 (investment spaces B, D, and F) are regressed on

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TABLE 8: Regression analysis of excess monthly returns of the DFA Small Cap Value Fund and various hypothetical Fama and French small cap value and growth portfolios. Testing for seasonal anomalies. May 1994 to December 2007 (n = 164)

Monthly DFA returns are obtained from Datastream. All other data including excess monthly returns of the six Fama and French portfolios, 3-factor model returns, as well as the risk free rate are obtained from the website of Kenneth French. The Fama and French 3-factor model is re-estimated by adding two dummy variables to determine whether calendar anomalies during the months of December and January can help explain the variation in DFA's excess returns.

$$Rpt - Rft = a + b[\mathrm{R}mt - \mathrm{R}ft] + s\mathrm{SMB}t + h\mathrm{HML}t + j\mathrm{D1}t + d\mathrm{D2}t + et$$

Portfolio	a	b	s	h	j	d	Adj. R^2	σ
DFA	0.02	1.07	0.80	0.72	0.12	-7.59	0.90	5.27
	(0.18)	*(43.55)*	*(17.49)*	*(17.52)*	*(0.28)*	*(-6.89)*		
Small Value								
FF Portfolio (B)	0.06	1.00	0.84	0.77	0.24	-0.31	0.98	4.62
	(1.15)	*(76.03)*	*(46.19)*	*(38.81)*	*(1.20)*	*(-2.14)*		
FF Portfolio (D)	0.16	0.97	0.95	0.68	2.08	-0.51	0.91	5.12
	(1.20)	*(30.08)*	*(24.06)*	*(13.64)*	*(3.84)*	*(-1.05)*		

FF Portfolio (F)	0.28	0.90	0.92	0.66	3.48	-1.10	0.79	5.25
	(1.33)	*(17.71)*	*(15.21)*	*(8.60)*	*(4.29)*	*(-1.52)*		

the re-estimated regression equation. The two Fama and French portfolios representing the smallest size stocks (D and F) exhibit a statistically significant positive January anomaly in returns ($j_{(D)}$ = 2.08%, t = 3.84 and $j_{(F)}$ = 3.48%, t = 4.29), but not a December anomaly.[89] The adjusted R-squares of the three FF portfolios are unchanged from Table 2 indicating that seasonal factors do not improve the explanatory power of the standard 3-factor model during the sample period. The month of January as well as December can therefore be identified as a source of DFA relative underperformance when fund returns are compared to the smallest two FF value portfolios D and F.

To provide further clarification for results shown previously in Table 2, DFA returns are once again compared to the Fama and French portfolios representing the smallest, most value and growth-oriented investment spaces. This time, however, returns for the months of January and December are omitted to analyze the seasonal impact on DFA returns. Results from this re-evaluation show that seasonality issues are clearly having a meaningful impact on the inability of the DFA fund to capture the value premium. Shown in Table 9, return differences between the DFA Small Cap Value Fund and FF (F), the smallest of the three value-oriented FF portfolios, for each of the two months of January and December, are large, negative, and statistically significant. The average difference in monthly excess returns between May 1994 and December 2007 for the thirteen Januarys in the sample are -3.60% (t = -5.28) and for the fourteen December months are -6.55% (t = 4.44). In contrast, when the remaining ten calendar months of returns are evaluated each year, average monthly returns for the DFA fund are not statistically different from the FF (F) value-oriented portfolio – a condition one would have expected at the outset of this research. The average return difference is only -0.14% per month (t = -0.68).

Most interestingly, when DFA returns are once again compared to the FF (E) small growth-oriented portfolio, but with January and December months omitted, the DFA Small Cap Value Fund finally captures the value premium. The difference in average monthly returns between the DFA fund and the FF (E) growth portfolio is positive (1.51%) and statistically significant (t = 2.72). This compares to results showing a weak value premium (r = 0.39%, t = 0.67) in Table 2 without the adjustment for seasonality.

[89] Results consistent with comments made by Eugene Fama; "Professor Fama Answers the Critics Interview by Gene Fama Jr." 1 Dec. 1999, URL: http://www.indexfunds.com/PFarticles/19991201_famaint_iss_int_GF.htm

Seasonal shocks exist in DFA returns throughout the sample period, but are not pronounced until the beginning of the dotcom boom when these shocks become very large. During the dotcom period, negative relative return shocks for the month of December actually overtake the problems

TABLE 9: Average monthly return differences between DFA and the FF (F) small value and FF (E) small growth investment space. May 1994 to December 2007.

Monthly DFA returns are obtained from Datastream. Monthly returns of the Fama and French small value and small growth portfolios are obtained from the website of Kenneth French.

	DFA-FF (F) small value				DFA-FF (E) small growth			
	Jan	Dec	Feb to Dec	Feb to Nov	Jan	Dec	Feb to Dec	Feb to Nov
1994		0.82	-0.57	-0.77		6.21	2.22	1.65
1995	-0.88	1.92	-0.36	-0.58	-1.34	2.31	0.00	-0.23
1996	-2.45	-0.89	0.23	0.34	-4.17	3.03	2.68	2.65
1997	-2.30	-2.85	-0.24	0.02	-6.25	5.22	3.19	2.98
1998	-1.07	-6.72	-0.60	0.01	-0.77	-6.72	1.44	2.25
1999	-3.93	-10.07	-1.10	-0.21	-13.95	-23.10	-3.28	-1.30
2000	-7.15	-2.81	1.64	2.08	-18.79	12.08	6.20	5.61
2001	-5.91	-18.72	-2.14	-0.48	-30.58	-20.15	0.10	2.13
2002	-6.93	-10.52	-1.47	-0.57	1.08	-4.10	1.94	2.54
2003	-4.74	-5.70	-2.92	-2.64	-3.03	-0.60	-1.56	-1.66
2004	-6.23	-9.81	-0.33	0.61	-3.28	-10.45	0.97	2.11
2005	-1.96	-8.34	-1.01	-0.27	2.21	-8.40	0.58	1.48
2006	0.39	-10.88	-1.08	-0.10	-2.29	-8.41	0.50	1.39
2007	-3.70	-7.11	-0.33	0.35	-0.08	-8.19	-1.19	-0.49
Average	-3.60	-6.55	-0.74	-0.14	-6.25	-4.38	0.96	1.51
Std Dev	2.46	5.52	3.43	2.50	9.42	9.91	7.03	6.48
t-stat	*-5.28*	*-4.44*	*-2.64*	*-0.68*	*-2.39*	*-1.65*	*1.68*	*2.72*

experienced in January. This suggests that the issue is not necessarily related to the so-called January Effect in stock returns but rather, once again, point to year-end trading at DFA. The annual rebalancing mechanism employed in the various hypothetical Fama-French portfolios cannot explain underperformance for the periodic January returns since they are rebalanced in June of each year. It is possible, of course, that seasonality in DFA returns may originate in the fund's highly touted liquidity management techniques. These techniques may in fact be counter-productive and reduce returns. However, problems associated with transaction costs and stock illiquidity is likely universal to all value fund portfolios. Both Agarwal and Wang (2007) and Brown, Crocker, and Foerster (2009) find that value

stocks suffer from greater trading costs than growth stocks. The value premium may simply disappear once applied to managed portfolios that operate in real market conditions. The problem with explanations attributing seasonality in DFA returns to transaction costs is that DFA returns are uniquely impacted during the month of December (and January). This explanation would require DFA to engage in portfolio transactions at only one time of the year rather than throughout. Unfortunately, the origins of a seasonal phenomenon impacting results in Tables 8 and 9 cannot be exhaustively investigated without evaluating proprietary trading data from DFA. This data is unavailable. At this point, the issue can only be generally explained saying, trading strategies apparently drive turn-of-year return differences between the DFA Small Cap Value fund and the various Fama and French small cap value portfolios. The impact is especially felt during the dotcom boom and bust period.

Section 8: Conclusion

Contrary to predictions implied in the lineage of academic research, Houge and Loughran (2006) actually find that small-cap value funds slightly underperform small growth funds. The authors conclude that a value premium does not exist in managed mutual funds or in passive indexes. Davis (2001) similarly finds that value funds fail to capture the value premium when operating even in the most extreme size deciles. Phalippou (2008) finds no significant superior returns for high book-to-market stocks in stocks held by institutional investors. Phalippou does not say it is impossible for an institutional investor to capture the promised premium implied in Fama and French (1993), only that it would be difficult. This essay adds considerable evidence to Phalippou's thesis (and that of Hough and Loughran, and Davis) by showing that the DFA Small Cap Value Fund, a unique fund specifically designed to capture the value premium, apparently suffers from many of the trading maladies envisioned by Phalippou. The DFA Small Cap Value Fund investment philosophy and strategy are consistent with research evidence in academic literature on where and how to capture the value premium. However, consistent with a growing body of evidence for institutional portfolios, the DFA fund is shown to fail in its attempt to capture the premium.

Specific results are as follows: DFA excess monthly fund returns regressed on the Fama and French 3-factor model show similar BE/ME sensitivity to the Fama and French smallest size and highest BE/ME decile portfolio returns. However, the fund tilts toward larger stocks in its sensitivities to market risk and to size. The fund appears to underperform each of the three small cap value-oriented benchmark portfolios that have been shown to exhibit a premium return to their growth-oriented counterparts. Indeed, tests show that the DFA fund fails to capture the value premium implicitly promised in academic research.

The value premium in DFA returns are further decomposed by altering the method for a similar DFA fund tested in Keim (1999). DFA returns are analyzed to determine to what extent the fund's portfolio constituent rules and trading strategies impact its ability to capture the value premium. For the entire sample period, the difference in DFA returns attributed to portfolio constituency rules is negligible. Results suggest that the source of the value premium in Fama and French portfolios is largely the result of very poor performance by microcap growth stocks, not by any positive impact from microcap value stocks. Constituent restrictions provide very little if any benefit to DFA in their value-oriented investment space. However, results show that growth-oriented small cap stock investors can improve results by as much as 10.2% per annum by implementing similar portfolio constituency restrictions. A very large, statistically significant negative return impact can be attributed to trading strategies of the company.

3-factor regression results for the decomposed return differences show that portfolio rules generally tilt DFA returns toward lower market risk, and generally toward large cap and value stock characteristics. Trading strategies generate an opposite impact on market risk to that of portfolio rules. The regression intercept for the decomposed trading strategy returns is large, negative, and statistically significant suggesting that the 3-factor model representing market risk, size, and BE/ME effect has trouble explaining the decomposed returns. Dividing decomposed returns into two equal subset sample periods as well as into bear and bull market cycles fails to uncover any further characteristics of the large, negative, and statistically significant returns attributed to the company's trading strategies. When decomposed returns are evaluated during sub-periods when small stocks, large stocks, value stocks, and growth stocks each exhibit superior relative performance, no further meaningful information is gleaned from results. However, it is observed that the DFA fund is more likely to capture the value premium during bear markets and by definition in periods when large stocks and value stocks exhibit superior performance. The latter results are consistent with the large size tilt of the fund.

Noticeable and regular performance shocks are observed in the fund's tracking error. A small note in Keim (1999) hints that seasonality in a similar DFA fund's returns might help to explain underperformance in the Small Cap Value Fund. The month of January calendar anomaly does not seem to play a statistically significant role in explaining the variation in DFA returns. However, a calendar anomaly in the fund's December returns are indeed large, negative, and statistically significant. When returns for the two months of January and December are removed from the sample, the DFA Small Cap Value Fund captures the value premium implicitly promised in research.

APPENDIX A: Tests of style purity and time variation using Sharpe's RBSA

Sharpe (1992) devises a simple method to examine a fund's exposure to various risk defined asset classes. Traditional methods of examining a fund's asset class exposure requires a tedious and time-consuming *internal* analysis of fund holdings and characteristics, but Sharpe argues that an equally useful *external* fund analysis could be performed using only the fund's returns. He argues that regressing fund returns on a series of asset class factors can document risk-based variations in historical fund sensitivities to each factor. Variations in these asset class regression slopes over time could be monitored by pension plan sponsors and other investment management clients who wish to avoid the burden of time-consuming investigations of fund holdings.

Sharpe's method is today known as Return Based Style Analysis (RBSA) and is used quite extensively in investment practice to monitor style drift by fund managers. Moreover, industry consultants use RBSA to construct proper performance benchmarks for an investment manager rather than relying on off-the-shelf index benchmarks which may or may not accurately reflect a manager's targeted portfolio content over time. After hiring an investment manager (or fund), an investor typically desires the asset class factor sensitivities of that fund to remain somewhat constant over time and not drift. Any drift can expose the overall portfolio to market risks not desired by the investor. To monitor drift, industry consultants can observe a manager's historical asset class sensitivity profile using RBSA and then monitor future returns for comparison. This method significantly improves upon comparisons to broad benchmark indexes such as the S&P 500 during periods when the manager's primary investment style systematically out-performs or underperforms that index.

According to Sharpe, to use RBSA properly, it is critical that the choice of asset classes be exhaustive to the fund's potential investable universe. They should also be mutually exclusive and not overlap in content. Finally, Sharpe argues the choice of asset classes should be limited to those with low correlations to each other. If the latter is not possible, then the choice should represent asset classes with considerable difference in volatility or standard deviation of returns. In other words, according to Sharpe, the classes should have "returns that differ".

To evaluate DFA returns using Sharpe's RBSA, asset class portfolios are selected from the four equity style quadrants: large cap growth, large cap value, small cap growth and large cap value - the same as found in Hardy (1997) and in Bendor, Jagannathan, and Meir (2003) who used the same four size and BE/ME style classes for the equity component of their RBSA analysis. International stocks and

various fixed income classes that are often found in RBSA studies are not used here. Those classes are not likely to have any influence when testing the strict passive characteristics of the DFA Small Cap Value Fund for issues relating to the value premium.[90]

RBSA is evaluated using the same size and BE/ME space as shown before in Figure 1 for each of the four value/growth and small/large asset classes. This avoids factor selection problems identified in Bendor, Jagannathan, and Meir (2003) when equity factors have dramatically different portfolio characteristics. The four Fama and French factor portfolios used in the RBSA analysis are constructed using an initial sort on size thus ensuring the two value and growth small cap factors and the two value and growth large cap factors have similar size characteristics. A subsequent independent sort on BE/ME ensures the two large and small value factors and the two large and small growth factors have similar book-to-market characteristics. However, after the two sorts, each of the four portfolios represent a unique investable universe thus satisfying the requirements in Sharpe (1992) while avoiding the criticisms expressed by Bendor et al.

Atkinson, Averill and Hardy (2001) criticize prior research that use a set of market indexes as asset class factors that fail to cover the entire equity spectrum. When the authors retest the same returns after filling in the holes in asset class coverage, they observed somewhat different RBSA factor coefficients. The four Fama/French portfolios chosen as asset classes in this analysis also have gaps in coverage. The *neutral*, or middle area between the growth and value BE/ME characteristics shown later in the style map in Chart A of Figure A1 is one such hole. Charts B and C of Figure A1 identify additional coverage gaps when performing RBSA tests using the more extreme size and BE/ME investment space. However, coverage gaps should not be similarly problematic for tests in this essay because first, DFA is a passive, not active, portfolio representing strict coverage of a specific size and style space, and second, coverage issues are more important for benchmark identification and subsequent future performance comparisons not evaluated here.[91] The 3 value-oriented asset classes selected for this analysis more

[90] Criticisms of RBSA raised by Corrielli and Meucci (2004) center upon the identification of an investment manager's strategy, or *strong* style analysis as defined by the authors. However, this essay is not interested in the manager's active investment strategy relating to market timing or stock selection. Since the DFA fund is passively designed to provide investors with exposure to an investment style, this essay is interested only in the relationship, or tracking characteristics of a sample of stocks that have shown to possess a superior return when compared to another sample of stocks. Corrielli and Meucci refer to this as *weak* style analysis. They offer no criticism in that regard.

[91] Another asset class stipulation often found in the literature [see Hardy, 1997] states that the asset must be readily investable. The four Fama/French asset class portfolios are hypothetical and not traded. As stated earlier, since I am not constructing a performance benchmark for future performance comparison, the requirement that the asset class be investable is unnecessary.

properly represent the targeted small value-oriented investable universe of the passive DFA fund and allow computation of the value premium with respect to growth-oriented factor portfolios in the same targeted space. Plus, the use of the more extreme size and BE/ME portfolios lowers the factor cross correlations, an issue which could have a greater impact on coefficients and impede proper RBSA observations. Christopherson (1995) argues that certain RBSA results may be spurious if the asset classes under consideration are highly correlated. The RBSA quadratic programming algorithm might find it difficult to determine the precise style coefficient of a factor highly correlated to another. Table A1 shows the correlation of returns between the small value, small growth, large value and large growth asset classes for each of the three size and BE/ME sorts used in this analysis. For each of the three size sorts shown in Table A1, the Fama/French small cap value and small cap growth portfolio returns are indeed highly correlated. However, in all three size sorts, the standard deviation of the small cap growth portfolio is almost twice the size of the small cap value portfolio, thus potentially satisfying Sharpe's RBSA requirement for testing returns that *differ*.

It's important to explain that RBSA will not precisely illuminate the DFA fund's actual asset class weightings. For example, Sharpe explains that the RBSA for a utility fund will typically show sensitivities to bonds despite the absence of any fixed income securities in the fund. RBSA in that instance tells investment clients that many of the high dividend-paying securities usually found in utility funds generate returns similar to various fixed income classes. RBSA alerts investors that various components of the fund behave in a manner consistent with certain fixed income securities – not a surprising result.

TABLE A1: Volatility and correlation of returns between asset classes

Average monthly returns for each of Fama and French asset classes shown in Panels A, B, and C are obtained from the website of Kenneth French. Standard deviation and correlation coefficients are computed from these monthly returns.

Panel A: Size deciles 1-5 (small), 6-10 (large), BE/ME deciles 1-3 (growth), 8-10 (value)

	FFSm1-5/Lo1-3	FFSm1-5/Hi8-10	FFLg6-10Lo1-3	FFLg6-10Hi8-10
Std Dev.	7.29	4.62	4.39	4.02
FFSm1-5/Lo1-3				
FFSm1-5/Hi8-10	0.84			
FFLg6-10Lo1-3	0.72	0.62		
FFLg6-10Hi8-10	0.43	0.64	0.68	

TABLE A1: continued

Panel B: Size deciles 1-2 (small), 9-10 (large), BE/ME deciles 1-2 (growth), 9-10 (value)

	FFSm1-2/Lo1-2	FFSm1-2/Hi9-10	FFLg9-10/Lo1-2	FFLg9-10/Hi9-10
Std Dev.	9.07	5.12	4.48	4.66
FFSm1-2/Lo1-2				
FFSm1-2/Hi9-10	0.83			
FFLg9-10/Lo1-2	0.60	0.51		
FFLg9-10/Hi9-10	0.26	0.41	0.59	

Panel C: Using the four FF 10th size and 10th BE/ME portfolios.

	FFSm1/Lo1	FFSm1/Hi10	FFLg10/Lo1	FFLg10/Hi10
Std Dev.	10.84	5.96	5.29	5.85
FFSm1/Lo1				
FFSm1Hi/10	0.86			
FFLg10/Lo1	0.50	0.42		
FFLg10/Hi10	0.42	0.49	0.63	

Results of the single period RBSA exposure analysis for the DFA fund on the four asset classes of each size and BE/ME sort in Panel A of Table A1 are shown in Table A2. [92] Regression coefficients are constrained to be greater than zero and force the sum of the coefficients to equal 1. See Sharpe (1992) for a full discussion of the pros and cons of this method. Results shown in Table A2 reflect the style exposure for the DFA fund over the entire sample period. As expected, the largest impact on fund returns come from exposure to small cap value stocks for both the constrained and unconstrained RBSA. However, the precise exposure varies as a function of the investable space used to define the asset class. As the size of stocks represented in the asset classes fall from the 50th percentile to the 10th, and BE/ME characteristics change from the 30th lowest (highest) growth (value) percentile to the 10th, the

[92] According to Sharpe, since the portfolio variance is quadratic in the style weights, it is preferable to use the non-linear optimization Generalized Reduced Gradient (GRG2) algorithm of Lasdon and Waren (1978) to solve for the minimum variance. See Sharpe (1987) for a background on the use of GRG in Sharpe (1992). Also see Deb, Banerjee, and Chakrabarti (2007) and Mayes, Jay and Thurston (2000) among others which use GRG2 to perform RBSA and Jackson and Staunton (1999) and Beninga (2002) for a discussion of RBSA computations using off-the-shelf statistical analysis tools.

TABLE A2: DFA Small Cap Value Fund: constrained and unconstrained RBSA Exposures to four Asset Classes. May 1994 to Dec 2007 (n = 164)

Determining the equity style exposure of the DFA Small Cap Value fund using RBSA as in Sharpe (1992) requires the minimisation of the variance of the period by period tracking error rather than minimisation of the sum of squared differences used in OLS regressions. Where: e_t is the difference (period by period tracking error) between returns of the DFA fund R_t and the sum of the four Fama/French large growth, small growth, large value, and small value asset classes representing the mutually exclusive (but not exhaustive) investable universe of the DFA fund. The independent and dependent variables are each computed using excess monthly returns over the 90 day T bill rate. [93]

$$e_t = R_t - [b_1 F_{1t} + b_2 F_{2t} + b_3 F_{3t} + b_4 F_{4t}]$$

		Size and BE/ME Sort		
Asset Class		**Sm1-5/Lo1-3**	**Sm1-2/Lo1-2**	**Sm1/Lo1**
Small Growth	Constrained	5.92%	0.00%	0.00%
	Unconstrained	5.10%	-1.37%	-15.38%
Asset Class		**Sm1-5/Hi8-10**	**Sm1-2/Hi9-10**	**Sm1/Hi10**
Small Value	Constrained	85.86%	76.54%	58.87%
	Unconstrained	87.17%	78.53%	77.52%
Asset Class		**Lg1-5/Lo1-3**	**Lg1-2/ Lo1-2**	**Lg1/Lo1**
Large Growth	Constrained	6.33%	10.63%	29.47%
	Unconstrained	7.42%	11.94%	30.17%
Asset Class		**Lg1-5/Hi8-10**	**Lg1-2/Hi9-10**	**Lg1/Hi10**
Large Value	Constrained	1.89%	12.83%	11.66%
	Unconstrained	1.93%	12.34%	2.98%

RBSA exposure to effects from small cap value stocks actually fall. Exposures fall from 85.86% of returns to 58.87% using the constrained RBSA method. The significant variation in exposures between the 3 size and BE/ME sorted portfolios illustrates how important it is for researchers and practitioners to identify appropriate asset classes when using RBSA to create performance benchmarks for managed portfolios. Since the precise investable universe for the DFA Small Cap Value fund is not presumed in this research, the three small cap value portfolios (and their growth counterparts) effectively surround and capture

[93] Mayes, Jay and Thurston (2000) correctly point out that while the error term in the regression represents the portion of the variation in returns explained by manager skill, it may also be attributable to model mis-specification.

the fund's size and BE/ME profile. Therefore, exposures shown in Table A2 represent only general characteristics for the DFA fund.

The DFA Small Cap Value Fund is passive rather than active in its portfolio constituency selection process and is therefore not likely to change styles dramatically over time. However, the fund's unique trading strategies can potentially tilt the portfolio away from its original target style space. Of course, there is also a remote possibility that the pressures of the competitive marketplace might cause a passive fund manager to surreptitiously employ certain active or information-based methods during periods when the manager's passive methodology is not being systematically rewarded by the market. Moreover, evaluating RBSA over time can potentially identify non-disclosed structural changes in the passive methodology employed by the company. To illuminate any time-varying nature in style exposures, researchers typically use a 36 or 60 month rolling RBSA computation. However, the weakness in this method is similar to that of the static RBSA evaluation over the entire sample period. RBSA analysis using 36 or 60 month segments also assumes a stationary style profile, albeit evaluated over shorter time horizons.

Results of a rolling 60 month RBSA style exposure analysis are shown in the three charts of Figure A1 using the same four sets of Fama/French large cap/small cap size and growth/value book-to-market portfolios as equity asset classes. Once again, the time-varying exposure analysis uses the GRG2 quadratic programming algorithm to compute regression coefficients on four asset classes under the following constrained conditions: sum of coefficients = 1, coefficients >= 0. Independent and dependent variables are each computed using excess monthly returns over the 90 day T bill rate.

Chart A of Figure A1 tests the rolling 60 month style exposure of the DFA Small Cap Value Fund using the four Fama/French 50th size (small and large) and 30th BE/ME (high and low) percentiles as asset classes. The style map presented above the chart legend provides a visual illustration of the coverage of the four equity asset classes used to generate results presented in Chart A. As expected, DFA returns exhibit characteristics similar to returns of the FFSm1-5/Hi8-10 small cap value portfolio asset class. This result is consistent with the overall mission of the fund. However, the middle of the rolling sample period shows an odd exposure to FFLg6-10/Lo1-3 large cap growth portfolio characteristics. It's likely that any large cap growth asset class exposure during the observation period results from large growth stocks acting like distressed small value stocks in the post-dotcom bust era. The most curious if not potentially troubling result is the increasing exposure to the FFSm1-5/Lo1-3 small growth asset class characteristic in the last half of the observation period. Keim (1999) found the

FIGURE A1: Exposure analysis using quadratic programming to compute regression coefficients on four asset classes.

Constraints: sum of coefficients = 1, coefficients ≥ 0; independent and dependent variables are computed using excess monthly returns over the 90-day T bill rate; Sixty month rolling exposure computation; X axis is sixty months period ending. This method assumes that style is constant during each sixty month period.

Chart A. Using the four FF portfolios, size deciles 1-5 (small), 6-10 (large) and BE/ME deciles 1-3 (growth), 8-10 (value).

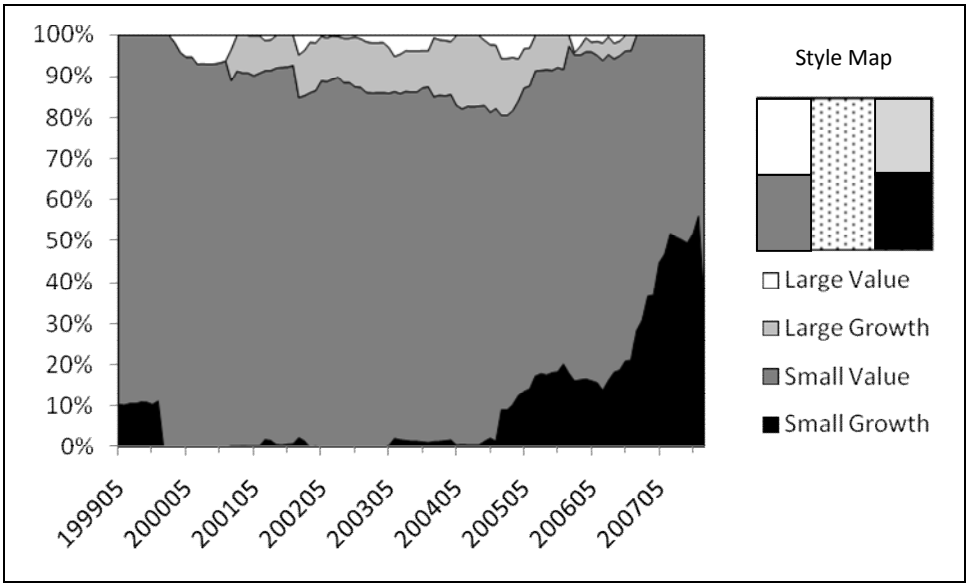


Chart B. Using the four FF portfolios, size deciles 1-2 (small), 9-10 (large) and BE/ME deciles 1-2 (growth), 9-10 (value).

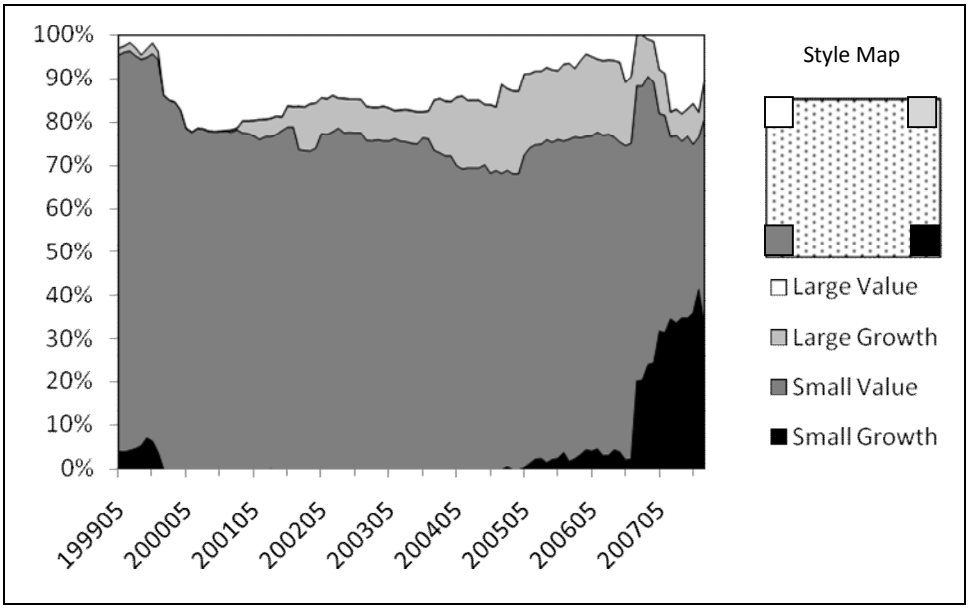
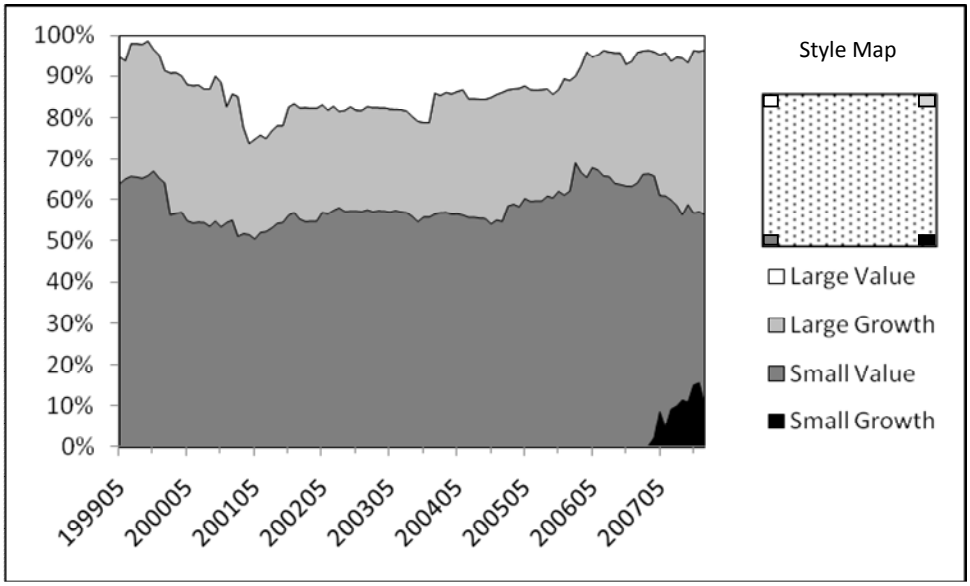


FIGURE A1 continued

Chart C. Using the four FF portfolios, size decile 1 (small), 10 (large) and BE/ME decile 1 (growth), 10 (value).



DFA small cap 9-10 fund had a slight growth tilt as well. But unlike Keim, the growth exposure shown in Chart A of Figure A1 seems larger than a *tllt* and quite unusual even for actively managed funds. At the end of the analysis, for the 60 months ending December 2007, the exposure to the Fama/French small growth asset class was actually larger than the exposure to characteristics of the small value class.

Chart B of Figure A1 tests the rolling 60 month style exposure of the DFA Small Cap Value Fund using the four Fama/French 20th size (small and large) and 20th BE/ME (high and low) percentiles as asset classes. The style map in Chart B shows that the four asset classes in this analysis represent a more extreme size and style investment space than that used in Chart A. Results are generally similar to that shown in Chart A with the small value stock exposure falling dramatically over the last several years of the sample period ending December 2007.

Chart C of Figure A1 tests the rolling 60 month style exposure of the DFA Small Cap Value Fund using the four most extreme Fama/French 10th size (large and small) and 10th BE/ME (high and low) percentiles as asset classes. Rolling 60 month RBSA results vary significantly from the two previous charts. Exposure to large growth stock characteristics is large and clearly meaningful when using asset

classes from the most extreme size and BE/ME percentiles. The fund's exposure to small growth stocks virtually disappear in this analysis.

Not unexpectedly, exposures are more stable in the purest, most extreme size and style percentiles. Exposures to small cap value stocks shown in Chart C vary only 5.49% from the mean per 60 month rolling period over the entire sample period. This compares with 10.83% in Chart B and 12.07% in Chart A. Overall, rolling 60 month RBSA results from the three charts in Figure 3 suggest that returns of the DFA Small Cap Value fund act as if stocks in the portfolio are performing in a similar fashion to low BE/ME growth stocks. This might explain why fund returns did not reflect a premium to the growth portfolio returns shown earlier in Table 2. Although results from Figure 3 are promising as an explanation, they still may not explain the fund's high tracking error compared to the Fama/French small *value* benchmarks. Figure 3 provides no illumination to the latter outcome. For example, if small growth stocks generated return characteristics somewhat similar to small value stocks during the more recent sample period; i.e. the value premium was weak in the small cap space during the period, then it would not be totally unexpected to see a significant RBSA exposure to small growth stocks in DFA fund returns. Indeed, high correlation coefficients shown previously in Table A1 between the small cap value asset class and the small cap growth asset class seem to suggest this possible explanation. However, high positive correlations do not appear to explain significant exposure to large cap growth return characteristics shown in Chart C, for the most extreme size and book-to-market asset class.

Tests using Sharpe's RBSA analysis on DFA returns show a persistent exposure to growth-oriented stock characteristics. Many growth stocks exhibited distress characteristics in the post-dotcom boom period similar to that typically found in value stocks, so the RBSA may have captured exposures of two asset classes that simply have similar characteristics during the period. Indeed, high correlation coefficients observed between the small value and small growth asset classes may have prevented the RBSA from properly differentiating between asset class influences.

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CHAPTER FIVE:

Can investors capture the value premium: Summary conclusions and opportunities for future research

Section 1: Summary conclusions

After more than a decade of research confirming the existence of the value premium in stock returns, value and growth investment managers are still left with two key unanswered questions: 1) If findings of a value premium in returns is correct, then how can value investment managers earn the promised rewards, or 2) If the premium is statistically valid, then do trading and market barriers exist to prevent the premium's capture? These two unanswered questions are addressed over the course of three original essays in this work.

The first of three essays evaluates the nature of the value premium within and across industry sectors. Findings of Banko and Conover (2006) that industry groups exhibit large differences in BE/ME characteristics are indeed confirmed in this work. In an applied context, this finding may offer opportunities for investors to capture the value premium in average returns by strategically allocating funds to targeted industry groups. Further, this essay adds to the findings of Banko and Conover by showing that the annual ranking of industry BE/ME appears to be relatively stable and potentially predictable for investors. Results also suggest that relatively poor returns generated by low BE/ME growth stocks may largely originate in a few persistently poor performing growth-oriented industry groups.

Tests of the value premium using industry segmented data adds to the debate in Loughran (1997) and Fama and French (2006) who both use aggregated market-wide data to determine whether the premium is pervasive across all size strata. Results in this essay show that the value premium disappears in large cap stocks both within and across industry sectors - consistent with results in Loughran (1997) and problematic for the explanatory power of the 3-factor model and a risk-based book-to-market effect. Indeed, During this unique return sample period covering the dotcom boom/bust/recovery period, the value premium is stronger in low BE/ME growth sectors, and value stocks in growth sectors outperform value stocks in value sectors - an outcome contrary to a risk-pricing thesis argued in Chen and Zhang (1998) as well as Banko and Conover (2006). But since growth industry sectors are found to simultaneously experience unusual distress conditions during the sample period, arguments by Banko and Conover that the value premium is a function of investor risk-pricing of distress cannot be rejected.

Next, results in the first essay show that a strong January anomaly exists in more recent time periods, thus confirming results in Haug and Herschey (2006). From an applied perspective, if the January anomaly is found to subsume the value premium, then investors would be better served to ignore the value premium and concentrate their strategies on capturing the seasonal anomaly. However, the average value premium computed across GICS industry sectors does not appear to be impacted by January returns. In fact, the average across-sector value premium is virtually identical when computed with, or without, January returns - contrary to findings in Loughran (1997). Results also show the value premium is not stronger in the eleven months, January excluded, as argued by Dhatt, Kim, and Mukherji (1999).

The second of the three essays asks whether the value premium exists in passive investment vehicles. Results in this essay are consistent with those in Houge and Loughran (2006) who observe that the value premium is absent at the index return level. Similarly, observations of a statistically significant value premium by Dhatt, Kim, and Mukherji (1999) in the Russell 2000 index constituents are not confirmed through tests of another set of competitive indexes. If the value premium does not exist in passive index returns or in returns of index constituencies themselves, then it is unlikely that investment managers - who use index benchmarks as effective investment universes – will easily capture the return premium identified in the academic literature.

The third of the three essays attempts to directly answer whether value investment managers can capture the premium in stock returns. This essay evaluates the nature of returns of the DFA Small Cap Value Fund, an existing market-based fund uniquely designed to capture the premium. Findings in this essay support those in Phalippou (2008) who suggests that the premium exists only in small, relatively illiquid stocks held by individual investors, not stocks available to large institutional investors. While the DFA Small Cap Value Fund is shown to operate with a philosophy and investment strategy consistent with evidence in academic research, the fund is nevertheless shown to fail in its attempt to capture the premium. The fund apparently suffers from many of Phalippou's predicted maladies when trading small, relatively illiquid stocks. Indeed, it is becoming clear that institutional funds will find it quite difficult (if not impossible) to capture the value premium promised in a long lineage of academic research.

Section 2: Remaining research questions on the value premium in managed portfolios

While the nature and origin of the value premium in average stock returns have been extensively studied over almost two decades, few studies have analysed the difference between value and growth

equity management techniques. Further light on the difference in equity style returns in applied portfolios might, in turn, shed light on earlier empirical tests of stocks in the academic literature. Future research might look at several questions to help reconcile the differences between what has been observed in academic work and what has been observed in industry. These questions include, 1) what characteristics differentiate growth from value in managed portfolios? 2) Who are value managers and how do they invest? 3) How do market and business cycles impact managed portfolio investment strategies and returns? And finally, 4) Are value mutual fund portfolios indeed riskier than growth portfolios?

2.1 Growth and value portfolio differences: the industry effect

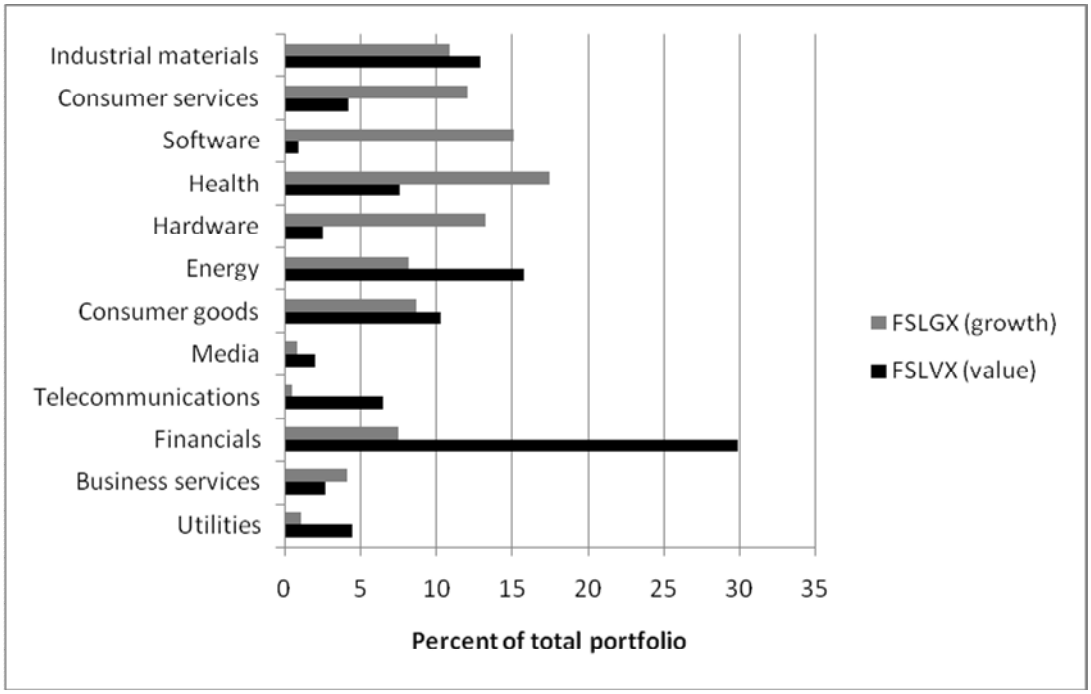
Value investment managers typically make relatively larger portfolio allocations to stocks in the financial, utilities, and industrial sectors while growth managers typically invest in technology, health care and telecommunications companies. Figure 2 shows a snapshot of portfolio sector weights at 30 September 2007 for two equity style mutual funds, the Fidelity Large Cap Value Fund (FSLVX) and the Fidelity Large Cap Growth Fund (FSLGX). As is typical, the value fund holds approximately 30% of its assets in high BE/ME financial stocks. The growth fund holds only about 7% of its portfolio in financials. Conversely, the growth fund holds considerably larger positions of its portfolio in traditionally low BE/ME sectors such as software, hardware, and health care.

The fundamental driver of these allocations is clearly related to the managers' investment methodology and screening techniques. Value managers often use metrics such as BE/ME or P/E while growth managers use metrics such as price-to-earnings growth rate ratios. However, these ultimate portfolio allocations beg the question, what is the actual driver of return differences in these portfolios, the underlying screening variable such as BE/ME (or a common risk factor for which it acts as a proxy) or the differing industry risks resulting from these screens?

An industry effect has been widely tested in explanatory market models as in Hamelink (2001) and Kuo and Satchell (2001). However, research thus far has largely excluded the industry effect as a superior explanatory variable to BE/ME in the cross section of average stock returns. A question remains whether a better explanation of different style performance in managed portfolios can be found in sector allocations where actively managed growth and value portfolios typically reveal consistently different sector clustering over time.

FIGURE 2: Sector Clustering - Fidelity Large Cap Growth Fund vs. Fidelity Large Cap Value Fund at 30 September 2007

Snapshot of portfolio sector weights at 30 September 2007 for two equity style mutual funds, the Fidelity Large Cap Value Fund (FSLVX) and the Fidelity Large Cap Growth Fund (FSLGX). Data Source: Morningstar Inc.



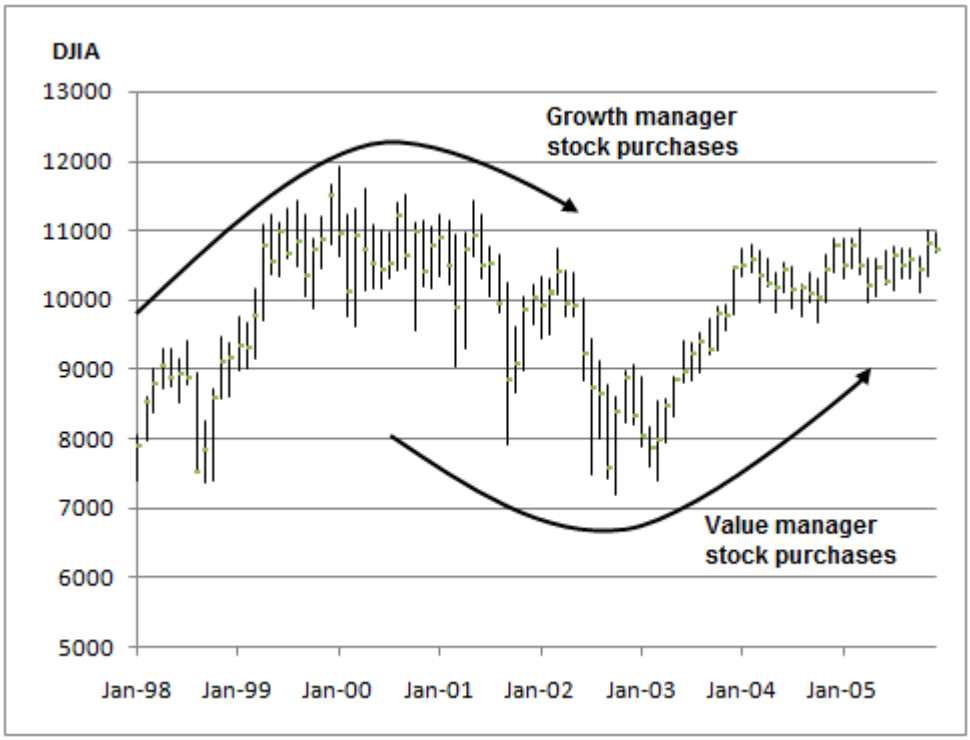
2.2 How do equity style investment management techniques differ?

Much of the discussion about investment methods with respect to equity style has not appeared in academic literature but has appeared in industry publications and mass media press. The work of Benjamin Graham is a notable early example. Within academic journals, investment methods have been addressed by Chen, Jagadeesh, and Wermers (2000) who use US mutual fund stockholdings to evaluate stock selection skills by growth and value managers in a performance attribution exercise. Using a behavioural emphasis, Chen et al. evaluate whether growth managers possess any unique ability to select underpriced growth stocks. But, identifying how value managers invest and what type of stocks they tend to buy (or tend not to buy) may help explain the authors' research outcomes and why managers may or may not be able to capture the value premium.

Another research question might evaluate key traits that differentiate the two styles of management, namely portfolio turnover rates and the timing of buys and sells in various market

cycles.[94] The traditional view by professional investors is that value managers purchase stocks earlier in a down market cycle than their growth counterparts. Value managers also tend to sell earlier in an up market cycle. Figure 3 illustrates this thesis on a chart of the Dow Jones Industrial Average for the dotcom boom and bust stock market cycle. Any meaningful difference in timing could shed considerable light on why value and growth manager returns appear to be equal over long periods of time, but differ considerably in shorter evaluation periods.

FIGURE 3: Theorized timing of value and growth manager trading activity over varying market cycles. Dow Jones Industrial Average between January 1998 and December 2005



Data for the DJIA from Dow Jones, Inc.

[94] The industry definition of value and growth management is unfortunately not homogeneous. For example, the 2000 CFA Level III exam materials on portfolio management list sub-styles for value as low P/E, contrarian, and yield, and consistent-growth and momentum-growth for growth sub-styles. Other sources such as S&P list dramatically different value and growth management sub-styles.

2.3 Do value managers buy the right stocks?

Davis (2001) tests growth and value funds for abnormal returns. Chan et al. (2002) and Brown and Harlow (2002) test growth and value funds for style consistency, and Teo and Woo (2001) and Ibbotson and Patel (2002) test growth and value funds for style adjusted winner persistence. Few papers, however, actually evaluate fundamental fund characteristics that may drive observations found in the above research. Uniquely, Faugere, Shawky, and Smith (2006) observe the P/E, P/B, and earnings growth characteristics of 4,754 US mutual funds between 2001 and 2003 and find that value funds hold stocks with "significantly higher financial leverage" than growth funds. This is not a surprise.

The question of leverage is only one issue that could facilitate the reconciliation between outcomes suggested by risk-based advocates of the value premium and what has been observed in managed portfolios. Fund holdings could be statistically mapped to the Fama and French BE/ME quintile portfolio constituents. Using this information, findings in Chan et al. (2002) could be confirmed that value and growth managers do not stray far from major benchmark indexes. Moreover, results from this examination might show that value fund portfolios omit certain distressed stocks shown to be associated with higher average returns. This outcome would confirm findings by Phalippou (2008) that stocks held by institutional investors do not exhibit the value premium. Mapping portfolio holdings may begin to reconcile how a value premium can be observed in high and low BE/ME stocks themselves, but not captured in managed portfolios to date, and more importantly, may provide industry participants with a path to capture the premium. In other words, can *deep value* managers succeed where their mainstream value counterparts have apparently failed?

2.4 Do UK investment managers capture the value premium?

Few academic studies evaluate the value premium in non-US managed portfolios. Uniquely, Ainsworth, Fong, and Gallagher (2008) observe style drift in Australian equity fund characteristics. Quigley and Sinquefield (2000) evaluate HML factor loadings for all UK unit trusts. Dimson, Nagel, and Quigley (2003) ask whether investors can capture the value premium in non-US markets, but the authors evaluate the premium in individual UK stocks rather than in market-based UK unit trusts. A UK market extension of Houge and Loughran (2006) specifically asking whether UK unit trust managers can capture the value premium would be valuable for two reasons. First, like Davis, Fama, and French (2000) who test longer periods of stock returns to confirm that the value premium is not sample dependent, an evaluation of UK unit trust performance will potentially expose time varying or market specific factors relating to the question of capturing the value premium. Second, investment methodologies employed

by UK value manager are often materially different from their US counterparts. UK managers often rely more heavily on macroeconomic inputs for their portfolio allocations. If UK trust managers are found to have historically captured the value premium while their US counterparts have not done so, then further investigation of the methodological differences would be of high importance to market participants.

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